

The Physics of Data. Part VI

[# The Physics of Data - Part VI.](#) | [Alfonso R. Reyes](#)

Known and Unknown Physics

Addressing a question in one of the posts about what happens when the [Physics](#) is not well understood. How do we treat [data](#) in a dynamic system in which part of the physics is still unknown?

What we could do is isolating the governing system [equations](#) in two sub-systems; what is known and unknown. See figure attached.

Known Physics

What is known in the physics shouldn't be difficult to solve; perhaps coefficients would need to be adjusted for the particular system at current conditions.

Unknown Physics

It is the unknown physics part of the dynamic system what is the real challenge. Because we have to set up the differential equation *independent variables*, and then find the *coefficients* of the new equation to match the data. By using [Machine Learning](#) at this stage we kill two birds with a stone: less [data](#) is necessary to tune the equation, and the ML algorithm makes the set up process faster.

Physics vs pure data-driven machine learning models

Here is where physics vs pure data-driven machine learning models **start to diverge**. While a [ML](#) model needs abundant data points and continuous feeding to perform the training, in a physics controlled model, **training is not necessary**. Just as a another physics process, periodical calibration or verification would be all that is required. Example, the elliptical orbits of the planets is one equation that applies to all celestial bodies.

Unknown physics in terms of PDEs

In this post I am using a Partial Differential Equation, or [PDE](#), example because you are not going to find anything more complex than this. In practical examples, that soon I will be presenting, Ordinary Differential Equations ([ODE](#)) are rich and sophisticated enough to cover field cases that are common in harsh industrial environments where data is small.

Physics and mechanistic models must have priority

Placing physics at the front seems like is self evident; I have always had enormous respect for [science](#); I get it. Why then we subordinate physics to [Data Science](#), or machine learning, or [Artificial Intelligence](#)? Shouldn't be the other way around?

I have found dozens of papers on Physics Informed Neural Networks, also called [PINNs](#). In them, [Neural Networks](#) are placed front and center, and physics provides some sort of validation to them. Machine Learning, neural networks, generative adversarial networks, etc., are tools. Tools to uncover new [mechanistic](#) equations in the data stream that goes from the [sensors](#) to the data gathering point. There is a huge gap here because we have been distracted by the algorithms powered by the [GPUs](#) in the cloud.

I am proposing that physics should retake its main role in producing models of dynamic systems, and use machine learning [algorithms](#) sparingly to fill in the gaps.

[AI Differential Equations](#) [SPE Petroleum Engineering](#) [energy](#) [SciML](#) [Physics Of Data](#)

Thanks for the question Divyanshu Vyas

In terms of Partial Differential Equations (PDE)

$$\frac{\partial \mathbf{u}}{\partial t} + \overbrace{\mathcal{F}[\mathbf{u}, \mathbf{u}^2, \dots, \nabla \mathbf{u}, \nabla^2 \mathbf{u}, \dots]}^{\text{Partially known physics}} = 0$$
$$\mathcal{F}(\mathbf{u}) = f[\underbrace{\mathcal{K}(\mathbf{u})}_{\text{Known physics}}, \underbrace{\mathcal{U}(\mathbf{u})}_{\text{Unknown physics}}]$$



Alfonso R. Reyes ✓ • You

VP Artificial Intelligence Engineering - Energy Division

10mo • Edited •

...

The Physics of Data - Part VI. Unknown Physics

Addressing a question in one of the posts about what happens when the [#physics](#) is not well understood. How do we treat [#data](#) in a ****dynamic system**** in which part of the physics is still unknown?

What we could do is isolating the governing system [#equations](#) in two sub-systems; what is known and unknown. See figure attached.

Known Physics

What is known in the physics shouldn't be difficult to solve; perhaps coefficients would need to be adjusted for the particular system at current conditions.

Unknown Physics

It is the unknown physics part of the dynamic system what is the real challenge. Because we have to set up the differential equation ***independent variables***, and then find the ***coefficients*** of the new equation to match the data. By using [#machinelearning](#) at this stage we kill two birds with a stone: less [#data](#) is necessary to tune the equation, and the ML algorithm makes the set up process faster.

Physics vs pure data-driven machine learning models

Here is where physics vs pure data-driven machine learning models ****start to diverge****. While a [#ML](#) model needs abundant data points and continuous feeding to perform the training, in a physics controlled model, ****training is not necessary****. Just as a another physics process, periodical calibration or verification would be all that is required. Example, the elliptical orbits of the planets is one equation that applies to all celestial bodies.

Unknown physics in terms of PDEs

In this post I am using a ****Partial Differential Equation****, or [#PDE](#), example because you are not going to find anything more complex than this. In practical examples, that soon I will be presenting, ****Ordinary Differential Equations**** ([#ODE](#)) are rich and sophisticated enough to cover field cases that are common in harsh industrial environments where data is small.

Physics and [#mechanistic](#) models must have priority

Placing physics at the front seems like is self evident; I have always had enormous respect for [#science](#); I get it. Why then we subordinate physics to [#datascience](#), or machine learning, or [#ArtificialIntelligence](#)? Shouldn't be the other way around?

I have found dozens of papers on Physics informed neural networks, also called [#PINNs](#). In them, [#neuralnetworks](#) are placed front and center, and physics provides some sort of validation to them. Machine Learning, neural networks, generative adversarial networks, etc., are tools. Tools to uncover new [#mechanistic](#) equations in the data stream that goes from the [#sensors](#) to the data gathering point. There is a huge gap here because we have been distracted by the algorithms powered by the [#GPUs](#) in the cloud.

I am proposing that physics should retake its main role in producing models of dynamic systems, and use machine learning [#algorithms](#) sparingly to fill in the gaps.

[#AI](#) [#DiffEq](#) [#spe](#) [#petroleumEngineering](#) [#energy](#) [#SciML](#) [#PhysicsOf](#)

Thanks for the question [Divyanshu Vyas](#)

In terms of Partial Differential Equations (PDE)

$$\frac{\partial \mathbf{u}}{\partial t} + \overbrace{\mathcal{F}[\mathbf{u}, \mathbf{u}^2, \dots, \nabla \mathbf{u}, \nabla^2 \mathbf{u}, \dots]}^{\text{Partially known physics}} = 0$$
$$\mathcal{F}(\mathbf{u}) = f[\underbrace{\mathcal{K}(\mathbf{u})}_{\text{Known physics}}, \underbrace{\mathcal{U}(\mathbf{u})}_{\text{Unknown physics}}]$$

 75

24 comments · 4 reposts

 Like

 Comment

 Repost

 Send

 7,018 impressions

[View analytics](#)