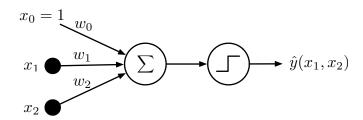
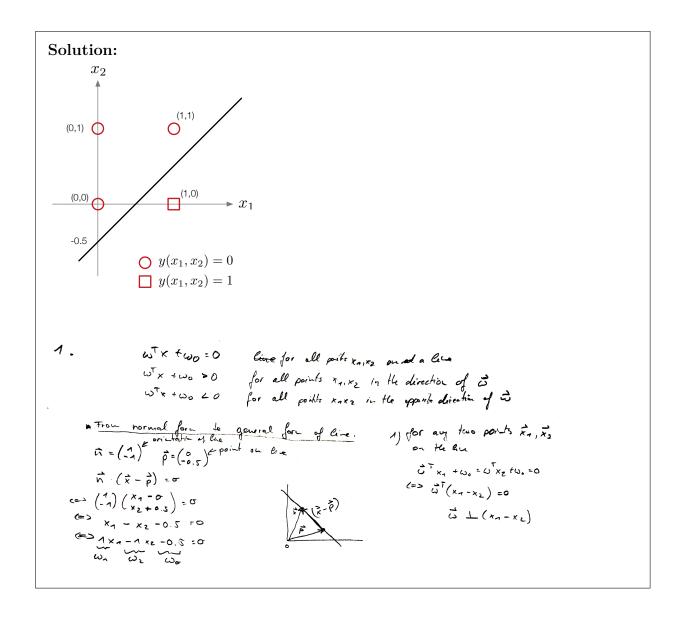
## Exercise Sheet

## Learning Goals

- Perceptron
- Logistic Regression
- 1.  $\bullet^{OO}$  For a single perceptron, find an assignment to the parameters  $w_0, w_1, w_2$  such that the perceptron implements the boolean function  $y(x_1, x_2) = x_1 \wedge \neg x_2$  for binary variables  $x_1$  and  $x_2$ . (Use the Heaviside step function  $\varphi(x) = \max(sign(x), 0)$  as activation function.)





A single perceptron computes the sum  $\sum w_i \cdot x_i = w_0 \cdot x_0 + w_1 \cdot x_1 + w_2 \cdot x_2$  (without applying the heaviside function). The weights of the perceptron are just the coefficients from the equation of the line:  $w_0 = -0.5$ ,  $w_1 = 1$ ,  $w_2 = -1$ . Through the heaviside function, the perceptron maps any  $(x_1, x_2)$  with  $\sum_i w_i \cdot x_i > 0$  to 1 and any  $(x_1, x_2)$  with  $\sum_i w_i \cdot x_i \leq 0$  to 0. (all points in the direction of  $\mathbf{w}$  map to 1, points on the other side of the line to 0).

As a check, compute the output of the perceptron  $\hat{y}(x_1, x_2) = \max(\operatorname{sgn}(w_0 + w_1 x_1 + w_2 x_2), 0)$ : it holds  $\hat{y}(1, 0) = \max(\operatorname{sgn}(0.5) = 1, 0) = 1$  and  $\hat{y}(0, 1) = \max(\operatorname{sgn}(-1.5) = -1, 0) = 0$ ,  $\hat{y}(1, 1) = \max(\operatorname{sgn}(-0.5) = -1, 0) = 0$  and  $\hat{y}(0, 0) = \max(\operatorname{sgn}(-0.5) = -1, 0) = 0$ .

2. ••O Apply the perceptron training algorithm, as described in the lecture notes, on the following four data points to learn the parameters of a perceptron (use the heaviside step function as defined in 1).

Normally, the algorithm would pick a data point randomly, update the parameters and repeat until convergence. Here, go through the data points in the given order only once. The learning rate is  $\eta = 0.4$  and the weights are initialized with  $\mathbf{w} = (w_0, w_1, w_2) = (0.5, 1, -1)$ . In each iteration (parameter update from a data point) list:  $\mathbf{w}^T \mathbf{x}$ ,  $\varphi(\mathbf{w}^T \mathbf{x})$ , error,  $\Delta \mathbf{w}$  and the new parameter vector  $\mathbf{w}$ .

$x_1$	$x_2$	$y(x_1, x_2)$				
0	0	0				
0	1	0				
1	0	1				
1	1	0				

## **Solution:**

We start with a learning rate  $\eta = 0.4$  and initial weights  $\mathbf{w}^{(0)} = (0.5, 1.0, -1.0)$ . In each iteration, we calculate:

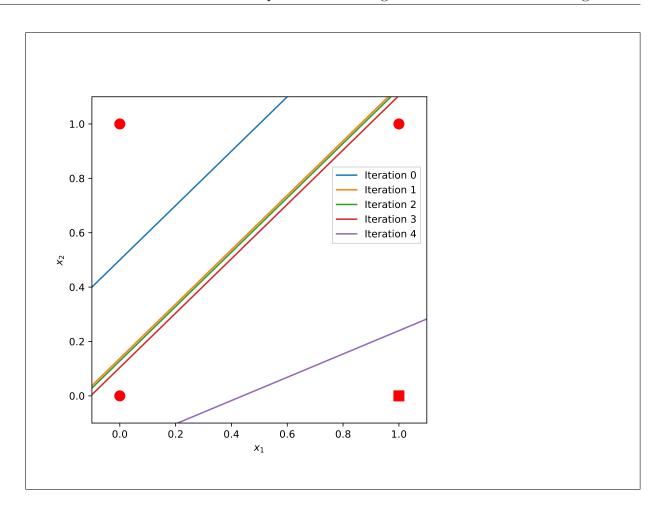
$$err = y(\mathbf{x}) - \varphi(\mathbf{w}^T \mathbf{x})$$

$$\Delta \mathbf{w} = \boldsymbol{\eta} \cdot \text{err} \cdot \mathbf{x}$$

and update the parameters:

$$\mathbf{w}^{(i+1)} = \mathbf{w}^{(i)} + \Delta \mathbf{w}$$

i	$x_0$	$x_1$	$x_2$	$y(\mathbf{x})$	$\mathbf{w}^T \mathbf{x}$	$\varphi(\mathbf{w}^T\mathbf{x})$	err	$\Delta w_0$	$\Delta w_1$	$\Delta w_2$	$w_0$	$w_1$	$w_2$
0											0.5	1.0	-1.0
1	1	0	0	0	0.5	1.0	-1.0	-0.4	0.0	0.0	0.1	1.0	-1.0
2	1	0	1	0	-0.9	0.0	0.0	0.0	0.0	0.0	0.1	1.0	-1.0
3	1	1	0	1	1.1	1.0	0.0	0.0	0.0	0.0	0.1	1.0	-1.0
4	1	1	1	0	0.1	1.0	-1.0	-0.4	-0.4	-0.4	-0.3	0.6	-1.4



3. Implement a Logistic Regression Classifier. The jupyter notebook attached to this exercise sheet contains a skeleton implementation of a LogReg Classifier. Complete the implementations of the functions fit(...) and predict(...).