

# Physics of Data. Part XVIII

[Physics of Data. Part XVIII](#) | [Alfonso R. Reyes](#)

Unscientific claims by the hyped [AI](#) is not without risks. Let's also be aware that wrongly applied [science](#) and [engineering](#) may harm human beings.

"[AI] methods that are more accurate, interpretable, and efficient." than classical data-driven machine learning <— YES.

"[AI] methods that are more accurate, interpretable, and efficient." than classical physics differential equation solvers <— NO

"leverages AI to augment traditional physics-based modeling." <— FALSE

"Physics-informed machine learning enables tasks such as predicting phenomena with greater precision and less data, as well as solving differential equations more efficiently." <— FALSE.

Physics-informed machine learning enables tasks such as predicting phenomena with greater precision and less data, than classical machine learning methods <— TRUE

"... you can develop AI models that leverage governing physics to enhance analysis and decision-making in engineering and science." <— DANGEROUSLY FALSE. Potentially prosecutable if harming human beings or property.

Physics Informed Machine Learning and Scientific ML are great at specific settings, prototyping, and controlled applications. It is not a replacement of sound [Physics](#) and science, in which humanity has invested millions of man-hours in discretizing differential equations in [simulation](#) and [modeling](#) tools during the digital age.

Summarizing:

- PINNs are not a replacement of classical physics solvers.
- PINNs are an excellent prototyping tool. Test fast, fail fast.
- PINNs are not intelligent; they use field data which is contrasted with results generated by differential equations through loss functions in the [Neural Networks](#).
- PINNs are just one tool of many physics-informed methods in the field of Scientific Machine Learning, or SciML.
- PINNs do not require large amounts of data as ML since they are constrained by the physics of [Differential Equations](#).
- PINNs will not provide solutions more accurate than classical physics based solvers.
- PINNs, as model surrogates, may be faster than classical physics solvers, but at a very small scale, sacrificing [accuracy](#), stability, and generalizability
- PINNs are cool and inexpensive because you use open source software such as [PyTorch](#), or [TensorFlow](#).

- PINNs are hard because they involve deep knowledge of the physics of the process.
- PINNs ideal niche is discovering unknown differential equations at the “last mile” of a [dynamical](#) system



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VP Artificial Intelligence Engineering - Energy Division

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Home



My Network



Jobs



Messaging



Notificatio

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