

Bridging Theory and Practice in Stein Variational Gradient Descent: Gaussian Approximations, Finite-Particle Rates, and Beyond

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Stein Variational Gradient Descent (SVGD) has emerged as a powerful interacting particle-based algorithm for nonparametric sampling, yet its theoretical properties remain challenging to unravel. This talk delves into two complementary perspectives about SVGD. First, we explore Gaussian-SVGD, a framework that projects SVGD onto the family of Gaussian distributions via a bilinear kernel. We establish rigorous convergence results for both mean-field dynamics and finite-particle systems, demonstrating linear convergence to equilibrium in strongly log-concave settings and unifying recent algorithms for Gaussian variational inference (GVI) under a single framework. Second, we analyze the finite-particle convergence rates of SVGD in Kernelized Stein Discrepancy (KSD) and Wasserstein-2 metrics. Leveraging a novel decomposition of the relative entropy time derivative, we achieve near-optimal rates with polynomial dimensional dependence and extend these results to bilinear-enhanced kernels.

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