Interim Report

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Capstone

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Due to the relatively new nature of the topic (PINN), our first goal was to familiarize ourselves with it by reading and checking papers, such as

* Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686-707.
* Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2017). Physics informed deep learning (part i): Data-driven solutions of nonlinear partial differential equations. arXiv preprint arXiv:1711.10561.
* Raissi, M., Perdikaris, P., & Karniadakis, G.E. (2017). Physics Informed Deep Learning (Part II): Data-driven Discovery of Nonlinear Partial Differential Equations. ArXiv, abs/1711.10566.
* Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., & Yang, L. (2021). Physics-inform ed machine learning. Nature Reviews Physics, 3(6), 422-440.
* Lawal, Z. K., Yassin, H., Lai, D. T. C., & Che Idris, A. (2022). Physics-Informed Neural Network (PINN) Evolution and Beyond: A Systematic Literature Review and Bibliometric Analysis. Big Data and Cognitive Computing, 6(4), 140.
* Raissi, M., & Karniadakis, G. E. (2018). Hidden physics models: Machine learning of nonlinear partial differential equations. Journal of Computational Physics, 357, 125-141.
* Кенжебек, Е., Иманкулов, Т. С., & Ахмед-Заки, Д. Ж. (2021). ПРОГНОЗИРОВАНИЕ ДОБЫЧИ НЕФТИ С ПОМОЩЬЮ ФИЗИКО-ИНФОРМИРОВАННОЙ НЕЙРОННОЙ СЕТИ. «Физико-математические науки», 76(4), 45-50.
* Dana, S., & Kadeethum, T. (2021). Physics informed deep learning for coupled flow and poromechanics. Mandel’s problem.

According to the papers above, PINNs are a new class of universal function approximators that can encode any underlying physical laws that govern a dataset. Those papers focus on developing data-driven algorithms for inferring solutions to general nonlinear PDEs and constructing computationally efficient physics-based surrogate models.

Secondly, we looked at the codes of our main papers written by Raissi. <https://github.com/maziarraissi/PINNs>.

Our work plan from this point is to start working on the coding part. We are going to use libraries such as Numpy, Pandas, SciPy, Matplotlib, etc., for the general coding part, and for the deep learning part, we are going to use TensorFlow and PyTorch separately and compare the results afterward. The final code will be implemented only in PyTorch.

In the scope of this capstone, we will try to perform data-driven discovery, and a data-driven solution of the specific PDE called the complex Ginzburg-Landau equation. The complex Ginzburg–Landau equation (CGLE), probably the most celebrated nonlinear equation in physics, describes generically the dynamics of oscillating, spatially extended systems close to the onset of oscillations. We will use CGLE as a loss function during our experiments. During the optimization process, we will minimize not only the neural network loss but also the PDE loss as well. This will give us a model which makes predictions based on physics. First, we will run our model on the synthetic data that is generated during the numerical experiments. After having success, we will do the same on the real experimental data.