Learning to build physical structures better over time

Anonymous CogSci submission

Abstract

Our ability to plan and build a wide array of physical structures, from sand castles to skyscrapers, is a defining feature of modern human intelligence. What cognitive tools enable us to create such complex and varied structures? Here we investigate how practice "reverse-engineering" a set of physical structures impacts the procedures that people subsequently use to build those structures, as well as how well they build them over time. Participants (N=49) viewed 2D silhouettes of 8 unique structures in a virtual environment simulating rigid-body physics, and aimed to reconstruct each one in less than 60 seconds. We found that people learn to build each target structure more accurately and quickly across repeated attempts, and that these gains reflect both decreases in planning time and increases in movement fluency, as well as the discovery of qualitatively different procedures for building each one. Taken together, our study provides novel insight into how humans learn from prior experience to discover better solutions to physical reasoning problems over time.

Keywords: planning; spatial reasoning; intuitive physics; construction; action

Our ability to plan and build a wide array of physical structures, from sand castles to skyscrapers, is a defining feature of modern human intelligence. Humans have profoundly transformed the landscape of every continent with buildings, bridges, and monuments of our own design. A central challenge in cognitive science is to uncover the core cognitive mechanisms that enable us to create such complex and varied structures. Towards solving this challenge, a natural starting point is to consider the problem of how people learn to "reverse-engineer" existing structures — that is, infer an appropriate decomposition of it that can be translated into a sequence of actions to recreate it from simpler components. Such problems are likely to recruit general-purpose mechanisms for physical reasoning and planning, in addition to mechanisms for learning from prior experience. Here we investigate the role of practice in guiding how people discover better solutions to such problems over time.

This paper builds on classic work investigating how people reason about the properties of physical objects and how they interact with one another (McCloskey, 1983), a suite of abilities known as intuitive physics. A useful proposal emerging from more recent work on intuitive physics is that people reason about how physical systems evolve over time via mental simulation, which may provide a noisy approximation to real physical dynamics (Battaglia, Hamrick, & Tenenbaum, 2013; Sanborn, Mansinghka, & Griffiths, 2013; Hegarty, 2004). These ideas have been fruitfully applied to develop new algorithms that perform variety of physical tasks, including the inference of object properties from visual data (Ullman, Stuhlmüller, Goodman, & Tenenbaum, 2018; Wu, Lu, Kohli, Freeman, & Tenenbaum, 2017) and the prediction of object motion over time (Mrowca et al., 2018; Smith & Vul, 2013). While many of the most common physical tasks in this literature involve passive judgments about physical scenes, a promising new direction has been to consider tasks that involve active interventions on physical systems to achieve various goals (Allen, Smith, & Tenenbaum, 2019; Hamrick et al., 2018). In particular, the current study takes inspiration from both classic and recent investigations of how evaluating the consequences of such physical interventions can be beneficial for downstream performance on various physical reasoning tasks (Dasgupta, Smith, Schulz, Tenenbaum, & Gershman, 2018; Kirsh & Maglio, 1994).

The current study also builds upon recent advances in theories of human planning that make use of similar ideas about the pervasive role of mental simulation in guiding human sequential decision making (Solway & Botvinick, 2015, 2012; Daw, Gershman, Seymour, Dayan, & Dolan, 2011). When these simulation mechanisms are combined with reasonable assumptions about the cognitive costs of conducting mental simulations (Callaway et al., 2018; Hamrick, Smith, Griffiths, & Vul, 2015), the resulting resource-rational theories provide stronger approximations to human planning behavior than classical (De Groot, 2014) or heuristic-based (Huys et al., 2012) approaches. While this progress has been galvanizing, the generalizability of current theories to the domain of construction behavior is potentially limited by the historically narrow focus on tasks defined by relatively low state-space complexity (van Opheusden, Galbiati, Bnaya, Li, & Ma, 2017), as well as abstract action spaces and state transitions (Daw et al., 2011; Solway & Botvinick, 2015) that are far removed from the physical environment. Moreover, these theories do not address our core question of how people make efficient use of prior task experience to overcome inherent cognitive resource limitations, thereby learning how to plan better over time.

Here we investigate how practice "reverse-engineering" a set of physical structures in a 2D virtual environment impacts

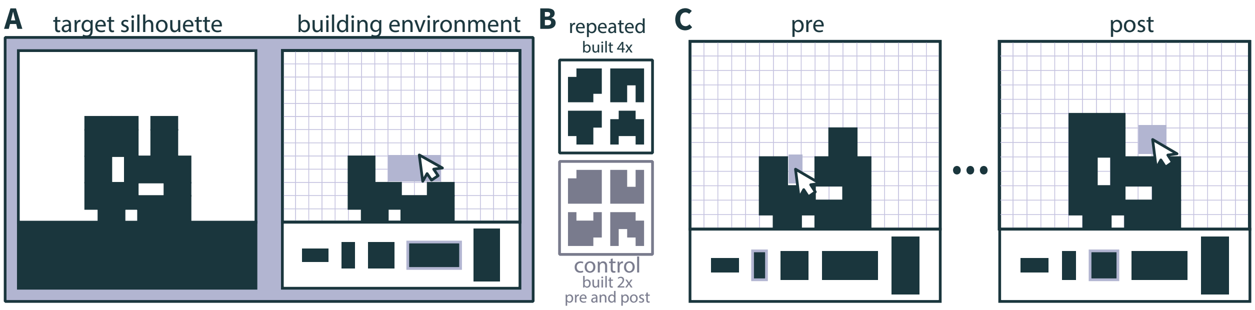

Figure 1: (A) Schematic of task display. The left window contained a target silhouette, and the right contained a building environment. (B) For each participant the 8 silhouettes were randomly assigned to conditions, 4 in repeated and 4 in control. (C) In pretest and posttest phases, participants built all items from both repeated and control conditions. In repetition phases, repeated condition structures were build an additional 2 times.

the procedures participants subsequently use to build those structures, and how well they build them across repeated attempts. Our experimental approach draws most direct inspiration from prior work in developmental psychology (Cortesa et al., 2018; Dietz, Landay, & Gweon, 2019; Bullock & Lütkenhaus, 1988) and artificial intelligence (AI) (Bapst et al., 2019; Hamrick et al., 2018; Jones, Hager, & Khudanpur, 2019) that have examined physical construction behavior. The current study advances these prior investigations in three ways: *first*, we develop a web-based environment for physical construction, enabling the simultaneous recruitment of larger samples of participants than feasible in laboratory settings; *second*, we examine how participants build the same structure multiple times, providing quantitative insight into how people adapt their strategies based on prior performance; *third*, we show that healthy adult participants learn in a highly sample-efficient manner from previous construction attempts, providing a novel benchmark for AI construction agents to emulate and explain.

Part I: How does physical construction accuracy change with practice?

The primary goal of our experiment was to understand how practice "reverse-engineering" a set of physical structures impacts the procedures they subsequently use to build those structures, as well as how well they build them over time. To accomplish this, we developed a web-based environment in which people could construct various block structures under simulated rigid-body physics. On each trial, participants aimed to reconstruct a specific target structure in less than 60 seconds using a fixed inventory of rectangular blocks. What made this task challenging is that only silhouettes of these towers were provided, requiring participants to "reverse-engineer" them — that is, infer which blocks to use, where to place them, and in what order. Over the course of an experimental session, participants built each structure either two or four times, allowing us to measure the degree to which prior experience led to task-general vs. structure-specific learning.

Methods

Participants 51 U.S.-based participants were recruited from Amazon Mechanical Turk. After accounting for technical issues during data acquisition (i.e., missing data), data from 49 participants were retained (28 female, mean age: 35.5 years). Participants provided informed consent in accordance with the UC San Diego IRB.

Stimuli To identify a set of block structures of similar complexity, we randomly sampled a large number of stable configurations of 8-16 blocks, then manually selected 8 of these that could be reconstructed using the same blocks in different ways (Fig. 4A).

Task Procedure On each trial, participants were presented with two adjacent display windows: on the left, a target block tower was presented as a silhouette centered on the floor in a 18x13 rectilinear grid environment (Fig. 1A); on the right, they were provided an empty building environment and a fixed inventory of five types of rectangular blocks that varied in their dimensions (i.e., `1x2`, `2x1`, `2x2`, `2x4`, `4x2`). The building environment contained gridlines to ease perceptual discrimination of the size and location of each block before placing it. Participants' goal was to build a tower that matched the shape of the target silhouette in less than 60 seconds using any combination of the blocks provided. To select a specific block type, they clicked on its image in the block inventory. Then, by hovering the mouse cursor over the building environment, a translucent block would appear, showing where the block would be placed when they clicked the mouse again. Blocks could be placed on any level surface in the building environment (i.e., either the floor or on top of another block). To minimize the intrusion of low-level motor noise in block placement, the locations of each block were 'snapped' to the grid. After the placement of each block, participants' towers became subject to gravity, simulated using `Matter.js`). Thus, if their tower was not sufficiently stable, single blocks or even the entire tower could fall over. After 60 seconds had elapsed or if any block fell, the trial immediately ended and participants moved onto the next tower. We truncated trials on which any block fell for two main reasons: first, to ensure that all recorded block placements could in principle form part of a forward plan to build the target silhouette, rather than reflect online corrections for error; and second, to strongly incentivize the production of stable towers. Participants were incentivized to perform accurately and also quickly: the more accurate their reconstruction, the larger the monetary bonus they received. If they perfectly reconstructed the target silhouette, they would earn an additional bonus for speed.

Design For each participant, the 8 block towers were randomly assigned 2 sets containing 4 towers each: a *repeated* set and a *control* set (Figure 1 B). Each experimental session consisted of three phases: pretest, repetition, and posttest. During the repeated phase, all 4 repeated towers were built 2 times each, in a randomized order. Before and after the repeated phase, all towers from both conditions were built once each, also in a randomized order. Thus there were a total of 24 trials (8 pretest; 8 repetition; 8 posttest).

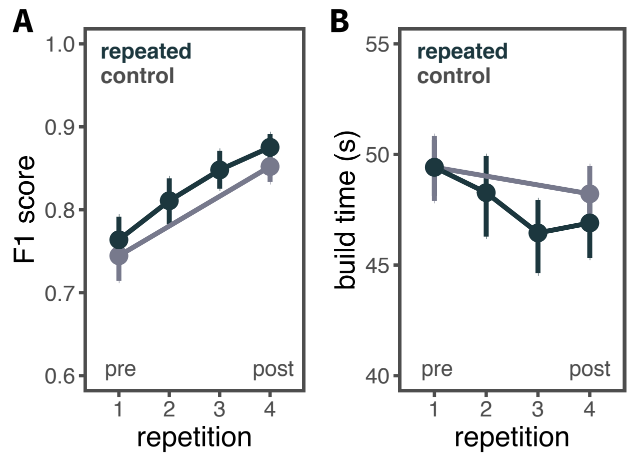

Figure 2: (A) Reconstruction accuracy across repetitions. (B) Build time across repetitions. Error bars represent 95% CI.

Results

We used the F_1 score as our primary measure of reconstruction accuracy, which reflects the degree to which the shape of participants' reconstruction coincided with the target silhouette, and lies in the range $[0,1]$, where higher scores indicate higher accuracy. It is computed by taking the harmonic mean of the *precision* (i.e., the proportion of participants' reconstruction that coincided with the target silhouette) and *recall* (i.e., the proportion of the target silhouette that coincided with the participants' reconstruction): $F_1 = 2/(recall^{-1} + precision^{-1})$.

In the pretest phase, participants' reconstructions were moderately accurate, suggesting that they were engaged with the task but not at ceiling performance (repeated: $F_1 = 0.767$, 95% CI: $[0.743, 0.788]$; control: $F_1 = 0.746$, 95% CI: $[0.714, 0.773]$). To evaluate changes in reconstruction accuracy over time, we fit a linear mixed-effects model predicting F_1 score from phase (pretest, posttest) and condition as fixed effects, including random intercepts for participant and tower. We found a reliable main effect of phase ($b = 0.108$, $t = 7.30$, $p < 0.001$), showing that participants learned to reconstruct each tower more accurately between the pretest and posttest phases. We found no reliable effect of condition ($b = 0.024$, $t = 1.61$, $p = 0.109$), and no evidence of an interaction between phase and condition ($b = 0.00392$, $t = 0.188$, $p = 0.851$), suggesting that the improvement was primarily attributable to task-general learning, rather than being tower-specific.

To quantify how quickly participants completed their reconstructions, we measured the amount of time elapsed between the start of each trial and the final block placement on that trial. In the pretest phase, participants used nearly all of the time allotted (repeated: $49.4s$, 95% CI: $[48.2, 50.7]$; control: $49.5s$, 95% CI: $[48.2, 51.0]$), and appeared to use less time to build each tower across repetitions (Fig. 2B). To evaluate changes in build time between the pretest and posttest phases, we fit a linear mixed-effects model with the same structure as that previously used to predict F_1 score. This analysis revealed no reliable effect of phase ($b = -1.20$, $t = -1.35$, $p = 0.176$), condition ($b = -0.0645$, $t = -0.072$, $p = 0.943$), nor interaction between phase and condition ($b = -1.31$, $t = -1.05$, $p = 0.297$), suggesting that participants generally followed instructions to prioritize accuracy throughout each session. In additional exploratory analyses, we found that 22.5% of trials contained perfect reconstructions of the target silhouette. When we augmented the above regression model with an additional binary variable indicating whether a trial contained a perfect reconstruction, we discovered that these 'perfect' reconstructions did reliably take less time in the posttest than the pretest (i.e., reliable interaction between phase and perfect-reconstruction indicator variable: $b = -7.11$, $t = -2.92$, $p = 0.00363$), consistent with the possibility that only once participants discovered a way of producing a perfect reconstruction were they able to learn to also complete the tower more quickly.

Part II: What explains improvements in reconstruction accuracy?

The results so far establish that people can learn to build physical structures better over time, even after one or a small number of construction attempts. These findings raise the question: to what extent do these gains reflect low-level changes in motor behavior (e.g., fluency with the task interface) vs. higher-level changes to their construction plan (i.e., which blocks to use, in what order)? To understand the contributions of these different factors, we conducted a series of fine-grained analyses of the set of actions participants performed on each trial and how this set of actions changed across repetitions.

Results

Perhaps the most natural explanation for why participants' reconstructions improved over time is that participants became better able to place each block directly over target locations (Fig. 4). To explore this hypothesis, we visualized the spatial distribution of block placements by constructing a heat map in which the intensity of each pixel reflects the proportion of participants who had placed a block in that location. Participants appeared to be placing a greater proportion of blocks outside of target locations in the pretest compared to the posttest. To evaluate this hypothesis, we calculated an aggregate measure of spatial error by weighting the proportion of placements/non-placements at a particular location by the squared city block distance from the target structure, and taking the root sum of these values. We calculated the mean difference in spatial errors between pretest and posttest, averaging over structures ($m = -0.483$, 95% CI: $[-0.907, -0.0416]$, $p = 0.034$; confidence intervals generated via bootstrap resampling). These negative error differences confirm that participants make fewer and less extreme errors in the posttest compared to the pretest.

Next we explored the degree to which participants were able to successfully place more blocks within the time allotted on each trial. To evaluate this possibility, we modeled the change in the number of blocks used between the pretest and posttest phases using a linear mixed-effects model otherwise identical in structure to that previously used to analyze accuracy. This analysis revealed a strong main effect of phase ($b = 1.50$, $t = 6.78$, $p < 0.001$), showing that participants were able to consistently use more blocks in the posttest than in the pretest (Fig. 3A). There was no evidence of an effect of condition ($b = 0.142$, $t = 0.637$, $p = 0.525$) nor of an interaction between phase and condition ($b = 0.148$, $t = 0.471$, $p = 0.638$). There are at least two distinct reasons why participants may have been able to place more blocks in the posttest: *first*, their fluency with the construction task interface may have improved, allowing them to select and place more blocks more quickly over time; *second*, they may have been able to recall previously used procedures for building a given tower, and thus required less preparation time to devise an action plan prior to placing their first block. We estimated task fluency by computing the mean time between successive block placements within a single trial. We estimated preparation time by computing the time between trial onset and the placement of the first block. We found that both task fluency ($b = -1.26$, $t = -6.32$, $p < 0.001$) and preparation time ($b = -2.69$, $t = -6.96$, $p < 0.001$) decreased between the pretest and posttest, suggesting that the improvement observed in Part I may reflect changes in both. We also found a robust effect of condition on thinking time ($b = -0.799$, $t = -2.05$, $p = 0.0404$), but no reliable interaction between condition and phase ($b = 0.176$, $t = 0.320$, $p = 0.7488$).

While the decrease in preparation time is *suggestive* of participants' ability to reuse procedures they had previously used to build each tower, this measure provides only indirect evidence for this possibility. In order to directly quantify the degree to which participants reused previous plans, we needed a way of measuring the degree to which the set of actions performed on two trials overlapped. Our approach was to define an *action* as the placement of a specific block type (e.g., `2x2`) in a particular location (i.e., $< x, y >$ coordinate), and to estimate plan reuse as the proportion of actions initially taken in the pretest to reconstruct a specific target silhouette that were identical to actions taken in the posttest (i.e., same block type at exactly the same location), regardless of when they were taken in either trial. We hypothesized that the degree of plan reuse may be dependent on how accurately a participant had reconstructed that tower in the pretest (Fig. 3B), such that if a participant achieved relatively high accuracy for a tower in the pretest they were likely to reuse most of their previous actions, whereas if they achieved relatively low pretest accuracy for a tower they would reuse a smaller proportion of their previous actions. We modeled variation in the proportion of plan reuse as a function of the accuracy quartile a specific tower fell into in the pretest, where accuracy quartile were determined within participant. Consistent with our hypothesis, this analysis revealed that the degree to which participants reused their plans was proportional to how accurately they had reconstructed that tower in the pretest ($b = 0.133$, $t = 3.68$, $p = 0.00031$, Fig. 3B). This is also consistent with the possibility that practice building structures may provide an important learning signal that shapes future planning behavior on similar physical construction problems.

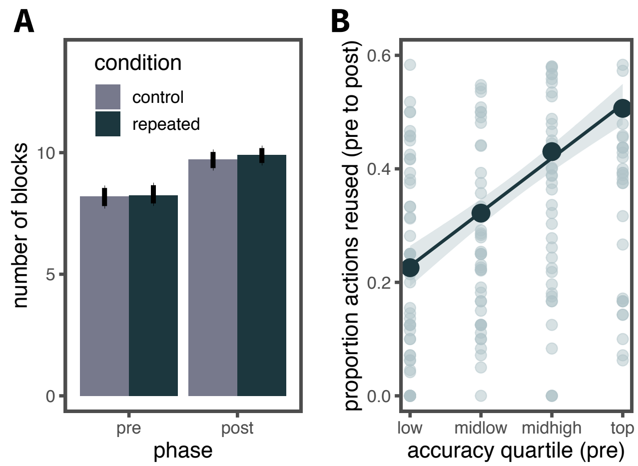

Figure 3: (A) Mean number of blocks used by participants in the pretest and posttest phase. Error bars reflect 95% CIs. (B) Proportion of total actions taken in the pretest that were reused when building the same target silhouette in the posttest, broken down by accuracy quartile in the pretest. Each action is defined as the placement of a specific block type in a particular location. Accuracy quartiles were determined within-participant. The proportion of reused actions was positively related to pretest accuracy. Error ribbons represent 95% CI.

The results so far provide some evidence for both low-level changes in movement fluency (i.e., more blocks), as well as higher-level changes to action plans. To what extent do either of these changes actually explain variation in learning? We jointly estimated the contribution of both factors in a new linear mixed-effects model predicting the change in reconstruction accuracy (F_1) between the pretest and posttest within each tower and participant, including the change in the number of blocks used and plan reuse as fixed effects, and participant as random effects. We found that both the block number ($b = 0.0322$, $t = 12.0$, $p < 0.001$) and the proportion of plan reuse ($b = -0.103$, $t = 3.54$, $p = 0.000445$) were highly reliable predictors of accuracy improvements. Nested model comparison affirmed these results, revealing that including block number ($\chi^2_1 = 122$, $p < 0.001$) and plan reuse ($\chi^2_1 = 11.8$, $p = 0.000583$) significantly improved model fit. Taken together, these results provide more direct evidence that the improvements in reconstruction accuracy observed in Part I reflect at least in part their ability to improve upon previously unsuccessful action plans, in addition to gains in movement fluency.

Discussion

In this paper, we investigated how people learn from prior experience to make better decisions during physical construction. In a task that required participants to reverse engineer and create towers of blocks we observed that people adapt their plans to produce better solutions, even after a small number of construction attempts. Moreover, we found that the procedures used to generate these solutions consisted of more precise actions made with higher movement fluency, and that they took less time to plan. Furthermore, by analyzing changes in the specific configurations of blocks that participants chose to use, we showed that the decision to reuse a prior plan was sensitive to how successful that previous plan had been. Taken together, our findings provide novel insight into how ongoing experience shapes subsequent planning and decision making.

One of the primary contributions of this paper is the development of a web-based platform for investigating how humans solve physical construction problems, enabling us to measure detailed patterns of behavior with greater precision by recruiting larger samples of participants than is typically feasible in laboratory settings. Such datasets will be critical for elucidating the cognitive mechanisms that support humans' ability to reason about and discover solutions to physical reasoning problems. In particular, future work should investigate how do mental simulation and physical experience interact to support physical reasoning, as well as how people decide when to rely on mental simulation alone vs. apply a physical intervention during physical problem solving (Dasgupta et al., 2018; Kirsh & Maglio, 1994).

As block structures were randomly allocated to the repeated and control conditions, we were surprised to find evidence for differences in performance between conditions. Upon exploring our data further, we noticed that the the

Figure 4: (A) 8 target silhouettes used in the experiment. (B-C) Heat map representations of the spatial distribution of block placements for each tower, in each phase. The intensity of each pixel reflects the proportion of participants who had placed a block in that location. Brighter: more participants.

distribution of structures were numerically imbalanced across conditions. In ongoing work, we are collecting a larger dataset, which will also enable us to gain insight into sources of consistency and variability between structures. Our study generally revealed task-general improvements, though it is possible that allowing participants to practice building each structure across more than four repetitions may also yield signatures of structure-specific learning.

Overall, the highly sample-efficient learning exhibited by human participants differs starkly from the learning demonstrated in the most sophisticated reinforcement learning agents, which require substantial amounts of data to achieve good performance on similar tasks (Bapst et al., 2019). Our study provides both a novel empirical benchmark for AI construction agents to emulate and explain, as well as a strong candidate for task domain that can be fruitfully studied in both cognitive psychology and AI research to advance computational theories of planning (van Opheusden & Ma, 2019). Such strong alignment between empirical studies of human behavior and the development of novel learning algorithms may lead to both more robust artificial intelligence and a deeper understanding of human cognition.

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