How attention shapes simplified mental representations for planning

Jason da Silva Castanheira
Department of Experimental Psychology, University College London
(j.castanheira@ucl.ac.uk)

Nicholas Shea
Institute of Philosophy, School of Advanced Study, University of London
(nicholas.shea@sas.ac.uk)

Stephen M. Fleming
Department of Experimental Psychology,

Max Planck UCL Centre for Computational Psychiatry and Ageing Research
University College London
(stephen.fleming@ucl.ac.uk)

Abstract

Naturalistic behaviour involves complex problems with multi-step actions, making searching for a solution challenging. Despite this hurdle, human planning is efficient—it frugally deploys limited cognitive resources—and flexible—adapting to novel problems. Recent work suggests that humans reason about difficult decisions by constructing simplified representations of their environment. However, how these simplified representations are constructed remains unknown. Here, we characterize how visual attention controls which aspects of a scene enter a task representation for use in planning. When task-relevant information is spatially confined to a visual hemifield, people can more easily construct simplified and useful task representations. Inspired by the 'spotlight of attention' analogy, we incorporate the effects of visuospatial attention into a novel computational model of constructing task representations for planning. Together, our work bridges computational models of decision-making and perception to better understand how individuals represent their environments in aid of planning.

Keywords: Planning; Attention; Cognitive neuroscience; Psychology; Computational modelling

Introduction

Humans have an impressive ability to plan. Yet, even simple decisions involve myriad potential actions, which makes systematically evaluating every possible option impossible (Callaway et al., 2022; Huys et al., 2012; Newell & Simon, 1956). Explaining how humans efficiently and flexibly plan under these circumstances has been a long-standing challenge for researchers who aim to understand human intelligence and replicate it with machines (Griffiths et al., 2019; Hassabis et al., 2017).

Previous work (Daw et al., 2005; Dezfouli & Balleine, 2013; Keramati et al., 2016; Kool et al., 2016) has largely assumed that a decision-maker has a fixed representation of the problem. A recent model challenges this work and proposes that a value-guided process is involved in constructing the representation over which planning takes place (Ho et al., 2022). The value-guided construal model (VGC) suggests that an ideal, cognitively limited decision-maker selects a manageable subset of information over which to plan (i.e., task representation) (Ho et al., 2022). However, how these simplified representations are constructed remains unknown. Despite pioneering efforts to incorporate attentional constraints into models of decision-making (Ho et al., 2022; Niv, 2019), we lack a basic understanding of how attention influences planning. Here, we demonstrate how visual attention controls which aspects of a task representation enter subjective awareness for planning.

Methods

Experimental Task. Participants (experiment 1: N=194; experiment 2: N=161; experiment 3: N=35) were asked to navigate through a series of mazes to a goal using the arrow keys (Ho et al., 2022) (see Figure 1, top panel). At the end of each trial, participants rated their awareness of obstacles using a nine-point scale. See (Ho et al., 2022) for details.

For the in-person experiment sample, mazes had task-relevant stimuli either i) lateralized to a single hemifield, or ii) equally distributed across space.

VGC model. We fit the previously described VGC model to our maze stimuli (Ho et al., 2022). Briefly, this model holds that a decision-maker combines a subset of cause-effect relationships to represent their environment in aid of planning. This simplified representation maximizes the value of the representation (VOR) while also minimizing the cognitive cost of keeping information in mind:

$$VOR(c) = U(\pi_c) - C(c).$$

where c is a specific task representation (i.e., construal), $U(\pi_c)$ is the utility of a construed plan π_c, and $C(c)$ represents the cost of keeping that information in mind.

The optimal task representation is selected according to a SoftMax decision rule. We compute a marginalized probability for each obstacle in the maze being included within a construal, $P(\text{Obstacle}_i)$, and include it as a predictor of participants' awareness reports. See (Ho et al., 2022) for a detailed explanation of the computational model.

Lateralization index. To test for effects of spatial attention on construal we developed a lateralized index of task-relevance. We divided each maze into a right and left hemifield and computed the ratio of task-relevant obstacles on both sides. We tested whether the lateralization index moderated the relationship between the VGC model predictions and participants' reports using a hierarchical linear regression model.

Attention spotlight model. Inspired by previous literature comparing visuospatial attention to a *spotlight* that moves across the visual field, we developed an extension of the VGC model to account for the effects of attentional selection in forming task representations.

To do this, we recomputed the $P(\text{Obstacle}_i)$ as a weighted average of its neighbours, within 3 squares (Manhattan distance) away from obstacle_i. The distance of 3 squares reflects the 'width' of the attentional *spotlight* and was chosen based on the median distance between neighbouring obstacles.

Results

We observed a significant moderation effect whereby the greater lateralization of task-relevant information across the vertical meridian, the better the VGC model predicted participants' awareness reports (βinteraction = 0.01, SE = 2.65*10-3, 95% CI [0.01, 0.02], $p_{FDR} < 0.001$). We replicated these findings in a re-analysis of previous data (Ho et al., 2022) ($p_{FDR} < 0.01$). These results indicate that participants' representations are more closely aligned with the ideal observer (i.e., the VGC model) when task-relevant information is presented unilaterally.

Notably, these filtering effects of attention on value-guided construal are not part of the original VGC model. We explicitly incorporate the influence of a spotlight of attention in a computational model of planning and observed that the attentional spotlight model predicted participants' awareness reports better than the original VGC model (exp. 1: ΔBIC= 84.63; exp. 2: ΔBIC= 203.43; exp. 3: ΔBIC= 70.72). This significant improvement in model fit was exclusively observed for non-lateralized maze stimuli (ΔBIC= 161.93), which suggests that the spotlight model is particularly useful in improving our ability to explain human behaviour in situations when attentional filtering is more complex.

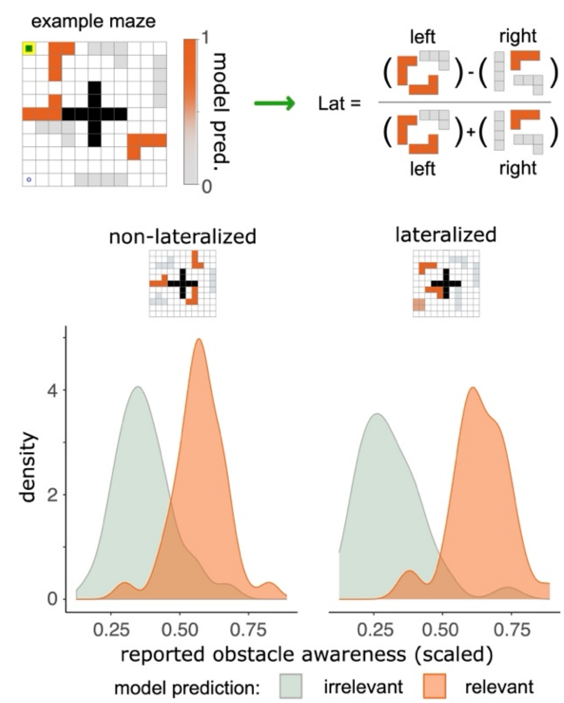

Figure 1: Lateralization of task-relevant information affects task representations.

Discussion

We shed light on multi-step decision-making by clarifying the role of visuospatial attention in forming simplified perceptual representations to aid in planning. We build on previous work and develop a computational model which explicitly incorporates the role of attention in value-guided construal. Our model bridges the literature on perceptual attention and computational models of planning to provide a more complete computational account of human cognition. We believe these results can inform future research on interactions between perception and cognition, and inspire novel biologically-informed intelligent algorithms.

References

Callaway, F., van Opheusden, B., Gul, S., Das, P., Krueger, P. M., Griffiths, T. L., & Lieder, F. (2022). Rational use of cognitive resources in human planning. Nature Human Behaviour, 6(8),1112–1125. https://doi.org/10.1038/s41562-022-01332-8

Daw, N. D., Niv, Y., & Dayan, P. (2005). Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control. Nature Neuroscience, 8(12), 1704–1711. https://doi.org/10.1038/nn1560

Dezfouli, A., & Balleine, B. W. (2013). Actions, Action Sequences and Habits: Evidence That Goal-Directed and Habitual Action Control Are Hierarchically Organized. PLOS Computational Biology, 9(12), e1003364. https://doi.org/10.1371/journal.pcbi.1003364

Griffiths, T. L., Callaway, F., Chang, M. B., Grant, E., Krueger, P. M., & Lieder, F. (2019). Doing more with less: Meta-reasoning and meta-learning in humans and machines. Current Opinion in Behavioral Sciences, 29, 24–30. https://doi.org/10.1016/j.cobeha.2019.01.005

Hassabis, D., Kumaran, D., Summerfield, C., & Botvinick, M. (2017). Neuroscience-Inspired Artificial Intelligence. Neuron, 95(2), 245–258. https://doi.org/10.1016/j.neuron.2017.06.011

Ho, M. K., Abel, D., Correa, C. G., Littman, M. L., Cohen, J. D., & Griffiths, T. L. (2022). People construct simplified mental representations to plan. Nature, 606(7912), Article 7912. https://doi.org/10.1038/s41586-022-04743-9

Huys, Q. J. M., Eshel, N., O'Nions, E., Sheridan, L., Dayan, P., & Roiser, J. P. (2012). Bonsai Trees in Your Head: How the Pavlovian System Sculpts Goal-Directed Choices by Pruning Decision Trees. PLOS Computational Biology, 8(3), e1002410. https://doi.org/10.1371/journal.pcbi.1002410

Keramati, M., Smittenaar, P., Dolan, R. J., & Dayan, P. (2016). Adaptive integration of habits into depth-limited planning defines a habitual-goal–directed spectrum. Proceedings of the National Academy of Sciences, 113(45), 12868–12873. https://doi.org/10.1073/pnas.1609094113

Kool, W., Cushman, F. A., & Gershman, S. J. (2016). When Does Model-Based Control Pay Off? PLOS Computational Biology, 12(8), e1005090. https://doi.org/10.1371/journal.pcbi.1005090

Newell, A., & Simon, H. (1956). The logic theory machine–A complex information processing system. IRE Transactions on Information Theory, 2(3), 61–79. IRE Transactions on Information Theory. https://doi.org/10.1109/TIT.1956.1056797

Niv, Y. (2019). Learning task-state representations. Nature Neuroscience, 22(10), 1544–1553. https://doi.org/10.1038/s41593-019-0470-8