Accelerating policy optimisation in agent-based models with causal abstractions

Joel Dyer
Senior Research Associate, Department of Computer Science
Senior Research Fellow, Oxford Institute for New Economic Thinking
University of Oxford

Introductions

- PhD in Mathematics with J. Doyne Farmer
- Briefly a Research Scientist at Improbable
- Now: Postdoc at Oxford Computer Science Department & Oxford INET

Personal website: joelnmdyer.github.io

Introductions

Our group on "Robust Agent-based Modelling at Scale":






Group website: `LargeAgentCollider.github.io`

(Some of) the tools we have developed for agent-based modelling

1. Parameter inference/calibration

Journal of Economic Dynamics and Control
Volume 161, April 2024, 104827

Black-box Bayesian inference for agent-based models

Joel Dyer [a b], Patrick Cannon, J. Doyne Farmer [a c d], Sebastian M. Schmon

sbi4abm Public

Black-box Bayesian inference for agent-based models

Python ☆ 15 7

GitHub: https://github.com/joelnmdyer/sbi4abm

(Some of) the tools we have developed for agent-based modelling

1. Parameter inference/calibration

Forecasting Macroeconomic Dynamics using a Calibrated Data-Driven Agent-based Model*

Samuel Wiese[a,b,†], Jagoda Kaszowska-Mojsa[a,c,d], Joel Dyer[a,b], José Moran[e,a], Marco Pangallo[a,f], François Lafond[a,g], John Muellbauer[a,h], Anisoara Calinescu[a,b], J. Doyne Farmer[a,e,g,i]

GitHub: https://github.com/joelnmdyer/sbi4abm

(Some of) the tools we have developed for agent-based modelling

1. Parameter inference/calibration (with model gradients)

Gradient-Assisted Calibration for Financial Agent-Based Models

Joel Dyer*
University of Oxford
Oxford, United Kingdom
joel.dyer@cs.ox.ac.uk

Arnau Quera-Bofarull*
University of Oxford
Oxford, United Kingdom
arnau.quera-bofarull@cs.ox.ac.uk

Ayush Chopra
Massachusetts Institute of Technology
Boston, USA
ayushc@mit.edu

J. Doyne Farmer
University of Oxford
Oxford, United Kingdom
doyne.farmer@inet.ox.ac.uk

Anisoara Calinescu
University of Oxford
Oxford, United Kingdom
ani.calinescu@cs.ox.ac.uk

Michael Wooldridge
University of Oxford
Oxford, United Kingdom
mjw@cs.ox.ac.uk

BlackBIRDS

Contributors 2

arnauqb Arnau Quera-Bofarull

joelnmdyer Joel Dyer

PyPI link: https://pypi.org/project/blackbirds/

(Some of) the tools we have developed for agent-based modelling

1. Parameter inference/calibration (with model gradients)

Some challenges of calibrating differentiable agent-based models

Arnau Quera-Bofarull [*1] **Joel Dyer** [*1 2] **Anisoara Calinescu** [1] **Michael Wooldridge** [1]
[1]Department of Computer Science, University of Oxford [2]Institute for New Economic Thinking, Oxford
[*]Equal contribution

PyPI link: https://pypi.org/project/blackbirds/

(Some of) the tools we have developed for agent-based modelling

2. Synthetic population & scenario generators

Full Research Paper | AAMAS 2024, May 6–10, 2024, Auckland, New Zealand

Population Synthesis as Scenario Generation for Simulation-based Planning under Uncertainty

Joel Dyer
University of Oxford
joel.dyer@cs.ox.ac.uk

Arnau Quera-Bofarull
University of Oxford

Nicholas Bishop
University of Oxford

J. Doyne Farmer
University of Oxford

Anisoara Calinescu
University of Oxford

Michael Wooldridge
University of Oxford

joelnmdyer / **synthpop** Public

Populating agent-based models with agents who give rise to dynamics and scenarios of interest

MIT license

8 stars 1 fork Branches Tags Activity

GitHub link: https://github.com/joelnmdyer/synthpop

(Some of) the tools we have developed for agent-based modelling

3. Tools for experimenting with policies and interventions **(this talk)**

Interventionally Consistent Surrogates for Complex Simulation Models

Joel Dyer*
University of Oxford

Nicholas Bishop
University of Oxford

Yorgos Felekis
University of Warwick

Fabio Massimo Zennaro
University of Bergen

Anisoara Calinescu
University of Oxford

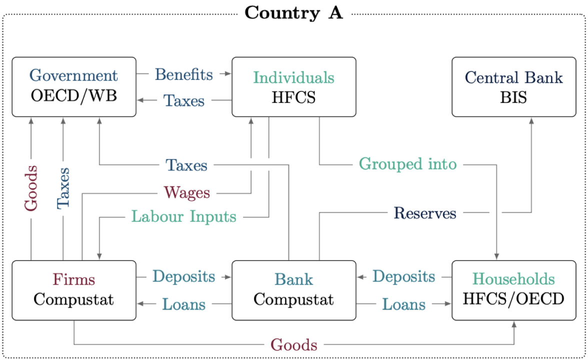
Theodoros Damoulas
University of Warwick

Michael Wooldridge
University of Oxford

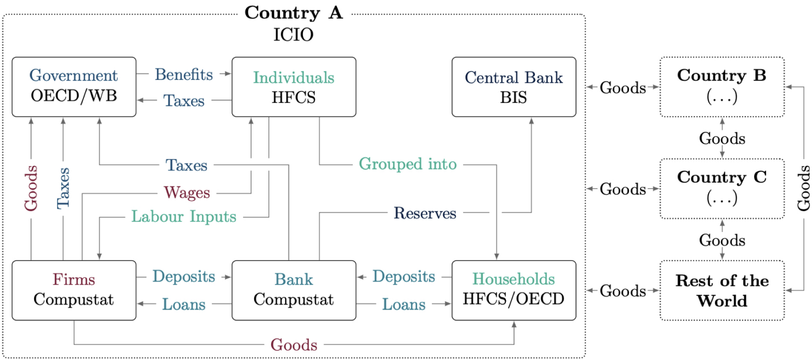
Accepted and forthcoming at *NeurIPS* 2024

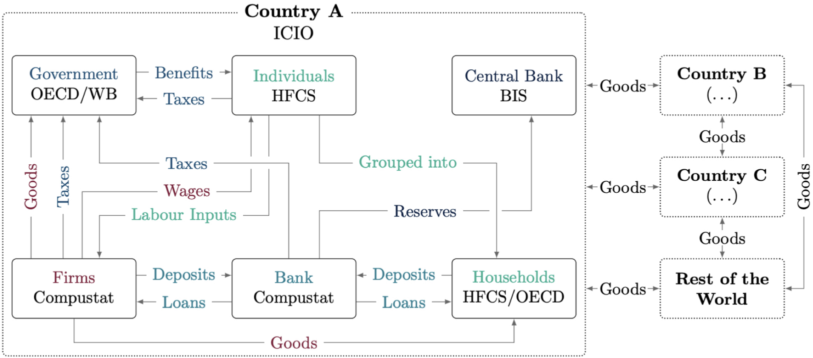
A complex simulation model: INET's macroeconomic ABM



A complex simulation model: INET's macroeconomic ABM



A complex simulation model: INET's macroeconomic ABM



Things can quickly become computationally expensive!

Emergent properties are often the ultimate points of interest

- In the INET macroeconomic model (Wiese et al., 2024), aggregate macro quantities (GDP, consumption, investment, inflation etc.) are of primary interest.
- In models of flood risk mitigation behaviours (e.g., Geaves et al. (2024)), quantities of interest are things like the proportion of the population that adopts different precautionary measures in response to flood risks (e.g., do nothing, purchasing insurance, purchase property-level protection etc.).
- In pandemic simulators (e.g., Kerr et al. (2021)), aggregate quantities such as the number of infections/tests/hospitalisations/etc. by region and over time are of interest.

We'd like to experiment with ABMs to model the potential effects of policy interventions on these macroscopic, emergent properties of interest.

How can we reduce the computational cost of these kinds of experiments?

Interventionally consistent surrogates for complex simulation models

Possible solution:

- Find cheaper *surrogate* model that:
  - behaves consistently with the complex agent-based model, with respect to interventions of interest;
  - models the macroscopic/emergent dynamics of interest to the policymaker directly.
- Optimal intervention(s) can then be found by *experimenting with the cheaper surrogate model*.

Need to ensure surrogate is "causally" consistent with the original, complex simulator; more specifically, **interventionally** consistent. How could we achieve this?

How to train your interventionally consistent surrogate model

How to train your interventionally consistent surrogate model

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How to train your interventionally consistent surrogate model

$$\boldsymbol{\iota} \xrightarrow[\boldsymbol{M}]{\hspace{8em}}$$

How to train your interventionally consistent surrogate model

$$\iota \xrightarrow[M]{\qquad\qquad} \mathbb{P}_{M_\iota}$$

How to train your interventionally consistent surrogate model

$$\begin{tikzcd} & {} \\ \iota \arrow[r, "M"'] & \mathbb{P}_{M_\iota} \arrow[u, "\tau"'] \end{tikzcd}$$

How to train your interventionally consistent surrogate model

$$
\begin{tikzcd}
 & \tau_{\#}\left(\mathbb{P}_{M_\iota}\right) \\
\iota \arrow[r, "M"'] & \mathbb{P}_{M_\iota} \arrow[u, "\tau"']
\end{tikzcd}
$$

How to train your interventionally consistent surrogate model

$$
\begin{tikzcd}
\omega(\iota) & \tau_{\#}\left(\mathbb{P}_{M_\iota}\right) \\
\iota \arrow[u, "\omega"] \arrow[r, "M"'] & \mathbb{P}_{M_\iota} \arrow[u, "\tau"']
\end{tikzcd}
$$

$$\begin{tikzcd}
\omega(\iota) \arrow[r, "M'"] & {} & \\
& & \tau_{\#}\left(\mathbb{P}_{M_\iota}\right) \\
\iota \arrow[uu, "\omega"] \arrow[rr, "M"'] & & \mathbb{P}_{M_\iota} \arrow[u, "\tau"']
\end{tikzcd}$$

$$
\begin{tikzcd}
\omega(\iota) \arrow[r, "M'"] & \mathbb{P}_{M'_{\omega(\iota)}} & \\
& & \tau_{\#}\left(\mathbb{P}_{M_\iota}\right) \\
\iota \arrow[uu, "\omega"] \arrow[rr, "M"'] & & \mathbb{P}_{M_\iota} \arrow[u, "\tau"']
\end{tikzcd}
$$

How to train your interventionally consistent surrogate model

$$
\begin{tikzcd}
\omega(\iota) \arrow[r, "M'"] & \mathbb{P}_{M'_{\omega(\iota)}} \arrow[dr, leftrightarrow, "d\left(\tau_{\#}\left(\mathbb{P}_{M_\iota}\right), \mathbb{P}_{M'_{\omega(\iota)}}\right)"] & \\
 & & \tau_{\#}\left(\mathbb{P}_{M_\iota}\right) \\
\iota \arrow[uu, "\omega"] \arrow[rr, "M"'] & & \mathbb{P}_{M_\iota} \arrow[u, "\tau"']
\end{tikzcd}
$$

$$\min_{\substack{\omega \in \Omega, \\ M' \in \mathscr{M}}} \quad d\left(\tau_{\#}\left(\mathbb{P}_{M_\iota}\right), \mathbb{P}_{M'_{\omega(\iota)}}\right)$$

How to train your interventionally consistent surrogate model

$$\min_{\substack{\omega \in \Omega, \\ M' \in \mathscr{M}}} \max_{\iota} d\left(\tau_{\#}\left(\mathbb{P}_{M_\iota}\right), \mathbb{P}_{M'_{\omega(\iota)}}\right)$$

(See Beckers et al. (2020))

How to train your interventionally consistent surrogate model

$$\min_{\substack{\omega \in \Omega, \\ M' \in \mathscr{M}}} \mathbb{E}_{\iota \sim \eta} \left[d \left(\tau_{\#} \left(\mathbb{P}_{M_\iota} \right), \mathbb{P}_{M'_{\omega(\iota)}} \right) \right]$$

(See Dyer et al. (2024))

η can be chosen to reflect your/the policymaker's preferences for different policies/interventions.

How to train your interventionally consistent surrogate model

$$\min_{\substack{\phi \in \Phi, \\ \psi \in \Psi}} \mathbb{E}_{\iota \sim \eta} \left[d\left(\tau_{\#}\left(\mathbb{P}_{M_\iota}\right), \mathbb{P}_{M^{\psi}_{\omega^{\phi}(\iota)}} \right) \right]$$

$$\Omega = \{\omega^{\phi} \mid \phi \in \Phi\} \qquad \mathscr{M} = \{M^{\psi} \mid \psi \in \Psi\}$$

How to train your interventionally consistent surrogate model

We use the Kullback-Leibler (KL) divergence, and take gradient steps:

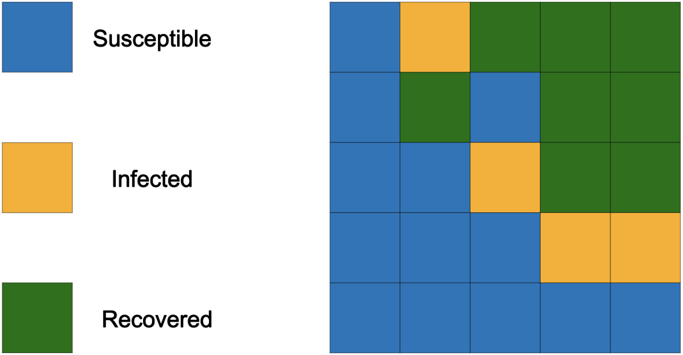
$$\nabla_{\phi,\psi}\mathbb{E}_{\iota\sim\eta}\left[\mathrm{KL}\left(\tau_{\#}\left(\mathbb{P}_{M_\iota}\right)\,\middle\|\,\mathbb{P}_{M^{\psi}_{\omega^{\phi}(\iota)}}\right)\right]$$

$$\approx \frac{1}{B}\sum_{b=1}^{B} -\nabla_{\phi,\psi}\log q^{\psi}_{\omega^{\phi}(\iota^{(b)})}\left(y^{(b)}\right),$$

$$\iota^{(b)} \sim \eta, \qquad y^{(b)} \sim \tau_{\#}\left(\mathbb{P}_{M_{\iota^{(b)}}}\right)$$

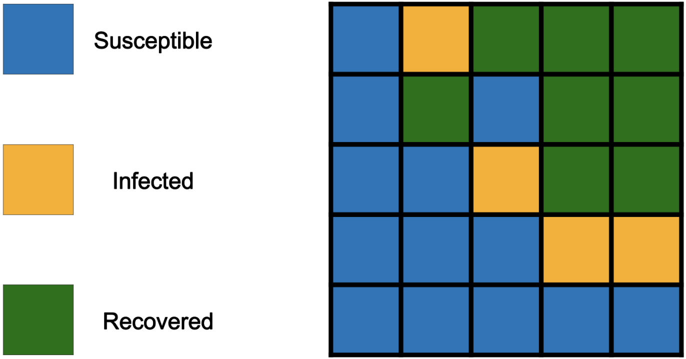
Case study: SIRS Epidemics

Business as usual:

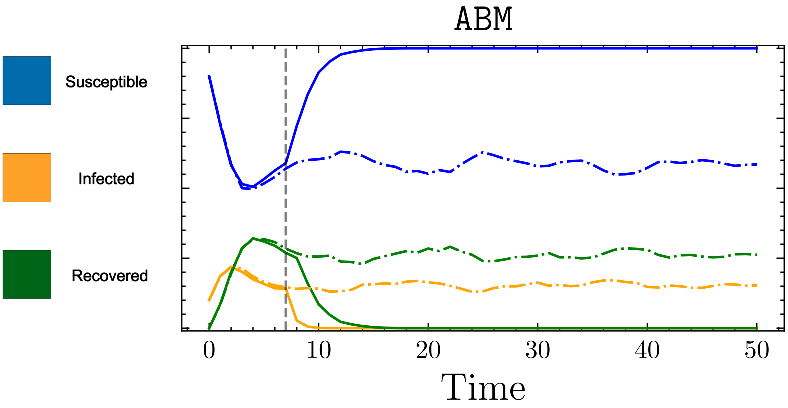


Case study: SIRS Epidemics

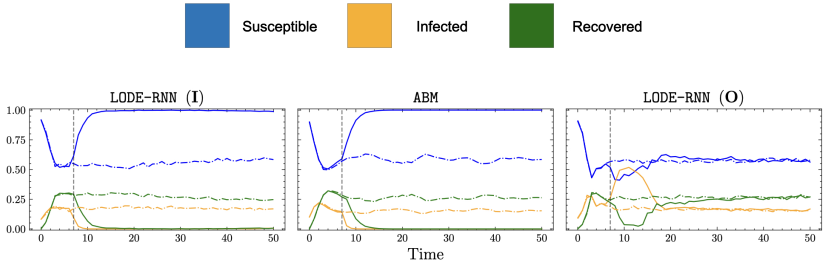
Lockdown:



Case study: SIRS Epidemics



Case study: SIRS Epidemics



Case study: SIRS Epidemics

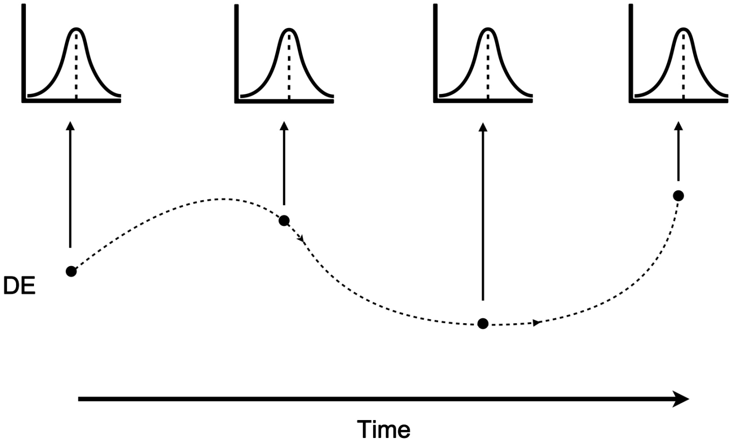
What benefits do we see from finding an interventionally consistent surrogate model using our method?

Table 1: Metrics for interventionally (**I**) & observationally (**O**) trained surrogates on interventional (**I′**) & observational (**O′**) test sets ($\text{median}_{\text{first quartile}}^{\text{third quartile}}$ from 5 repeats). **Bold** denotes best performance.

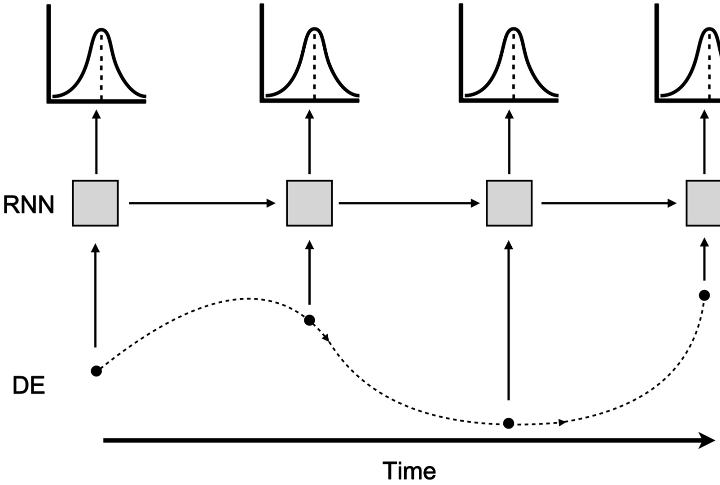
Test	Model	LRNN		LODE-RNN		LODE	
	Train	**I**	**O**	**I**	**O**	**I**	**O**
I′	AMSE ($\times 10^{-1}$)	$\mathbf{3.48_{3.41}^{3.91}}$	$49.4_{46.7}^{52.6}$	$\mathbf{3.35_{3.18}^{3.41}}$	$18.5_{17.1}^{21.9}$	$\mathbf{8.15_{8.06}^{8.24}}$	$22.4_{22.1}^{22.7}$
	ANLL ($\times 10^{3}$)	$\mathbf{2.09_{2.03}^{2.16}}$	$21.8_{20.1}^{22.9}$	$\mathbf{1.99_{1.98}^{2.00}}$	$8.40_{8.27}^{9.89}$	$\mathbf{4.01_{4.00}^{4.02}}$	$10.0_{9.91}^{10.1}$
O′	AMSE ($\times 10^{-1}$)	$4.13_{4.11}^{4.26}$	$\mathbf{2.95_{2.62}^{3.16}}$	$3.59_{3.54}^{3.68}$	$\mathbf{2.52_{2.16}^{2.78}}$	$18.4_{18.1}^{18.7}$	$\mathbf{4.36_{4.32}^{4.40}}$
	ANLL ($\times 10^{3}$)	$2.22_{2.16}^{2.23}$	$\mathbf{1.64_{1.43}^{1.71}}$	$1.86_{1.85}^{1.97}$	$\mathbf{1.43_{1.27}^{1.53}}$	$7.63_{7.52}^{7.74}$	$\mathbf{2.15_{2.13}^{2.17}}$

- Only slight reduction in performance on non-interventional distributions compared to standard surrogate methods.
- Dramatic reduction in state space: 1000s to 3 (over time).
- Substantial reduction in simulation time: 3-30x reduction in CPU time.

What surrogate families could you use?



What surrogate families could you use?



Transfer of experiments between causal models

Causally Abstracted Multi-armed Bandits

Fabio Massimo Zennaro[1] Nicholas Bishop[2] Joel Dyer[2] Yorgos Felekis[3] Anisoara Calinescu[2]
Michael Wooldridge[2] Theodoros Damoulas[3]

Oral at The 40th Conference on Uncertainty in Artificial Intelligence (2024)

Summary & conclusion

- We present the first practical method for learning interventionally consistent surrogates for complex (e.g., agent-based) simulation models.
- Our approach is well-motivated by, and theoretically grounded in, the theory of causal abstractions.
- We demonstrated in two case studies* that our learning procedure produces surrogates that preserve relevant causal relationships of interest, facilitating rapid experimentation with, and optimisation of, policy interventions.

Thank you!

*We see qualitatively similar results for predator-prey simulator.

Sander Beckers, Frederick Eberhardt, and Joseph Y Halpern. Approximate causal abstractions. In *Uncertainty in artificial intelligence*, pages 606–615. PMLR, 2020.

Joel Dyer, Nicholas Bishop, Yorgos Felekis, Fabio Massimo Zennaro, Anisoara Calinescu, Theodoros Damoulas, and Michael Wooldridge. Interventionally consistent surrogates for complex simulation models. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL https://openreview.net/forum?id=UtTjgMDTFO.

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