15-381/781
Fall 2016
Deep Learning & Computer Vision

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Deep Learning & Computer Vision: Review & Overview

- Neural networks & nodes as features
- Nonlinearity: choices, implications for learning
- Benefits of deep over shallow
- How to train/fit/learn
- New ideas for tackling vision applications
- What if we don't have much data?

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Recall: Supervised ML

Input features $x^{(i)} \in \mathbb{R}^n$

Outputs $y^{(i)} \in \mathcal{Y}$ (e.g. $\mathbb{R}$, $\{-1, +1\}$, $\{1, \ldots, p\}$)

Model parameters $\theta \in \mathbb{R}^k$

Hypothesis function $h_\theta : \mathbb{R}^n \to \mathbb{R}$

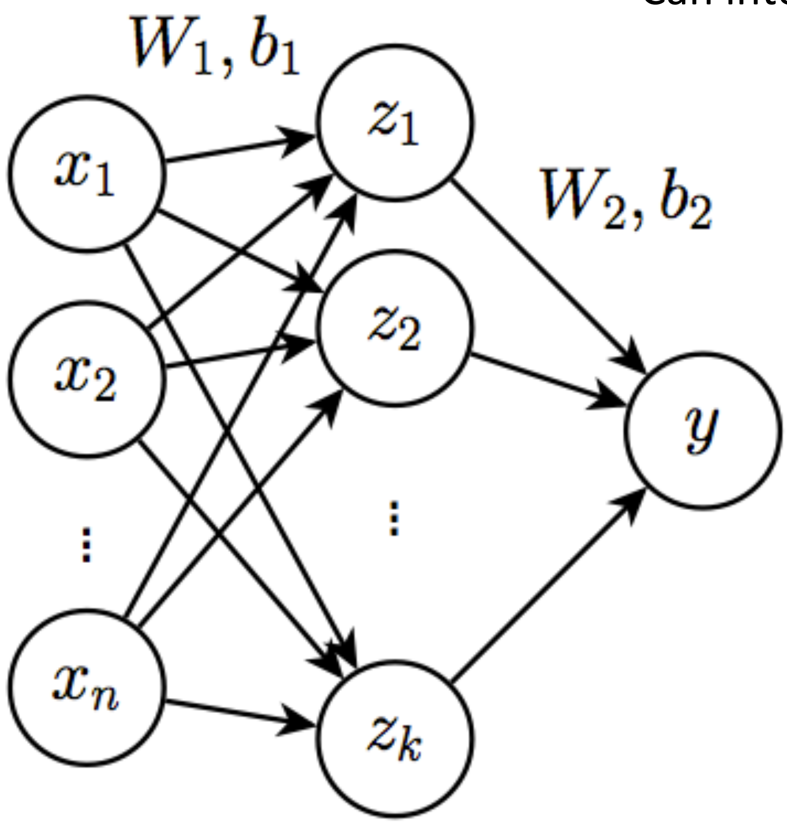
Loss function $\ell : \mathbb{R} \times \mathcal{Y} \to \mathbb{R}_+$

Machine learning optimization problem

$$\underset{\theta}{\text{minimize}} \quad \sum_{i=1}^{m} \ell(h_\theta(x^{(i)}), y^{(i)})$$

Neural Networks for Classification

Can interpret "z"s as features



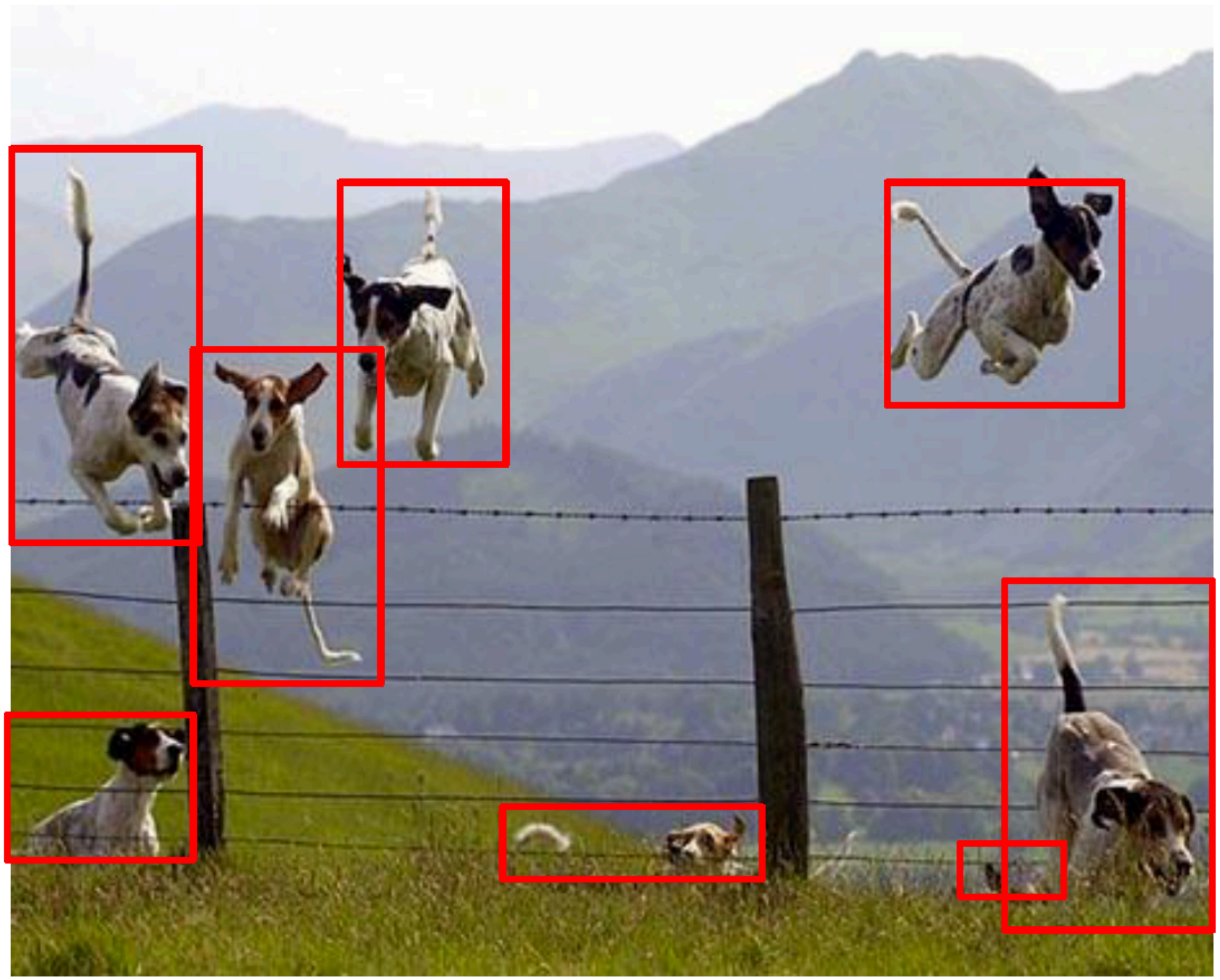
Output class is computed based on these features instead of directly on input x

$$h_\theta(x) = f_2(W_2 f_1(W_1 x + b_1) + b_2)$$

Why Do We Want Hidden "Features"?

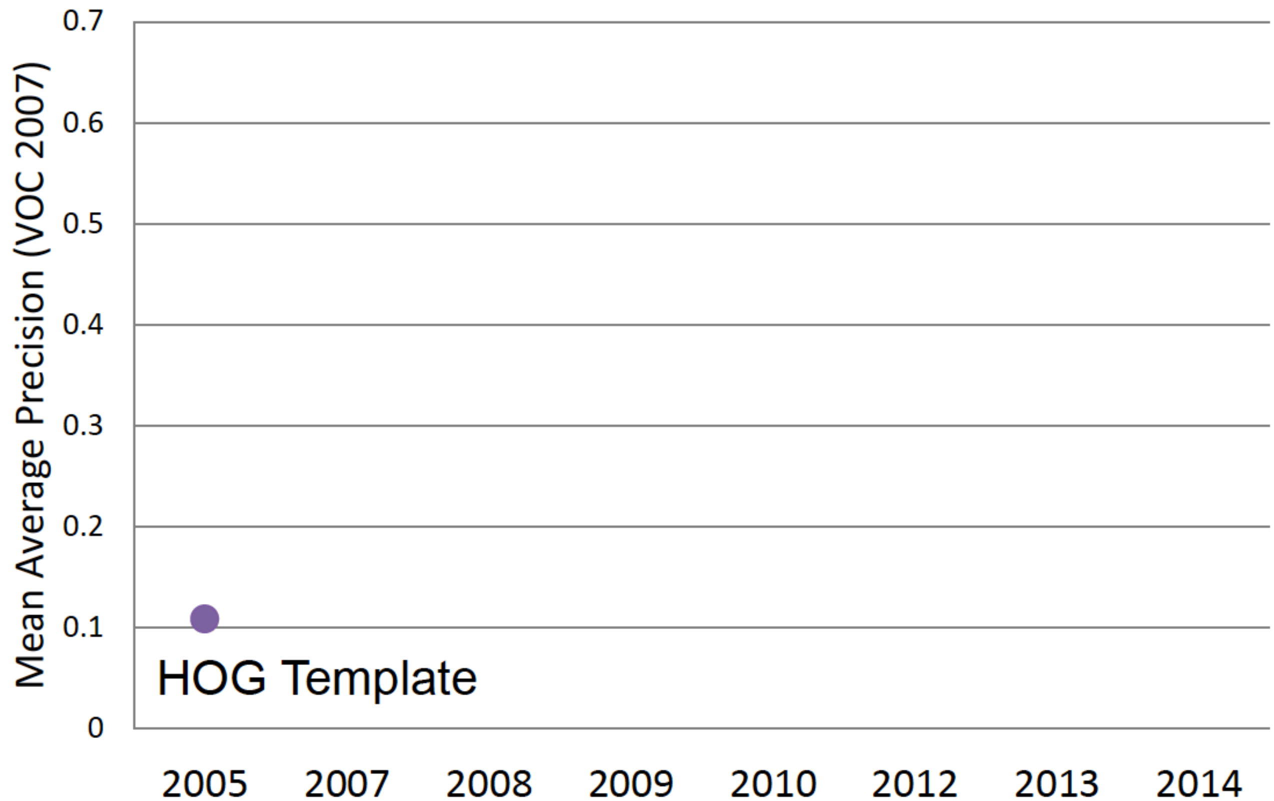
- May help us generalize to new input (easier and more robust to identify people by wearing hats than that pixel346 is red)
  - Can be useful for interpretation
- Can equivalently just be viewed as allowing more complex function class to relate input x and output y

Object detection



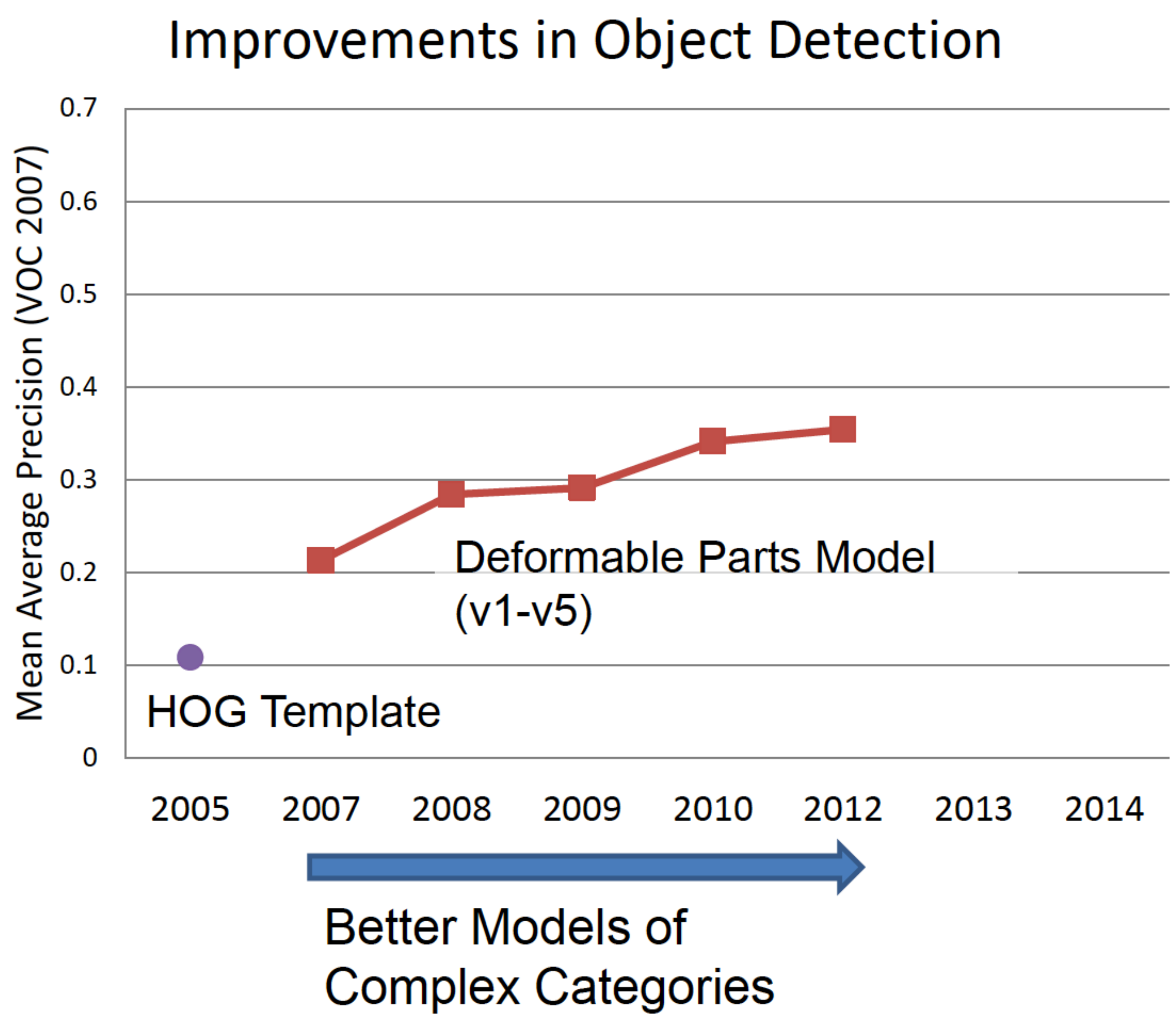
Where are
the objects of
interest?

Improvements in Object Detection

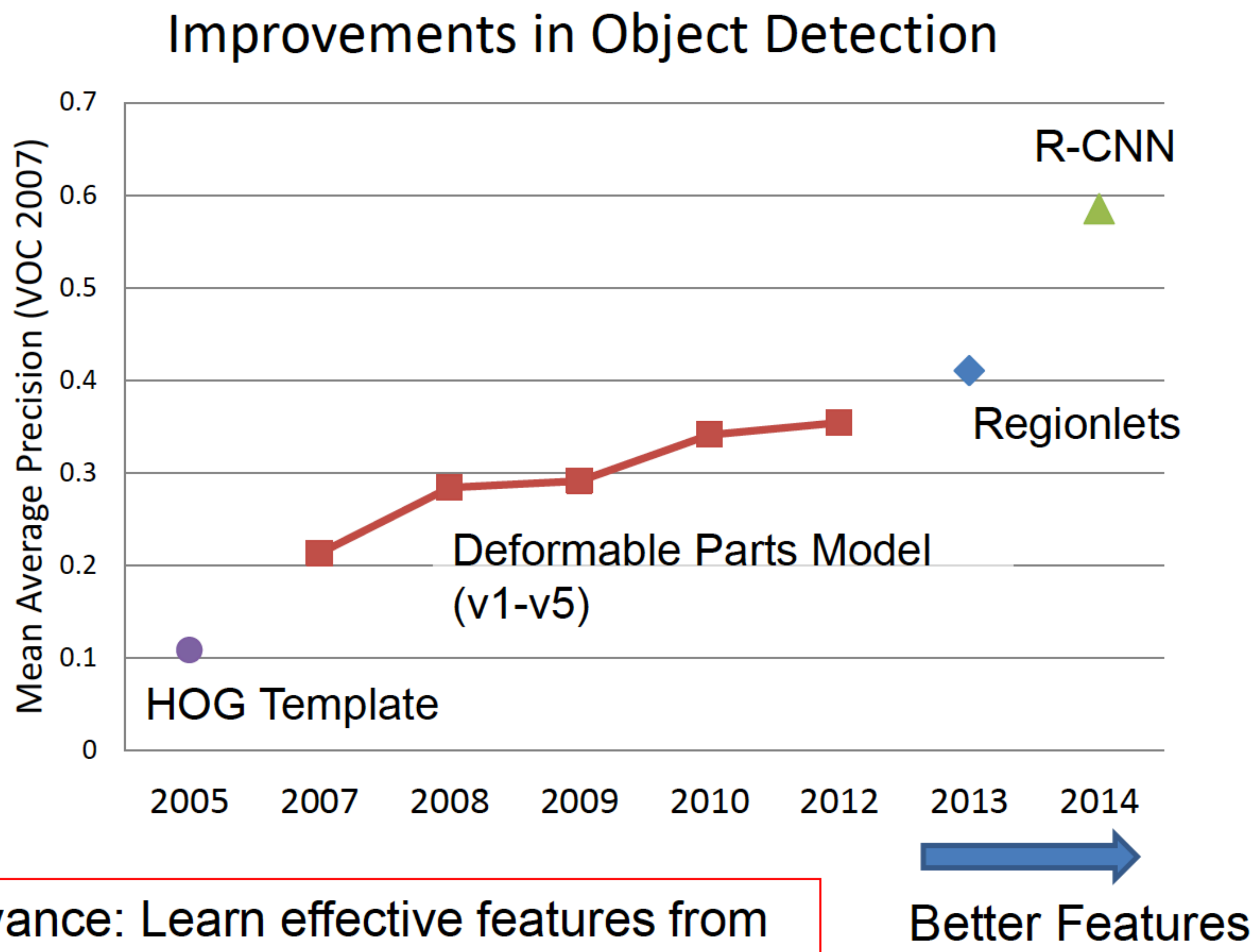


Statistical Template Matching

HOG: Dalal-Triggs 2005



HOG: Dalal-Triggs 2005 DPM: Felzenszwalb et al. 2008-2012

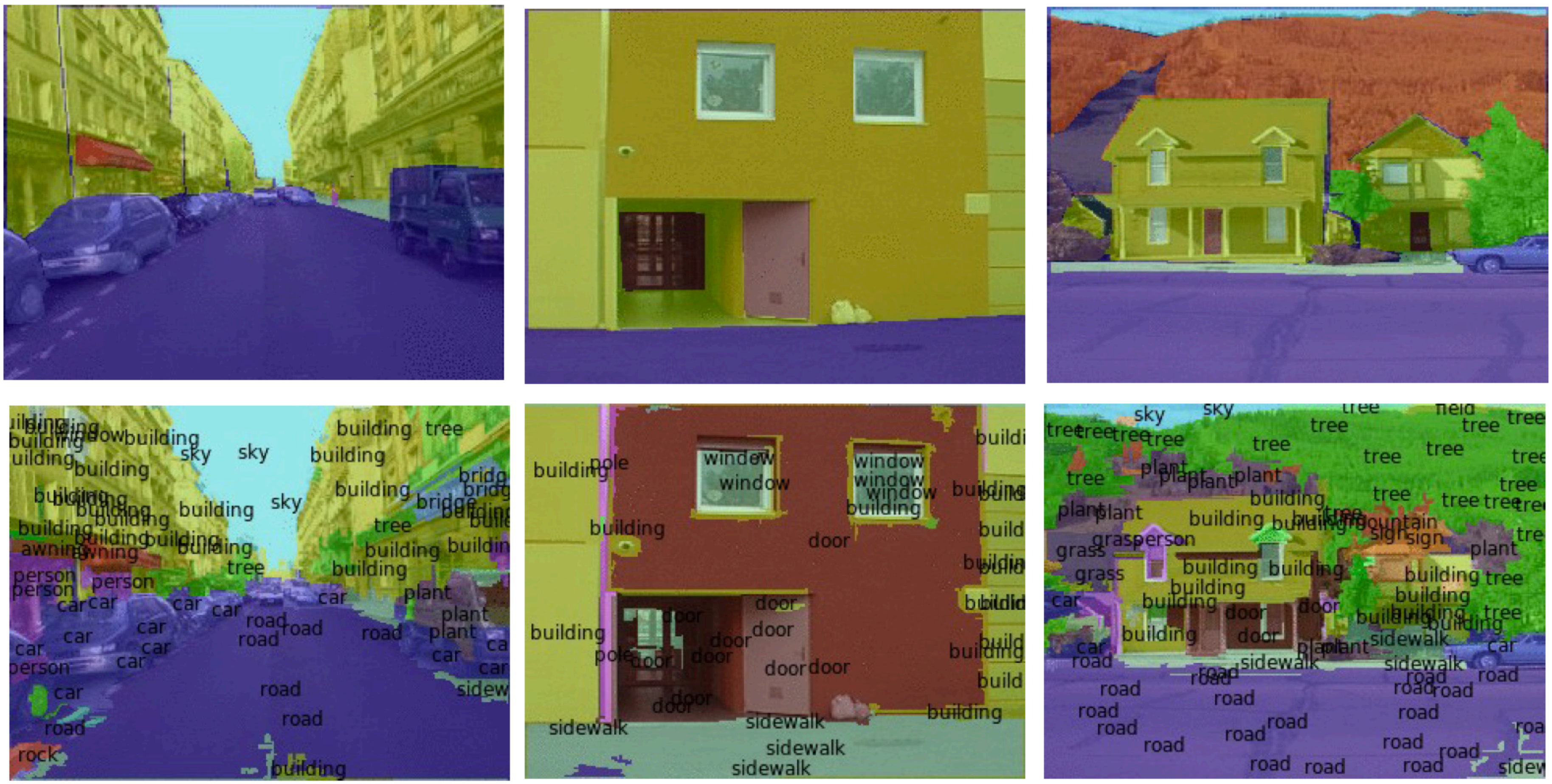


Key Advance: Learn effective features from massive amounts of labeled data *and* adapt to new tasks with less data

HOG: Dalal-Triggs 2005 DPM: Felzenszwalb et al. 2008-2012 Regionlets: Wang et al. 2013 R-CNN: Girshick et al. 2014

CONV NETS: EXAMPLES

- **Scene Parsing**



Farabet et al. “Learning hierarchical features for scene labeling” PAMI 2013

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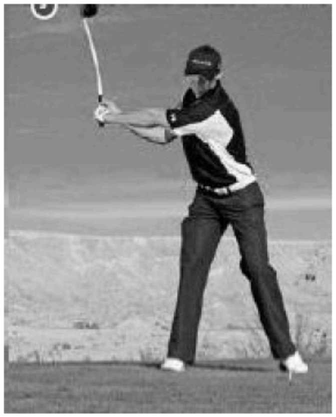
Ideal Features Are Non-Linear

I_1  → **Ideal Feature Extractor** →

- club, angle = 90
- man, frontal pose
...

? → **Ideal Feature Extractor** →

- club, angle = 270
- man, frontal pose
...

I_2  → **Ideal Feature Extractor** →

- club, angle = 360
- man, side pose
...

Ideal Features Are Non-Linear

I_1

→ **Ideal Feature Extractor** →

- club, **angle = 90**
- man, frontal pose

...

INPUT IS NOT THE AVERAGE!

→ **Ideal Feature Extractor** →

- club, **angle = 270**
- man, frontal pose

...

I_2

→ **Ideal Feature Extractor** →

- club, **angle = 360**
- man, side pose

...

Ideal Features Are Non-Linear

I_1

→ **Ideal Feature Extractor** →

- club, **angle = 90**
- man, frontal pose

...

→ **Ideal Feature Extractor** →

- club, **angle = 270**
- man, frontal pose

...

I_2

→ **Ideal Feature Extractor** →

- club, **angle = 360**
- man, side pose

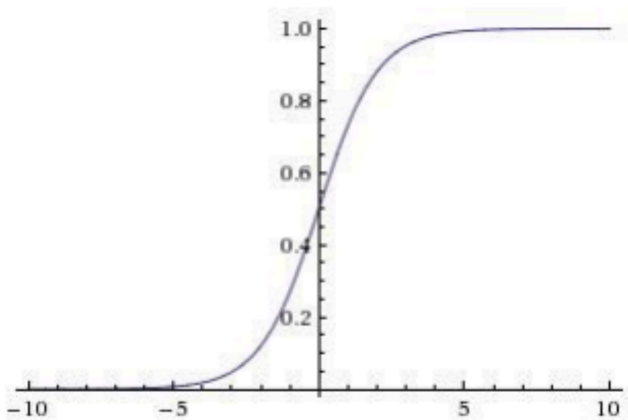
...

NonLinear Transformation

- Increases expressive power
  - Universal function approximator with 1 hidden layer
- When chaining nonlinear transformations, makes optimization harder
  - Not convex
  - Potentially lots of local optima

Which NonLinear Functions to Use?

Activation Functions



Sigmoid

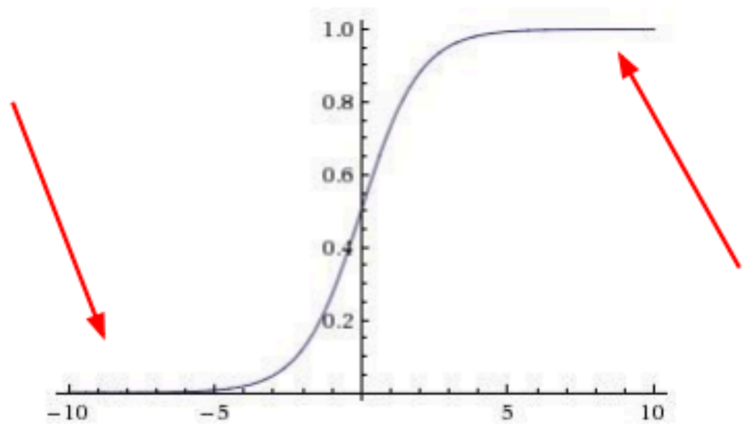
$$\sigma(x) = 1/(1 + e^{-x})$$

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron

2 BIG problems:

Which NonLinear Functions to Use?

Activation Functions



Sigmoid

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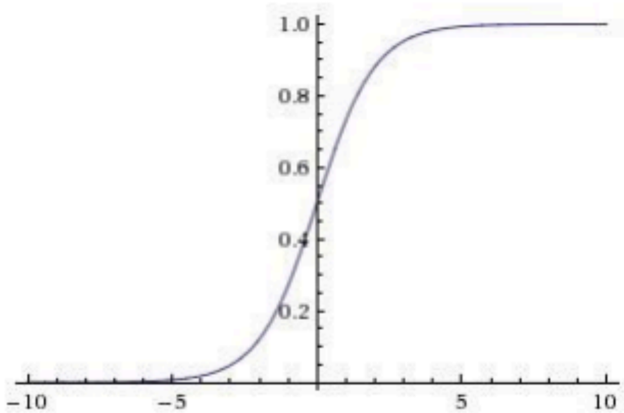
2 BIG problems:

1. Saturated neurons "kill" the gradients

Which NonLinear Functions to Use?

Activation Functions



Sigmoid

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

- Squashes numbers to range [0,1]
- Historically popular since they have nice interpretation as a saturating "firing rate" of a neuron

2 BIG problems:

1. Saturated neurons "kill" the gradients
2. Sigmoid outputs are not zero-centered

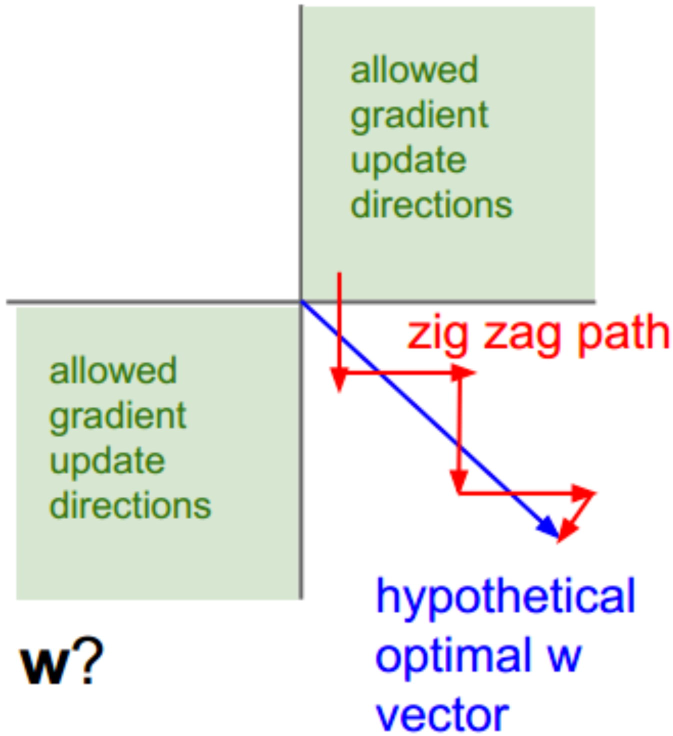
Consider what happens when the input to a neuron is always positive...

$$f\left(\sum_i w_i x_i + b\right)$$

What can we say about the gradients on **w**?

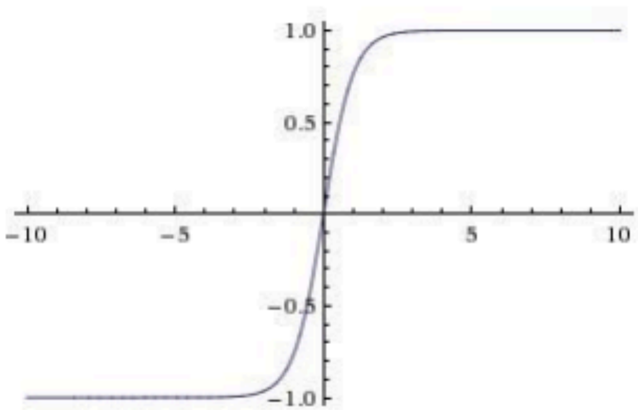
Consider what happens when the input to a neuron is always positive...

$$f\left(\sum_i w_i x_i + b\right)$$



What can we say about the gradients on **w**?
Always all positive or all negative :(
(this is also why you want zero-mean data!)

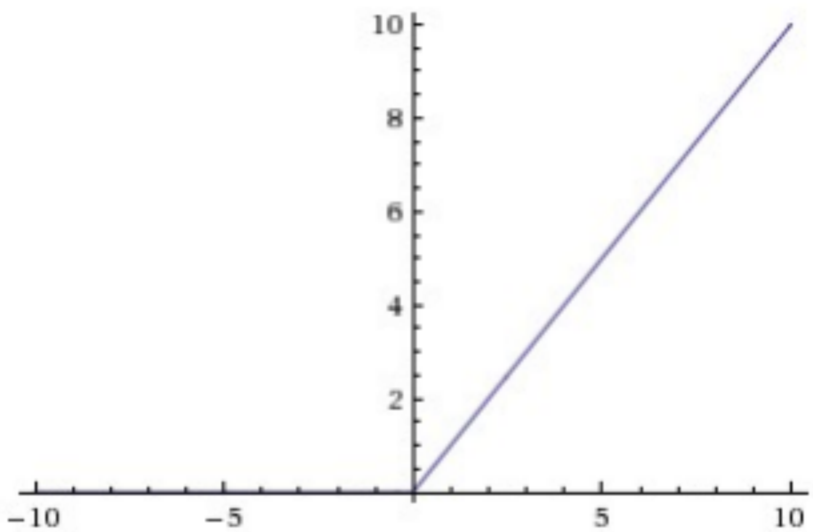
Activation Functions



tanh(x)

- Squashes numbers to range [-1,1]
- zero centered (nice)
- still kills gradients when saturated :(

Activation Functions



ReLU

$$f(x) = \max\{0, x\}$$

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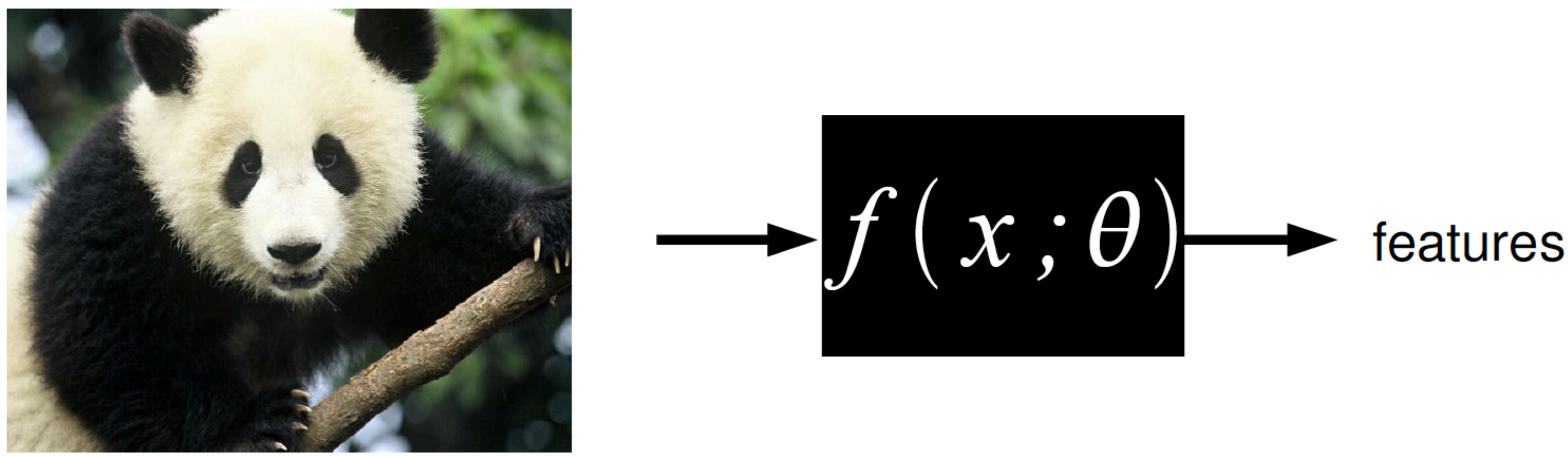
Learning Non-Linear Features

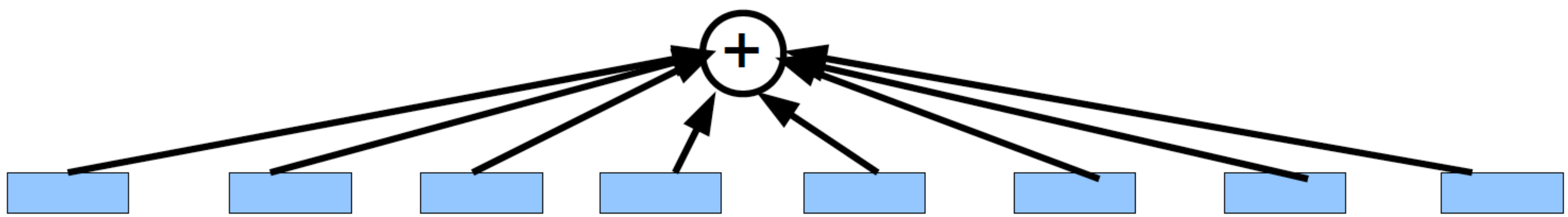


Q.: which class of non-linear functions shall we consider?

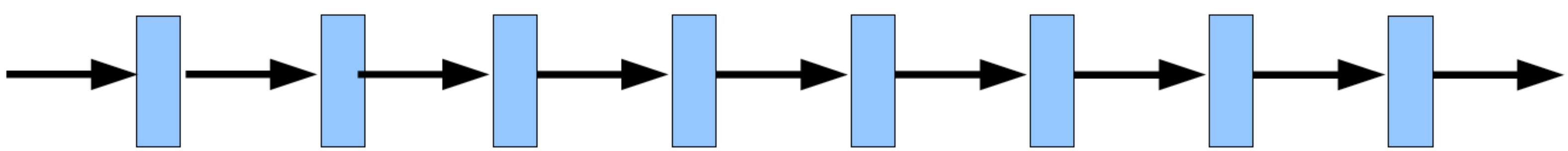
Learning Non-Linear Features

Given a dictionary of simple non-linear functions: $g_1, \ldots, g_n$

Proposal #1: linear combination $f(x) \approx \sum_j g_j$



Proposal #2: composition $f(x) \approx g_1(g_2(\ldots g_n(x)\ldots))$



Learning Non-Linear Features

Given a dictionary of simple non-linear functions: $g_1, \ldots, g_n$

Proposal #1: linear combination $f(x) \approx \sum_j g_j$

- Kernel learning
- Boosting
- ...

Shallow

Proposal #2: composition $f(x) \approx g_1(g_2(\ldots g_n(x)\ldots))$

- Deep learning
- Scattering networks (wavelet cascade)
- S.C. Zhou & D. Mumford "grammar"

Deep

- Theoretician's dilemma: "We can approximate any function as close as we want with shallow architecture. Why would we need deep ones?"

$$y = \sum_{i=1}^{P} \alpha_i K(X, X^i) \qquad y = F(W^1.F(W^0.X))$$

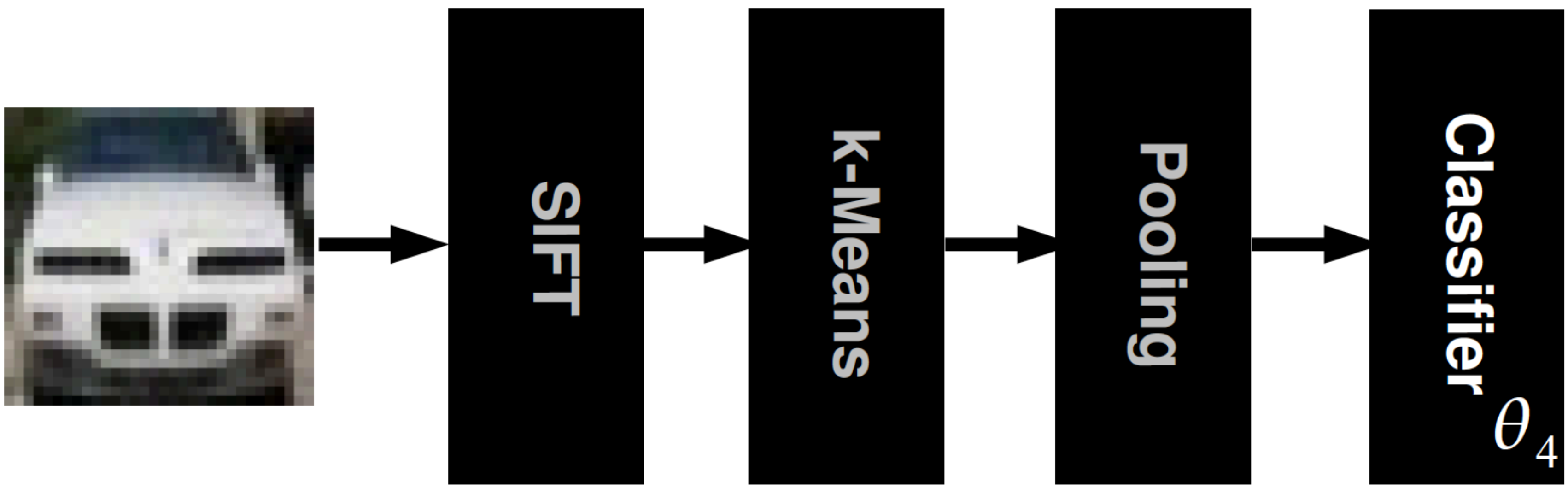
  - kernel machines (and 2-layer neural nets) are "universal".

- Deep learning machines

$$y = F(W^K.F(W^{K-1}.F(....F(W^0.X)...)))$$

- Deep machines are more efficient for representing certain classes of functions, particularly those involved in visual recognition
  - they can represent more complex functions with less "hardware"
- We need an efficient parameterization of the class of functions that are useful for "AI" tasks (vision, audition, NLP...)

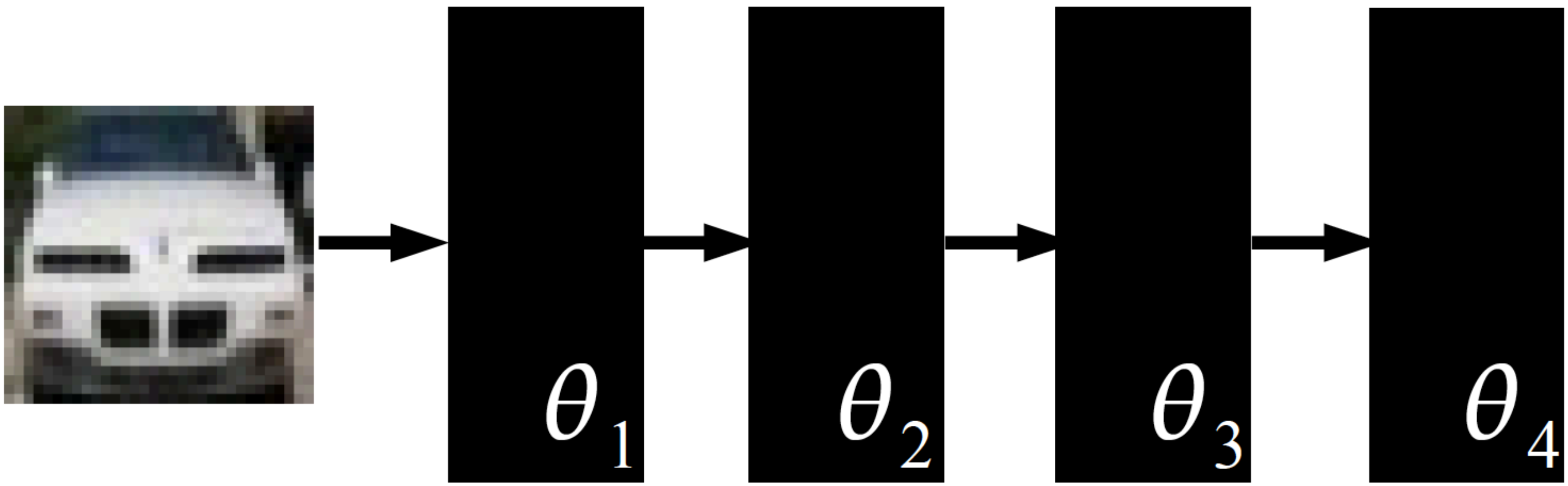
Computer Vision: Earlier Approaches



Solution #1: Freeze first N-1 layers (engineer the features)
Essentially turns it into **shallow** learning

Computer Vision: Now

Optimization is difficult: non-convex, non-linear system



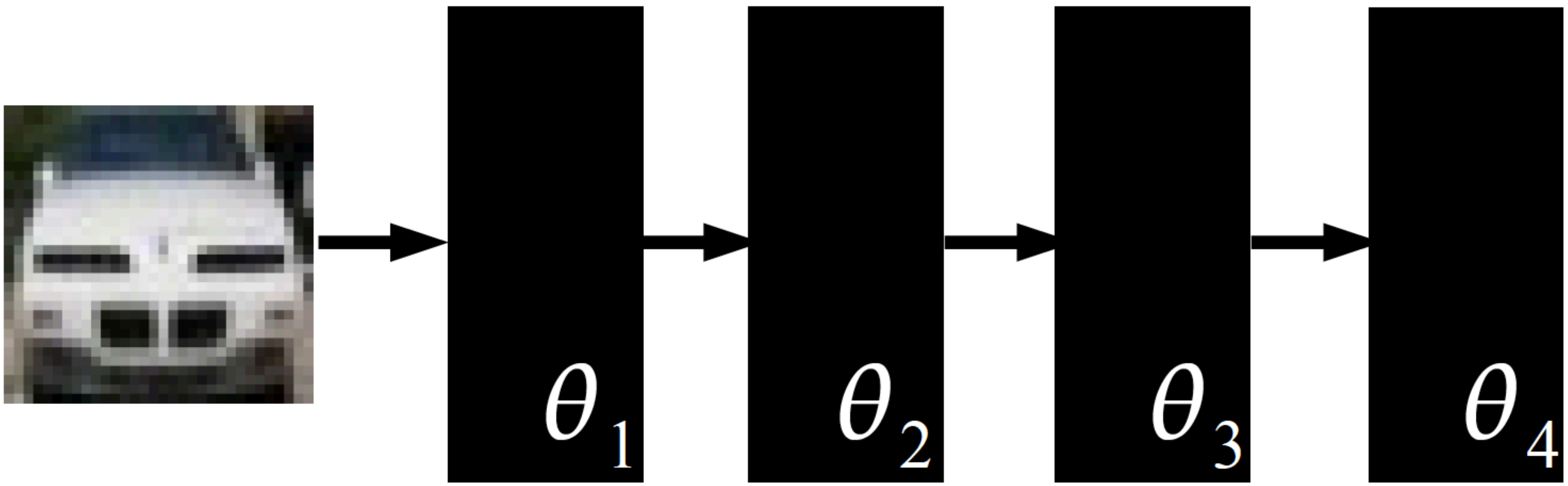
Solution #2: live with it!

It will converge to a local minimum.

It is much more powerful!!

Deep Learning in Practice

Optimization is easy, need to know a few tricks of the trade.



Q: What's the feature extractor? And what's the classifier?

A: No distinction, end-to-end learning!

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Stochastic gradient descent for neural networks

Recall that stochastic gradient descent computes gradients with respect to loss on each example, updating parameters as it goes

function SGD($\{(x^{(i)}, y^{(i)})\}, h_\theta, \ell, \alpha$)
  Initialize: $W_j, b_j \leftarrow$ Random, $j = 1, \ldots, k$
  Repeat until convergence:
    For $i = 1, \ldots, m$:
      Compute $\nabla_{W_j, b_j} \ell(h_\theta(x^{(i)}), y^{(i)}),\ j = 1, \ldots, k-1$
      Take gradient steps in all directions:
        $W_j \leftarrow W_j - \alpha \nabla_{W_j} \ell(h_\theta(x^{(i)}), y^{(i)}),\ \ j = 1, \ldots, k$
        $b_j \leftarrow b_j - \alpha \nabla_{b_j} \ell(h_\theta(x^{(i)}), y^{(i)}),\ \ j = 1, \ldots, k$
  return $\{W_j, b_j\}$

So how do we compute the gradients $\nabla_{W_j, b_j} \ell(h_\theta(x^{(i)}), y^{(i)})$, this is a complex function of the parameters

Backpropagation

Backpropagation is a method for computing all the necessary gradients using one “forward pass” (just computing all the values at layers), and one “backward pass” (computing gradients backwards in the network)

The equations sometimes look complex, but it’s just an application of the chain rule of calculus

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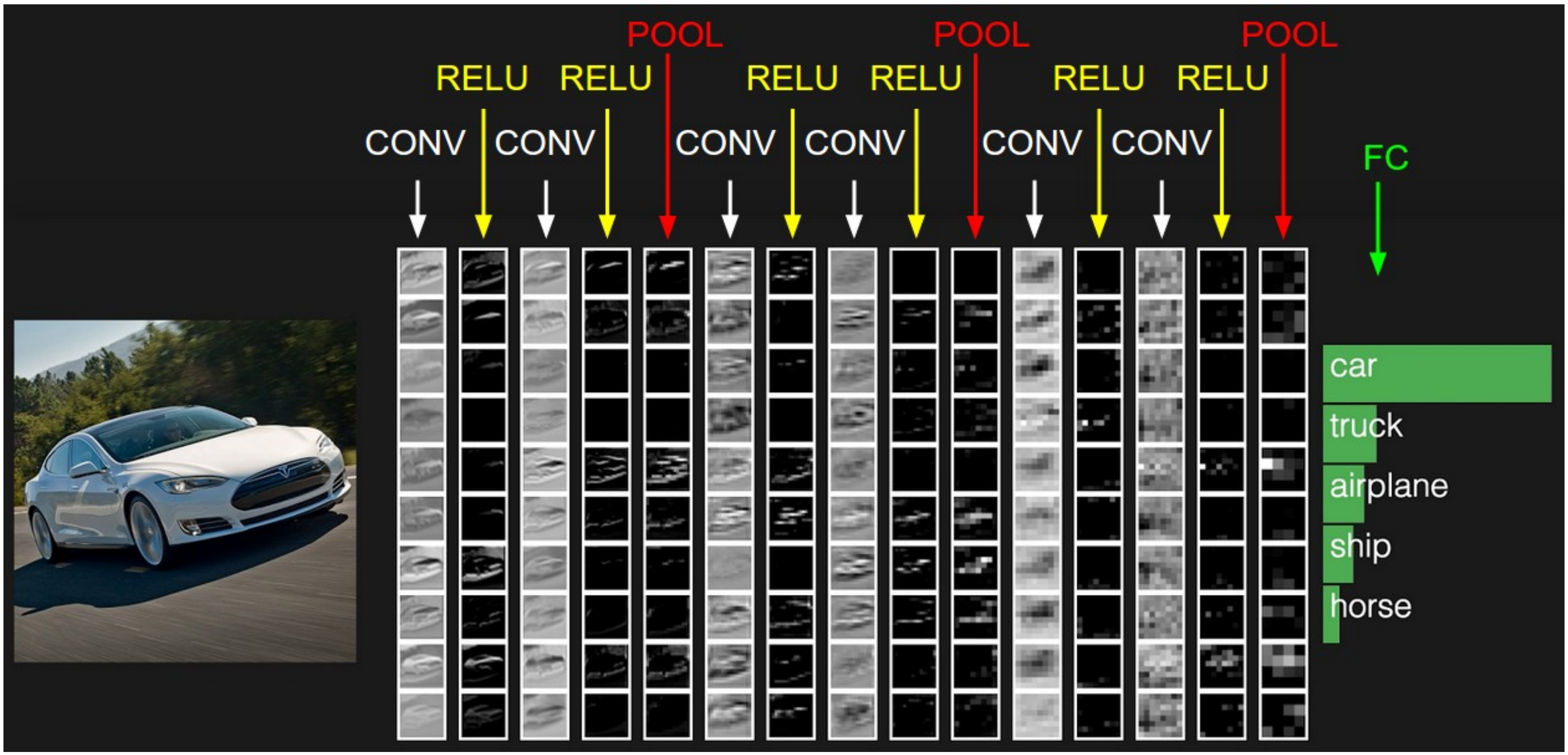
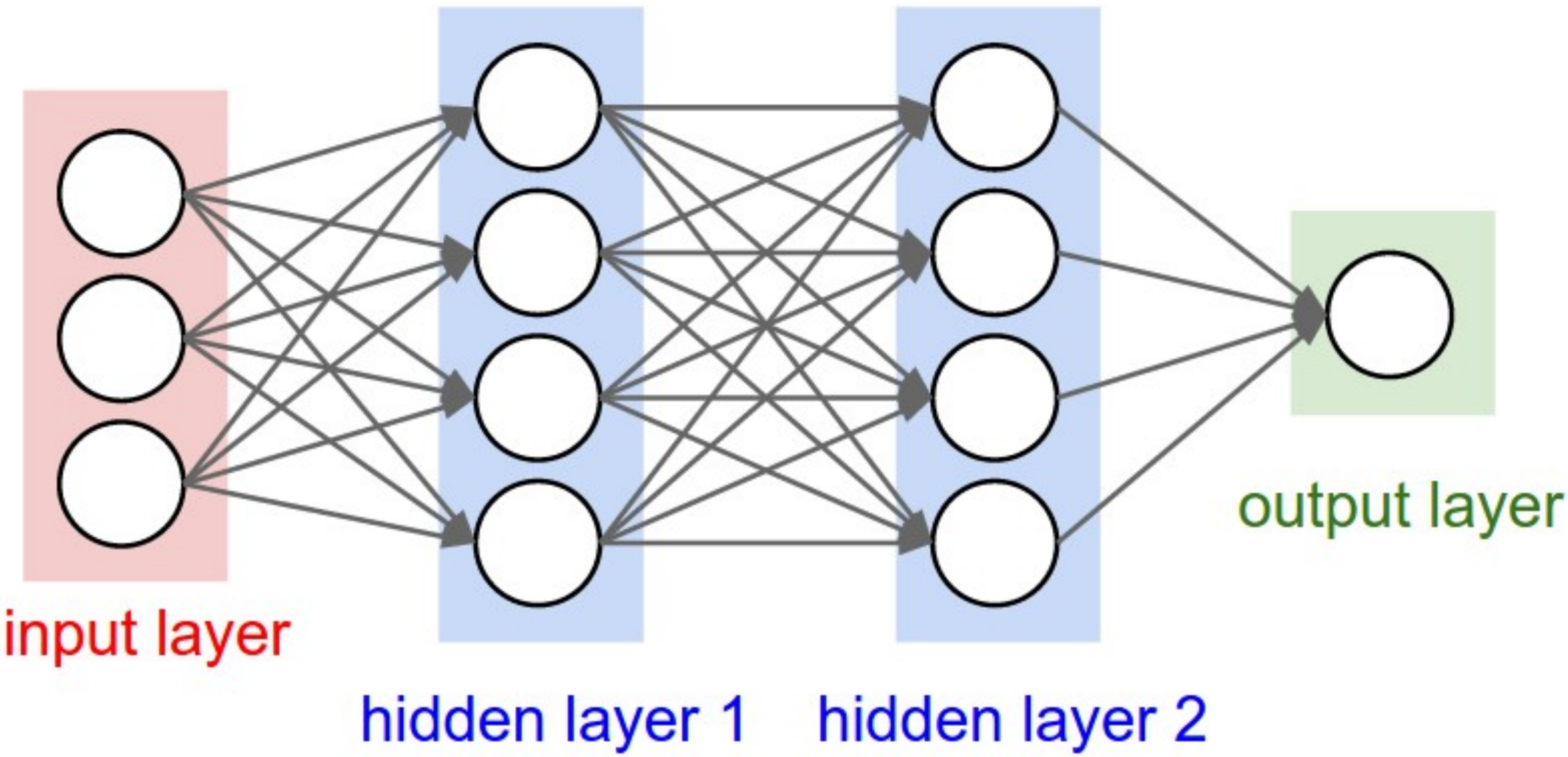
Convolutional Neural Network



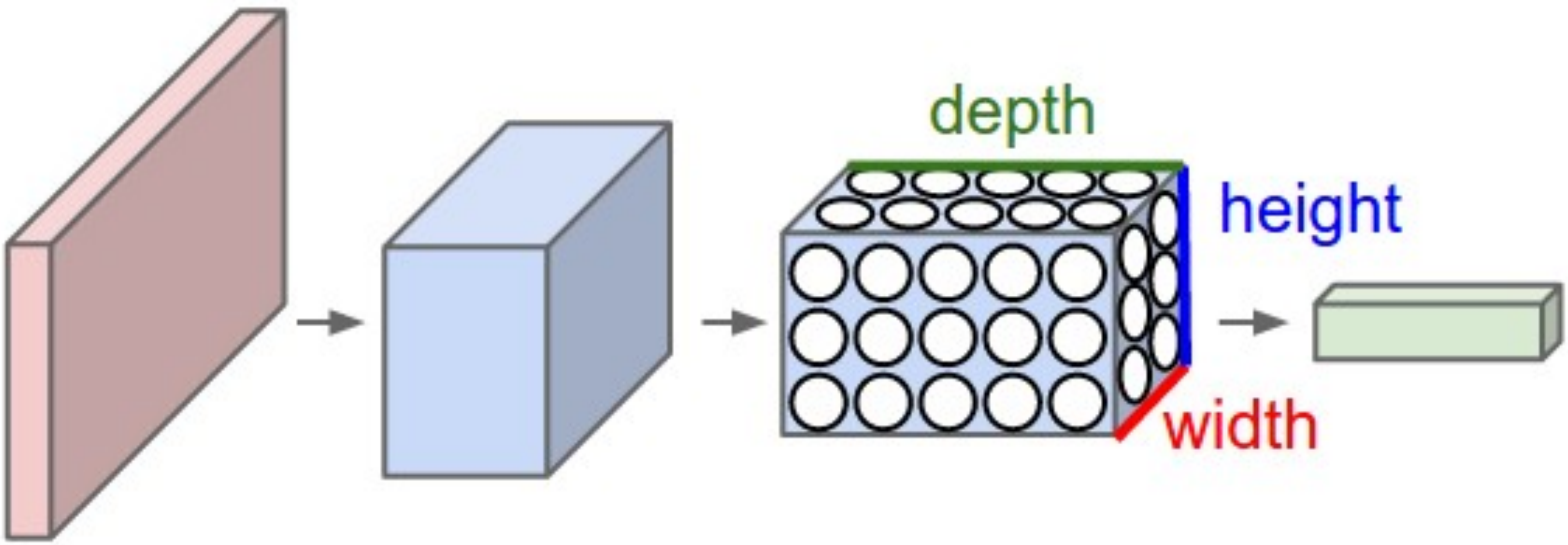
http://cs231n.github.io/

Standard Neural Network



- Each internal node is connected to all nodes in prior layer
- Each node in the same layer independent (separate set of weights)

CNN
- uses volumes

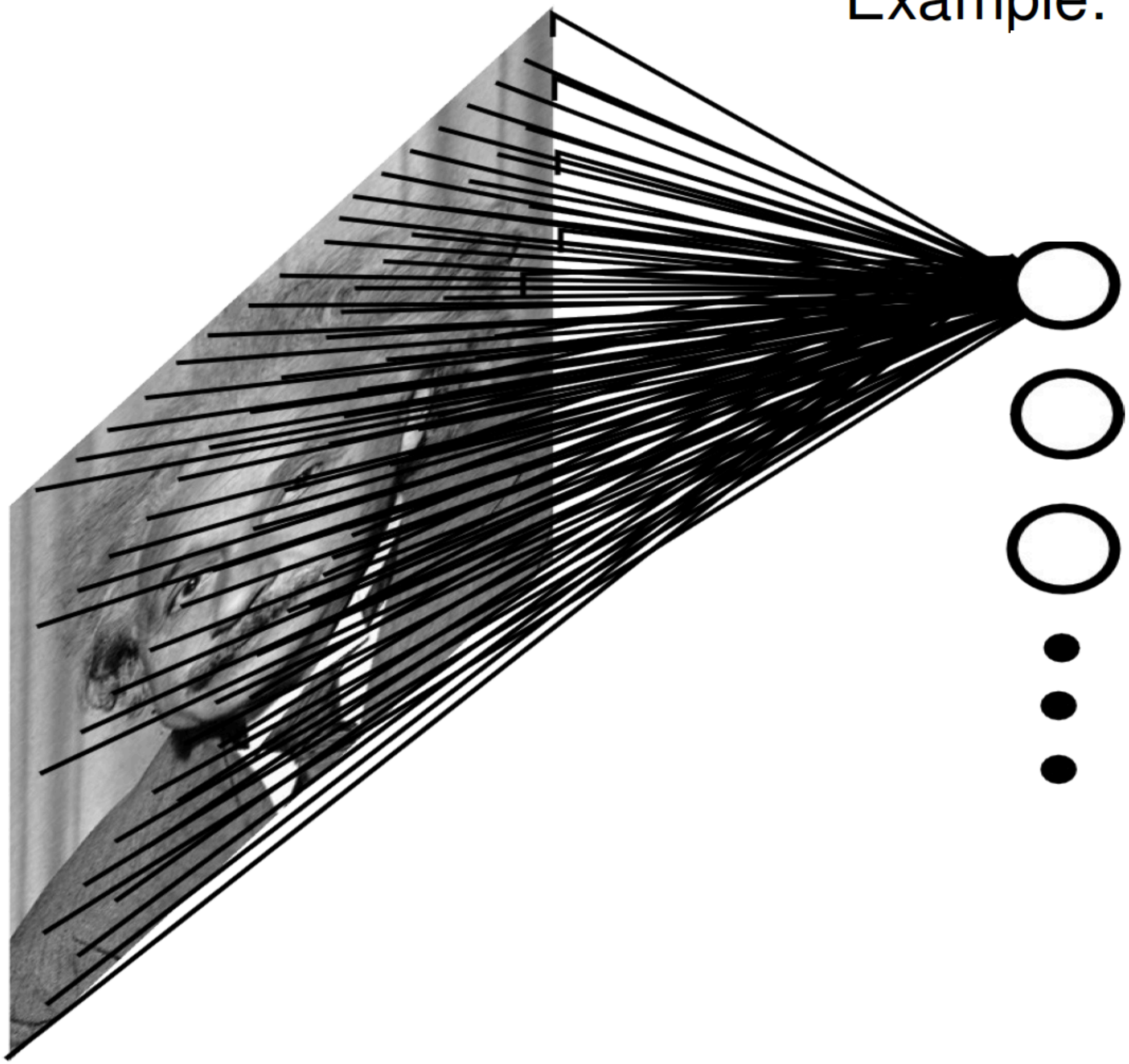


E.g. height and
width are the size
of the image
Depth = 3 color
values per pixel

Output is scores for each
Of the possible classes
Depth ~= # of classes
Height=width=1

FULLY CONNECTED NEURAL NET

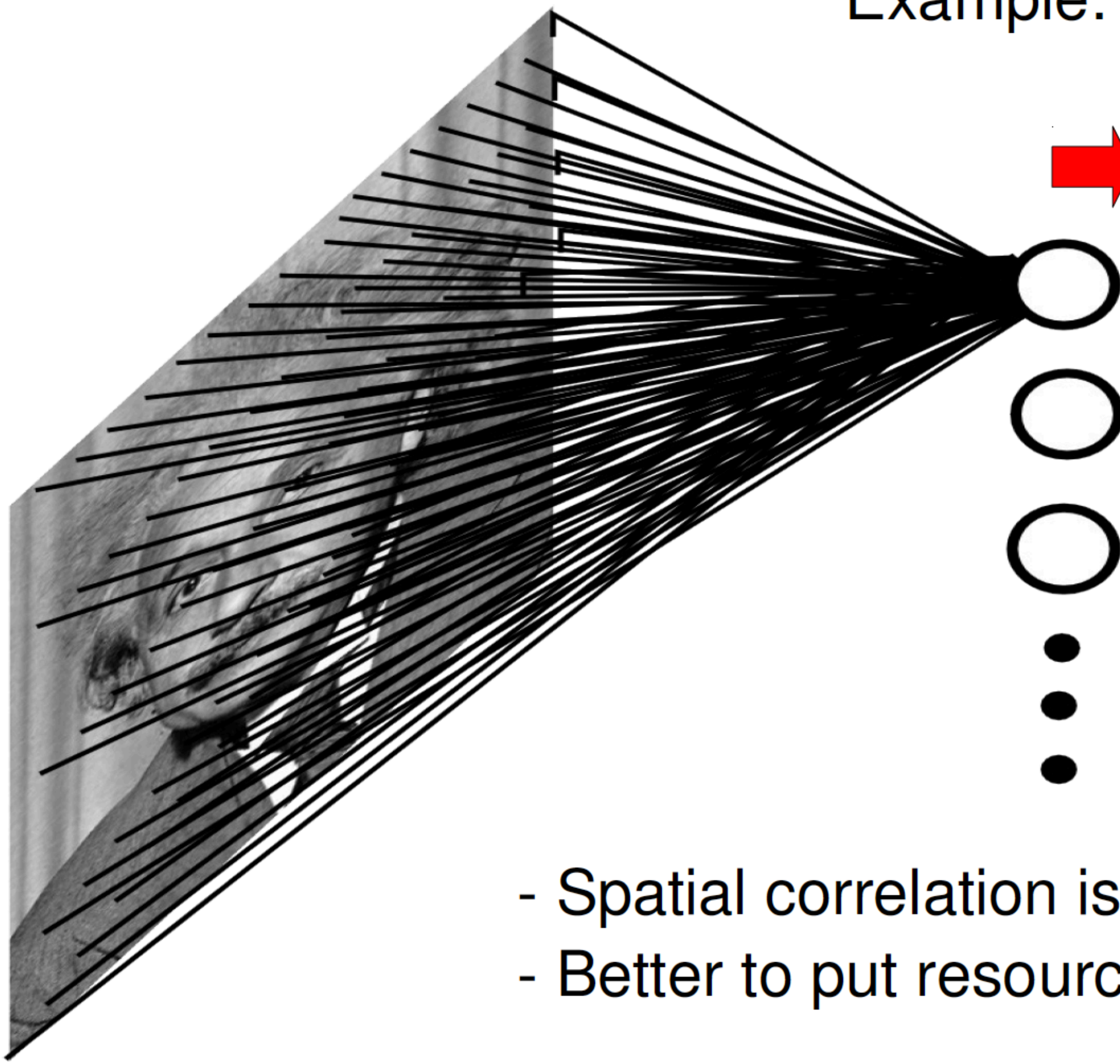
Example: 1000x1000 image



How many weight parameters for a single node which is a linear combination of input?

Ranzato

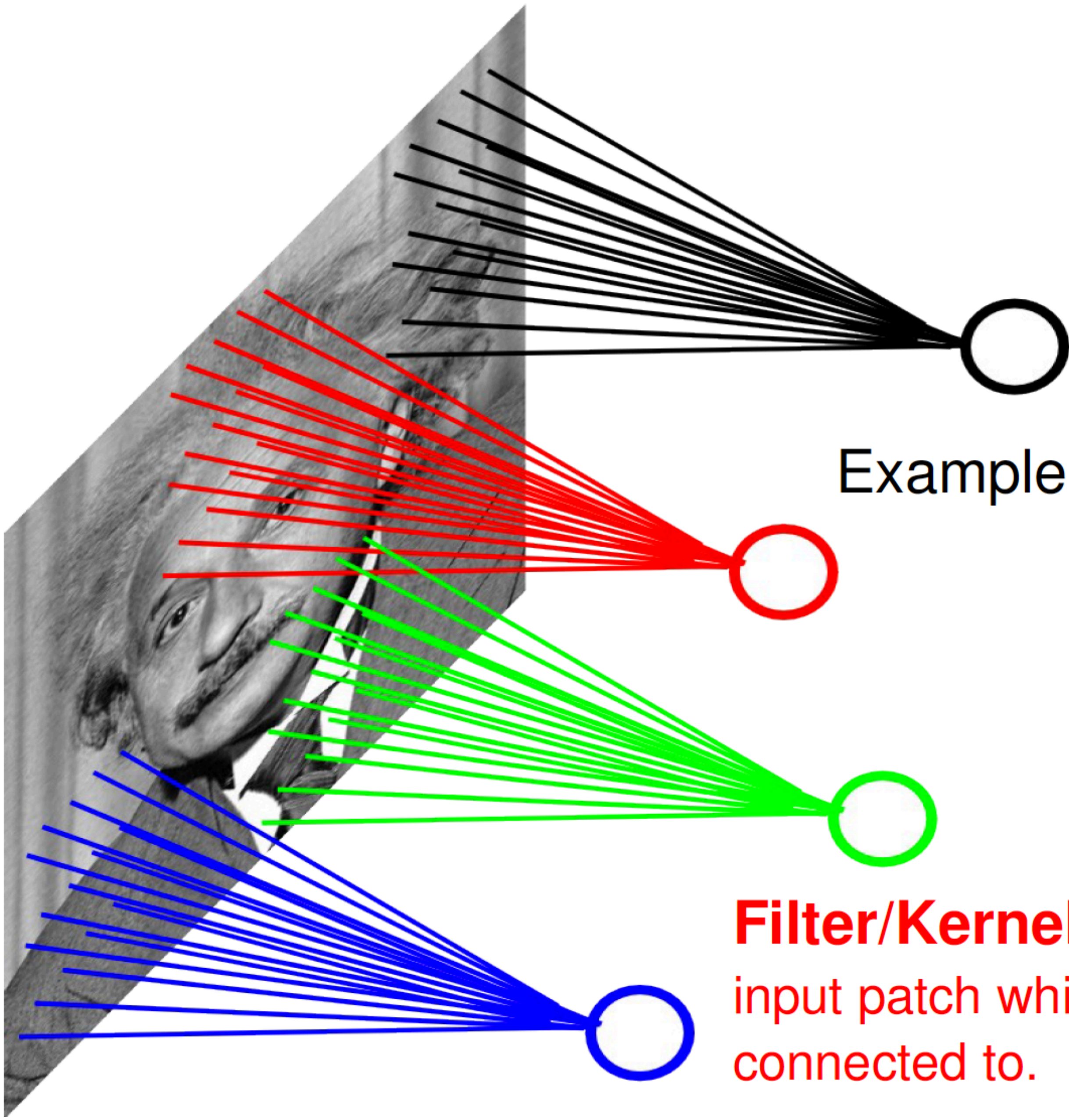
FULLY CONNECTED NEURAL NET



Example: 1000x1000 image
1M hidden units
10^12 parameters!!!

- Spatial correlation is local
- Better to put resources elsewhere!

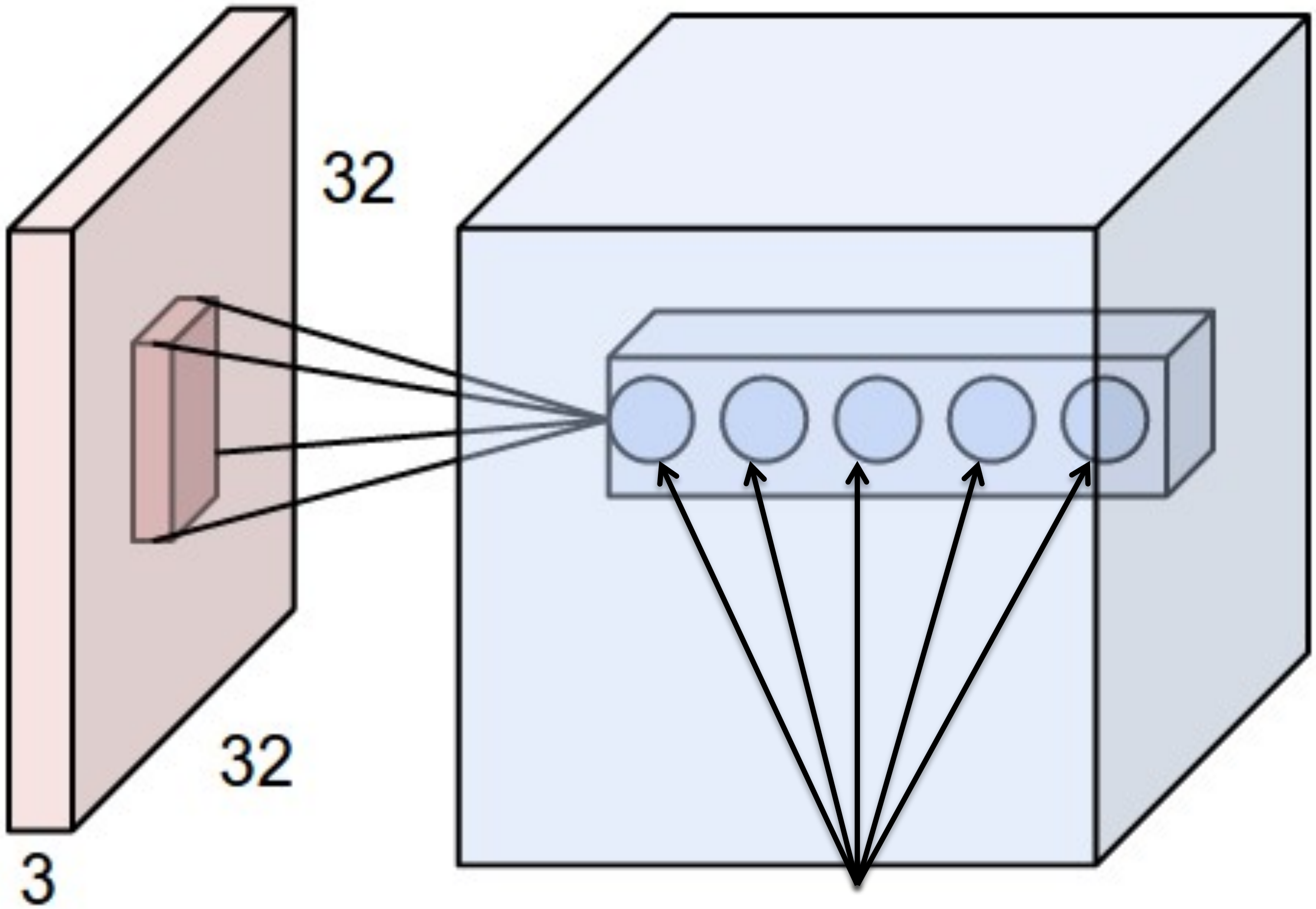
LOCALLY CONNECTED NEURAL NET



Example: 1000x1000 image
1M hidden units
Filter size: 10x10
100M parameters

Filter/Kernel/Receptive field:
input patch which the hidden unit is connected to.

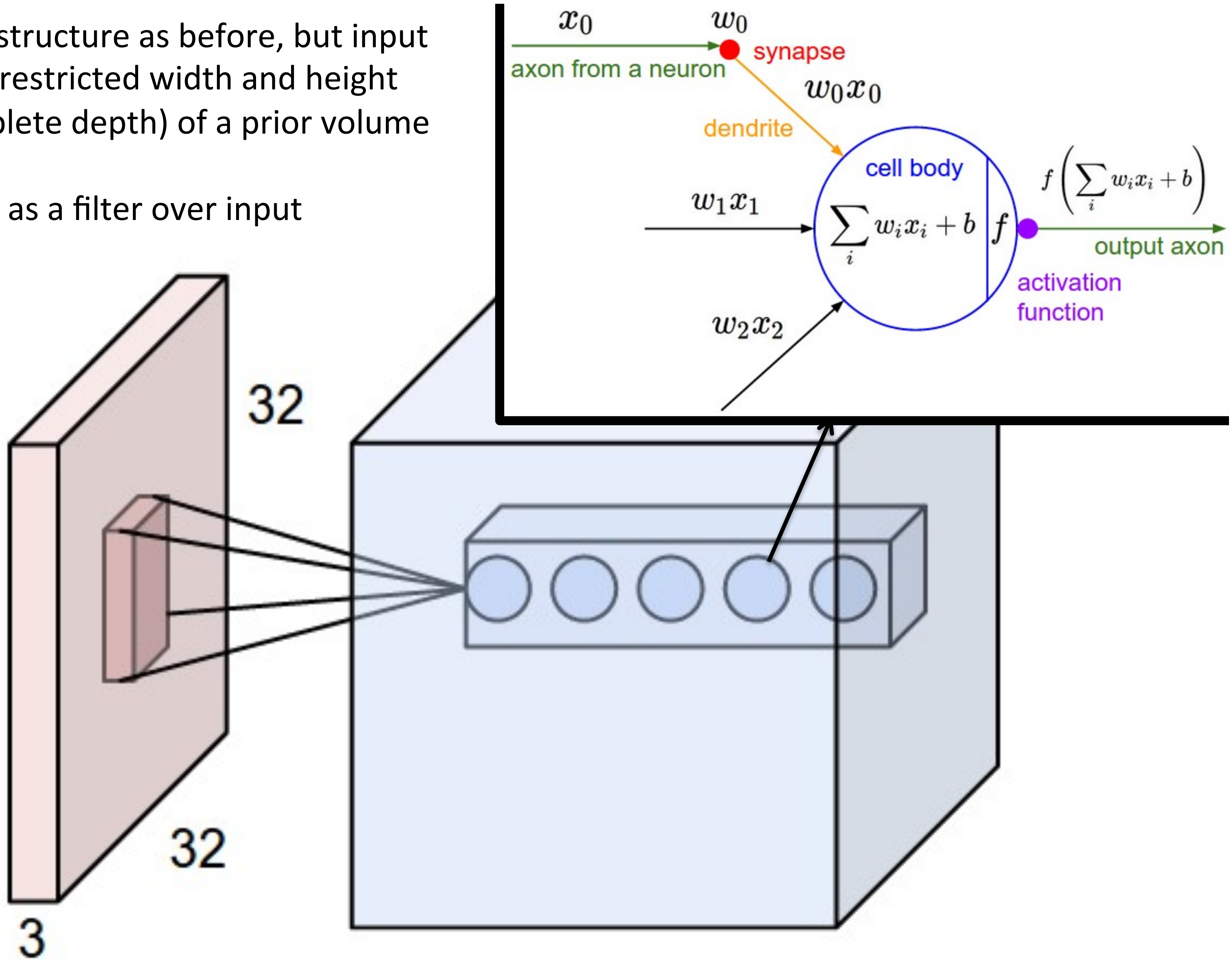
Volumes and Depths



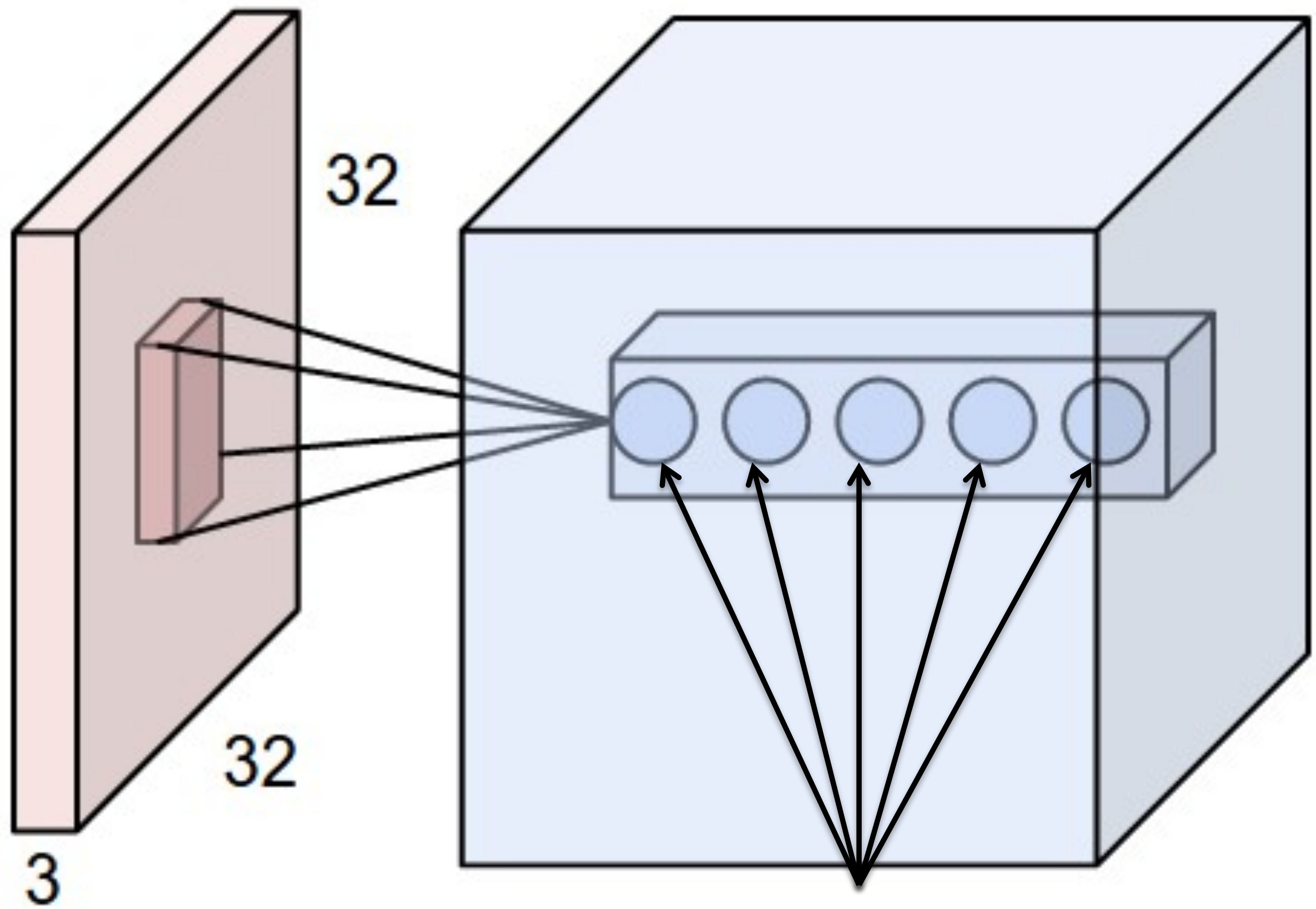
Each node here has the same input but different weight vectors (e.g. computing different features of same input)

Nodes: same structure as before, but input is only over a restricted width and height (but the complete depth) of a prior volume

Think of node as a filter over input

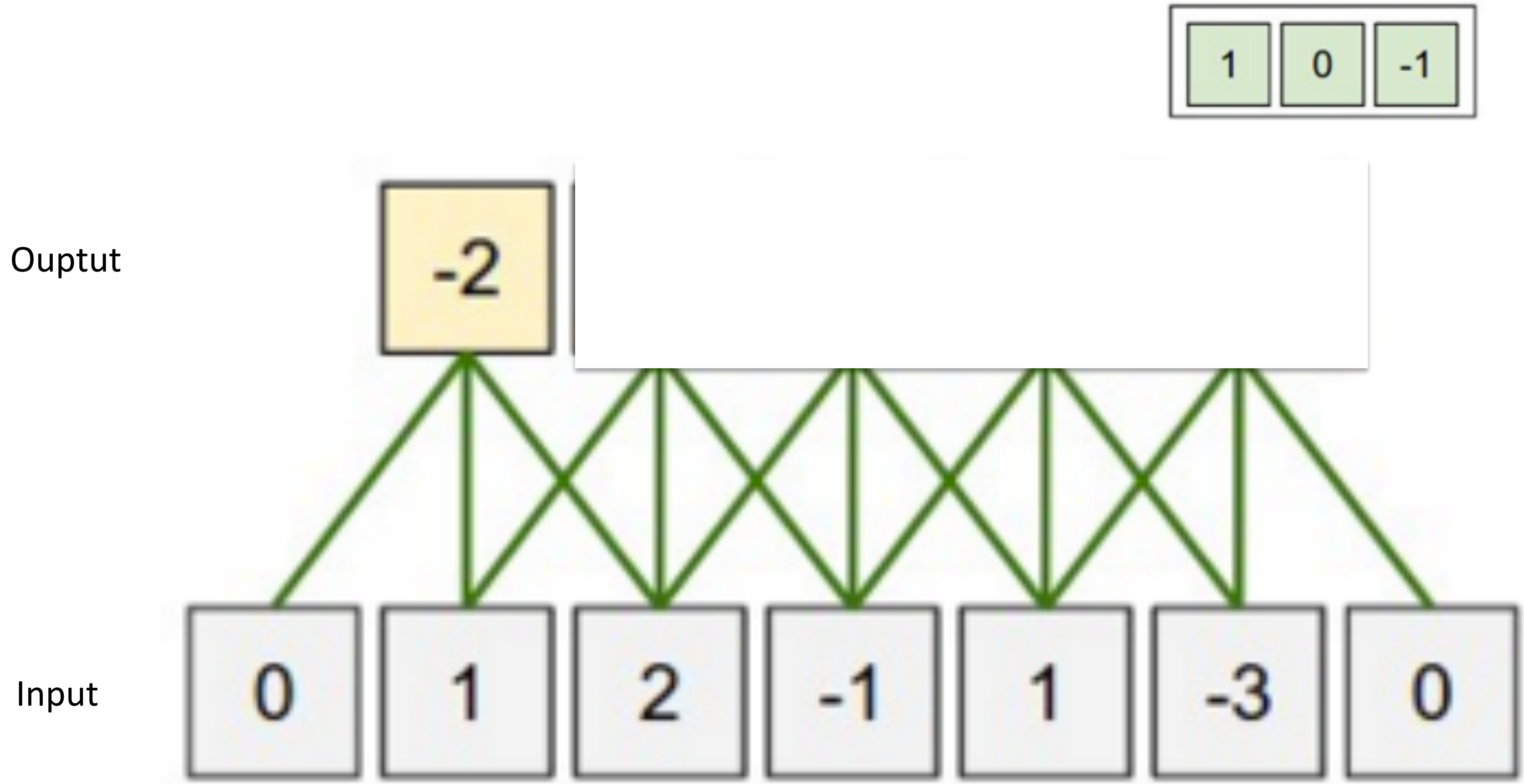


What is the size of the volume in the next layer? Depth, Stride, Zero Padding



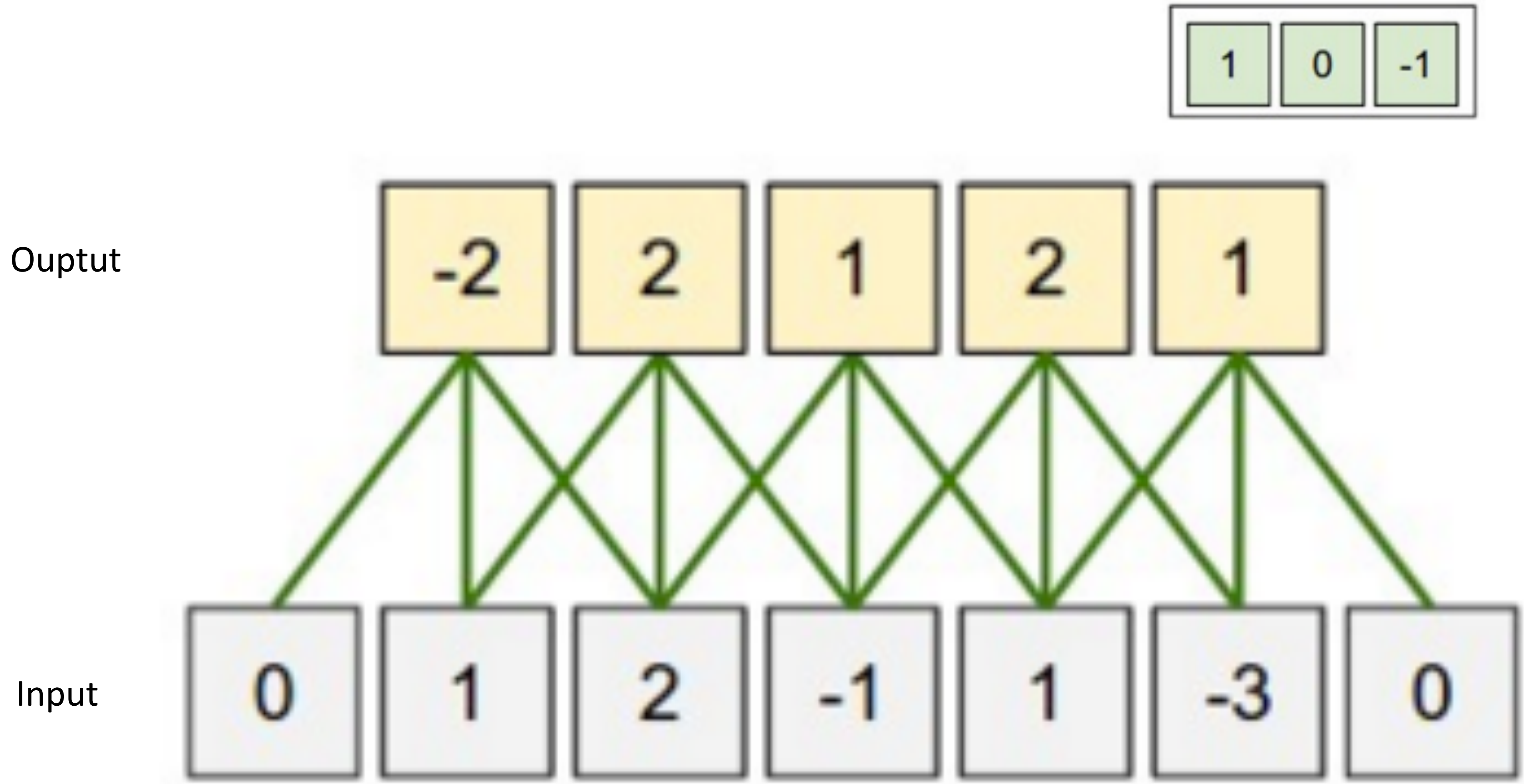
Each node here has the same input but different weight vectors (e.g. computing different features of same input)

Stride and Zero Padding



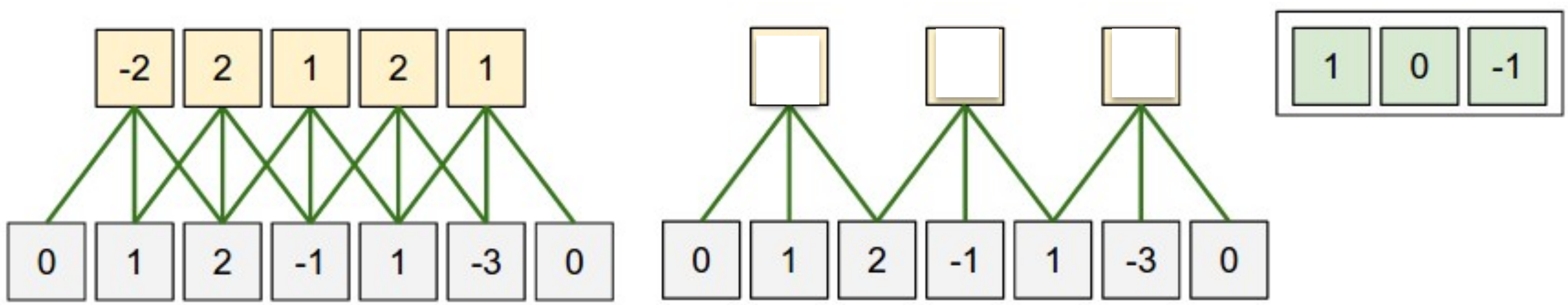
Stride: how far (spatially) move over filter
Zero padding: how many 0s to add to either side of input layer

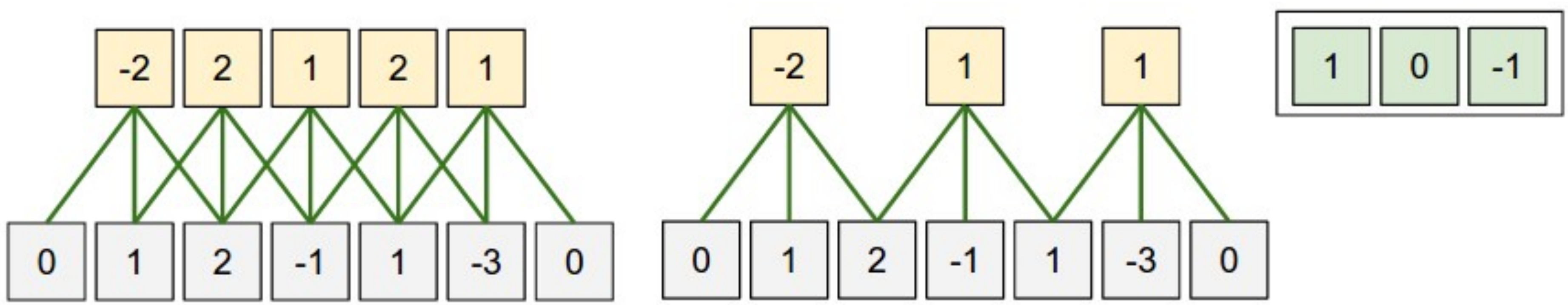
Stride and Zero Padding



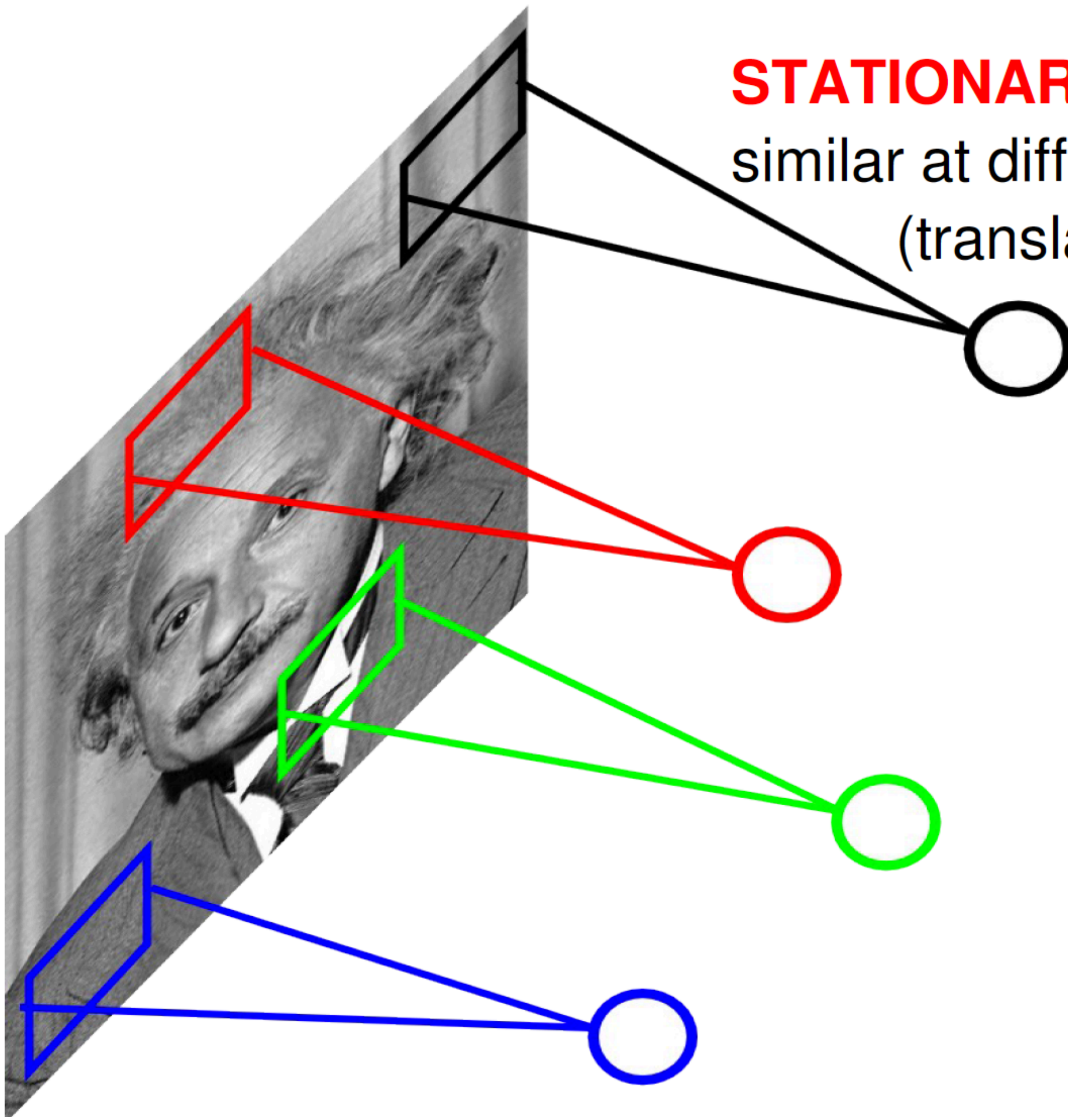
Stride: how far (spatially) move over filter
Zero padding: how many 0s to add to either side of input layer

What is the Stride and the Values in the Second Example?



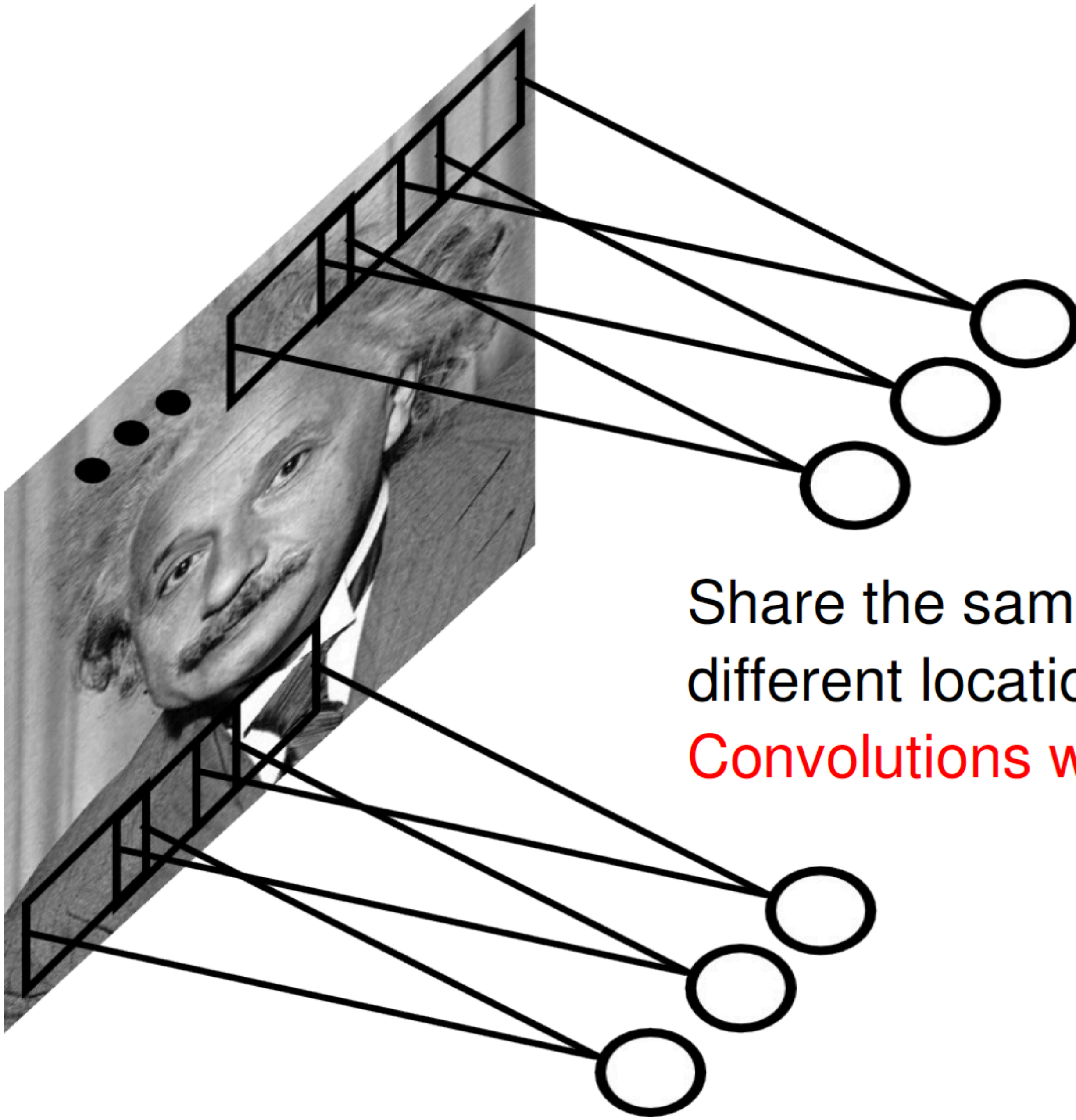

-2 2 1 2 1
0 1 2 -1 1 -3 0
-2 1 1
0 1 2 -1 1 -3 0
1 0 -1

LOCALLY CONNECTED NEURAL NET



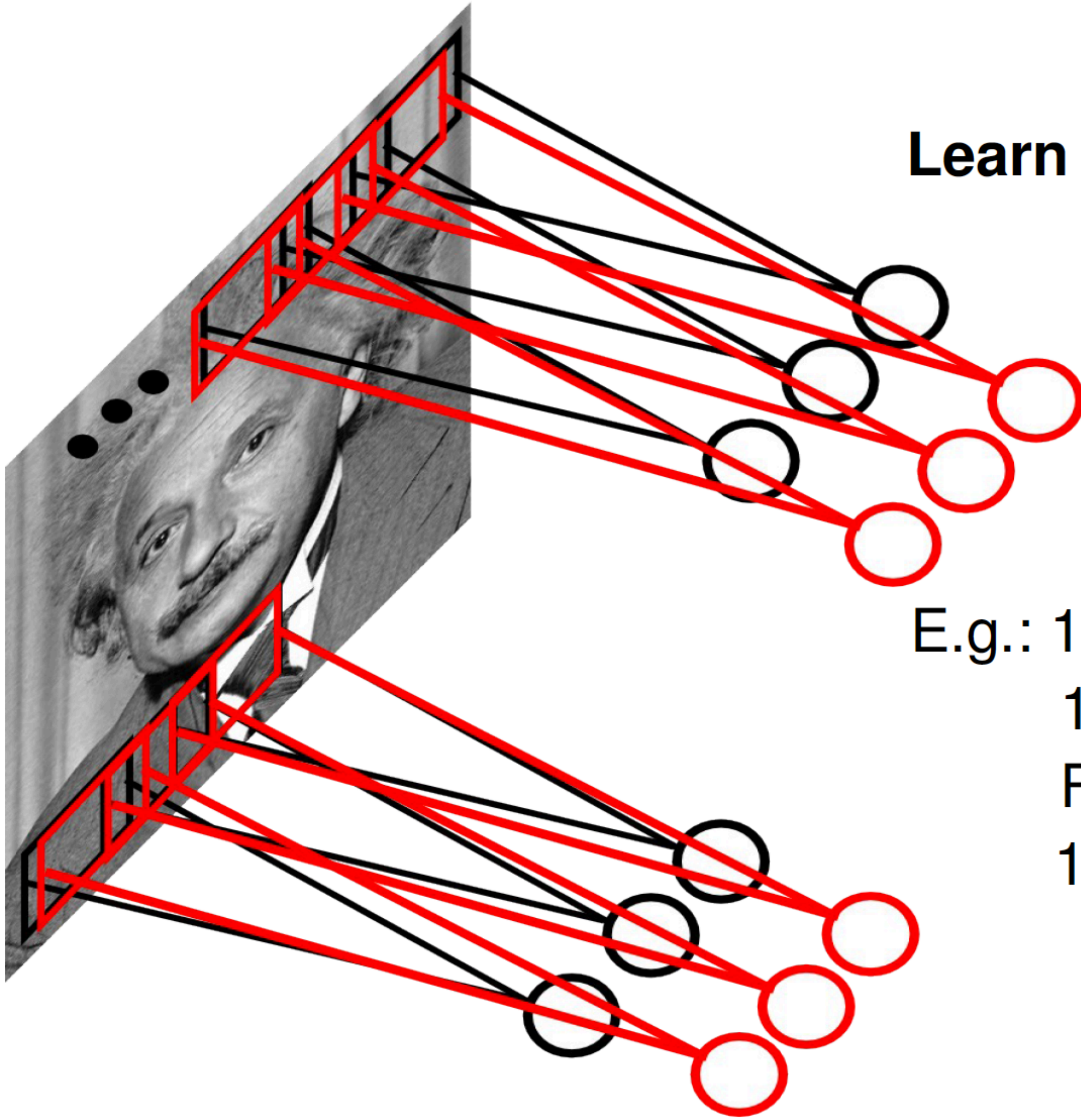
STATIONARITY? Statistics are similar at different locations (translation invariance)

CONVOLUTIONAL NET



Share the same parameters across different locations:
Convolutions with learned kernels

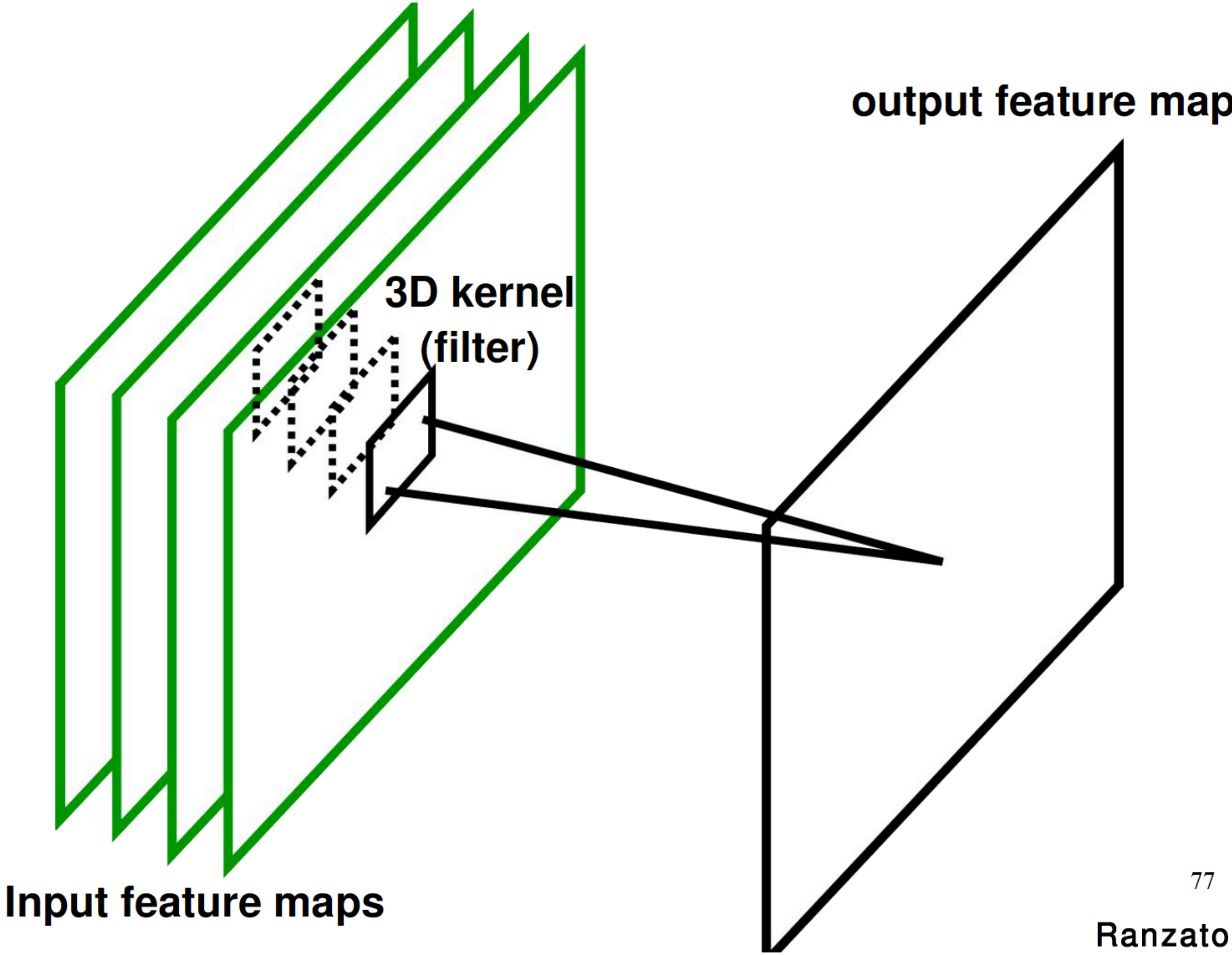
CONVOLUTIONAL NET



Learn multiple filters.

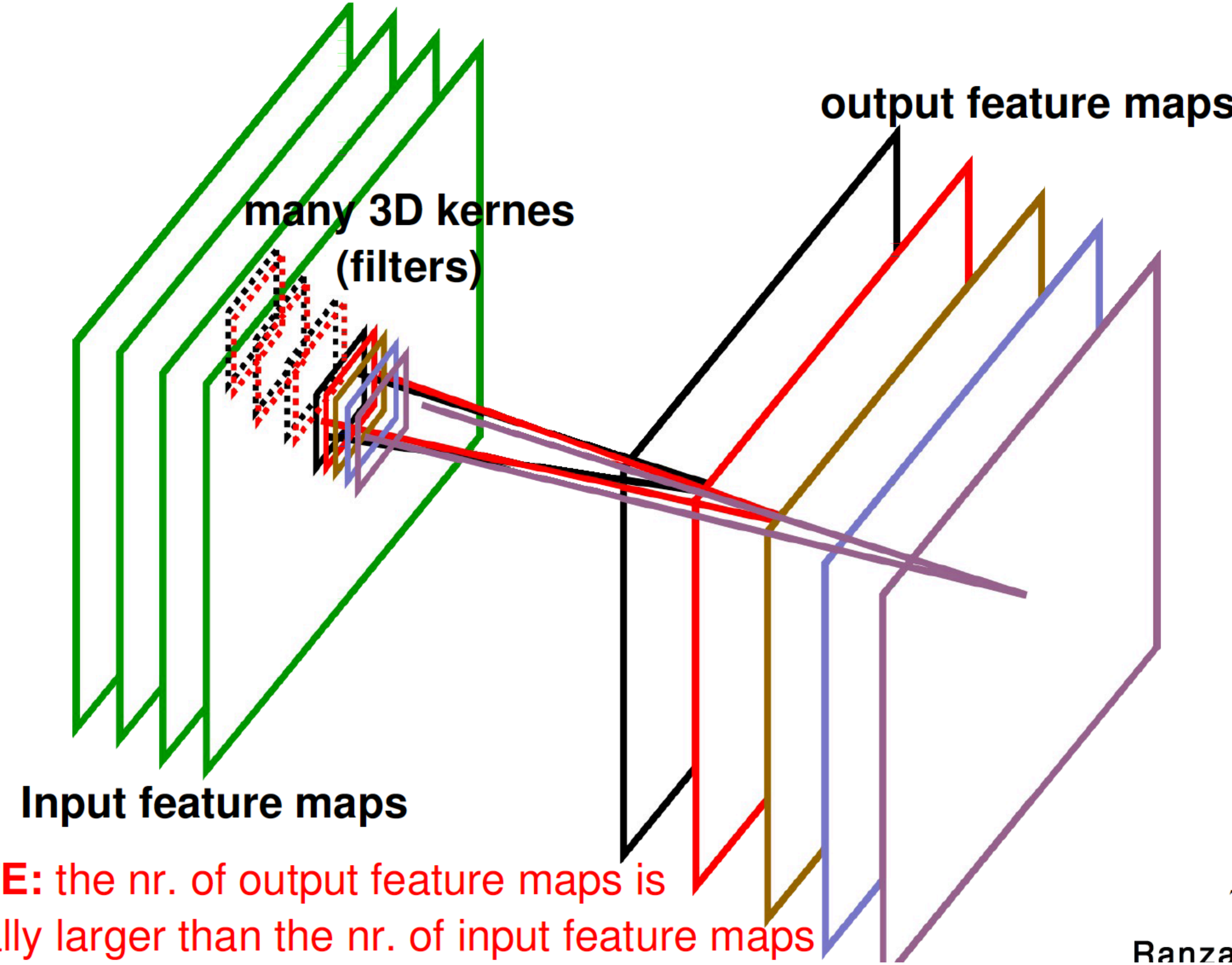
E.g.: 1000x1000 image
100 Filters
Filter size: 10x10
10K parameters

CONVOLUTIONAL LAYER



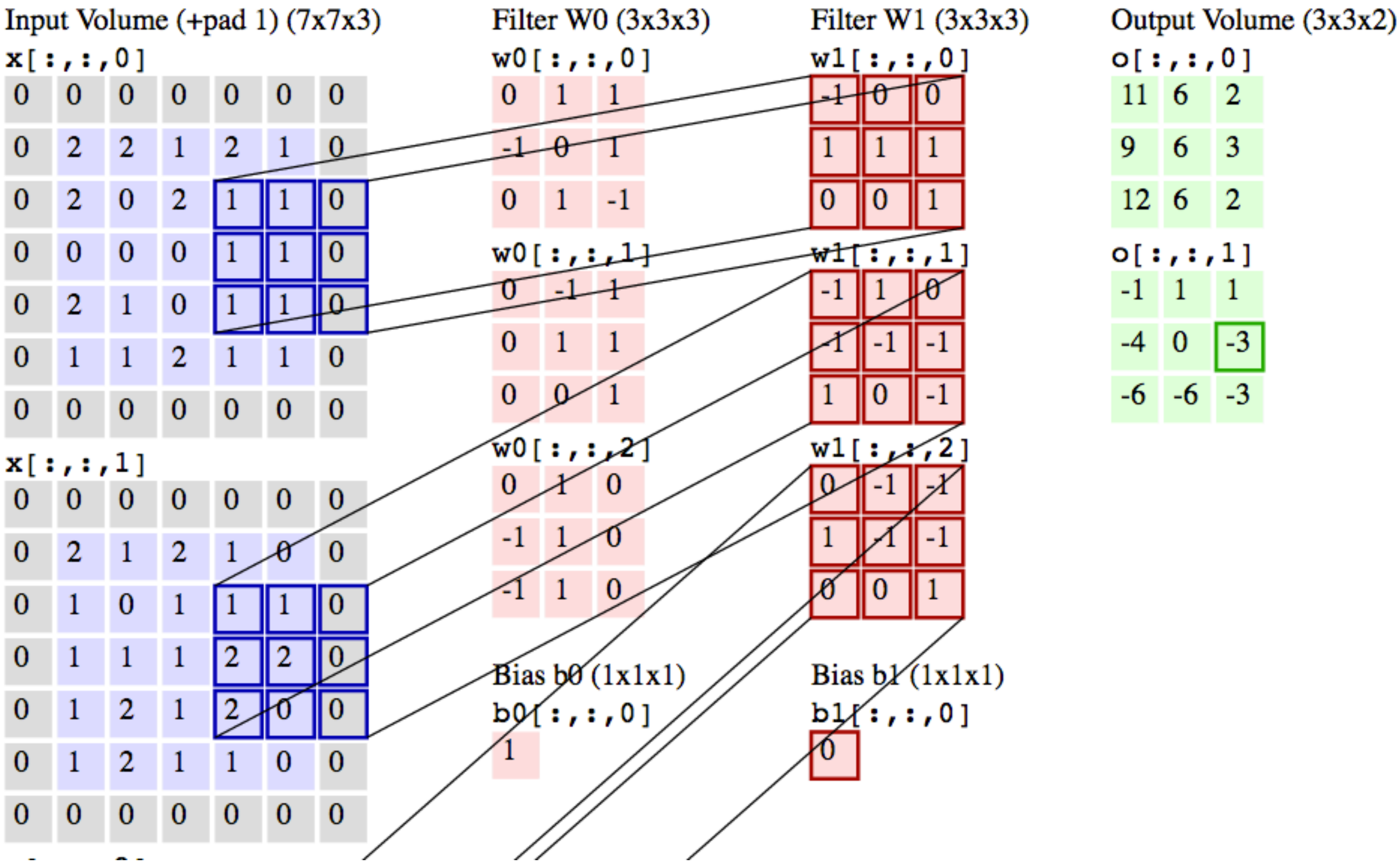
Ranzato

CONVOLUTIONAL LAYER



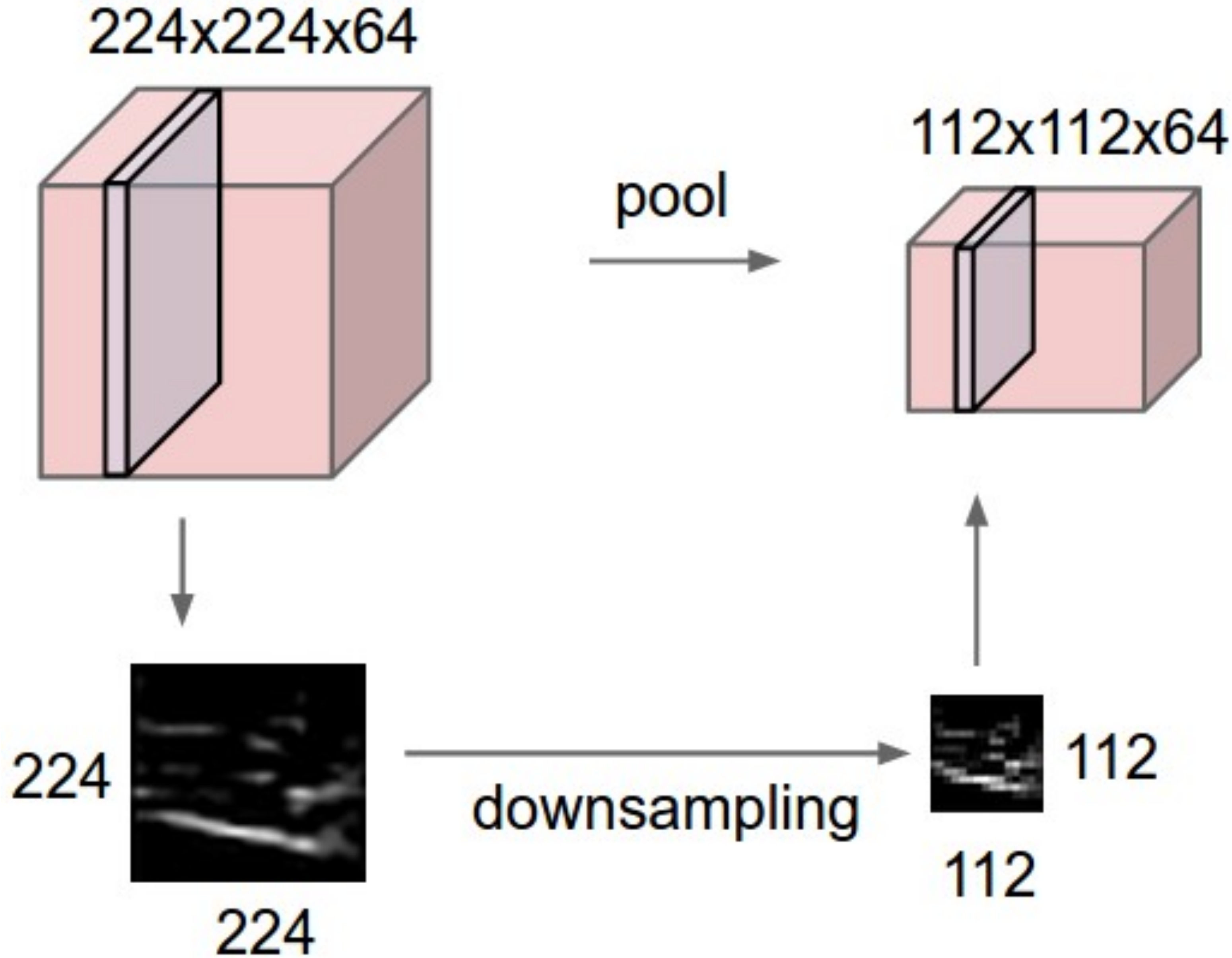
NOTE: the nr. of output feature maps is usually larger than the nr. of input feature maps

Ranzato

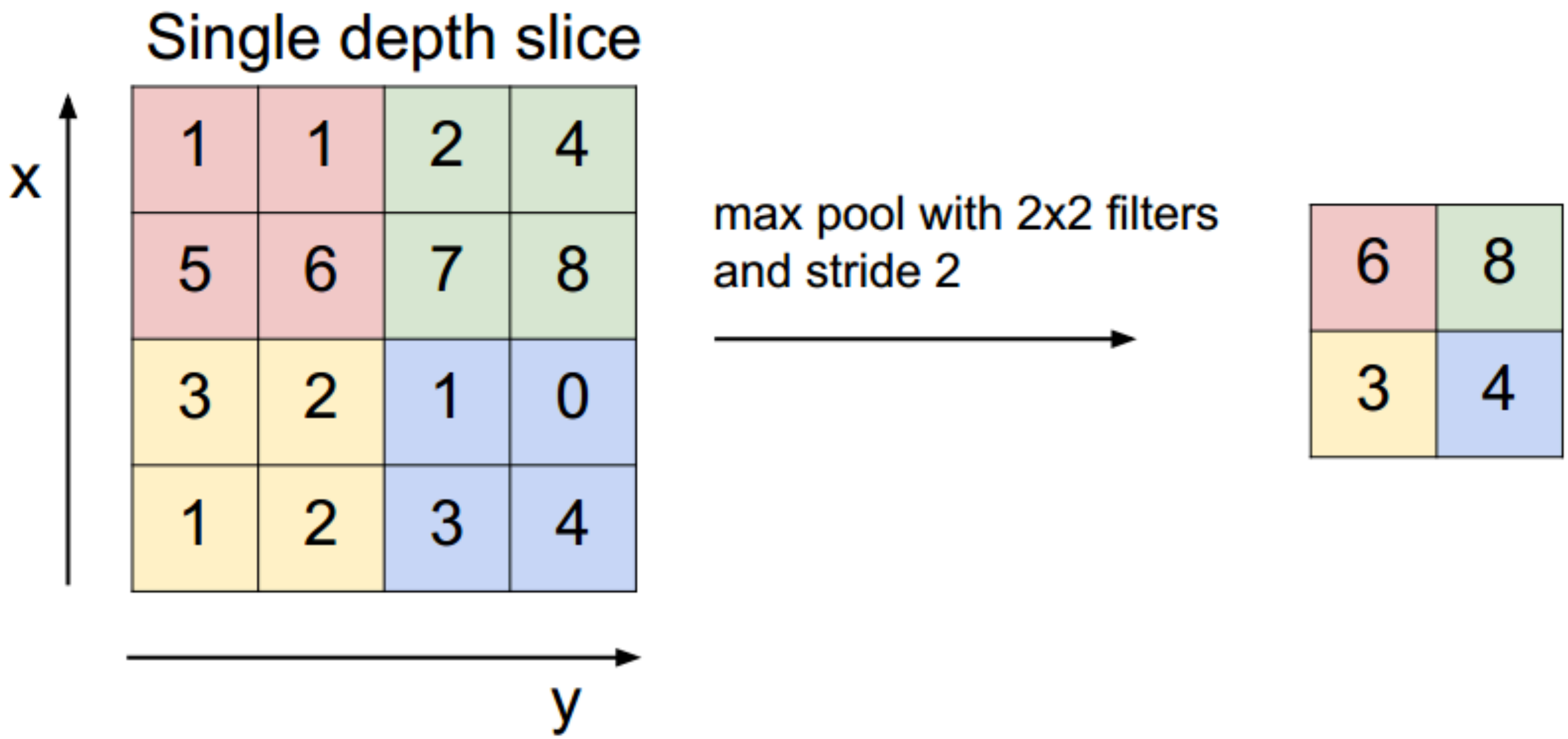

Input Volume (+pad 1) (7x7x3)
x[:,:,0]
0 0 0 0 0 0 0
0 2 2 1 2 1 0
0 2 0 2 1 1 0
0 0 0 0 1 1 0
0 2 1 0 1 1 0
0 1 1 2 1 1 0
0 0 0 0 0 0 0
x[:,:,1]
0 0 0 0 0 0 0
0 2 1 2 1 0 0
0 1 0 1 1 1 0
0 1 1 1 2 2 0
0 1 2 1 2 0 0
0 1 2 1 1 0 0
0 0 0 0 0 0 0
Filter W0 (3x3x3)
w0[:,:,0]
0 1 1
-1 0 1
0 1 -1
w0[:,:,1]
0 -1 1
0 1 1
0 0 1
w0[:,:,2]
0 1 0
-1 1 0
-1 1 0
Bias b0 (1x1x1)
b0[:,:,0]
1
Filter W1 (3x3x3)
w1[:,:,0]
-1 0 0
1 1 1
0 0 1
w1[:,:,1]
-1 1 0
-1 -1 -1
1 0 -1
w1[:,:,2]
0 -1 -1
1 -1 -1
0 0 1
Bias b1 (1x1x1)
b1[:,:,0]
0
Output Volume (3x3x2)
o[:,:,0]
11 6 2
9 6 3
12 6 2
o[:,:,1]
-1 1 1
-4 0 -3
-6 -6 -3

Special Layers

- Pooling
- Contrast Normalization (No More Used It Seems)

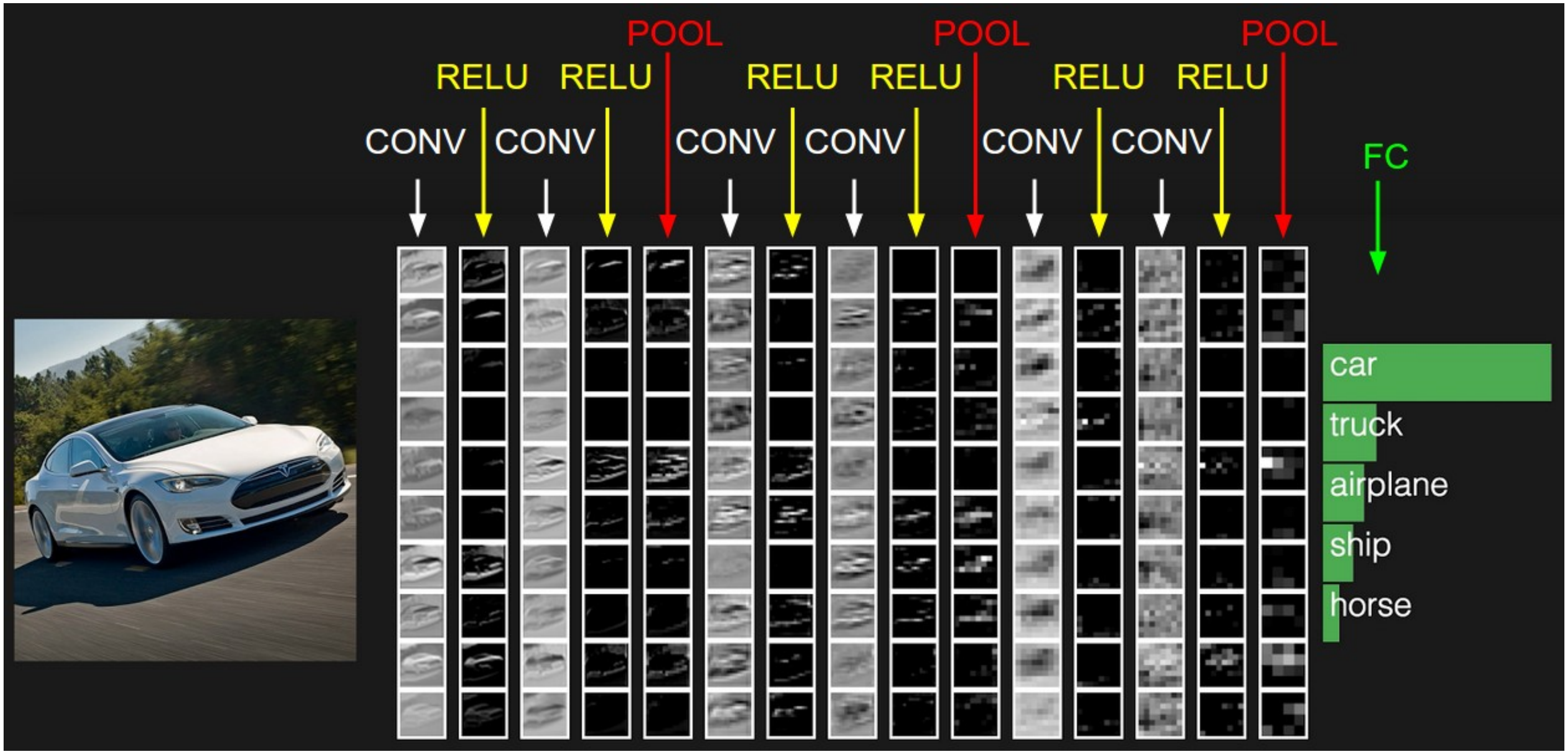

224x224x64
pool
112x112x64
224
224
downsampling
112
112

MAX POOLING



How many model parameters does this introduce into learning model?

Last Layer, Fully Connected



Deep Learning & Computer Vision: Review & Overview

- Neural networks & nodes as features
- Nonlinearity: choices, implications for learning
- Benefits of deep over shallow
- How to train/fit/learn
- New ideas for tackling vision applications
- What if we don't have much data?

- Want to build a “is parking spot 3A outside of Wean Hall free” detector
- Have 100 pictures (1 an hr, taken over last few days) with labels as free or not free

- Can deep learning help?

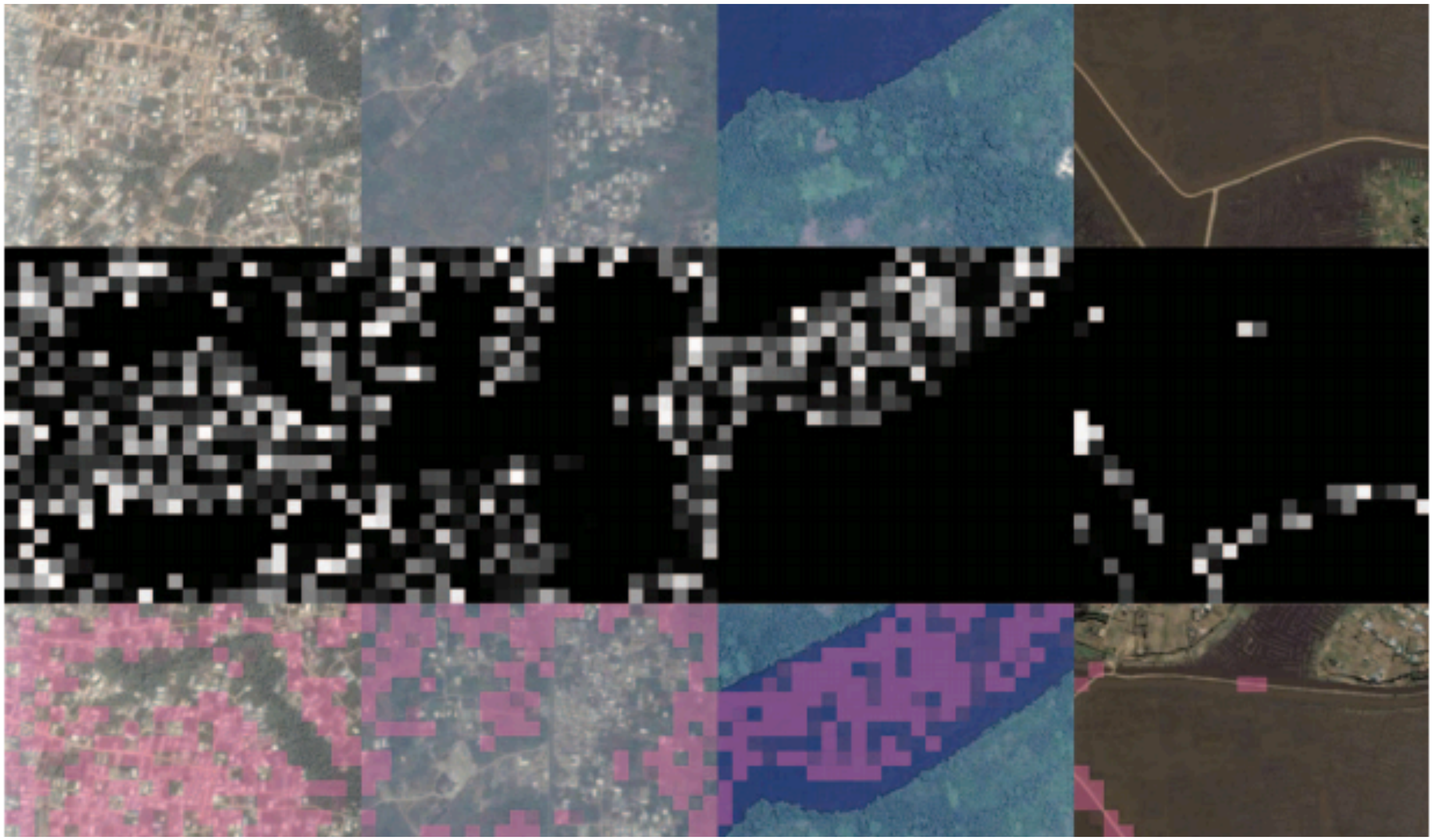
Yes! Transfer Learning

Yes! Transfer Learning

- Use features from a really large dataset (e.g. N-1 layers of CNN) and just retrain final fully connected layer

- Start from an existing trained CNN and then train a bit further

Predicting Poverty Using Deep Transfer Learning (Ermon & colleagues)



What You Should Know

- Neural networks & nodes as features
  - Internal nodes can be viewed as features
  - Make more complicate function mapping input to output
- Benefits of deep over shallow
  - Number of parameters need to express complicated function may be way smaller
  - Important in terms of amount of data to train / fit classifier
- Nonlinearity: choices, implications for learning
  - Sigmoid (bad), ReLu (good)
  - Increases ezpressive power (1 hidden layer, universal approximator)
  - Optimization harder (not convex, many local optima)
- How to train/fit/learn
  - Gradient descent, backpropagation
  - Be able to derive gradient for simple case and use to update w
- New ideas for tackling vision applications
  - Convolutional networks
  - Reduce # parameters, exploit nodes as filters
  - How many parameters are involved?
  - Define common node types: conv, pooling, fully connected
- What if we don't have much data?
  - Transfer learning!
  - Learn features using big data, then use for other applications