Announcements

Assignments:

- HW4
  - Due tonight!
- HW5
  - Due date Thu, 2/27, 11:59 pm

Midterm

- See Piazza post for details

Canvas updated

- Participation points

Plan

Last time

- Neural Networks
  - Universal Approximation
  - Optimization / Backpropagation

Today

- Wrap-up Optimization / Backpropagation
- Course Survey
- Convolutional Neural Networks

Introduction to Machine Learning

Neural Networks

Instructor: Pat Virtue

Reminder: Calculus Chain Rule (scalar version)

$$y = f(z)$$
$$z = g(x)$$

$$\frac{dy}{dx} = \frac{dy}{dz}\frac{dz}{dx}$$

Network Optimization

$$J(\mathbf{w}) = z_3$$

$$z_3 = f_3(w_3, z_2)$$

$$z_2 = f_2(w_2, z_1)$$

$$z_1 = f_1(w_1, x)$$

$$\frac{\partial J}{\partial w_3} = \frac{\partial J}{\partial z_3}\frac{\partial z_3}{\partial w_3}$$

$$\frac{\partial J}{\partial w_2} = \frac{\partial J}{\partial z_3}\frac{\partial z_3}{\partial z_2}\frac{\partial z_2}{\partial w_2}$$

$$\frac{\partial J}{\partial w_1} = \frac{\partial J}{\partial z_3}\frac{\partial z_3}{\partial z_2}\frac{\partial z_2}{\partial z_1}\frac{\partial z_1}{\partial w_1}$$

Lots of repeated calculations

Backpropagation (so-far)

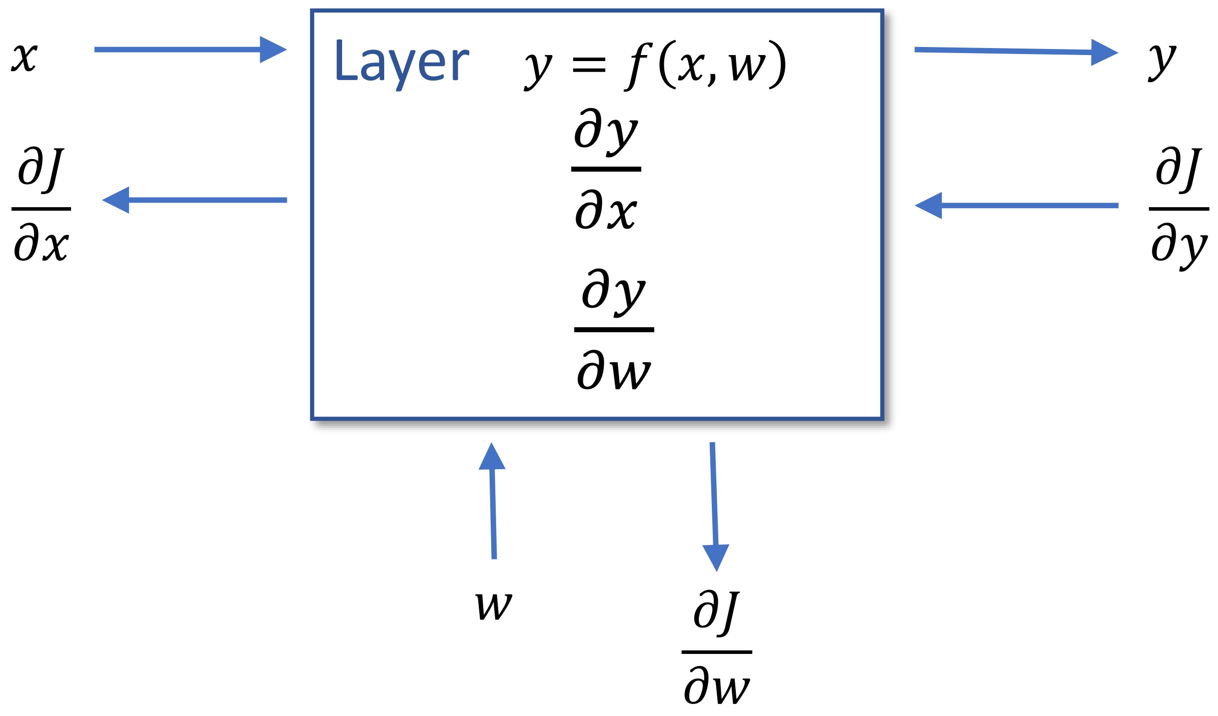
Compute derivatives per layer, utilizing previous derivatives

Objective: $J(\boldsymbol{w})$

Arbitrary layer: $y = f(x, w)$

Need:

- $\frac{\partial J}{\partial x} = \frac{\partial J}{\partial y}\frac{\partial y}{\partial x}$
- $\frac{\partial J}{\partial w} = \frac{\partial J}{\partial y}\frac{\partial y}{\partial w}$



Reminder: Matrix Calculus

Gradient, Jacobian, etc

Calculus Chain Rule

Scalar:

$y = f(z)$

$z = g(x)$

$$\frac{dy}{dx} = \frac{dy}{dz}\frac{dz}{dx}$$

Multivariate:

$y = f(\mathbf{z})$

$\mathbf{z} = g(x)$

$$\frac{dy}{dx} = \sum_j \frac{\partial y}{\partial z_j}\frac{\partial z_j}{\partial x}$$

Multivariate:

$\mathbf{y} = f(\mathbf{z})$

$\mathbf{z} = g(\mathbf{x})$

$$\frac{dy_{\mathrm{i}}}{dx_{\mathrm{k}}} = \sum_j \frac{\partial y_i}{\partial z_j}\frac{\partial z_j}{\partial x_{\mathrm{k}}}$$

Piazza Poll 1:

$$y = f(\boldsymbol{z})$$

$$\boldsymbol{z} = g(\boldsymbol{x})$$

$$\frac{\partial y}{\partial \boldsymbol{x}} = \cdots$$

A. $\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}$

B. $\frac{\partial y}{\partial \boldsymbol{z}}^T \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}$

C. $\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}^T$

D. $\frac{\partial y}{\partial \boldsymbol{z}}^T \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}^T$

E. $\left(\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}\right)^T$

F. None of the above

Piazza Poll 1:

$$y = f(\boldsymbol{z})$$

$$\boldsymbol{z} = g(\boldsymbol{x})$$

$$\frac{\partial y}{\partial \boldsymbol{x}} = \cdots$$

A. $\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}$

B. $\frac{\partial y}{\partial \boldsymbol{z}}^T \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}$

C. $\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}^T$

D. $\frac{\partial y}{\partial \boldsymbol{z}}^T \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}^T$

E. $\left(\frac{\partial y}{\partial \boldsymbol{z}} \frac{\partial \boldsymbol{z}}{\partial \boldsymbol{x}}\right)^T$

F. None of the above

Network Optimization

$J(\boldsymbol{w}) = z_4$

$z_4 = f_4(w_D, w_E, z_2, z_3)$

$z_3 = f_3(w_C, z_1)$

$z_2 = f_2(w_B, z_1)$

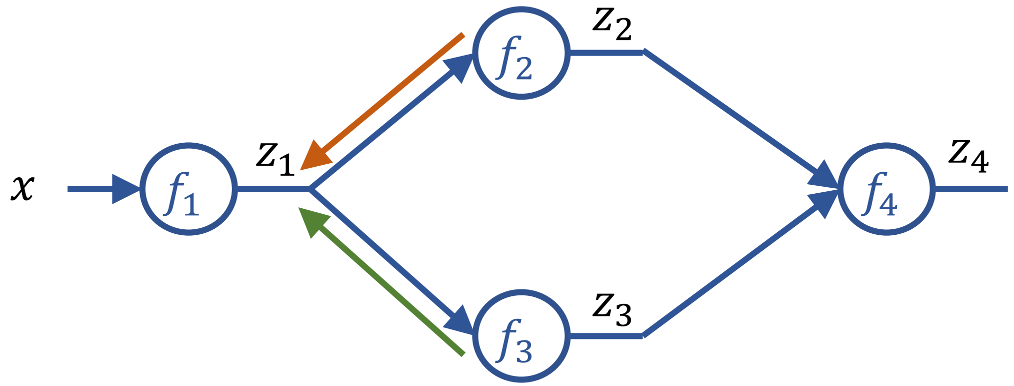
$z_1 = f_1(w_A, x)$

Need multivariate chain rule!

Network Optimization

$$J(\boldsymbol{w}) = z_4$$
$$z_4 = f_4(w_D, w_E, z_2, z_3)$$
$$z_3 = f_3(w_C, z_1)$$
$$z_2 = f_2(w_B, z_1)$$
$$z_1 = f_1(w_A, x)$$

Need multivariate chain rule!



$$\frac{\partial J}{\partial w_E} = \frac{\partial J}{\partial z_4}\frac{\partial z_4}{\partial w_E}$$

$$\frac{\partial J}{\partial w_D} = \frac{\partial J}{\partial z_4}\frac{\partial z_4}{\partial w_D}$$

$$\frac{\partial J}{\partial z_3} = \frac{\partial J}{\partial z_4}\frac{\partial z_4}{\partial z_3}$$
$$\frac{\partial J}{\partial z_2} = \frac{\partial J}{\partial z_4}\frac{\partial z_4}{\partial z_2}$$

$$\frac{\partial J}{\partial w_C} = \frac{\partial J}{\partial z_3}\frac{\partial z_3}{\partial w_C}$$
$$\frac{\partial J}{\partial w_B} = \frac{\partial J}{\partial z_2}\frac{\partial z_2}{\partial w_B}$$

$$\frac{\partial J}{\partial z_1} = \frac{\partial J}{\partial z_2}\frac{\partial z_2}{\partial z_1} + \frac{\partial J}{\partial z_3}\frac{\partial z_3}{\partial z_1}$$

$$\frac{\partial J}{\partial w_A} = \frac{\partial J}{\partial z_1}\frac{\partial z_1}{\partial w_A}$$

Backpropagation (updated)

Compute derivatives per layer, utilizing previous derivatives

Objective: $J(\boldsymbol{w})$

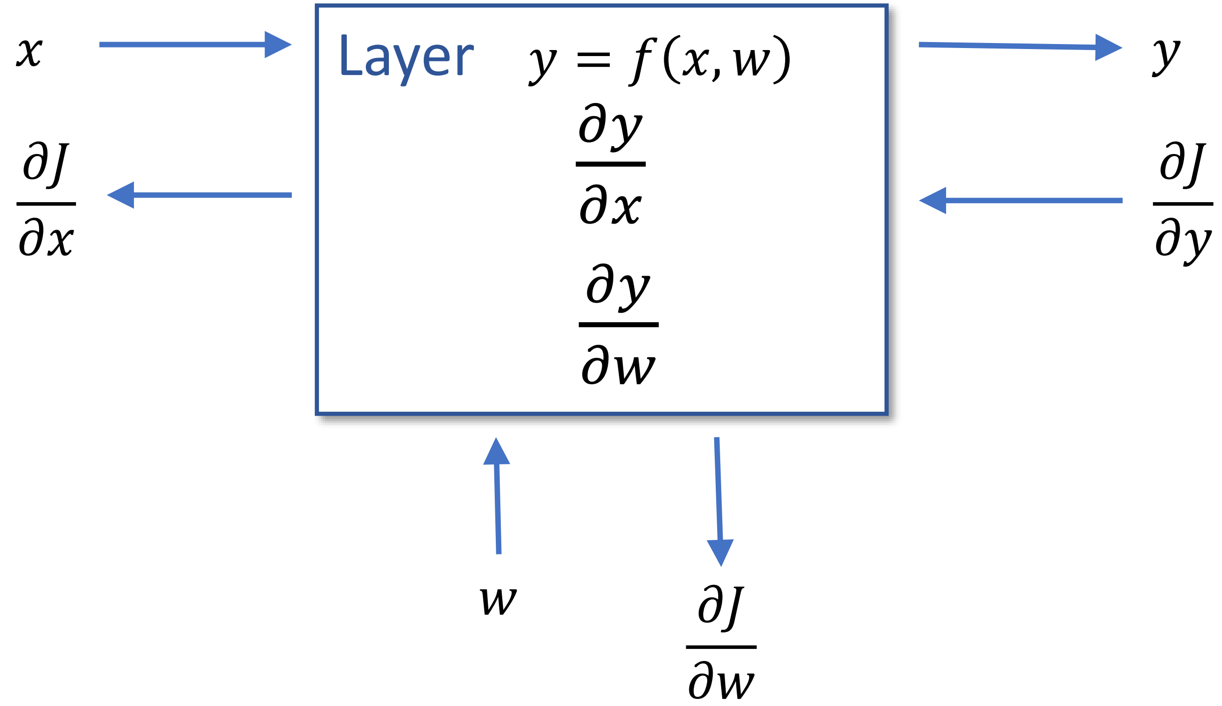
Arbitrary layer: $y = f(x, w)$

Init:

- $\frac{\partial J}{\partial x} = 0$
- $\frac{\partial J}{\partial w} = 0$

Compute:

- $\frac{\partial J}{\partial x} \mathrel{+}= \frac{\partial J}{\partial y}\frac{\partial y}{\partial x}$
- $\frac{\partial J}{\partial w} \mathrel{+}= \frac{\partial J}{\partial y}\frac{\partial y}{\partial w}$



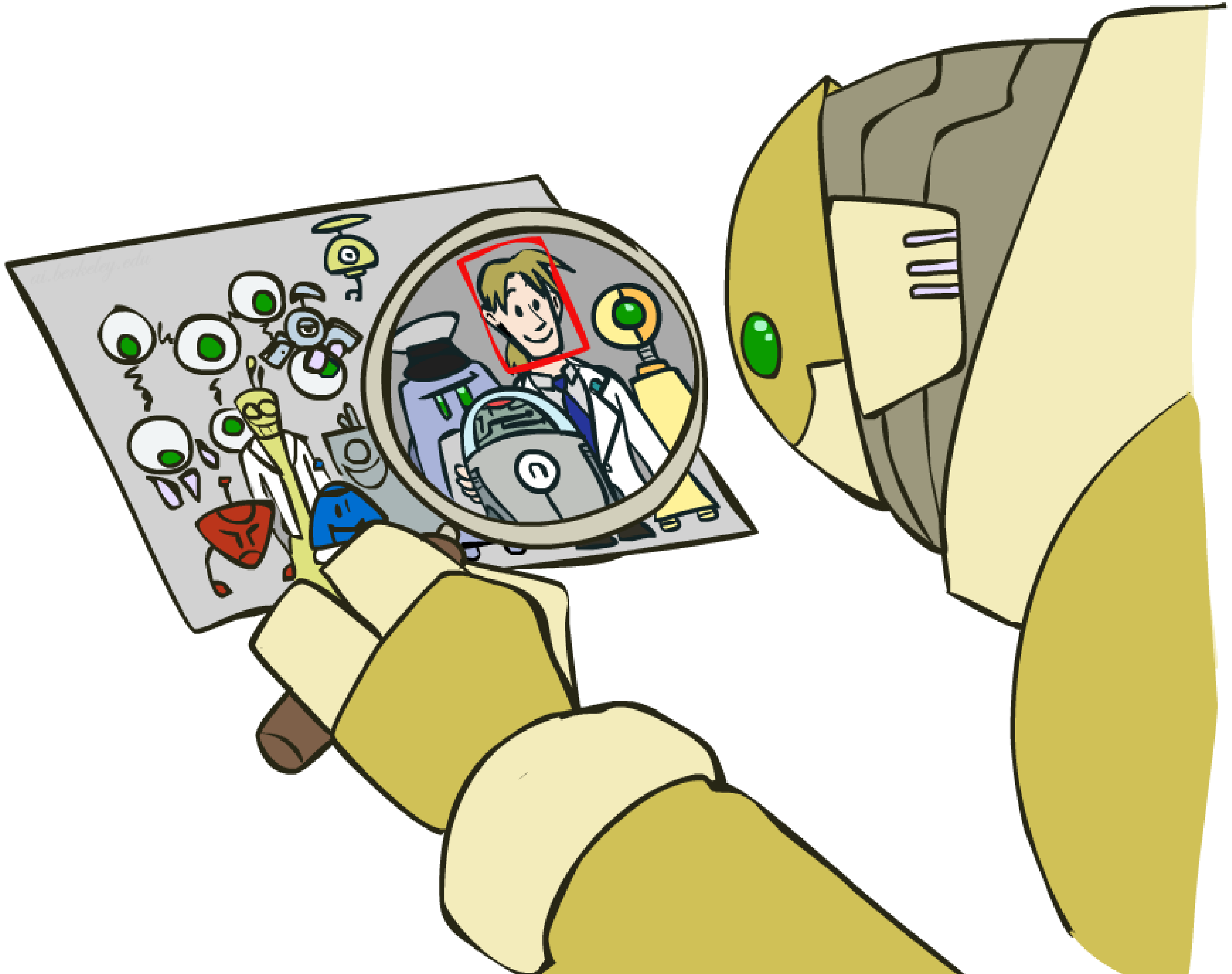
Course Survey

Introduction to Machine Learning

Convolutional Neural Networks

Instructor: Pat Virtue

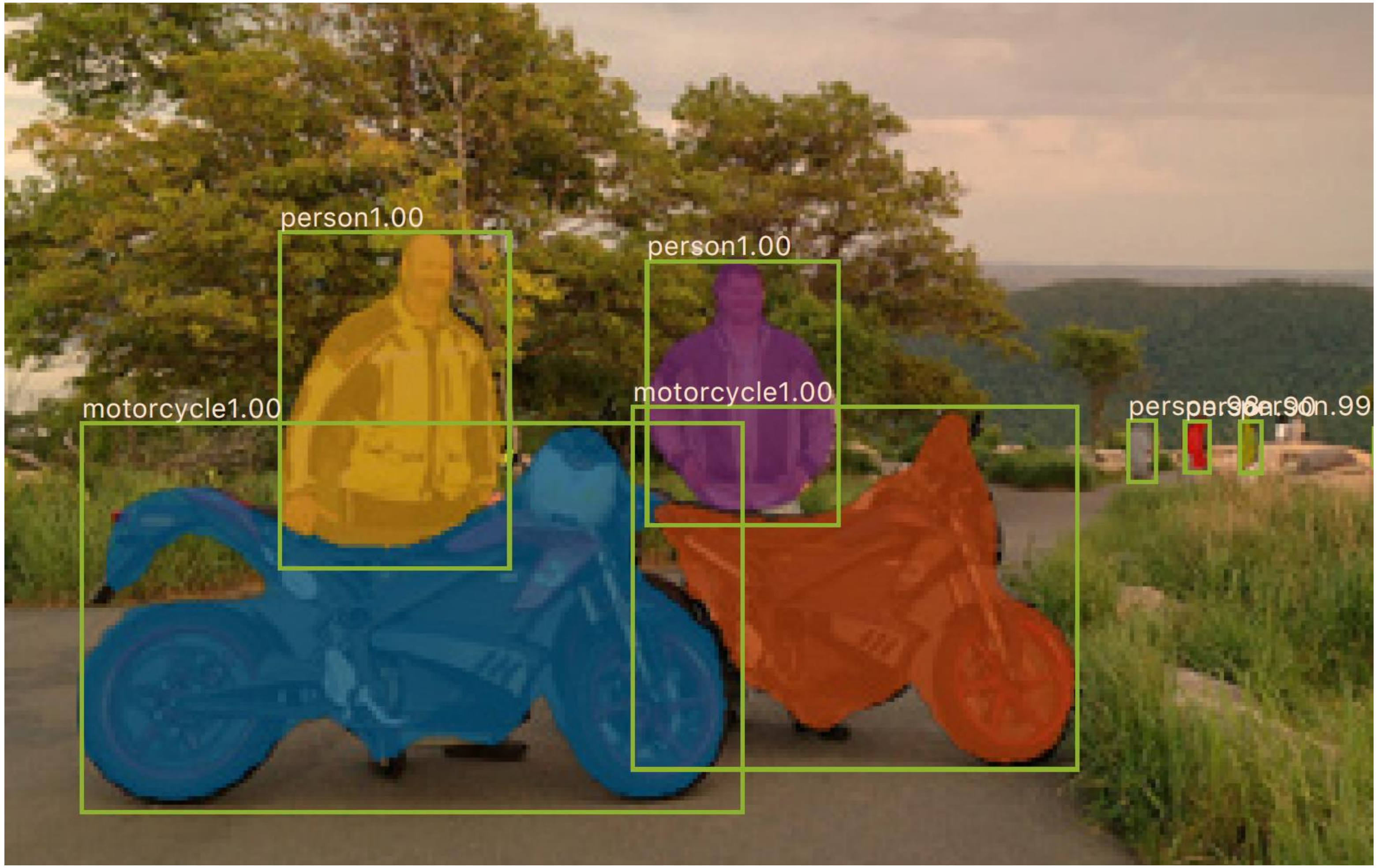
Computer Vision: How far along are we?



Computer Vision: How far along are we?

Terminator 2, 1991

Computer Vision: How far along are we?



0.2 seconds per image

Mask R-CNN

He, Kaiming, et al. "Mask R-CNN." *Computer Vision (ICCV), 2017 IEEE International Conference on*. IEEE, 2017.

Computer Vision: How far along are we?

“My CPU is a neural net processor, a learning computer”

Terminator 2, 1991

Computer Vision: Autonomous Driving

Tesla, Inc: https://vimeo.com/192179726

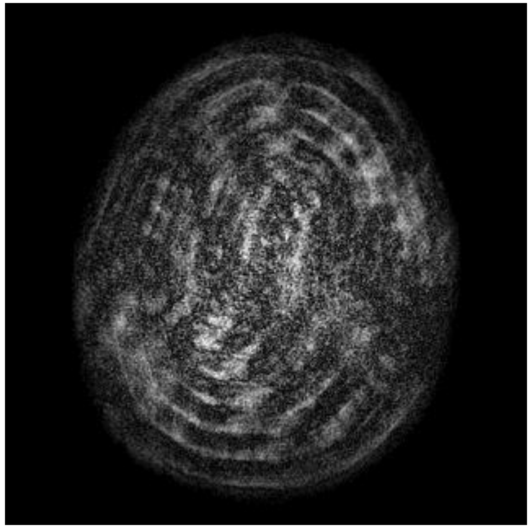
Computer Vision: Domain Transfer

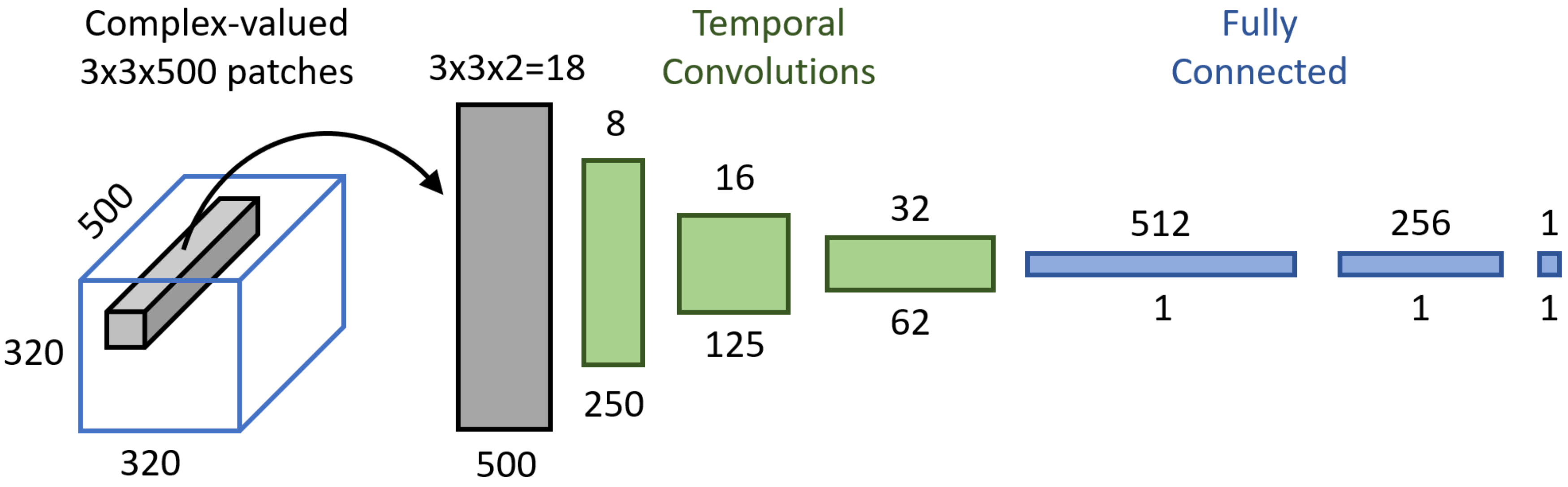
CycleGAN

Jun-Yan Zhu*, Taesung Park*, Phillip Isola, and Alexei A. Efros. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks", ICCV 2017.

Temporal Convolution

MR Fingerprinting





Patrick Virtue , Jonathan I Tamir , Mariya Doneva , Stella X Yu , and Michael Lustig. "Learning Contrast Synthesis from MR Fingerprinting", ISMRM 2018.

Outline

1. Measuring the current state of computer vision
2. Why convolutional neural networks
   - Old school computer vision
   - Image features and classification
3. Convolution "nuts and bolts"

Image Classification

What's the problem with just directly classifying raw pixels in high dimensional space?

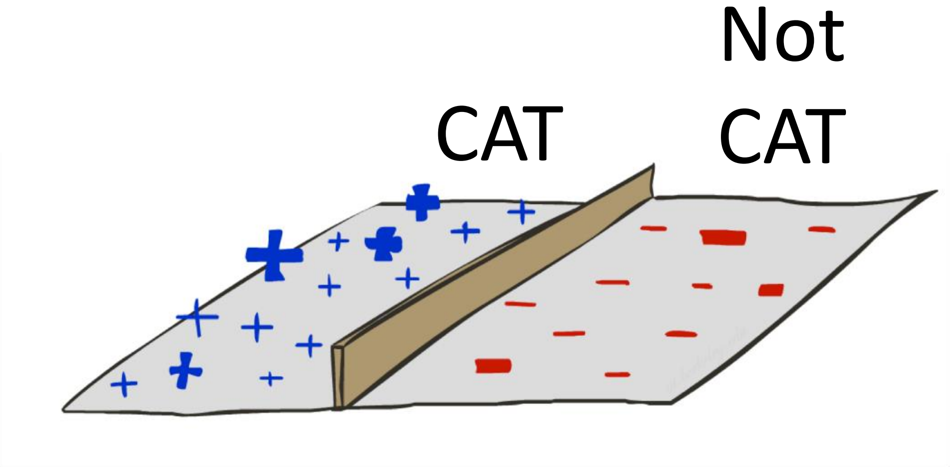


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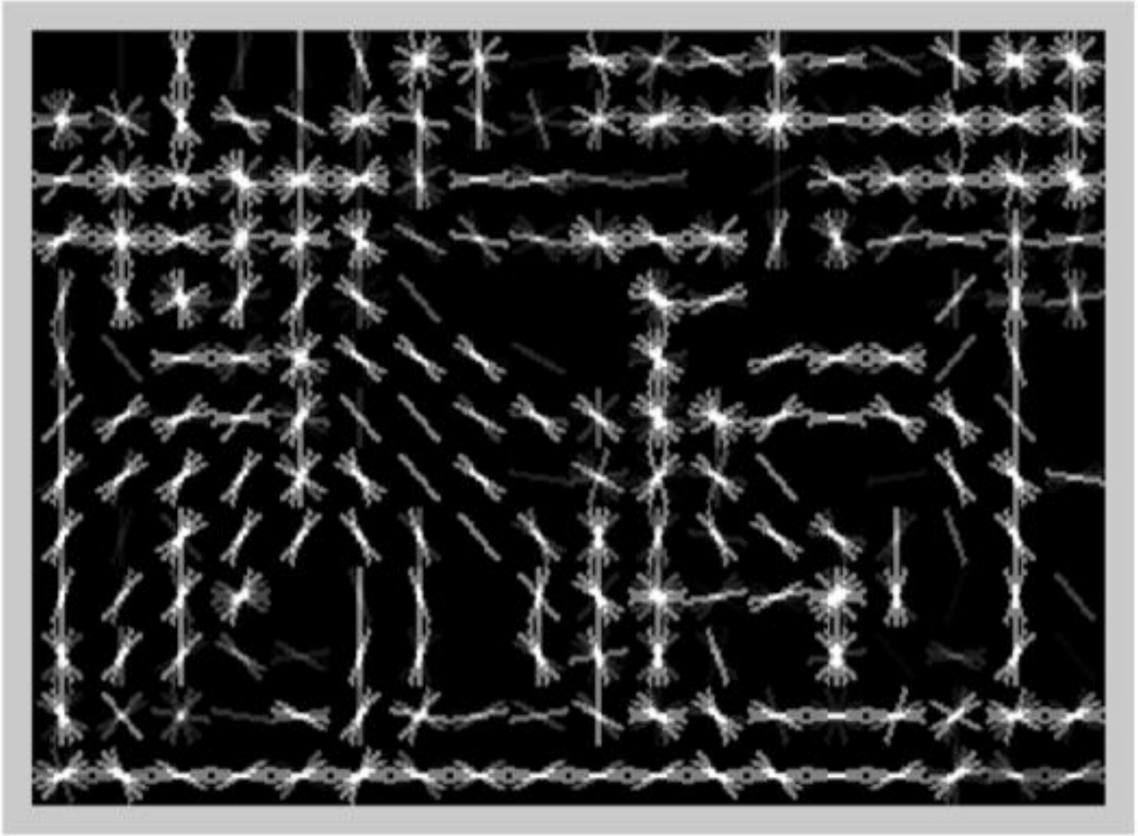
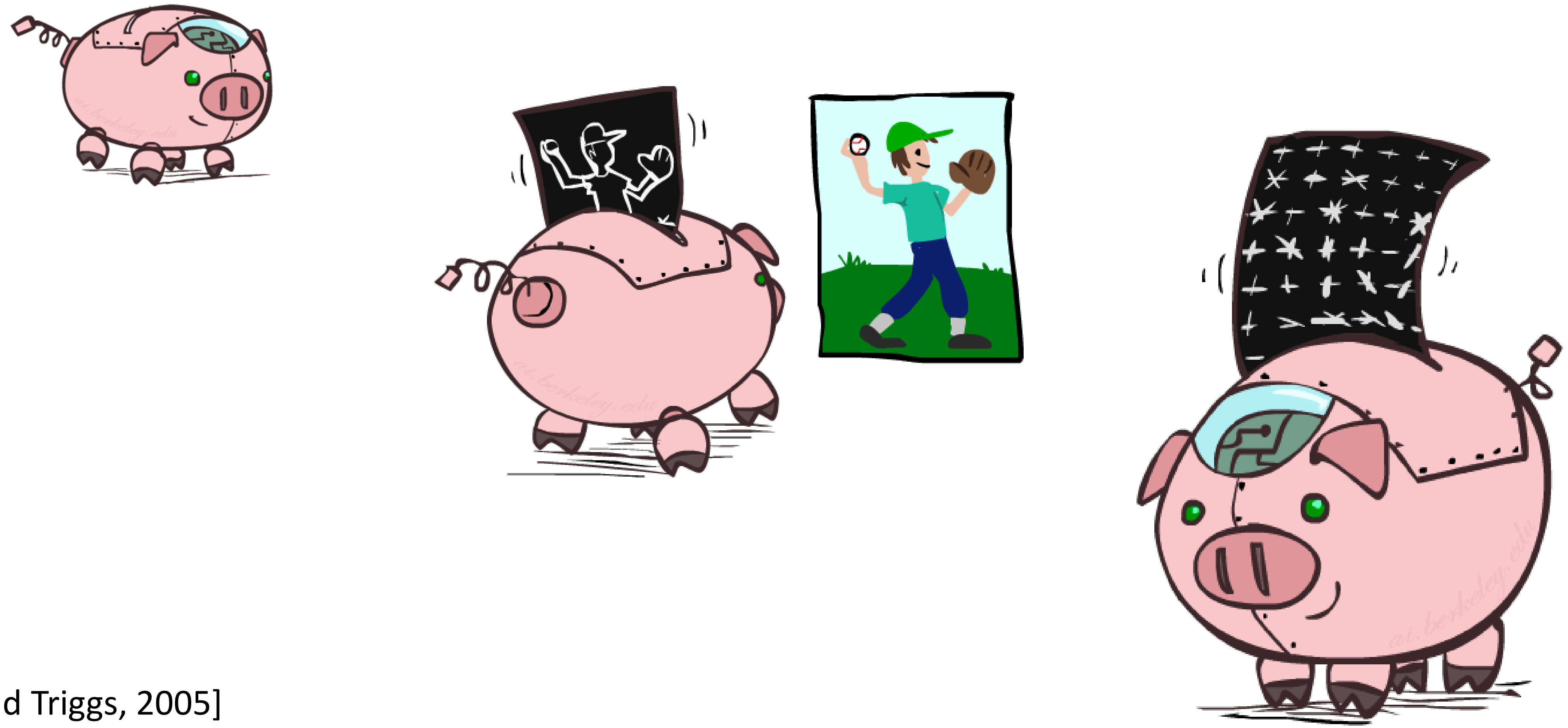
Image Classification



[Dalal and Triggs, 2005]

HoG Filter

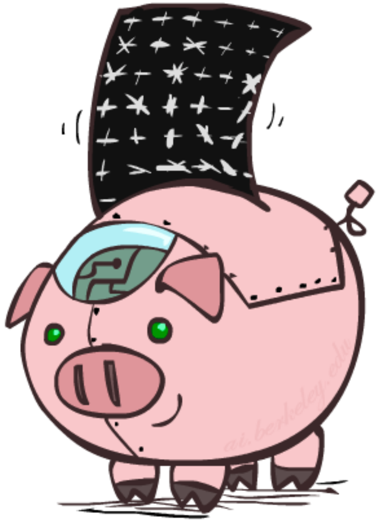
HoG: Histogram of oriented gradients



[Dalal and Triggs, 2005]

Image Classification

HOG features passed to a linear classifier (SVM)



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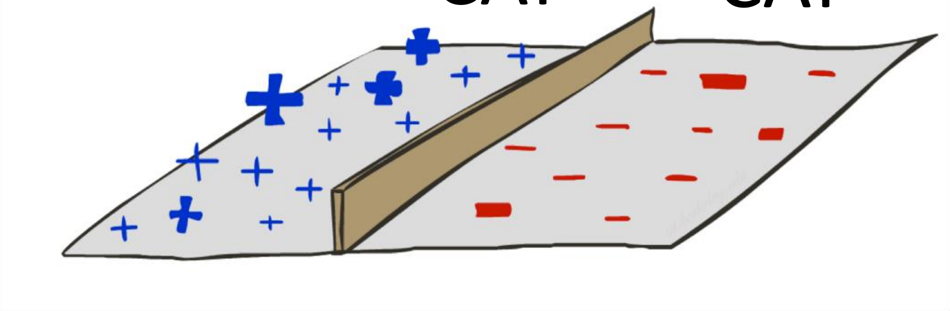
Not CAT



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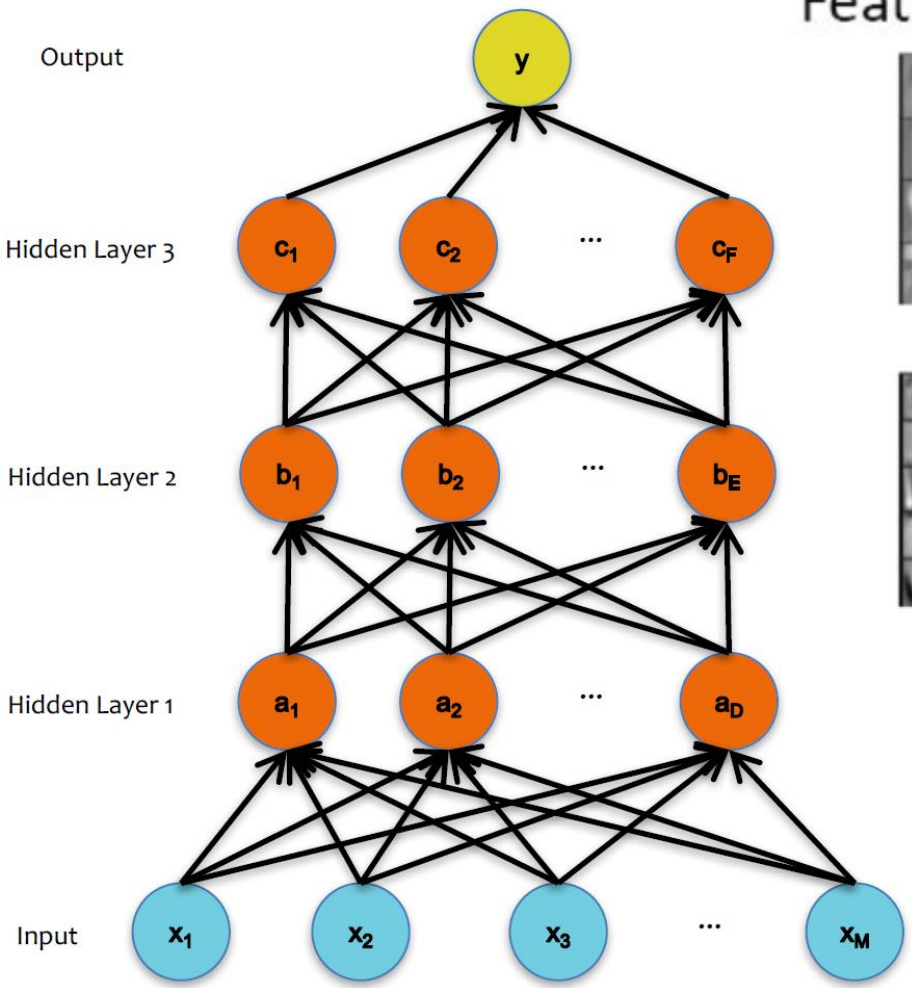
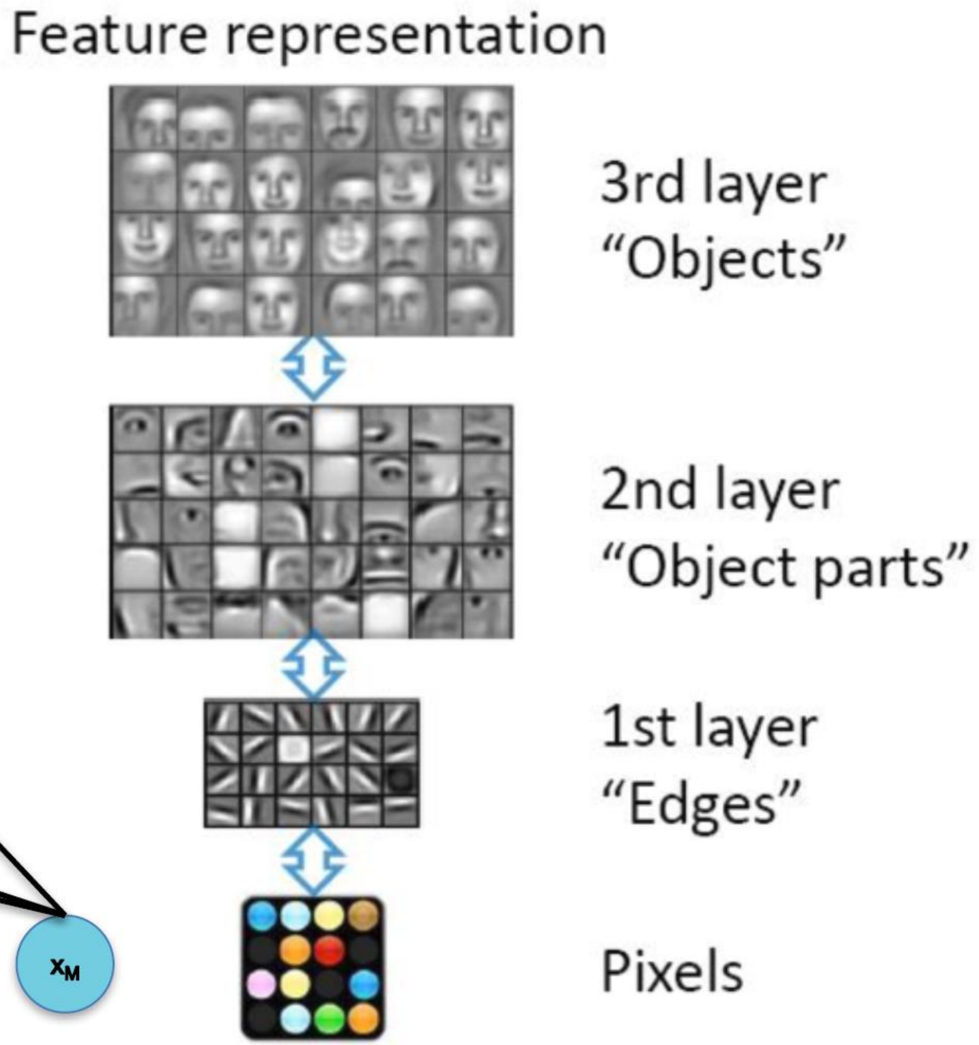
Classification: Learning Features

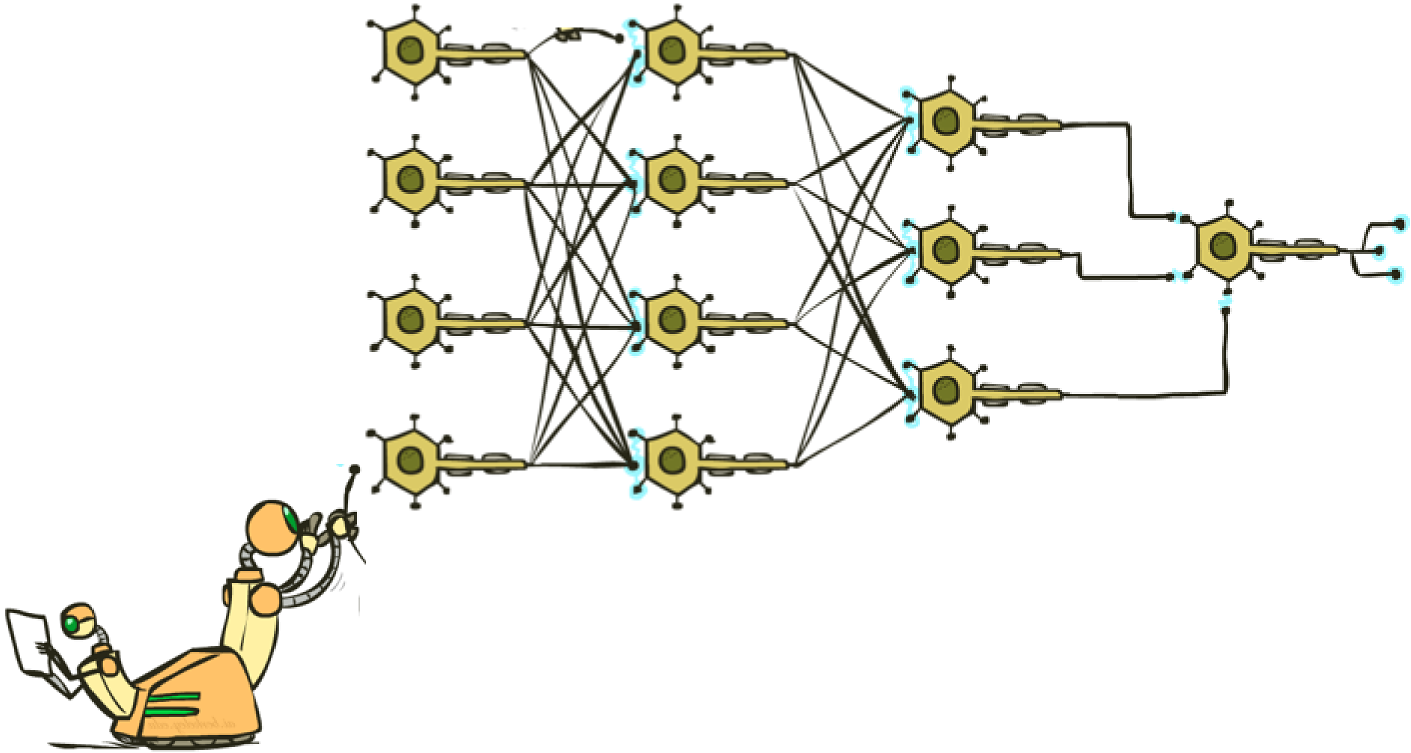




Example from Honglak Lee (NIPS 2010)

Classification: Deep Learning

Fully connected neural network?



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Convolution

Signal processing definition

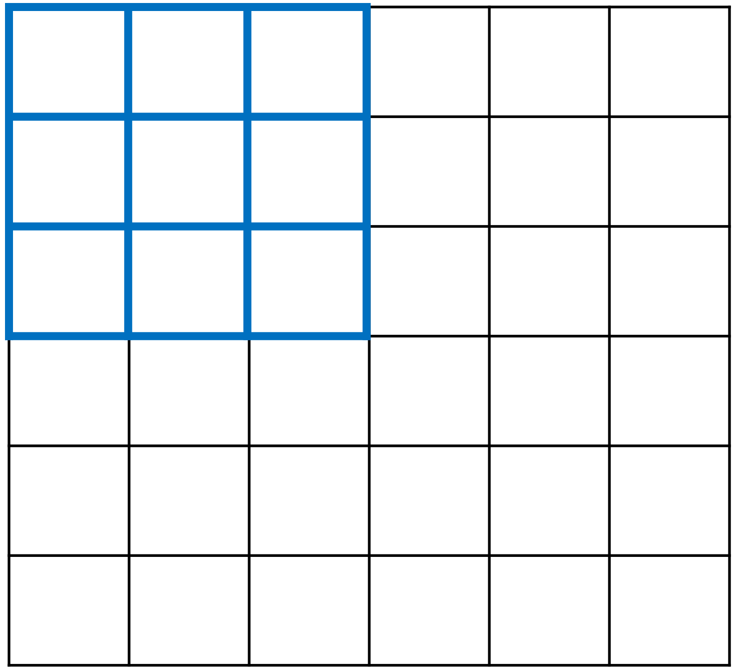
$$z[i,j] = \sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} x[i-u, j-v] \cdot w[u\,, v]$$

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

Relaxed definition

- Drop infinity; don’t flip kernel

$$z[i,j] = \sum_{u=0}^{\mathrm{K}-1} \sum_{v=0}^{\mathrm{K}-1} x[i+u, j+v] \cdot w[u\,, v]$$



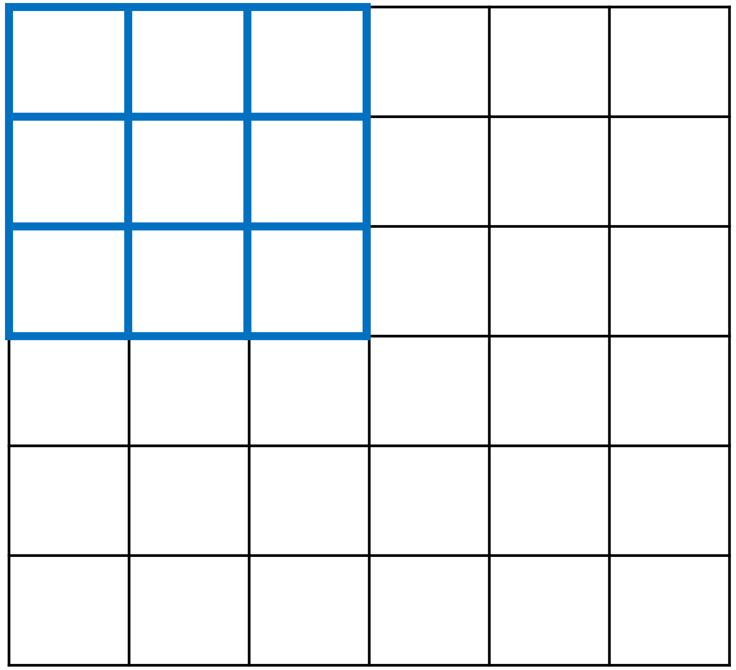
Convolution

Relaxed definition

$$z[i,j] = \sum_{u=0}^{K-1} \sum_{v=0}^{K-1} x[i+u, j+v] \cdot w[u,v]$$

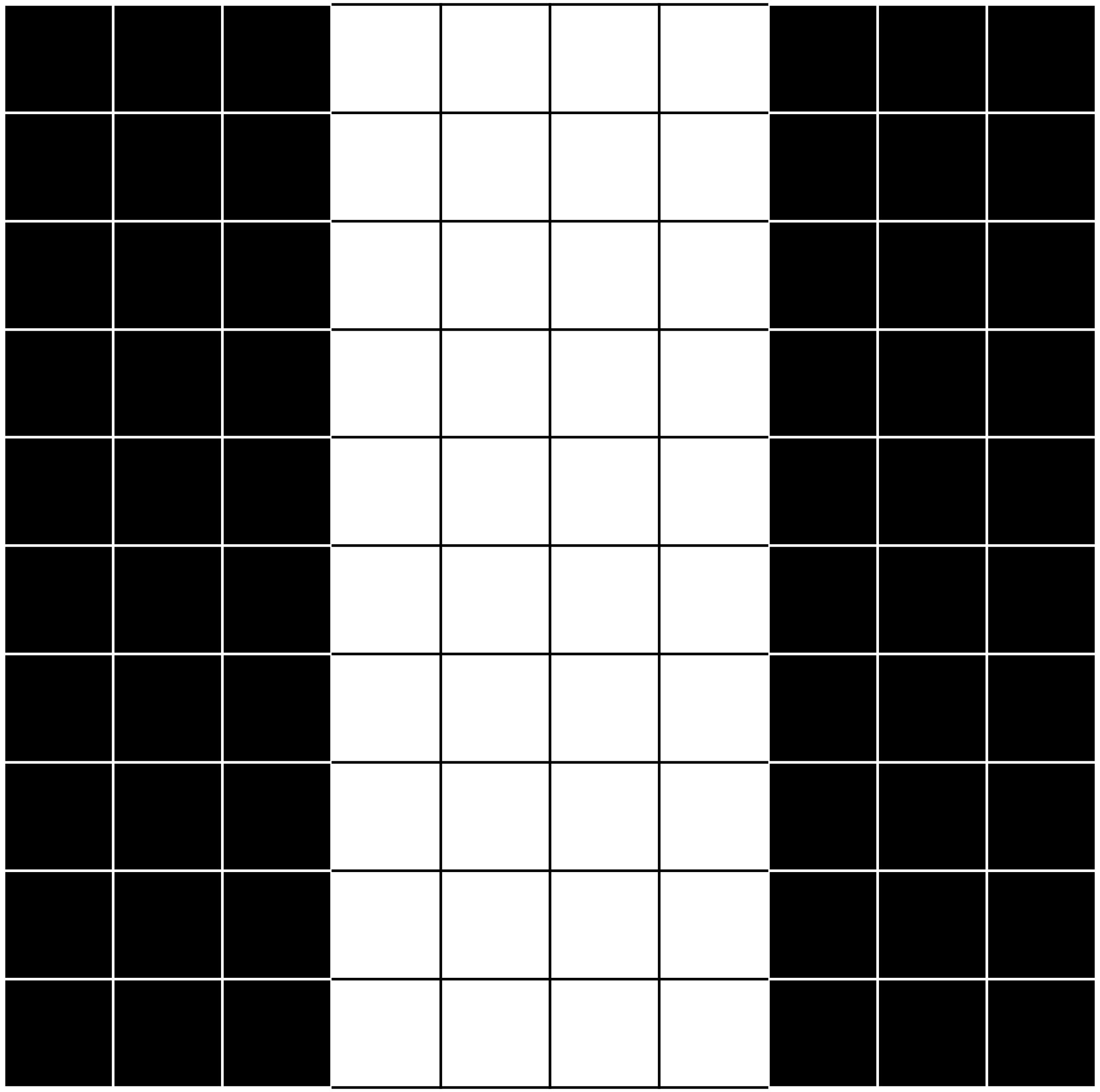
-1	0	1
-2	0	2
-1	0	1

```
for i in range(0, im_width - K + 1):
  for j in range(0, im_height - K):
    im_out[i,j] = 0
    for u in range(0, K):
      for v in range(0, K):
        im_out[i,j] += im[i+u, j+v] * kernel[u,v]
```



GPU!!

Convolution



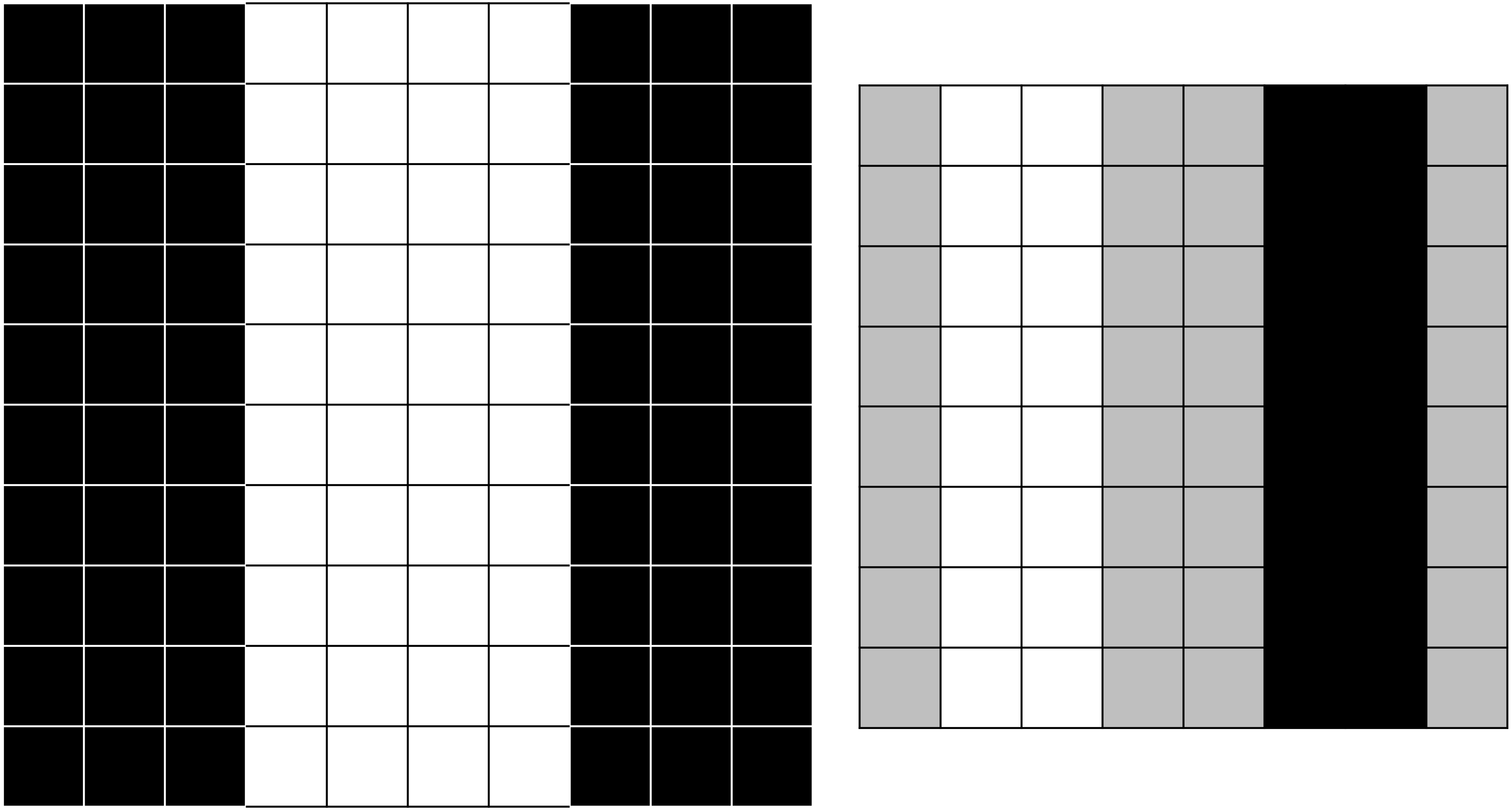
-1	0	1
-1	0	1
-1	0	1

Convolution

0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0

-1	0	1
-1	0	1
-1	0	1

Convolution



-1	0	1
-1	0	1
-1	0	1

Convolution: Padding

0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0
0	0	1	1	1	1	0	0

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

Piazza Poll 2 : Which kernel goes with which output image?

Input

K1

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

K2

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

K3

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

Im1

Im2

Im3

Piazza Poll 2 : Which kernel goes with which output image?

Input

K1

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

K2

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

K3

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

Im1

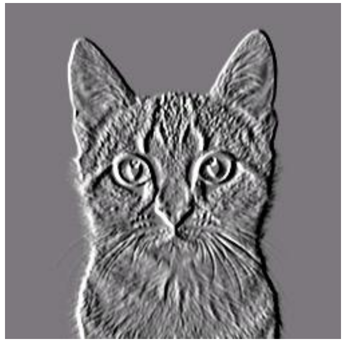
Im2

Im3

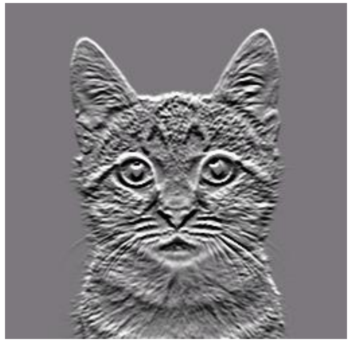
Convolutional Neural Networks

Convolution

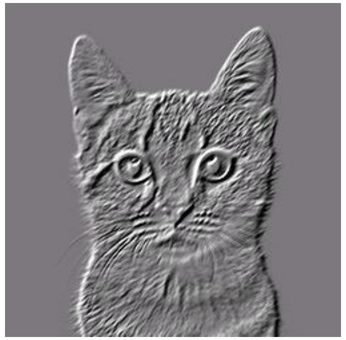
-1	0	1
-2	0	2
-1	0	1

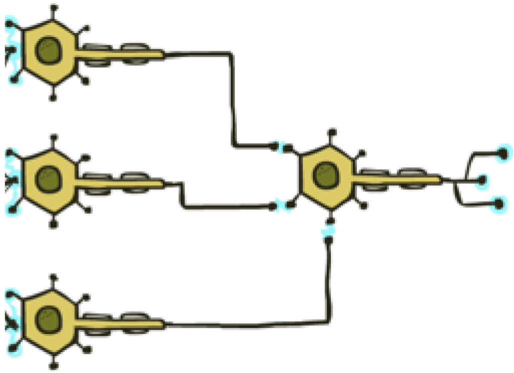


-1	-2	-1
0	0	0
1	2	1



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





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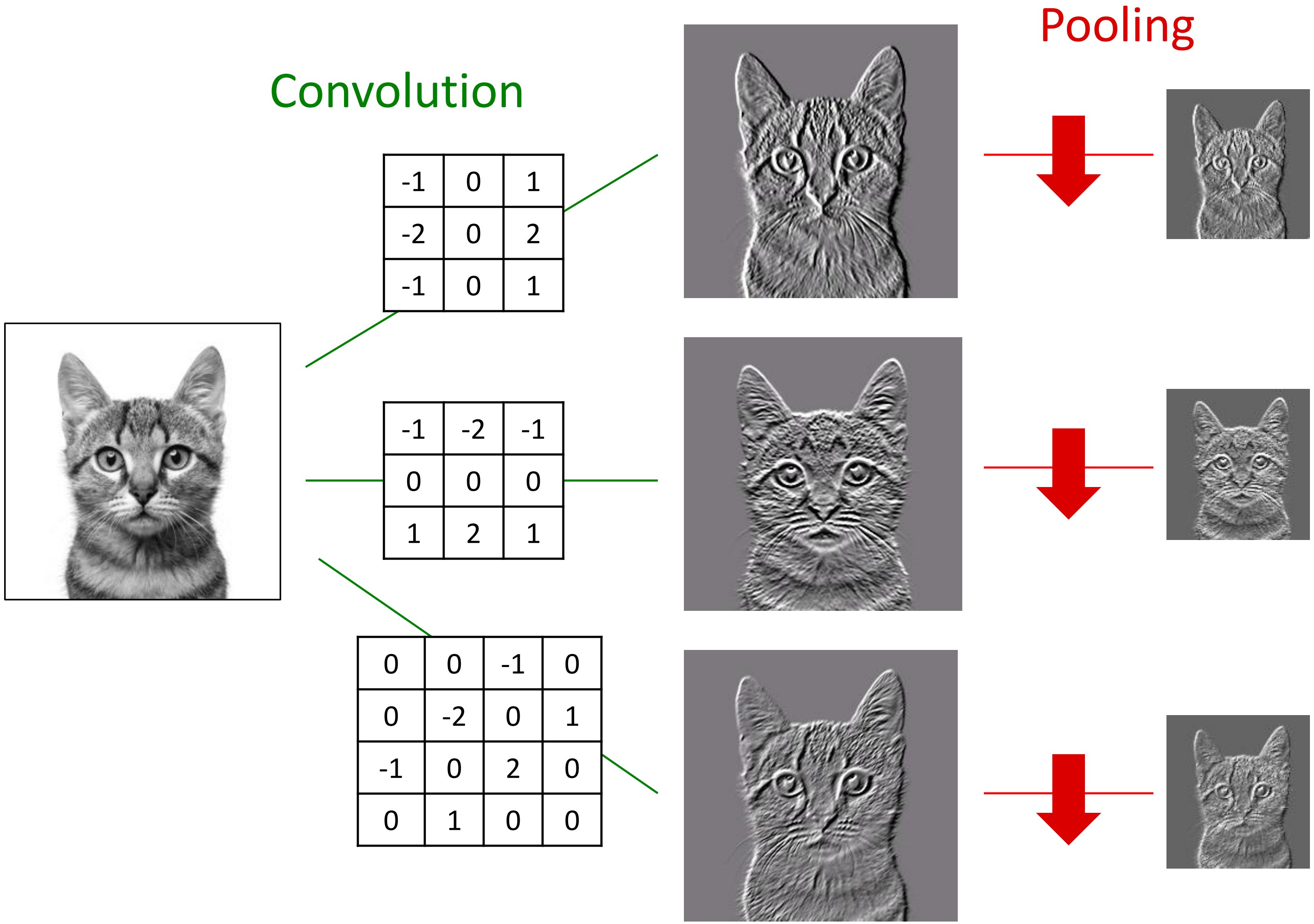
Convolutional Neural Networks



Convolution: Stride=2

0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0
0	0	0	1	1	1	1	0	0	0

.25	.25
.25	.25

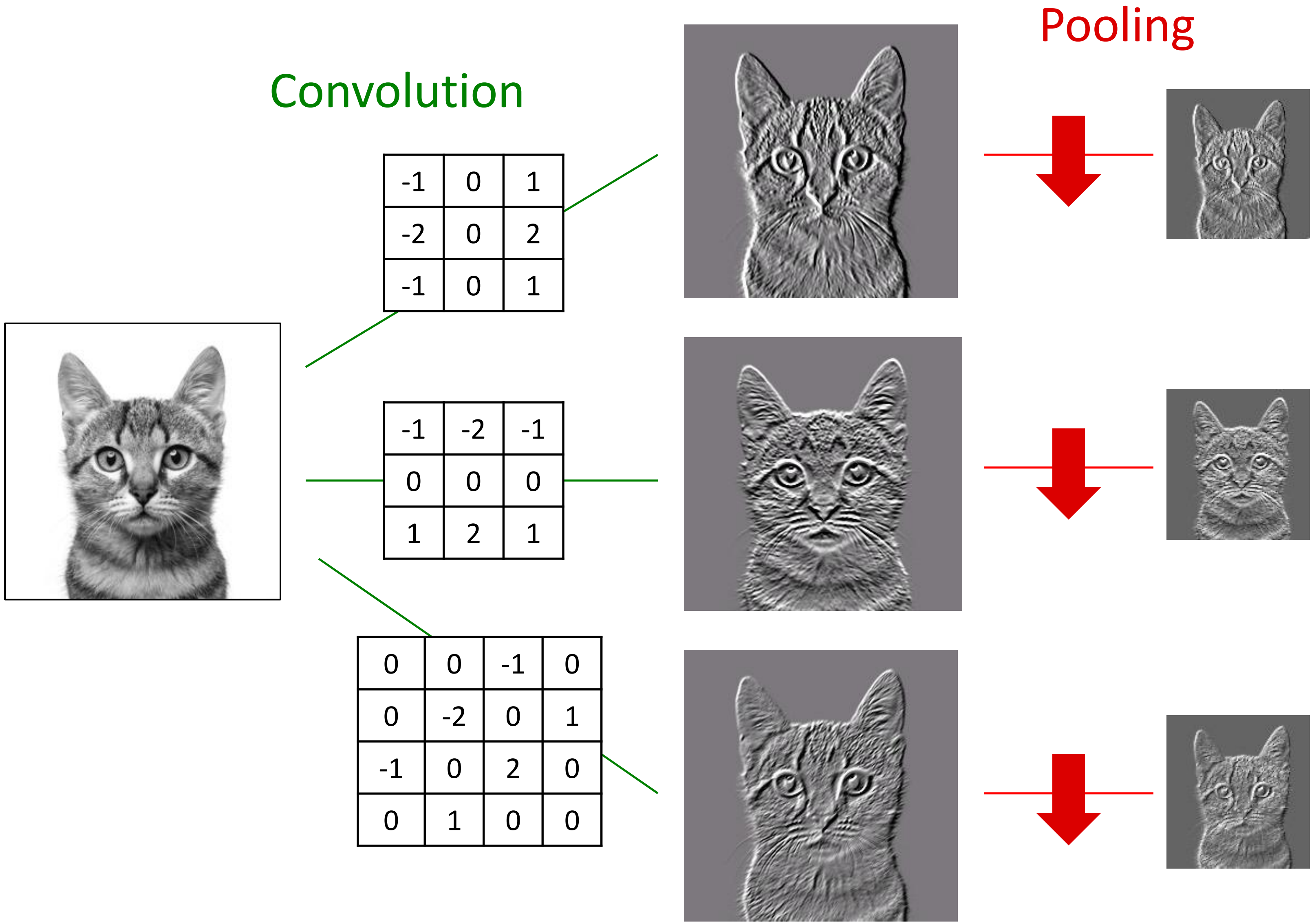
Stride: Max Pooling

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

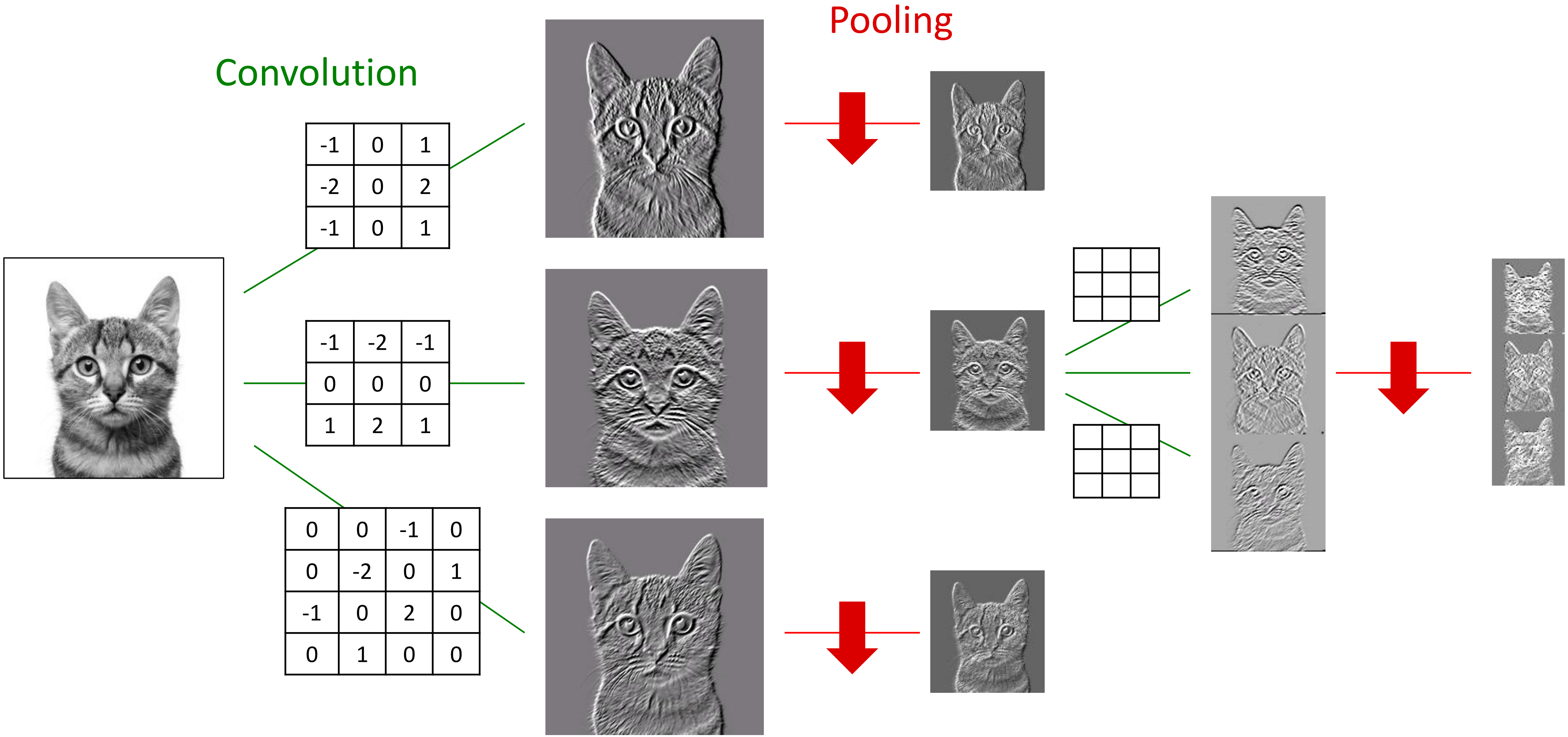
max pool with 2x2 filters
and stride 2

6	8
3	4

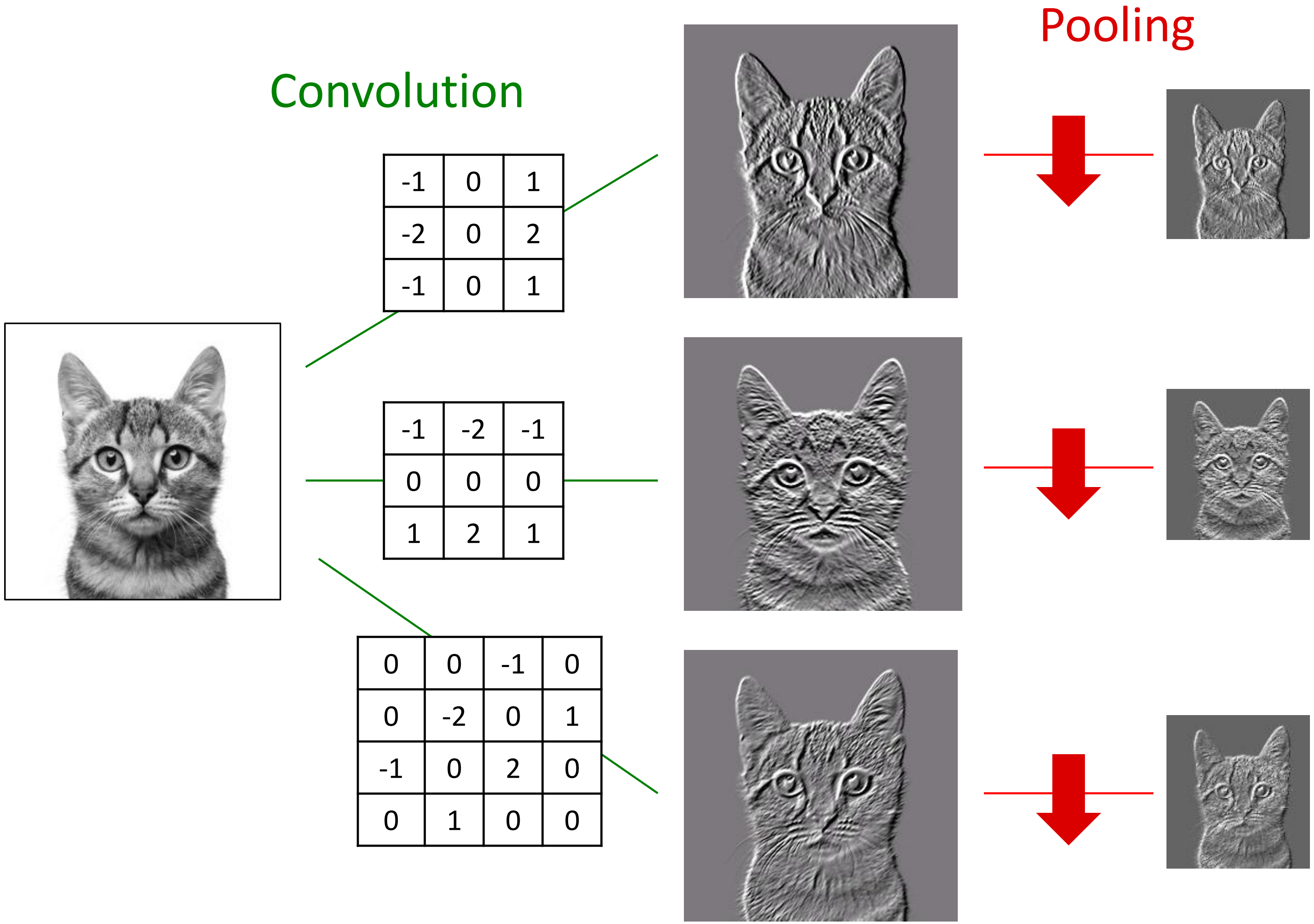
Convolutional Neural Networks



Convolutional Neural Networks



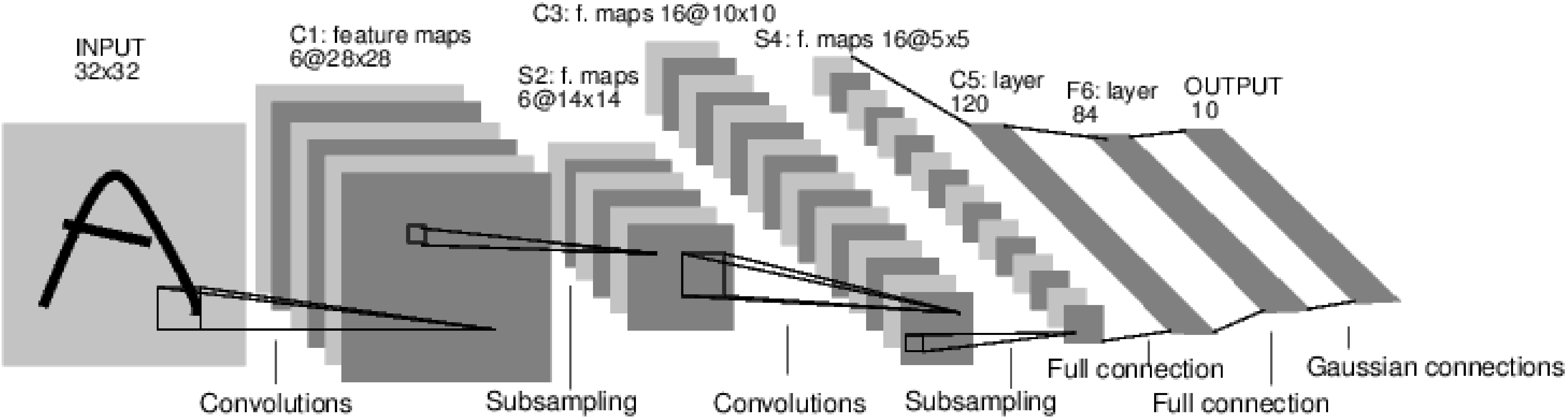
Convolutional Neural Networks



Convolutional Neural Networks

Lenet5 – Lecun, et al, 1998

- Convnets for digit recognition

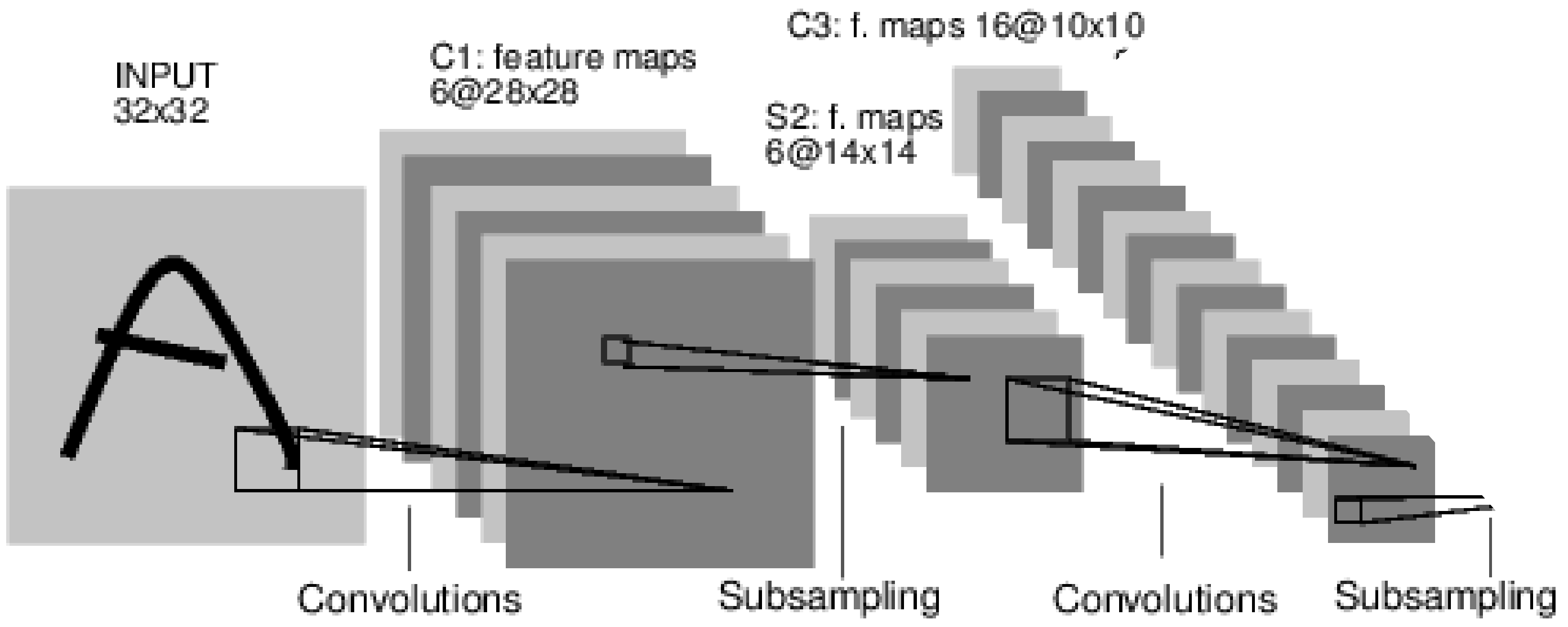


LeCun, Yann, et al. "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86.11 (1998): 2278-2324.

Question:

How big many convolutional weights between S2 and C3?

- S2: 6 channels @14x14
- Conv: 5x5, pad=0, stride=1
- C3: 16 channels @ 10x10



Question:

How big many convolutional weights between S2 and C3?

- S2: 6 channels @14x14
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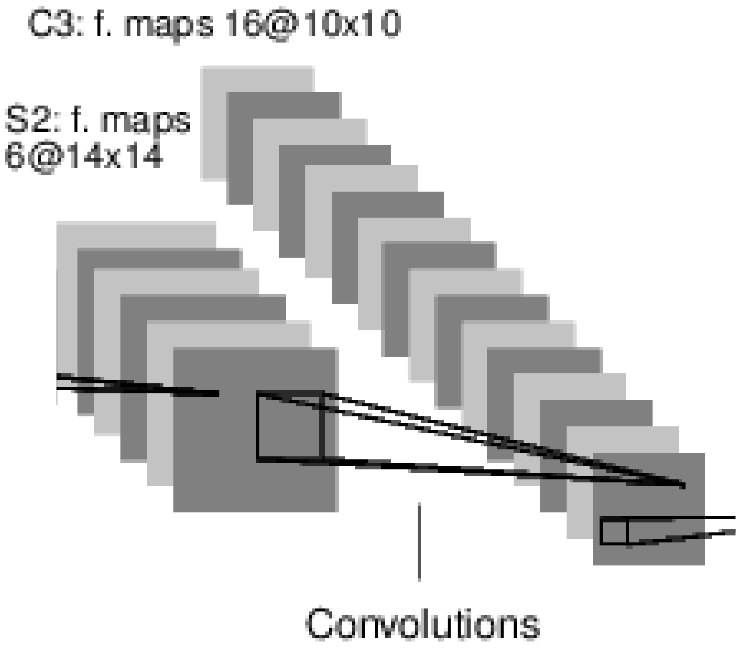
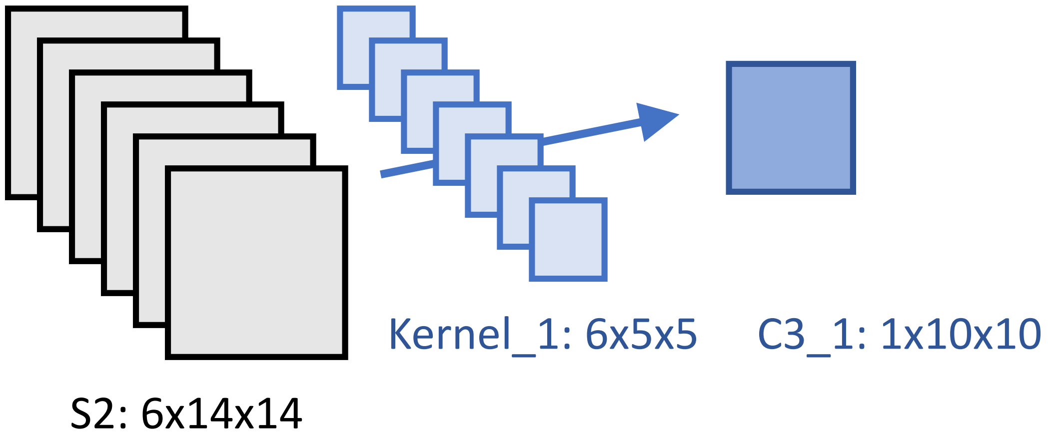
- C3: 16 channels @ 10x10



One image in C3 is actually the result of a 3D convolution

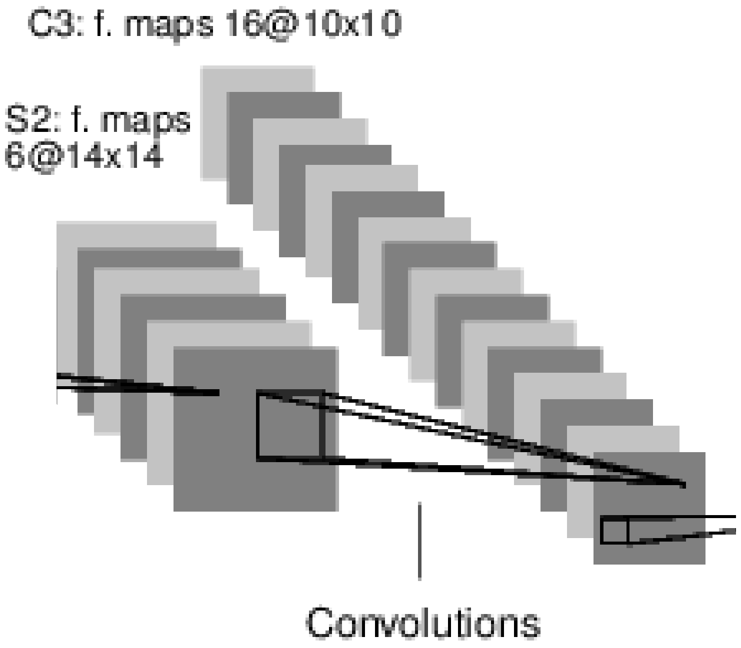


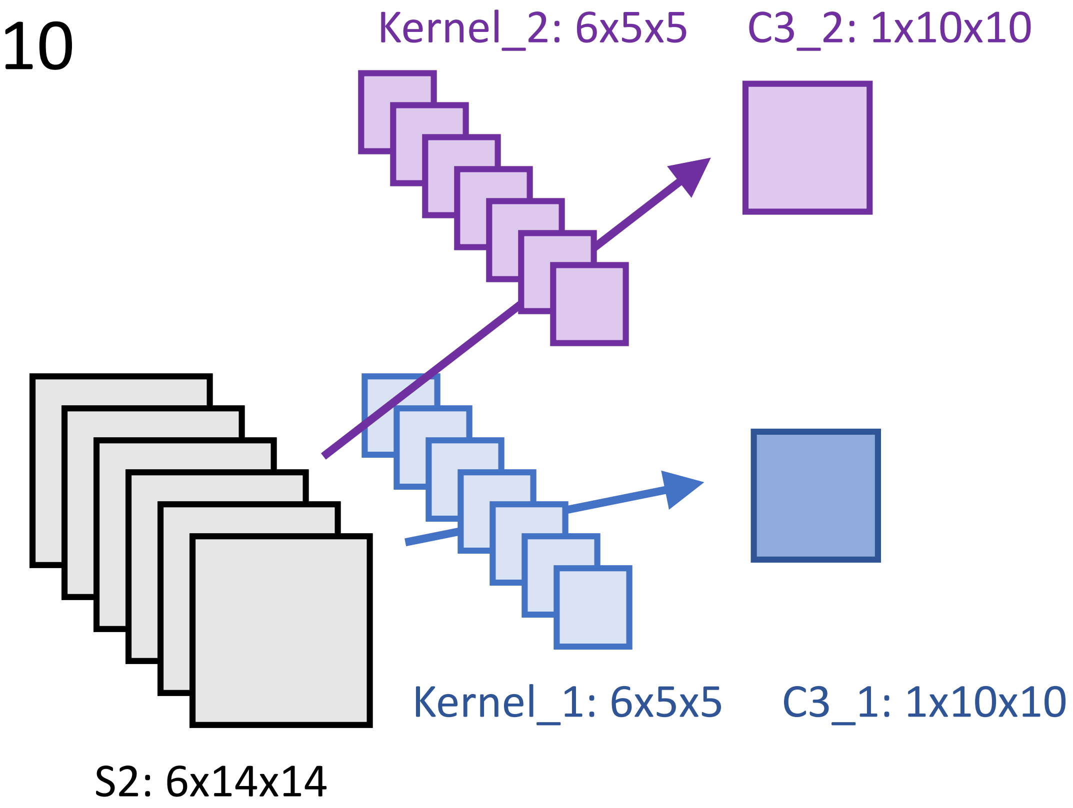
Question:

How big many convolutional weights between S2 and C3?

- S2: 6 channels @14x14
- Conv: 5x5, pad=0, stride=1
- C3: 16 channels @ 10x10

Each image in C3 convolved S2
convolved with a different 3D kernel



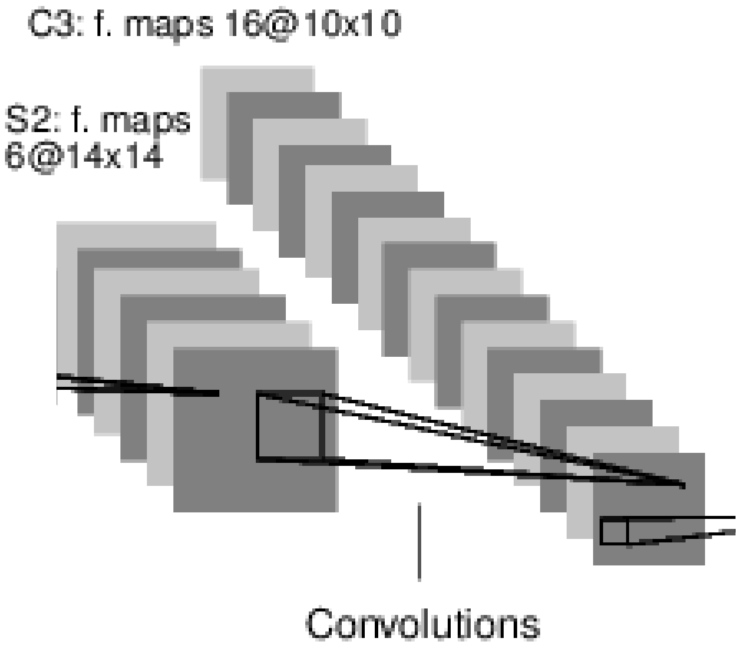


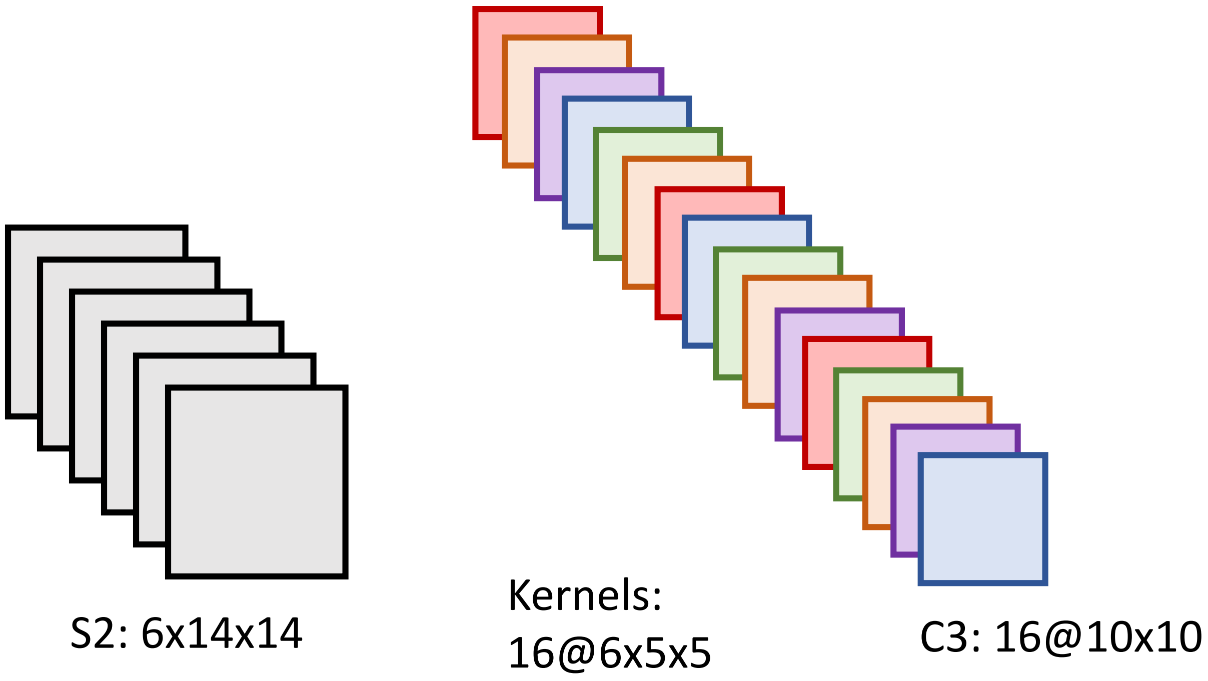
Question:

How big many convolutional weights between S2 and C3?

- S2: 6 channels @14x14
- Conv: 5x5, pad=0, stride=1
- C3: 16 channels @ 10x10

The 16 images in C3 are the result of doing 16 3D convolutions of S2 with 16 different 6x5x5 kernels. Assuming no bias term, this is 16x6x5x5 weights!

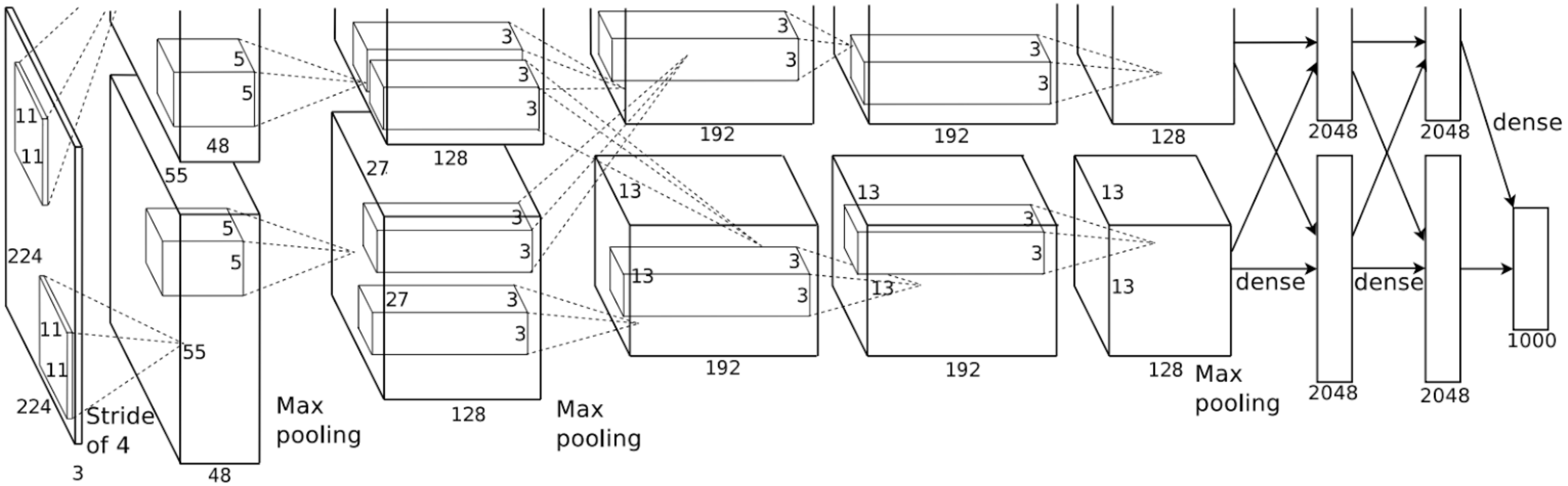




Convolutional Neural Networks

Alexnet – Lecun, et al, 2012

- Convnets for image classification
- More data & more compute power



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." NIPS, 2012.