Robust and Efficient Approximate Bayesian Computation: A Minimum Distance Approach

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15 October 2020, 10.30 UK time

Abstract
Approximate Bayesian computation (ABC) is now routinely applied to conduct inference in complex models. However, there remain at least two significant hurdles to the widespread adoption of ABC methods in practice. First, since ABC replaces the observed sample with summary statistics and the likelihood function with a given metric (for the summaries), ABC-based inference inevitably entails a loss in statistical efficiency. Second, the choice of summaries and metric in ABC ensures that, as a general method, ABC may not be robust to deviations from the underlying model structure: different summaries/metrics can lead to significantly different inferences under model misspecification. Motivated by these efficiency and robustness concerns, we construct a new approximate Bayesian inference approach that delivers point estimators that are as efficient as those obtained by exact Bayesian inference, even when the latter is infeasible to implement, while also simultaneously displaying robustness to deviations from the underlying model assumptions. Several examples demonstrate that this new approach outperforms state of the art approaches to ABC-based inference, and compares favorably with exact Bayes inference in correctly-specified models, while outperforming these approaches when the model is misspecified.

References

[1] D.T. Frazier (2020). Robust and Efficient Approximate Bayesian Computation: A Minimum Distance Approach, arXiv:2006.14126.