



Workshop on Stochastic Analysis

IMECC - Unicamp

From August 10th to 13th, 2026



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Adaptive Learning via Off-Model Training and Importance Sampling for Fully Non-Markovian Optimal Stochastic Control

Abstract

We discuss continuous-time stochastic control problems whose controlled states are fully non-Markovian and depend on unknown model parameters. Such problems arise naturally in path-dependent stochastic differential equations, rough-volatility hedging, and systems driven by fractional Brownian motion. Our main contribution is twofold. First, we construct explicit dominating training laws and Radon–Nikodym weights for several representative classes of non-Markovian controlled systems. This yields an off-model training architecture in which a fixed synthetic dataset is generated under a reference law, while the dynamic programming operators associated with a target model are recovered by importance sampling. Second, we use this structure to design an adaptive update mechanism under parametric model uncertainty, so that repeated recalibration can be performed by reweighting the same training sample rather than regenerating new trajectories. For fixed parameters, we establish non-asymptotic error bounds for the approximation of the embedded dynamic programming equation via deep neural networks. For adaptive learning, we derive quantitative estimates that separate Monte Carlo approximation error from model-risk error. Numerical experiments illustrate both the off-model training mechanism and the adaptive importance-sampling update in structured linear-quadratic examples.