Q1. Summary:

Physics-informed machine learning aims to integrate available data and mathematical physics modelings, even in uncertain, partially understood, and high-dimensional contexts. It can potentially address numerous general issues of pure machine learning models. On the one hand, applying a machine learning algorithm, a neural network for example, typically does not provide a systematic learning paradigm for a problem. On the other hand, ready-to-use and adequate data for a high number of problems are restricted. In this regard, the more complex a problem is, the smaller the available data for struggle. The uncertainty quantification in computer simulations should also be accounted for these complicated problems that may involve hundreds of uncertain parameters, oftentimes rendering such computations infeasible in practice. Therefore, the quick adaptability of machine learning models to unprecedented and complex tasks in the face of a limited number of data has become a rising challenge.

Machine learning models generally suffer different sorts of biases. The most considerable ones are observational biases, which can be represented directly through data; inductive biases, which correspond to prior assumptions; and learning biases, which are related to the appropriate choice of the hyper-parameters of a machine learning algorithm. Integrating physics-informed learning and machine learning models can play a significant role in not only addressing the bias issue but also covering the aforementioned limitations of machine learning models. Here, the physics-informed neural networks (PINN) emerged as a hybrid approach to integrate both the measurements and partial differential equations (PDEs) by embedding the differential equations into the loss function of a neural network. Classical numerical methods can be connected to neural networks for solving PDEs.

PINNs can be used in different sciences and fields to meet many challenges, while they have several specific merits and limitations. Focusing on advantages, they can find meaningful solutions in the face of incomplete models and imperfect data. They can enhance trainability and generalization and provide theoretical insight for machine learning models. Thanks to deep model structure, they are also able to tackle with high dimensionality. However, they might have challenges tackling multiscale and multiphysics problems, and classical numerical models that usually is used for PINNs might not have an appropriate performance to find the optimal solution. Also, there is still no various range of benchmarks and metrics to evaluate a PINN model.

Comments:

This is an outstanding publication, and I learned a lot of new things from it. I am not a specialist in this field to comment, but here are my general comments as a GAR.

I would guess the paper could discuss more meta-learning even though there are several references. Meta-learning, as one the newest and most effective approaches, can potentially be helpful for struggling with the discussed problems. We might think of physics-informed meta-leaning methods for future discussions and addressing remaining issues.

The bias problem of machine learning models and how physics-informed learning can steer the learning process toward identifying consistent solutions is comprehensively represented throughout the paper. However, it could be more interesting if a discussion of the potential biases caused by a physics-informed scheme was also investigated.

Based on my understanding, the analysis of the computational cost-accuracy trade-off may be considerable for physics-informed machine learning models, as it seems a majority of these models have high computational costs. One of the main approaches to solving this issue might be the exploitation of transfer learning, which could be discussed in future works. Nevertheless, PINNs seem to be problem-specific models which cannot easily be generalized between different domains