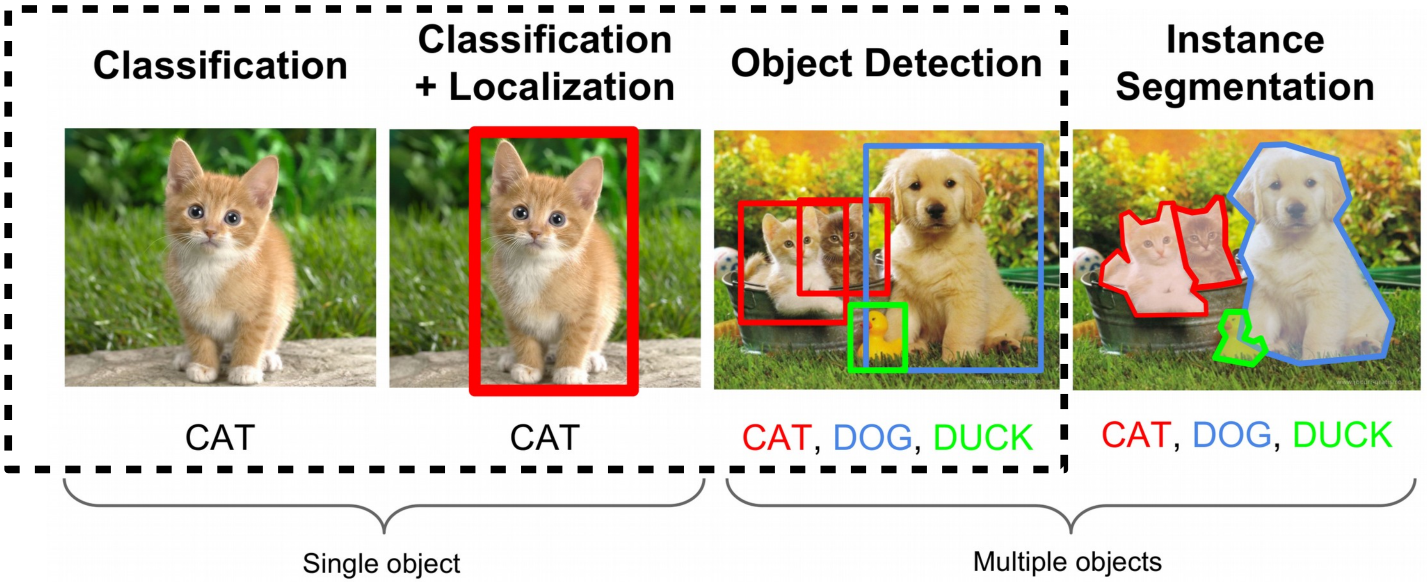
Deep Learning for Perception

Robert Platt
Northeastern University

Perception problems

We will focus on these applications



<u>We will ignore these applications</u>
– image segmentation
– speech-to-text
– natural language processing
– …

.. but deep learning has been applied in lots of ways...

Supervised learning problem

Given:

– A pattern exists

– We don't know what it is, but we have a bunch of examples

Machine Learning problem: find a rule for making predictions from the data

Classification vs regression:

– if a labels are discrete, then we have a *classification* problem

– if the labels are real-valued, then we have a *regression* problem

Problem we want to solve

Input: x

Label: y

Data: $\mathbb{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$

Given $\mathbb{D}$, find a rule for predicting x given y

Problem we want to solve

Discrete *y* is classification
Continuous *y* is regression

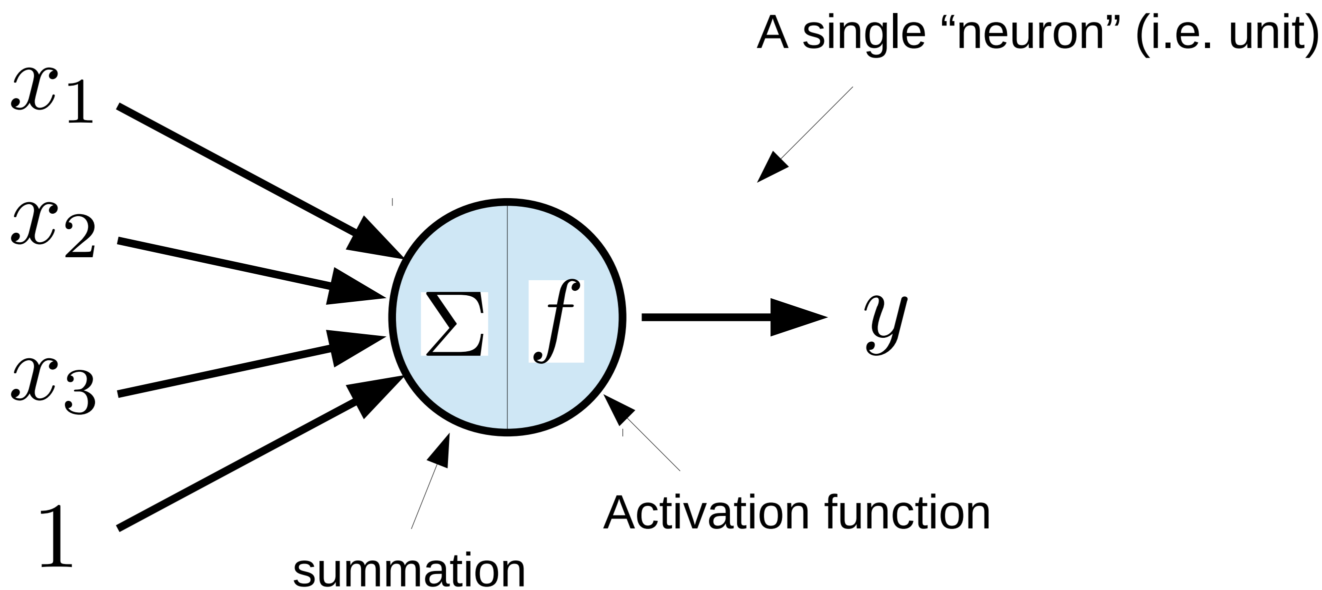
Input: x

Label: y

Data: $\mathbb{D} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$

Given $\mathbb{D}$, find a rule for predicting x given y

The multi-layer perceptron

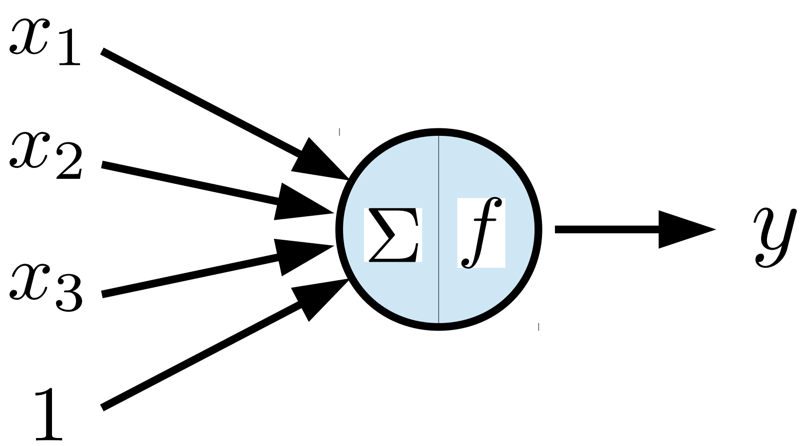


$$y = f(w_1 x_1 + w_2 x_2 + w_3 x_3 + \cdots + b)$$

$$= f(w^T x + b)$$

$$x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \qquad w = \begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix}$$

The multi-layer perceptron

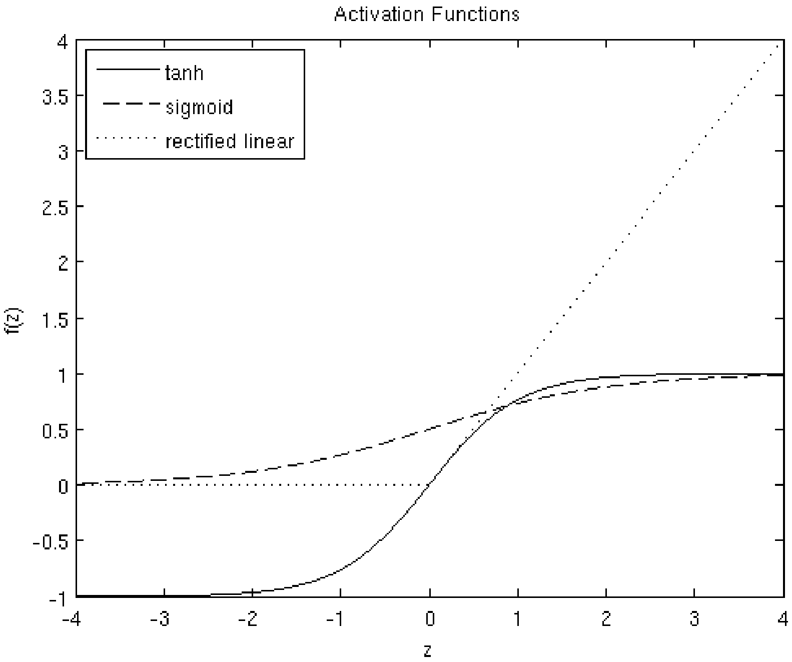


Different activation functions:

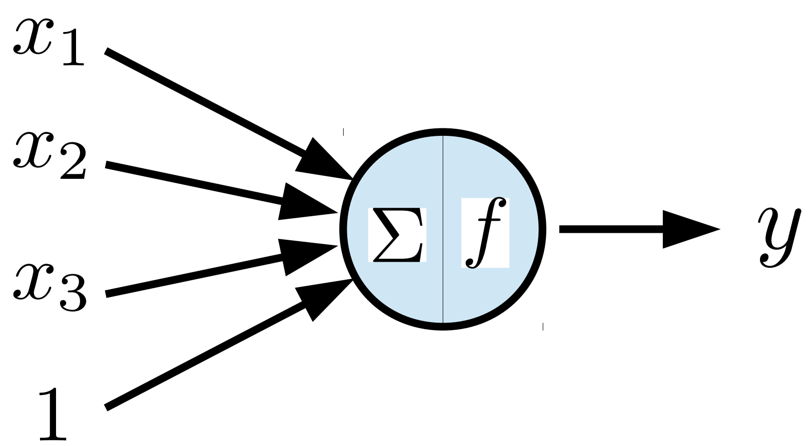
– sigmoid $$f(z) = \frac{1}{1+e^{-z}}$$

– tanh $$f(z) = tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

– rectified linear unit (ReLU) $$f(z) = \max(0, z)$$



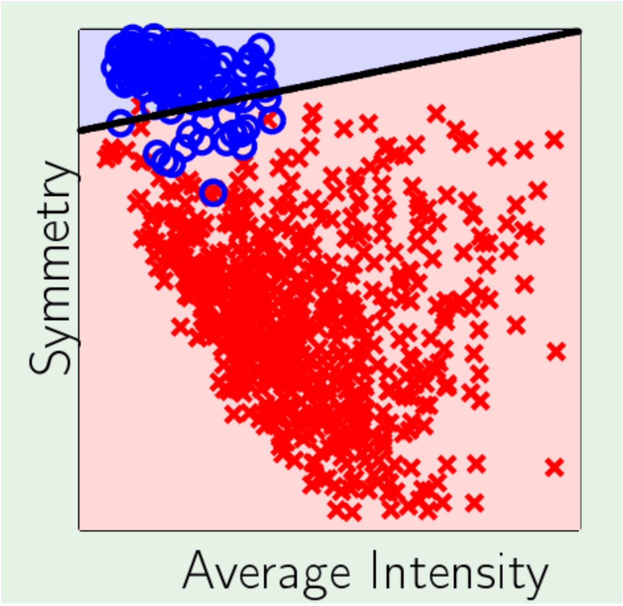
A single unit neural network



One-layer neural network has a simple interpretation: linear classification.

$$y = f(w^T x + b)$$

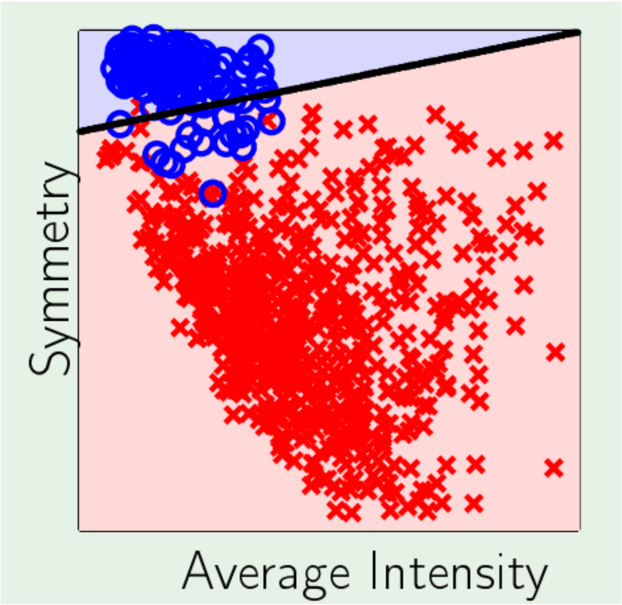
X_1 == symmetry
X_2 == avg intensity
Y == class label (binary)



Think-pair-share

$$y = f(w^T x + b)$$

X_1 == symmetry
X_2 == avg intensity
Y == class label (binary)



What do *w* and *b* correspond to in this picture?

Training

Given a dataset: $D = \{(x^1, y^1), (x^2, y^2), \ldots, (x^n, y^n)\}$

Define loss function: $L(D; w, b) = \frac{1}{2} \sum_{(x^i, y^i) \in D} \left[(y^i - f(w^T x^i + b))^2 \right]$

Training

Given a dataset: $D = \{(x^1, y^1), (x^2, y^2), \ldots, (x^n, y^n)\}$

Define loss function: $L(D; w, b) = \frac{1}{2} \sum_{(x^i, y^i) \in D} \left[(y^i - f(w^T x^i + b))^2 \right]$

Loss function tells us how
well the network classified data

Training

Given a dataset: $D = \{(x^1, y^1), (x^2, y^2), \ldots, (x^n, y^n)\}$

Define loss function: $L(D; w, b) = \frac{1}{2} \sum_{(x^i, y^i) \in D} \left[(y^i - f(w^T x^i + b))^2 \right]$

Loss function tells us how well the network classified data

Method of training: adjust *w, b* so as to minimize the net loss over the datas

i.e.: adjust *w, b* so as to minimize: $L(D; w, b)$

The closer to zero, the better the classification

Training

Method of training: adjust *w, b* so as to minimize the net loss over the dataset

i.e.: adjust *w, b* so as to minimize: $L(D; w, b)$

How?

Training

Method of training: adjust *w, b* so as to minimize the net loss over the dataset

i.e.: adjust *w, b* so as to minimize: $L(D; w, b)$

How?

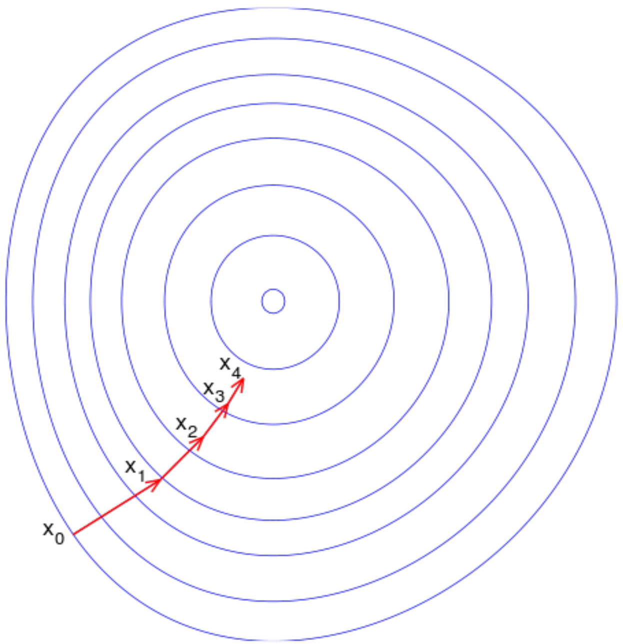
Gradient Descent

Time out for gradient descent

Suppose someone gives you an unknown function F(x)
- you want to find a minimum for F
- but, you do not have an analytical description of F(x)

Use gradient descent!
- all you need is the ability to evaluate F(x) and its gradient at any point x

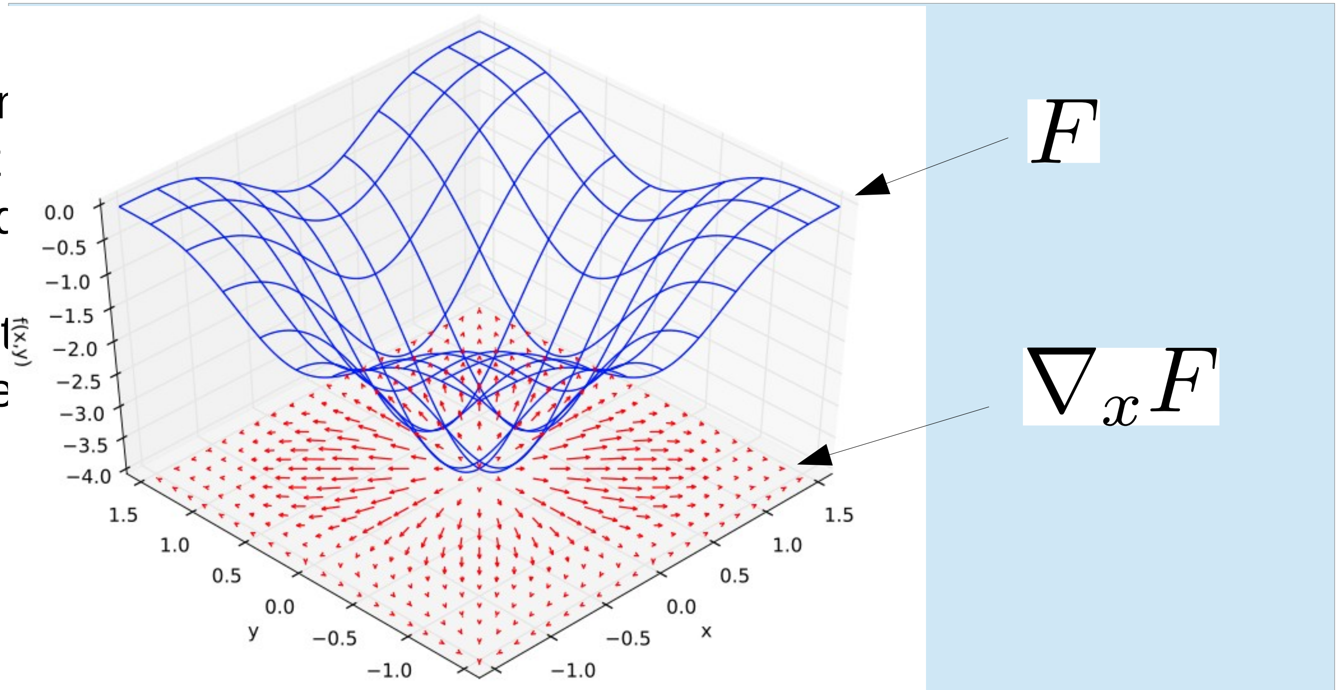
1. pick x_0 at random
2. $x_1 = x_0 - \alpha \nabla_x F(x_0)$
3. $x_2 = x_1 - \alpha \nabla_x F(x_1)$
4. $x_3 = x_2 - \alpha \nabla_x F(x_2)$
5. ...



Time out for gradient descent

Suppose sor
– you want
– but, you c

Use gradient
– all you ne



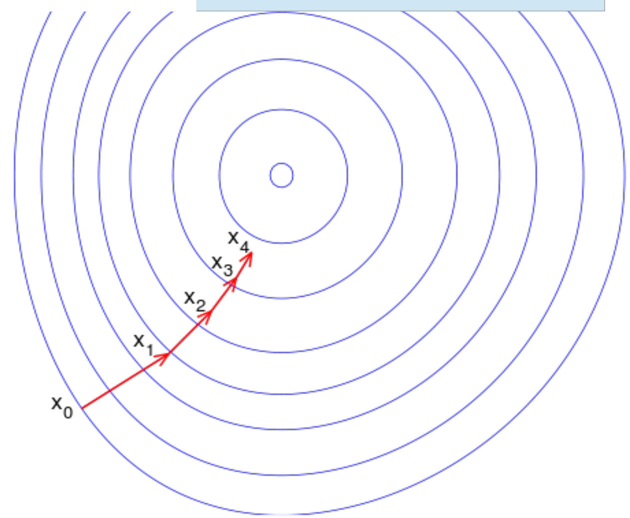
1. pick x_0 at random

2. $x_1 = x_0 - \alpha \nabla_x F(x_0)$

3. $x_2 = x_1 - \alpha \nabla_x F(x_1)$

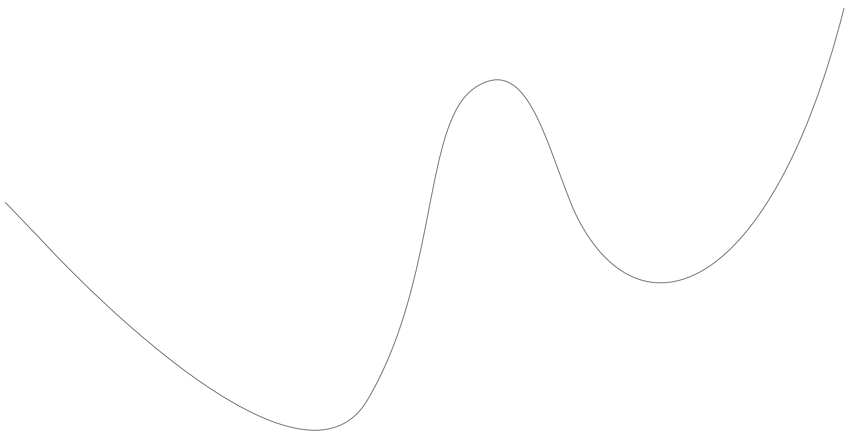
4. $x_3 = x_2 - \alpha \nabla_x F(x_2)$

5. ...

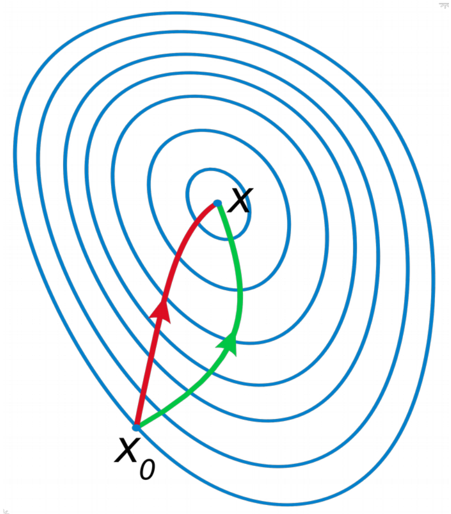


Think-pair-share

1. Label all the points where gradient descent could converge to:



2. Which path does gradient descent take?



Training

Method of training: adjust *w, b* so as to minimize the net loss over the dataset

i.e.: adjust *w, b* so as to minimize: $L(D; w, b)$

Do gradient descent on dataset:

1. repeat

2. $$w \leftarrow w - \alpha \nabla_w L(D; w, b)$$

3. $$b \leftarrow b - \alpha \nabla_b L(D; w, b)$$

4. until converged

Where:

$$\nabla_w L(x^i, y^i; w, b) = -(y^i - f(w^T x^i + b)) f'(w^T x^i + b) x^i$$

$$\nabla_b L(x^i, y^i; w, b) = -(y^i - f(w^T x^i + b)) f'(w^T x^i + b)$$

Training

Method of training: adjust *w, b* so

i.e.: adjust *w, b* so as to minimize:

This is the similar to logistic regression
– logistic regression uses a cross entropy loss
– we are using a quadratic loss

<u>Do gradient descent on dataset:</u>

1. repeat

2. $$w \leftarrow w - \alpha \nabla_w L(D; w, b)$$

3. $$b \leftarrow b - \alpha \nabla_b L(D; w, b)$$

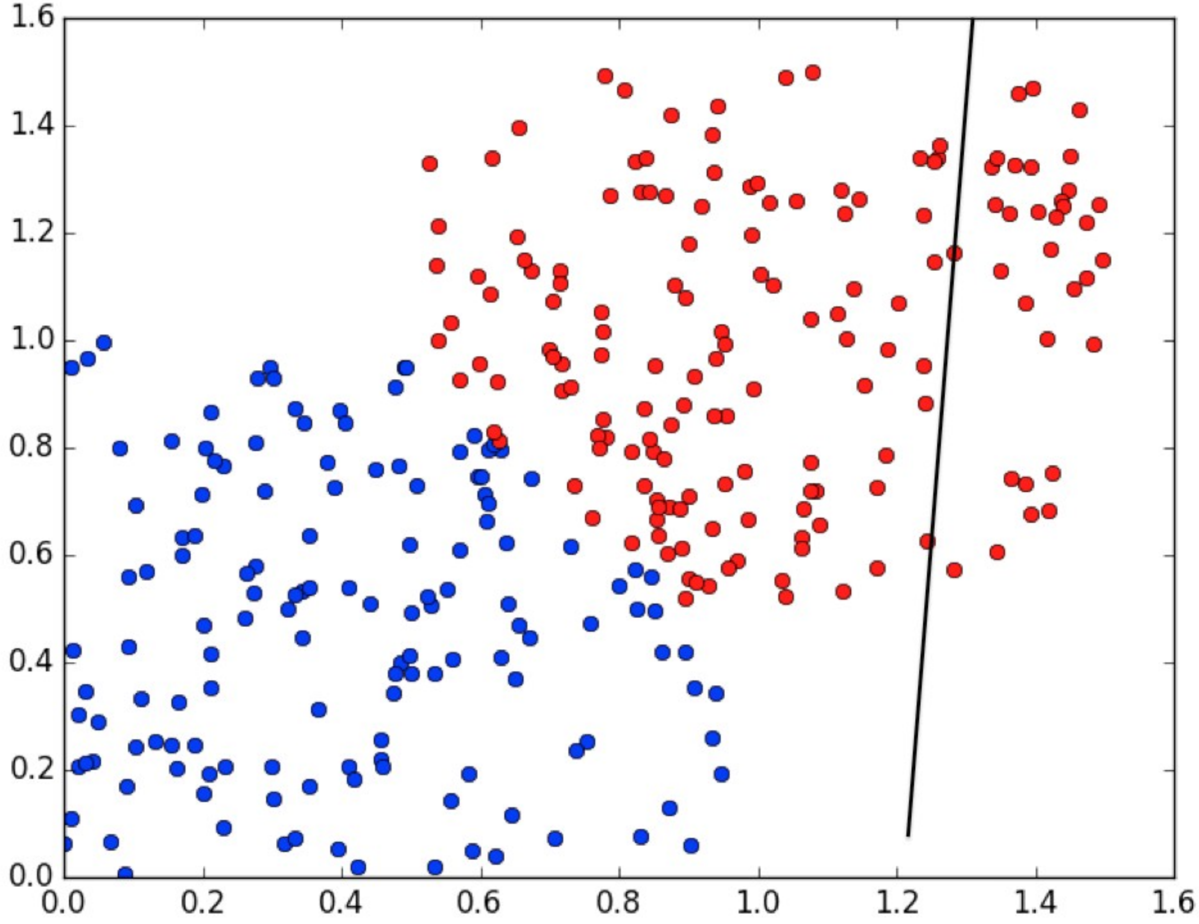
4. until converged

Where:

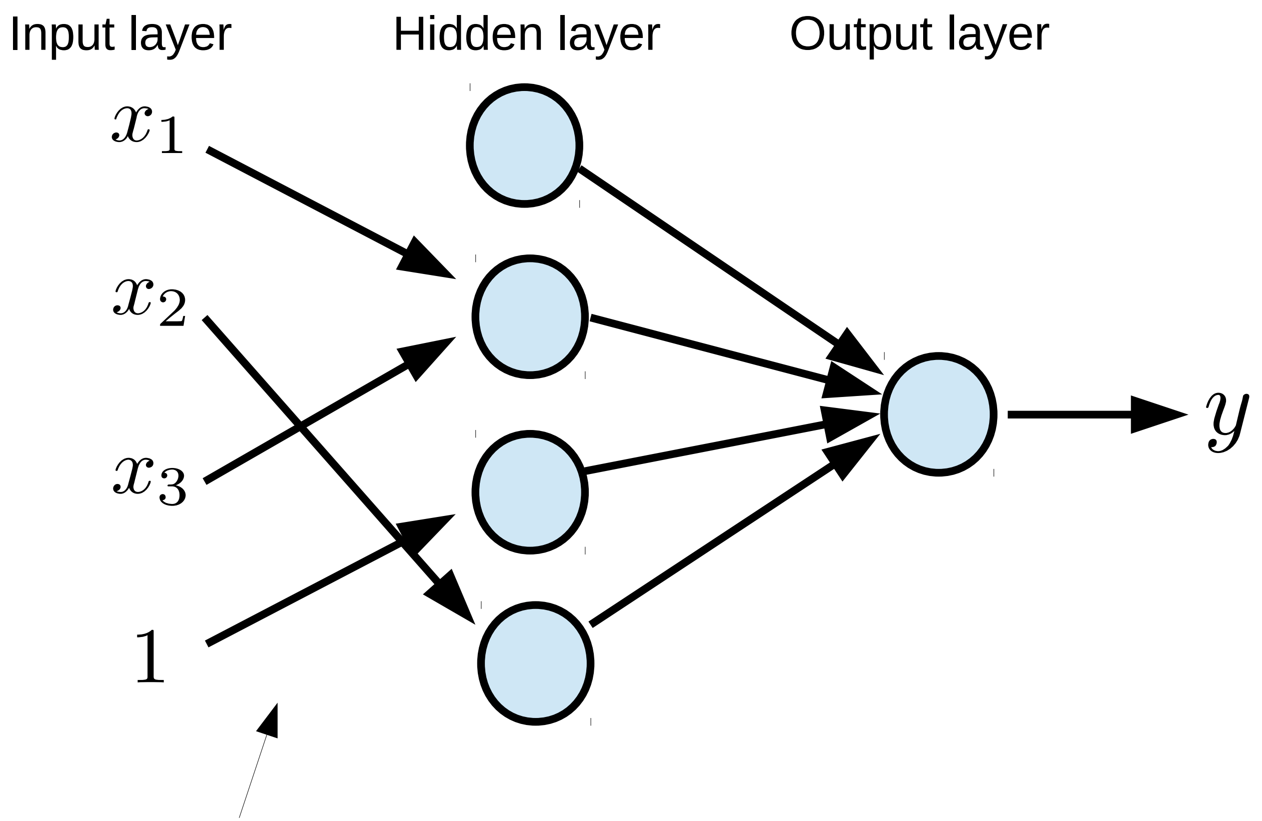
$$\nabla_w L(x^i, y^i; w, b) = -(y^i - f(w^T x^i + b)) f'(w^T x^i + b) x^i$$

$$\nabla_b L(x^i, y^i; w, b) = -(y^i - f(w^T x^i + b)) f'(w^T x^i + b)$$

Training a one-unit neural network

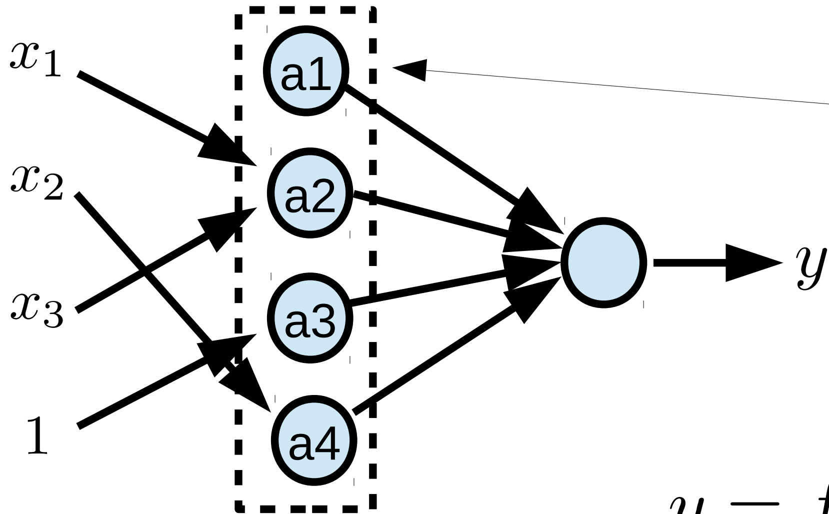


Going deeper: a one layer network



Each hidden node is
connected to every input

Multi-layer evaluation works similarly



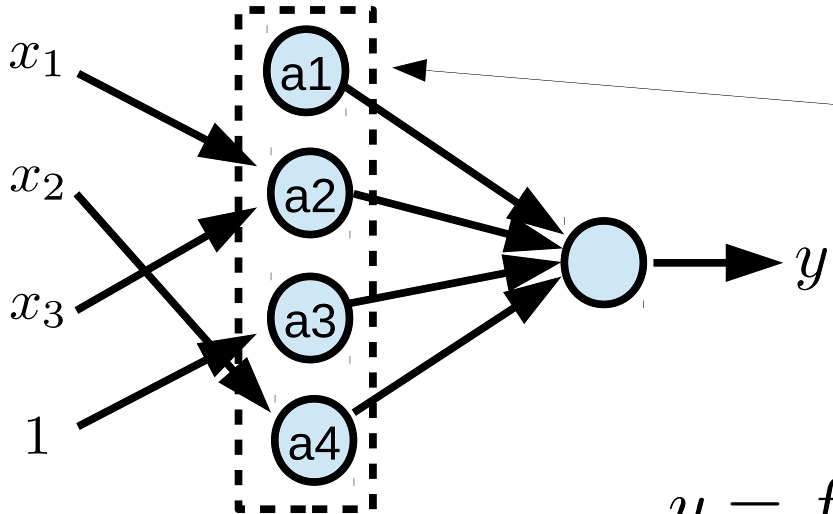
$$a = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix}$$

Vector of hidden layer activations

$$y = f({w^{(2)}}^T a^{(1)} + b^{(2)})$$

Single activation: $a_i^{(1)} = f(\underbrace{{w_i^{(1)}}^T x + b_i^{(1)}}_{z^{(1)}})$

Multi-layer evaluation works similarly



$$a = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix}$$

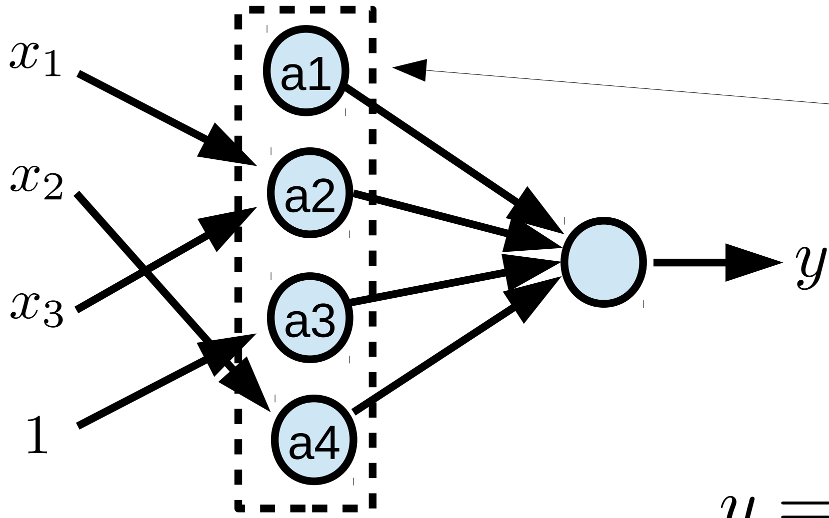
Vector of hidden layer activations

$$y = f({w^{(2)}}^T a^{(1)} + b^{(2)})$$

Single activation: $a_i^{(1)} = f(\underbrace{{w_i^{(1)}}^T x + b_i^{(1)}}_{z^{(1)}})$

Called "forward propagation" – b/c the activations are propogated forward...

Think-pair-share



$$a = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{pmatrix}$$

Vector of hidden layer activations

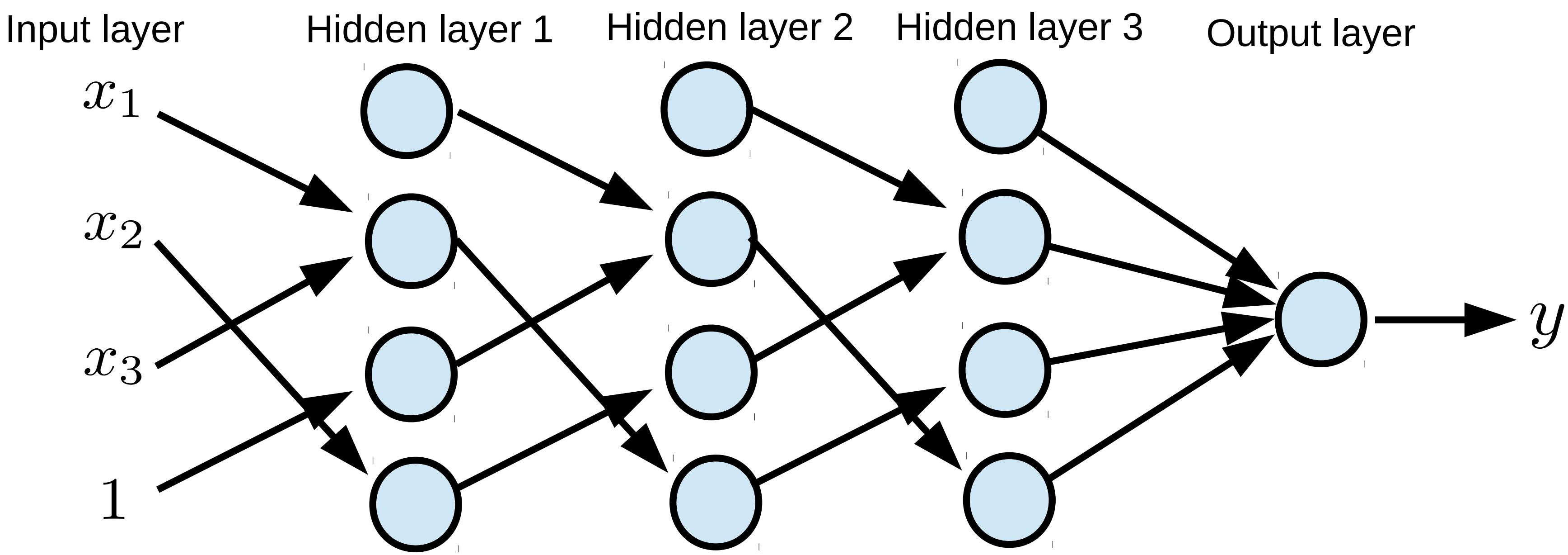
$$y = f({w^{(2)}}^T a^{(1)} + b^{(2)})$$

Single activation: $a_i^{(1)} = f({w_i^{(1)}}^T x + b_i^{(1)})$

<u>Write a matrix expression for *y* in terms of *x*, *f*, and the weights</u>

(assume f can act over vectors as well as scalars...)

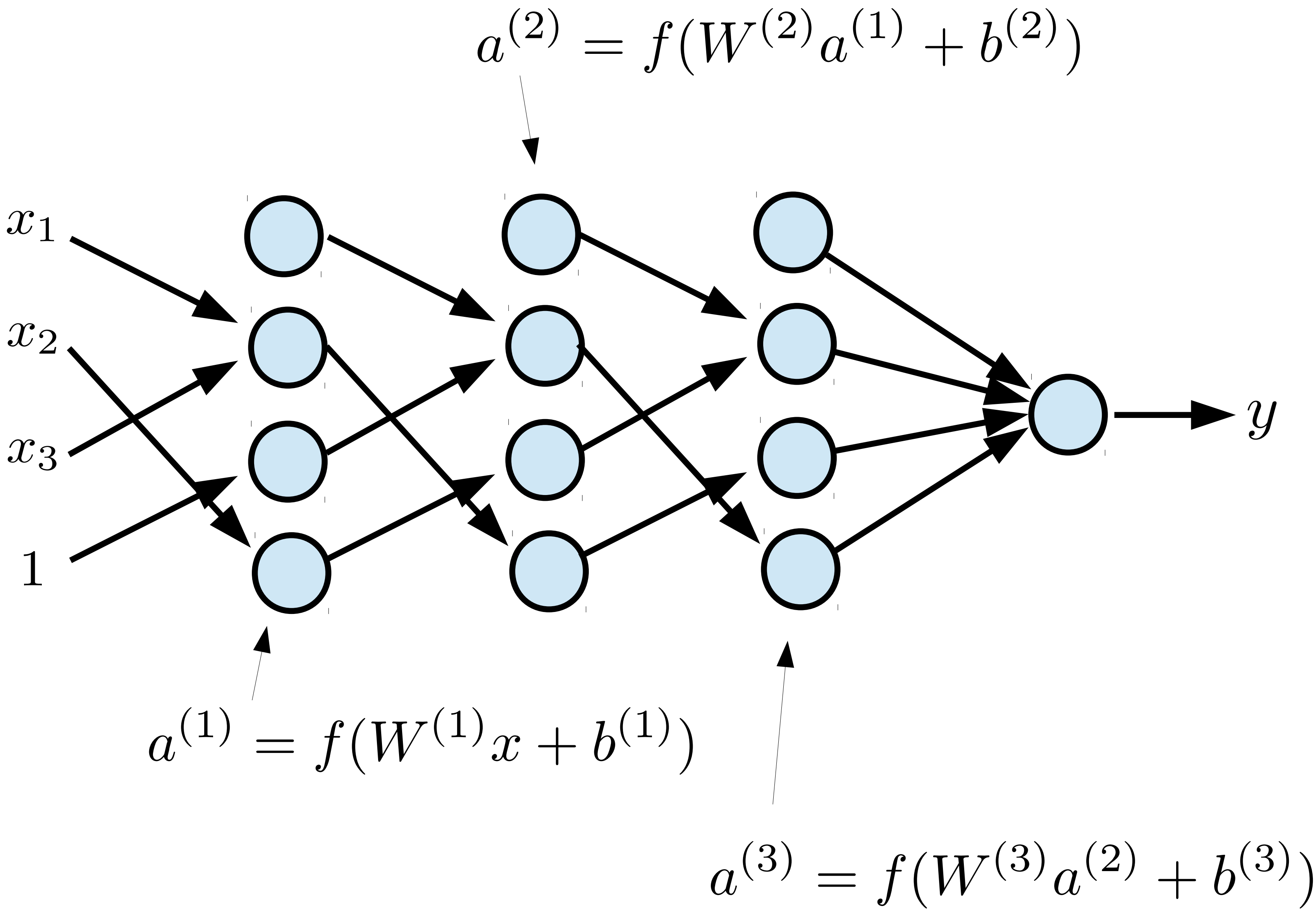
Can create networks of arbitrary depth...



– Forward propagation works the same for any depth network.

– Whereas a single output node corresponds to linear classification, adding hidden nodes makes classification non-linear

Can create networks of arbitrary depth...



How do we train multi-layer networks?

Almost the same as in the single-node case...

<u>Do gradient descent on dataset:</u>

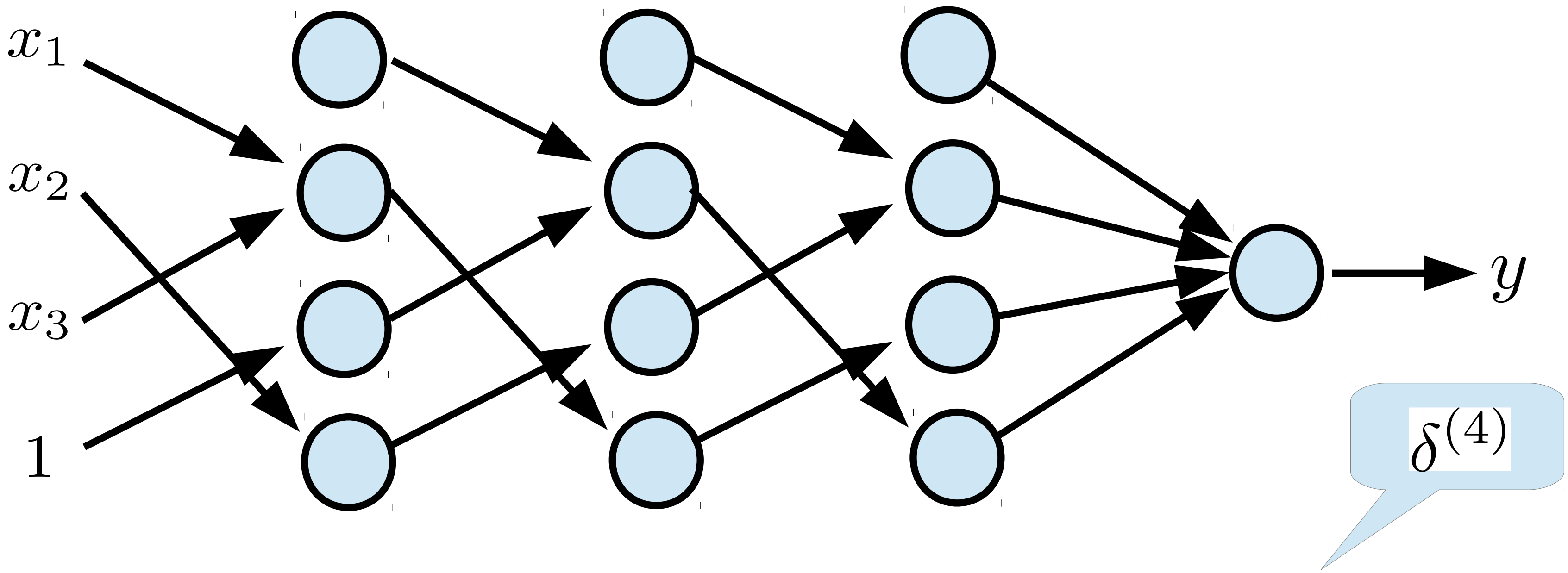
1. repeat
2. $$w \leftarrow w - \alpha \nabla_w L(D; w, b)$$
3. $$b \leftarrow b - \alpha \nabla_b L(D; w, b)$$
4. until converged

Now, we're doing gradient descent on all weights/biases in the network – not just a single layer

– this is called *backpropagation*

Backpropagation

<u>Goal</u>: calculate $\dfrac{\partial L}{\partial(W^{(i)}, b^{(i)})}, \forall i$



$$
\begin{tikzcd}
\dfrac{\partial L}{\partial z^{(1)}} \arrow[d] & \dfrac{\partial L}{\partial z^{(2)}} \arrow[l] \arrow[d] & \dfrac{\partial L}{\partial z^{(3)}} \arrow[l] \arrow[d] & \dfrac{\partial L}{\partial z^{(4)}} \arrow[l] \arrow[d] \\
\dfrac{\partial L}{\partial W^{(1)}, b^{(1)}} & \dfrac{\partial L}{\partial W^{(2)}, b^{(2)}} & \dfrac{\partial L}{\partial W^{(3)}, b^{(3)}} & \dfrac{\partial L}{\partial W^{(4)}, b^{(4)}}
\end{tikzcd}
$$

Backpropagation

1. Perform a feedforward pass, computing the activations for layers L_2, L_3, and so on up to the output layer L_{n_l}.

2. For each output unit i in layer n_l (the output layer), set

$$\delta_i^{(n_l)} = \frac{\partial}{\partial z_i^{(n_l)}} \frac{1}{2} \|y - h_{W,b}(x)\|^2 = -(y_i - a_i^{(n_l)}) \cdot f'(z_i^{(n_l)})$$

3. For $l = n_l - 1, n_l - 2, n_l - 3, \ldots, 2$

   For each node i in layer l, set

$$\delta_i^{(l)} = \left(\sum_{j=1}^{s_{l+1}} W_{ji}^{(l)} \delta_j^{(l+1)} \right) f'(z_i^{(l)})$$

4. Compute the desired partial derivatives, which are given as:

$$\frac{\partial}{\partial W_{ij}^{(l)}} J(W, b; x, y) = a_j^{(l)} \delta_i^{(l+1)}$$

$$\frac{\partial}{\partial b_i^{(l)}} J(W, b; x, y) = \delta_i^{(l+1)}.$$

http://ufldl.stanford.edu/tutorial/supervised/MultiLayerNeuralNetworks/

Stochastic gradient descent: mini-batches

A batch is typically between 32 and 128 samples

1. repeat
2. randomly sample a mini-batch: $B \subset D$
3. $$w \leftarrow w - \alpha \nabla_w L(B; w, b)$$
4. $$b \leftarrow b - \alpha \nabla_b L(B; w, b)$$
5. until converged

Training in mini-batches helps b/c:
– don't have to load the entire dataset into memory
– training is still relatively stable
– random sampling of batches helps avoid local minima

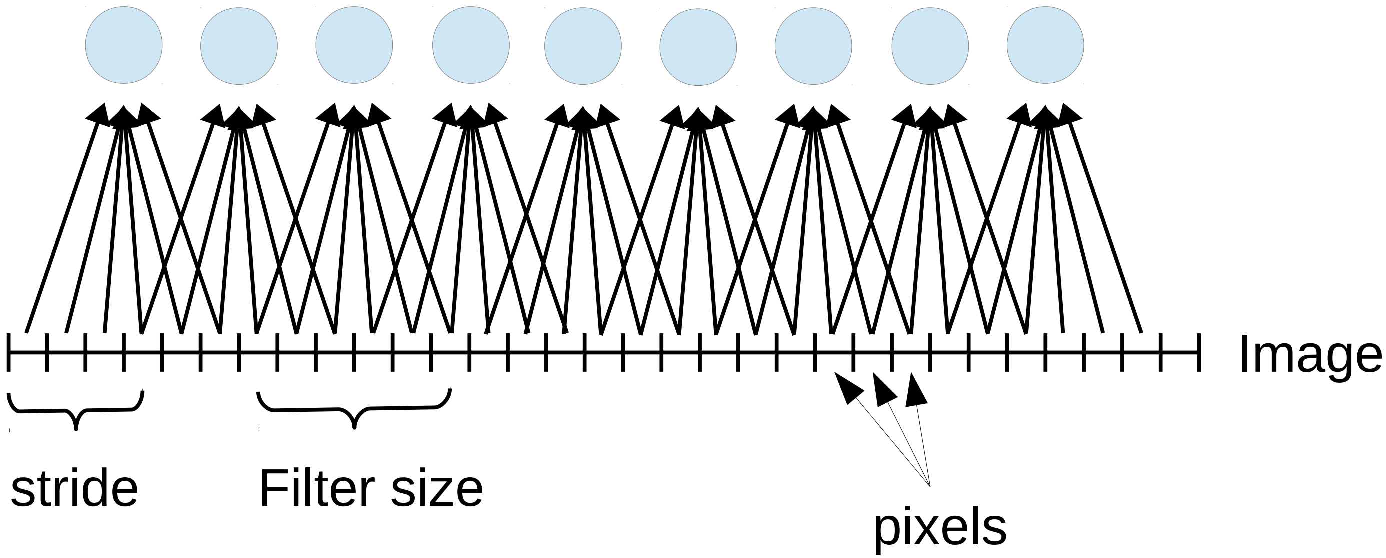
Convolutional layers

Deep multi-layer perceptron networks
– general purpose
– involve huge numbers of weights

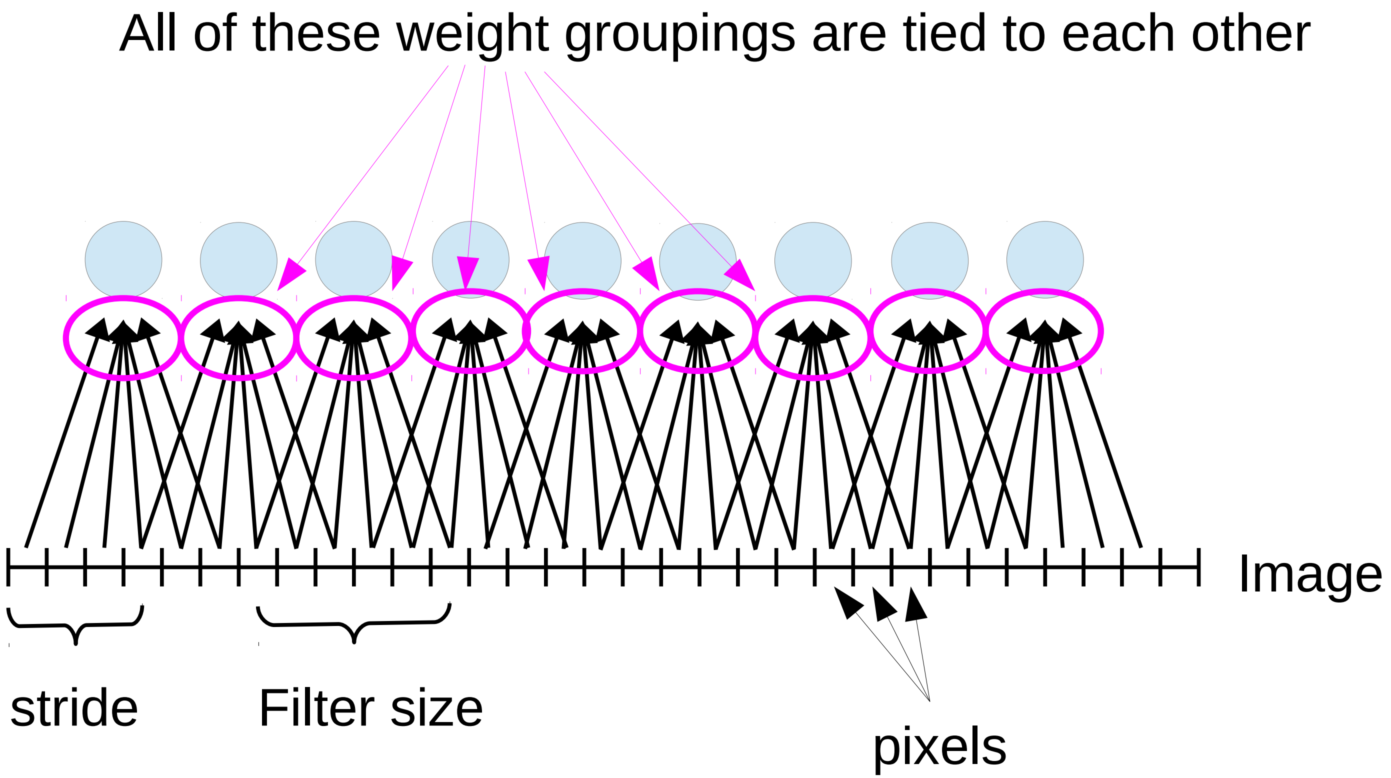
We want:
– special purpose network for image and NLP data
– fewer parameters
– fewer local minima

Answer: convolutional layers!

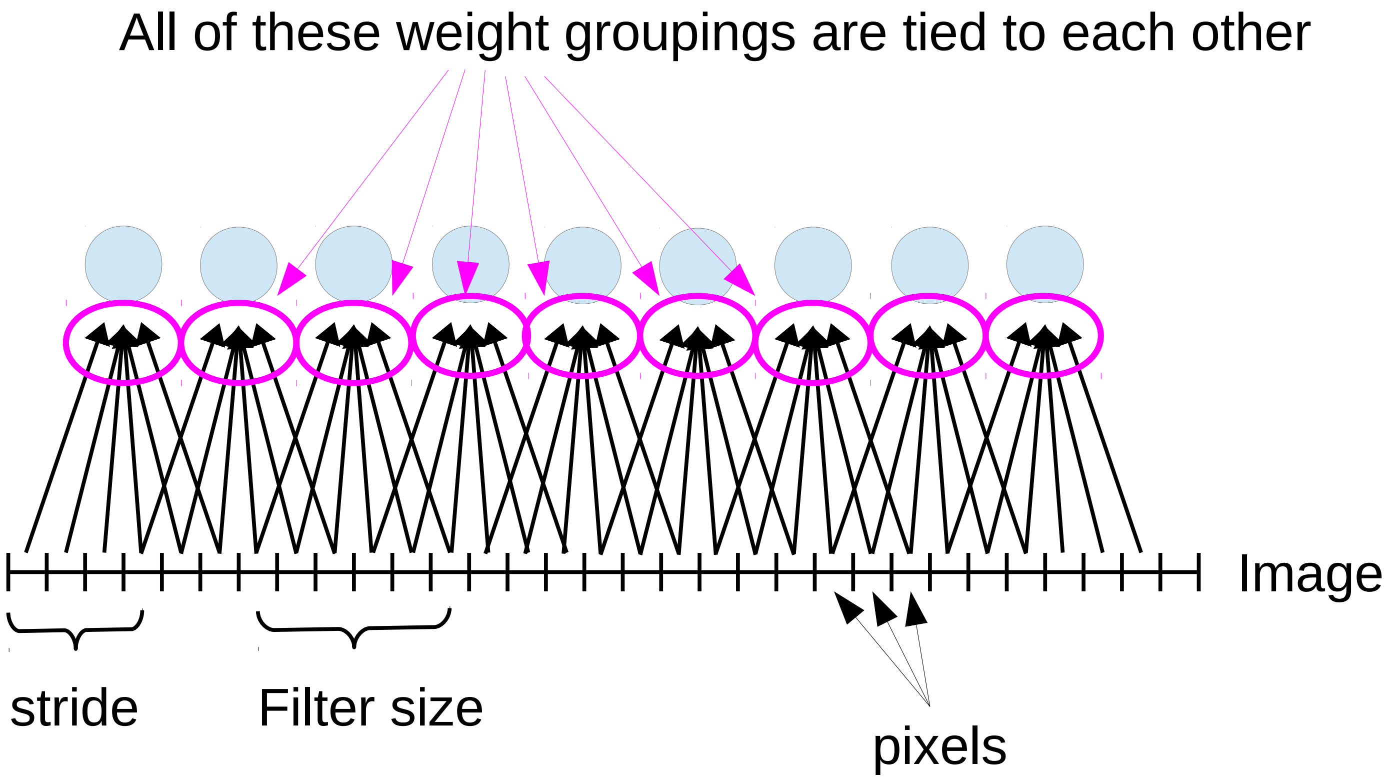
Convolutional layers



Convolutional layers



Convolutional layers

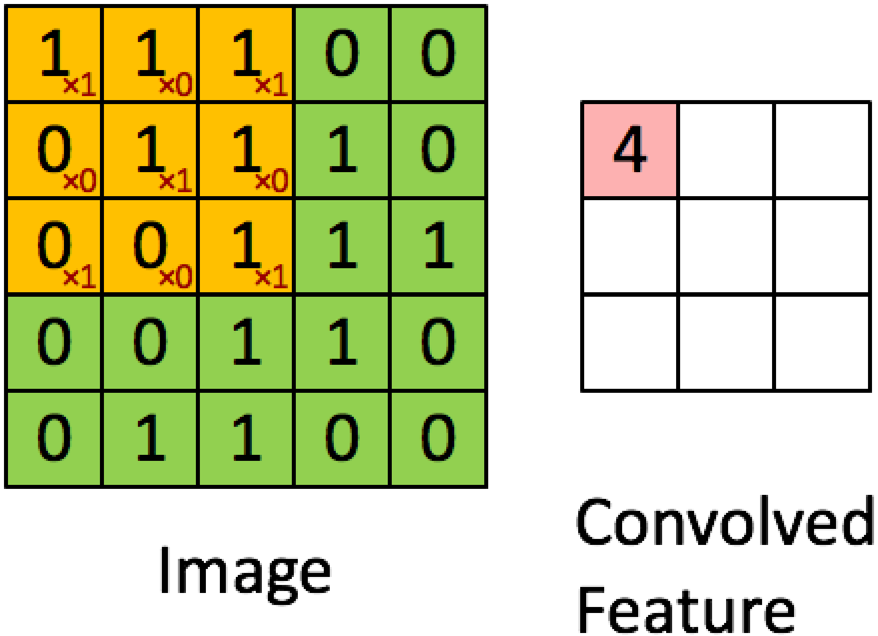


Because of the way weights are tied together
– reduces number of parameters (dramatically)
– encodes a prior on structure of data

In practice, convolutional layers are essential to computer vision...

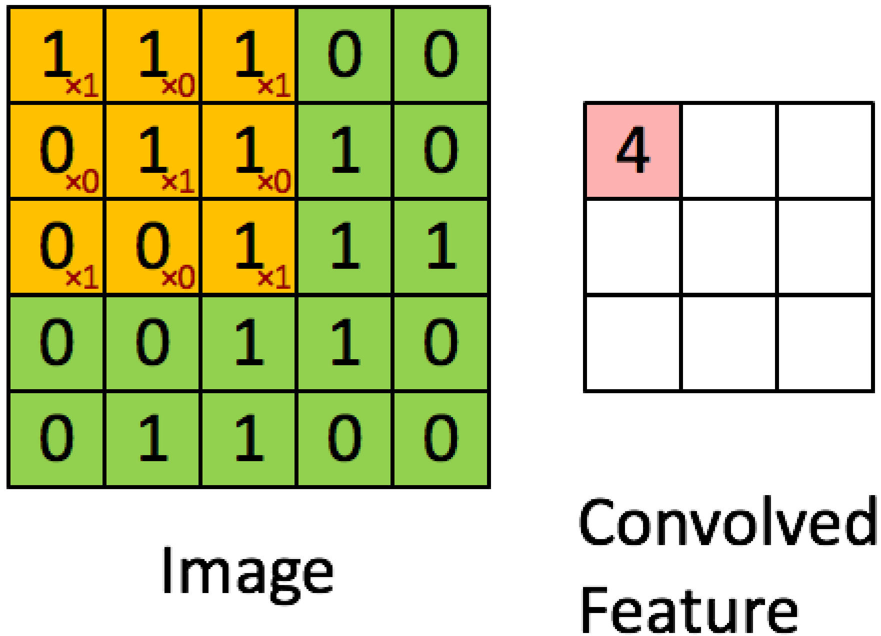
Convolutional layers

Two dimensional example:



Why do you think they call this “convolution”?

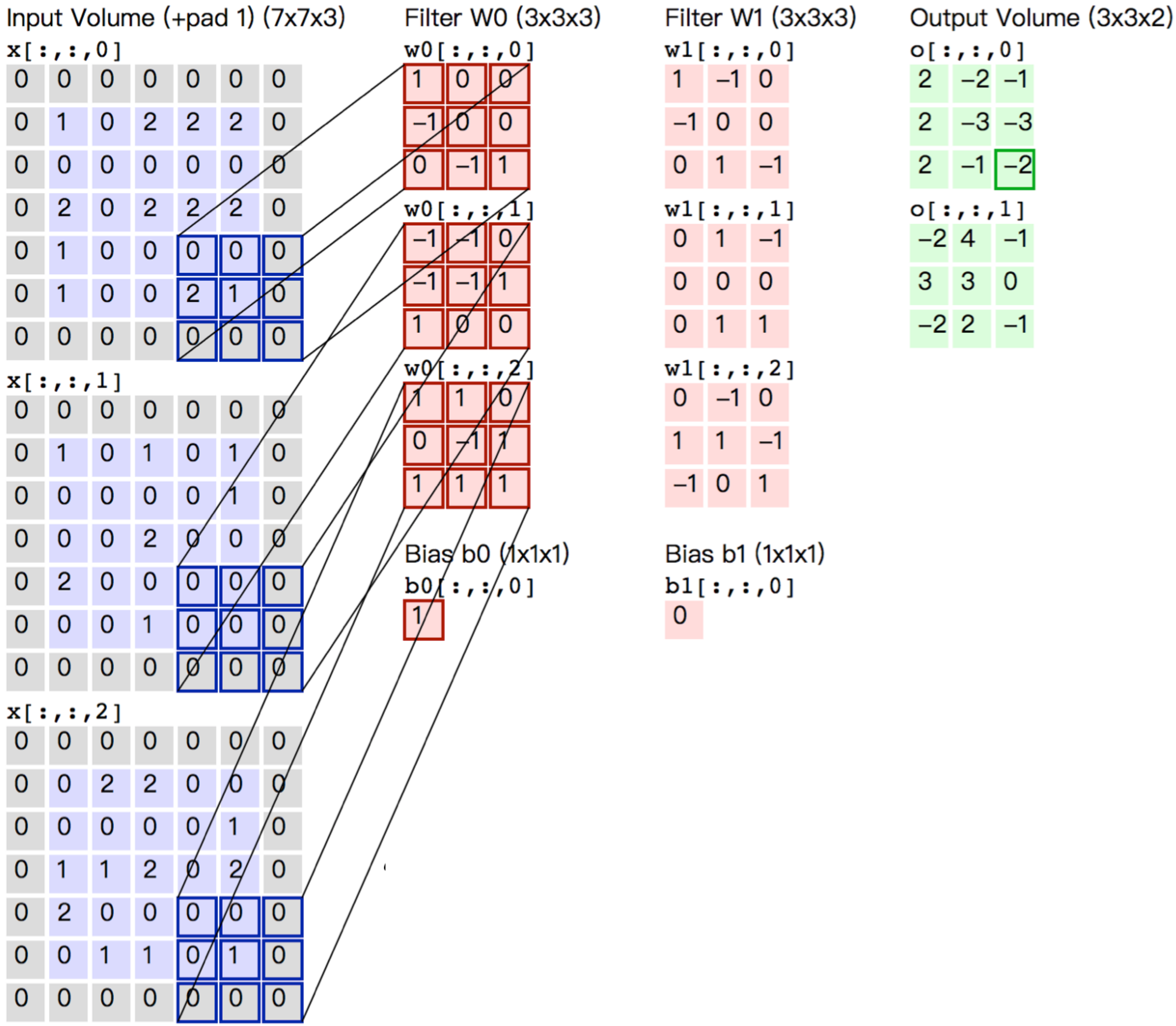
Think-pair-share



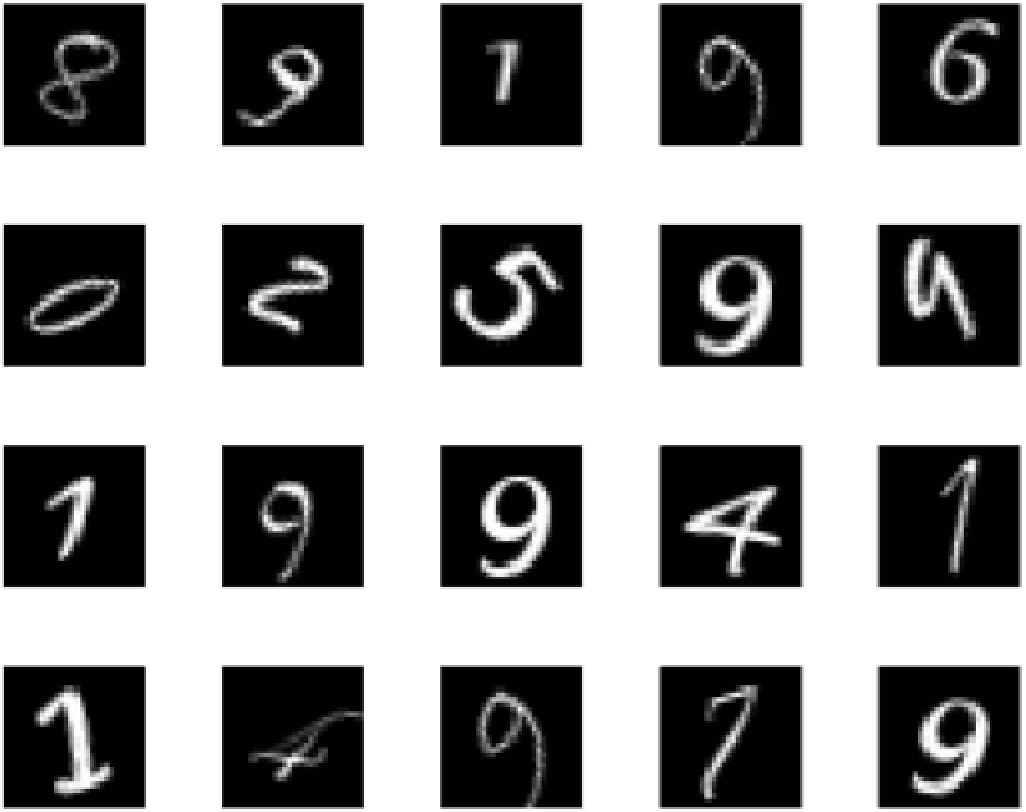
What would the convolved feature map be for <u>this</u> kernel?

$$\begin{matrix} 1 & 1 & 1 \\ 0 & 1 & 0 \\ 1 & 1 & 1 \end{matrix}$$

Convolutional layers



Example: MNIST digit classification with LeNet

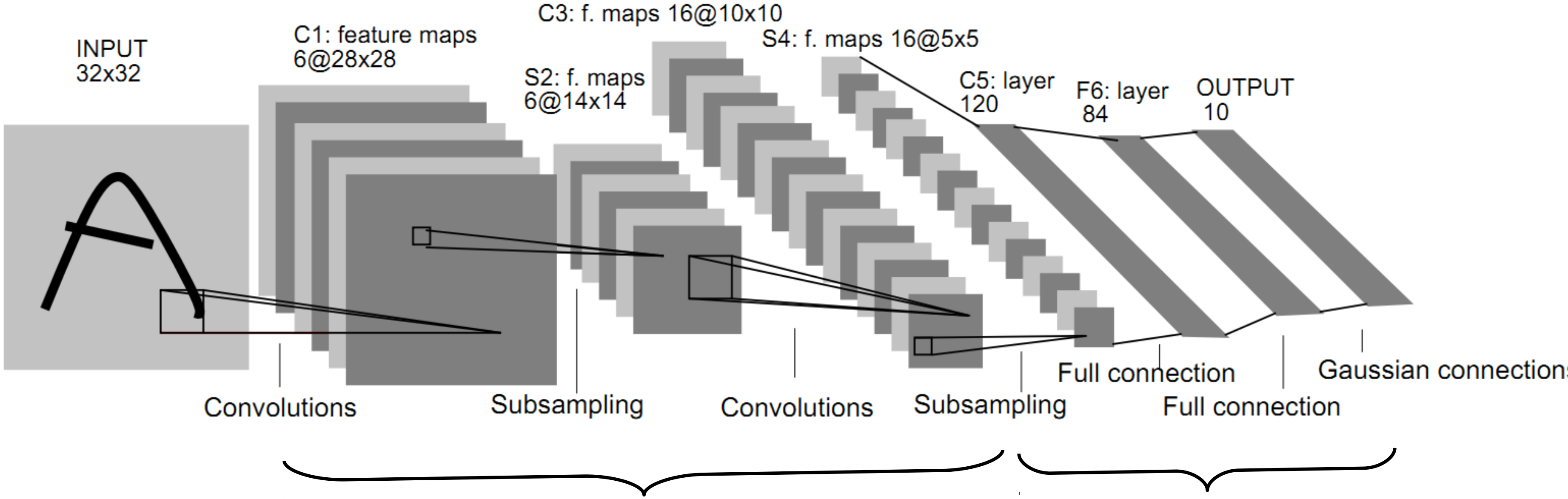


MNIST dataset: images of 10,000 handwritten digits

Objective: classify each image as the corresponding digit

Example: MNIST digit classification with LeNet

LeNet:



two convolutional layers
– conv, relu, pooling

two fully connected layers
– relu
– last layer has logistic
activation function

Example: MNIST digit classification with LeNet

Load dataset, create train/test splits

```
digitDatasetPath = fullfile(matlabroot,'toolbox','nnet','nndemos',...
    'nndatasets','DigitDataset');
digitData = imageDatastore(digitDatasetPath,...
    'IncludeSubfolders',true,'LabelSource','foldernames');

trainNumFiles = 750;
[trainDigitData,valDigitData] = splitEachLabel(digitData,trainNumFiles,'randomize');
```

Example: MNIST digit classification with LeNet

<u>Define the neural network structure:</u>

```
layers = [
    imageInputLayer([28 28 1])
    convolution2dLayer(3,16,'Padding',1)
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(3,32,'Padding',1)
    batchNormalizationLayer
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    convolution2dLayer(3,64,'Padding',1)
    batchNormalizationLayer
    reluLayer
    fullyConnectedLayer(50)
    reluLayer
    fullyConnectedLayer(10)
    softmaxLayer
    classificationLayer];
```

Input

Conv1

Conv2

FC1

FC2

```
options = trainingOptions('sgdm',...
'MaxEpochs',3, ...
'ValidationData',valDigitData,...
'ValidationFrequency',30,...
'Verbose',true,...
'ExecutionEnvironment','gpu',...
'Plots','training-progress');
```

Example: MNIST digit classification with LeNet

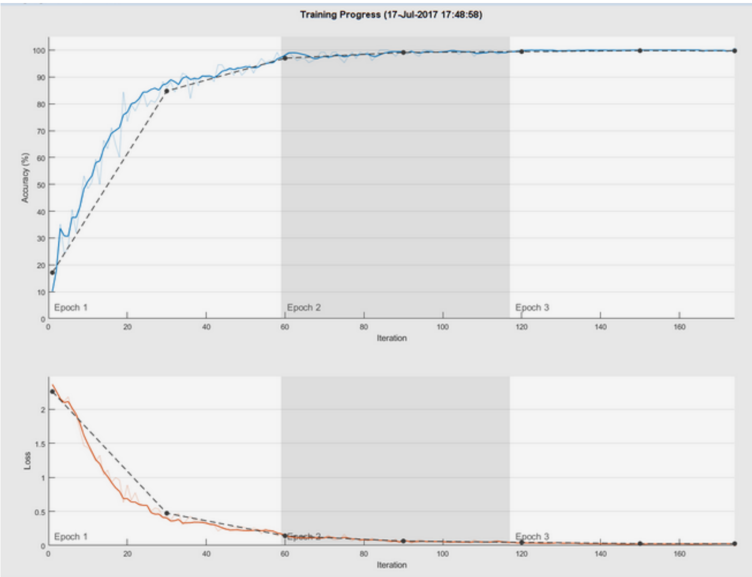
Train network, classify test set, measure accuracy

– notice we test on a different set (a holdout set) than we trained on

```
net = trainNetwork(trainDigitData,layers,options);

predictedLabels = classify(net,valDigitData);
valLabels = valDigitData.Labels;

accuracy = sum(predictedLabels == valLabels)/numel(valLabels);
```



Using the GPU makes
a huge differece...

Deep learning packages

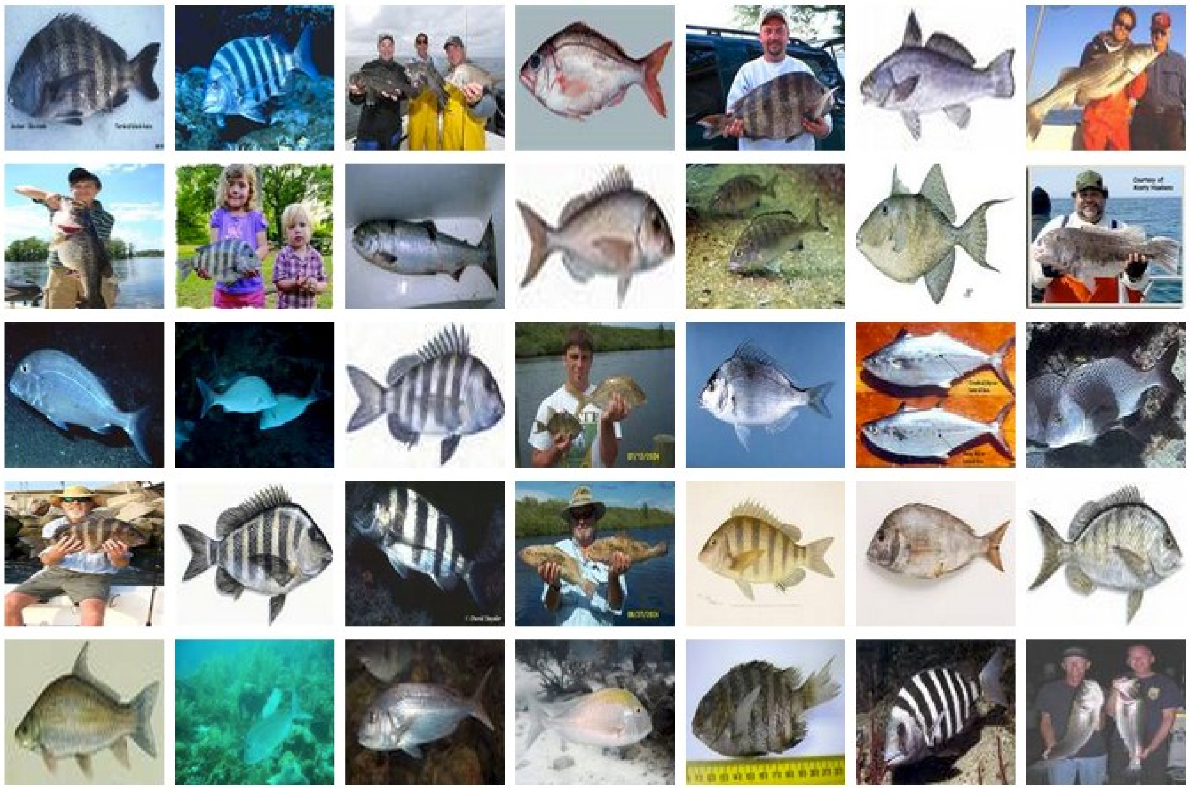
PYTORCH

Caffe

TensorFlow

theano

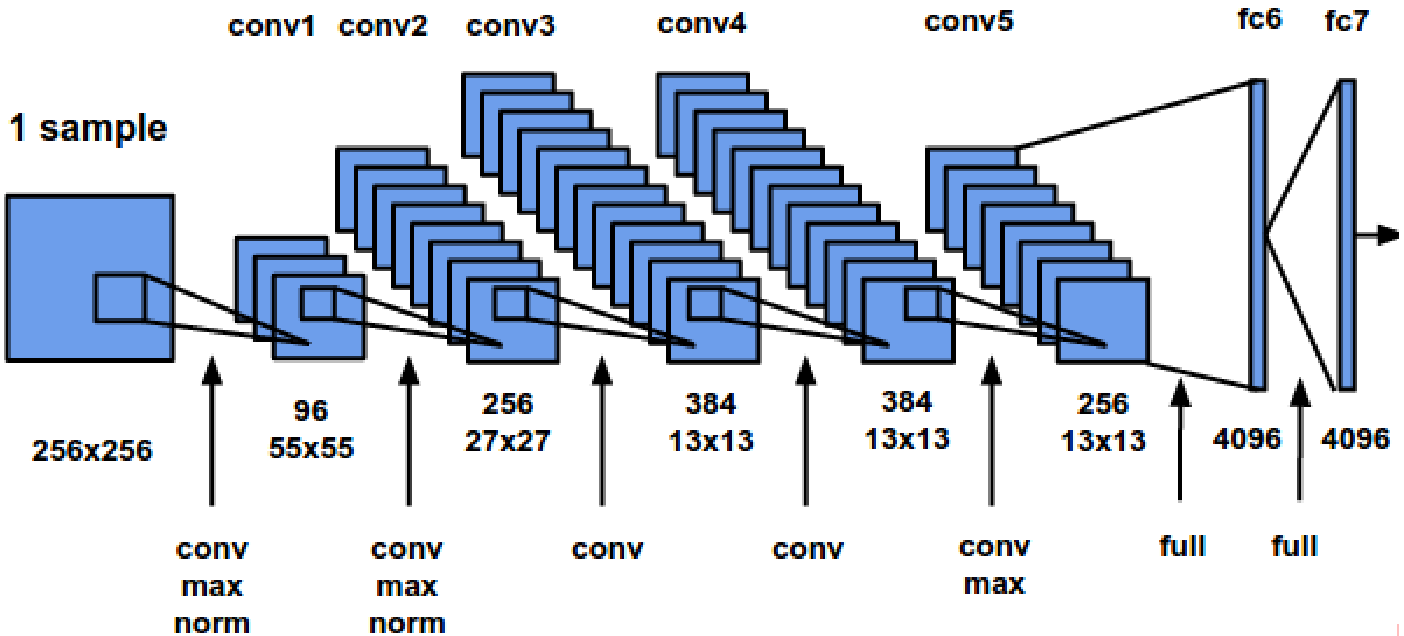
Another example: image classification w/ AlexNet



ImageNet dataset: millions of images of objects

Objective: classify each image as the corresponding object (1k categories in ILSVRC)

Another example: image classification w/ AlexNet



AlexNet has 8 layers: five conv followed by three fully connected

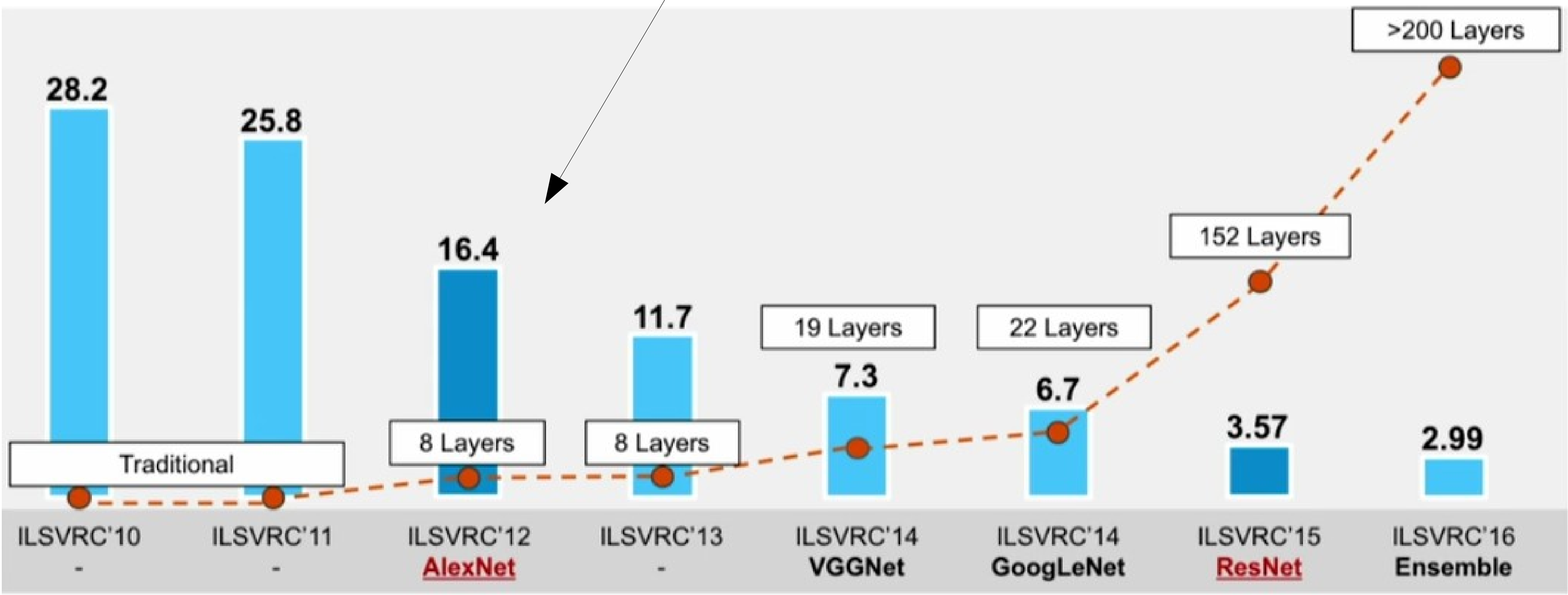
Another example: image classification w/ AlexNet

```
 1   'data'     Image Input                    227x227x3 images with 'zerocenter' normalization
 2   'conv1'    Convolution                    96 11x11x3 convolutions with stride [4  4] and padding [0  0]
 3   'relu1'    ReLU                           ReLU
 4   'norm1'    Cross Channel Normalization    cross channel normalization with 5 channels per element
 5   'pool1'    Max Pooling                    3x3 max pooling with stride [2  2] and padding [0  0]
 6   'conv2'    Convolution                    256 5x5x48 convolutions with stride [1  1] and padding [2  2]
 7   'relu2'    ReLU                           ReLU
 8   'norm2'    Cross Channel Normalization    cross channel normalization with 5 channels per element
 9   'pool2'    Max Pooling                    3x3 max pooling with stride [2  2] and padding [0  0]
10   'conv3'    Convolution                    384 3x3x256 convolutions with stride [1  1] and padding [1  1]
11   'relu3'    ReLU                           ReLU
12   'conv4'    Convolution                    384 3x3x192 convolutions with stride [1  1] and padding [1  1]
13   'relu4'    ReLU                           ReLU
14   'conv5'    Convolution                    256 3x3x192 convolutions with stride [1  1] and padding [1  1]
15   'relu5'    ReLU                           ReLU
16   'pool5'    Max Pooling                    3x3 max pooling with stride [2  2] and padding [0  0]
17   'fc6'      Fully Connected                4096 fully connected layer
18   'relu6'    ReLU                           ReLU
19   'drop6'    Dropout                        50% dropout
20   'fc7'      Fully Connected                4096 fully connected layer
21   'relu7'    ReLU                           ReLU
22   'drop7'    Dropout                        50% dropout
23   'fc8'      Fully Connected                1000 fully connected layer
24   'prob'     Softmax                        softmax
25   'output'   Classification Output          crossentropyex with 'tench', 'goldfish', and 998 other classes
```

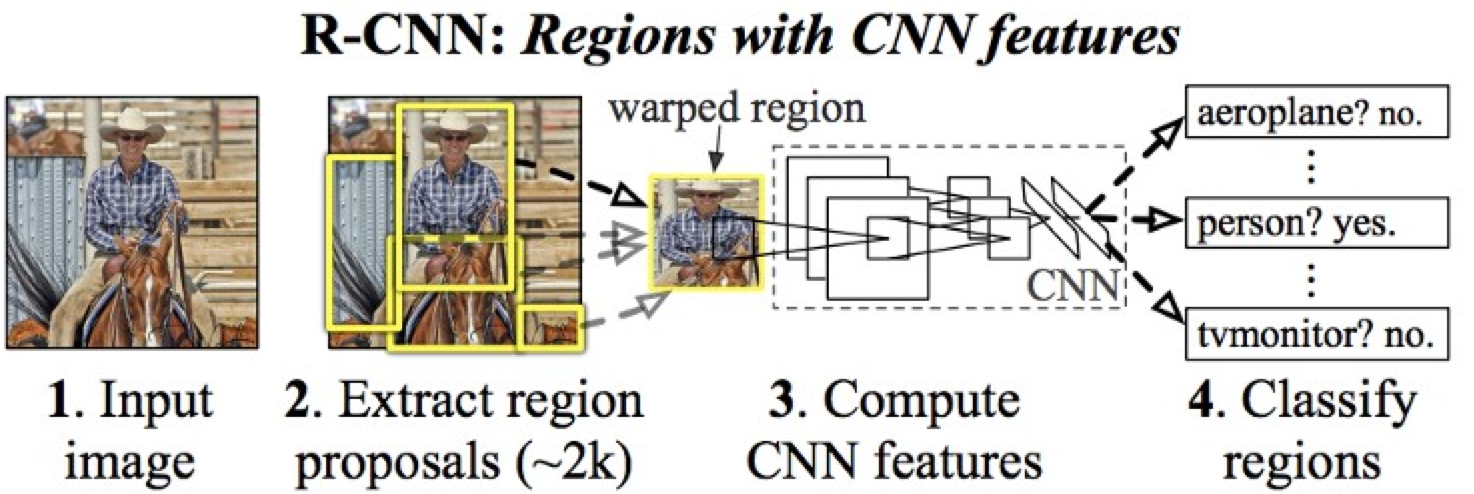
AlexNet has 8 layers: five conv followed by three fully connected

Another example: image classification w/ AlexNet

AlexNet won the 2012 ILSVRC challenge
– sparked the deep learning craze

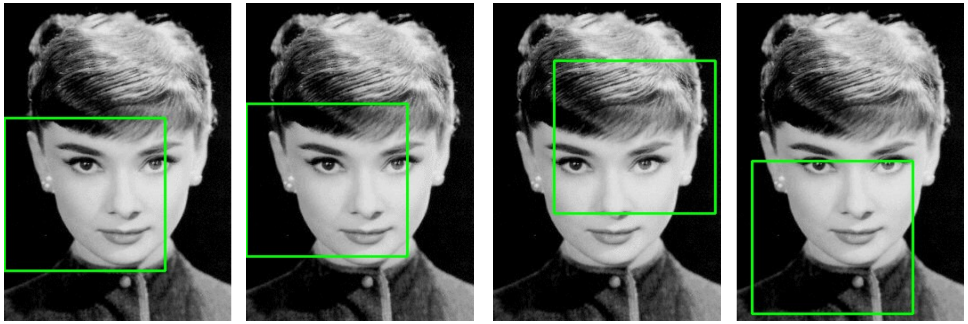


Object detection



Proposal generation

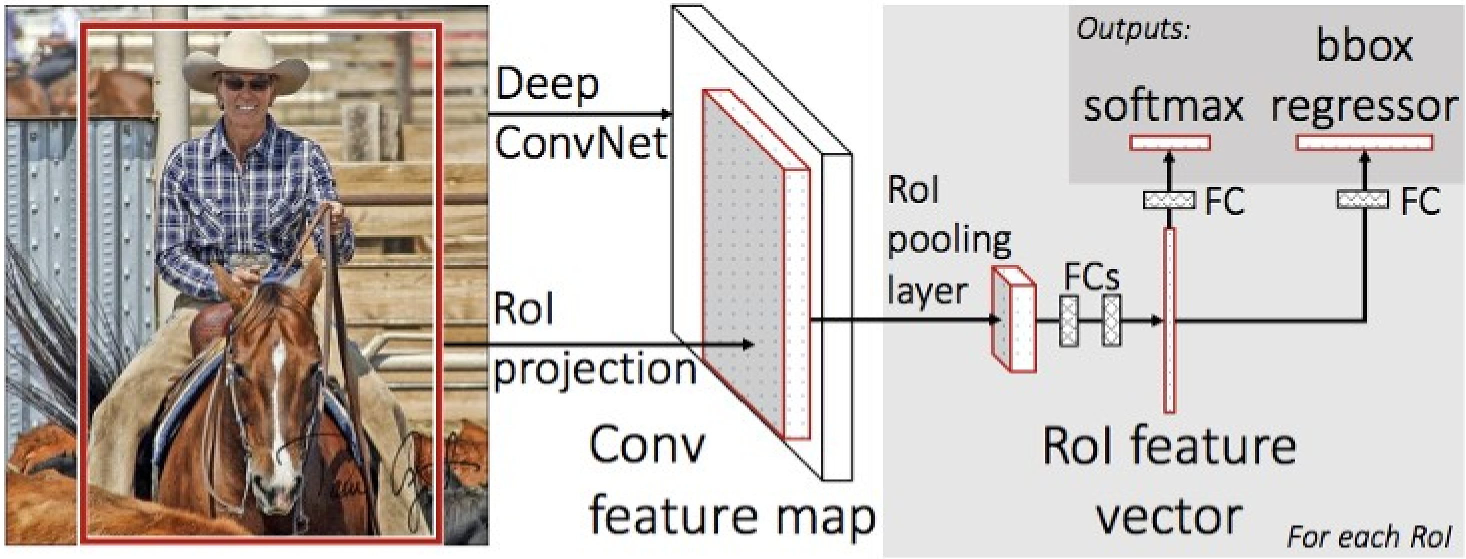
Exhaustive: Sliding window:



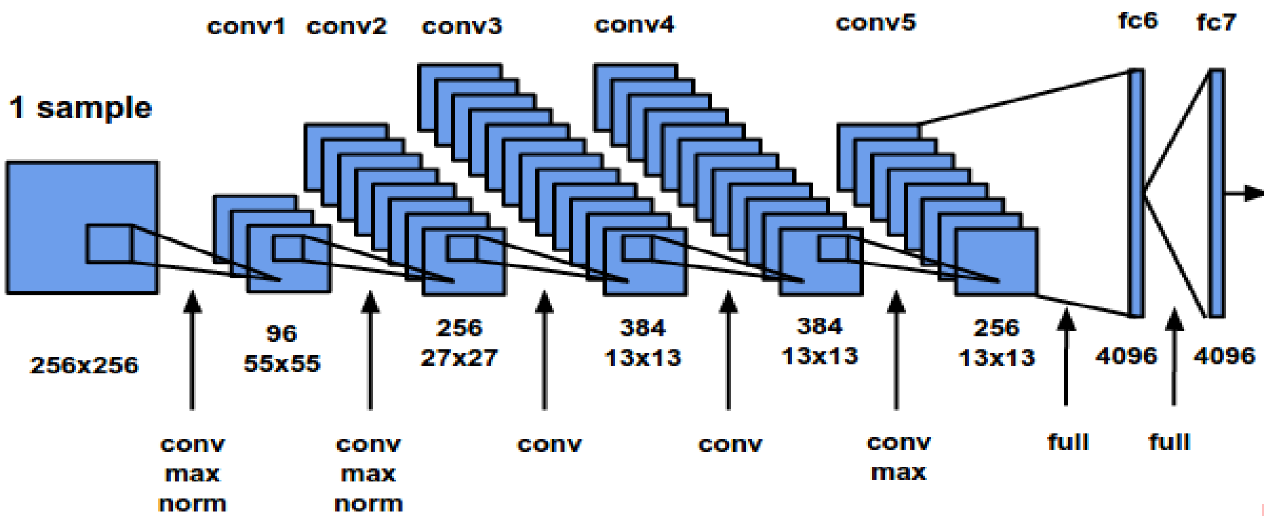
Hand-coded proposal generation:

(selective search)

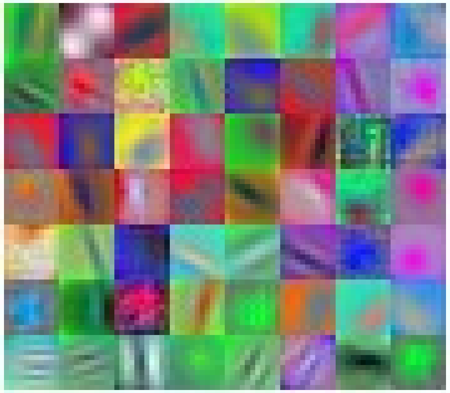
Fully convolutional object detection



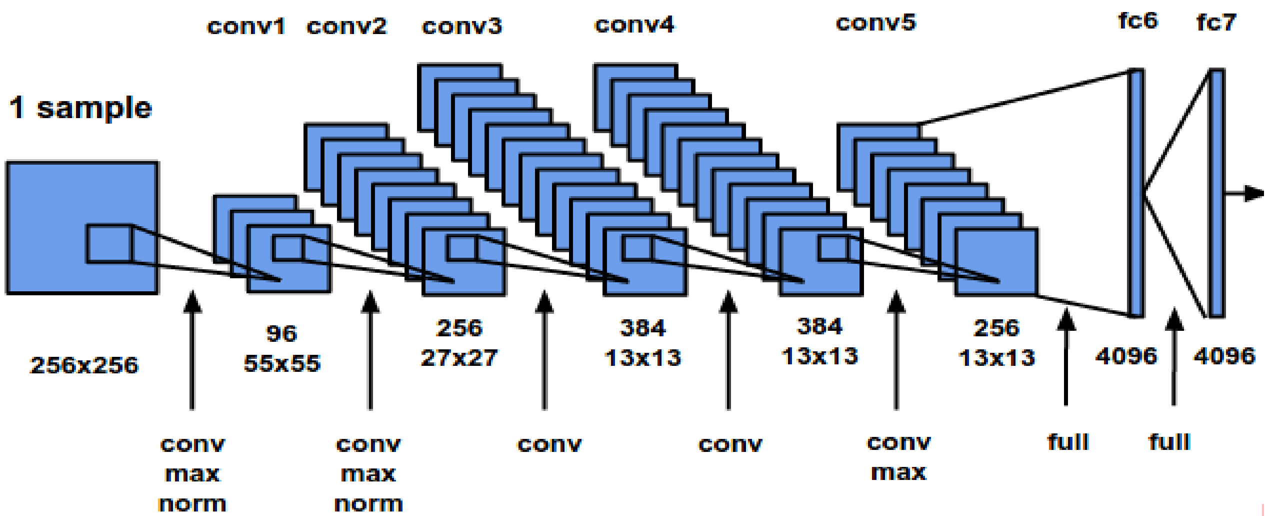
What exactly are deep conv networks learning?



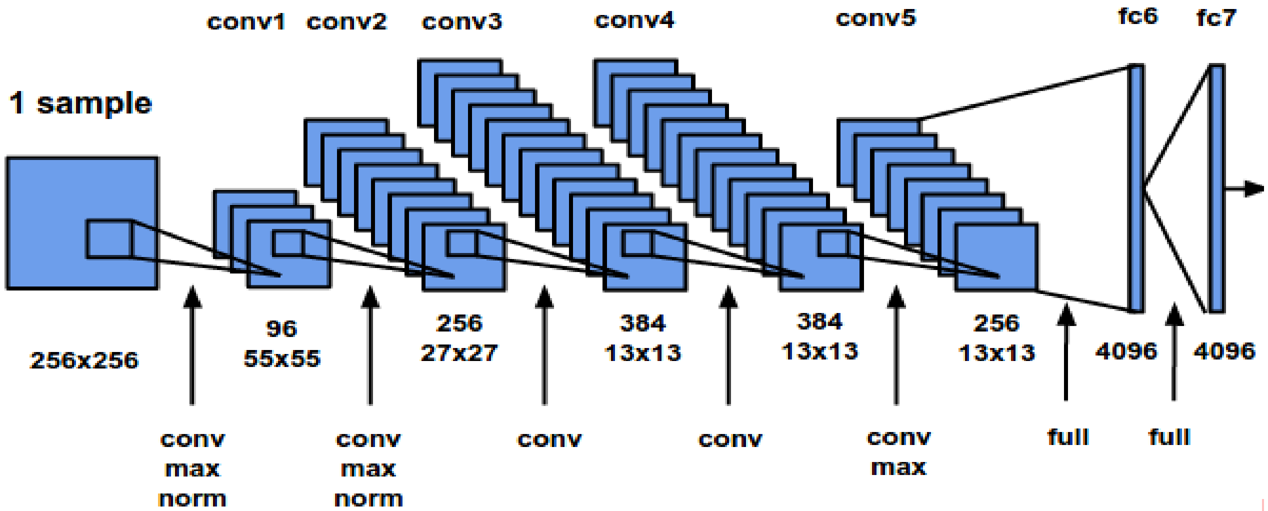
Layer conv1 Features



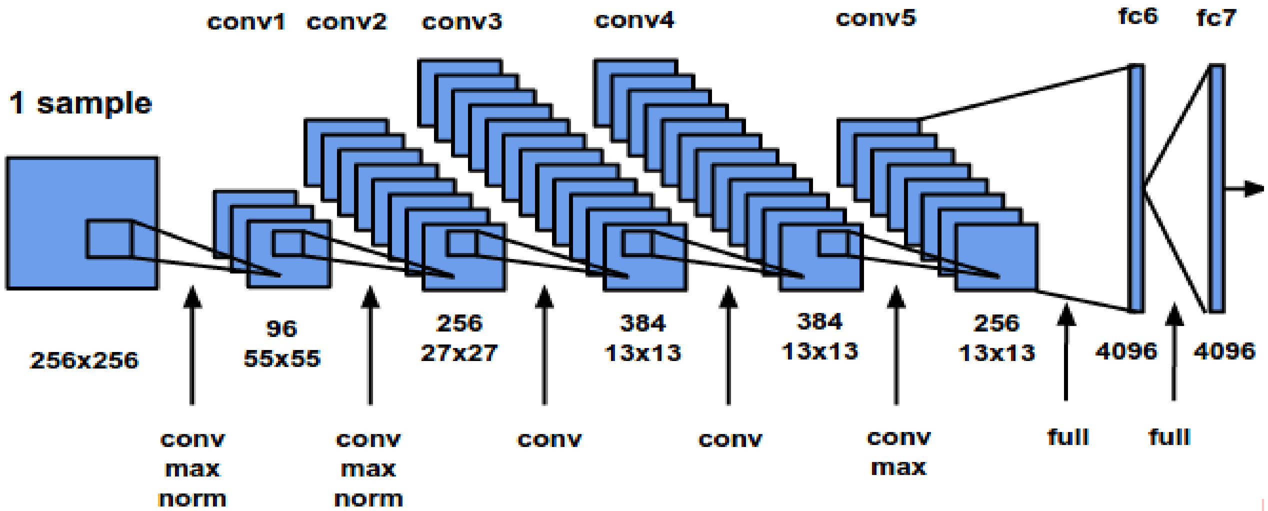
What exactly are deep conv networks learning?



What exactly are deep conv networks learning?

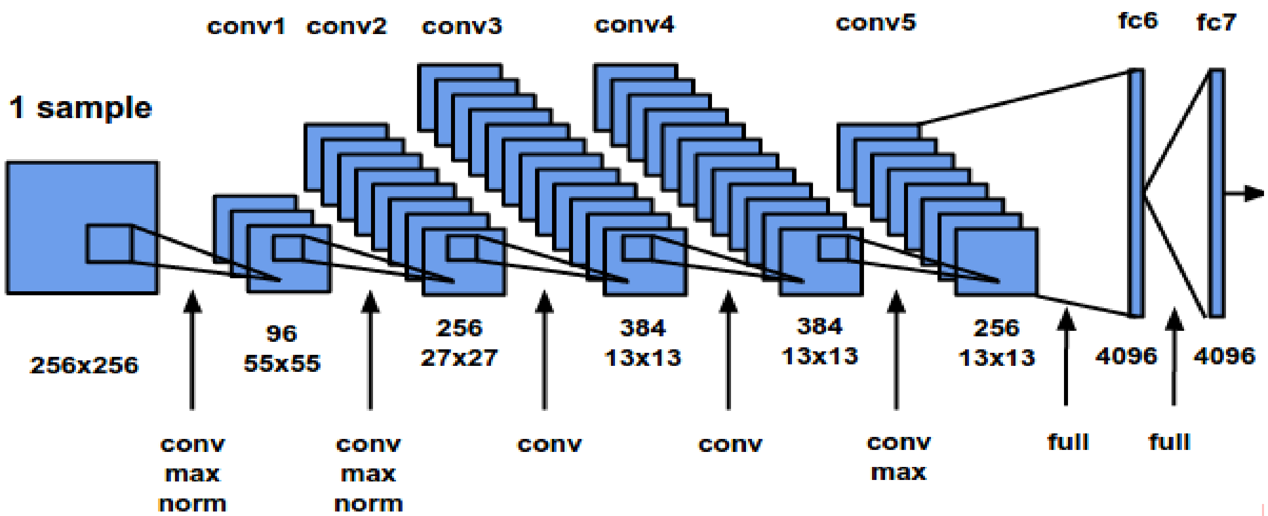


What exactly are deep conv networks learning?

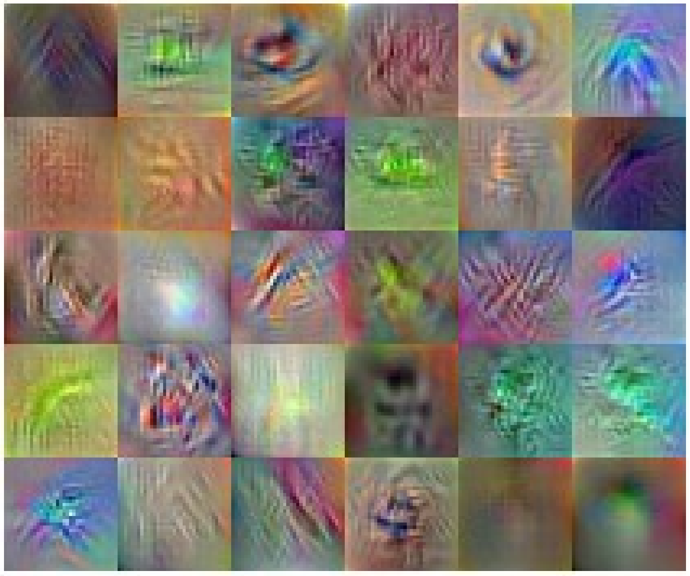


Layer conv4 Features

What exactly are deep conv networks learning?

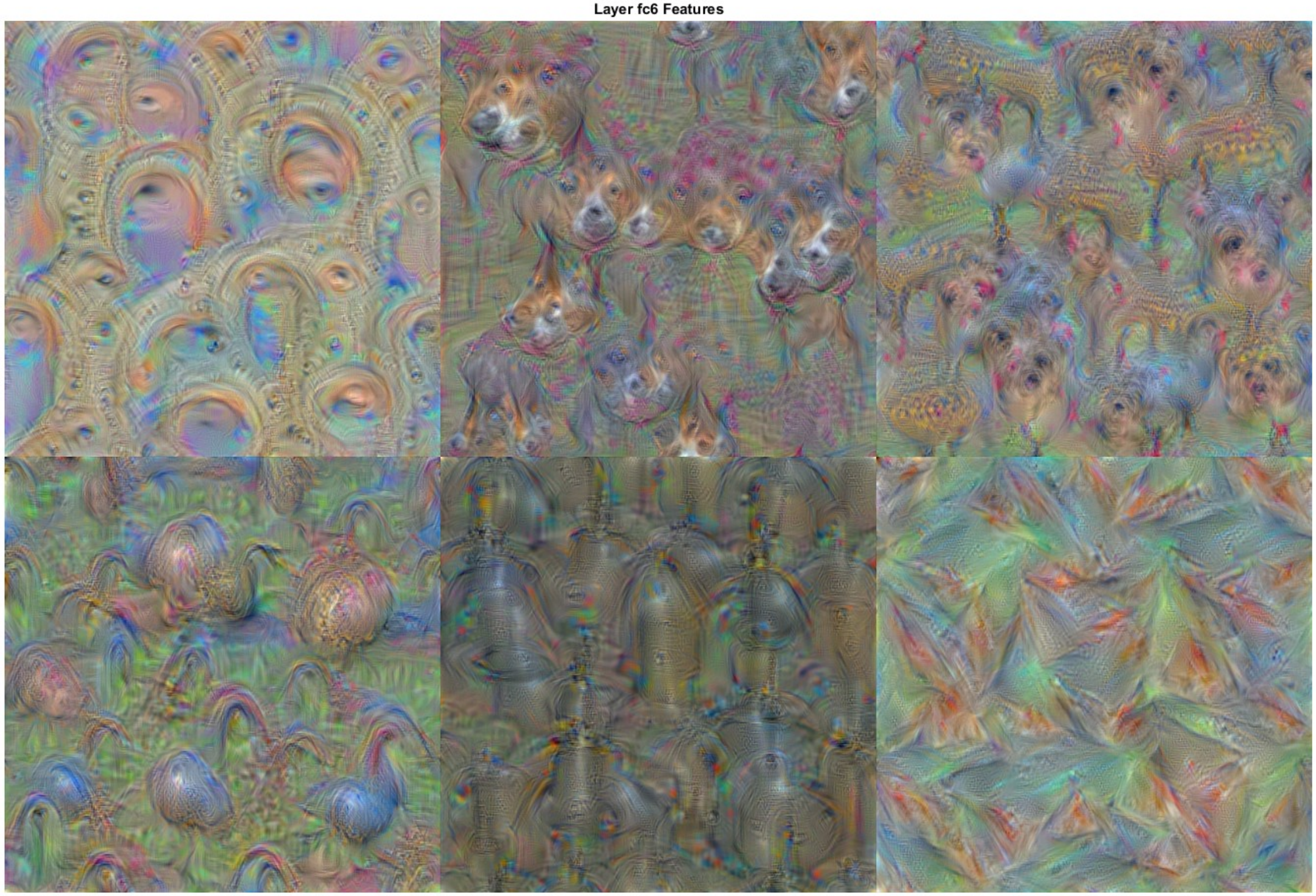


Layer conv5 Features



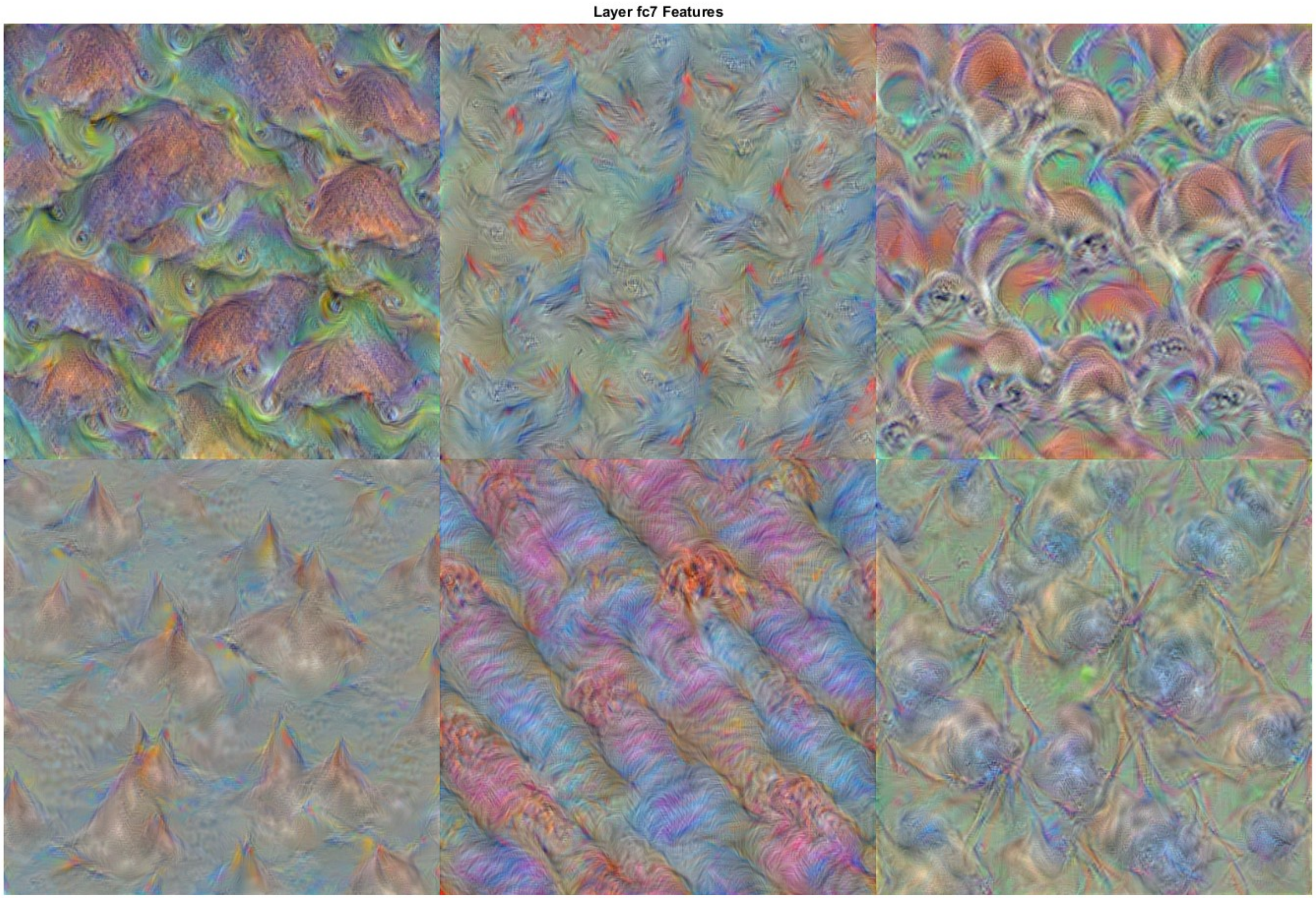
What exactly are deep conv networks learning?

FC layer 6



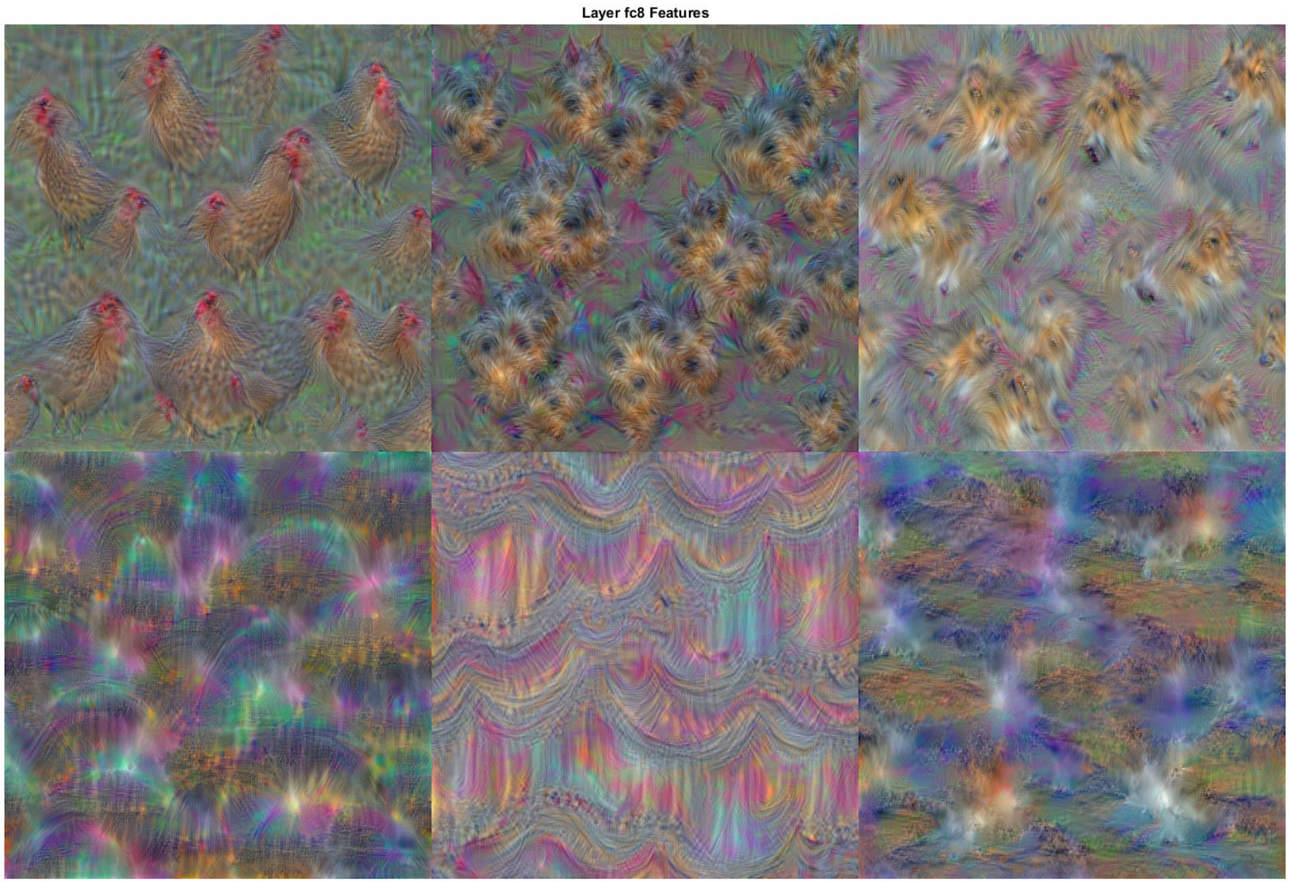
What exactly are deep conv networks learning?

FC layer 7



What exactly are deep conv networks learning?

Output layer



Finetuning

AlexNet has 60M parameters
– therefore, you need a very large training set (like imagenet)

Suppose we want to train on our own images, but we only have a few hundred?
– AlexNet will drastically overfit such a small dataset… (won't generalize at all)

Finetuning

<u>Idea:</u>
1. pretrain on imagenet
2. finetune on your own dataset

AlexNet has 60M parameters
– therefore, you need a very large training set (like imagenet)

Suppose we want to train on our own images, but we only have a few hundred?
– AlexNet will drastically overfit such a small dataset… (won't generalize at all)