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|       | abstract        | Bayesian inference problems require sampling or approximating high-dimensional probability distributions. The focus of this paper is on the recently introduced Stein variational gradient descent methodology, a class of algorithms that rely on iterated steepest descent steps with respect to a reproducing kernel Hilbert space norm. This construction leads to interacting particle systems, the mean-field limit of which is a gradient flow on the space of probability distributions equipped with a certain geometrical structure. We leverage this viewpoint to shed some light on the convergence properties of the algorithm, in particular addressing the problem of choosing a suitable positive definite kernel function. Our analysis leads us to considering certain nondifferentiable kernels with adjusted tails. We demonstrate significant performs gains of these in various numerical experiments | abstract | Bayesian inference problems require sampling or approximating high-dimensional probability distributions. The focus of this paper is on the recently introduced Stein variational gradient descent methodology, a class of algorithms that rely on iterated steepest descent steps with respect to a reproducing kernel Hilbert space norm. This construction leads to interacting particle systems, the mean-field limit of which is a gradient flow on the space of probability distributions equipped with a certain geometrical structure. We leverage this viewpoint to shed some light on the convergence properties of the algorithm, in particular addressing the problem of choosing a suitable positive definite kernel function. Our analysis leads us to considering certain nondifferentiable kernels with adjusted tails. We demonstrate significant performs gains of these in various numerical experiments. Comment: 39 pages, 4 figure |          |     |
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