# BAYESIAN MECHANISMS IN SPATIAL COGNITION: TOWARDS REAL-WORLD CAPABLE COMPUTATIONAL COGNITIVE MODELS OF SPATIAL MEMORY

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# Abstract


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Computational cognitive models of spatial memory often neglect difficulties posed by the real world, such as sensory noise, uncertainty, and high spatial complexity. However, since cognition and its neural bases have been shaped by the structure and challenges of the physical world, cognitive models should take these into account as well.

This work takes an interdisciplinary approach towards developing a cognitively plausible spatial memory model able to function in real-world environments, despite the sensory noise and high spatial complexity. We investigated how spatially relevant brain areas might maintain an accurate location estimate of mammals, despite accumulating sensory noise, hypothesizing that hippocampal place cells might perform Bayesian cue integration, and that hippocampal reverse replay might play a role in cognitive map correction. We proposed biologically plausible mechanisms facilitating these statistically near-optimal mechanisms, and reported modelling results of single-neuron recordings from rats and behaviour data from humans acquired outside this PhD to support the former, and sketch map accuracy data collected in experiments performed online supporting the latter hypothesis.

In addition to dealing with sensory noise and uncertainty, in realistic environments, large-scale representations also have to be stored and used efficiently. Hierarchical spatial representations help dealing with large amounts of spatial information by increasing the speed and efficiency of retrieval search and of route planning, as well as facilitating economical storage. It has been suggested that cognitive maps in humans are hierarchical, but the computational principles underlying these hierarchies have

received little attention. We investigated features influencing cognitive map structure using collected spatial memory data concerning real-world and virtual reality environments, and proposed a computational mechanism (clustering in psychological space) which might give rise to sub-map structures. We validated our proposed mechanism using spatial memories of human subjects in over a hundred cities world-wide, and implemented a computational model able to predict, in advance, their sub-map structures based on our hypothesis.

Based on these insights, we developed a spatial memory module for a general cognitive architecture (the LIDA model of cognition), integrating it with the other cognitive mechanisms built into LIDA. We demonstrated the ability of the resulting model to deal with the challenges of the real world by running it in simulated environments, modelled after our participants actual urban environments, using high-fidelity robotic simulation software (including a physics engine) which provides the same interfaces as a real robot. Our LIDA-based spatial memory model could reproduce the spatial representation errors of human participants in different recreated environments, substantiating the plausibility of the computational implementation of our hypotheses.

# Declaration

No portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

# Copyright

# Acknowledgements

I would like to thank...

# Chapter 1

# Introduction

Brains have evolved to move bodies through space in order to increase the chances of survival and reproduction, through numerous complex behaviours such as fleeing from threats or searching for nutrients or potential mates. The ability to remember spatial information, e.g. previously encountered food sources or shelters, has provided sufficient evolutionary advantage that all known organisms with brains (and even some without, such as the slime mold[1] - Reid et al. (2012)) have at least a rudimentary ability to utilize representations of space for more efficient navigation. Higher mammals have evolved a network of brain areas implementing spatial memory, a system for storing and recalling spatial information about the environment and about their location in it.

Representing spatial information accurately in the real world is hard, for several reasons. Sensors and actuators are limited, erroneous and noisy (in the sense of noise interfering with the signal). There are additional sources of uncertainty or unknown information, such as external events, actions of other organisms, unperceived or currently unperceivable objects or events. Furthermore, physical environments can be highly complex, and yet cognitive resources (amount of memory, processing power, time and energy available) are necessarily limited by biological and physical constraints.

In artificial intelligence (AI) and robotics research, probabilistic models have provided key tools for dealing with such challenges, facilitating the quantitative characterization of beliefs and uncertainty in the form of probability distributions, and the machinery of Bayesian inference for updating them with new data. They have also inspired the 'Bayesian brain' (Knill & Pouget, 2004) and 'Bayesian cognition' (Chater et al., 2010) paradigms in the cognitive sciences. These paradigms have been successful in explaining human behaviour in tasks as diverse as the integration of sensory cues (Ernst, 2006) including spatial information (Cheng et al., 2007; Nardini et al., 2008), sensorimotor learning (Körding & Wolpert, 2004), visual perception (Yuille & Kersten, 2006) or reasoning (Oaksford & Chater, 2007). Their success suggests an answer to what biological cognition might be doing to cope with the above-mentioned challenges: approximate Bayesian inference.

[1] Slime molds are able to avoid previously explored areas using externalized spatial memories, and to solve mazes using nutrient gradients

## 1.1 Motivation

Despite of this success and of the suitability of probabilistic models to deal with uncertain and noisy spatial information, there have been few attempts to use them for modelling spatial memory within cognitive modelling, the branch of cognitive science concerned with computationally simulating mental processes. There is a gap in literature between probabilistic spatial models in robotics (called Simultaneous Localization and Mapping or SLAM) (Thrun & Leonard, 2008), which are capable of dealing with real-world noise, uncertainty, and complexity to some extent, but are cognitively implausible[2], and between computational cognitive models of spatial memory, which are designed to model biological spatial cognition, but cannot deal with all of these challenges, and are thus confined to simplistic simulations (see Chapter TODO for a review).

In addition, although spatial representations in humans have been argued early to be hierarchical (Hirtle & Jonides, 1985; McNamara et al., 1989; Wiener & Mallot, 2003), similarly to some robotic implementations having to deal with large, complex environments (Kuipers, 2000; Wurm et al., 2010), it is not known how (by which process) these hierarchical spatial maps might be structured. Although many computational models of spatial memory running in simplified environments exist, there is a lack of biologically and psychologically plausible 'algorithms' serving as models of human cognitive computations related to spatial information processing which can function in realistic, uncertain, complex environments.

The deprioritization of the problems of uncertainty and noise in favour of tractably modelling other human cognitive mechanisms is also pronounced in cognitive architectures, which try to account for a large number of mental processes in a unified, comprehensive, systems-level model (as opposed to computational cognitive models, which usually focus on a single phenomenon). In their overview of the field, Langley et al. (2009) argue that *" we should attempt to unify many findings into a single theoretical framework, then proceed to test and refine that theory"*, supporting the arguments of Newell (1973) that *"you can't play 20 questions with nature and win"*, highlighting the importance of systems-level research in the cognitive sciences. Although a few such cognitive architectures do model spatial mechanisms in navigation space (Harrison et al., 2003; Schultheis & Barkowsky, 2011; Sun & Zhang, 2004), they all run in simple, noise-free environments. According to a comparative table of cognitive architectures (Samsonovich, 2011) available in updated form online[3], there is currently no cognitive architecture implementing both Bayesian update and an empirically validated 'cognitive map' at the same time[4].

[2]In our usage of the terms, a computational model is 'psychologically plausible' (or 'cognitively plausible') to the extent that it is consistent with psychological findings and can accurately reproduce psychology data, i.e. behaviours. Analogously, it is 'biologically plausible' (or 'neurally plausible') to the extent that it is consistent with neuroscience and can reproduce neural data, e.g. single-cell recordings or brain imaging results.

[3]http://bicasociety.org/cogarch/architectures.htm

[4]CogPrime (Goertzel et al., 2013) claims to implement both Bayesian update and cognitive maps, but

The present work was motivated by these gaps in literature, and aims to take computational cognitive models of navigation-scale[5] spatial memory one step closer to modelling behaviour in realistic environments, such as high-fidelity robotic simulations or physical environments, by means of proposing probabilistic mechanisms of spatial cognition which are implementable in brains and can reproduce behaviour data. Situated within cognitive modelling and cognitive architectures, the goal of this work is to contribute to the understanding of information processing in human cognition. As such, although it is computational in nature, the extent of its success is determined by its ability to predict and explain the kinds of behaviour data it is intended to model, as well as its consistency with established findings in psychology and neuroscience. It is not aiming for performance, or accuracy of learned spatial representations (these are the domains of robotics), or for maximizing neurobiological fidelity at the cellular level or below. Although building on neuroscientific evidence, our concern is modelling spatial information processing on Marr's algorithmic level of analysis (Marr & Poggio, 1976; Poggio & Marr, 1977), as opposed to e.g. biological neural networks - see Table 1.1 -, with a single exception.

| ↓ Level of analysis | Description | In this work |
|---|---|---|
| 1. Computational | What problem(s) does the system solve, and why? | Localization, Map error correction, Map structuring |
| **2. Algorithmic/ Representational** | How might it solve them? (Using what representations and processes?) | Cognitive models of spatial memory |
| 3. Implementation | How is it implemented physically? | Place, grid, head-direction, border cells, ... (Hartley et al., 2014) |

Table 1.1: Marr's (1976) three levels of analysis in the context of spatial mechanisms investigated in this thesis. The present work is mostly concerned with the second level.

Unlike the rest of our work, we have investigated the plausibility of Bayesian spatial cue integration on Marr's implementation level (see Chapter TODO), in order to maintain the desirable criteria of both psychological and neural plausibility for our other models. Although this mechanism has been empirically substantiated on a behavioural level (Cheng et al., 2007; Nardini et al., 2008), its neural implementation has remained in doubt, with current mechanistic models of Bayesian inference in brains

neither of these mechanisms have been evaluated against human data, or indeed claim to be modelling human cognitive phenomena at all. Instead, CogPrime aims for artificial general intelligence, as opposed to closely adhering to human cognition.

[5]Human cognition needs to keep track of the space of navigation as well as the spaces immediately around the body (e.g. reachable objects) and of the body (e.g. body-part configurations). Although uncertainty and noise play are important in the latter two spaces as well, we will confine ourselves to navigation-scale spatial mechanisms in this work.

making assumptions not fully consistent with the anatomy or activity of the hippocampus (the major brain area representing world-centered spatial information) - see next Section. This doubt of biological implementability has motivated our investigation of single-cell electrophysiological data (acquired outside this PhD) to provide the first evidence for Bayesian updating on a neuronal level, and our proposal of a plausible mechanism for implementing it. This evidence of biological plausibility, presented in Chapter TODO, is the foundation for the rest of our work, which is concerned with processes on the algorithmic/representational level.

## 1.2 Probabilistic models of space in brains and minds

## 1.3 Outline and Contributions

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