Lecture 4: Convolutional Neural Network (CNN)

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CIS 6217 – Computer Vision for Data Representation

College of Computer Science, King Khalid University

Outline

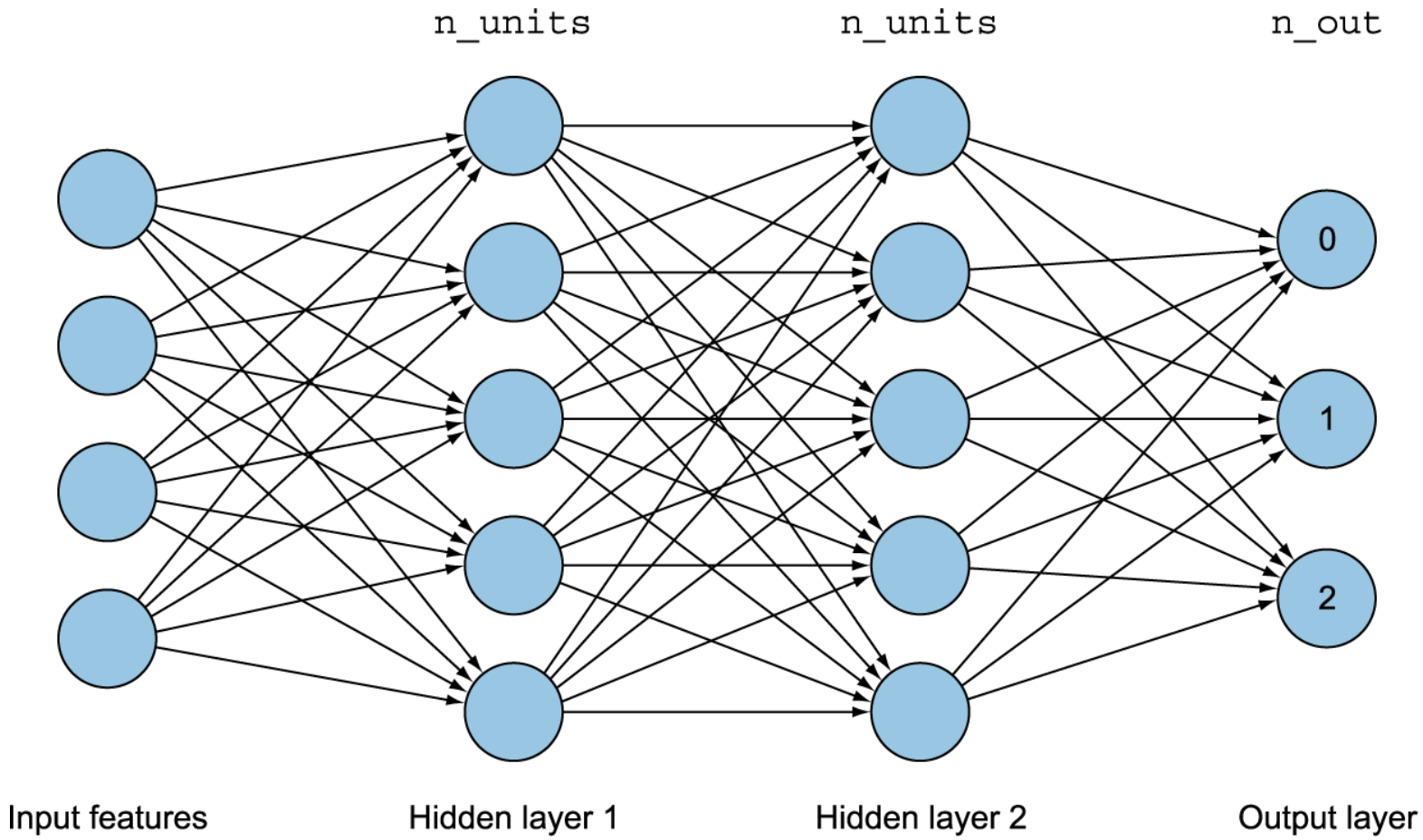
1. Why Not Feed-Forward for Images?
2. CNN Architecture
3. Filters/Kernels & Feature Maps
4. Pooling Layers
5. CNN Building Blocks (Conv, Pool, FC)
6. Lab: Building CNN
7. Summary

Learning Outcomes

- Explain why fully connected NNs are inefficient for images.
- Describe the concepts of local receptive fields, weight sharing, and convolutions.
- Understand filters/kernels and how they extract spatial features.
- Explain the role of pooling layers in reducing dimensions.
- Illustrate a basic CNN architecture for image classification.
- Implement a simple CNN using PyTorch

Why not feed forward for images?

Remember the NN Structure!



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Input Layer

28 × 28
= 784 pixels

0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	87	157	156	187	215	81	0	0	0	0	0
0	0	0	0	0	0	0	0	5	25	54	25	96	140	215	215	251	254	254	254	254	254	163	0	0	0	0	0
0	0	0	0	0	0	0	0	157	254	254	254	0	254	254	254	254	254	254	254	254	241	100	0	0	0	0	0
0	0	0	0	0	0	0	0	156	117	184	214	214	156	117	49	19	19	141	254	241	158	23	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	173	254	246	70	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90	247	254	219	58	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	43	203	254	250	121	15	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	43	145	254	254	229	111	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	4	137	245	254	254	238	40	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	130	254	254	254	254	254	235	106	23	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	55	196	196	114	194	223	254	254	216	23	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	75	245	253	55	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	150	254	134	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	200	254	134	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	246	253	59	0	0	0	0	0	0	0	0	0
0	0	0	17	11	18	0	0	0	0	0	0	0	0	67	254	254	170	0	0	0	0	0	0	0	0	0	0
0	0	0	128	254	159	0	0	0	0	0	0	20	140	248	254	254	9	0	0	0	0	0	0	0	0	0	0
0	0	0	154	254	229	80	79	79	161	176	218	254	254	254	104	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	29	203	254	254	254	215	254	254	254	250	95	11	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	5	80	155	155	156	111	58	58	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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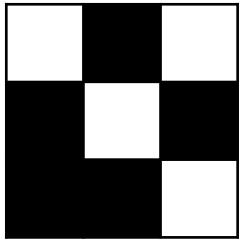

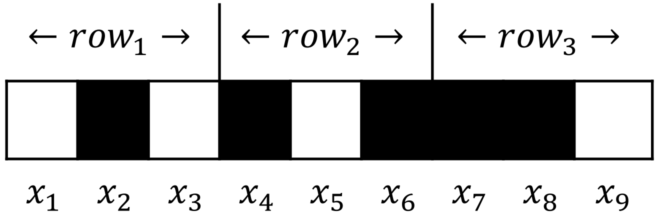

$Input = [\quad ,\quad ,\quad ,\quad ,\quad ,\quad ,\quad ,\quad ,\quad]$

Image flattening: The process of transforming Input image into 1-dimensional vector.

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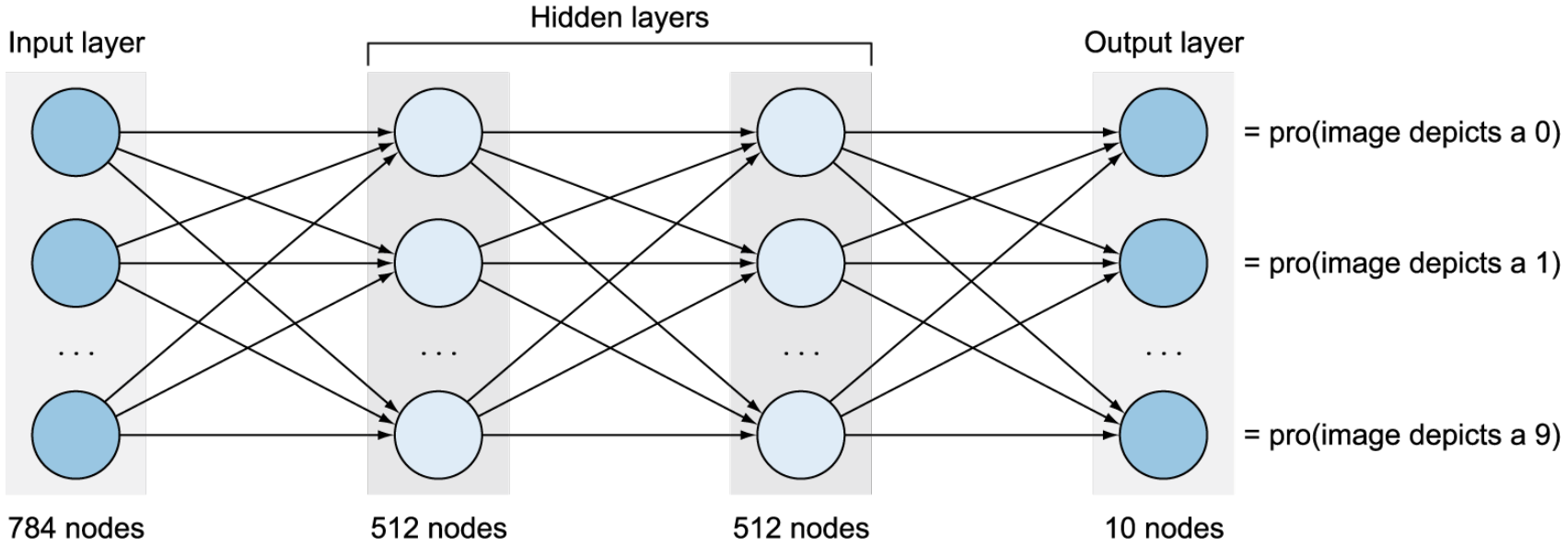
Hidden Layers

- Choose the number of layers
- Choose the number of nodes per layer
- Choose activation function!

Output Layer

- In the digit example, how many nodes should be in the output layer?
- We need to identify the number in the image 0,1,2,…,9



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Code

```python
from keras.models import Sequential
from keras.layers import Flatten, Dense

model = Sequential()

model.add( Flatten(input_shape = (28,28) ))

model.add(Dense(512, activation = 'relu'))
model.add(Dense(512, activation = 'relu'))

model.add(Dense(10, activation = 'softmax'))
model.summary()
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/reshaping/flatten.py:37: U
  super().__init__(**kwargs)
```

Model: "sequential"

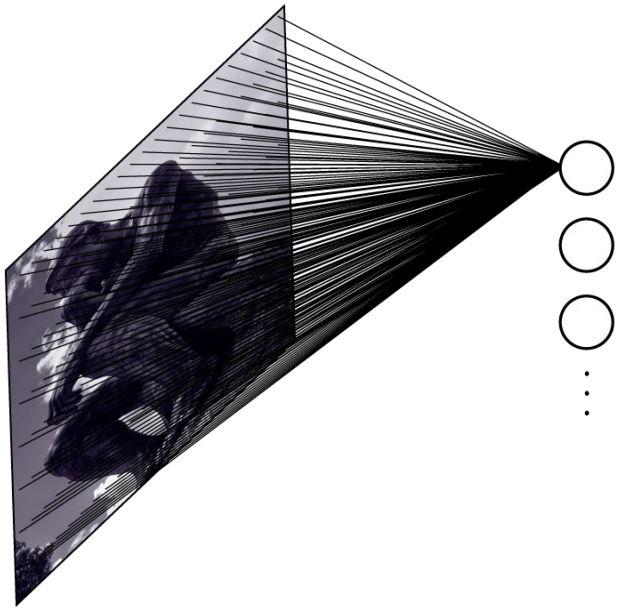
Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 512)	401,920
dense_1 (Dense)	(None, 512)	262,656
dense_2 (Dense)	(None, 10)	5,130

Total params: 669,706 (2.55 MB)
Trainable params: 669,706 (2.55 MB)
Non-trainable params: 0 (0.00 B)

MLPs Drawbacks

1. Large number of parameters (complexity)

Fully connected neural net



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2. Spatial Feature Loss

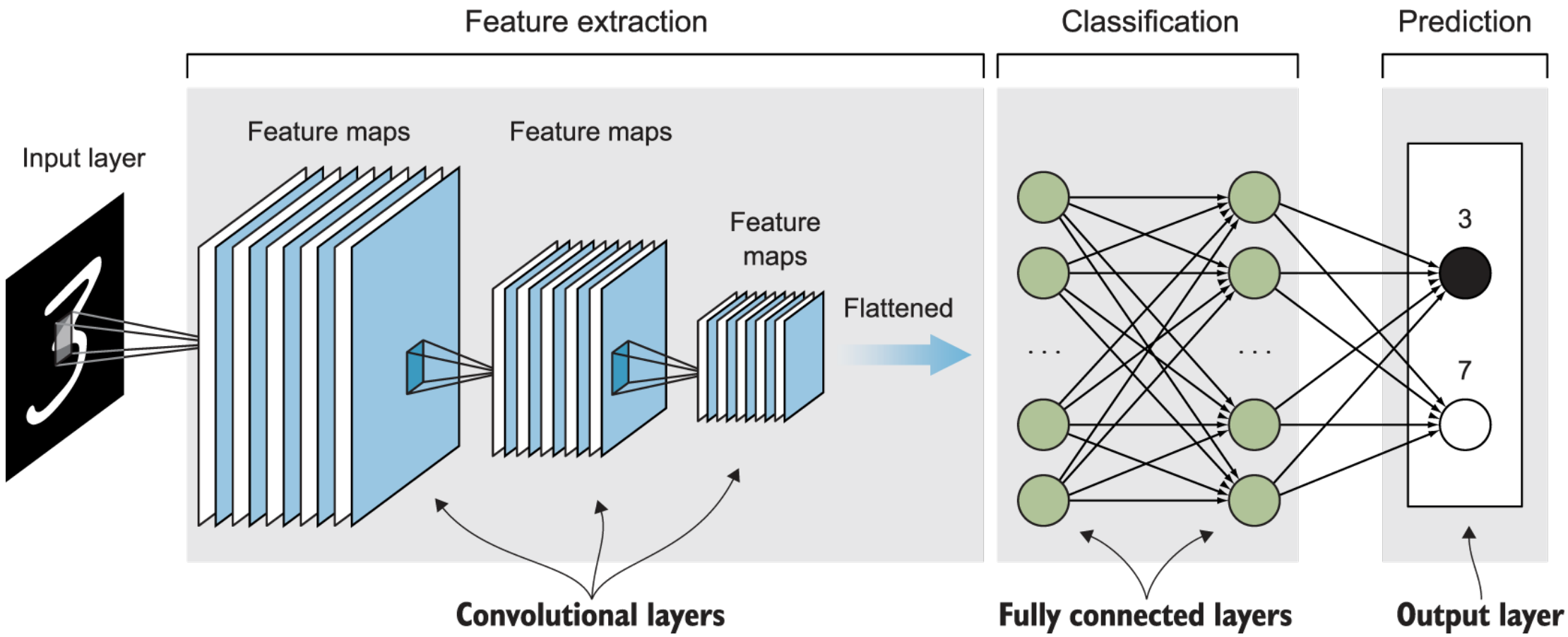
1	1	0
1	1	0
0	0	0

$\leftarrow row_1 \rightarrow$			$\leftarrow row_2 \rightarrow$			$\leftarrow row_3 \rightarrow$		
1	1	0	1	1	0	0	0	0
x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9

0	0	0
0	1	1
0	1	1

CNN

CNN Architecture



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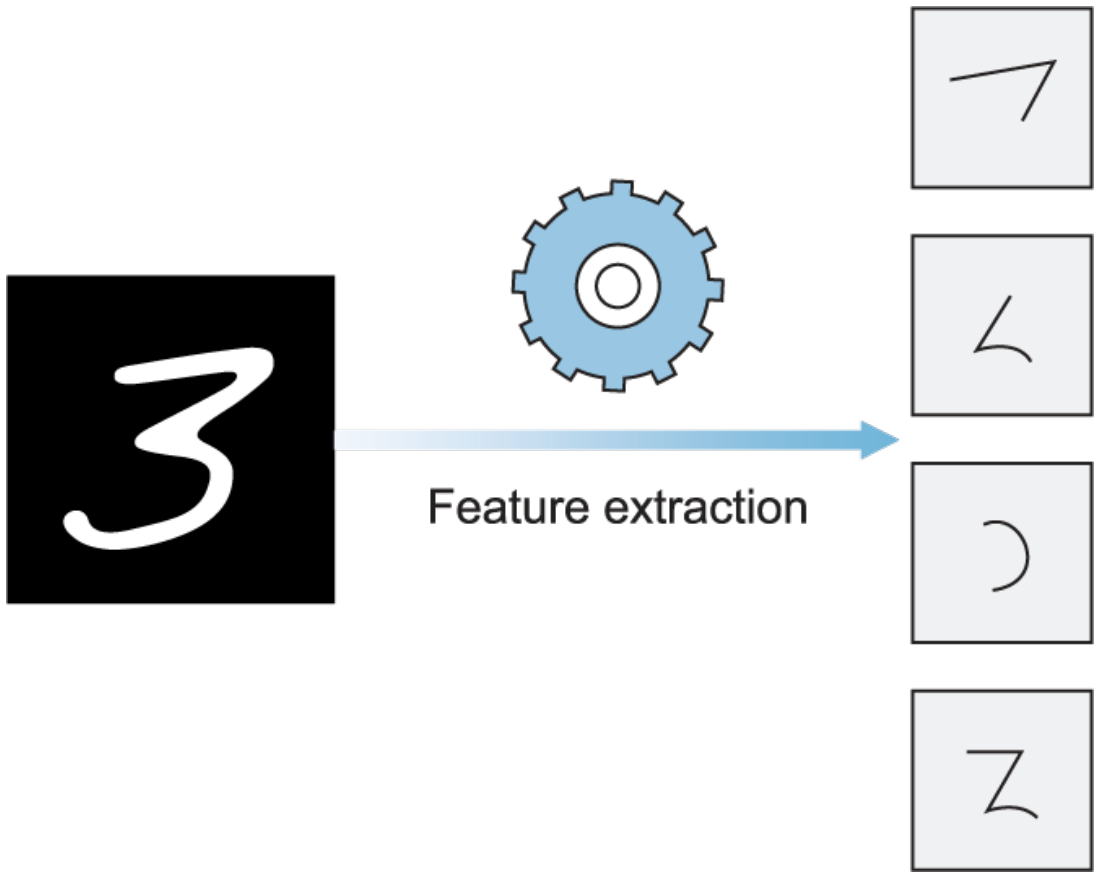
Feature Extraction

- Feature map: one filter applied to the previous layer.
- Mapping of where a specific feature is found in an image



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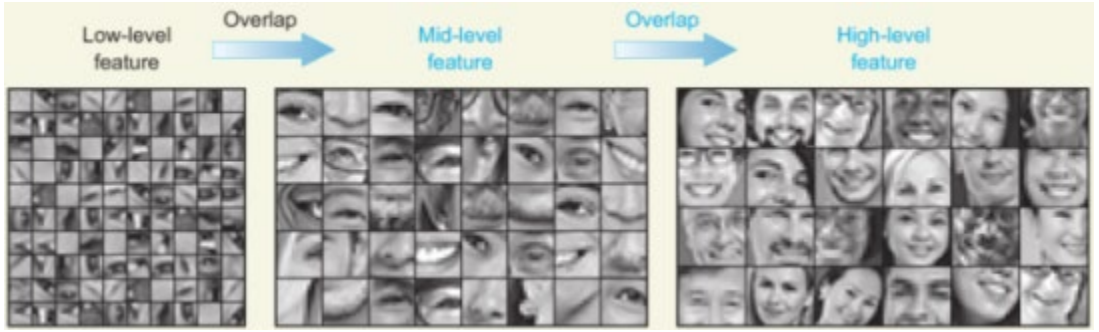
Classification

- Fully connected layer for classification
- It is a regular MLP

- How CNN Learns Patterns



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Components of CNN

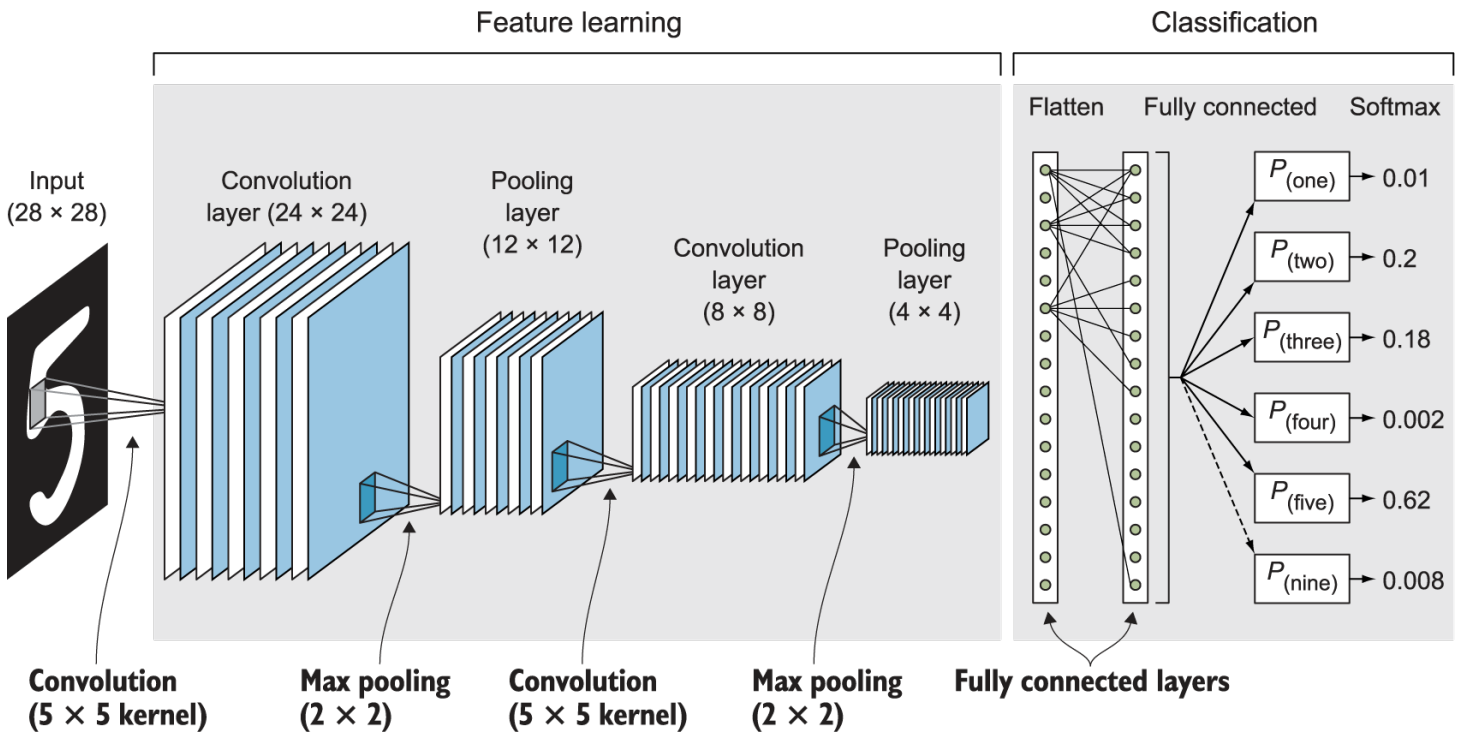
Convolutional layer (CONV)

Pooling layer (POOL)

Fully connected layer (FC)

Convolutional Layer

Basic Components of CNN



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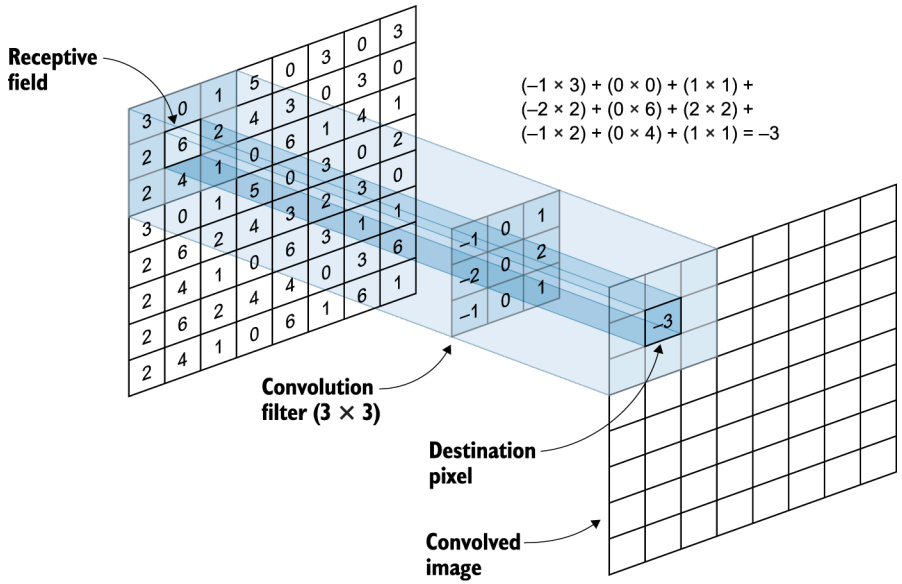
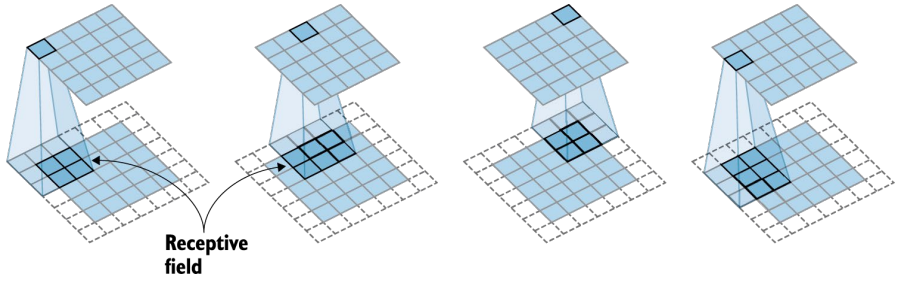
Convolutional Layers



- Kernel is the convolution filter
- It slides over the original image pixel by pixel

- Receptive field: is the area of the image that the filter convolves



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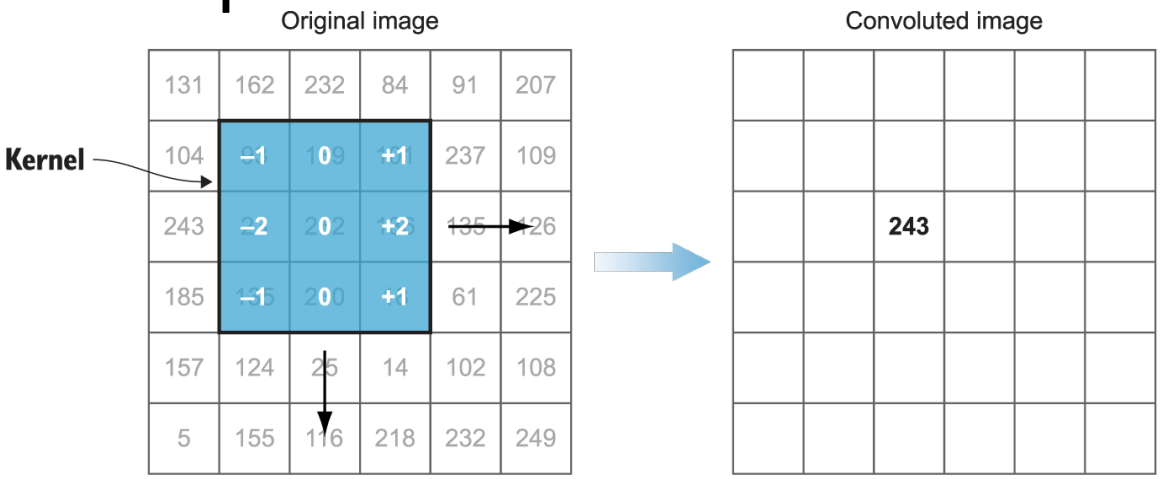
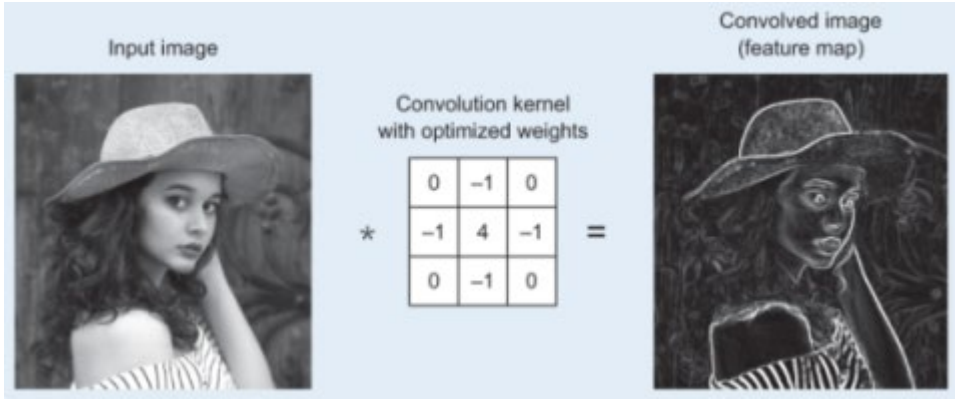
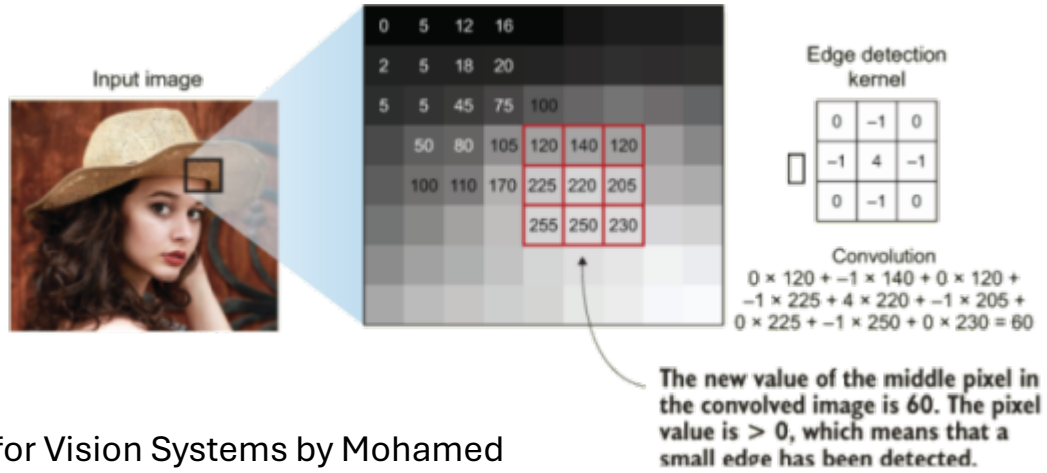
Convolutional Operations



- Example: apply edge detection filter





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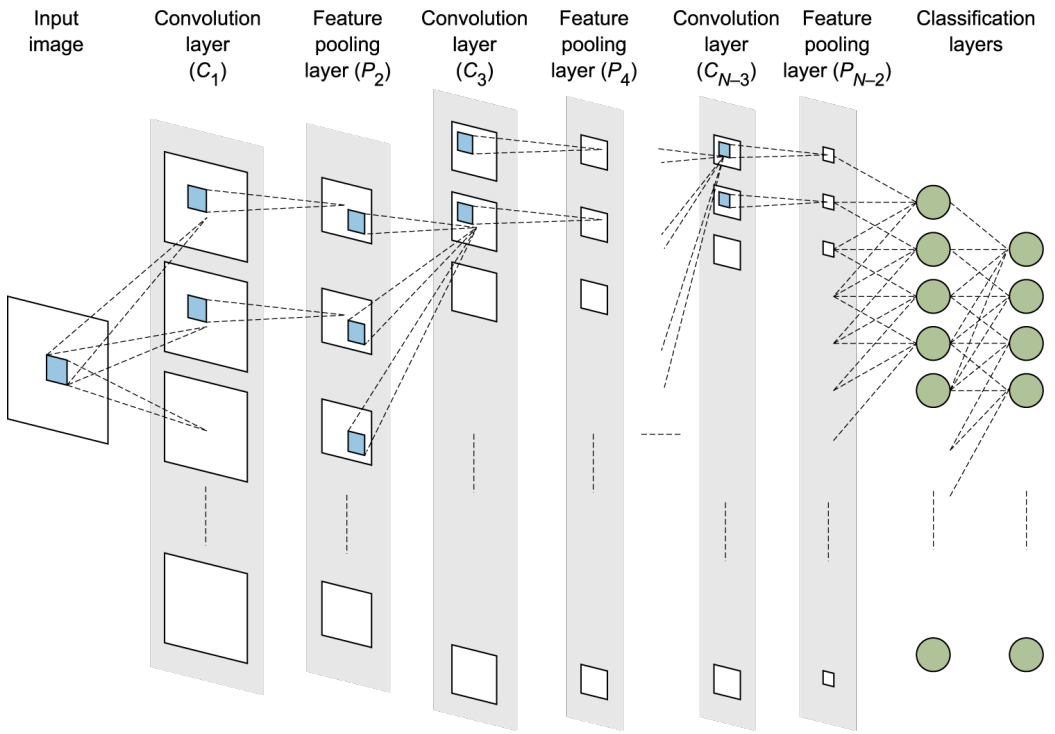
Number of filters

- Each convolutional layer has one or more filters.



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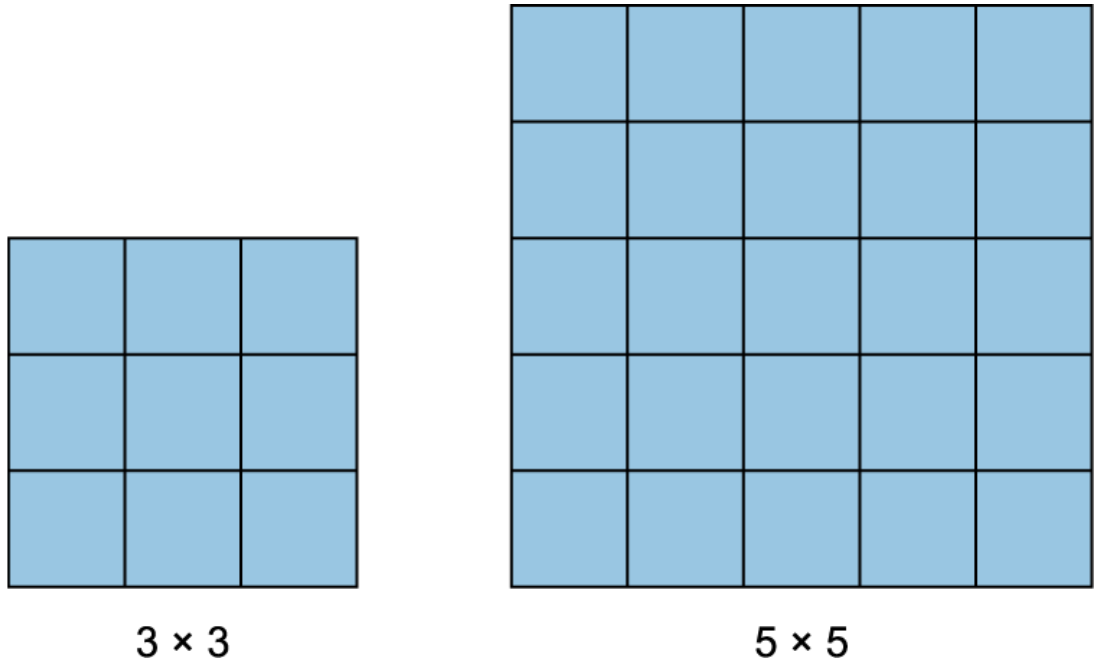
Kernel Size

- Dimensions of the convolutional filter



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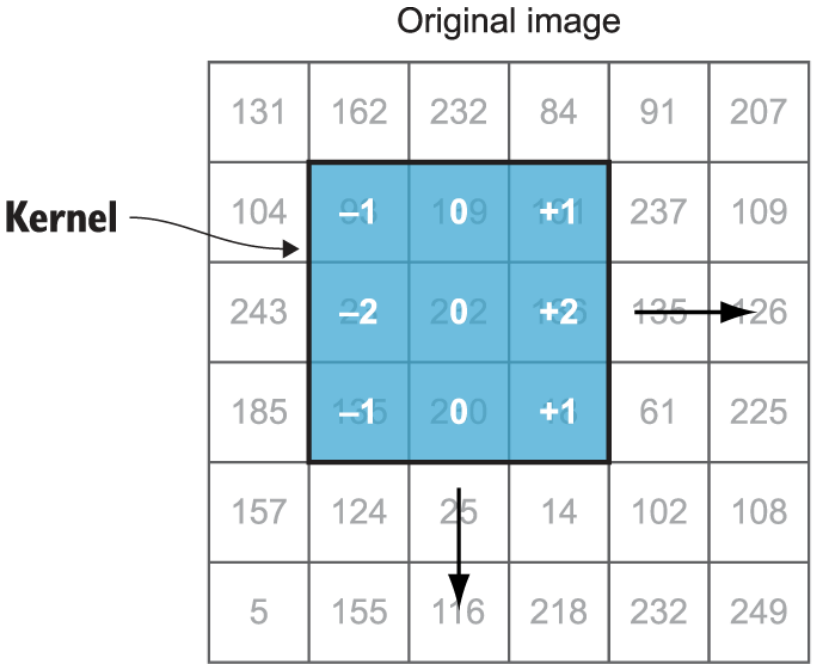
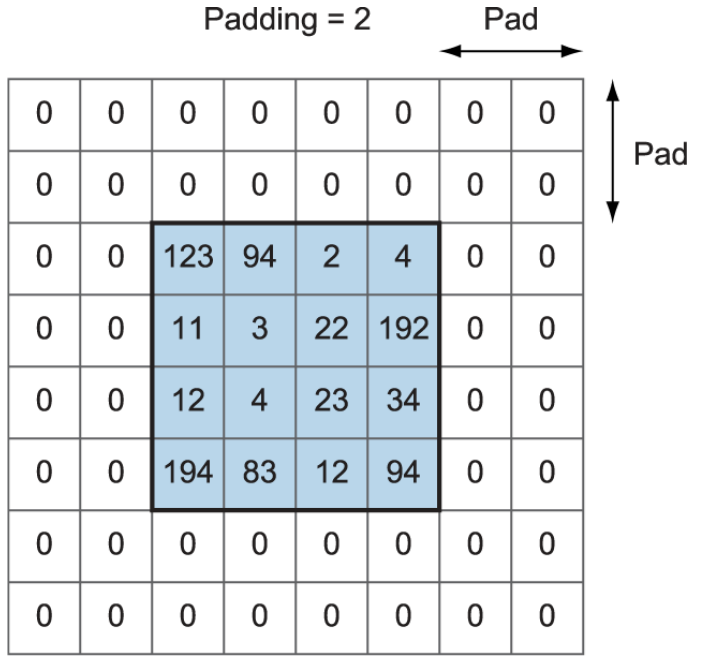
Strides and Padding

- *Strides* --The amount by which the filter slides over the image.
- Often called zero-padding because we add zeros around the border of an image





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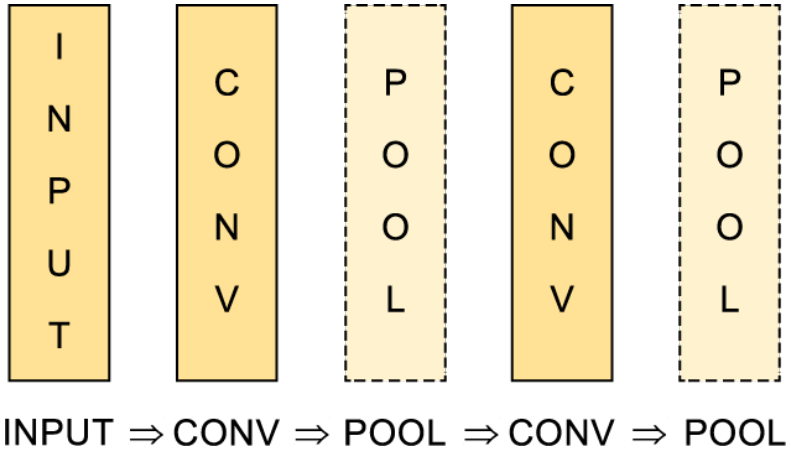
Pooling Layer

Pooling Layers

- The goal of the pooling layer is to downsample the feature maps produced by the convolutional layer into a smaller number of parameters, thus reducing computational complexity.



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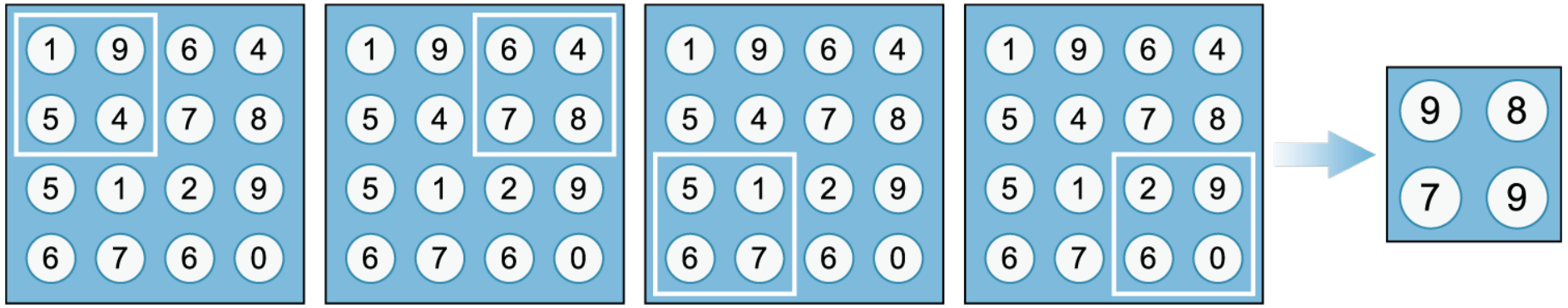
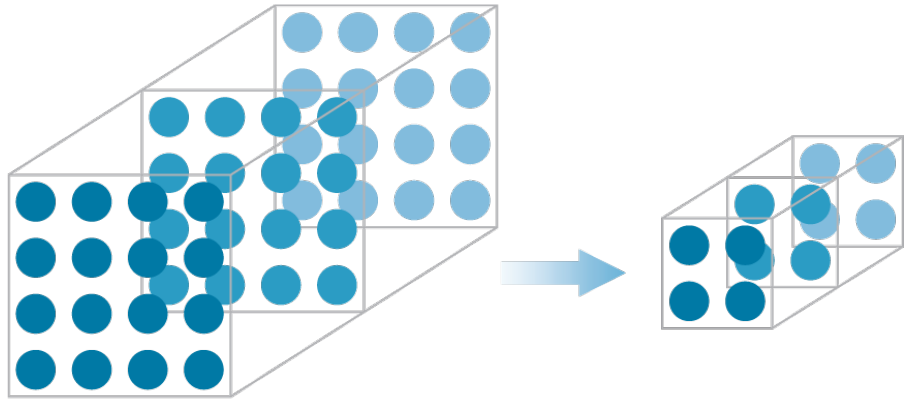
Max Pooling





CONV layer
(4 × 4 × 3)

POOL layer
(2 × 2 × 3)

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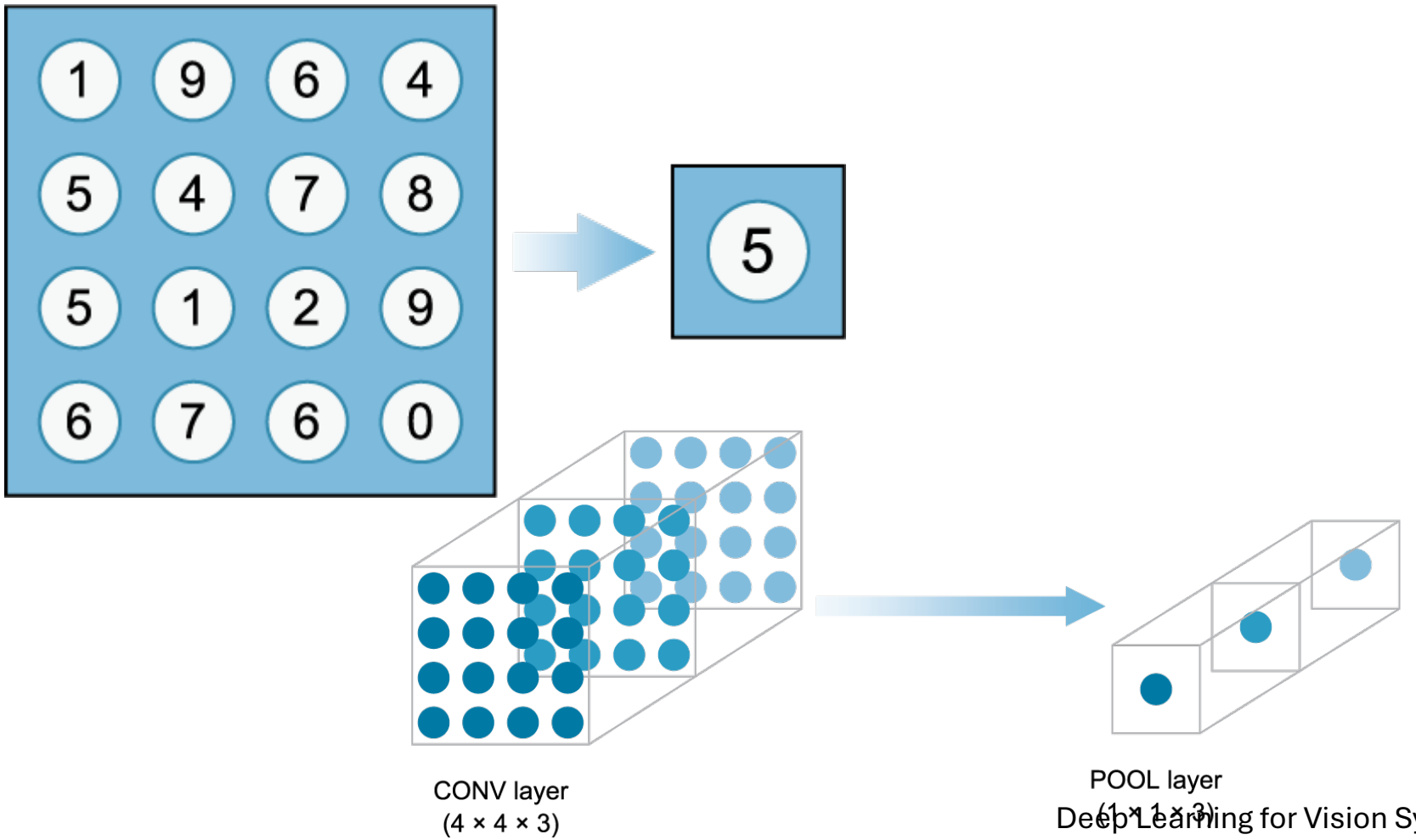
Average Pooling



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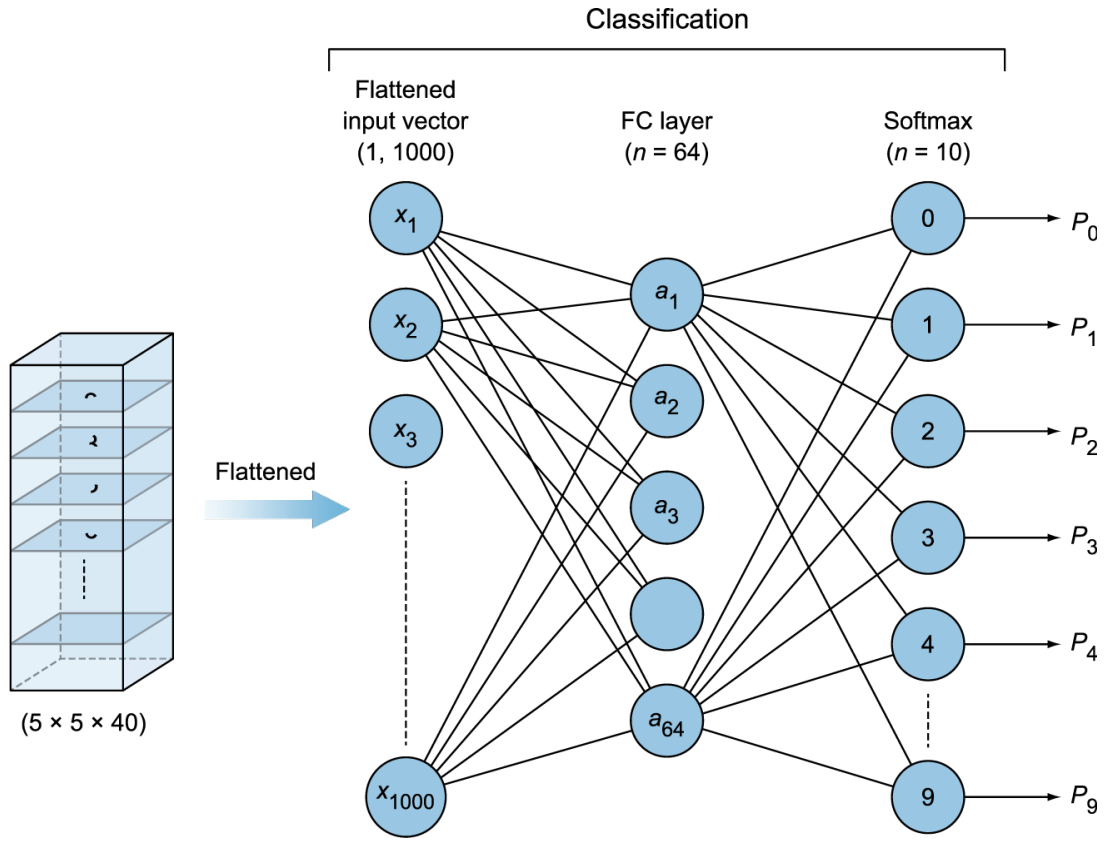
Fully Connected

Fully Connected Layer

- Input flattened vector
- Hidden Layer
- Output Layer



Deep Learning for Vision Systems by Mohamed Elgendy (2020)

Lab: Building CNN

```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout

model = Sequential()

model.add(Conv2D(32, kernel_size=(3, 3), strides=1, padding='same',
          activation='relu', input_shape=(28,28,1)))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), strides=1, padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())

model.add(Dense(64, activation='relu'))

model.add(Dense(10, activation='softmax'))

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 32)	320
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 64)	0
flatten (Flatten)	(None, 3136)	0
dense (Dense)	(None, 64)	200,768
dense_1 (Dense)	(None, 10)	650

Total params: 220,234 (860.29 KB)
Trainable params: 220,234 (860.29 KB)
Non-trainable params: 0 (0.00 B)

References

- Guide to CNNs for CV – Khan et al. (2018)
- Deep Learning with Python – Chollet (2018)
- Deep Learning in Computer Vision – Awad & Hassaballah (2020)

- Deep Learning for Vision Systems by Mohamed Elgendy (2020)