

# Cognitive maps and novel inferences: a flexibility hierarchy

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Cognitive maps come in all shapes and sizes. Here, we review the literature on cognitive maps and their role in novel inferences during decision making, focusing on the representations and computations in the hippocampus, entorhinal cortex, and ventral prefrontal cortex. We suggest that cognitive maps can be seen as balancing representational complexity and online computational demand. Recent evidence suggests the hippocampal formation and orbital frontal cortex both form and use cognitive maps along this spectrum, ranging from simple elementary associations to explicit maps of 2D relational spaces that leverage structural inference. These representations can be conceptualized in terms of the degrees of behavioral flexibility they afford.

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**Current Opinion in Behavioral Sciences** 2021, **38**:141–149

This review comes from a themed issue on **Computational cognitive neuroscience**

Edited by **Angela J Langdon and Geoffrey Schoenbaum**

For a complete overview see the [Issue](#) and the [Editorial](#)

Available online 1st April 2021

<https://doi.org/10.1016/j.cobeha.2021.02.017>

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There has been a wave of renewed interest in the long-standing idea that ‘cognitive maps’ play a pivotal role in flexible goal-directed behaviors. The term ‘cognitive map’ was originally coined by Edward Tolman as early as the 1940s to explain an array of rat behaviors on diverse tasks that could not be readily accounted for by the palette of stimulus-response reinforcement learning [1] (Figure 1). The behaviors required to perform these tasks successfully can be understood in terms of degrees of behavioral flexibility.

For example, during Tolman’s latent learning experiments, rats explored the layout of a maze in the absence of any reinforcement (Figure 1a). Rats subsequently exploited their acquired knowledge of the layout to reach a newly introduced reward, even though the particular sequence of actions had never been reinforced previously.

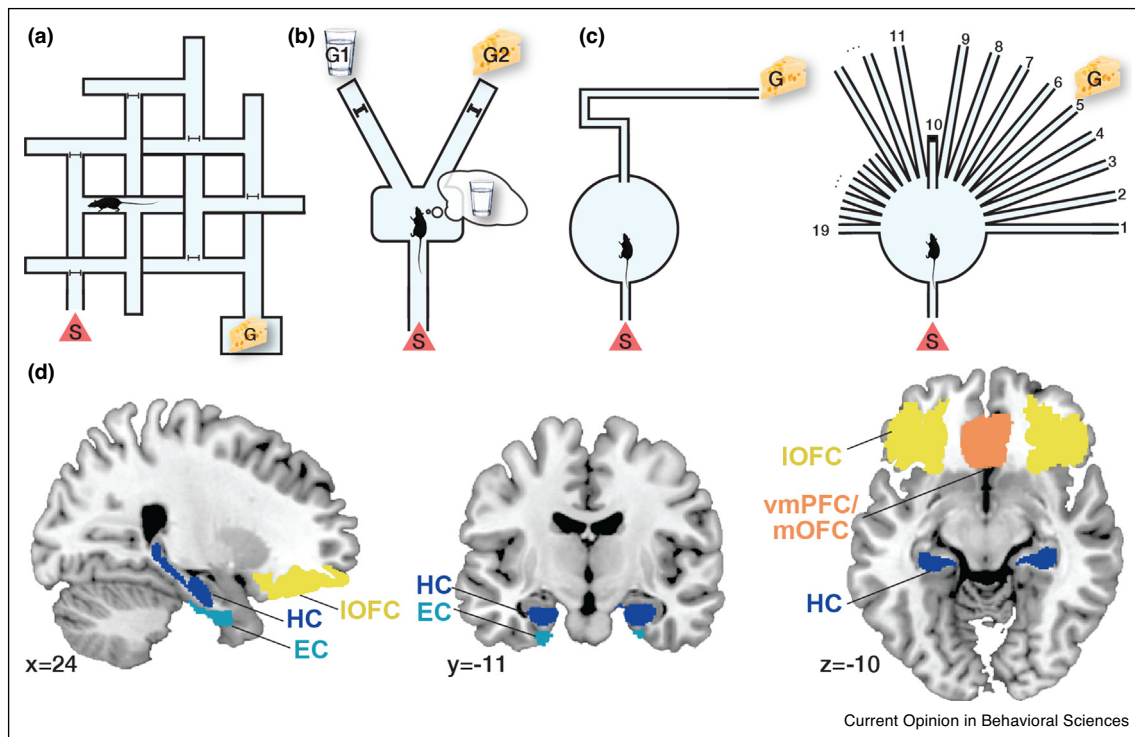
Even more impressive, studies showed that many rats trained to find a reward in a route-like maze configuration could subsequently vector navigate directly to that reward’s location when the maze was changed to a radial maze, suggesting they had inferred a direct shortcut (Figure 1c). Tolman argued that these experiments showed that rats form and use a cognitive map of the environment to guide their behavior. Moreover, he envisioned cognitive maps as being abstract and domain-general, transcending physical space, and perspicaciously foresaw their utility for a wide range of goal-directed behaviors.

In principle, a cognitive map of the relationships between states in a task space [2] or entities in the world [3–5] would likewise be powerful because it would allow new relationships to be inferred, as in physical space. This ability can be shown to dramatically accelerate learning through generalization and inform novel decisions (Figure 2d) [4,6\*\*]. Notably, however, there are different definitions of what constitutes a cognitive map in the literature, and an array of different paradigms used to evaluate flexible behaviors that may rely on a cognitive map. We suggest these behaviors can be understood in terms of a flexibility hierarchy that balances online computational demands and representational complexity (Figure 2a). Here, we review both the evidence concerning the roles of the hippocampus (HC), entorhinal cortex (EC), and ventral prefrontal cortex (Figure 1d), each emerging in the field as prime candidate substrates for cognitive maps [4,7–10], and how recently developed theories cast light on the putative computations these neural systems may implement.

## Classic inference paradigms

Classic inference paradigms have been utilized across species to investigate the relational coding or integration of previously experienced associations that can be considered a type of cognitive map. For instance, transitive inference (TI) and associative inference (AI) paradigms have been commonly used to investigate relational coding or integration of previous experiences, and have primarily focused on the hippocampal formation and ventromedial prefrontal cortex (vmPFC) [11–14]. TI paradigms typically involve inferring the hierarchical relationship between elements of a set (e.g.  $A > B > C > D > E$ ) that were not compared during learning (e.g.  $B > D$ ) based only on direct comparisons between ‘premise pairs’ that differ by only one rank (e.g.  $B > C$ ). Early studies first demonstrated that disconnecting the rat hippocampus

Figure 1



(a)–(c) Examples of maze experiments Tolman described as evidence for the existence of cognitive maps [1]. (a) Example of latent learning maze. After exploring the maze for several days in the absence of reward, rats quickly exploited their ‘latent learning’ of the maze’s layout once a reward was first introduced. (b) Y-maze used to test the effects of reinforcer devaluation. The animals learned the location of different rewards while they were neither hungry nor thirsty. The two groups of solely hungry or solely thirsty animals tended to choose the location where the currently desired outcome used to be. (c) After learning the goal location from a route-like maze (left), animals were more likely to discover a direct novel route closest to the goal location when the maze was replaced with a radial maze (right). S-starting point; G-goal location. (d) Human hippocampus (HC), entorhinal cortex (EC), ventromedial prefrontal cortex (vmPFC)/medial orbitofrontal cortex (mOFC), and lateral orbitofrontal cortex (IOFC) regions of interest proposed to organize relational information into a cognitive map.

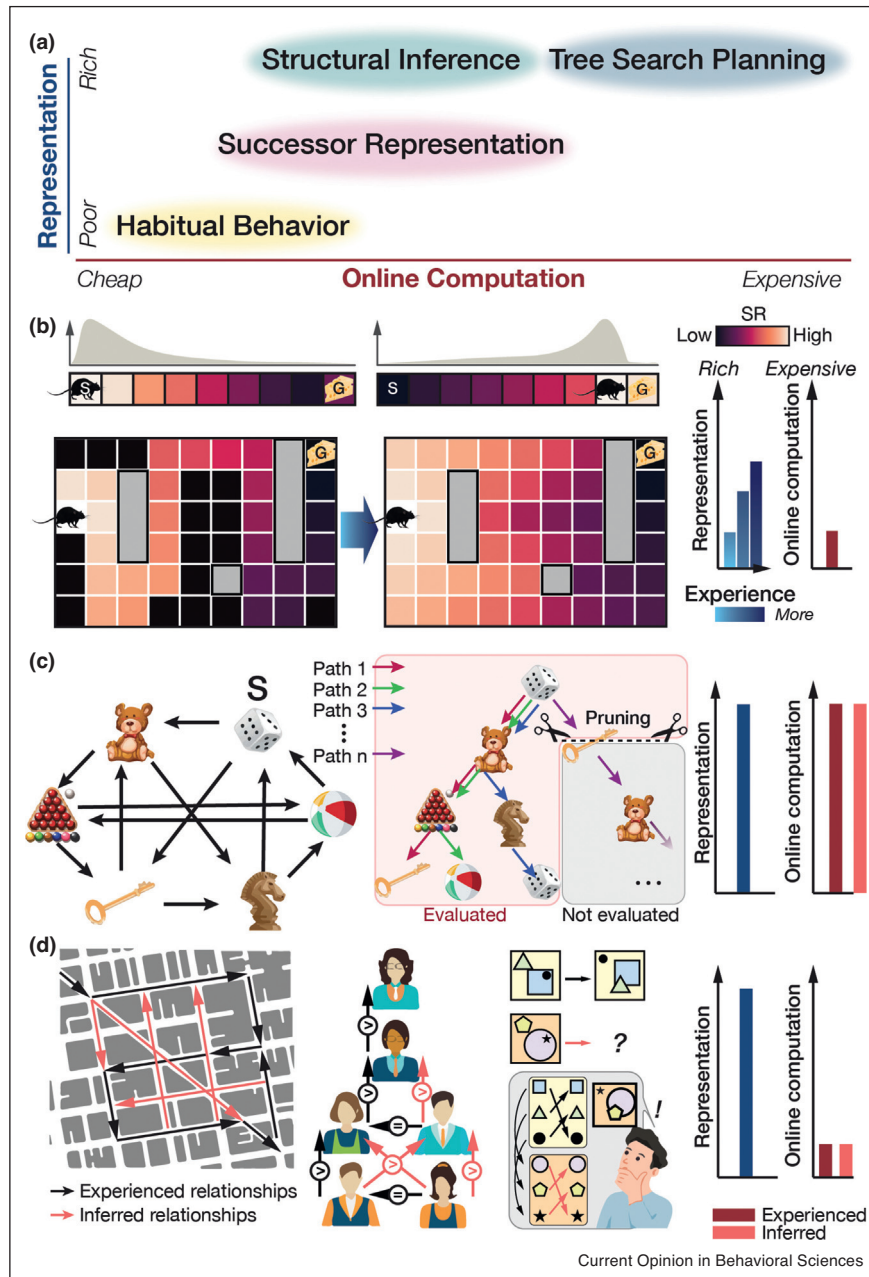
(HC) and (pre)frontal cortex through perirhinal and entorhinal cortex (EC) lesions or fornix transection led to profound deficits on TI tasks, specifically for inferred relational pairs (BvsD), but not directly learned ‘premise’ pairs (BvsC) [12]. In humans, increasing BOLD activity in the HC and vmPFC has been found for increasing power rank in both social and non-social hierarchies during TI [13], and vmPFC-damaged patients show selective TI impairments [15]. Notably, human learning of ordinal social hierarchies is better accounted for by a Bayesian inference scheme that updates the distribution over all ranks than leading ‘model-free’ ranking algorithms that update only compared entities [14].

Similarly, in AI paradigms, partly overlapping associations (AB, BC) enable successful transfer to novel test probes (AC). Inferences in these tasks are likewise impaired following HC [16] and vmPFC damage [17]. Moreover, reactivation of A during encoding of BC is associated with successful novel AC inferences, and pattern similarity between integrated items A and C has been found to

increase post-learning in anterior HC and vmPFC [11,18]. Different theories and associated neural network models have been proposed to account for inference behavior in TI and AI tasks. One class of models builds off complementary learning systems (CLS) [19] supplementing it with the capacity for rapid integration/generalization of separately experienced but overlapping associations through reactivation, with different proposed circuit mechanisms [20–22]. Other models instead propose the HC-EC system, or other cortical areas [23], build and use an explicit representation of a relational map between items, entities, or states, thereby enabling direct inferences over the map (see Structural Inference) [3,6••].

In sensory preconditioning paradigms used to study novel decisions in reinforcement learning, a stimulus A leads to another stimulus X and stimulus B to Y; subsequently, stimulus X but not Y is rewarded. Animals and people will often select A over B when presented as novel decisions [24,25]. However, following OFC inactivation post-learning, this preference for the inferred choice A is

Figure 2



**(a)** Different behaviors can be understood in terms of a flexibility hierarchy that balances the online computational demand for choice and the richness of the underlying representation. **(b)** Successor representation (SR) represents the expected discounted future state occupancy. The place field skews against the preferred movement direction on a one-dimensional track (top) because the population vectors encode the expected future states. Each colored cell in the 2-D maze represents the firing rate of the SR located along the route that the animal has experienced (bottom left). As the animal explores the maze more, the estimate of the SR is updated incrementally using temporal difference learning (bottom right). The more experience, the richer the representation animals have (right). The strengths of the SR lie in its use of computationally simple updating to ultimately compute a relatively rich representation of the possible transitions in a well-explored environment, enabling efficient on-the-fly computations during planning and navigation. On the other hand, the standard SR lacks the flexibility of full-fledged model-based algorithms because it incrementally learns the SR only through direct experience under a specific policy, implying that changes to the environment (e.g. a new detour) lead to relatively slow changes to the SR through new experience and hence re-planning, though faster than standard model-free algorithms. **(c)** Example tree-search planning task [77]. With perfect knowledge of the transition structure (rich representation), an agent can find the optimal sequence of actions by exploring all sequences ( $2^M$  sequences, where  $M$  indicates the number of possible moves;  $M = 3$  in this example) and choose the sequence maximizing the cumulative reward. The number of sequences evaluated can be reduced by pruning the states incurring a large loss (e.g. key) (middle). Tree-search planning endows the agent with extreme flexibility in decision making – for example, when encountering sudden environmental or goal changes – but suffers from computationally expensive online planning for multi-step behavior (right).

abolished, despite intact preference for the directly rewarded choice X [24]. Moreover, coactive HC cells in sharp wave ripple activity during rest appears to link the separately experienced associations via a direct association ( $X$  and  $X \rightarrow A \rightarrow \text{reward}$ ). Optogenetic silencing of HC during decisions further impaired correct inferences, while HC neuronal ensembles showed a prospective code of the associated but unrepresented stimulus ( $X$ ) during decisions. The inferred preference could thus either be achieved using a retrieval of each paired association through ‘model-based reasoning’, offline replay mechanisms that ‘connect the dots’, generalizing reward value over the reactivated experience at the time of reward [26], or some combination of the above. Notably, dopamine bursts are also necessary, not only for the reward association with  $X$ , but also the initial association  $A \rightarrow X$  [27]. Taken together, while it has proven challenging to determine whether these different inference tasks do in fact utilize an explicit cognitive map *per se*, or instead the reactivation of associated experiences, a noteworthy commonality is the requirement to leverage an associative scaffold to link items, entities, or rewards experienced separately to guide novel decisions, processes that depend on the HC-EC system, and the interconnected IOFC and/or neighboring vmPFC [28].

### Predictive maps

In the context of sequential behavior, recent evidence has suggested animals may use a ‘predictive map’ of both spatial and non-spatial transitions between states (Figure 2). In contrast to models that propose an explicit forward model that specifies the likely transitions between states given potential choices is used to compute values on-the-fly [29], the successor representation (SR) [30] stores a precompiled, cached prediction of likely future state occupancies from a given state under a policy, thereby enabling efficient online computations (Figure 2). The value function for a given state ( $V(s)$ ) can then be factorized into a reward function ( $R(s')$ ) and a transition function ( $M(s, s')$ , known as the successor representation (SR)). This factorization enables more flexible re-planning following changes to the reward (e.g. in reward devaluation (Figure 1b)) and, to a lesser extent, the environment (e.g. detours) than standard model-free methods [31]. However, for multi-step problems, re-planning is still relatively slow compared to fully fledged ‘model-based’ algorithms because the standard SR is incrementally updated only through new experience (Figure 2) (though see Ref. [32]).

It has recently been suggested that hippocampal population coding may reflect the SR [33] (or related predictive coding models). HC place cells in rodents have been

shown to fire in anticipation of locations along well-traveled trajectories, leading to an elongated place field opposite the direction of movement [33] (Figure 2b). In humans navigating virtual environments that incorporated teleportation shortcuts, HC BOLD pattern similarity increased with both spatial and temporal proximity, consistent with a predictive map [34]. Supporting a more general role outside of space, BOLD adaptation and pattern similarity in HP/EC has likewise been shown to reflect the predictability of implicitly learned statistical transitions between visual stimuli, which can be captured by the SR [35,36]. Interestingly, the eigenvectors of both the SR and the covariance of HC place cell population activity resemble EC grid cell activity, which in combination with other identified HC/EC cell types, can theoretically be used to find new routes and shortcuts during spatial navigation [4,33,37\*].

Another recent convergence across species has indicated that both dopamine recordings in the VTA [38] and BOLD activity in the dopamine-rich midbrain [39–41] reflect not only reward prediction errors, but also value-neutral state or identity prediction errors, and are both necessary and sufficient for learning about state-state (or sensory) associations [27], pointing to a more general role for dopamine in updating beliefs, and in a manner that may even incorporate uncertainty in belief distributions [42]. These signals could theoretically underlie updating of both predictions about future states and rewards, thereby informing both transition and reward functions.

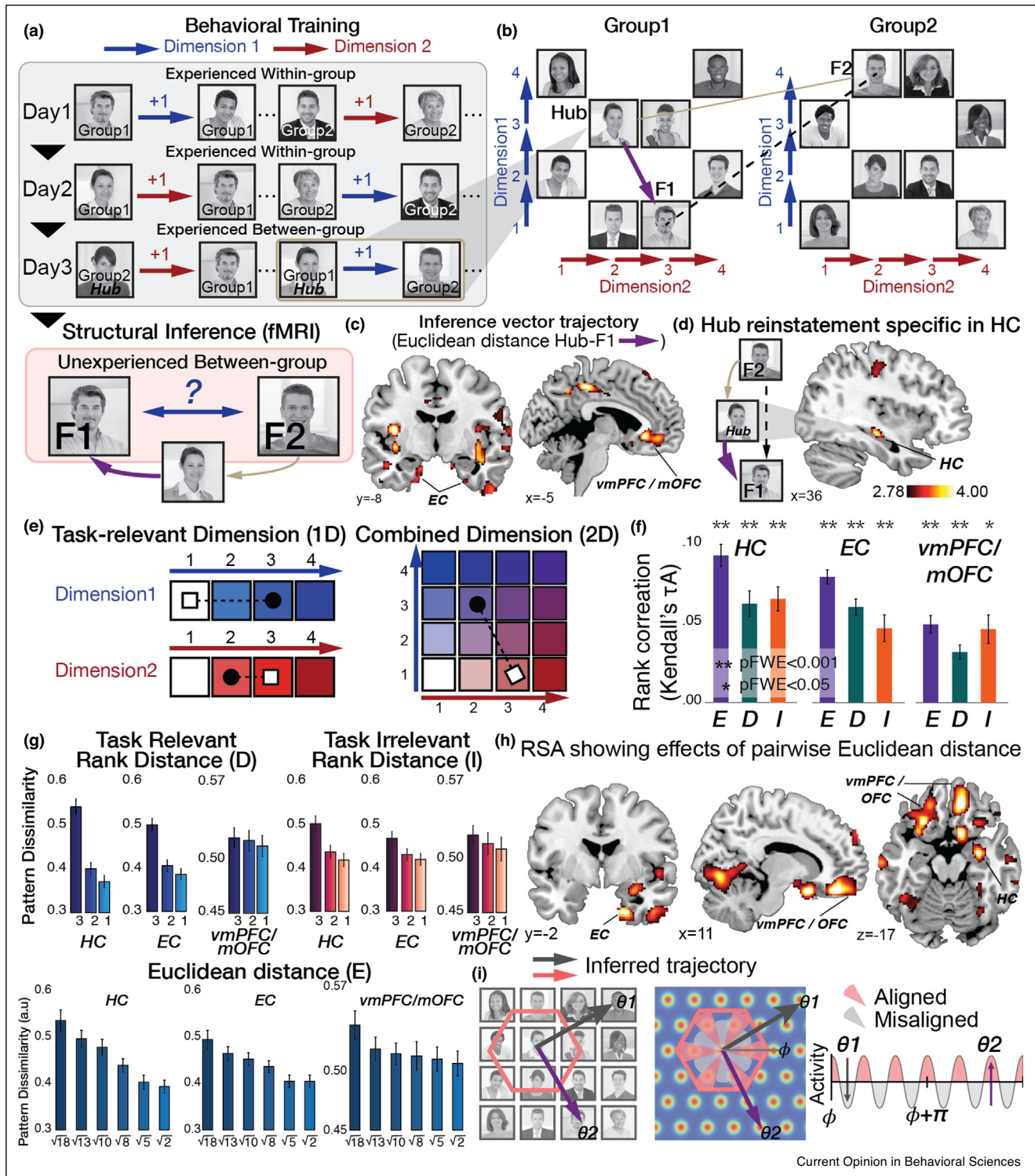
### Online planning in ‘model-based’ behavior

Unlike the SR, online planning (e.g. Monte Carlo tree search) makes use of a full model of the transitions between states given actions to compute an estimate of the action value function iteratively  $Q(s, a) = R_s^a + \gamma \sum_{s' \in S} T_{ss'}^a \max_{a'} Q(s', a')$  where  $R_s^a$  is the reward function and  $T_{ss'}^a$  is the transition function that specifies the probability of transitioning from state,  $s$  to some future successor state  $s'$  (also referred to as the ‘model’ in model-based RL). This formalization allows for tremendous flexibility for re-planning when either the goal or the environment changes but suffers from heavy online computational demands as the number of states considered increases exponentially with planning steps [43] (Figure 2c). A wealth of evidence also suggests critical roles for the HC-EC system, and OFC/vmPFC (among other areas) in the creation, updating, and flexible use of a cognitive map for online planning, central to ‘model-based’ behaviors [29] (Figure 2c). Consistent with a role in look-ahead online planning, hippocampal place cell sequences ‘pre-play’ future traveled routes during

(d) Using structural inference, an agent can organize states, items, or entities into an explicit representation of relationships. This enables the agent to discover novel direct routes in spatial navigation (left), infer new hierarchical relationships in a social hierarchy (middle), and generalize structural knowledge divorced from the experienced content to a novel problem (right). Structural inference thus affords high flexibility using inexpensive online computation (right).



Figure 3



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Novel inferences in a social hierarchy use a cognitive map. **(a)** The behavioral training procedure [72]. Participants learned the relative status in the social hierarchy between two individuals through a series of binary decisions, having never seen the true structure. During training participants learned every possible relationship between within-group pairs (8 people) who had one rank difference in a given dimension, with each dimension learned on a separate day. They then experienced only limited between-group pairs involving ‘hubs’ on day 3. During fMRI participants were asked to make novel inferences of the relative rank between unlearned between-group pairs (F1 and F2) in only one dimension at a time. **(b)** An example decision trajectory over a cognitive map. Participants could reinstate the hub who had been compared with both F1 and F2 and use the vector from the hub to F1 (purple arrow) as an inferred decision trajectory. **(c)** The Euclidean distance of the inferred trajectory accounted for decision-related activity in the EC and

so-called fictive trial-and-error at decision points [44,45], can reflect locations distal from the animal, including reward goal locations [46], and exhibit theta phase precession with further look-ahead sweeps for further goals [47]. In humans, prospective activity representing future goal locations [48] and future visited stimuli in sequential decision-making tasks has been found in HC and category-selective cortex [49], respectively, while magnetoencephalography (MEG) decoding has revealed compressed reversed pre-play of future sequences during non-spatial planning [50], altogether consistent with a role in forward planning and prospection [51,52]. Notably, expected value and expected outcome identity signals, computed using tree search or inferred from a model of the task structure, have been consistently identified in HC, OFC, and (in humans) vmPFC [40,53,54]. Moreover, HC and mPFC suppression has been shown to reflect imagined novel foods (e.g. tea-jelly) likely to be experienced in the future that were constructed online from past experiences with the constituent components separately [55]. Recent studies further point to important interactions between HC and both vmPFC and OFC [40,56,57,58\*\*], which harness theta phase coupling during planning for spatial navigation [56] and value-guided decisions [58\*\*]. One intriguing possibility is that cognitive maps of both spatial and non-spatial relationships in HC/EC, and abstract relationships in OFC, may be leveraged to infer expected outcomes and their subjective values in IOFC and vmPFC, with more specific stimulus-defined outcomes preferentially represented in lateral OFC [59] and generalized values in vmPFC [60,61].

### Structural inference

Even more impressive, animals, and humans in particular, can infer new routes and solutions to new problems, and rapidly transfer knowledge to similar problems in new situations. Such behaviors can be formalized as hierarchical inference problems over graphs that capture different structural forms [62]. There is emerging evidence that the EC, HC, and OFC/(v)mPFC may play key roles in the learning, abstraction, and use of explicit structural representations that can guide both rapid, novel inferences and generalization (Figure 2d). Building on models that represent spatial and non-spatial problems as a connected graph (e.g. Refs. [33,36], recent proposals suggest that an

environment or task's structural form (e.g. spatial and non-spatial transitions or relationships) can be factorized from its content (e.g. items) [4,63–65]. One such model formalizes and extends earlier theories proposing spatial context is explicitly represented in posteromedial (retrosplenial/posterior cingulate) and parahippocampal cortex with connections to medial EC separately from its item content in perirhinal cortex with connections to lateral EC, which are bound together conjunctively in HC [66,67]. When spatially navigating a 2-D topology, abstracting the transition rules of similar spatial problems would theoretically enable the direct shortcuts reported in Tolman's radial mazes (Figure 1c; Figure 2d). In spatial navigation, these inferred direct routes are seen as the defining feature of a genuine cognitive map of space [10].

In support of the proposal that cognitive maps can reflect structural inferences, hippocampal replay in rodents has been shown to reflect composed novel shortcuts that stitch together separately traversed paths [68] and construct trajectories through spaces that have been seen but never visited [69], capabilities that can in principle be achieved using an abstracted cognitive map [6\*\*,37\*]. Another recent study identified abstract temporal event codes for traversed lap number in HC that generalized to the same lap(s) across different track geometries, consistent with an abstracted temporal task structure [70\*]. In humans, a recent study showed that the abstracted ordinal position in a sequence could be decoded separately from the content in the sequence during rapid offline replay events from the distribution of activity over MEG sensors [71\*\*]. Intriguingly, the structural code preceded the content code temporally during replay and replay-aligned high-frequency oscillations consistent with sharp-wave ripples were source-localized to the HP/EC.

Further support that cognitive maps reflect structural inferences comes from two recent studies, where a 2D social hierarchy defined by two independent social dimensions of popularity and competence could be reconstructed from the outcomes of binary comparisons between pairs with 1-rank level difference learned on one dimension at a time, with each dimension learned on a different day (Figure 3a) [72]. The true 2D hierarchies were never shown, nor were subjects ever asked to

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vmPFC/mOFC better than other alternative distances. (d) Suppression analyses revealed the latent hub associated with both F1 and F2 in the given dimension was specifically reinstated in the HC during inference decisions. (e) These findings suggest that participants integrate the two separately learned social dimensions and have a combined 2D representation (right), rather than alternating between two 1D cognitive maps according to the dimension relevant to the current task (left). (f) Representational similarity analysis (RSA) showed that the activity patterns in HC, EC, and medial and lateral OFC reflect the pairwise Euclidean distances (e) between individuals in the 2D social hierarchy. Separate analyses showed effects of both the task-relevant dimension (D) and irrelevant dimension (I). (g) The dissimilarity between activity patterns between two individuals increases in proportion with not only D, but also with I, consistent with a 2D map, since E is decomposed into D and I. (h) The whole-brain searchlight analysis showing the effects of E. (i) A separate experiment [73\*\*] tested for hexadirectional modulation of direct inferred trajectories over the same 2D social space, consistent with a grid-like code, during discrete decisions. Activity in the EC and mPFC (idealized hypothesized activity shown) was higher when the direction of the inferred trajectory was aligned to the EC grid orientation ( $\phi$ ) in sixfold symmetry (e.g. purple trajectory,  $\theta 2$ ), compared to when the trajectory is misaligned (e.g. gray trajectory,  $\theta 1$ ).

construct them spatially, but they could be reconstructed through transitive inferences within a day and integration between dimensions across days (Figure 3b). Although the two dimensions never had to be combined for behavior, pattern similarity analyses of BOLD in the HC, EC, and OFC supported a 2D over a 1D cognitive map, such that closer individuals in the true 2D social space (measured by Euclidian distance) were represented progressively and linearly more similarly (Figure 3e–h). In one study, the 16-person hierarchy was learned in two separate groups of 8. Subjects then observed select comparisons of hubs who could be used to link the two groups and potentially combine them into one hierarchy (Figure 3a). During novel inferences about unlearned pairs between the two groups, there was evidence for both associative inferences through reactivation of the hub that linked the groups and direct inferences from the hub to the other pair in the hub's group. Specifically, decision-related activity in EC, IOFC, and vmPFC (but not HC) reflected the Euclidian distance between people and their hubs in the 2D map over alternative metrics (Figure 3c), while suppression analyses indicated the hub was reactivated in HC (Figure 3d) [72]. Moreover, a second study using the same  $4 \times 4$  social hierarchy found evidence for grid-like coding in EC, mPFC, and PCC (but not HC) for *inferred* direct trajectories over the reconstructed 2D social space during novel decisions (Figure 3i) [73\*\*]. Importantly, these direct trajectories were never learned during training, during which only 1-rank-level differences were ever compared on one dimension at a time and on different days (Figure 3a–b), but could be utilized if subjects had inferred a 2D space.

Taken together, these two studies suggest that local observations sampled piecemeal may be reconstructed into an explicitly represented global cognitive map in HC, EC, and OFC, allowing for direct inferences to be computed or used in EC and OFC/vmPFC during novel decisions. These findings shed light onto why lesions/inactivation of the HC-EC system, vmPFC, and/or OFC impair inferences during classic inference paradigms [12,15,17,24]. These direct inferences in abstract relational space are analogous to the direct shortcuts Tolman's rats traversed in physical space (Figure 1c).

In terms of a division of labor, these findings further suggest that while cognitive map-like representations are found in HC, EC, and OFC (and some studies that are beyond the scope of this review additionally suggest in parietal cortical regions [23,73\*\*,74,75]), direct inferences based on cognitive maps may be computed efficiently in EC, OFC, and vmPFC based on these precompiled cognitive maps. Furthermore, recent studies point to a critical role for coordination between HC and OFC, with causal manipulations of HC output impairing OFC representations of the inferred latent context during

reversal learning [57], and closed loop HC theta stimulation disrupting theta-locked value coding in OFC that has a causal role in stimulus-reward learning [58\*\*]. Thus, one intriguing possibility is that the precompiled relational map in the HC-EC system is used to guide efficient goal-directed inferences for both learning and choice in prefrontal regions such as OFC and vmPFC.

Collectively, do these findings imply that the HC-EC system and OFC/vmPFC always explicitly represent an abstracted cognitive map for rapid generalization and flexible behavior? Rather, the literature reviewed here suggests these regions can reflect different representations along the proposed flexibility hierarchy (Figure 2a), with a likely transition between processes that chain together elemental associations on the one hand, and an explicitly represented map on the other, such as those requiring structural inference that can draw on a multitude of previous experiences, depending on both the demands for flexibility and degree of familiarity with the problem type. This putative transition may be viewed as analogous to the transition between route and survey maps in spatial navigation [76]. Uncovering how the brain balances the needs for flexibility and computational efficiency, and how it transitions between different representations through experience are likely to be fruitful areas for further investigation [64].

## Conflict of interest statement

Nothing declared.

## Acknowledgements

We gratefully acknowledge support from an NSF CAREER Award 1846578 and an R56 MH119116 from N.I.H.

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have a factorized representation of the contents and the structure of experiences, respectively. These factorized representations of different principal components of experience are flexibly recombined and create a conjunctive representation in HC. In doing so, HC can represent a novel experience by generalizing from previous related experiences and also serve to guide structural inferences before direct experience.

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