Agent-based social insurance modelling: Using Markov decision processes to improve the connection with data

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Abstract: This talk reports on the development of an Agent-Based Model (ABM) framework built on a Markov Decision Process (MDP) representation of agent dynamics. Common criticisms of ABMs are (1) their supposed recalcitrance towards empirical validation, and (2) their limited amenability to mathematical analysis. Whilst rejecting these criticisms in their full generality, this talk contends that employing MDPs in ABMs facilitates empirical validation as well as mathematical analysis.

The ABM framework is being developed to model social insurance systems such as the NDIS, WorkSafe and the TAC. The latter provide the specific empirical context and, in fact, the TAC are not only providing their data but are participating closely to ensure a realistic representation of their scheme. In this context, then, agents represent clients — typically crash victims — and their state represents their claim, which of course changes over the course of a clients' journey to recovery. Changes to a claim, for example when a client needs additional services (e.g. physiotherapy or drugs), may be the result of a deliberative process involving TAC people, external experts and so on. It is in order to model such processes, that an ABM approach is taken.

At the time of writing, the ABM framework is in an early stage of development making it premature to speak of results. However, for the TAC context, the framework is being used to provide a solid empirical base line (responding to first criticism, above). Using claim history data, a Markov Chain of clients' trajectories through the state space of possible claims is constructed. This Markov Chain serves as an MDP under a default — or rather, 'average'—policy. This allows calibration and validation of the agent-based modelling of the decision processes, with every agent rule-set corresponding to a policy in the associated MDP.

In regard to the second criticism, Markov Chains are eminently amenable to mathematical analysis. Any quantitity of interest will be a function or statistic of the state of the system. So, given the transition probabilities everything within reach of calculation— in principle. In particular, the long-term behaviour (equilibria, independence of initial conditions) can be analysed. This connection between Markov Chains and ABMs has been pointed out and exploited by Young (2006) and Izquierdo et al. (2009). The ABM framework discussed in this talk takes the next step of formalising the state space in Markovian terms in advance, rather than post hoc.

While the framework proposed here clearly is not limited to modelling social insurance systems, the expectation is that it will bring the models closer to the data. This ought to increase confidence in policy experiments etc. More ambitiously, one could in principle (1) infer the agents' decision rules from the data (see e.g. Arora & Doshi 2021) and (2) given some reward function, infer an optimal set of decision rules (Francès et al. 2015).

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