Towards Dynamic Cognitive Maps in Agent-Based Models of Cities

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Abstract. Agents are the core component of the modelling paradigm and their behaviour to a great extent determines the outcomes of the model. Yet, even though agents are expected to be conceived as intelligent, sociable, and autonomous entities, the design of cognitive agents remains a challenge in agent-based modelling, particularly in research on cities as complex systems. Urban simulation models have mostly represented cognition as solely influenced by the physical properties of the environment, thus neglecting the role of socio-cultural forces in human cognition. In previous work, a framework to computationally obtain *cognitive maps* – cognitive representations of urban space - from geospatial datasets of cities was advanced and incorporated into an agent-based model of pedestrian movement. Although the agent population made use of such cognitive maps to plan their routes, the agents were conceived as "solitary" entities and their cognitive map did not change after interactions with others. The primary aim of this work is to further develop the concept of computational cognitive maps to accommodate alterations and changes in spatial knowledge deriving from social interactions between agents. First, dynamic and agent-specific cognitive maps are included in an agent-based model of pedestrian simulation in cities. Second, a set of social interactions in the context of route choice behaviour, as well as its impact on the agents' cognitive maps and their navigational strategies, is characterised in the model. Finally, to assess the role of the social component on the micro- and macro-level patterns of the model, the outputs of the model are analysed in relation to the development of cognitive maps during the simulation and the distribution of agents across the street network.

Keywords: cognitive maps · pedestrian simulation · agent interaction · cities

1 Introduction

Urban dynamics emerge from the interaction between different complex systems: human cognition, society, cultural structures, transport networks, and so forth. Only by accounting for these different components can one come close to understanding urban systems [3]. Cognitive maps have become one of the core concepts in cognitive geography, environmental cognition, and spatial cognition [17, 23] in the study of spatial behaviour in cities. The notion of cognitive map owes its reputation to studies on the relationship between the configuration of the city and people's mental images inaugurated by Kevin Lynch [18]. Today, the term cognitive map refers to the cognitive processes and representations employed to comprehend and interact with the external world [7, 22]. Cognitive maps constitute the minimum requirement to plan routes and move within the environment [2], but they also support meaning attribution processes, place evaluation, and the definition of individual goals [15, 21, 25].

In previous work, an approach was advanced to derive computational cognitive maps (CCMs) from spatial datasets of cities [12]. While this conceptualisation of cognitive maps was included in an ABM of pedestrian movement in urban spaces [see: 10, 11, 9], the agent population was only equipped with a static and undifferentiated CCM of the city and no interaction was not characterised by any form of interaction. In consideration of recent advancements in spatial cognition research on the role of other individuals in route choice behaviour [6, 1], this constitutes one of the main limitations of the work. Social influence and interactions play a significant role in shaping spatial decisions made by individuals while navigating in cities [26]. This extends to both the *prospective planning* phase, when individuals plan their routes before starting their trip, and the *situated planning* phase, which involves taking decisions along the path. During these interactions, individuals may be influenced by family members, friends, colleagues, whom they perceive as more knowledgeable in navigating complex urban environments. Not only do others influence route choice behaviour or specific spatial decisions, but they also impact the general structure of an explorer's cognitive map by exposing them to unknown areas, alternative routes, and urban elements that could be recalled for supporting decisions at a later time.

The aim of the present work is to advance a preliminary formalisation of dynamic Computational Cognitive Maps (CCMs) that accounts for alterations and adjustments in the structure and the content of cognitive maps, following repeated social interactions with other agents. Here, it is illustrated how to derive differentiated and dynamic CCMs that can be incorporated into ABMs of urban phenomena that underlie human decision-making processes or a fundamental cognitive component. The usage of dynamic CCMs for a population of agents is demonstrated in an ABM of pedestrian movement in cities.

2 From Static to Dynamic Computational Cognitive Maps

Previous work: A Static Computational Cognitive Map

The theory of the Image of the City [18] was previously adopted to facilitate the inclusion of cognitive maps in computational models of cities. We devised a computational approach to the Image of the City that derives CCMs from geospatial datasets of cities (street network, buildings, artefacts, and natural areas of the city) making use of GIScience and network analysis methods. The so-obtained CCMs include information on a series of meaningful urban elements that have been described as the fundamental bricks of people's cognitive representation of the city. The five elements are *paths*, *nodes*, *landmarks*, which can be ranked on the basis of a score of meaningfulness or salience, and *regions* and *edges* (barriers), whose salience is categorical; they can be recognised and remembered, or not[1].

The CCM of a city was incorporated as a shared static *community cognitive map*[2] [20] into an ABM for the simulation of pedestrian movement in cities, *PedSimCity*. The (cognitive) pedestrian agents were equipped with a) a representation of the environment in which they were situated and b) the ability to exploit this representation when interacting with the external world [4]. However, agents neither interacted with each other nor were aware of others' movements and decisions.

A Dynamic Computational Cognitive Map

The first step in making the CCM dynamic is to generate agent-specific CCMs. While Lynch derived a shared cognitive map of a city from individual superimposed mental images, an opposite abstraction is carried out here. Each agent, after the initialisation of the environment in an ABM, is assigned with partial and local cognitive maps as follows:

1. Meaningful urban elements, likely to be widely represented across the population (e.g. global landmarks, the main road structure, central districts featured by a great diversity of land uses, etc.), are extrapolated and employed to define the *skeleton* of each agent's CCM [see: 19].
2. For each agent, this skeletal cognitive map is further enriched with knowledge about the areas around the agent's residential and working places (or any other place associated with daily routines[3]) and between them. This *activity space* [see: 5, 14, 13], associated with most activities of an individual, generates more vivid and detailed cognitive representations, compared to less visited areas, and can be represented by familiarity buffers [24] (see Fig. 1).
3. Furthermore, a *spatial knowledge* score K is randomly defined to represent individual differences in spatial knowledge [see: 16] and the degree of knowledge of a certain urban area; for example, someone who has lived in the same city for several years might have developed more precise and extensive knowledge than a person who has recently relocated. The score is operationalised

[1] The computational definition of the elements and the corresponding methods are detailed in [12].

[2] The crucial urban elements of the community cognitive map are the ones around which there is more agreement amongst people, namely those that are more likely to be part of people's individual cognitive maps.

[3] Home and work places are random nodes identified on the basis of land use distribution across the urban environment.

to indicate the portion of elements known and stored in the corresponding agent's CCM, over the entire city; e.g. a score of 0.75 will indicate that the agent knows around 75% of the buildings that are either local or global landmarks in the city.

Thus, the resulting CCM is a *cognitive collage* that can accommodate knowledge of newly explored areas and destinations through the use of the Standard Deviational Ellipse (SDE) [24], a statistical method advanced in time geography to represent the spatial dispersion and variability of a set of visited locations. In essence, the SDE calculates an ellipse that best fits the distribution of the most visited locations, depicting an area where individuals are more likely to be exposed to opportunities due to their daily activities.

In this work, different SDEs are generated to capture varying levels of spatial awareness in different parts of the urban space based on the agent's movements and spatial experiences. This process of updating and expanding, with different degrees of accuracy and vividness, the initial cognitive map can be seen as a form of *incremental learning*, where the agent refines its knowledge of the environment over time.

Fig. 1. The activity space of an individual, as defined, for instance, by a series of trips between her residential and work place, results in a vivid mental representation of the same area, as concerns information about the presence of landmarks, or the structure of the street network.

3 Incorporating Dynamic Cognitive Maps in a Pedestrian Simulation Model

Dynamic CCMs are incorporated into the existing behavioural module of *PedSimCity*. A set of pedestrian agents (A) generate routes between different pairs of locations, origin-destination pairs, in the urban environment using the urban elements, relations, and attributes contained in their CCMs. Two types of experience can trigger spatial learning processes, namely changes in cognitive maps: a) repeated (new) spatial experiences and b) social spatial experiences. In this work, each trip is considered a spatial experience, but only changes related to social experiences are modelled; alterations that occur following solitary spatial experiences are not considered.

Social Influence in Route Choice Behaviour

The *leader-follower* model to social influence, widely adopted in egress and evacuation agent-based simulations [8], is here readapted to regulate how prone an agent is to reshape its cognitive map following experiences and interactions with other agents[4]. In *PedSimCity*, each agent is characterised by a *leader-follower* score l, ranging from 0.0 (high conformism, low influence on others) to 1.0 (low conformism, high influence on others). Prior to each trip e, an agent g can either be assigned to a group of other agents P or formulate the route on its own. In the first case, within each of the formed groups, an agent g plays one of the following roles [see: 6]:

- *Leader* or instructor: the agent g selects the destination and formulates the route, guiding all the other agents in P, from the meeting point with the agents in P.
- *Follower*: the leader counterpart; the agent g follows one or more leaders to the destination, from the meeting point with the agents in P.
- *Co-leader*: the agent g identifies the destination and formulates the route together with at least one other agent in P, from the meeting point with the agents in P.

Any agent g who is not assigned to a group may use other agents as *environmental cues*, when its leader-follower trait is below a random threshold. In this case, the other agents do not collaborate directly with the agent g; instead, they are employed by g to take spatial decisions at not well-known junctions or within unexplored areas (e.g. the agent may decide to take routes that are more crowded, following other people). In all other cases, the agent g formulates the route independently, although its CCM might have been shaped by previous social interactions.

[4] This is a simplified approach to social influence in route choice behaviour, far from capturing all dimensions involved in this process.

A "social" trip may lead to readjustments and changes in the CCMs of followers and co-leaders, when the *alteration likelihood* c is greater than the leader-follower trait of the agent l_g; c_e is defined as:

$$c_e = \frac{M_e + l_p}{2} \tag{1}$$

where M_e is the meaningfulness of the experience e and l_p is the average leader-follower score of the other social agents involved in the experience. M_e is a combined measure of *novelty* (how different or unique the path is compared to previous paths taken by the agent), *exposure to significant locations* (e.g. global landmarks, symbolic landmarks, central districts), and *path complexity* (the diversity and intricacy of the spatial features encountered along the path). M_e is computed on the basis of the rescaled $z - scores$ of these three factors, depending on the characteristics of the previous paths traversed by the agents, as:

$$M_e = (novelty_e + exposure_e + complexity_e)/3 \tag{2}$$

For example, $complexity_e$ is calculated as:

$$complexity_e = CDF\left(\frac{complexity_e - \mu_{complexity_R}}{\sigma_{complexity_R}}\right) \tag{3}$$

where $complexity_e$ indicates the complexity of the path e, R is the set of previously walked paths, $\mu_{complexity_R}$ the average complexity of the paths in R, and $\sigma_{complexity_R}$ the standard deviation of the complexity score in R[5]. The cumulative distribution function (CDF) of the standard normal distribution is used to rescale each of the factors' z-score to a probability between 0 and 1. It should be noted that M_e could be defined otherwise, depending on the purposes of the model (e.g, traffic simulation, residential mobility, gentrification processes) and the role of cognitive maps in shaping agent behaviour.

Here, when a cognitive map change is triggered, the SDE method described above is employed to expand the coverage or improve the accuracy and structure of the agent's CCM. The ellipse obtained on the basis of the urban elements visited or traversed by the agent during its last trip may lead to two distinct outcomes, reshaping the agent's CCM in different ways. On the one hand, the SDE may result in a new "branch" being added to the CCM, signifying the inclusion of new information about salient urban elements. This readjustment allows the agent to incorporate fresh (but partial and inaccurate) knowledge into its CCM. On the other hand, when the SDE overlaps parts of the existing CCM, it reinforces the vividness of the agent's representation of a certain urban area. Repeated exposures to the same urban features may enhance the agent's ability to recall and store more precise attributes associated with these elements.

[5] For the first agent trip, the home to work path is used as a reference.

Additionally, the agent's CCM may encompass a larger or more granular set of local urban elements, thus refining its knowledge of the urban environment. This incremental learning approach to cognitive mapping space also entails a memory decay mechanisms; ellipses of areas visited long ago, one or a few times, might be gradually discarded from the CCM to ensure that the agent's cognitive representation is actually built around its experiences in the urban environment.

Model Execution and Evaluation

The ABM is executed under three different *social* configurations, with an increasing number of trips J that each agent has to complete ($J = 1000$, 10000, and 100000, respectively). The three configurations are executed T times as Monte Carlo simulations to balance the randomness caused by the stochastic functions of the ABM. Additionally, three *solitary* configurations are also executed for the same amounts of trips. Per each configuration, the volume of pedestrians is determined from the median pedestrian count of the street segments over the T executions of the model. Lastly, the model generates a set of variables that describe the characteristics of the agents' CCMs (accuracy, completeness, etc.).

On the one hand, the pedestrian patterns of the social and solitary configurations are compared to identify, possibly, after how many trips, the inclusion of dynamic CCMs in the ABM leads to pedestrian volumes across the street network (*macro-level patterns*) significantly different from an ABM featured solely by static CCMs. On the other hand, by looking at the set of variables describing the agent's CCMs characteristics in the social configurations, it will be explored how CCMs change in time across the agent population, (*micro-level patterns*).

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