Efficient Learning of the State in Dynamic Systems from Model-Based to Data-Based.

# Abstract

Predicting states in dynamic systems, a core challenge across various domains, entails estimating evolving signals from historical observations or understood system rules, with obstacles rooted in observational errors, unknown variables, and rule complexities. This dissertation grapples with state estimation under information constraints, emphasizing the crucial balance between data volume and prediction accuracy. Typically, system information sources bifurcate into measurements—historic data, often limited by technology—and models—theoretical blueprints, sometimes elusive for intricate systems. The study first ventures into model-based estimation, emphasizing the pitfalls of uncertainties, notably when humans act as sensors in cyber-physical-human systems, transmitting binary feedback. Transitioning to data-based estimation for undefined models, the research centers on the dual challenges of limited data and elusive system dynamics. Here, a fusion of physics-informed neural networks (PINN) and deep operator networks (DeepONet) is proposed. The method unfolds in two stages: an initial deep dive into system dynamics spotlighting short-term dependencies, illustrated by an ultra-high magnetic response system case, followed by a focused effort on curbing error accumulation using a DeepONet framework, enriched with short-term dependency insights. Collectively, the dissertation unveils innovative perspectives on state estimation for information-restricted dynamic systems, bearing significant repercussions for related disciplines.