PROGRESSIVE PHYSICS LEARNING FROM DATA

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Data-driven modeling or physics discovery process has a notorious appetite for "good" quality data. This data, which could be harvested from high-fidelity models, experimental results, or field measurements, also does not come cheap, hindering data-driven modeling's applicability to realistic engineering applications. To mitigate this shortcoming, we propose a progressive physics discovery framework to lessen the data craving and empower the practicality of data-driven modeling, creating a large-scale model with a minimum turnaround.

We adapt the idea of progressive learning from [1]. Our framework approach is to progressively and selectively transfer knowledge from previously trained models through gates, which enhance the flow of information if it is valuable and filtered out any not-valuable pieces of information. This is analogous to how we, as humans, learn from our teachers, where we can pick and choose what we want to learn and neglect information we deem unnecessary. Additionally, we usually learn fundamental courses before progressing to more advanced ones (i.e., Calculus I and then II). Through a series of test cases with known physics problems, we demonstrate that retaining information from the previously learned models and smartly utilizing a part of that information to improve the physics discovery and achieve a similar or even better accuracy with only a fraction of data. For instance, our framework with four parents outperforms its no-parent counterpart, with training data nine times larger.

We have shown a sample of our results in Fig. 1. Our framework can also be used to understand possible correlations among physics and topologies (i.e., we can do bootstrapping sets of parents and identify which combination results in an optimal accuracy gain), leading a better interpretable model. From Fig. 1, one can observe that there is not much difference in accuracy gain when we add the fourth parent, which implies that there is no correlation of underlying data structure between the fourth parent and the problem at hand. While this approach can be applied to any deep learning-based data-driven models, we illustrate its application and performance using the Barlow Twins reduced order model [2].

To this end, as our framework focuses on physics learning from a data paradigm, it can be applied to any physical problems (e.g., fluid or solid mechanics) or sources of data (e.g., high-fidelity numerical simulations or field measurements). This behavior is preferable since the framework can accumulate its knowledge from various sources.

References

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[2] Kadeethum, T., Ballarin, F., O'malley, D., Choi, Y., Bouklas, N., & Yoon, H. (2022). Reduced order modeling for flow and transport problems with Barlow Twins self-supervised learning. Scientific Reports, 12(1), 1-18.

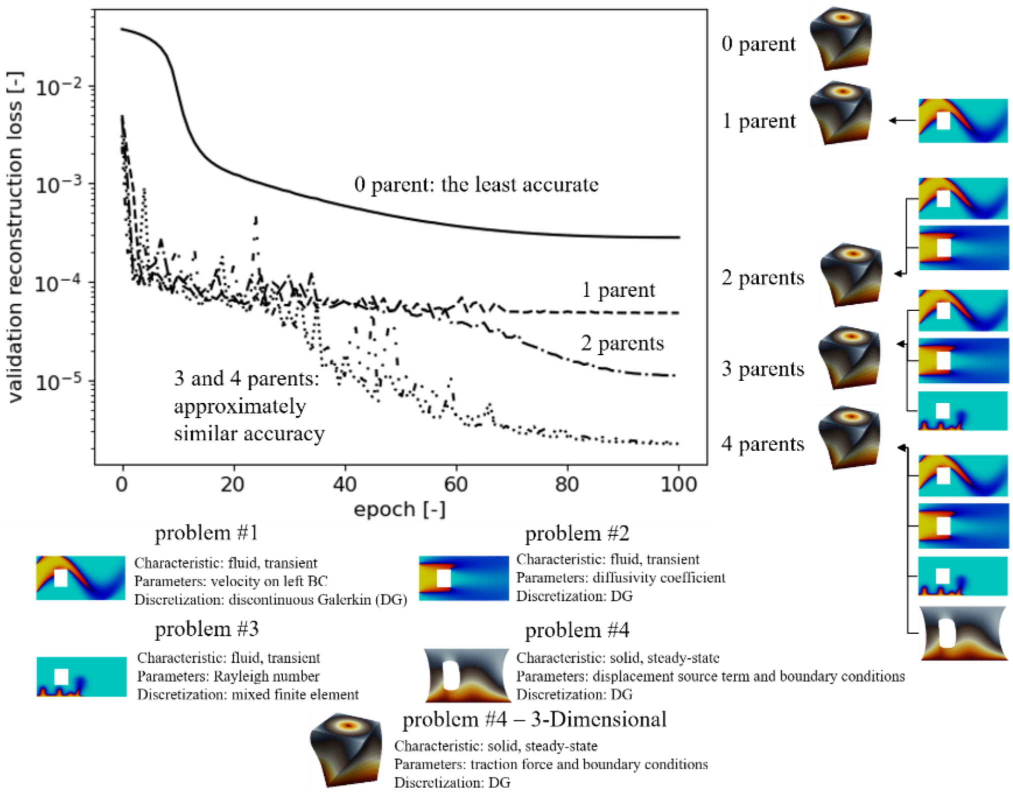

Figure 1 An example of our framework capability where we have shown that as we add more parents to the model, our model grows its performance significantly