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Sequential Importance Sampling With Corrections For Partially Observed States

Valentina Di Marco · Jonathan Keith · Daniel Spring

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1 Introduction

Andrieu and Doucet (2002)

We consider an evolving system for which a sequence of observations is being made, with each observation revealing additional information about current and past states of the system. We suppose each observation is made without error, but does not fully determine the state of the system at the time it is made. Our motivating example is drawn from invasive species biology, where it is common to know the precise location of invasive organisms that have been detected by a surveillance program, but at any time during the program there are invaders that have not been detected.

We propose a sequential importance sampling strategy to infer parameters under a Bayesian model of such a system. The strategy involves simulating multiple alternative states consistent with current knowledge of the system, as revealed by the observations. However, a difficult problem that arises is that observations made at a later time are invariably incompatible with previously simulated states.

To solve this problem, we propose a two-step iterative process in which states of the system are alternately simulated in accordance with past observations, then corrected in light of new observations. We identify criteria under which such corrections can be made while maintaining appropriate importance weights.

Firstly we have demonstrated the application of this methodology using an AR1 model as a toy problem. We then applied the new method to a self-exciting point process model for the Red Imported Fire Ants (RIFA) invasion in Brisbane. The issue of handling missing data in self-exciting point processes have been recently addressed by Tucker et al. (2018).

Possible Applications

We compare the results of our algorithm with the results obtained with

In statistics, imputation is the process of replacing missing data with substituted values.

$https://en.wikipedia.org/wiki/Imputation_(statistics)$
An explanation of the problem we are trying to solve The applications Other approaches to the problem (citations) How our approach differ Applications How the paper will be organised

2 Section title

Text

2.1 Subsection title

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Valentina Di Marco
School of Mathematical Science, Monash University, Clayton Campus, VIC 3800, Australia
Tel.: +61-4-23330509
E-mail: valentina.dimarco@monash.edu

Jonathan Keith
School of Mathematical Science, Monash University, Clayton Campus, VIC 3800, Australia

Daniel Spring
School of Ecosystem and Forest Sciences, The University of Melbourne, Parkville, Victoria 3010, Australia

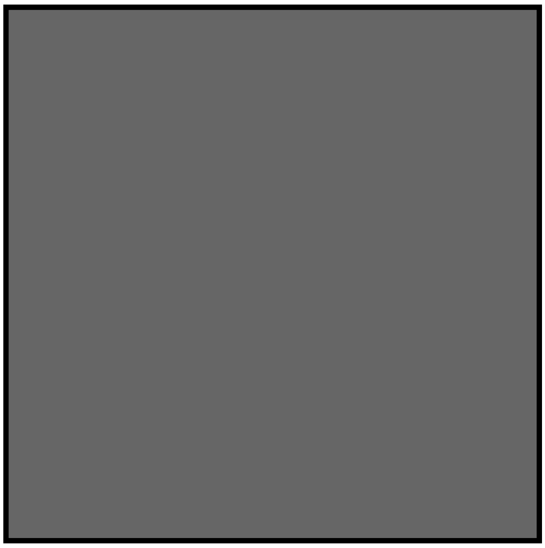

Fig. 1 Please write your figure caption here

Table 1 Please write your table caption here

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Paragraph headings Use paragraph headings as needed.

$$a^2 + b^2 = c^2 \tag{1}$$

References

Tucker D.J., Shand L., Lewis J.R.: Handling missing data in self-exciting point process models. Spatial Statistics (2018). https://doi.org/10.1016/j.spasta.2018.12.004

Andrieu C., Doucet A.: Particle filtering for partially observed Gaussian state space models. Journal of the Royal Statistical Society (2002). https://doi.org/10.1111/1467-9868.00363

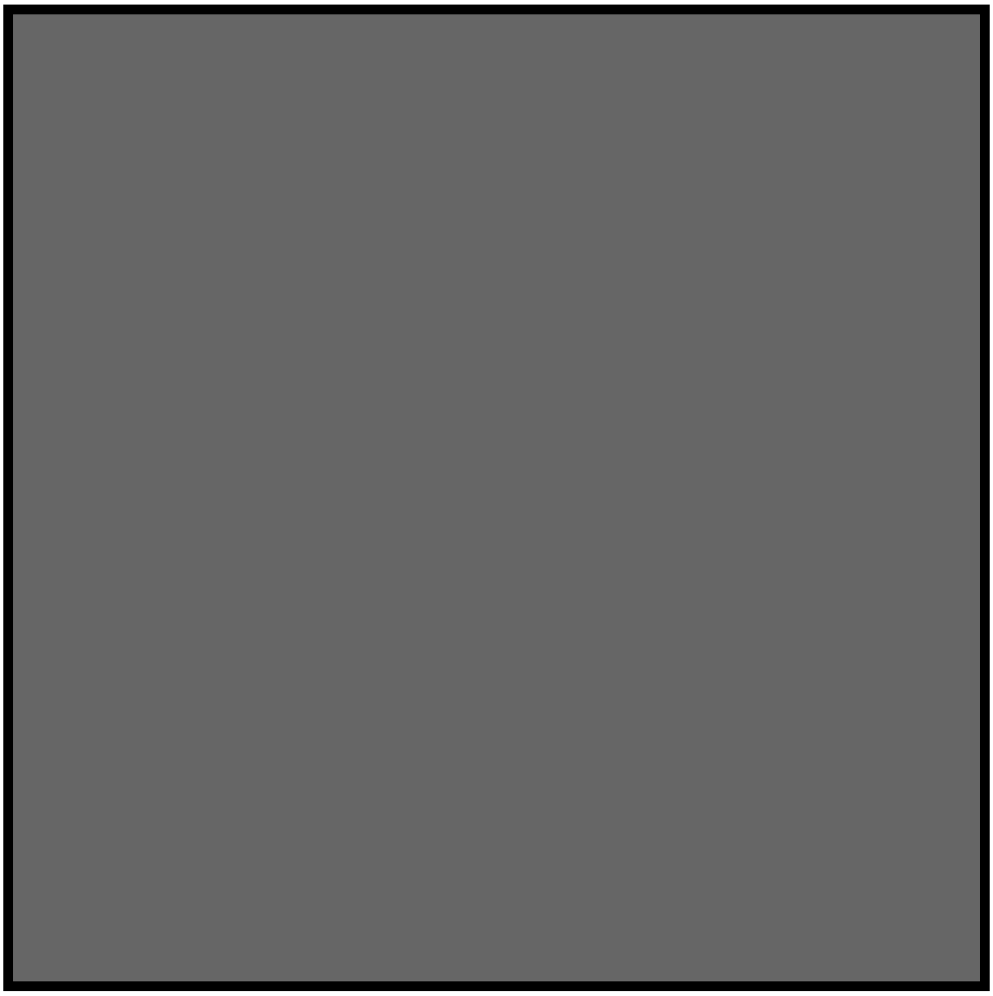

Fig. 2 Please write your figure caption here