mDPVI – only experiment part

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Abstract

The recently developed Particle-based Variational Inference (ParVI) methods drive the empirical distribution of a set of particles towards a given unconstrained target distribution π by iteratively updating particles' positions. To tackle the limitation that ParVI methods can only handle unconstrained target distributions, mirrored ParVI methods, e.g. mirrored SVGD method, are proposed to handle constrained target distributions by evolving fixed-weight particles in a dual space defined by a mirror map. However, the fix weight restriction in dual space greatly confines the approximation ability of distributions in primal space. In this paper, we develop a general Mirrored Dynamic-weight Particle-based Variational Inference (MDPVI) framework according to a novel continuous composite flow, which evolves the positions and weights of particles simultaneously in a dual space to approximate constrained target distribution efficiently. We show that the mean-field limit of our composite flow is actually a Mirrored-Wasserstein-Fisher-Rao gradient flow of the associated dissimilarity functional. By using different finite-particle approximations in our general framework, we derive several efficient MDPVI algorithms. The empirical results demonstrate the superiority of our derived MDPVI algorithms over their fixed-weight counterparts1.

Introduction

Recently, Particle-based Variational Inference (ParVI) have drawn much attention in the Bayesian inference literature, due to their success in approximating unconstrained target distributions (Liu and Wang 2016; Liu and Zhu 2018; Liu and Wang 2018; Pu et al. 2017; Zhu, Liu, and Zhu 2020). The core of ParVIs lies at evolving the empirical distribution of M *fixed-weight* particles by simulating a *continuity equation* through its easy-to-calculate finite-particle position transport approximation (Liu et al. 2019). However, these ParVI methods would break down for sampling constrained target, like distributions on the simplex or the targets of post-selection inference. (Shi, Liu, and Mackey 2022) tackle this challenge by apply Stein methods to fix-weight particles in dual space defined by a mirror map to approximate target constrained distributions in primal space.

Experiments

In this section we conduct empirical studies with our mirror DPVI algorithms (), their duplicate/

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