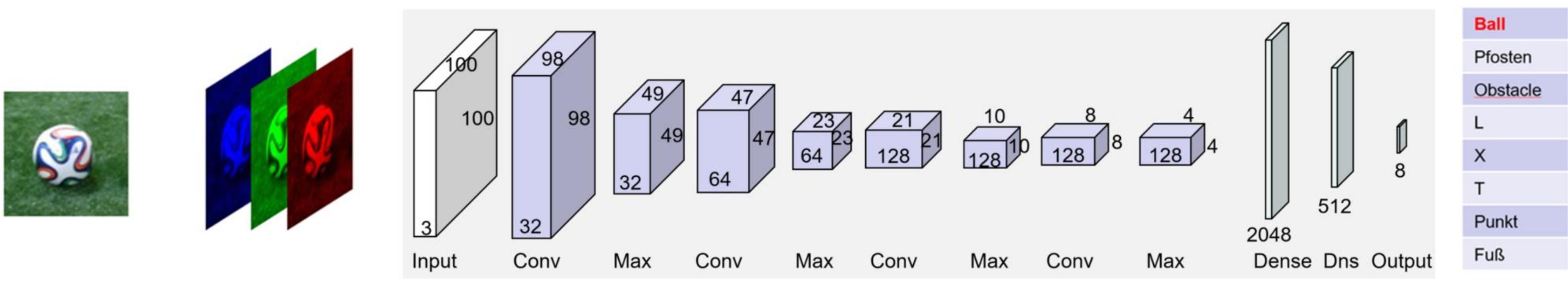
# Summer School

# Deep Learning

Prof. Dr. Klaus Dorer

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# Overview

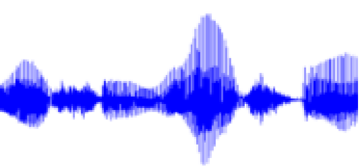
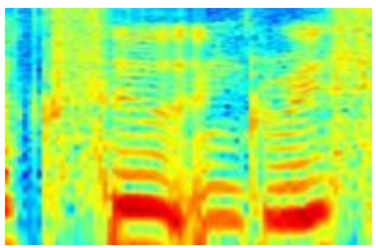
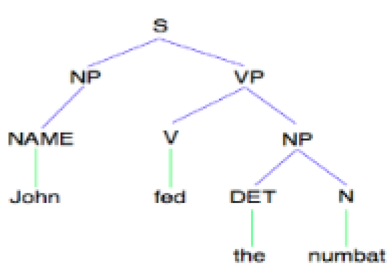
- Neural Networks
  - Introduction
  - Model of a Neuron
  - Perceptron
  - Backpropagation Networks
  - Convolutional Neural Networks

- Goals
  - Know the elements of deep neural networks
  - Have an estimation of their applicability

# Why is deep learning so hot?

- More data
  - Youtube: 500 hours video per minute
  - Facebook: 300 milion images per day
- More computing power
  - GPU acceleration
  - GPU/CPU Cluster
- ‚New' Deep Learning approaches
  - Deep Neural Networks
  - Convolutional Neural Networks
  - better activation functions, optimizer, initialization, …
- Freely available frameworks
  - Keras, TensorFlow, Theano, DeepLearning4J, …

# Machine Learning before Deep Learning

| Input | Feature Extraction (Feature Engineering) | Klassification Detektor | Result |
|---|---|---|---|
|  |  | SVM, (flat) neural network, … |  |
|  |  | HMM, (flat) neural net, … | Language recognition, .... |
|  |  | Clustering, HMM, … | Machine translation, topic identification, .... |



http://on-demand.gputechconf.com/gtc/2015/webinar/deep-learning-course/intro-to-deep-learning.pdf

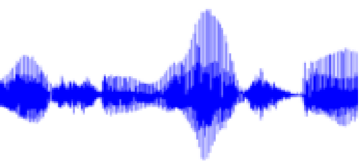
# Machine Learning with Deep Learning

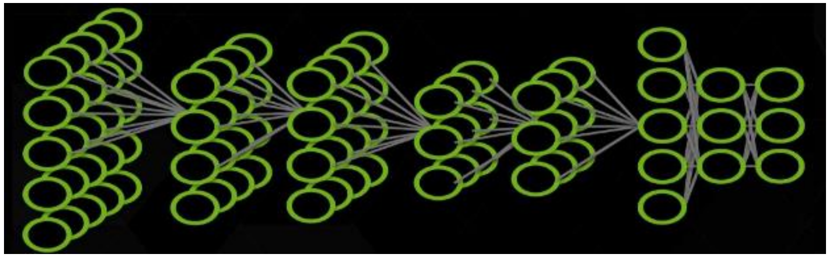
Input

Result

Deep
Network

„stapler"





„stapler"

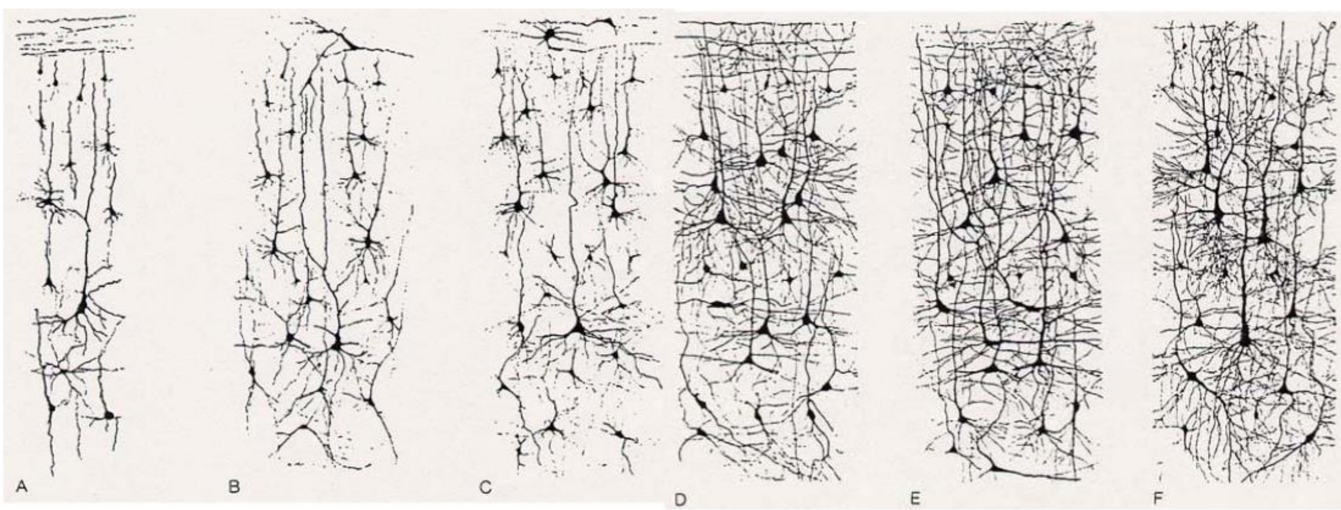
„Manual for a stapler"

....

nach http://on-demand.gputechconf.com/gtc/2015/webinar/deep-learning-course/intro-to-deep-learning.pdf

# Human Brain

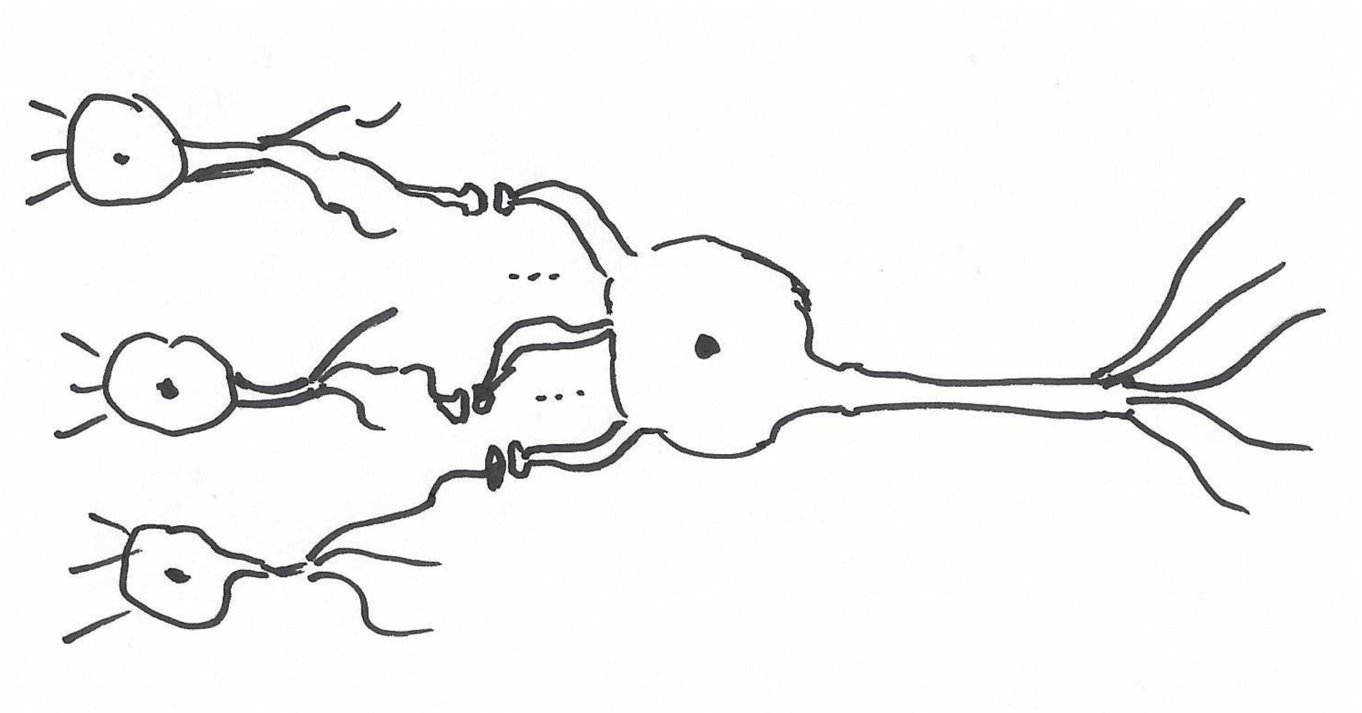
- Learning is performed by
  - Creating links between neurons
  - Reinforcing and weakening links between neurons




Die sechs Bilder vermitteln einen Eindruck von der Entwicklung des Gehirns von der Geburt bis zu einem Alter von zwei Jahren; zum Zeitpunkt der Geburt (A), nach einem Monat (B), nach drei (C), nach sechs (D), nach 15 (E) und nach 24 Monaten (F). Abgebildet ist ein Ausschnitt aus der Großhirnrinde in der Nähe des Broca Sprachareals.

Quelle: http://nwg.glia.mdc-berlin.de/media/pdf/education/Legasthenie.pdf

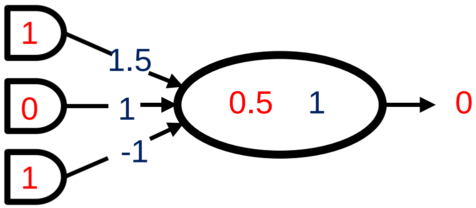
# Human Brain



# Deep Learning

# Model of a Neuron

Prof. Dr. Klaus Dorer

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# Overview

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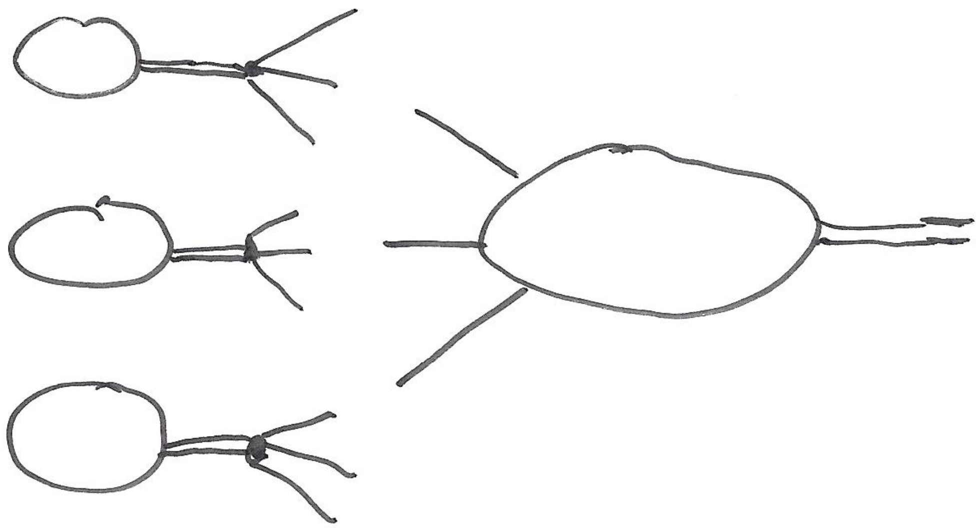
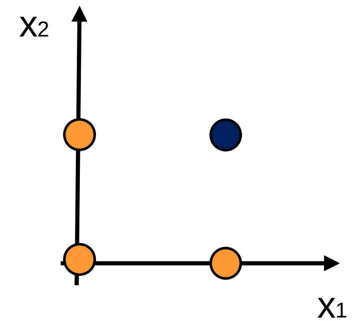
  - Introduction
  - Model of a Neuron
  - Perceptron
  - Backpropagation Networks
  - Convolutional Neural Networks

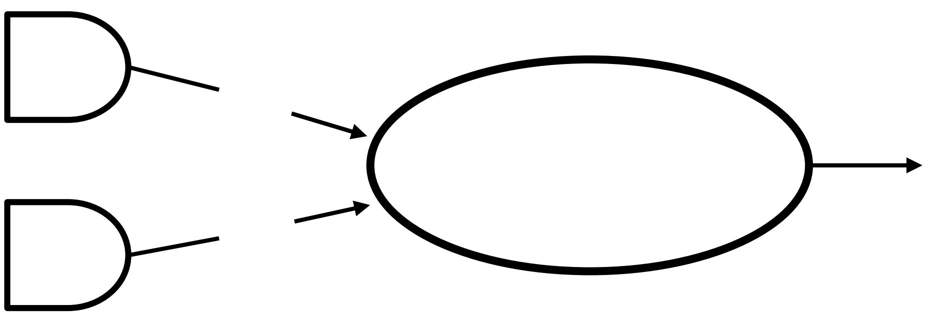
# Model of a Neuron

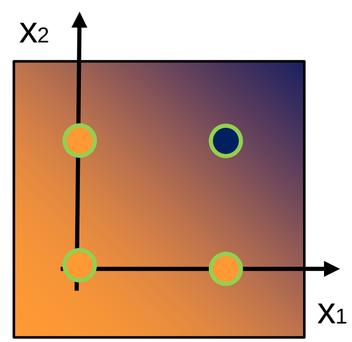


# Model of a Neuron
## Example: And Function

| $x_1$ | $x_2$ | $y_1$ |
|---|---|---|
| 0 | 0 | **0** |
| 0 | 1 | **0** |
| 1 | 0 | **0** |
| 1 | 1 | **1** |



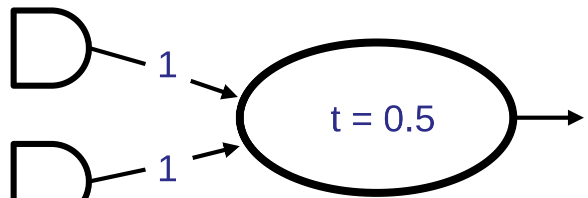





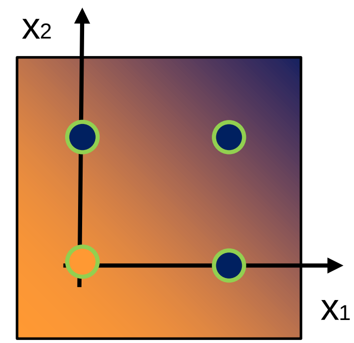

$$o_j = Step_t(\sum_i w_{i,j} x_i) = Step_t(Wx)$$

# Model of a Neuron
## Or and Not Function

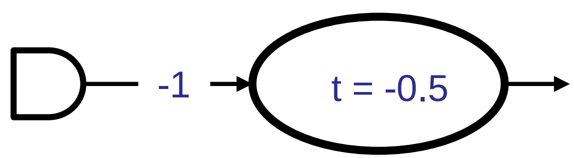
| $x_1$ | $x_2$ | $y_1$ |
|---|---|---|
| 0 | 0 | **0** |
| 0 | 1 | **1** |
| 1 | 0 | **1** |
| 1 | 1 | **1** |



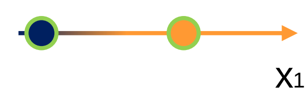

OR




| $x_1$ | $y_1$ |
|---|---|
| 0 | **1** |
| 1 | **0** |

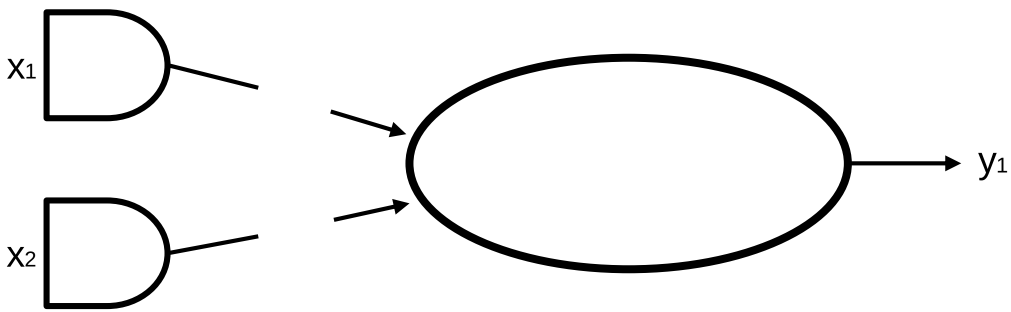


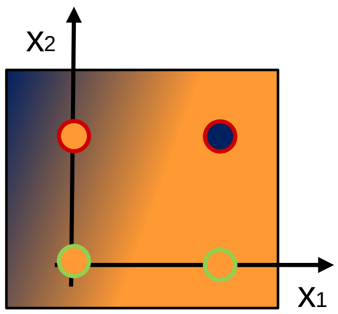

NOT



# Model of a Neuron
## Find suitable weights



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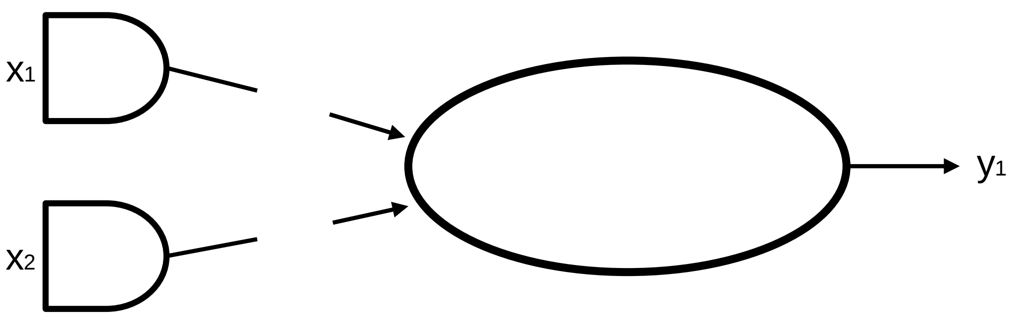
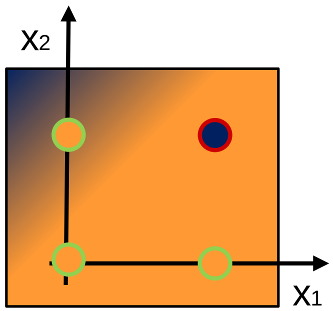
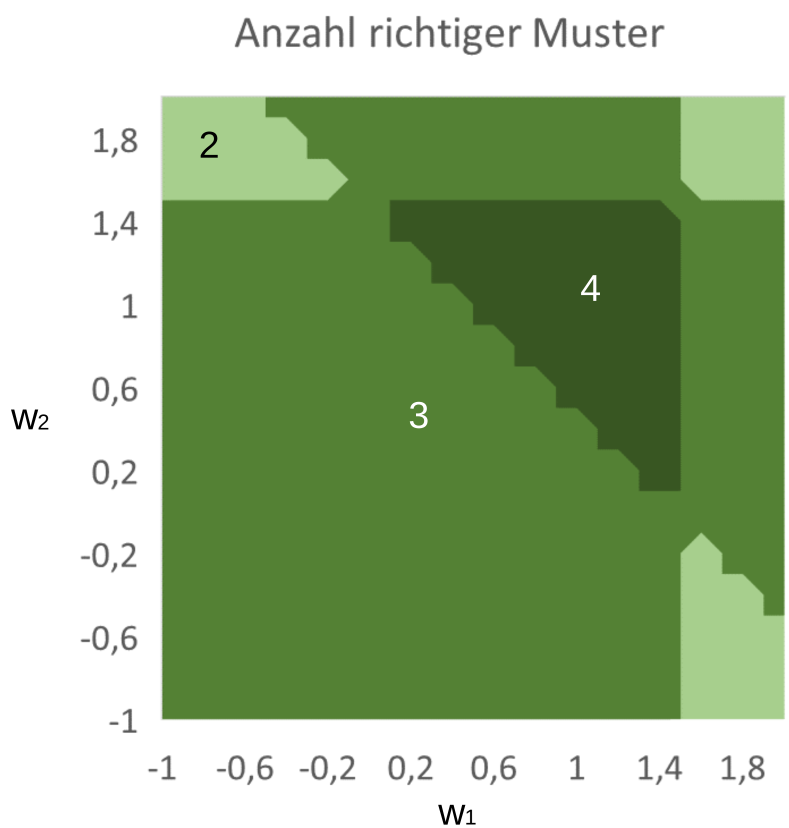


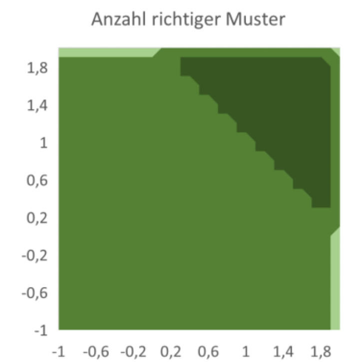
# Model of a Neuron
## Find suitable weights



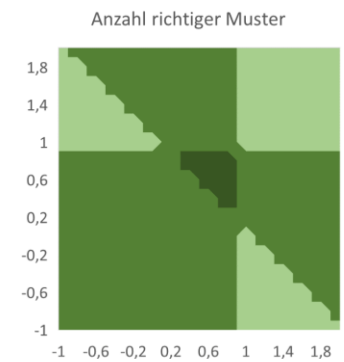
t=1.5



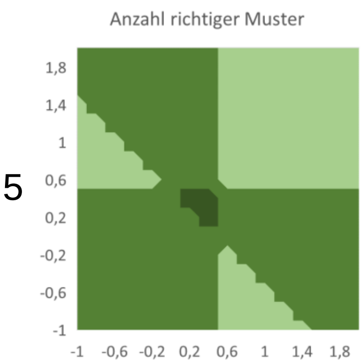

t=2




t=1

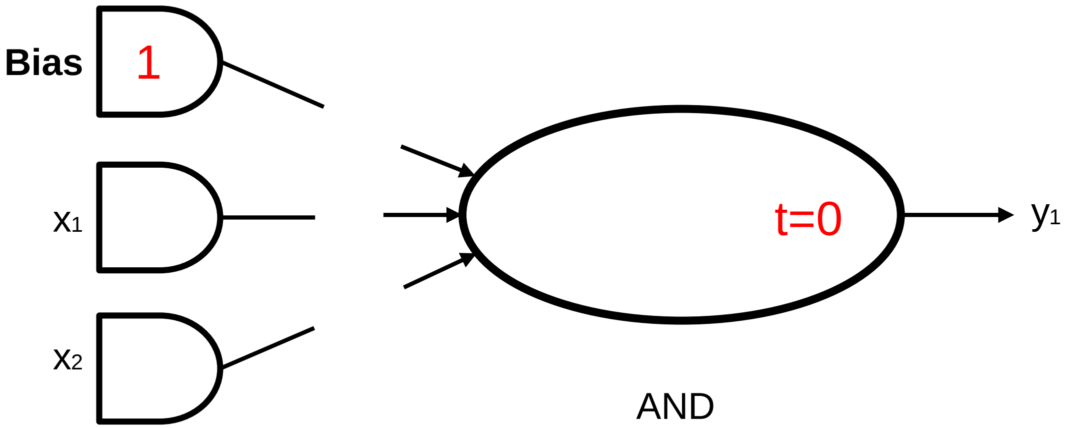


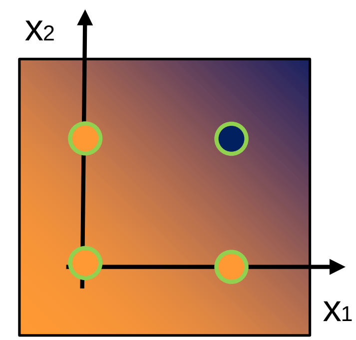

t=0.5



# Model of a Neuron
## Find suitable weights

- Bias




$$o_j = Step_0\left(\sum_{i+1} w_{i,j} x_i\right)$$

# Model of a Neuron
## Find suitable weights



- Weights w are -1 and 1
- Loss function
  - Absolute error (L1 Norm)

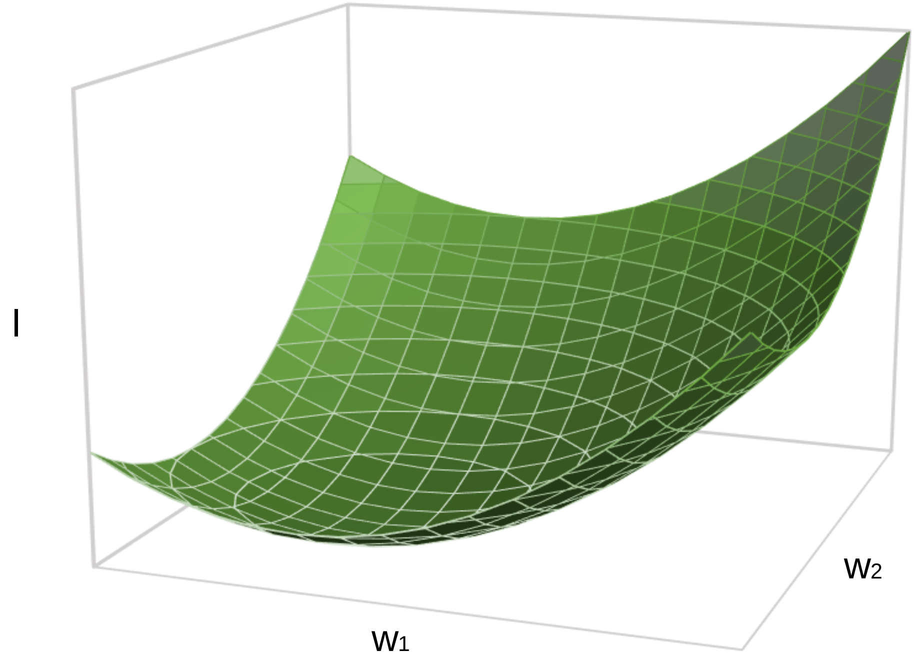
$$l = \sum_i | y_i - o_i | = \| y - o \|_1$$

  - Sum of squared error (L2 Norm)

$$l = \sum_i (y_i - o_i)^2 = \| y - o \|_2^2$$

- Gradient descent

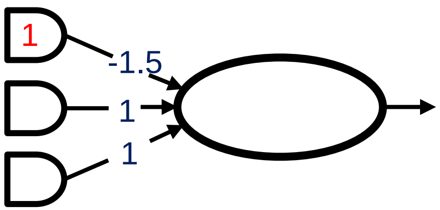
| $x_1$ | $x_2$ | $y_1$ | $o_1$ | l |
|---|---|---|---|---|
| 0 | 0 | 0 | 0 | |
| 0 | 1 | 0 | 0 | |
| 1 | 0 | 0 | 1 | |
| 1 | 1 | 1 | 0 | |



# Model of a Neuron
## Summary



- Input function
- Bias
- Activation function

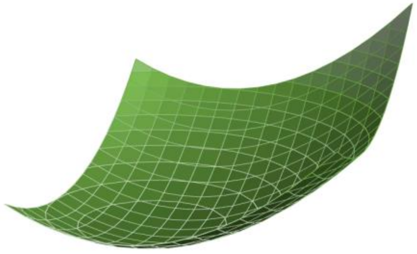



$$o_j = Step_0\left(\sum_{i+1} w_{i,j} x_i\right)$$

- Loss function

$$l = \| y - o \|_2^2$$

- Gradient descent



# Deep Learning

# Perceptron

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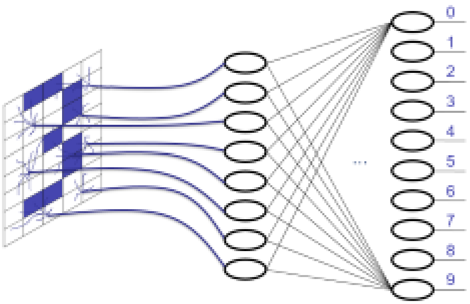


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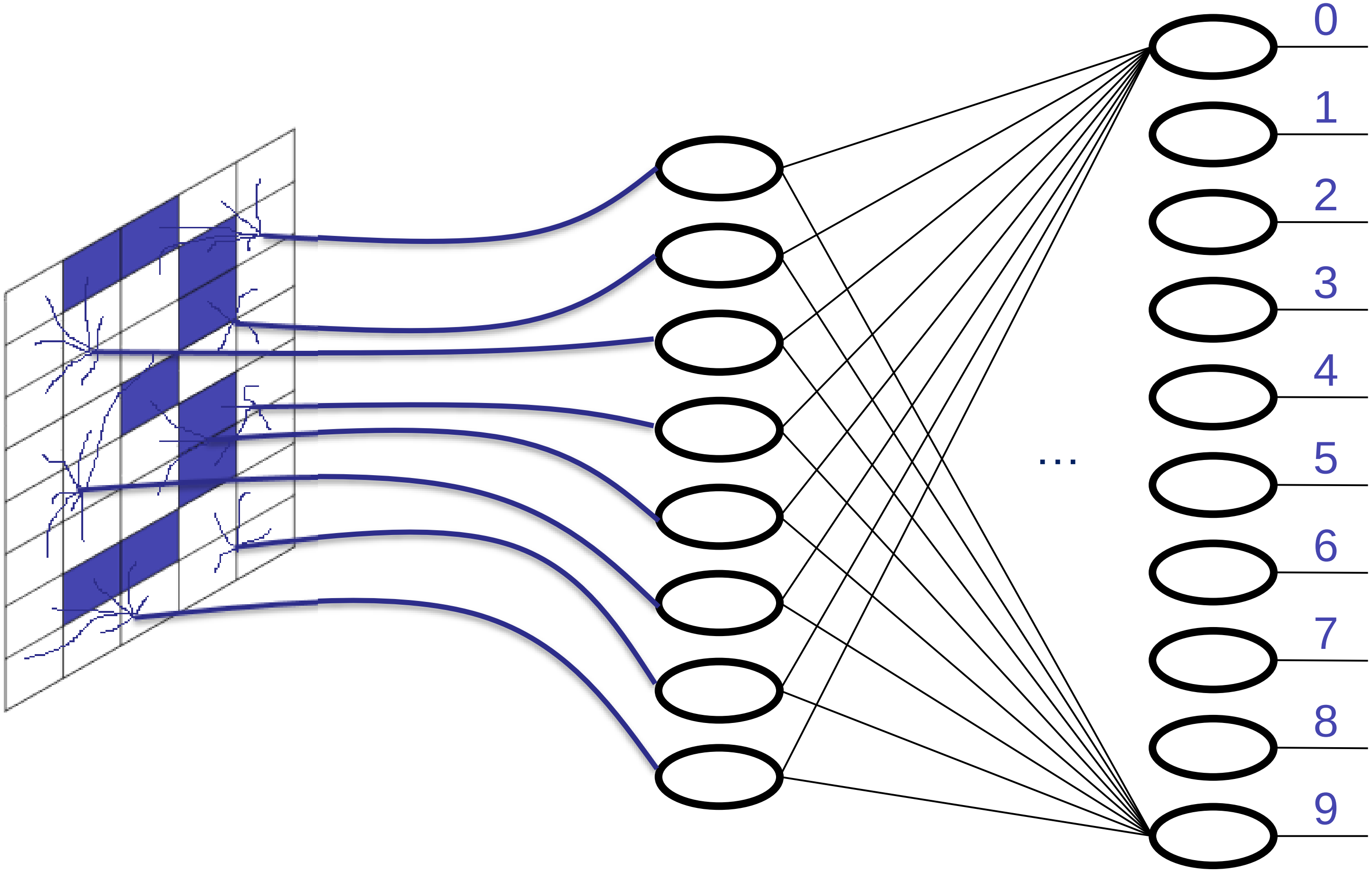
# Perceptron

- Single layer feed forward network (1958 Frank Rosenblatt)



# Perceptron



- Calculation of output

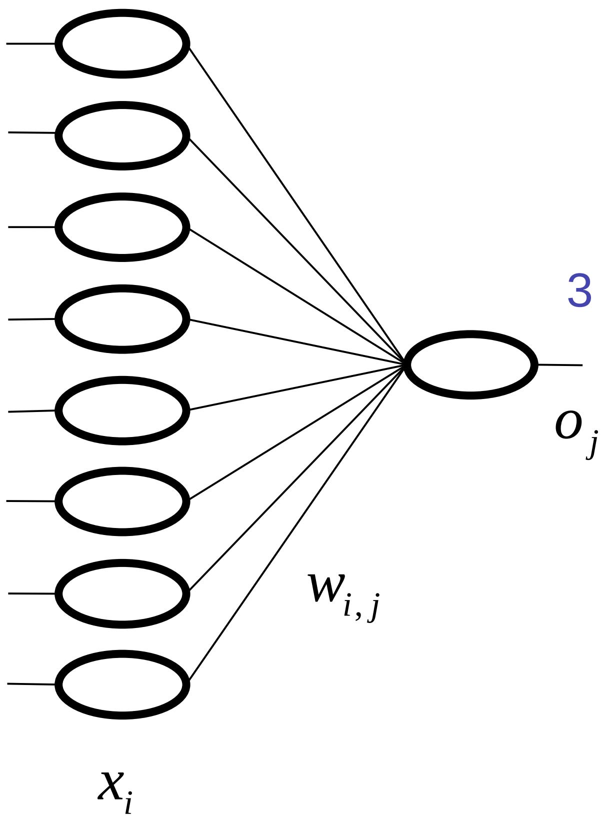
$$o_j = Step_0\left(\sum_{i+1} w_{i,j} x_i\right)$$

- Learning rule (delta rule)

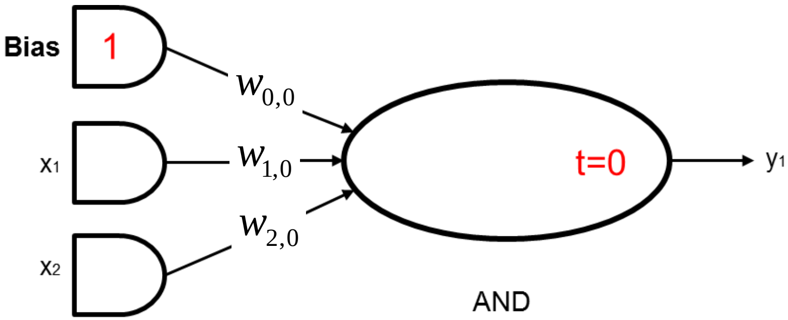
$$w_{i,j} = w_{i,j} + \alpha \cdot x_i \cdot (y_j - o_j)$$

- Algorithm

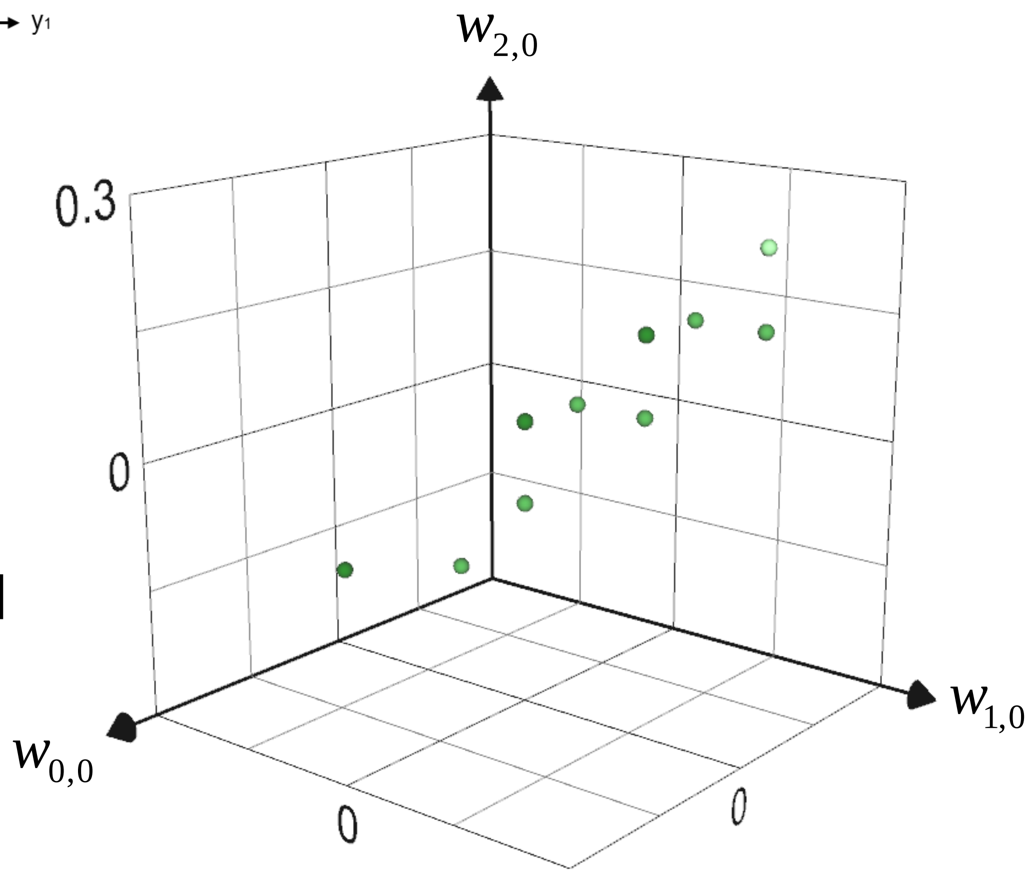
```
Initialize weights randomly
do
   for each e in examples
      calculate output
      adjust weights
while (loss too high and other
        termination criteria not
        reached)
```



# Perceptron
## And Funktion




- Random start
  - $w_{x,0}$ [0.028; -0.258; -0.189]
  - 3 patterns wrong
- Train the four patterns
  - $w_{x,0}$ [-0.072; -0.158; -0.189]
  - 2 patterns wrong
- …
  - 0 patterns wrong



# Perceptron
## Learning Rate and Gradient Descent

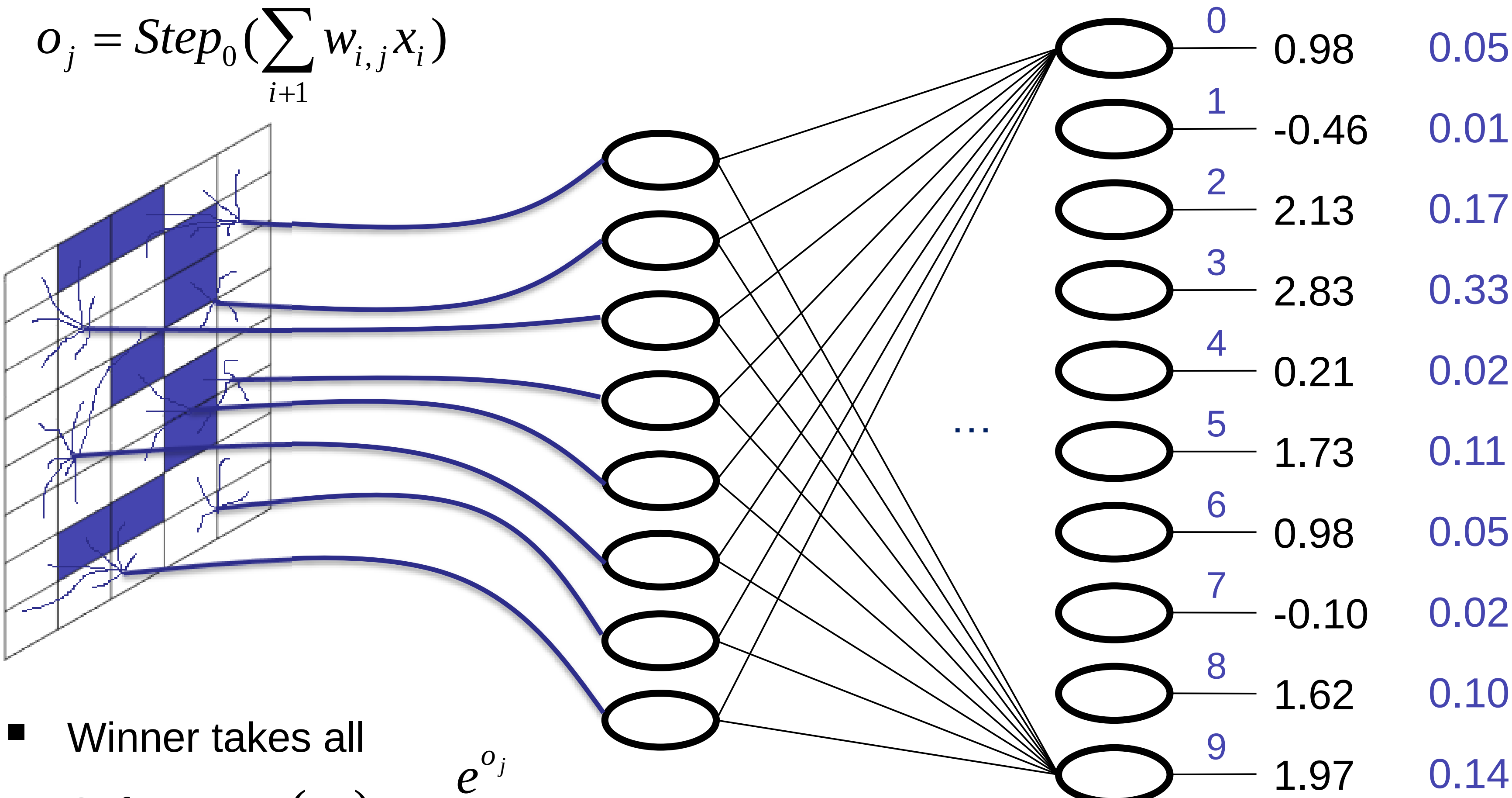
- Small learning rate


- Big learning rate


- Stochastic Gradient Descent
- Batch Learning

# Perceptron
## Real-valued Inputs and Outputs

$$o_j = Step_0(\sum_{i+1} w_{i,j} x_i)$$

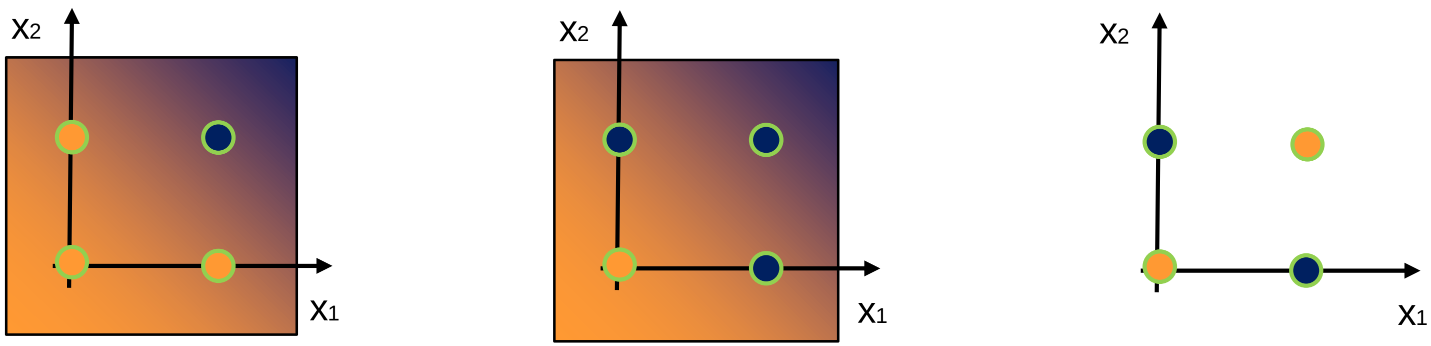



- Winner takes all
- Softmax $\sigma(o_j) = \frac{e^{o_j}}{\sum_k e^{o_k}}$

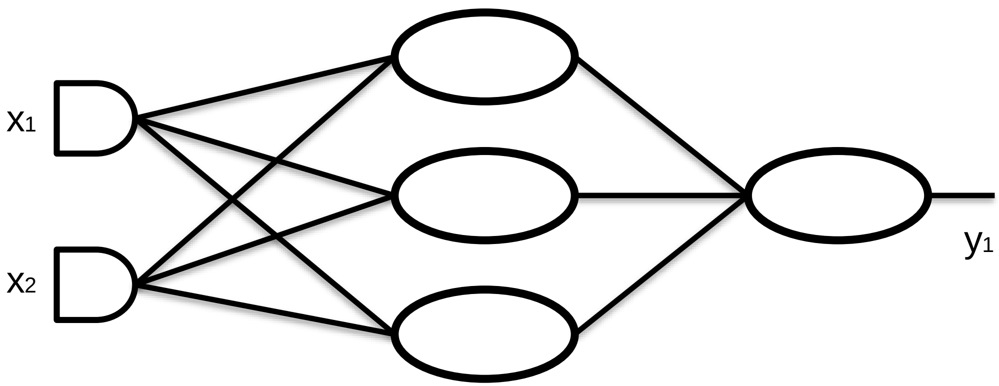
# Perceptron
## Limitations



- Perceptrons can only represent linearly separable problems




AND OR XOR



# Perceptron
## Summary

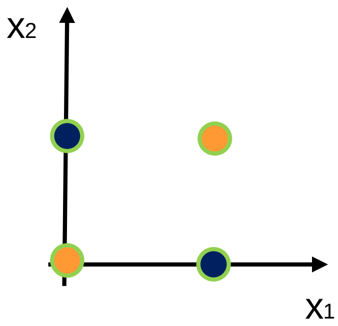
- Learning rule
  - Learning rate
  - Stochastic/Batch Gradient Descent

$$w_{i,j} = w_{i,j} + \alpha \cdot x_i \cdot (y_j - o_j)$$

- Output function
  - Winner takes all
  - Softmax

$$\sigma(o_j) = \frac{e^{o_j}}{\sum_k e^{o_k}}$$

- Problem linear separability




XOR

# Deep Learning

## Backpropagation Networks

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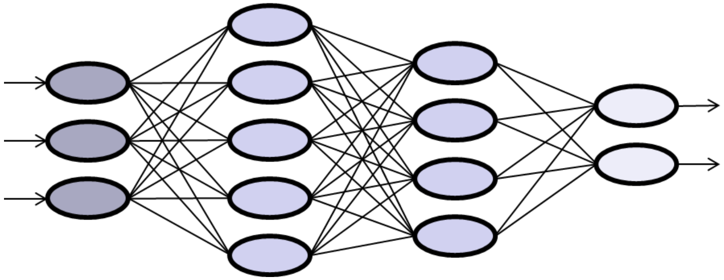

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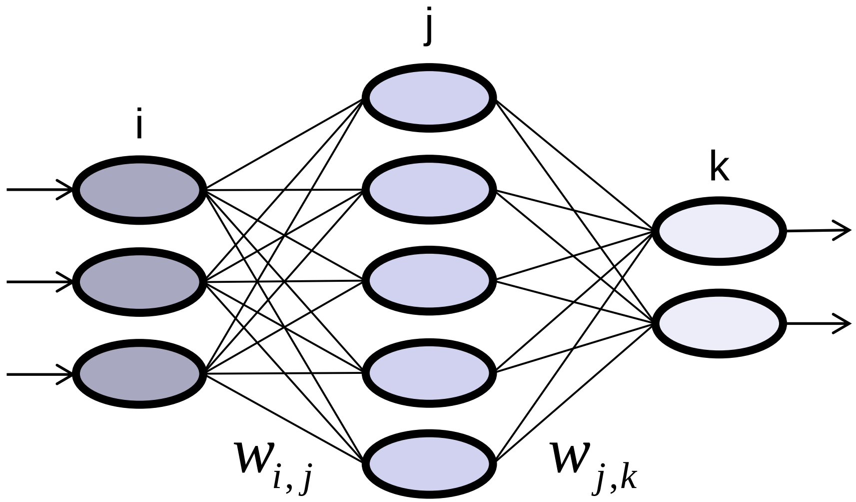
# Backpropagation Networks

- To learn XOR oder similar problems we require
  - Multi-layer networks
  - A non-linear activation function
- Problem
  - How to adjust the weights of a hidden layer?
  - How can we propagate the error of the output back to previous layers?
- Solution
  - Backpropagation of Error
  - Bryson & Ho 1969, Rumelhart, Hinton & Wiliams 1986

# Backpropagation Networks
## Learning Rule

- Calculation of outputs

$$o_j = \sigma\Big(\sum_{i+1} w_{i,j} x_i\Big)$$




- Learning rule
  - Weights to output

$$w_{j,k} = w_{j,k} + \alpha \cdot o_j \cdot \Delta_k \text{ mit } \Delta_k = \sigma'(in_k) \cdot (y_k - o_k)$$

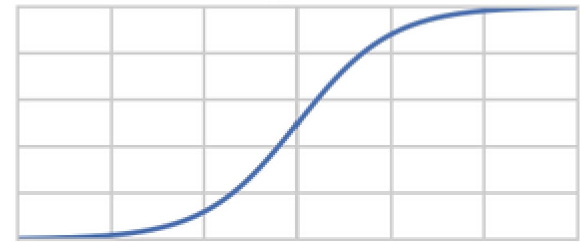
  - Weights to a hidden layer

$$w_{i,j} = w_{i,j} + \alpha \cdot o_i \cdot \Delta_j \text{ mit } \Delta_j = \sigma'(in_j) \cdot \sum_k w_{j,k} \Delta_k$$

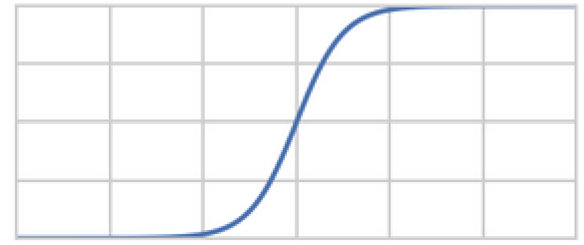
# Backpropagation Networks
## Algorithm

```
initialize weights randomly
do
  for each e in examples
    calculate output (recall)
    calculate Δ values for output units
    repeat for each layer(backward from the outputs)
      propagate Δ values back to previous layer
      adjust weights
while (loss too big and other stop criteria not reached)
```

- Sigmoid
  - Function $$\sigma(x) = \frac{1}{1+e^{-x}}$$
  - Derivative $$\sigma'(x) = \sigma(x)(1-\sigma(x))$$

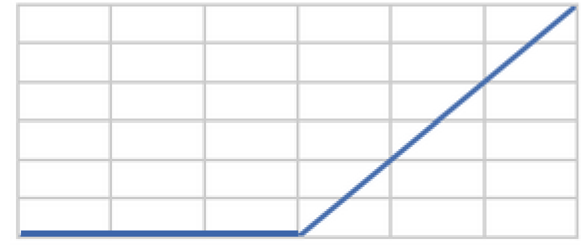



- Tanh $$\sigma(x) = \tanh(x)$$



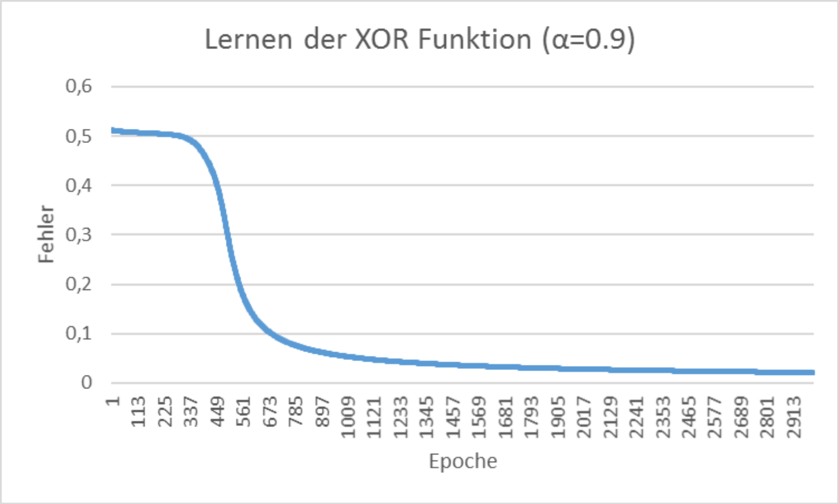

- Relu $$\sigma(x) = \max(0, x)$$

  (Rectified linear unit)

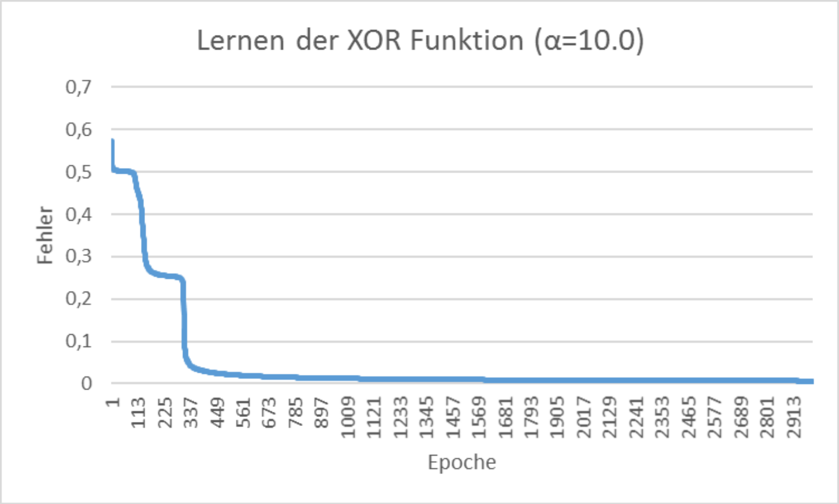


# Backpropagation Networks
## Example: XOR Function

- A 3 – 3 – 1 network can learn XOR
  - Learning rate 0.9

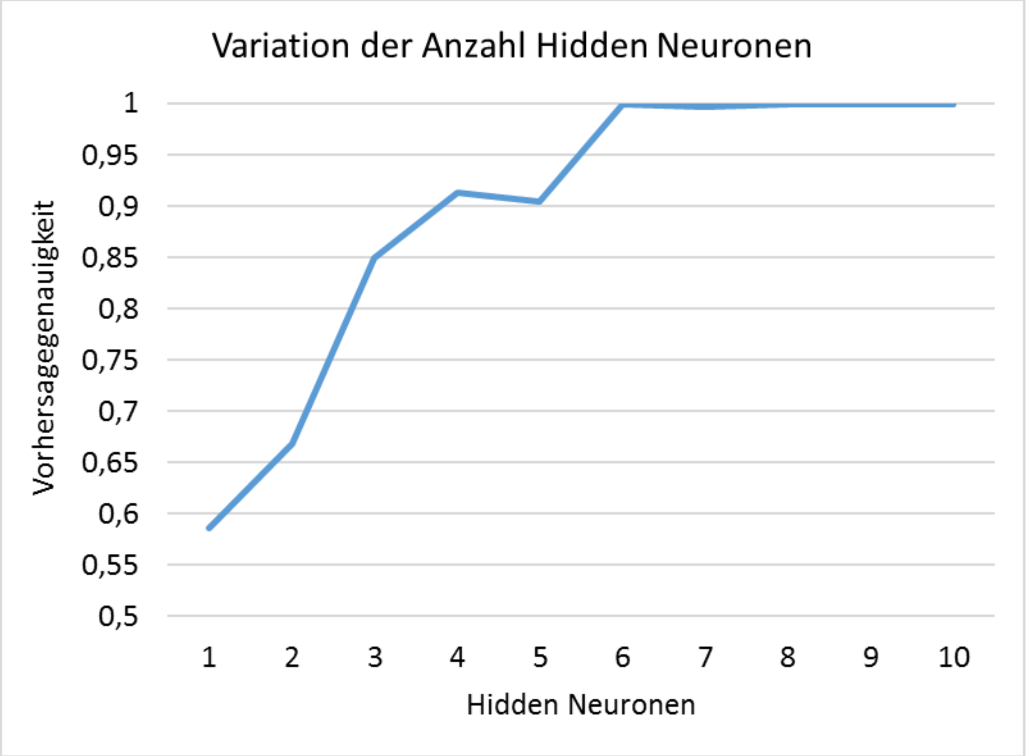



  - Learning rate 10



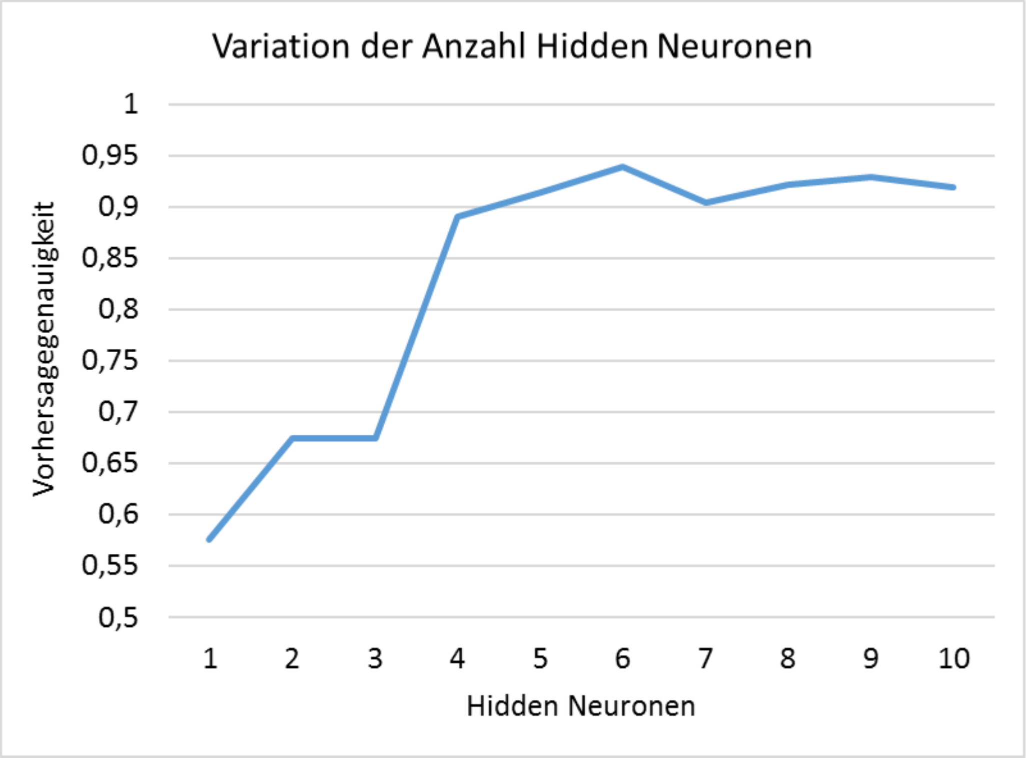
# Backpropagation Networks
## Example: classification

- What is a good size of the network?
  - To represent the training patterns?
  - Test of accuracy on training data
- Data
  - 864 patterns training
  - 864 patterns test
  - 6 attributes (4,4,4,3,3,3)
  - Class: yes/no
- Network
  - 21 input neurons
  - x hidden neurons
  - 2 output neurons



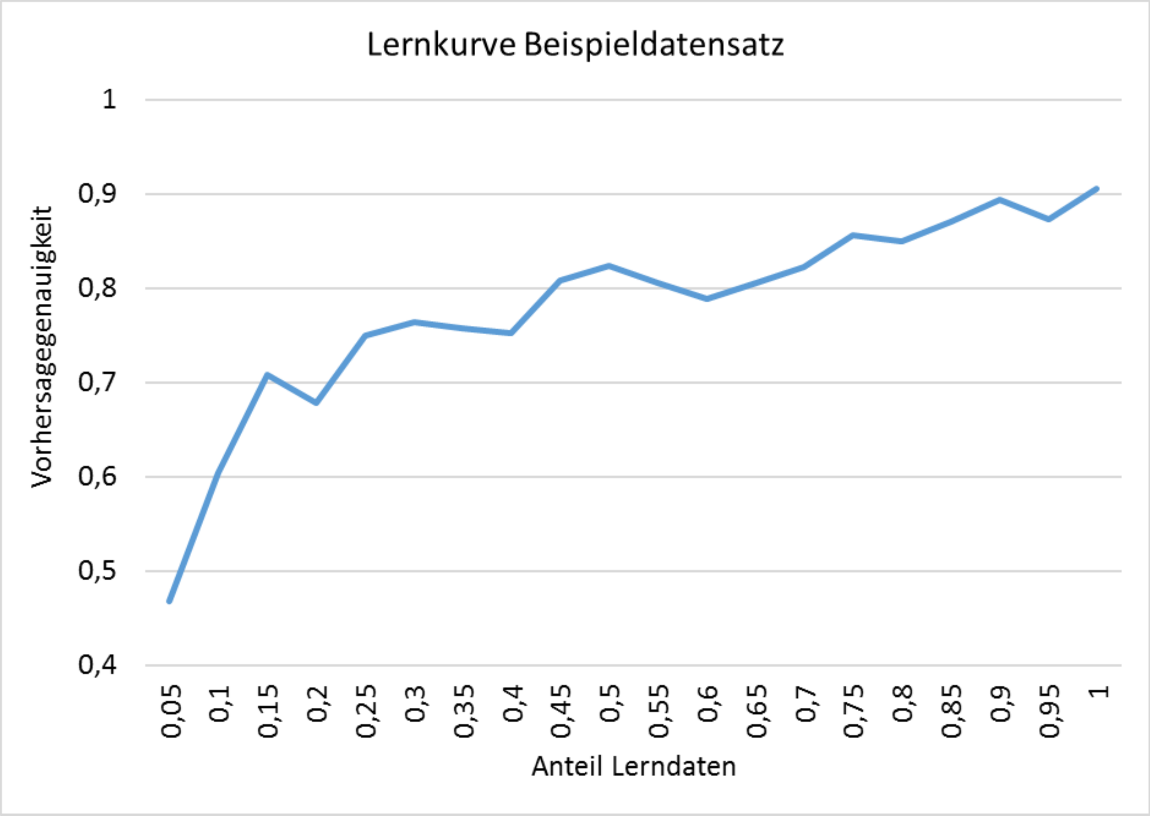
# Backpropagation Networks
## Generalization

- What is a good size of the network?
  - To properly predict unknown patterns?
  - Test of accuracy on test data



# Backpropagation Networks
## Learning Curve

- How many patterns are required for the network to generalize?
  - The more the better



# Backpropagation Networks
## Summary

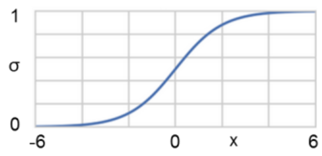


- Learning rule

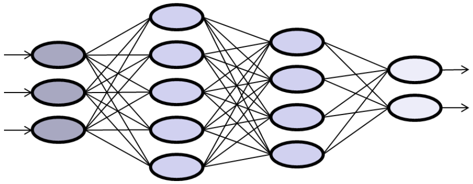
$$w_{i,j} = w_{i,j} + \alpha \cdot o_i \cdot \Delta_j \text{ mit } \Delta_j = \sigma'(in_j) \cdot \sum_k w_{j,k} \Delta_k$$

- Activation function

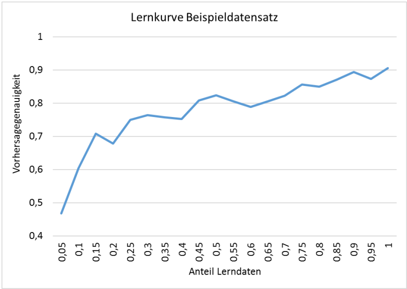
$$\sigma(x) = \frac{1}{1+e^{-x}}$$




- Network size



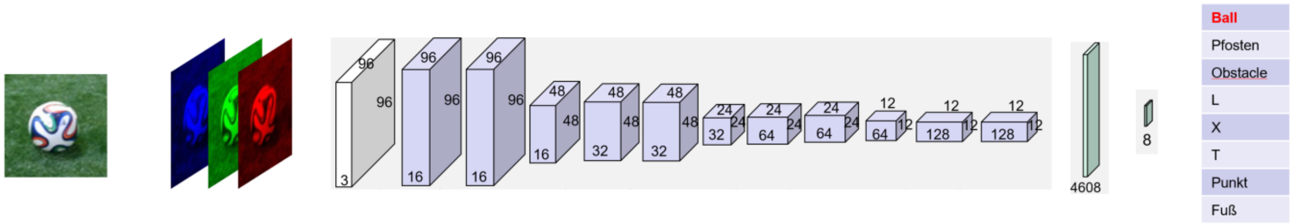
- Learning curve



# Deep Learning

# Convolutional Neural Networks

Prof. Dr. Klaus Dorer

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# Overview

- Neural Networks
  - Introduction
  - Model of a Neuron
  - Perceptron
  - Backpropagation Networks
  - Convolutional Neural Networks
    - Structure
    - Application
    - Deep Learning Frameworks

# Convolutional Neural Networks

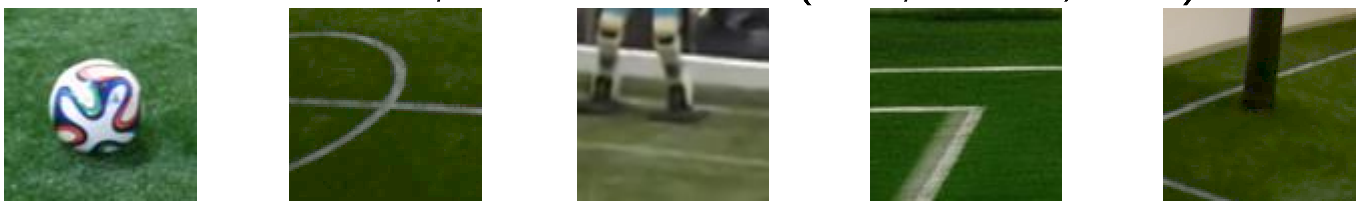
- Sweaty is a soccer robot
- It needs to see things on its camera images
- No matter where in the picture

- No matter how bright the light

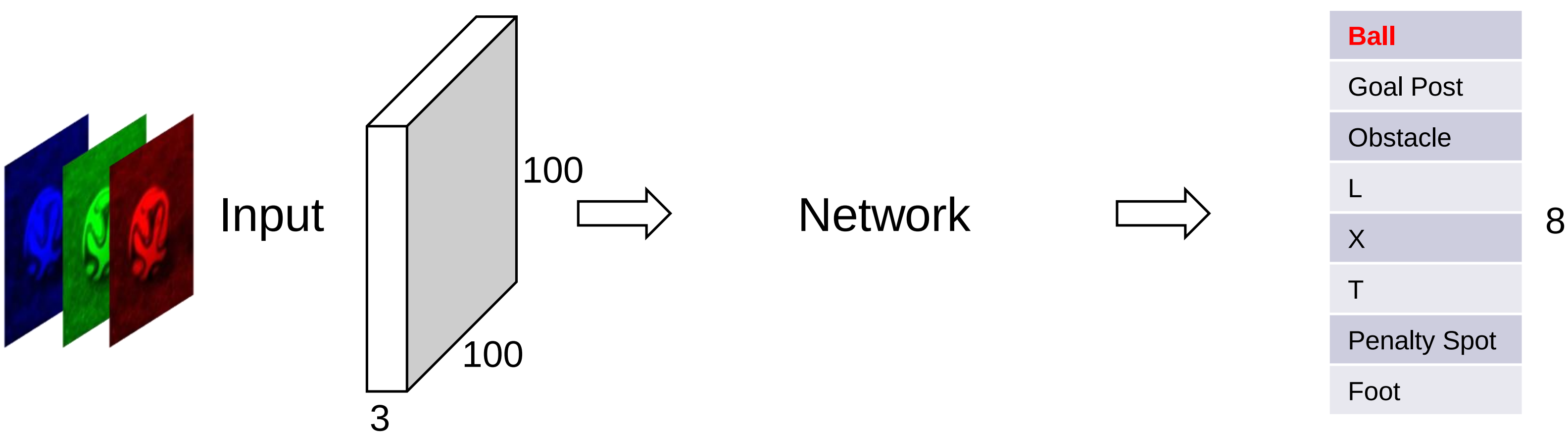
- No matter what color, pattern

# Convolutional Neural Networks

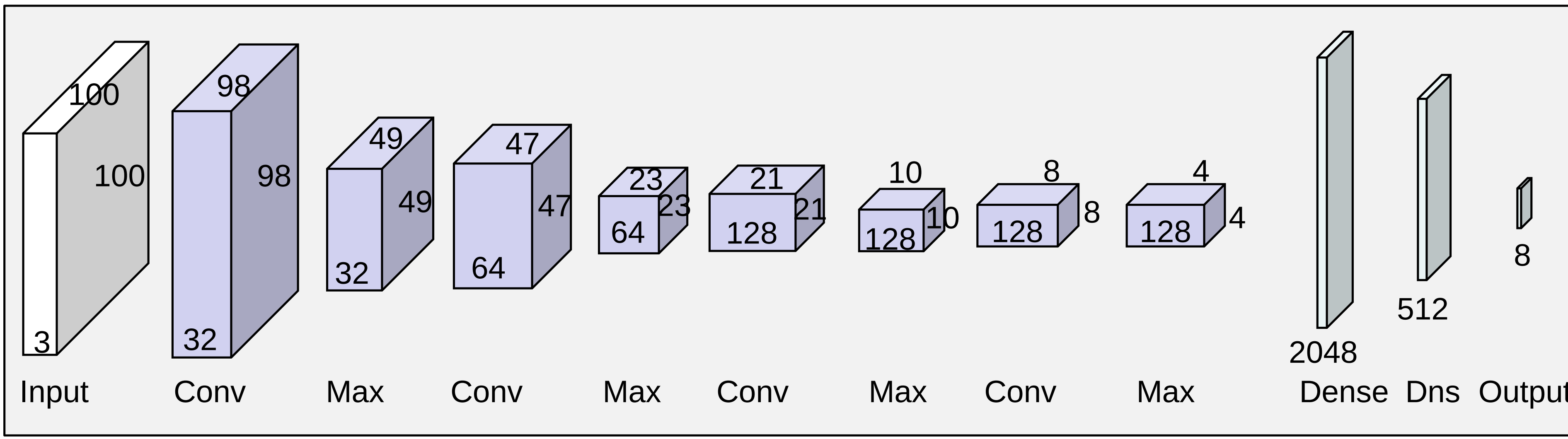
- Input is a 3D matrix
  - Here: 100x100 Pixel, 3 color chanels (Red, Green, Blue)



- Output is a feature-vector
  - Ball X-Line Robot L-Line Obstacle



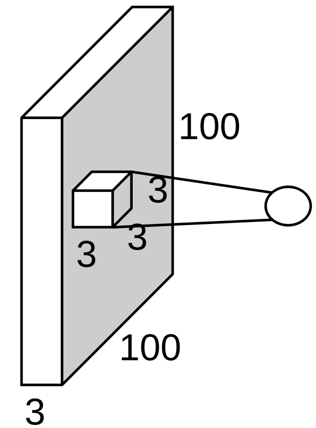
# Convolutional Neural Networks
## Example Architecture



# Convolutional Neural Networks
## Convolution Layer



- Filter (kernel) runs (convolves) over the input
- Calculates input for neuron in activation map
- Activation function here: ReLU
  - Y = ReLU(Wx+b)




W:

| | | |
|---|---|---|
| 1 | 0 | 1 |
| 0 | 1 | 0 |
| -1 | 0 | 1 |

x:

| | | | |
|---|---|---|---|
| 1 | 1 | 1 | 0 |
| 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 |
| 0 | 0 | 1 | 1 |

b:

| |
|---|
| -1 |

o:

| | | | |
|---|---|---|---|
| | | | |
| | 3 | | |
| | | | |
| | | | |

ReLU ( W * x + b ) = o

- Repeated with n filters: n activation maps
- Padding: how do we deal with pixels at the border
- Strides: step size, > 1 means activation map shrinks

# Convolutional Neural Networks
## Pooling Layer

- Reduces the size of the activation map
- Pooling function
  - Usually Max-Pooling
  - Sometimes Avg-Pooling
- Example
  - 2x2 filter with 2,2 strides

| | | | |
|---|---|---|---|
| 2 | 3 | 5 | 7 |
| 6 | 4 | 3 | 2 |
| 1 | 2 | 3 | 2 |
| 0 | 1 | 1 | 0 |

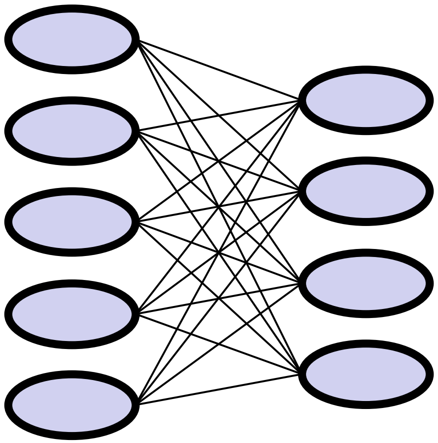
Input

| | |
|---|---|
| 6 | 7 |
| 2 | 3 |

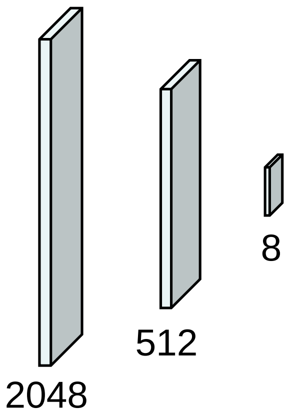
Output
Max- Pooling

# Convolutional Neural Networks
## Fully Connected Layer

- Already known: backpropagation layer
- On a pretrained network it may suffice to only learn these layers on new images
- Contains a majority of learnable weights



- In our example
  - 2048 * 512 + 512 = 1.049.088 weights
  - 512 * 8 + 8 = 4.104 Gewichte
- To compare with
  - 3*3*3*32 + 32 = 896 weights in the first convolution layer



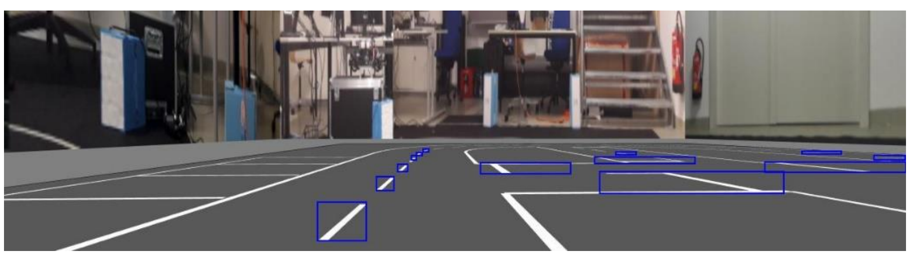
# Convolutional Neural Networks
## Learning

- Image tagging
  - A teacher has to assign the proper class to each image
  - In case of object localization also a bounding box is required
- Image learning
  - Present training image to network
  - Network calculates output and loss
  - Network performs gradient descent on loss function
- Accuracy is measured on test data
- Application
  - Stored network cann be applied to live images
  - Fast recall

# Convolutional Neural Networks
## Overfitting

- Train many images
- What if we do not have too many?
  - Augment existing images

  - Create synthetic images



- Dropout
  - Do not use a fraction (e.g. 0.5) of random neurons during learing
  - Avoids single ‚important' connections

# Deep Learning
## Applications: Hochschule

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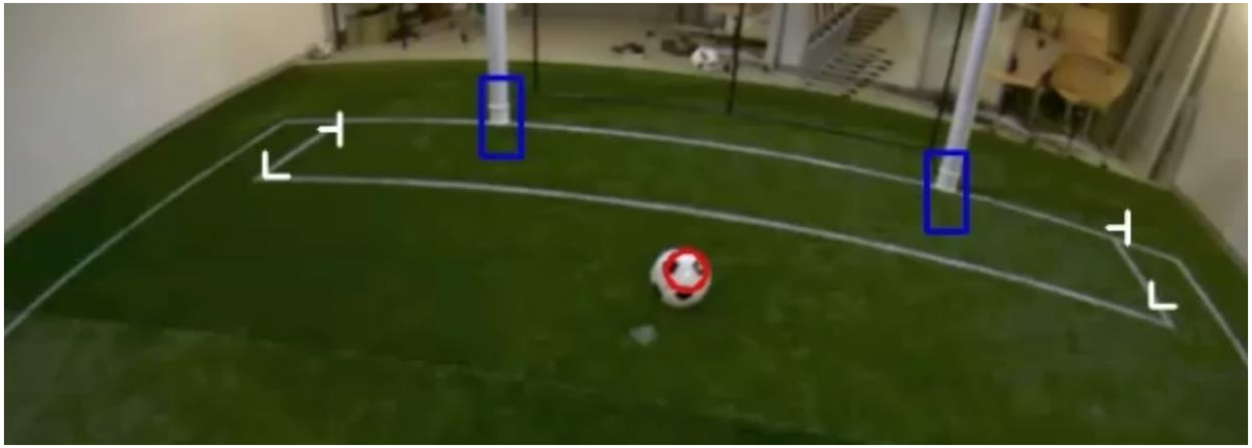
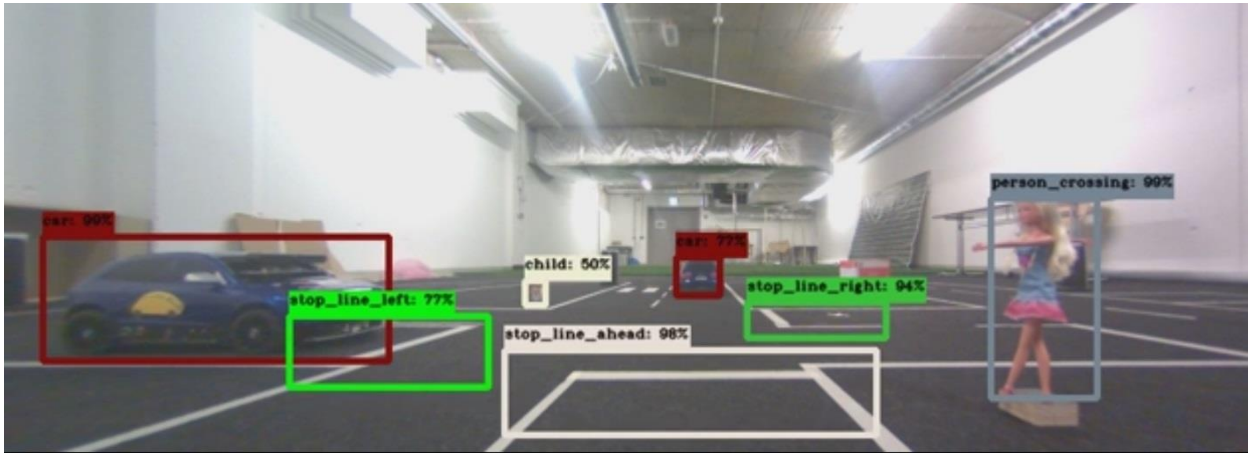
- RoboCup

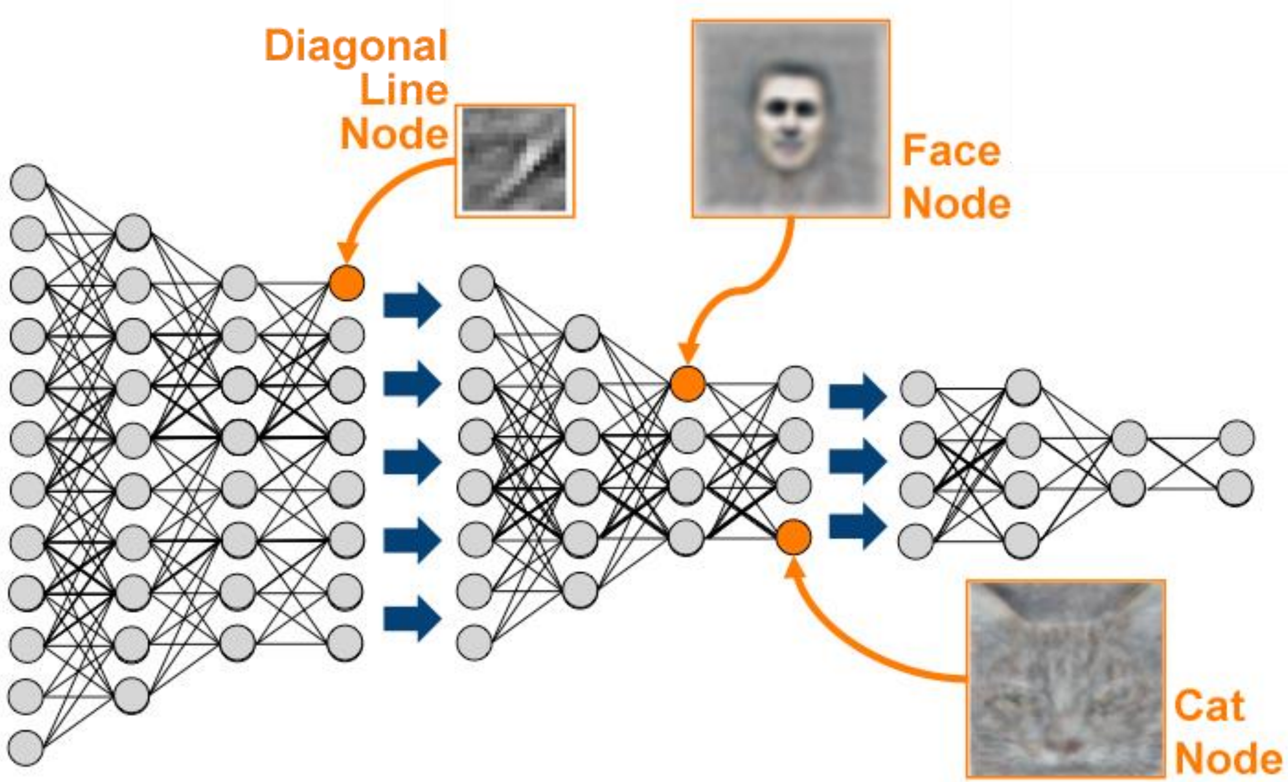


- AudiCup



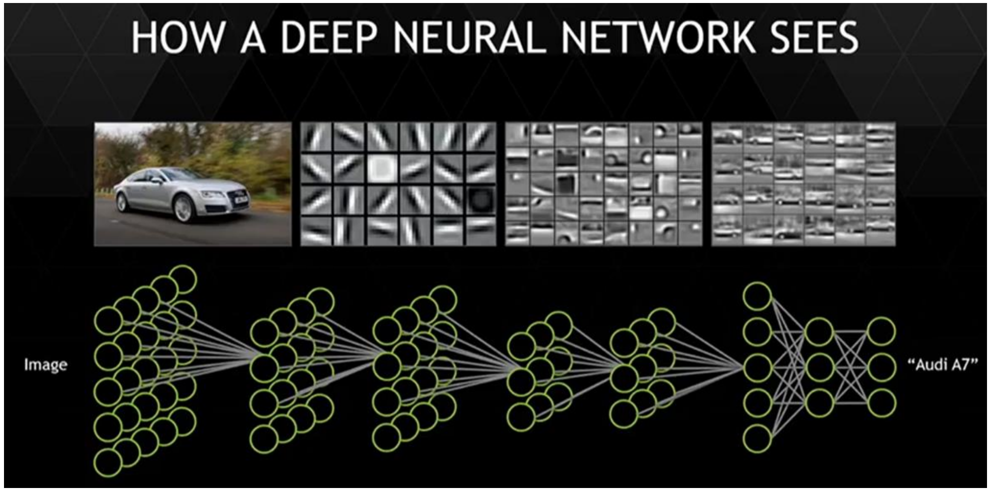
# Deep Learning
## Applications: Google

- Input
  - 10 mio images (200 x 200 pixel)
- Learning
  - 1 Mio weights
  - 16.000 cores
  - 3 days



# Deep Learning
## Applications: NVIDIA

- Example NVIDIA
  - First layer detects lines and circles
  - Parts of a car
  - Cars
  - Car types
- Learning
  - Days
    (on a GPU cluster)
- Recall
  - 2 Megapixel
  - 30 fps
  - 75 objects

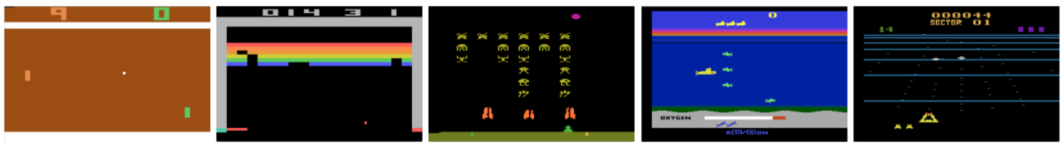




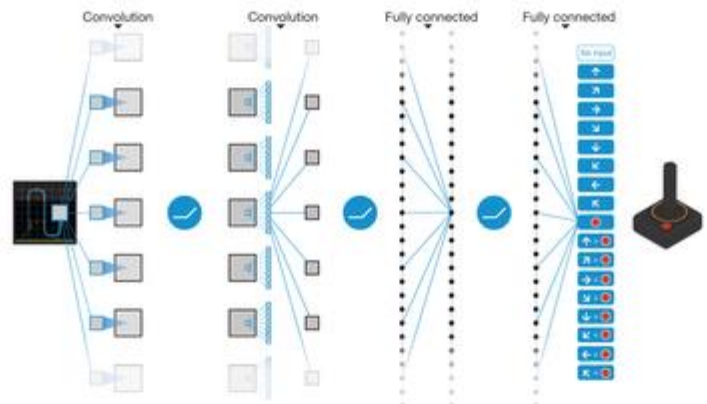
https://www.youtube.com/watch?v=zsVsUvx8ieo

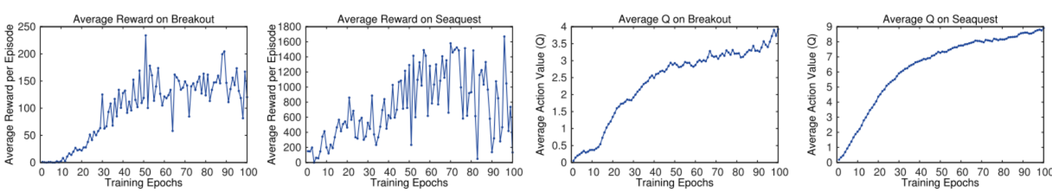
# Deep Learning
## Applications: DeepMind

- Deep Reinforcement Learning of computer games

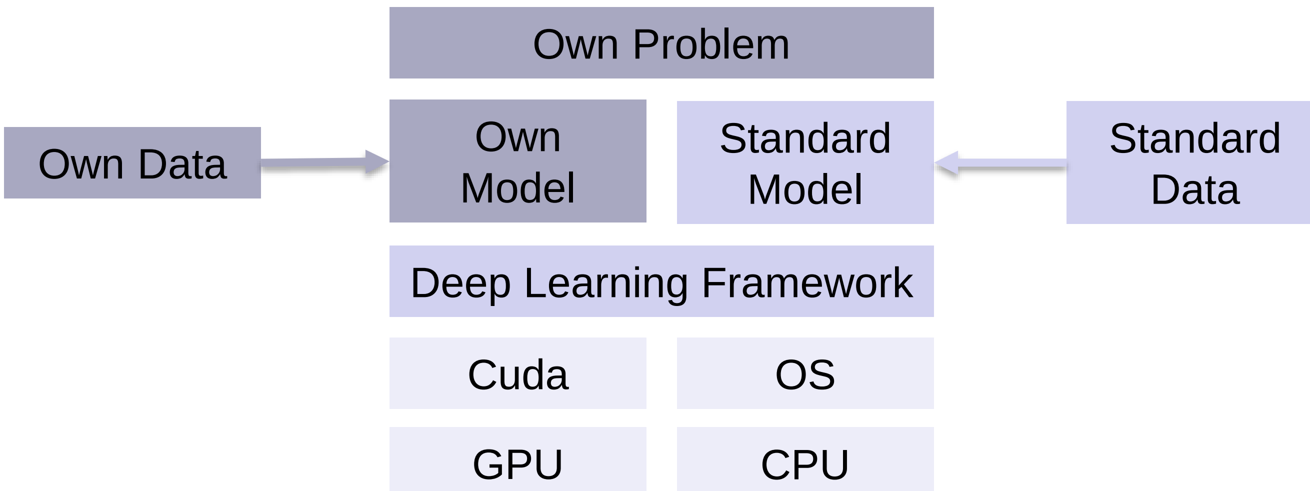


- Input
  - 84*84*4 downsampled live video input
- Network
  - 4 layers, 2 convolutional (8x8, 4x4),
    2 fully connected
- Result
  - 4 of 7 games played better than human expert



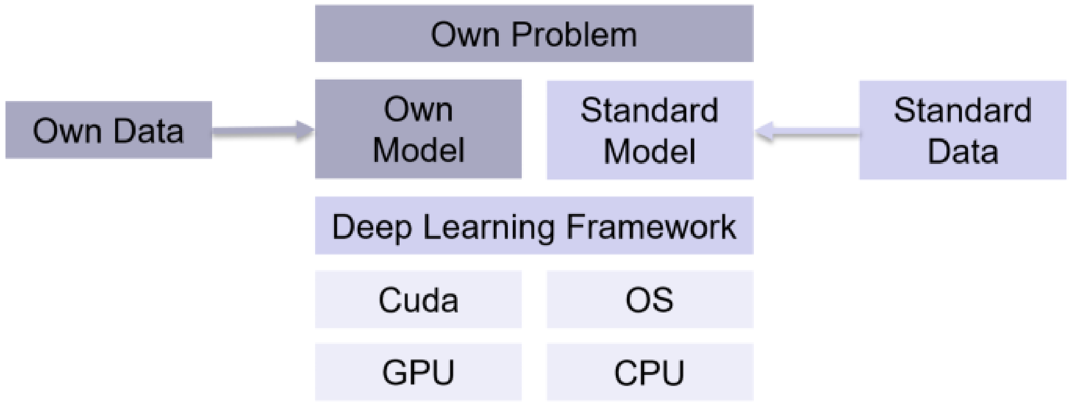




https://www.cs.toronto.edu/~vmnih/docs/dqn.pdf und http://www.nature.com/nature/journal/v518/n7540/full/nature14236.h


Own Problem
Own Data
Own Model
Standard Model
Standard Data
Deep Learning Framework
Cuda
OS
GPU
CPU

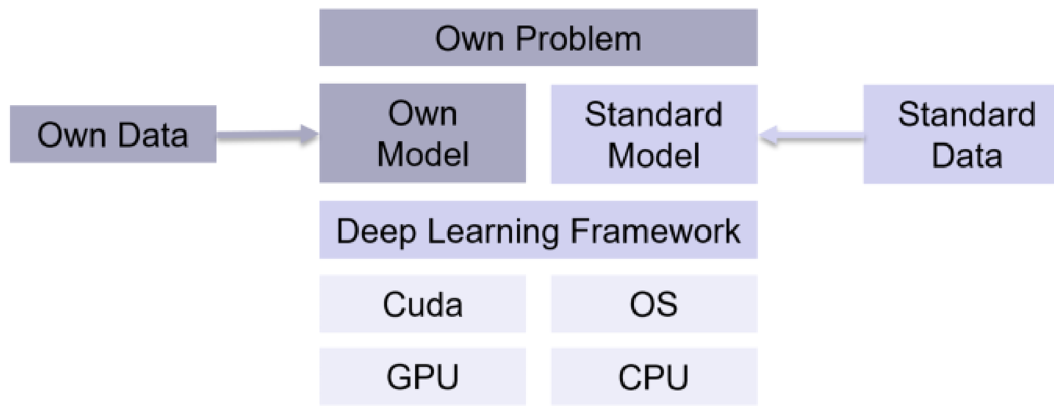
# Deep Learning
## Frameworks

- TensorFlow
  - Google Brain team
  - https://www.tensorflow.org/
- Torch, PyTorch
  - Communities
  - http://pytorch.org/
- Deeplearning4j
  - Skymind engineering team, Deeplearning4j community
  - https://deeplearning4j.org/
- Caffe
  - Berkeley Vision and Learning Center
  - http://caffe.berkeleyvision.org/
- Caffe2
  - Facebook
  - https://research.fb.com/downloads/caffe2/



# Deep Learning
## Standard Data

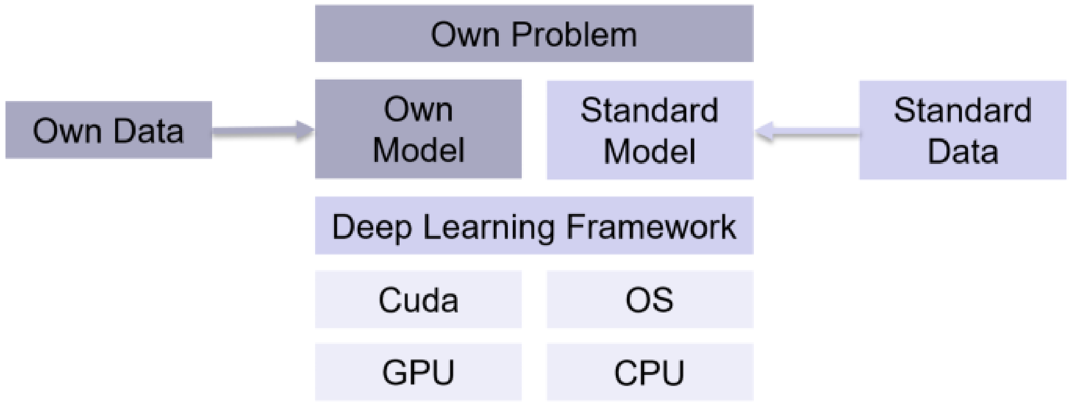
- ImageNet
  - 14 Mio tagged images
  - 21.000 categories
  - http://www.image-net.org
- MNIST
  - 70.000 hand written digits
  - http://yann.lecun.com/exdb/mnist/
- COCO (common objects in context)
  - 200.000 tagged and segmented images
  - http://cocodataset.org/#home
- Music, faces, speech, texts, …



# Deep Learning
## Standard Network Models

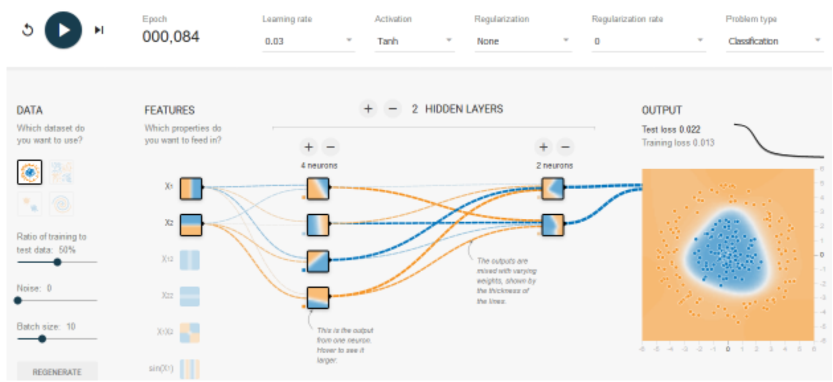


- LeNet-5 (1990)
  - 5 layers (4,1)
  - MNIST
- AlexNet (2012)
  - 8 layers (5,3)
  - ImageNet (16.4% Fehler)
- GoogLeNet (2014)
  - 22 layers
  - ImageNet (6.7%)
- ResNet-152 (2015)
  - 152 layers
  - ImageNet (3.6%), COCO

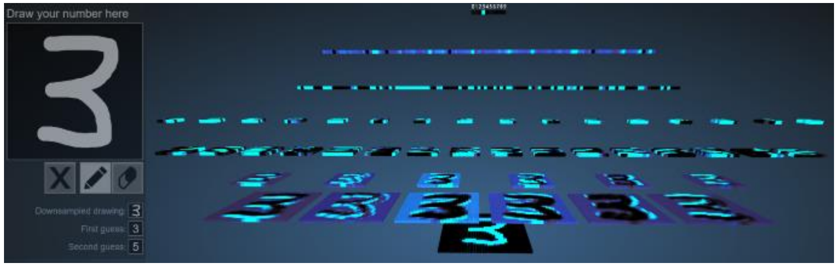



- VGGNet
- Mobilenet
- Inception
- …

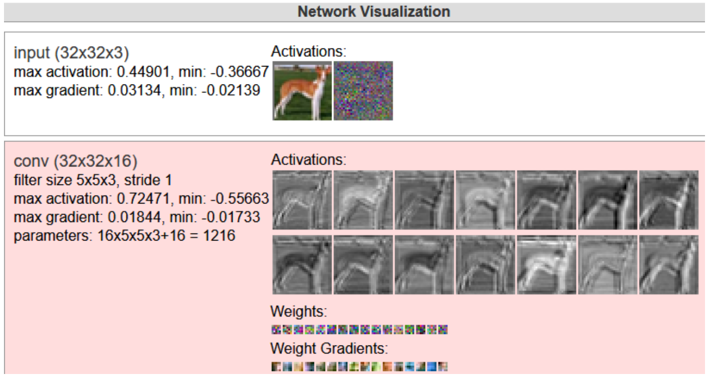
- Google Playground
  - http://playground.tensorflow.org




- 3D digit recognition (Adam Harley)
  - http://scs.ryerson.ca/~aharley/vis/conv




- ConvnetJS (Andrej Karpathy)
  - https://cs.stanford.edu/people/karpathy/convnetjs



# Summary



- Deep Convolutional Neural Networks
  - Convolution layers
  - Max layers
  - Dense layers

- Applications
  - Image recognition, speech recognition, predictive maintenance, …

- Many pretrained networks available for download