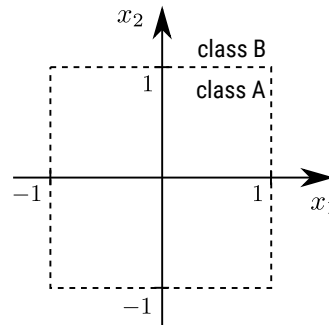


Exercise Sheet 1–2

Exercise 1: Building a Neural Network (10 P)

We would like to implement a neural network that classifies data points in \mathbb{R}^2 according to decision boundary given in the figure below.

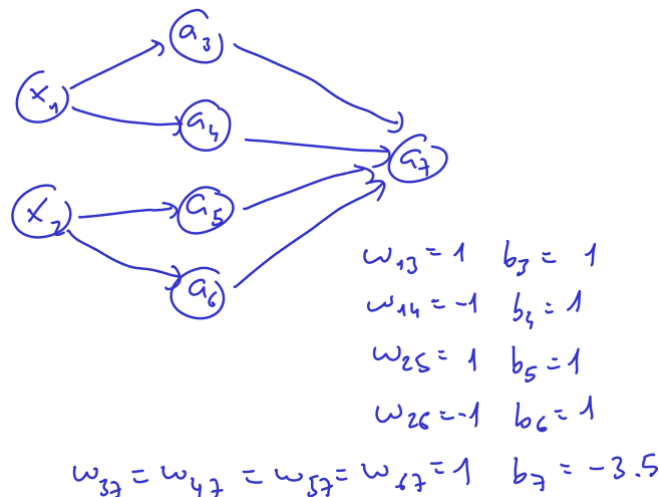


We consider as an elementary computation the *threshold neuron* whose relation between inputs $(a_i)_i$ and output a_j is given by

$$z_j = \sum_i a_i w_{ij} + b_j \quad a_j = I(z_j > 0).$$

where I is an indicator function that outputs 1 when the statement given as input is true, and 0 otherwise.

(a) *Design* at hand a neural network composed of two layers of parameters, that takes x_1 and x_2 as input and produces the output “1” if the input belongs to class A, and “0” if the input belongs to class B. *Draw* the neural network model and *write down* the weights w_{ij} and bias b_j of each neuron.



Exercise 2: Backpropagation in the Error Function (5 + 5 + 5 + 5 P)

Let y be the prediction of a neural network for some data point \mathbf{x} . The true target value that the network should predict is given by t . We define the error function to be

$$E = \log \cosh(y - t).$$

This error function can be used as an alternative to the square error and is more robust to outliers.

(a) *Compute* the gradient of the error with respect to the output y of the neural network.

Observe that error can be decomposed as

$$z = y - t \quad (1)$$

$$E = \log \cosh(z) \quad (2)$$

Application of the chain rule gives

$$\frac{\partial E}{\partial y} = \frac{\partial E}{\partial z} \frac{\partial z}{\partial y} \quad (3)$$

$$= \tanh(z) \cdot 1 \quad (4)$$

$$= \tanh(y - t) \quad (5)$$

(b) Assume we have a dataset composed of neural network inputs $\mathbf{x}_1, \dots, \mathbf{x}_N$ and associated targets t_1, \dots, t_N . We denote by y_1, \dots, y_N the predictions of the neural network for these points. We define the error

$$E = \frac{1}{N} \sum_{k=1}^N E_k \quad \text{with} \quad E_k = \log \cosh(y_k(\mathbf{x}_k, \mathbf{w}) - t_k)$$

State the chain rule for transmitting the gradient from the output of the neural network to the model parameters.

$$\frac{\partial E}{\partial \mathbf{w}} = \sum_k \frac{\partial E}{\partial E_k} \frac{\partial E_k}{\partial y_k} \frac{\partial y_k}{\partial \mathbf{w}}$$

(c) Assume that $y_k(\mathbf{x}_k, \mathbf{w}) = \sum_{i=1}^d w_i x_i^{(k)}$ where $x_i^{(k)}$ denotes the i th element of the vector \mathbf{x}_k . Compute the gradient of the error function w.r.t. the parameter w_i , i.e. compute $\partial E / \partial w_i$.

$$\begin{aligned} \frac{\partial E}{\partial w_i} &= \sum_{k=1}^N \frac{\partial E}{\partial E_k} \frac{\partial E_k}{\partial y_k} \frac{\partial y_k}{\partial w_i} \\ &= \sum_{k=1}^N \frac{1}{N} \cdot \tanh(y_k - t_k) \cdot \frac{\partial}{\partial w_i} \left(\sum_{i'=1}^d w_{i'} x_{i'}^{(k)} \right) \\ &= \frac{1}{N} \sum_{k=1}^N \tanh(y_k - t_k) x_i^{(k)} \end{aligned}$$

Exercise 3: Backpropagation in a Multilayer Network (10 + 10 P)

We consider a neural network that takes two inputs x_1 and x_2 and produces an output y based on the following set of computations:

$$z_3 = x_1 \cdot w_{13} + x_2 \cdot w_{23}$$

$$a_3 = \tanh(z_3)$$

$$z_4 = x_1 \cdot w_{14} + x_2 \cdot w_{24}$$

$$a_4 = \tanh(z_4)$$

$$z_5 = a_3 \cdot w_{35} + a_4 \cdot w_{45}$$

$$a_5 = \tanh(z_5)$$

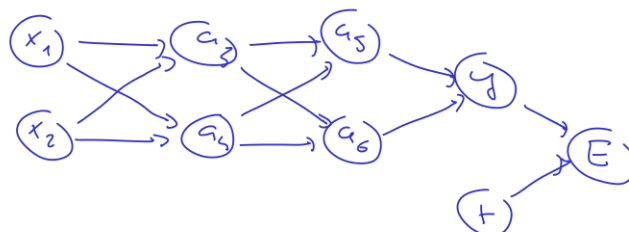
$$z_6 = a_3 \cdot w_{36} + a_4 \cdot w_{46}$$

$$a_6 = \tanh(z_6)$$

$$y = a_5 + a_6$$

$$E = (y - t)^2$$

(a) Draw the neural network graph associated to this set of computations.



(b) Write the set of backward computations that leads to the evaluation of the partial derivative $\partial E/\partial w_{13}$. Your answer should avoid redundant computations. Hint: $\tanh'(t) = 1 - (\tanh(t))^2$.

$$\begin{aligned}\delta_y &= 2(y - t) \\ \delta_6 &= \delta_y \\ \delta_5 &= \delta_y \\ \delta_3 &= w_{36}(1 - a_6^2)\delta_6 + w_{35}(1 - a_5^2)\delta_5 \\ \frac{\partial y}{\partial w_{13}} &= x_1(1 - a_3^2)\delta_3\end{aligned}$$

Exercise 4: Backpropagation with Shared Parameters (5 + 5 + 5 + 5 P)

Let x_1, x_2 be two observed variables. Consider the two-layer neural network that takes these two variables as input and builds the prediction y by computing iteratively:

$$z_3 = x_1 w_{13}, \quad z_4 = x_2 w_{24}, \quad a_3 = 0.5 z_3^2, \quad a_4 = 0.5 z_4^2, \quad y = a_3 + a_4.$$

(a) Draw the neural network graph associated to these computations.

(b) We now consider the error $E = (y - t)^2$ where t is a target variable that the neural network learns to approximate. Using the rules for backpropagation, compute the derivatives $\partial E/\partial w_{13}$ and $\partial E/\partial w_{24}$.

$$\frac{\partial E}{\partial w_{13}} = \underbrace{\frac{\partial z_3}{\partial w_{13}}}_{x_1} \cdot \underbrace{\frac{\partial a_3}{\partial z_3}}_{z_3} \cdot \underbrace{\frac{\partial y}{\partial a_3}}_1 \cdot \underbrace{\frac{\partial E}{\partial y}}_{2 \cdot (y-t)} \quad \frac{\partial \ell}{\partial w_{24}} = \dots$$

(c) Let us now assume that w_{13} and w_{24} cannot be adapted freely, but are a function of the same shared parameter v :

$$w_{13} = \log(1 + \exp(v)) \quad \text{and} \quad w_{24} = -\log(1 + \exp(-v))$$

State the multivariate chain rule that links the derivative $\partial E/\partial v$ to the partial derivatives you have computed above.

(d) Using the computed $\partial E/\partial w_{13}$ and $\partial E/\partial w_{24}$, write an analytic expression of $\partial E/\partial v$.

$$\frac{\partial E}{\partial v} = \frac{\partial w_{13}}{\partial v} \cdot \frac{\partial \ell}{\partial w_{13}} + \frac{\partial w_{24}}{\partial v} \cdot \frac{\partial E}{\partial w_{24}} \quad \text{where} \quad \frac{\partial w_{13}}{\partial v} = \frac{e^v}{1 + e^v}, \quad \frac{\partial w_{24}}{\partial v} = \frac{e^{-v}}{1 + e^{-v}}$$

Exercise 5: Programming (30 P)

Download the programming files on ISIS and follow the instructions.