"Let them learn": an ABM framework with adaptable agents

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Agent-Based Models (ABMs) are a popular approach to modelling social systems. They provide a flexible and intuitive framework that can be applied to a wide range of contexts, from economic markets and political systems to epidemiological models, allowing for the emergence of macro-level patterns [1, 2]. However, ABMs have inherent drawbacks in terms of data availability, interpretation, and sensitivity to initial conditions and parameters [3]. They require defining the micro-scale behaviours of agents that lead to the emergent macro-scale patterns. This approach is limiting, as the conclusions derived are dependent on those hard-coded behaviours and, in some contexts, the micro-scale behaviours themselves may be unknown. Reinforcement Learning (RL) approaches, on the other hand, set incentives for agents, and train them based on those incentives —without the need of hard-code behaviours. Since RL only requires the specification of agents' incentives, the model gains in flexibility and robustness to noise or environmental changes, while permitting to observe a wider range of behaviours – sometimes unexpected.

While standard RL typically consists of a single agent and single incentive metric, Multi-Agent RL (MARL) considers multiple agents with different controllers, incentives (often conflicting), observations, and ways in which they can influence other agents and the environment. This allows to model agents that operate on different scales, and abstractions of the environment. In the context of computational social science, RL (alongside other Machine Learning techniques) has been incorporated into ABMs, as surveyed in [4, 5] —notably for agents to learn to improve their decision-making from experience and explore a wider behavioural space [6, 7]. Still, applications of MARL to social science have been few and far between. This is partially due to the fact that current RL and MARL methods and tools require significant prior technical and mathematical knowledge. In addition, standardisation between tools is inconsistent, and there is a lack of a shared vocabulary between concepts used in artificial intelligence, social sciences, and complex system research.

To fill this gap, we propose an interface to combine multi-scale ABMs and multi-agent RL, framed as an extension of the AgentPy Library, an existing library that can be used to easily build ABMs with Python [8]. The interface enables researchers to seamlessly incorporate into their ABMs both learning and hard-coded agents interacting at different temporal scales (micro, meso, macro), as illustrated Figure 1. This is relevant to many social science applications, as most social systems are composed of multiple agents whose behaviour unfolds across different scales of analysis. Together with the library extension, we provide guidelines on how to combine RL and ABMs, bridging and explaining terms and methods used in different fields.

To demonstrate the versatility of the extension, we use it to model two different systems: a multi-party voting system, and an energy network. In the former, three types of agents, namely voters, media, and political parties, interact at different temporal scales. We train behavioural policies for political parties and media organisations such that they maximise their number of voters and listeners by adapting their discourse and the type of message that they amplify, respectively. In the latter, we model an energy network composed of consumers, energy companies and energy producers, also operating across different scales. Here, consumers learn how to regulate their consumption patterns based on energy prices, and we explore the interactions between their behaviours (at a faster timescale), the management of loads by energy companies (at the meso-scale), and the change in energy infrastructure, driven by bottom-up behaviour (at the macro-scale). In both examples, for each type of learning agent we define distinct action and state spaces, and distinct incentives to guide their learning. While these two examples are purely illustrative, they show the potential of combining RL and ABMs to describe multi-scale and multi-agent systems. This extends the realm of applications of ABMs to situations where there is no prior knowledge of micro-scale behaviours, while there is awareness of the incentives guiding the agents' behaviour. In doing so, the range of social dynamics that can be explored through these modelling approaches is also extended.

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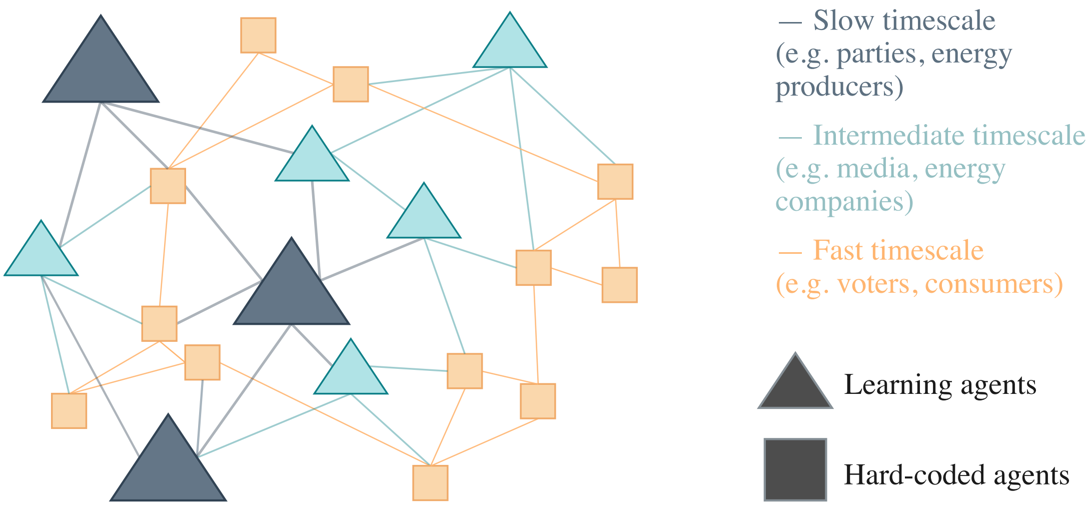

Figure 1: **Schematics of the framework.** Our proposed framework allows to integrate hard-coded agents (square-shaped) used in standard ABMs with learning agents (triangle-shaped) whose behaviour emerge from incentives rather than being explicitly defined ab initio. The framework allows for agents to operate at different timescales simultaneously (e.g. along three timescales as illustrated here).