Fachhochschule Nordwestschweiz
Hochschule für Architektur, Bau und Geomatik

GeoPython2019

Workshop June 24, 2019

Deep Learning using Airborne Imagery

Workshop team

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Professor für Angewandte Mathematik und Statistik, FHNW

Workshop schedule

1. introducing talk
2. practical excercise 1
3. practical excercise 2
4. discussion

Talk

Machine Learning …

- basic concepts

Deep Learning …

- a modern implementation of Machine Learning
- what it is
- is it learnable
- benefits in context of airborne imagery
- historical overview and perspectives

Practical part

Deep Learning …

- in remote sensing applications
- related to research projects of our institute

Goals of this Workshop

You know the basic principles of Machine Learning

You know some potential applications of Deep Learning in geosciences

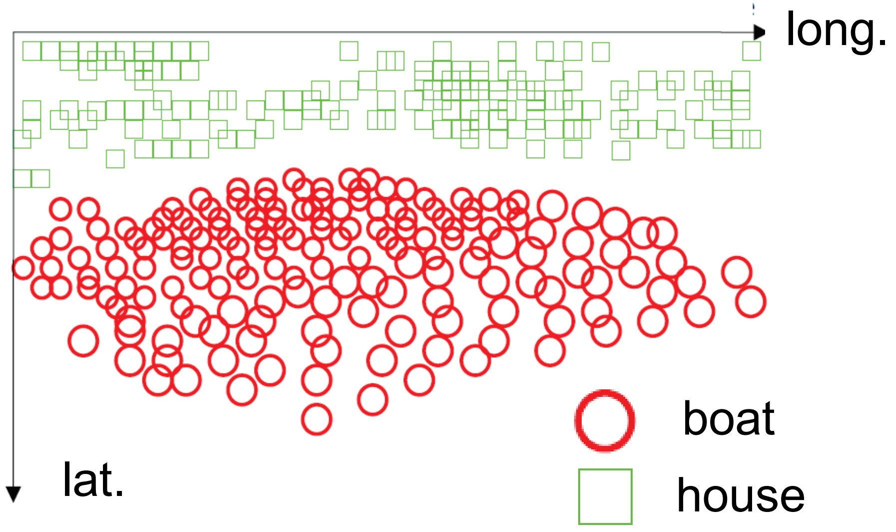
You work out Deep Neural Networks by yourself

Machine Learning – what it is

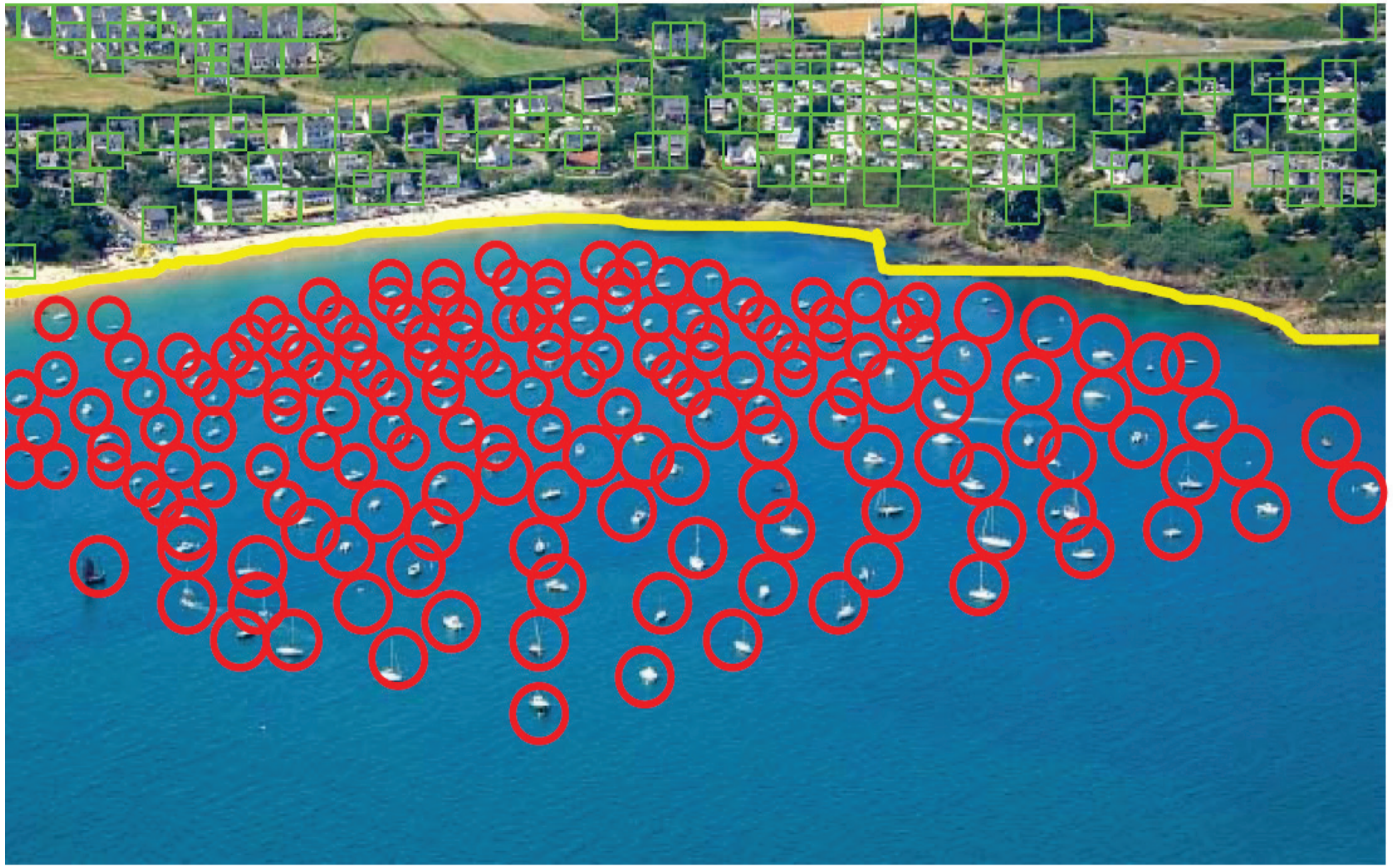
Task: detection house vs. boat (**classes**)

Machine Learning:

- teach: specify objects / classes



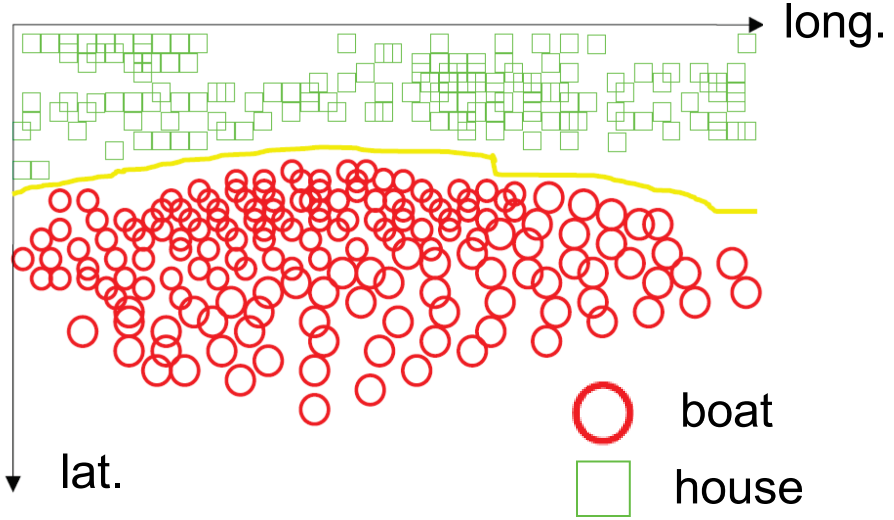
Machine Learning – what it is



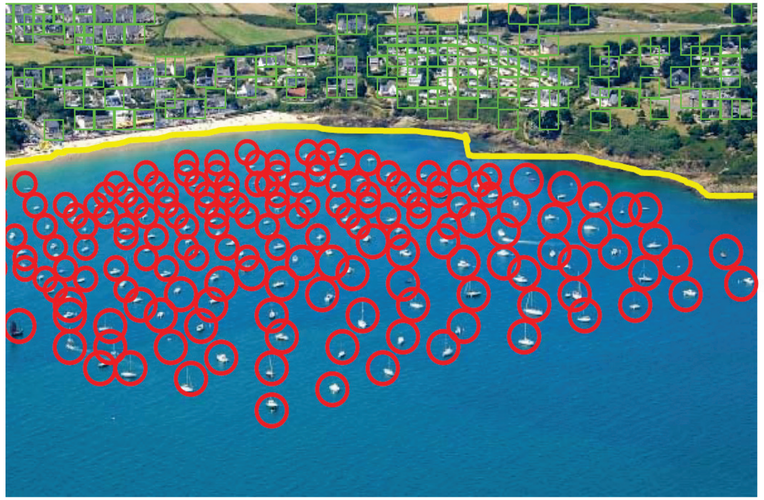
Task: detection house vs. boat (**classes**)

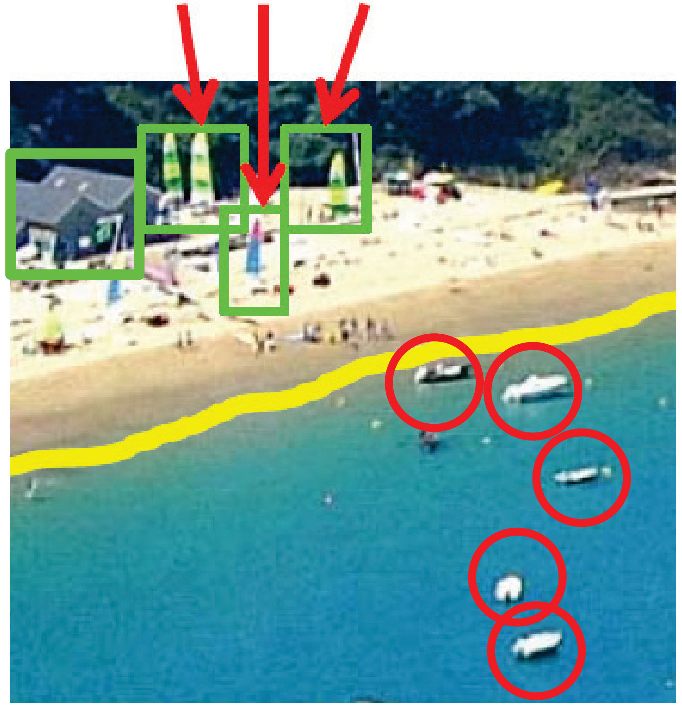
Machine Learning:
- teach: specify objects / classes
- learn rules to detect objects
  → coastline for separation of both classes

training



Machine Learning – what it is





Task: detection house vs. boat (**classes**)

Machine Learning:

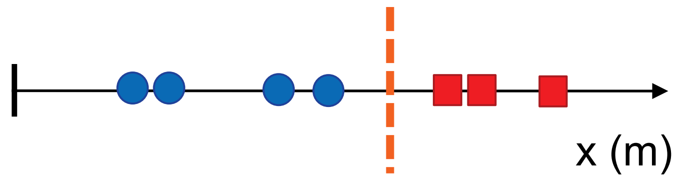
- teach: specify objects / classes
- learn rules to detect objects
  → coastline for separation of both classes

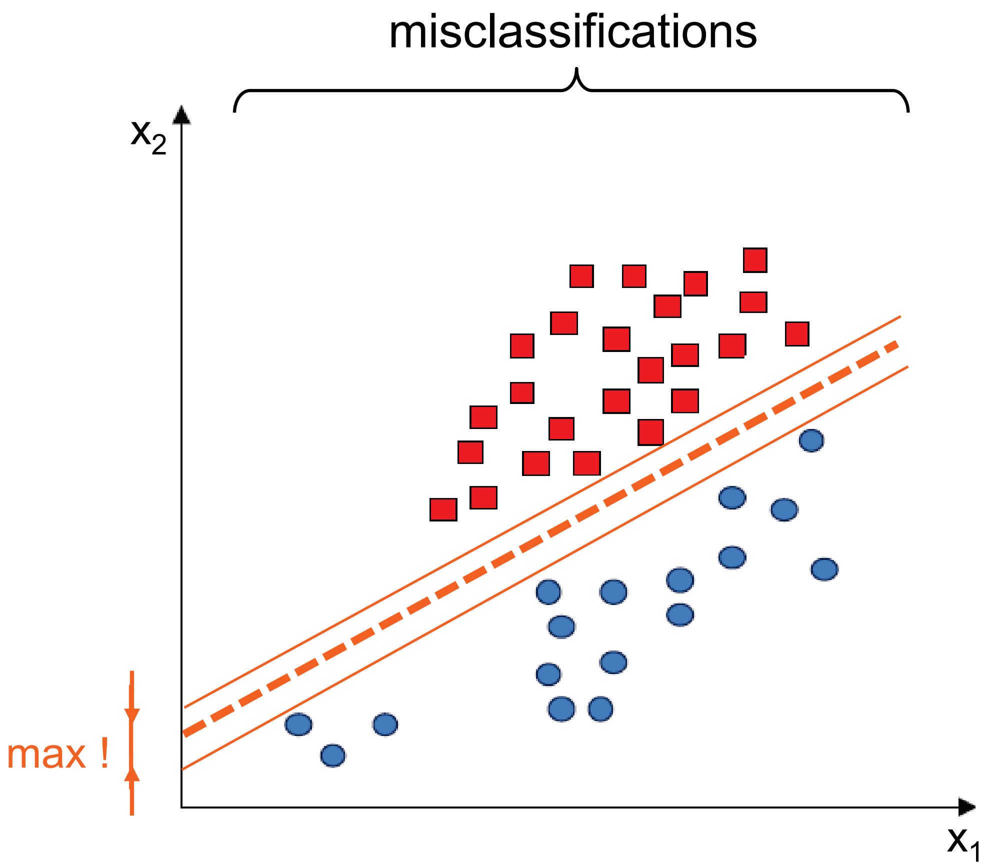
training

- apply successfully learned rules to new data
  → can the rules be generalized?
  → quality of classification?

misclassified boats
→ coastline not a perfect rule

Machine Learning – what it is



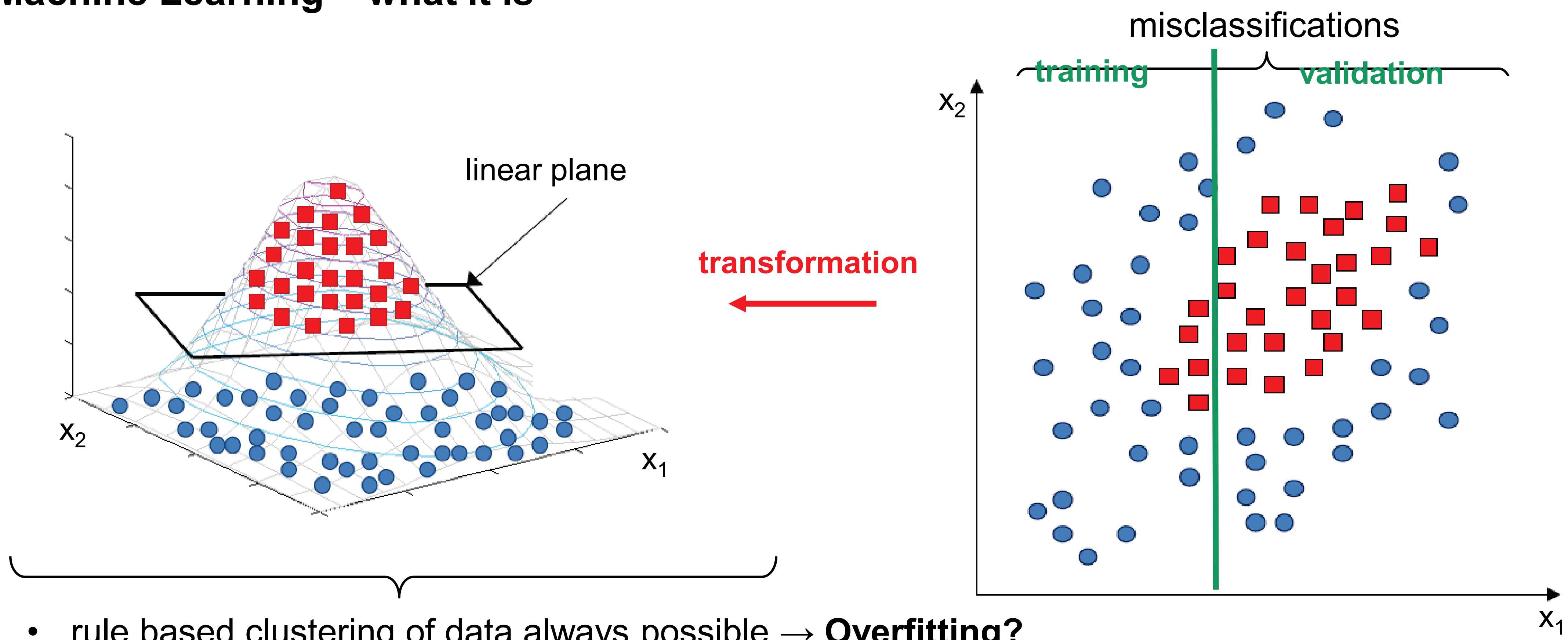


Thresholding

- geometric distance maximization

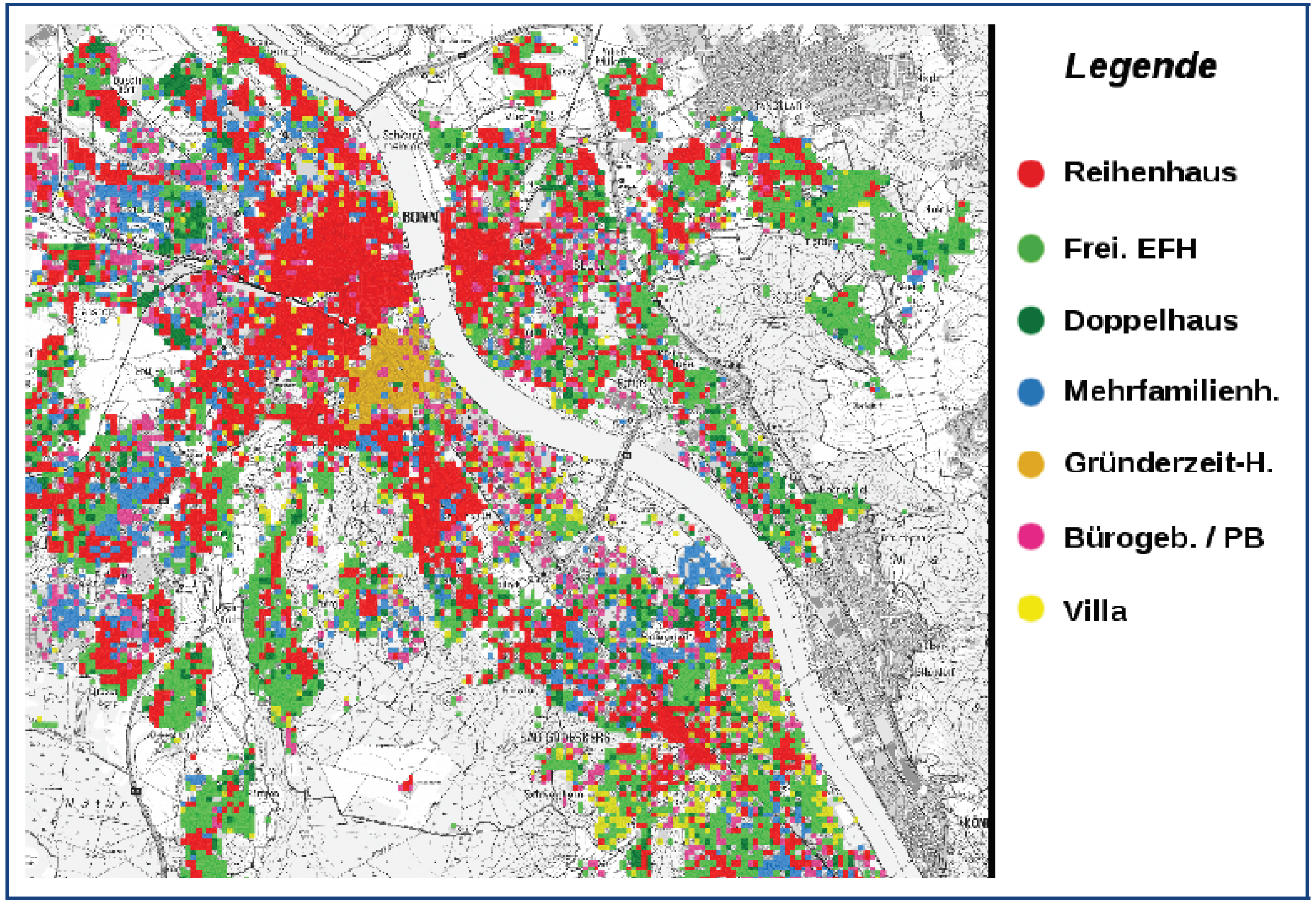
  → **Support Vector Machine** (SVM)
- **k-Nearest Neighbor** (kNN)
- **Random Forest** (RF)
- **Deep Neural Networks** (DNN) → later on

Machine Learning – what it is



- rule based clustering of data always possible → **Overfitting?**
- basic techniques for proper Machine Learning usage:
  → separation of training and validation data to simulate a generalization within the data, or even cross validation
  → inclusion of high number of data representing the whole problem
  → presentation of independent test data that the machine has never seen → evidence of meaningful rules

Machine Learning in Remote Sensing



High dimensional problem
→ based on many features

Feature	Gewicht
Anzahl der Gebäude im Block	1.000
Länge	0.842
Anzahl direkter Nachbarn ($d_{L,R} = 0$)	0.607
Fläche	0.565
Breite	0.553
Abstand Kultur	0.421
Abstand Universität	0.415
Volumen	0.411
Höhe	0.328
Anzahl der Polygonpunkte	0.327
Verhältnis Länge zu Breite	0.249
Abstand Industrie	0.237
Abstand Bahnhof	0.204
Abstand Krankenhaus	0.191
Abstand Gewerbe	0.186
...	...

expert identifies relevant properties related to classification task:

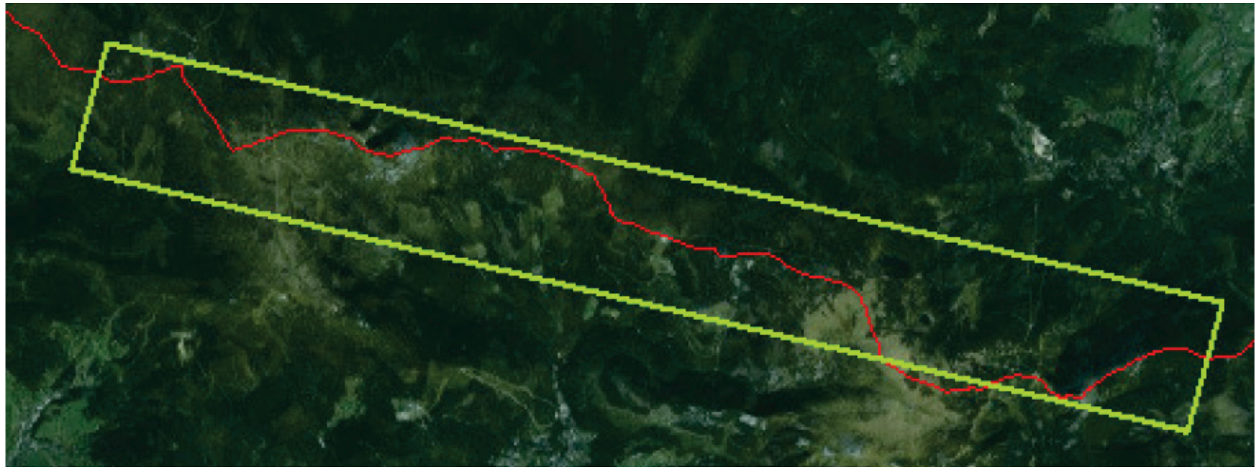
Feature Engineering

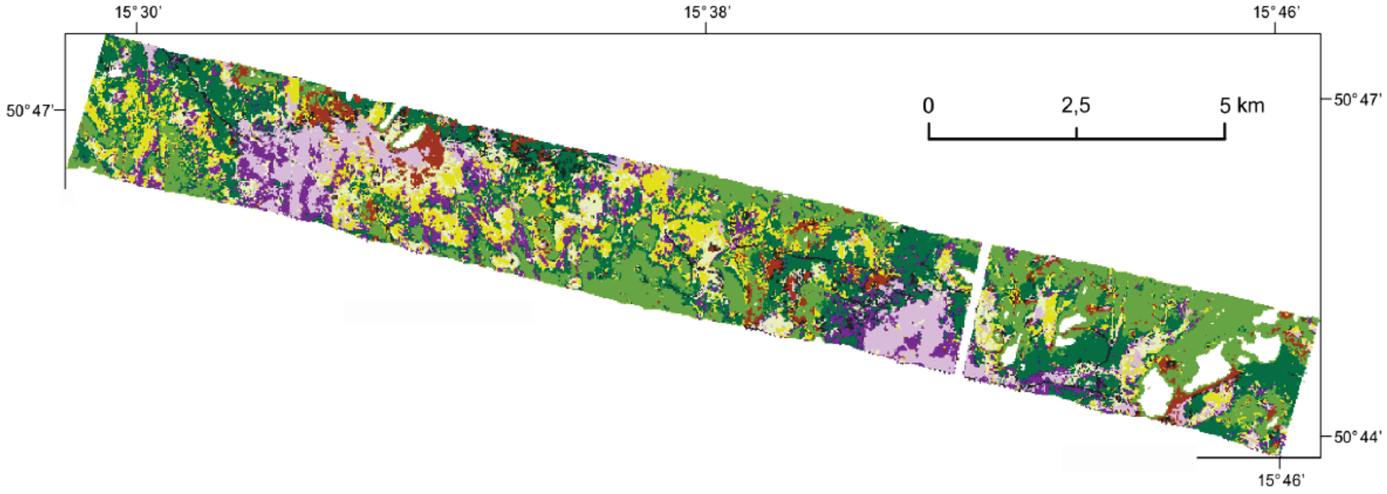
Results

→ accuracy at 90%

Henn A et al.: Automatic classification of building types in 3D city models using SVMs: GeoInformatica 2011; 15: 1-26.

Machine Learning in Remote Sensing





Jedrych M et al.: Polish Cartographical Review 2017; 49(3): 107-119.

Data and classes

- UNESCO biosphere reserve (Poland - Czech Rep.)
- Sentinel-2 and EnMAP
- multispectral / multitemporal
- 9 classes of mountain vegetation

- data driven feature selection for SVM

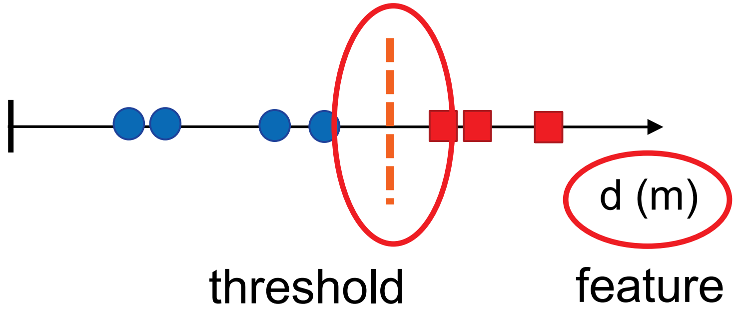
  → 5 pixel based main principal components (PCA) of multispectral und – temporal channels

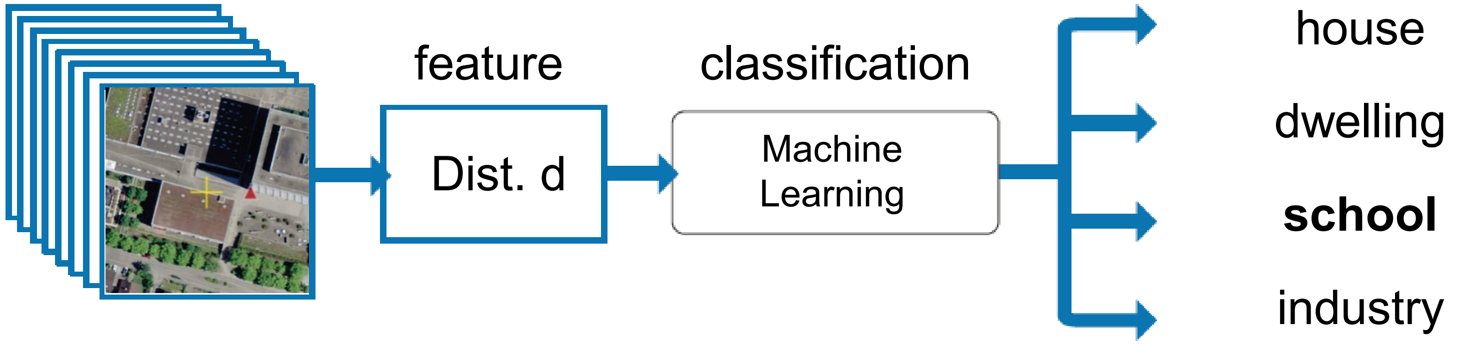
Results

→ Accuracy at 83%

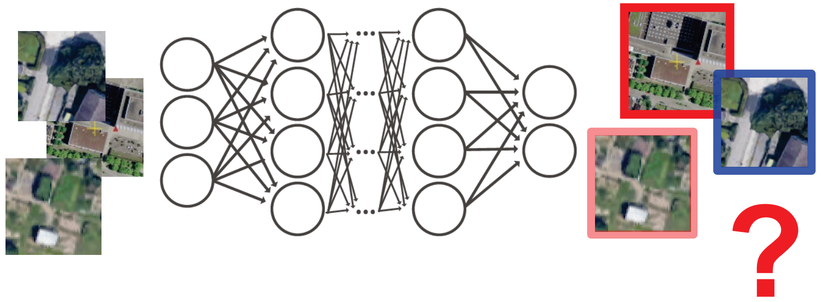
Deep Learning – a modern interpretation of Machine Learning

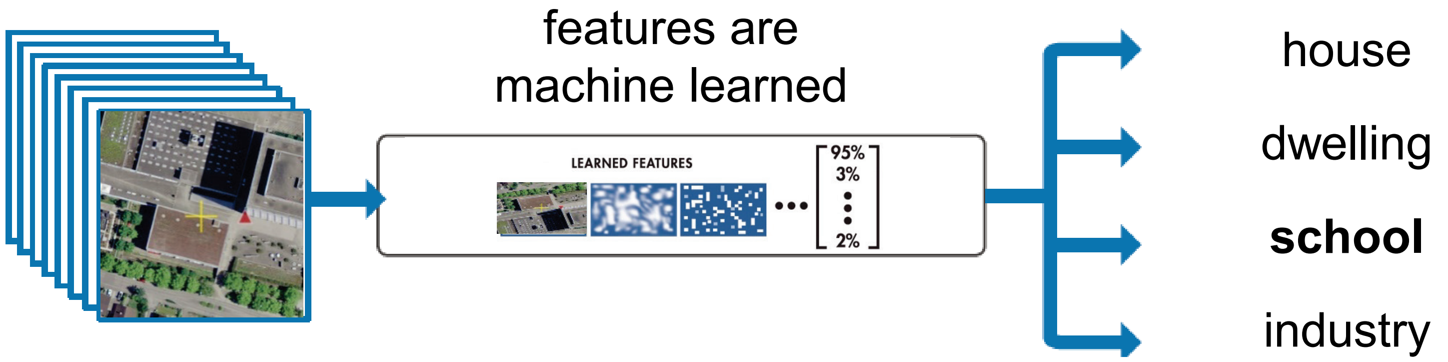
Conventional Machine Learning





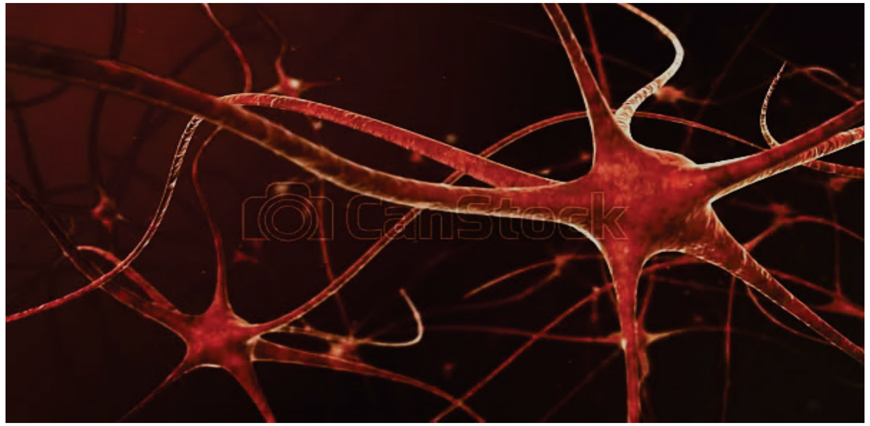
Deep Learning





Deep Learning – what it is

Neurophysiology of the human brain

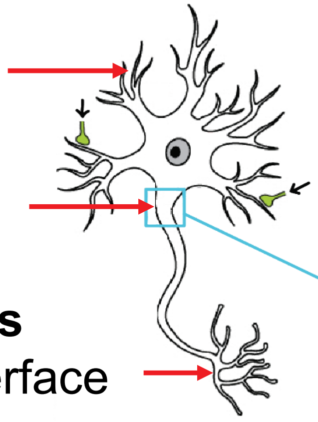


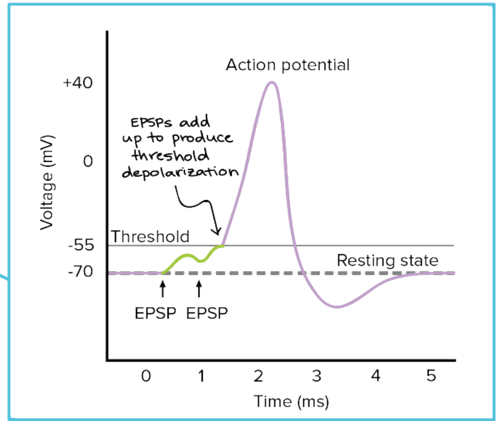
Neurons and action potentials

Dendritic tree
→ input (stimulus)

Soma (cell body)
→ action potential

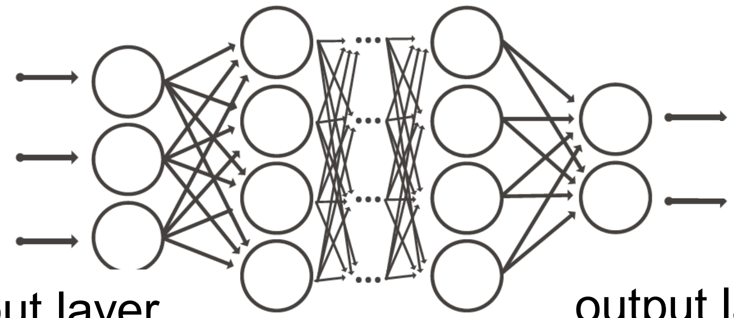
Axon and Synapses
→ transmission, interface





Deep Neural Network (DNN)

input



output

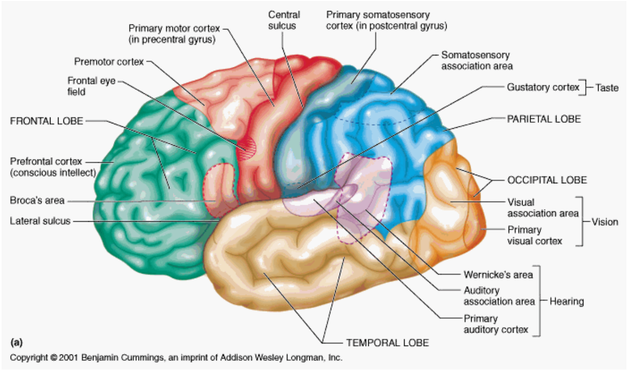
input layer

output layer

Hidden layers (e.g. 150)

Functional networks of the brain

Cortical layers

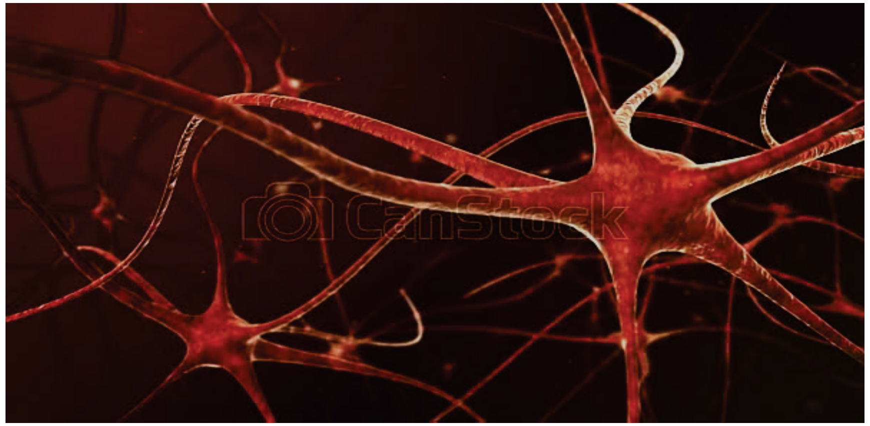


higher layers

lower layers

Deep Learning – what it is

Neurophysiology of the human brain



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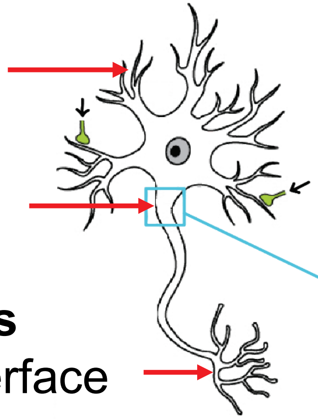
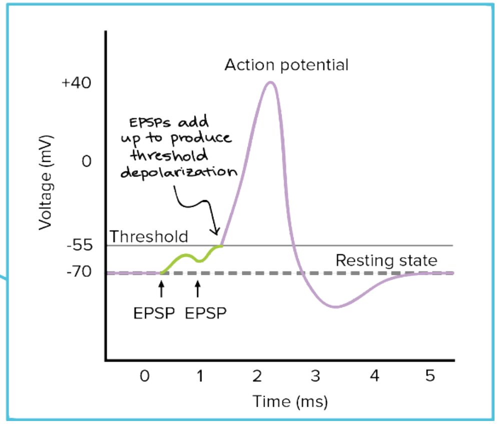
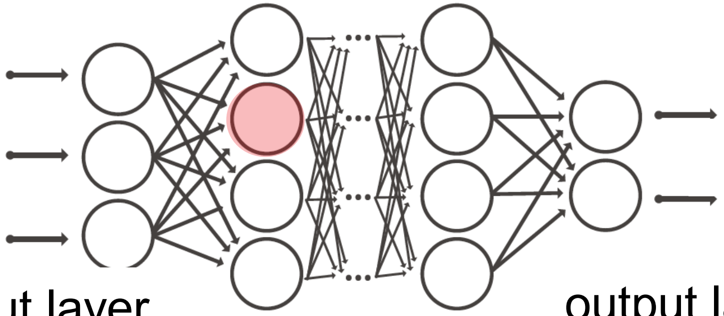
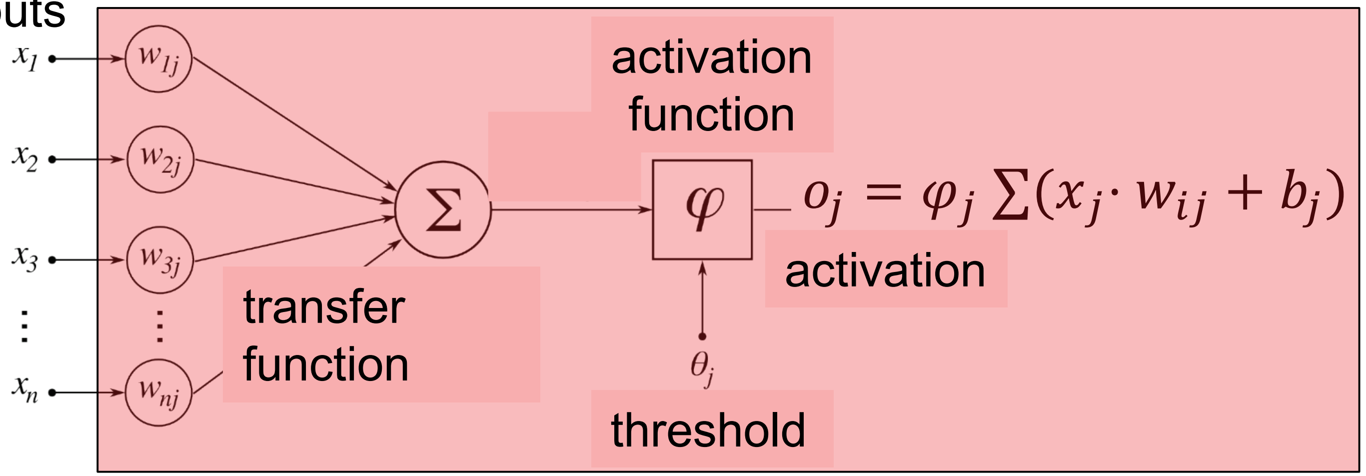


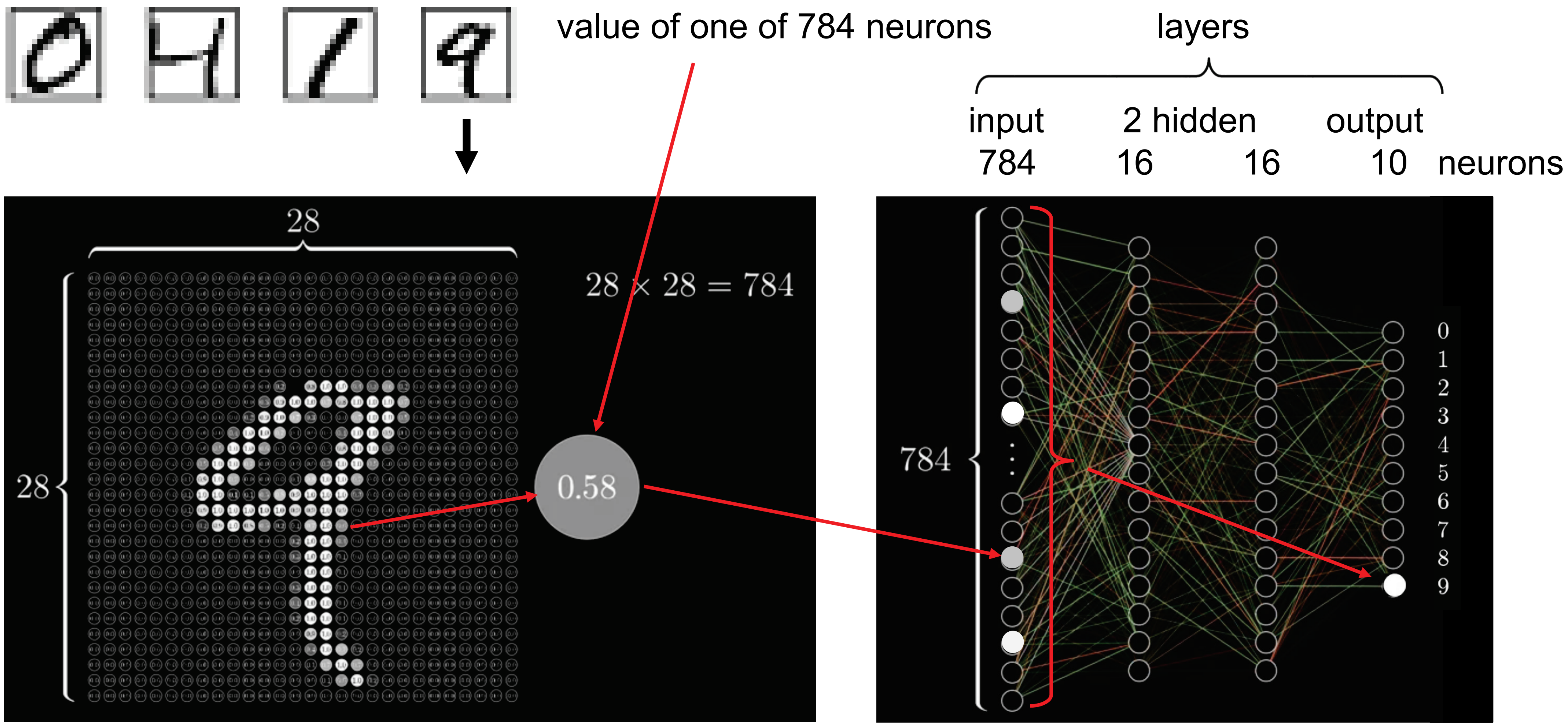


Deep Neural Network (DNN)

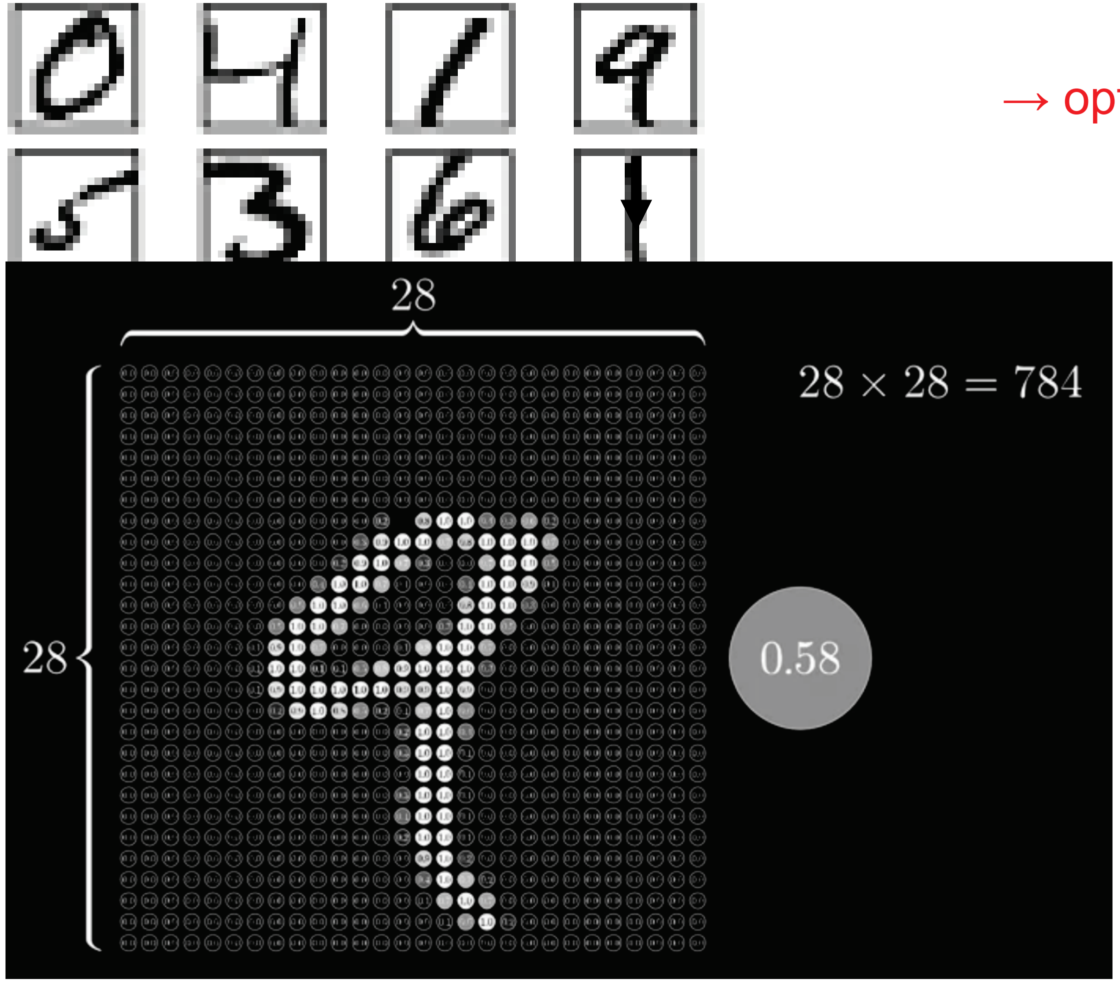




Deep Learning – how it works

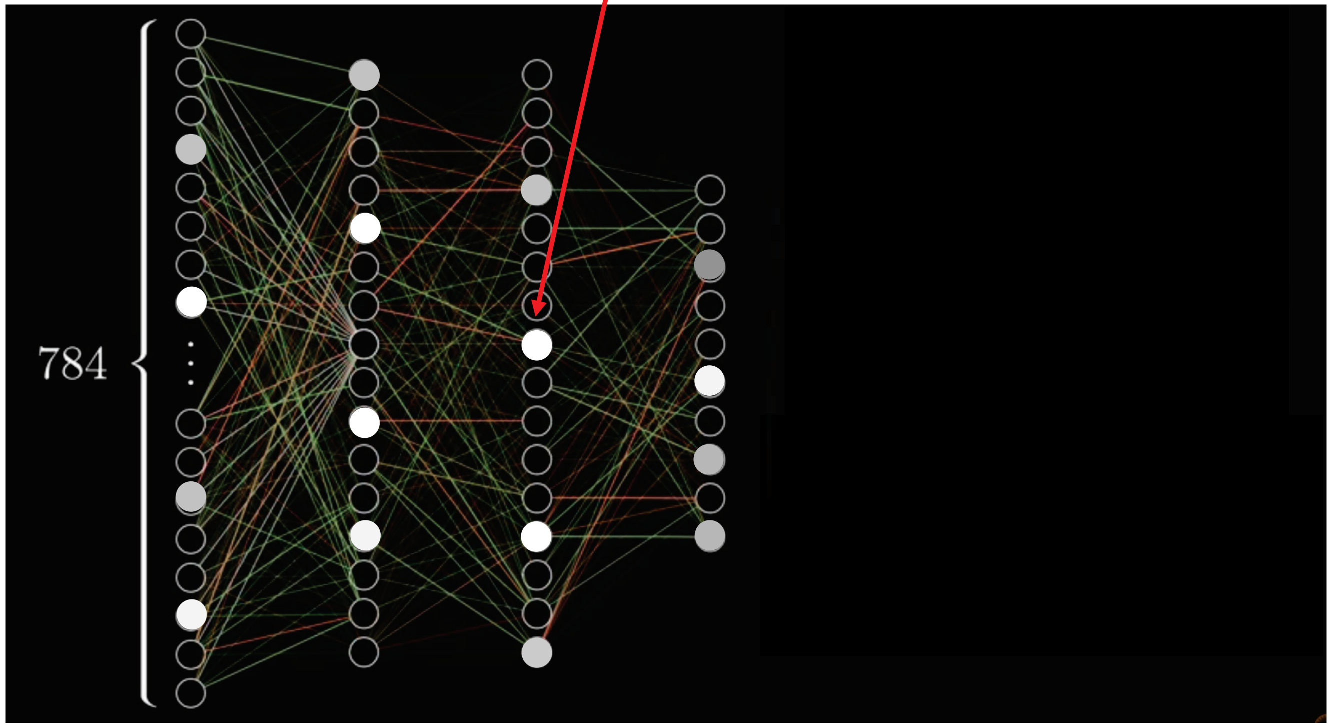


Deep Learning – how it works

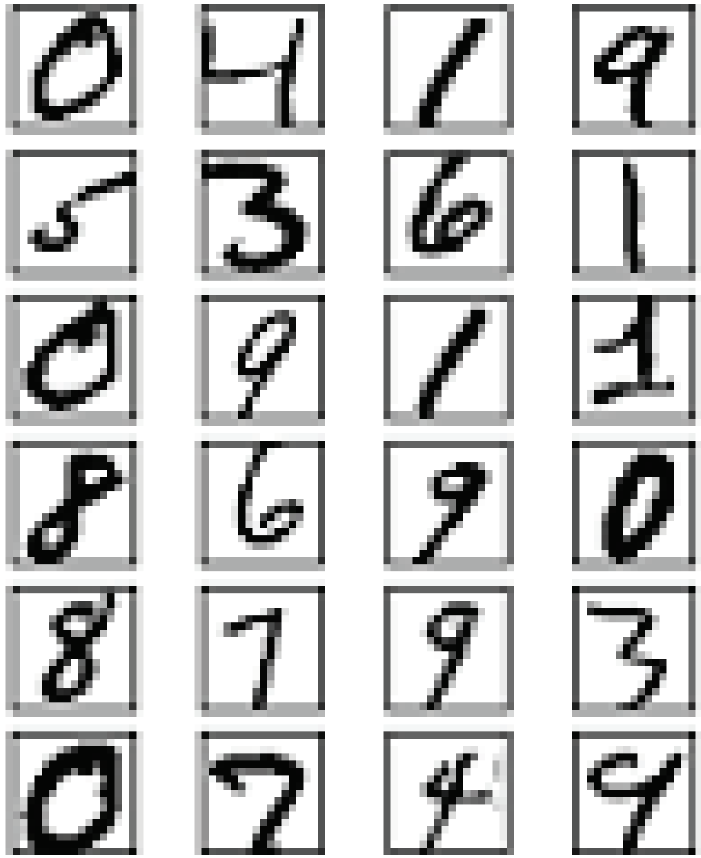


→ optimization strategy required: optimal setting of w_{ij}, b_j in

$$o_j = \varphi_j \sum(x_j \cdot w_{ij} + b_j)$$

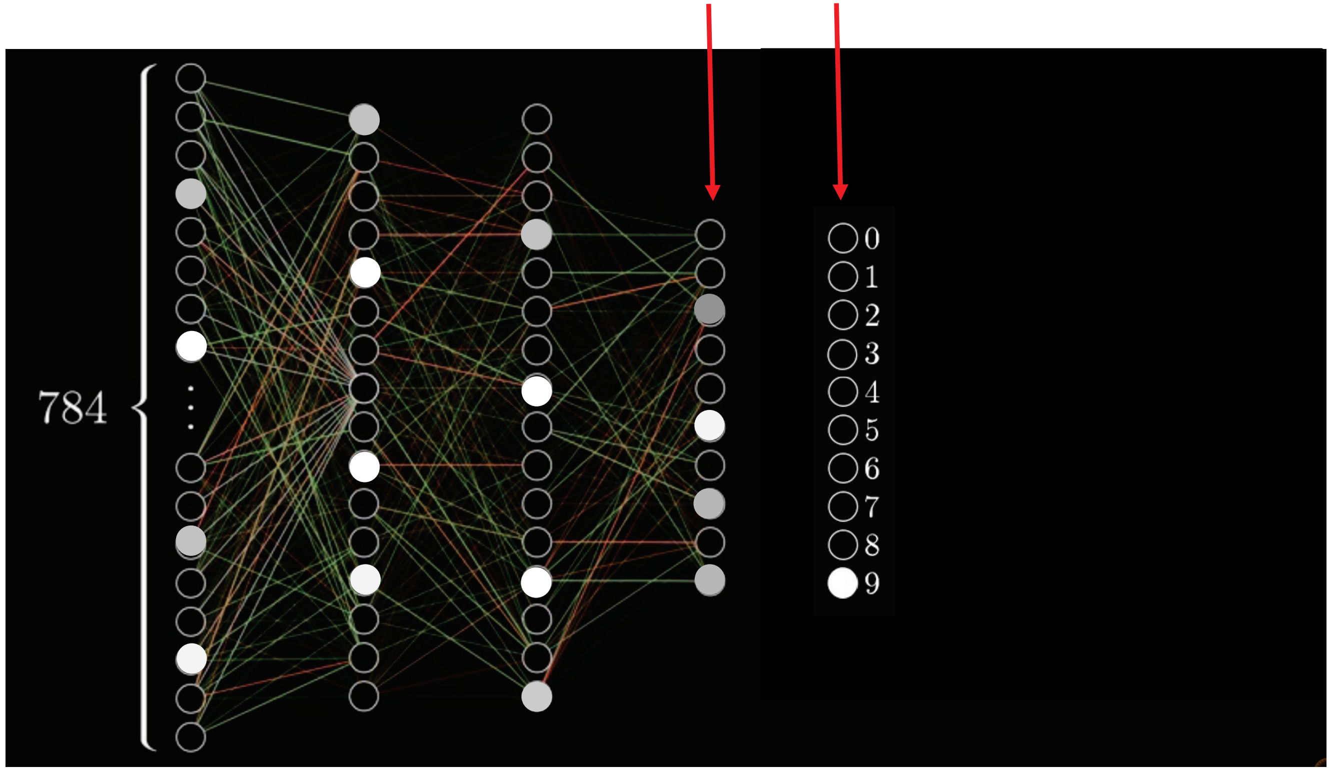


Deep Learning – how it works

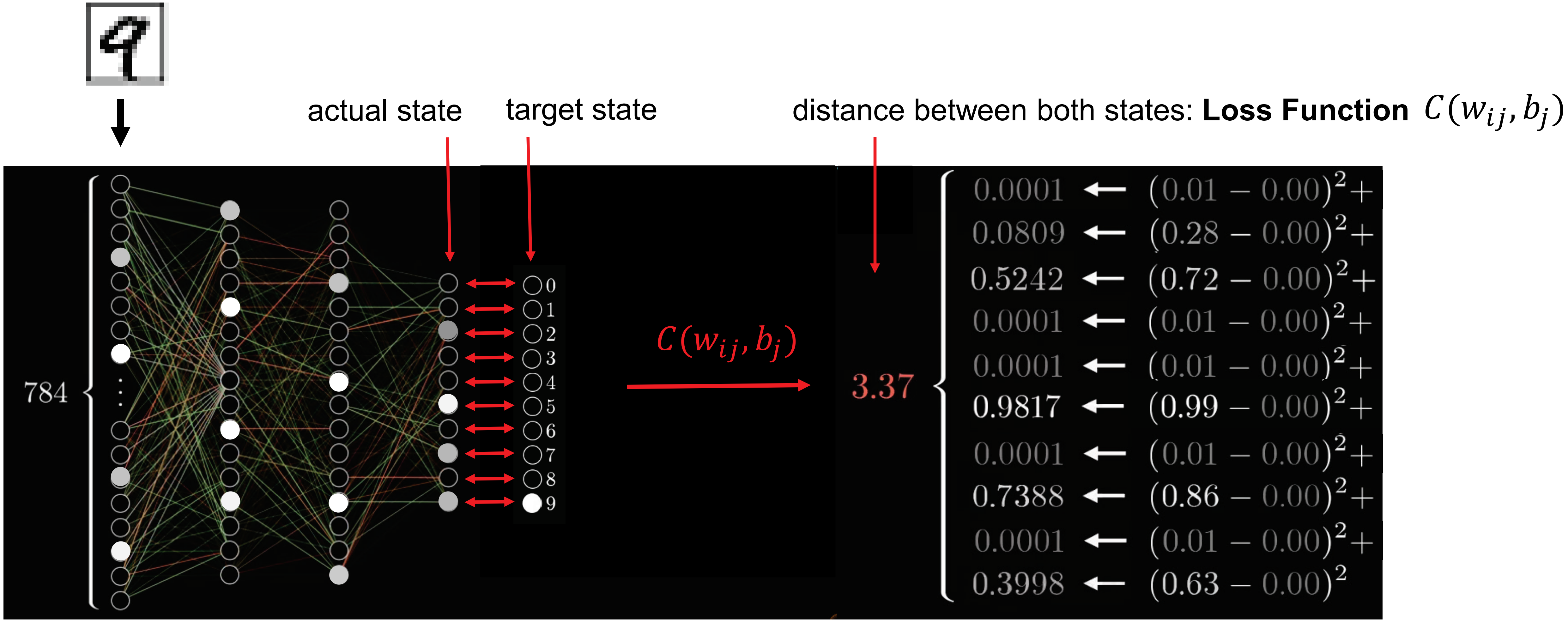


→ optimization strategy: achieved by an iterative training process

actual state known target state



Deep Learning – how it works

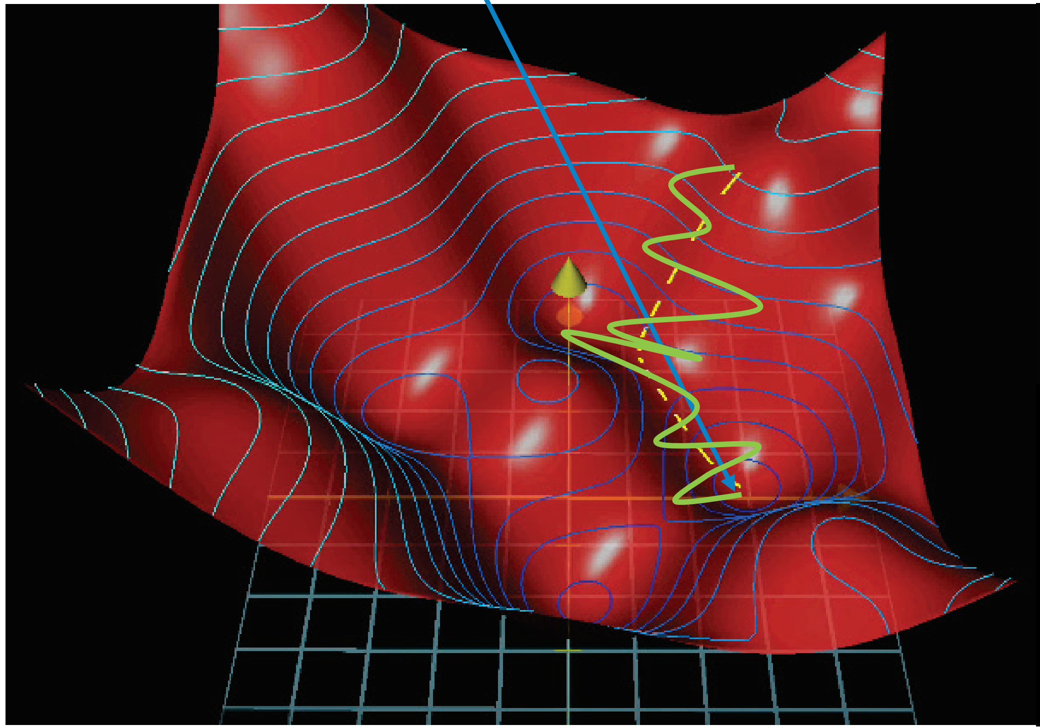


Deep Learning – how it works

Problem: difficult to handle (comp. intensive)
Idea: **Gradient Descent**

- provides backpropagation
- with random mini batches
- in every iteration step:
  → set of better model parameters

Minimum of **Loss-Function** $C(w_{ij}, b_j)$? → negative gradient shows shortest way



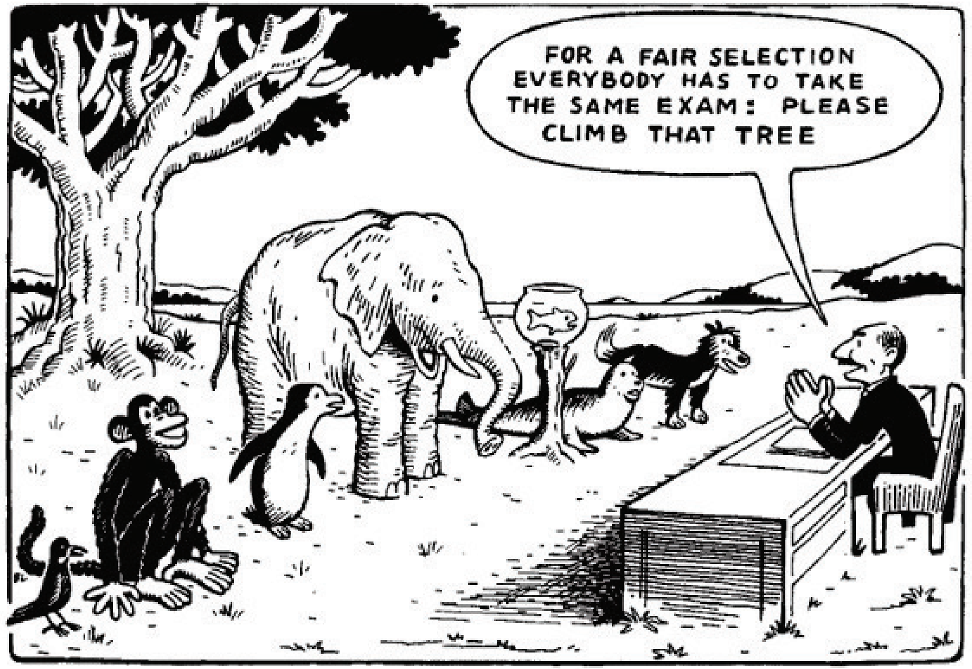
$$-\nabla C(\underbrace{\ldots}_{w_{ij},\, b_j}) = 0$$

$$\delta^L = \nabla_a C \odot \sigma'(z^L)$$

$$\delta^l = ((w^{l+1})^T \delta^{l+1}) \odot \sigma'(z^l)$$

$$\frac{\partial C}{\partial b_j^l} = \delta_j^l$$

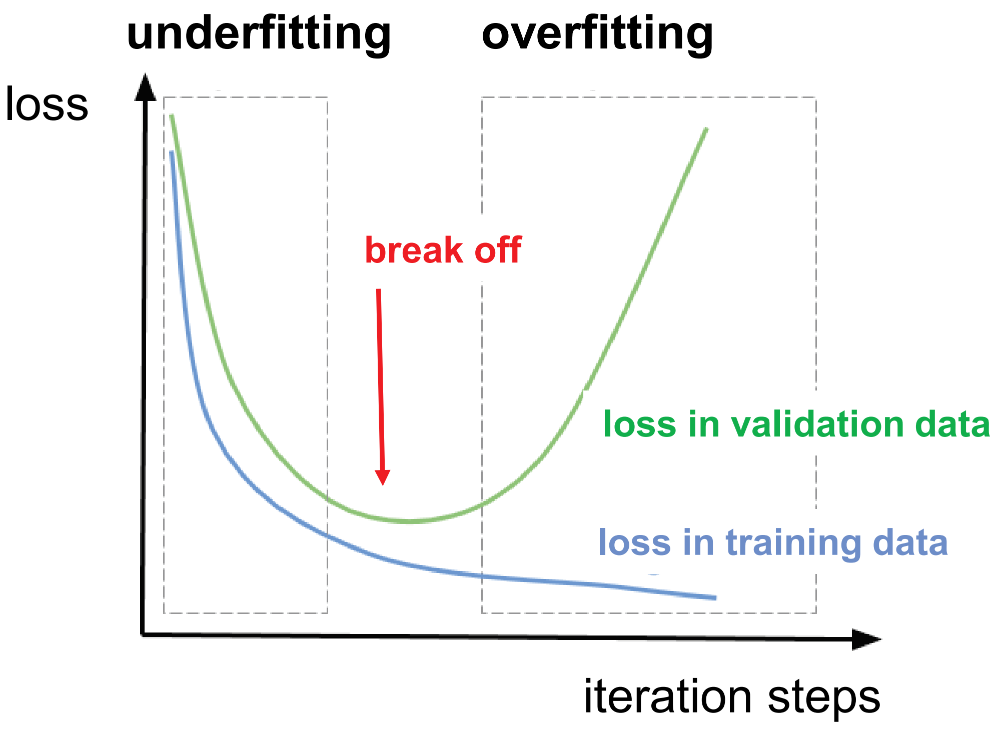
Deep Learning – how it works



Brake off criterion for iterative optimization

- Can one trust the **local** minimum loss found by gradient descent?
- What is a fair break off criterion for iterative optimization?

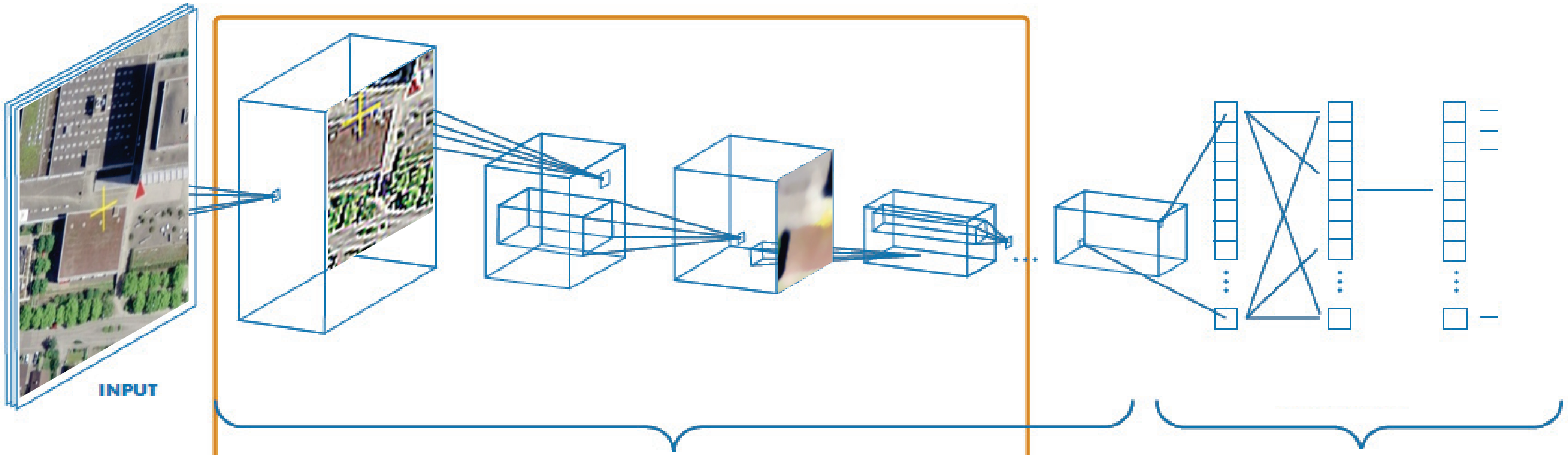
Common approach



Many **statistical metrics** for classifier assessment
→ very important, but not part of the present introduction

Deep Learning – how it works

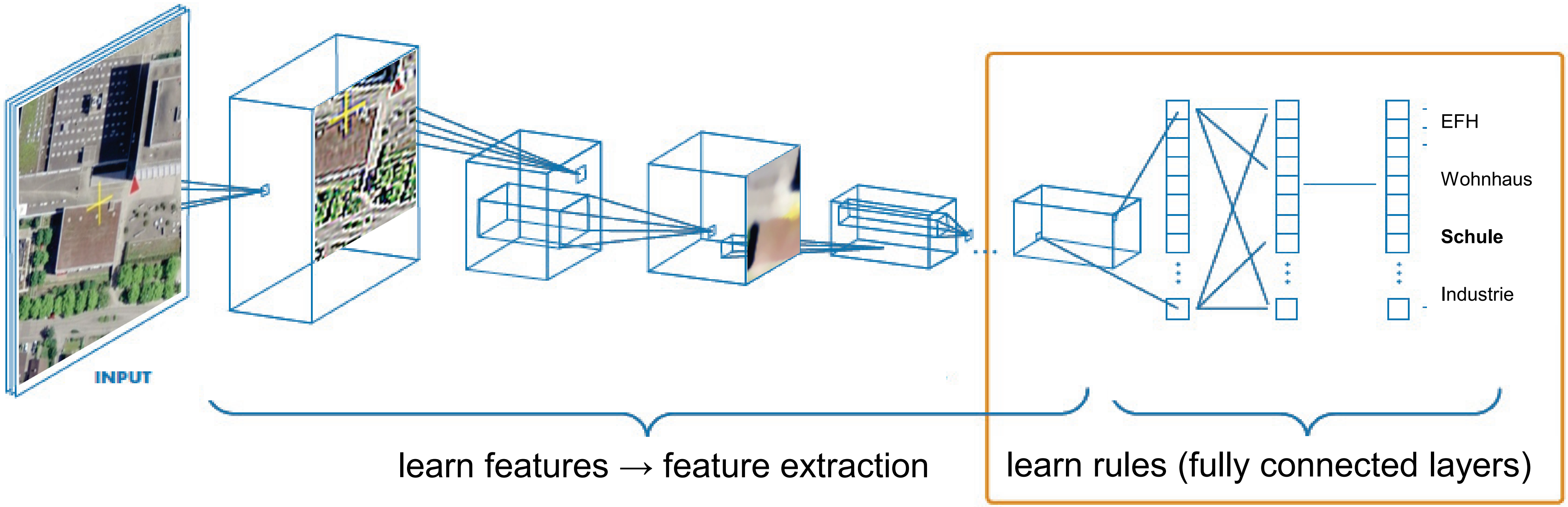
Convolutional Neural Network (CNN)



learn features by convolution and pooling

Deep Learning – how it works

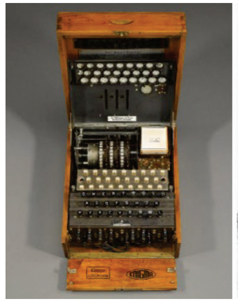
Convolutional Neural Network (CNN)

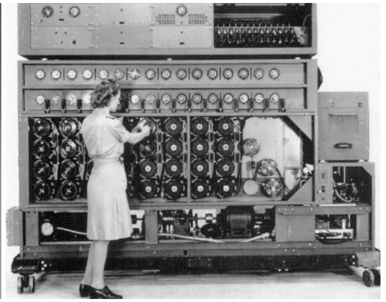


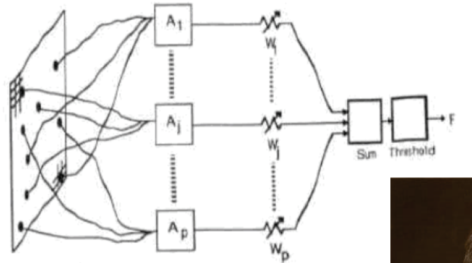
Deep Learning – where it comes from

Roots of Deep Learning

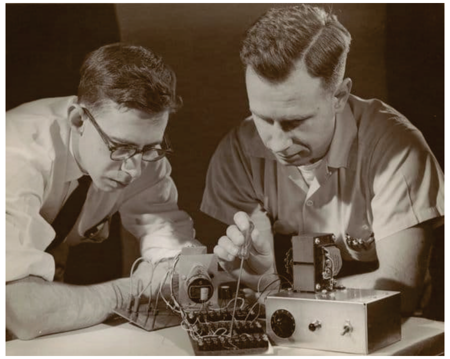
- **1931** **Kurt Gödel** fundamental axioms of set theory and logic
- **1936** **Ronald A. Fisher** separation of high dimensional data achieved by hyperplanes → basis of SVM
- **since 1937** **Alan Turing**
  - theoretical fundaments for modern (finite) algorithms
  - proof of theoretical limits of self-learning machines
  - machine to decode the German Enigma encoding in the 2nd WW → Shortening the War







Original Perceptron
(From Perceptrons by M. L Minsky and S. Papert, 1969, Cambridge, MA: MIT Press. Copyright 1969 by MIT Press.

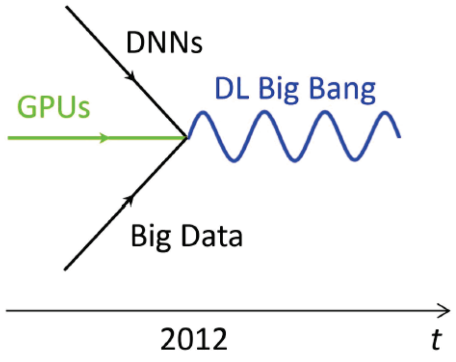


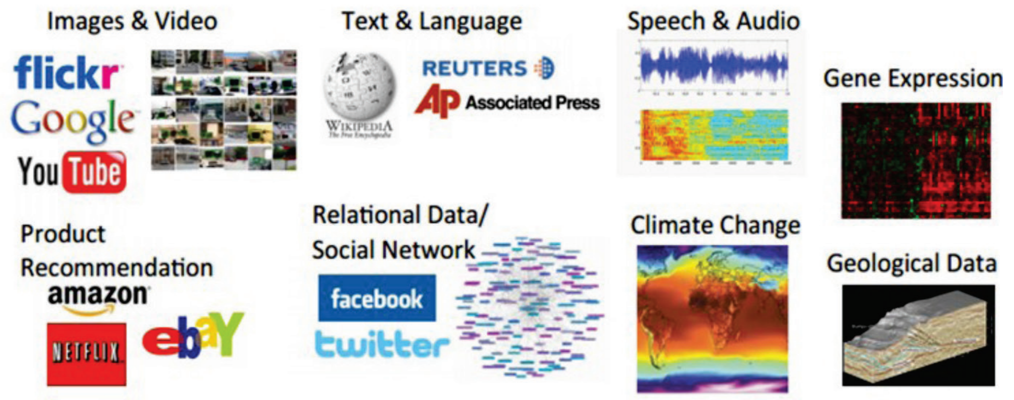
- **1967** **Frank Rosenblatt**
  construction of **Perceptron** as an artificial electrical neuron

Deep Learning – where it comes from

Roots of Deep Learning

- **1972** **Alain Colmerauer** artificial intelligence languages (e.g. PROLOG)
  → British physician shows expert system supporting diagnosis of abdominal diseases
- **since 1986** progress in computer technology leads to a renaissance of neuronal networks → reading texts aloud
- **since 1997** **RoboCup** football championship held by "intelligent" robots
- **2009** **Google** self driving car in California
- **2011** **IBM** software Watson understands and replies sentences, beats champion of an US television show
- **since 2012** **Deep Learning** classifies images and is becoming more and more important
  → support of medical diagnoses
  → consumer behavior
  → intelligent geoinformation
  → engineering,
  e.g. machine health





Deep Learning – where to go

Appealing

- Machine Learning and **Big Data**
  open algorithms / data available

Figure 3.1: Deep learning frameworks [43]

Zugänglichkeit
von Frameworks

- very many fields of application, especially in the geosciences

- potential for new added value

Points to think about

- jobs fall away

- «perfect» tool to control a society

- errors: responsibility for wrong decisions?

- Google & Pentagon, NZZ 2018

Soll Google in den Krieg ziehen?

Dass Google neuerdings mit dem Pentagon kooperiert, hat unter den Mitarbeitern einen Aufschrei ausgelöst. Die Debatte wirft grundsätzliche Fragen zum Thema Technologie und Militär auf.

Marie-Astrid Langer, San Francisco
2.6.2018, 05:30 Uhr

Learn Deep Learning in practice …

- by programming Networks by yourself
- in projects of the Institute of Geomatics of the FHNW
- **Daniel** will introduce in classification of airborne imagery and
- **Adrian** continues with an adapted framework using bounding boxes to detect solar panels

Deep Learning – how it works

Important terms for the assessment of a machine learning process

- **Loss** distance between actual and true output
- **Confusion Matrix**

		Predicted class	
		P	*N*
Actual Class	*P*	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

- **Precision** $\frac{\mathrm{TP}}{\mathrm{TP+FP}}$ Model with no FP gets Precision 1 (equivalent: **Positive Predictive Value**)
- **Recall** $\frac{\mathrm{TP}}{\mathrm{TP+FN}}$ Model with no FN gets Recall 1 (equivalent: **Sensitivity** or **True Positive Rate**)
- **Accuracy** $\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$ as amount of correct classified samples over total amount of samles
- **Training and Validation Data, independent Test Data**
- **Cross validation**

avoiding overfitting