Physics-Informed Spatiotemporal Deep Learning

Introduction.

Physics-Informed Spatiotemporal Deep Learning (PISTDL) is a field that combines physics-based models and deep learning techniques to solve spatiotemporal problems. The main idea is to use the knowledge about the underlying physical phenomenon of the problem and guide the learning process for improving the accuracy of the predictions. It has a wide range of applications, including forecasting problems, modeling problems, etc. It has many advantages against to traditional state-of-art model. For instance, it performs better on small amounts of data, although in the scope of the traditional models, we can observe overfitting, and the model cannot perform accurate predictions.

Necessary Background

This field requires theoretical and practical knowledge about deep learning, Ordinary Differential Equations (ODE), Partial Differential Equation (PDE), and physics. We will use the following tools, languages, and libraries in the scope of the capstone

- Python General Knowledge:
  - Numpy
  - Pandas
  - SciPy
  - Matplotlib
  - Seaborn (Optional)
- Working with Deep Learning libraries
  - PyTorch: Ability to convert TensorFlow code into PyTorch on demand
- Automatic Differentiation Tools
  - Torch.autograd

In the scope of the capstone, you will research to find all the necessary literature.

Literature Review

In this link, you may find literature that needs to be covered. Before reading, look into the short article, where the author, in simple terms, explains the main article without much complex scientific terminology.

This is the order of reading.

- 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-informed 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.

You can do any additional reading on demand. Some (if not all) above-mentioned literature will be included in the bibliography of the capstone. Also, look at the short presentation of the primary author (see Google Drive link).

For doing more convenient research use the following links

- Google Scholar
- Sci-Hub
- Library Genesis

Coding Part

In the scope of this capstone, we will do a lot of work with the already implemented models however, sometimes, we will write code by ourselves.

The following links contain different implementations of PINNs (in general in PyTorch, but the first implementation is in TensorFlow)

- The Maziar Raissi (main author) Assistant Professor repository:
  https://github.com/maziarraissi/PINNs
  His blog about PINNS: https://maziarraissi.github.io/PINNs/
- Yongho Kim implementation: https://github.com/kimy-de/pinns
- Nandita Doloi PhD implementation: https://github.com/nanditadoloi/PINN
- Jay Roxis PhD implementation: https://github.com/jayroxis/PINNs

Dataset

In the scope of the capstone during the initial state, retry all experiments of the attached GitHub links. After getting the same result as the authors got, we can conduct the numerical experiments of our spatiotemporal data. I will give some synthetic data for conducting our experiments. Before conducting our experiments, we will discuss them in more detail.

Problem Statement

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 doing 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. The details will be discussed later.

The novelty of this capstone will be data-driven discovery and data-driven solutions with PINNs by using the complex Ginzburg-Landau equation on the synthetic generated data, and at the end on the real experimental data.

Methodology

TBA

Deliverables

TBA

Timeline

I expected from you to do

- As much reading as you can (attached articles, physics & deep learning book, any supplementary materials, etc.). This can take 2-3 weeks.
- Watch many videos as you can. I am attaching some video links. You are free to watch any additional material on demand. This can take 1-2 weeks.
    - "Hidden Physics Models: Machine Learning of Non-Linear Partial Differential Equations" Maziar Raissi - Brown University
    - NVIDIA | PHYSICS INFORMED NEURAL NETWORKS
    - How Do Physics-Informed Neural Networks Work?
    - A Hands-on Introduction to Physics-informed Machine Learning
    - What Are Physics Informed Neural Networks (PINNs)?
    - Rethinking Physics Informed Neural Networks [NeurIPS'21]
    - Designing Next-Generation Numerical Methods with Physics-Informed Neural Networks
    - Scientific Machine Learning: Physics-Informed Neural Networks with Craig Gin
    - Physics-Informed Neural Network
    - Physics Informed Neural Networks (Different Link)
    - George Karniadakis - From PINNs to DeepOnets
    - Physics Informed Machine Learning Channel With Many Useful Videos
- After collecting all the necessary theoretical data, you can run the codes and retry the conducted experiments results. You are free to reach to this step earlier by doing "reading-listening-coding" cycle. This can take 1 weeks.
- Then we can discuss future details.

Conclusion

During the capstone work process, if you will have any questions, please let me know. We can conduct online/offline meetings to discuss all incomprehensible details.