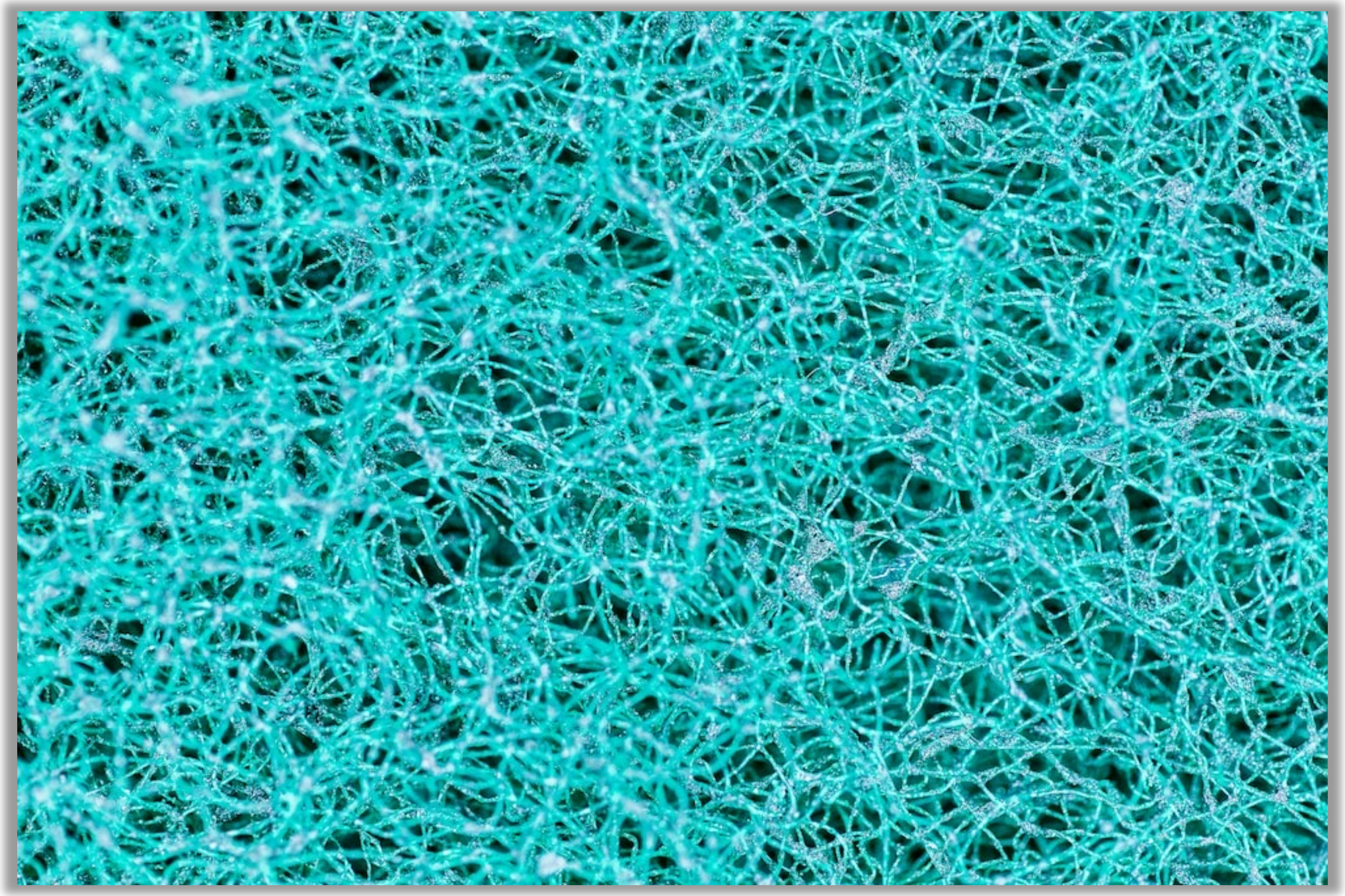
Intro to Deep Learning

neural networks, CNNs, backpropagation



CSC420
David Lindell
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cs.toronto.edu/~lindell/teaching/420
Slide credit: Babak Taati ←Ahmed Ashraf ←Sanja Fidler

TCIG Toronto Computational Imaging Group

Logistics

- HW2 is out, due in 3 weeks

Overview

- Motivation
- Fully-connected Networks
- Convolutional Neural Networks
- Training networks

The Recognition Tasks

- Let's take some typical tourist picture. What all do we want to recognize?

[Adopted from S. Lazebnik]

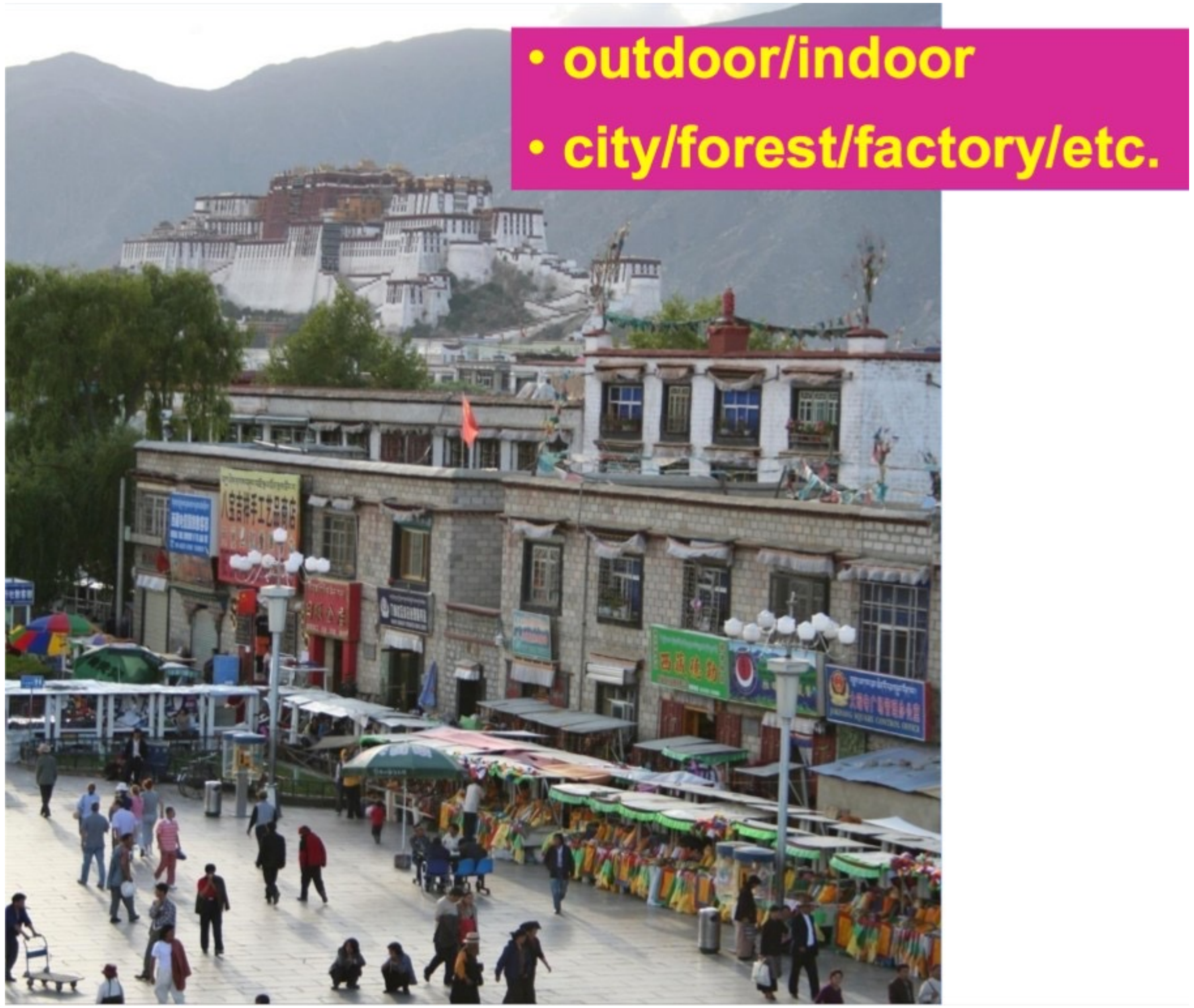
The Recognition Tasks

- Identification

[Adopted from S. Lazebnik]

The Recognition Tasks

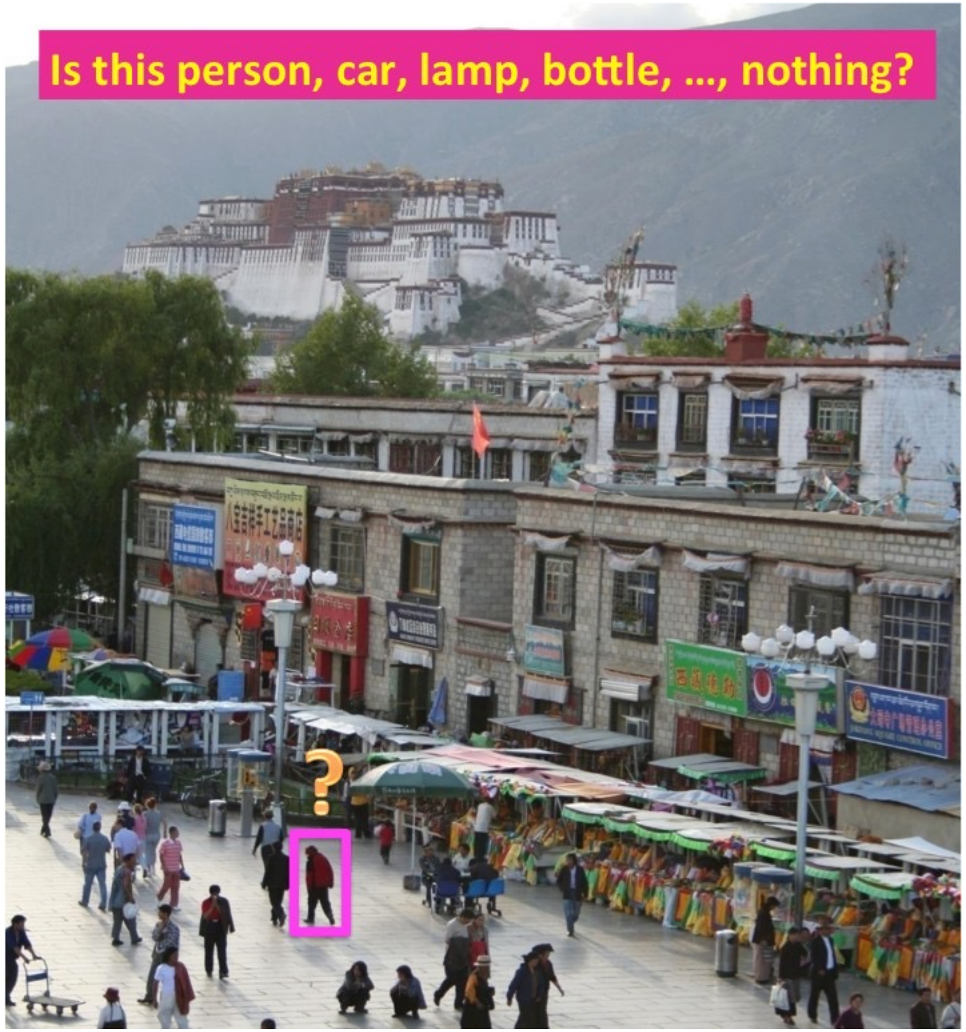
- Scene classification: what type of scene is the picture showing?



[Adopted from S. Lazebnik]

The Recognition Tasks

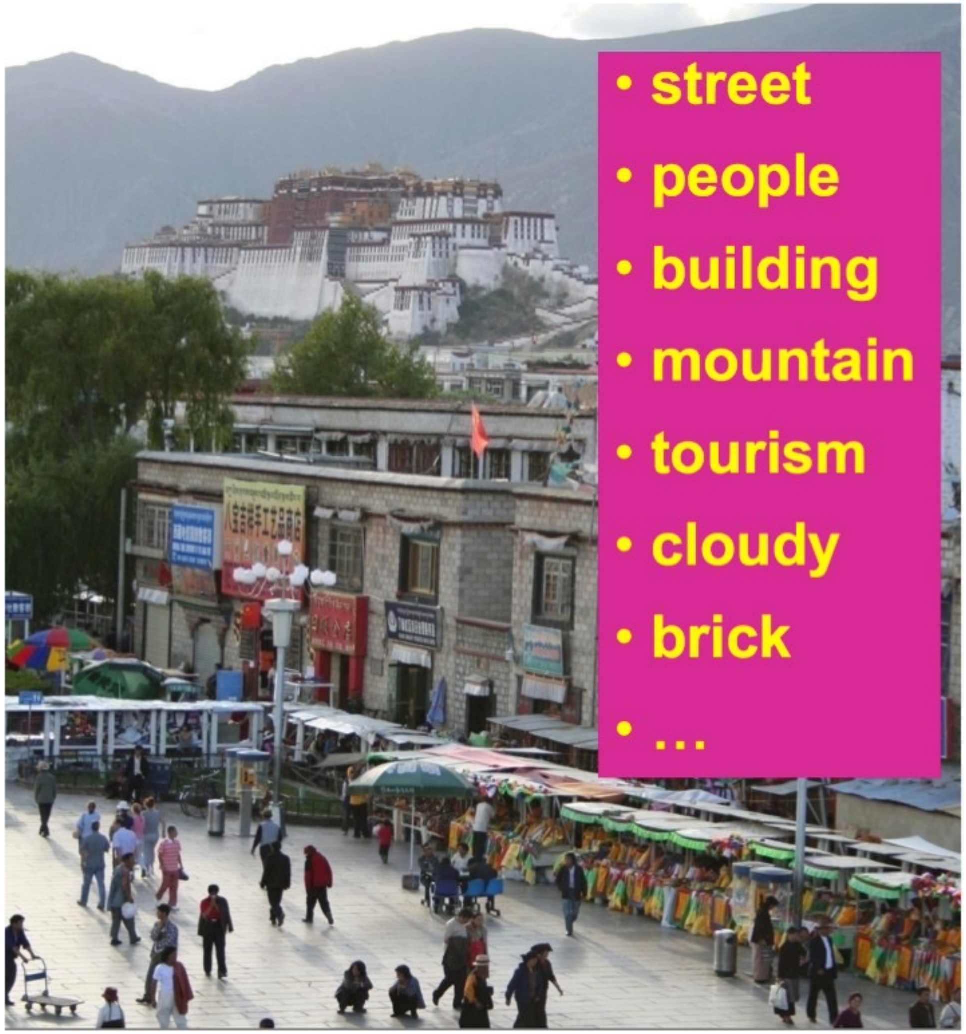
- Classification: Is the object in the window a person, a car, etc



[Adopted from S. Lazebnik]

The Recognition Tasks

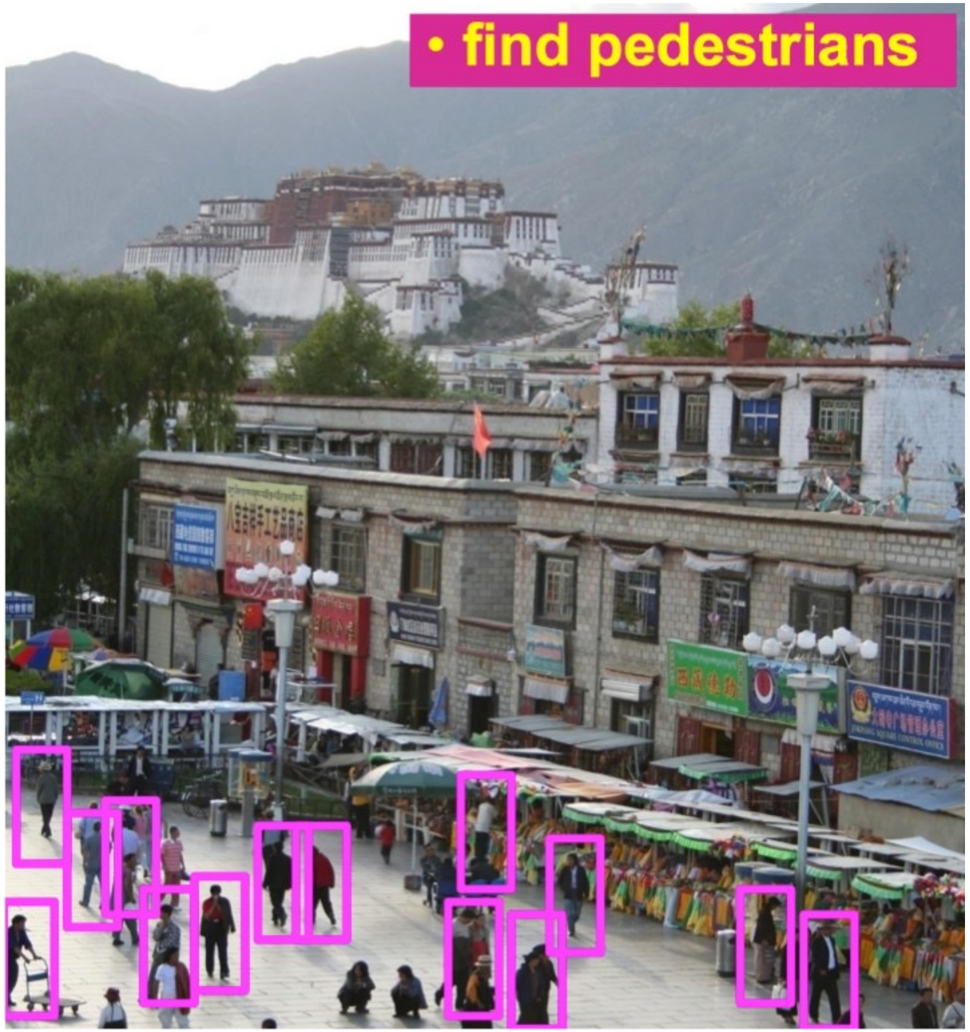
- Image Annotation: Which types of objects are present in the scene?



[Adopted from S. Lazebnik]

The Recognition Tasks

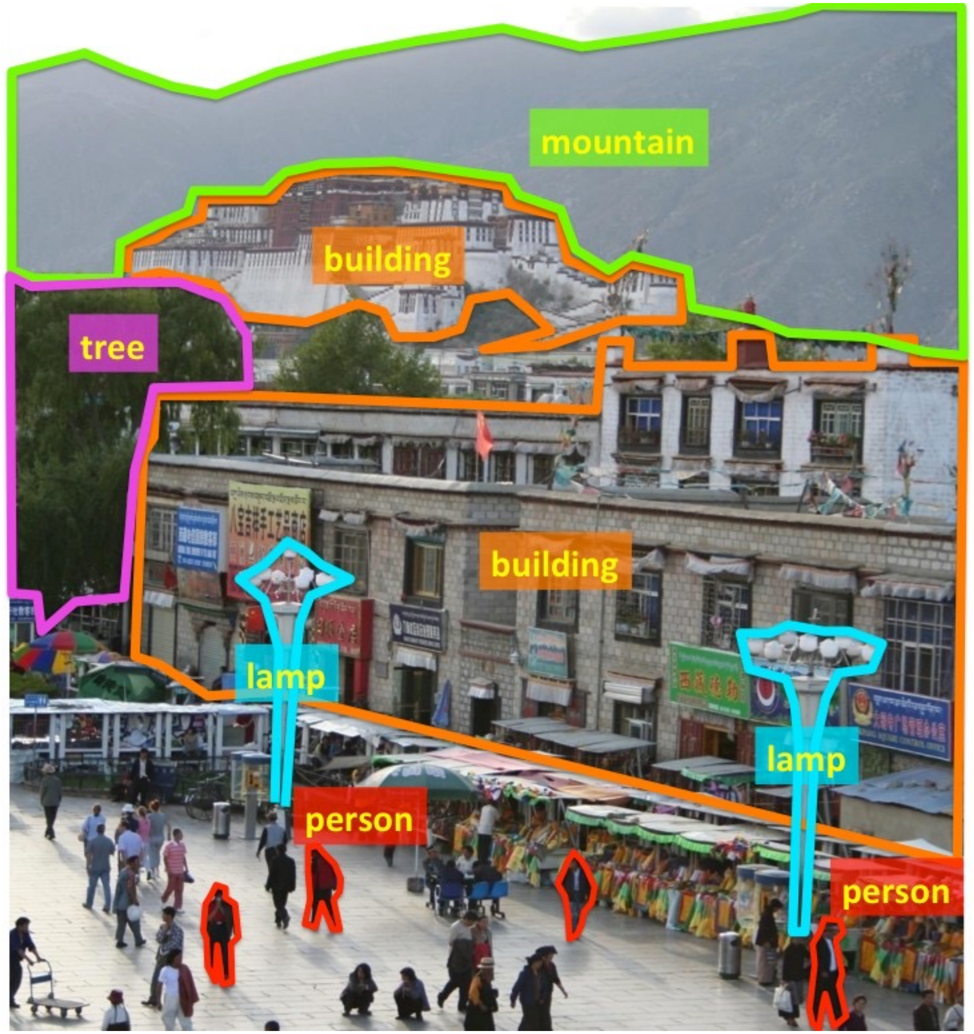
- Detection: Where are all objects of a particular class?



[Adopted from S. Lazebnik]

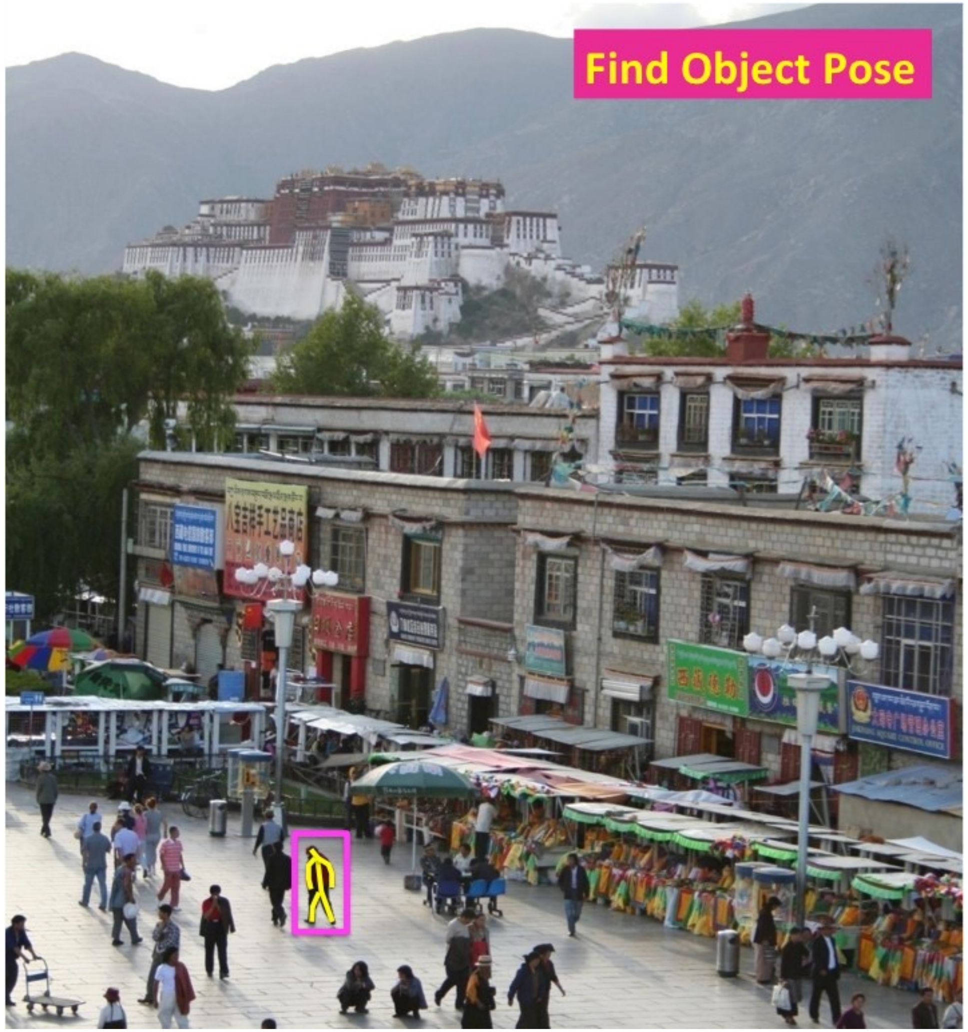
The Recognition Tasks

- Segmentation: Which pixels belong to each class of objects?



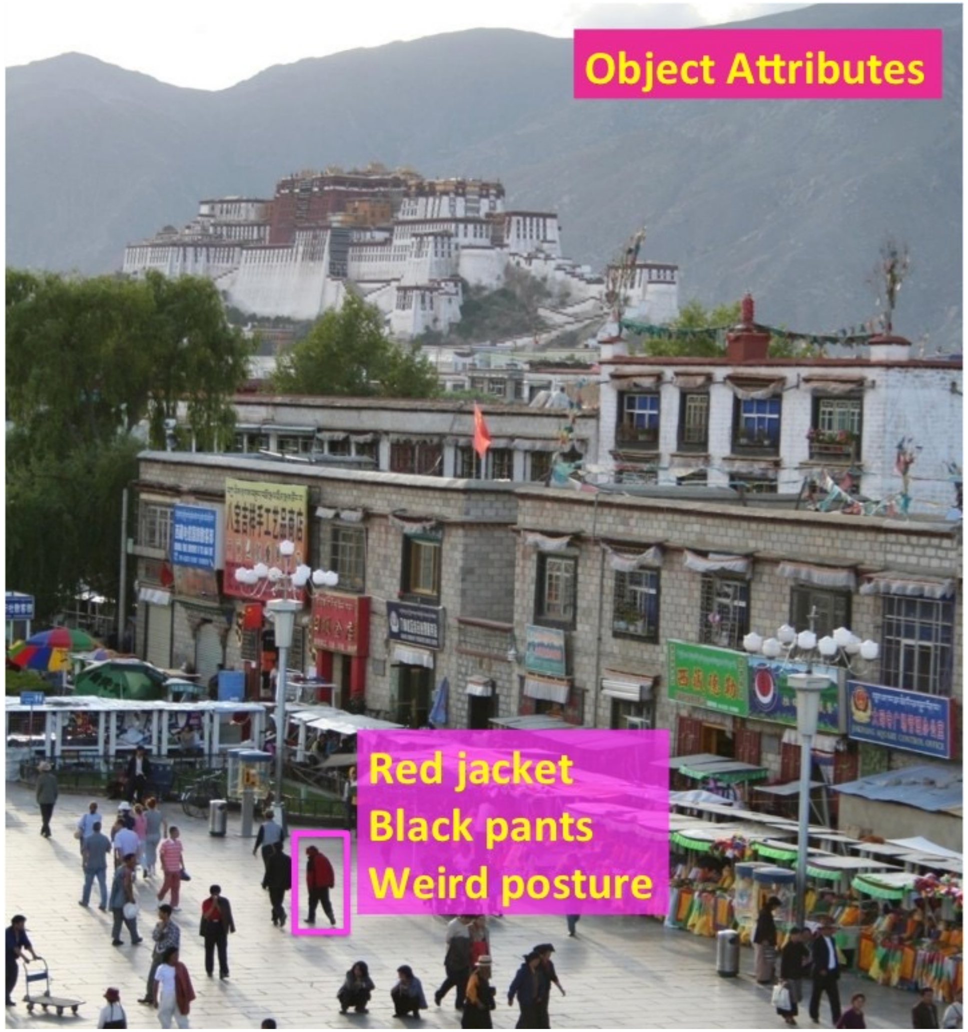
The Recognition Tasks

- Pose estimation: What is the pose of each object?



The Recognition Tasks

- Attribute recognition: Estimate attributes of the objects (color, size, etc)



The Recognition Tasks

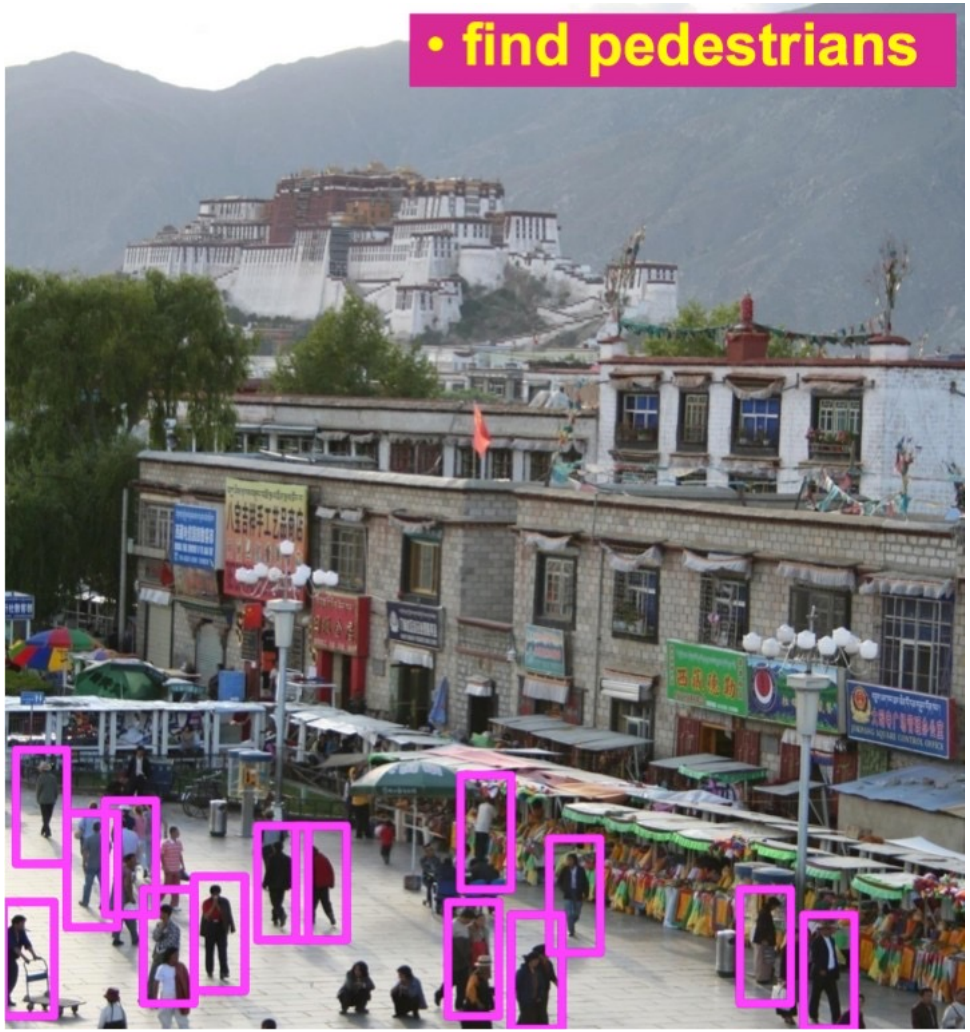
- Action recognition: What is happening in the image?

The Recognition Tasks

- Surveillance: Why is something happening?

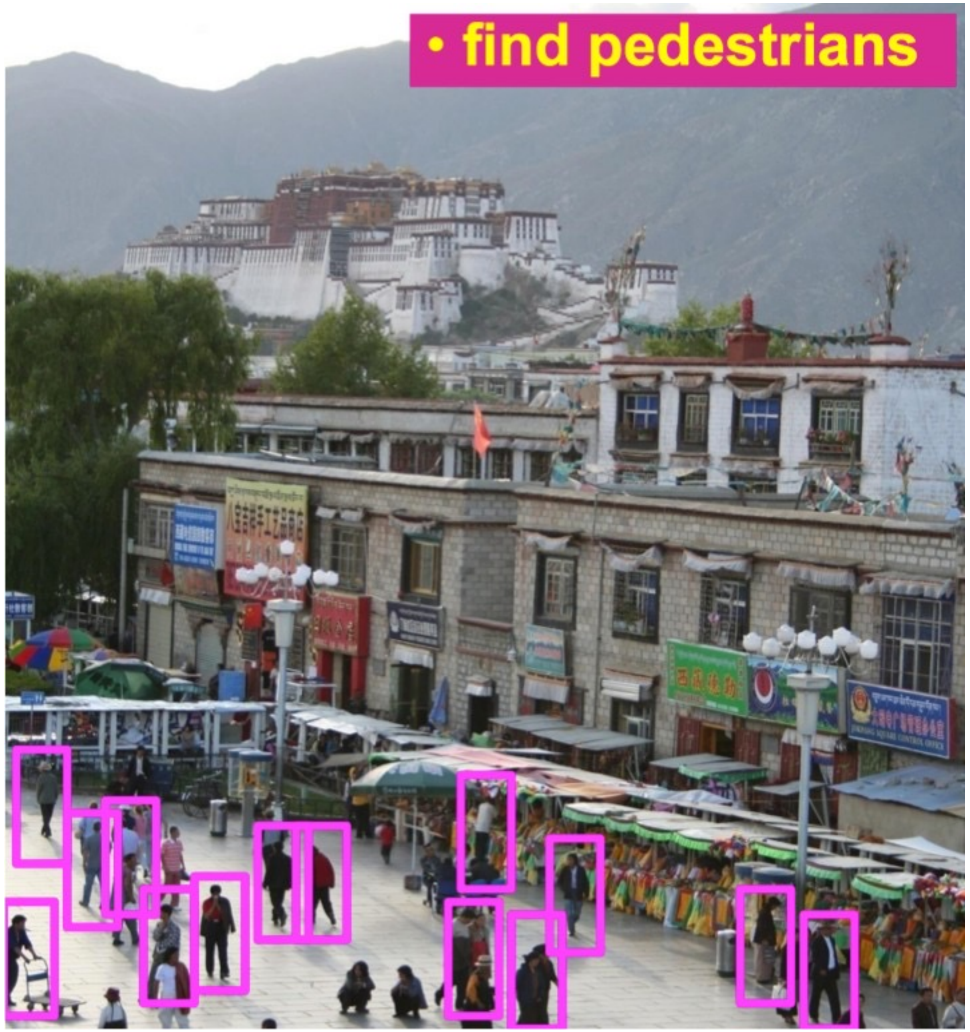
Have we encountered these things before?

- Before we proceed, let's first give a shot to the techniques we already know
- Let's try detection (how?)



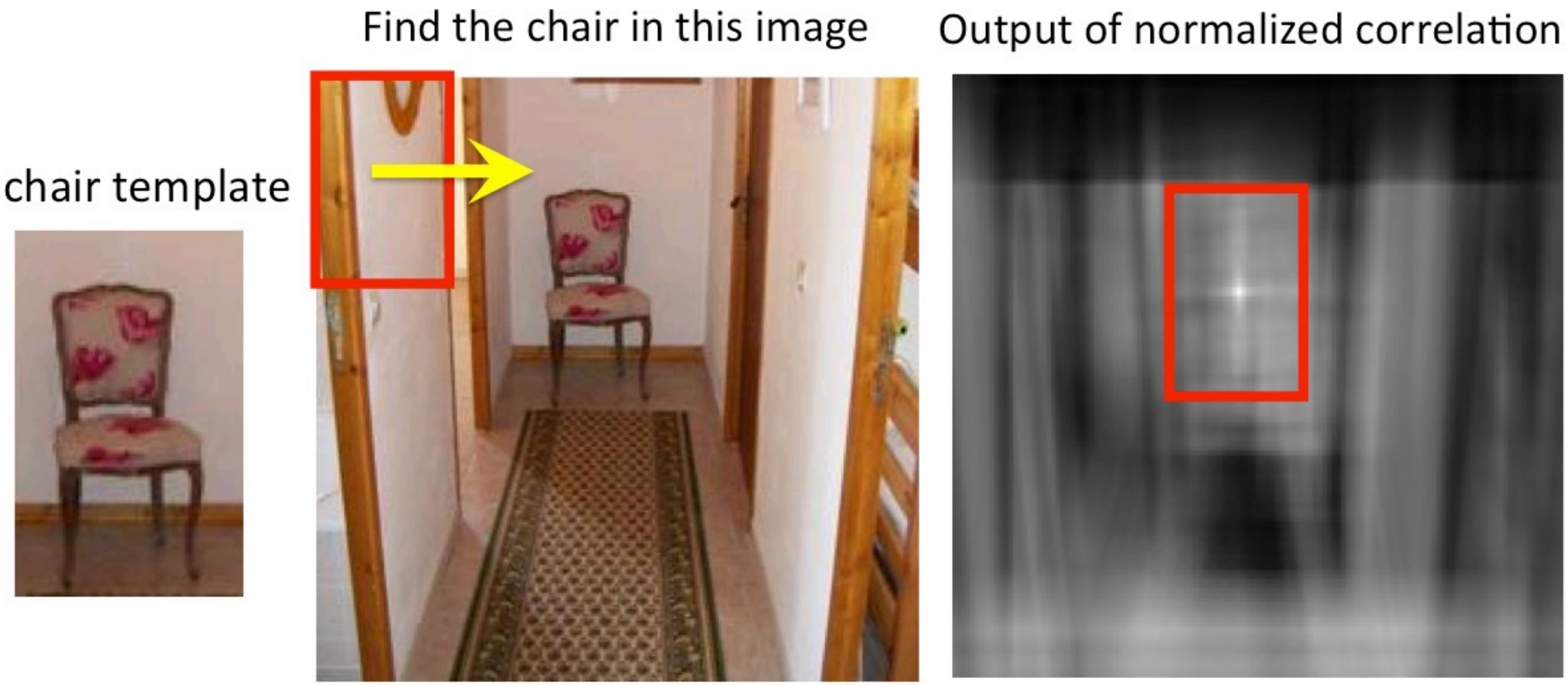
Have we encountered these things before?

- Before we proceed, let's first give a shot to the techniques we already know
- Let's try detection (how?)
- Example techniques:
  - Template matching (remember Waldo in Lecture 3-5?)
  - Large-scale retrieval: store millions of pictures, recognize new one by finding the most similar one in database. This is a Google approach.



Template Matching

- Template matching: normalized cross-correlation with a template (filter)



[Slide from: A. Torralba]

Template Matching

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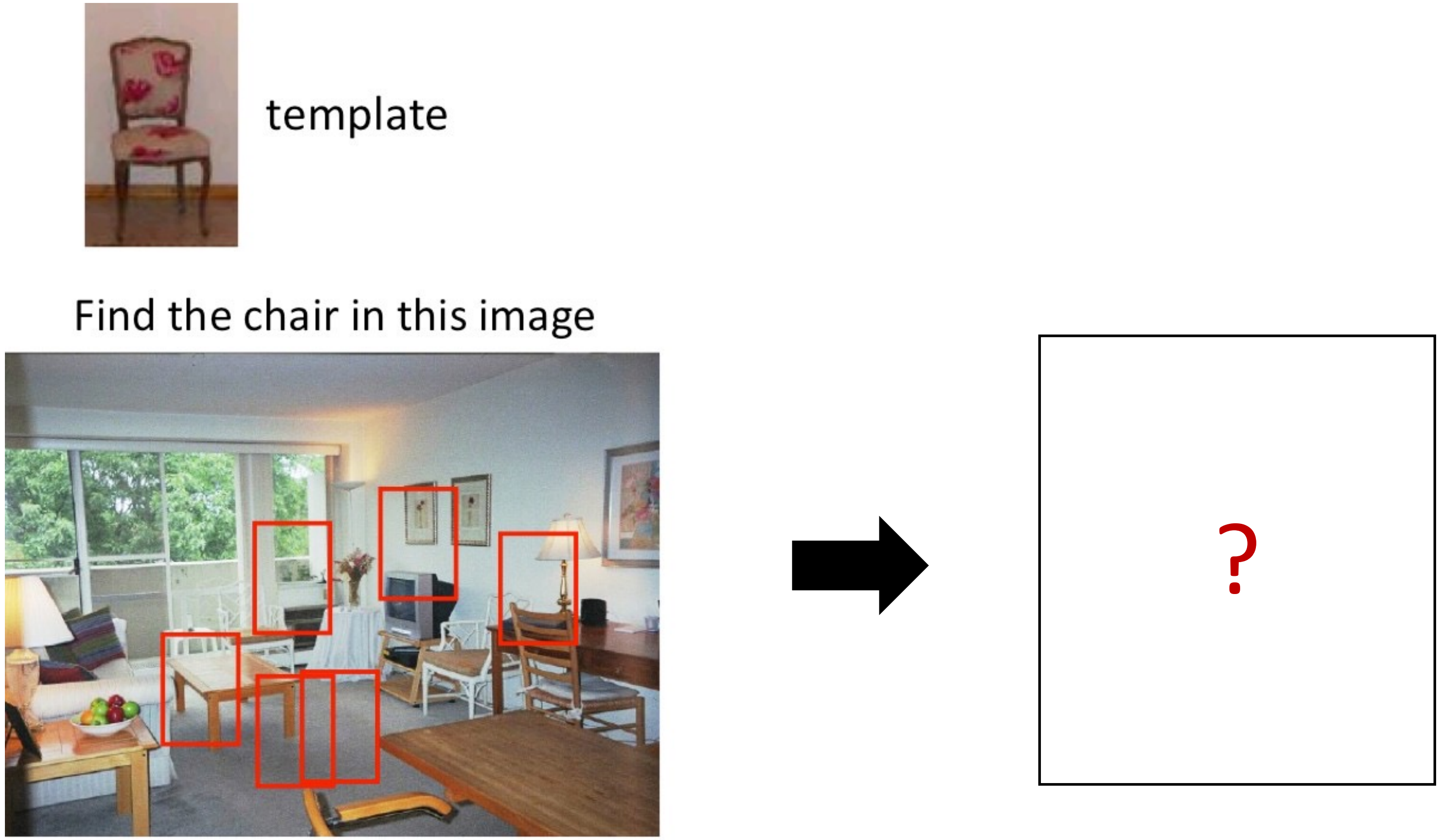


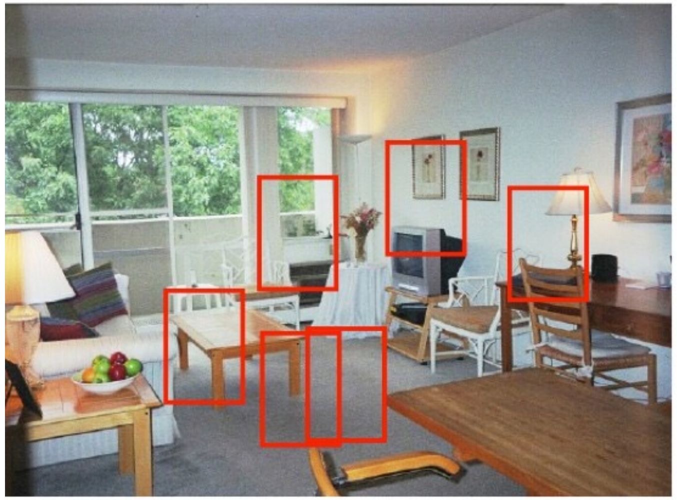
[Slide from: A. Torralba]

Template Matching

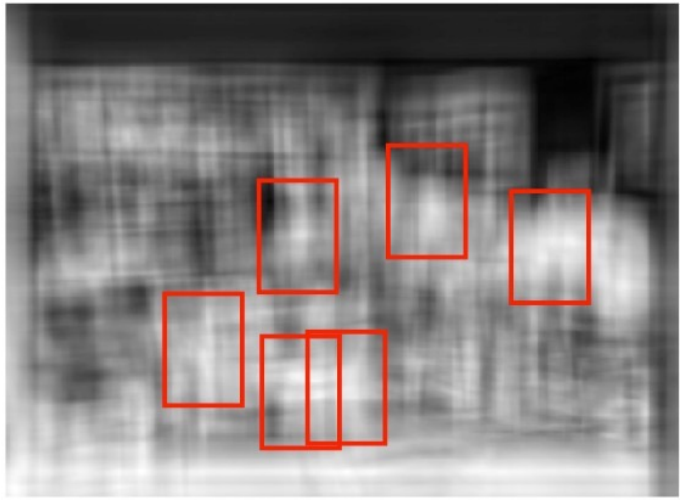
- Template matching: normalized cross-correlation with a template (filter)

template

Find the chair in this image



Pretty much garbage
Simple template matching is not going to make it



why?

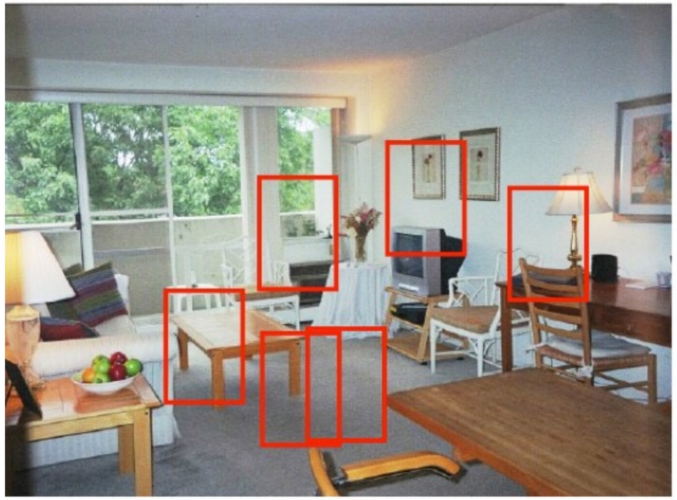
[Slide from: A. Torralba]

Template Matching

- Template matching: normalized cross-correlation with a template (filter)

template

Find the chair in this image



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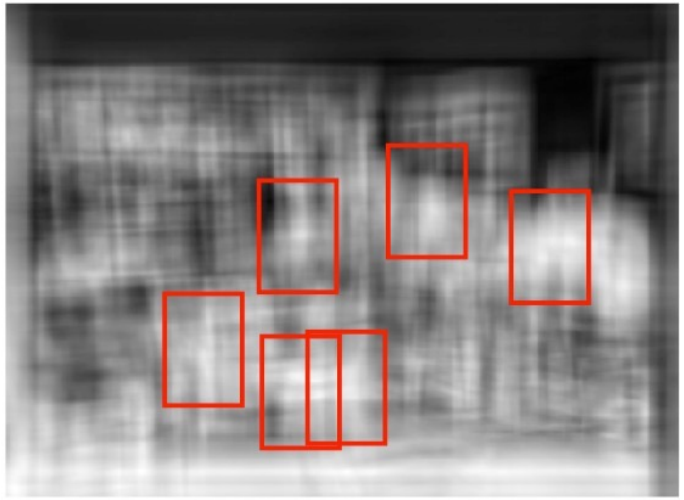
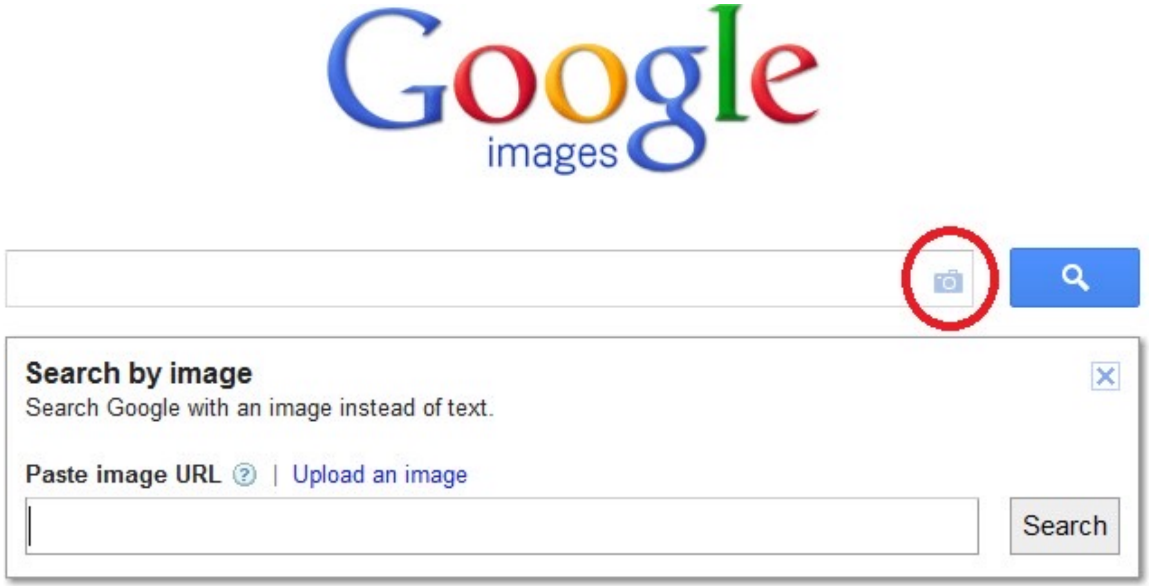


A "popular method is that of template matching, by point to point correlation of a model pattern with the image pattern. These techniques **are inadequate for three-dimensional scene analysis for many reasons, such as occlusion, changes in viewing angle, and articulation of parts**." Nevatia & Binford, 1977.

[Slide from: A. Torralba]

Recognition via Retrieval by Similarity

- Upload a photo to Google image search and check if something reasonable comes out



query

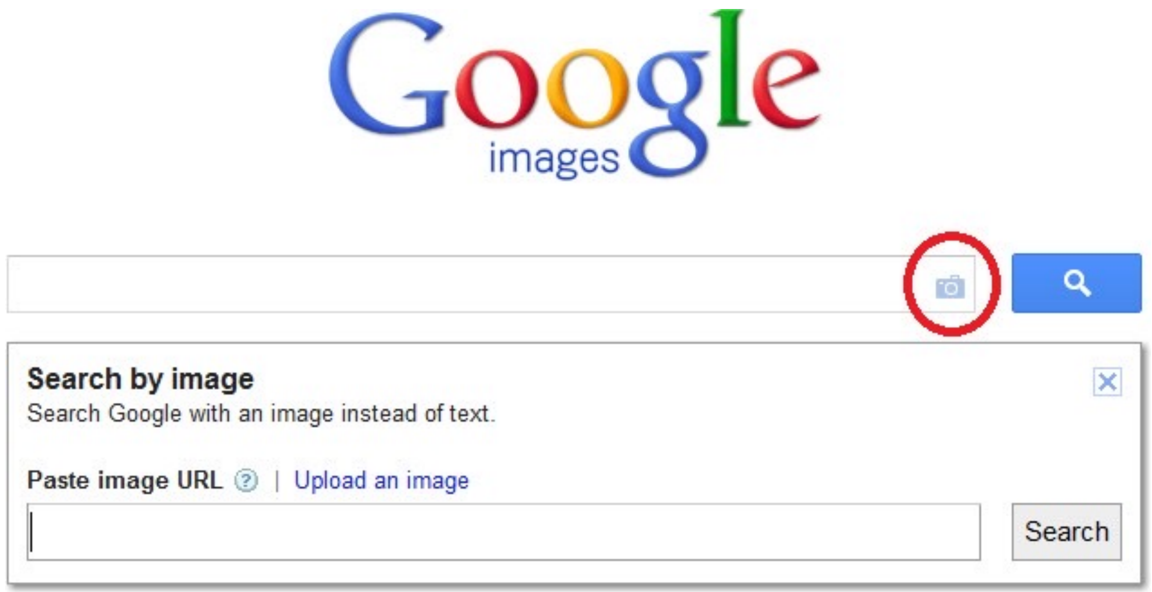
Recognition via Retrieval by Similarity

- Upload a photo to Google image search
- Pretty reasonable, both are Golden Gate Bridge

query

Recognition via Retrieval by Similarity

- Upload a photo to Google image search Let’s try a typical bathtub object



query

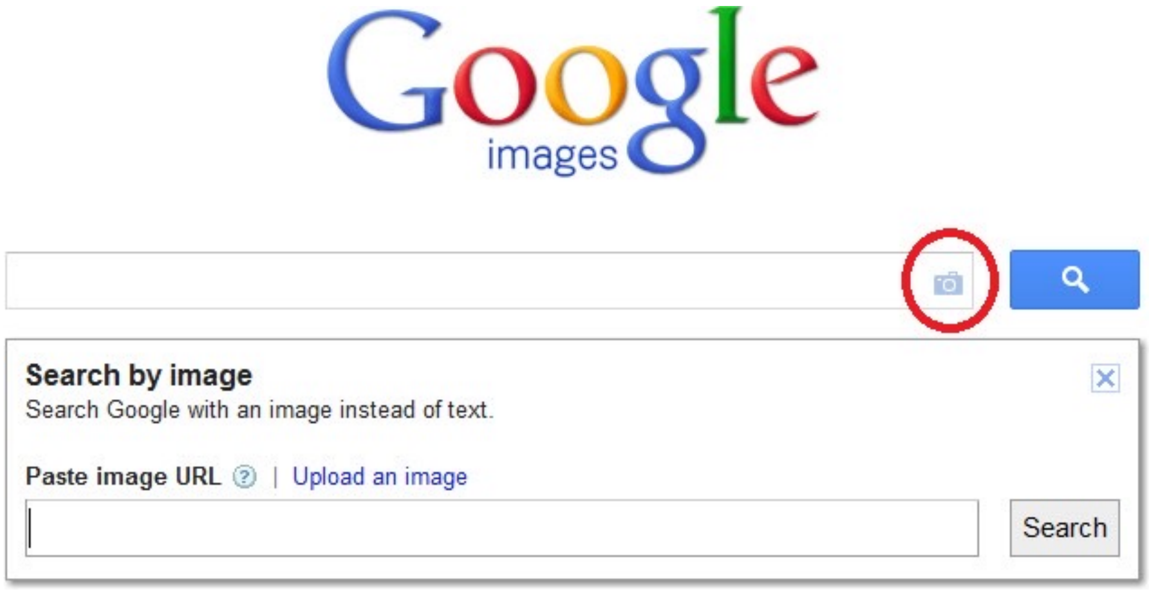
Recognition via Retrieval by Similarity

- Upload a photo to Google image search
- A bit less reasonable, but still some striking similarity

query

Recognition via Retrieval by Similarity

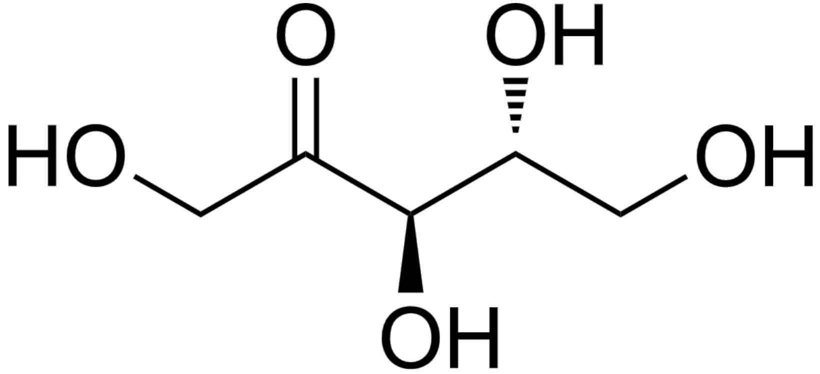
- Make a beautiful drawing and upload to Google image search
- Can you recognize this object?



query

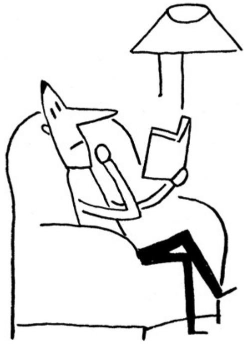
Recognition via Retrieval by Similarity

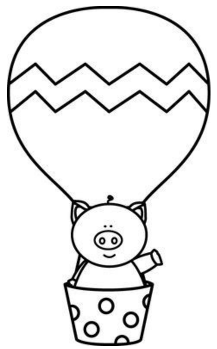
- Make a beautiful drawing and upload to Google image search
- Not a very reasonable result



query

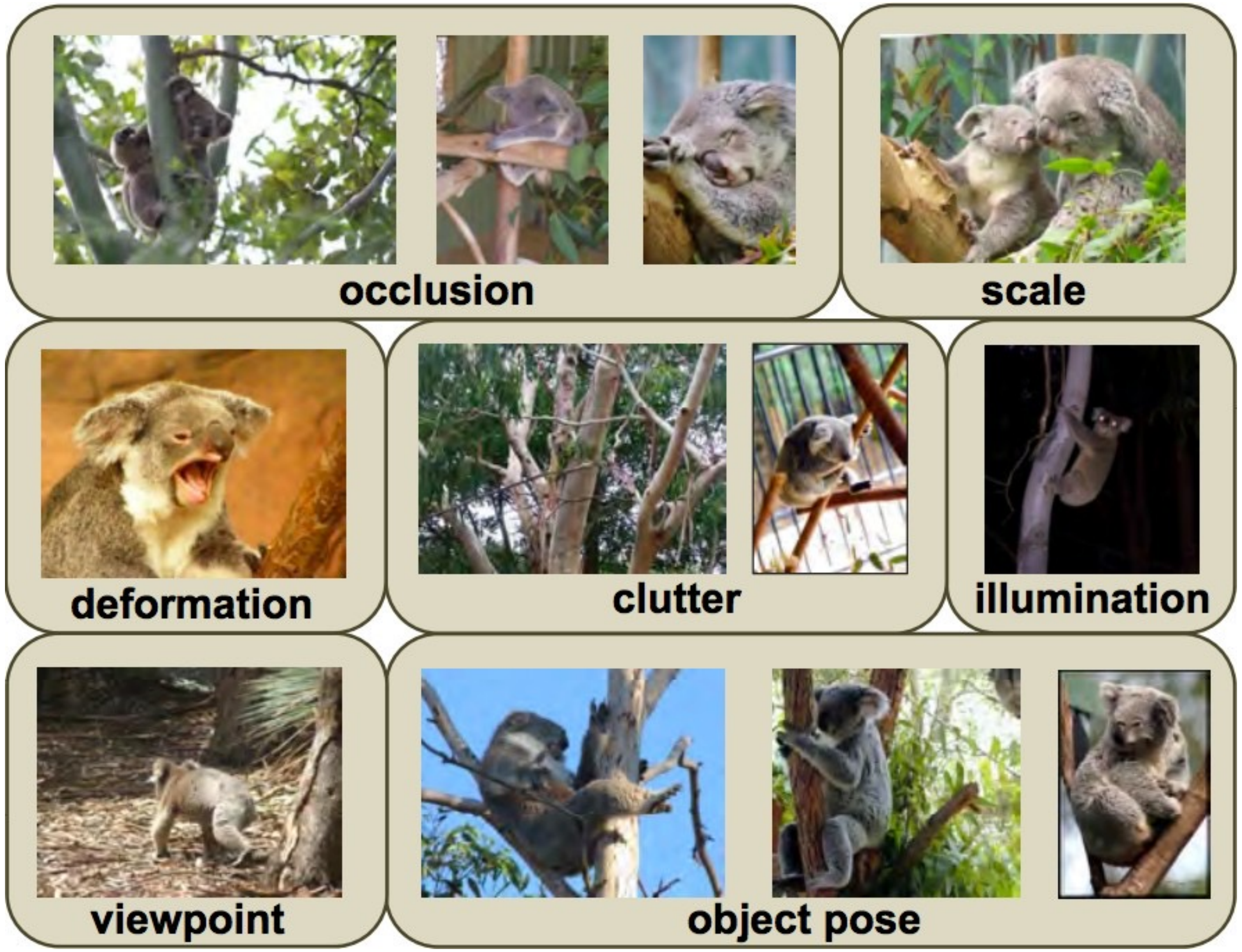
other retrieved results:





Why is it a Problem?

- Difficult scene conditions



[From: Grauman & Leibe]

Why is it a Problem?

- Huge within-class variations. Recognition is mainly about modeling variation.

[Pic from: S. Lazebnik]

Why is it a Problem?

- Tons of classes

Biederman

Overview

- We cannot explicitly model these variations!

Overview

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- Instead our models should be relatively simple and we should learn let complexity live in the data

Overview

- We cannot explicitly model these variations!
- Instead our models should be relatively simple and we should learn let complexity live in the data
- Neural networks follow this paradigm

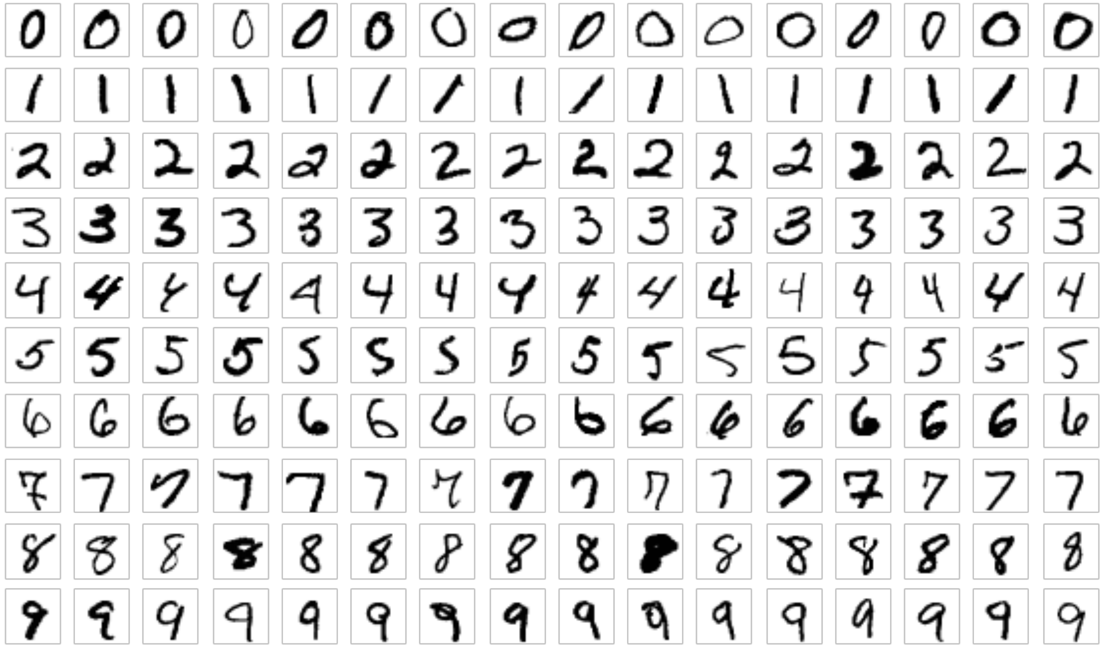
Overview

- Motivation
- Fully-connected Networks
- Convolutional Neural Networks
- Training networks

Image Classification

- Image classification example

Images

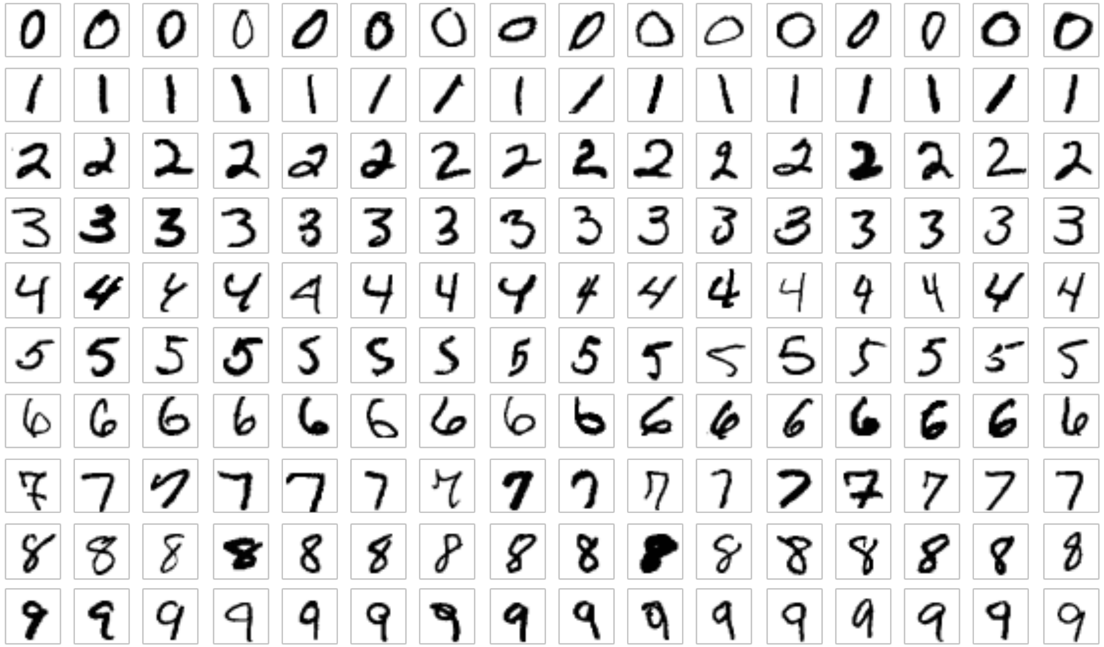


MNIST Dataset

Image Classification

- Image classification example

Images



Class

"zero"
"one"

…

"nine"

Image Classification

- Image classification example

What the computer "sees"

Images

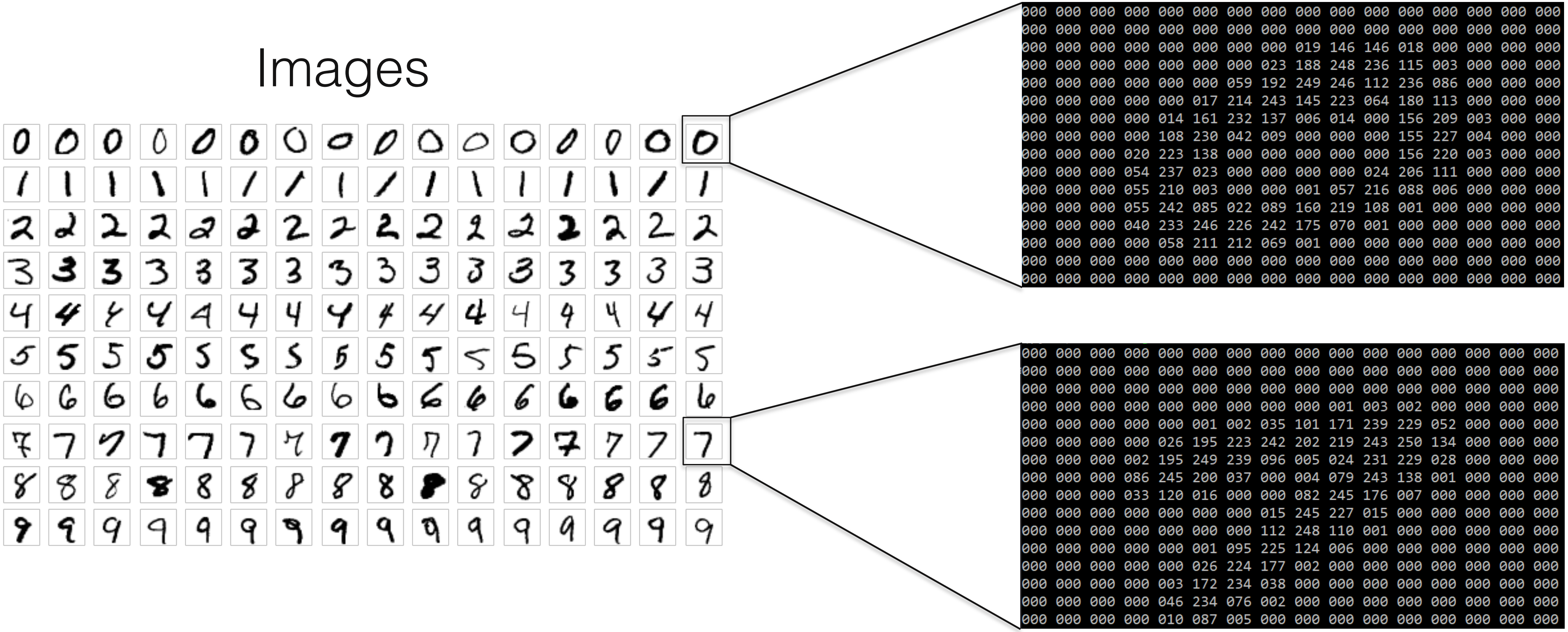
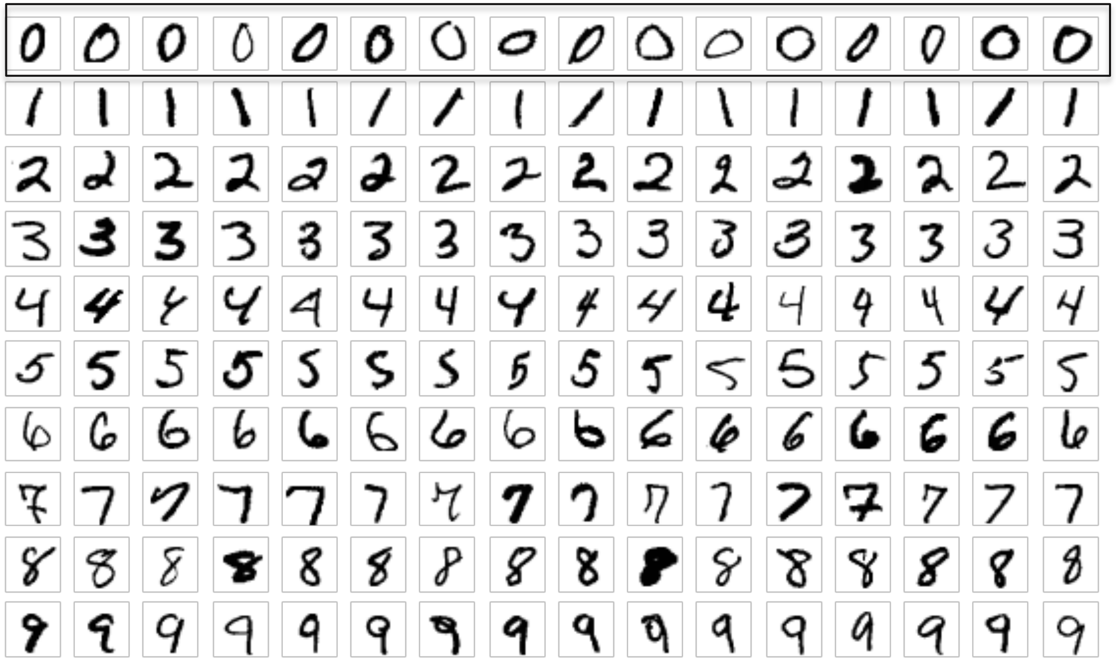


Image Classification

- Image classification example

Images



Challenges

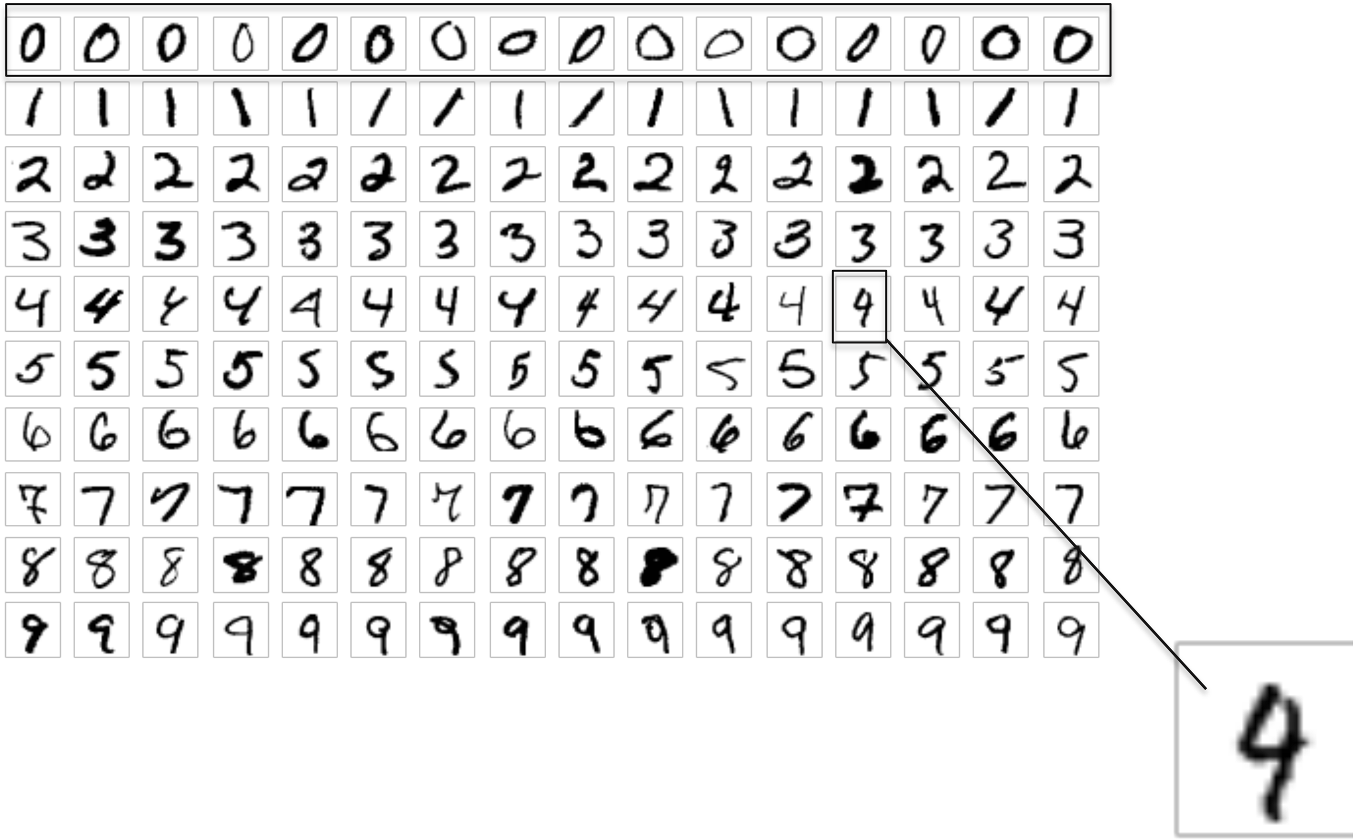
Intra-class variation

- stroke widths
- alignment
- writing styles

Image Classification

- Image classification example

Images



Challenges

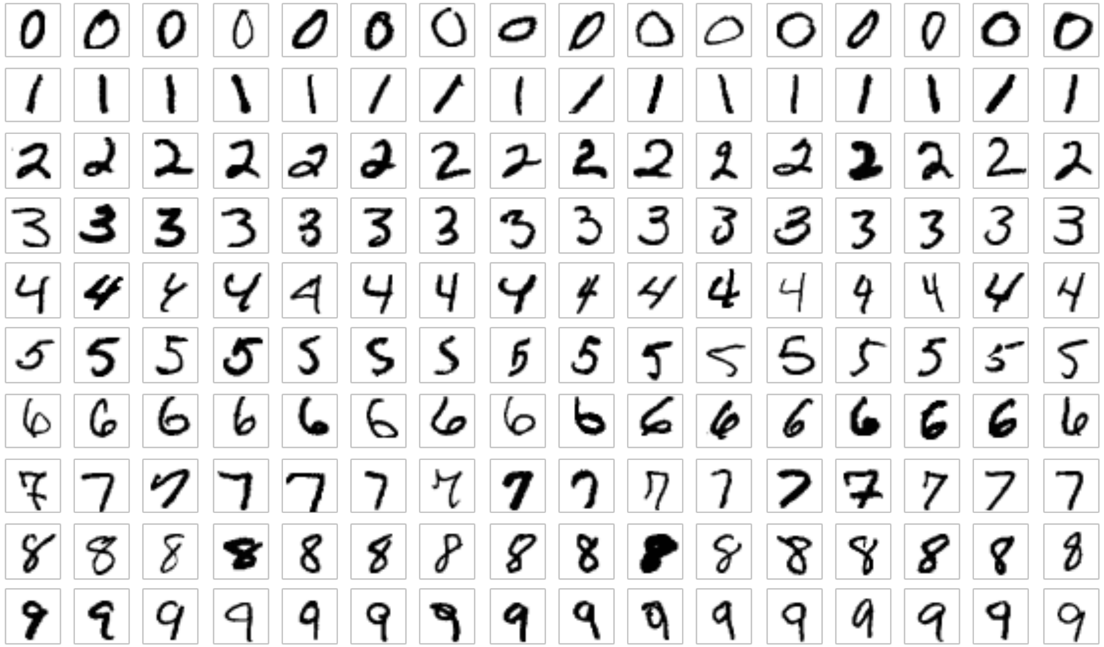
Intra-class variation
- stroke widths
- alignment
- writing styles

Inter-class similarities
- “four” or “nine”?

Image Classification

- Image classification example

Images



Implementation?

```
def classify_digit(image):
    # ???
    return image_class
```

Can’t hardcode solution!

Image Classification

- Data-driven approach
  - Collect training images and labels
  - Train a classifier using machine learning
  - Evaluate the classifier on unseen images

Implementation?

```
def train(images, labels):
    # machine learning model
    return image_class

def evaluate(model, test_images):
    # machine learning model
    return test_labels

```

Image Classification

- Linear Model $f(x, W) = Wx$

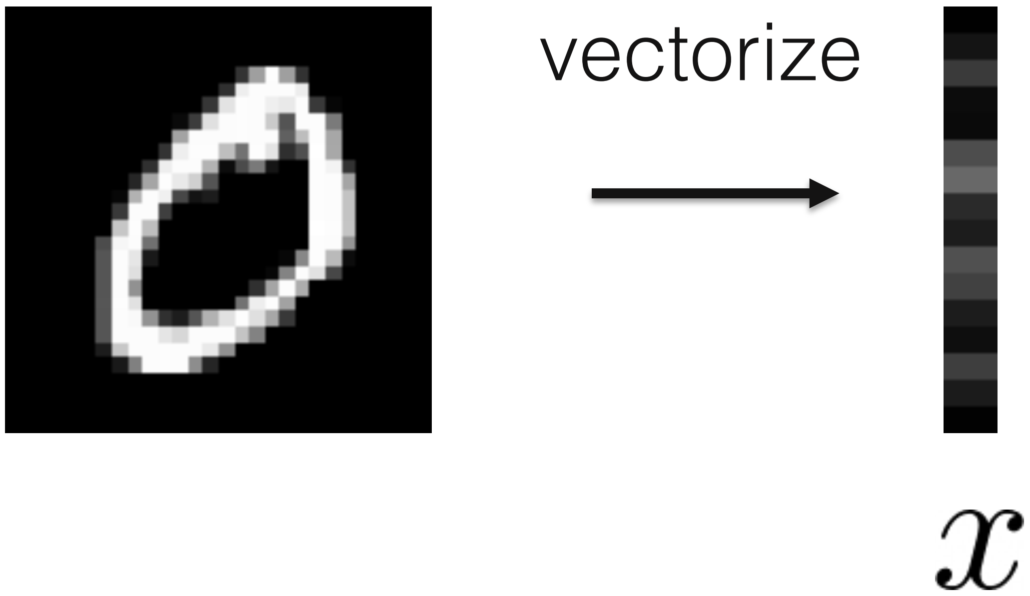


Image Classification

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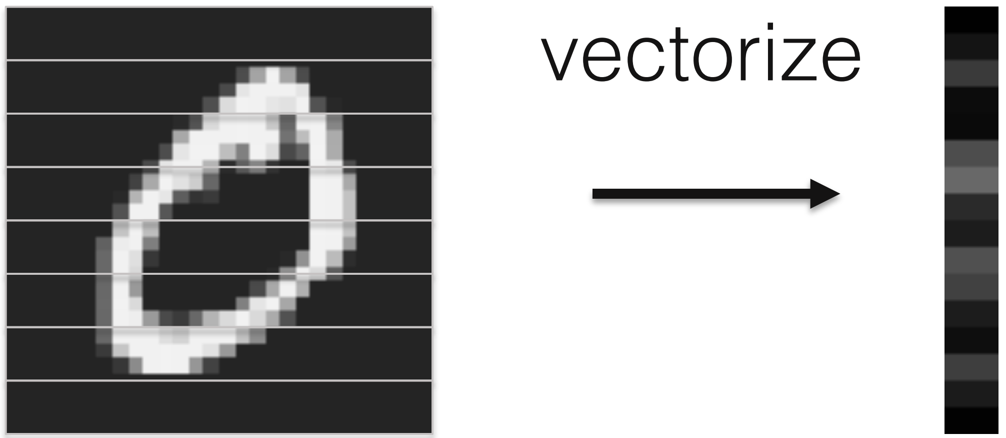
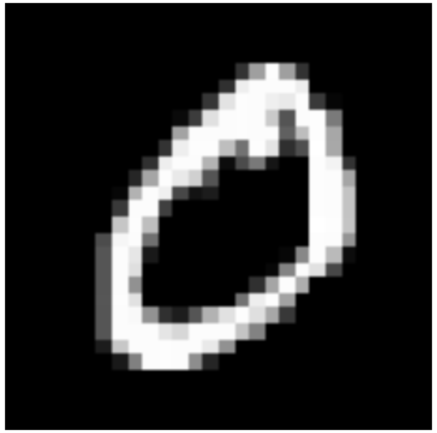


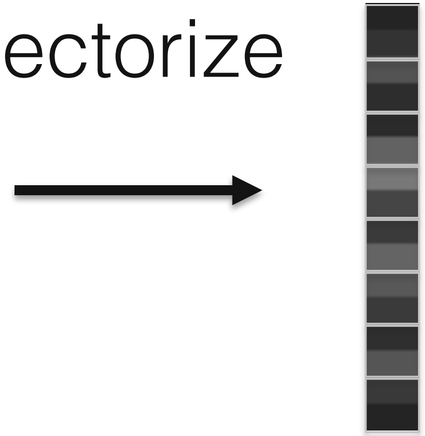
x

Image Classification

- Linear Model $$f(x, W) = Wx$$



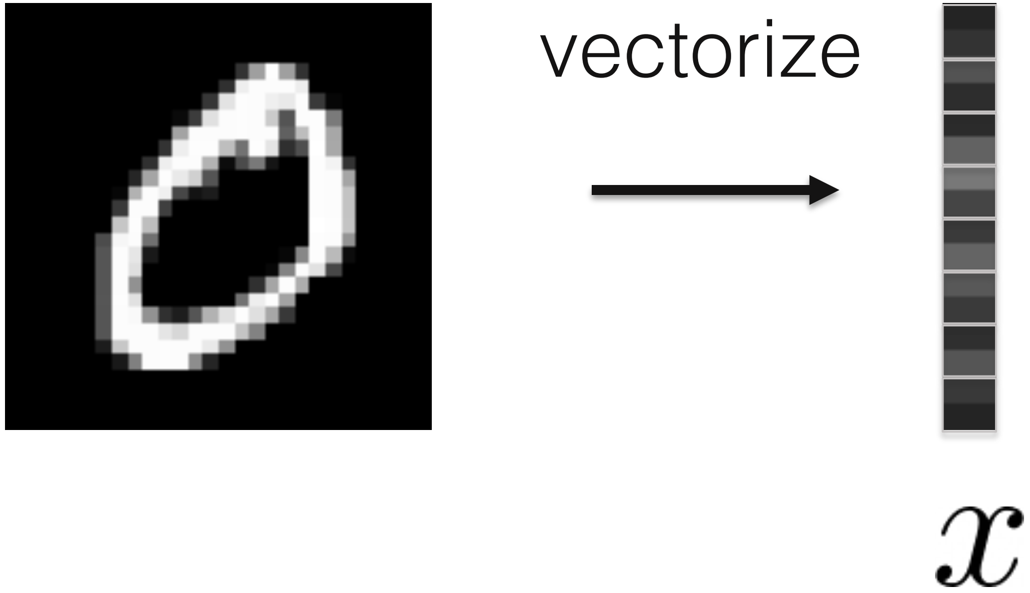
vectorize



$$x$$

Image Classification

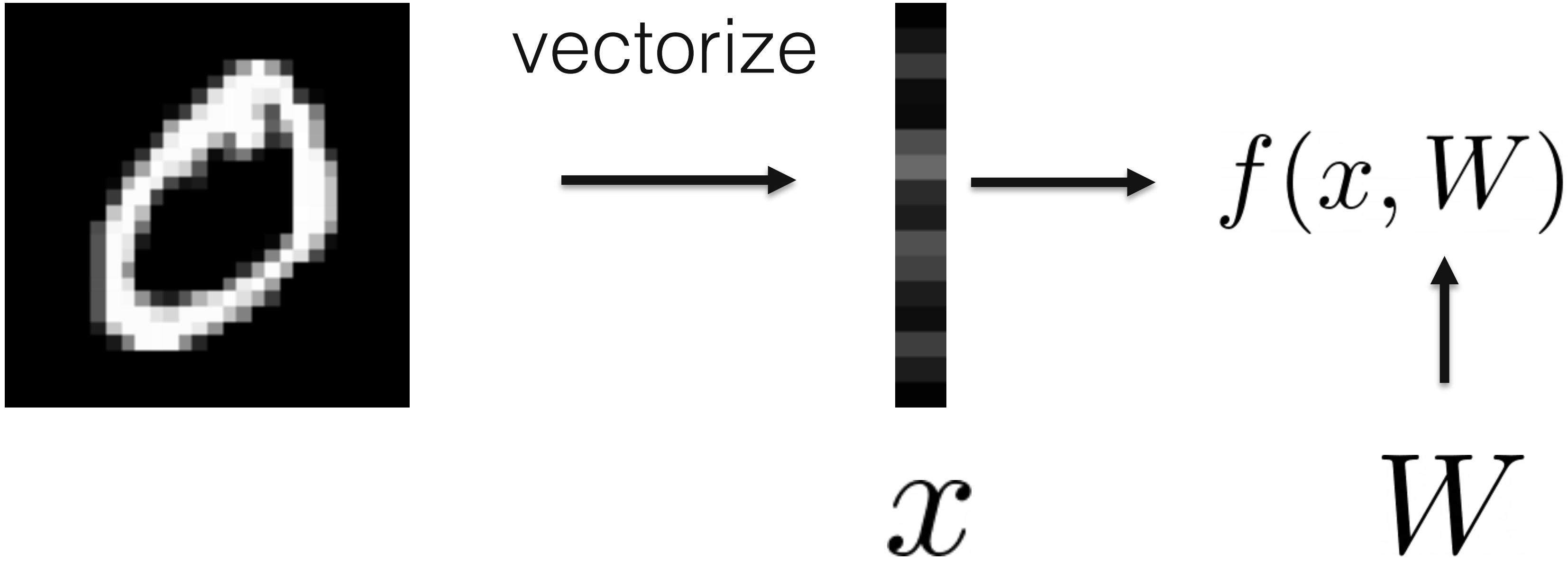
- Linear Model $$f(x, W) = Wx$$



Length of this vector is the “dimensionality” of our problem!

Image Classification

- Linear Model $f(x, W) = Wx$



In general: $Wx + b$

Image Classification

- Linear Model $f(x, W) = Wx$

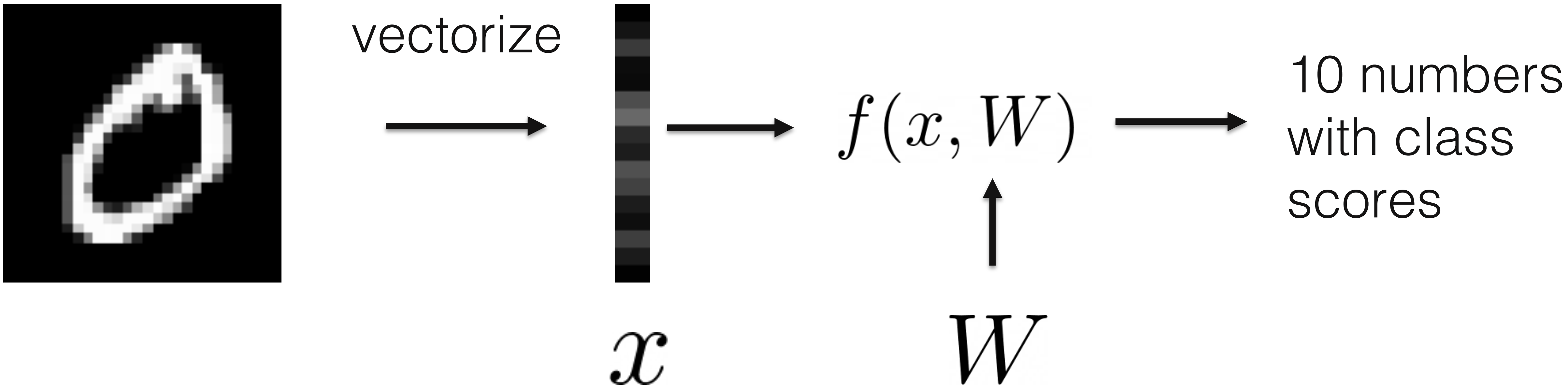
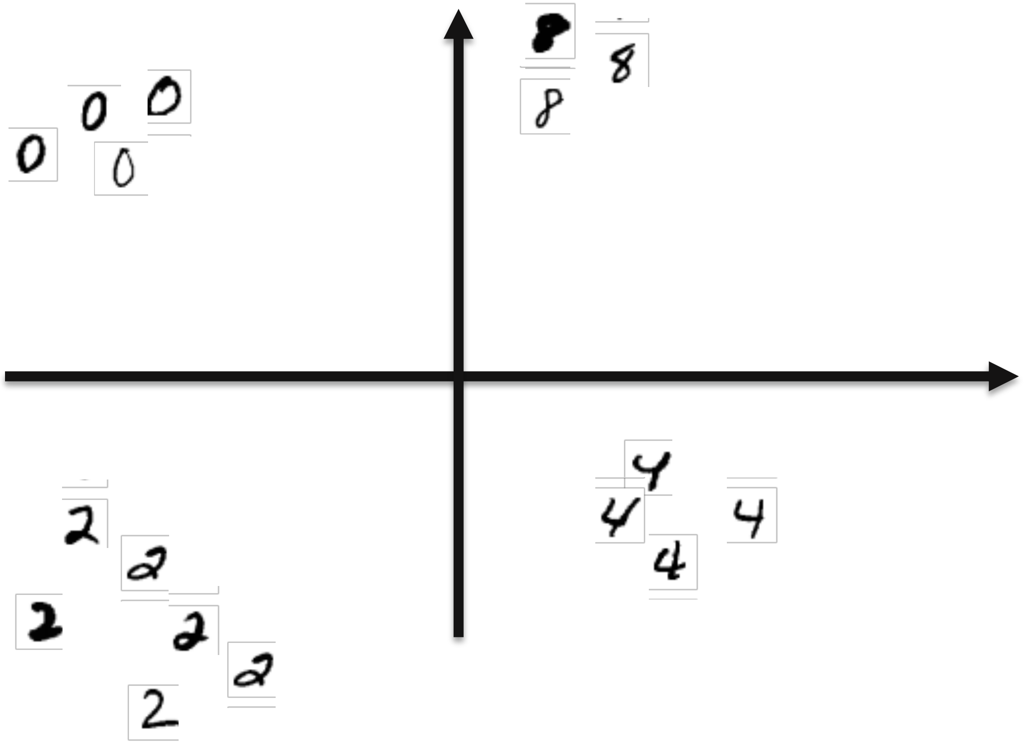


Image Classification

- Linear model: geometric intrepretation

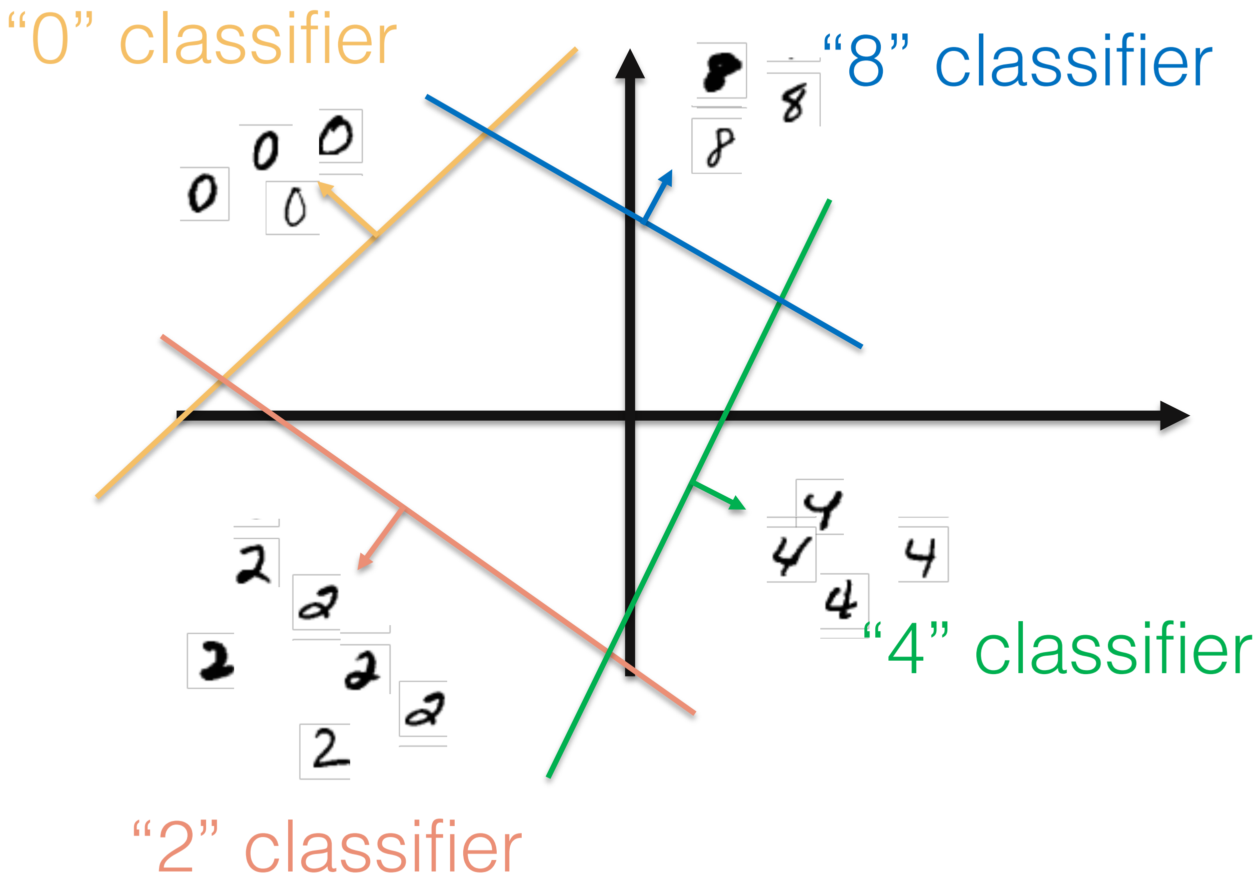


Each image is a point in an N-dimensional space

- N is the number of pixels

Image Classification

- Linear model: geometric interpretation



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

Computes inner product between rows of W and x!

- Each row of W is a hyperplane
- Sign of inner product tells you which side of the hyperplane
- "separates" the digits

Image Classification

- Linear model (visual interpretation)

Learned filters (rows of W)

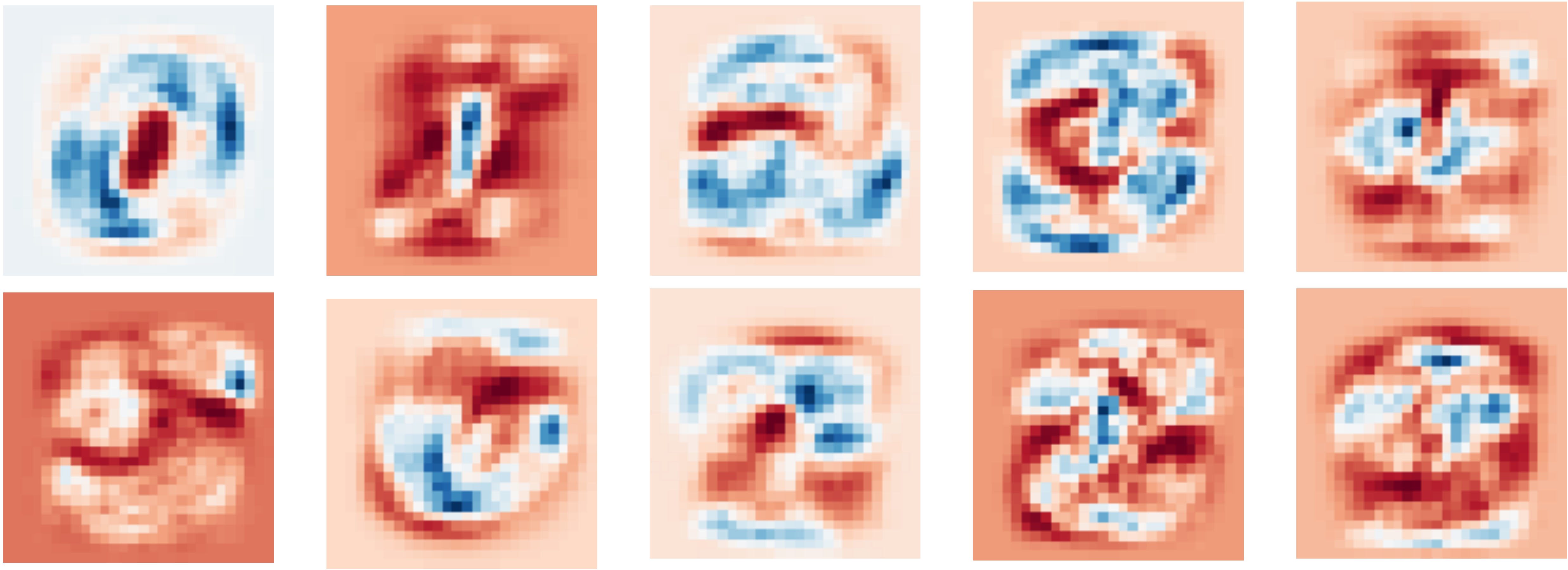
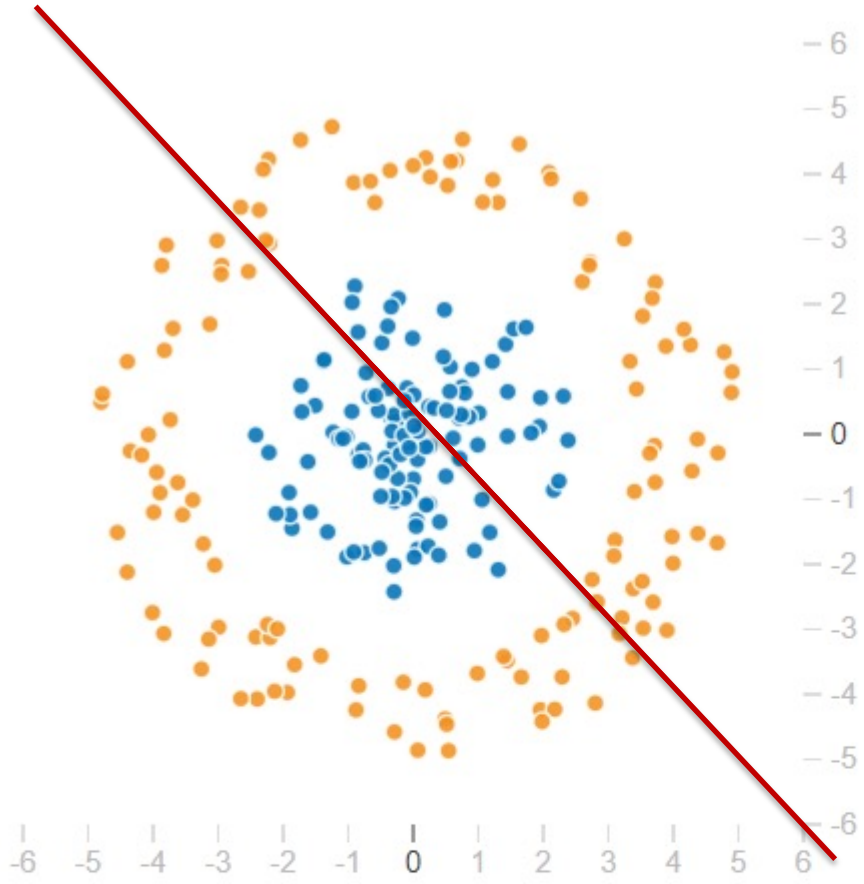


Image Classification

- Limits of linear classifiers

Linear classifiers learn linear decision planes

What if dataset is not linearly separable?



Multilayer Perceptrons (MLPs)

- Linear Model $f = Wx$
- 2-layer MLP $f = W_2 \max(0, W_1 x)$

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Multilayer Perceptrons (MLPs)

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- 3-layer MLP $f = W_3 \max(0, W_2 \max(0, W_1 x))$

Non-linearity/activation function between linear layers

Multilayer Perceptrons (MLPs)

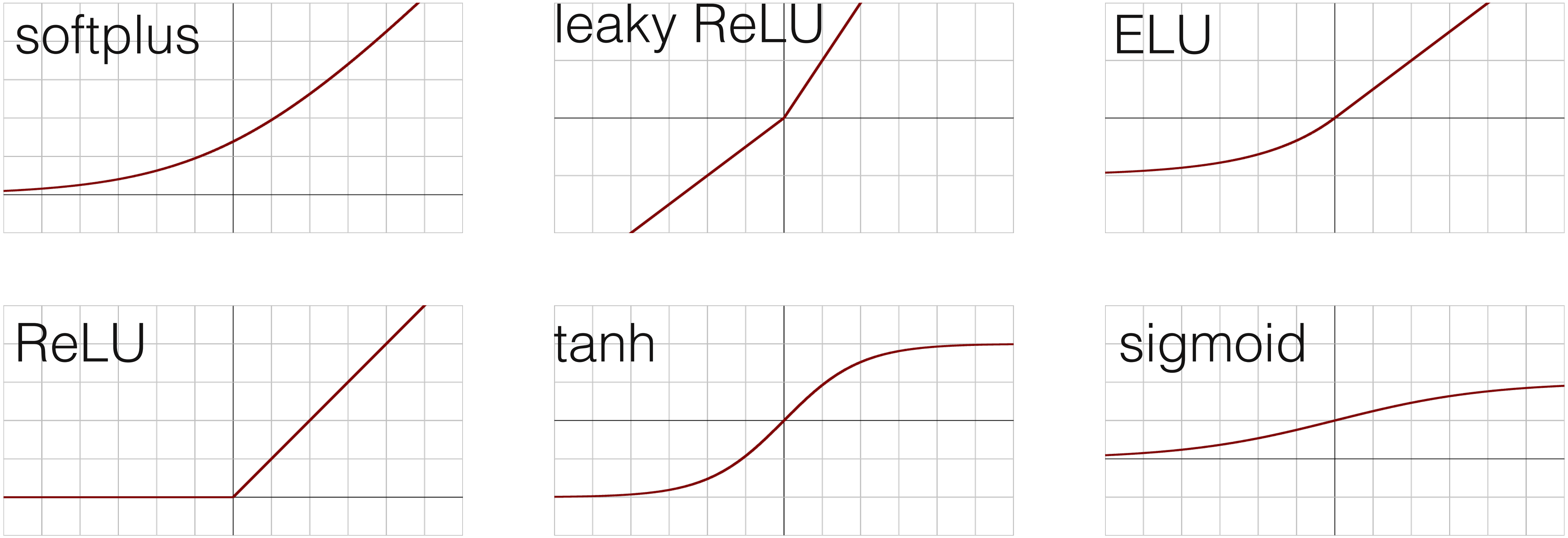
- Linear Model $f = Wx$
- 2-layer MLP $f = W_2 \max(0, W_1 x)$
- 3-layer MLP $f = W_3 \max(0, W_2 \max(0, W_1 x))$

Otherwise we have:

$$f = W_3 W_2 W_1 x$$

Activation Functions

…many to choose from



… ReLU is a good general-purpose choice: ReLU(x) = max(0, x)

Multilayer Perceptrons (MLPs)

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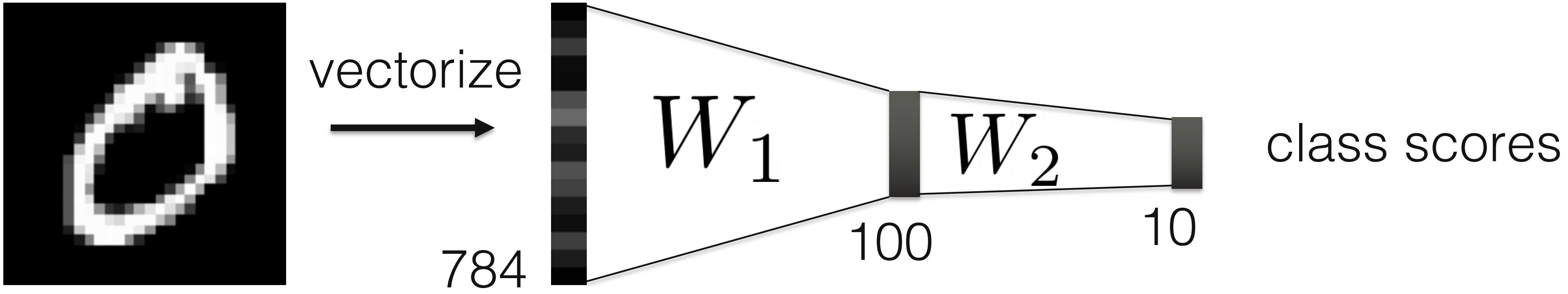
- 2-layer MLP $f = W_2 \max(0, W_1 x)$

Back to our classification example…



$$x \in \mathbb{R}^D,\ W_1 \in \mathbb{R}^{H \times D},\ W_2 \in \mathbb{R}^{C \times H}$$

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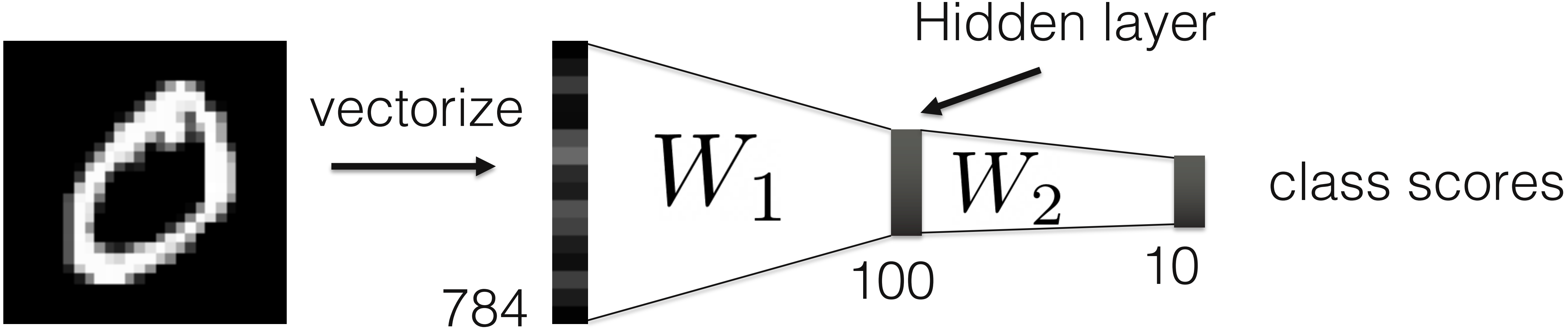

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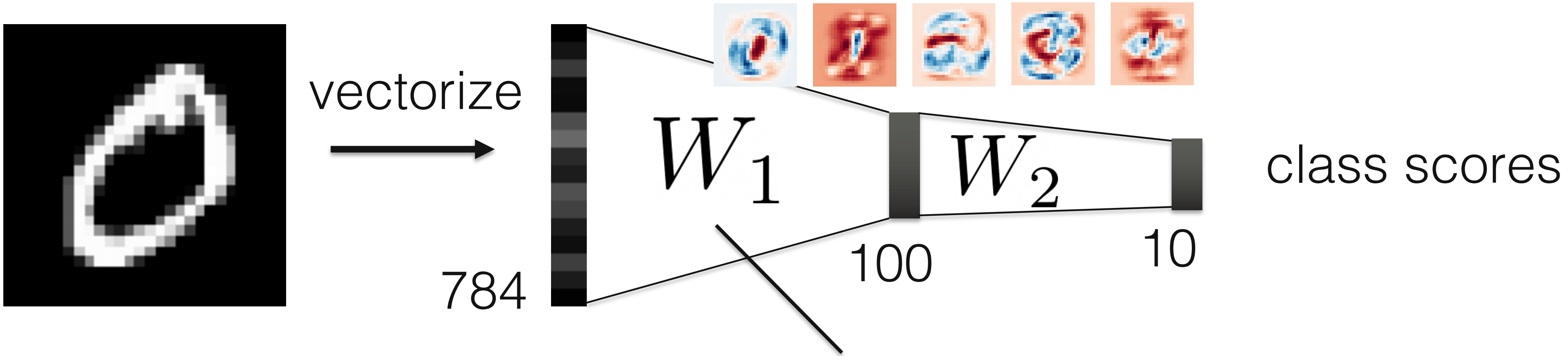
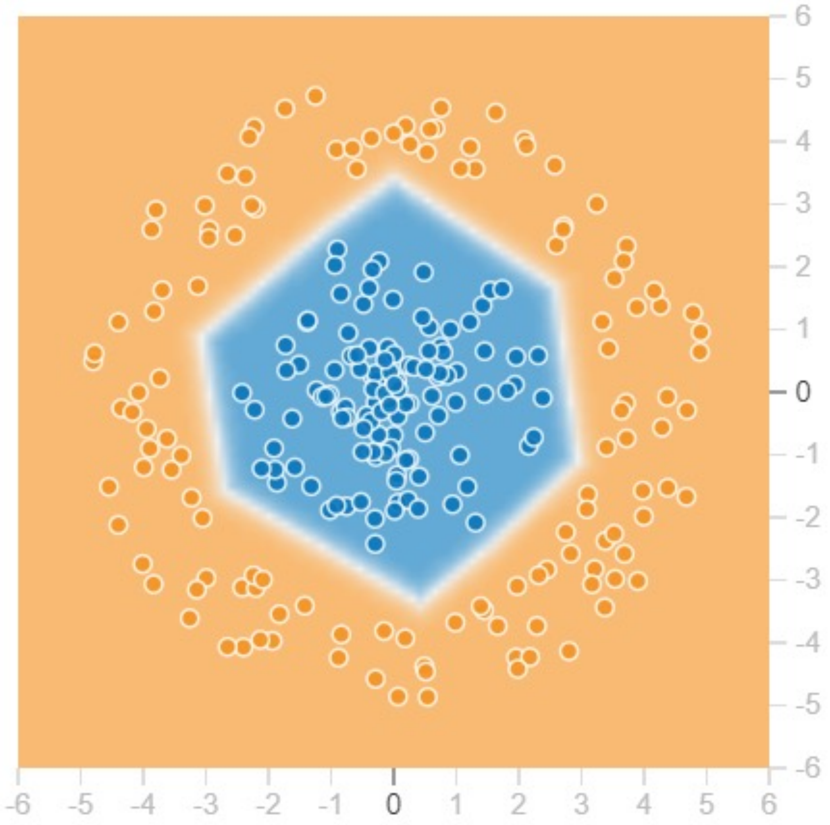


Now we have 100 shape templates, shared between classes

Multilayer Perceptrons (MLPs)

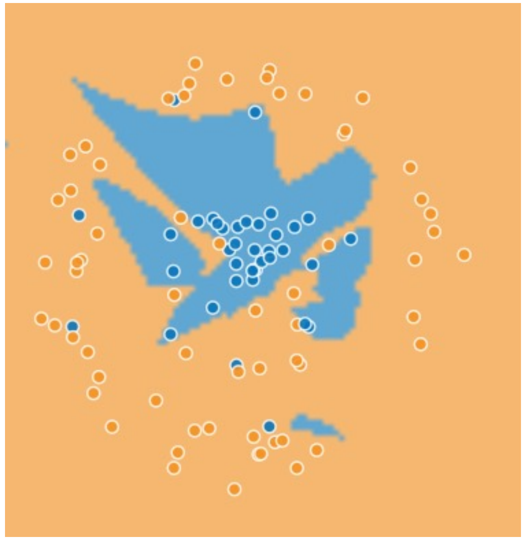
- Overcomes limits of linear classifiers
  - Can learn non-linear decision boundaries
  - Complexity scales with the number of neurons/hidden layers



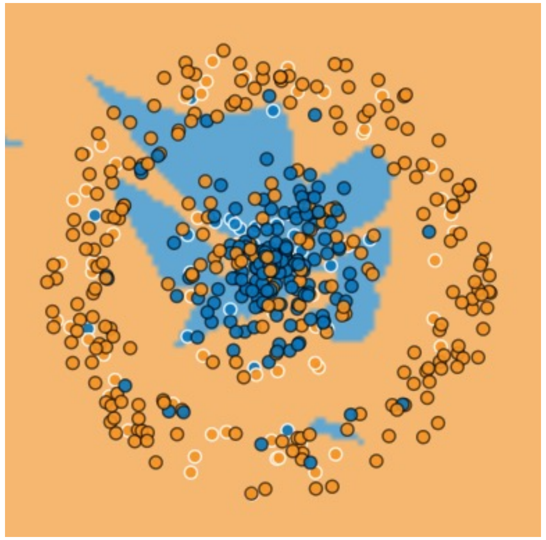
Multilayer Perceptrons (MLPs)

- More parameters is not always better!
  - Can lead to overfitting the training data
  - Performance on test data is worse

train

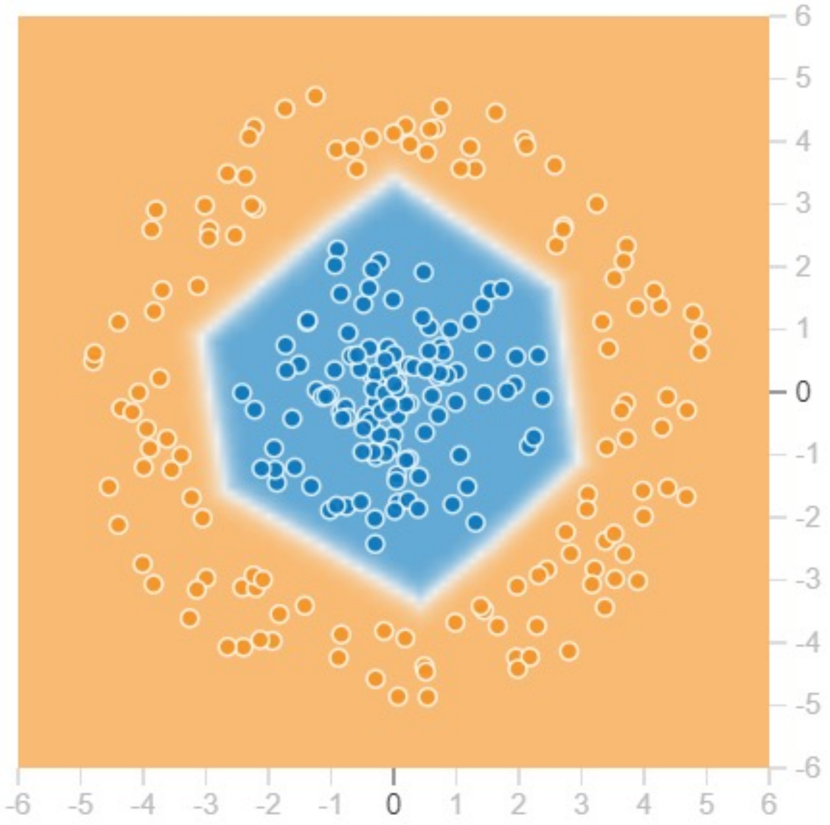


test

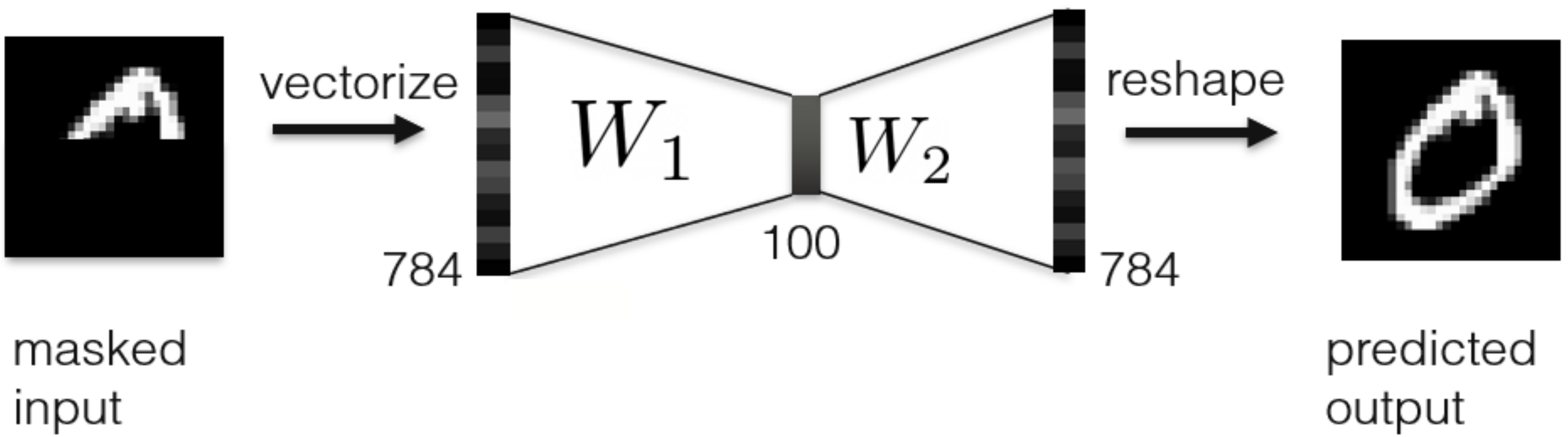


Multilayer Perceptrons (MLPs)

- More on classification…
  - https://cs231n.github.io/linear-classify/
  - https://csc413-uoft.github.io/



Why “neural” network?



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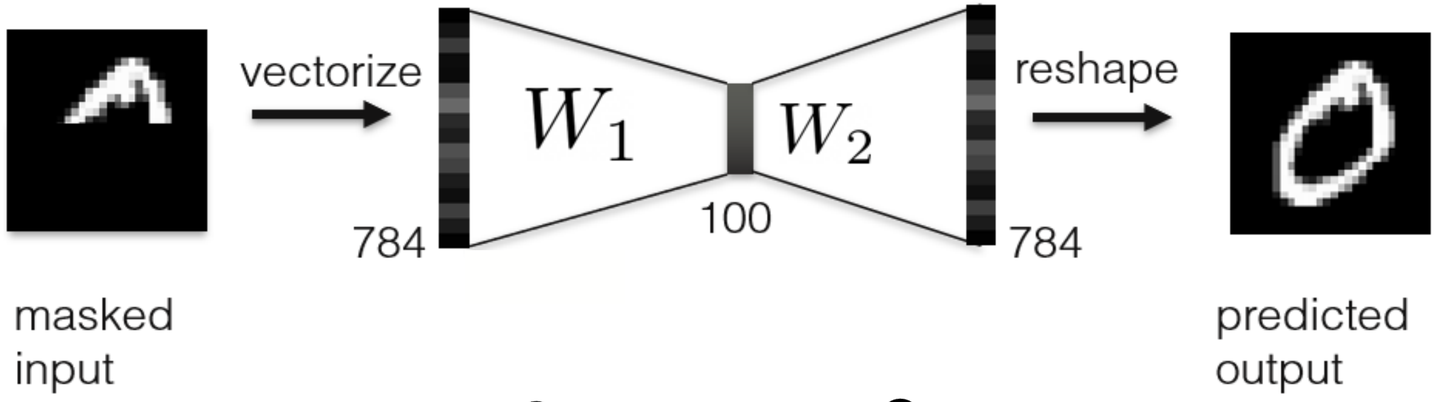
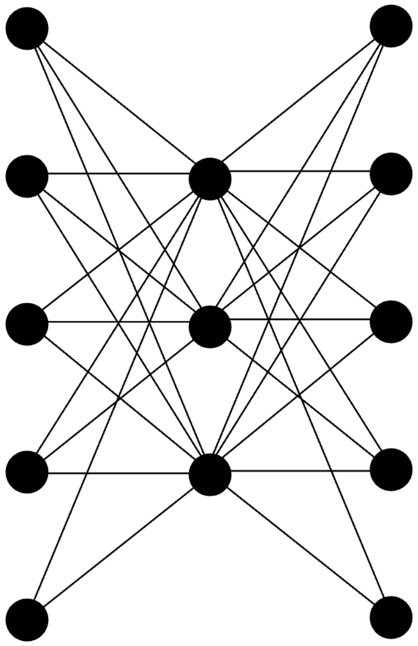
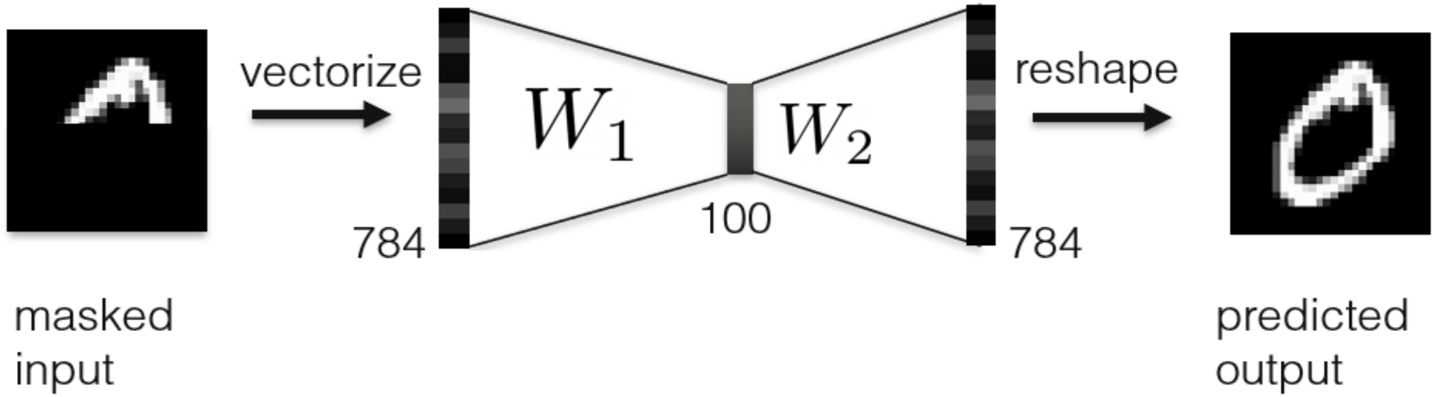
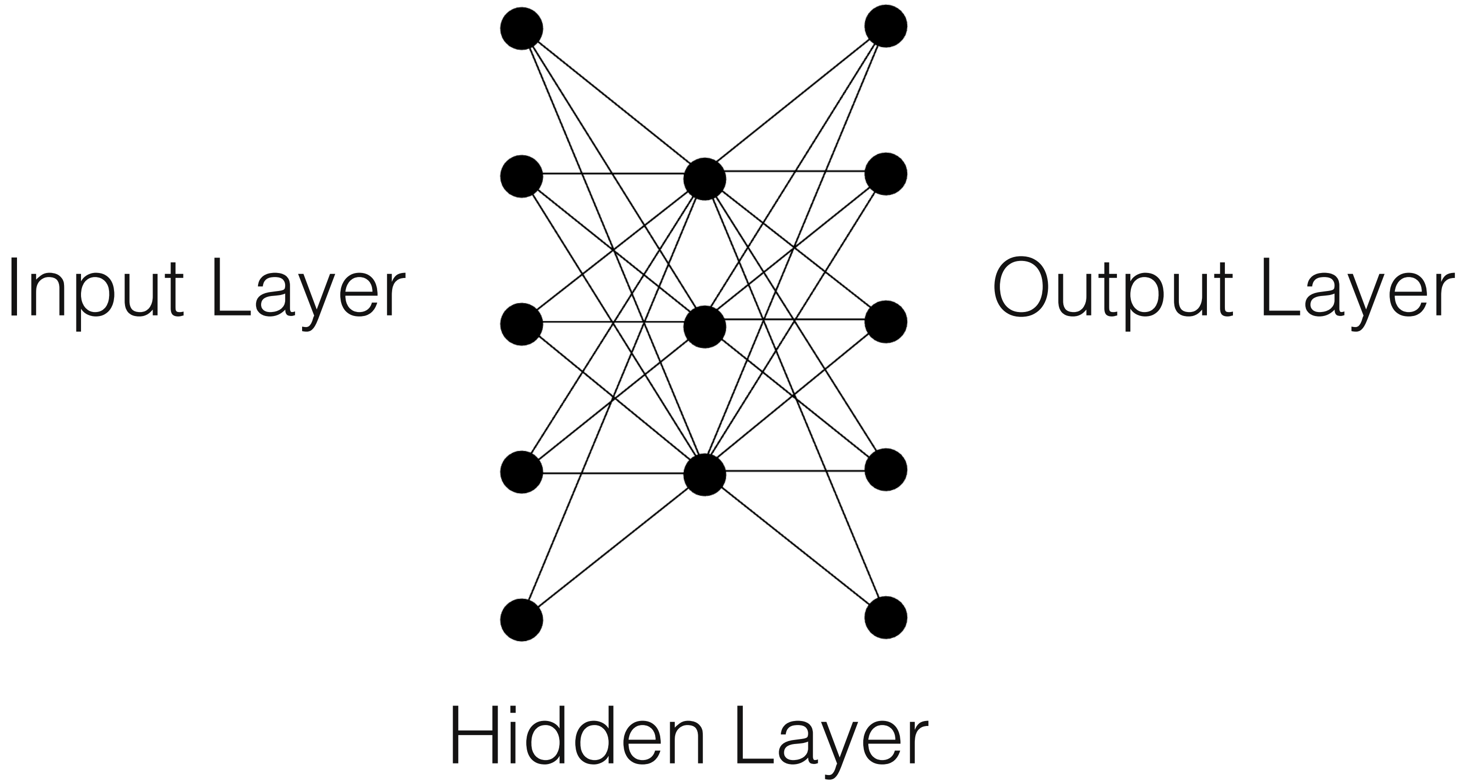




Why “neural” network?





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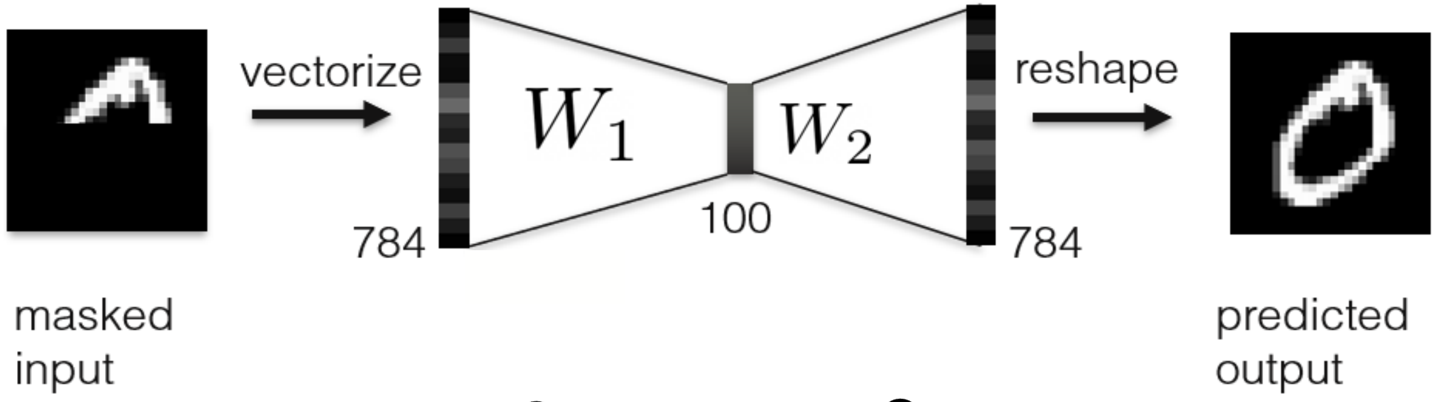
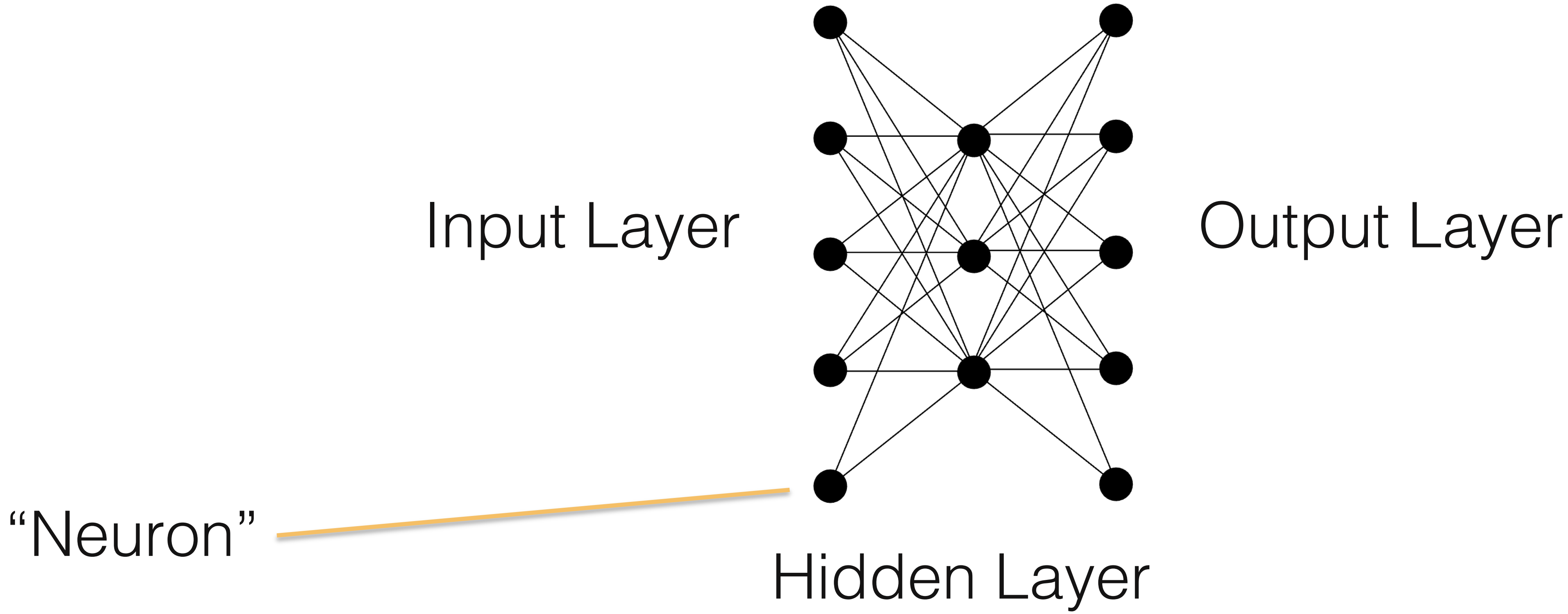
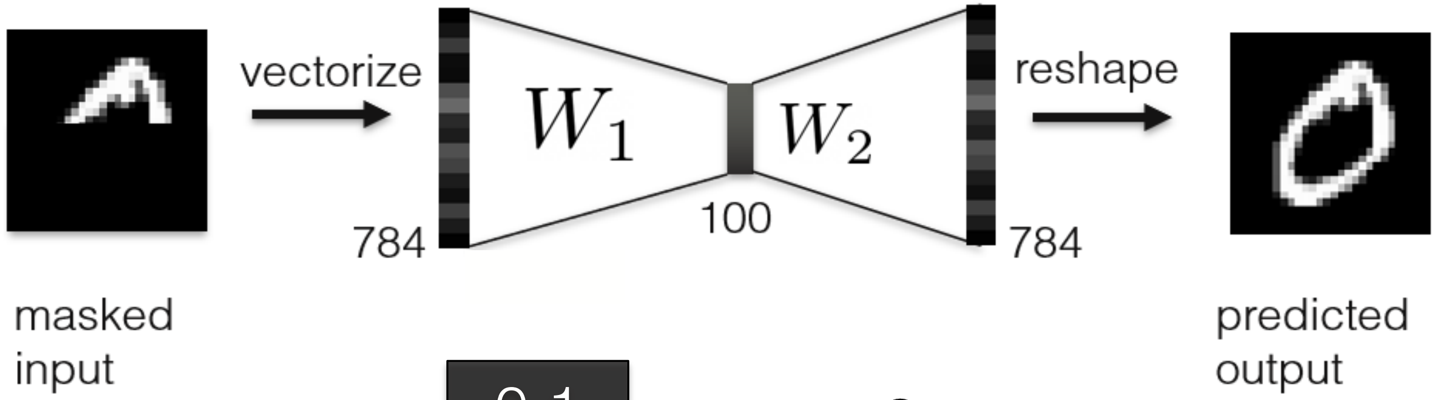
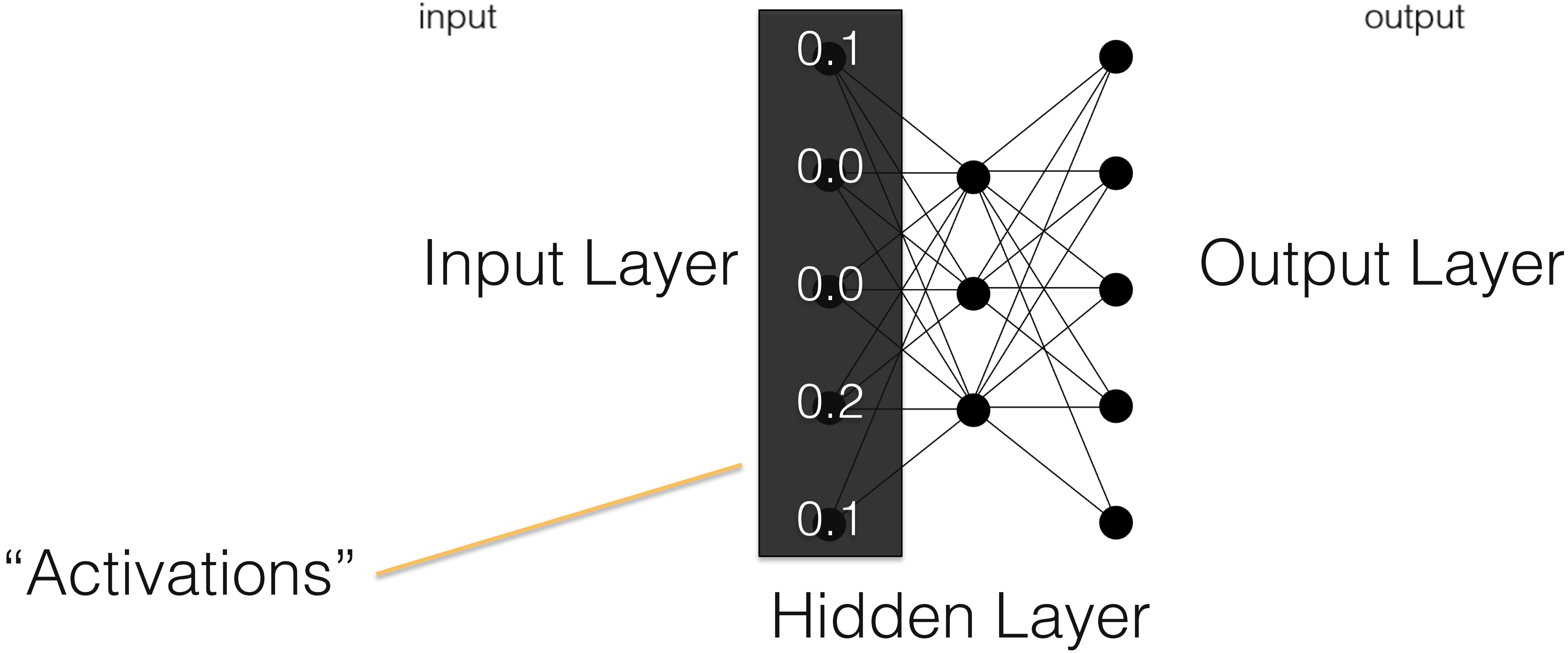


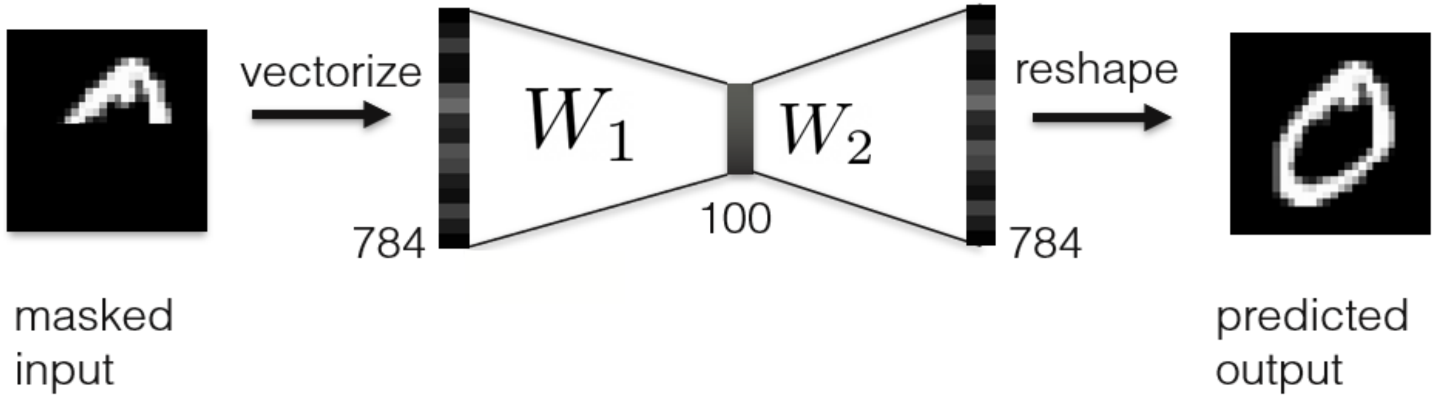


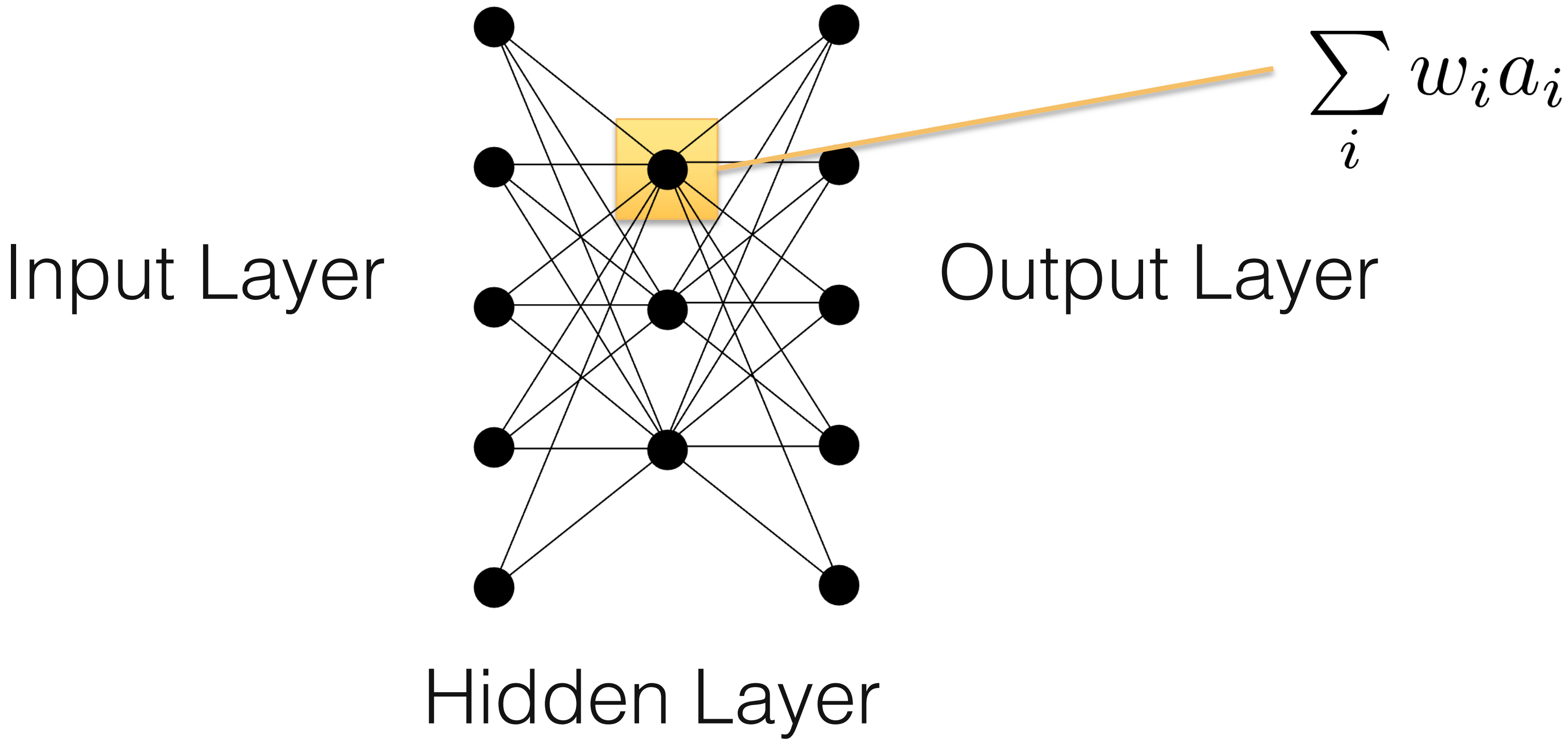
Why "neural" network?

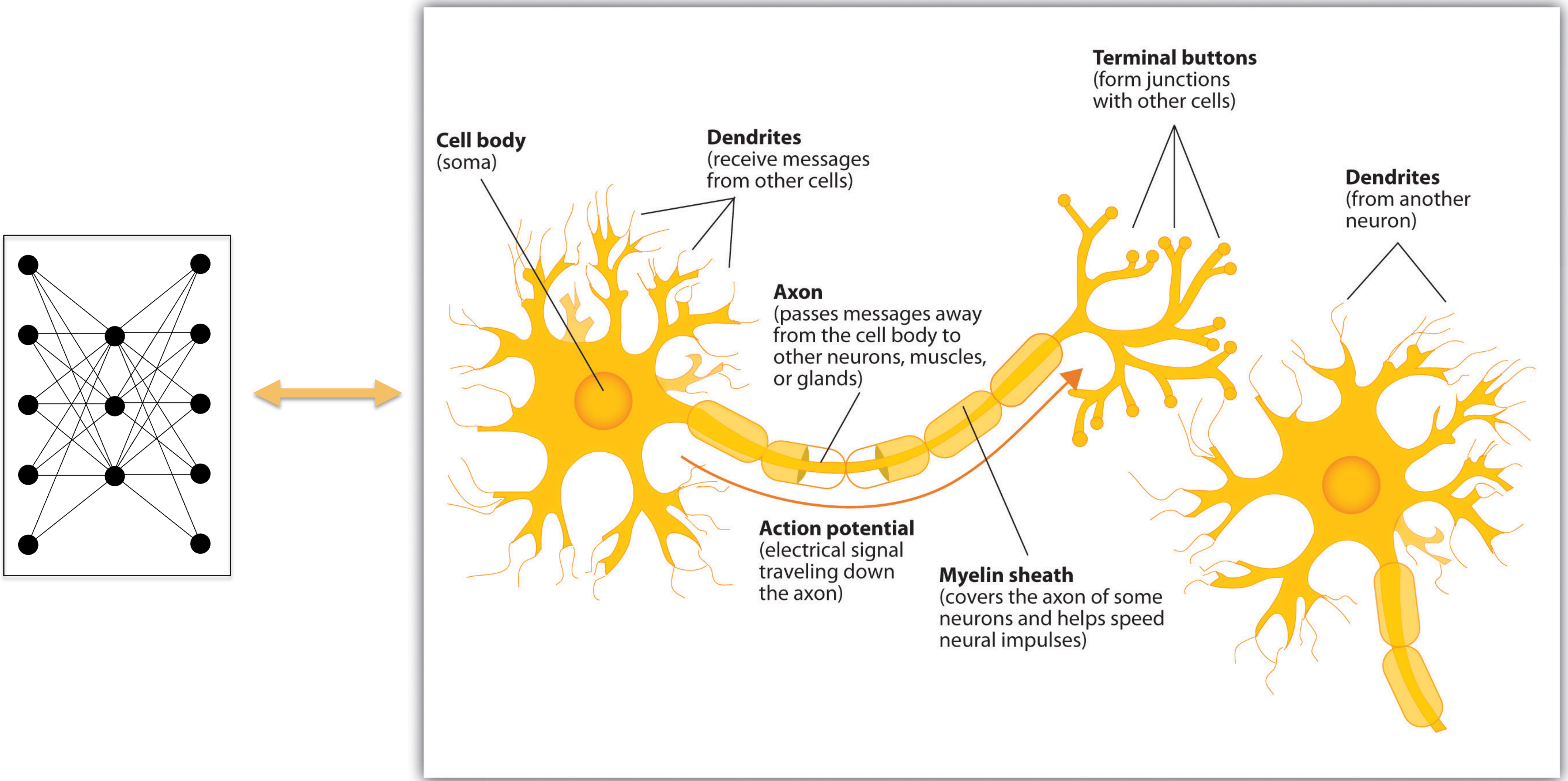




Why “neural” network?





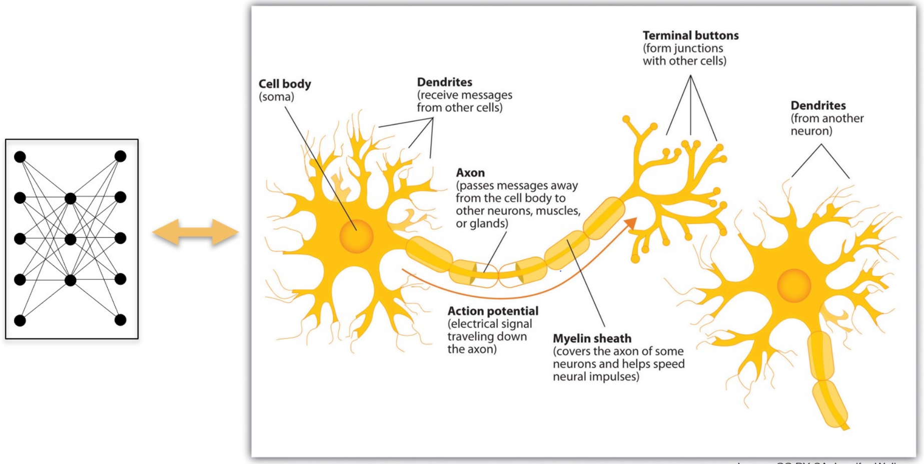

Cell body
(soma)
Dendrites
(receive messages
from other cells)
Terminal buttons
(form junctions
with other cells)
Dendrites
(from another
neuron)
Axon
(passes messages away
from the cell body to
other neurons, muscles,
or glands)
Action potential
(electrical signal
traveling down
the axon)
Myelin sheath
(covers the axon of some
neurons and helps speed
neural impulses)

Loose analogy!

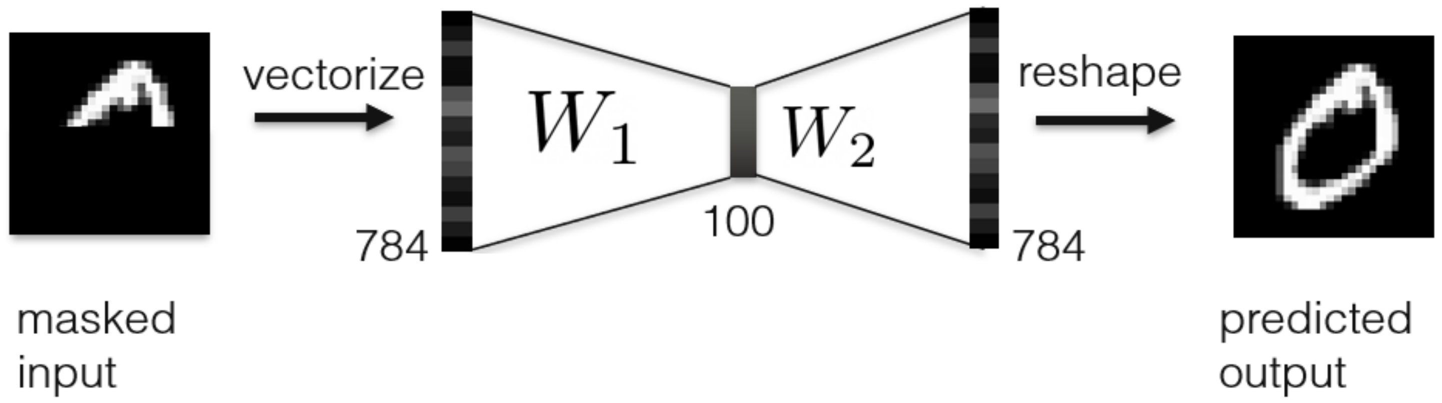
- Neurons have activation potentials, all-or-none firing behavior

- Interconnectivity between actual neurons is dense and complicated

- Connection between neurons is complex non-linear dynamical system



Drawbacks of fully-connected networks



- spatial structure is destroyed
- fully-connected weights do not scale

Overview

- Motivation
- Fully-connected Networks
- Convolutional Neural Networks
- Training networks

Convolutional Neural Networks

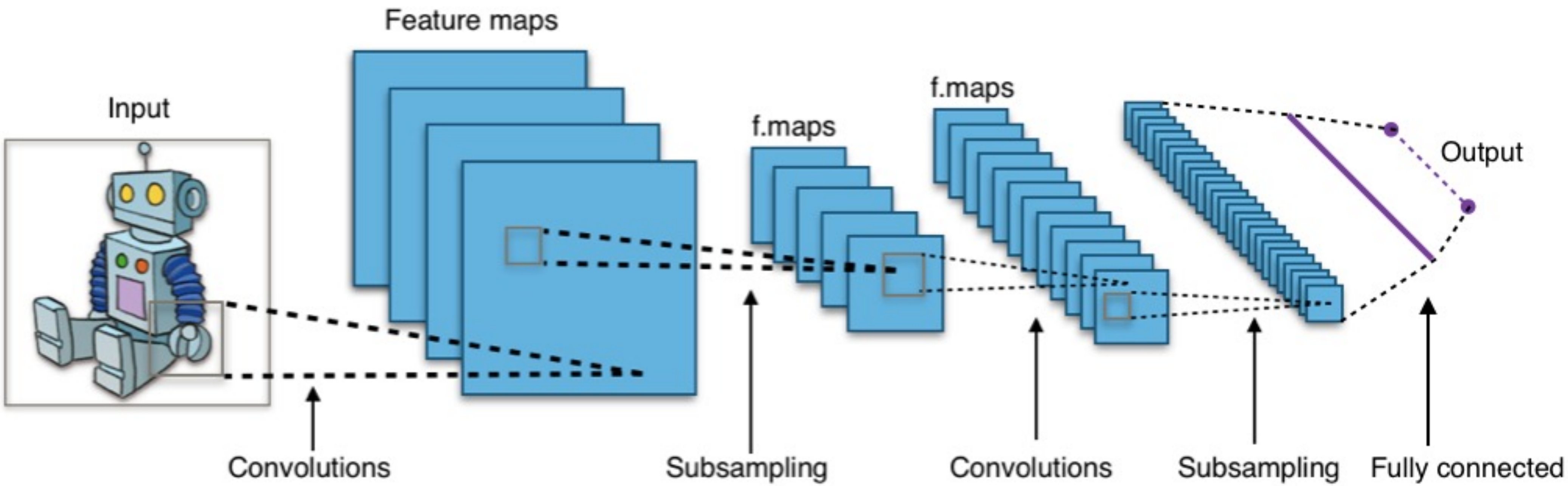


Image: CC Aphex34

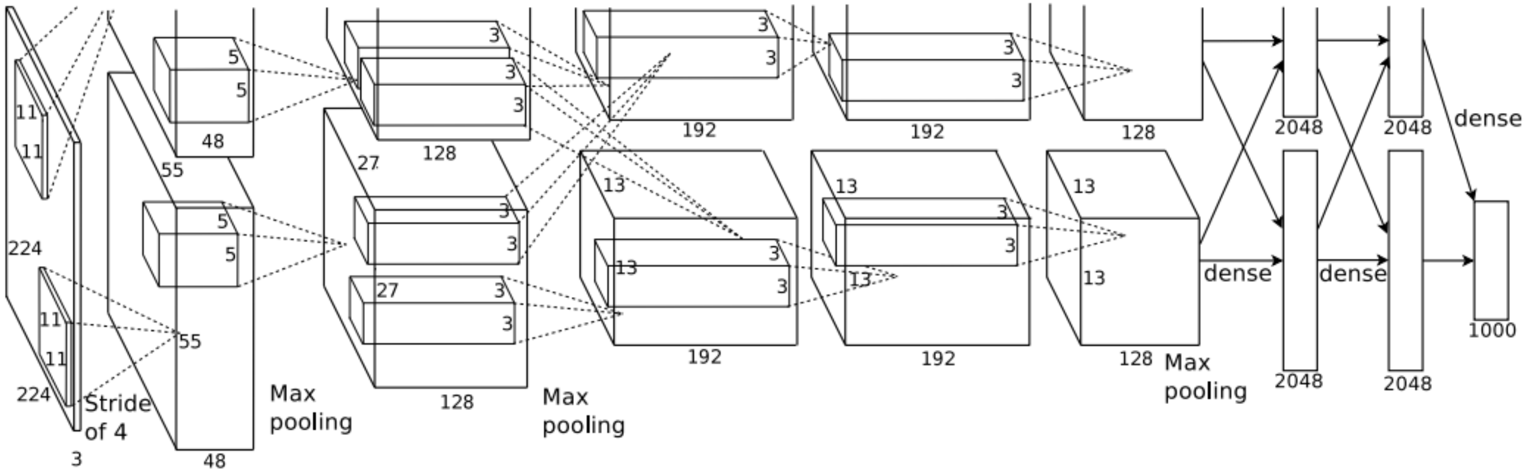
- Exploit spatial structure
- Scale to large inputs with fewer parameters
- Remarkable performance for processing visual data

AlexNet & surge in popularity

2010: ImageNet Large Scale Visual Recognition Challenge

- 14 million labeled images

First convolutional network for image classification



AlexNet [Krizhevsky '12]

AlexNet & surge in popularity

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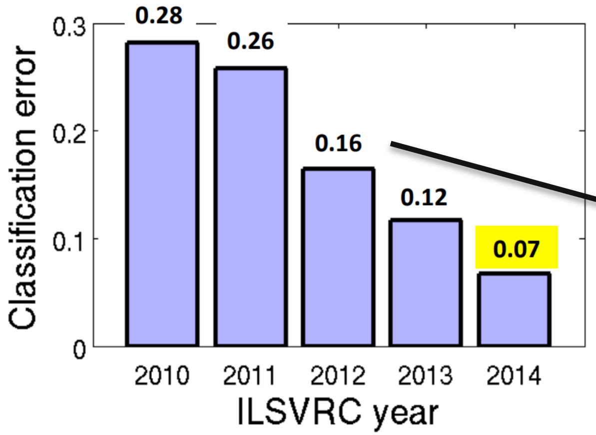
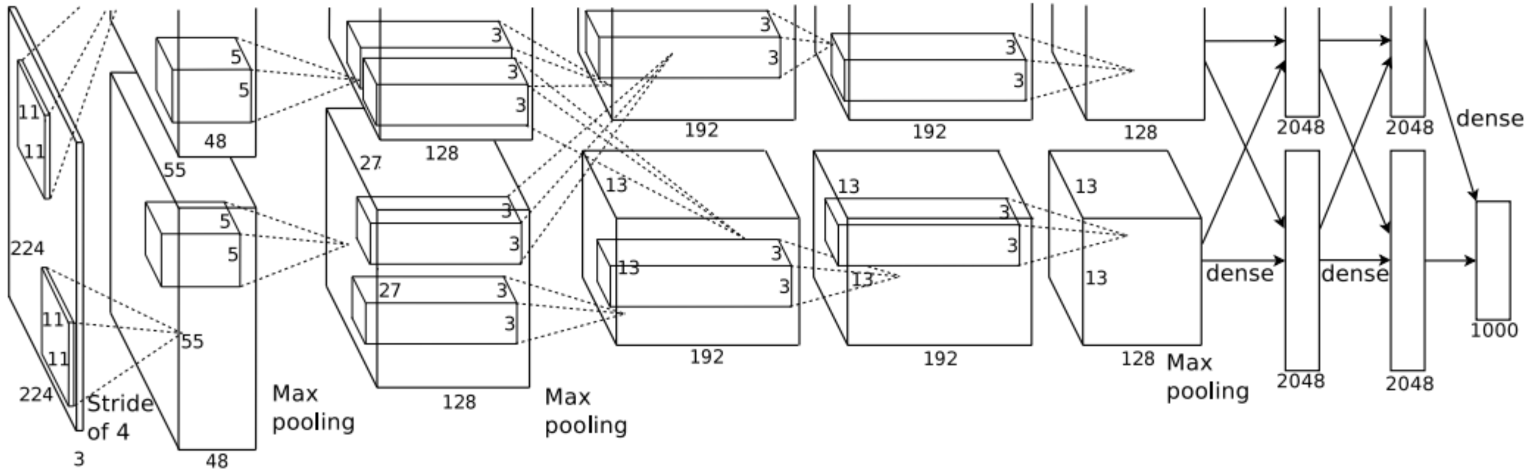


[Russakovsky '15]



AlexNet [Krizhevsky '12]

CNNs

AlexNet & surge in popularity

2010: ImageNet Large Scale Visual Recognition Challenge

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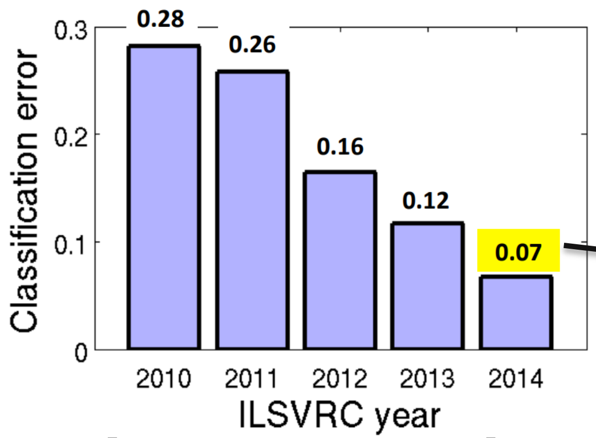
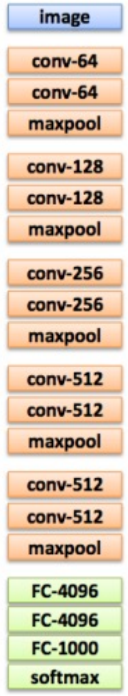


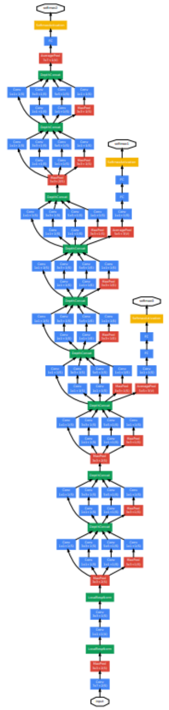
[Russakovsky '15]

Deep networks



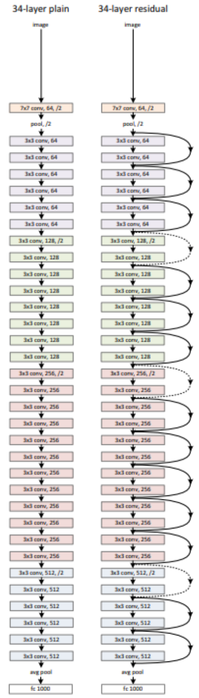
VGG

[Simonyan '14]



GoogLeNet

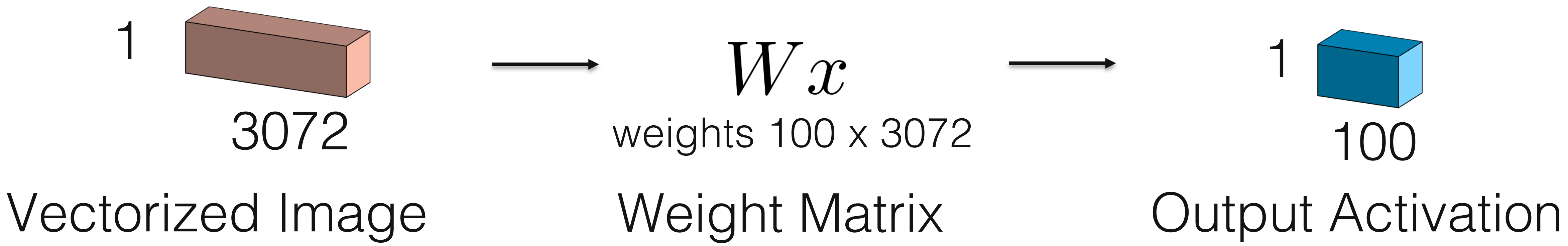
[Szegedy '14]



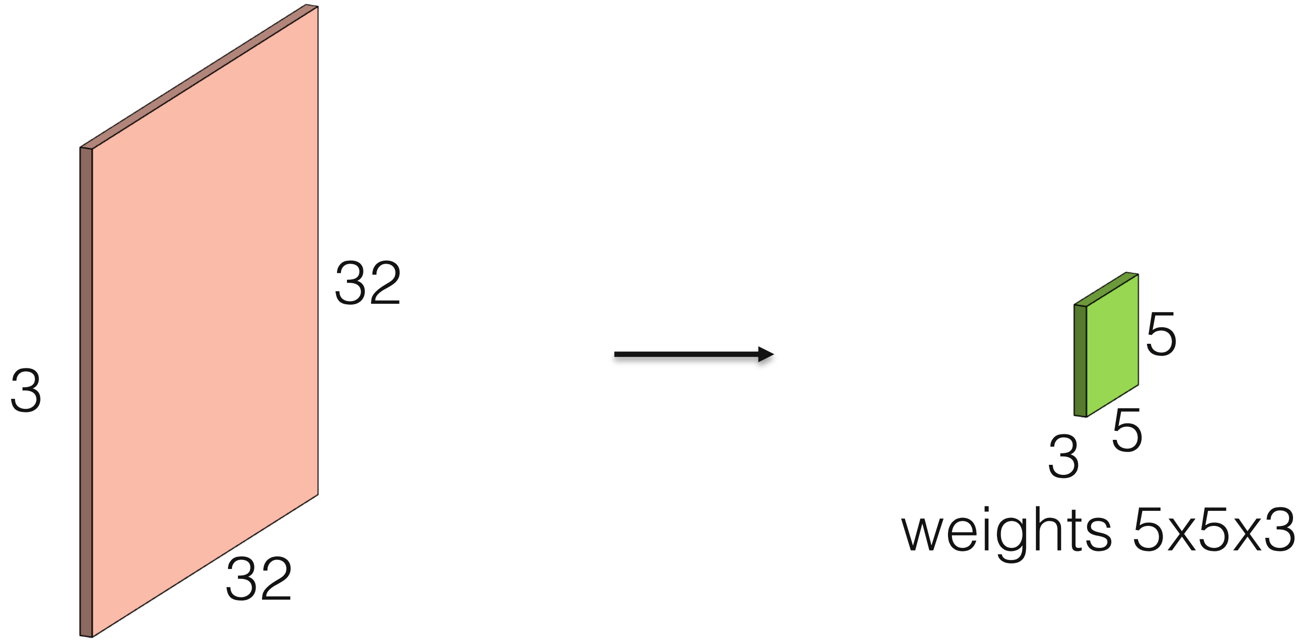
ResNet

[He '15]

Fully-Connected Layer



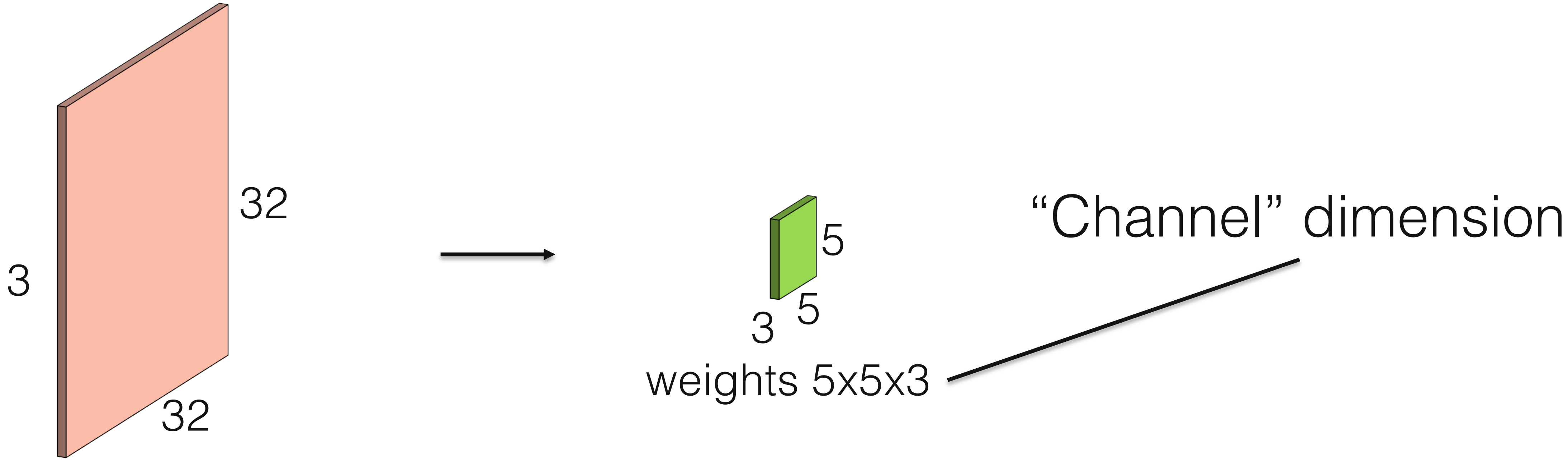
Convolutional Layer



Input Image

Filter

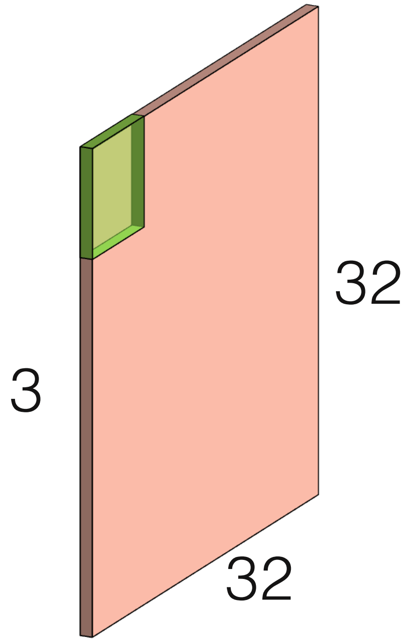
Convolutional Layer



Input Image

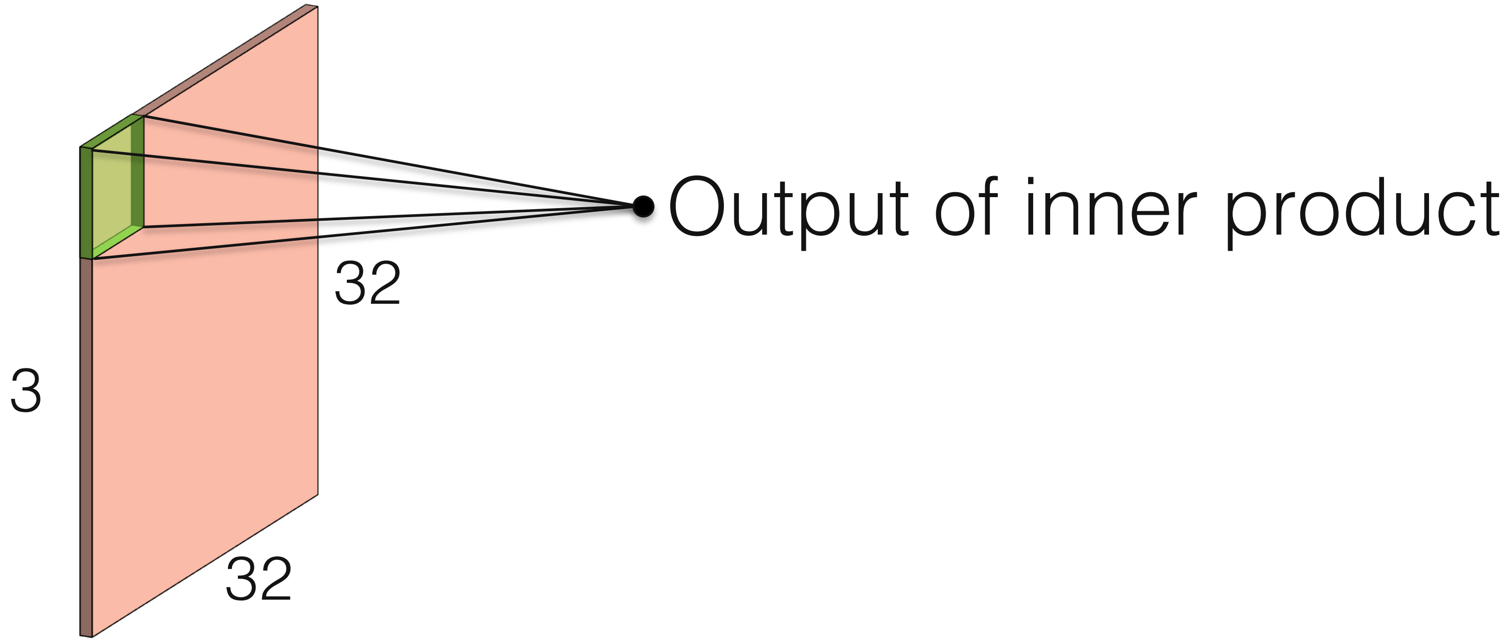
Filter

Convolutional Layer



Input Image

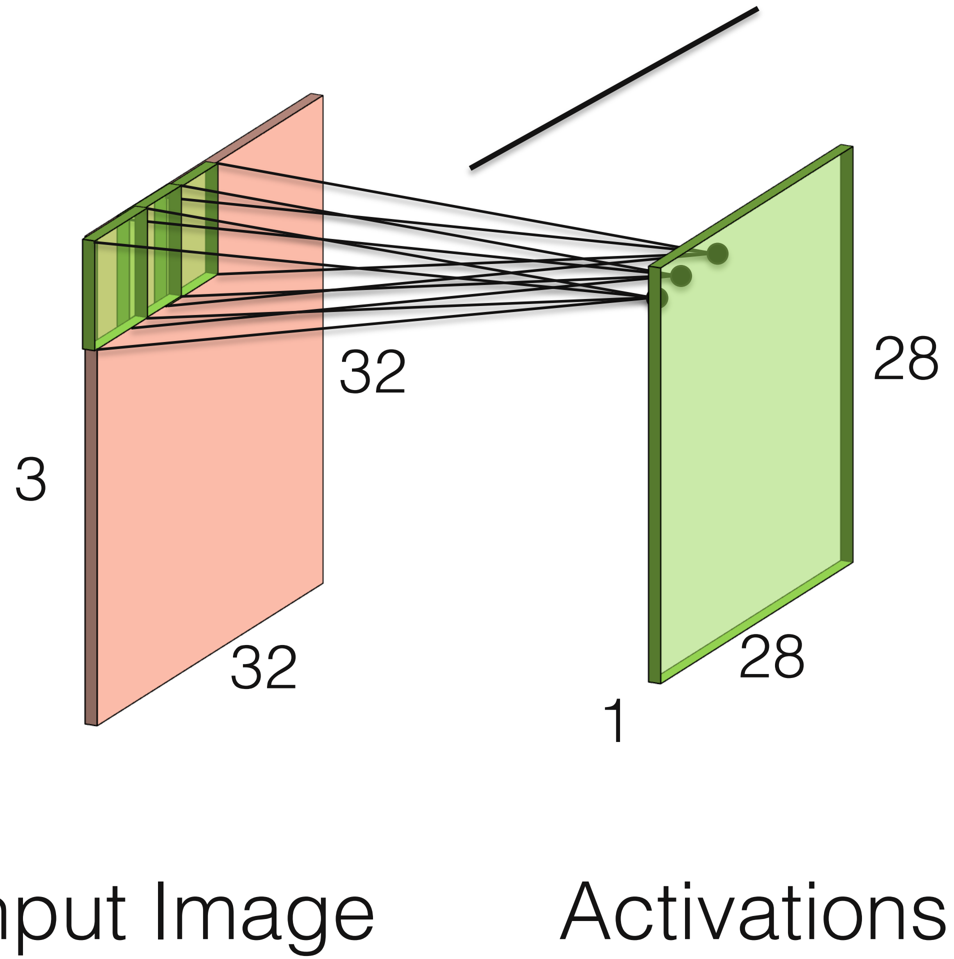
Convolutional Layer



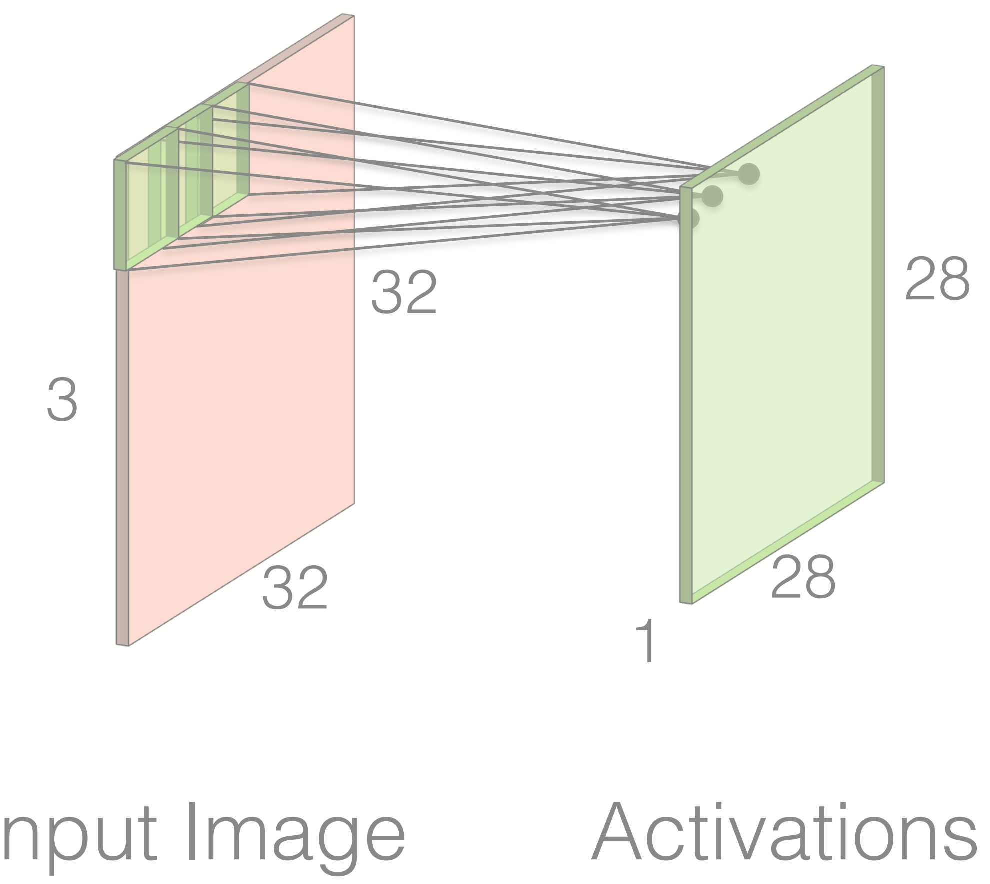
Input Image

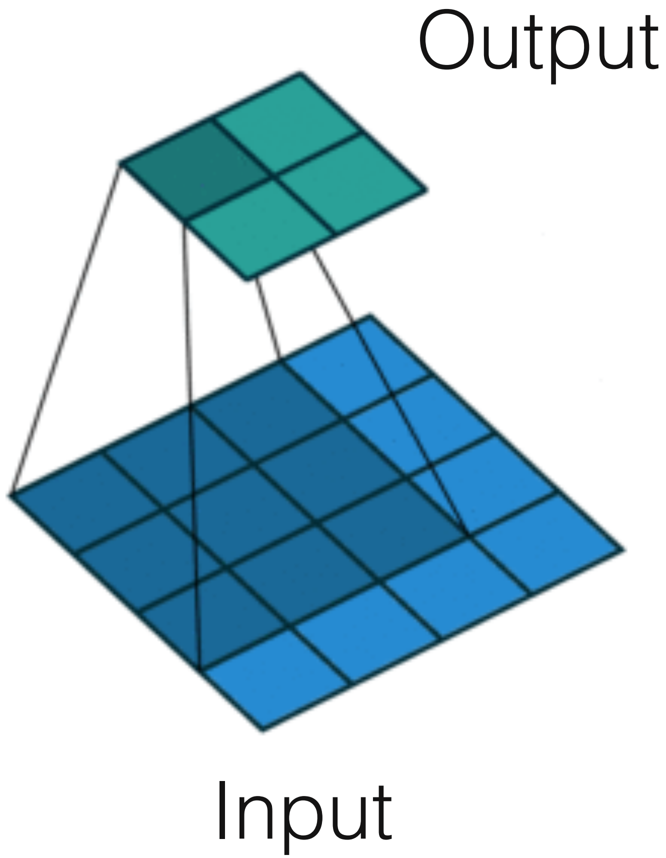
Convolutional Layer

Convolution = sliding window + inner product



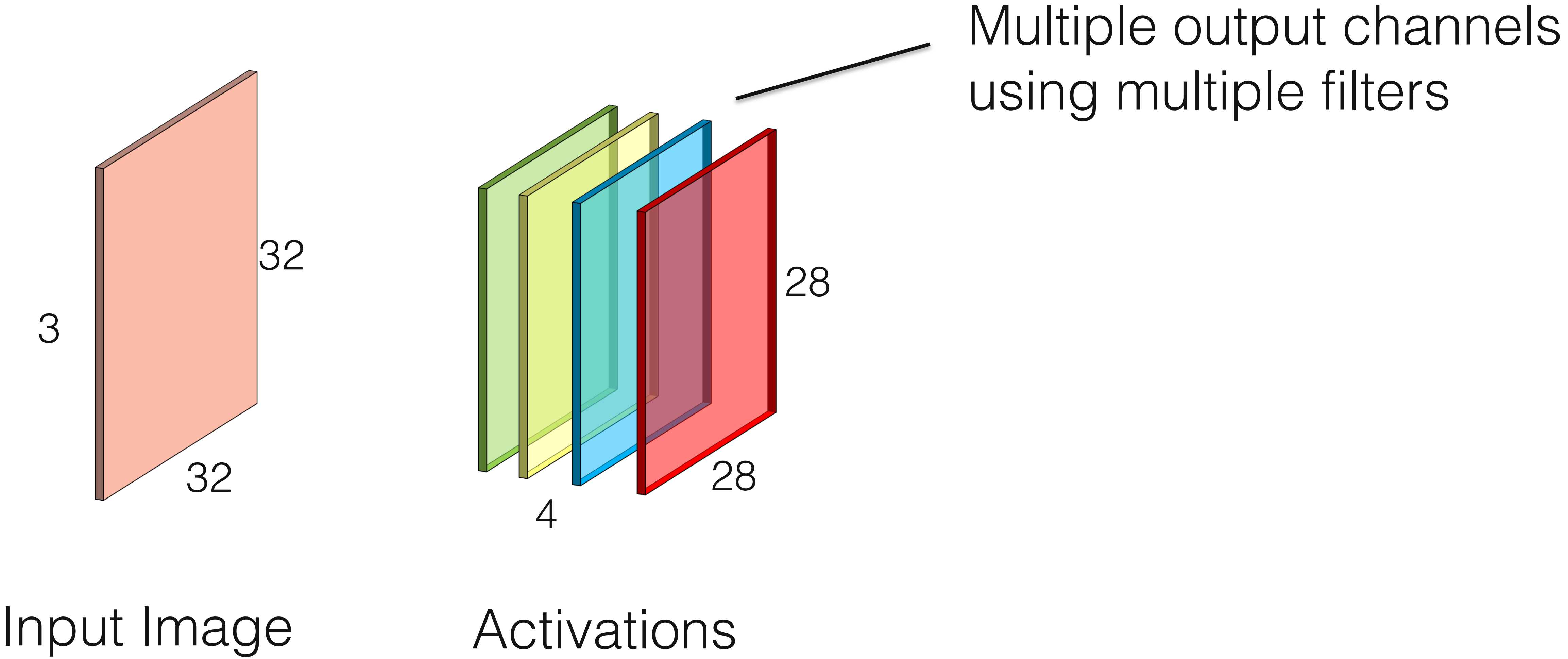
Convolutional Layer



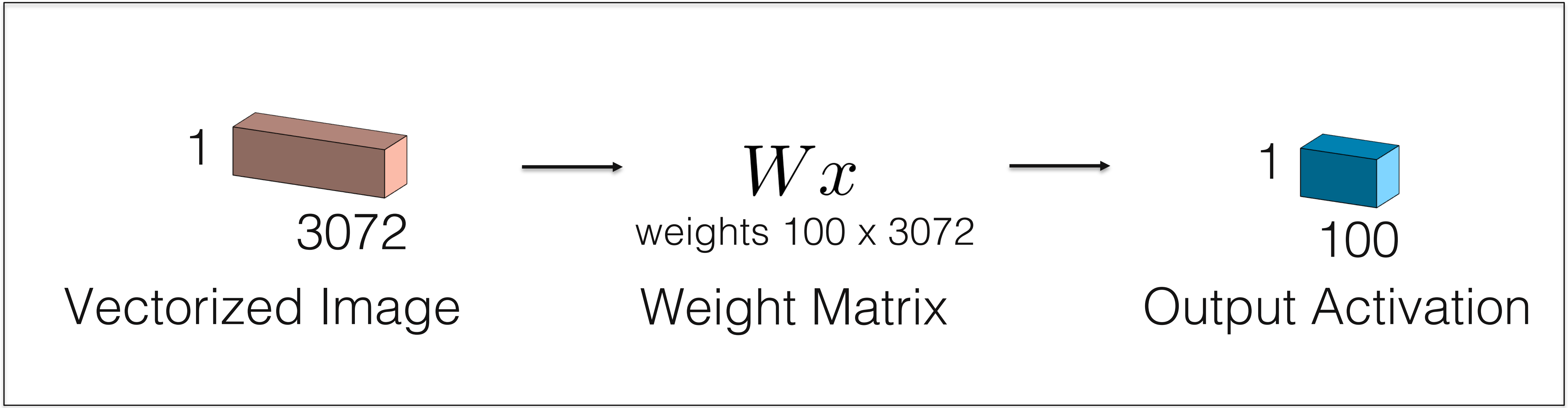


https://github.com/vdumoulin/conv_arithmetic

Convolutional Layer

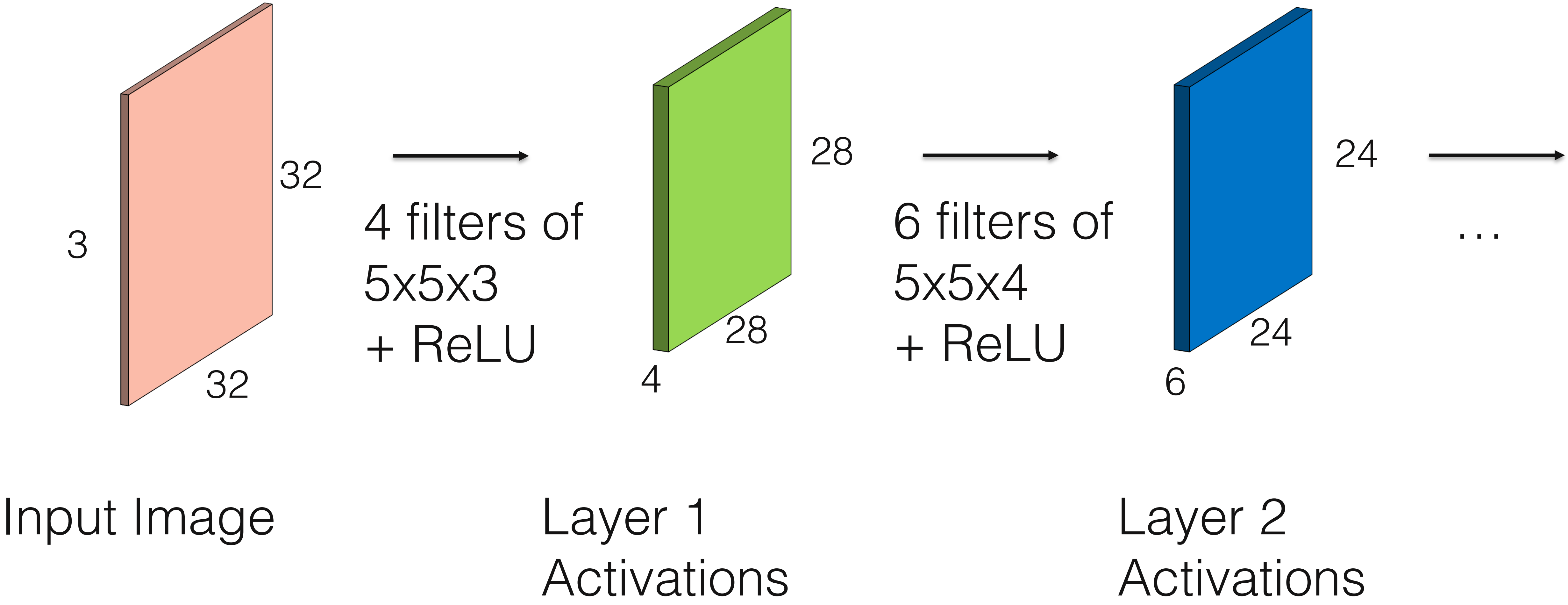


Fully-Connected Layer



Special case of convolutional layer when filter size = input size!

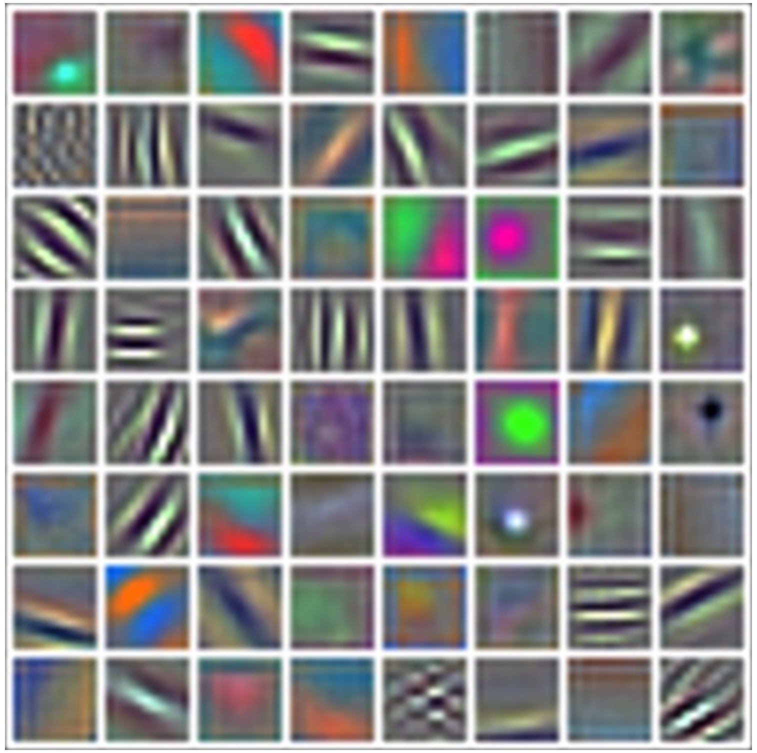
Convolutional Neural Network



Case Study: AlexNet

Input Image

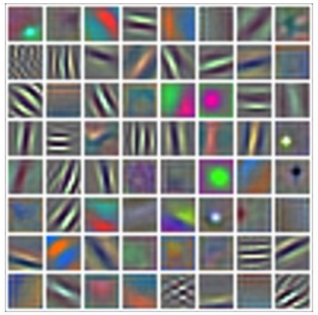
First-layer Filters

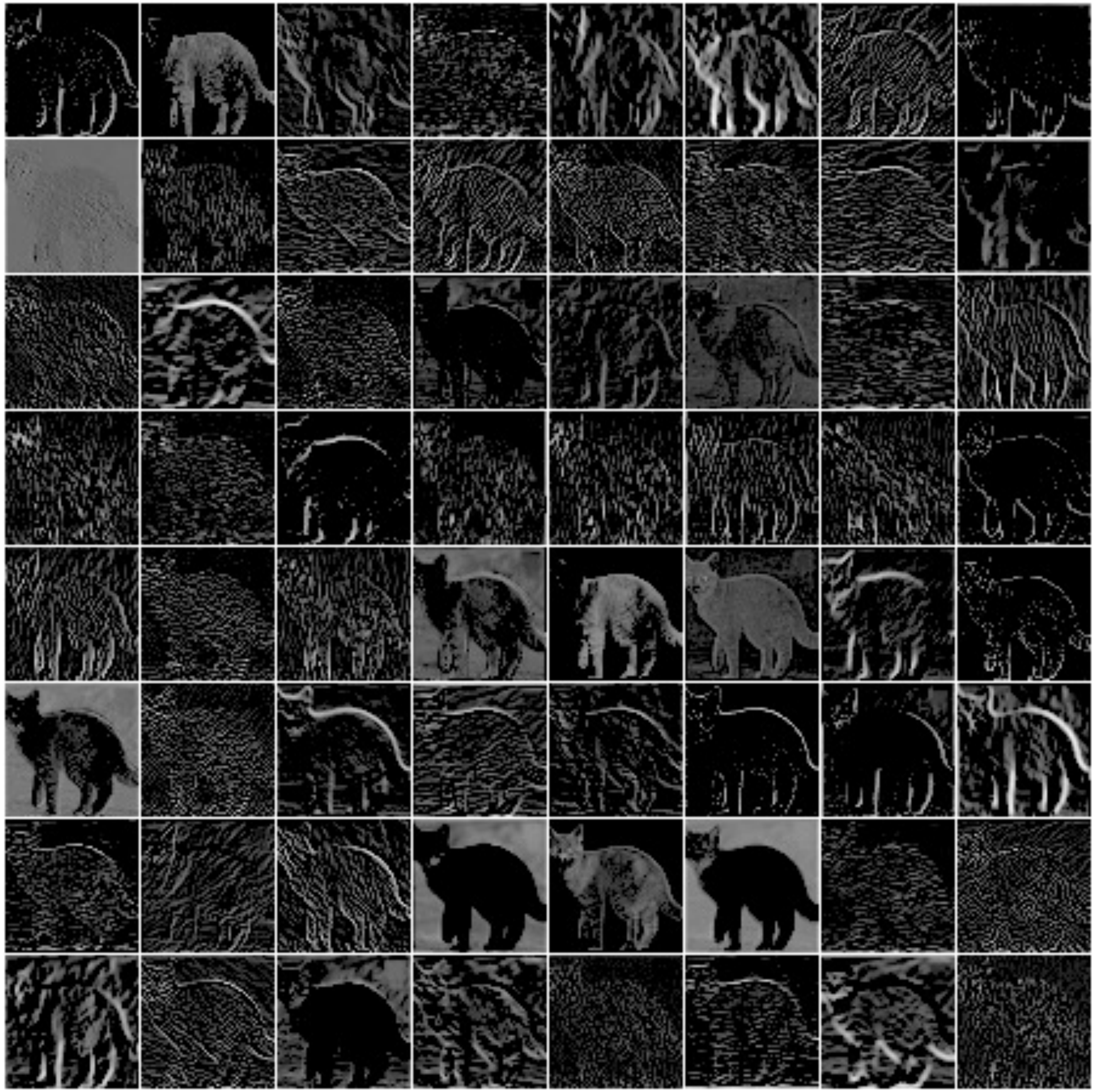


Case Study: AlexNet

Input Image

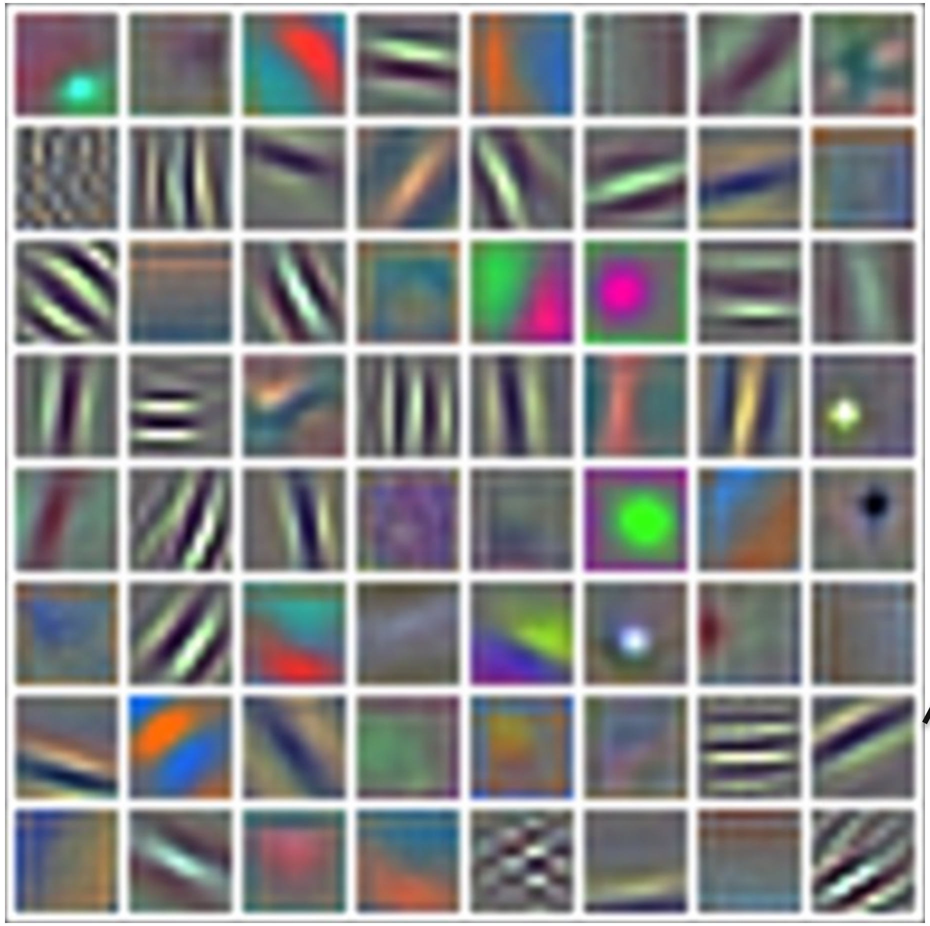
First-layer Filters





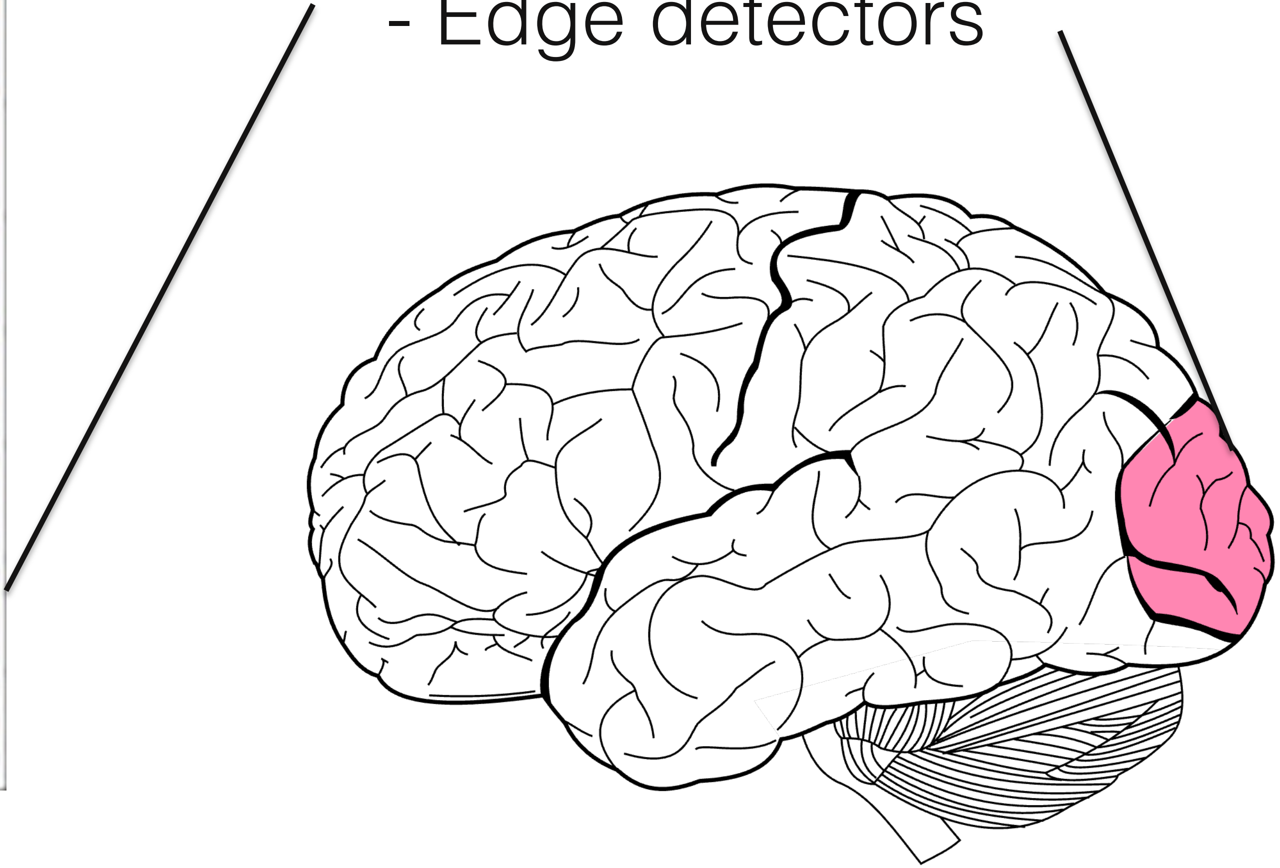
Activations

Case Study: AlexNet



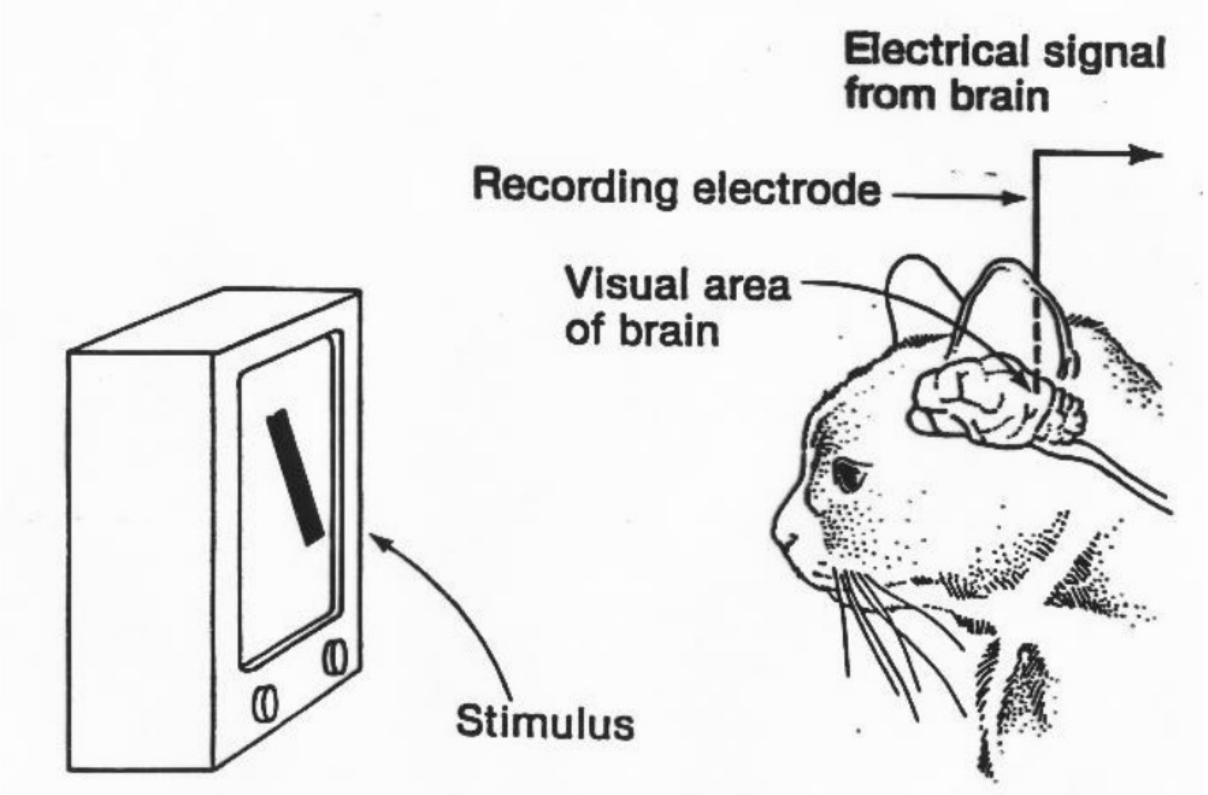
First-layer Filters

Similar to simple cells in visual cortex!
- Edge detectors



Case Study: AlexNet

[Hubel & Wiesel 1959]



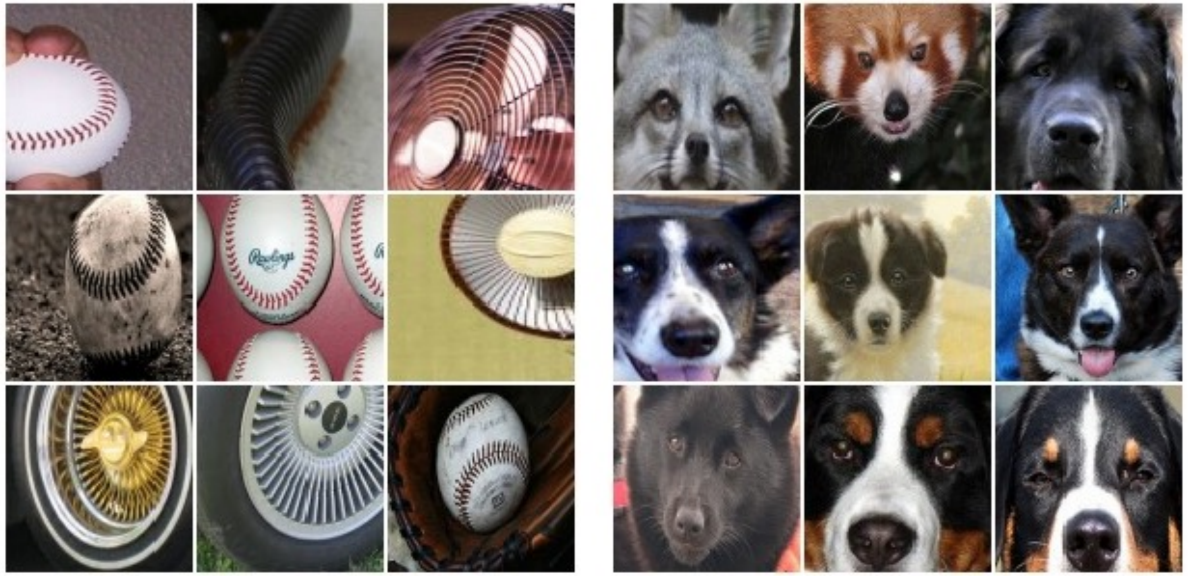
Simple cells in visual cortex detect edges, complex cells compose earlier responses

CNN higher layer filters

Dataset examples that maximize neuron outputs

[Olah '17]

CNN higher layer filters



Dataset examples that maximize neuron outputs

[Olah ‘17]

CNN higher layer filters

Dataset examples that maximize neuron outputs

[Olah ‘17]

CNN higher layer filters

Dataset examples that maximize neuron outputs

[Olah ‘17]

CNN Building Blocks

Design choices:

- filter size
- number of filters
- padding
- stride

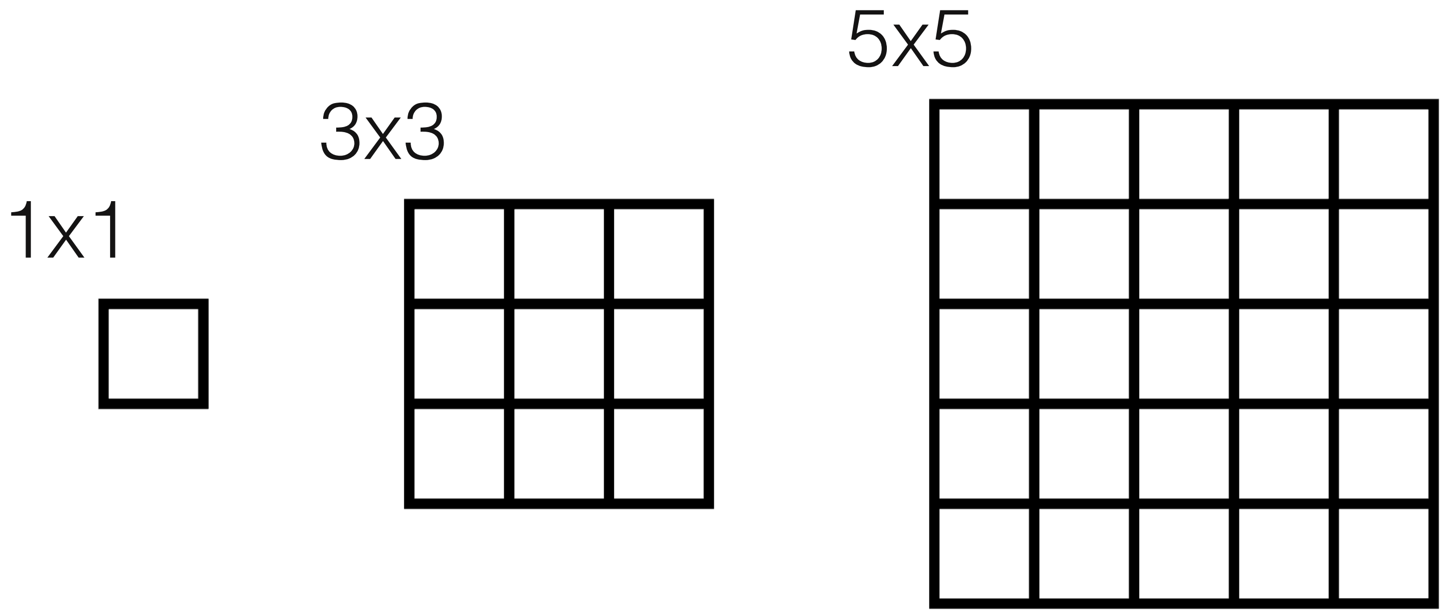
Layer types:

- pooling
- transpose convolutions
- upsampling layers*
- batch normalization*
- softmax layers*

**no time to cover all of these layers! Check out PyTorch docs for details…*
e.g., https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html

CNN Building Blocks

Filter size



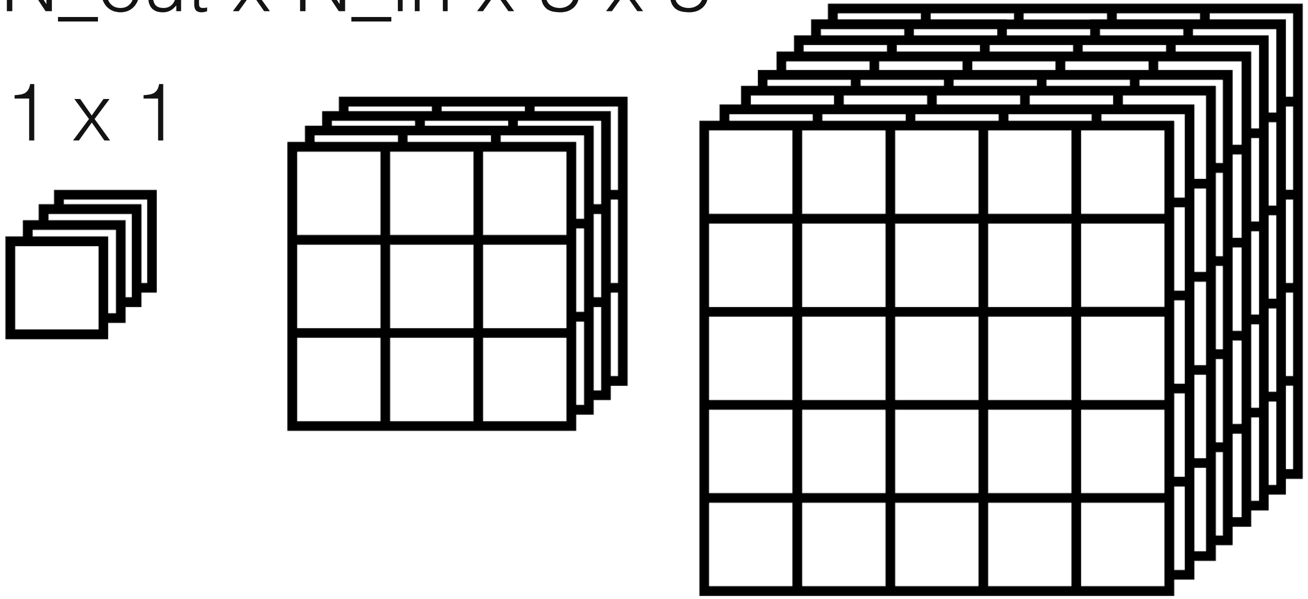
CNN Building Blocks

Number of channels

N_out x N_in x 5 x 5

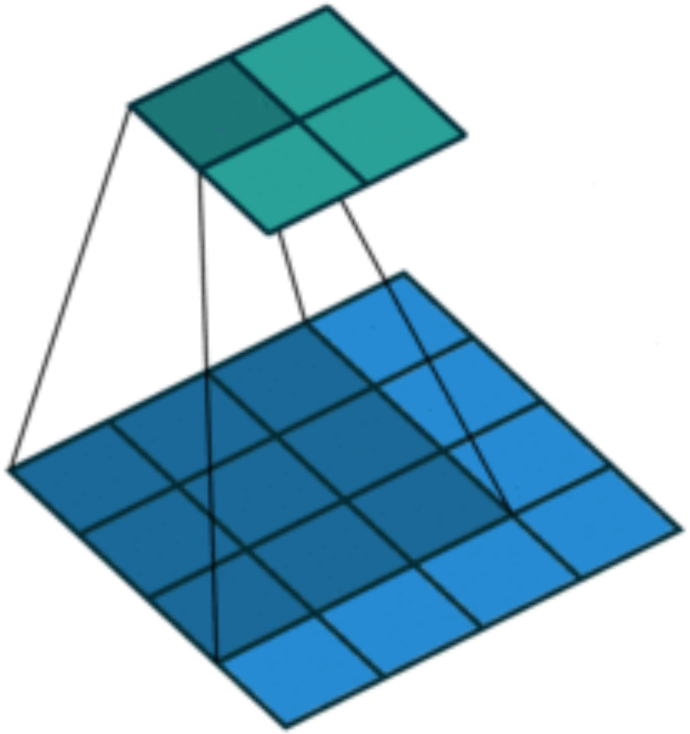
N_out x N_in x 3 x 3

N_out x N_in x 1 x 1

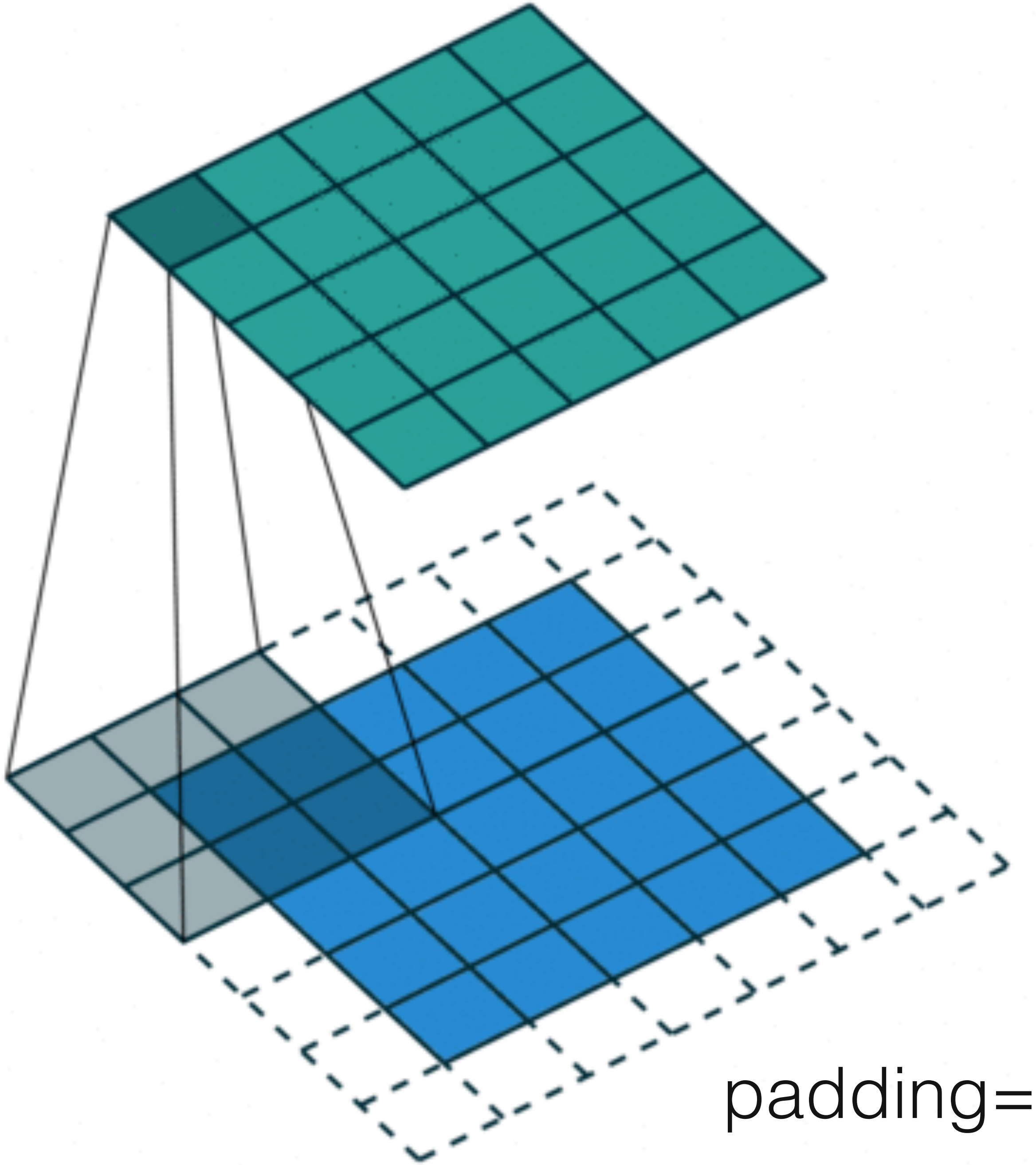


CNN Building Blocks

padding



No padding

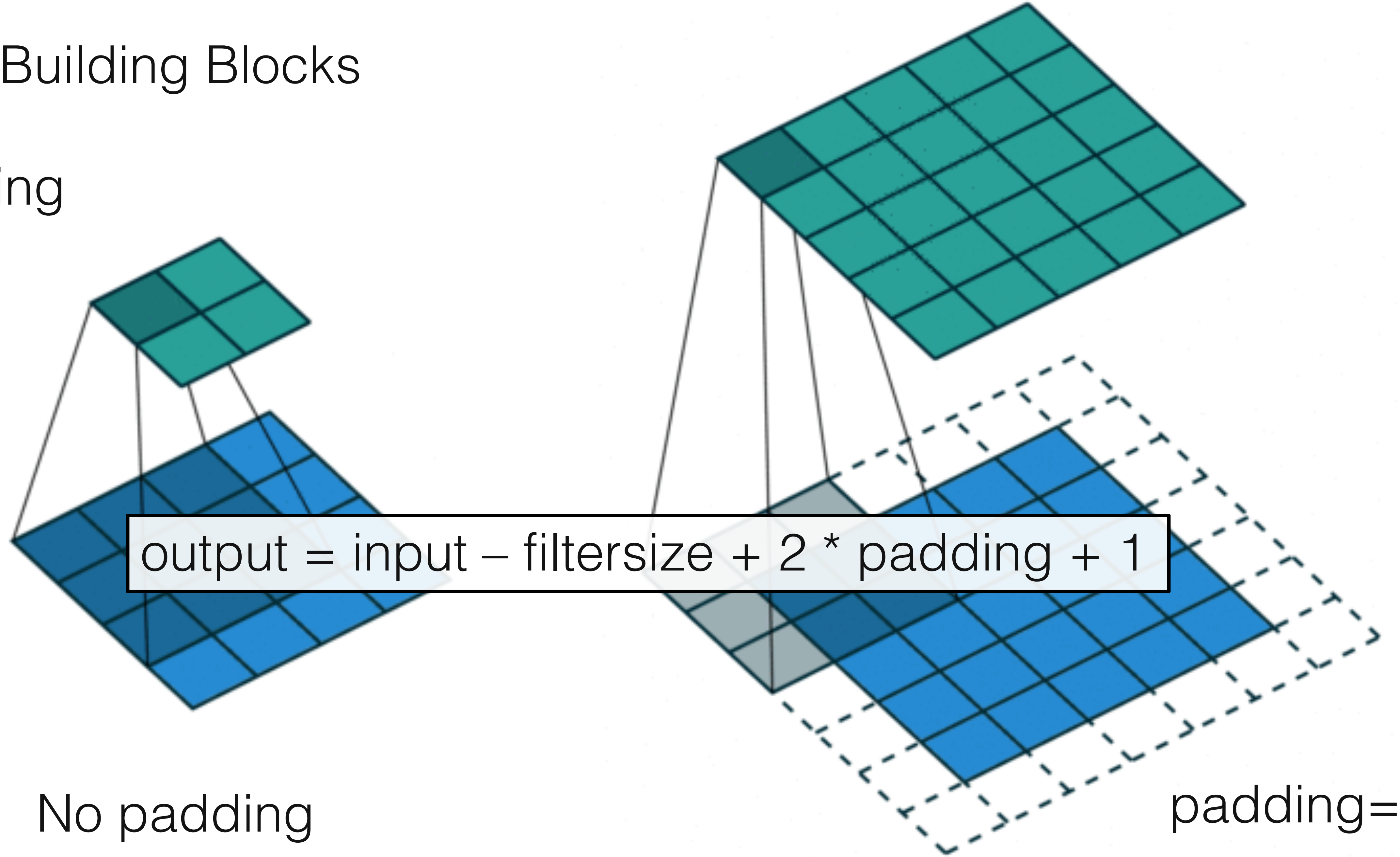


padding=1

https://github.com/vdumoulin/conv_arithmetic

CNN Building Blocks

padding



output = input – filtersize + 2 * padding + 1

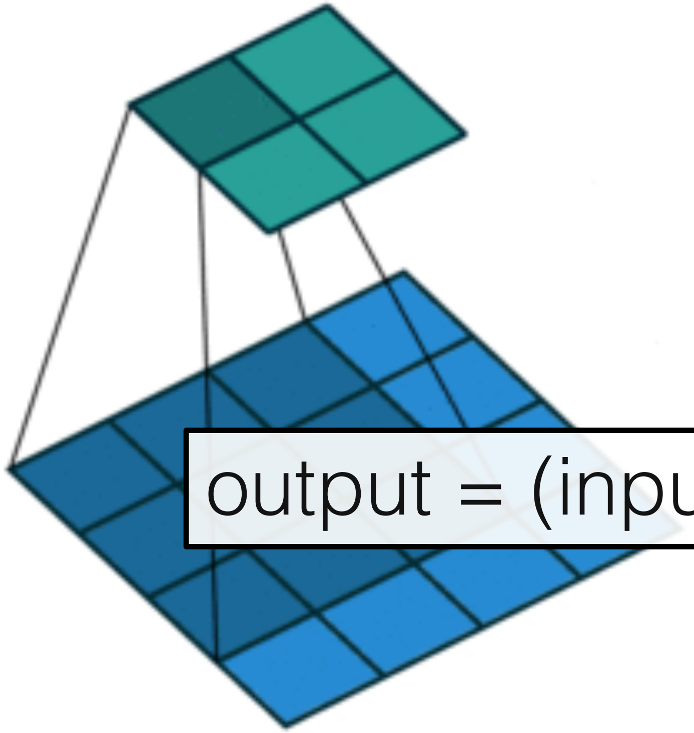
No padding

padding=1

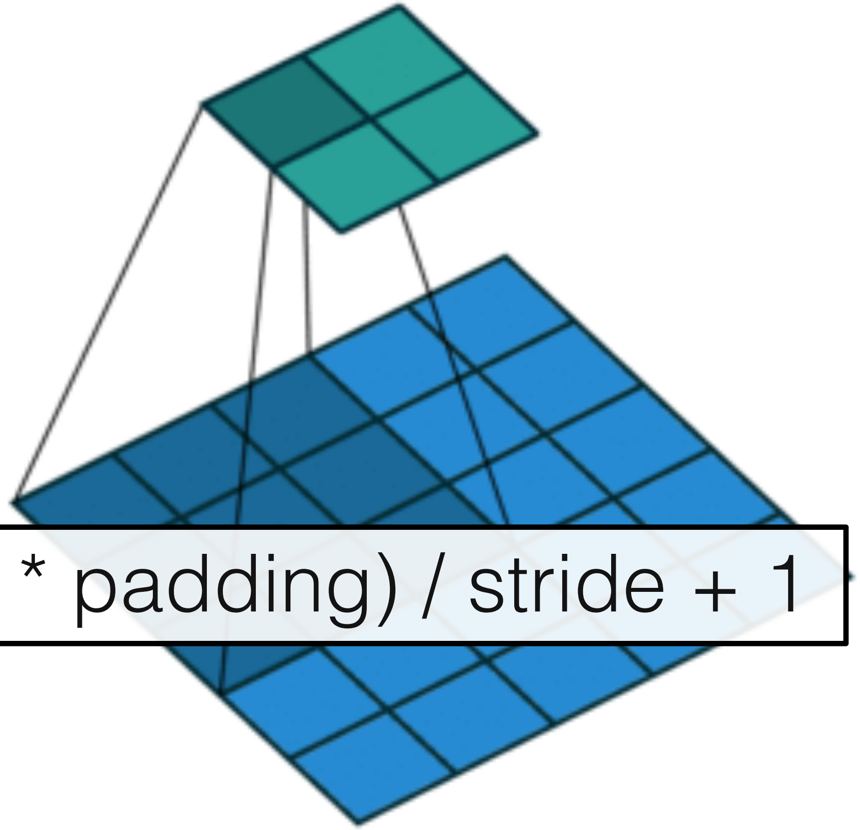
https://github.com/vdumoulin/conv_arithmetic

CNN Building Blocks

stride



stride = 1

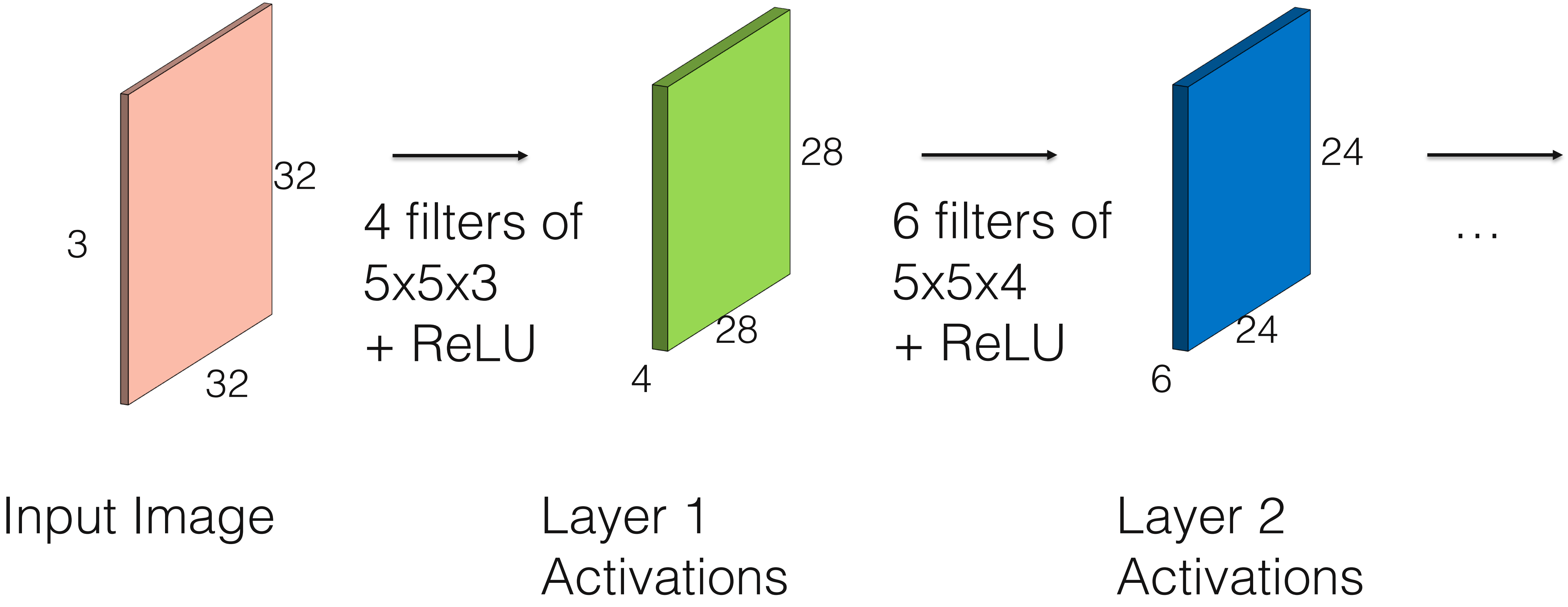


stride = 2

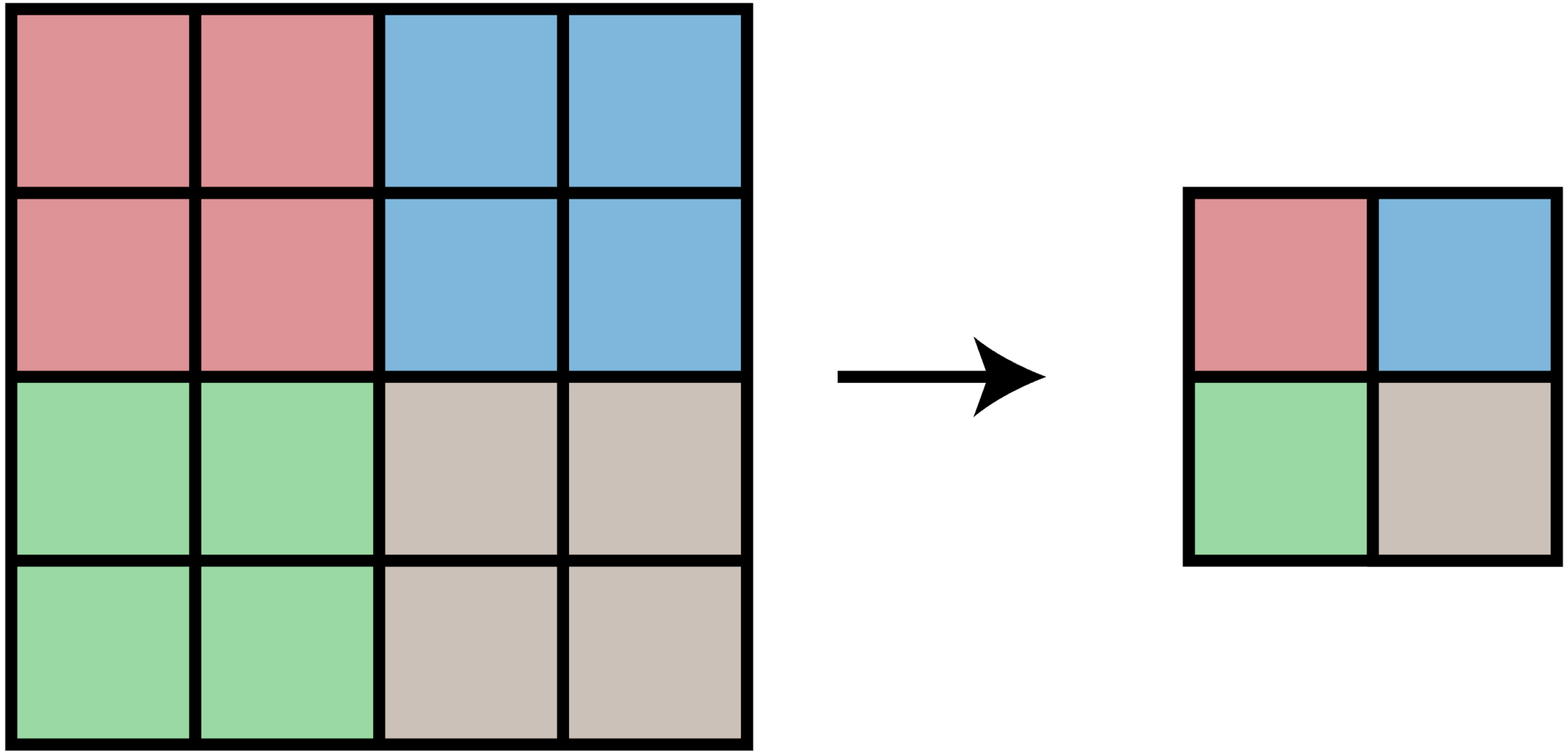
output = (input – filtersize + 2 * padding) / stride + 1

https://github.com/vdumoulin/conv_arithmetic

Convolutional Neural Network



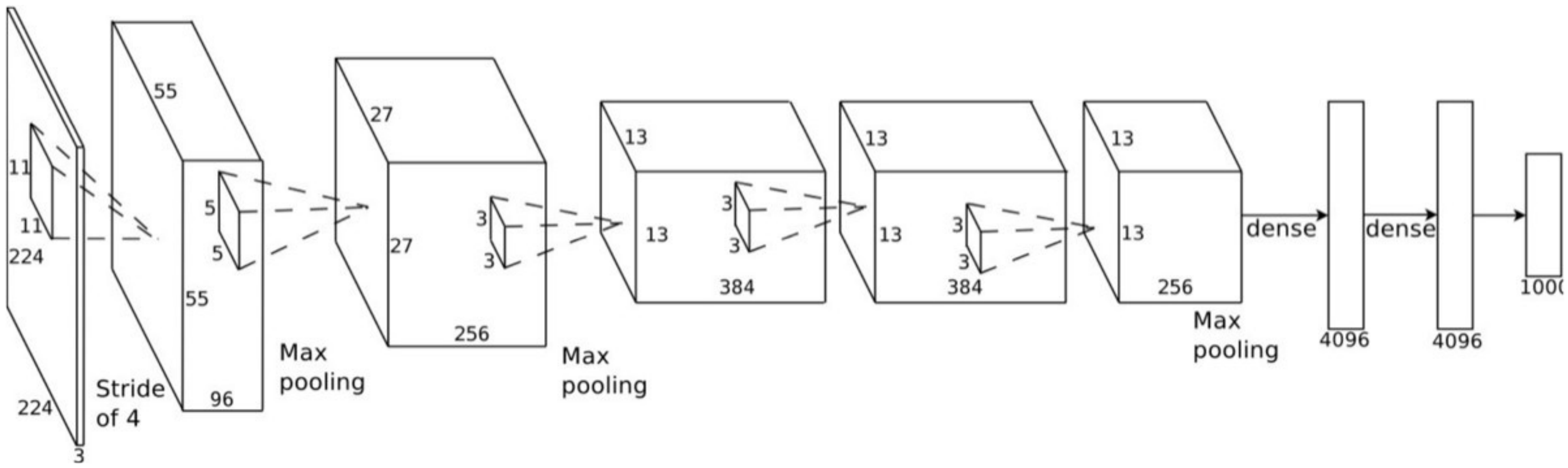
Layer types: Pooling



e.g., max pool size=2, stride=2

Convolutional Neural Networks (CNN)

- AlexNet (from UofT!): A. Krizhevsky, I. Sutskever, G. E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS 2012. This network won the Imagenet Challenge of 2012, and revolutionized computer vision.



[Pic adopted from: A. Krizhevsky]

Convolutional Neural Networks (CNN)

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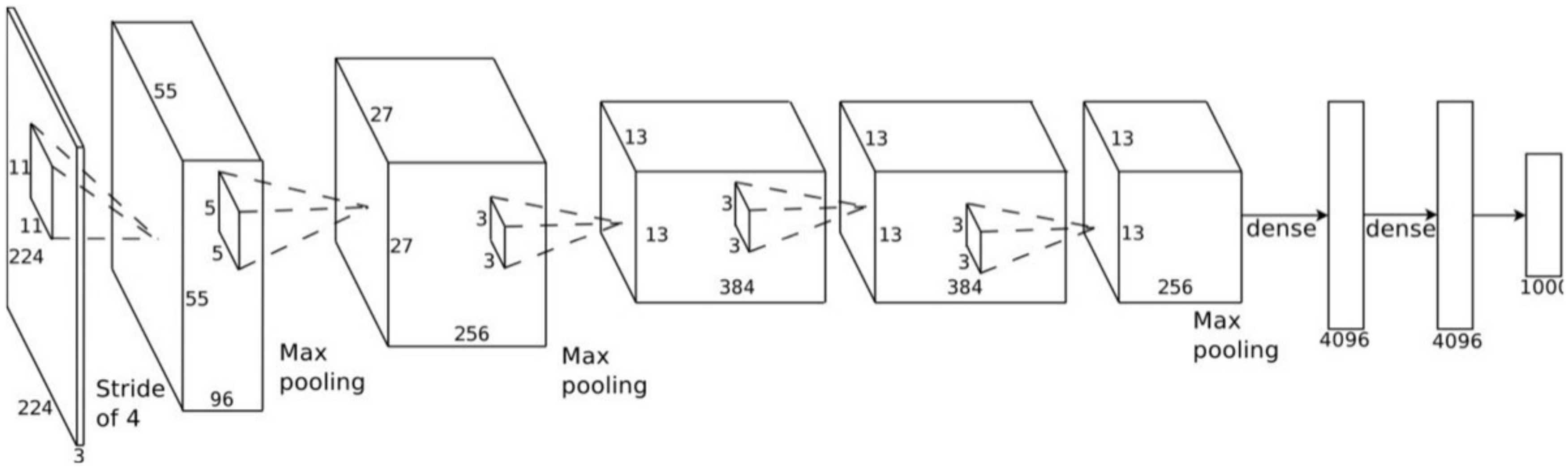
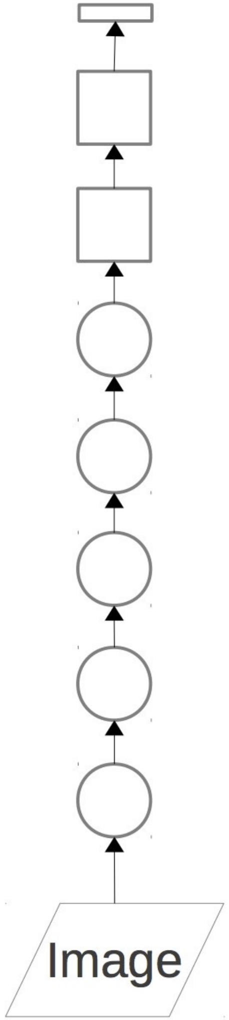
- How many parameters (weights) does this network have?



[Pic adopted from: A. Krizhevsky]

Convolutional Neural Networks (CNN)



- Trained with stochastic gradient descent on two NVIDIA GPUs for about a week
- 650,000 neurons
- 60,000,000 parameters
- 630,000,000 connections
- **Final feature layer:** 4096-dimensional

Convolutional layer: convolves its input with a bank of 3D filters, then applies point-wise non-linearity

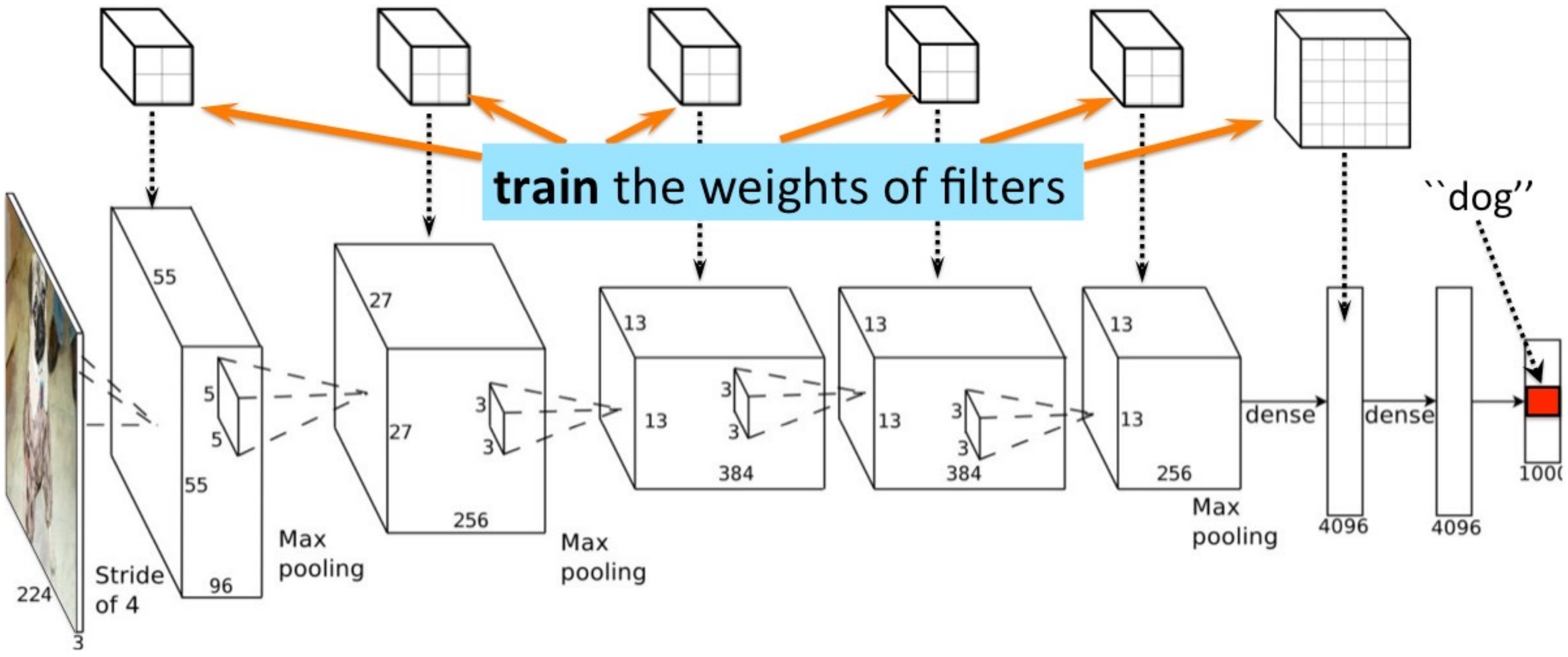
Fully-connected layer: applies linear filters to its input, then applies point-wise non-linearity

Figure: From http://www.image-net.org/challenges/LSVRC/2012/supervision.pdf

[Pic adopted from: A. Krizhevsky]

Convolutional Neural Networks (CNN)

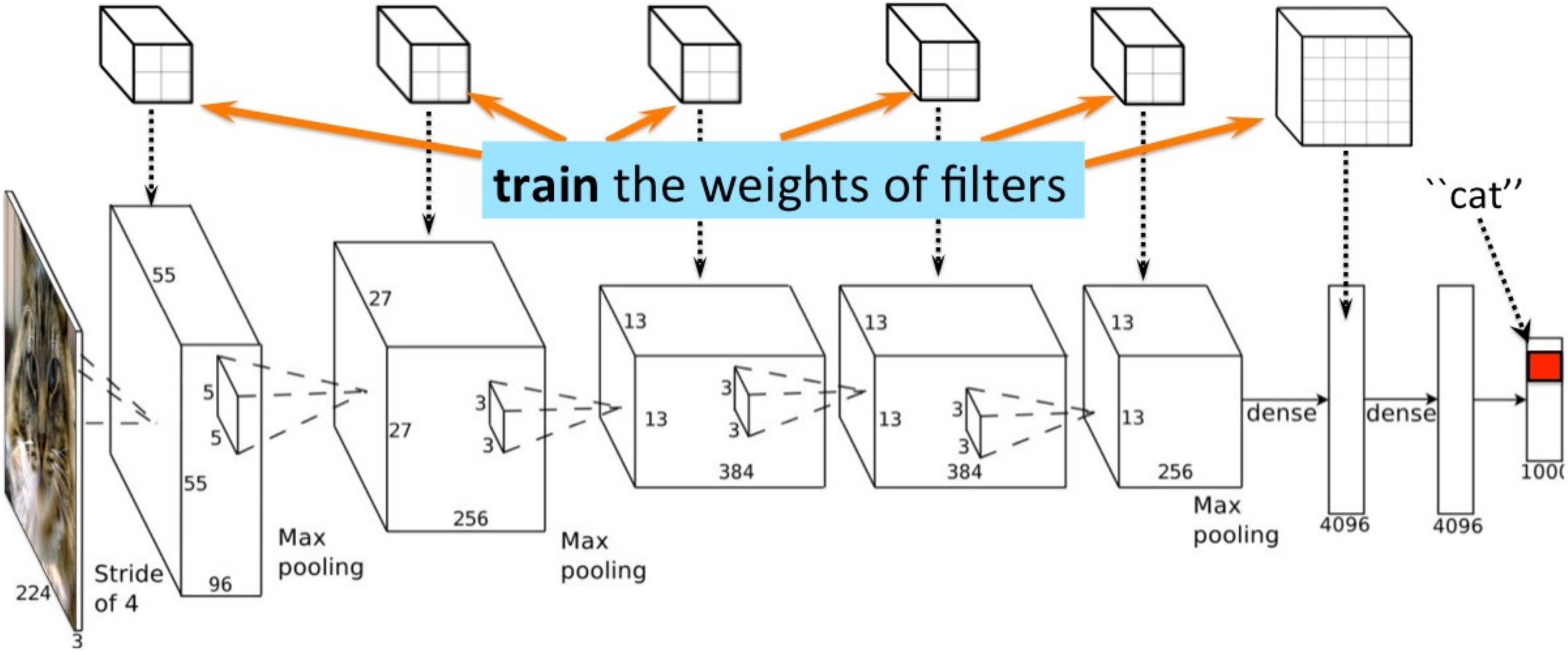
- The trick is to not hand-fix the weights, but to train them. Train them such that when the network sees a picture of a dog, the last layer will say “dog”.



[Pic adopted from: A. Krizhevsky]

Convolutional Neural Networks (CNN)

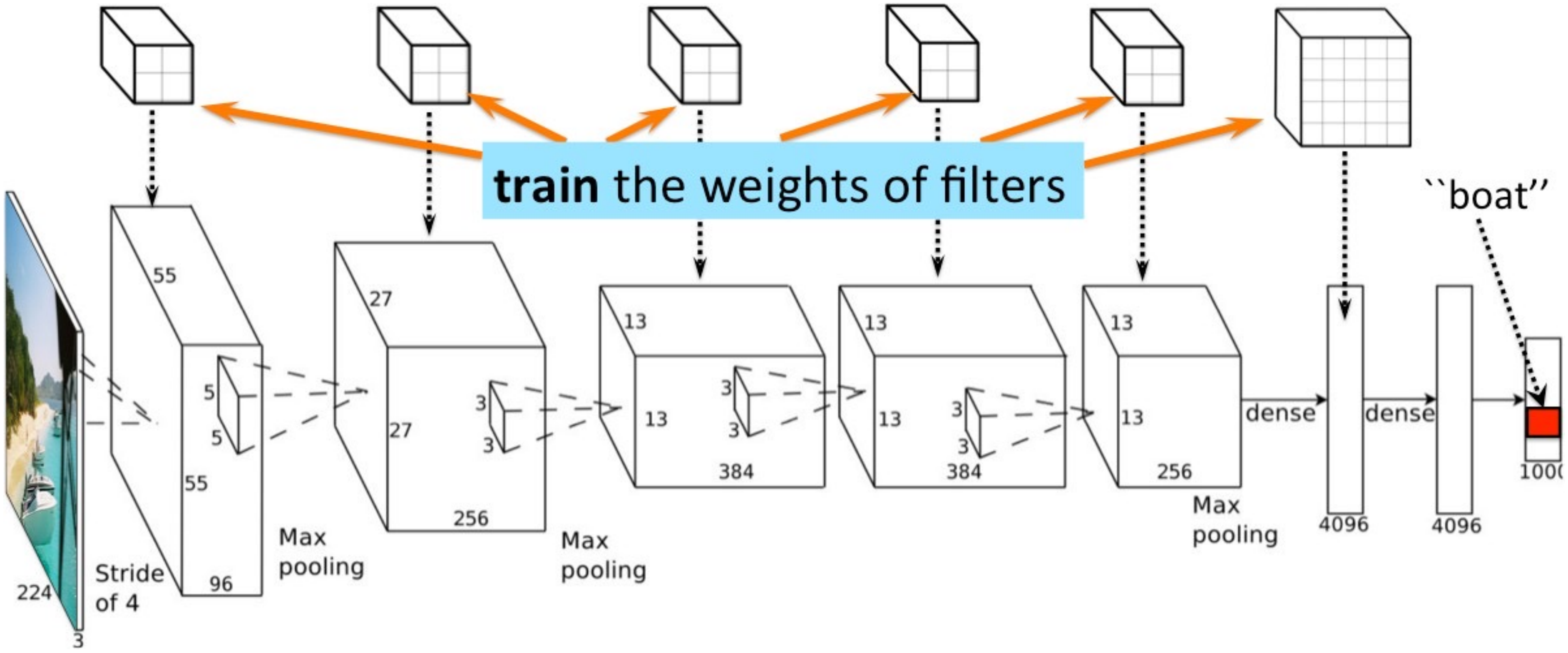
- Or when the network sees a picture of a cat, the last layer will say "cat".



[Pic adopted from: A. Krizhevsky]

Convolutional Neural Networks (CNN)

- Or when the network sees a picture of a boat, the last layer will say "boat"... The more pictures the network sees, the better.



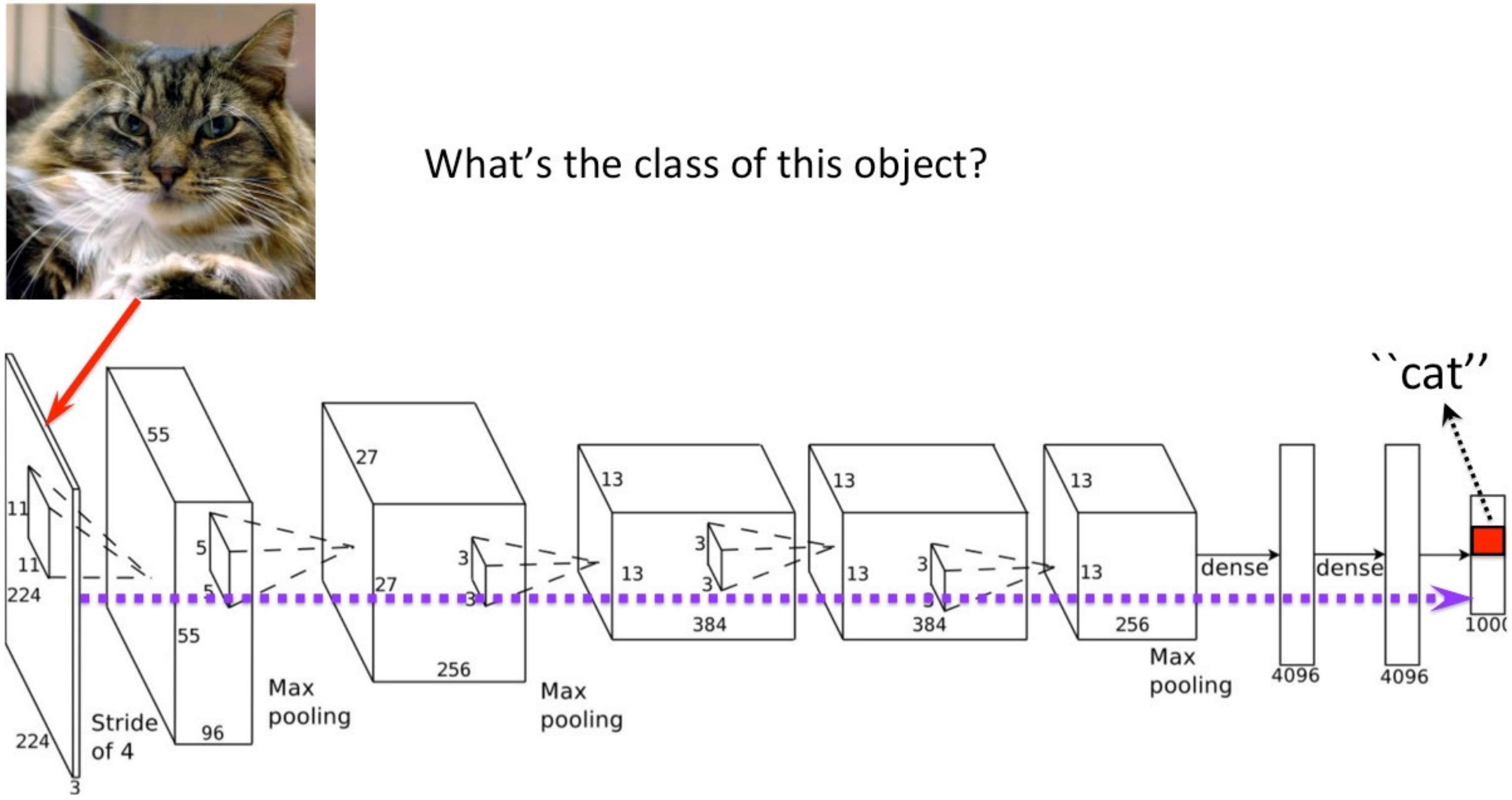
Train on **lots** of examples. Millions. Tens of millions. Wait a week for training to finish.

Share your network (the weights) with others who are not fortunate enough with GPU power.

[Pic adopted from: A. Krizhevsky]

Classification

- Once trained we can do classification. Just feed in an image or a crop of the image, run through the network, and read out the class with the highest probability in the last (classification) layer.



Overview

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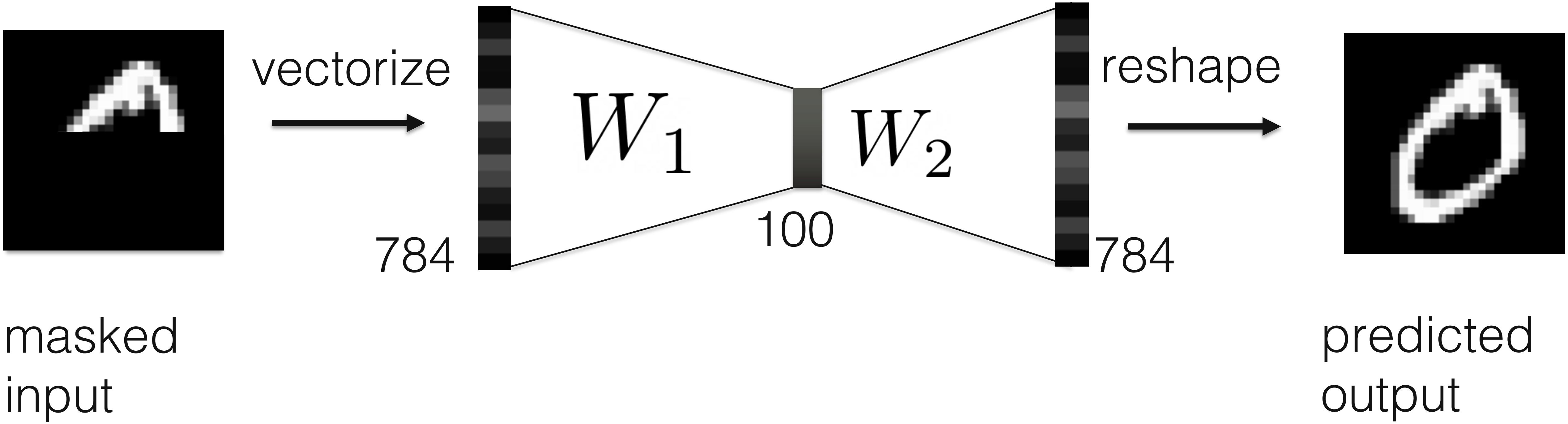
Image Inpainting



Training the MLP

masked images

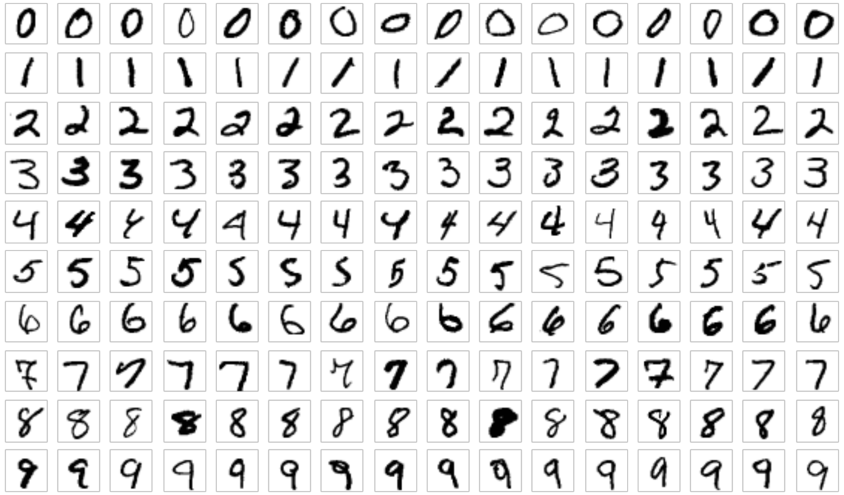
Image inpainting example

Training dataset:

- masked and complete image pairs

- train network to predict the complete image

ground truth



Training the MLP

Train the network to minimize the loss function

$$\mathcal{L}_\theta = \frac{1}{2}||y - \hat{y}||_2^2$$

network parameters

$\theta = \{W_1, W_2\}$

Training the MLP

Train the network to minimize the loss function

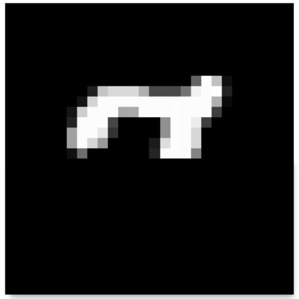
$$\mathcal{L}_\theta = \frac{1}{2}||y - \hat{y}||_2^2$$

network parameters

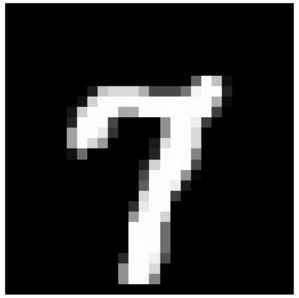
$\theta = \{W_1, W_2\}$

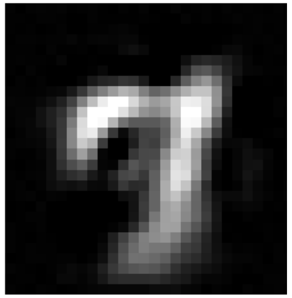
ground truth image

network prediction



input





Training the MLP

How do we figure out θ ?

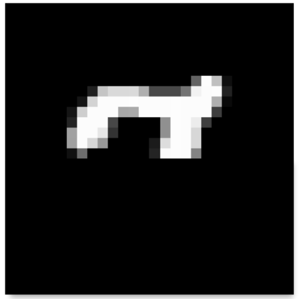
$$\mathcal{L}_\theta = \frac{1}{2}\|y - \hat{y}\|_2^2$$

network parameters

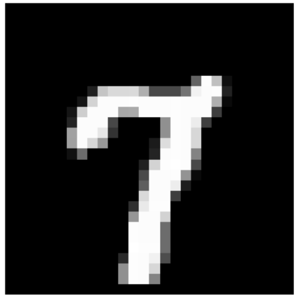
$\theta = \{W_1, W_2\}$

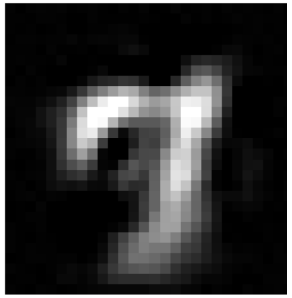
ground truth image

network prediction



input

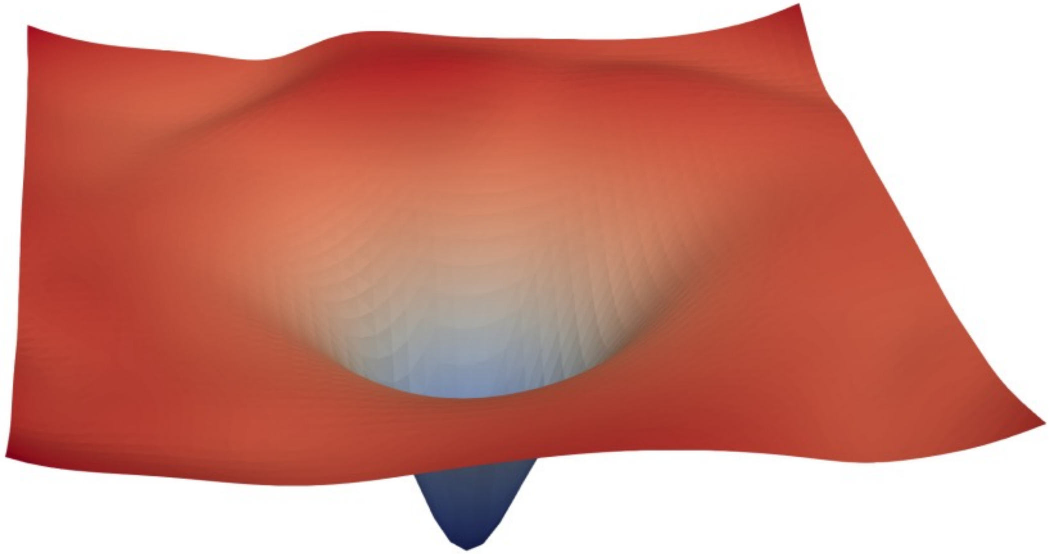




Training the MLP

Gradient-based optimization

$$\theta^{(k+1)} = \theta^{(k)} - \nabla_\theta \mathcal{L}_\theta$$



Loss Landscape

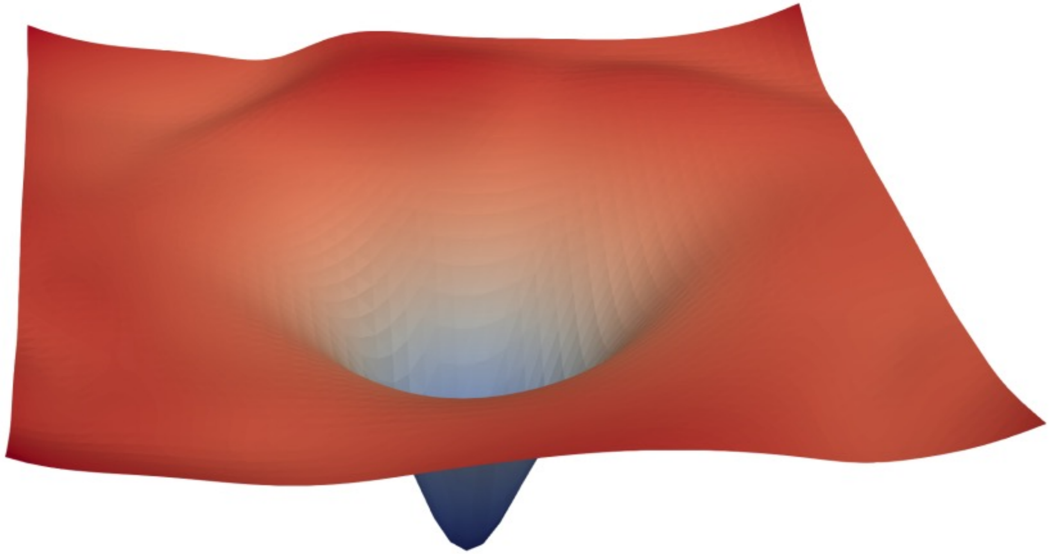
[Li et al. '18]

Training the MLP

Gradient-based optimization

$$\theta^{(k+1)} = \theta^{(k)} - \nabla_\theta \mathcal{L}_\theta$$

Need to calculate the partial derivative with respect to each parameter



Loss Landscape

[Li et al. '18]

Training the MLP

Generally there are 3 options

1. Numerical differentiation
2. Symbolic differentiation
3. “Automatic” differentiation

Numerical Differentiation

$$\frac{\partial f(x)}{\partial x} \approx \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

Not very accurate, computationally expensive

Easy to implement! Can be used to check your analytical answers..

Symbolic Differentiation

$$\begin{aligned}\frac{\partial \mathcal{L}_\theta}{\partial W_1} &= \frac{\partial}{\partial W_1}\frac{1}{2}\|y-\hat{y}\|_2^2 \\ &= \frac{\partial}{\partial W_1}\frac{1}{2}\left(W_2\sigma(W_1x)\right)^T\left(W_2\sigma(W_1x)\right) \\ &= \frac{\partial}{\partial W_1}\frac{1}{2}\sigma(W_1x)^T W_2^T W_2\sigma(W_1x) \\ &= \ldots \quad \text{chain rule, product rule…}\end{aligned}$$

Accurate, but must be manually calculated for each term
Tedious!

Automatic Differentiation

Think about the problem as a "computational graph"

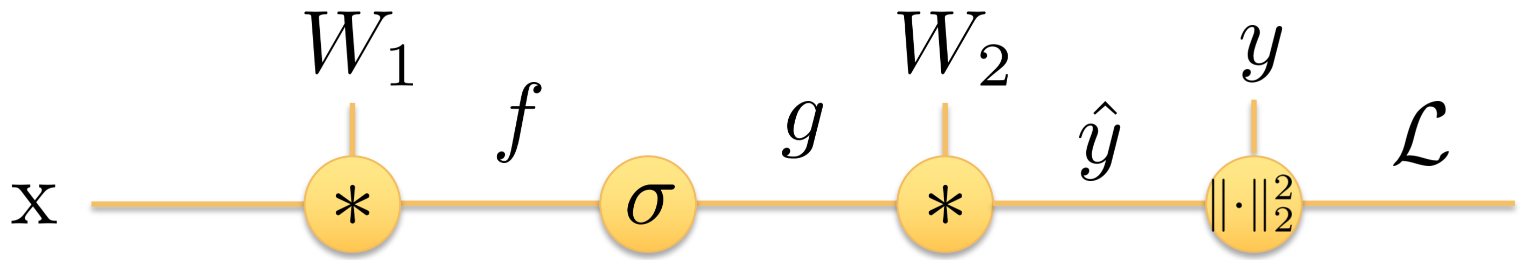
Divide and conquer using the chain rule

Enables "backpropagation" – an efficient way to take derivatives of all parameters in a computational graph

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule



Automatic Differentiation

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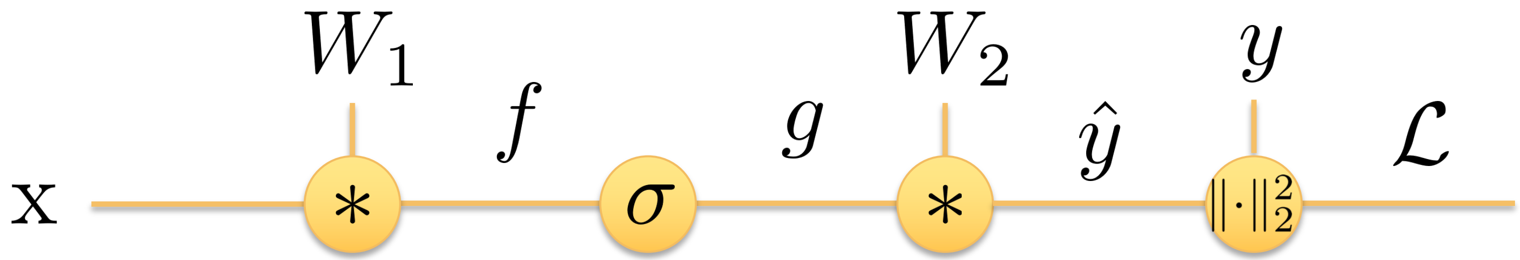
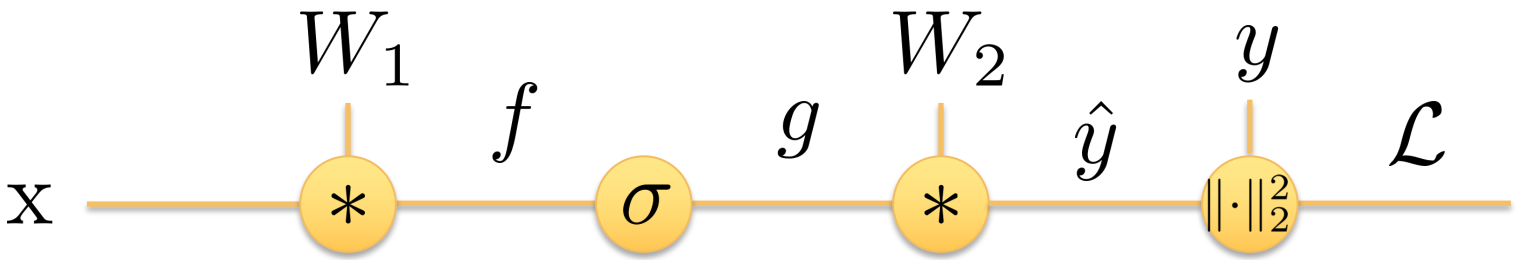


$$\frac{\partial \mathcal{L}}{\partial W_2} = \frac{\partial \hat{y}}{\partial W_2}\frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule

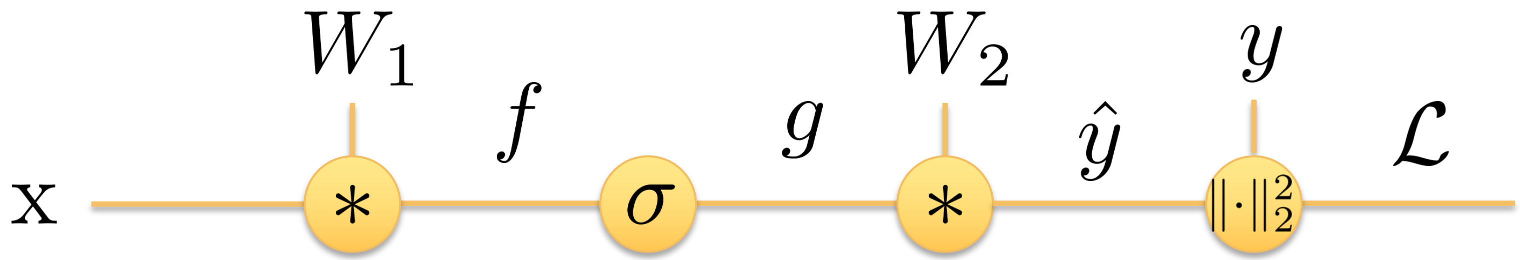


$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Automatic Differentiation

Think about the problem as a "computational graph"

Divide and conquer using the chain rule

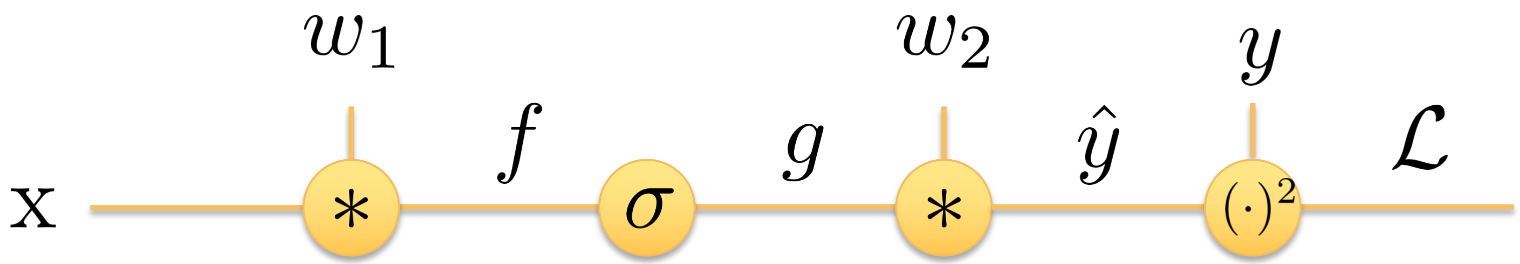


$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

We can calculate analytical expressions for each of these terms and then plug in our values

Autodiff Example

(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1}\frac{\partial g}{\partial f}\frac{\partial \hat{y}}{\partial g}\boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}}$$

Autodiff Example

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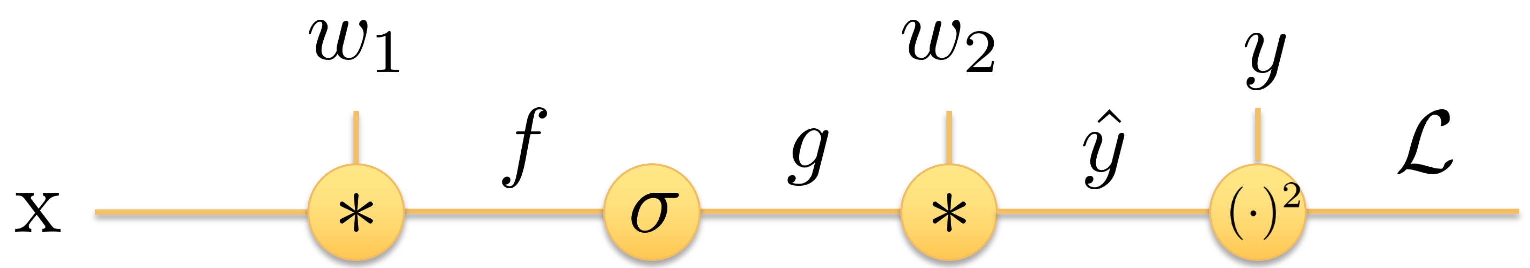
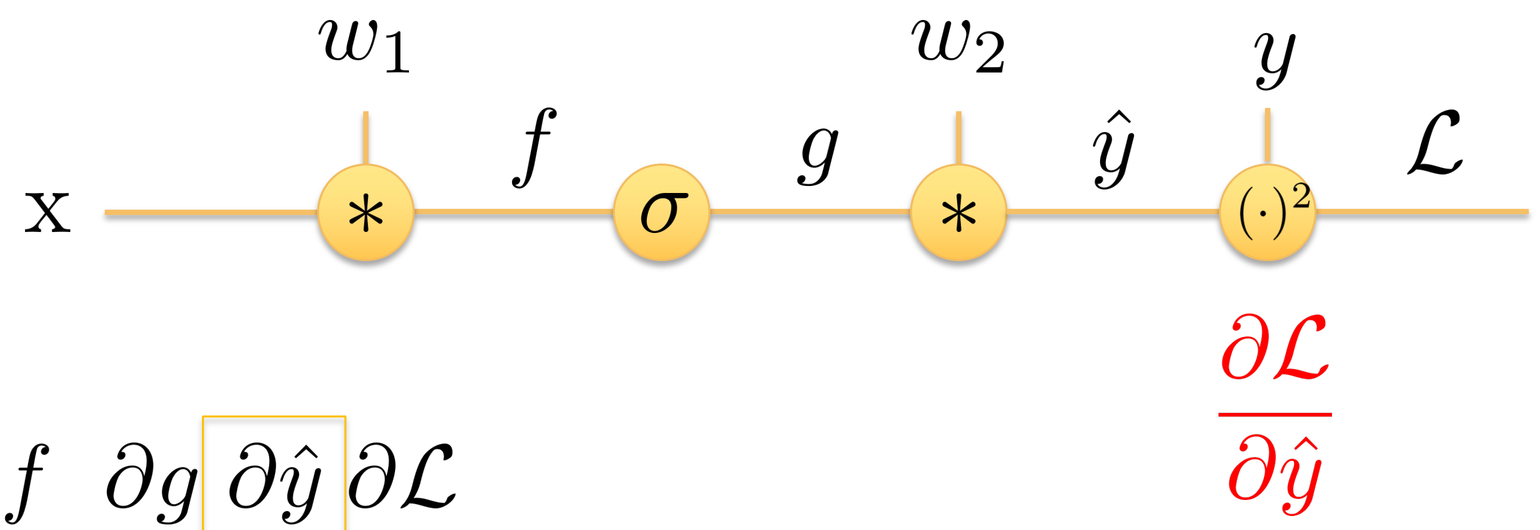


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \boxed{\frac{\partial \mathcal{L}}{\partial \hat{y}}}$$

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \frac{\partial}{\partial \hat{y}} \frac{1}{2} (\hat{y} - y)^2 = \hat{y} - y$$

Autodiff Example

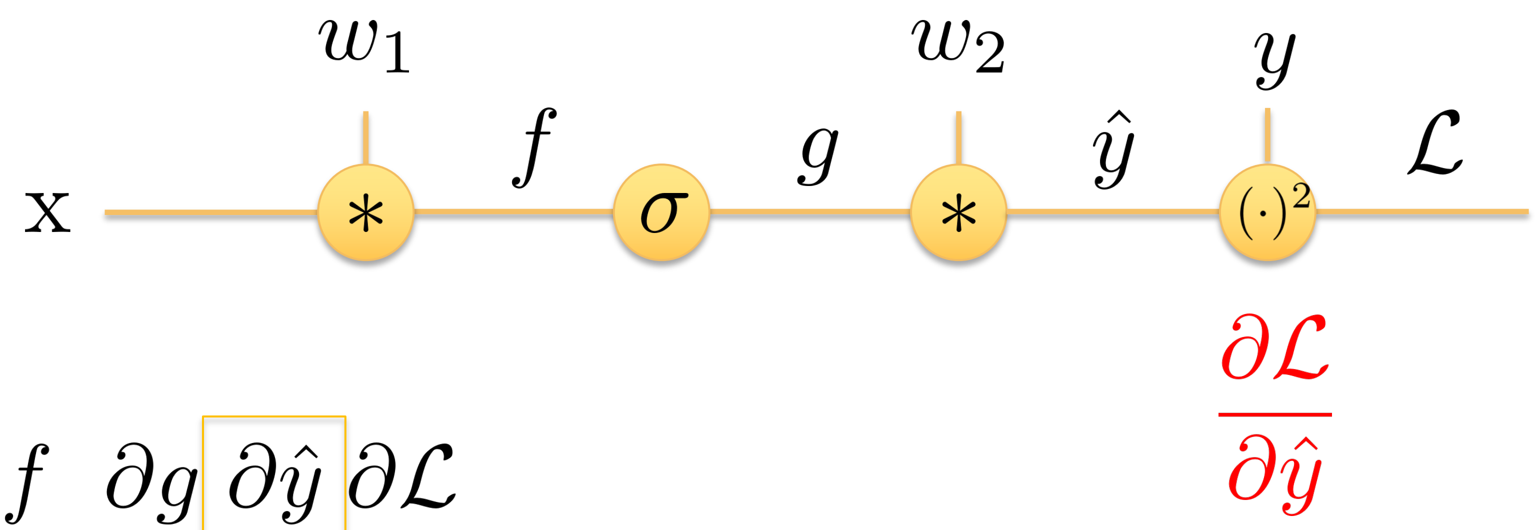
(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \boxed{\frac{\partial \hat{y}}{\partial g}} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

(assume scalar values for now)

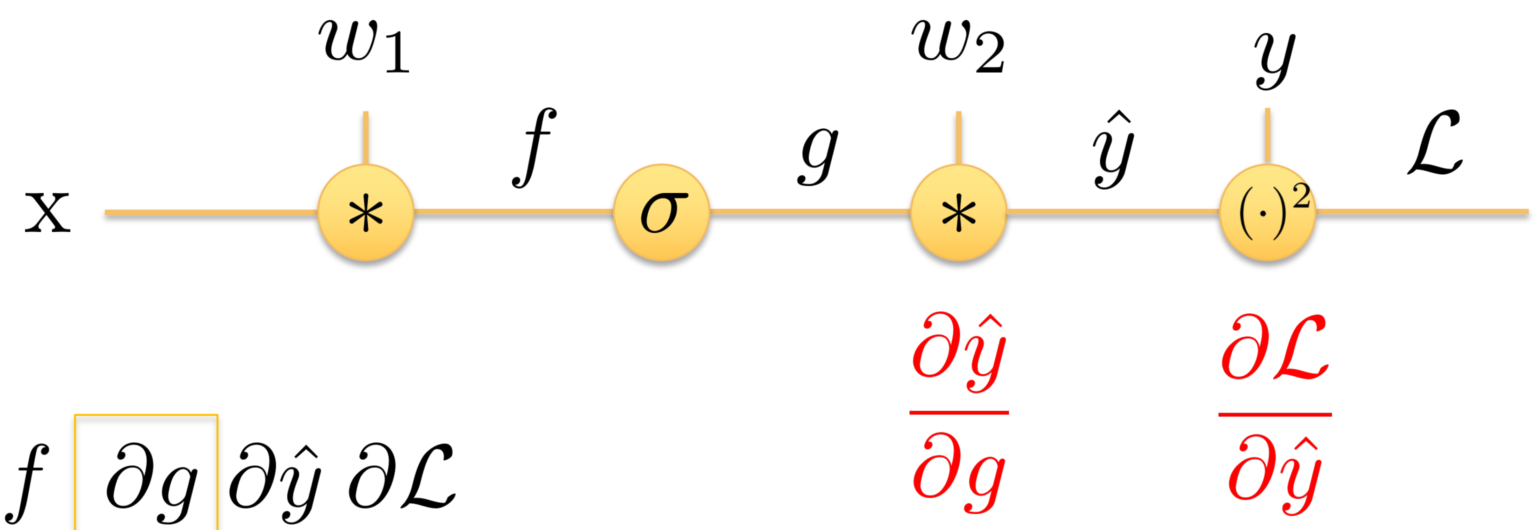


$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \frac{\partial g}{\partial f} \boxed{\frac{\partial \hat{y}}{\partial g}} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial \hat{y}}{\partial g} = \frac{\partial}{\partial g} w_2 \cdot g = w_2$$

Autodiff Example

(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \boxed{\frac{\partial g}{\partial f}} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

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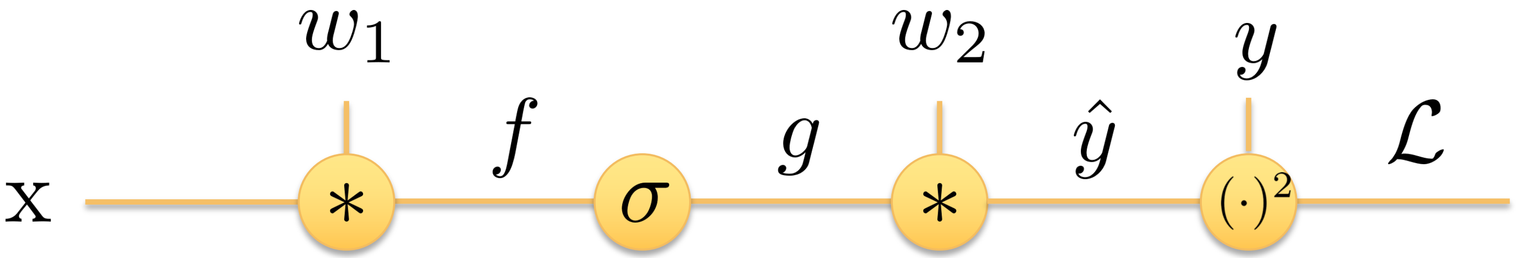


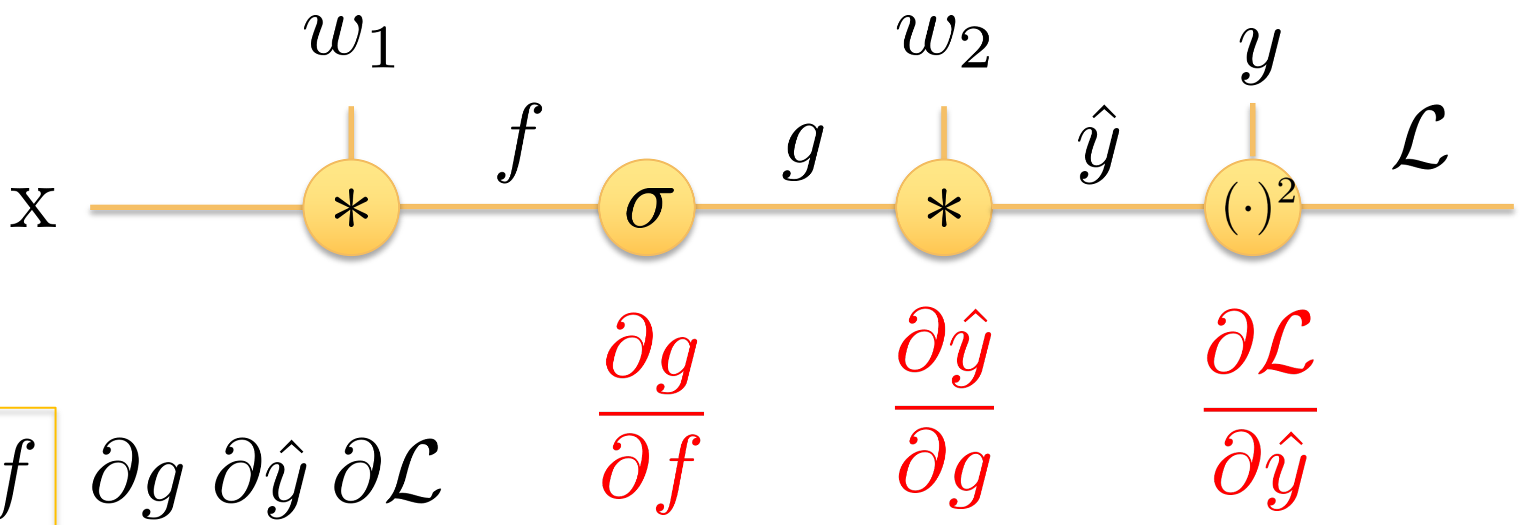
$$\frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial \mathcal{L}}{\partial w_1} = \frac{\partial f}{\partial w_1} \boxed{\frac{\partial g}{\partial f}} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial g}{\partial f} = \frac{\partial}{\partial f}\sigma(f) = \frac{\partial}{\partial f}\max(0, f) = \begin{cases} 0, & f < 0 \\ 1 & \text{else} \end{cases}$$

Autodiff Example

(assume scalar values for now)



$$\frac{\partial \mathcal{L}}{\partial w_1} = \boxed{\frac{\partial f}{\partial w_1}} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example

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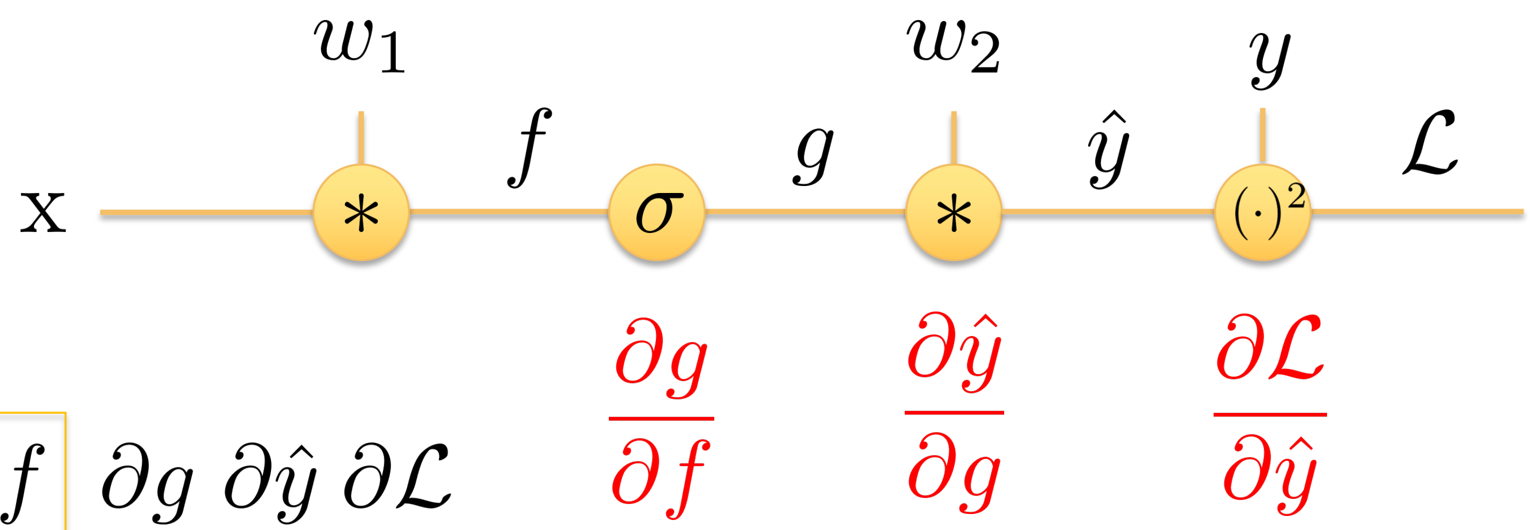
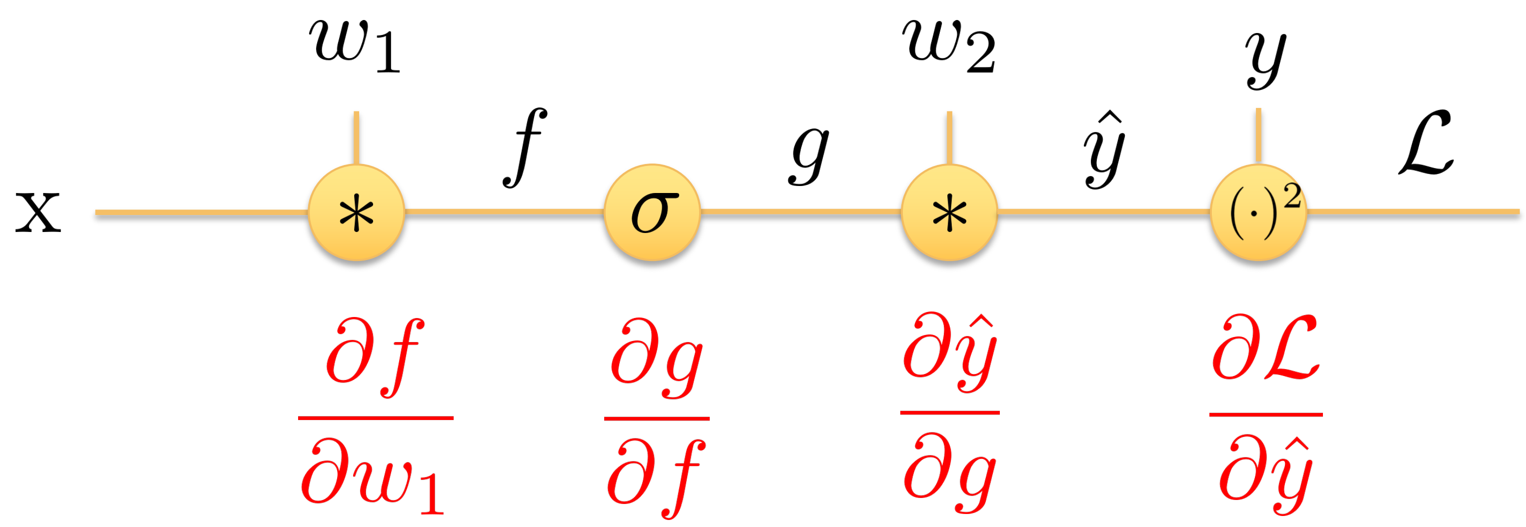


$$\frac{\partial \mathcal{L}}{\partial w_1} = \boxed{\frac{\partial f}{\partial w_1}} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

$$\frac{\partial f}{\partial w_1} = \frac{\partial}{\partial w_1} w_1 \cdot x = x$$

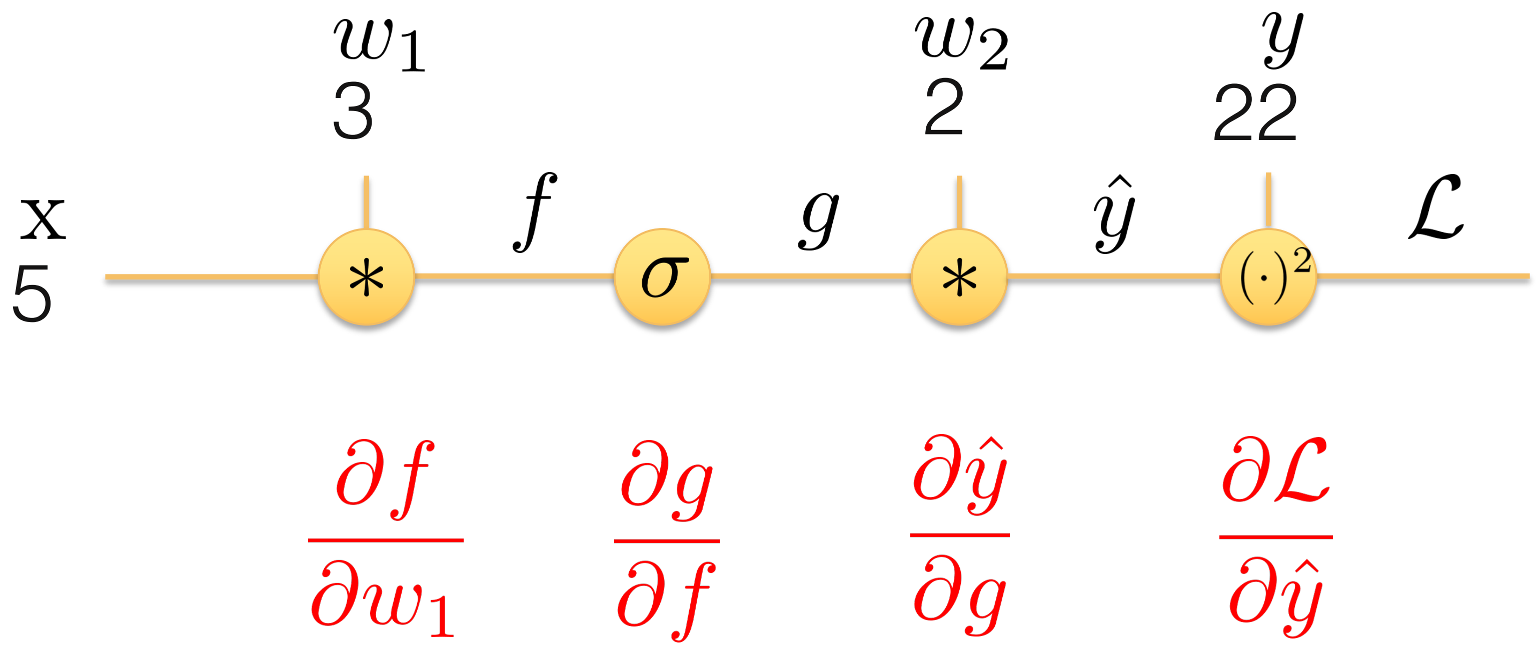
Autodiff Example

(assume scalar values for now)



Autodiff Example

Let's plug in the values now…



Autodiff Example

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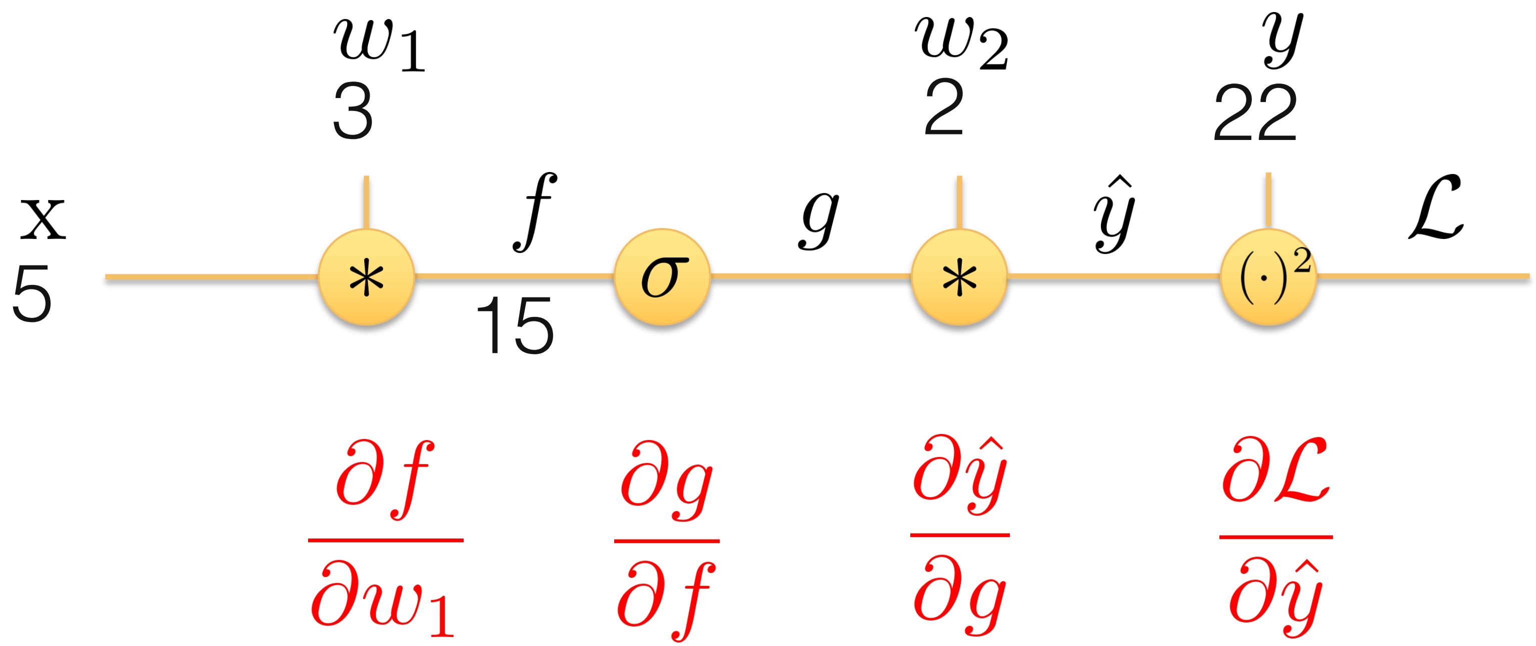

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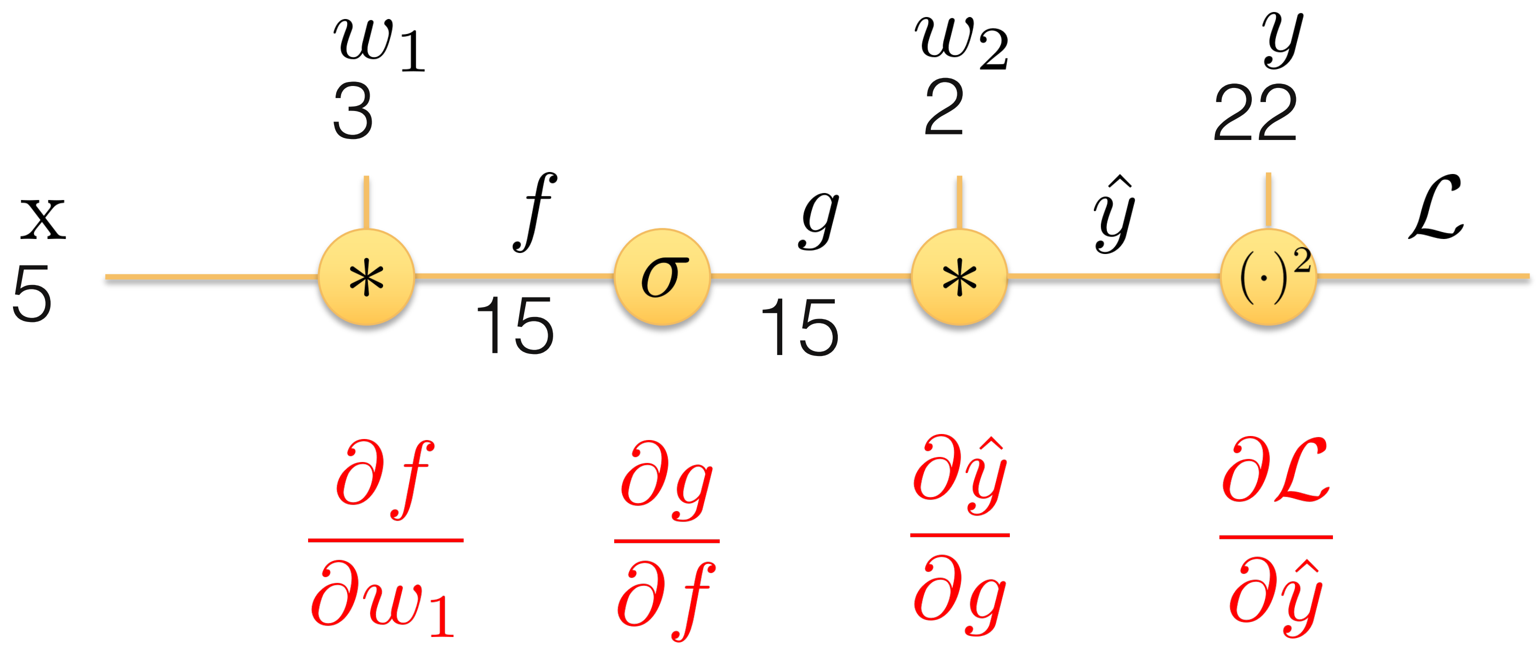

Autodiff Example

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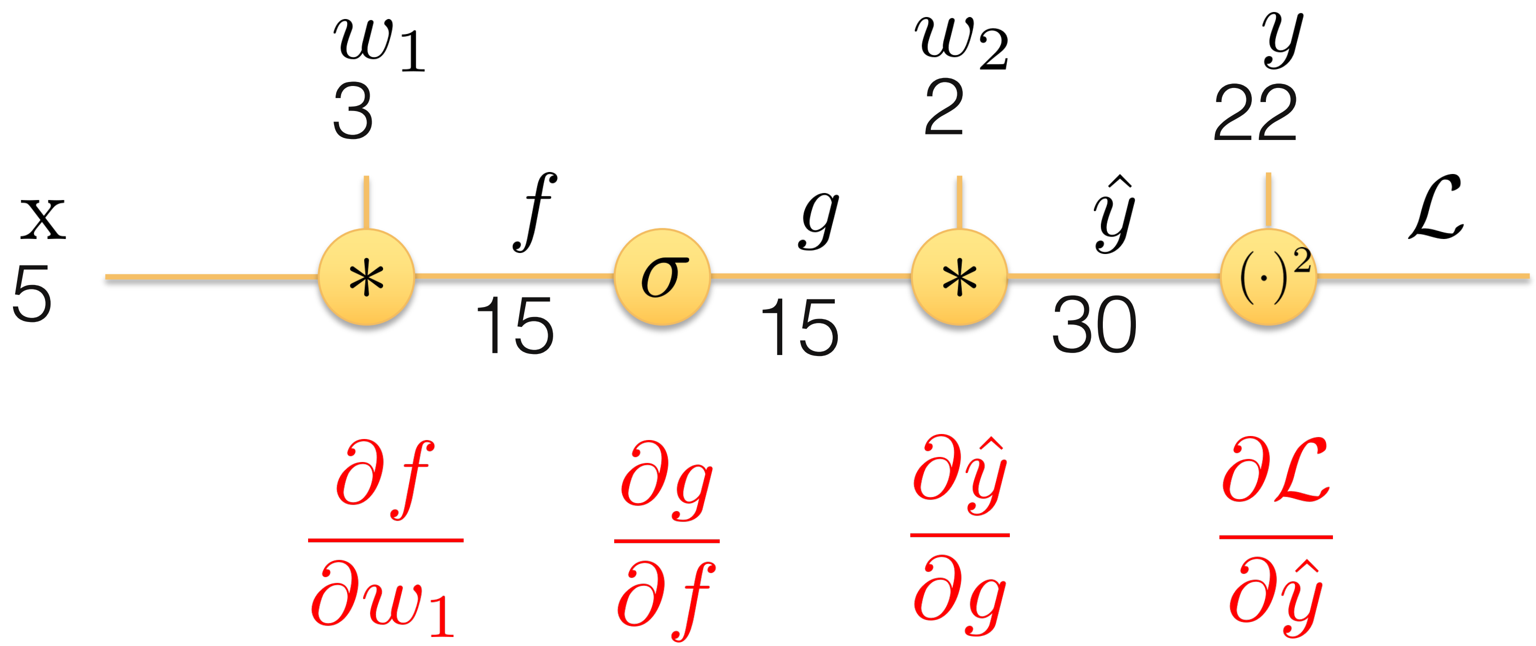

Autodiff Example

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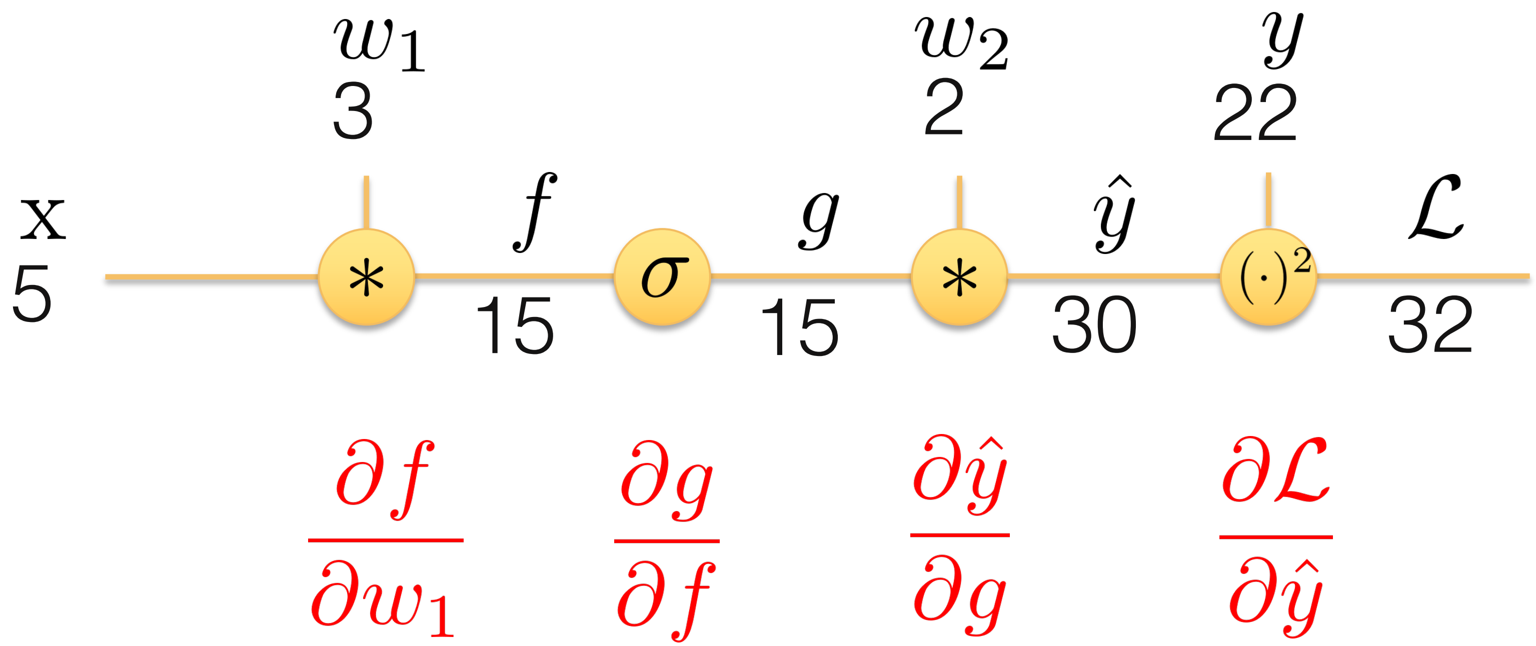
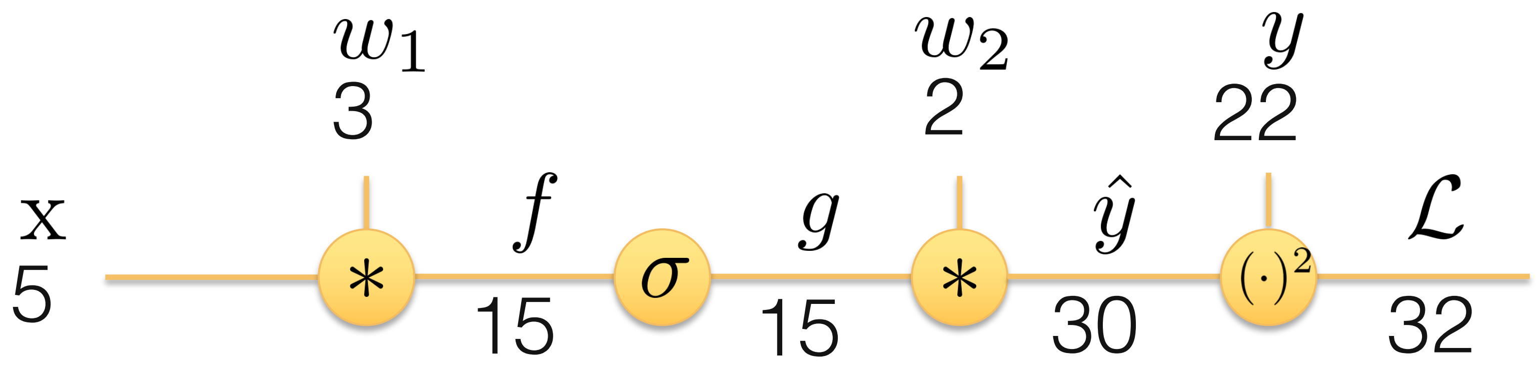


Autodiff Example

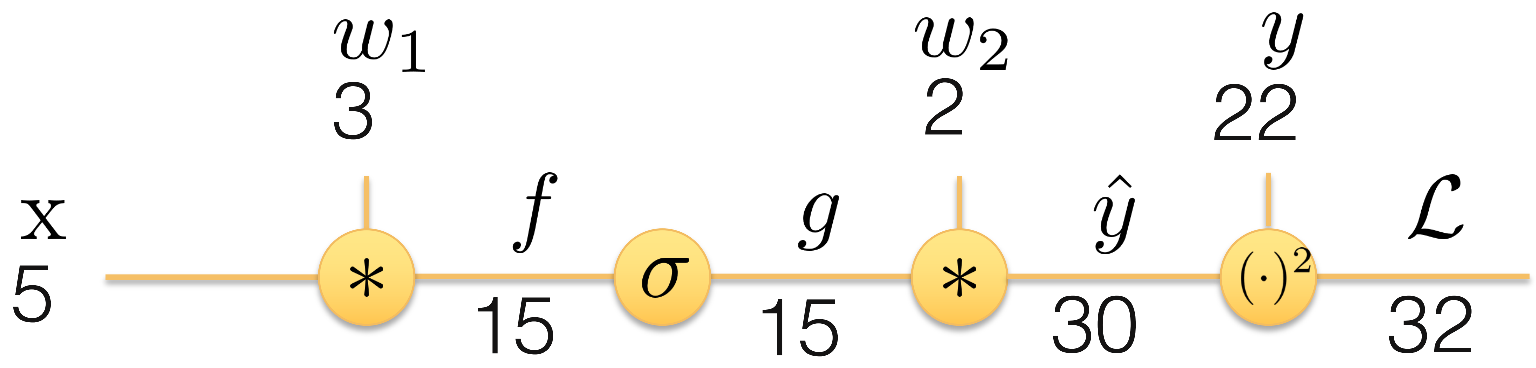
Let's plug in the values now…



$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

Autodiff Example

Let's plug in the values now…

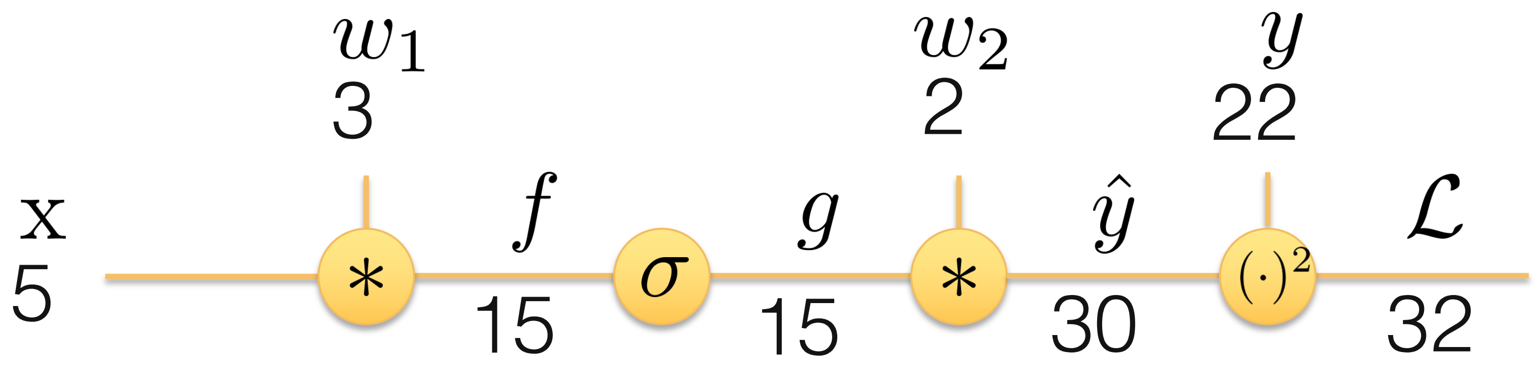


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

8

Autodiff Example

Let's plug in the values now…



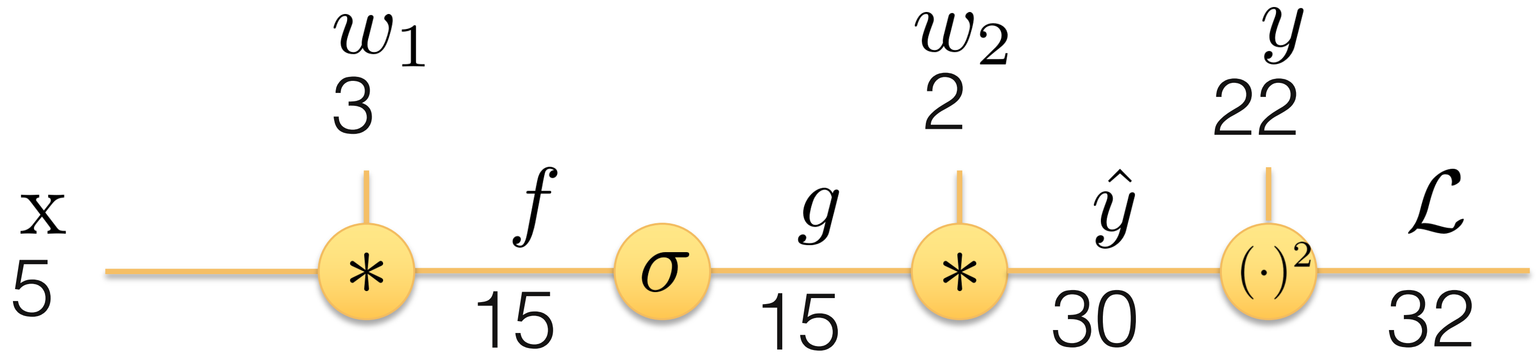
$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

$\frac{\partial \hat{y}}{\partial g}$: 2

$\frac{\partial \mathcal{L}}{\partial \hat{y}}$: 8

Autodiff Example

Let's plug in the values now…

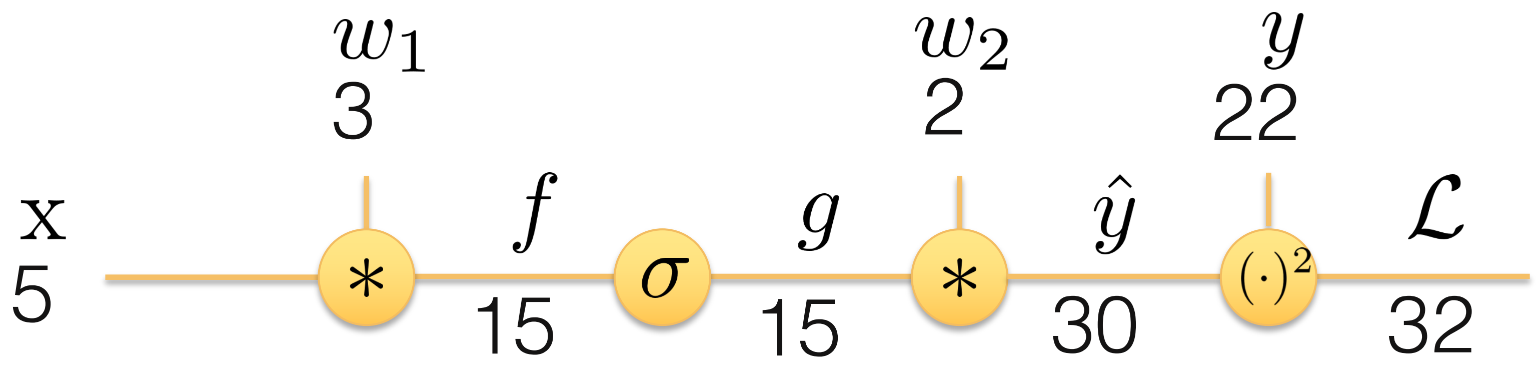


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

1 2 8

Autodiff Example

Let's plug in the values now…

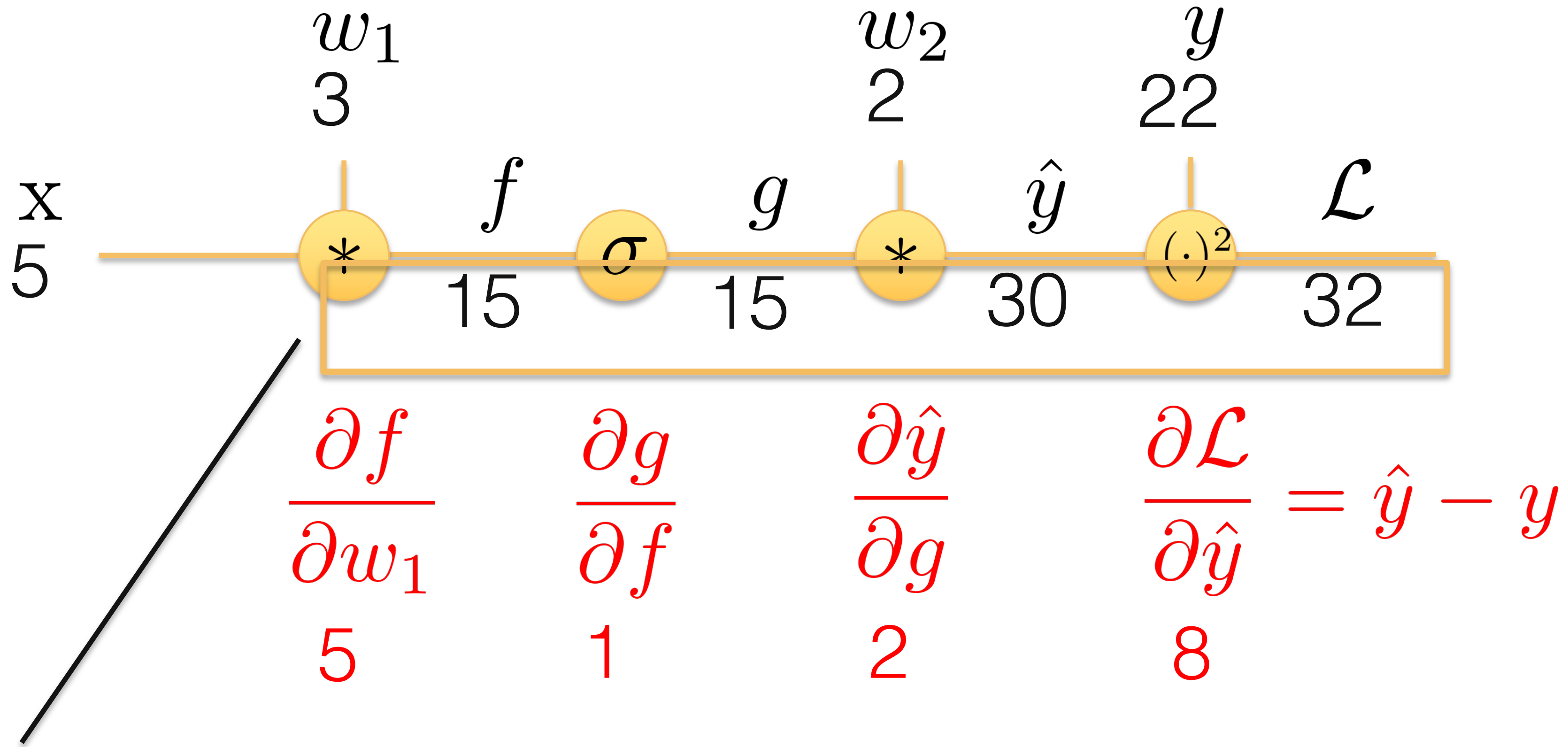


$$\frac{\partial f}{\partial w_1} \qquad \frac{\partial g}{\partial f} \qquad \frac{\partial \hat{y}}{\partial g} \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

5 1 2 8

Autodiff Example

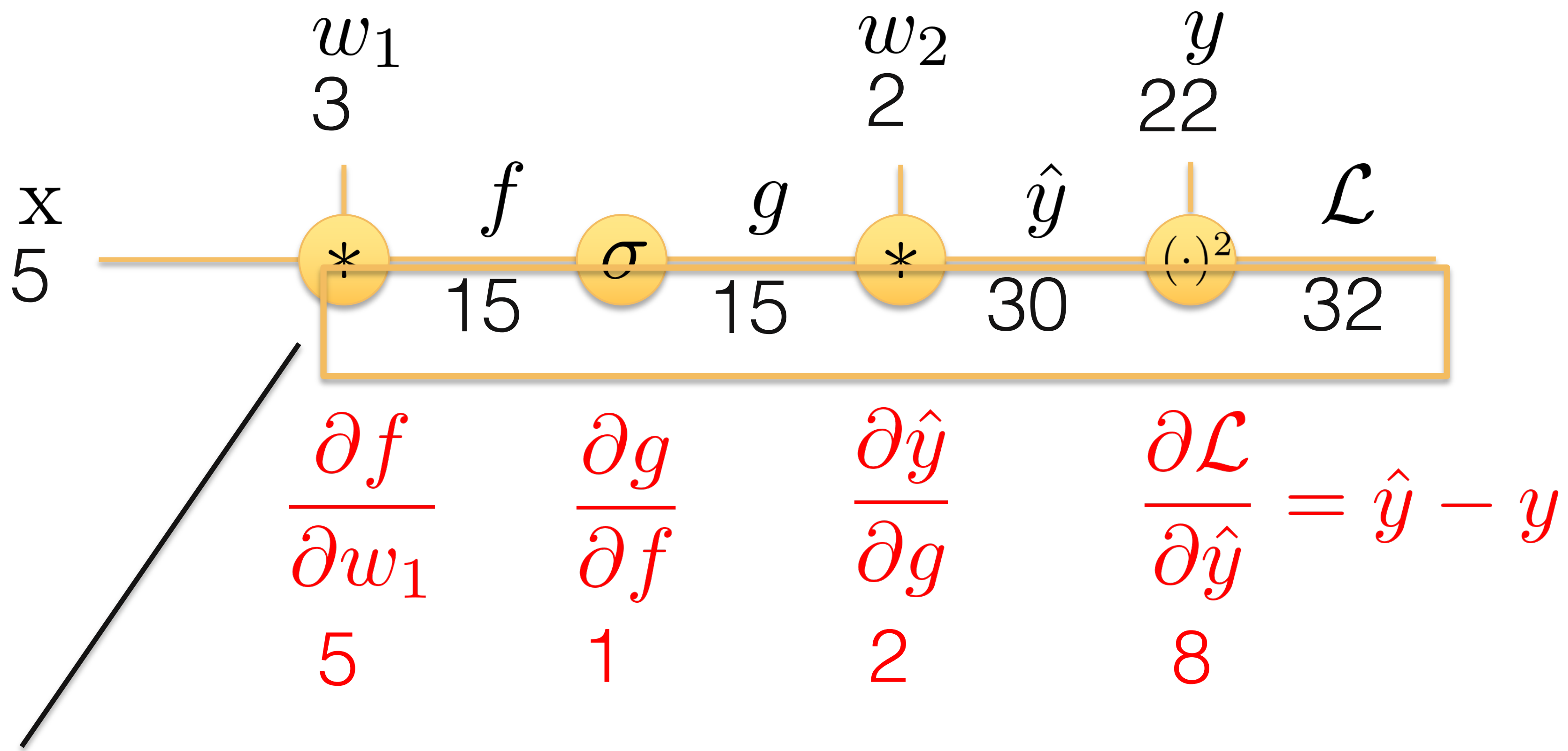
What is backpropagation?



Save these intermediate values during forward computation

Autodiff Example

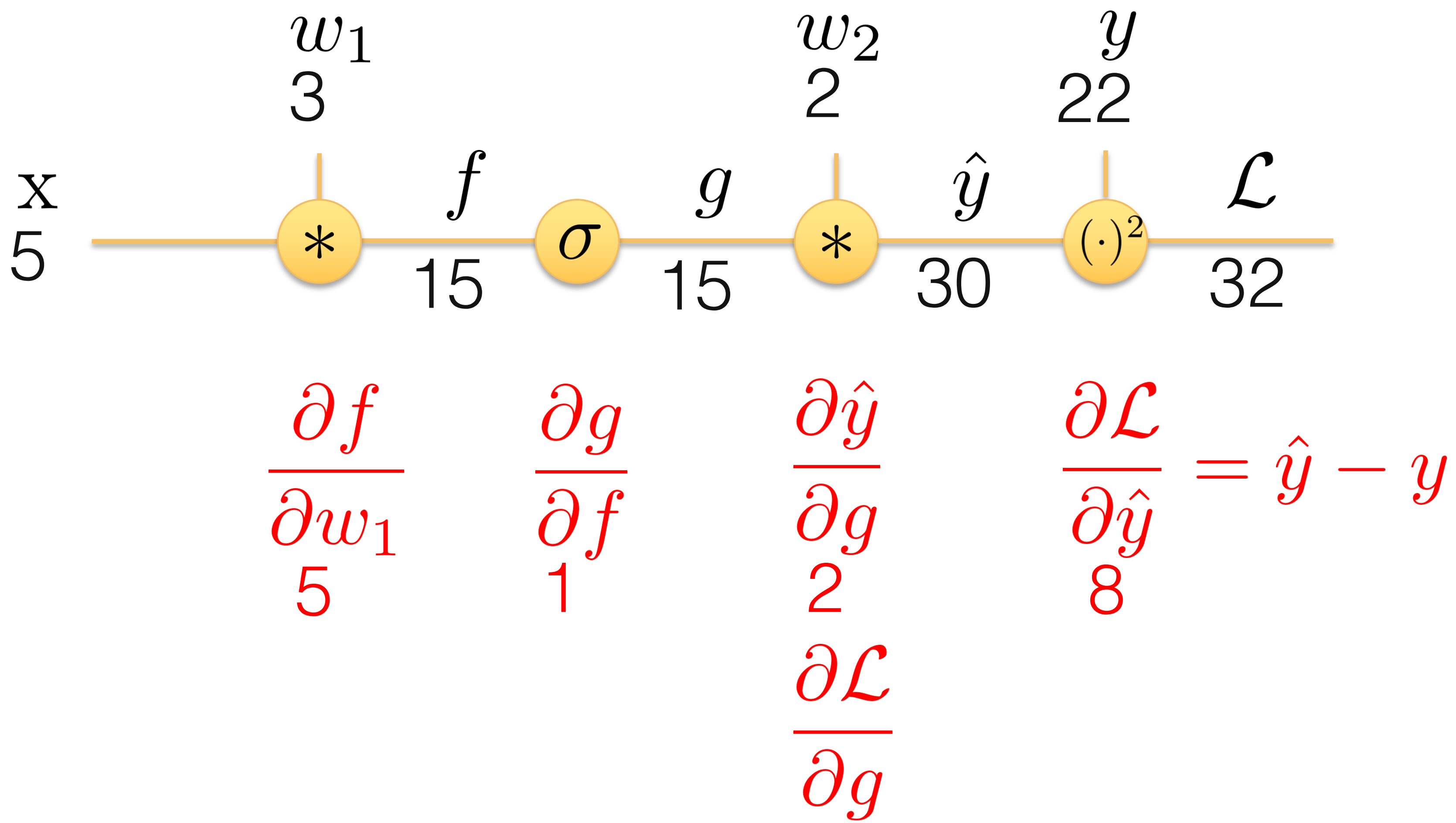
What is backpropagation?



Then we perform a "backward pass"

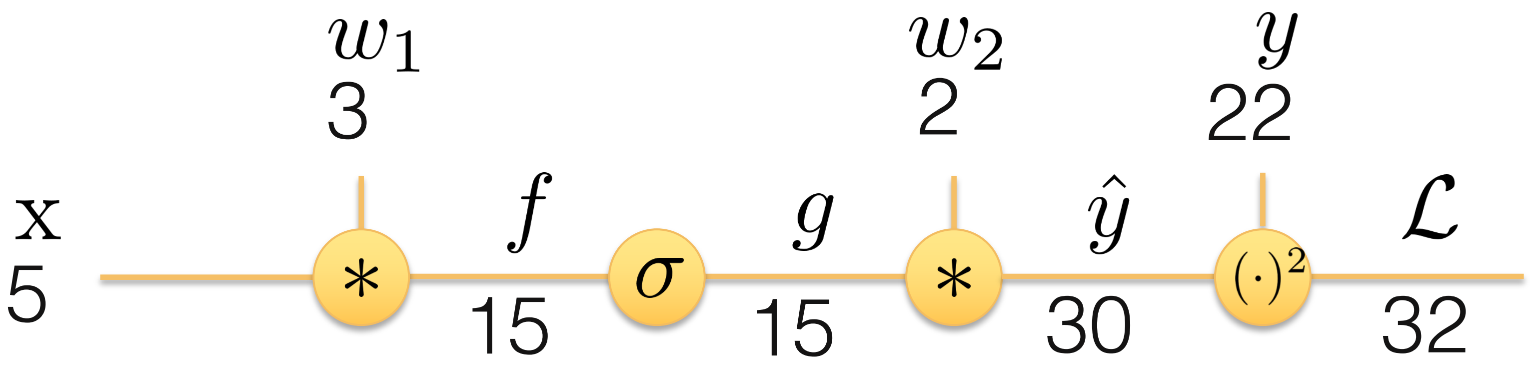
Autodiff Example

What is backpropagation?



Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
5

$$\frac{\partial g}{\partial f}$$
1

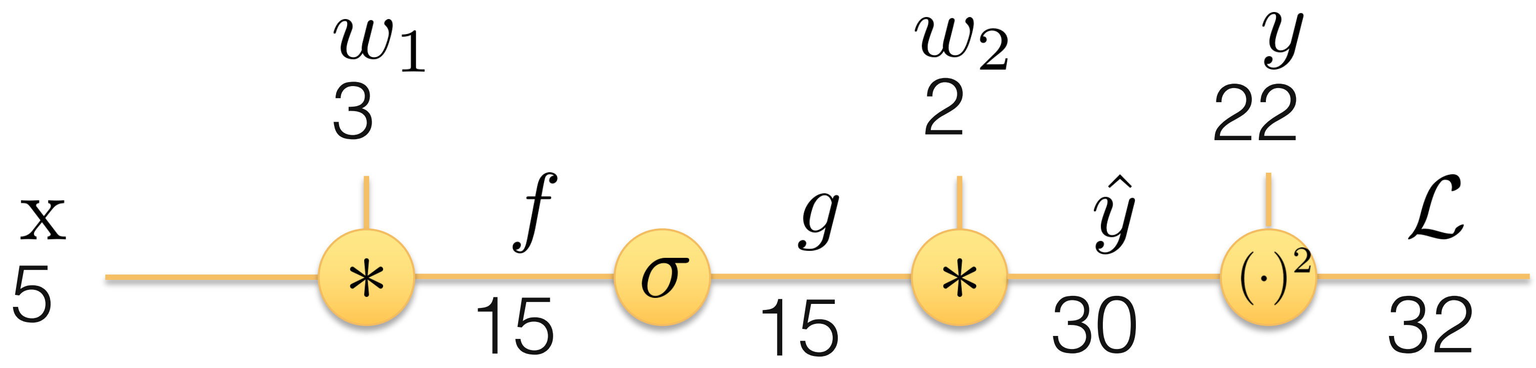
$$\frac{\partial \hat{y}}{\partial g}$$
2

$$\frac{\partial \mathcal{L}}{\partial g}$$
16

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

Autodiff Example

What is backpropagation?



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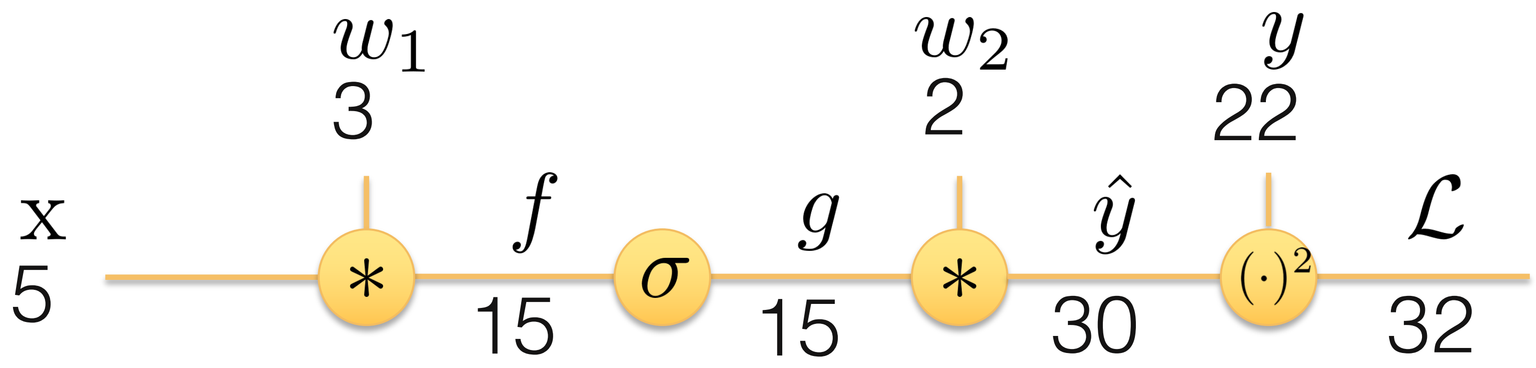
Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
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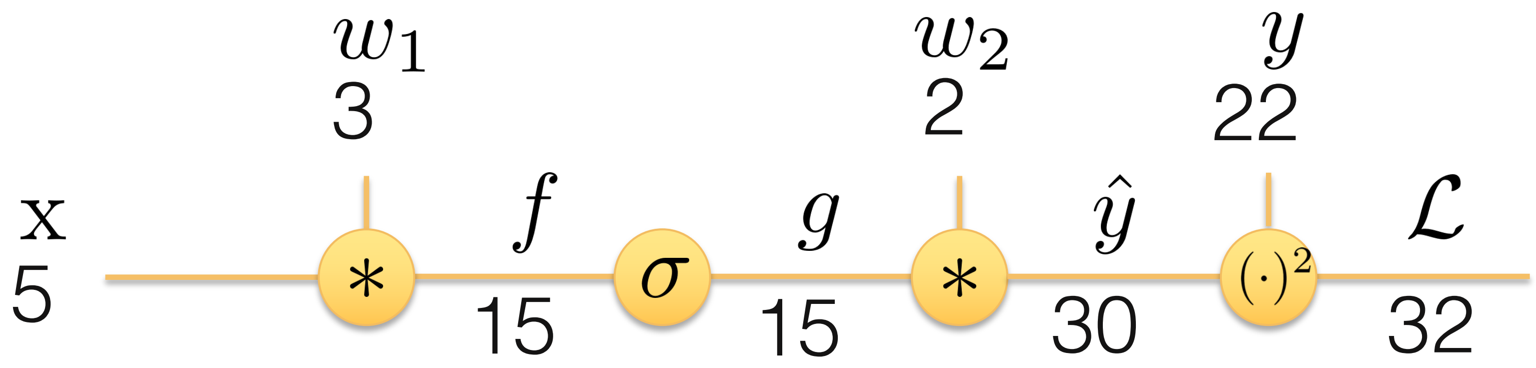
Autodiff Example

What is backpropagation?



$$\frac{\partial f}{\partial w_1}$$
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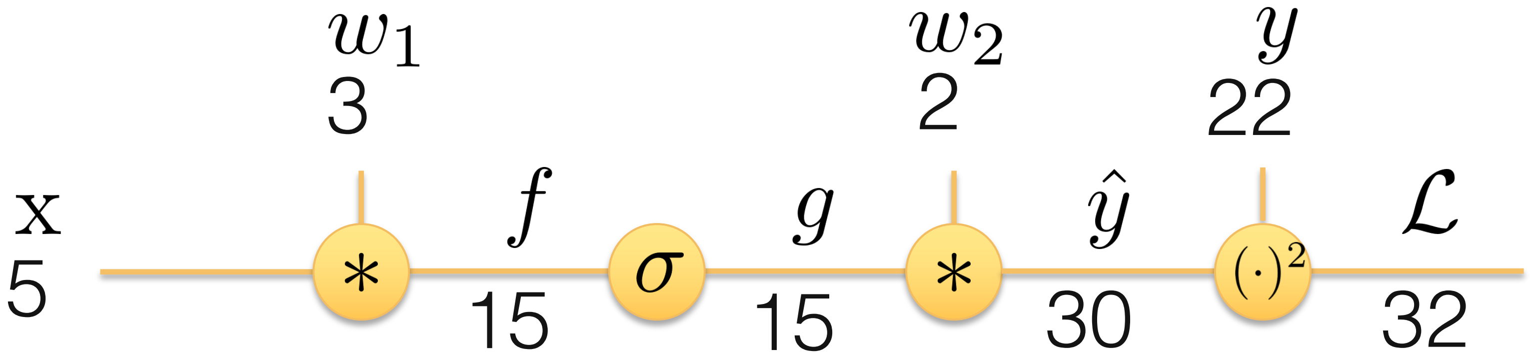
$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$
8

Autodiff Example

What is backpropagation?



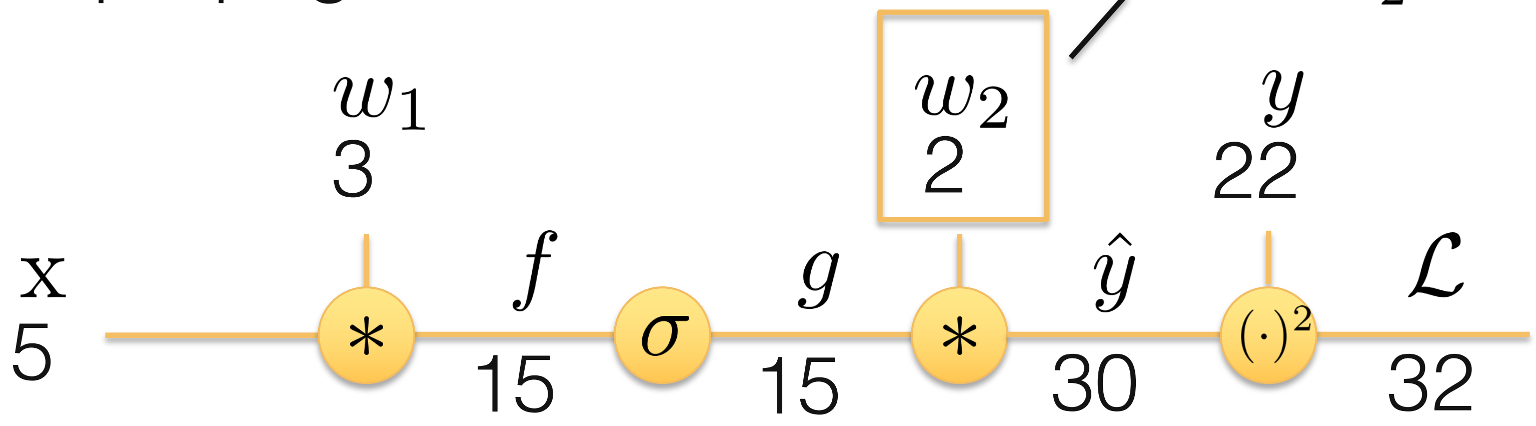
$$\frac{\partial f}{\partial w_1} \quad 5 \qquad \frac{\partial g}{\partial f} \quad 1 \qquad \frac{\partial \hat{y}}{\partial g} \quad 2 \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y \quad 8$$

$$\frac{\partial \mathcal{L}}{\partial w_1} \quad 80 \qquad \frac{\partial \mathcal{L}}{\partial f} \quad 16 \qquad \frac{\partial \mathcal{L}}{\partial g} \quad 16$$

Autodiff Example

What is backpropagation?

What about $\frac{\partial \mathcal{L}}{\partial w_2}$?



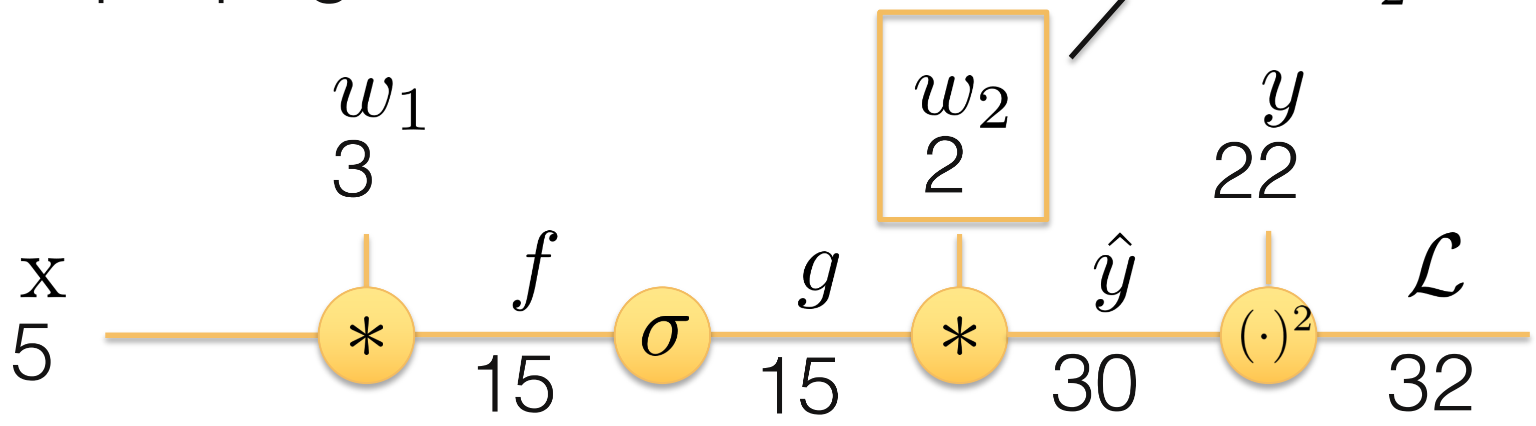
$$\frac{\partial f}{\partial w_1} \quad 5 \qquad \frac{\partial g}{\partial f} \quad 1 \qquad \frac{\partial \hat{y}}{\partial g} \quad 2 \qquad \frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y \quad 8$$

$$\frac{\partial \mathcal{L}}{\partial w_1} \quad 80 \qquad \frac{\partial \mathcal{L}}{\partial f} \quad 16 \qquad \frac{\partial \mathcal{L}}{\partial g} \quad 16$$

Autodiff Example

What is backpropagation?

What about $\frac{\partial \mathcal{L}}{\partial w_2}$?



$\frac{\partial f}{\partial w_1}$ 5

$\frac{\partial \mathcal{L}}{\partial w_1}$ 80

$\frac{\partial g}{\partial f}$ 1

$\frac{\partial \mathcal{L}}{\partial f}$ 16

$\frac{\partial \hat{y}}{\partial g}$ 2

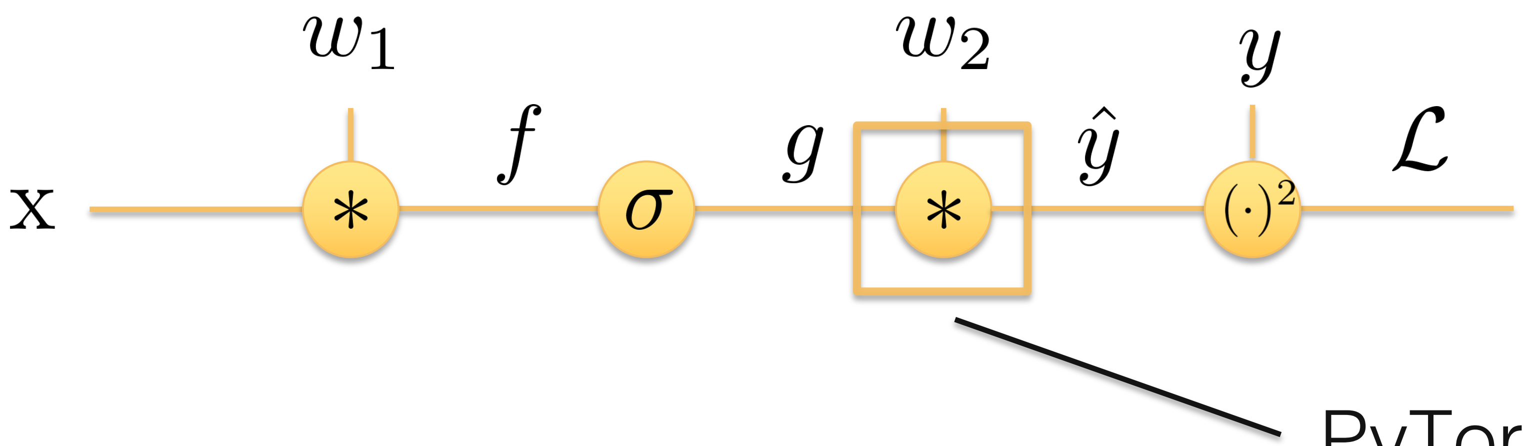
$\frac{\partial \mathcal{L}}{\partial g}$ 16

$$\frac{\partial \mathcal{L}}{\partial \hat{y}} = \hat{y} - y$$

We can re-use computation!

$$\frac{\partial \mathcal{L}}{\partial w_2} = \frac{\partial \hat{y}}{\partial w_2} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

Autodiff Example



PyTorch Code:

```
class Multiply(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x, y):
    ctx.save_for_backward(x, y)
    z = x * y
    return z
  @staticmethod
  def backward(ctx, grad_z):
    x, y = ctx.saved_tensors
    grad_x = y * grad_z    # dz/dx * dL/dz
    grad_y = x * grad_z    # dz/dy * dL/dz
    return grad_x, grad_y
```

Need to stash some values for use in backward

Upstream gradient

Multiply upstream and local gradients

Image Inpainting Training Loop

1. Sample batch of images from dataset

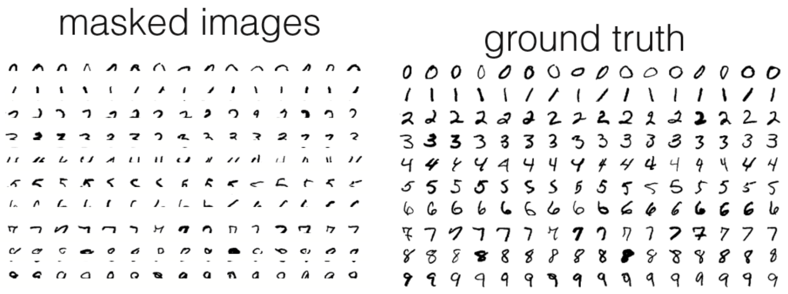


Image Inpainting Training Loop

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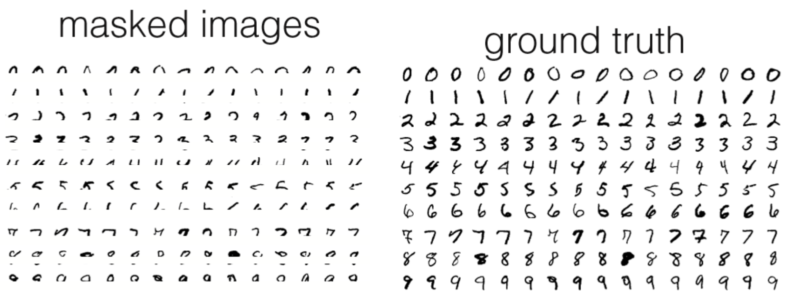

2. Run forward pass to calculate network output for each image

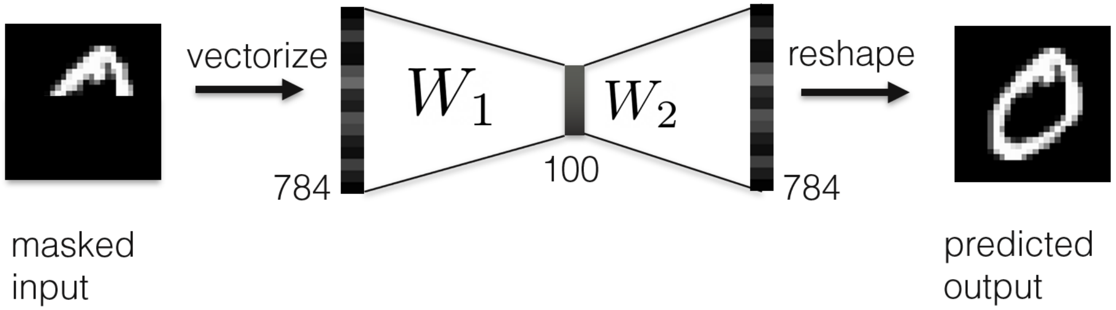

Image Inpainting Training Loop

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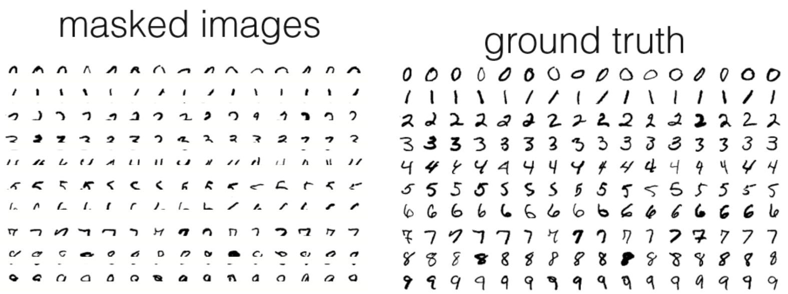

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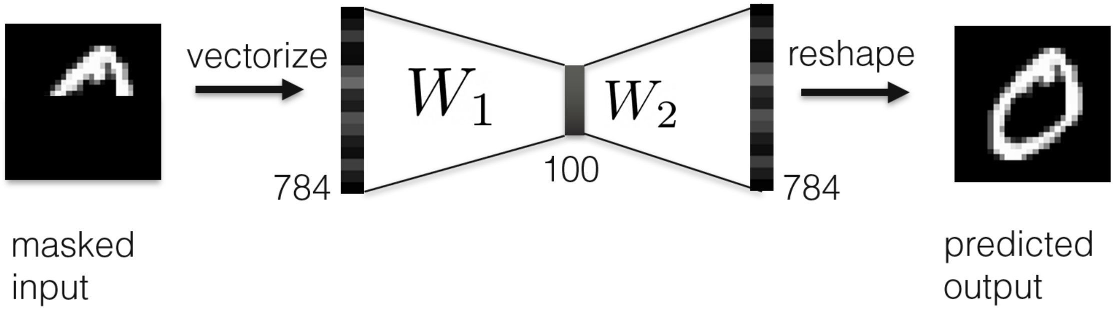
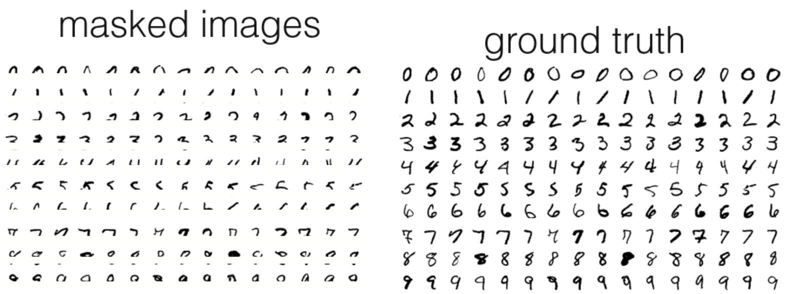


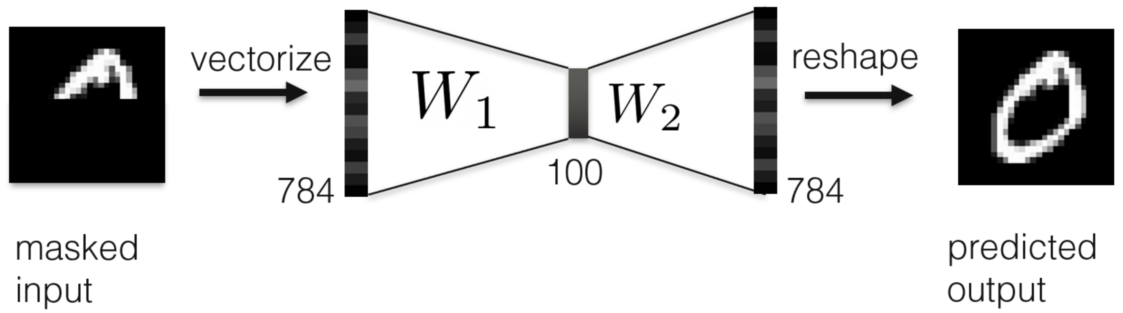
3. Run backward pass to calculate gradients with backpropagation

Image Inpainting Training Loop

1. Sample batch of images from dataset



2. Run forward pass to calculate network output for each image



3. Run backward pass to calculate gradients with backpropagation

4. Update parameters with stochastic gradient descent

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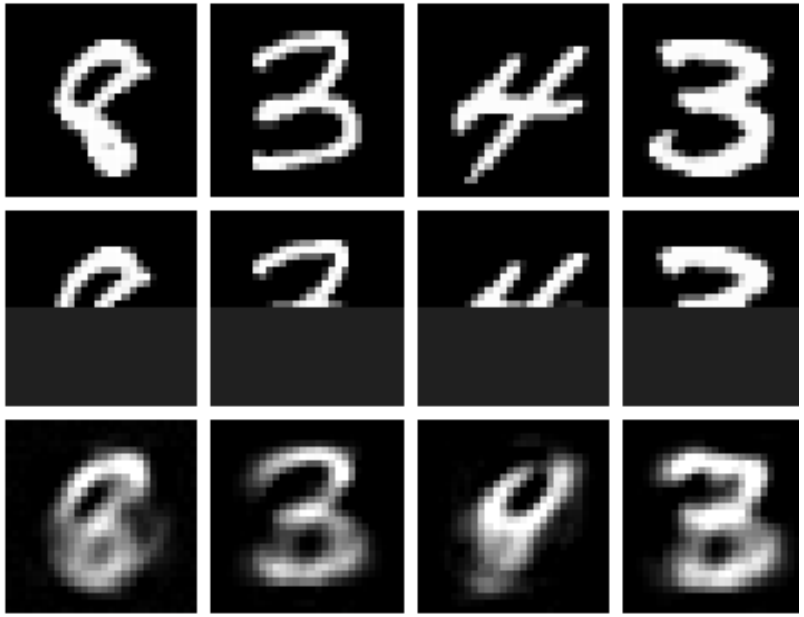
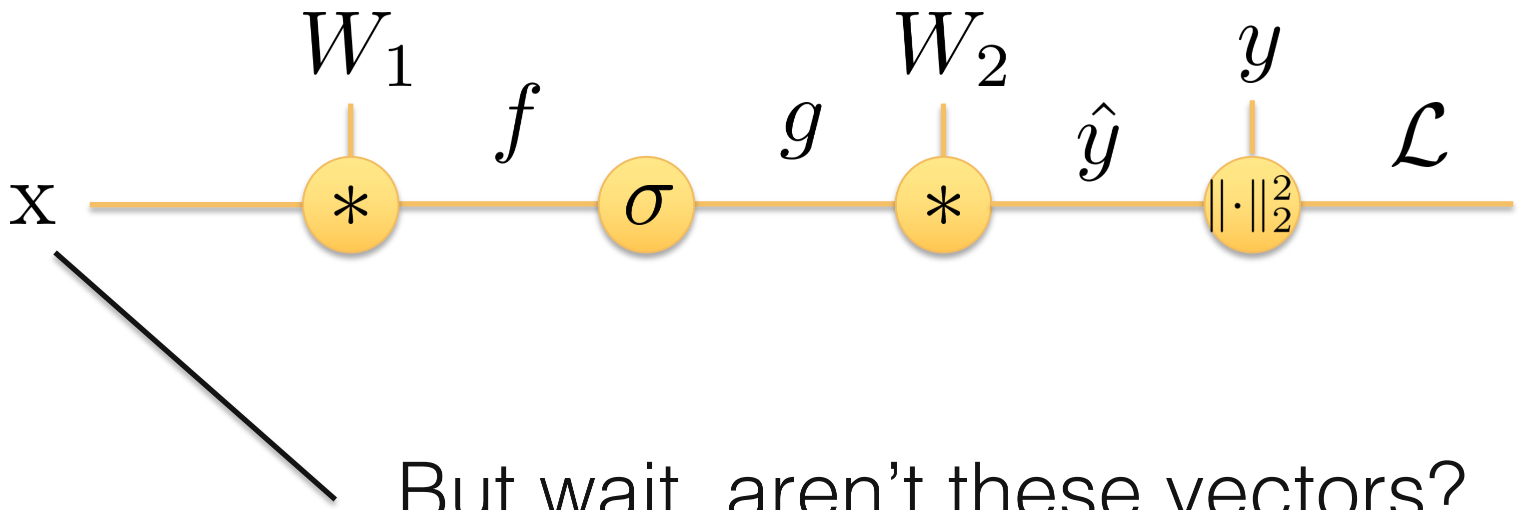
$$\mathcal{L}_\theta = \|y - \hat{y}\|_2^2$$

$$W_2^{(k+1)} = W_2^{(k)} - \alpha \frac{\partial \mathcal{L}}{\partial W_2}$$

$$W_1^{(k+1)} = W_1^{(k)} - \alpha \frac{\partial \mathcal{L}}{\partial W_1}$$



Vector Differentiation



But wait, aren't these vectors?
(see supplemental slides for vector differentiation)

Takeaways

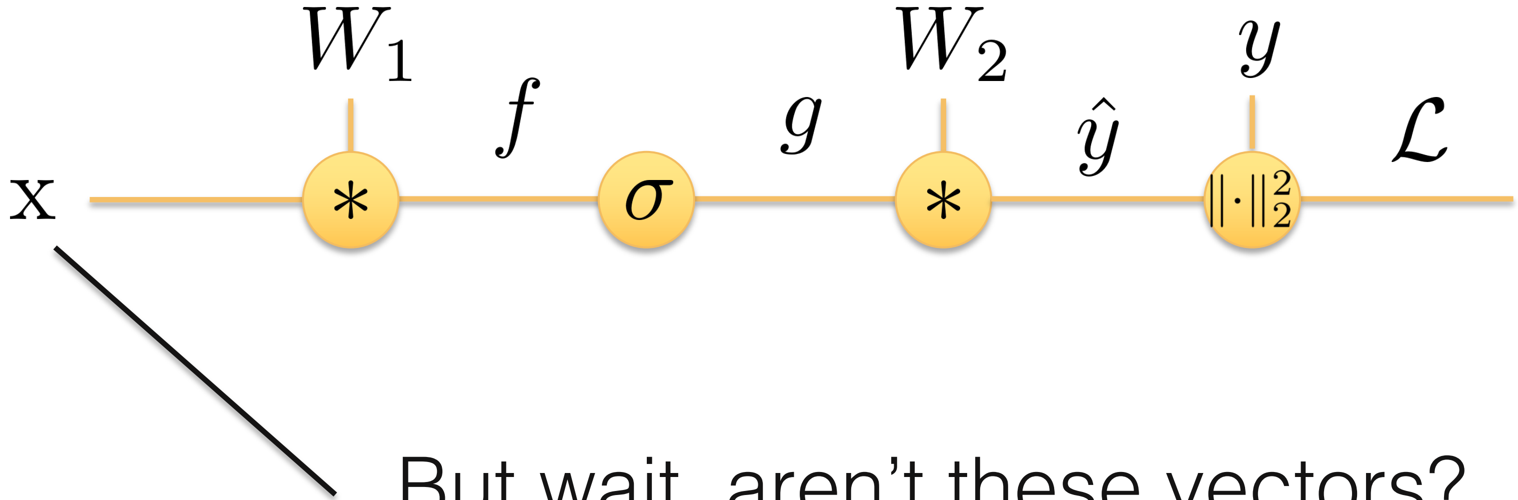
- What is a neural network? (can you write the equation for an MLP?)
- Basic building blocks/architecture of CNN
- Backpropagation, automatic differentiation, and gradient descent

Next Time

- Embedded ethics lecture!

Supplemental Slides

Vector Differentiation



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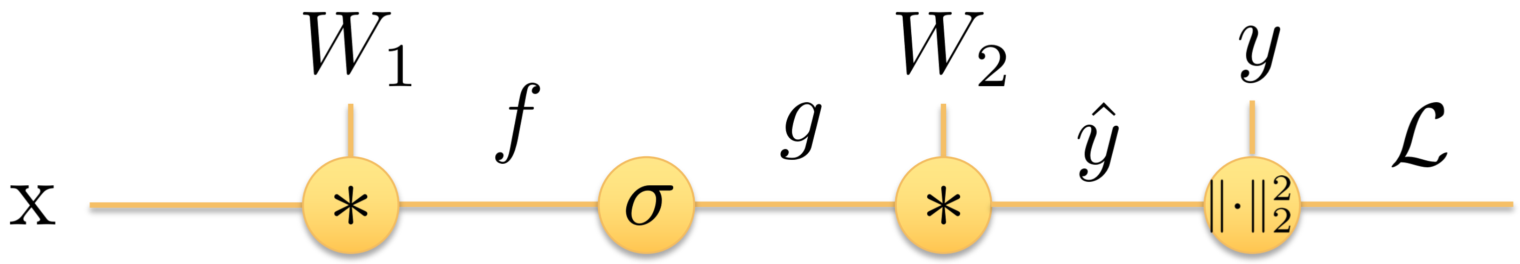
Vector Differentiation



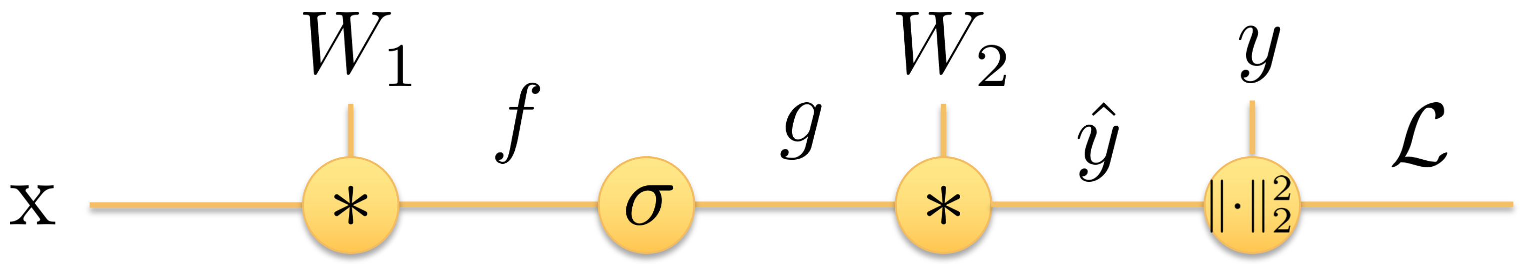
Recap: vector differentiation

Scalar by Scalar

$$x, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \mathbb{R}$$

Vector Differentiation



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Scalar by Scalar

$$x, y \in \mathbb{R}$$

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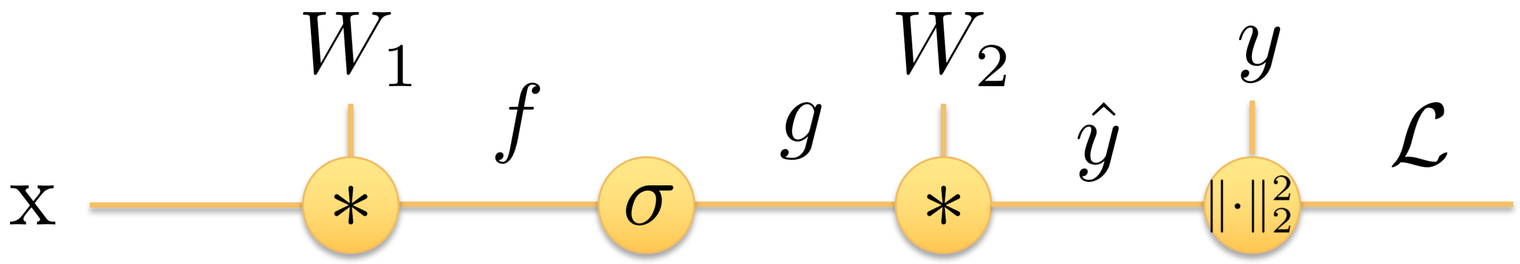
Scalar by Vector

$$x \in \mathbb{R}^N, y \in \mathbb{R}$$

$$\frac{\partial y}{\partial x} \in \mathbb{R}^N$$

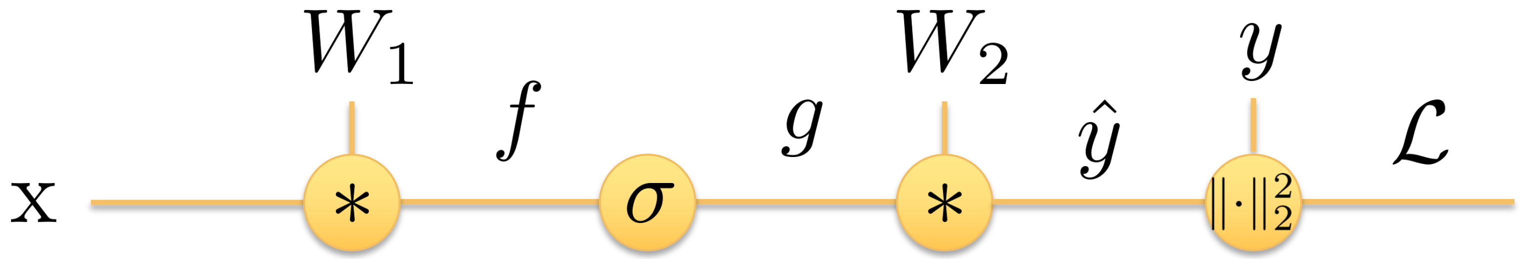
Vector Differentiation



Recap: vector differentiation

Scalar by Scalar	Scalar by Vector	Vector by Vector
$x, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}$	$x \in \mathbb{R}^N, y \in \mathbb{R}^M$
$\frac{\partial y}{\partial x} \in \mathbb{R}$	$\frac{\partial y}{\partial x} \in \mathbb{R}^N$	$\frac{\partial y}{\partial x} \in \mathbb{R}^{N \times M}$

Recap: vector differentiation



Example 1: matrix multiply

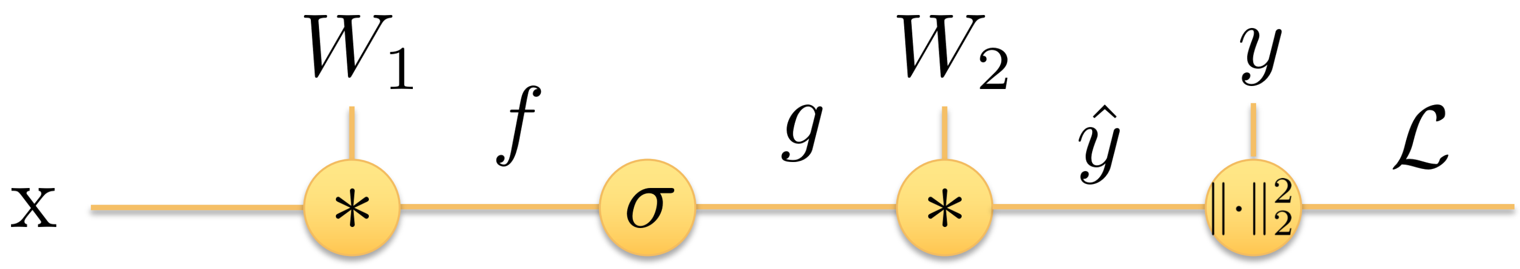
$$\frac{\partial \hat{y}}{\partial g} = \frac{\partial}{\partial g} W_2 g$$

$$W_2 \in \mathbb{R}^{M \times N}$$

$$g \in \mathbb{R}^{N}$$

$$\frac{\partial \hat{y}}{\partial g} \in \mathbb{R}^{N \times M}$$

Recap: vector differentiation



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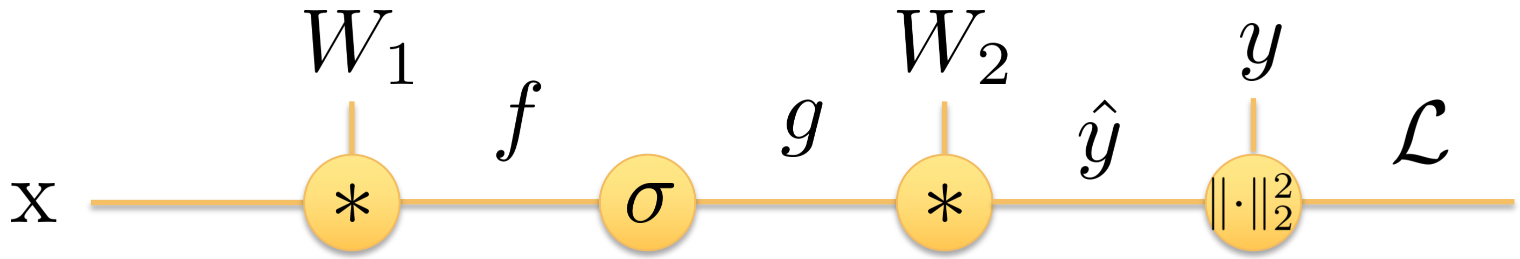
$$\frac{\partial}{\partial g} W_2 g$$

$$= \frac{\partial}{\partial g} \begin{bmatrix} w_{11} g_1 + \cdots + w_{1n} g_n \\ \vdots \quad \ddots \quad \vdots \\ w_{m1} g_1 + \cdots + w_{mn} g_n \end{bmatrix}$$

Recap: vector differentiation



$$\frac{\partial \hat{y}}{\partial g} = \begin{bmatrix} \frac{\partial \hat{y}_1}{\partial g_1} & \cdots & \frac{\partial \hat{y}_m}{\partial g_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \hat{y}_1}{\partial g_n} & \cdots & \frac{\partial \hat{y}_m}{\partial g_n} \end{bmatrix}$$

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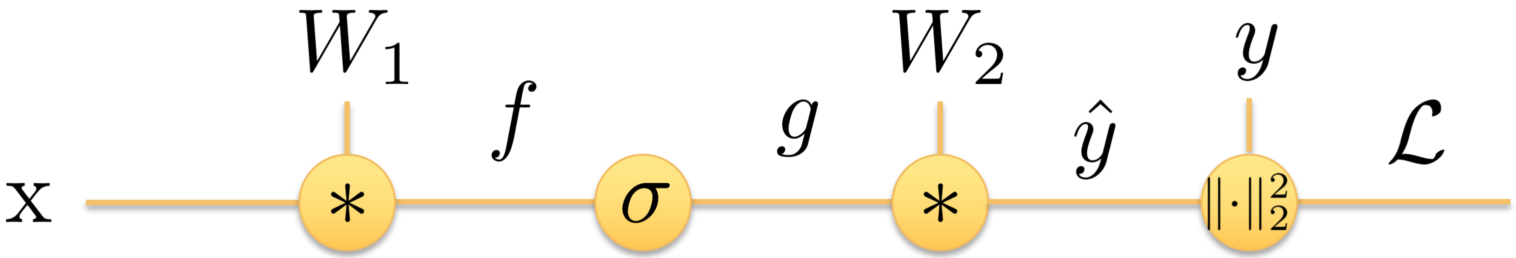
Recap: vector differentiation



$$\frac{\partial \hat{y}}{\partial g} = \begin{bmatrix} \frac{\partial \hat{y}_1}{\partial g_1} & \cdots & \frac{\partial \hat{y}_n}{\partial g_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial \hat{y}_1}{\partial g_n} & \cdots & \frac{\partial \hat{y}_n}{\partial g_n} \end{bmatrix}$$

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$$= \boxed{W_2^T}$$

Recap: vector differentiation

Example 2: elementwise functions

$$h = f \odot g$$

$$f \in \mathbb{R}^N$$

$$g \in \mathbb{R}^N$$

$$\frac{\partial h}{\partial f} \in \mathbb{R}^{N \times N}$$

Recap: vector differentiation

Example 2: elementwise functions

$$\frac{\partial h}{\partial f} = \begin{bmatrix} \frac{\partial h_1}{\partial f_1} & \cdots & \frac{\partial h_n}{\partial f_1} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_1}{\partial f_n} & \cdots & \frac{\partial h_n}{\partial f_n} \end{bmatrix}$$

$$h = f \odot g$$

$$f \in \mathbb{R}^N$$

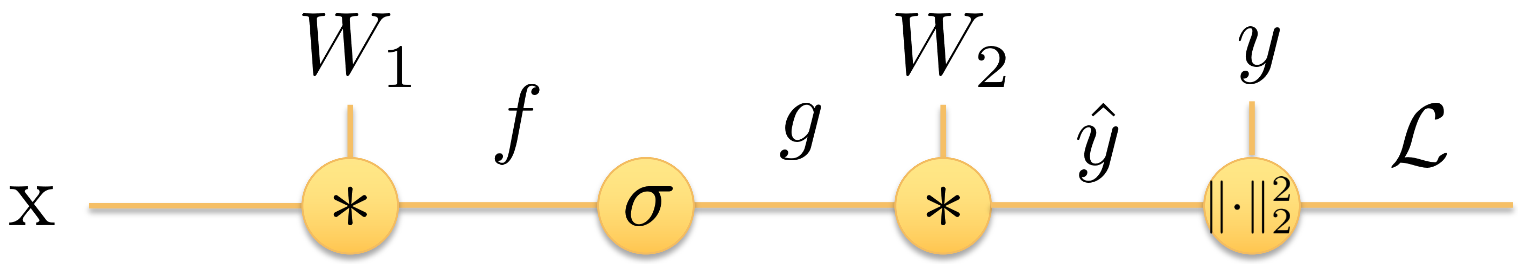
$$g \in \mathbb{R}^N$$

$$\frac{\partial h}{\partial f} \in \mathbb{R}^{N \times N}$$

$$\frac{\partial h}{\partial f} = \begin{bmatrix} g_1 & & 0 \\ & \ddots & \\ 0 & & g_n \end{bmatrix} = \mathrm{diag}(g)$$

Recap: vector differentiation

Final hint: dimensions should always match up!



$$\frac{\partial \mathcal{L}}{\partial W_1} = \frac{\partial f}{\partial W_1} \frac{\partial g}{\partial f} \frac{\partial \hat{y}}{\partial g} \frac{\partial \mathcal{L}}{\partial \hat{y}}$$

You should be able to calculate derivatives of each of these terms and then perform matrix multiplications without issues

Extra backpropagation example (adapted from Stanford CS231n)

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

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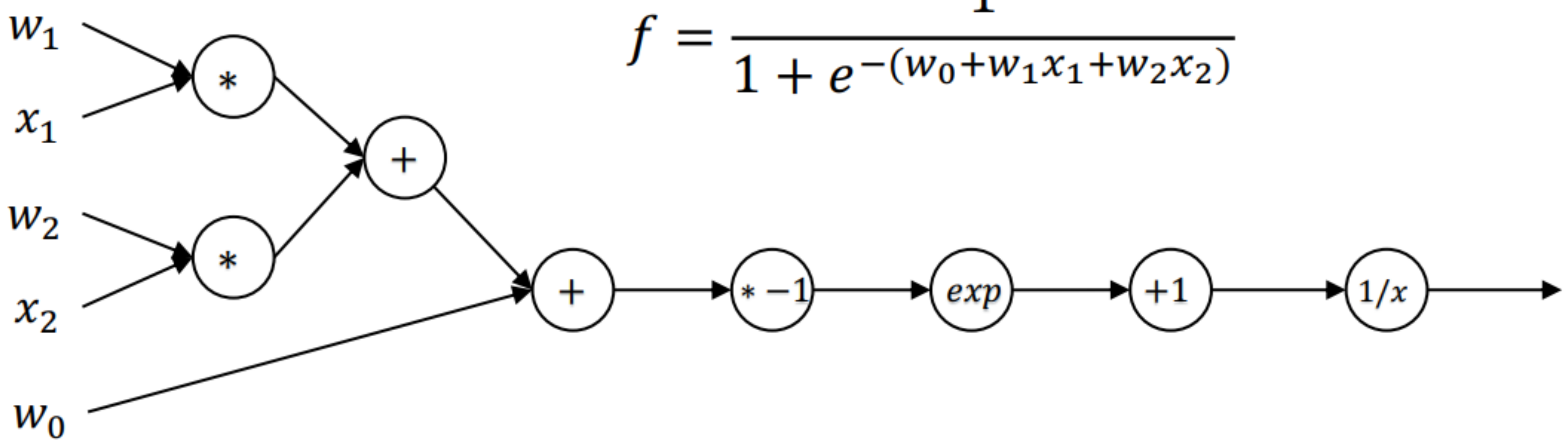

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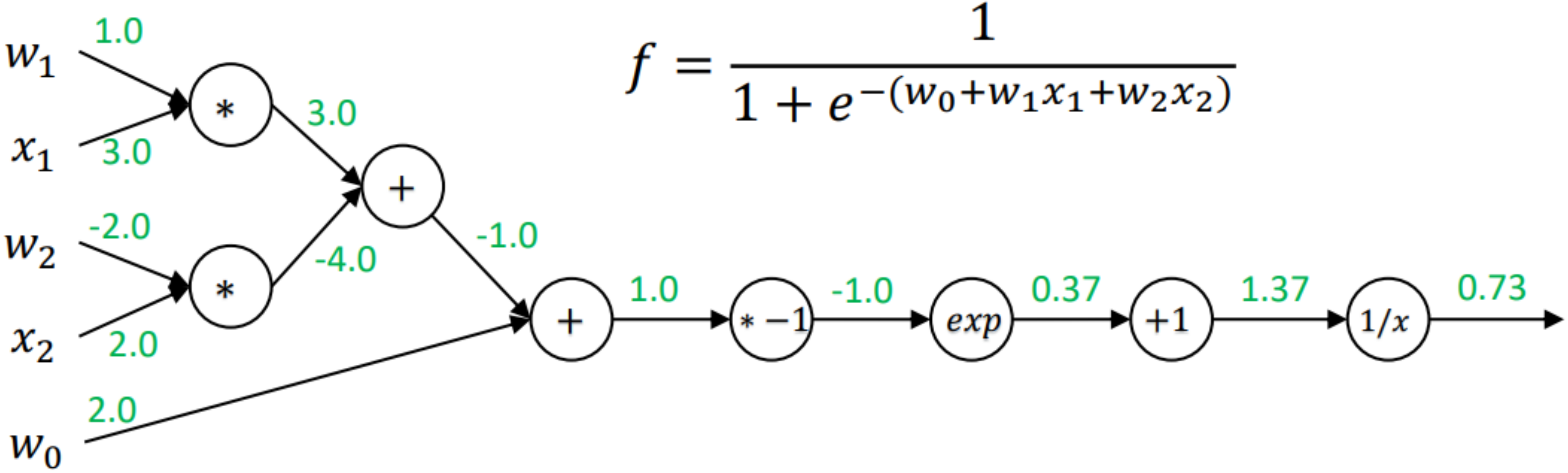

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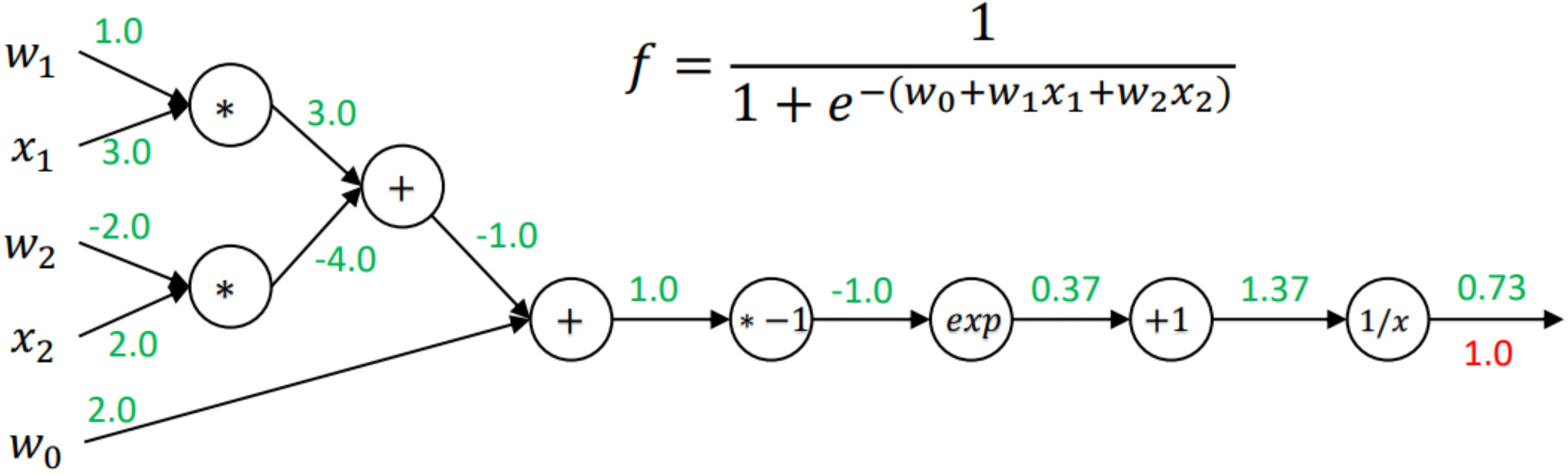

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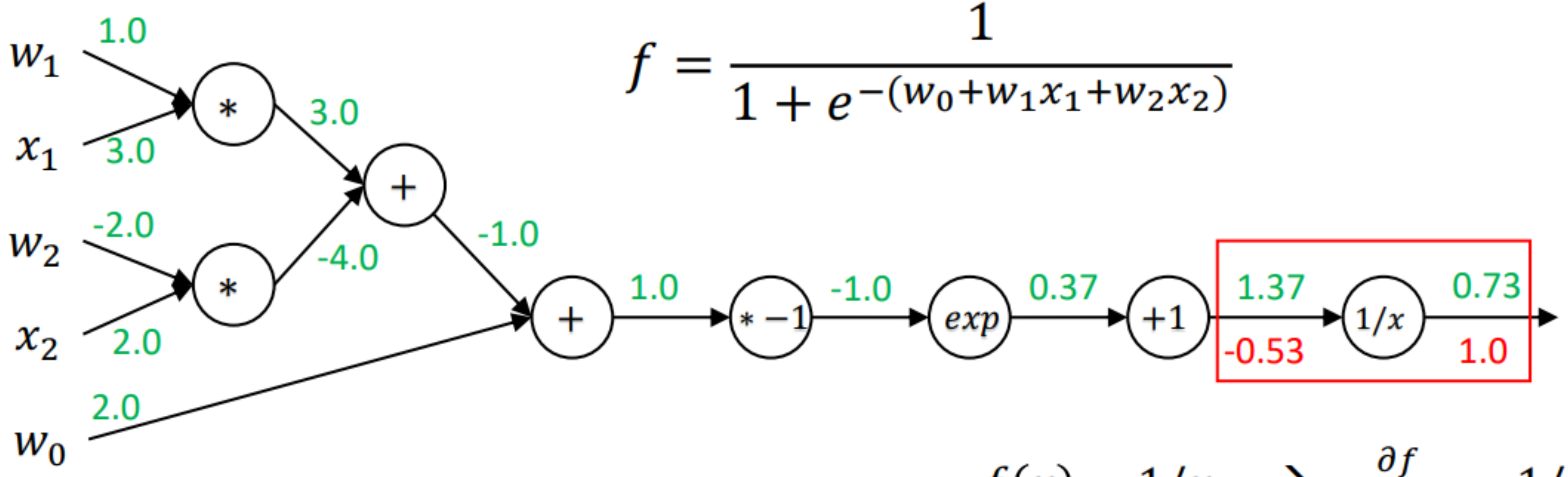
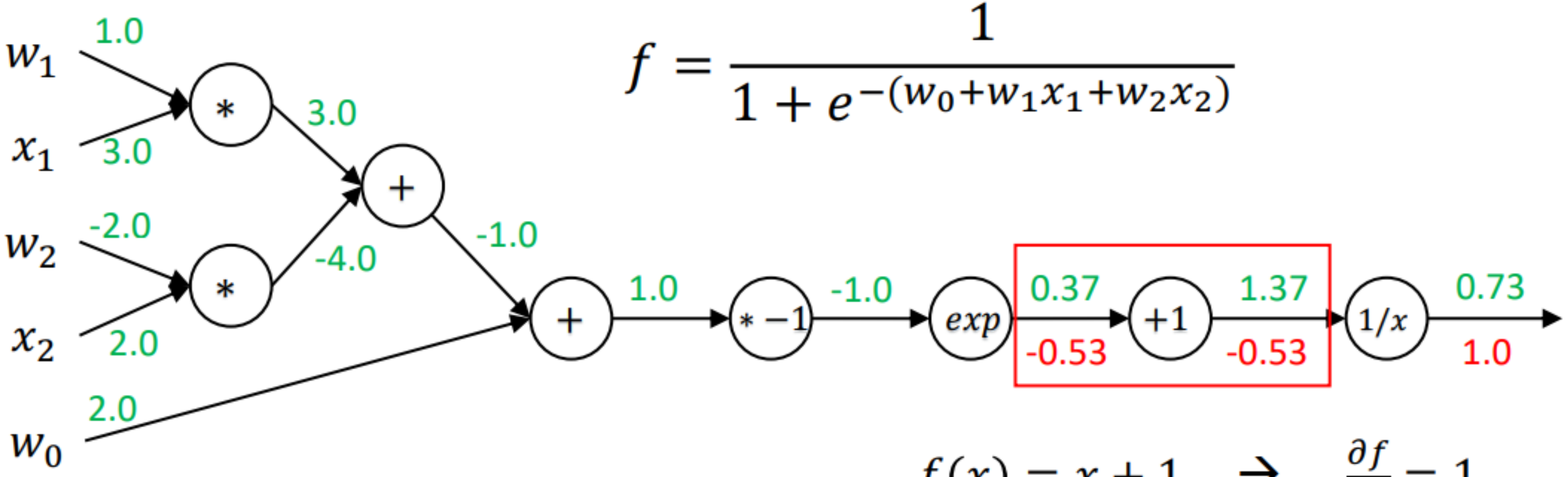


$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

$$f(x) = 1/x \quad \rightarrow \quad \frac{\partial f}{\partial x} = -1/x^2$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial f}\frac{\partial f}{\partial x} = -1/x^2$$

Extra backpropagation example

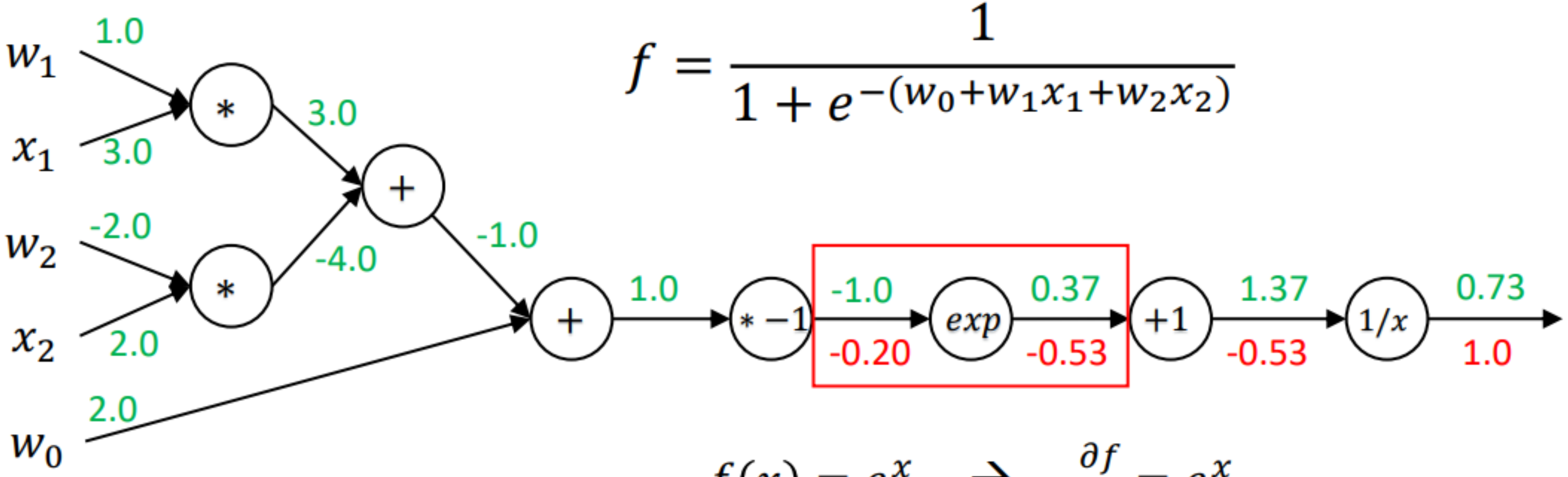


$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

$$f(x) = x + 1 \quad \rightarrow \quad \frac{\partial f}{\partial x} = 1$$

Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$

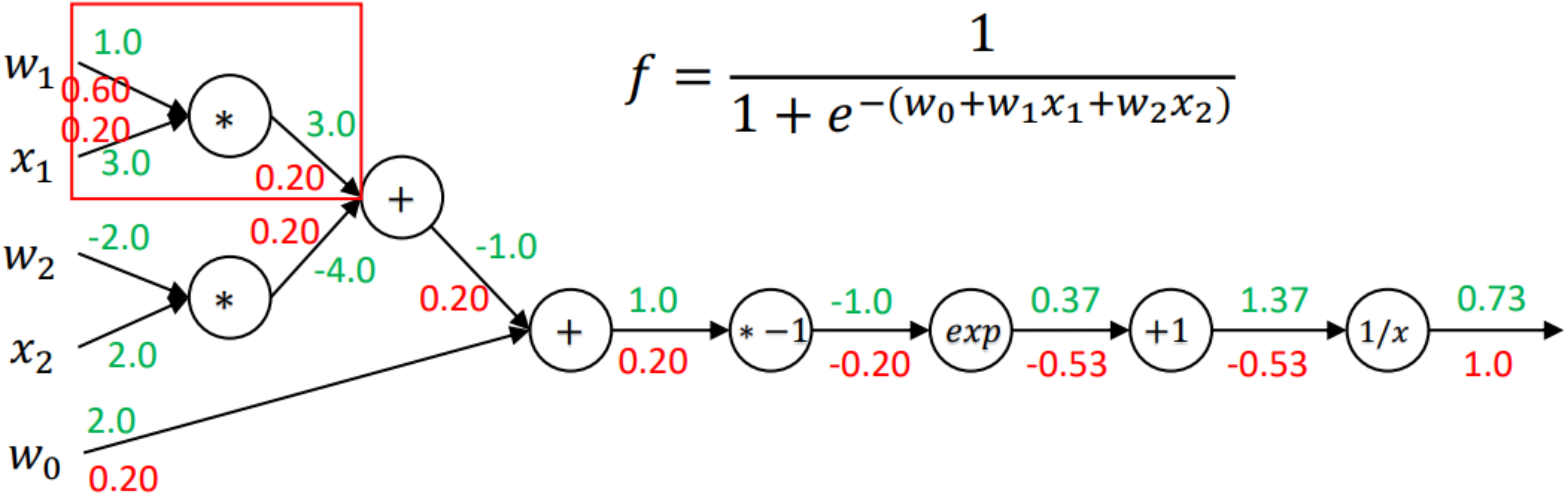


$$f(x) = e^x \quad \rightarrow \quad \frac{\partial f}{\partial x} = e^x$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial f}\frac{\partial f}{\partial x} = \frac{\partial J}{\partial f} \cdot e^x$$

Extra backpropagation example

$$f = \frac{1}{1 + e^{-(w_0 + w_1 x_1 + w_2 x_2)}}$$



$$f(x, w) = xw \quad \rightarrow \quad \frac{\partial f}{\partial x} = w, \; \frac{\partial f}{\partial w} = x$$

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