Scientific Machine Learning for Closure Models in Multiscale Problems: A Review

Scientific Achievement

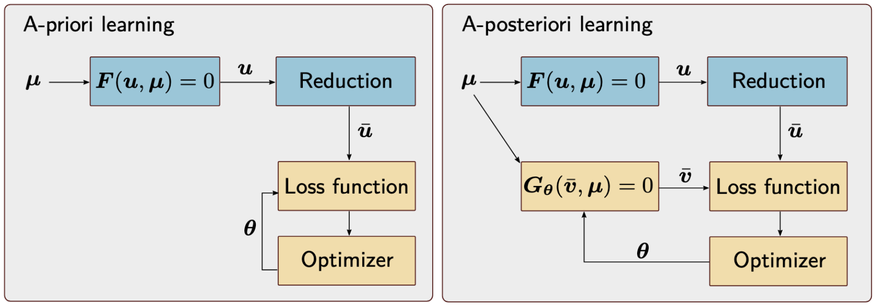
- Provided an overview of recent scientific machine learning approaches to the closure problem and the open challenges faced by the community.

Significance and Impact

- Closure problems are omnipresent during the simulation of multiscale systems, where some quantities and processes cannot be fully prescribed despite their effects on the simulation's accuracy.
- Scientific machine learning approaches have been proposed as a way to tackle the closure problem, combining traditional (physics-based) modeling with data-driven (machine learning) techniques.

Technical Approach

- The importance of adhering to physical laws when choosing the reduced model form and choosing the learning method is discussed.
- The effect of spatial and temporal discretization and recent trends toward discretization-invariant models are reviewed.
- Connections are made between closure problems and several other research disciplines: inverse problems, Mori–Zwanzig theory, and multifidelity methods.



A priori vs. a posteriori learning. Training data $\boldsymbol{u}$ and $\bar{\boldsymbol{u}}$ are obtained from solving the high-fidelity model $\boldsymbol{F}$. In blue: simulation of the high-fidelity model, from which the ground truth $\bar{\boldsymbol{u}}$ is derived. In yellow: training. In a posteriori learning, the loss function includes evaluating the gradients of the reduced model, while in a priori learning, only the residual must be evaluated.

PI(s)/Facility Lead(s): Panos Stinis
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ASCR PM: Margaret Lentz
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