# Differentiation of ODE-based functions

## **ODE-defined functions**

- Instead of a fixed-value system, a layer can be modelled implicitly by an ordinary differential equation with function  $f : \mathbb{R} \times \mathbb{R}^n \to \mathbb{R}^n$  and an initial value  $y_0 \in \mathbb{R}^n$  $\dot{y}(t) = f(t, y(t))$  $y(0) = y_0$
- We can use any ODE solver to solve *y*(*t*) for future values of *t*, for instance Euler integration, or Runge-Kutta

Differential equations in neural networks







- Say we have the ODE (Lorentz system)  $\partial_t y(t, x, y, z) = \begin{bmatrix} \sigma(y - x) \\ x(\rho - z) - y \\ xy - \beta z \end{bmatrix}$
- Forward propagating, we can have various trajectories



## Differentiating through an ODE

- We can differentiate via all steps in the sequence, but we would have the same problems with memory and instability as with fixed-point layers
- Instead, we can follow a similar route with the implicit function theorem

## JVP for ODE-based layers

- For the model:  $\partial_t y(t, a, b) = f(t, y(t, a, b), a)$  with initial conditions: y(0, a, b) = 0
- nudge parameters *a*, *b*
- We first need to compute the derivative with respect to parameters a

$$\begin{aligned} \partial_a \Big( \partial_t y(t, a, b) \Big) &= \partial_a \Big( f(t, y(t, a, b), a) \Big) = \partial_a f(t, y, a) + \partial_y f(t, y, a) \partial_a y(t, a, b) \Rightarrow \\ \partial_t \underbrace{\partial_a y(t, a, b)}_{z(t, a, b)} &= \partial_a f(t, y, a) + \partial_y f(t, y, a) \partial_a y(t, a, b) \\ \underbrace{\partial_t z(t, a, b)}_{z(t, a, b)} &= \partial_a f(t, y, a) + \partial_y f(t, y, a) z(t, a, b) \end{aligned}$$

Differential equations in neural networks

• We are interested in how much the solution to the ODE function will change if we

## JVP for ODE-based layers

lacksquaremust solve another ODE

With initial conditions

 $\begin{vmatrix} y(0,a,b) \\ z(0,a,b) \end{vmatrix} = \begin{vmatrix} b \\ Ab \end{vmatrix}$ 

Differential equations in neural networks

That is, to compute how much a nudge in the parameters affects the gradient we

 $\begin{bmatrix} \partial_t y(t, a, b) \\ \partial_t z(t, a, b) \end{bmatrix} = \begin{bmatrix} f(t, y(t, a, b), a) \\ \partial_a f(t, y, a) + \partial_y f(t, y, a) z(t, a, b) \end{bmatrix}$ 

#### JVP on our example

• Let's say we want to see how the Lorentz trajectory will change when we nudge the third dimension of the output

$$\partial_t y(t, x, y, z) = \begin{bmatrix} \sigma(y - x) \\ x(\rho - z) - y \\ xy - \beta z \end{bmatrix}$$

Differential equations in neural networks



#### JVP on our example

• Or if we nudge the parameter  $\sigma$  $\partial_t y(t, x, y, z) = \begin{bmatrix} \sigma(y - x) \\ x(\rho - z) - y \\ xy - \beta z \end{bmatrix}$ 

Differential equations in neural networks



#### JVP on our example

