

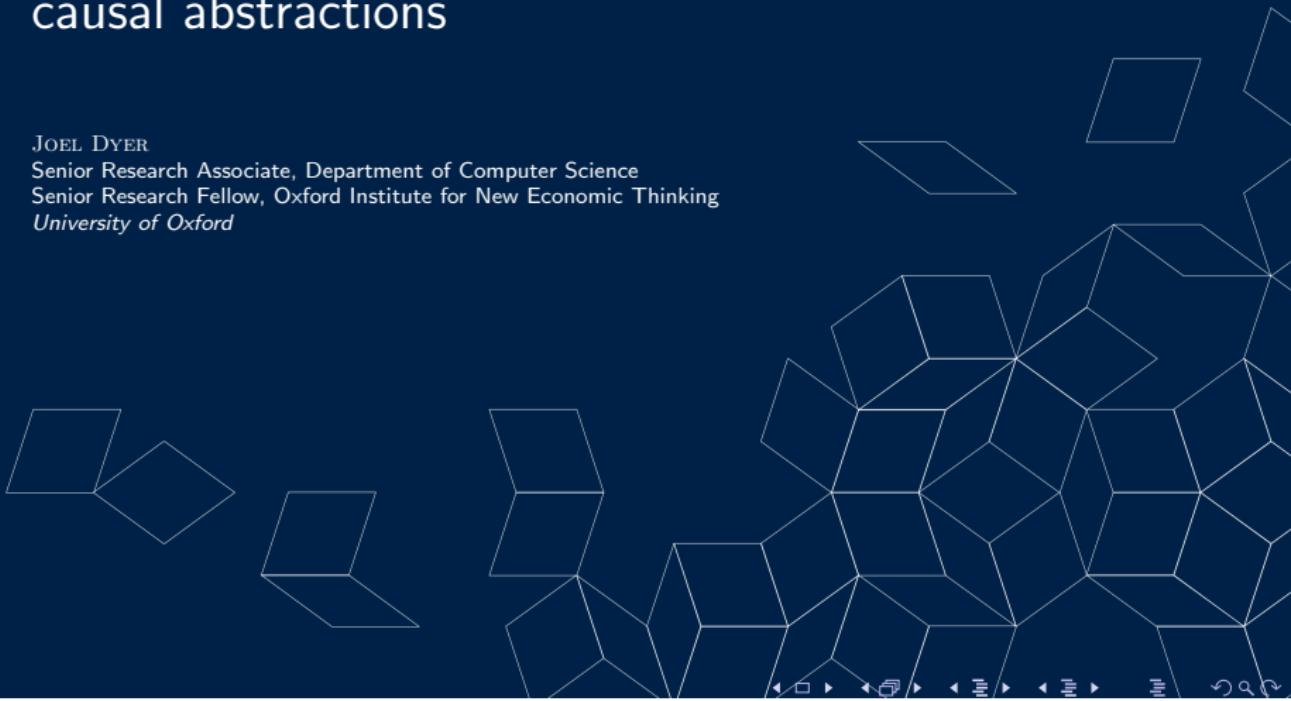
Accelerating policy optimisation in agent-based models with causal abstractions

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

The screenshot shows a GitHub repository card for 'sbi4abm'. At the top, it displays the journal logo for 'Journal of Economic Dynamics and Control' (Volume 161, April 2024, 104827), the article title 'Black-box Bayesian inference for agent-based models', and the authors' names: Joel Dyer, Patrick Cannon, J. Doyne Farmer, and Sebastian M. Schmon. Below this, the GitHub card includes the repository name 'sbi4abm', the status 'Public', a description 'Black-box Bayesian inference for agent-based models', a language indicator 'Python', a star count of '15', and a commit count of '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		
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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^{*12} Anisoara Calinescu¹ Michael Wooldridge¹

¹Department of Computer Science, University of Oxford ²Institute 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](https://github.com/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

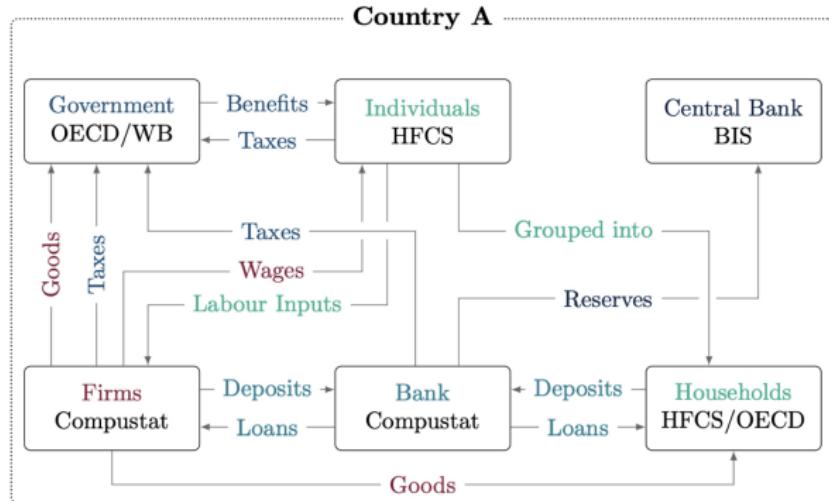
Theodoros Damoulas
University of Warwick

Michael Wooldridge
University of Oxford

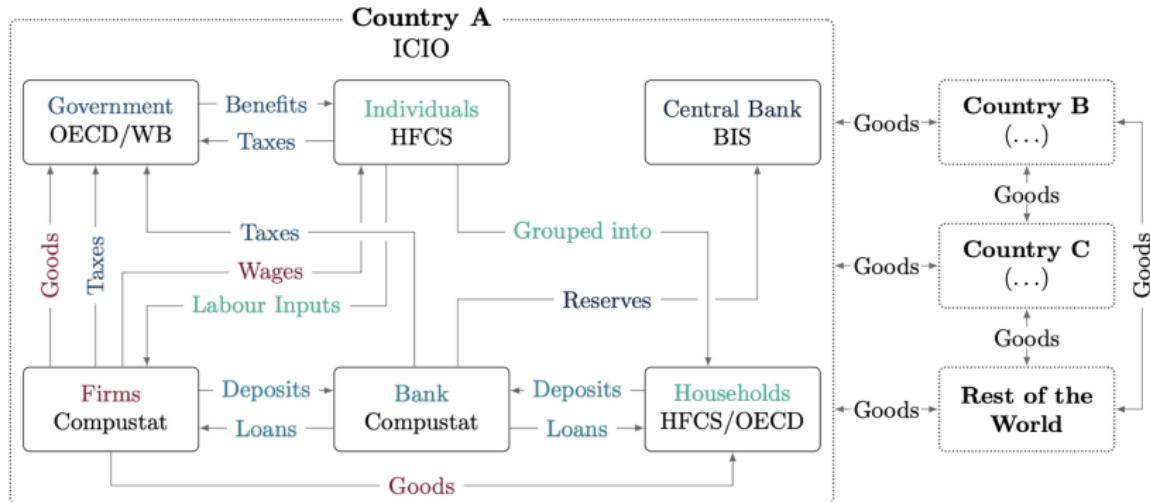
Accepted and forthcoming at *NeurIPS 2024*



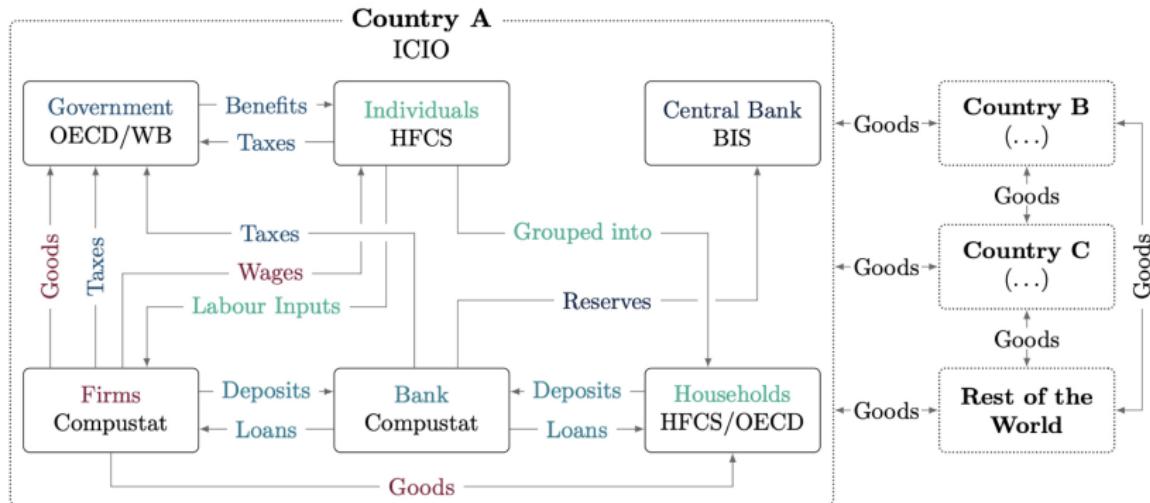
A complex simulation model: INET's macroeconomic ABM



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?

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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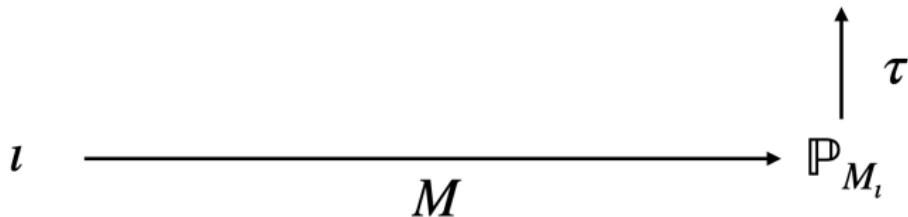
How to train your interventionally consistent surrogate model

$$l \longrightarrow M$$

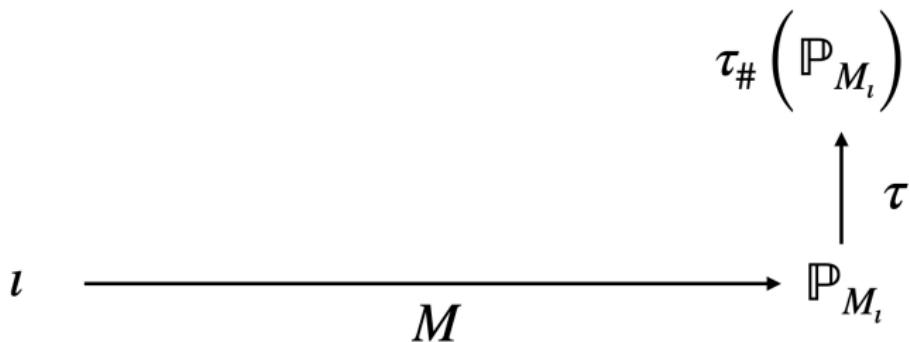
How to train your interventionally consistent surrogate model

$$l \xrightarrow{M} \mathbb{P}_{M_l}$$

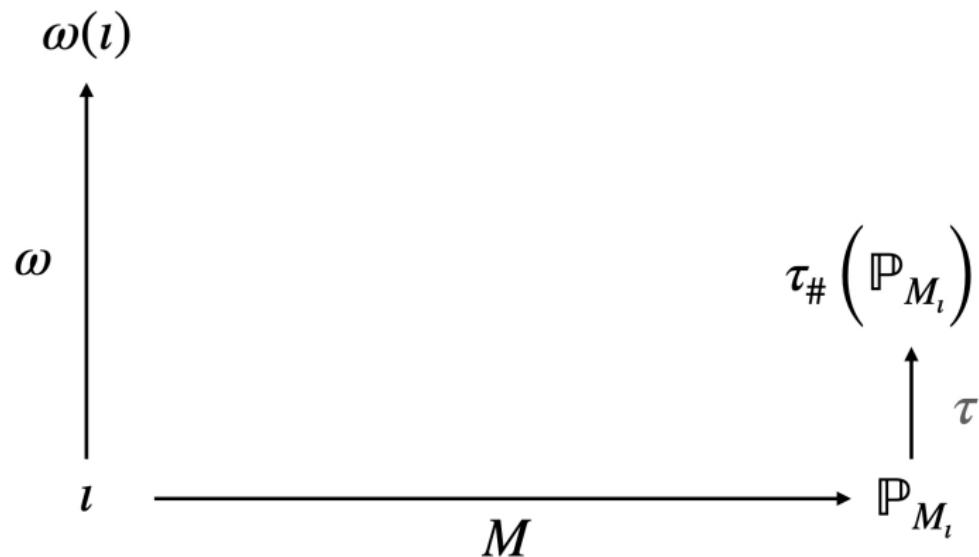
How to train your interventionally consistent surrogate model



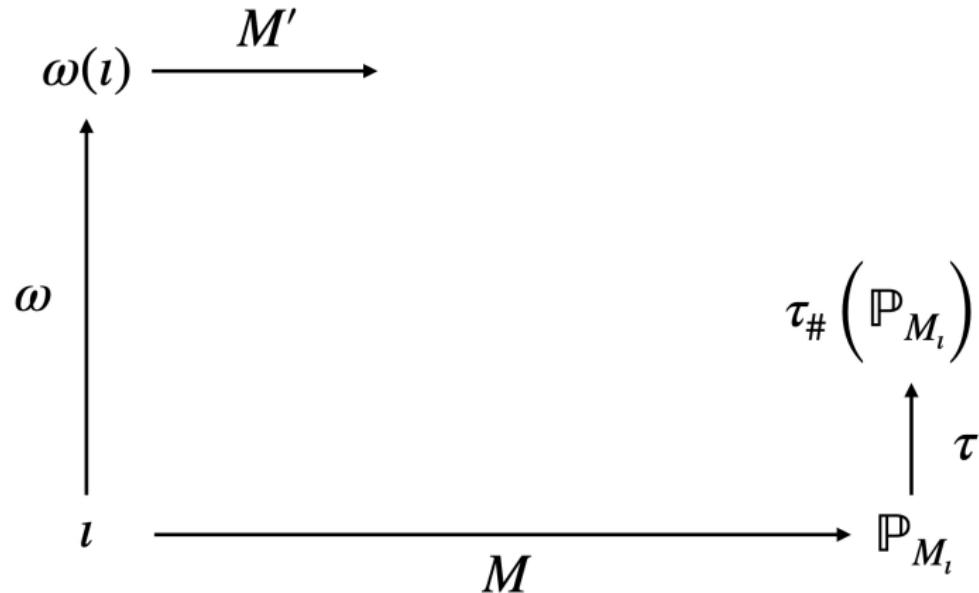
How to train your interventionally consistent surrogate model



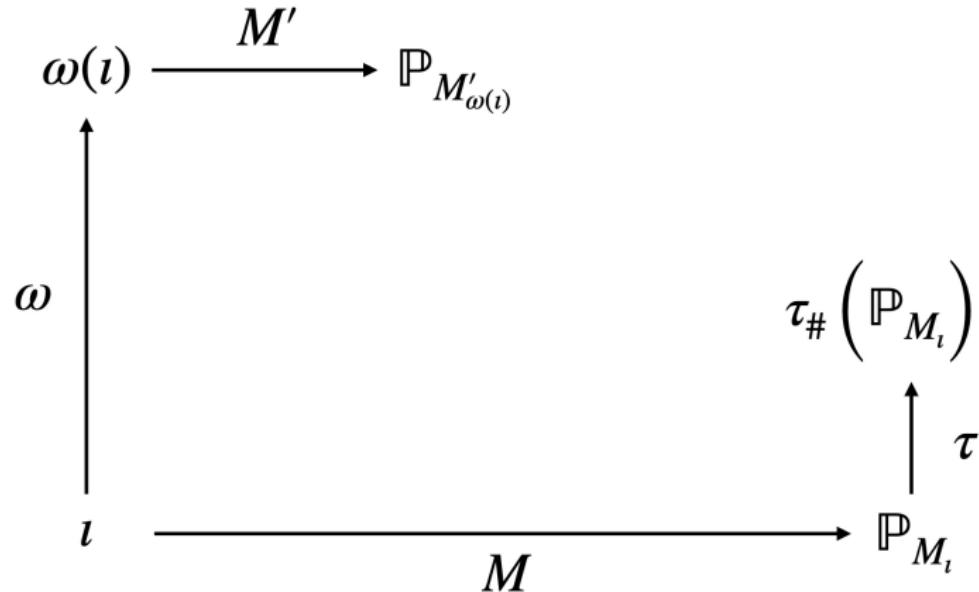
How to train your interventionally consistent surrogate model



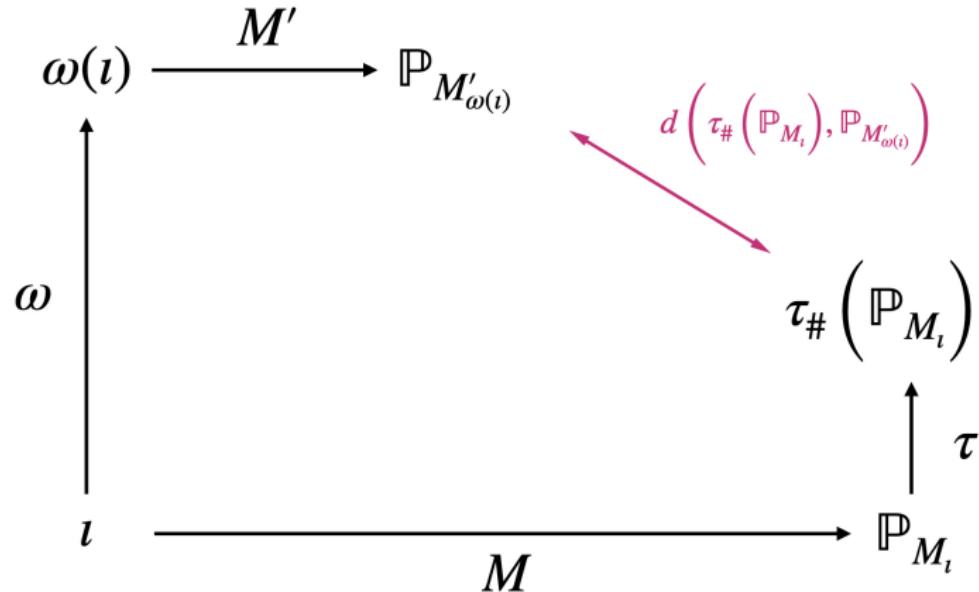
How to train your interventionally consistent surrogate model



How to train your interventionally consistent surrogate model



How to train your interventionally consistent surrogate model



How to train your interventionally consistent surrogate model

$$\min_{\substack{\omega \in \Omega, \\ M' \in \mathcal{M}}} d \left(\tau_{\#} \left(\mathbb{P}_{M_l} \right), \mathbb{P}_{M'_{\omega(l)}} \right)$$

How to train your interventionally consistent surrogate model

$$\min_{\omega \in \Omega, M' \in \mathcal{M}} \max_l d \left(\tau_{\#} \left(\mathbb{P}_{M_l} \right), \mathbb{P}_{M'_{\omega(l)}} \right)$$

(See Beckers et al. (2020))

How to train your interventionally consistent surrogate model

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

(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

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

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

How to train your interventionally consistent surrogate model

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

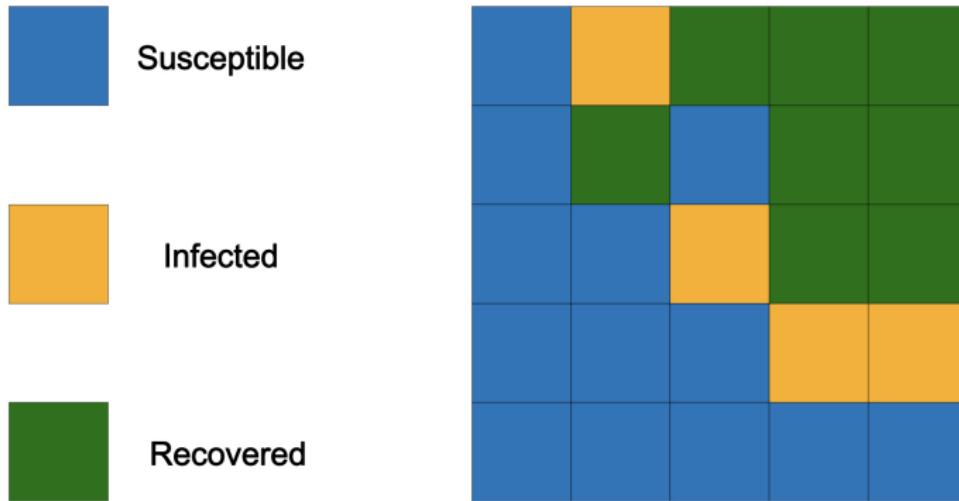
$$\nabla_{\phi,\psi} \mathbb{E}_{l \sim \eta} \left[\text{KL} \left(\tau_{\#} \left(\mathbb{P}_{M_l} \right) \parallel \mathbb{P}_{M_{\omega^{\phi(l)}}}^{\psi} \right) \right]$$

$$\approx \frac{1}{B} \sum_{b=1}^B -\nabla_{\phi,\psi} \log q_{\omega^{\phi(l^{(b)})}}^{\psi} (y^{(b)}),$$

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

Case study: SIRS Epidemics

Business as usual:



Case study: SIRS Epidemics

Lockdown:



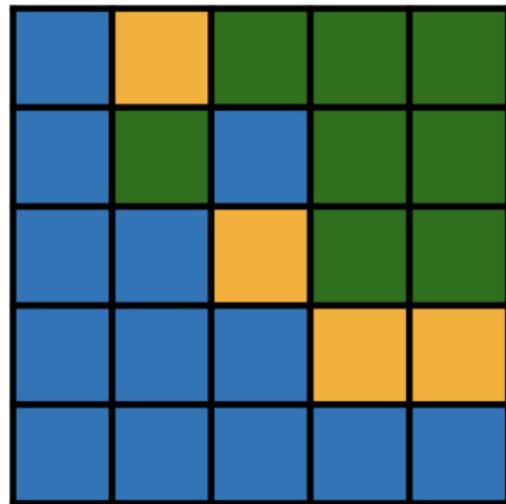
Susceptible



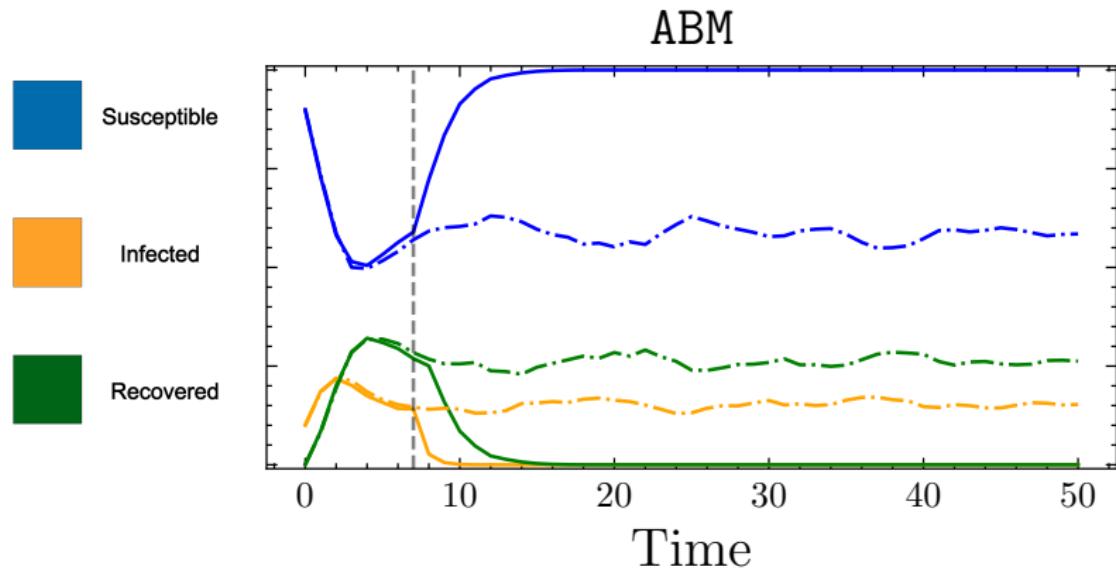
Infected



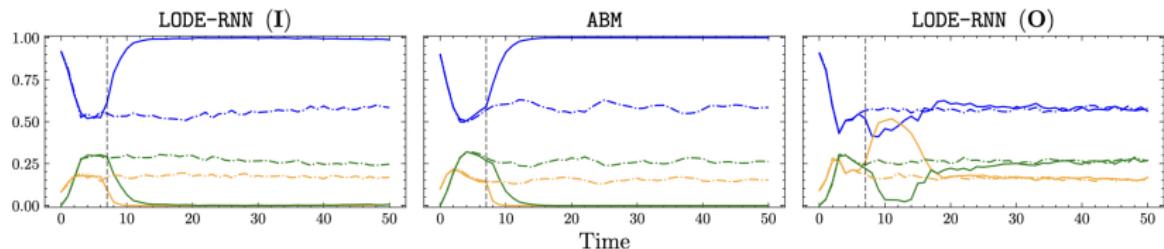
Recovered



Case study: SIRS Epidemics



Case study: SIRS Epidemics



Case study: SIRS Epidemics

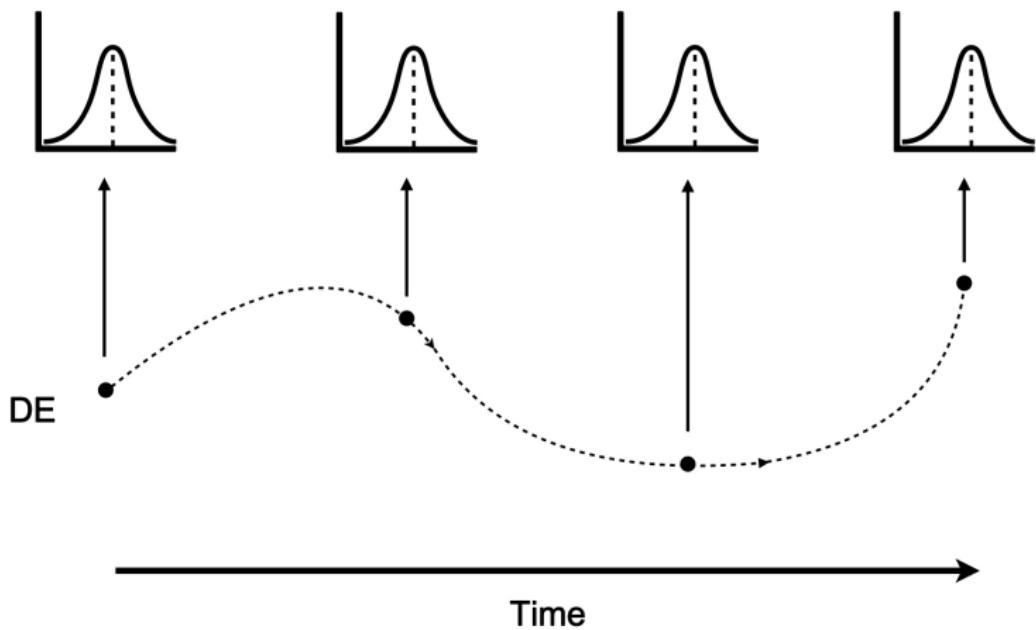
What benefits do we see from finding an interventionally consistent surrogate model using our method?

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

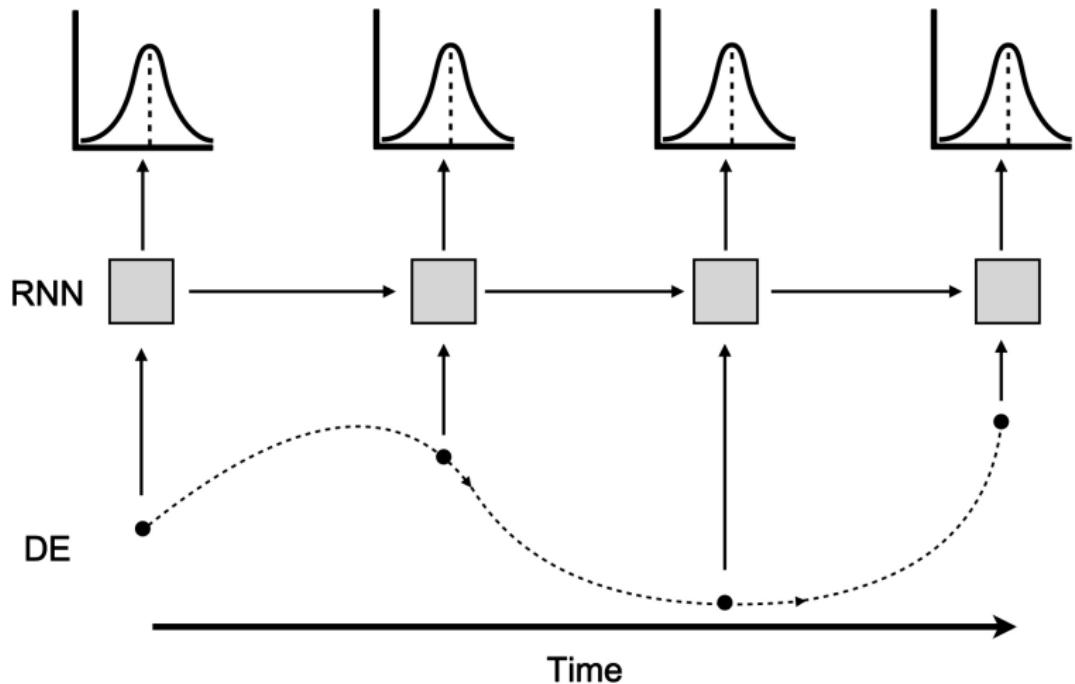
Test	Model Train	LRNN		LODE-RNN		LODE	
		I	O	I	O	I	O
I'	AMSE ($\times 10^{-1}$)	3.48^{3.91}_{3.41}	49.4 ^{52.6} _{46.7}	3.35^{3.41}_{3.18}	18.5 ^{21.9} _{17.1}	8.15^{8.24}_{8.06}	22.4 ^{22.7} _{22.1}
	ANLL ($\times 10^3$)	2.09^{2.16}_{2.03}	21.8 ^{22.9} _{20.1}	1.99^{2.00}_{1.98}	8.40 ^{9.89} _{8.27}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

- ▶ 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 Zennaro¹

Nicholas Bishop²

Joel Dyer²

Yorgos Felekis³

Anisoara Calinescu²

Michael Wooldridge²

Theodoros Damoulas³

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!

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* 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>.
- Linda Geaves, Jim Hall, and Edmund Penning-Rowsell OBE.
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Samuel Wiese, Jagoda Kaszowska-Mojsa, Joel Dyer, Jose Moran, Marco Pangallo, Francois Lafond, John Muellbauer, Anisoara Calinescu, and J Doyne Farmer. Forecasting macroeconomic dynamics using a calibrated data-driven agent-based model.

arXiv preprint arXiv:2409.18760, 2024