



NTNU

Neural network aided simulation of ordinary differential equations

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In collaboration with Marta Betcke, and Lisa Maria Kreusser

Solving initial value problems with neural networks

- ▶ We aim to solve the autonomous initial value problem (IVP)

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- ▶ Using **neural networks** to replace or modify the map $\varphi^{\Delta t}$ can be useful when
 - ▶ the dimension d is large
 - ▶ one desires to have a (piecewise) continuous approximate solution
 - ▶ one wants to also fit some observed data while approximately solving the IVP

Physics-informed neural networks

- We introduce a parametric map $\mathcal{N}_\theta(\cdot; \mathbf{x}_0) : [0, T] \rightarrow \mathbb{R}^d$ such that $\mathcal{N}_\theta(0; \mathbf{x}_0) = \mathbf{x}_0$, and choose its weights so that

$$\mathcal{L}(\theta) := \frac{1}{C} \sum_{c=1}^C \|\mathcal{N}'_\theta(t_c; \mathbf{x}_0) - \mathcal{F}(\mathcal{N}_\theta(t_c; \mathbf{x}_0))\|_2^2 \rightarrow \min$$

for some collocation points $t_1, \dots, t_C \in [0, T]$.

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- ▶ Then, $t \mapsto \mathcal{N}_\theta(t; \mathbf{x}_0)$ will solve a different IVP

$$\begin{cases} \mathbf{y}'(t) = \mathcal{F}(\mathbf{y}(t)) + (\mathcal{N}'_\theta(t; \mathbf{x}_0) - \mathcal{F}(\mathbf{y}(t))) \in \mathbb{R}^d, \\ \mathbf{y}(0) = \mathbf{x}_0 \in \mathbb{R}^d, \end{cases}$$

where **hopefully** the residual $\mathcal{N}'_\theta(t; \mathbf{x}_0) - \mathcal{F}(\mathbf{y}(t))$ is small in some sense.

A-posteriori error estimate

Theorem: Quadrature-based a-posteriori error estimate

Let $\mathbf{x}(t)$ be the solution of the IVP

$$\begin{cases} \mathbf{x}'(t) = \mathcal{F}(\mathbf{x}(t)) \in \mathbb{R}^d, & \mathcal{F} \in \mathcal{C}^{p+1}(\mathbb{R}^d, \mathbb{R}^d), \\ \mathbf{x}(0) = \mathbf{x}_0. \end{cases}$$

Suppose that $\mathcal{N}_\theta(\cdot; \mathbf{x}_0) : [0, \Delta t] \rightarrow \mathbb{R}^d$ is smooth and satisfies

$$\|\mathcal{N}'_\theta(t_c; \mathbf{x}_0) - \mathcal{F}(\mathcal{N}_\theta(t_c; \mathbf{x}_0))\|_2 \leq \varepsilon, \quad c = 1, \dots, C$$

for C collocation points $0 \leq t_1 < \dots < t_C \leq \Delta t$ defining a quadrature rule of order p . Then, there exist $\alpha, \beta > 0$ such that

$$\|\mathbf{x}(t) - \mathcal{N}_\theta(t; \mathbf{x}_0)\|_2 \leq \alpha(\Delta t)^{p+1} + \beta\varepsilon, \quad t \in [0, \Delta t].$$

Training issues with neural network

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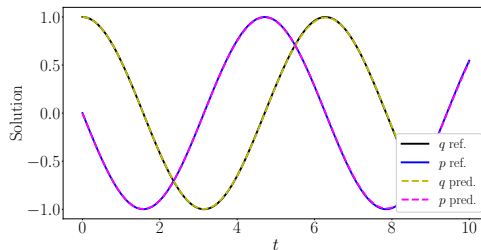


Figure: Solution comparison after reaching a loss value of 10^{-5} . The training time is of 87 seconds (7500 epochs with 1000 new collocation points randomly sampled at each of them).

Training issues with neural network

It is hard to solve initial value problems over long time intervals.

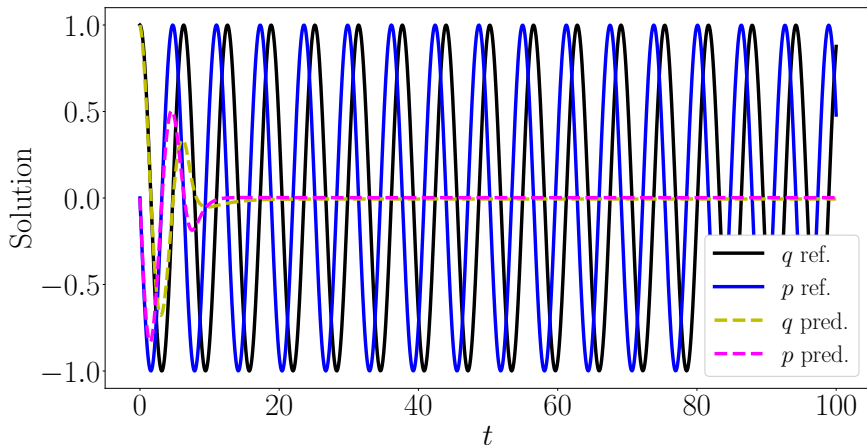


Figure: Solution comparison after 10000 epochs.

Forward invariant sets: Flow map approach

- Suppose $\phi^t(\mathbf{x}_0) \in \Omega \subset \mathbb{R}^d$ for $t \geq 0$.
- We can then work with $\mathcal{N}_\theta : [0, \Delta t] \times \Omega \rightarrow \mathbb{R}^d$, where¹

$$\mathcal{L}(\theta) := \frac{1}{C} \sum_{c=1}^C \|\mathcal{N}'_\theta(t_c, \mathbf{x}_0^c) - \mathcal{F}(\mathcal{N}_\theta(t_c, \mathbf{x}_0^c))\|_2^2 \rightarrow \min.$$

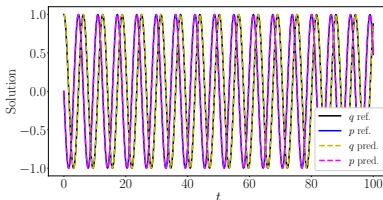


Figure: Network trained with $\Delta t = 1$ and applied up to $T = 100$.

¹Sifan Wang and Paris Perdikaris. “Long-time integration of parametric evolution equations with physics-informed DeepONets”. In: *Journal of Computational Physics* 475 (2023), p. 111855.

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- ▶ Let $t_n = n\Delta t$, $n = 0, \dots, N$, $\Delta t = T/N$. We can solve in sequence the initial value problems

$$\begin{cases} \mathbf{x}'_n(t) = \mathcal{F}(\mathbf{x}_n(t)) \in \mathbb{R}^d, & t \in [t_n, t_n + \Delta t], \\ \mathbf{x}_n(t_n) = \hat{\mathbf{x}}_n, \end{cases}$$

with $t \mapsto \mathcal{N}_{\theta_n}(t - t_n; \hat{\mathbf{x}}_n)$. We set $\hat{\mathbf{x}}_0 = \mathbf{x}_0$ and $\hat{\mathbf{x}}_{n+1} = \mathcal{N}_{\theta_n}(\Delta t; \hat{\mathbf{x}}_n)$.

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- ▶ **Problem:** Training these N networks can be extremely expensive.

Extreme learning machines (ELMs)

- ▶ ELMs are networks where **only part of the weights are trained**.
- ▶ We consider two-layer ELMs $\mathcal{N}_\theta(\cdot; \mathbf{x}_0) : [0, \Delta t] \rightarrow \mathbb{R}^d$ of the form

$$\mathcal{N}_\theta(t; \mathbf{x}_0) = \mathbf{x}_0 + \theta(\sigma(\mathbf{a}t + \mathbf{b}) - \sigma(\mathbf{b})), \quad \mathbf{a}, \mathbf{b} \in \mathbb{R}^H, \quad (1)$$

with $\theta = [\mathbf{w}_1 \quad \dots \quad \mathbf{w}_H] \in \mathbb{R}^{d \times H}$, $a_h, b_h \in \mathcal{U}([-1, 1])$, $h = 1, \dots, H$.

Theorem: Approximation properties of ELMs

For any smooth activation function $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ and any set $\{(t_c, \mathbf{y}_c)\}_{c=1}^C$, if $H = C$ then with probability one there is matrix $\theta \in \mathbb{R}^{d \times H}$ in (1) such that $\mathcal{N}'_\theta(t_c; \mathbf{x}_0) = \mathbf{y}_c$ for $c = 1, \dots, C^a$.

^aGuang-Bin Huang, Qin-Yu Zhu, and Chee-Kheong Siew. "Extreme learning machine: Theory and applications". In: *Neurocomputing* 70.1-3 (2006), pp. 489–501.

Exploiting the efficiency of ELMs to solve IVPs

- ▶ One option would be to split the time domain into subintervals and solve each of the obtained IVPs with an ELM². Each of these ELMs could be trained as a normal physics-informed neural network.

²Gianluca Fabiani et al. "Parsimonious physics-informed random projection neural networks for initial value problems of ODEs and index-1 DAEs". In: *Chaos: An Interdisciplinary Journal of Nonlinear Science* 33.4 (2023), p. 043128.

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- ▶ Possible problems with this approach are:
 - ▶ Solutions completely based on networks are not always reliable.
 - ▶ Increased accuracy has to come from more collocation points.

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- ▶ Possible problems with this approach are:
 - ▶ Solutions completely based on networks are not always reliable.
 - ▶ Increased accuracy has to come from more collocation points.
- ▶ We consider a hybrid approach: replacing the coarse propagator in the Parareal method with an ELM.

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Parareal method

- ▶ Divide the time interval $[0, T]$ into N sub-intervals of size $\Delta t = T/N$.
- ▶ Choose a (cheap) coarse integrator $\varphi_C^{\Delta t}$, and a more accurate fine integrator $\varphi_F^{\Delta t}$.
- ▶ Update iteratively the approximate solution \mathbf{x}_n^i at the time $t = t_n = n\Delta t$ as follows:

$$\mathbf{x}_0^0 = \mathbf{x}_0, \mathbf{x}_n^0 = \varphi_C^{\Delta t}(\mathbf{x}_{n-1}^0), \quad n \geq 1$$

$$\mathbf{x}_{n+1}^{i+1} = \varphi_F^{\Delta t}(\mathbf{x}_n^i) + \varphi_C^{\Delta t}(\mathbf{x}_n^{i+1}) - \varphi_C^{\Delta t}(\mathbf{x}_n^i), \quad n \geq 1, i \geq 0.$$

Convergence of Parareal

Theorem: Convergence of the Parareal method

Let $\varphi_F^{\Delta t} = \phi^{\Delta t}$. Assume that there exist $p \in \mathbb{N}$, a set of continuously differentiable functions c_{p+1}, c_{p+2}, \dots , and $\alpha > 0$ such that

$$\varphi_F^{\Delta t}(\mathbf{x}) - \varphi_C^{\Delta t}(\mathbf{x}) = c_{p+1}(\mathbf{x})(\Delta t)^{p+1} + c_{p+2}(\mathbf{x})(\Delta t)^{p+2} + \dots, \quad \text{and}$$

$$\|\varphi_F^{\Delta t}(\mathbf{x}) - \varphi_C^{\Delta t}(\mathbf{x})\|_2 \leq \alpha(\Delta t)^{p+1}$$

for every $\mathbf{x} \in \mathbb{R}^d$, and also that there exists $\beta > 0$ such that

$$\|\varphi_C^{\Delta t}(\mathbf{x}) - \varphi_C^{\Delta t}(\mathbf{y})\|_2 \leq (1 + \beta\Delta t) \|\mathbf{x} - \mathbf{y}\|_2, \quad \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^d.$$

Then there exists a positive constant γ such that

$$\|\mathbf{x}(t_n) - \mathbf{x}_n^i\|_2 \leq \frac{\alpha}{\gamma} \frac{(\gamma(\Delta t)^{p+1})^{i+1}}{(i+1)!} (1 + \beta\Delta t)^{n-i-1} \prod_{j=0}^i (n-j).$$

Parareal method with ELMs

Algorithm Hybrid Parareal algorithm based on ELMs

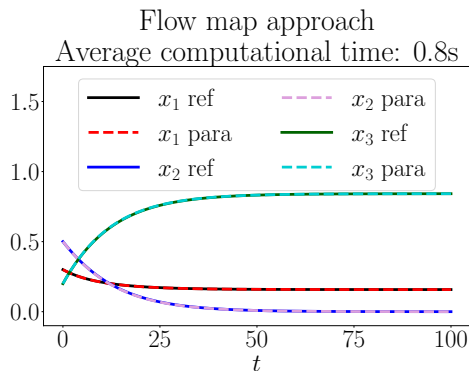
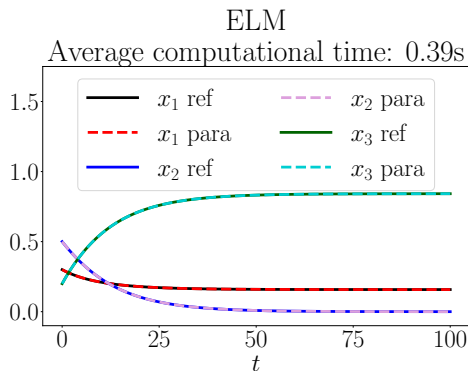
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1: while  $i < \text{max\_it}$  and  $\text{error} > \text{tol}$  do
2:    $\text{error} \leftarrow 0$ 
3:    $\mathbf{x}_{n+1}^F \leftarrow \varphi_F^{\Delta t}(\mathbf{x}_n^i), n = 0 \text{ to } N - 1$  ▷ Fine integrator, Parallel
4:    $\mathbf{x}_0^i \leftarrow \mathbf{x}_0$ 
5:   for  $n = 0 \text{ to } N - 1$  do
6:     Find  $\theta_n^{i+1} = \arg \min_{\theta \in \mathbb{R}^{H \times d}} \sum_{c=1}^C \|\mathcal{N}'_{\theta}(t_c; \mathbf{x}_n^{i+1}) - \mathcal{F}(\mathcal{N}_{\theta}(t_c; \mathbf{x}_n^{i+1}))\|_2^2$ 
7:      $\mathbf{x}_{n+1}^S \leftarrow \mathcal{N}_{\theta_n^{i+1}}(\Delta t; \mathbf{x}_n^{i+1})$  ▷ Next coarse approximation
8:      $\mathbf{x}_{n+1}^{i+1} \leftarrow \mathbf{x}_{n+1}^F + \mathbf{x}_{n+1}^S - \mathbf{x}_{n+1}^{S,-1}$  ▷ Parareal correction
9:      $\mathbf{x}_{n+1}^{S,-1} \leftarrow \mathbf{x}_{n+1}^S$ 
10:     $\text{error} \leftarrow \max \left\{ \text{error}, \left\| \mathbf{x}_{n+1}^{i+1} - \mathbf{x}_{n+1}^i \right\|_2 \right\}$ 
11:  end for
12:   $i \leftarrow i + 1$ 
13: end while

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Example with the SIR problem

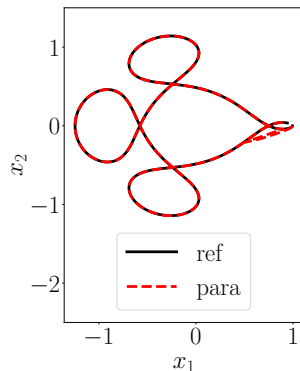
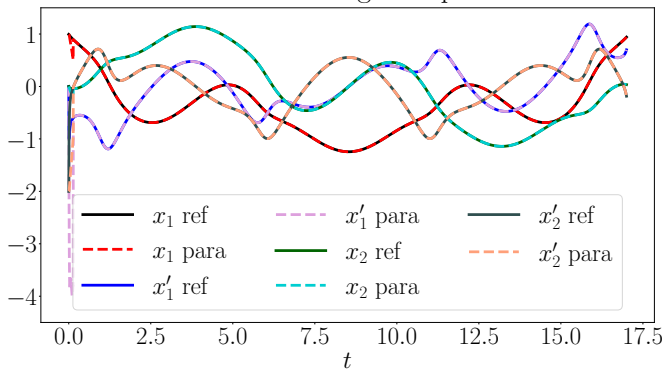
Timing breakdown	ELM	Flow
Offline training phase	0s	~20 minutes
Average cost coarse step in the zeroth iterate	0.0009773s	0.0002729s
Total	0.3940s	0.8047s



Example with the Arenstorf orbit

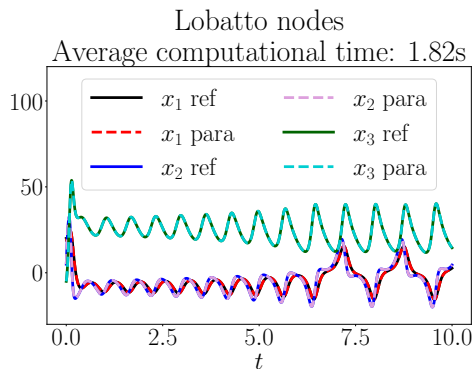
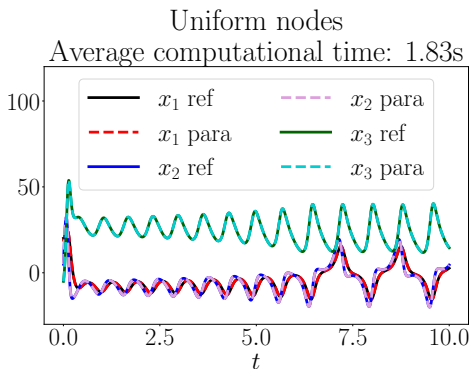
Timing breakdown	ELM
Average cost coarse step in the zeroth iterate	0.001912s
Average cost to produce the solution	9.7957s

Average computational time: 9.8s



Example with the Lorenz equation




Timing breakdown	Uniform	Lobatto
Average cost coarse step in the zeroth iterate	0.0009430s	0.0009371s
Average cost to produce the solution	1.8312s	1.8184s



THANK YOU FOR THE ATTENTION

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Link to the preprint: davidemurari.com/ELM.pdf

-  Fabiani, Gianluca et al. "Parsimonious physics-informed random projection neural networks for initial value problems of ODEs and index-1 DAEs". In: *Chaos: An Interdisciplinary Journal of Nonlinear Science* 33.4 (2023), p. 043128.
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