Remediating Cognitive Decline with Cognitive Tutors

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Abstract

As people age, their cognitive abilities tend to deteriorate, including their ability to make complex plans. To remediate this cognitive decline, many commercial brain training programs target basic cognitive capacities, such as working memory. We have recently developed an alternative approach: intelligent tutors that teach people cognitive strategies for making the best possible use of their limited cognitive resources. Here, we apply this approach to improve older adults' planning skills. In a process-tracing experiment we found that the decline in planning performance may be partly because older adults use less effective planning strategies. We also found that, with practice, both older and younger adults learned more effective planning strategies from experience. But despite these gains there was still room for improvement – especially for older people. In a second experiment, we let older and younger adults train their planning skills with an intelligent cognitive tutor that teaches optimal planning strategies via metacognitive feedback. We found that practicing planning with this intelligent tutor allowed older adults to catch up to their younger counterparts. These findings suggest that intelligent tutors that teach clever cognitive strategies can help aging decision-makers stay sharp.

Keywords: aging; planning; cognitive training; cognitive plasticity

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1 Introduction

Many cognitive abilities deteriorate with normal aging, including planning. Commercial brain training programs promised to remediate this cognitive decline by training basic cognitive capacities – especially working memory. But they have often failed to live up to their promises (*A consensus on the brain training industry from the scientific community*, 2014). More effective methods for combating this decline or even improving planning abilities have yet to be discovered. One new approach could be to discover and teach people cognitive strategies that make the best possible use of their bounded cognitive resources (Lieder et al., 2019, 2018; Lieder, Krueger, Callaway, & Griffiths, 2017).

Previous studies have found that older adults have trouble formulating plans and updating them in the light of feedback (Allain et al., 2005; Sorel & Pennequin, 2008). We hypothesized that the reason why older adults perform worse is that their planning strategies are less effective than those of younger adults. If this is the case, then it should be possible to mitigate this aspect of cognitive decline by teaching older adults better planning strategies. Here we investigate this hypothesis using the intelligent cognitive tutor we developed in previous work (Lieder et al., 2019, 2018, 2017). In Experiment 1, we characterized the planning strategies used by people of different age groups in order to determine whether age affects the types of planning strategies used. In Experiment 2, we investigated whether cognitive tutoring can help close the performance-gap between younger and older adults. Our results suggest that cognitive tutoring is a promising approach that should be explored as an intervention for improving people's decision-making competency and remediating cognitive decline.

2 Experiment 1

2.1 Methods

We recruited participants younger than 25 years old to form our younger adults group ($n = 49$) and adults older than 47 years old to form our older adults group ($n = 29$). The experiment was conducted online via Amazon Mechanical Turk. In the experiment, participants completed 30 trials of Mouselab-MDP paradigm (Callaway, Lieder, Krueger, & Griffiths, 2017) with a three-step route planning task. On each trial, participants were shown a map of gray circles (Figure 1) and instructed to move the spider in the middle to one of the outermost nodes, picking up the rewards hidden on the circles along the way. For each trial, rewards are independently drawn from discrete uniform distributions; in the first step the possible values were $\{-4, -2, +2, +4\}$; in the second step the possible values were $\{-8, -4, +4, +8\}$; and in the third step the possible values were $\{-48, -24, +24, +48\}$. Participants could uncover rewards beforehand by clicking on the gray circles and paying a cost of -1 for each reveal. Participants were instructed to maximize their rewards and were incentivized with a monetary bonus based on their in-game score.

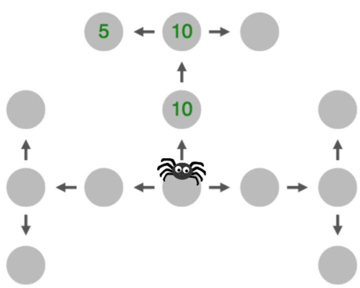

Figure 1: A typical Mouselab-MDP trial used in Experiment 1 and the control condition of Experiment 2. Some of the rewards have already been revealed by the participant.

We use the clicks our participants made to infer which kind of planning strategy they used. We considered six different planning strategies: depth-first search, breadth-first search, best-first search, progressive deepening, the optimal planning strategy, and an impulsive strategy that chooses randomly without collecting any information. Depth-first search explores a single path at a time – from its beginning to its end. Once it reaches the end of this path, it returns to the most recent unexplored fork in that path and continues exploring until all nodes have been inspected. Breadth-first search explores the first nodes of all possible paths, then the second nodes, and so on until all paths have been explored. Best-first search explores paths in the order of highest expected sum of rewards. Progressive deepening is a strategy proposed by Newell and Simon (1972) and is similar to depth-first search. The main difference is that after exploring a path in its entirety, progressive deepening skips back to the starting node, treating branches as part of another path for later exploration. Callaway et al. (2018) found that the optimal strategy for the task environment used in this experiment is to first set a goal by evaluating potential final destinations. As soon as inspecting a potential final destination uncovers the highest possible reward ($+48$), the optimal strategy selects the path that leads to it and terminates planning. If multiple potential final destinations are good (i.e., $+\$48$) but none is perfect then the optimal strategy collects additional information about them by planning backwards from potential goals.

2.2 Modeling Strategies

We modeled participants' click sequences as a combination of following one of the six strategies described above and some random moves. Formally, the probability of making click c when following strategy k is defined as

$$(1 - \epsilon) \cdot \sigma(c; V_{b,M_k}, \tau) + \epsilon \cdot \text{Uniform}(c; C_b) \tag{1}$$

where the first term, $\sigma(c; V_{b,M_k}, \tau)$, is a softmax over the possible clicks c in state b when following strategy k and τ is the temperature parameter. The second term, $\text{Uniform}(c; C_b)$, can account for actions that are inconsistent with strategy k; the probability of such "random clicks" is modeled by a uniform distribution over all possible clicks and the action of stopping planning. Finally, ϵ is the probability that a random click will be made.

The random strategy can therefore be modeled by the second term alone. The systematic behavior of the other strategies was modeled in terms of the values $V_{b,M}(c)$ they assign to different clicks c and the decision to terminate planning. For example, in the depth-first search model, the preference function $V_{b,DFS}(c)$ is the depth of the node inspected by click c if that node lies on a partially explored path and a large negative value otherwise. As a result, deeper nodes are prioritized and partially explored paths will be explored to the end before others are considered. In the optimal strategy model, the value assigned to $V_{b,O}$ is given by the optimal solution to the problem of deciding how to plan. In previous work, we formalized this problem as a meta-level Markov Decision Process and computed its solution for the environment used in this study using backwards induction (Callaway et al., 2018). Aside from the random and optimal strategy models, all of our strategy models also capture previous findings that people often act as soon as they have identified an alternative they deem good enough (i.e., satisficing; Simon, 1956) and tend to stop considering a course of action when they realize it would entail a large loss at one point or another (i.e., pruning; Huys et al., 2012). To model satisficing and pruning, our models include two free parameters for the participant's aspiration level and pruning threshold respectively. When the expected reward for terminating in belief state b exceeds the aspiration level, then our models assign a very large value to the terminate planning action. Conversely, if the expected sum of rewards for any path falls below the pruning threshold, then clicks on the remaining unobserved nodes on that path are assigned a large negative value such that the strategy was discouraged from continuing to explore that unprofitable path. We fit all models to each trial for each participant using maximum likelihood estimation for all model parameters (i.e., τ, ϵ, and the thresholds for satisficing and pruning). We then performed model comparisons using the Bayesian Information Criterion (Schwarz et al., 1978) to determine which strategy each participant is most likely to have used on each trial.

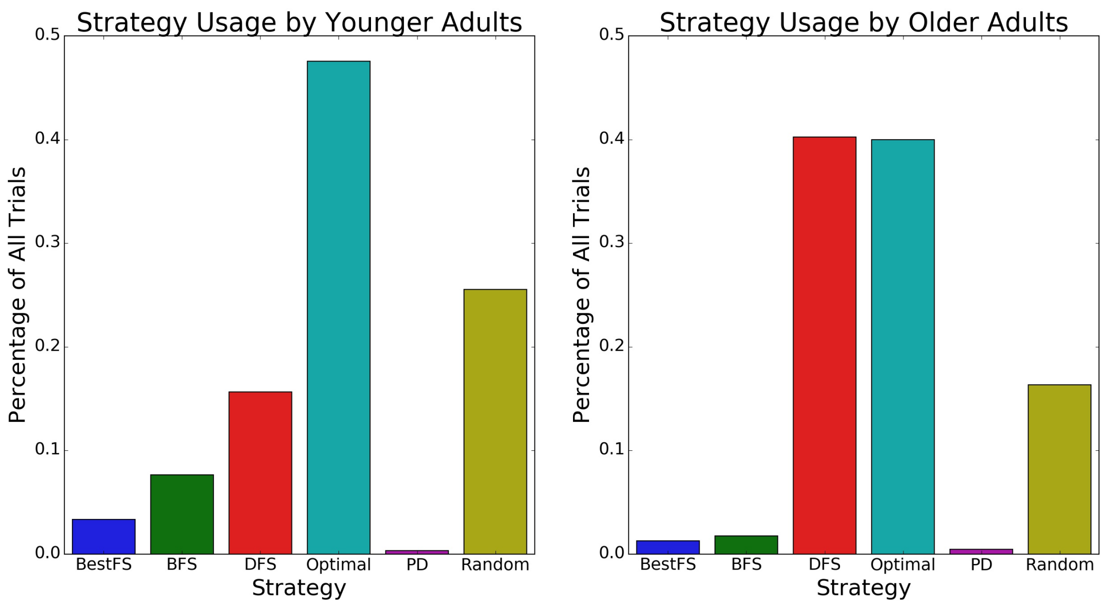

Figure 2: Strategy usage frequencies for younger adults versus older adults over all trials. The strategies we modeled are (from left to right): Best-first search, breadth-first search, depth-first search, optimal, progressive deepening, and random.

2.3 Results

In Experiment 1, we found that older adults differed significantly from younger adults in how often they used each of the six planning strategies introduced above ($\chi^2(5) = 205.43, p < .001$). While both age groups used the optimal strategy the most, older adults also favored the depth-first search strategy, using it almost as much as the optimal strategy (Figure 2). Taking a look at how participants' strategy usage evolved over time indicates that older adults were adopting the optimal strategy later in the experiment compared to younger adults (Figure 3). However, by the end of the experiment, the older adults were still not using the optimal strategy as frequently as the younger adults (avg. frequency in the last five trials: 69.0% vs. 58.6%, $\chi^2(1) = 3.86, p < 0.05$). We also found that older adults were performing worse on the task compared to younger adults, even after discovering the optimal strategy on their own (avg. score in the last five trials: 24.7 vs. 37.4, $t(76) = -2.87, p < 0.01$). This is consistent with our expectation that using the optimal strategy less than another group will lead to lower scores. If this difference in strategy usage is due to older participants being unaware of the existence of the optimal strategy, then it should be possible to remedy their deficits by teaching them the optimal strategy using our cognitive tutor. We tested this hypothesis in Experiment 2.

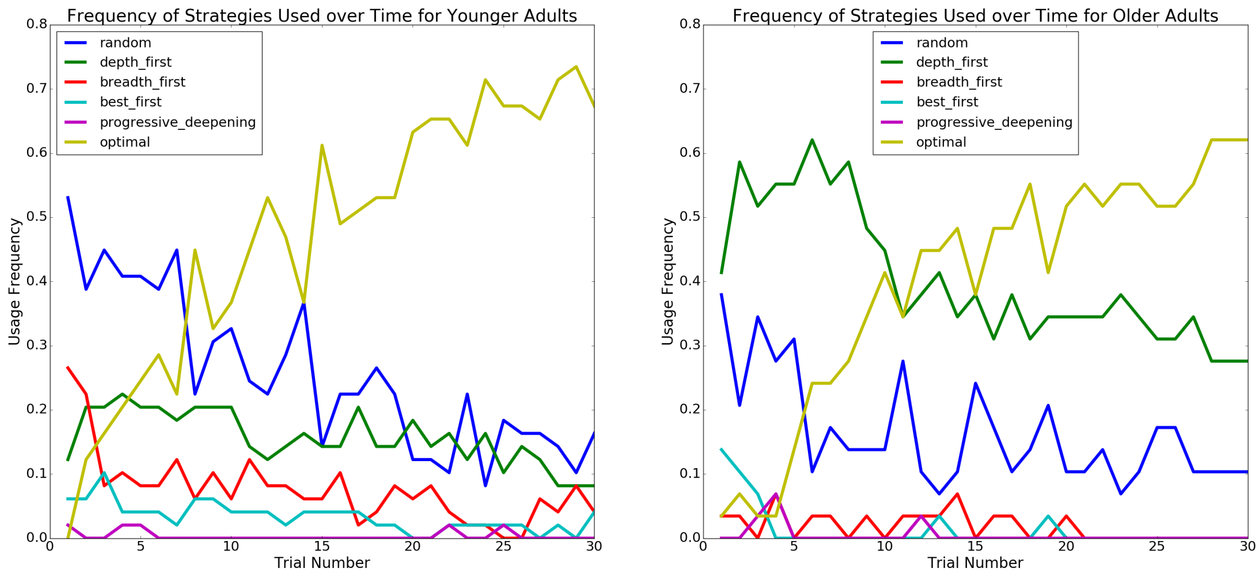

Figure 3: The frequencies of strategy usage for every trial in the experiment for younger adults (left) and older adults (right). The strategies shown are best-first search (cyan), breadth-first search (red), depth-first search (green), optimal (yellow), progressive deepening (magenta), and random (dark blue).

3 Experiment 2

3.1 Methods

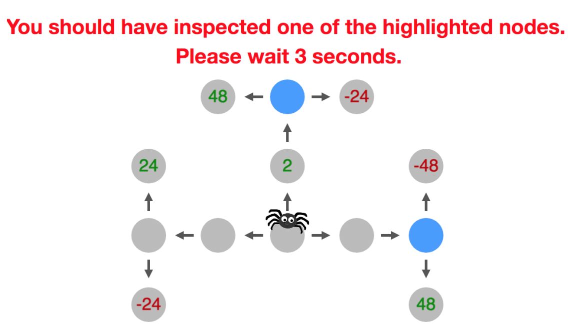

Figure 4: Example feedback from the cognitive tutor in the training phase of Experiment 2.

For Experiment 2, we recruited and sorted participants into two groups: younger than 25 ($n = 41$) and older than 47 ($n = 37$). We conducted the experiment via Amazon Mechanical Turk. Participants were randomly assigned to either train with the cognitive tutor (feedback condition, $n_{young} = 24, n_{old} = 23$) or to practice the task on their own (control condition, $n_{young} = 17, n_{old} = 14$). Participants in the control condition performed 30 trials of the Mouselab-MDP task described in the Methods section of Experiment 1. Participants in the feedback condition were first given 15 trials where they practiced the Mouselab-MDP task while receiving our cognitive tutor's optimal metacognitive feedback (Lieder et al., 2019, 2018, 2017). They were then given 15 test trials of Mouselab-MDP without any feedback, identical to the trials given to the control group. The tutor's feedback was based on the optimal planning strategy for Mouselab-MDP, discovered by Callaway et al. (2018). In brief, if a participant took a sub-optimal planning action, the cognitive tutor would make them wait for a number of seconds that was proportional to how sub-optimal their planning operation was. Additionally, whenever the tutee makes an error our cognitive tutor demonstrates what they should have done instead (Figure 4).

3.2 Results

Consistent with Experiment 1, we found that older people ($Mean = 23.23, SEM = 2.16$) performed worse in the first half of the experiment than younger people ($Mean = 29.40, SEM = 2.33$; $F(1, 772) = 18.39, p < 0.001$).

Encouragingly, practicing with our cognitive tutor was effective at improving decision-making skills regardless of age. Specifically, older and younger adults who practiced with the cognitive tutor scored significantly higher in the test block than their counterparts in the control condition ($t(39) = 3.31, p < 0.01$ and $t(35) = 3.56, p < 0.01$ respectively). Even more encouragingly, for older people the benefit of training with our cognitive tutor was so large that they did not only catch up to younger people but even scored significantly higher than younger people who had practiced the task on their own ($t(38) = 2.41, p < 0.05$). Furthermore, it appears that older adults benefited more from the cognitive tutor than younger adults. According to a three-way ANOVA the advantage of young people gradually vanished over time in both conditions ($\beta_{\text{trial}\times\text{young}} = -0.13, F(1, 2332) = 5.21, p < 0.05$) and was more pronounced in the training block than in the test block ($\beta_{\text{training block}\times\text{young}} = 5.55, F(1, 1406) = 7.36, p < 0.01$) in the feedback condition. This indicates that older adults were catching up to younger adults over time. As a consequence, we could no longer detect a significant difference between younger versus older adults ($t(45) = -1.02, p = 0.31$) after 15 trials of training with the cognitive tutor. The results suggest that cognitive tutors can help older adults catch up to the younger generations – and sometimes even overtake them.

4 Discussion

Why do older people have a harder time making complex plans and how can we help aging adults retain their planning skills? In Experiment 1, we found that older adults' decision making skills appear to be limited by their reliance on sub-optimal planning strategies. In Experiment 2, we found that this deficit can be remedied by letting older adults practice planning with a cognitive tutor that teaches them an optimal planning strategy via metacognitive feedback. While both older and younger adults benefited from cognitive tutoring, older adults benefited more. As a result, cognitive training with our intelligent tutor decreased the performance gap between older and younger adults.

Our findings suggest that cognitive tutoring could be a promising new approach to remediating cognitive decline. Future work will evaluate whether cognitive tutors can indeed help older adults stay sharp in daily life and how its efficacy compares to more conventional approaches such as working memory training. Developing cognitive tutors for a wide range of different cognitive skills and tailoring them to the needs of various age groups and (psychiatric) populations are exciting directions for future research.

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