Reinforcement Learning Driven Adaptive Time Stepping Schemes for Cahn-Hilliard Equation

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Abstract

Adaptive time-stepping techniques are essential in efficiently solving differential equations while maintaining accuracy, especially for stiff problems, since using a fixed step size may result in increased computational expenses or instability or even capture the wrong dynamics. The main aim of this study is to create an adaptive time-stepping strategy for partial differential equations (PDEs) using reinforcement learning (RL), specifically for the Cahn-Hilliard equation that describes phase separation in binary mixtures.

Our approach teaches a neural network to adaptively choose the best time increments according to the system's dynamics. The RL agent monitors the error and cost at every step, aiming to boost accuracy and reduce computational burden, adjusting its strategy to address the diverse time scales seen in stiff ODEs. Preliminary findings indicate that this technique is more effective than traditional fixed-step approaches in terms of both precision and speed. The successful results achieved with ODEs indicate the potential for expanding to more complicated PDE systems like the Cahn-Hilliard equation, which presents similar difficulties related to variable dynamics and the requirement for adaptive time stepping.