### Exercise 2b - MLP

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#### Task

With this exercise you should use your framework for applying an MLP approach to the MNIST dataset.

The goal of this exercise is to train an MLP with one hidden layer. And experiment with different parameters.

learning rate c: 0.1, 0.05, 0.011, 0.01

# (training) epochs: 100

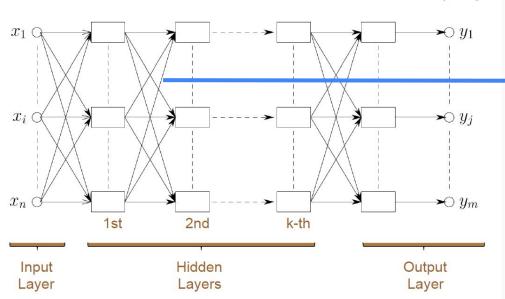
size of hidden layer: 20, 40, 60, 80

Test accuracy with the best parameters found during cross-validation.

4-fold-cross-validation

### Theoretical Background: MLP





$$y = g(w'x) = g\left(\sum_{i=1}^{n} w_i x_i\right)$$

#### Softmax function:

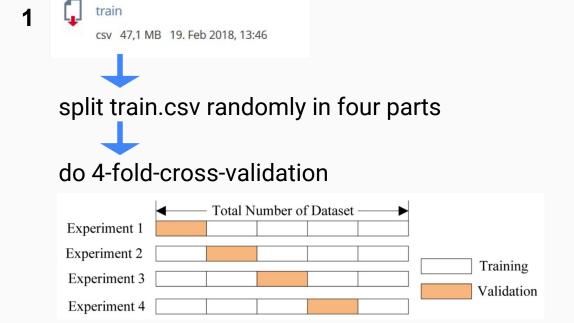
$$egin{aligned} \sigma: \mathbb{R}^K & o (0,1)^K \ \sigma(\mathbf{z})_j &= rac{e^{z_j}}{\sum_{k=1}^K e^{z_k}} \end{aligned} ext{ for } j$$
 = 1, ...,  $K$ .

#### Learning rate:

for all predecessors j of neuron i do  $\hat{w}_{ji} = w_{ji} + c \cdot out(j) \cdot \delta_i$  end for

source or pictures, recture sinces,

## Theoretical Background: 4-fold-cross-validation



2 test

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final accuracy calculation

source of picture: ILIAS,





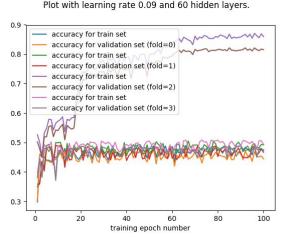
- library for numerical computation using data flow graphs
- built to scale
- currently one of the most widely used deep learning libraries in research and industry
- every operation (matrix multiplication, softmax function, placeholder, variables etc) is represented as a node in a graph.
- placeholder and variables always n-dimensional
- graphs are lazy-evaluated

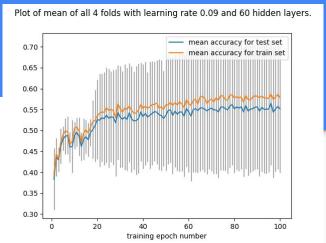
### Code Samples

```
W 1 = tf.Variable(tf.random uniform([size input layer, self.size hidden layer])) # weights input to hidden
70
        b_1 = tf.Variable(tf.random_uniform([self.size_hidden_layer])) # biases hidden
        W 2 = tf.Variable(tf.random uniform([self.size hidden layer, size output layer])) # weights hidden to output
        b 2 = tf.Variable(tf.random uniform([size output layer])) # biases output
74
                                                                                                                           MIP
        # Matrix with dimension [batch size x size hidden layer], each row represents the hidden layer for one input row.
        # Use softmax as activation function.
        hidden layer = tf.nn.softmax(tf.matmul(x, W 1) + b 1)
78
        # Matrix with dimension [batch size x size output layer], each row represents the output layer for one input row.
        # Use softmax as activation function.
        output layer = tf.nn.softmax(tf.matmul(hidden layer, W 2) + b 2)
                  # Optimize model with the current batch
                                                                                                                          training = optimization
                  self.sess.run(optimizer, feed dict={x: batch xs, y labels: batch ys})
              # print the accuracy on training and validation set after each training epoch
              # and store it in an array
              self.accurancy train set.append(self.sess.run(accuracy, feed dict={x: train x, y labels: train y}))
                                                                                                                          cross-validation
              self.accurancy valid set.append(self.sess.run(accuracy, feed dict={x: test x, y labels: test y}))
```

Results: plots of cross-validation.

learning rates c: 1, 0.5, 0.1, 0.05, 0.09, 0.011, 0.01, 0.009, 0.005





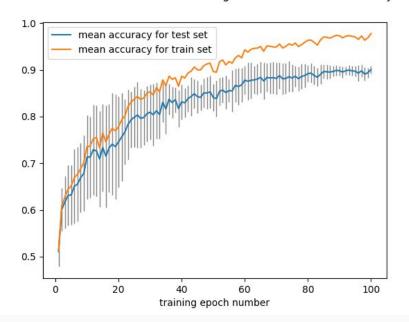
# (training) epochs: 100

size of hidden layer: 20, 40, 60, 80

Learning rates of 1 and 0.5 did not produce useful results

## Results: best parameter found in cross-validation

Plot of mean of all 4 folds with learning rate 0.01 and 60 hidden layers.



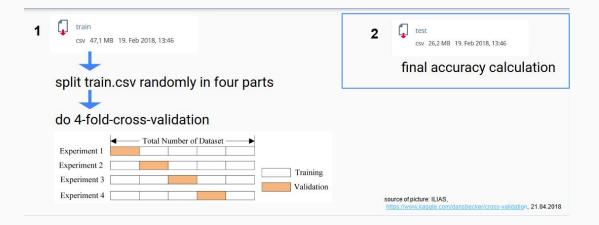
learning rate c: 0.01

size of hidden layer: 60

results in an accuracy of 0.90

for the cross-validation

# Results: accuracy for test set



final accuracy: 0.92

#### Comparison

0.91 (20 hidden layers, learning rate 0.02)

https://mmlind.github.io/Simple\_3-Layer\_Neural\_Network\_for\_MNIST\_Handwriting\_Recognition/ [21.4.2018]

0.953 (300 hidden layers)

Y. LeCun, L. Bottou, Y. Bengio and P. Haffner: Gradient-Based Learning Applied to Document Recognition, Proceedings of the IEEE, 86(11):2278-2324, November 1998, p.13 <a href="https://ieeexplore.ieee.org/stamp/stamp.isp?tp=&arnumber=726791">https://ieeexplore.ieee.org/stamp/stamp.isp?tp=&arnumber=726791</a> [21.4.2018]

### Possible Improvements

Testing with more layers

Preprocess data (slant correction, cropping, resizing)

Use other threshold functions instead of soft-max

Use dynamic learning rate (start with greater learning rate and then decrease)