TRANSPORT MAP ACCELERATED-PAIS, AND APPLICATION TO INVERSE PROBLEMS ARISING FROM MULTISCALE STOCHASTIC REACTION NETWORKS

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Abstract. In many applications, inverse problems arise where where there are complex correlations between the different parameters which we wish to infer from data. The correlations often manifest themselves as lower dimensional manifolds on which the likelihood function is invariant, or varies very little. This can be due to trying to infer unobservable parameters, or due to sloppiness in the model which is being used to describe the data. In such a situation, standard sampling methods for characterising the posterior distribution which do not incorporate information about this structure will be highly inefficient. Moreover, most methods are inherently serial in nature, and as such are not expoiting the parallelised nature of modern computer infrastructure. In this paper, we seek to develop a method to tackle this problem, using optimal transport maps to simplify posterior distributions which are concentrated on lower dimensional manifolds.

We demonstrate the approach by considering inverse problems arising from partially observed stochastic reaction networks. In particular, we consider systems which exhibit multiscale behaviour, but for which only the slow variables in the system are observable. We demonstrate that certain multiscale approximations lead to more consistent approximations of the posterior than others.

1. Introduction. In Section 2 we show how an appropriate transport map can be constructed from importance samples which maps the posterior close to a reference Gaussian measure. In Section 3 we show how such a map can be incorporated into a sophisticated parallel MCMC infrastructure in order to accelerate mixing. In Section 4 we consider how likelihoods can be approximated using multiscale methodologies in order to carry out inference for multiscale and/or partially observed stochastic reaction networks. In Section 5 we present some numerical examples, which serve to demonstrate the increased efficiency of the described sampling methodologies, as well as investigating the posterior approximations discussed in the previous section. We conclude with a discussion in Section 6.

2. Construction of transport maps in importance sampling.

3. T-PAIS.

4. Multiscale approximations of likelihoods in stochastic reaction networks.

5. Numerical Examples.

6. Conclusions.