Large Agent Collider

Studying complexity with agent-based models

Nicholas Bishop, Joel Dyer, Imran Hashmi, Arnau Quera-Bofarull, Hao Zhou, Anisoara Calinescu, Doyne Farmer, Michael Wooldridge

Department of Computer Science, University of Oxford

{name.surname}@cs.ox.ac.uk

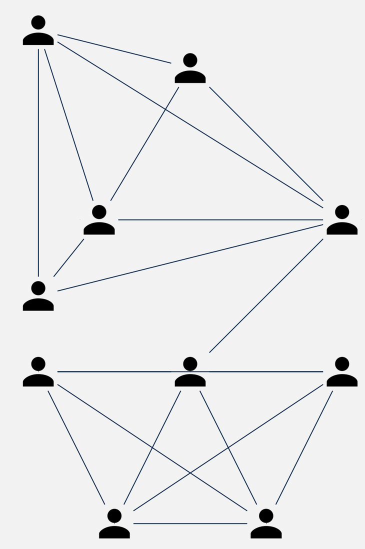
1. Agent-Based Models

- Agent-based modelling (**ABMing**) is a simulation technique to study complex systems.
- In ABMing, we simulate the actions and interactions of autonomous agents in order to understand the emerging collective behaviour of the system.
- Agent-based models (**ABMs**) are used in many fields, including biology, economics, and sociology.

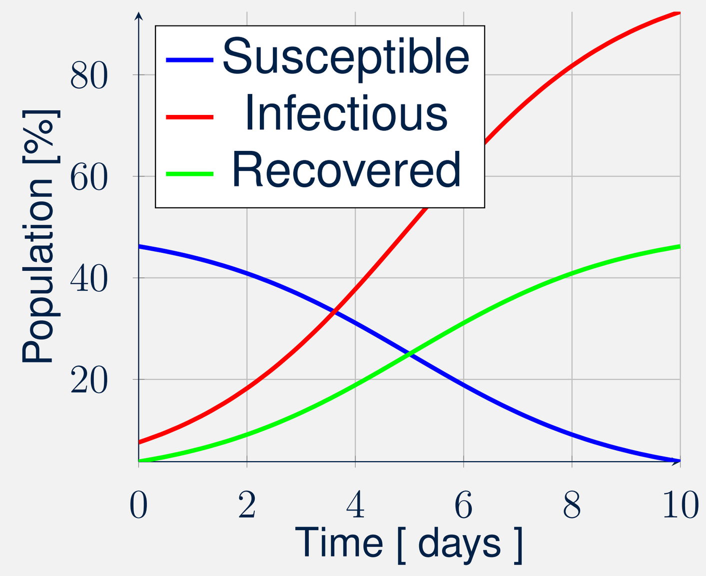
Figure: The flocking of a pack of birds is an emergent feature of the bird's individual behaviour.

2. Example : Epidemiology

- We can study the spread of a disease in a population using an ABM.
- We do so by simulating the movement and interactions of individuals in a population.
- A good example is the agent-based SIR (Susceptible, Infectious, Recovered) model, where disease can spread after a contact with an infectious individual.



(a) Graph representing the contacts of the population.



(b) Percentage of the population in each state over time.

- The spread of the disease will depend on multiple factors, including the behaviour and contact patterns of individuals.

3. Challenges of Agent-Based Modelling

The effective use of ABMs in wider settings such as policy making is hindered by:

- **A. Expensive to simulate**: ABMs involve simulating potentially millions of agents, which is computationally expensive.
- **B. Data availability:** The granularity of ABMs requires a lot of data, which is often not available.
- **C. Tough to calibrate**: ABMs are often used to make predictions about the real world, but it is difficult to validate the truthfulness of the model.
- **D. Difficult to analyse**: The complexity of ABMs makes it difficult to understand the causal relationships between the agents and the emergent behaviour of the system.
- **E. Hard to reproduce**: Programming ABMs is difficult, and it is often hard to reproduce the results of a model done by another researcher.

4. How are we tackling these challenges?

In our research group, we are tackling these challenges using the following techniques:

- **A. Tensorized simulation**: By leveraging modern software for tensorized computation, we can simulate ABMs orders of magnitude faster than traditional implementations.
- **B. Scenario-generation**: When fine-grained data not available, we can use ABMs as a scenario-based planning tool to help policy making under uncertainty.
- **C. Differentiable programming**: We can use automatic differentiation to enable gradient-based calibration of ABMs.
- **D. Causal inference**: Causal inference techniques can help us understand the causal relationships between the agents and the emergent behaviour of the system.
- **E. Open-source software**: All our research software is open-source, and we use modern software engineering practices to ensure reproducibility.

5. Results and Impact

- We have dramatically accelerated the simulation, calibration, and analysis of ABMs involving millions of agents in epidemiological and financial domains [2, 4, 5, 6, 8].
- We have developed an open-source package for the Bayesian calibration of differentiable simulators using the developed techniques [7].
- We have developed a novel methodology for scenario-generation based planning under uncertainty using ABMs [3].
- We have adapted secure multi-party computation techniques to enable privacy-preserving simulation, calibration, and analysis of ABMs [1].
- TODO: Causal stuff?

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