Simulating the Physical, Cognitive, and Social: a Multi-Level Approach

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Abstract. It is increasingly desirable to put together multiple models, capturing various aspects, when developing complex agent-based simulations. This paper presents a multi-level framework combining social, cognitive and physical aspects of an agent split across different components. The models individually encapsulate different levels of concern, but collectively form a consistent view of the reasoning agent in the simulation. We present this framework in the context of a large-scale evacuation scenario involving more than 35,000 vehicles. Results show that inclusion of the social level substantially affect evacuation outcomes.

Keywords: Social Network Diffusion · Mass Evacuations · BDI agents

1 Introduction

Combining models for a simulation application is increasingly useful as it allows scrutiny from different perspectives, while saving time and effort in building models from scratch (e.g., [23], [6]). In this work, building on [24] we propose a tiered agent reasoning framework consisting of a social, cognitive and a physical level. We are motivated by the observation that these aspects are often required together but exist in separate specialised systems. The physical level is commonly represented in agent-based platforms [1] that generally contain a 'thin' cognitive layer where single-agent reasoning is limited to reactive rules. On the other hand, mature cognitive reasoning systems exist today [3] but these are not typically concerned with physical environments. Moreover, these deal mostly in single-agent reasoning and lack learnings from social network diffusion research [13].

While creating monolithic systems that incorporate all concerns might be possible at times, combining systems to present a consolidated and consistent view of a reasoning agent split across several systems is often required. In [23] we address the case where the reasoning agent is conceptually represented across two separate but related agent-based models (ABMs). The approach was to build an external controller to orchestrate the progression of the models, inspecting/overwriting state variables, and rolling back steps as needed, in order to maintain a meta-level world-view that was consistent across both component simulations. Our BDI-ABM infrastructure [24] is useful where a new model is being built and it is desirable to combine specialised components–physical and cognitive–to realise ABMs that support complex reasoning agents [3].

A multi-level view of agents is indeed useful in simulations, and social networking, particularly diffusion in social networks, is an important aspect that has previously not been considered in this context. In this work we take the BDI-ABM components described previously [24] and add a new social layer. Specifically, we present a generic approach for incorporating network-based diffusion processes [15, 18, 11], which capture the spread of various influences (e.g., information, opinion, innovation), into simulations with complex reasoning agents. We apply our framework to a large-scale flood evacuation scenario and show that social influence can very significantly impact evacuation outcomes compared to optimised evacuation plans that assume people do as they are told.

2 System Architecture

We support simulation of reasoning agents that are conceptually split across the physical dimension represented in an ABM, the cognitive in a Belief-Desire-Intention (BDI) system, and the social in a newly added social network model (SNM). Here an ABM is a bottom-up system of interacting autonomous agents in an environment for representing complex systems. A BDI program [9, 20] is essentially a collection of plan rules of the form $G : \psi \leftarrow P$, which implies that plan P is reasonable to achieve goal G when (context) condition ψ is believed by the agent to be true, and is particularly useful for modelling human behaviour in social simulations [16, 2, 3]. A SNM manages the social network structure connecting the agents along with the network-dependant diffusion process.

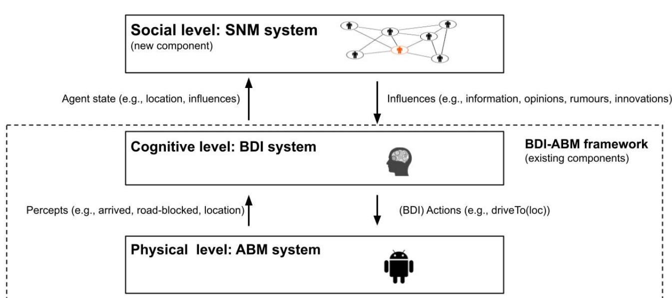

Fig. 1. Conceptual overview of the multi-level agent framework.

The architecture (Figure 1) is implementation-agnostic, affording choice in underlying models based on need. The modular architecture of the new SNM component allows easy swapping of network and diffusion models (via a configuration file), facilitating re-usability across applications. Numerous well known network (e.g., random, small-world) and diffusion (e.g., Independent Cascade, Linear Threshold Model (LTM) [10], Competitive LTM, separated-threshold version [4]) model implementations already exist in the system.

Technically, the conceptual agent is identified in each subsystem by a common identifier. The BDI-ABM machinery [24] allows BDI reasoning to instantiate actions that are then carried out in the ABM system, while observations from the ABM simulation generate percepts which are passed back to the BDI system to inform further reasoning. We allow an influence received by an agent via a diffusion process in the SNM to affect a specific belief in its BDI counterpart. This can then either directly trigger a goal, which instantiates a whole new set of plans and actions, or it can influence the achievement of existing goals, by affecting which plans are chosen, and what actions are eventually taken by the ABM counterpart. The opposite flow of a percept from the ABM triggering some BDI deliberation that results in communication via the SNM is also possible, though we do not demonstrate this in the scenario here.

The decision on how to split reasoning depends on functionality provided by each system. For our scenario, it makes sense to use BDI for evacuation decision making of an agent based on its circumstance, but leave path planning to the ABM that maintains the road network model. We discuss such design choices in [24, 25]. Interactions between agents can occur in each layer: directly (via messages) or indirectly (via the environment) in the ABM; inter-agent communication in the BDI system; or through the diffusion processes in the SNM. Which mechanism to use again depends on what aspects of the complex system are important to model. In our example, interactions occur at the physical level (congestion on roads) and social level (spread of influence).

We maintain synchronisation between the three subsystems with respect to simulation time and data. The ABM and SNM are time-stepped models that may internally run at different atomic time steps, and the BDI system is event-based and does not explicitly model time (end of the BDI reasoning cycle is used to progress time [24]). At initialisation and subsequently at each temporal synchronisation point, the physical, cognitive, and social data are shared across the systems to maintain a consistent view of the conceptual agent. For instance, physical aspects (managed by the ABM) are abstracted out as percepts (e.g., arrived at a location, road blocked) for the BDI system. The SNM system may also require physical information, for example, geographical locations of agents are sent to the SNM side (at initialisation) to generate proximity based social networks (e.g., neighbourhoods).

3 A Flood Evacuation Case Study

Optimal evacuation schedules (e.g., [8, 19]) often assume that people will follow their assigned plans diligently. However, empirical studies show that residents rely on social networks amongst other things for evacuation decision making in addition to official warnings [17, 7, 21]. To understand this better, we examine how social influence affects outcomes of an optimised evacuation simulation.

We used optimised evacuation plans from Data61[4] for 38,343 agents in the Hawkesbury region, NSW, Australia as the *baseline*, and compared these with

[4] https://data61.csiro.au/

simulations that incorporate social influence, across a range of configurations. In the social scenario, an agent reasons and modifies its scheduled evacuation start time based on level of influence from others, which causes it to either evacuate early (low influence), on-time (moderate level of influence) or late (high influence). We experimented with two networks (a random network and a proximity-based network), and three input factors (seed[5] (5%-20%), activation threshold (0.3-0.5), and degree[6](2-10)). We ran 340 simulations (5 iterations * 17 configurations (combinations of seed, threshold, and degree values, selected using the Latin Hypercube Sampling method [22]) * 2 networks * 2 effects (diffusion and evacuation)). Before considering evacuation effects, we first analysed how the chosen factors affect diffusion dynamics, to fully understand their influence on the diffusion process. The social, cognitive, and physical aspects of our evacuating agents were encoded in the LTM [10] for diffusion of social influence [14], JACK platform [5] for cognitive reasoning, and Multi-Agent Transport Simulation (MATSim) [12] for simulating road traffic, respectively. We find that:

- *Social influence has a substantial impact on evacuation outcomes.* In the worst case ≈41% of the population is exposed to higher traffic congestion, resulting in delays of up to three hours. Whereas in another run where high levels of information diffusion were evident, the time to evacuate the whole population improved by as much as 2hrs from a baseline of 10hrs.
- *Precise effects on evacuation behaviour vary a great deal based on specific characteristics of the social network as well as the diffusion process.* Network structure can have substantial impact, for instance, a neighbourhood network may lead to 8821 more evacuated agents compared to a random network. Threshold level is the most influential factor, followed by seed and network degree, when it comes to the sensitivity of the spread of influence on the diffusion process parameters. For example, in two contrasting configurations for threshold but with similar values for other inputs, the number of evacuated agents changed from 8131 (21%) to 38,343 (100%).

4 Conclusion

We propose a multi-level agent reasoning framework for social simulations that extends the cognitive-physical integration provided by the BDI-ABM layers [24] with a new social networking layer encapsulated in a social network model. This allows different kinds of social networks along with well understood information/influence diffusion mechanisms to be included in simulations with complex agents. In the context of a flood evacuation scenario, we show that the social level with its network-dependant diffusion processes is an important aspect that can have a substantial impact on simulation outcomes. The SNM-BDI-ABM framework presented here provides a good basis for further research combining social networking, cognitive reasoning, and agent-based simulation.

[5] Set of agents that have initially adopted the influence to start the diffusion process.
[6] The degree refers to the number of links an agent has in its social network.

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