Computational Paradigms in Scientific Machine Learning

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Scientific Machine Learning (SciML) has emerged as a powerful tool for solving partial differential equations (PDEs) and addressing a wide spectrum of real-world challenges. This surge in interest has led to a reassessment and rethinking of traditional numerical methods, highlighting the need for more efficient and reliable approaches that integrate both model-driven and data-driven methodologies. In this context, Physics-Informed Neural Networks (PINNs) are novel deep learning frameworks for solving forward and inverse problems associated with nonlinear PDEs. Although PINNs have showcased remarkable effectiveness, several emerging Artificial Intelligence (AI) methodologies warrant consideration in addressing even more intricate and demanding applications. In this presentation, we will explore some novel theoretical and applied challenges related to the fascinating world of AI as it intersects with SciML.

REFERENCES

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