Neuronale Netze - Eine kurze Einführung mit Implementierungen in Python

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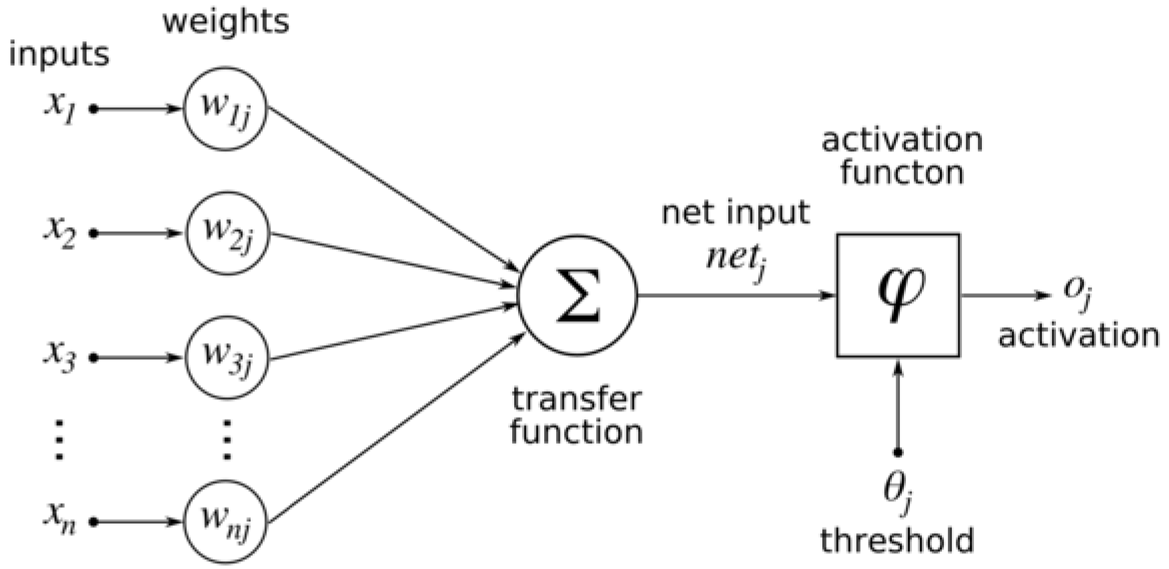
The origin - a linear classifier

$H_i = <x,w> = ¥sum¥limits_j{x_j w_j} + ¥theta$



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 $¥rightarrow ¥min¥limits_{w}$ 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)

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

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.

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

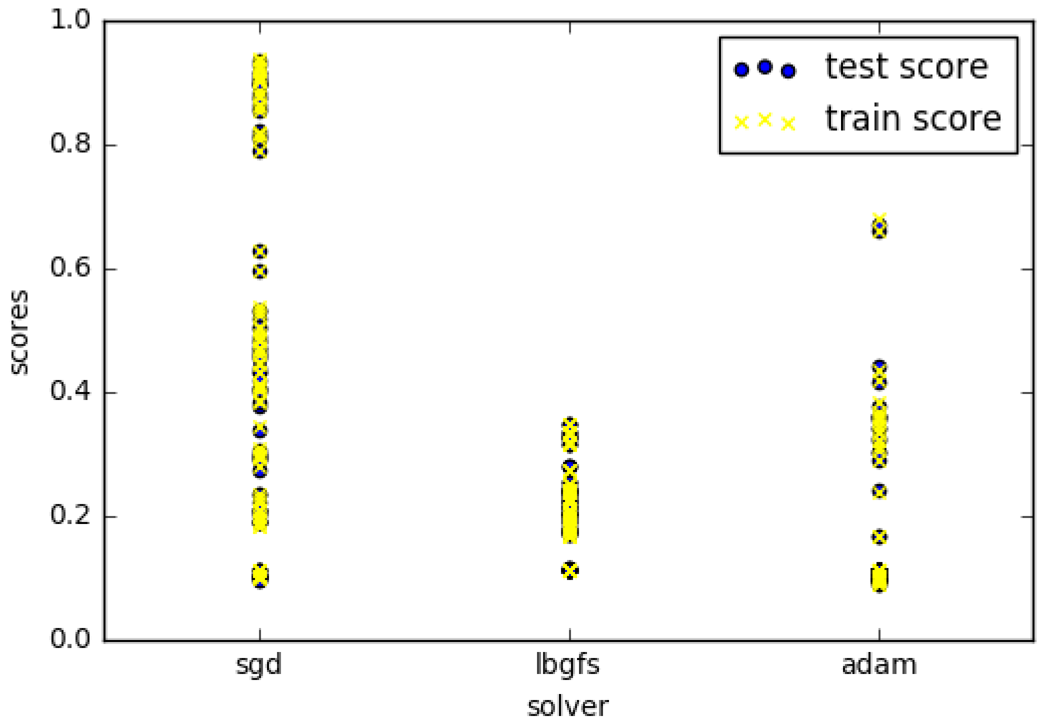
cartesian product of:

```
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]
```

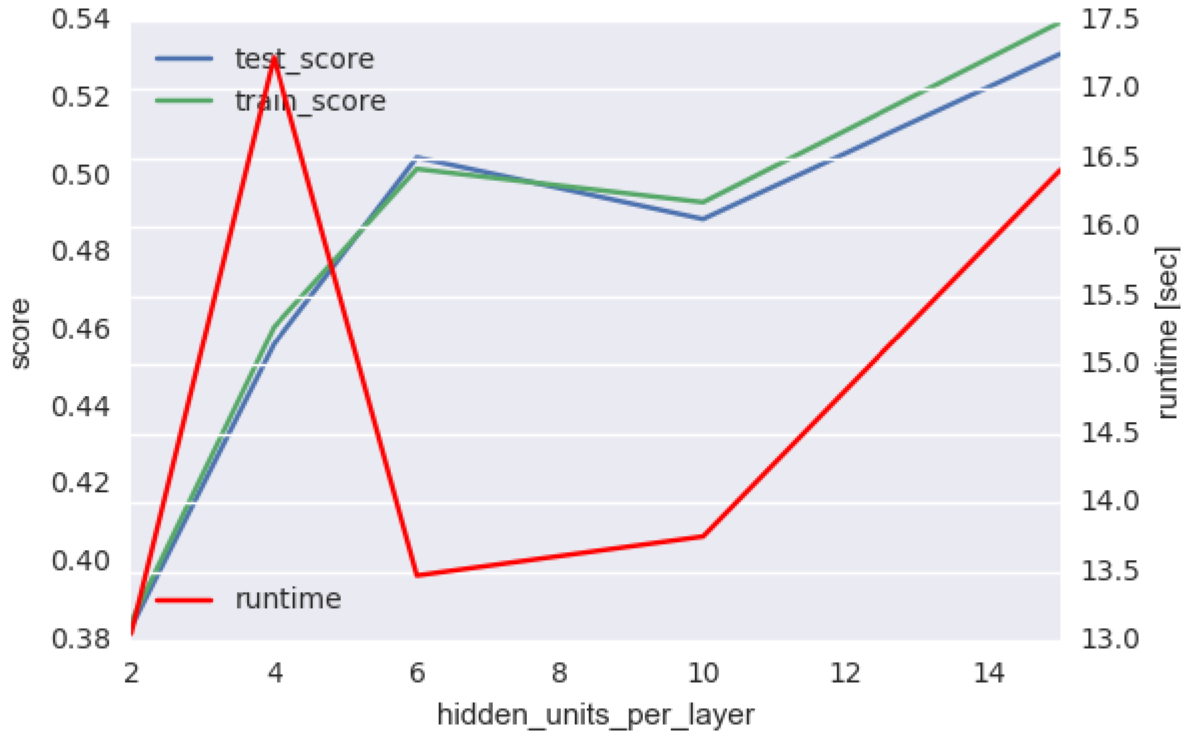
$¥rightarrow$ 270 runs

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

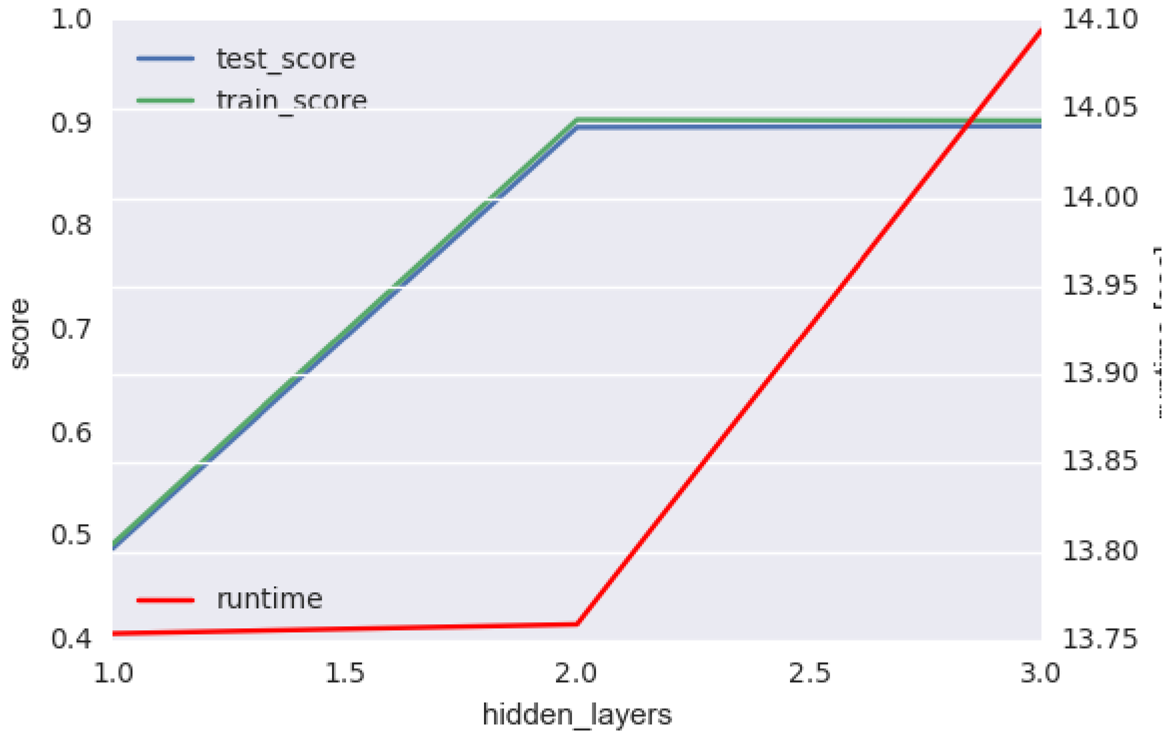
Influence of the solver



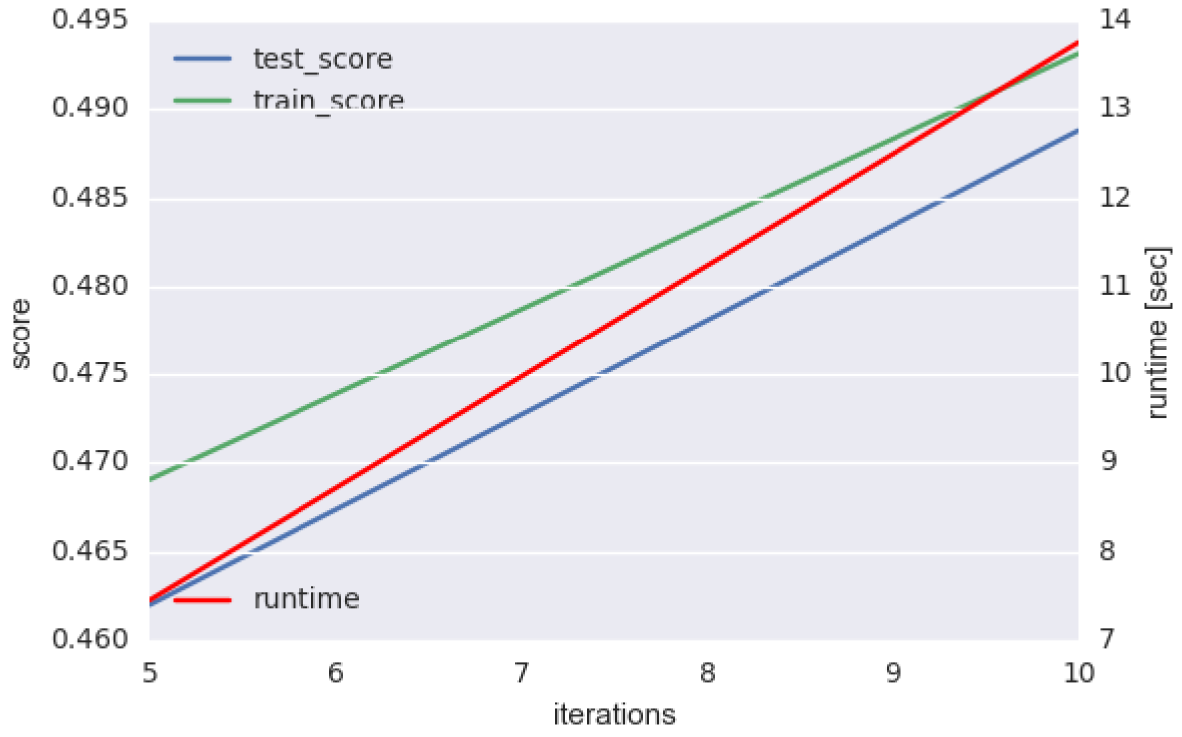
Number of hidden units per layer



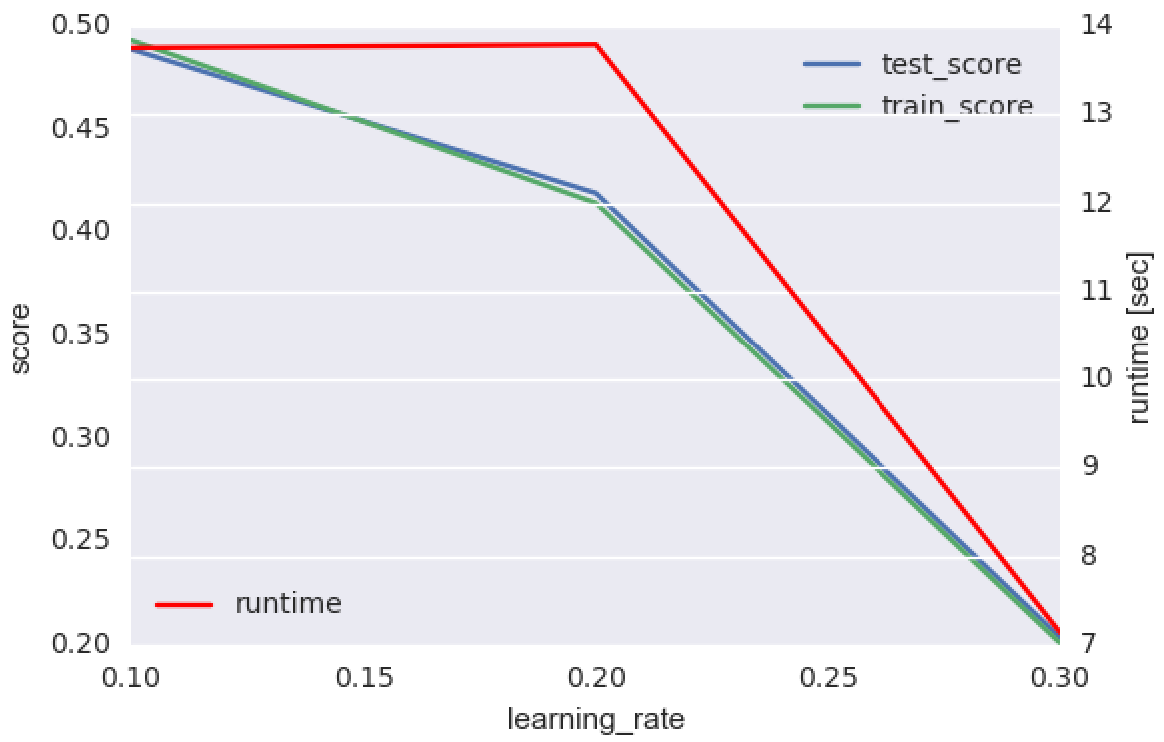
Number of hidden layers



Number of iterations



Influence of the learning rate



Some Code

Roadmap:

- perceptron.py
- randomweights.py
- pocket.py
- xorish.py
- basicnn.py
- mnistimages.py
- hellosklearn.py
- sknngrid.py
- hellotf.py
- 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

randomweights.py