Neural Signatures of Tree Search

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Abstract

From the moon landing to meal preparation, people plan sequences of actions to achieve their goals. A leading theoretical framework proposes that human planning follows an algorithm akin to tree search. This framework predicts that during the decision-making process, the brain updates its estimate of the value of the current state by iteratively expanding a tree of future states. To test this prediction, we collected whole-brain BOLD activity from participants as they planned their move in a strategic game. Activity in the ventral striatum was modulated by the state value estimated by a tree search model. Moreover, in this area, the activity earlier (later) in the trial was more strongly modulated by the value predicted by the model earlier (later) in the tree search. Searchlight analysis revealed areas associated with the Default Mode Network to represent features critical for planning. This work contributes to an emerging understanding of the neural basis of tree search.

Keywords: planning; tree search; fMRI

Background and Introduction

Planning, the process of simulating sequences of future decisions, is a cognitive capacity crucial in many domains, from navigation to social interaction. Despite recent progress in characterizing the cognitive computations involved in planning (Callaway et al., 2022; Mattar & Lengyel, 2022; van Opheusden et al., 2023), our conceptual understanding of the neural mechanisms of planning is still limited.

Existing studies that rely on spatially localized brain lesions, and fMRI studies that contrast brain activation during planning versus rest states have revealed a network of brain regions involved in planning such as prefrontal cortex (PFC) (Unterrainer & Owen, 2006), dorsomedial striatum (DMS) (Wunderlich et al., 2012), ventral striatum (VS) (O'Doherty et al., 2004), and hippocampus (Vikbladh et al., 2019). More recently, an MEG study, has found neural markers of sequence rollouts, localized to the anterior medial temporal lobe (Vikbladh et al., 2024). However, there has been no account of the neural basis of the planning process as it unfolds during a trial.

Task and Experiment Design. We used Four-in-a-Row (van Opheusden et al., 2023), a task that combined with the tree search algorithm, allows the trial based analysis of the neural data. On a 4x9 grid, players attempt to place four of their own pieces in a row horizontally, vertically, or diagonally. We recruited 35 paid participants. Each took part in two experiment sessions. In Session 1, the participant played 35 matches against a computer opponent (outside the scanner). In session 2 after an anatomical scan, the participant completed 216 trials in which they were presented with a board position chosen to differ in immediate and post-tree-search value assessment, and asked to choose the best move while undergoing fMRI data collection. The participant was allowed 15 s to choose, with a warning displayed at 10 s (Fig. 1). To encourage planning, we made the participant wait for the full 15 seconds, even if they responded early. Immediately after the fMRI session, the participant played a match against the computer for a monetary bonus, from one of the board positions they had chosen.

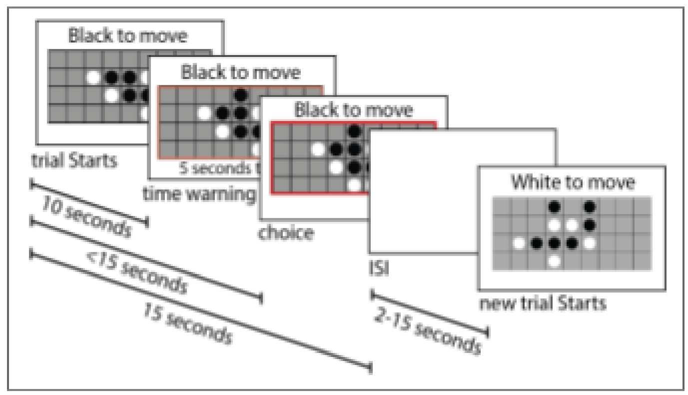

Figure 1: Timeline of an example trial.

Results

Computational Model. The model implemented a form of heuristic search with two main components: a heuristic function and a tree search algorithm. The heuristic function provided an estimate of the value of a state as the weighted linear sum of 5 features: “4-in-a-row”, “3-in-a-row”, “unconnected 2-in-a-row”, “connected 2-in-a-row” and “center feature” (higher for pieces closer to the center of the board). The value V(s) was defined as the difference of the weighted feature counts of oneself and the opponent. The tree search algorithm improved the accuracy of value estimates by expanding nodes of a decision tree and recursively backpropagating the maximal value of the successor nodes to the predecessor nodes. To account for choice variability, we added three sources of noise. Prior to tree search, a feature may be randomly dropped with a probability δ, accounting for attentional oversight. During tree search, Gaussian noise is added to V(s) at each node, and a generic lapse rate λ. The algorithm stops randomly with probability γ on each iteration.

We fit the computational model to the choices of each participant in the first session, to estimate, for each encountered position during the scanned session, which future states participants likely simulated, how they valued the position, and which moves they likely preferred over the course of planning.

Value Representation. We first confirmed the ability of the model to predict participants' choices, then used the fitted models to compute the participant's "myopic value" (value assessment of the board position by the heuristic function before tree search) and the "tree search value" (final value assessment after tree search) for each board position in the fMRI session. We used standard univariate general linear models (GLMs) to estimate the degree to which the BOLD signal in each voxel was significantly modulated by the estimated "myopic value" and "tree search value". Voxels within VS were modulated by tree search value ($p=0.004$) (Fig 2A). By design, search-derived values were uncorrelated with the myopic values, which (together with the long planning period) allowed us a strong test of both components of the model: the fast feature-based heuristic valuation and its hypothesized refinement by tree search, at the timescale of fMRI.

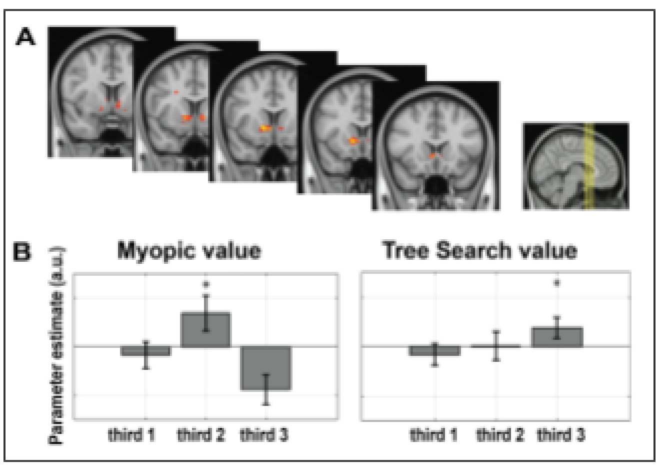

Figure 2: A. BOLD responses in the ventral striatum were modulated by "tree search value". B. Modulation in Ventral Striatum in trial thirds.

We next decomposed the BOLD response in ventral striatum temporally by dividing each planning period into three parts . The correlation of the signal with myopic value (Fig 2B, left) peaked earlier in the trial than the tree-search-informed value (Fig 2B, right) , supporting the hypotheses that values are quickly estimated then slowly refined by mental simulation (Fig. 2B, right).

Feature Representation. Next, to examine computational precursors of value representation, we used representational similarity analysis to seek evidence that the brain represented boards in terms of the features used by the heuristic function. For each board, we calculated the vector of features (e.g. the counts of "3-in-a-row"), for the player and the opponent. We then constructed the similarity matrix of all pairs of boards using their distance in the space of z-scored feature vectors. We also constructed neural similarity matrices (in a "searchlight" analysis, using Pearson correlation across board responses in spheres centered at each voxel). Finally, we compared the feature similarity and the response similarity matrices using Spearman correlations. This analysis identified precuneus and angular gyrus as reflecting similarity of boards for all features belonging to the player (Fig 3A) and angular gyrus and middle frontal gyrus as representing similarity in terms of the features belonging to the opponent (Fig 3B). These results suggest that regions of the Default Mode Network represent board features that are critical for planning.

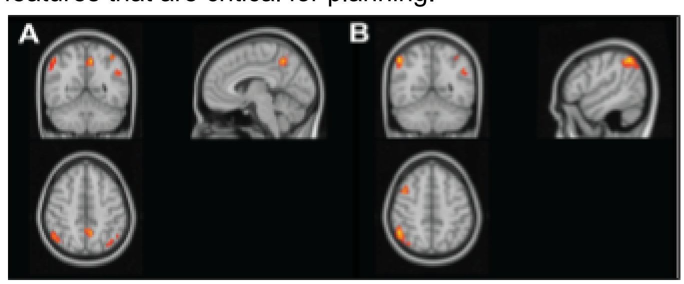

Figure 3: A.Precuneus and Angular Gyrus track presence/Absence of features for self, and B. angular gyrus and middle frontal gyrus for the opponent

Discussion and Future Direction

These results contribute to an emerging understanding of the neural basis of tree search, revealing where and when the brain represents features and values. In later analysis, we aim to seek the representations of board features that have been likely simulated during the planning process based on our model predictions.

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