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Plasma Simulation Methods Based on Machine Learning

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For a long time, numerical simulations of plasmas and scientific simulations have been basing on computational methods. For complex plasma systems, computationally-based plasma simulations have achieved fruitful results in algorithm research and practical applications. Learning and computation are equally important in the development of science. With the rise of a new wave of artificial intelligence represented by deep learning and large models, learning-based surrogate models and techniques have begun to emerge. Therefore, machine learning-based plasma simulation methods have become one of the topics urgently in need of research. This talk will introduce machine learning-based surrogate modeling research, neural network-based plasma system solvers, and structure preserving neural networks for plasma researches, their properties, and their applications on specific problems. Structure preserving machine learning will provide useful tools for AI + Plasma science. It has built in physical generalization abilities due to the preservation of physical structures as well as similar flexibility as standard machine learning methods.

We will take the simulation of alpha particle dynamics in tokamak fields for example, to discuss in detail the performance of PINN solver and the Volume-preserving Neural Network.

Residual Modules

$$\mathcal{R}^{i,j}(x) = \begin{pmatrix} x[:i] \\ x[i:j] + \hat{\sigma}_\theta(\overline{x[i:j]}) \\ x[j:] \end{pmatrix} \qquad \hat{\sigma}_\theta(\overline{x[i:j]}) = a\sigma(K\overline{x[i:j]} + b)$$

Linear Modules

$$L^{i,j} = \left\{ S^{i,j} \in \mathbb{R}^{D\times D} \,\middle|\, S^{i,j} = \begin{pmatrix} I_{(i-1)\times(i-1)} & 0_{(i-1)\times(j-i)} & 0_{(i-1)\times(D-j+1)} \\ U_{(j-i)\times(i-1)} & I_{(j-i)\times(j-i)} & V_{(j-i)\times(D-j+1)} \\ 0_{(D-j+1)\times(i-1)} & 0_{(D-j+1)\times(j-i)} & I_{(D-j+1)\times(D-j+1)} \end{pmatrix} \right\}$$

$$\mathcal{L}(x) = \left(\prod_{m=1}^{M} S_m\right) x + b$$

Linear Modules

$$\mathcal{A}^{i,j}(x) = \begin{pmatrix} x[:i] \\ x[i:j] + a\sigma(\overline{x[i:j]}) \\ x[j:] \end{pmatrix}$$

Figure 1. Three modules for Volume-preserving neural networks

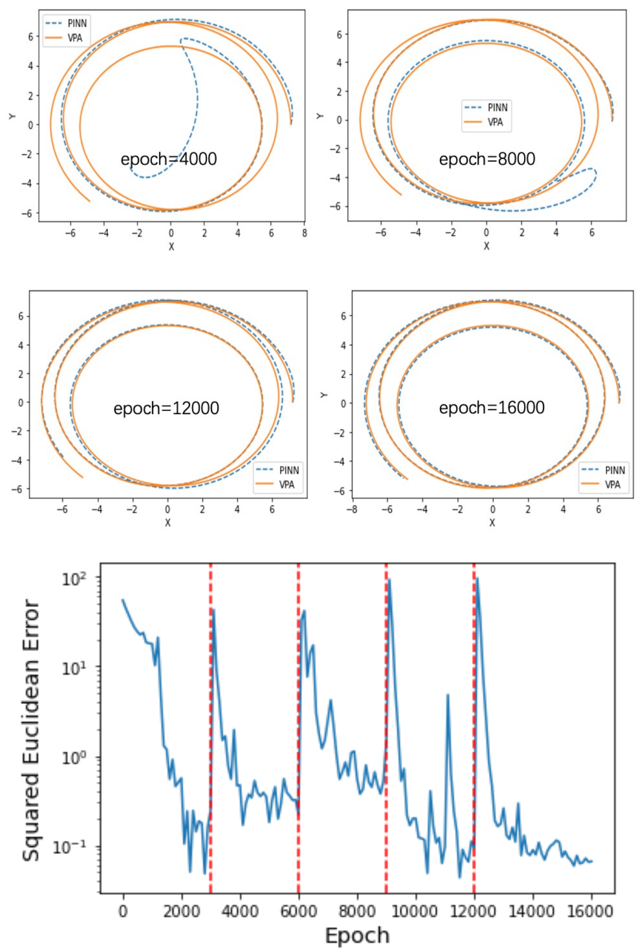

Figure 2. Long-term simulation results using PINN and optimized training strategies.

References

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