Neuronale Netze - Eine kurze Einführung mit Implementierungen in Python

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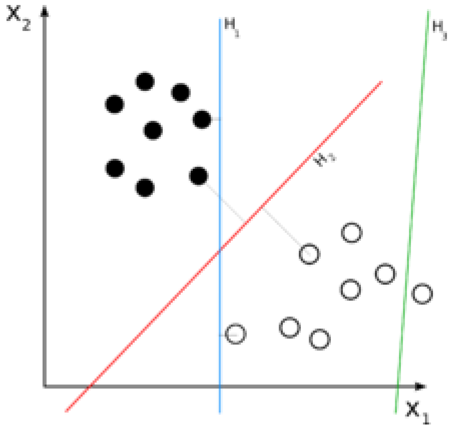
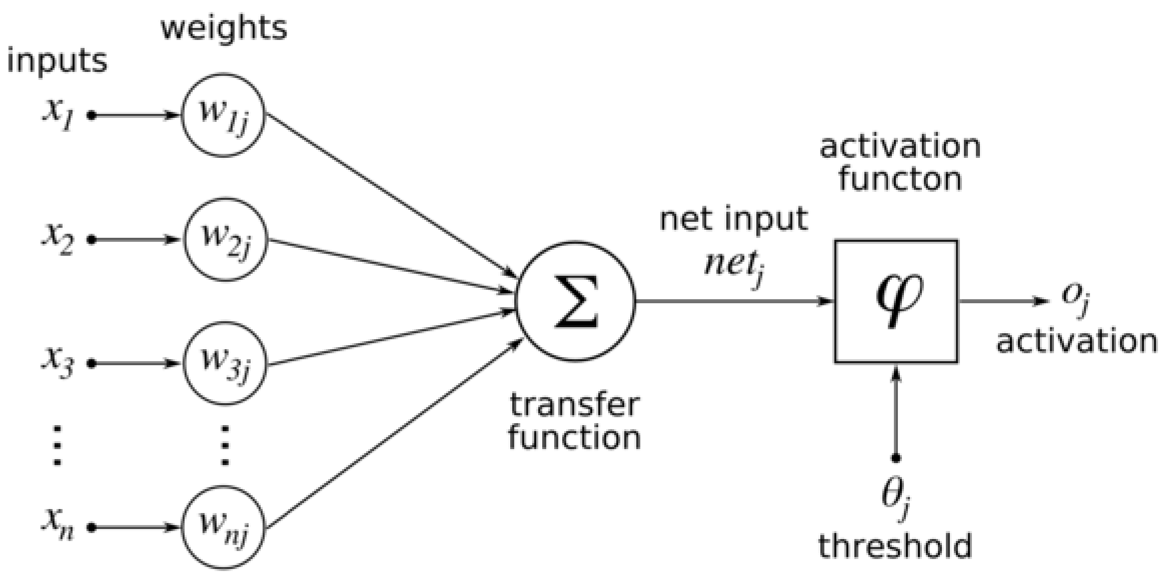
The origin - a linear classifier



$$H_i = < x, w > = \sum_j x_j w_j + \theta$$

Idea of a perceptron as classifier



Activation function can vary e.g.:

- step function

$$o_j = \begin{cases} 1, & \text{if } net_j \geq 0 \\ 0, & \text{else} \end{cases}$$

How to obtain the weights?

The objective is a good model fit.

- trial an error $\rightarrow$ inefficient
- optimization $\rightarrow \min\limits_{w} \text{Cost}(t, w)$

  with:

  t: target value

  w: weight vector

e.g. squared error as in linear regression

$\Rightarrow$ optimization theory

- one efficient way for solving the problem is the use of backpropagation (error is "propagated" backwards through the grid)

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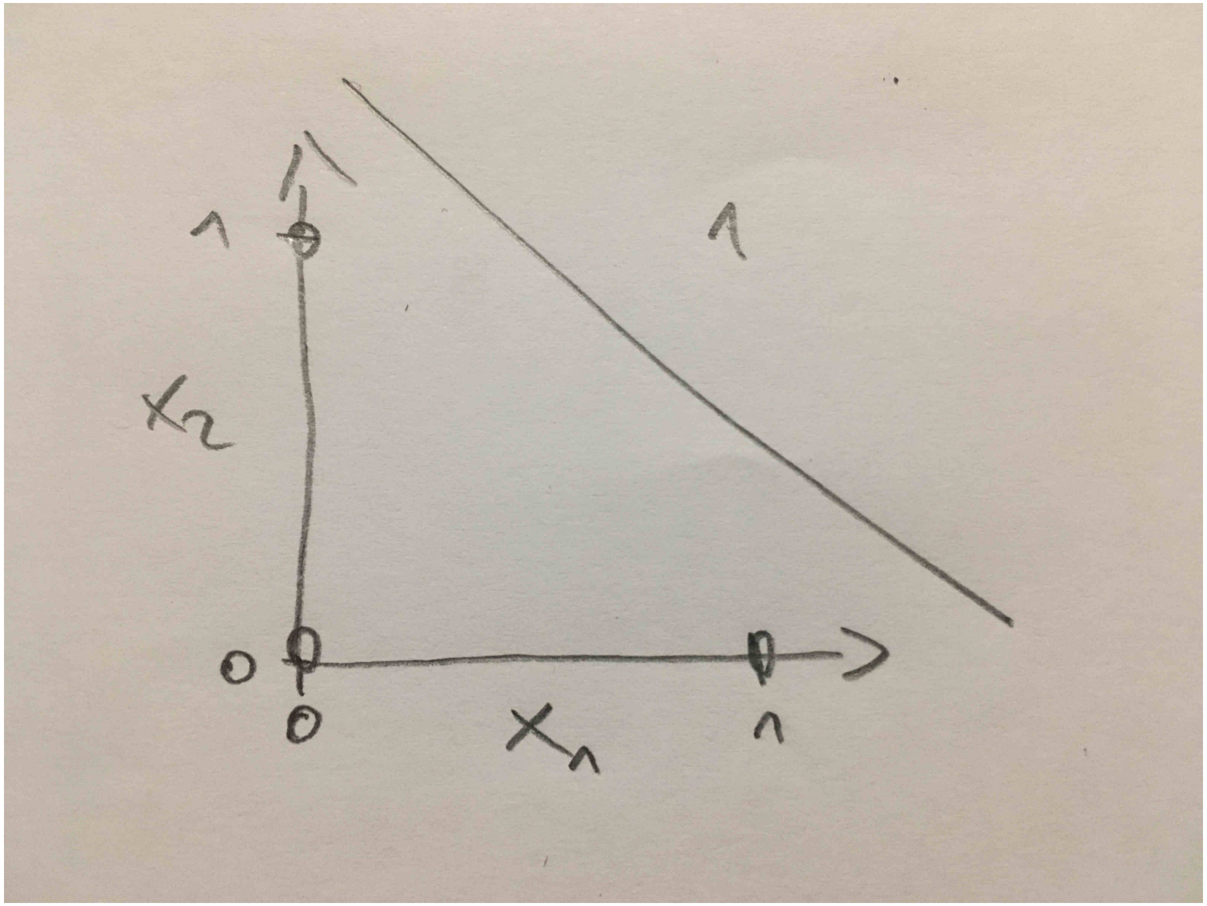
x	x	AND	OR	XOR

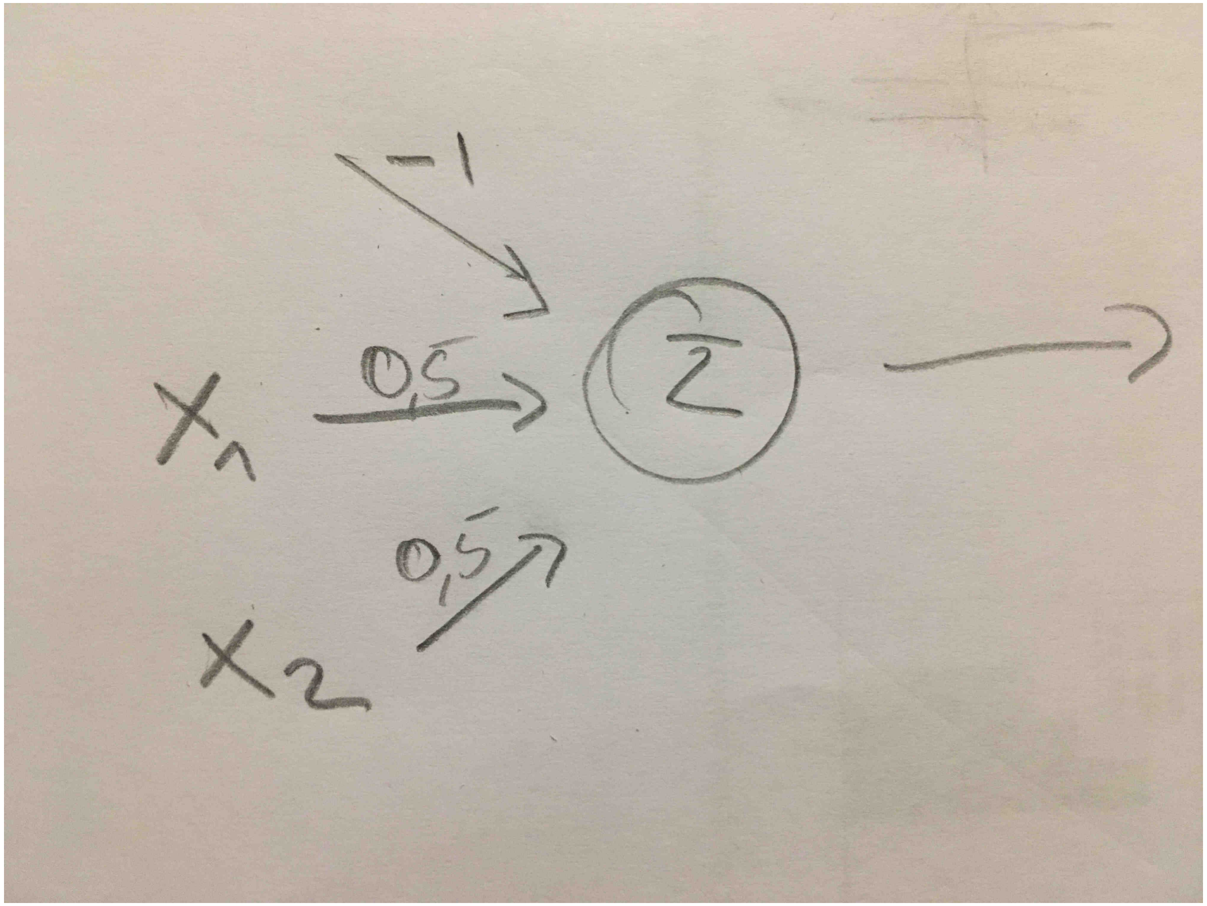
Representing Boolean Algebra as Classifiers

x_1	x_2	AND	OR	XOR
0	0	0	0	0
0	1	0	1	1
1	0	0	1	1
1	1	1	1	0

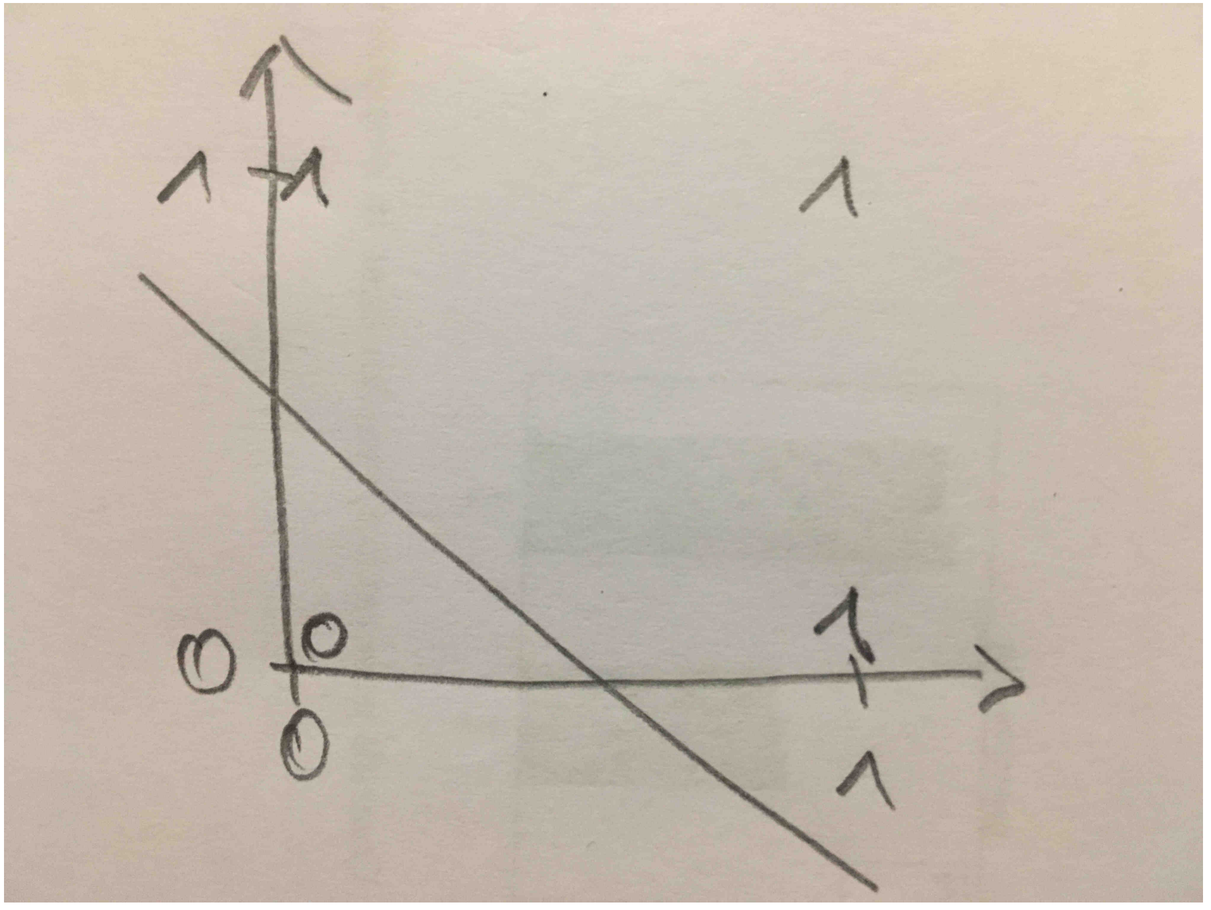
AND is linearly seperable



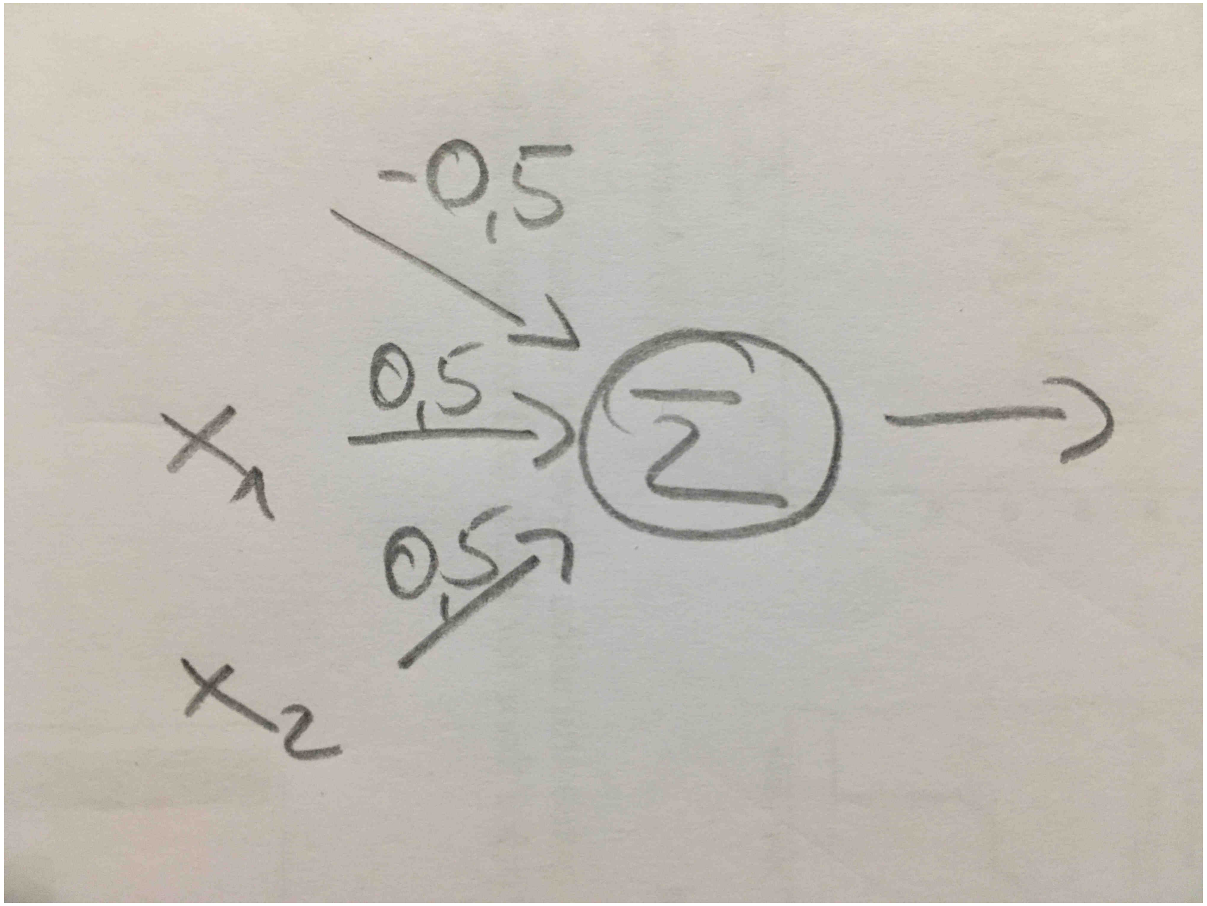
One possible AND perceptron



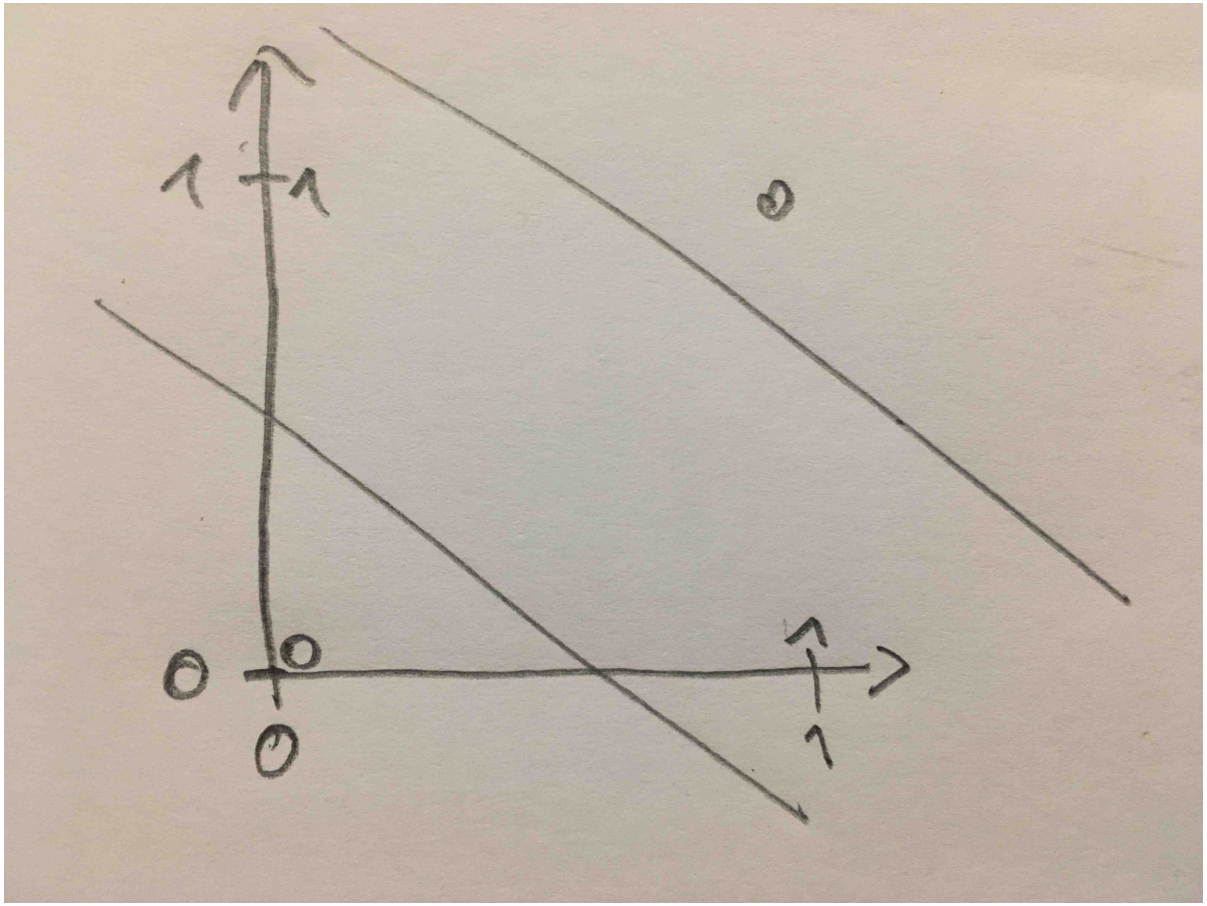
OR(/NOR) is linearly seperable



One possible AND perceptron



XOR is not linearly separable



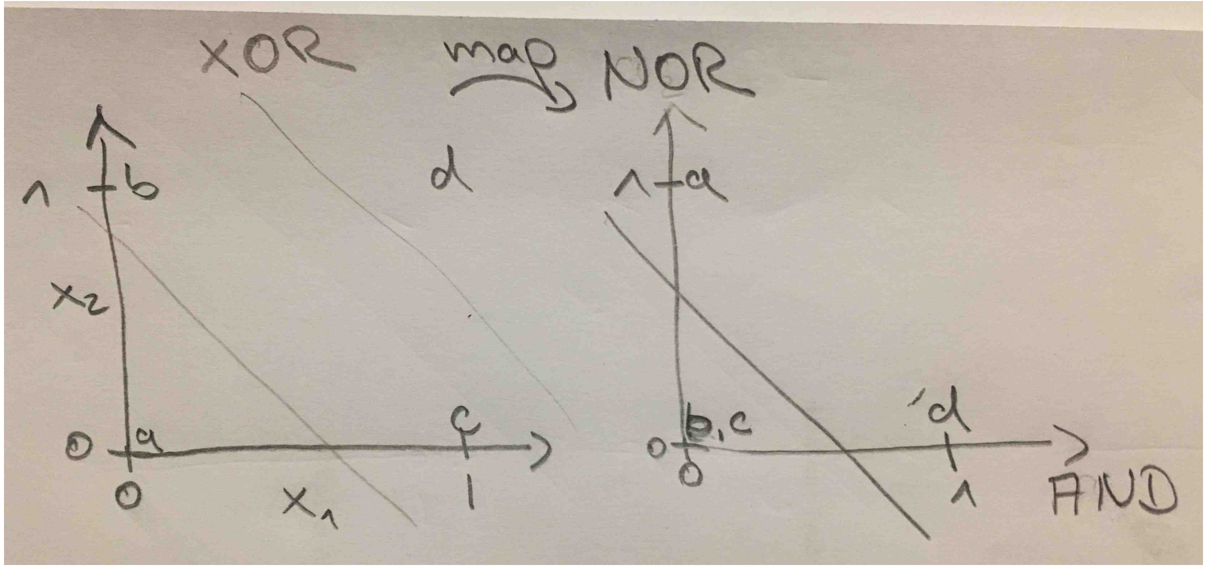
point	x	x	(AND	NOR	NOR)	XOR

XOR can be represented by a combination of two mappings

XOR = NOR (AND, NOR)

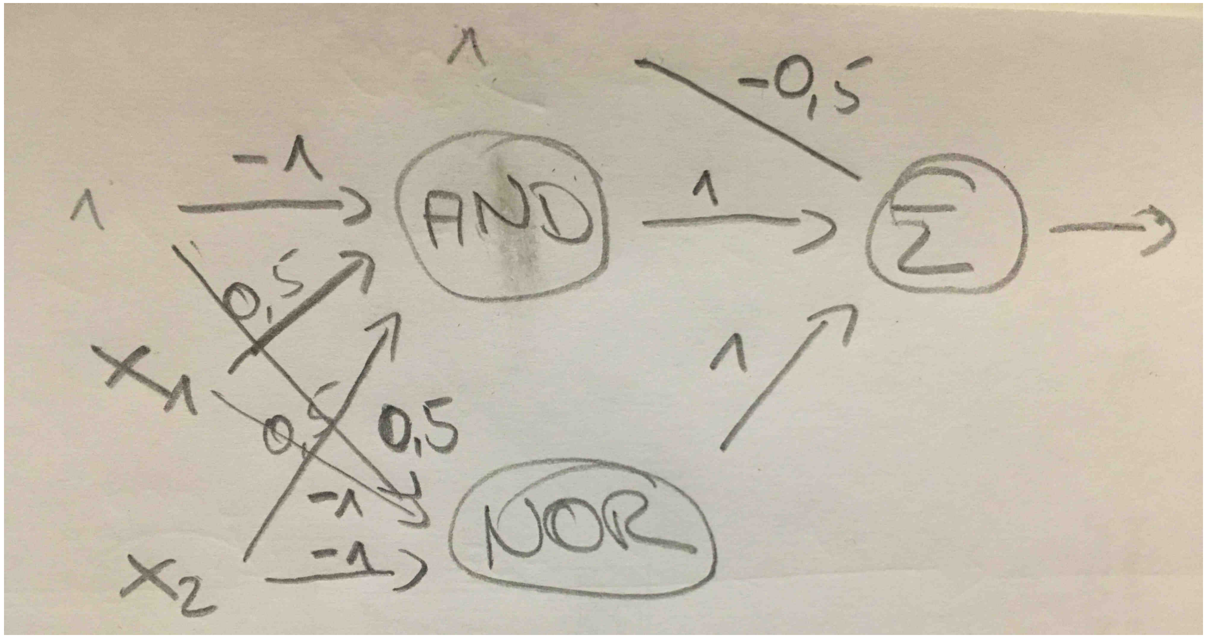
point	x_1	x_2	(AND	NOR	NOR)	XOR
a	0	0	0	0	1	0
b	0	1	0	1	0	1
c	1	0	0	1	0	1
d	1	1	1	0	0	0

The extra mapping can be visualized



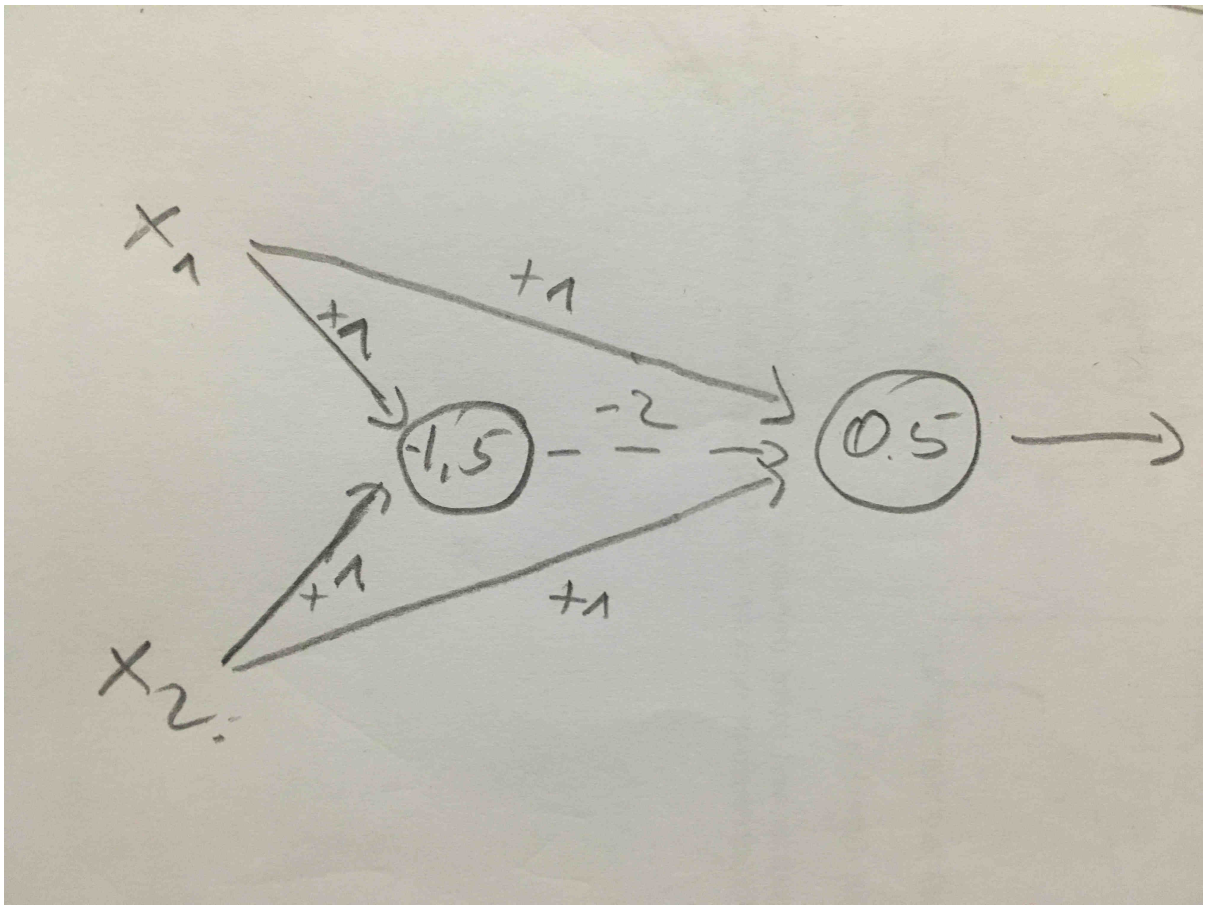
One possible XOR Net (#1)

The ones are fixed input (bias) units



One alternative XOR Net (#2)

The number within the perceptron represents the inherent bias unit/or a translational shift when the unit jumps.



	Net #1	**Net #2**

Two nets with the same result - why care?

	Net #1	**Net #2**
# weights	9	5

- Net #1 has more free variables
- Net #1 has a higher dimensional weight space ($\mathbb{R}^9$ vs. $\mathbb{R}^5$)
- Net #2 has less degrees of freedom and should generalize better.

Why is that?

- This architecture of the net has a direct effect on the optimization problem and the search space.

The MNIST Dataset for benchmarking

Playing with MNIST and scikit-learn

```
from sklearn.neural_network import MLPClassifier
from sklearn.datasets import fetch_mldata

MNIST = fetch_mldata("MNIST original")
split = 60000  # number of training examples
X, y = MNIST.data / MNIST.data.max(), MNIST.target
X_train, X_test = X[:split], X[split:]
y_train, y_test = y[:split], y[split:]
mlp = MLPClassifier(hidden_layer_sizes=(n_units, n_layers),
        max_iter=n_iterations, alpha=1e-4, solver=solver,
        verbose=10, tol=1e-4, random_state=1,
        learning_rate_init=alpha)
mlp.fit(X_train, y_train)
score = mlp.score(X_test, y_test)
```

Evaluating the parameter space

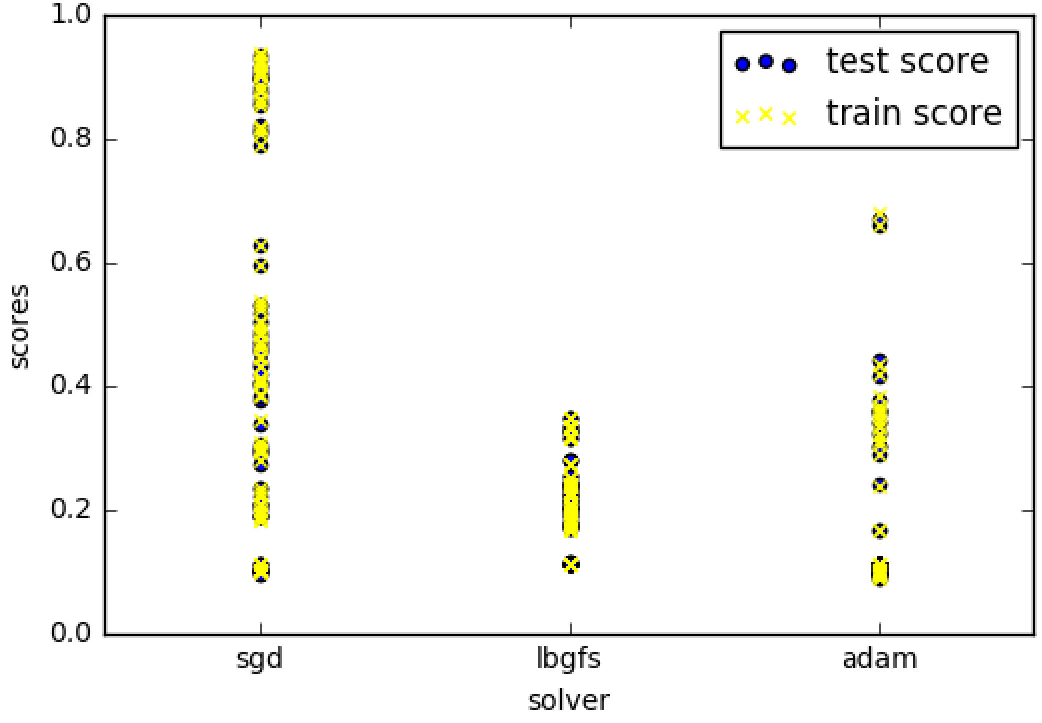
cartesian product of:

```
hidden_units_per_layer = [2, 4, 6, 10, 15]
hidden_layers = [1, 2, 3]
learning_rate = [0.1, 0.2, 0.3]
solver = ['lbgfs', 'sgd', 'adam']
max_iter = [5, 10]
```

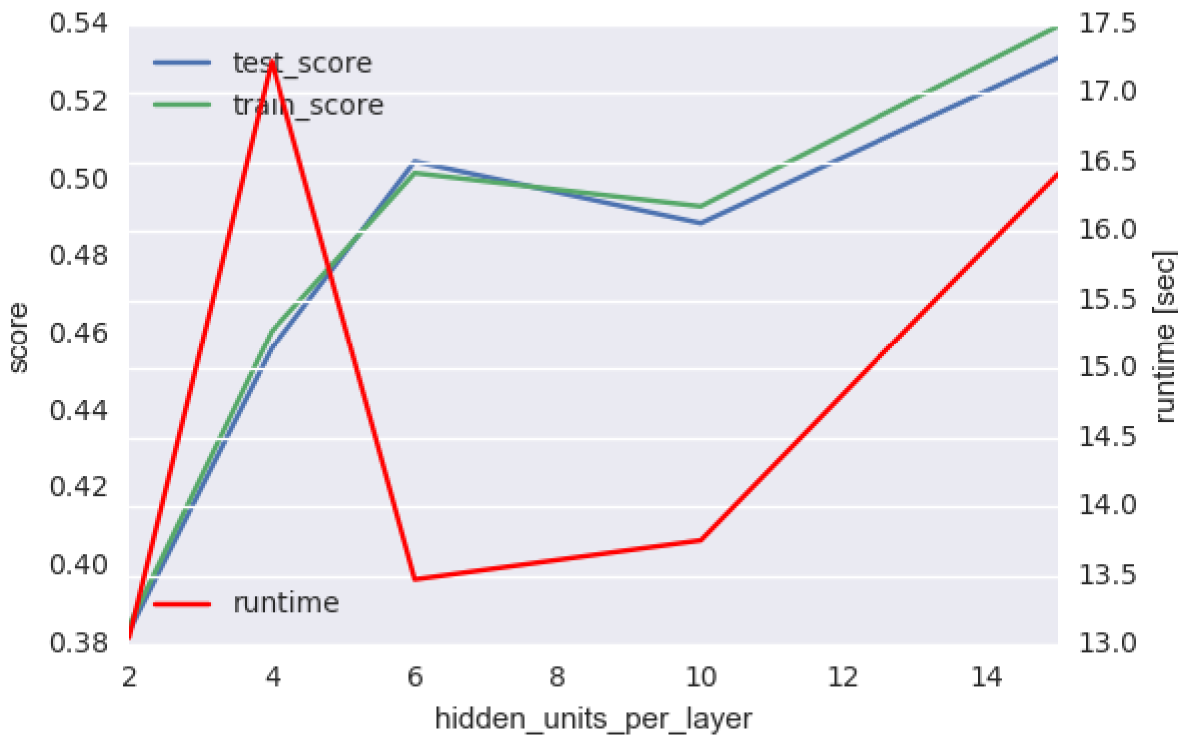
$\longrightarrow$ 270 runs

```
base_config = {'hidden_units_per_layer': 10.0,
               'iterations': 10.0,
               'hidden_layers': 1.0,
               'solver': 'sgd',
               'learning_rate': 0.1}
```

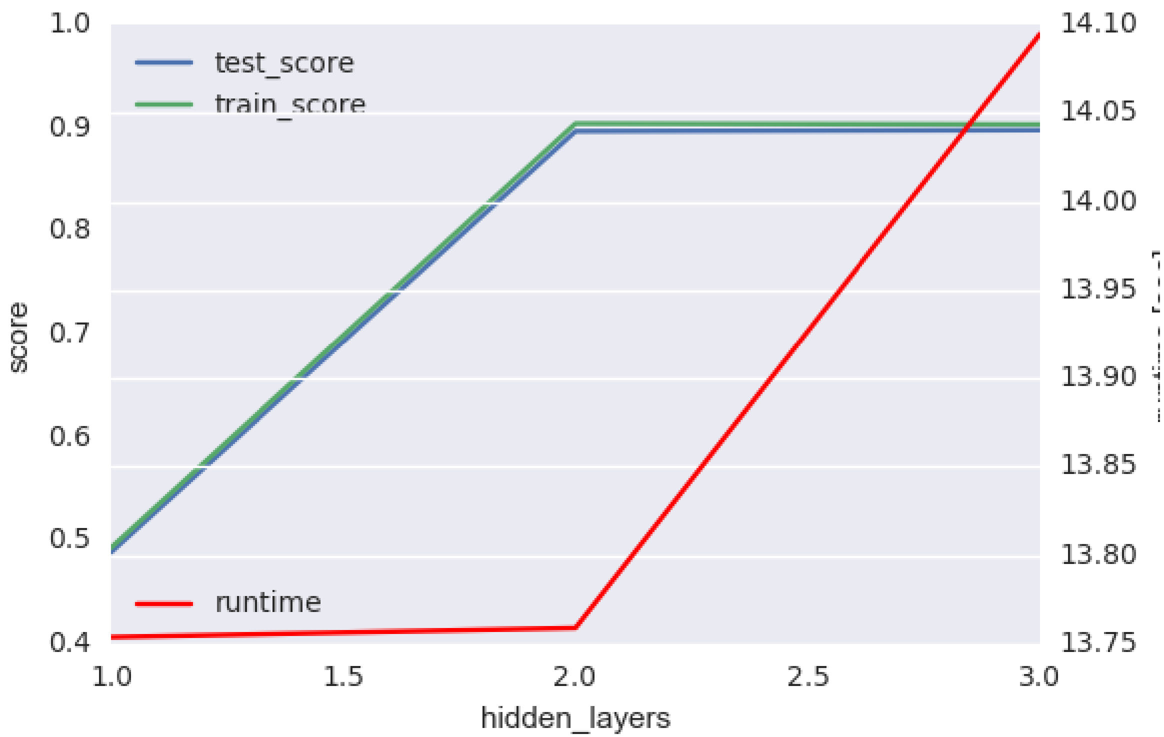
Influence of the solver



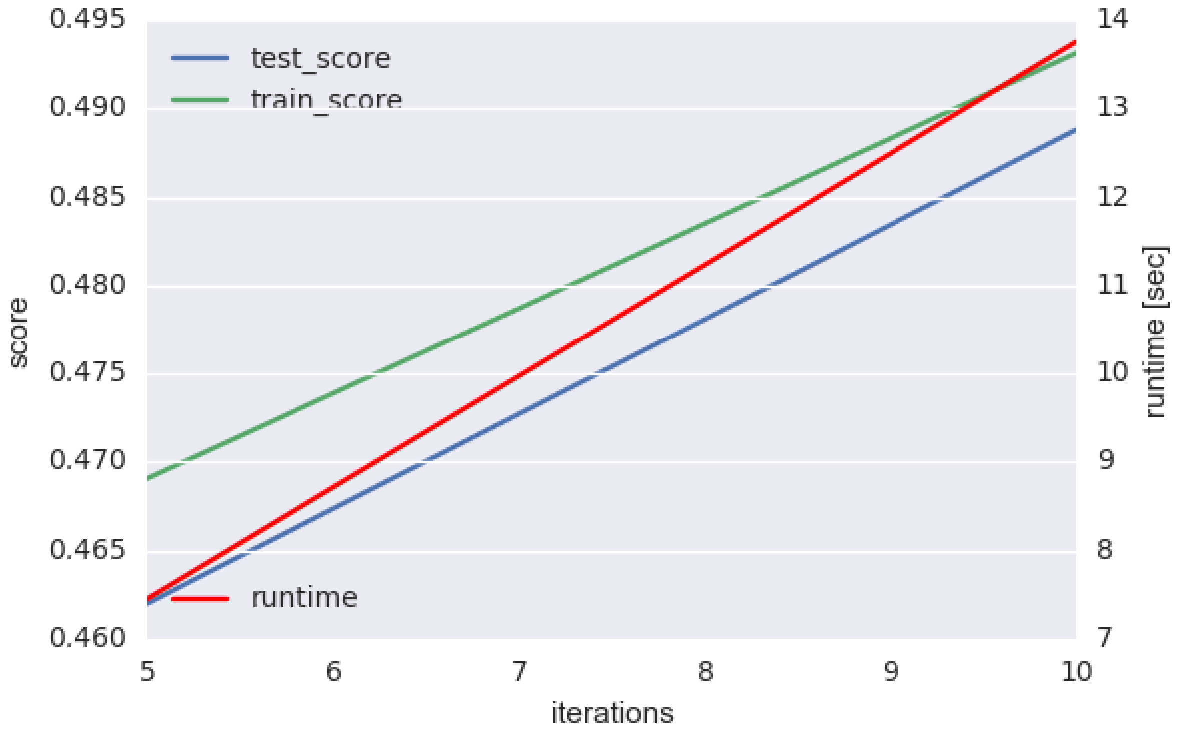
Number of hidden units per layer



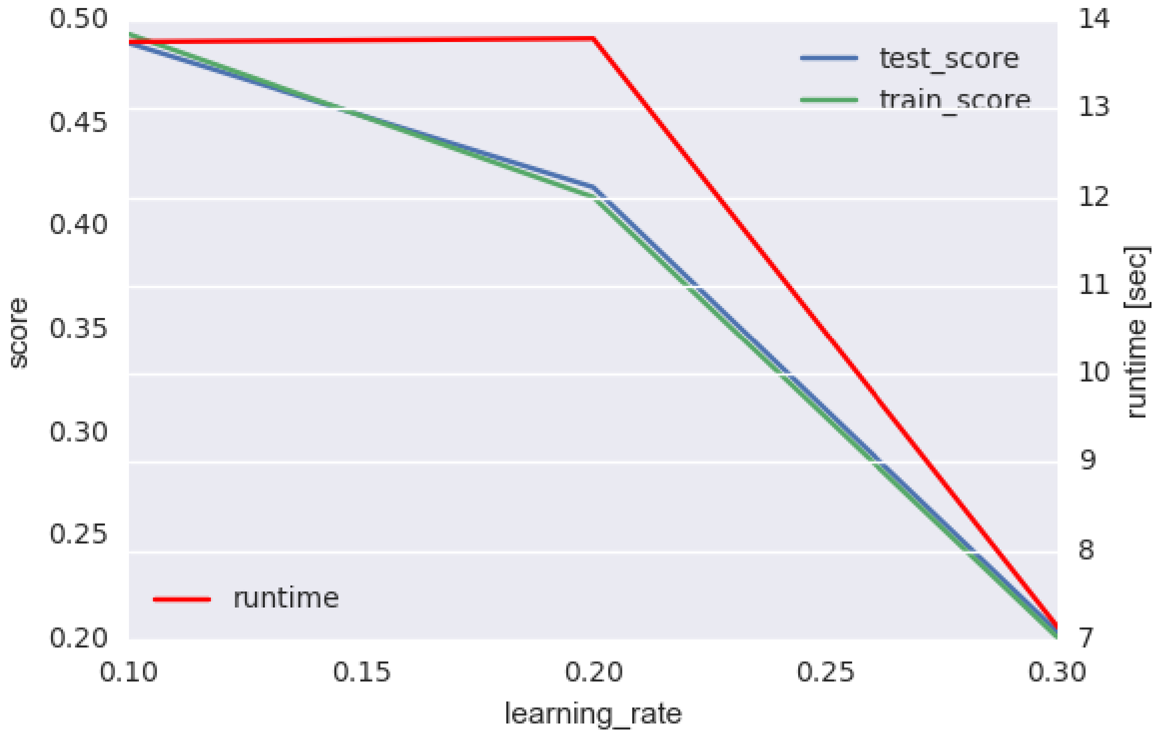
Number of hidden layers



Number of iterations



Influence of the learning rate



Roadmap

- Basic: perceptron.py, randomweights.py, pocket.py, xorish.py, basicnn.py
- Data set: mnistimages.py
- scikit-learn: hellosklearn.py, sknngrid.py
- Tensorflow: hellotf.py
- Keras: hellokeras.py

perceptron.py

A simple perceptron plus lots of boilerplate for gif.

- simple update rule
- relatively fast, given the weight space is infinite
- works on separable data

The algorithm is short.

```
misses = misclassfied_points(W)
...
point = random.choice(misses)
W = W + point[1] * point[0]
```

randomweights.py

Gets worse with more dimensions.

pocket.py

Like perceptron, but works on non-separable data.

xorish.py

The writing was on the wall. Neither pocket, not perceptron will do too well on such data.

basicnn.py

Enter: an activation function.

> The purpose of the activation function is to introduce non-linearity into the network.

> http://stackoverflow.com/q/9782071

Also: Feed-forward, Backpropagation.

mnistimages.py

Examples from the dataset.

hellosklearn.py

scikit-learn makes working with multi-layer perceptrons easy.

sknngrid.py

How to find a suitable architecture? Grid search to the rescue.

Similar settings in modern neural nets with dozens of layers.

> In Deep Learning, Architecture Engineering is the New Feature Engineering. (https://is.gd/osMZaZ)

hellotf.py

Tensorflow, released almost exaclty a year ago by Google.

> Used in commercial Google products, such as speech recognition, Gmail,
> Google Photos, and search [...].

hellokeras.py

Keras is a duplo layer upon deep learning library lego.

> Keras is a high-level neural networks library, written in Python and capable of running on top of either TensorFlow or Theano. It was developed with a focus on enabling fast experimentation.

Wrap-up

Things not covered:

- more theory
- getting and preparing data
- problem formulation
- model evaluation

But hopefully showed that getting started is not too hard.

Thanks!