## The Physics of Data. Part X

## The Physics of Data. Part X | Alfonso R. Reyes

It's not that the <u>neural network</u> is solving physics. The solving is done by a differential equation solver. You use the neural network to find the right values of the <u>Differential Equations</u> parameters, or confirm a state variable -or variables-, in the equation based on some minimal data. It's more like calibration than really learning.

The beauty of combining a neural network with <u>Physics</u> is that it uses auto differentiation, so common in machine learning libraries such as <u>PyTorch</u> or <u>TensorFlow</u>, and <u>Julia</u> to confirm or validate the spatial temporal collocation points, in other words, the data.

There has been software for computationally solving <u>Differential Equations</u> for more than 40-50 years. This is nothing new.

What is happening now is that some physicists found out that they can use the modern machine learning libraries with <u>GPU</u> support, such as <u>PyTorch</u>, <u>TensorFlow</u>, <u>Julia</u> as (1) functional approximators; (2) as validators of the actual data points that are being supplied; (3) as minimization tools on the loss function to find the parameters of the differential equations; (4) discovery tools of <u>Hidden Physics</u> within the data. (5) as a new instrument to reduce the dependency on huge amounts of data.

The real revolutionary fact is that <u>PINNs</u> - and their cousins - do not need huge amounts of data or <u>Big</u> <u>Data</u> to perform reliable <u>predictions</u>, because the model and the data are constrained by the laws of physics. The world of PINNs is of <u>Small Data</u>.

The big <u>challenge</u> ahead is getting the expertise to spot the latent differential equation variables; their order; the number of simultaneous differential equations; the type - if ordinary, <u>ODE</u>, or partial, <u>PDE</u>, -, the right dimension -  $\underline{1D}$ ,  $\underline{2D}$ , or 3D, and identifying the data thread-or stream- that needs a differential equation. Usually the most of <u>nonlinear</u> characteristics.

Most of the challenges in data science and machine learning will remain unsolved until the subject matter expertise and <a href="Physics">Physics</a> combined, address them. It will not be an easy feat because requires understanding of physics, <a href="Computational Physics">Computational Physics</a>, advanced calculus, where machine learning plays just a little bit part of it.

PINNs have nothing to do -yet- with artificial intelligence. They involve more physics and differential equations than machine learning. Like 95% to 5% ratio. Actually, the neural networks is the easy part.

So, PINNs are not your typical weekend data science or machine learning project. The current <u>Artificial Intelligence</u> wave does not involve any physics at all; just huge amounts of data producing very fragile predictions.

What lies ahead is a world awaiting for human intelligence to apply laws of nature to dynamical systems to reign in on the data.

You can get a taste of it by browsing any paper on PINNs.

hashtags:: <u>Physics Of Data Machine Learning Petroleum Engineering SPE Data Science digital</u>
<u>Transformation SciML SEG Oil and Gas Energy Engineering Artificial Lift AI</u>

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