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LIKELIHOOD-FREE GIBBS SEQUENTIAL MONTE CARLO SAMPLING

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Abstract: Approximate Bayesian computation (ABC) has become a standard tool to conduct Bayesian inference for models with intractable likelihoods. However, most existing ABC methods suffer from the curse of dimensionality when the number of parameters is large. To solve this problem, we introduce a Gibbs Sequential Monte Carlo (SMC) method that utilizes a Gibbs kernel to update parameters within the SMC framework and approximate the conditional distribution of the parameters using a variety of regression adjustment methods. We discuss the computational advantage of our method over existing approaches and establish the theoretical property of the Gibbs kernel. We further demonstrate the superior numerical performance of our method using simulation studies and an application to cell motility example.

Key words and phrases: Approximate Bayesian computation, cell motility, Markov chain Monte Carlo, random forest, regression adjustment.

1. Introduction

In Bayesian statistics, Approximate Bayesian Computation (ABC) is a powerful method designed to tackle the challenges posed by intractable likelihood functions. The first ABC-related ideas date back to the 1980s (Rubin, 1984). The main idea of the ABC is to simulate data from the model with different sets of parameters and retain the parameter values if their corresponding simulated data are sufficiently close to the observed data (e.g., within a tolerance level). Since its first appearance in genetics (Tavaré et al., 1997; Pritchard et al., 1999), ABC has received a lot of attention in many applications, such as ecology, epidemiology, and material science (François et al., 2008; Marin et al., 2012; Blum and Tran, 2010; Ravandi and Hajizadeh, 2022). Numerous extensions to the standard ABC methodology have been proposed in the literature. Some studies focus on discrepancy measurement between simulated and observed data without relying on summary statistics (Bernton et al., 2019; Zhu, Zuo and Wang, 2023). Others explore the integration of MCMC techniques within the ABC framework to enhance parameter space exploration efficiency (Marjoram et al., 2003). Additionally, there are approaches employing regression adjustment methods to mitigate discrepancies arising from mismatches between observed and

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