Data Assimilation for Agent-Based Modelling: An Implementation of the Ensemble Kalman Filter

Keiran Suchak*[1], Nick Malleson†[1] and Jonathan Ward‡[2]

[1]School of Geography, University of Leeds
[2]School of Mathematics, University of Leeds

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A better understanding of how people move around their environment is of great utility to both academics and policy-makers. Such knowledge can be made use of in the contexts of urban planning, event management and emergency reposonse, particularly when considering urban environments. Furthermore, this would be of use to those interested in the social issues of mobility, inclusivity and accessibility of oppotunities.

When considering such concepts, investigators often make use of modelling techniques. At their most fundamental, models are a representation of our understanding of the system that we are studying — an understanding that may not be perfect. There exist modelling techniques for the simulation of how pedestrians move around urban spaces. However, these methods exist largely in isolation of the real-world — that is to say that whilst the simulations aim to reflect the real-world, there is no method by which we can incorporate up-to-date data into these models to stop their divergence from reality.

One of the most prevalant simulation methods in this field is that of Agent-Based Modelling. Such methods prescribe sets of rules by which individuals interact with each other and their local environments which often introduce some element of randomness in their evaluation. As a consequence we typically observe that simulation runs diverge from the real system.

Agent-based modellers often aim to combat this by using historical data to calibrate their model parameters and to set their model intial states (Thiele et al., 2014). Such a practice is appropriate for offline evaluations such as testing designs of new buildings or experimenting with different individual behaviours; however, when aiming to simulate events in real-time, this simply delays the inevitable divergence of the model from the real system. It may, therefore, appear that stochastic simulation methods are doomed to forever diverge from the real-systems that they seek to model, and one may

*K.Suchak@leeds.ac.uk
†N.S.Malleson@leeds.ac.uk
‡J.A.Ward@leeds.ac.uk

thus question the utility of modelling in the first place. Should we instead just rely on the data that is available to us?

The answer to this question is that there also exist issues with observational data from systems. Whilst models typically allow us to simulate a whole system, observations are typically sparse in either space or time (or both); this is to say that observations rarely provide complete coverage of the events that they seek to analyse.

This paper is consequently part of a wider programme of work[1] which aims to develop new methods that enable ABMs to make better use of real-world observations as they become available.

One of the methods by which we can combine the knowledge represented by our model with observations as they become available is through data assimilation techniques, which are most commonly used in the field of numerical weather prediction (Kalnay, 2003). Such techniques are typcically made up of two steps:

1. **Predict:** Run the model forward, estimating the state of the system, until new obserations become available.
2. **Update:** Upon receipt of new observations, combine the model's estimate of the system state with the new data.

These steps are repeated iteratively in a cycle.

The work that has been undertaken thus far to apply data assimilation techniques to agent-based modelling is relatively limited (Wang and Hu, 2015; Ward et al., 2016). This investigation, therefore, aims to follow-up on the work by Ward et al. (2016), which focused on the application of the Ensemble Kalman Filter data assimilation technique to a simple binary-state model. This investigation will apply the same data assimilation scheme to a more realistic model in which pedestrians are simulated as moving in 2-dimensional space. The talk will consequently aim to outline how data assimilation schemes work, how they can be applied to ABMs, and how such an implementation can be used to improve the accuracy with which the ABM models the real world.

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[1] `https://dust.leeds.ac.uk`