Cumulative improvements in iterated problem solving

As compared to other animals, humans are particularly skilled at using and improving tools and other solutions to problems that were first discovered by other people. Although the human capacity for cumulative cultural evolution is well-known, the effectiveness of inheritance as a form of problem solving is an area in need of further research. We report an experiment designed to understand how effectively solutions to problems accumulate over generations of problem solving. Using a tool-discovery game, we found that participants were consistently able to discover more tools in a 25 minute session than their ancestors. Participants who inherited more tools tended to discover fewer novel ones, but the ones they did discover were more complex. We also found that participants who inherited tools tended to generate less redundant guesses, suggesting a potential downstream consequence to iterated problem solving. We discuss the limitations of this work, and motivate future directions.

# Introduction

Humans are effective problem solvers, having solved a wide range of problems related to foraging, hunting, and preparing food, while surviving predators, each other, and a large range of terrestrial environments (Boyd 2018; Fernández-Armesto 2001). What has enabled our success in being able to solve such a diverse set of problems? Some have suggested that the answer lies more in our ability to inherit knowledge from others than our ability to make discoveries by ourselves (Richerson and Boyd 2005; Henrich 2015; Boyd 2018). Humans possess a number of advanced social learning abilities including teaching through verbal instruction and imitation that provide reliable ways of transferring problem solving knowledge across individuals (Dean et al. 2012). If problem solving knowledge can be acquired via social learning, then future generations can adapt and improve it, allowing cultures to accumulate technological complexity over generations.

However, the ability to learn socially from others is not sufficient to explain cumulative cultural evolution. Although social learning was once thought to be rare in the animal kingdom (e.g., Thorndike 1898), it has now been documented in a range of species from chimps (Whiten et al. 1999) to fish (Laland and Williams 1997) and even bees (Alem et al. 2016). If cumulative cultural evolution depended simply on social learning, we might expect these species to likewise show evidence of cumulative cultural evolution, yet such evidence is notably lacking (Dean et al. 2012; Tennie, Call, and Tomasello 2009). There are a few exceptions: New Caledonian crows have been argued to have improved the grub-skewers they craft from pandanus leaves (Hunt and Gray 2003), and at least one population of chimpanzees has evolved a more advanced termite probe (Sanz, Call, and Morgan 2009), but for the most part tool use in animals has remained largely unchanged (cf. Mercader et al. 2007).

Humans, in contrast, have demonstrated a remarkable ability to adapt and improve the tools and other innovations discovered by others. The history of human technology is argued to be better understood as a process of gradual refinement and repurposing rather than punctuated advances brought by the discoveries of rare geniuses (Basalla 1988; Solé et al. 2013). Rapid refinement of inherited innovations has not always been the case over the course of human history, as demonstrated by the long periods in the archaeological record of slow or stagnant growth in stone tool complexity (Torre 2011; Lycett and Gowlett 2008). As to what it was that allowed our ancestors to begin to develop more complex tools, an answer that has been proposed is that humans evolved more robust ways of transmitting cultural information to the next generation. This allowed future generations to more quickly learn the skills honed by their ancestors, and thus giving them more time to make improvements to those technologies (Sterelny 2012). On this view, human cultural evolution has been defined not by our ability to inherit the skills of our ancestors, but by the ability to exceed and improve them.

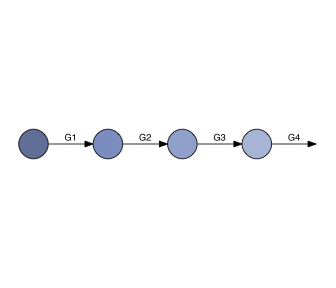


Figure 1 Iterated problem solving paradigm. Participants were assigned to generations within chains. Each participant completed the same problem solving task for 25 minutes. Participants in generations after the first began the problem solving task with the solutions that were discovered by the previous generation.

We investigated the human propensity to exceed our ancestors in a problem solving task using a transmission chain paradigm (Fig. 1). Previous research using this paradigm has found that problem solving performance for simple tasks like folding paper airplanes and building towers out of spaghetti can accumulate over generations (Caldwell and Millen 2008), although the mechanisms are unclear (Caldwell and Millen 2009). Morgan et al. (2015) more carefully manipulated the mechanisms of transmission, and found that teaching, and especially verbal instruction, was crucial for successful transmission of skilled behaviors along chains. Here we controlled for successful transmission by allowing future generations to inherit symbolic information about how to recreate the tools that had been discovered by an ancestor. Specifically, participants inherited the recipes for creating tools from the combination of items. Once inherited, the tools had to be created before they could be used in further combinations. We then measured the ability of participants to recreate and exceed the tools they inherited.

In addition to asking whether participants were able to exceed the total number of tools discovered by their ancestor, we also asked whether inheritance influenced the way in which future problems were solved. To answer this question, we analyzed whether participants who inherited more tools from their ancestors were more or less effective at discovering new tools. We also analyzed the guessing strategies used by participants who benefited from inheritance as compared to first generation participants who did not inherit from any ancestor. These analyses are used to address potential downstream consequences to iteratively inheriting from a previous generation.

# Methods

To understand how solutions to problems accumulate through vertical transmission, we used a transmission chain paradigm where participants were assigned to a single generation within a four-generation chain. Each participant attempted the same tool discovery task for 25 minutes. The recipes for how to create the tools that each participant had discovered by the end of the session were passed on to be inherited by a participant in the next generation of the chain. Thus, participants assigned to generations after the first began the experiment with information about how to create the tools inherited from the previous generation.

Participants played the “Totem” game adapted from Derex and Boyd (2015). Their task was to discover how to build tools with the ultimate goal of creating “a sacred totem to appease the gods.” To build a totem, participants first needed to construct an axe out of three independently discovered tools: a refined stick used as a handle, a sharpened rock for the blade, and a string wound from bark fibers for binding (Fig. 2). More advanced tools produce larger and more intricate totems, resulting in higher performance scores.



Figure 2 A sample of the solution landscape. The top row of 6 items were available to participants at the start of the game. New items could be produced through the combination of different items (more than one arrow points to the item) or through the refinement of a single item (a single arrow points to the item). The axe is required to construct the first totem pole.

Participants discovered new tools by combining existing items. Participants could refine individual items, or combine up to four items at a time (with replacement), meaning the initial six items could form a total of 209 combinations. Of all possible combinations, very few resulted in new items. For example, of all the guesses that could be formed from the initial items, only three (1.4%) yielded new tools.

As tools are accumulated, the number of possible combinations that can be made with those tools increases exponentially such that the discovery of later tools was less likely to happen by chance alone. This increase in combinatorial complexity suggests that later tools might be harder to discover than earlier tools. However, combinatorial complexity is not a perfect measure of difficulty in this task because of the way the solution space was designed, and because participants do not guess entirely at random. Based on previous research using this task, we know that participants are far more likely to make some guesses than others, indicating they are using previously acquired knowledge about the tools to generate combinations. For example, once discovering an axe, participants quickly discover that they can use the axe to chop down a tree, regardless of the other tools they may have at the time. At the same time, participants do not find all tools equally intuitive, and the difference in combinatorial complexity should not be ignored. In our results, we report performance based on both measures.

Once a tool was discovered, the recipe for its production—a list of the items that had to be combined in order to produce the tool—was recorded in an innovation record. Participants could review their past innovations and see the recipes for their previous discoveries. **Participants assigned to generations after the first inherited the innovation record of the previous generation participant.** From the beginning of the experiment, these participants could review the recipes for all the innovations that had been discovered by their ancestor. Note that the participants inherited the recipes, but not the tools themselves. In order use these tools in further combinations, the tools and all of their constituent parts first had to be recreated.

## Participants

Participants were recruited from the UW-Madison student body and received course credit in exchange for participation. Each participant was assigned to a single generation of a four-generation chain. Data was collected for a total of 42 complete chains (N=168 participants).

# Results

Our results are presented in three sections. First, we report performance over generations along each chain to determine the extent to which each new generation was able to exceed the innovations discovered by their ancestor. The remaining analyses were carried out to determine whether participants’ ability to discover new tools was influenced by the tools they inherited. In the second section, we report performance based on the number of inherited tools as opposed to generation. In the final section, we compare the guessing strategies of participants who inherited from an ancestor compared to first generation participants who did not benefit from inheritance.

## Performance by generation

We found that tools accumulated over generations such that participants in later generations were able to discover more tools in the same amount of time than their ancestors (Fig. 3). We tested this in multiple ways. First, we used Page’s trend test (a repeated measures test for monotonicity), and found evidence that the number of tools discovered within each chain increased over generations, Page’s *L* = 1193, = 234, *p* < 0.001. Next, we tested whether tools accumulated linearly or quadratically over generations. We fit a hierarchical regression model with polynomial contrasts to the number of tools discovered in each generation with random effects for chain. On average, second generation participants were able to discover 3.3 more tools than first generation participants, *b* = 3.27 (SE = 0.65), *t* = 5.04. This effect decreased by -0.4 each generation for third and fourth generation participants, *b* = -0.39 (SE = 0.20), *t* = -2.00. That the numbers of new tools per generation levels off for later generations could suggest that later generations have a harder time exceeding their ancestors, but it also could be due to these later generations, having inherited more tools, requiring more time in the experimental session to recreate the inherited items. We return to both of these potential explanations below.

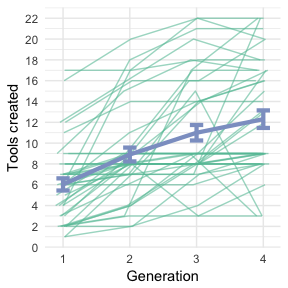


Figure 3 Performance by generation. Each of the thin green lines is a chain. The thick blue line is the model predictions with ±1 standard error.

Although later generation participants made fewer new discoveries, the discoveries they made were often more complex. We computed the complexity of a tool as the number of combinations that could be made given the number of items in the participants’ inventories at the time the tool was discovered. A tool that was discovered among 12 items was deemed more complex than a tool that was discovered among 6 items. Using a hierarchical regression model as reported above, we found that when discoveries were weighted by combinatorial complexity, participants discovered more complex tools with each generation, *b* = 0.04 (SE = 0.01), *t* = 4.92, and this benefit did not diminish for later generations, *b* = -0.0001 (SE = 0.0059), *t* = -0.01.

## Performance by inheritance size

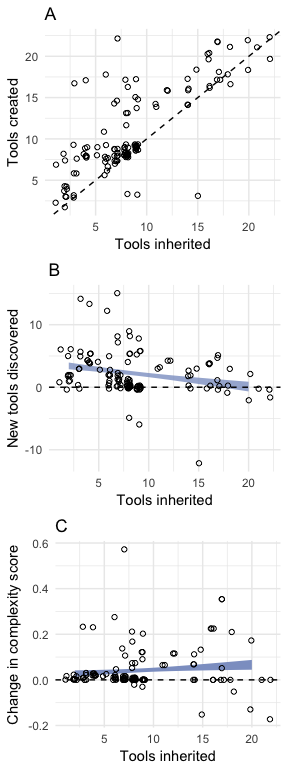


Figure 4 Performance by inheritance size. A. Number of tools created relative to those inherited. The dotted line is a reference with slope=1 such that points above the line indicate future generations exceeding their ancestors. B. Number of new tools relative to those inherited. The same reference line is now shown horizontally. C. Change in accumulated difficulty score. Analogous to B, but with innovations weighted by complexity. In B and C, the error ranges specify the model predictions with ±1 standard error.

Because there is no difference between a second generation participant who inherits 10 tools and a fourth generation participant who inherits the same tools, we also looked at problem solving performance relative to the number of tools that were inherited regardless of generation (Fig. 4). As the number of inherited tools increased, the number of new tools discovered decreased, *b* = -0.18 (SE = 0.06), *t* = -2.92 (Fig. 4B). That participants who inherited more items had a harder time exceeding them is expected based on the analysis of performance over generations reported above. However, when tools are weighted by combinatorial complexity, the amount by which participants are able to exceed their ancestors actually increases for larger inheritance sizes, *b* = 0.0021 (SE = 0.0017), *t* = 1.24 (Fig. 4C), though we are hesitant to draw strong conclusions from this finding as it may be explainable by the characteristics of the solution landscape, a point we return to in the Discussion.

Participants who inherited more tools also required more time to recreate those tools. We next asked whether inheriting more tools had an impact on the rate of new tool discovery, controlling for the length of time spent recreating inherited tools. Participants took on average 8.2 minutes of the 25 minute session (32.8%) to recreate the inherited tools—a portion of the experiment we refer to as the learning period. The length of the learning period correlated positively with the number of inherited tools (Fig. 5).

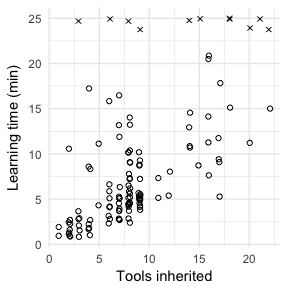


Figure 5 Learning rates. Correlation between the number of tools inherited and the time it took to recreate the inherited items. Outliers who were appear unwilling or unable to recreate the inherited items are shown as X’s, but included in all analyses.

We then calculated discovery rates for each participant: the number of new tools discovered relative to the amount of time out of the 25 minute session available to discover new tools (Fig. 6). The overall rate of problem solving was 5.6 minutes per new innovation (0.18 innovations per minute), *b* = 0.18 (SE = 0.04), *t* = 4.06. This rate was not found to vary based on the number of inherited tools, as revealed by comparing a model predicting novel tools from discovery time alone to one predicting novel tools from the interaction between discovery time and inheritance size, (2) = 0.5430, *p* = 0.762. This suggests that inheriting more tools did not meaningfully affect the rate of future problem solving.

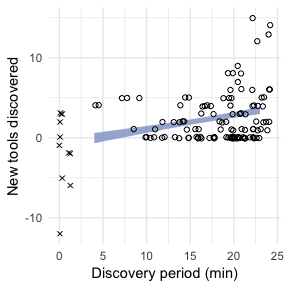


Figure 6 New tool discovery rates. Discovery time is the amount of time out of a 25 minute session dedicated to discovering new innovations that were not discovered by an ancestor. The line shows the predictions of the hierarchical regression model with ±1 standard error. The slope of this line did not significantly vary based on the number of inherited tools.

## Performance by inheritance

In this section, we report whether participants who inherited tools from an ancestor guessed differently than participants in the first generation who had to discover the first tools on their own. We found that participants who benefited from inheritance on average made fewer guesses per tool than when the same tools were attempted in the first generation, *b* = 14.04 (SE = 4.42), *t* = 3.18. As expected, this effect is especially pronounced for the tools that were inherited. We did not find any evidence that inheritance had an affect on the number of guesses per new tool, *b* = -3.97 (SE = 4.77), *t* = -0.83 (Fig. 7). This finding suggests that although inheritance benefits participants in recreating inherited solutions, it does not confer any benefits to future problem solving.

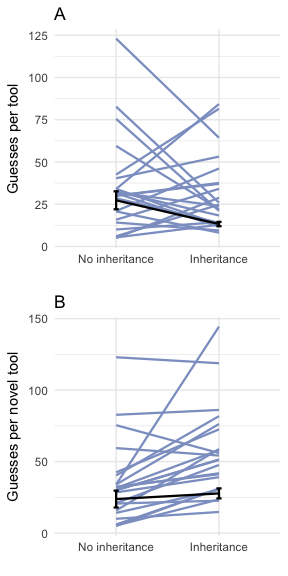


Figure 7 Guesses per tool by inheritance condition. Each line is the average number of guesses it took to discover a particular tool in either inheritance condition. Error bars show ±1 standard of the model predictions. A. Overall guesses per tool, including those inherited. B. Guesses per novel tool.

Finally, we analyzed the guessing strategy employed by participants who inherited from an ancestor versus those who did not. Guesses were categorized into one of four types: redundant guesses, repeat items, unique guesses, and unique items. Redundant guesses were incorrect guesses made once before. Repeat items were recreated tools. Unique guesses were incorrect guesses never made before. Unique items were unique guesses that created a new tool.

The proportion of guesses made by participants based on their inheritance condition is shown in Fig. 8. We found that participants who inherited solutions at the start tended to make fewer redundant guesses than first generation participants, *b* = 27.48 (SE = 4.27), *t*(166.0) = 6.43, *p* < 0.001, a difference of 12%, *b* = 0.12 (SE = 0.02), *t*(166.0) = 6.75, *p* < 0.001. This result suggests that starting off the problem solving task with solutions inherited from a previous generation may have influenced the way in which future guesses are generated.

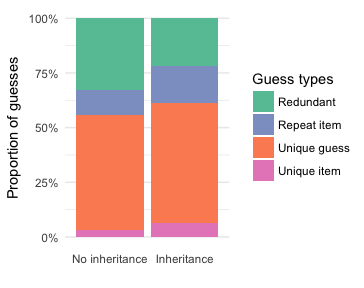


Figure 8 Guessing strategies by inheritance condition.

# Discussion

We found that participants were consistently able to solve more problems in a single 25 minute session than their ancestors, and thus were able to cumulatively improve upon the solutions they inherited. All participants were expected to be able to recreate the tools they inherited, but whether they could discover new tools, beyond those inherited, was unknown. Given the combinatorial complexity of the solution landscape, participants were unlikely to strike upon beneficial combinations by guessing at random. Because of this, some participants were unable to discover any new tools, but most did discover new tools, even when inheriting an already large number of previously discovered tools.

We also explored the impact of inherited solutions on future problem solving performance. Here our results were mixed. We found that participants who inherited more tools tended to discover fewer new tools than their ancestors, suggesting that the benefit to inheritance leveled off for later generations. However, if the combinatorial complexity of the solutions is taken into account, we found that participants were able to accumulate more complex tools than they would have been likely to discover on their own (i.e., as a first generation participant). In addition, we found that controlling for the amount of time each participant had to discover new tools (as opposed to recreating inherited tools) failed to reveal an effect of inheritance size on the rate of new tool discovery. Finally, we investigated whether starting off a problem solving task with inherited solutions influenced the way in which tools were discovered, and found that inheritance did not have an influence on the number of guesses required for new items, but that inheritance might benefit future generations by promoting a less redundant guessing strategy.

Our conclusions are limited by the design of the solution landscape in the Totem game, and the restriction in our methods to a single problem solving strategy. The sparsity of the solution landscape, where many combinations can be made but very few yield new tools, indicates that in order to succeed participants must use tacit knowledge to help form combinations that are most likely to yield new tools. This challenges the notion that the difficulty of a particular tool is directly related to its combinatorial complexity. In addition, we believe the accumulation of problem solving knowledge through vertical transmission must be compared with the accumulation of problem solving knowledge through other forms of problem solving that do not involve vertical transmission.

More than any other animal, humans are particularly skilled at inheriting and improving tools and other solutions to problems, but whether the ability to inherit from others has effects on problem solving beyond giving a head start to individual learning is not known. Although much work is still needed to fully understand the human propensity for cumulative cultural evolution, we believe our research is a valuable contribution to ongoing efforts to understand how and why human culture is so integrally cumulative.

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