The Physics of Data. Part VIII

The Physics of Data. Part VIII | Alfonso R. Reyes

What makes Physics-Informed Learning Machines superior to Machine Learning and Data Science

As I continue my research on the impact of Physics in Machine Learning - specifically, Neural Networks, I find unique pearls that makes clearer the concept of incorporating differential equations - ordinary (ODE) and partial (PDE) - into a neural network formulation.

I am sure in the standard machine learning, you haven't seen the loss function being defined as the linear sum of the loss due to physics; loss due to partial or imperfect boundary conditions (BC); loss due to Initial conditions (IC), and loss due to the data itself (L_{data}. Sorry, about the Latex there. Still keeping hope that LinkedIn includes markdown and Latex instead of faking posts with AI. See the figure with some of the losses mentioned.
The loss due to the physics term indicates how well you ODE or PDE was formulated; if the loss is high it will mean you still don't have the right differential equation, meaning the state variables and the parameters.

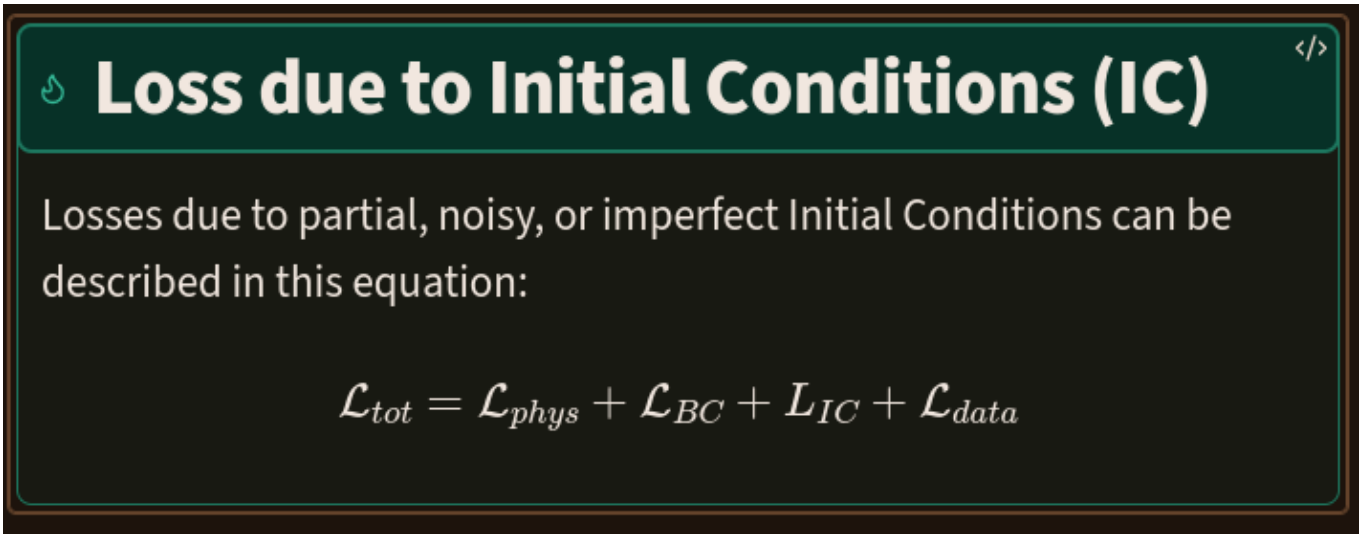
The loss due to BC or boundary conditions will show how near or how far your BCs were set. Sometimes we don't the luxury of having complete, or even at all, any BCs.

The L_{data} - loss due to the data, is the term we are so familiarized in the conventional machine learning world. Current ML algorithms will have difficult time matching real time data because they are always behind of physics-based models. Because ML works only in non-dynamical systems.

We usually blame at the data for not reaching acceptable levels of accuracy. The problem is not the data; it is the algorithm itself that ignores physics. Why? Because physics is hard! And setting up differential equations is even harder.

$$\mathcal{L}_{tot} = \mathcal{L}_{phys} + \mathcal{L}_{BC} + \mathcal{L}_{data}$$

If we take care of considering the initial conditions, then:



hashtags:: Petroleum Engineering SPE Artificial Intelligence Data Science SciML Physics Of Data

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What makes Physics-Informed Learning Machines superior to Machine Learning and Data Science

As I continue my research on the impact of physics in #machinelearning - specifically, #neuralnetworks, I find unique pearls that makes clearer the concept of incorporating #differentialequations - ordinary (ODE) and partial (PDE) - into a neural network formulation.

I am sure in the standard machine learning, you haven't seen the loss function being defined as the linear sum of the loss due to #physics; loss due to partial or imperfect boundary conditions (BC); loss due to Initial conditions (IC), and loss due to the data itself (L_{data}. Sorry, about the Latex there. Still keeping hope that LinkedIn includes #markdown and #Latex instead of faking posts with AI. See the figure with some of the losses mentioned.

The loss due to the physics term indicates how well you #ODE or #PDE was formulated; if the loss is high it will mean you still don't have the right differential equation, meaning the state variables and the parameters have not been yet correctly defined.

The loss due to BC or #BoundaryConditions will show how near or how far your BCs were set. Sometimes we don't the luxury of having complete, or even at all, any BCs.

The L_{data} - loss due to the data, is the term we are so familiarized in the conventional machine learning world. Current #ML algorithms will have difficult time matching #realtime data because they are always behind of physics-based models. The ML model will have low accuracy after the next prediction at $t+1$ with new data is performed; and we have to live with a high error prediction at time t. This is one of the reasons why conventional data-driven ML works only in non-dynamical systems! Or in the world of big data!

But what about the real world, folks working in the field with small data in real time?

We usually blame at the data for not reaching acceptable levels of #accuracy. The problem is not the data; it is the algorithm itself that ignores physics. Why? Because physics is hard! And setting up differential equations is even harder. Mind you, setting up and solving differential equations are not part of the curricula in data science or machine learning courses.

If we take care of considering the #initialconditions, then refer to the second figure.

This is not all. I haven't talked yet about conservation laws, which means you could include losses due to the deviation of your #algorithm with respect with conservation laws: energy, mass, momentum.

By now, with these simple equations, you should be able to grasp that there is a lot of work ahead of us in appropriately combining physics and machine learning. Your loss balance cannot be right just by considering #data.

#PetroleumEngineering #spe #PhysicsOfData #SciML #ArtificialIntelli