17 February 2025 ·
Qeios

Peer Review

Review of: "Inverse Evolution Data Augmentation for Neural PDE Solvers"

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The basic suggestion of the contribution is to exploit the freedom implicit in the data-driven nature of training neural operator networks for more efficient training data generation. Since the data generation starts at an arbitrary time, it does not require conventional time-stepping forward in time; instead, it is suggested to produce training data by stepping back in time. This allows for the employment of difference stencils in time that correspond to implicit time-stepping algorithms without the need to solve a non-linear equation system.

This idea seems very sharp and useful to me, since this should contribute to much more efficient training of neural operators and unlock one of the potentials of this neural technique.

The paragraph starting with "For the neural operators, data plays a very important role." could be shortened and/or (I suggest doing both) extended by some specific examples instead of the approximate descriptions starting with "Typically, ...".
To my knowledge, this time-step requirement is usually treated by mentioning the "Courant-Friedrichs-Lewys criterion" - and although this only applies to the explicit Euler, the phenomenon in question is instantaneously clear.

Lastly, I have to challenge the claim "The FNO architecture has demonstrated superiority in solving a variety of PDEs, achieving high accuracy and computational efficiency," especially since there are no citations or explanations given. This source https://link.springer.com/article/10.1007/s00521-024-10132-2 actually finds the opposite result for the comparison with DeepONet. I suggest editing this reasoning for choosing FNO and/or integrating DeepONet for another case study.

Declarations

 doi.org/10.32388/GHDZ1F

Potential competing interests: No potential competing interests to declare.