

## Homework 2: Neural Differential Equation (NDE)

Deadline Friday June 21, 17:00

### Notebook: Homework\_2\_pre.ipynb

In this exercise, you will explore the solution method of a neural differential equation, given by

$$\frac{d\mathbf{z}}{dt} = \mathbf{f}(\mathbf{z}, t, \theta) \quad (1)$$

over the time interval  $[t_0, t_1]$ . Here  $\mathbf{z} \in \mathbb{R}^n$  and  $\mathbf{f}$  is a neural network with parameter vector (weights)  $\theta$ . You will also study an application of an NDE to data from a simple linear differential equation.

The integral form of (1) is given by

$$\mathbf{z}(t) = \mathbf{z}(t_0) + \int_{t_0}^{t_1} \mathbf{f}(\mathbf{z}, \theta, t) dt \quad (2)$$

a.

Suppose we have data  $\mathbf{z}(t_k), k = 1, \dots, K$  of the solution. Formulate the loss function  $L$ , based on the mean squared error, used for fitting the weights of the NDE.

b.

Argue that when to optimise the loss function  $L$ , we need derivatives of  $L$  to  $\mathbf{z}$  and  $\theta$ .

c.

Let  $\mathbf{a}(t) = \partial L / \partial \mathbf{z}(t)$ . Using the chain rule,

$$\frac{\partial L}{\partial \mathbf{z}(t)} = \frac{\partial L}{\partial \mathbf{z}(t + \epsilon)} \frac{\partial \mathbf{z}(t + \epsilon)}{\partial \mathbf{z}(t)} \quad (3)$$

and (2), show that  $\mathbf{a}(t)$  can be determined from the equation

$$\frac{d\mathbf{a}}{dt} = -\mathbf{a}^T \frac{\partial \mathbf{f}(\mathbf{z}, t, \theta)}{\partial \mathbf{z}} \quad (4)$$

where the subscript  $T$  indicates transpose.

d.

Describe a numerical solution procedure to determine  $\mathbf{a}(t_0)$ .

e.

To determine  $\partial L / \partial \theta$ , the augmented vector  $\mathbf{x} = (\mathbf{z}, \theta, t)$  is used and the augmented equations are written as

$$\frac{d\mathbf{x}}{dt} = \mathbf{g}(\mathbf{z}, \theta, t) \quad (5)$$

where  $\mathbf{g} = (\mathbf{f}, \mathbf{0}, 1)^T$ . One introduces also  $\mathbf{b} = (\mathbf{a}, \mathbf{a}_\theta, \mathbf{a}_t)$ , where  $\mathbf{a}_\theta = \partial L / \partial \theta$  and  $\mathbf{a}_t = \partial L / \partial t$ .

Show that

$$\mathbf{a}_\theta(t_0) = - \int_{t_1}^{t_0} \mathbf{a}^T \frac{\partial \mathbf{f}(\mathbf{z}, t, \theta)}{\partial \theta} dt \quad (6)$$

and describe the connection with backward propagation (as used in FNNs).

f.

In the notebook, first data from the linear differential equation

$$\frac{d\mathbf{z}}{dt} = \begin{pmatrix} -0.1 & -1.0 \\ 1.0 & -0.1 \end{pmatrix} \mathbf{z} \quad (7)$$

is used to train ‘weights’ from a  $2 \times 2$  matrix. Determine how the loss function decreases versus the number of epochs for three different values of the number of data points  $K = 75, 100, 200$ . Use eweytime  $lr, n\_epochs = [0.01, 1000]$ .

g.

Also a more complicated ODE is formulated in the notebook (TestODEF and you are welcome to enter your own). Use  $K = 200$  and implement for  $\mathbf{f}$  a FNN with 1 hidden layer and 16 neurons to solve the NDE in this case. Plot the trajectory which results after the loss function has sufficiently decreased. Use this time  $lr = 0.001$  and estimate the number of epochs necessary for the loss function to decrease below a reasonable trashelhold.