

Experimental study of Neural ODE training with adaptive solver for dynamical systems modeling

Machine Intelligence and Learning Systems

ESPCI PARIS | PSL

Alexandre Allauzen ^{1,2}, Thiago Petrilli Maffei Dardis², Hannah Plath² ¹LAMSADE CNRS, Dauphine University-PSL, ²ESPCI-PSL

TAKE-HOME MESSAGE: WHATCH YOUR STEP SIZE!

- Neural Ordinary Differential Equations (ODEs) relies on solvers for inference and training.
- Some solvers can adapt their evaluation strategy depending on the complexity of the problem.
- By taking the Lorenz'63 system as a showcase, a naive application of the Fehlberg's method does not yield the expected results.
- Adaptive solvers cannot be seamlessly leveraged as a black-box:
 - \rightarrow For most of the numerical methods, the step size is adapted given the self-estimated error of the model.
 - → Neural ODE model is always self-confident, and the "adaptive" ability is under-used.
 - → A simple workaround:

use the supervision within the solver.

https://github.com/Allauzen/adaptive-step-size-neural-ode

FIRST ROUND

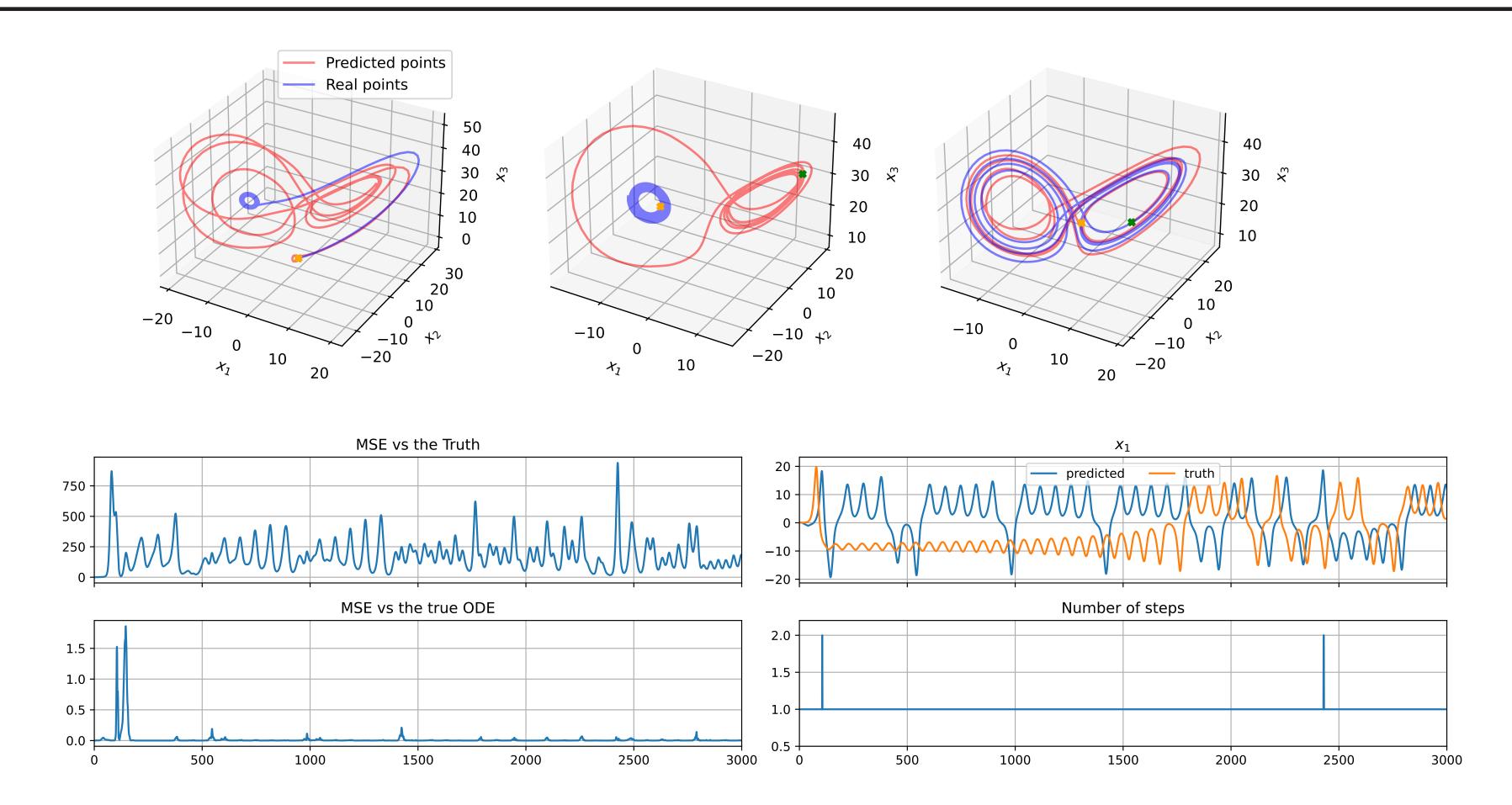


Figure 1: Time evolution of (from left to right and top to bottom): the MSE, the evolution of x_1 , the MSE w.r.t the true ODE of Lorenz'63, and the number of steps.

NEURAL ODE AND FEHLBERG'S METHOD

- Given $\mathcal{D} = (\tilde{\mathbf{x}}_i)_{i=1}^N$, Neural ODE learns: $\dot{\mathbf{x}} = f_{\theta}(\mathbf{x})$ (f_{θ} is a NNet ans θ its set of parameters).
- Inference requires a solver: $\mathbf{x}_i = \text{ODE_Solve}(f_{\theta}, \tilde{\mathbf{x}}_i)$ and the loss function is

$$\mathcal{L}(\boldsymbol{\theta}, \mathcal{D}) = \sum_{i=1}^{N} ||\tilde{\mathbf{x}}_i - \mathbf{x}_i||^2.$$

Fehlberg's solver: starting with a step size h = 1, compute:

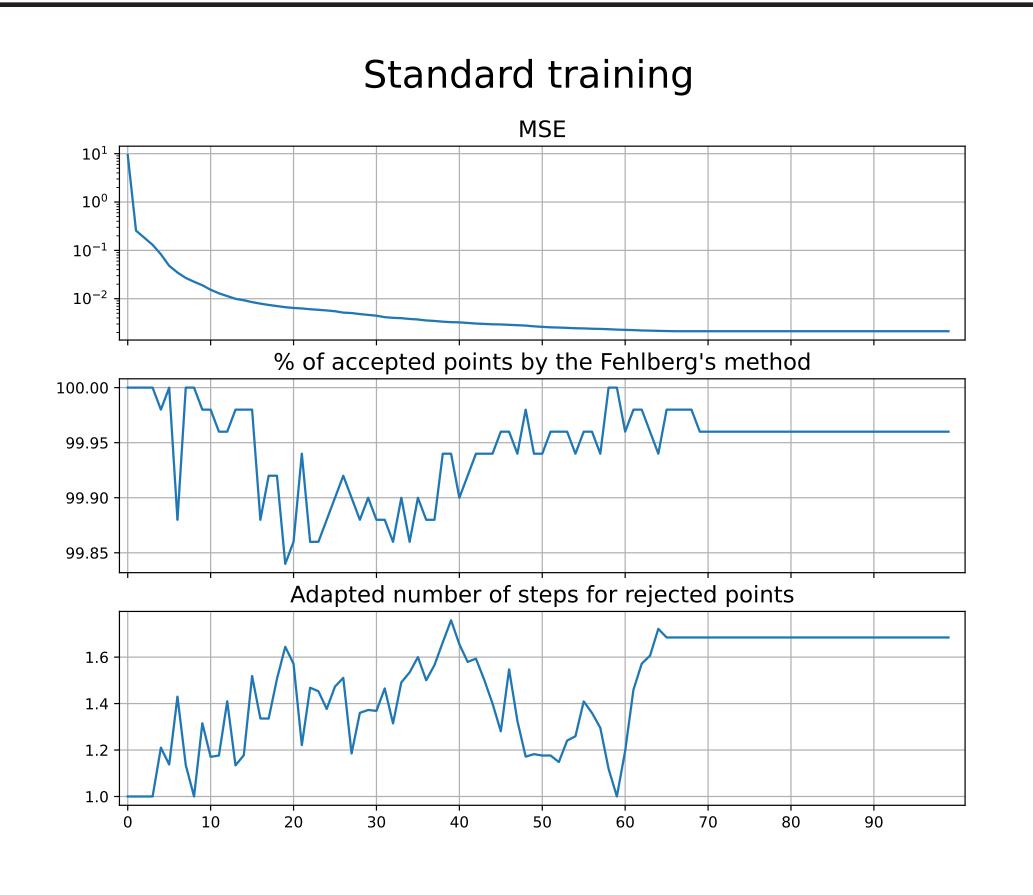
$$f_1 = f_{\theta}(\mathbf{x}_i), \qquad f_2 = f_{\theta}(\mathbf{x}_i + h f_1), \qquad f_3 = f_{\theta}(\mathbf{x}_i + \frac{h}{4}[f_1 + f_2]) \text{ then}$$

$$A_1 = \mathbf{x}_i + \frac{h}{2}[f_1 + f_2] \text{ (RK2)} \qquad A_2 = \mathbf{x}_i + \frac{h}{6}[f_1 + f_2 + 4f_3] \text{ (RK3)}. \qquad \rightarrow \qquad r = \frac{|A_1 - A_2|}{h} \approx Kh^2$$

With the error rate, then:

- If $r > \epsilon = 0.1$ (tolerance), A_2 is rejected and restart the computation with a new step size $h' = S \times h\sqrt{\epsilon/r}$, S = 0.9 is a safety factor.
- Otherwise accept A_2 as \mathbf{x}_{i+1}

FEHLBERG'S TRAINING



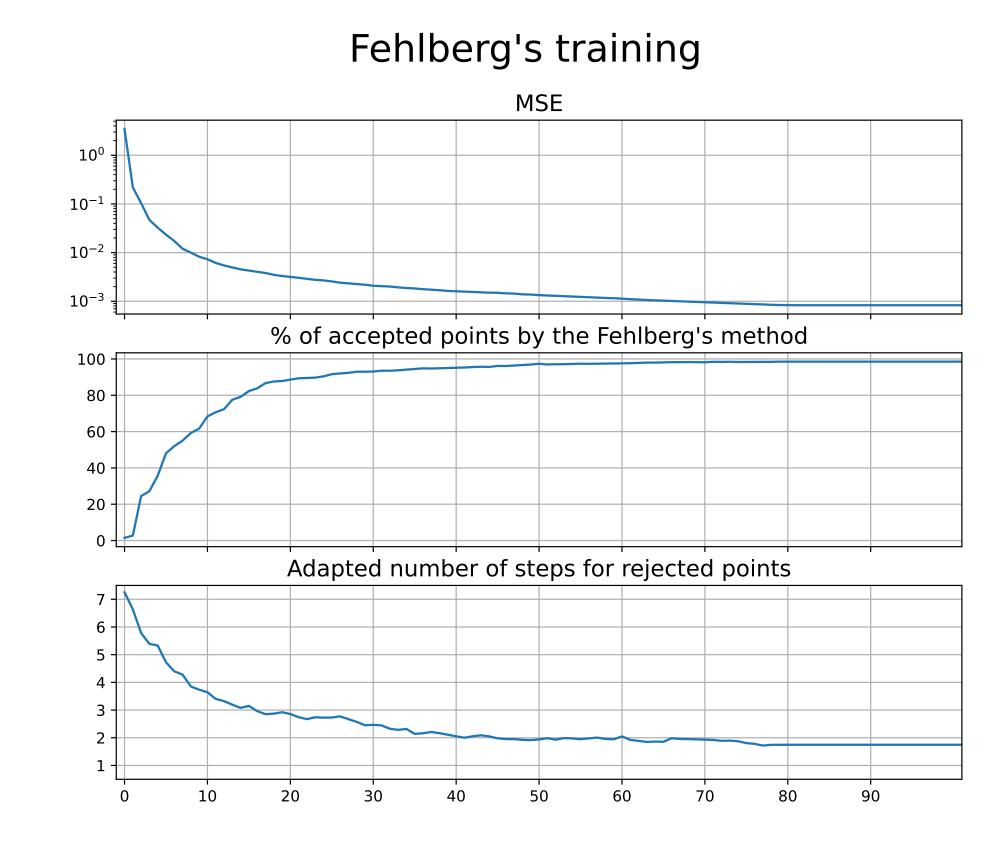


Figure 2: Time evolution for two training conditions of: the MSE loss; the percentage of accepted hypotheses A_2 ; the new number of steps for the rejected hypotheses (before rounding).

AKNOWLEDGMENT

This work was funded by the French National Research Agency (SPEED-20-CE23-0025).