INTRODUCTION TO DEEP LEARNING

PART II – ADVANCED CONCEPT AND CNN

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Institute of Data Science

DLR

Schedule

Date	Time	Activity
13.11.2025 Day 1	09:00 - 10:00	Introduction and basics
	10:00 - 10:30	Hands-on I
	10:30 - 10:45	Coffee break
	10:45 - 11:45	Advanced concept and Convolutional Neural Network
	11:45 - 12:15	Hands-on II
	12:15 - 12:30	Recap Day 1
14.11.2025 Day 2	09:00 - 10:00	Deep Generative Model
	10:00 - 10:30	Hands-on III
	10:30 - 10:45	Coffee break
	10:45 - 11:45	Transformer
	11:45 - 12:15	Hands-on IV
	12:15 - 12:30	Code and knowledge sources + closing

We’re here!

Curriculum

II. Advanced Concept and Convolutional Neural Network

- Regularization
- Variants of Neural Networks
- Convolutional Neural Networks (CNN)

Inspired by lectures from Paris Saclay and MIT; images taken from these, if not noted otherwise

Neural network concepts

Building the network
- Input layer
- Hidden layers
- Output layer

Forward propagate input
- Propagate input through neurons
- Apply non-linearities

Evaluate performance
- Compute the loss of the prediction

Back propagate
- Update weights according to the optimization algorithm

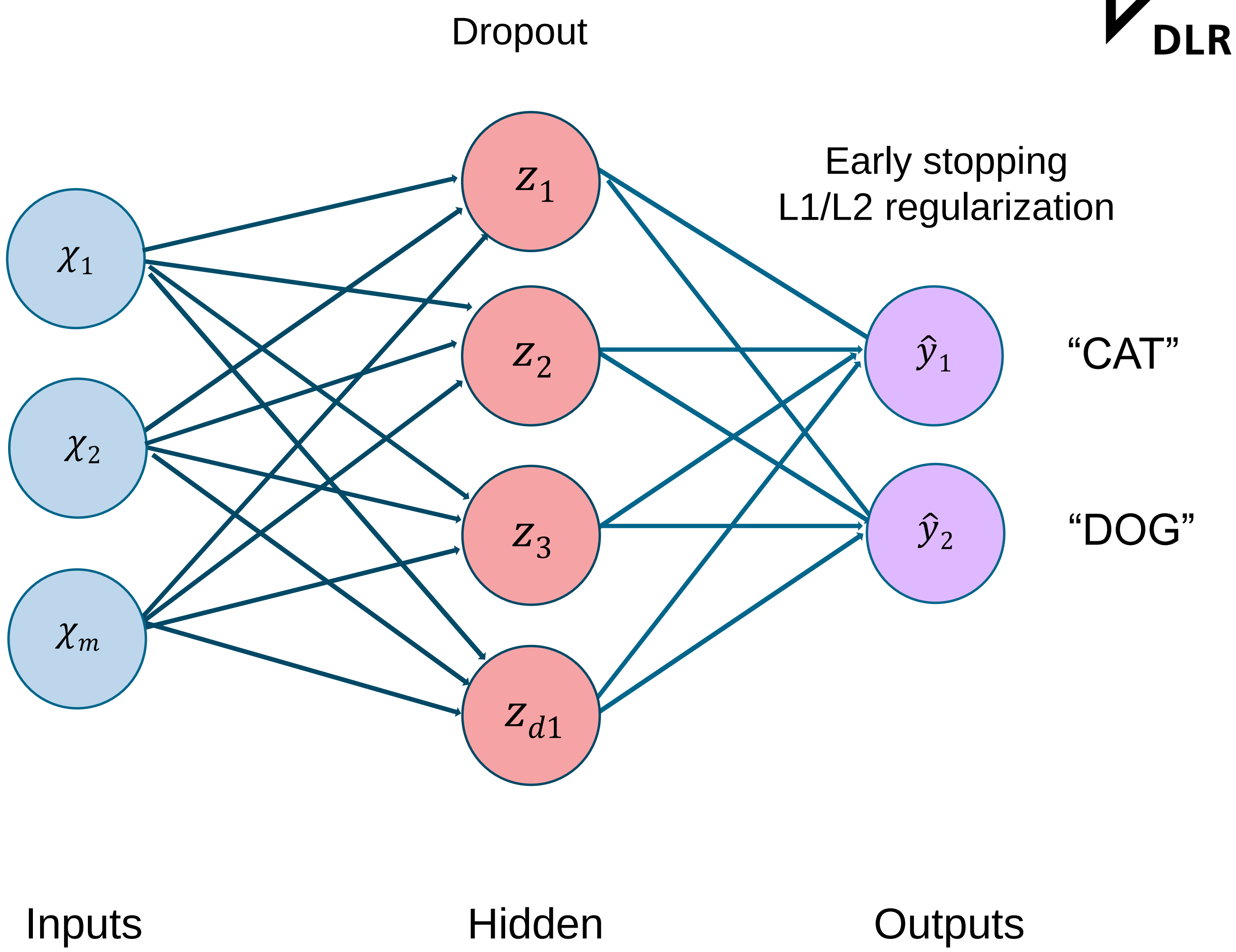
Improving the network
- Regularization,
- Advanced architectures

Improve the Network: Regularization

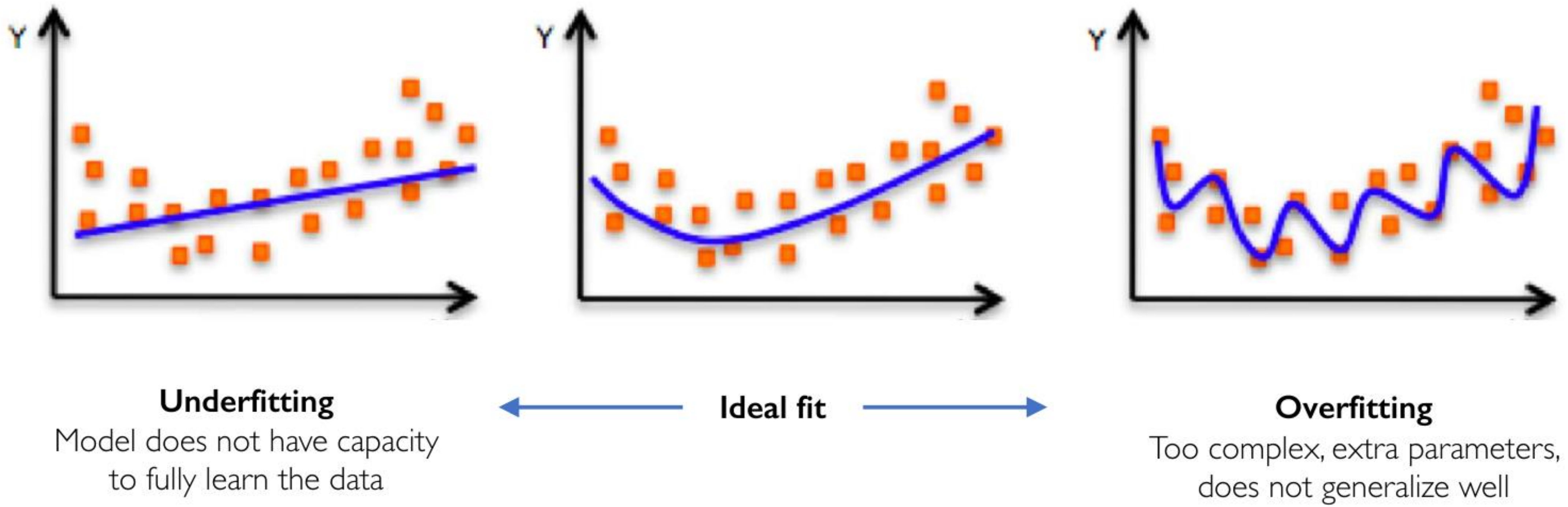
Data Augmentation

CAT

$$\begin{bmatrix} \chi_1 \\ \chi_2 \\ \chi_m \end{bmatrix}$$

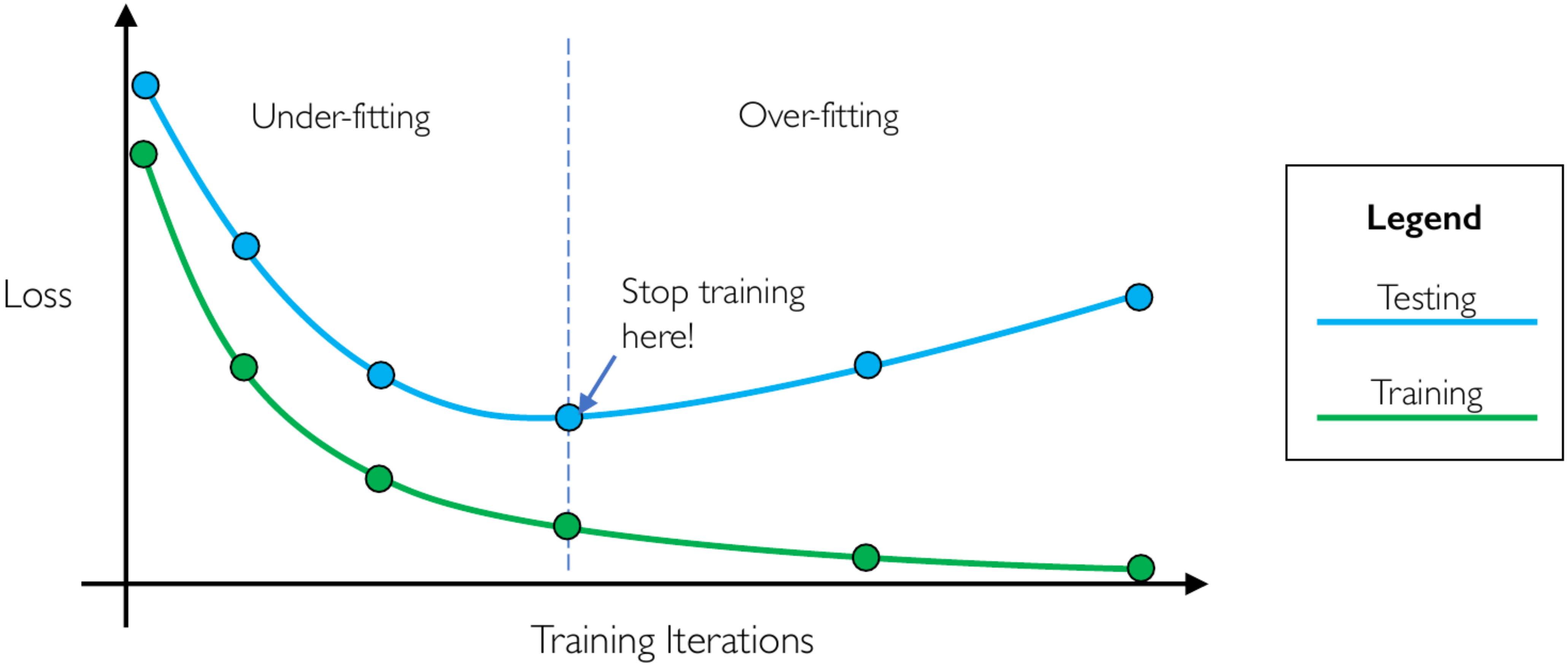


Regularization
The overfitting problem



= High bias | **Tradeoff** | = High variance

Regularization
Preventing overfitting: Early stopping



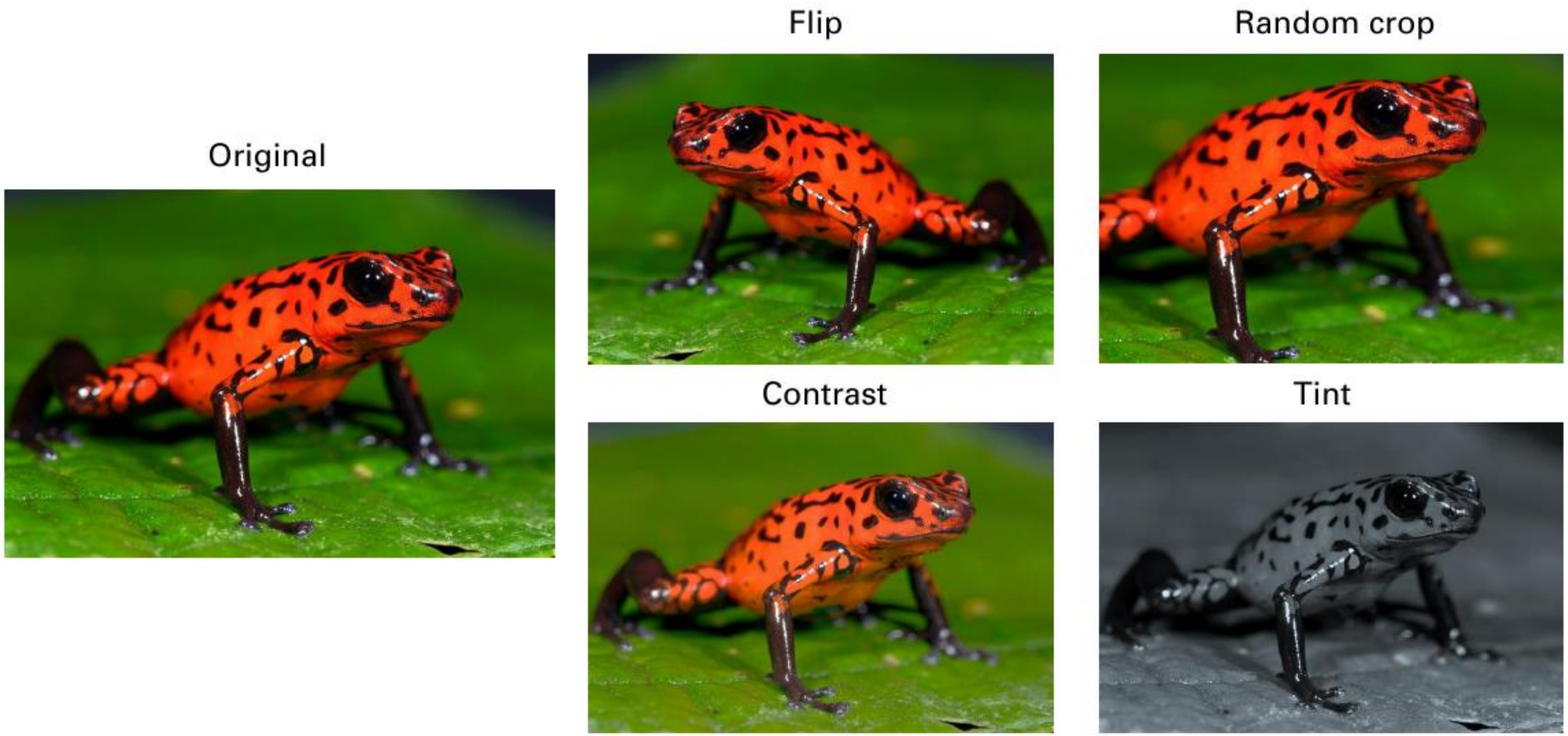
Regularization
Preventing overfitting: l_1 regularization

We want to find the network weights that **achieve the lowest loss**

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{argmin} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}(f(x^{(i)}; \boldsymbol{W}), y^{(i)}) + \frac{\lambda}{2} \sum_{l} |\boldsymbol{w}_l|$$

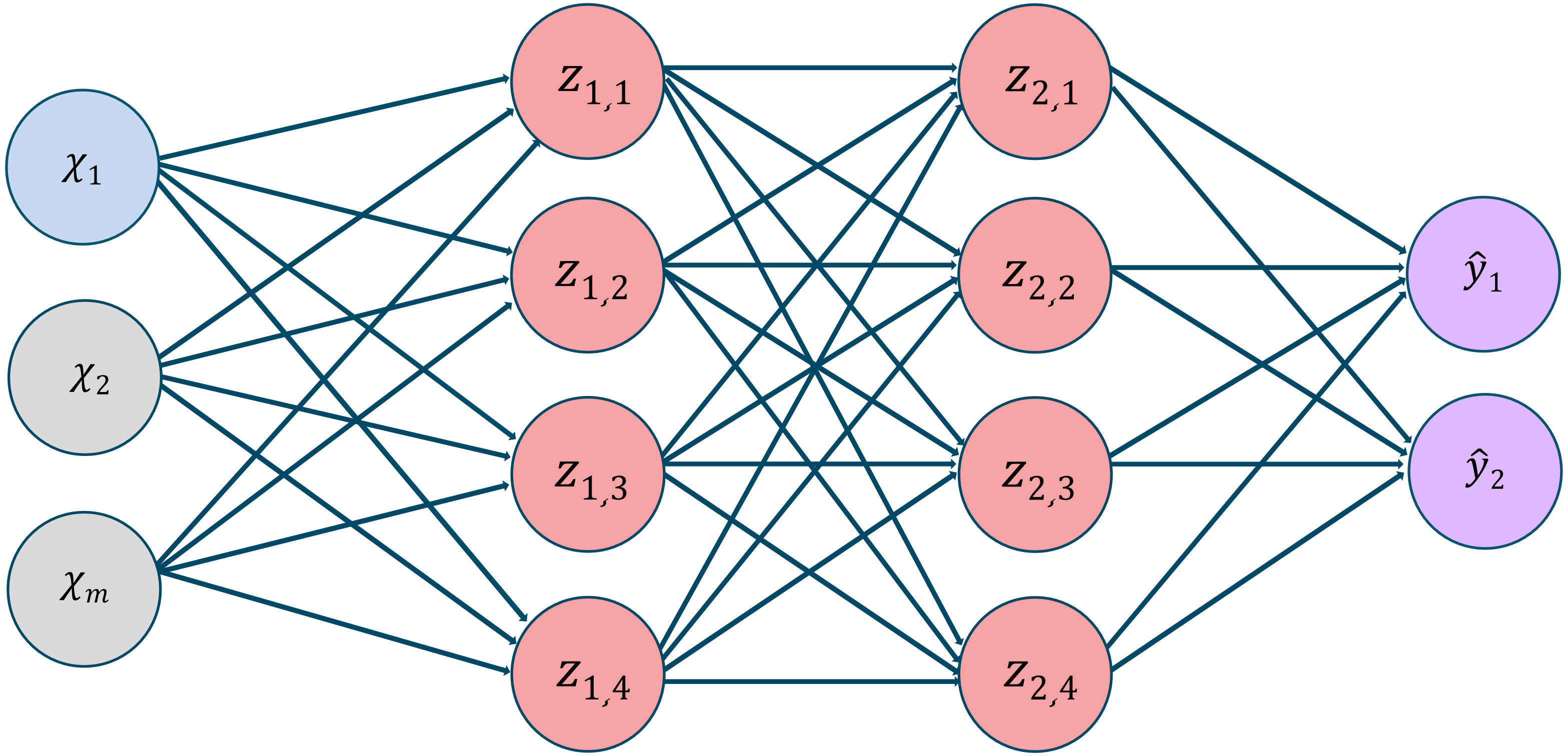
→ Leads to sparser weights (more zeroes in weights) that are not too adapted to the data at hand

Regularization
Preventing overfitting: Data augmentation



Regularization
Preventing overfitting: Dropout

During training, randomly set some activations to 0



Regularization
Preventing overfitting: Dropout

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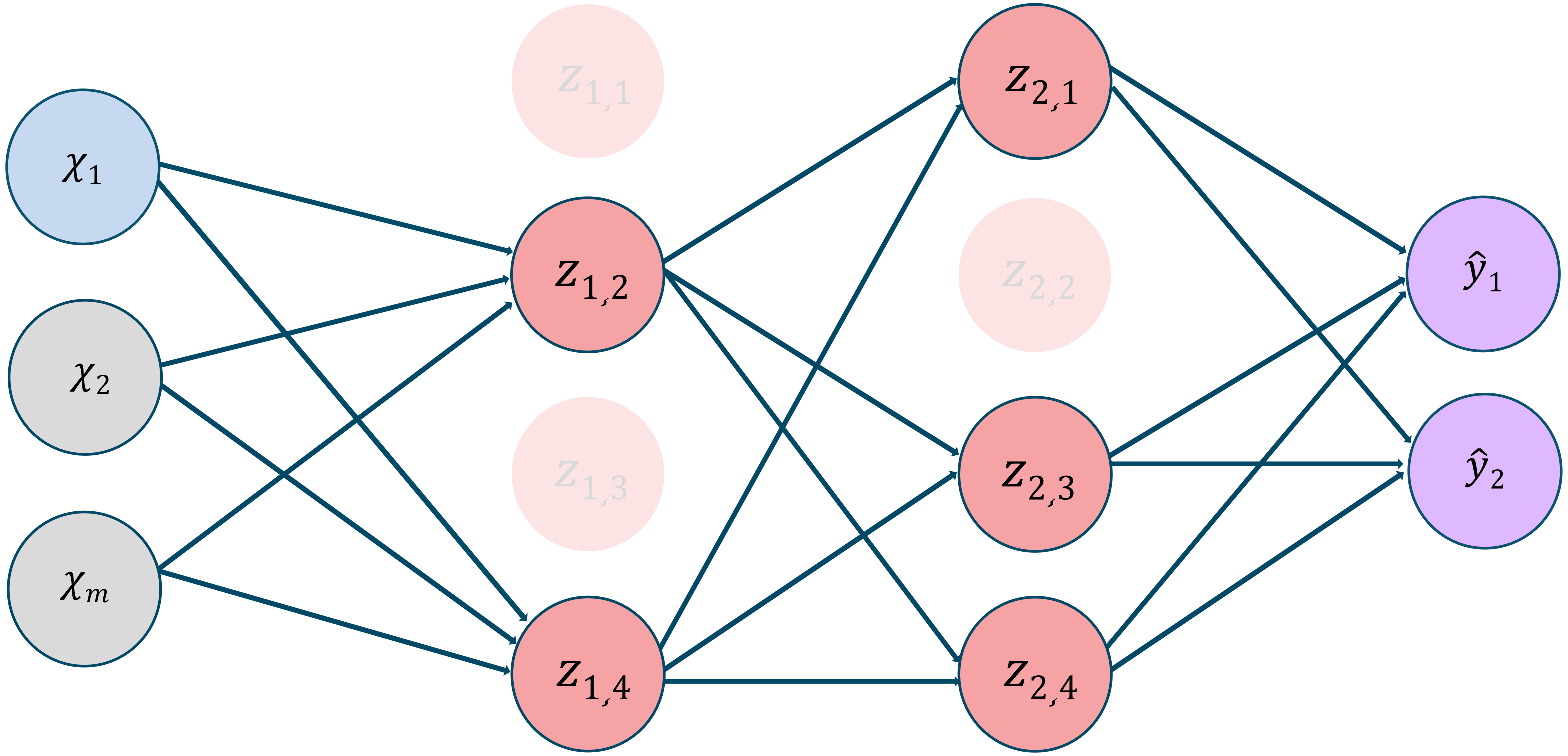


Other ways to improve the network

Data preprocessing

Data Cleaning (lack/noise)

Data Transformation (normalization, …)

Data Reduction (aggregation, …)

Network initialization

Random Initializations (e.g. Glorot)

Batch normalization

standardizes layer inputs to stabilize learning process & reducing training epochs

Optimizers

(Stochastic methods like Adam)

Training Schedules

Hyperparameters tuning

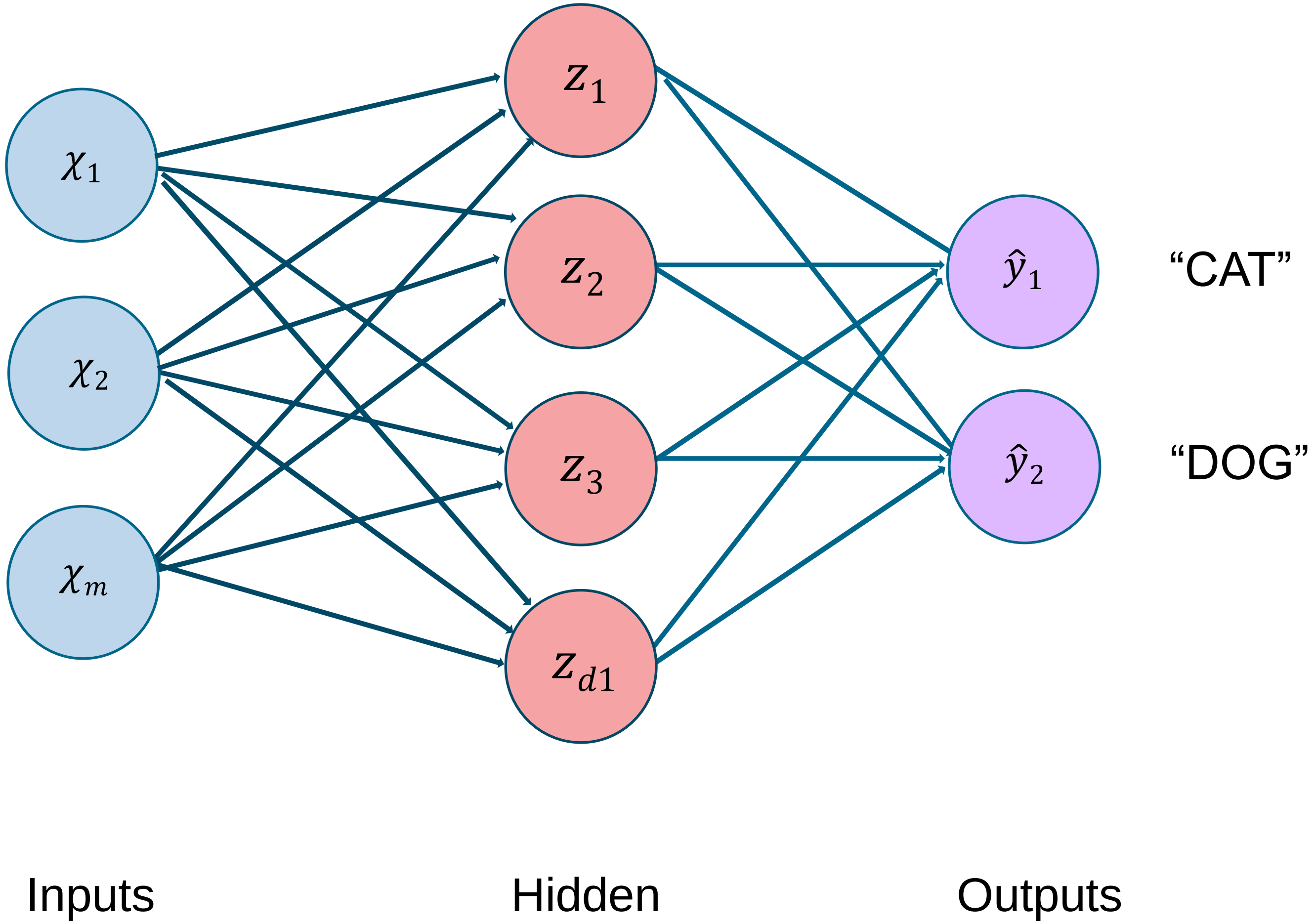
Minibatch composition

(shuffle data, take only a subset, …)

Variants of Neural Networks

CAT

$$\begin{bmatrix} \chi_1 \\ \chi_2 \\ \chi_m \end{bmatrix}$$

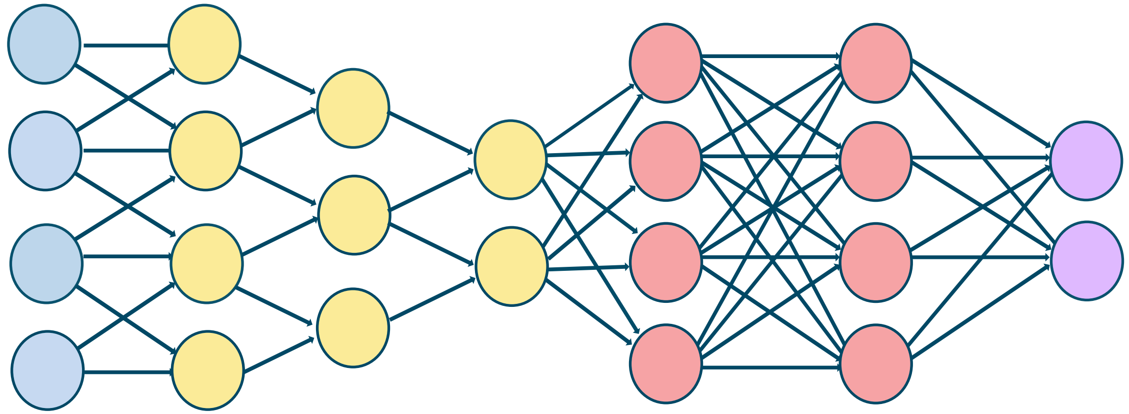


Types of Neural Networks Layer

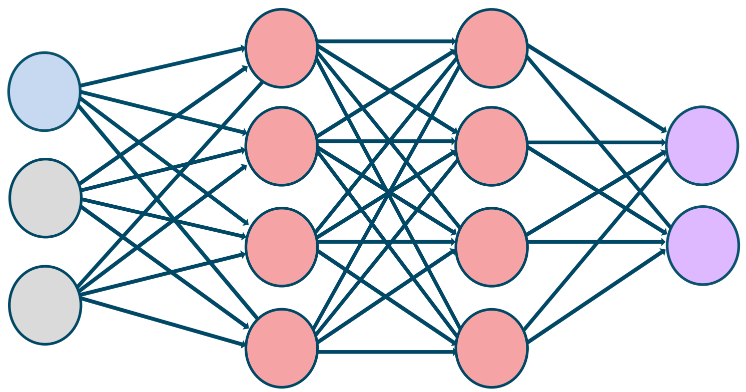
Application	Layer Type			
	Fully Connected (dense)	Convolution	Deconvolution	Recurrent
Image Classification	✓	✓		
Image segmentation		✓	✓	
Text processing	✓			✓
Speech recognition	✓			✓
Time series	✓			✓
Image-to-image translation (GAN)	✓	✓	✓	
Autoencoders	✓	✓		
Deepfake	✓	✓		✓

Variants of Neural Network - Examples

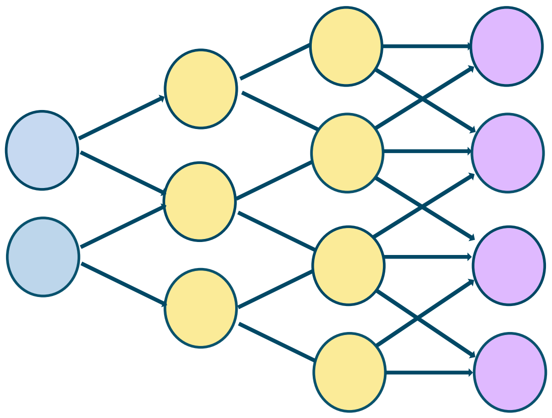
Deep convolution network (DCN)



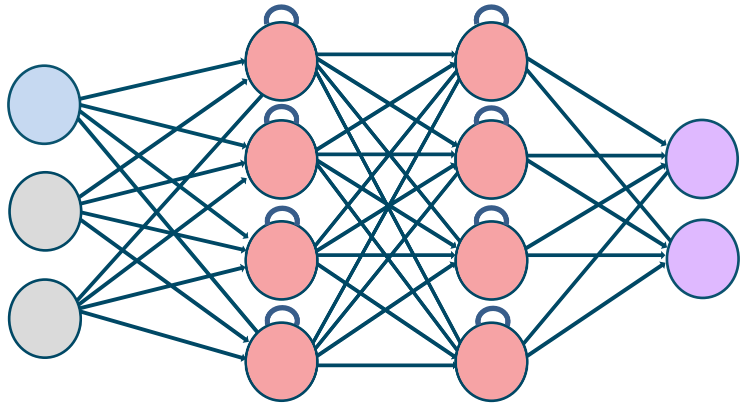
Deep Feed Forward (DFF) (fully connected)

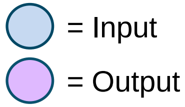


Deconvolution network (DN)

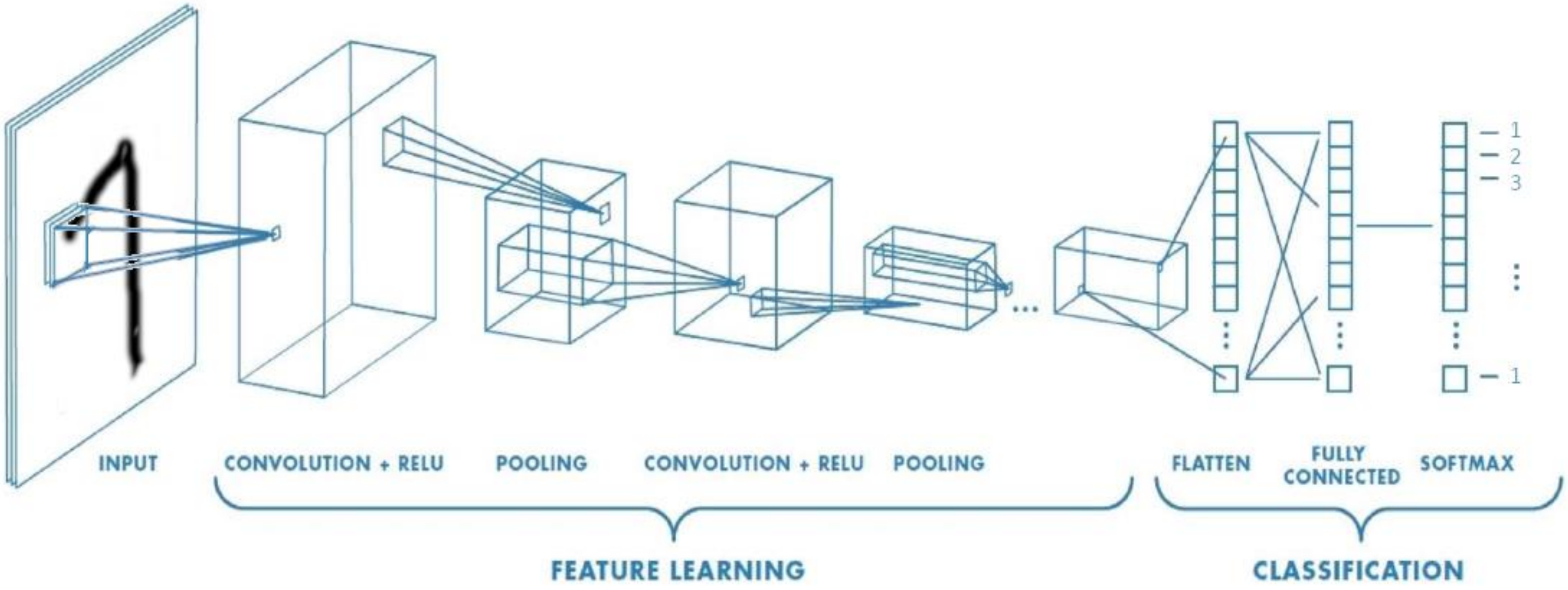


Recurrent neural network (RNN)

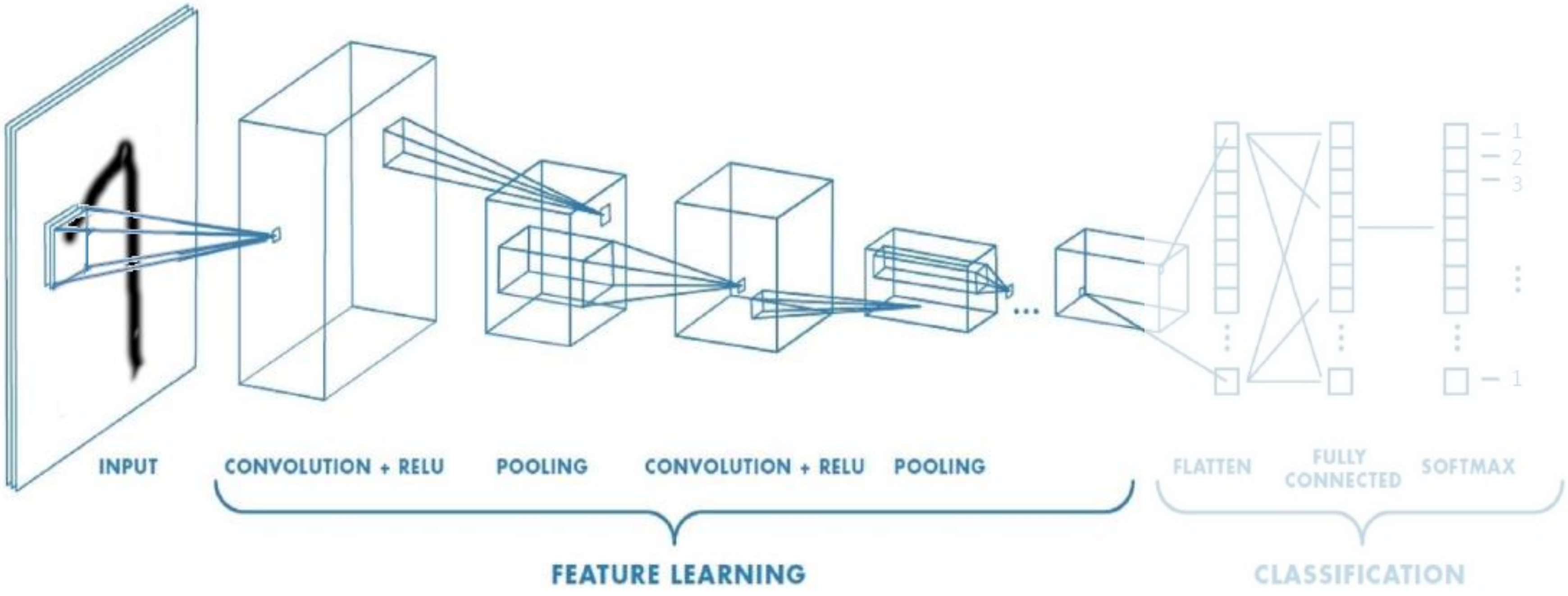




Convolutional Neural Networks



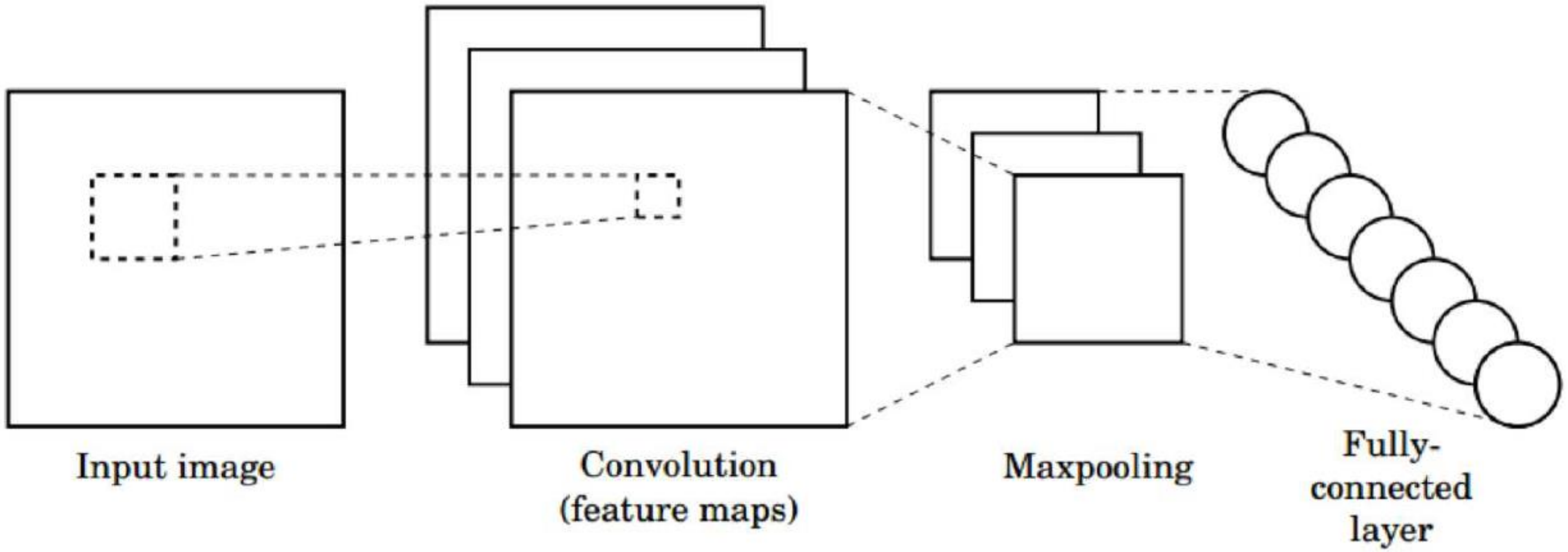
Feature Learning



1. Learn features in input image through **convolution**
2. Introduce **non-linearity** through activation function (real-world data is non-linear!)
3. Reduce dimensionality and preserve spatial invariance with **pooling**

Convolutional Neural Networks
Feature extraction with convolutions

Convolutional Neural Networks
Building a CNN

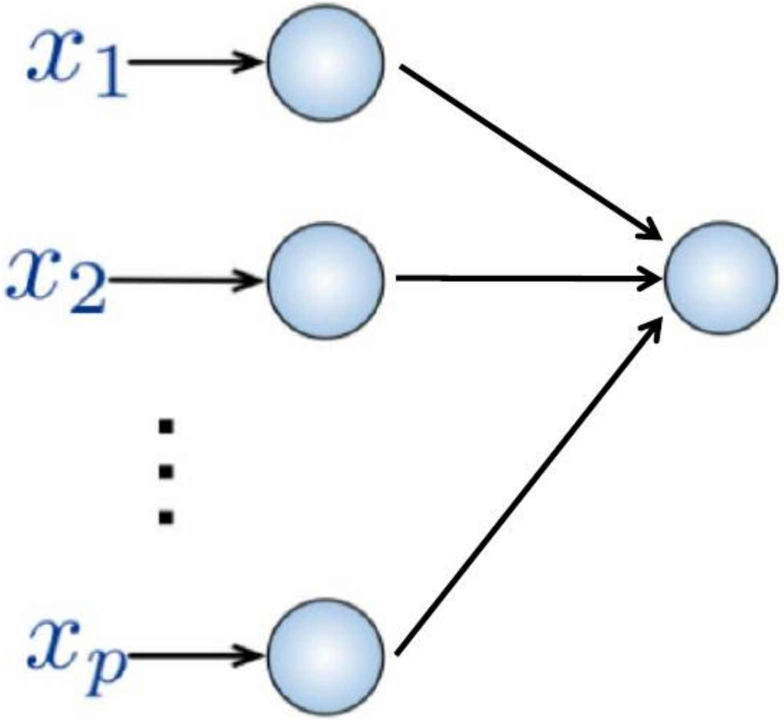


1. **Convolution**: Apply filters with learned weights to generate feature maps.
2. **Non-linearity**: Often ReLU.
3. **Pooling**: Downsampling operation on each feature map.

Train model with image data.
Learn weights of filters in convolutional layers.

Convolutional Neural Networks
Learning on image data

Input:
- 2D image
- Vector of pixel values



Fully Connected:
- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

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Convolutional Neural Networks
Learning on image data

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- 2D image
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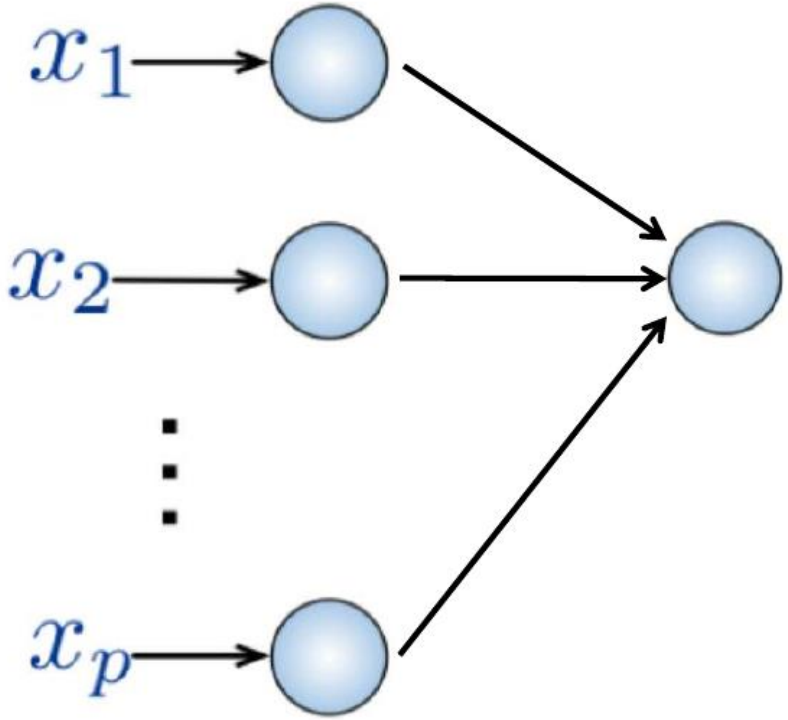

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- Connect neuron in hidden layer to all neurons in input layer
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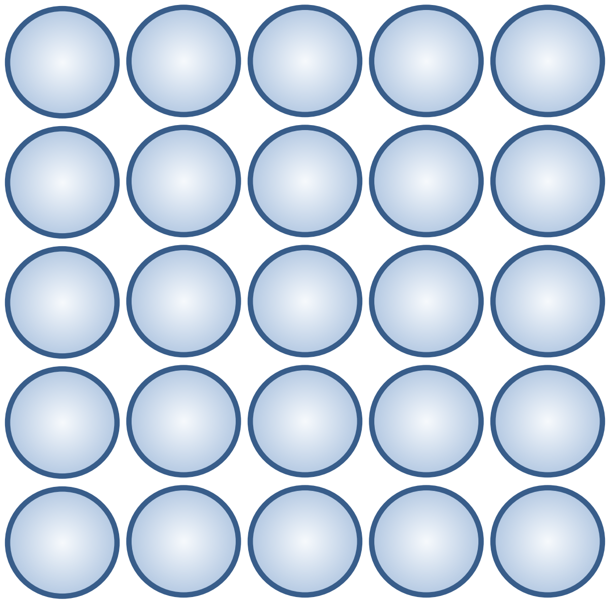
- And many, many parameters!

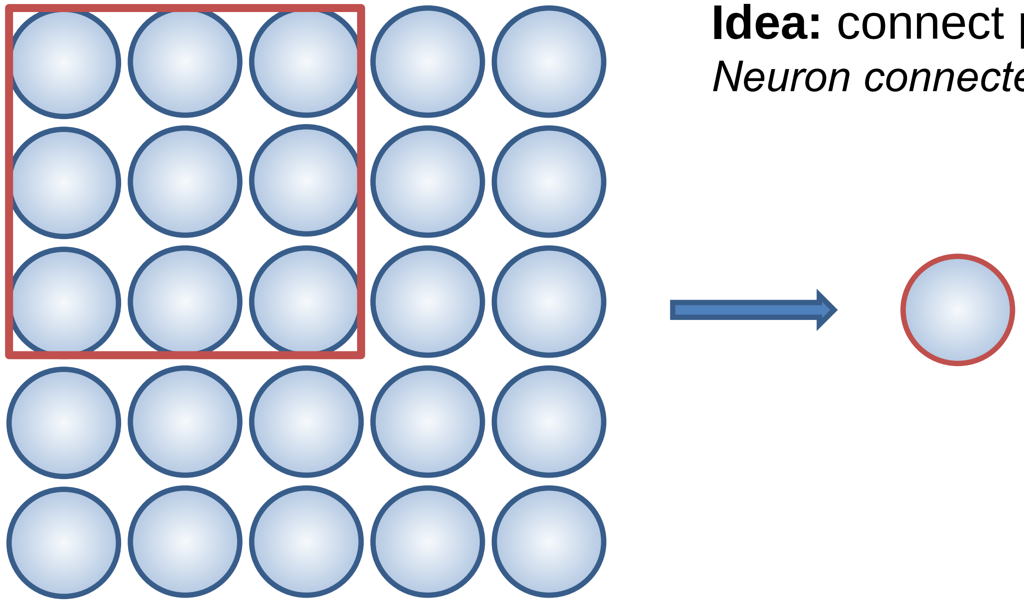
How can we use **spatial structure** in the input to inform the architecture of the network?

Convolutional Neural Networks
Learning on image data



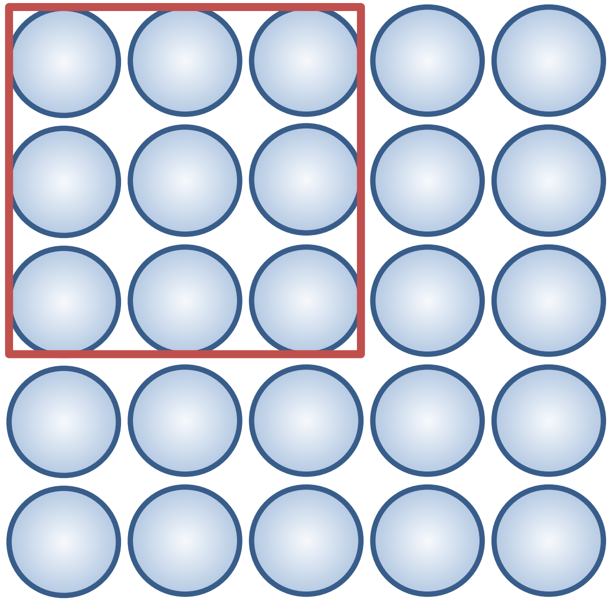
Input: 2D image (5x5 or 256x256 or …)
Array of pixel values

Convolutional Neural Networks
Learning on image data

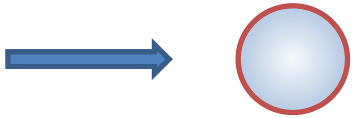


Idea: connect patches of input to neurons in hidden layer
Neuron connected to the region of input only „sees“ these values.

Convolutional Neural Networks
Learning on image data



For a neuron in hidden layer:
- Take inputs from patch
- Compute weighted sum
- Apply bias



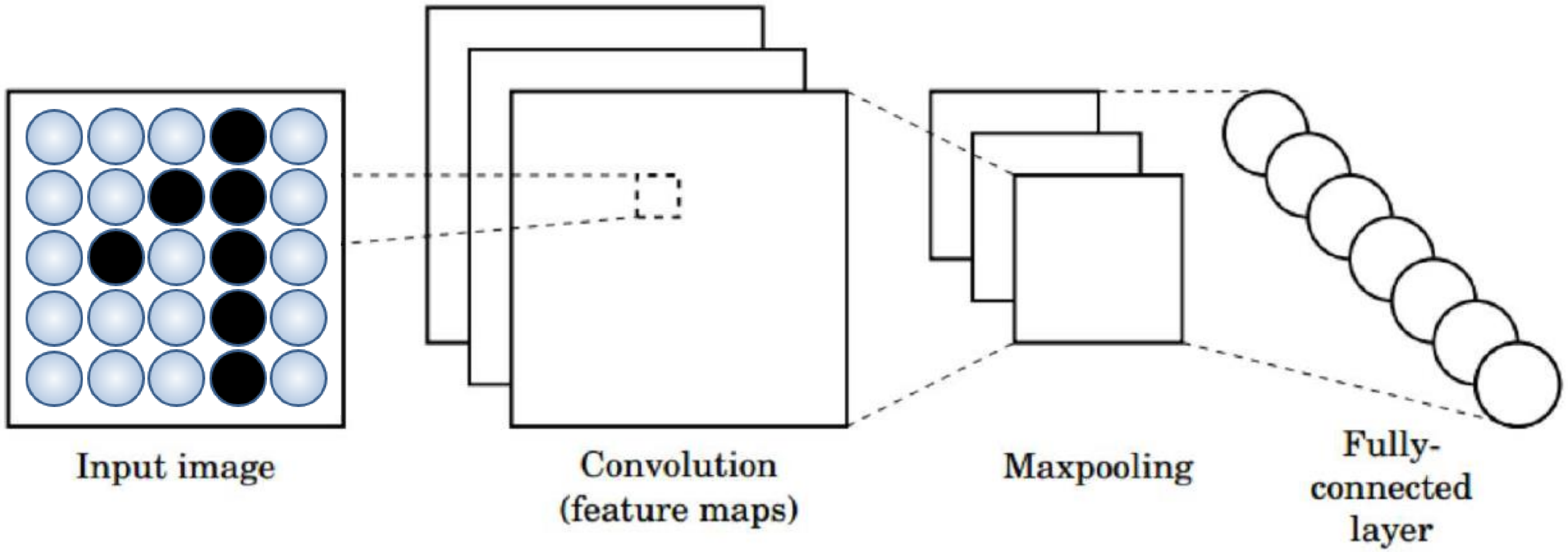
$$\sum_{i=1}^{3}\sum_{j=1}^{3} W_{ij}\, X_{i+p,j+q} + b$$

For neuron (p,q) in hidden layer

3x3 filter: matrix of weights W_{ij}

1) Applying a window of weights
2) Computing linear combinations
3) Activating with non-linear function

Convolutional Neural Networks
Building a CNN - Example



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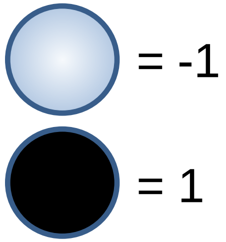
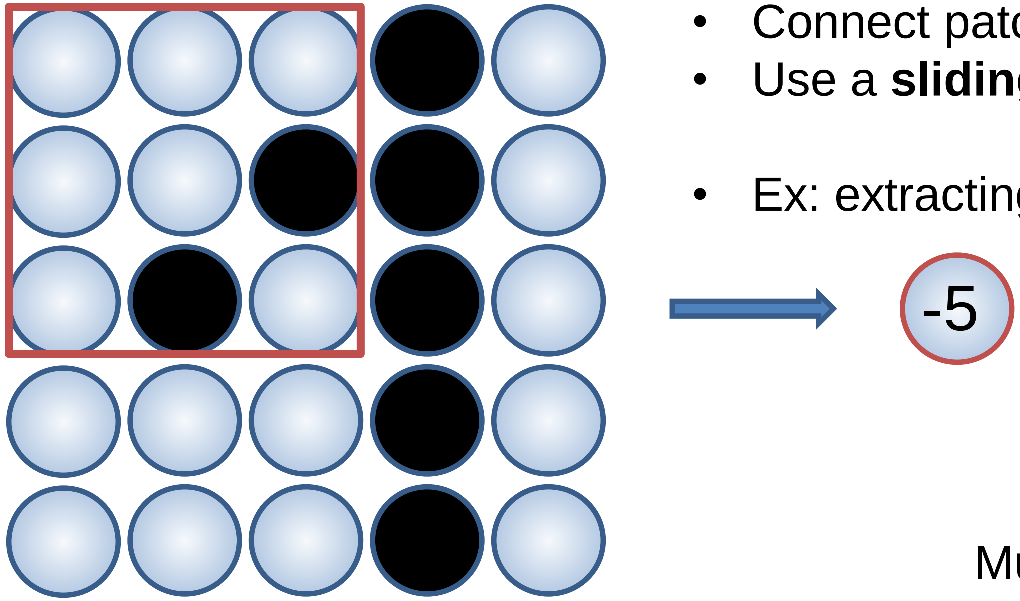
Convolutional Neural Networks
Learning on image data - Example





- Connect patch in input layer to a single neuron in subsequent layer
- Use a **sliding window** to define connections

- Ex: extracting feature with filter fi_0

Multiply same indices of clipping and filter and sum it up.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & -1 & 1 \\ -1 & 1 & -1 \end{bmatrix} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} = (-1)+(-1)+(-1)+(-1)+(-1)+1+(-1)+1+(-1) = -5$$

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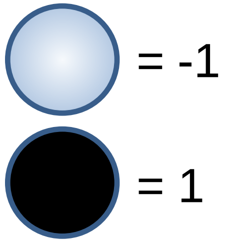
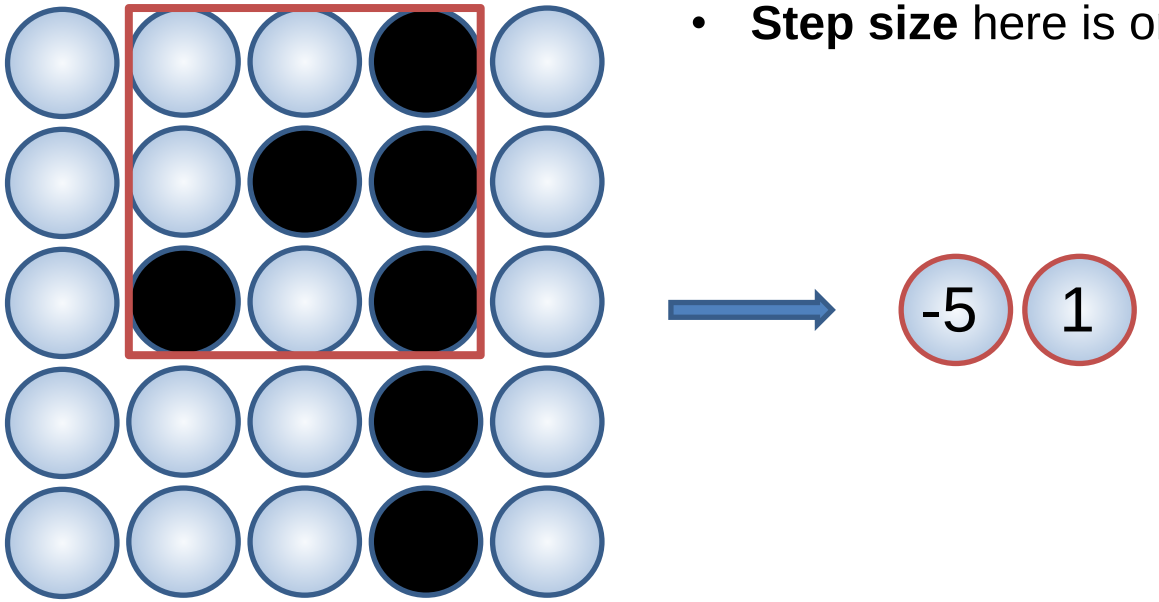
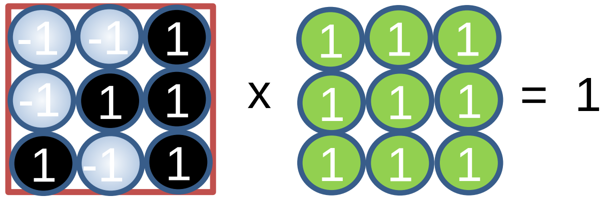
Convolutional Neural Networks
Learning on image data - Example

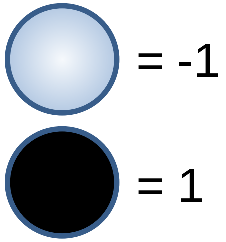


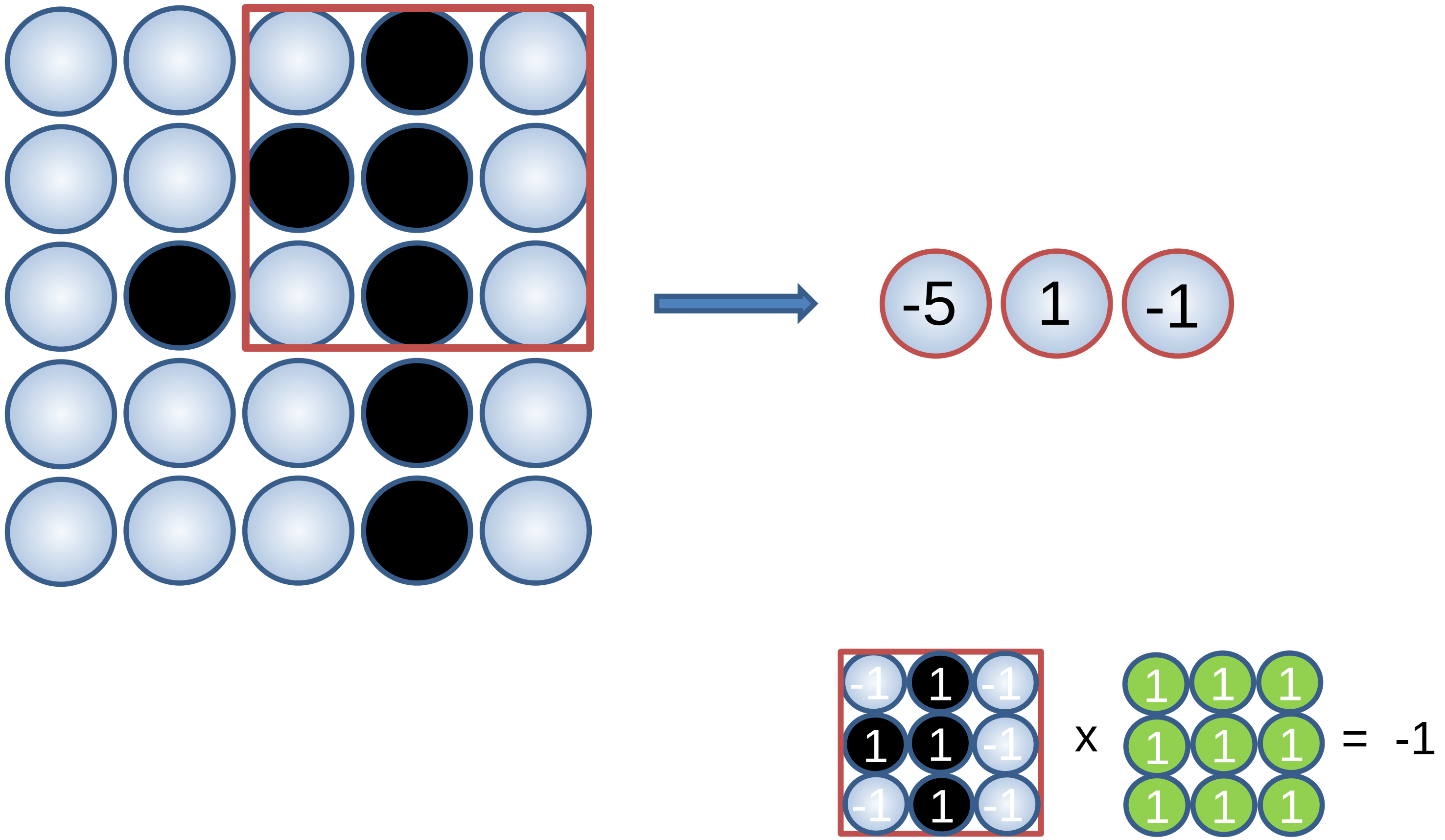
- **Step size** here is one and the clipping is 3x3



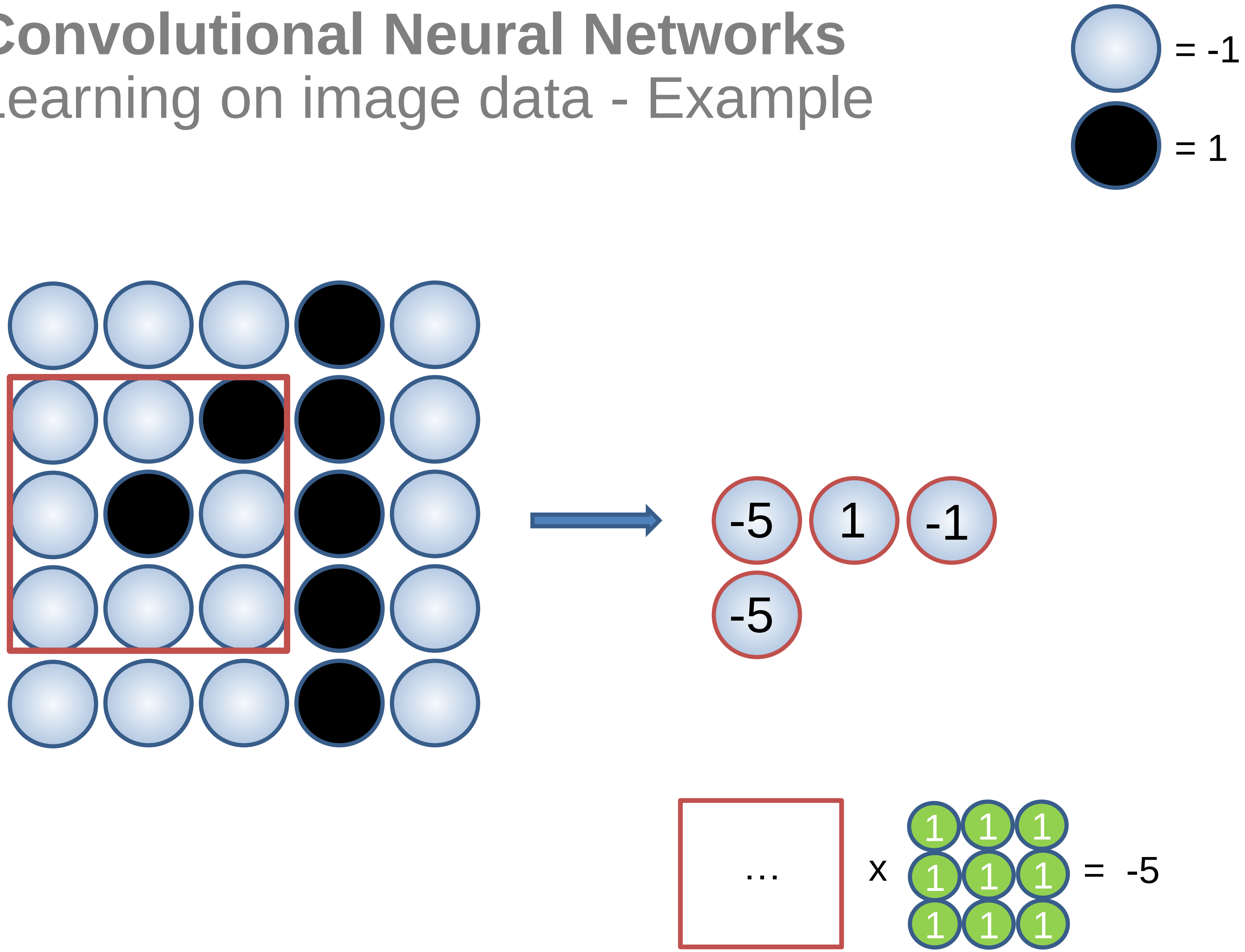


Convolutional Neural Networks
Learning on image data - Example

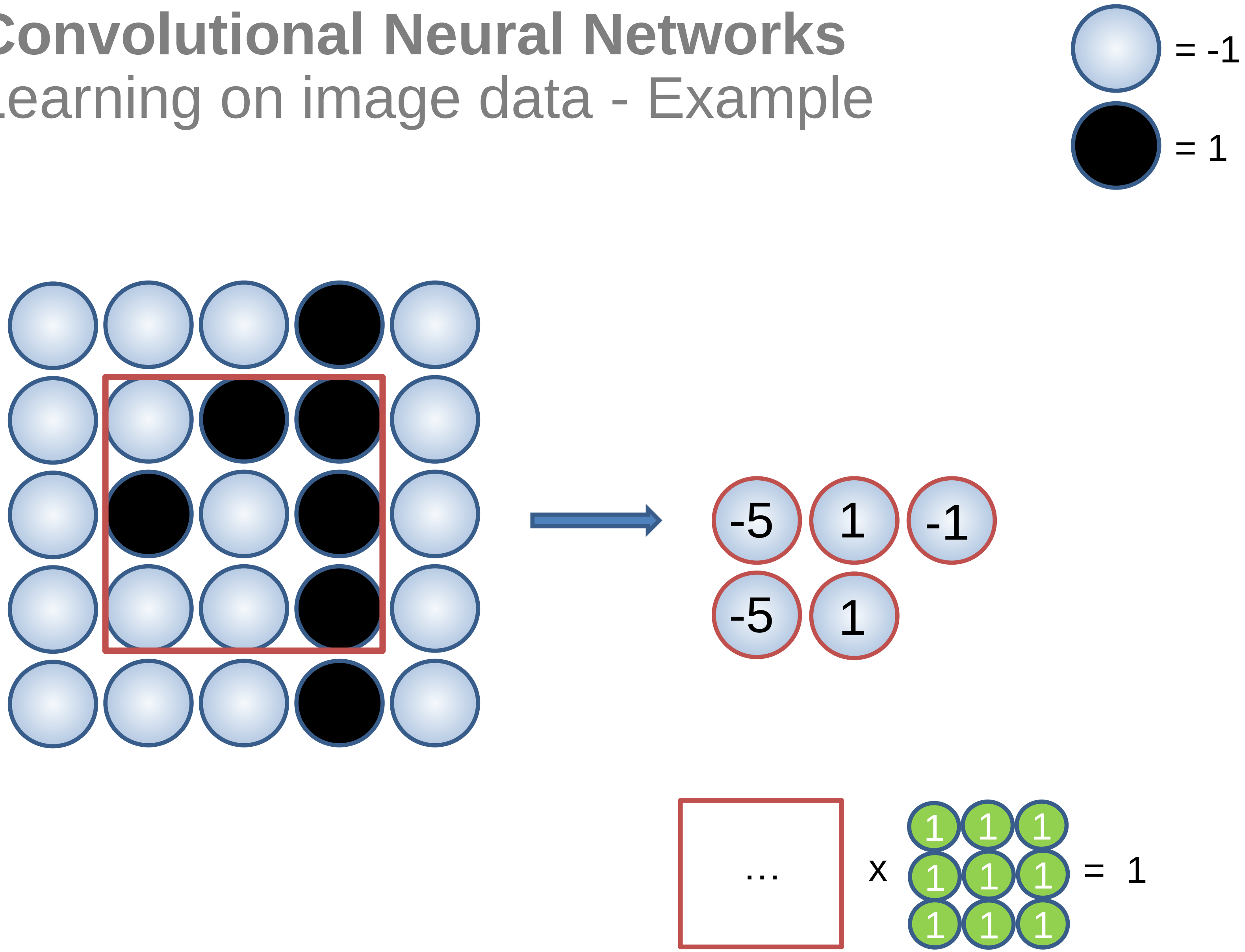




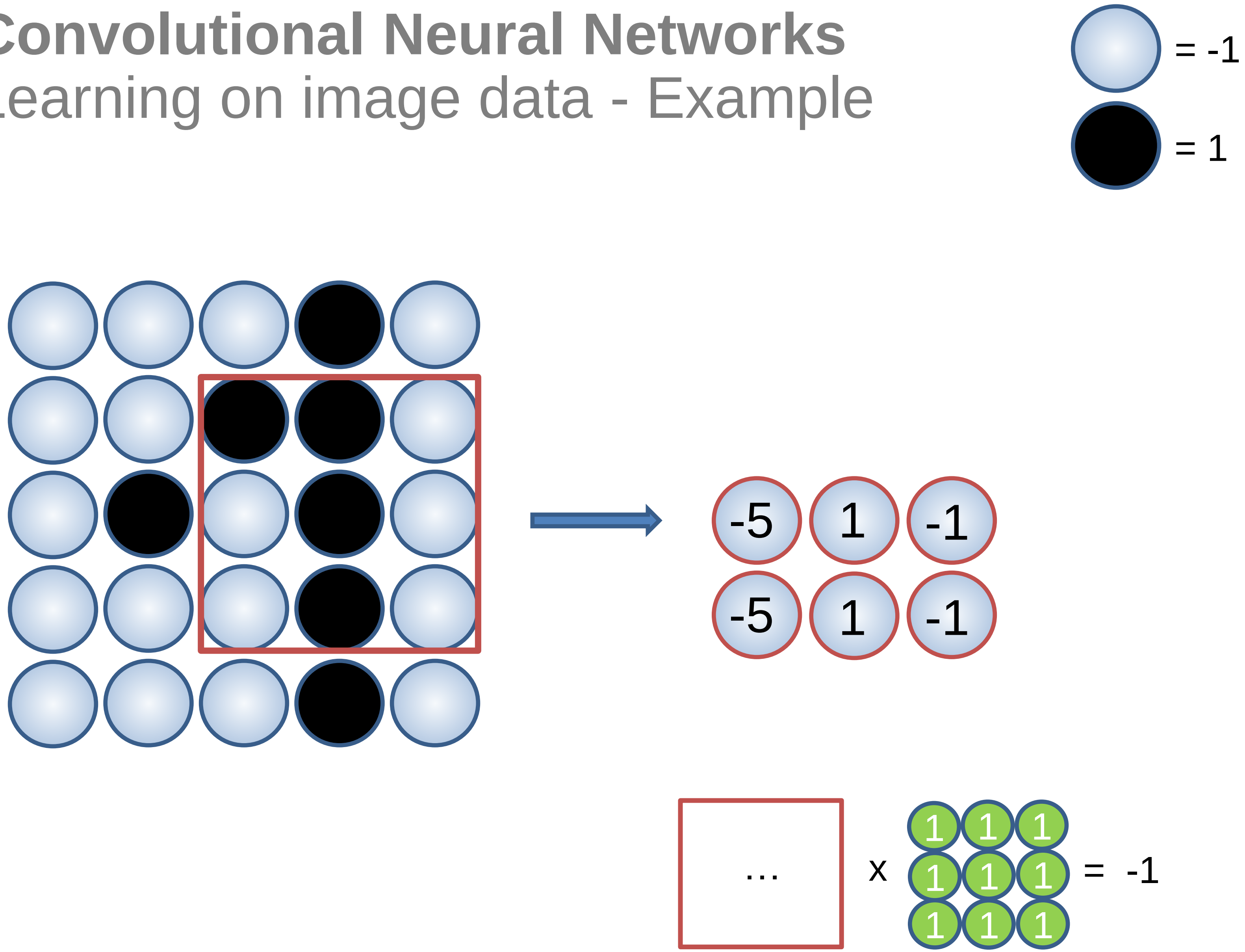
Convolutional Neural Networks
Learning on image data - Example



Convolutional Neural Networks
Learning on image data - Example



Convolutional Neural Networks
Learning on image data - Example



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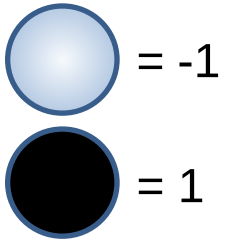
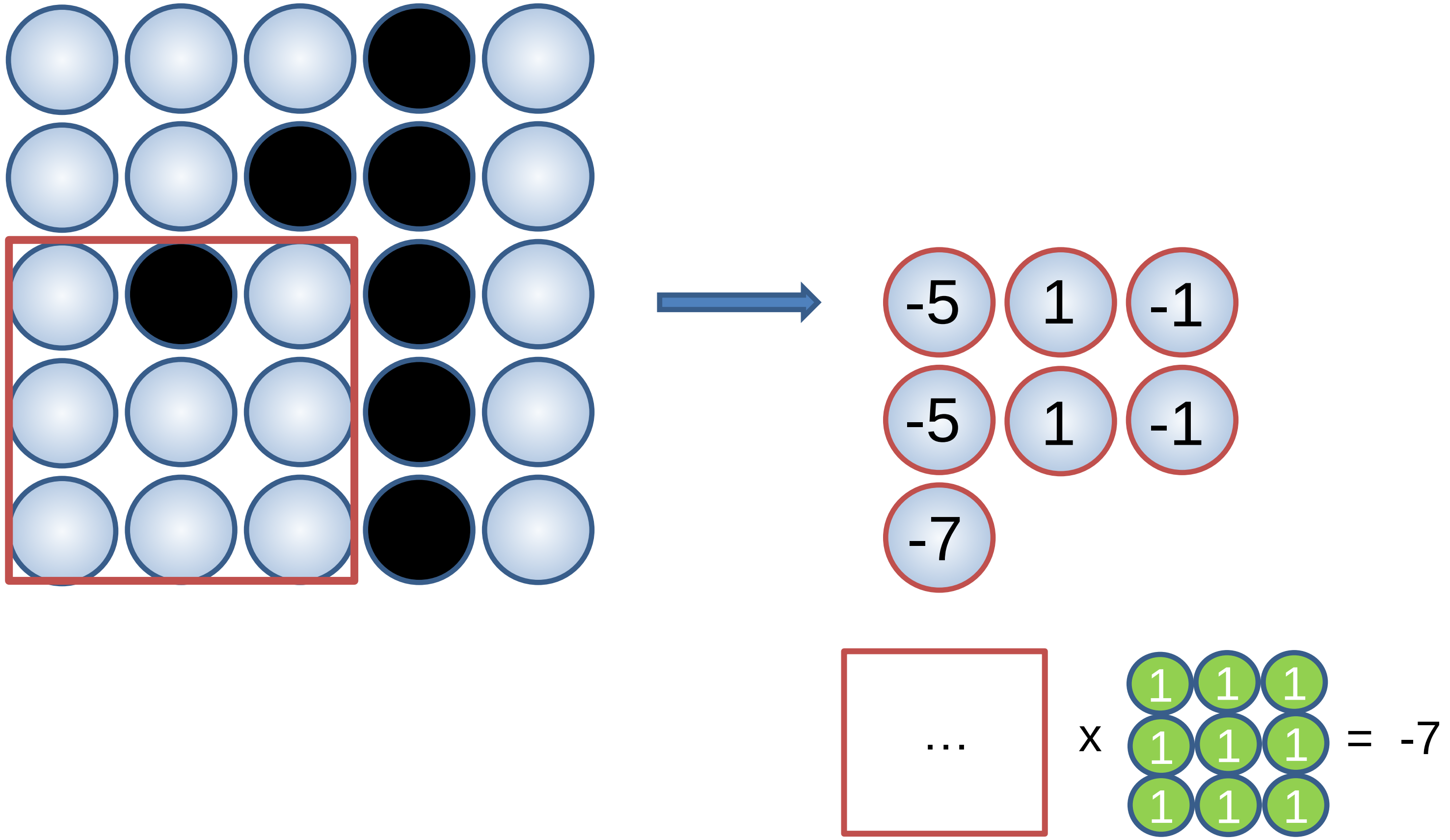
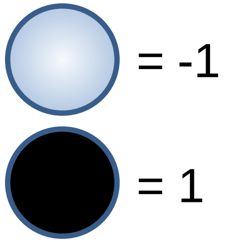
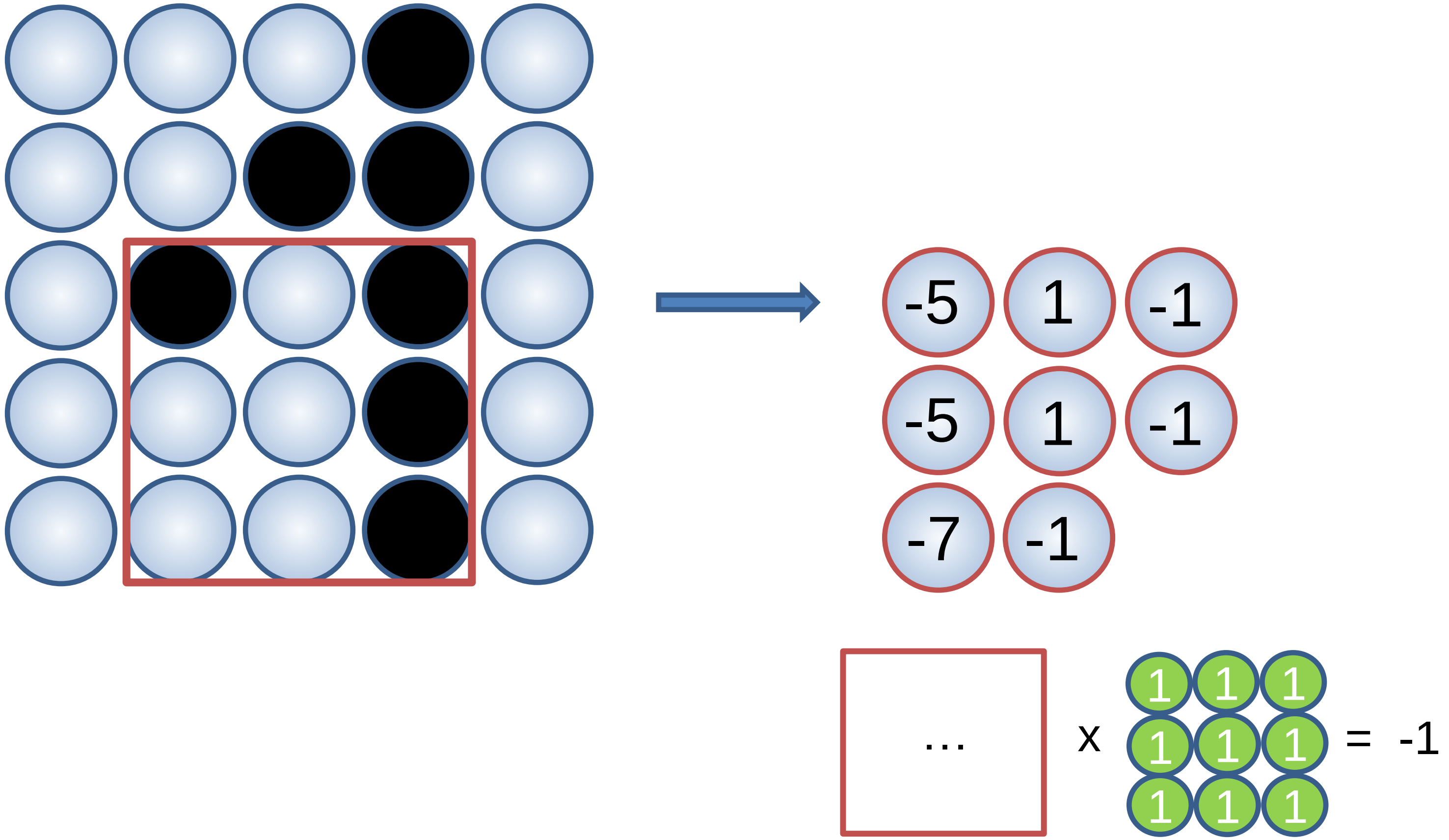
Convolutional Neural Networks
Learning on image data - Example



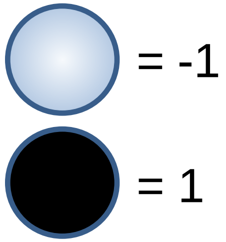


Convolutional Neural Networks
Learning on image data - Example

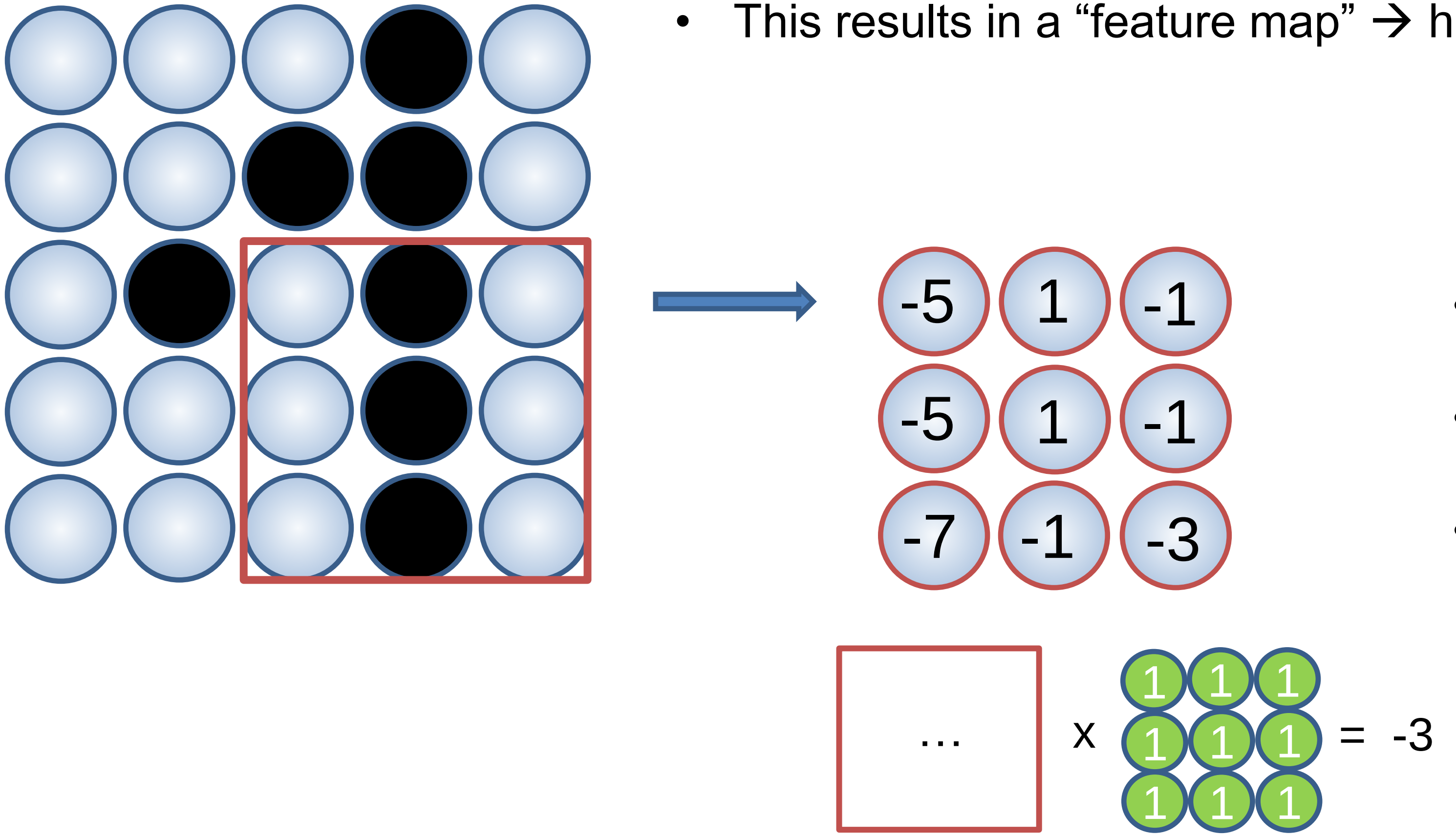




Convolutional Neural Networks
Learning on image data - Example

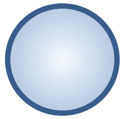


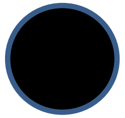
- This results in a “feature map” → here : 9 neurons for the 5x5 image

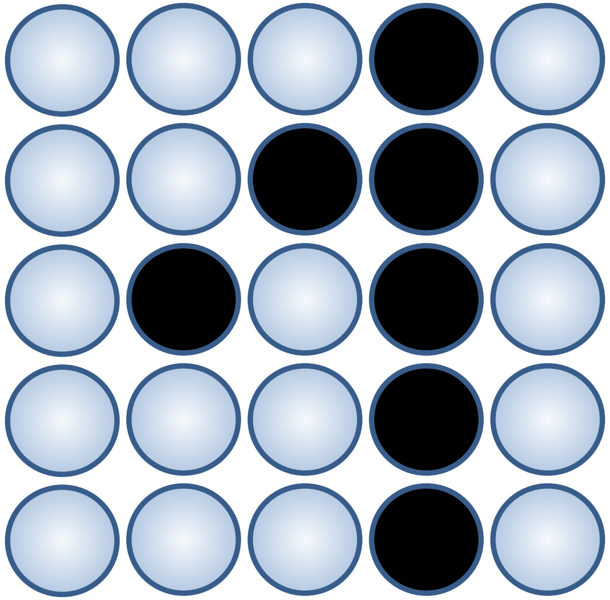


- Filter of size 3x3 → 9 separate weights
- Scan step wise the image with the filter
- That’s **Convolution**

Convolutional Neural Networks
Learning – Feature Extraction


= -1

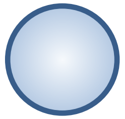

= 1



- Repeat the scan process with **multiple filters**

Next: extracting feature with filter $fi_1 = \begin{bmatrix} -1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & -1 & 1 \end{bmatrix}$

Convolutional Neural Networks
Learning – Feature Extraction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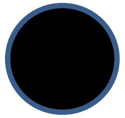
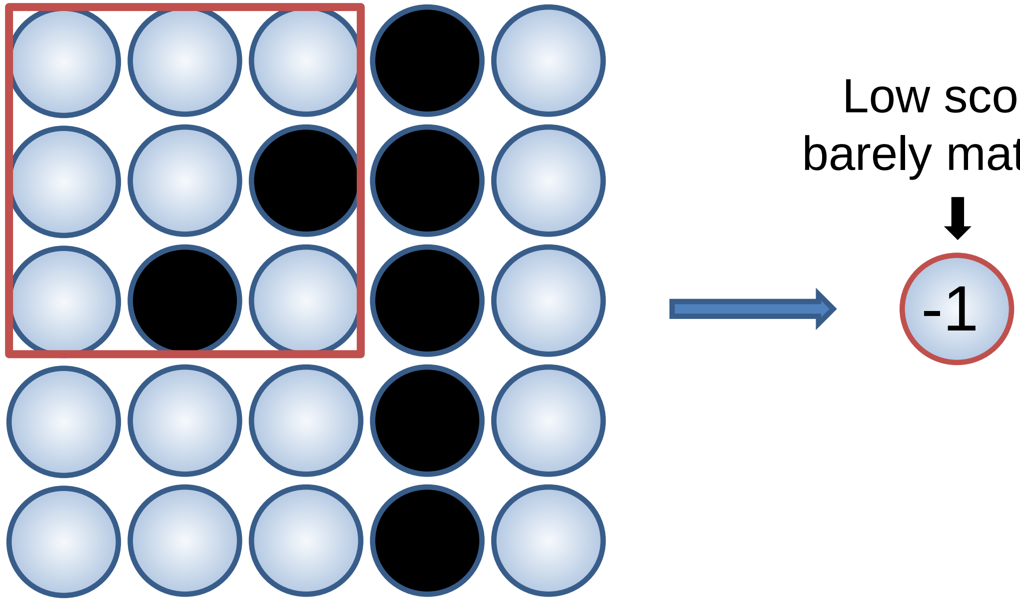
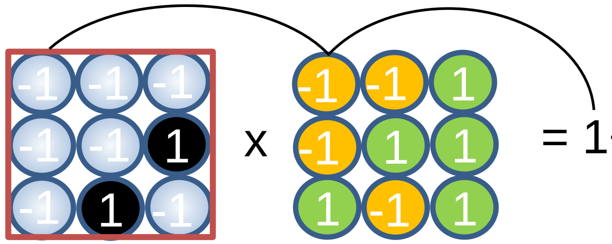

= 1

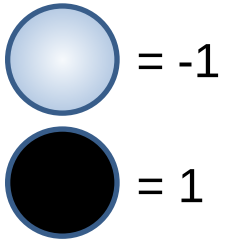


Low score !
barely matches

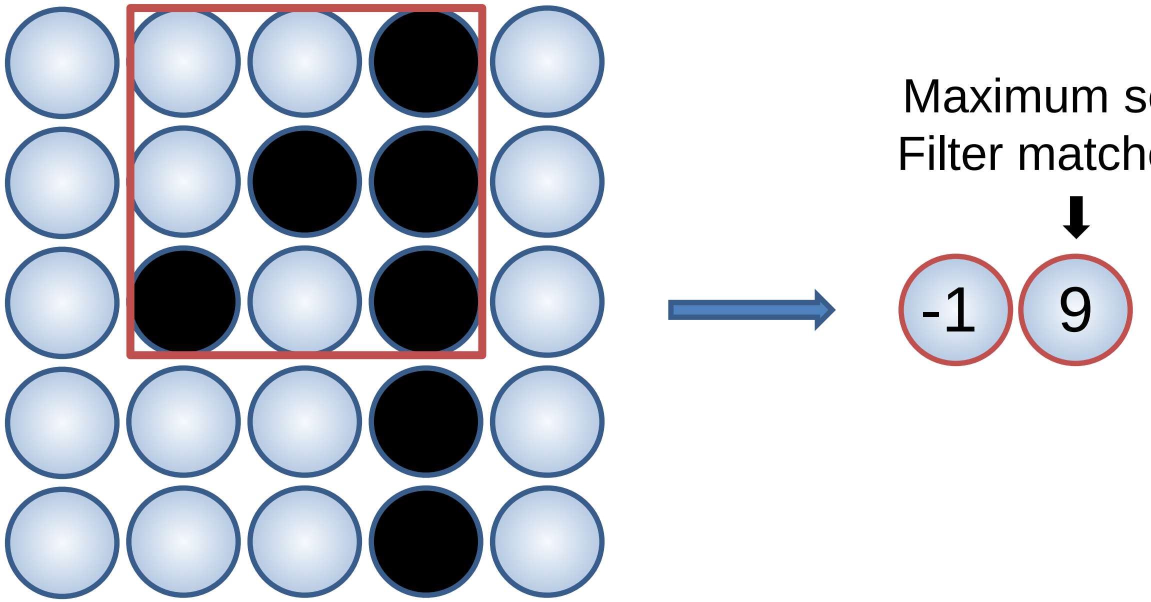


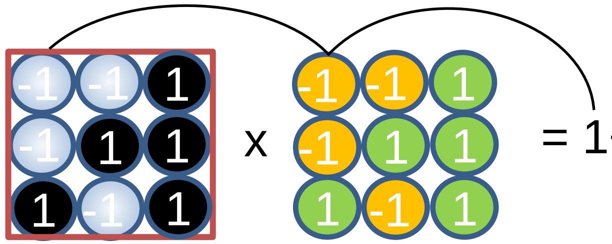
$= 1+1+(-1)+1+(-1)+1+(-1)+(-1)+(-1) = -1$

Convolutional Neural Networks
Learning – Feature Extraction



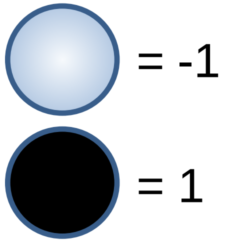
Maximum score !
Filter matches full



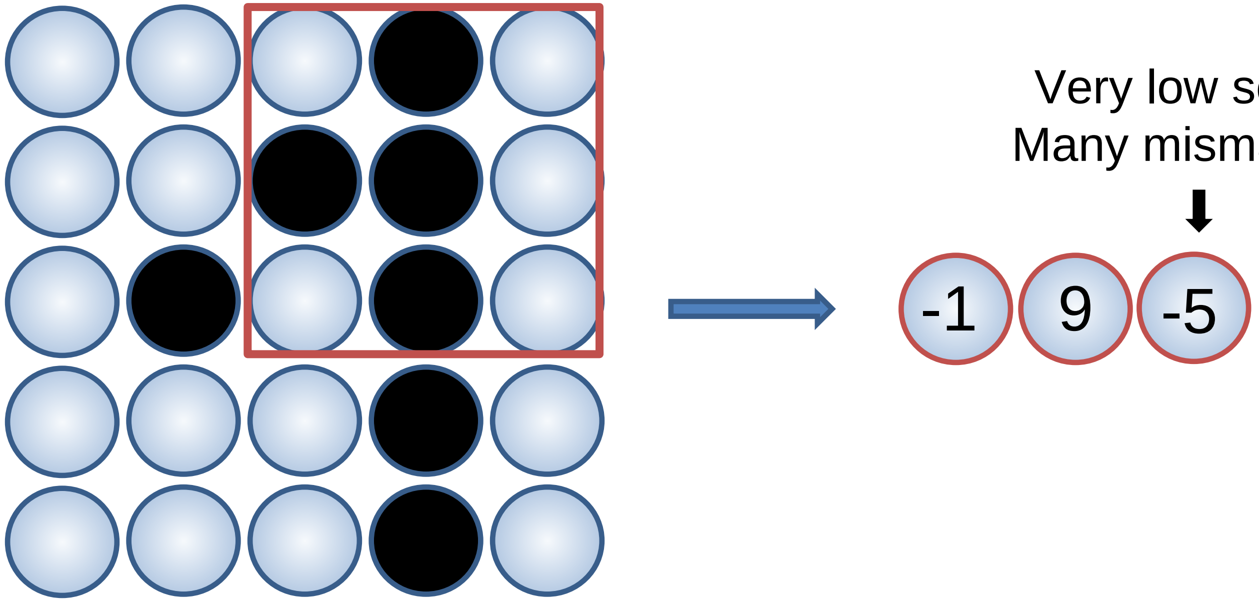


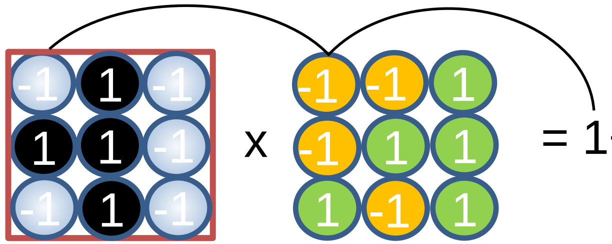
= 1+1+1+1+1+1+1+1+1 = 9

Convolutional Neural Networks
Learning – Feature Extraction



Very low score !
Many mismatches





$= 1+(-1)+(-1)+(-1)+1+(-1)+(-1)+(-1)+(-1) = -5$

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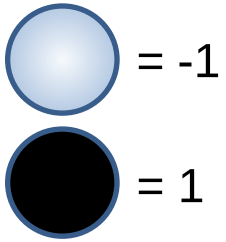
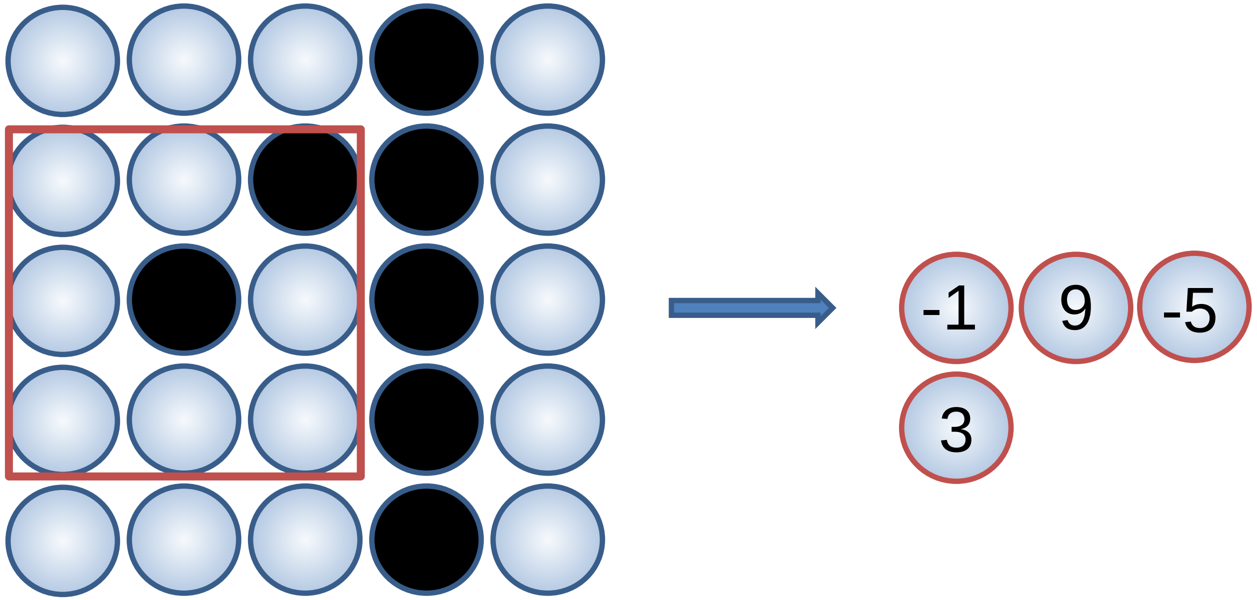
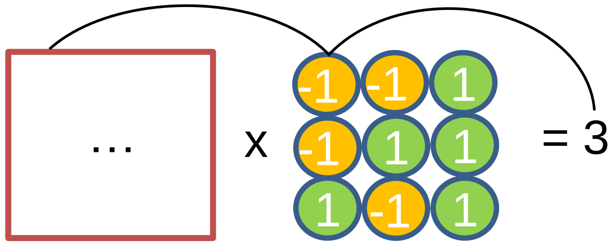
Convolutional Neural Networks

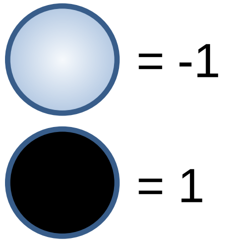
Learning – Feature Extraction

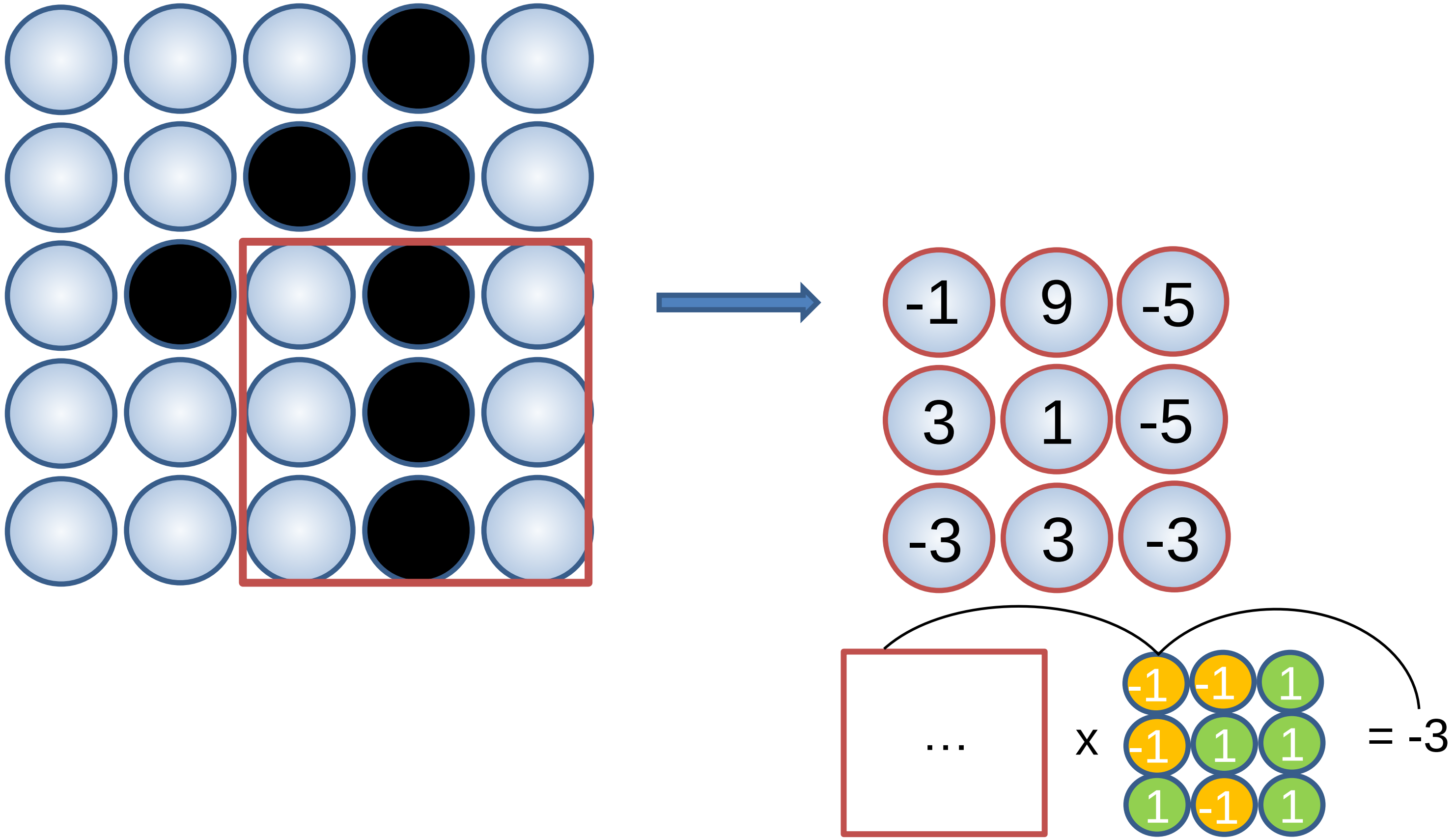




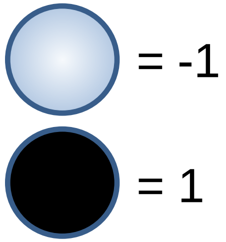


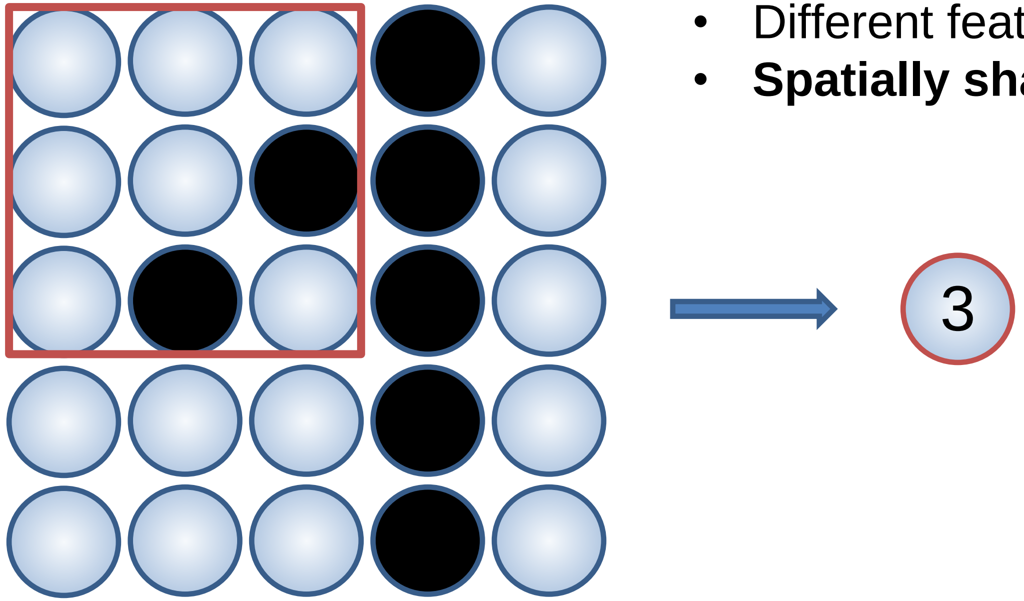
Convolutional Neural Networks
Learning – Feature Extraction





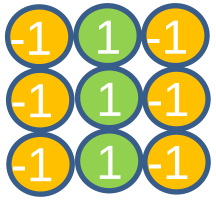
Convolutional Neural Networks
Learning – Feature Extraction

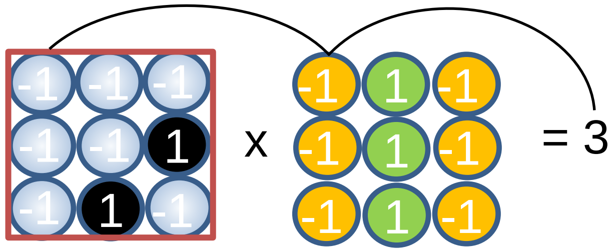




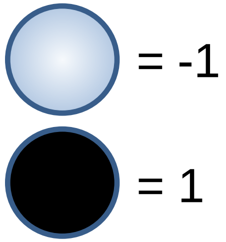
- Different feature will extract different features
- **Spatially share** parameters of each filter

Next filter $\mathbf{fi_2}$ =





Convolutional Neural Networks
Learning – Feature Extraction



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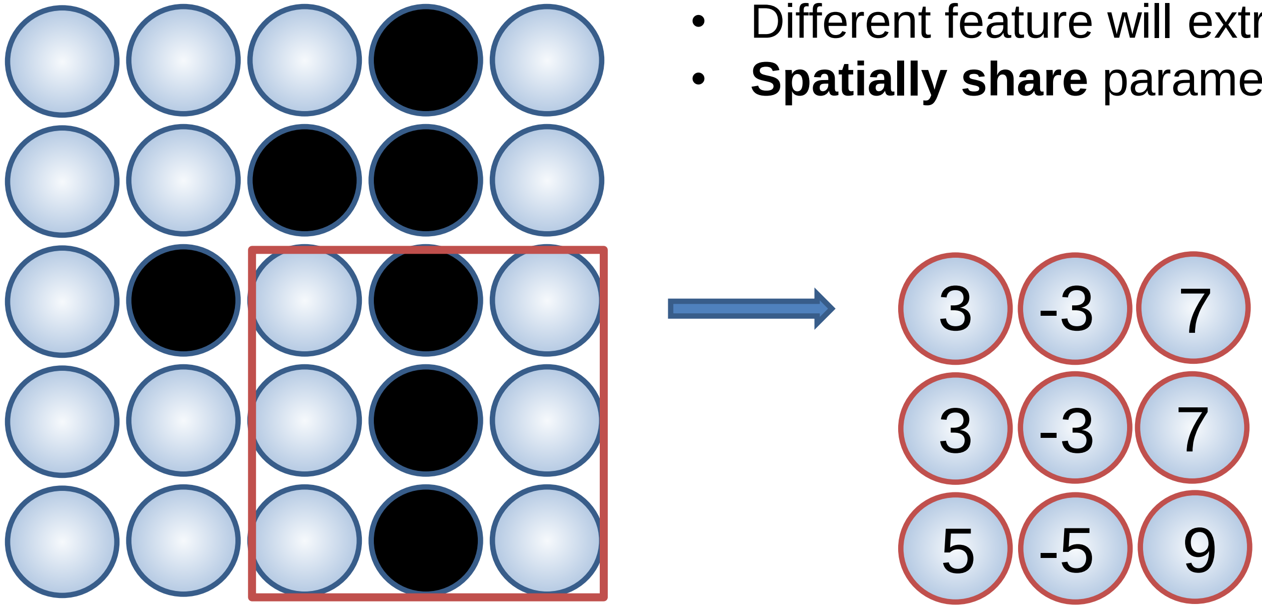

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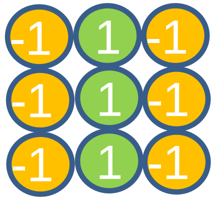
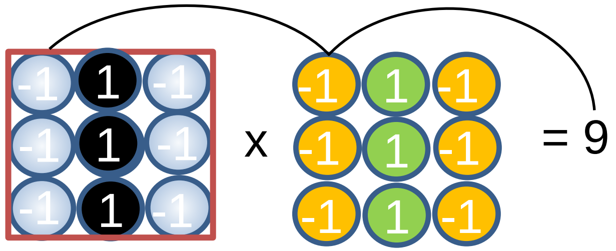
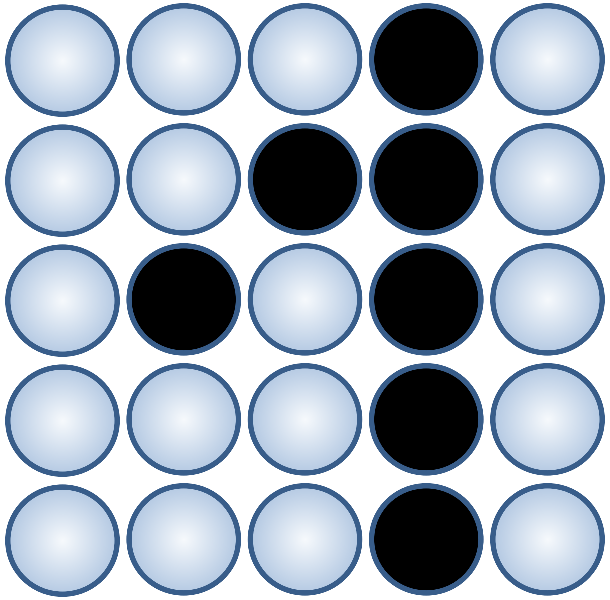
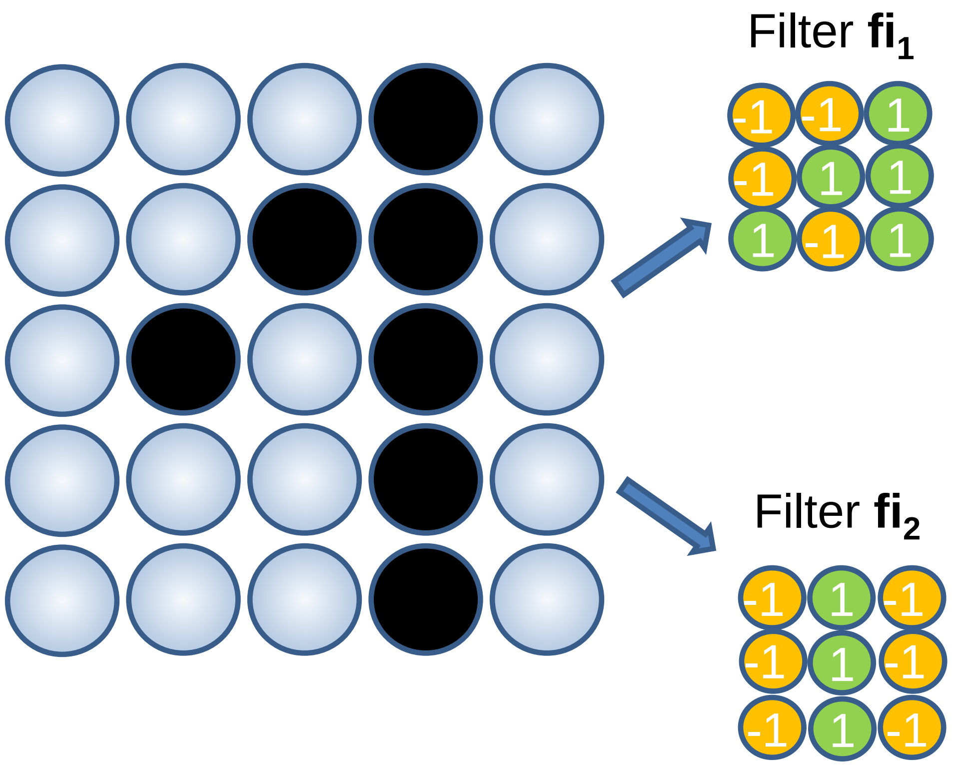




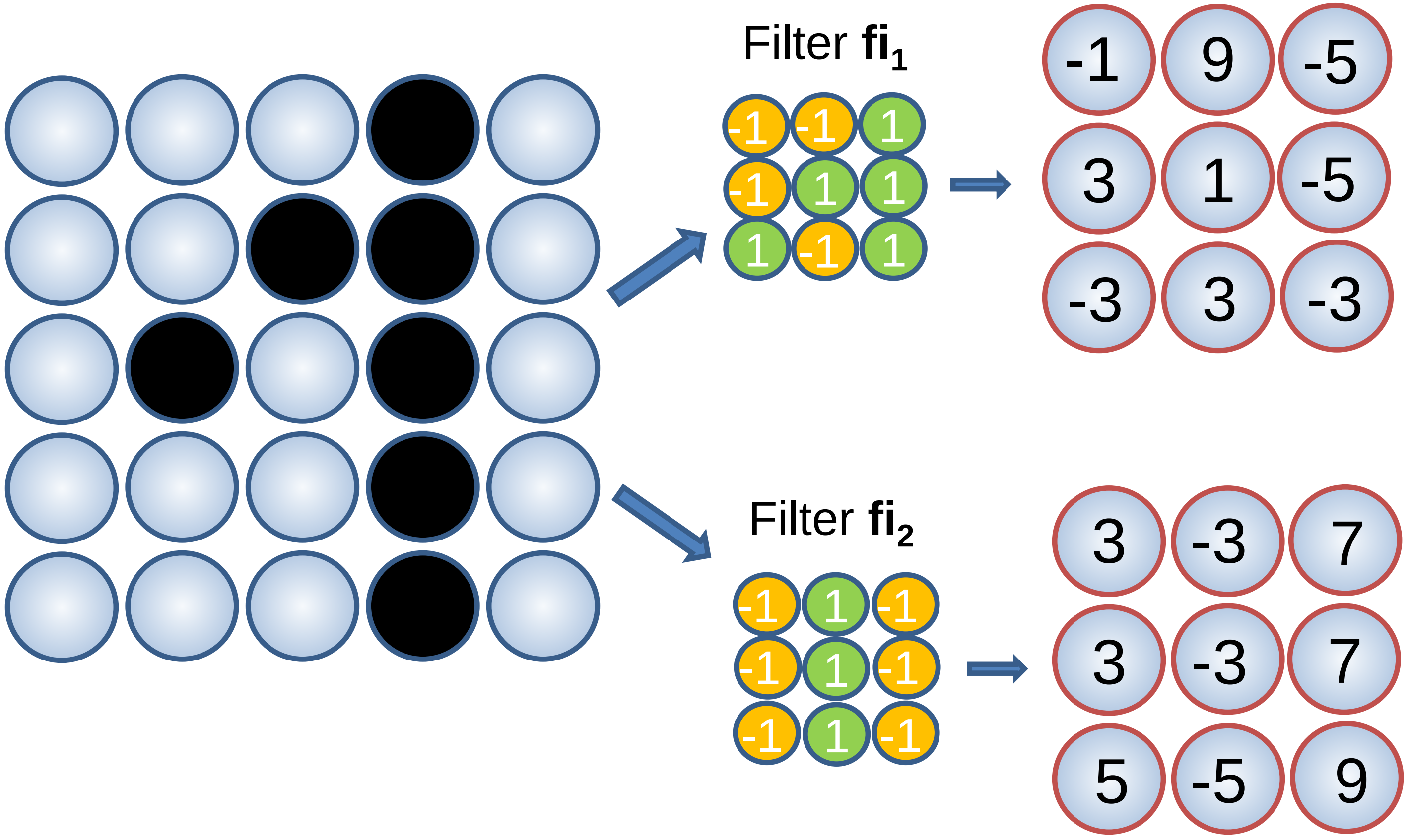
Convolutional Neural Networks
Learning – Feature Extraction: filter comparison



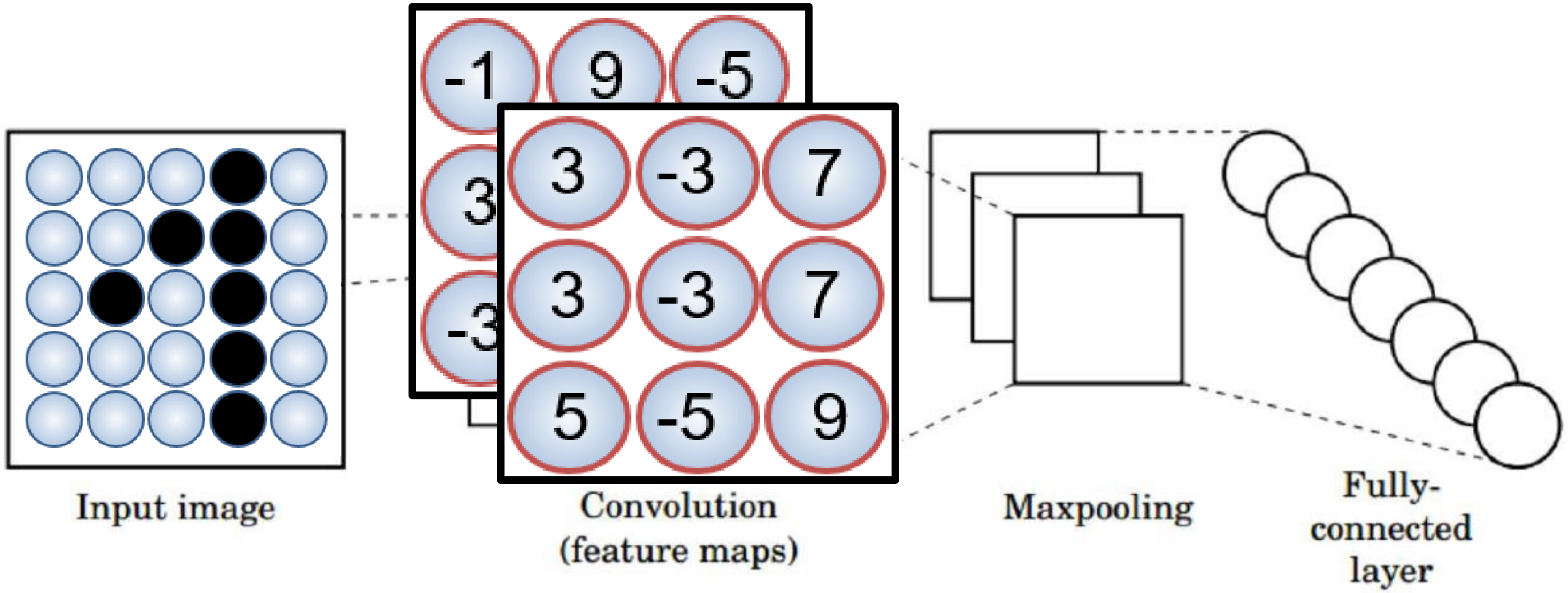
Convolutional Neural Networks
Learning – Feature Extraction: filter comparison



Convolutional Neural Networks
Learning – Feature Extraction: filter comparison



Convolutional Neural Networks
Building a CNN - Example



1. **Convolution**: Apply filters with learned weights to generate feature maps.
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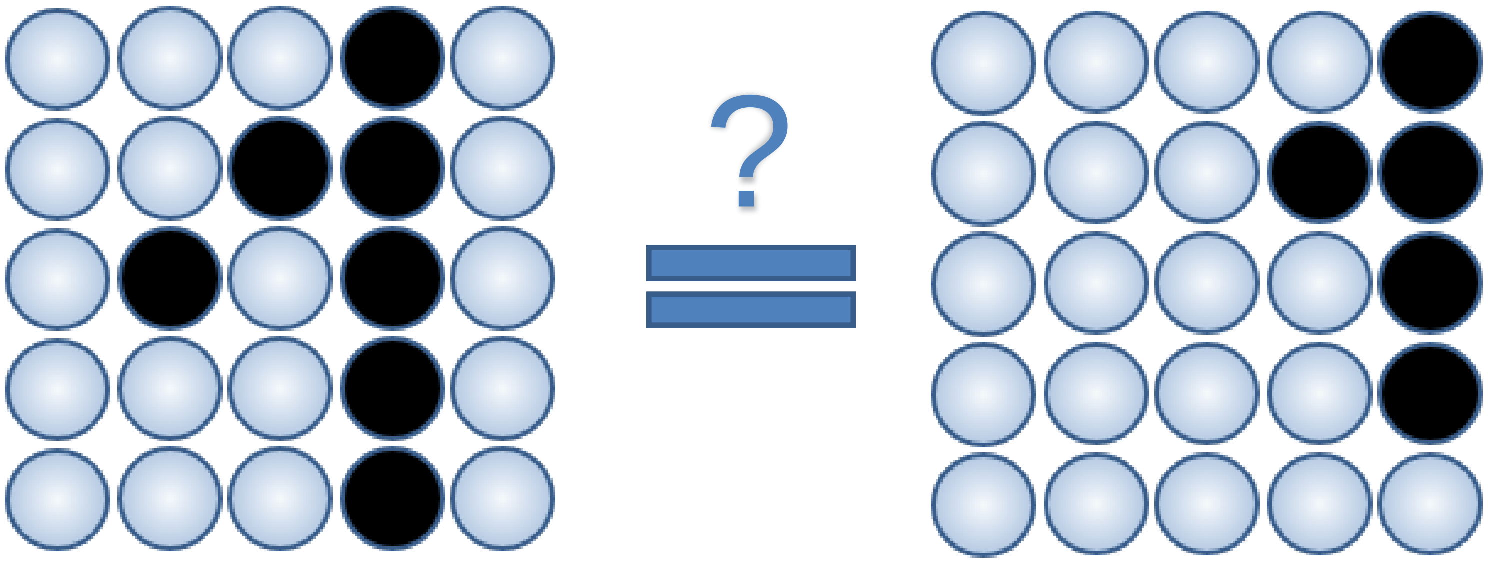
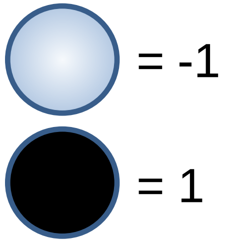
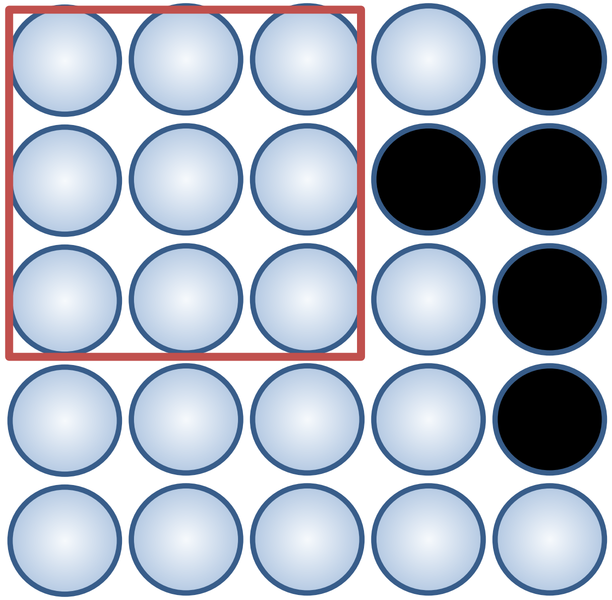
Train model with image data.
Learn weights of filters in convolutional layers.

Convolutional Neural Networks
Filters to detect features



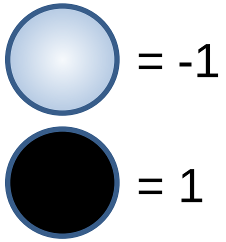
Convolutional Neural Networks
Filters to detect features

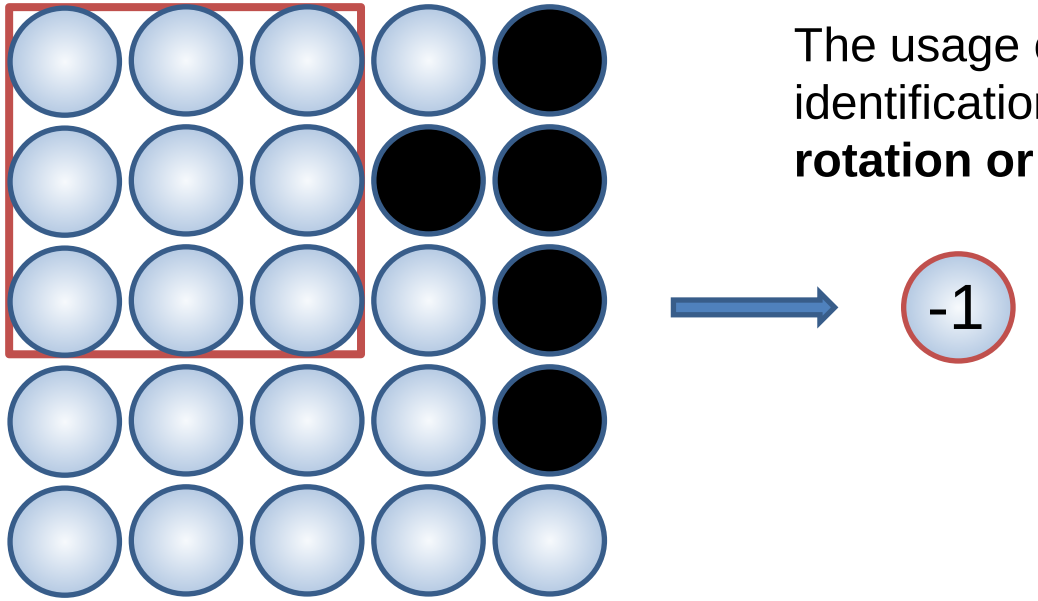




The usage of filters in detecting features allow good identification even in the event of **displacement, shrinkage, rotation or deformation**.

Convolutional Neural Networks
Filters to detect features



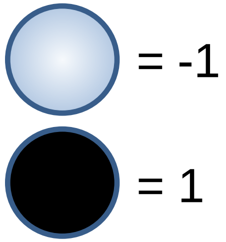


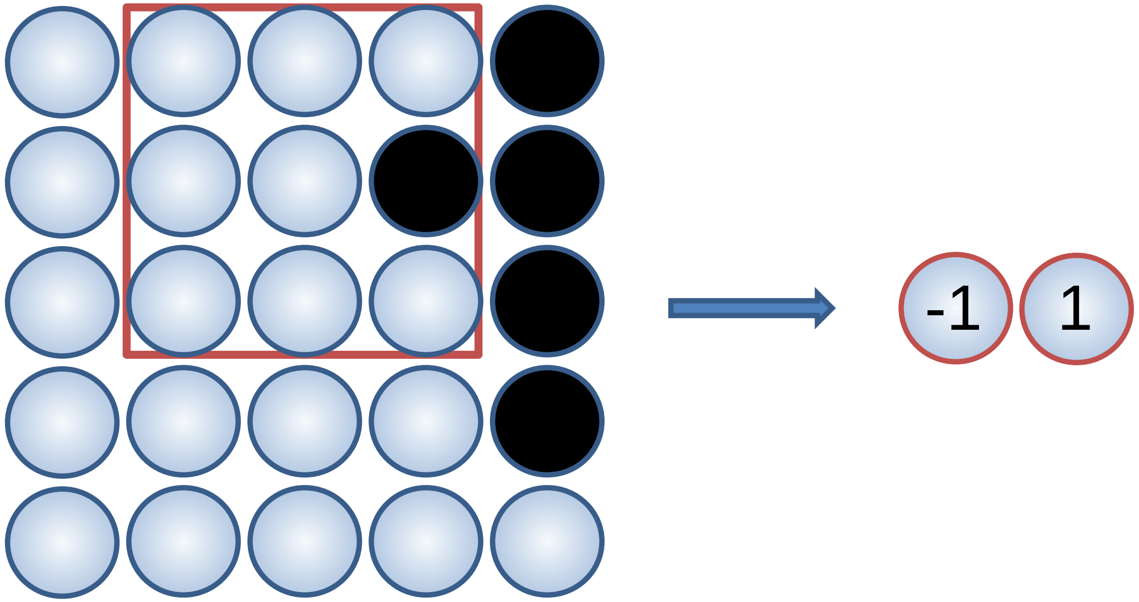
The usage of filters in detecting features allow good identification even in the event of **displacement, shrinkage, rotation or deformation**.

e.g. Filter $\mathbf{fi}_1$ = $\begin{bmatrix}-1 & -1 & 1\\ -1 & 1 & 1\\ 1 & -1 & 1\end{bmatrix}$

$$\begin{bmatrix}-1 & -1 & -1\\ -1 & -1 & -1\\ -1 & -1 & -1\end{bmatrix} \times \begin{bmatrix}-1 & -1 & 1\\ -1 & 1 & 1\\ 1 & -1 & 1\end{bmatrix} = \ldots$$

Convolutional Neural Networks
Filters to detect features



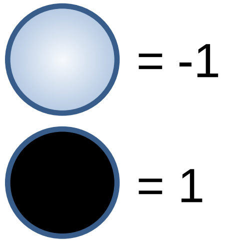


e.g. Filter $\mathbf{fi}_1 = \begin{matrix} -1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & -1 & 1 \end{matrix}$

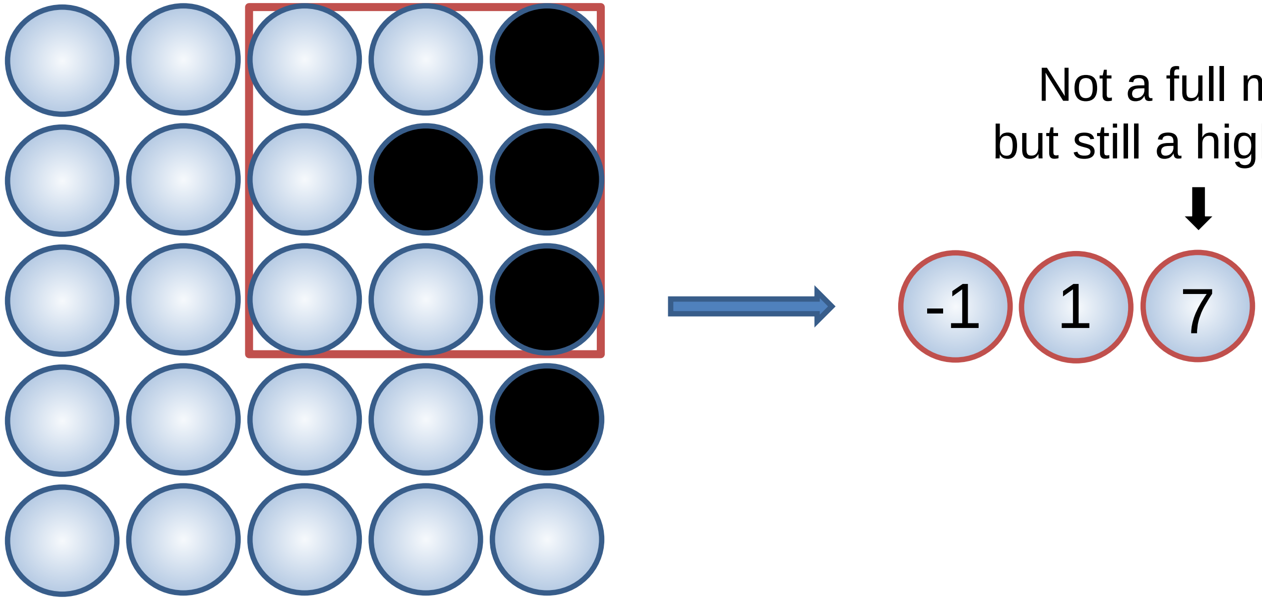
Feature/filter fi_1 still matches the deformed image well

$$\boxed{\begin{matrix} -1 & -1 & -1 \\ -1 & -1 & 1 \\ -1 & -1 & -1 \end{matrix}} \times \begin{matrix} -1 & -1 & 1 \\ -1 & 1 & 1 \\ 1 & -1 & 1 \end{matrix} = \ldots$$

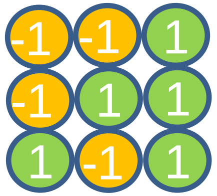
Convolutional Neural Networks
Filters to detect features



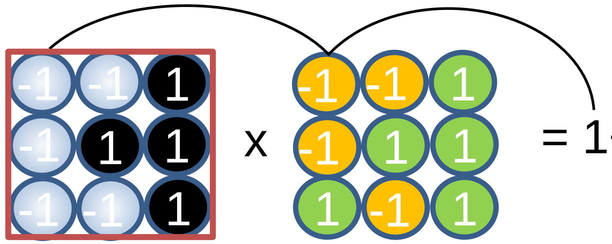
Not a full match
but still a high score



e.g. Filter $\mathbf{fi_1}$ =

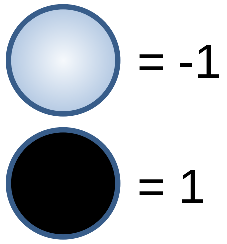


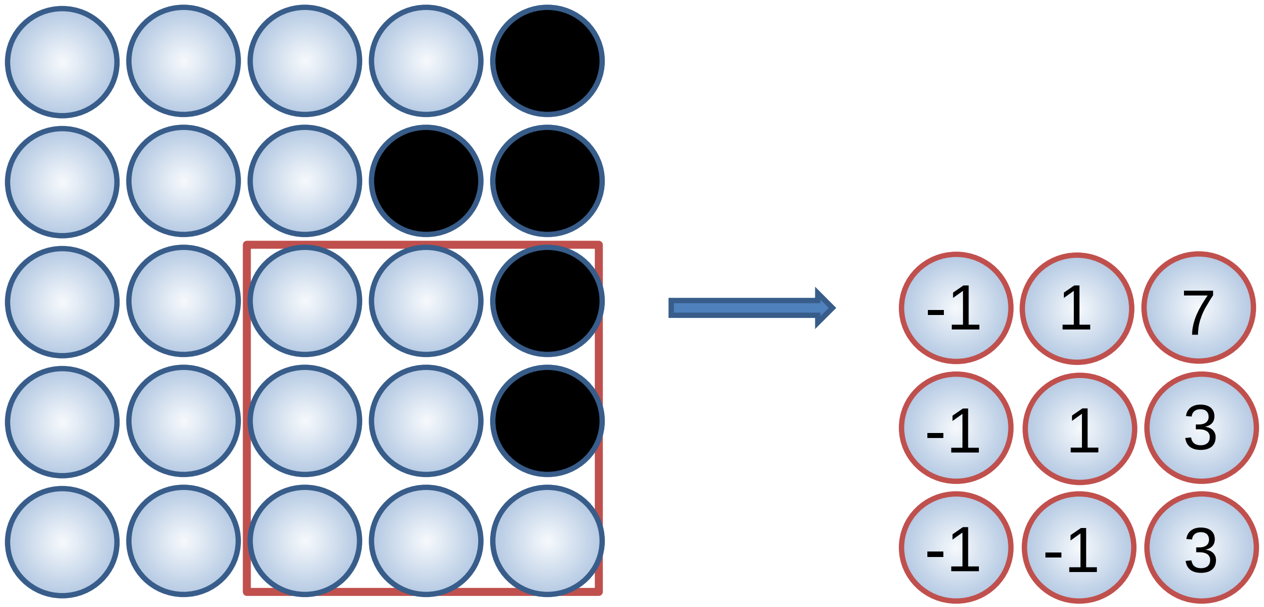
Feature/filter fi_1 still matches the deformed image well
Remember! **A full match would be 9**



= 1+1+1+1+1+1+(-1)+1+1 = 7

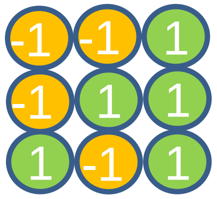
Convolutional Neural Networks
Filters to detect features



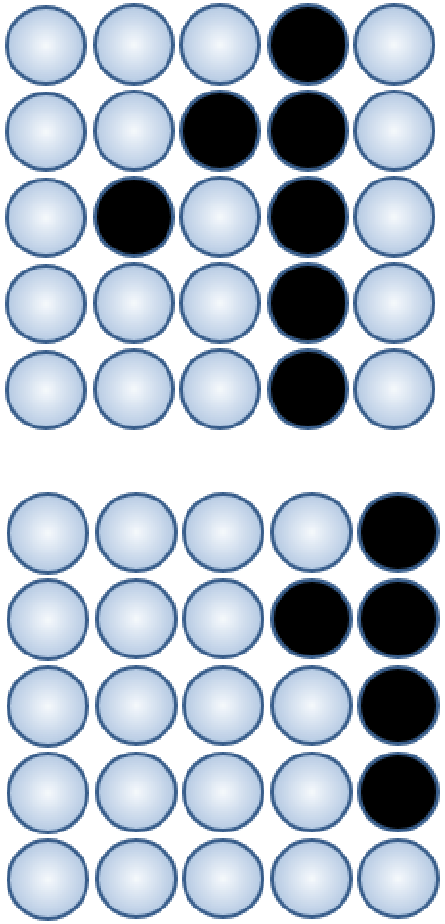


Finished feature map using filter $\mathbf{fi_1}$

e.g. Filter $\mathbf{fi_1}$ =



Convolutional Neural Networks
Filters to detect features: comparison



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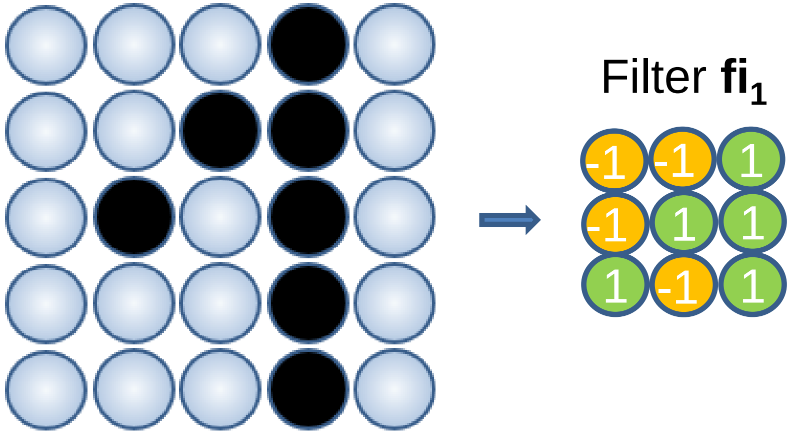
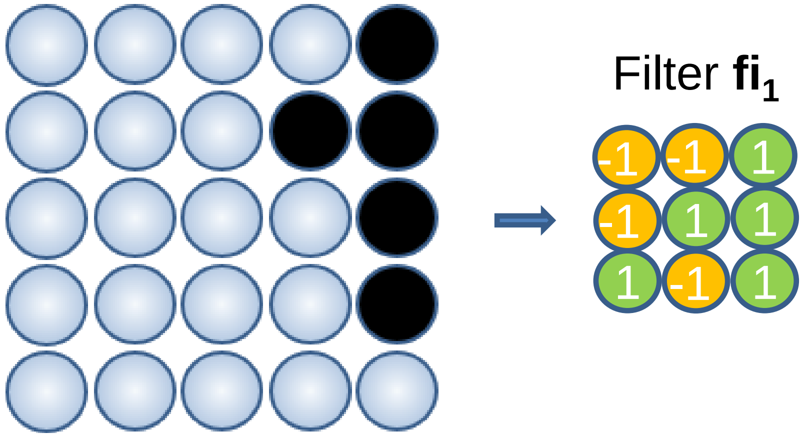
Filters to detect features: comparison





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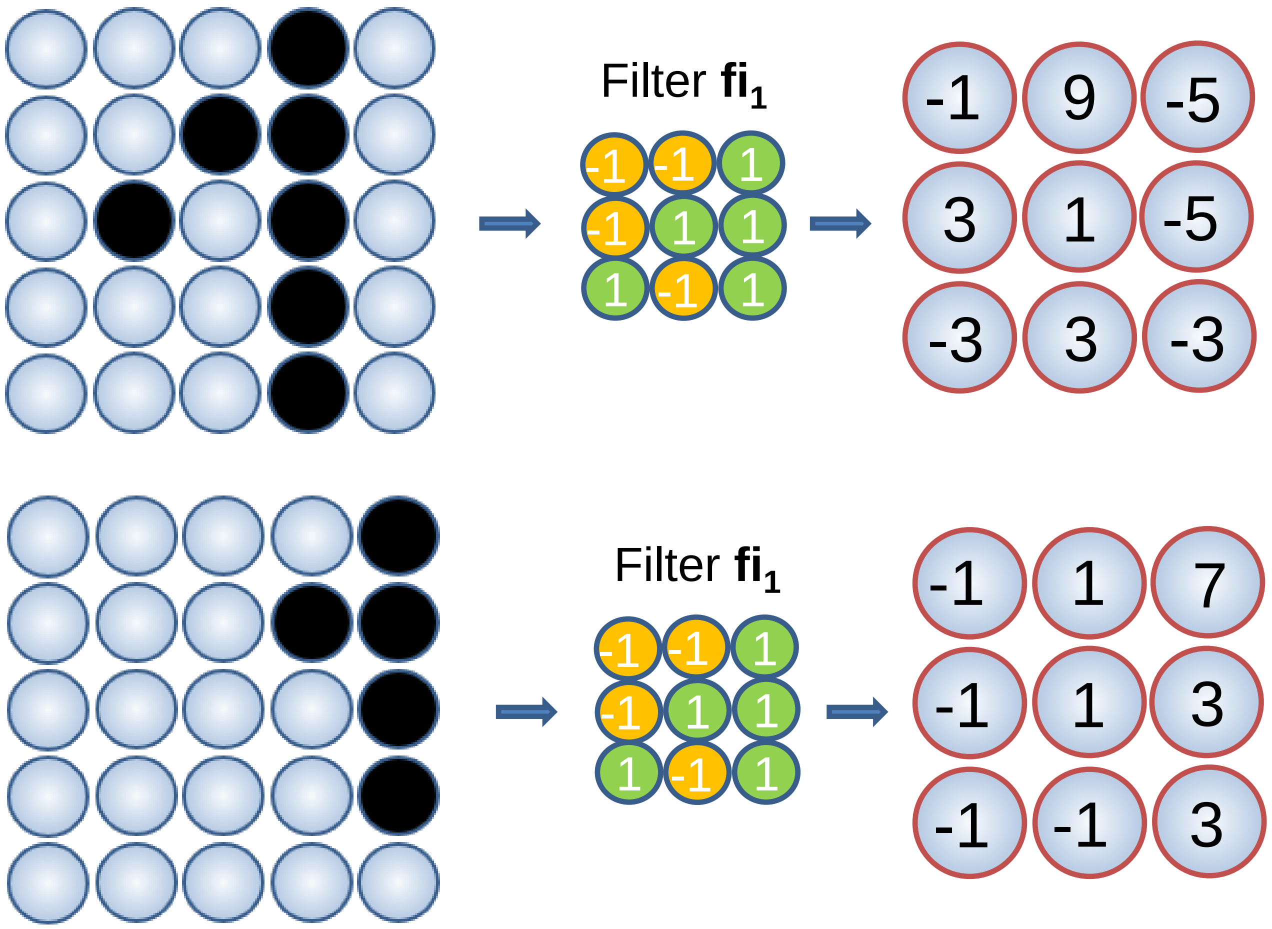
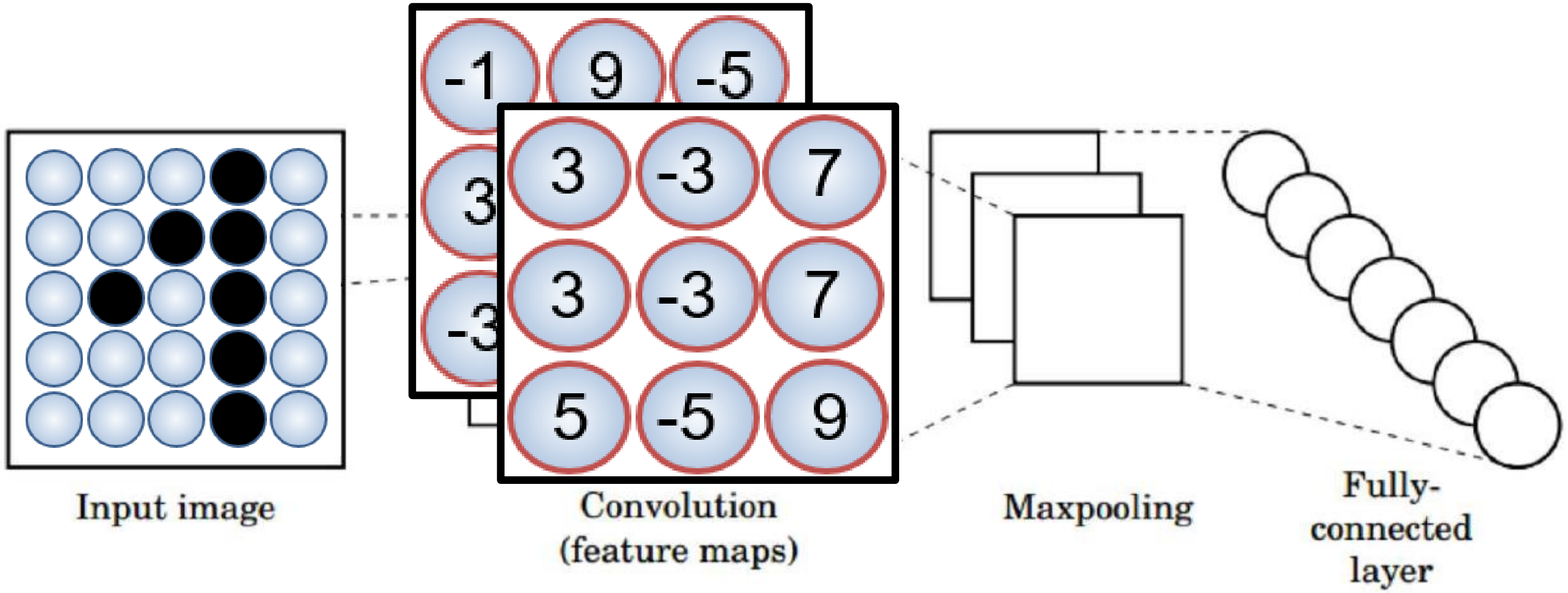


Convolutional Neural Networks
Pooling



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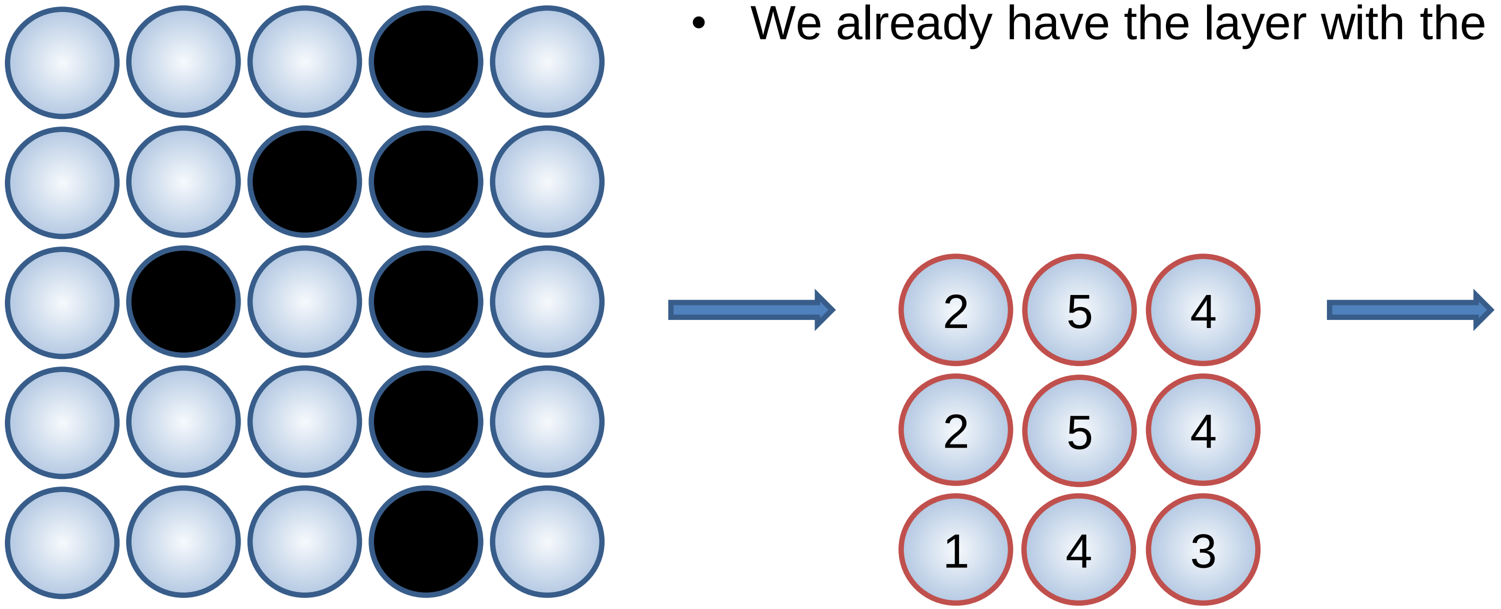
Convolutional Neural Networks
Max Pool – Example

- We already have the layer with the 9 neurons for the 5x5 image



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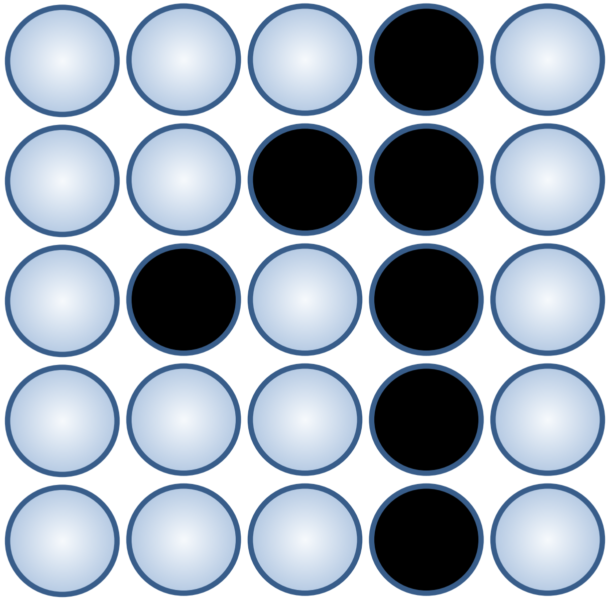
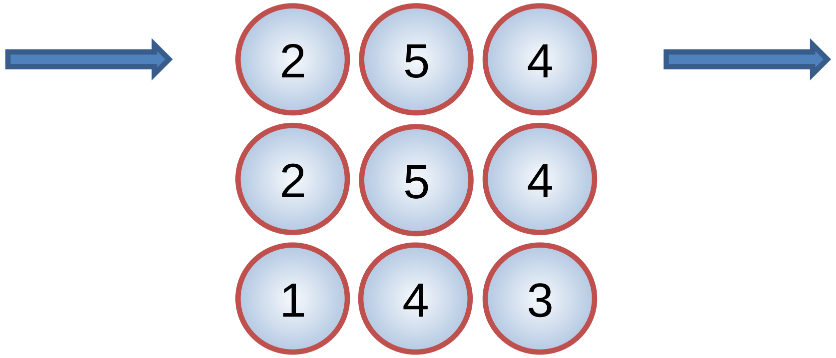


- We already have the layer with the 9 neurons for the 5x5 image
- Now we want to reduce dimensionality and spatial invariance



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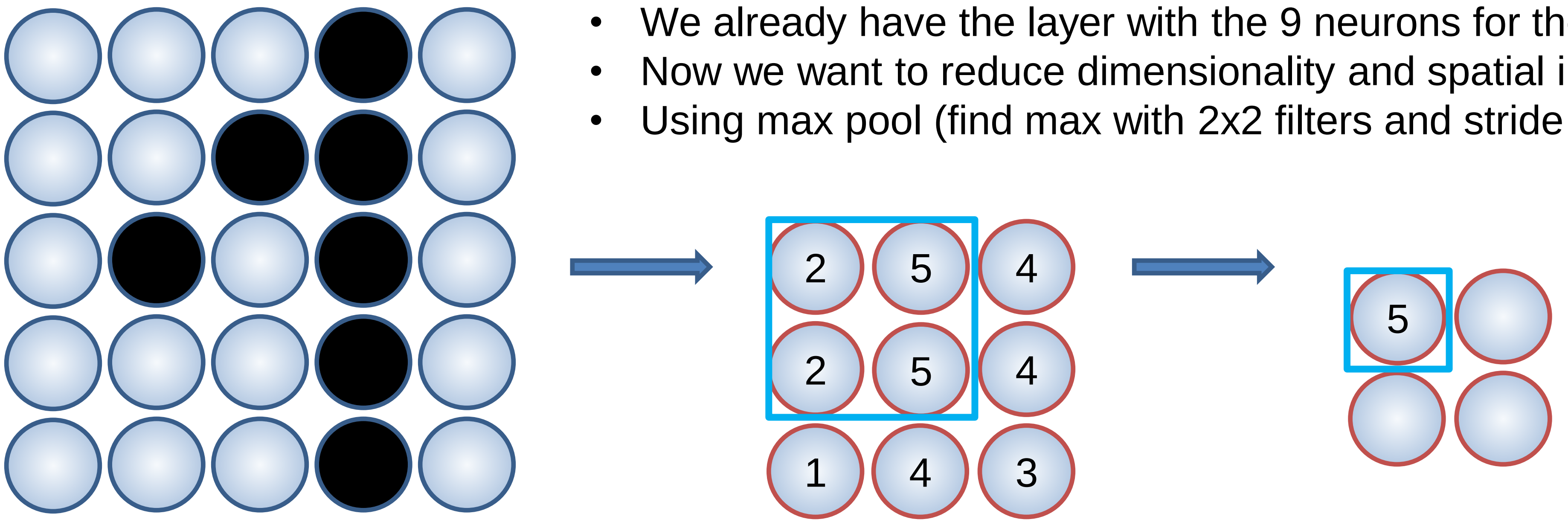
- We already have the layer with the 9 neurons for the 5x5 image
- Now we want to reduce dimensionality and spatial invariance
- Using max pool (find max with 2x2 filters and stride 1



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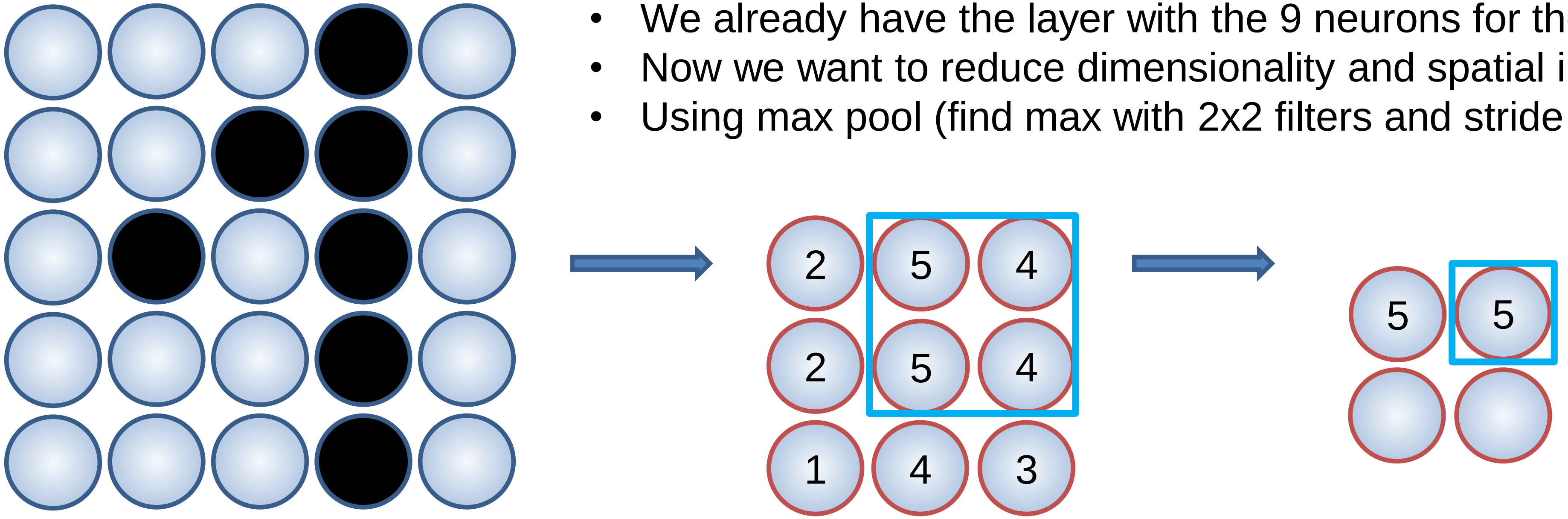

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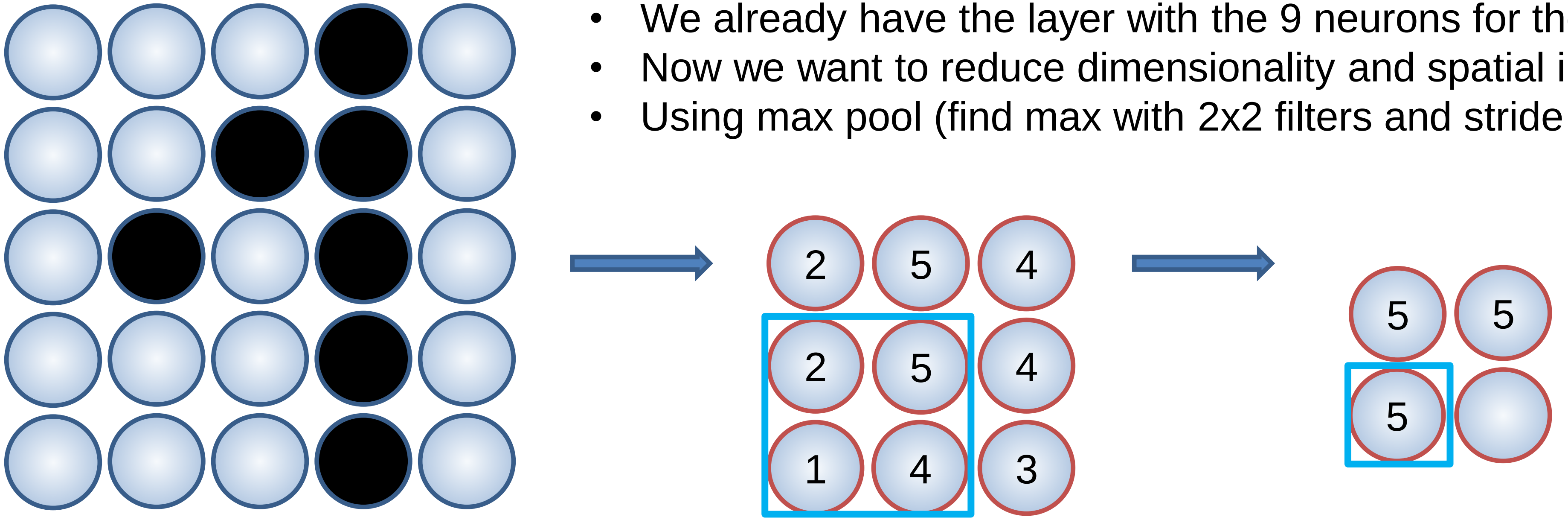

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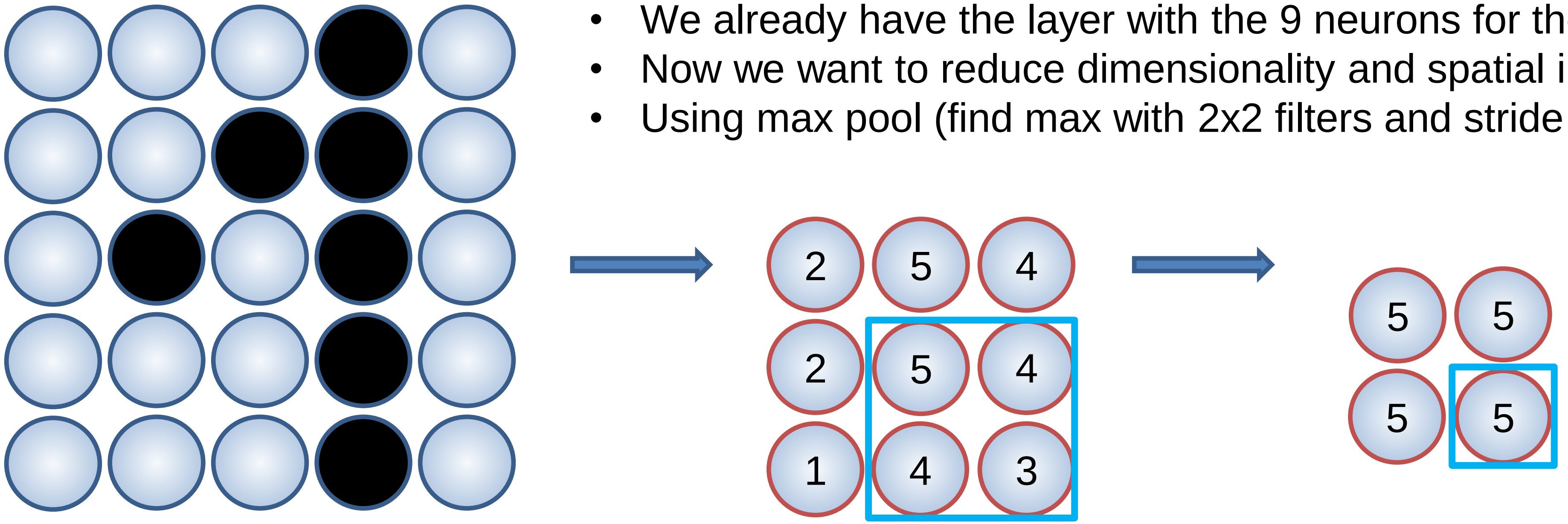
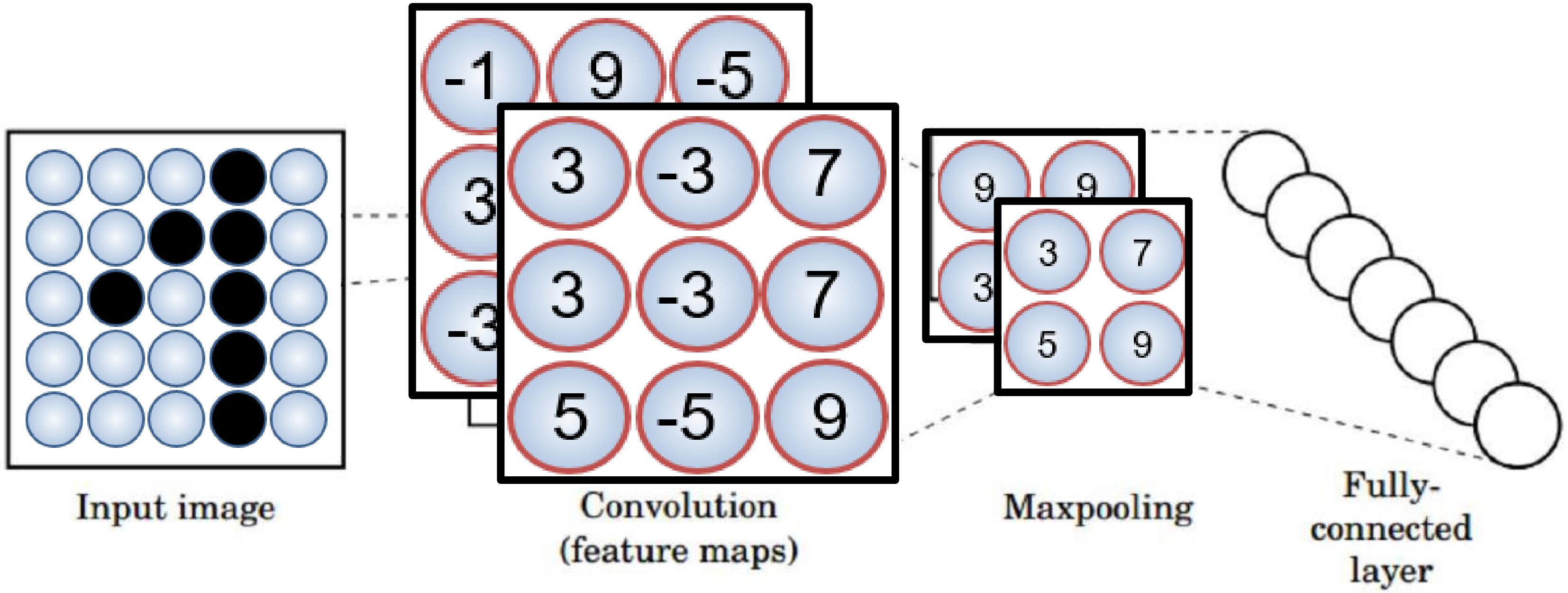


Convolutional Neural Networks
Building a CNN – Example



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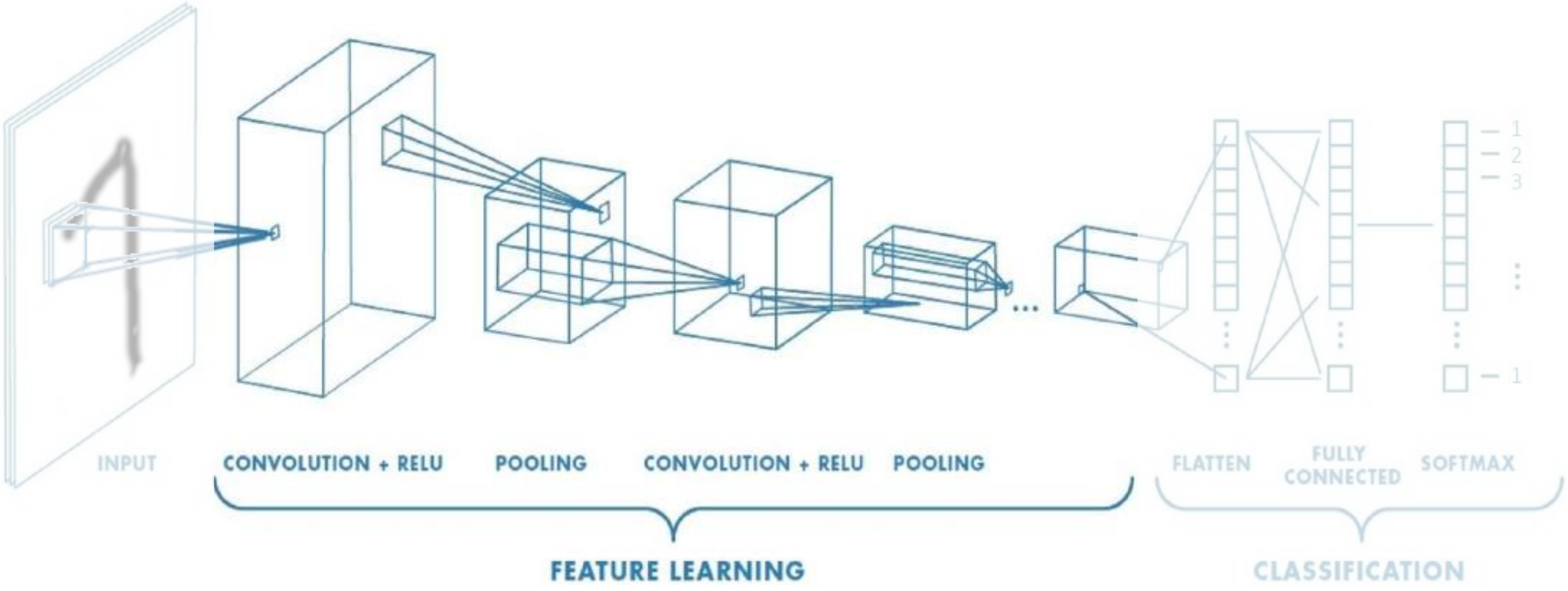
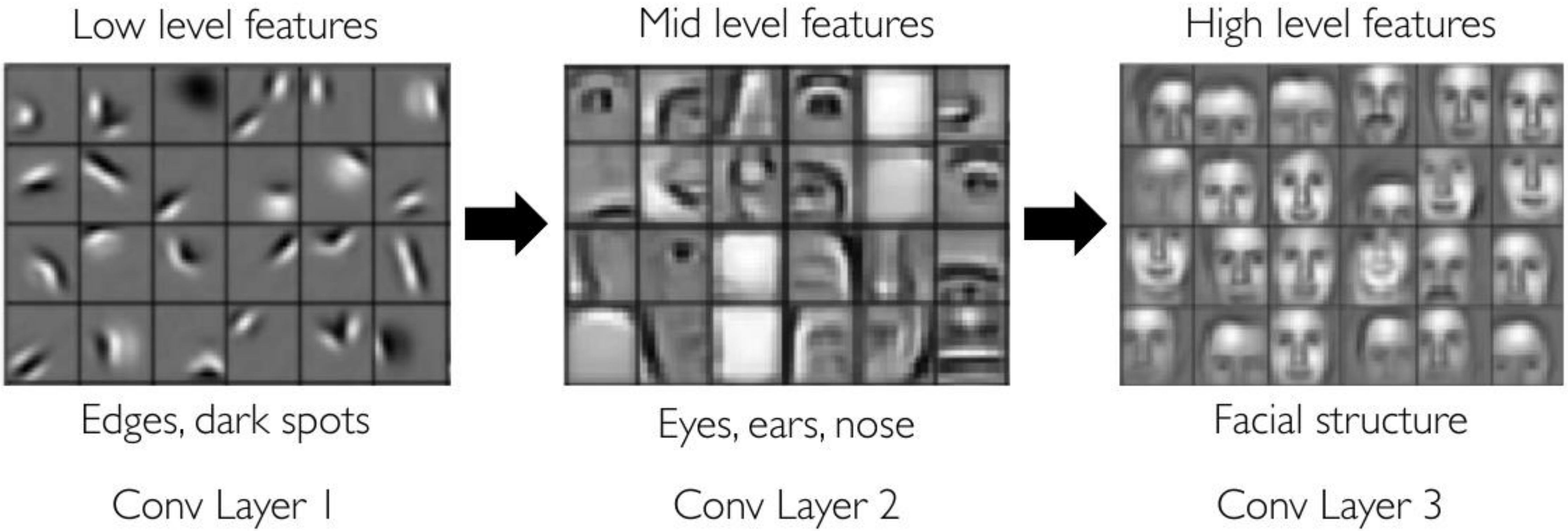
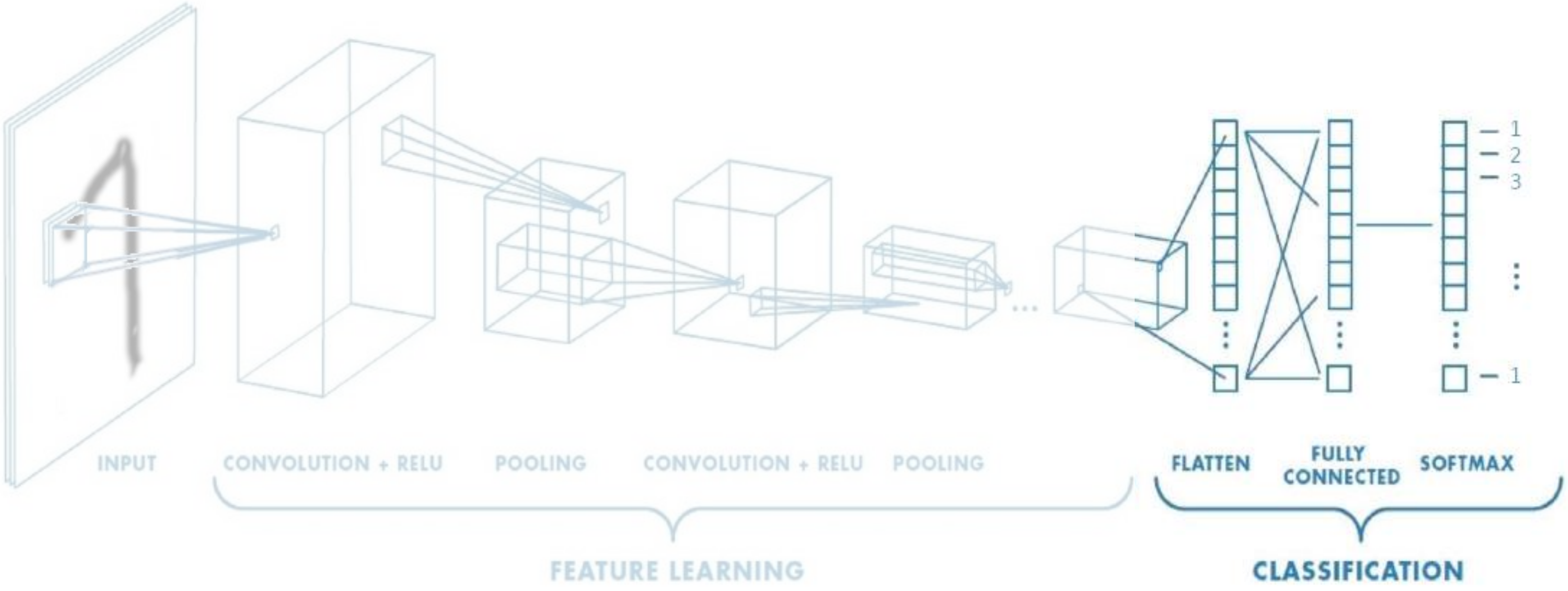
Representation Learning



Convolutional Neural Networks
Representation Learning



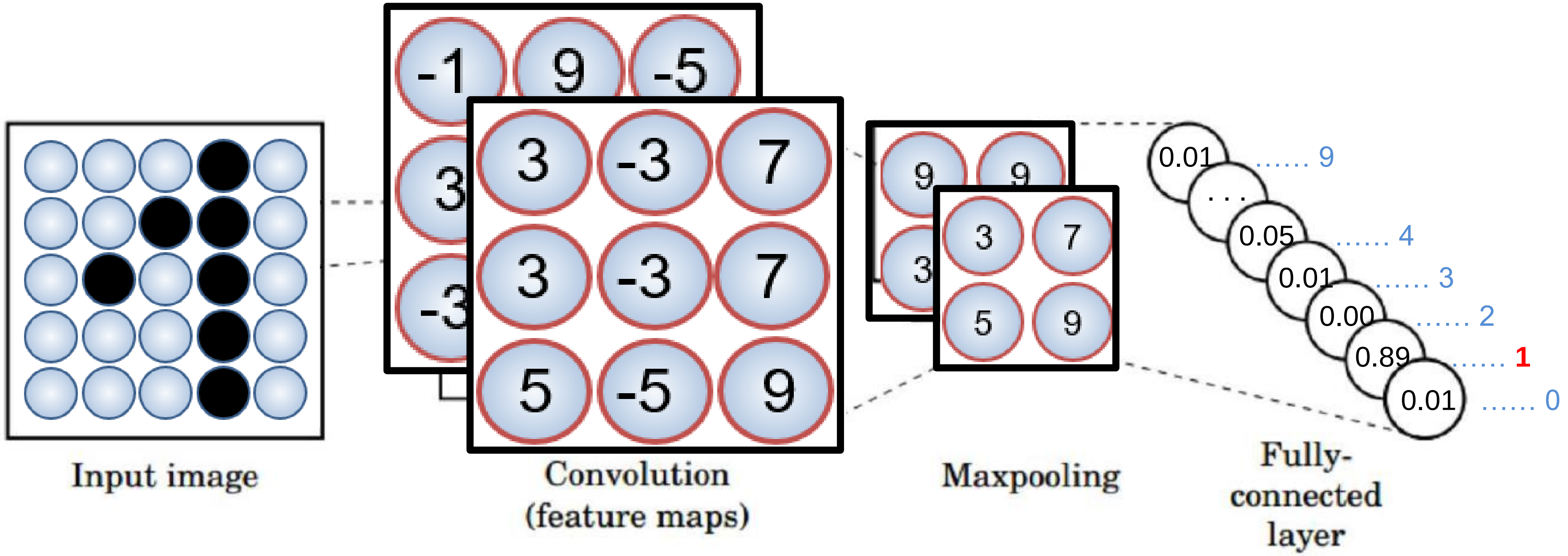
Classification



- CONV and POOL layers output high-level features of input
- Fully connected layer uses these features for classifying input image
- Express output as **probability** of image belonging to a particular class

$$\mathrm{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

Convolutional Neural Networks
Building a CNN – Example



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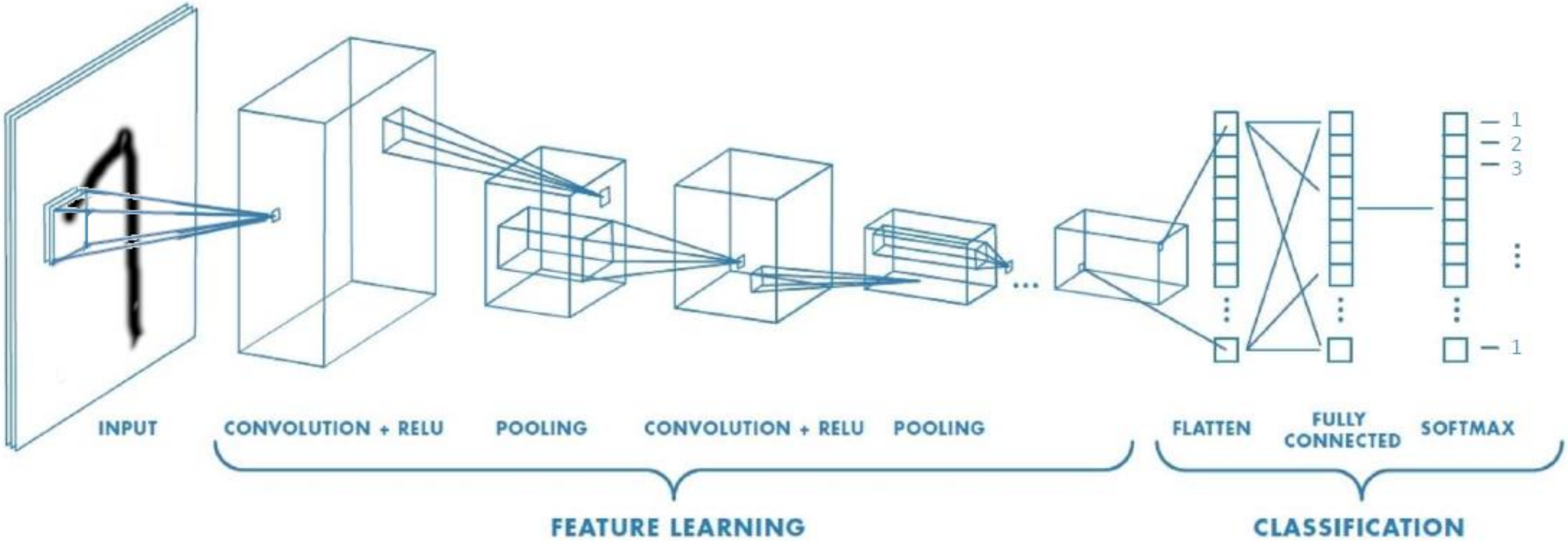
Convolutional Neural Networks
Training with backpropagation



Learn weights for convolutional filters and fully connected layers

Backpropagation: cross-entropy loss

$$\boldsymbol{J}(\boldsymbol{\theta}) = \sum_i y^{(i)} \log\left(\hat{\boldsymbol{y}}^{(i)}\right)$$

Curriculum

Next:

- Hands-on II

Imprint

Topic:	**Introduction to Deep Learning** Part II – Advanced Concept and Convolutional Neural Network
Date:	2025-11-13
Author:	Auliya Fitri, Sai Vemuri, Sreerag Naveenachandran
Institute:	Data Science
Image sources:	All images “DLR (CC BY-NC-ND 3.0)” unless otherwise stated