LECTURE 4:

CONVOLUTIONAL NEURAL NETWORKS

University of Washington, Seattle

Fall 2024

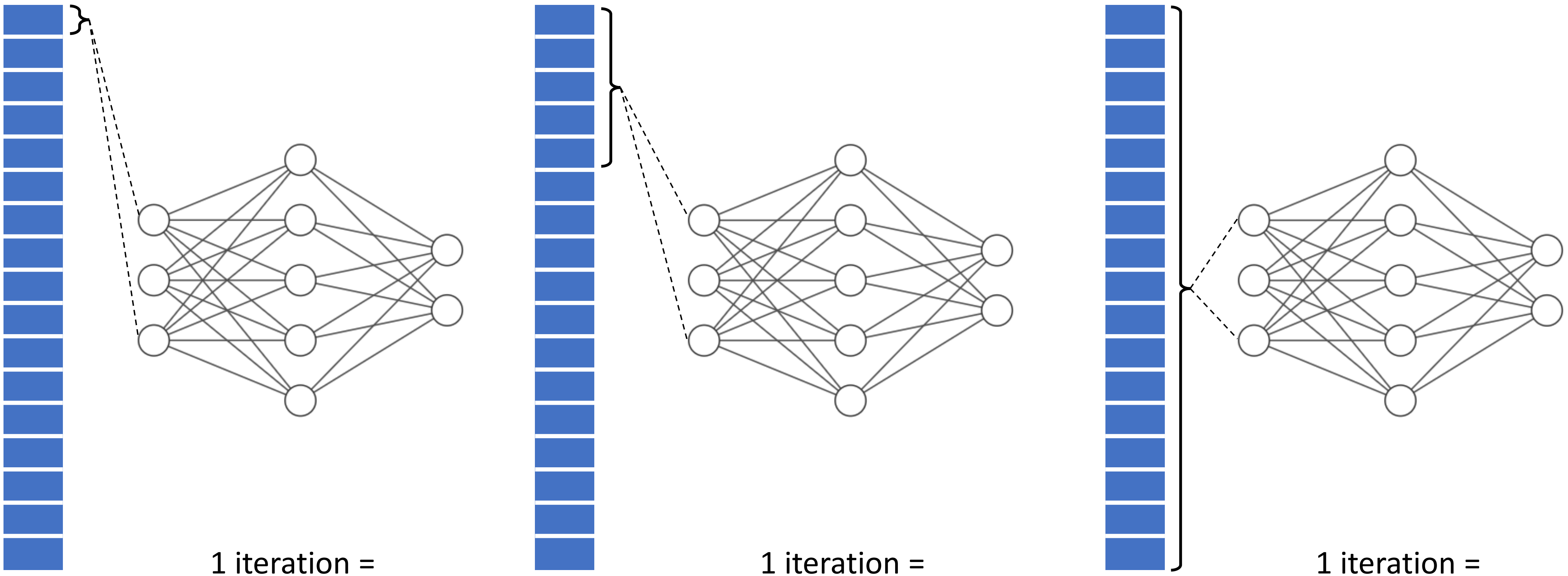
Previously in EEP 596…

Training Dataset

SGD

Mini-batch

Batch GD

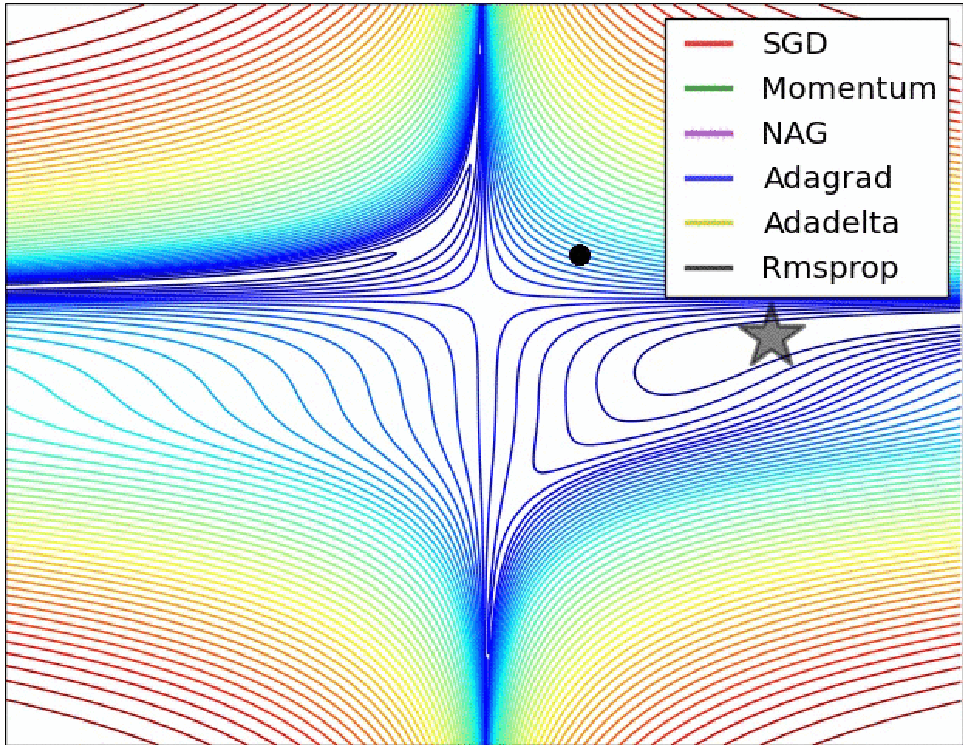


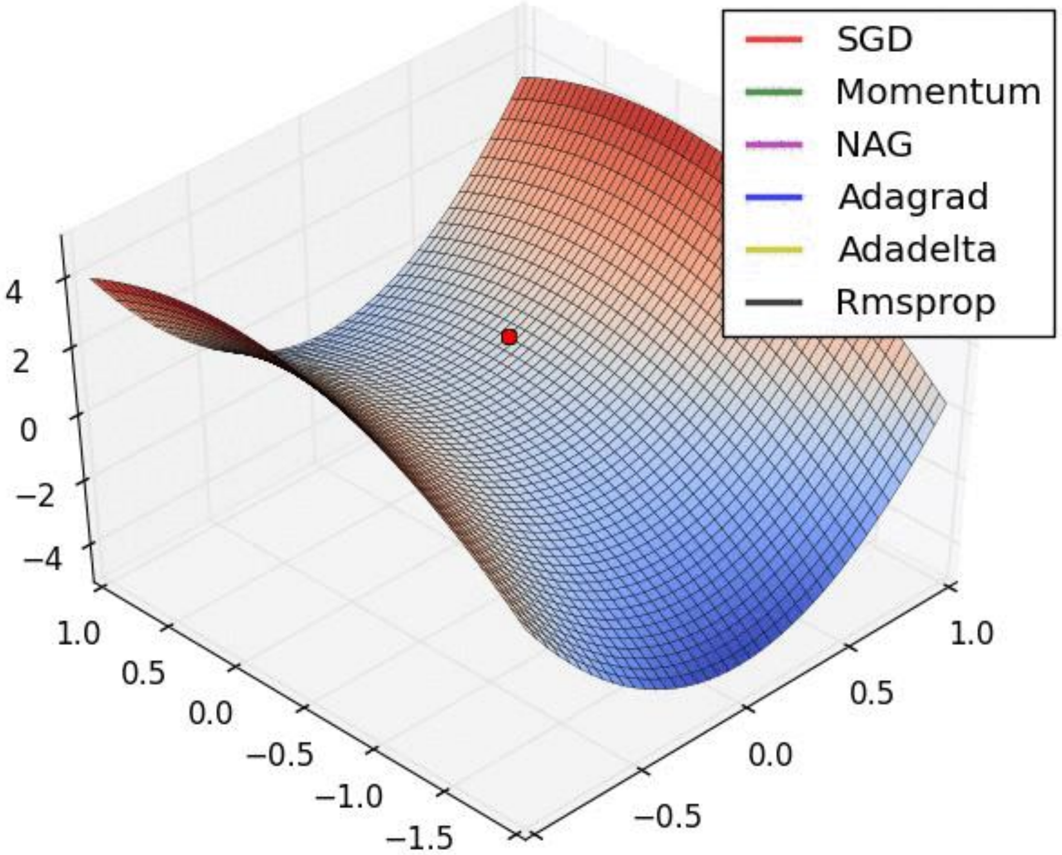
1 iteration =
Fwd/bwd pass 1 training sample

1 iteration =
Fwd/bwd pass n-training samples
(n < total # of training samples)

1 iteration =
Fwd/bwd pass full training samples

Previously in EEP 596...





Previously in EEP 596...

Optimizers

- Vanilla SGD
- Momentum
- AdaGrad
- RMSProp
- Adam

Balance

Optimization Techniques

- Data splitting (Train/Val/Test)
- Regularization
- Data normalization
- Batch-normalization
- Network initialization
- Hyperparameter tunings

OUTLINE

Part 1: Need for CNNs

- Limitation of MLP
- Convolution Layer

Part 2: Convolution Filters

- 2D convolution
- Stride
- Padding
- Volume convolutions

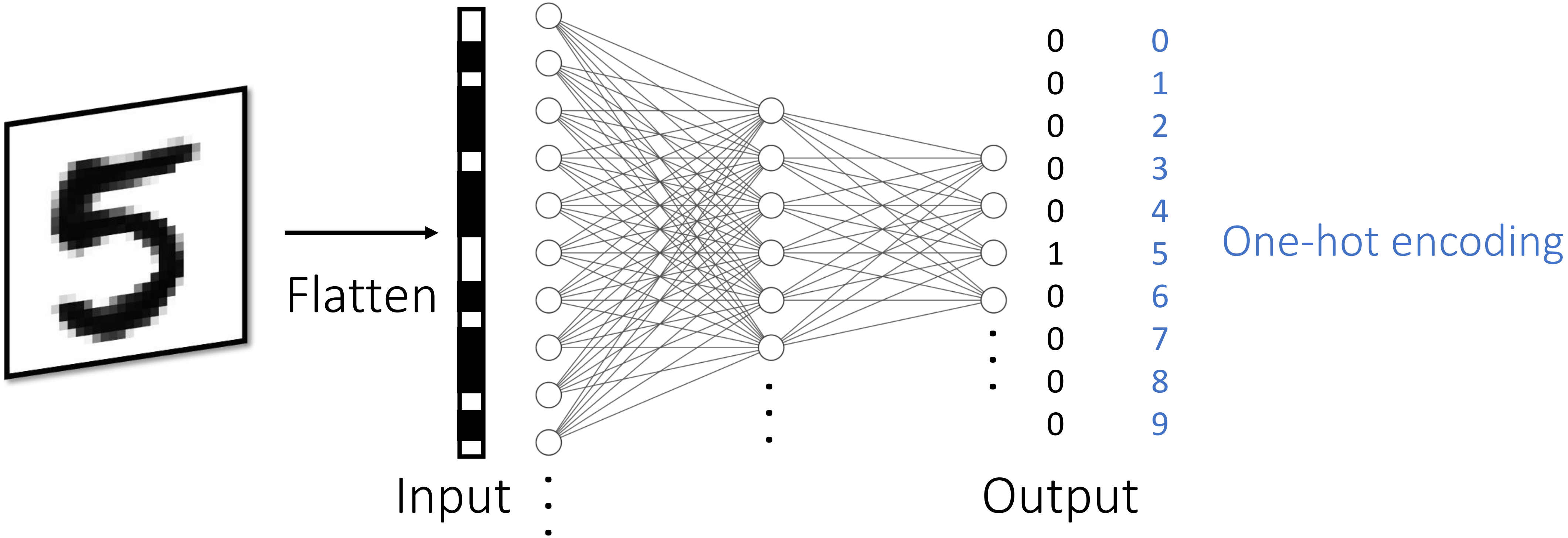
Part 3: Composing Convolutional Neural Networks

- Convolution Layer
- Pooling Layers
- Benefits and challenges of CNNs
- Historical CNN examples

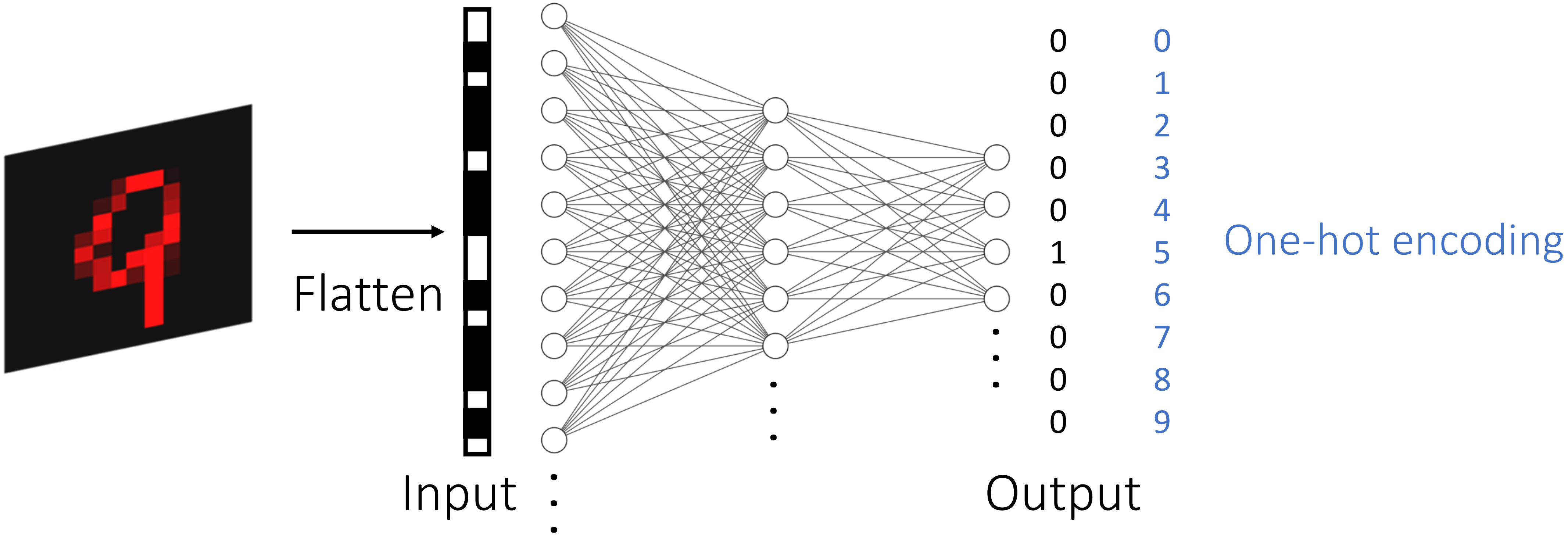
PART 1:

Need for CNNs

MLP for Image Classification (Lab 3)



MLP for Image Classification (Lab 3)



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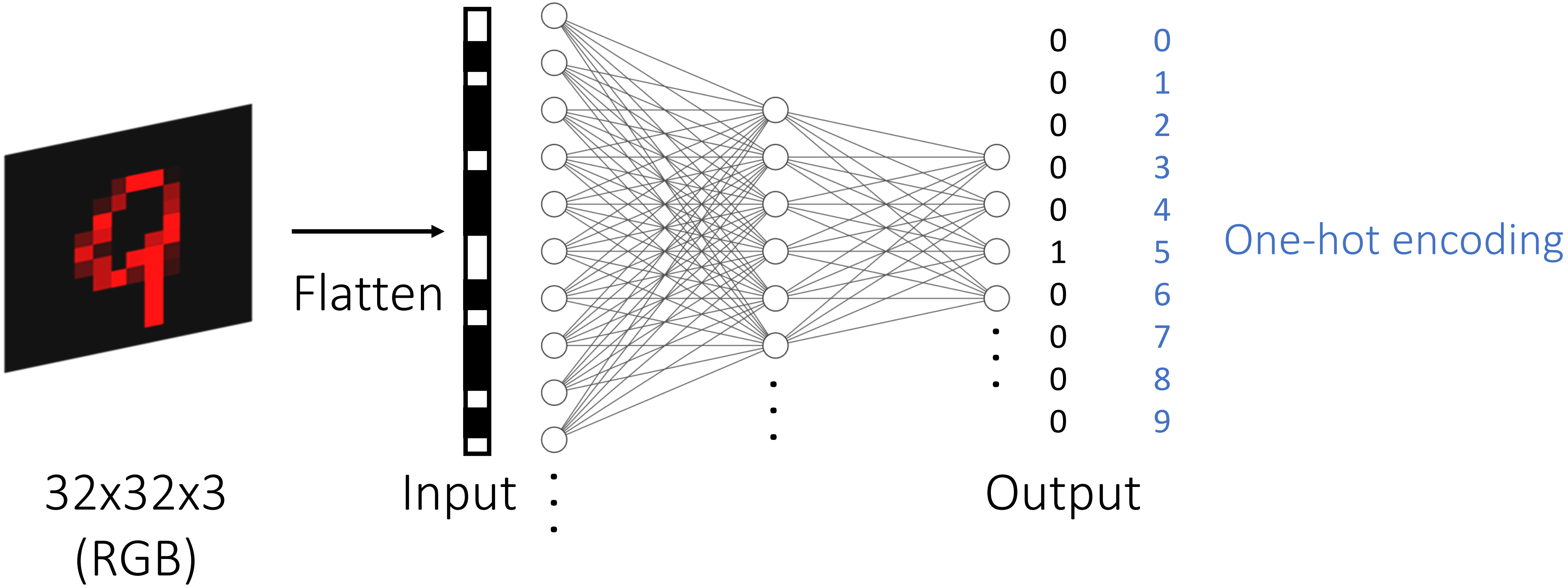

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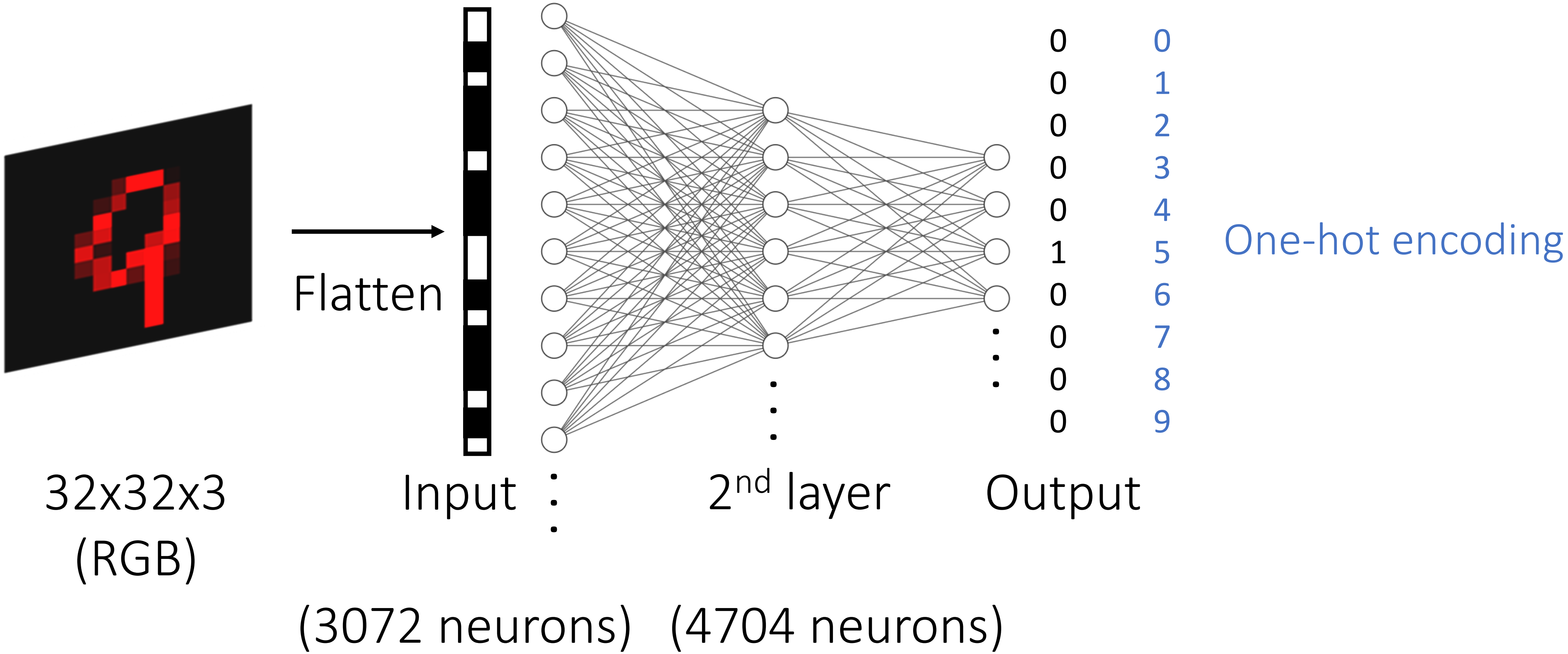
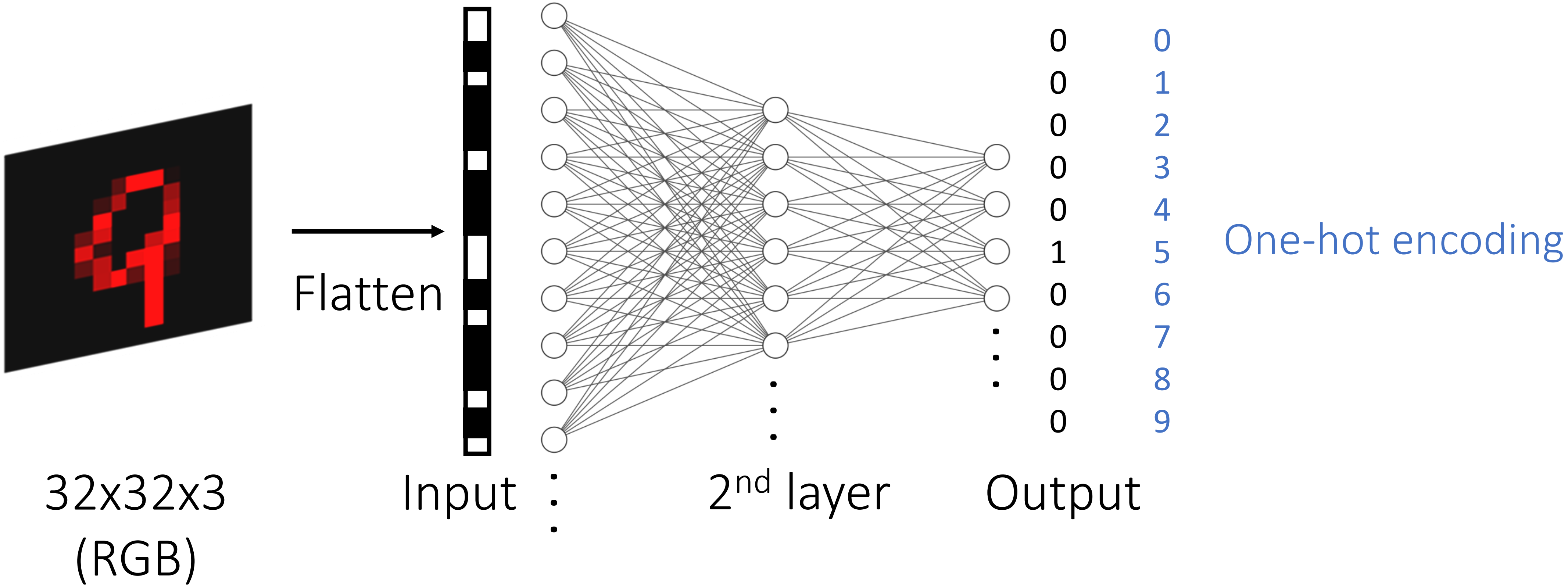


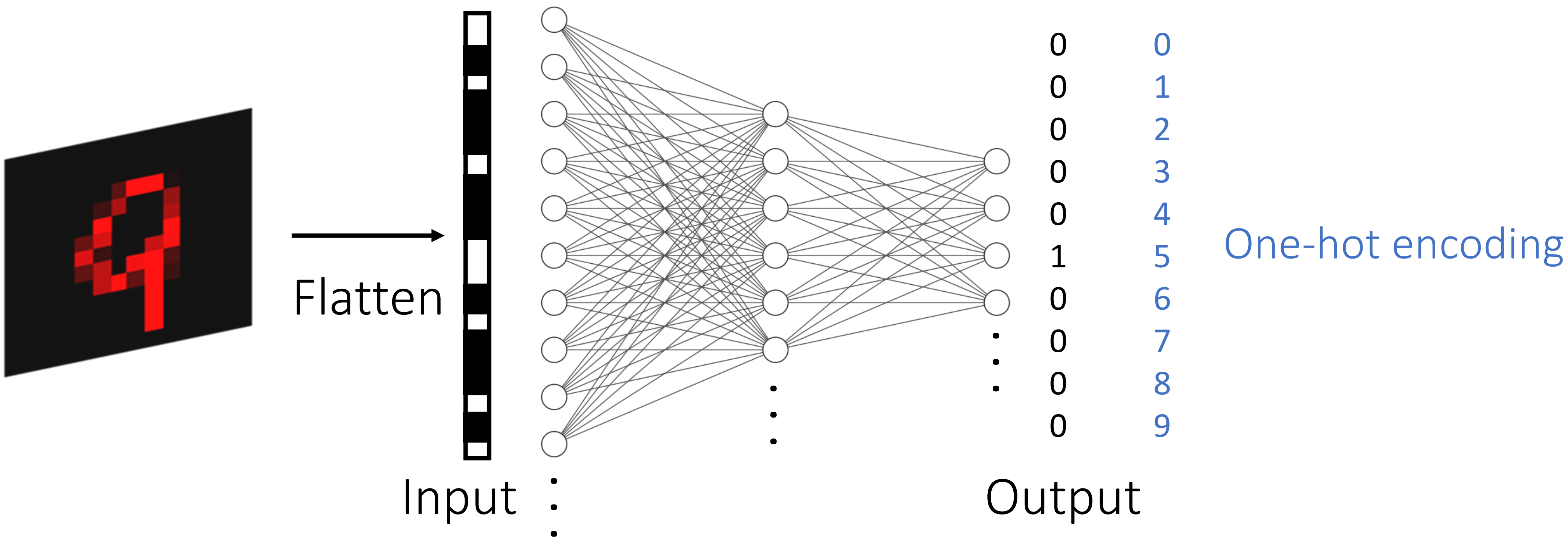
MLP for Image Classification (Lab 3)



(3072 neurons) (4704 neurons)

$$W^{[1]} = [n^{[l-1]}, n^{[l]}] = [3072, 4704] \approx 14M$$

MLP for Image Classification (Lab 3)

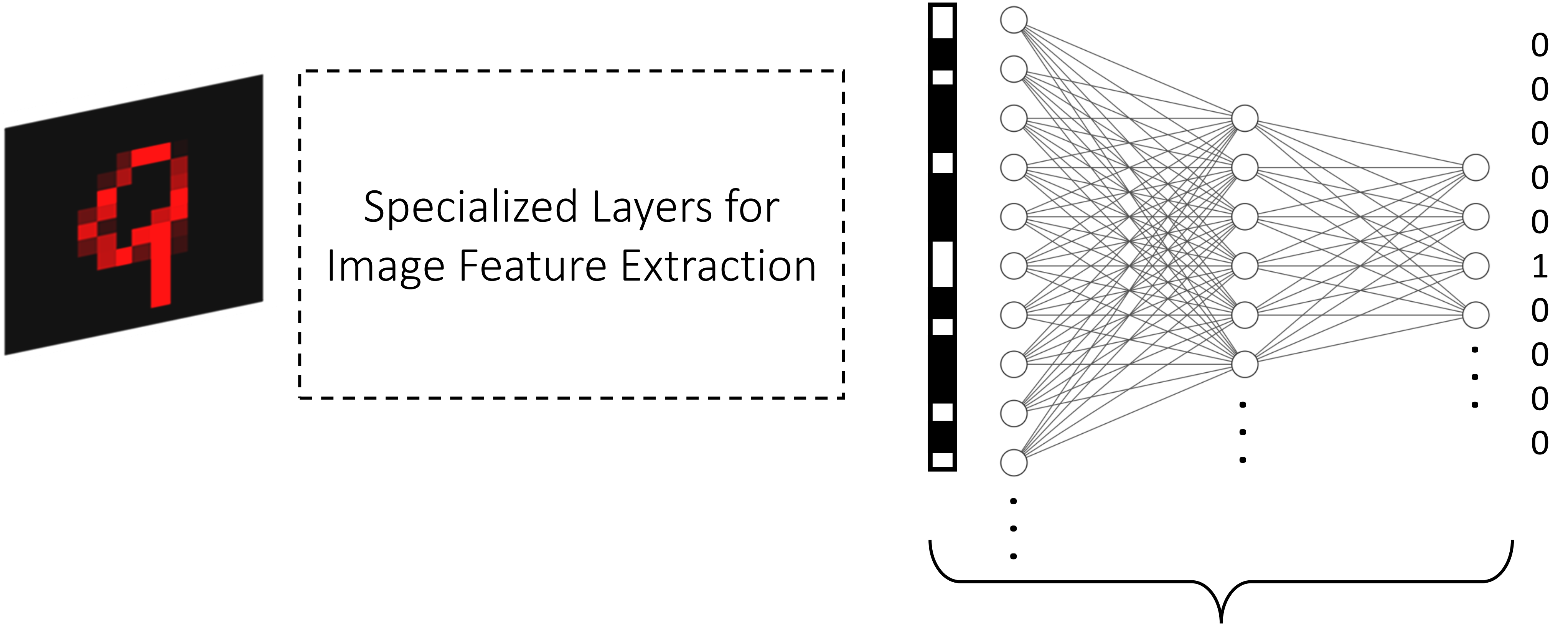


Great at Classification

Not as good with Extracting image features

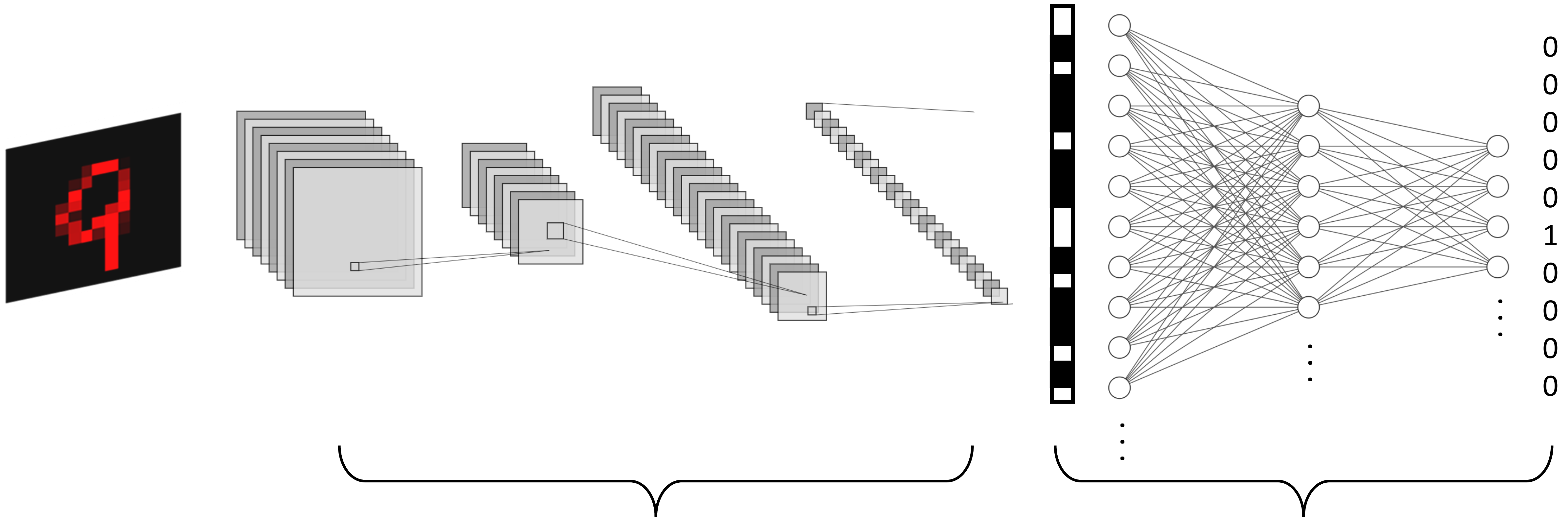
Too many parameters when Flattening images

Specialized Layers for Feature Extractions



Fully connected layers
(Classifier)

Full CNN Architecture



Convolution Layers + Pooling Layers
(Image feature extraction)

Fully connected layers
(Classifier)

PART 2:

Convolution Filters

Image Convolution

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

Input Image

$*$

1	0	1
0	1	0
1	0	1

Kernel

4	3	4

Convoluted Feature

$$(1 * 1) + (0 * 0) + (0 * 1) +$$
$$(0 * 1) + (1 * 1) + (0 * 0) +$$
$$(1 * 1) + (0 * 0) + (1 * 1) +$$

Traditional Convolution Filters

Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

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CNNs Learn these features instead of us guessing

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CNNs Learn these features instead of us guessing

1000 filters

3x3=9*1000 = **9K** parameters

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CNNs Learn these features instead of us guessing

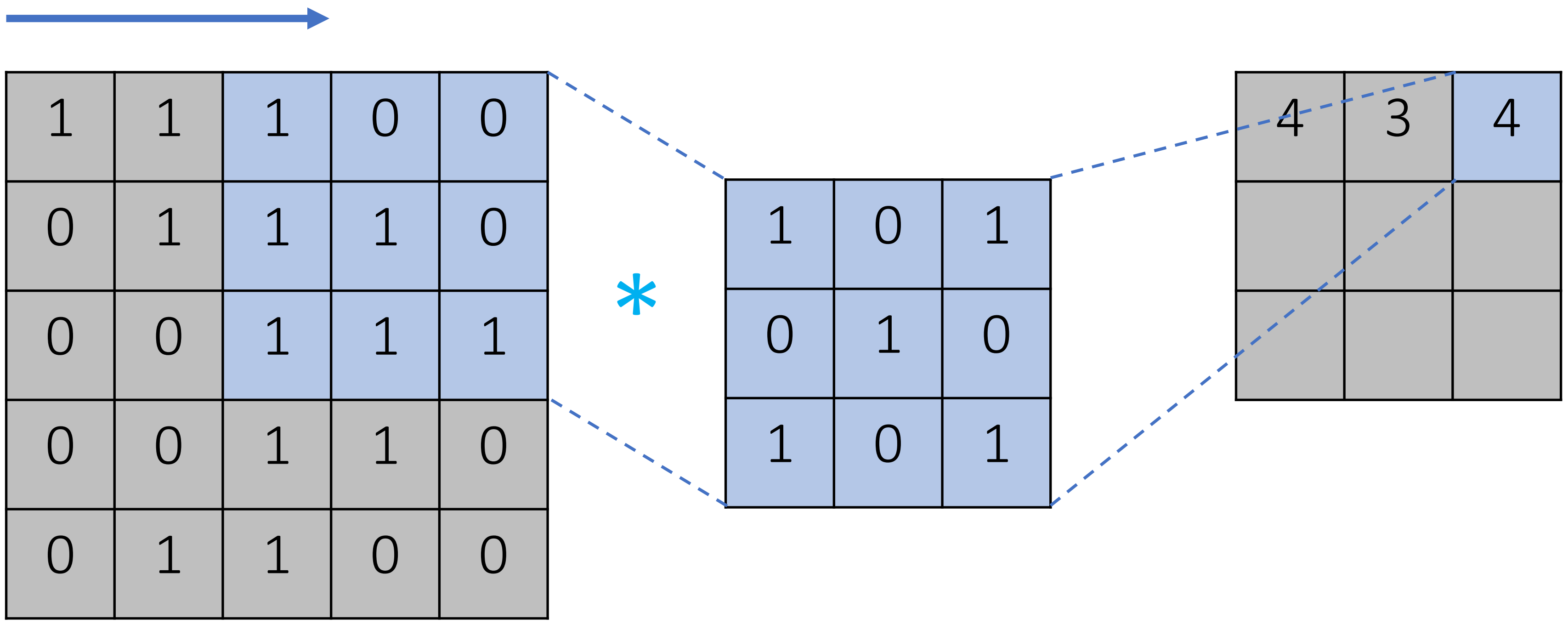
1000 filters

3x3=9*1000 = **9K** parameters

14M vs 9k

Several orders of magnitude of difference in parameters

Convolution Dimensions

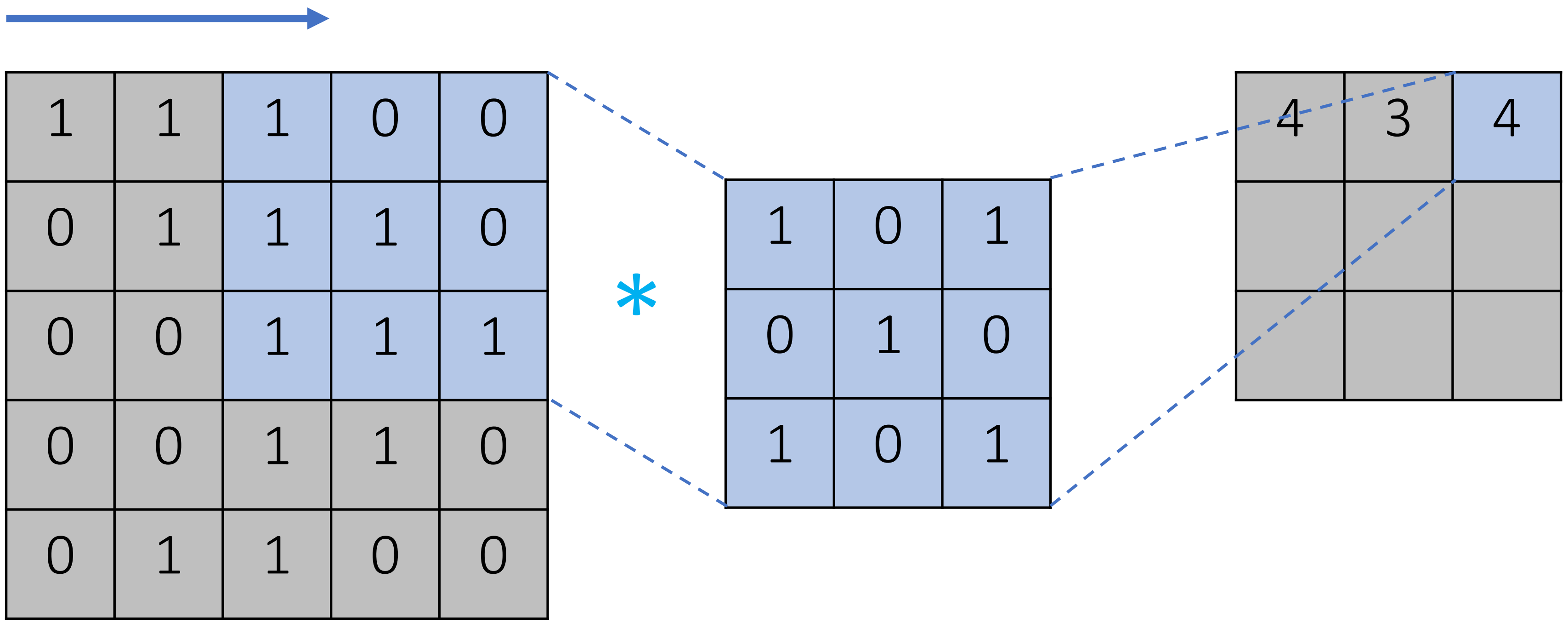


Input Image
(5 x 5)

Filter
(3 x 3)

Convoluted Feature
(3 x 3)

Convolution Dimensions



Input Image
(5 x 5)
n x n

Filter
(3 x 3)
f x f

Convoluted Feature
(3 x 3)
(n – f + 1) x (n – f + 1)

Stride

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

Input Image

1	0	1
0	1	0
1	0	1

Filter

4		

Convoluted Feature

Stride = 1

Stride

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

Input Image

*

1	0	1
0	1	0
1	0	1

Filter

4	3	

Convoluted Feature

Stride = 1

Stride

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

Input Image

*

1	0	1
0	1	0
1	0	1

Filter

4	3	4

Convoluted Feature

Stride = 1

Stride

Input = 5 x 5

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

Input Image

*

1	0	1
0	1	0
1	0	1

Filter

Output = 3 x 3

4	3	4
3		

Convoluted Feature

Stride = 1

Stride

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

Input Image

*

1	0	1
0	1	0
1	0	1

Filter

4	

Convoluted Feature

Stride = 2

Stride

Input Image

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

$*$

Filter

1	0	1
0	1	0
1	0	1

Convoluted Feature

4	4

Stride = 2

Stride

Input = 5 x 5

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

Input Image

*

1	0	1
0	1	0
1	0	1

Filter

Output = 2 x 2

4	4
2	

Convoluted Feature

Stride = 2

Padding

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

Input Image
(5x5)

Padding = 1

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

Padded Image
(7x7)

Padding

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

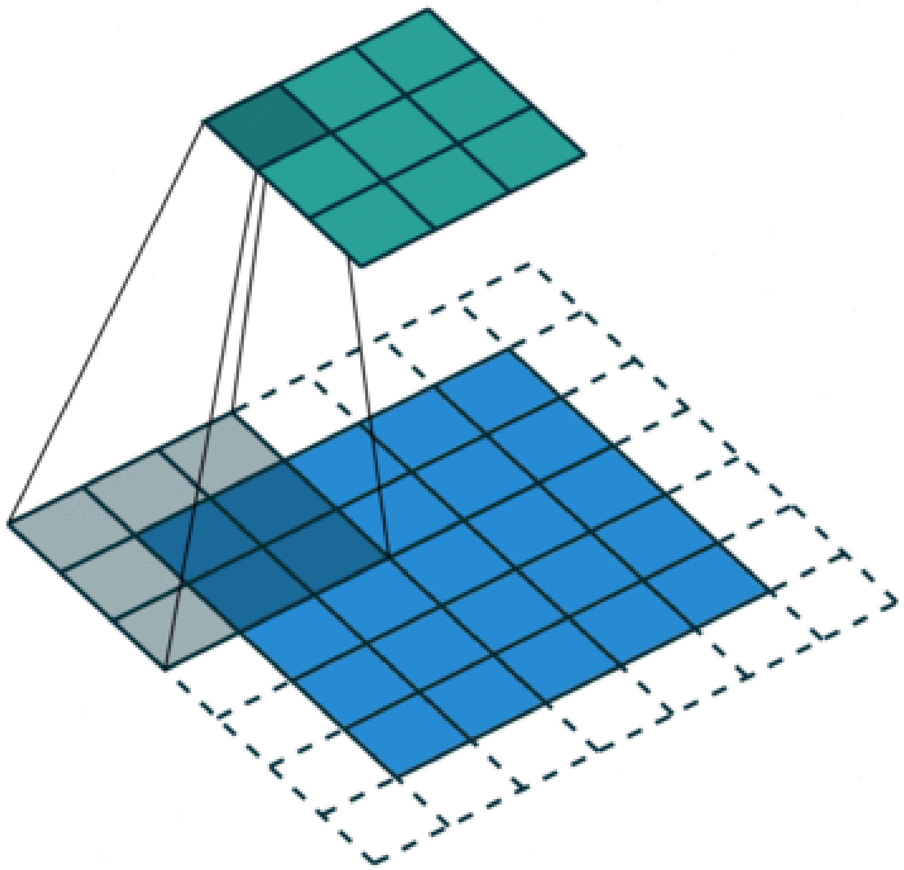
Input Image
(5x5)

Padding = 2

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

Padded Image
(9x9)

Generalized Dimensions



$$(n) * (n)$$

$$\downarrow$$

$$\left(\frac{n+2p-f}{s}+1\right) * \left(\frac{n+2p-f}{s}+1\right)$$

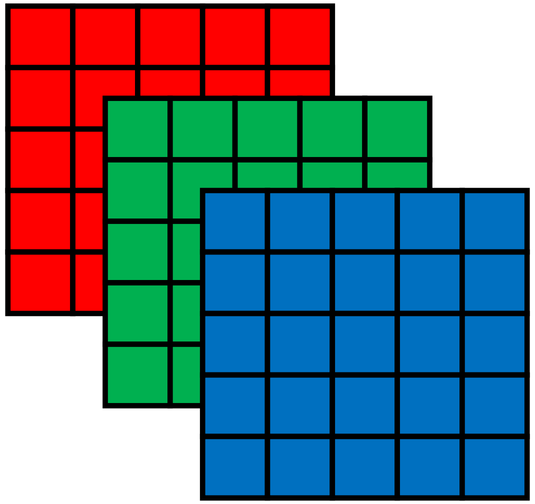
n: original image dimensions

p: padding size

f: filter dimension

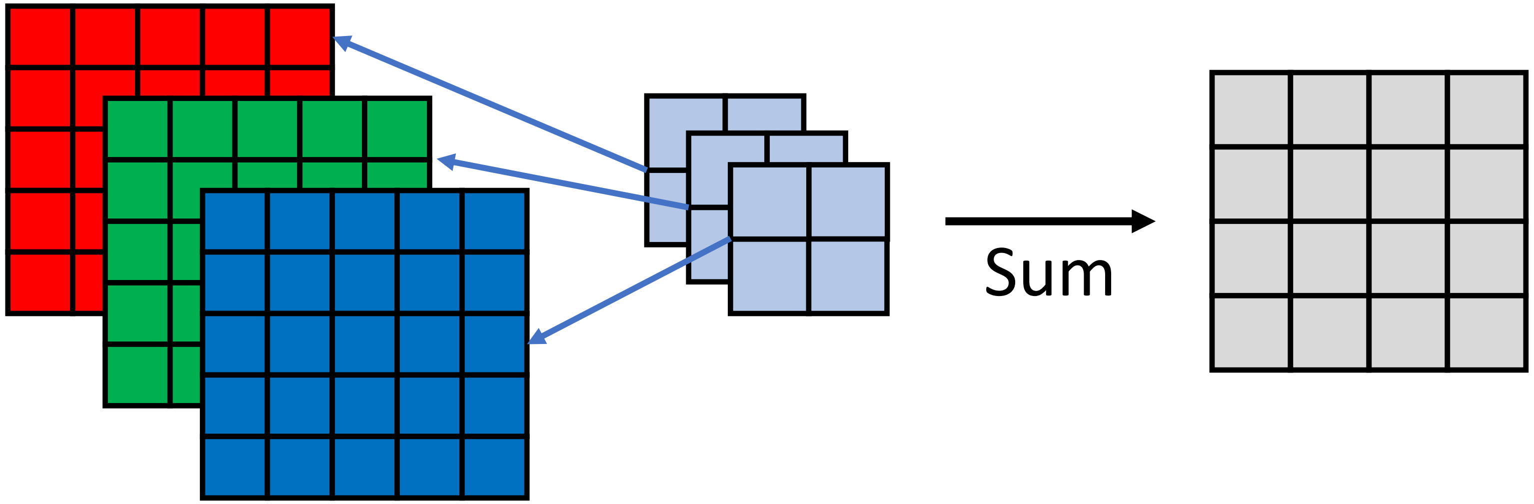
s: stride

Volume Convolution



Input
(5x5x3)

Volume Convolution



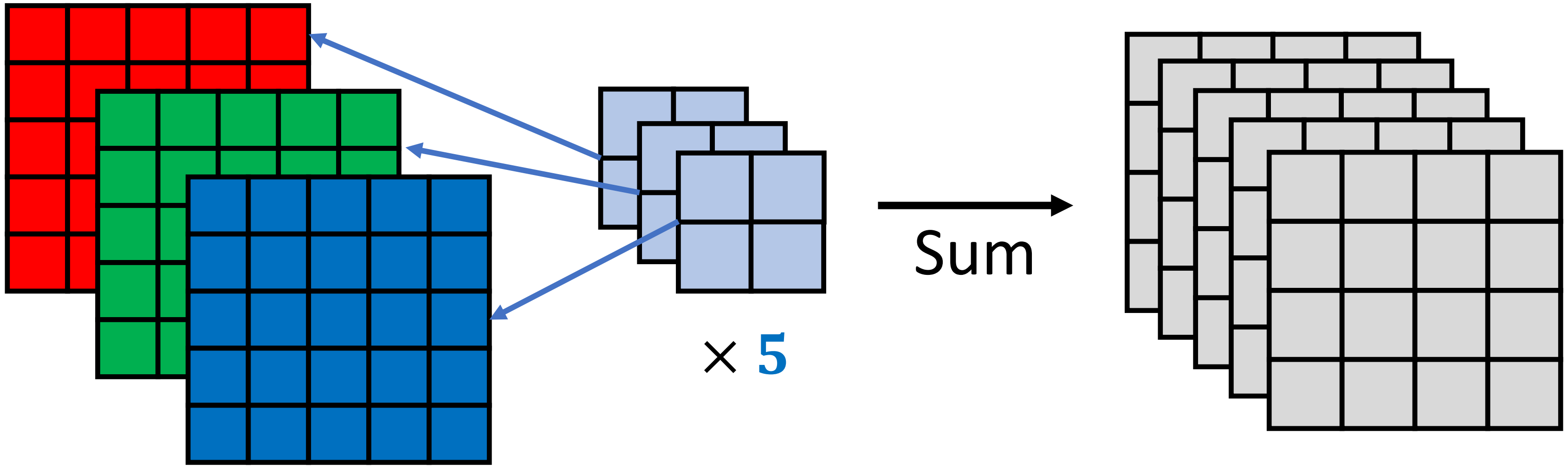
Input
(5x5x3)

Filters
(2x2x3)

Output
(4x4x1)

(Height x Width x Channels)

Volume Convolution (multiple filters)



Input
(5x5x3)

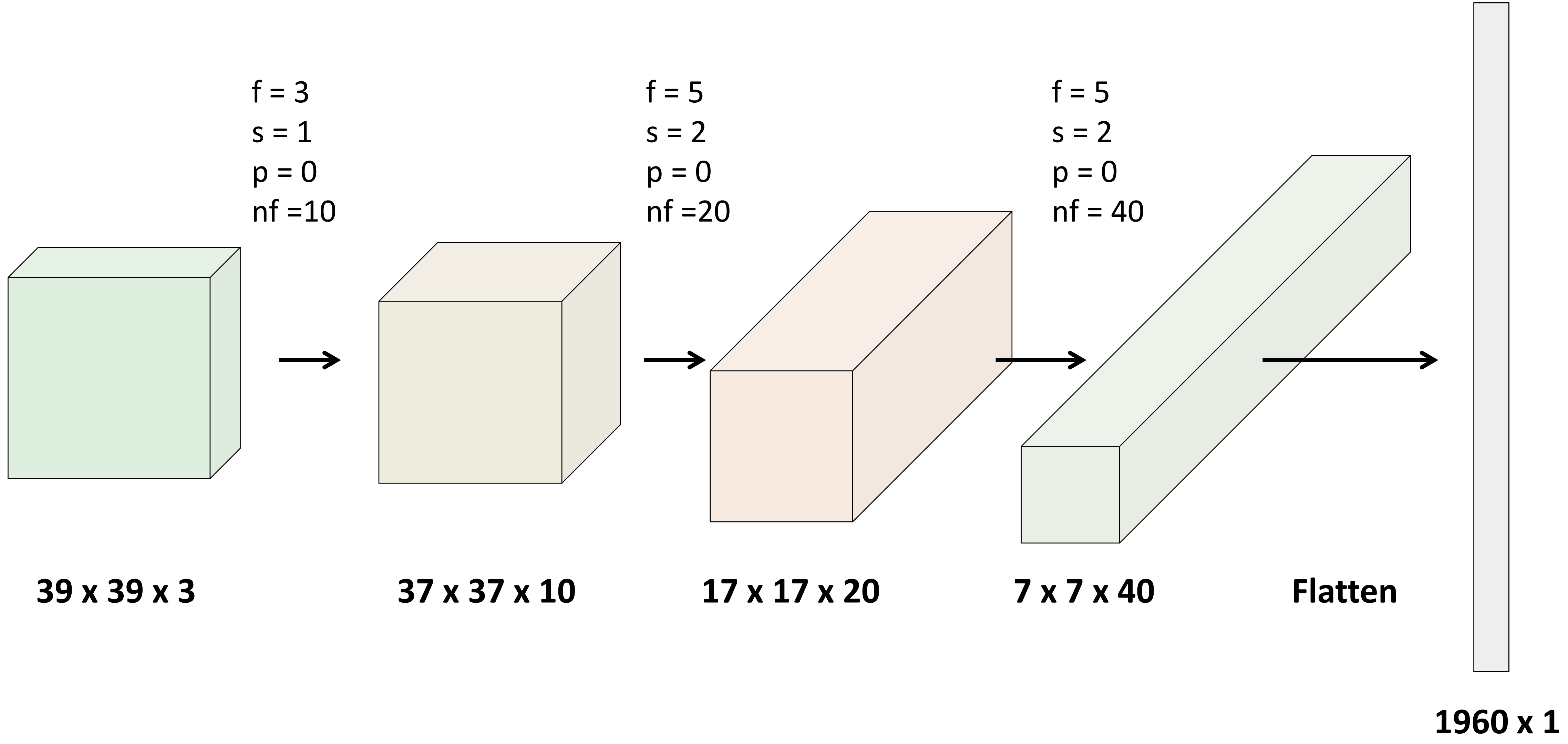
Filters
(5x2x2x3)

Output
(5x4x4x1)

PART 3:

Composing CNNs

CNN example


f = 3
s = 1
p = 0
nf =10
f = 5
s = 2
p = 0
nf =20
f = 5
s = 2
p = 0
nf = 40
39 x 39 x 3
37 x 37 x 10
17 x 17 x 20
7 x 7 x 40
Flatten
1960 x 1

Typical CNN Layers

- **Convolutional Layer (CONV)**
- Pooling Layer (POOL)
- **Fully Connected (FC)**
- Normalization (NORM)

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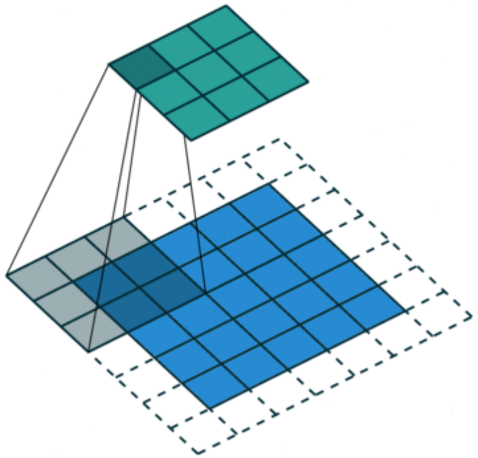
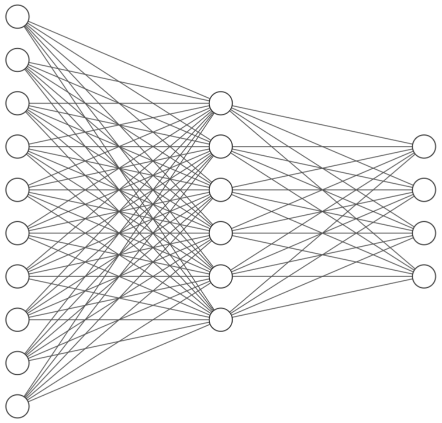
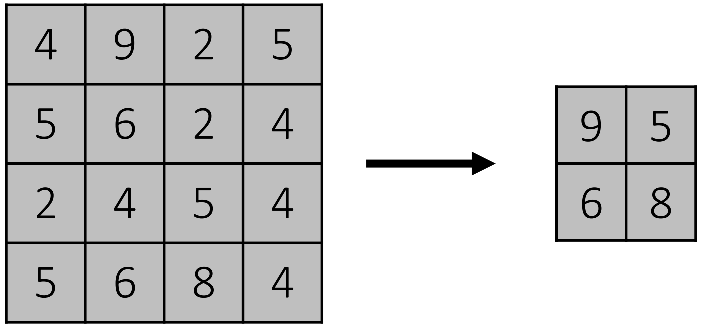
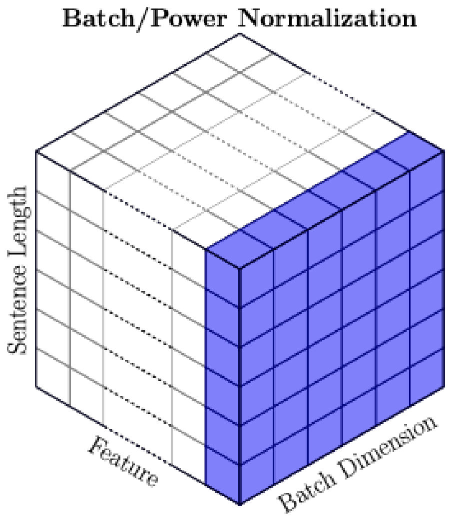




Typical CNN Layers

- Convolutional Layer (CONV)
- **Pooling Layer (POOL)**
- Fully Connected (FC)
- **Normalization (NORM)**
  Not commonly used





Max Pooling and Average Pooling

4	9	2	5
5	6	2	4
2	4	5	4
5	6	8	4

→

9	5
6	8

Max pool

4	9	2	5
5	6	2	4
2	4	5	4
5	6	8	4

→

6.0	3.3
4.3	5.3

Average pool

Pooling Layers

Input Image

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Max pool

Dim= 3 x 3

Stride = 1

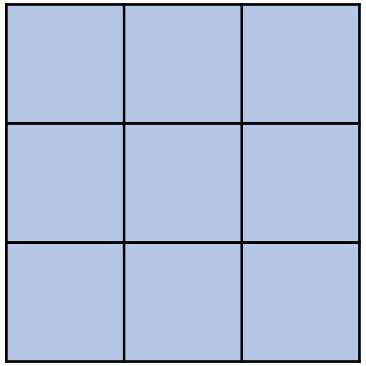
Pooled Feature

9		

Pooling Layers

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Input Image



Max pool

Dim= 3 x 3

Stride = 1

9	10	

Pooled Feature

Pooling Layers

Input Image

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Max pool

Pooled Feature

9	10	15

Dim= 3 x 3
Stride = 1

Pooling Layers

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Input Image

Avg pool

Dim= 3 x 3
Stride = 1

3		

Pooled Feature

Pooling Layers

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Input Image

Avg pool

3	4.8	

Pooled Feature

Dim= 3 x 3

Stride = 1

Pooling Layers

1	2	5	10	7
0	5	1	4	0
0	4	9	3	15
0	0	2	4	5
0	7	2	0	0

Input Image

Avg pool

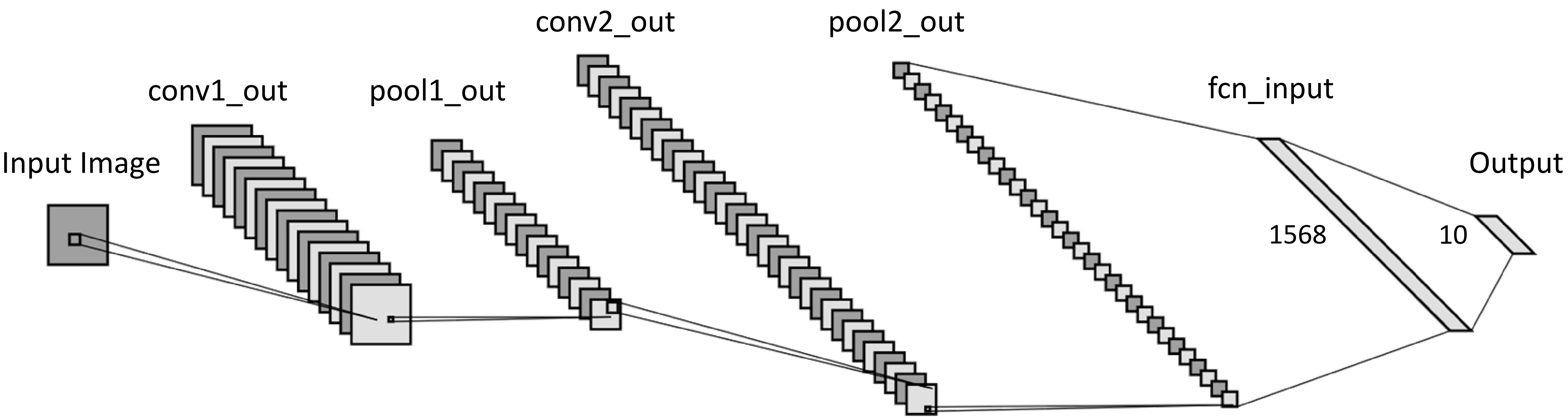
Dim= 3 x 3

Stride = 1

3	4.8	6

Pooled Feature

Full CNN example



self.cnn1
- In-channel # : 1
- Out-channel # : 16
- Kernel size : 5
- Stride = 1
- Padding = 2
- ReLU

self.maxpool1
Kernel size : 2

self.cnn2
- In-channel # : 16
- Out-channel # : 32
- Kernel size : 5
- Stride = 1
- Padding = 2
- ReLU

self.maxpool2
Kernel size : 2

Flatten

self.fc1
1568 → 10

Benefits of CNNs

Parameter Sharing

Filter can be useful in different parts of the input (image)

Sparsity of Connections

- In each layer each output value depends only on small number of inputs (local)
- Translation invariance

Challenges of CNNs

Computational Complexity

Convolutions are expensive $O(N^2 n^4)$

Deeper Structure Needed

In each layer each output value depends only on small number of inputs (local)

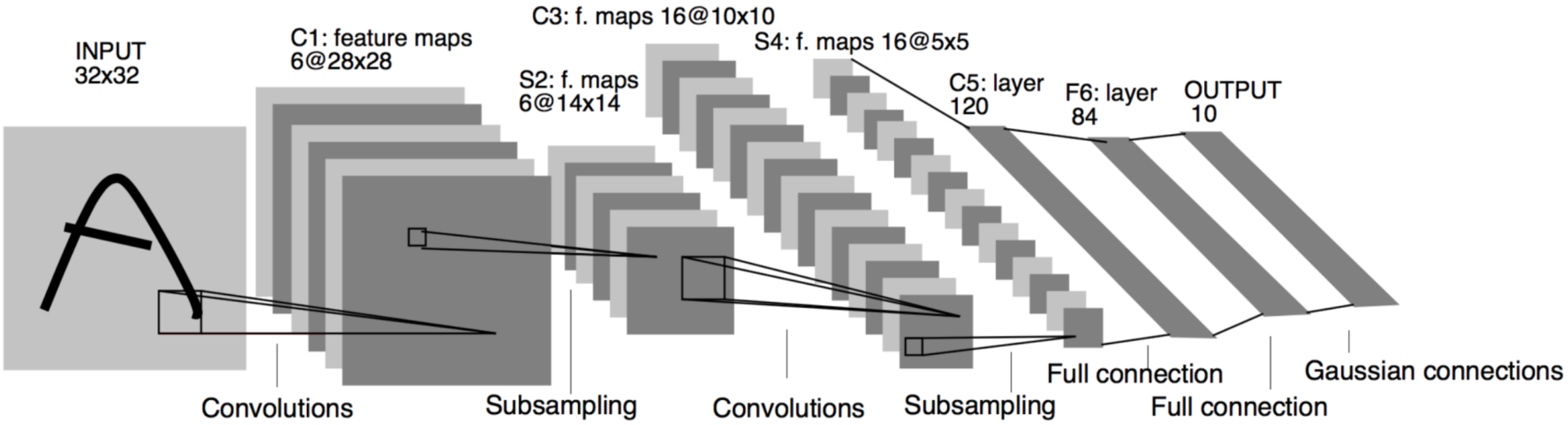
Popular CNN Architectures (LeNet 5)


Yann LeCun


Leon Bottou

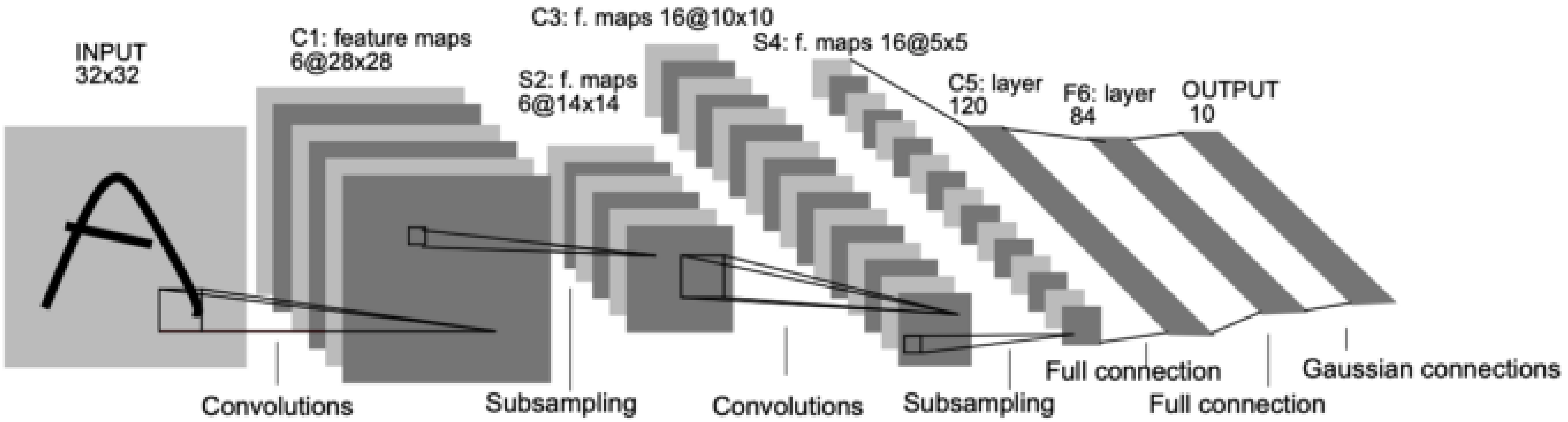

Yoshua Bengio


Patrick Haffner

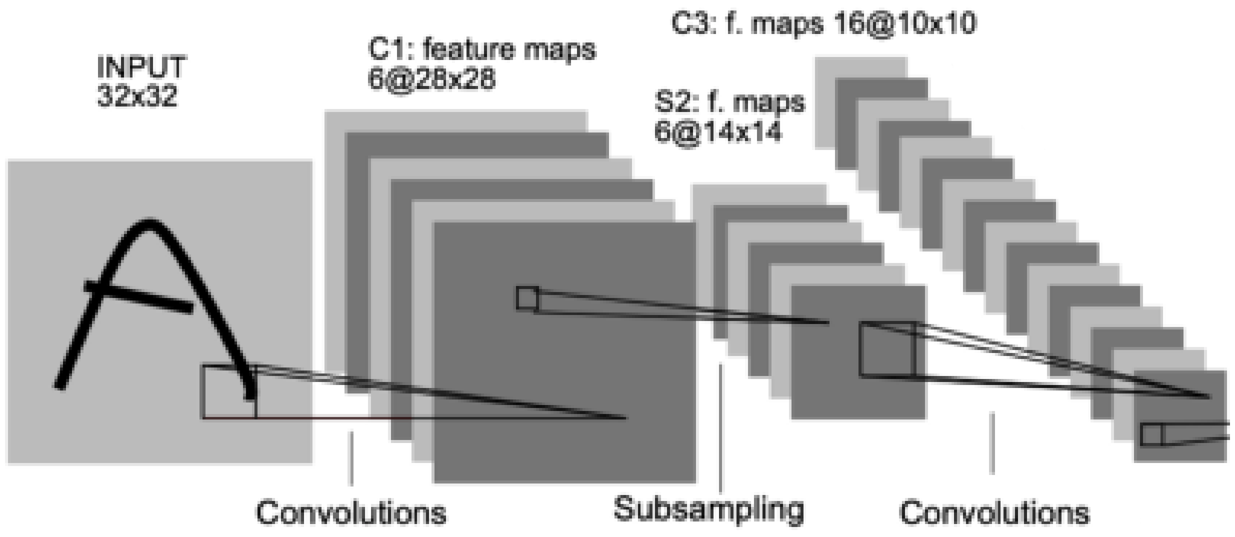


Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 1998.

LeNet-5 (1998)


INPUT
32x32
C1: feature maps
6@28x28
S2: f. maps
6@14x14
C3: f. maps 16@10x10
S4: f. maps 16@5x5
C5: layer
120
F6: layer
84
OUTPUT
10
Convolutions
Subsampling
Convolutions
Subsampling
Full connection
Full connection
Gaussian connections

LeNet-5 (1998)



Layer 1:

- Convolutional Layer with 6 kernels
- kernel size of 5x5
- Padding = 2, stride = 1

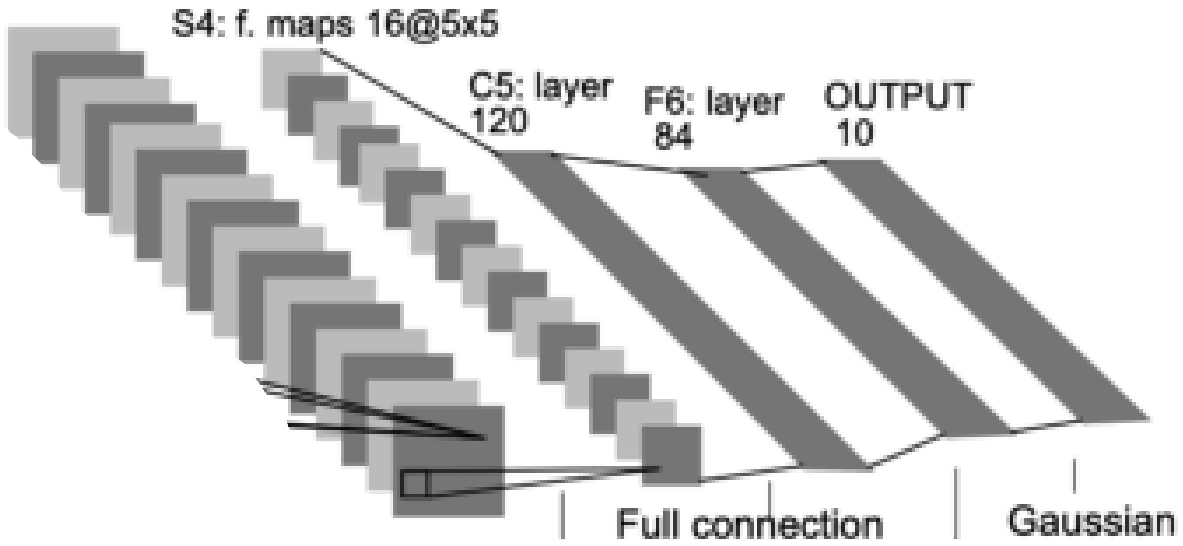
Layer 2:

- Average pooling (2x2 kernel)

Layer 3:

- Convolutional layer with 16 kernels
- kernel size of 5x5
- Padding = 0, stride = 1

LeNet-5 (1998)



Layer 4:

Average pooling (2x2 kernel)

Layer 5:

- Convolutional layer with 120 kernels
- Kernel size of 5x5
- Padding = 0, stride = 1

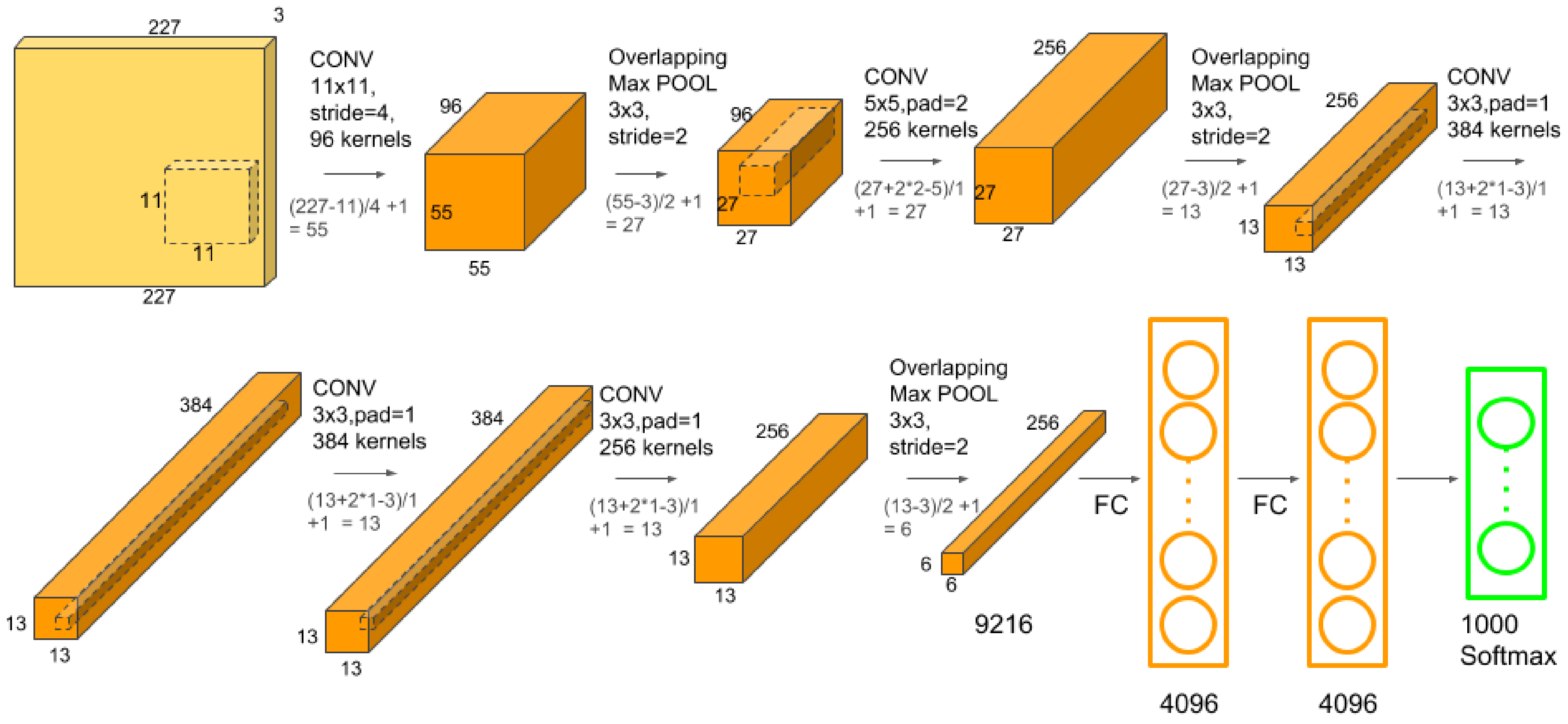
Layer 6:

- Fully Connected Layer
- Input dimension = 120
- Output dimension = 84

Layer 7:

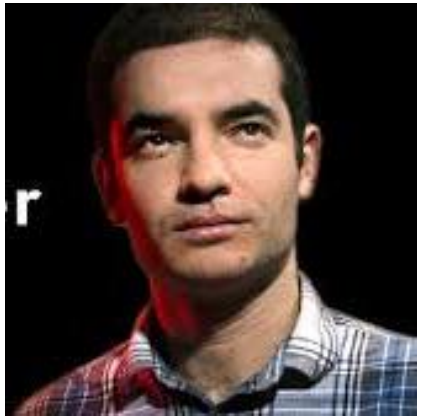
- Fully Connected Layer
- Input dimension = 84
- Output dimension = 10

AlexNet (2012)



AlexNet (2012)

Alex Krizhevsky

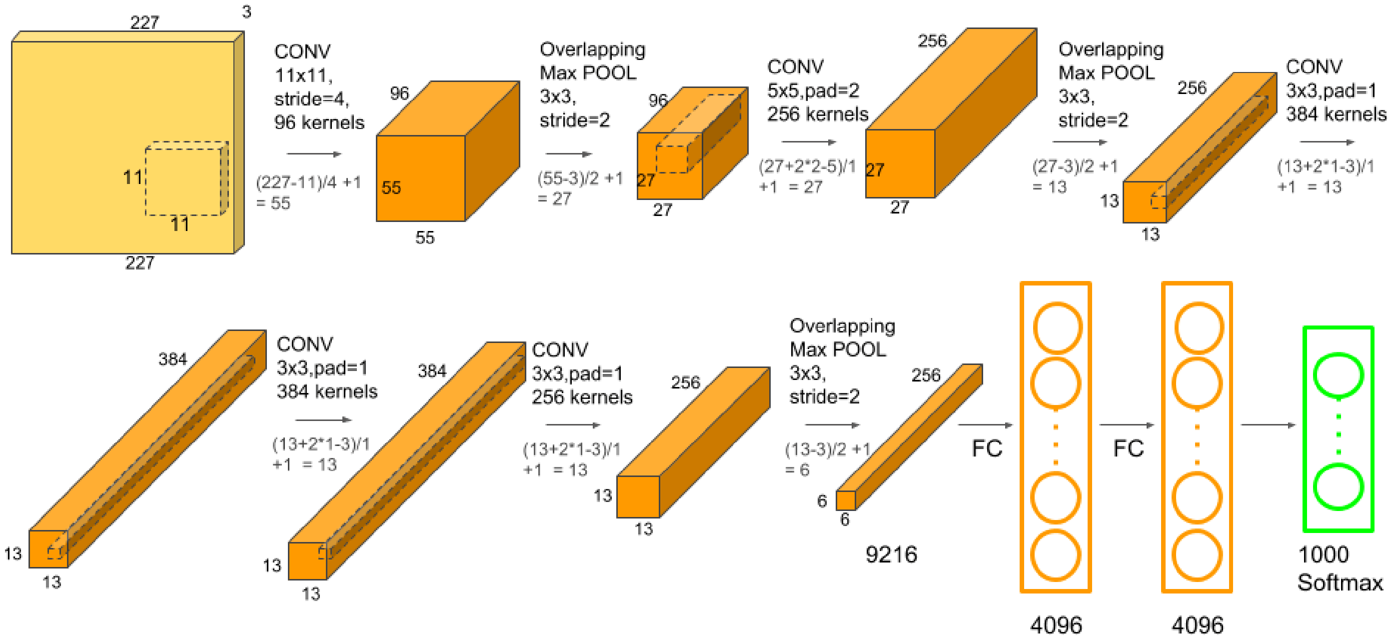


Ilya Sutskever

Jeoffrey Hinton

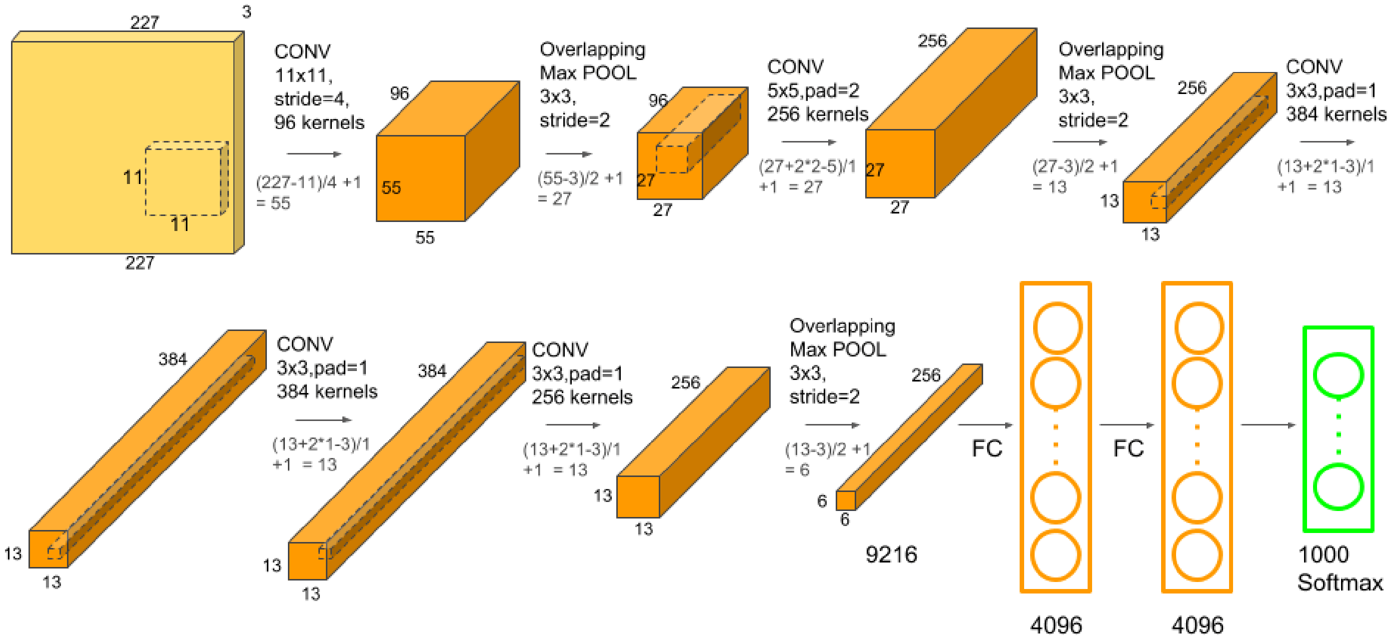
Krizhevsky et al., Imagenet classification with deep convolutional neural networks, 2012

Parameters (AlexNet)



Layer Name	Tensor Size	Weights	Biases	Parameters
Input Image	227x227x3	0	0	0
Conv-1	55x55x96	34,848	96	34,944
MaxPool-1	27x27x96	0	0	0
Conv-2	27x27x256	614,400	256	614,656
MaxPool-2	13x13x256	0	0	0
Conv-3	13x13x384	884,736	384	885,120
Conv-4	13x13x384	1,327,104	384	1,327,488
Conv-5	13x13x256	884,736	256	884,992
MaxPool-3	6x6x256	0	0	0
FC-1	4096×1	37,748,736	4,096	37,752,832
FC-2	4096×1	16,777,216	4,096	16,781,312
FC-3	1000×1	4,096,000	1,000	4,097,000
Output	1000×1	0	0	0
Total				**62,378,344**

Parameters (AlexNet)



- Much bigger than LeNet (60M parameters)
- ReLU
- Multiple GPUs
- Local Response Normalization (LRN)

VGG-16 (2014)

CONV: f=3, s=1, same

POOL: f=2, s=2

Order: CCP CCP CCCP CCCP CCCP FFS

Nf: 2^6 2^7 2^8 2^9 2^9

~138 mil parameters

VGG-16 (2014)

CONV: f=3, s=1, same

POOL: f=2, s=2

Order: CCP CCP CCCP CCCP CCCP FFS

Nf: 2^6 2^7 2^8 2^9 2^9

~138 mil parameters

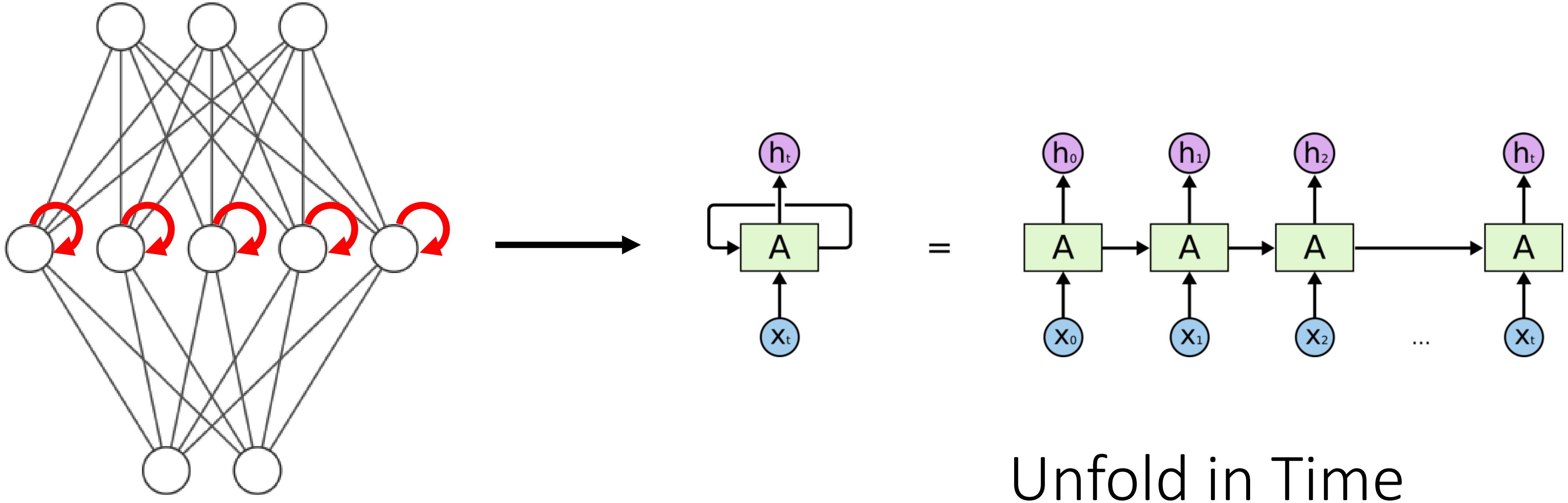
- Multiple convolution layers
- Smaller convolution filters
- Modularized architecture (VGG-19)

Next episode in EEP 596…

Output

Hidden

Input



Unfold in Time

Recurrent Neural Networks