Building cities from slime mould, agents and quantum field theory.

Keynote Talk

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ABSTRACT

Managing the unprecedented growth of cities whilst ensuring that they are sustainable, healthy and equitable places to live, presents significant challenges. Our current thinking conceptualise cities as being driven by processes from the bottom-up, with an emphasis on the role that individual decisions and behaviour play. Multi-agent systems, and agent-based modelling in particular, are ideal frameworks for the analysis of such systems. However, identifying the important drivers within an urban system, translating key behaviours from data into rules, quantifying uncertainty and running models in real time all present significant challenges. We discuss how innovations in a diverse range of fields are influencing empirical agent-based models, and how models designed for the simplest biological systems might transform the ways that we understand and manage real cities.

KEYWORDS

agent-based modelling; urban analytics; slime mould; data assimilation; quantum field theory; uncertainty; behaviour

1 CITIES ARE COMPLEX SYSTEMS

Recent thinking conceptualises cities as complex systems driven by human decisions [11] and flows of information, money and goods [2]. This thinking puts individuals, their behaviour and decisions at the centre of any simulation that seek to capture how cities currently operate, and how they may evolve into the future. An individual-based approach such as agent-based modelling is a natural paradigm for urban simulation with its ability to both capture individual behaviour and movement over space and time. The key challenges for the use of agent-based models in simulating cities, that we discuss here, are: identifying and embedding behaviour, validating models with real data, and the quantification of uncertainty.

2 IDENTIFYING AND EMBEDDING BEHAVIOUR

One of the most attractive facets of agent-based modelling is its ability to simulate individual behaviour and its consequences over space and time. Identifying important behaviour is often undertaken through simple data analysis, qualitative assessment or researcher assumptions. New, rich, individual level data provide an opportunity for diverse approaches to be used to formulate key behavioural rules. Examples are beginning to appear in the literature, but are sparse [1].

One of the key issues that modellers face when simulating behaviour is that we still build rule sets that by their nature can only ever support relatively simplistic behaviour. For applications where the behaviour is not well understood there is a danger that we are overlooking the key drivers of the system under consideration. Embedding behavioural realism into our models must be a priority if agent-based modelling is to transition from simple toy models to models of genuine utility for practitioners.

3 THE DARK ARTS: VALIDATION AND UNCERTAINTY QUANTIFICATION

Validation

The growth in available data, particularly high-resolution *temporal* data, coupled with increasing computing power, is fostering the development of innovative methods to tackle some of the most difficult and controversial aspects of agent-based modelling: namely validation.

The validation of agent-based models remains a dark art at worst and haphazard at best. It is well known that metrics are needed that can be applied to identifying and validating patterns (and thus processes) over multiple spatial and temporal scales, particularly when models include complex human decision models [10]. Some 'big' data sources offer the potential to validate behaviours directly, or at least over very fine spatial/temporal scales. For example, near real-time sensors that measure population flow rates have very limited information about the individuals themselves (which is absolutely essential to maintain personal privacy), but these data can be used to evaluate potential agent-based models of routine urban activity and thus shed light on the potential socio-demographics and activities of visitors to town centres [3].

The quality of the validation of agent-based models is also benefiting from a movement towards the use of standard tools and methods [13]. For example, Bayesian methods, such as Approximate Bayesian Computation, allow prior information to be included in the model estimation process which provides a more nuanced treatment of the uncertainty of the model and its parameters (more on this shortly) as well as potentially greater efficiency than typical simulated minimum distance techniques [6].

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Uncertainty Quantification

Although reliable validation helps to ensure that models are robustly simulating the target system, to achieve a level of credibility within policy arenas we need to be able to quantify the certainty in the predictions made. Uncertainty can be introduced through measurement noise, the choice of model parameter values, or as a result of the structure of the model itself [5], including through the behavioural rules used in agent-based simulations. Existing optimisation techniques can help to reduce parameter uncertainty and new data can help to reduce observation uncertainty, but what about *model* uncertainty?

To this end, new probabilistic modelling frameworks and associated probabilistic programming languages might offer an elegant means of better expressing internal uncertainty. For example, where specific model variables are uncertain these can be expressed as probability distributions rather than as specific values; see Evans et al. [4] for example. Or, to take it a step further, agent-based models could be built using the language of quantum field theory [12] as this has been developed to describe systems that are fundamentally uncertain. In cases where a model of a complex system can be shown to be performing adequately, but will still naturally diverge away from reality as the two systems evolve, *data assimilation* techniques can be adapted from fields such as meteorology to provide a means of re-aligning a model to the actual system in *real time* [8, 9, 14].

4 SUMMARY

We have outlined some recent innovations that have the potential to speed up the transition of urban agent-based modelling from an exploratory research tool to a trusted methodology that has an important place in policy decisions. However, all of the aforementioned approaches are largely untested, at least on real systems, and may not be appropriate for use with agent-based models or with systems built from discrete, decision-making entities in the first place. Hence simpler systems are needed to develop and test these new methods, but these systems must exhibit some complex behaviour (e.g. emergence, feedback loops, non-linear behaviour, etc.) and there must be sufficient data about them to allow their 'true' state to be observed. To this end, perhaps biological systems such as *Physarum polycephalum* – 'slime mould' – provide the ideal test bed. The rules that underpin their behaviour are reasonably well understood, they exhibit complex outcomes, they can (and have been) observed in great detail, and they can be modelled reliably using agent-based modelling [7]. Whilst there are many methodological challenges that agent-based modelling presents, ongoing work is moving the discipline towards robustly validated models containing behavioural realism.

BIOGRAPHY

Alison Heppenstall is Professor of Geocomputation at the University of Leeds (UK) and an ESRC-Turing Fellow at the Alan Turing Institute (London, UK). AH is currently developing approaches for the emerging field of urban analytics, including the detection of 'hidden' spatio-temporal patterns in 'big data', quantifying uncertainty in agent-based models and building more robust models of multi-agent systems through probabilistic programming and reinforcement learning. Her work has been funded by numerous funding agencies and the outputs have featured in national and international media outlets.

Nick Malleson is a Professor of Spatial Science at the University of Leeds, UK. He has a PhD in Geography and undergraduate degrees in Computer Science (BSc) and Multidiciplinary Informatics (MSc). Most of his research focuses on the development of agent-based models aimed at understanding and explaining social phenomena. He has particular interests in simulations of crime patterns, in models that can be used to describe the flows of people around cities, and in how âĂŸbig dataâĂŹ, agent-based modelling, and smart cities initiatives can be used to better understand the daily dynamics of cities and reduce the impacts of phenomena such as pollution or crime.

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REFERENCES

[1] Shaheen A. Abdulkareem, Yaseen T. Mustafa, Ellen-Wien Augustijn, and Tatiana Filatova. 2019. Bayesian networks for spatial learning: a workflow on using limited survey data for intelligent learning in spatial agent-based models. *GeoInformatica* 23, 2 (April 2019), 243–268. https://doi.org/10.1007/s10707-019-00347-0

[2] M. Batty. 2013. *The New Science of Cities*. MIT Press, Cambridge, MA. bibtex: batty_new_2013.

[3] Tomas Crols and Nick Malleson. 2019. Quantifying the Ambient Population Using Hourly Population Footfall Data and an Agent-Based Model of Daily Mobility. *GeoInformatica* 23, 2 (2019), 201–220. https://doi.org/10.1007/s10707-019-00346-1

[4] Owain Evans, Andreas Stuhlmüller, John Salvatier, and Daniel Filan. 2017. Modeling Agents with Probabilistic Programs. (2017).

[5] Zoubin Ghahramani. 2015. Probabilistic Machine Learning and Artificial Intelligence. *Nature* 521, 7553 (2015), 452–459. https://doi.org/10.1038/nature14541

[6] Jakob Grazzini, Matteo G. Richiardi, and Mike Tsionas. 2017. Bayesian Estimation of Agent-Based Models. *Journal of Economic Dynamics and Control* 77 (2017), 26–47. https://doi.org/10.1016/j.jedc.2017.01.014

[7] Jeff Jones. 2015. *From Pattern Formation to Material Computation: Multi-Agent Modelling of Physarum Polycephalum.*

[8] Le-Minh Kieu, Nicolas Malleson, and Alison Heppenstall. 2020. Dealing with Uncertainty in Agent-Based Models for Short-Term Predictions. *Royal Society Open Science* 7, 1 (2020), 191074. https://doi.org/10.1098/rsos.191074

[9] Jordan Lueck, Jason H. Rife, Samarth Swarup, and Nassin Uddin. 2019. Who Goes There? Using an Agent-Based Simulation for Tracking Population Movement. In *Winter Simulation Conference, Dec 8 - 11, 2019*. National Harbor, MD, USA.

[10] Birgit Müller, Friedrich Bohn, Gunnar Dreßler, Jürgen Groeneveld, Christian Klassert, Romina Martin, Maja Schlüter, Jule Schulze, Hanna Weise, and Nina Schwarz. 2013. Describing Human Decisions in Agent-Based Models – ODD + D, an Extension of the ODD Protocol. *Environmental Modelling & Software* 48 (2013), 37–48. https://doi.org/10.1016/j.envsoft.2013.06.003

[11] David OâĂŹSullivan, James Millington, George Perry, and John Wainwright. 2012. Agent-Based Models âĂŞ Because TheyâĂŹre Worth It? In *Agent-Based Models of Geographical Systems*. Springer, Dordrecht, 109–123. https://doi.org/10.1007/978-90-481-8927-4_6

[12] Daniel Tang. 2019. Data Assimilation in Agent-Based Models Using Creation and Annihilation Operators. *arXiv:1910.09442 [cs]* (2019). arXiv:cs/1910.09442

[13] Jan C. Thiele, Winfried Kurth, and Volker Grimm. 2014. Facilitating Parameter Estimation and Sensitivity Analysis of Agent-Based Models: A Cookbook Using NetLogo and 'R'. *Journal of Artificial Societies and Social Simulation* 17, 3 (2014). https://doi.org/10.18564/jasss.2503

[14] Minghao Wang and Xiaolin Hu. 2015. Data Assimilation in Agent Based Simulation of Smart Environments Using Particle Filters. *Simulation Modelling Practice and Theory* 56 (2015), 36–54. https://doi.org/10.1016/j.simpat.2015.05.001