Reconstruction of real-time planning processes in a multi-goal task using eye tracking

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Abstract:

Given a dynamically changing environment, it is essential for humans to establish diverse plans in order to flexibly adapt to such changes. However, examining the planning processes has proven difficult as they are not manifested in observed actions. Previous studies on planning utilized tree search models but they often implemented tasks in a stable environment that were too simple to effectively induce complexity in the process of planning. In this study, we designed a new arithmetic calculation paradigm that requires considering multiple plans before making decisions. To examine the real-time planning process, we reconstructed the planning process of each participant by an eye-tracking model and compared it with the result from a parameterized tree search model trained using their reported plans. Our eye-tracking model calculated the probability of possible plans in real-time based on the gaze location. The correlations observed between the likelihood of each possible plan derived from the eye-tracking and tree search models confirmed that the considered plans could be reliably inferred from the eye-tracking data. Beyond explaining the planning process through behavioral models, we demonstrate a new method for revealing the real-time process of plan generation.

Keywords: Eye-tracking, plan reconstruction, tree search model

Introduction

Human adaptive behavior is fundamental to higher cognitive processes, which requires diverse plans to prepare for potential changes in advance (Hunt et al., 2021; De Martino et al.,2023). Previous studies have demonstrated that utilizing tree search effectively models the human planning process. However, they mainly investigated the process of building a single plan in a stable environment (Callaway et al., 2022). Moreover, most planning research has examined the process of planning from end to end (Matter et al., 2022; Eluchans et al., 2023), which often overlooked the process of sequential plan formation.

In this study, we used calculations to induce diverse planning in participants. To elucidate the real-time planning processes of each individual, we constructed an eye-tracking model that accumulates the probability of each possible plan from eye-gaze location over time. The plans predicted by the eye-tracking model were statistically compared with those from a tree-search model (Matter et al., 2022, van Opheusden et al., 2023). Our results underscore the feasibility of reconstructing the planning process using eye-tracking data, providing a tool for reliably predicting the plans considered by participants in real-time.

Methods

Task design

Participants performed a calculation task consisting of three numbers and two operators selected from a larger pool of items displayed on the screen (Figure. 1). The goal was to formulate equations that would result in one of two target numbers. The task was divided into planning and execution stages. During the task, participants generated and reported up to three plans in 60 seconds, which guided their sequential decisions to select three numbers and two operators later during the execution stage. When they selected an item, each unselected number on the screen changed its value with a 35% chance. Therefore, participants needed to adapt their plans according to the changing numbers.

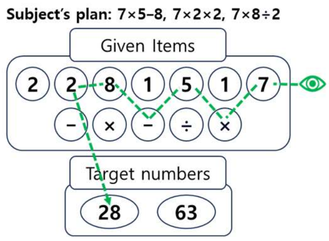

Figure 1. Task design. Participants were given seven numbers, five operators, and two target numbers. They generated and reported up to three plans to reach one of the target numbers.

Eye tracking model

We implemented an eye-tracking model to identify the plans participants were considering at each point during the planning stage. Using the eye movement data recorded during the task (60Hz video), we developed an eye-tracking model to calculate the probability of each plan at each frame. To predict the participants' plans, we identified the items they gazed at for each eye tracking video frame and recorded them in a binary matrix. This matrix was convolved with different windows optimized for each participant in order to compute the softmax probability across possible plans (Figure 2). This method allowed for updating the probability of every possible plan based on the gaze location and given items. We computed the average probability of each plan to assess the level of consideration during the overall planning process. The 180 frames (3 seconds) prior to the reporting of actual plans were excluded from analyses to discriminate the effect of planning from making an explicit report.

Tree search model

We developed a tree search model that utilizes best first search (Callaway et al., 2022) and pruning (Mattar et al., 2022) to compute the likelihood of each possible plan and compare it with the eye-tracking model. The tree search model predicted participants' plans by considering possible combinations of given items. The model behavior was determined by four parameters that guided the search process. The model performance was measured by the proportion of hits

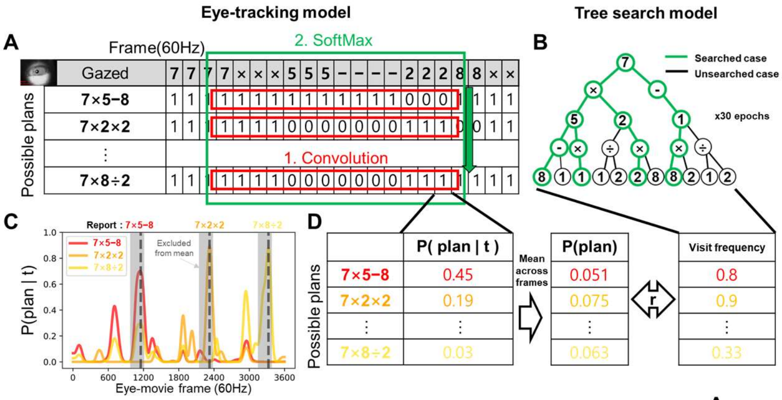

Figure 2. A. Recording table of gaze points for each plan across frames. Each column corresponds to an eye-tracking data frame and each row indicates whether the item is included in the plan. We applied convolution (linear weight function) for each plan and computed softmax across plans to calculate their respective probabilities. **B.** Schematic illustration of our tree search model. The model determines which nodes to visit (green). **C.** Example time-course of the probability of each plan. **D.** Mean probability over all frames (excluding 180 frames prior to the participants' reporting) was calculated (**C.** gray area). Correlation between the visit frequency and mean probability of each plan was computed for each trial.

among predicted plans during 30 epochs of model validations. We used a grid search to find the optimal parameters based on model performance, fitting the models accordingly. The model proved highly effective in predicting participants' plans (with an average hit ratio of 0.63). We calculated the visit frequency of each possible plan over 30 epochs to assess model's predictions.

Results

We analyzed the correlation between the average probability of plans from the eye-tracking model and the visit frequency for plans in the tree search model (Figure 3.A). We computed trial-wise averaged correlations for each participant (Figure 3.B) and conducted a permutation test by shuffling the individually tuned tree search model across participants. A paired t-test comparing the average correlation of each participant with the 95% confidence interval from the permutation test revealed a significant difference ($t=4.62$, $p < 0.001$). This result demonstrates that the tuned tree search model plays an important role in predicting the possible plans that match the predictions from the eye-tracking model. These results indicate that the planning process can be reconstructed using eye-tracking data.

Furthermore, we classified possible plans into three types: "reported plan" – plans reported by participants during the planning process, "valid plan" – plans that match the target number but were not reported by participants, and "invalid plan" – plans that do not match the target number (participants were instructed not to report invalid plans). The reported plans exhibited a significantly higher probability starting from -7.68 seconds before the report (Figure 3.C) compared to valid plans. Additionally, reported plans showed a significantly higher visit frequency compared to other plans (Figure 3.D). These findings suggest that the planning process reconstructed using eye-tracking data can predict which plans participants have in mind. Moreover, our eye-tracking model provides a distinct value beyond the tree search model by elucidating the real-time process of plan construction by the participant.

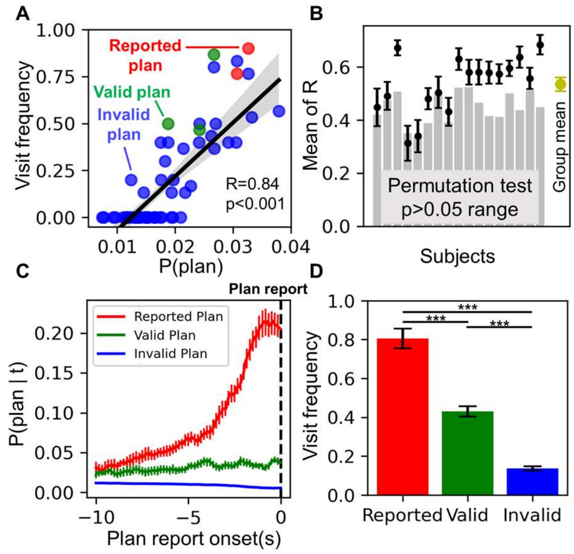

Figure 3. A. Correlation between the average probability of plans from the eye-tracking model and the visit frequency for plans in the tree search model in an example trial. **B.** The mean correlation across trials for each participant. Gray bars indicate the 95% confidence interval from the permutation test by shuffling the tree search model across participants. **C.** Average probability of plans across participants from 10 seconds before reporting. **D.** Average visit frequency in the tree search model for each plan condition across participants.

Conclusion

Our study demonstrates the feasibility of predicting the planning process of individuals using eye-tracking data. We developed a novel paradigm that induces diverse planning through calculations, enabling the reconstruction of participants' planning processes in real-time. By comparing the predictions of the eye-tracking model with those of the tree search model, we confirmed the accuracy and reliability of the eye-tracking method. The eye-tracking model effectively predicted participants' plans, highlighting the potential of this approach in understanding human planning behavior. Our findings contribute to the understanding of diverse planning processes in humans and demonstrates the utility of eye-tracking data in predicting individual planning behaviors.

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