Fast and accurate time partitioning model reduction for multiscale linear kinetic equations

Tianyu Jin, Zhichao Peng, Yang Xiang

Abstract

In this work, we present a non-intrusive model order reduction approach designed to mitigate the computational cost in solving the kinetic transport equation with multiscale nature. Our method aims to predict solutions at new parameter values based on observations from a limited set of sample parameters. The proposed algorithm is structured into two stages: an offline stage, where we derive a reduced-order representation from the original full-order snapshots, and an online stage, where we extrapolate latent variables at new parameters and recover them into the full-order space. Recognizing the Kolmogorov barrier of using solely a linear reduced space for time-dependent transport-dominant problems, we introduce a time-partitioning strategy that divides the time domain into several intervals, enabling efficient linear model reduction on the snapshots within each interval. Our complexity analysis indicates that this time-partitioning strategy significantly reduces both online and offline computational times, albeit at the cost of increased memory usage. To strike a balance between computational time and memory cost, we further introduce a time-coarsening strategy. Additionally, in cases where the linear method remains inefficient in certain time intervals, we employ a convolutional autoencoder to compress the data into an ultra-low-dimensional latent space, which facilitates an extremely fast online stage. Numerical experiments demonstrate that our proposed approaches successfully predict unseen full-order solutions at new parameter values with both efficiency and accuracy, highlighting their applicability in practical scenarios involving multiscale properties.