An experiment in iterated function learning

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Abstract

We present an *iterated learning* experiment with human subjects. We introduce the framework of iterated learning, where learners learn from data that is itself the result of a learning process. We review one such experiment from Kalish et al. (2007), based on *function learning*, where subjects learn a mapping from x to y values of an unknown function. We then describe three small novel experiments: one which replicates the original experiment of Kalish et al. (2007), one which contains a novel manipulation to subject's perception of the task, and one which tests a population of subjects with a high degree of mathematical training, and therefore, arguably different biases.

1. Introduction

'*Iterated learning*' refers to situations, such as in language acquisition or musical learning, where learners learn from data that is itself the result of a learning process. Iterated learning has been extensively studied in the iterated learning model (ILM), which was first formalized for the study of language evolution by Kirby (1998) and provides a framework for the empirical study of cultural transmission and how it effects the information being transmitted. ILMs can be implemented in a variety of ways, but they all contain these fundamental components:

1) A learning algorithm
2) Some form of information which is the input/output of the algorithm
3) Structured transmission of the information, where the output of one learner serves as the input for the next.

Some learning algorithms commonly used in ILMs are symbolic grammar induction algorithms (Brighton & Kirby, 2001), neural networks (Smith, 2002), Bayesian agents (Kalish et al., 2007), and human subjects (Cornish, 2006; Griffiths et al., 2006). The data can be linguistic input or numerical values and the transmission format could be any conceivable social structure, but is commonly kept to a parent-child chain for analytical ease.

The modeling work in Kalish et al. (2007) and Ferdinand & Zuidema (2008) has shown that if learners are perfectly Bayesian-rational, have perfect knowledge of the distributions from which data could be drawn, and sample from the posterior, then iterated learning will converge to the prior. If any of these conditions do not hold, then the prior, likelihoods, and selection strategy all influence the outcome of iterated learning.

Ultimately, we are interested in explanations for the structure of natural language and how cultural transmission mechanistically translates the properties of individual learners into the properties of human language. If we take this model seriously, then we would expect that human learning biases can be read off of the universal properties of human language. However, if we would like to make this claim and take an observed universal as evidence for a specific learning bias, then we must be sure that the likelihood structure and selection strategy are of the required kind. Likewise, if we want to predict what sort of universal will arise from a particular bias, then we need to know the state of the other parameters involved in order to make such a predictions.

Therefore, the ideal way to proceed is to study subjects where one or more of these requirements is known, so that the others can be inferred. Such a parameter analysis is straightforward within a computational model, however, it is difficult to know which combinations and ranges of parameters approximate language induction and transmission in an actual population of human learners. Clearly, by experimentally constructing an iterated learning model with human subjects, the uncertainties regarding the appropriateness of the learning algorithm are circumvented.

2. Previous work

Experimental ILMs with human subjects show promise as a powerful framework for testing predictions of both computational models and psychological studies regarding learning biases and the cultural transmission of language. Over the past couple years, some initial explorations into this framework have been made. In vertical transmission models, where information is transmitted serially, from one generation to the next, Kirby et al. (2008) demonstrated in human learners, the emergence of regularization, increased learnability, and compositionality due to a transmission bottleneck. Flaherty (2008) also demonstrated a learnability increase with children, however these language did not become regular. As for horizontal transmission models, where individuals repeatedly interact and negotiate a communication system, Galantucci (2005) showed the emergence of a communication system where the communication channel was undefined and Scott-Phillips (2008) showed the emergence of a symbolic communication system, even when communicative intent was not pre-established between subjects. Additionally, Kalish et al. (2007) demonstrated regularization and learnability in a vertical ILM with human subjects, but in the domain of function learning; not a communication system.

The present research will take up the experimental ILM in function learning, as put forward by Kalish et al. (2007). This is a simple paradigm with established results regarding the role of human learning biases and has been successfully modeled with a Bayesian ILM. Because these task-specific learning biases are more or less known, this task offers an ideal setting for studying the role of the data likelihoods in a population of human learners. In this paper, we will present a replication of Kalish et al. (2007) iterated function learning experiment with human subjects. Additionally, we will present a novel, second condition which tests if human subjects display a behavioral difference to a manipulation in their perceived reliability of the training data.

In both the original experiment and the present replication, subjects attempt to learn and then reproduce the underlying relationship between the lengths of two different bars over a series of trials (see Figure 3.2 for an example screen shot). The two lengths constitute (x,y) pairs, so this underlying relationship can be described as a function that relates these two data points over the complete set of (x,y) pairs. The x value serves as the subject's stimuli and is encoded by the length of a horizontal, blue bar. Each trial, a new stimuli bar length appears and subjects indicate the corresponding y value by adjusting the height of a vertical, red response bar. During the training phase, a feedback bar is presented alongside the subject's response bar, showing the correct response bar height for the target (x,y) pair. In the testing phase, this feedback bar does not appear and the subject's responses are recorded as the new y-values for the corresponding stimuli of each trial. At the end of the testing trials, a new set of (x,y) pairs has been obtained, and reflects what the subject inferred about the relationship behind the data in their training set. This new set of (x,y) pairs then serves as the training set for the next subject in the iterated learning chain.

With this experiment, Kalish et al. demonstrated that iterated learning reliably lead to human behavior that was consistent with the known bias for this task, within only a few generations. Their study consisted of 4 conditions, each containing 8 chains of nine generations. Each condition was defined by the initial function which was used to generate the (*x,y*) pairs of the first generation's training set. These four functions are positive linear, negative linear, u-shape, and random (*x,y*) pairs. Figure 3.1 shows representative chains from each condition, taken from Kalish et al. (2007).

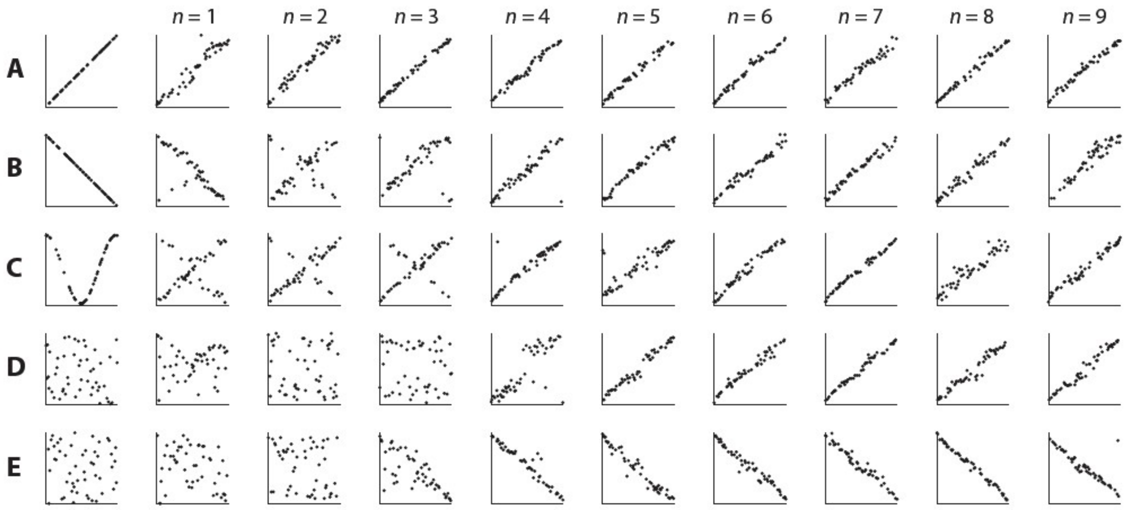

Figure 3.1
Results from Kalish et al. (2007) iterated function learning experiment with human subjects. Shown are 5 representative chains from the 4 conditions, where the initial function is: (A) positive linear, (B) negative linear, (C) U-shaped or (D) & (E) random. Each set of axes plot the testing phase responses of each subject, which was trained on the data to the left of it. Regardless of the initial data, iterated learning converges to the positive linear function, with the highest inductive bias, and occasionally to the negative linear function, with the next highest bias.

Regardless of the initial data, the subjects in the iterated learning chains converged to one of the a prior preferred solutions: a positive linear function with positive slope (with the highest bias), or one with negative slope (with the second-highest bias). Kalish et al. attest that these bias rankings are established in previous psychological studies on function learning, which show that linear functions with positive slope require the least training to learn (Brehmer, 1971 & 1974) and are consistent with subjects' initial responses (Busemeyer et al., 1997).

For all chains in all conditions, this study reports convergence to one of these two functions, with no exceptions. Assumedly, this also means that no intermediate, semi-stable states were obtained on the route to convergence. The consistency of this result, over so many subjects, is somewhat surprising, because there are other, conceivably easy, ways to solve this task, such as dividing the apparently-complex function into simpler sub-functions in order to approximate the whole (resulting in a discontinuous function), responding discretely to the continuous stimuli (resulting in a step function), or by hedging bets in the testing phase if the subject was undecided between two or more plausible underlying relationships. The last or these behaviors, bet hedging, seems to be evidenced in the original results. In Figure 3.1C, subjects 1-3 seem to be guessing between the positive and negative linear functions. Or perhaps, they inferred that both of these functions were generating their training data. However, the motivation behind subject's behaviors could only be obtained from an exit questionnaire, and cannot be concluded from their testing data alone.

It is important to note that this specific function learning task was developed by Kalish et al. (2004) to demonstrate knowledge partitioning and showed that subjects readily divided a complex function into multiple, simpler sub-functions. This study provides empirical evidence that individuals are capable of inferring a discontinuous function for this particular task paradigm. However, subjects were explicitly aware that the underlying function was somewhat complex, and this might have elicited additional strategies. If subjects were instructed in Kalish et al. (2007) that the relationship was simple, generated by one rule, or continuous, then this may have excluded some of these other possible behaviors. It is also possible that such a restriction to subjects' expectations of the possible, task-relevant hypotheses might have played into the demonstrated convergence to the prior, where other solutions could be equally stable for human learners. Therefore, in the present replication, we were careful to not over specify the nature of the function, so not to add additional expectations toward a specific class of functions (such as continuous, generated by a single rule, or based on one-to-one mappings). Leaving the nature of the function ambiguous establishes more potential for varied behavior. Additionally, any behavioral differences regarding the manipulation of the likelihoods may not be visible under a task in which subjects entertain a restricted set of hypotheses.

In the present study, the Kalish et al. experiment is replicated. The findings confirm that the majority of chains converge to the known bias, the positive linear function. However, this replication also obtained semi-stable discontinuous functions, discrete responses, and confirms through exit questionnaires, bet-hedging behavior. These behaviors will be discussed further in the Results section. A second experiment (condition 2) contains a novel manipulation to subjects' perceived reliability of their training data in comparison to the replication experiment (condition 1). This manipulation was accomplished by an addition to the instructions, informing participants that some of the trials in the training phase would be random pairs, to add a small level of noise to the training, and the testing phase would test how well they learned the underlying relationship. (See Appendix B for both instructions.) Only the instructions differed between conditions; otherwise, the set up of the experiment remained exactly the same. In both conditions of the following experiment, instructions, methodology, and stimuli were kept as similar as possible to the original study. Additionally, all chain initializations were set to a different set of random (x,y) pairs, corresponding to Kalish et al.'s 4th condition. Although Kalish et al. show that the initial data plays no role in the long run, this initialization was still used to rule out an initial bias in the data toward any specific function.

The chosen manipulation of subjects' perceive role of the data was motivated by the influential role which the data likelihoods played in the model. If the data likelihoods have a psychologically real correspondence within the process of human induction, then manipulating subjects' perceived role of the data should also affect the dynamics of convergence. However, it is important to note that model, of course, is at best a description of human behavior. We make no claims to be manipulating subjects' "data likelihoods", but instead manipulating how much the subjects might rely on the data when inferring the underlying relationship between the stimuli. However, according to the model, this manipulation would be best characterized by a change to the likelihood values, where less informative data is represented by flatter hypotheses than more informative data.

It is clear that human subjects are neither perfectly Bayesian-rational, nor do they have perfect knowledge of the distributions from which the data might be drawn. Additionally, their hypothesis choice strategy might fall on a continuum between maximizing and sampling. According to the modeling work, violating these assumptions does not exclude the prior from determining the outcome of iterated learning, but it does suggest that the likelihoods will play a role in determining this outcome. Assuming that the Bayesian model is a good approximation of human inductive inference, manipulating the role of the data should not affect which bias is converged to (because the priors are not the target of manipulation), but the dynamics of convergence themselves. For example, this could affect the rate of convergence, or the proportion of chains which conform to each hypothesis. This manipulation choice is supported by the known trade-off in Bayesian statistics between the influence of the prior vs. the influence of the data. Where data provides little information, the prior is more influential, and vice a versa. It is hypothesized that in the condition where the data are perceived to be less informative, chains will converge to the positive (or occasionally negative) linear function quicker than in the replication condition. Additionally, it is predicted that behavior corresponding to a wider variety of hypotheses will be obtained in condition 1 than in condition 2. And because both conditions leave the possible hypotheses unspecified, more varied behavior will be obtained in both conditions than in the original study by Kalish et al. (2007).

3. Method

3.2.1 *Participants*

Experiments 1 & 2: Participants were solicited by email invitation from an established mailing list experiment participants. 56 respondents completed the online experiment. Condition 1 consisted of 8 chains and 32 subjects and condition 2 consisted of 7 chains and 20 subjects. 4 subjects from condition 1 were automatically excluded due to contemporaneous login. Not all subjects completed the exit questionnaire, so the age range and gender is not known for all participants. **Experiment 3:** 9 graduate students of Logic and Cognitive Science constituted 1 chain. 3F/6M, aged 23-30. They took a computerized, offline version of the experiment in person.

3.2.2 *Apparatus and stimuli*

The experiment was implemented as an online java applet by Federico Sangati. The applet displayed all trials and collected all results. On each trial, two bars encoded the x and y values of the function by their lengths. The stimulus was the x-value and was presented as a horizontal blue bar in the upper left-hand corner of a 800 by 600 pixel applet window. The stimulus bar was 20 pixels wide, ranging from length 5 pixels ($x = 1$) to 480 pixels ($x = 100$). A response was made by rolling the mouse to adjust the length of a vertical red response bar, in the lower right-hand side of the screen. The response bar was 20 pixels wide, ranging from length 4 pixels ($y = 1$) to 400 pixels ($y = 100$). This proportion skew was copied from the original study as an additional measure against building a bias toward linearity into the task interface. The background was white and the maximum values of each bar were not marked (Figure 3.1).

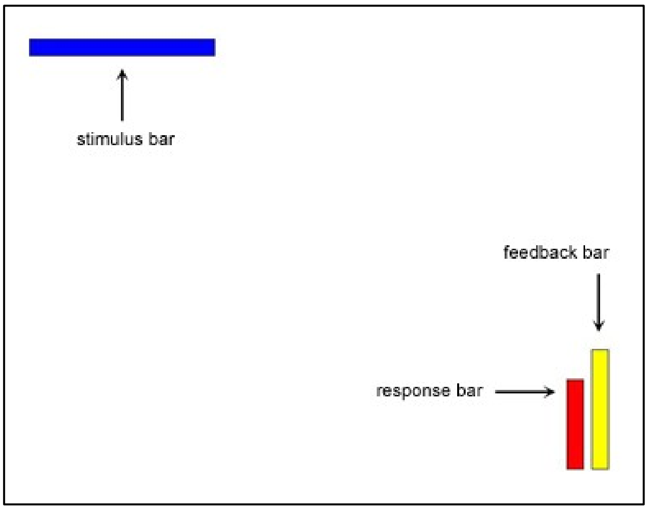

Figure 3.2
Example screen shot, with labels added. This is taken from the implementation of the present experiment, but is nearly identical to the original interface of Kalish et al. (2007).

At the beginning of a trial, the blue bar appeared. The response bar could be adjusted at will and no time constraint was imposed. When the subject had adjusted the bar to the desired height, they pressed the return key to record their response. During the training phase of the experiment, a feedback bar displayed the target response after the return key was pressed. The feedback bar was presented 10 pixels to the right of the response bar and had the same width and possible range as the response bar. If the response was correct (within a 5 unit / 20 pixel range of the correct *y* value) the feedback bar would appear in green and the screen remained as is for 1-second study period. If the response was incorrect, the feedback bar would be shown in yellow until the subject readjusted the response bar to the exact height of the feedback bar and pressed return again. This readjustment period looped until the correct answer was recorded. Once recorded, the feedback bar would be shown in green and the screen remained as is for a 2-second study period. Afterward, the next trial began. The testing phase was identical to the training phase, except no feedback in the form of the feedback bar was given. After the subject pressed the return key to record their first response, the next trial began. The training and testing phases each consisted of 50 trials.

3.2.3 *Procedure*

The experiment had a training and a testing phase, each consisting of 50 trials. The stimuli and responses of one subject's testing phase served as the stimuli and feedback bar for the next subject's training phase. Thus, each subject can be referred to as a "generation" in an iterated learning chain. All chains were initialized on a random training set: the training set of the first generation consisted of 50 randomized (*x,y*) pairings. The length of the stimuli bar encoded the *x* value and the feedback bar/response bar encoded the *y* value. The testing set for all generations, consisted of 50 *x* values; 25 selected randomly from the 50 training *x* values and 25 selected randomly from the 50 unused *x* values. The subject's responses in the testing phase were saved as the new set of 50 (*x,y*) pairs for the next generation's training set and presented in random order. This was the only form of contact between participants and they were unaware that their data would be used for another test-taker.

3.2.4 *Data Collection and Analyses*

When a subject accessed the experiment link, they would be directed at random to one of the chains, where the last recorded testing set of that chain would serve as their training set. Due to this implementation, the number of generations of each chain varies, and some chains did not receive enough subjects and remain un-converged. Additionally, some chains that showed convergence to the positive linear function for at least 2 generations were truncated by the experimenter. The original study displayed the robustness of this convergence state and it was preferred to initialize as many chains as possible with the limited number of subjects. If two or more subjects were directed to the same chain contemporaneously, both would complete the task, but only the first completed testing set would serve as the input to the next generation. IP addresses were also logged and each computer was blocked from running the experiment twice. Lastly, the testing phase was followed by a brief questionnaire (Appendix B).

Because this is a relatively new function learning paradigm, it is unclear what the best quantitative analyses might be. Kalish et al. (2007) mainly presented a qualitative characterization of their results. For their quantitative analysis, they computed the correlation of each function to the positive linear function, $y = x$. However, in the present experiment, not all chains converge to the positive linear function, and therefore such a correlation measure would not be equally informative for all chains. The present results will also be characterized qualitatively and focus on a comparison and contrast of the dynamics obtained here to those of the original study.

4. Results

Condition 1 constitutes a replication of Kalish et al. (2007). Figure 3.2 shows all chains collected for this condition. Of these 8 chains, 5 seem to converge to the positive linear function. The remaining chains show no sign of definite convergence, though chain #1 seems to be headed toward negative linear. Of the converged chains, estimated convergence to the positive linear function occurred by an average of 2.4 generations. Figure 3.3 shows all results from condition 2, where subjects where told a small level of noise existed in the training set. Of these 7 chains, 3 seem to converge to the positive linear function, and 1 to the negative linear function. Of the converged chains, estimated convergence to the positive or negative linear function occurred by an average of 2 generations.

Looking at these results cumulatively, some behavior is evident which was not conclusively obtained in the original study. First, is the phenomenon of bet hedging, which can be taken as evidence that subjects are sampling. However, there is no way to tell if they are in fact sampling from all possible hypotheses or just outputting according to their most probable current hypotheses. Bet hedging is apparent in condition 1, chain 1, generation 1 (C1-1-1), C1-1-5, and C2-7-2. As obtained from 2 exit questionnaires, subjects report that they guessed the rule is “red bar = either double or half of the blue bar” ($y = 2x$ or $\frac{1}{2}x$) but that they weren’t sure so they

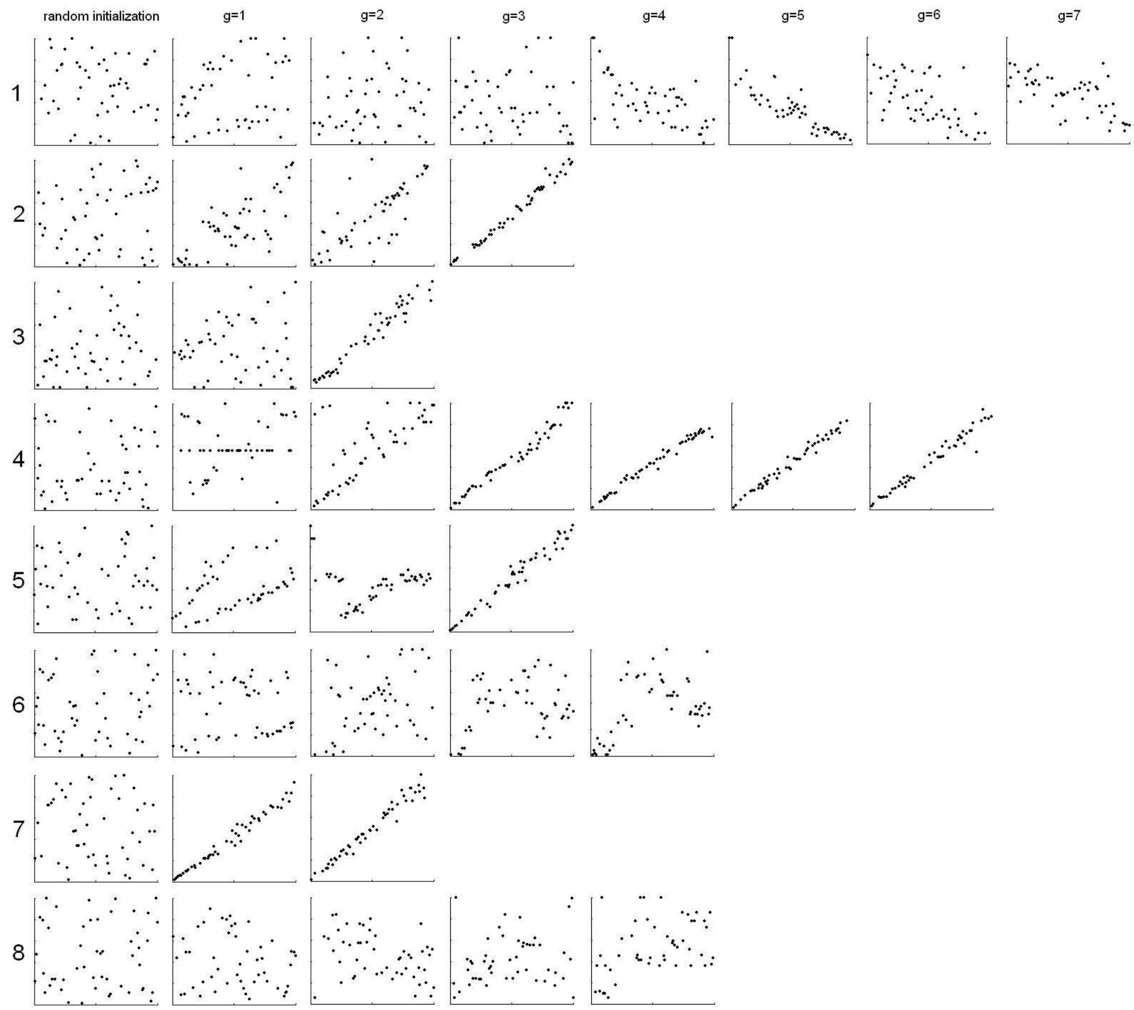

Figure 3.2
This figure shows the results from the 8 chains of condition 1. Each set of axes plot the testing phase responses of each subject, which was trained on the data to the left of it. The leftmost column shows the random initialization that the first subject of each chain was trained on. 5 of these chains seem to converge to a linear function with positive slope, and chain 1 seems to be headed toward a negative linear function. Bet hedging and discontinuous functions also appear.

responded by choosing randomly according to both rules, in attempt to "get at least some answers correct."

Second, is the appearance of discontinuous functions. C1-5-2, C1-6-3&4, C2-6-1,2&3 all appear to be categorizing certain lengths of the blue bar and applying different rules relating red bar size to each category. The strongest evidence of this shown in C2-7-3&4. Here, this discontinuous function seems relatively stable and clearly originated in the bet-hedging behavior of generation 2.

Additionally, C2-6-1 reported a different continuous solution, which was gradually increasing the red bar when the blue bar increased, but keeping the red bar in its mid range. Some participants also guessed the relationship could be related to time-course dependence (where one trial's answer was dependent on the trial before it), but none reported to output answers consistent with such a hypothesis. It is also clear, from the exit questionnaires, that when subjects had absolutely no idea of what the underlying

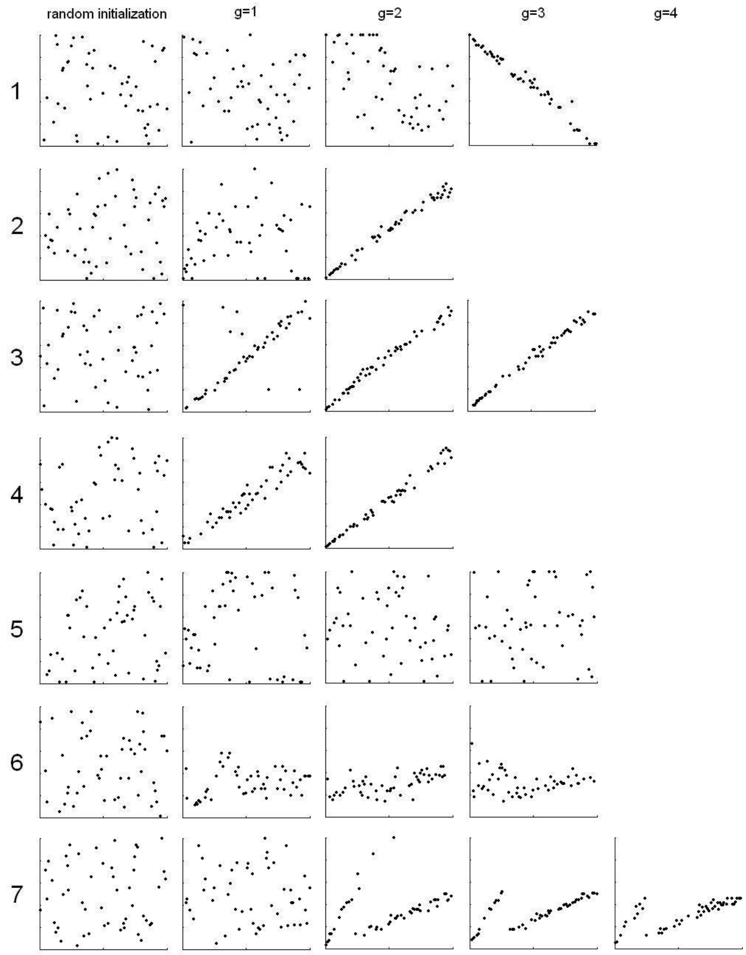

Figure 3.3
This figure shows the results from the 7 chains of condition 2. Each set of axes plot the testing phase responses of each subject, which was trained on the data to the left of it. The leftmost column shows the random initialization that the first subject of each chain was trained on. 3 of these chains seem to converge to a linear function with positive slope, and 1 to a linear function with negative slope. Chains 6 & 7 show additional behaviors, maintained for 3 generations.

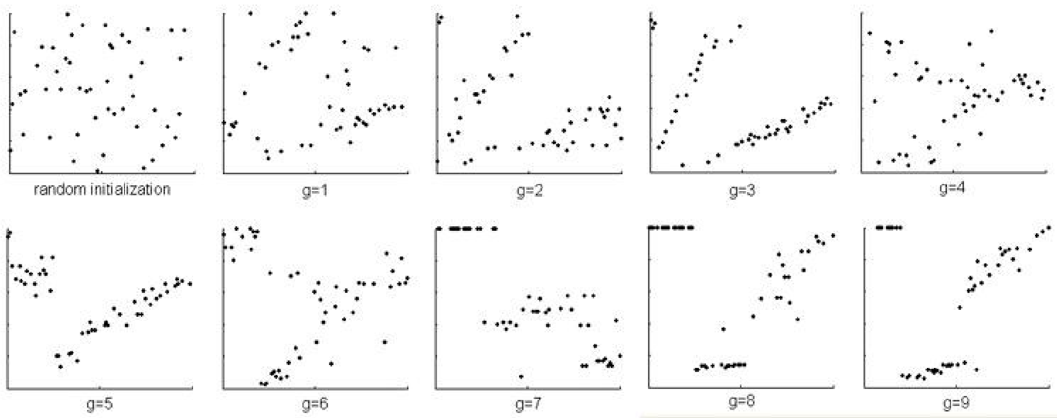

Figure 3.4
This figure plots the results of Experiment 3, where subjects are graduate student of logic and cognitive science and constitute one chain of iterations. The wider variation and higher fidelity of transmission suggest that these subjects entertained a wider variety of hypotheses than the subjects in the previous experiments.

relationship might be, they generated their testing answers by either simulating random responses or by matching the red bar to the blue bar length, resulting in a positive linear function. The latter was the case for C1-7-1, C2-2-2, and C2-4-1.

One additional, small experiment (Figure 3.4) was conducted with graduate students in logic and cognitive science, who were told that this was a function learning experiment. In general, these students displayed a lot of motivation to "correctly figure out" the underlying function. The resulting behavior of these subjects give rise to chain full of variation in hypotheses choice, but also

a higher degree of transmission fidelity between these more complex functions. It is possible that these subjects entertained a wider variety of hypotheses, or even have developed different learning biases for function learning tasks than the general population. It is also likely that these subjects took the data into account differently than subjects in the previous experiments, through higher attention levels or working memory capacity, explaining the increased transmission fidelity.

The subject in generation 1 reported bet hedging between $y = 2x$ and $y = ½ x$. This served as a foundation for the next 2 subjects who inferred that the relationship was generated by 2 rules, $y = 2x$ and $y = ½ x$. Subject 5 categorized the stimuli bar into two separate rules. Subject 6 found a continuous function based on a proportion of the stimulus bar's remainder. In generation 7, the extreme values of the previous subject are regularized as maximum response bar lengths for the smallest third of stimulus bar sizes. Last, subjects 8 and 9 reported using the same categorization and rules in the testing phase. It is doubtful that this chain will converge to a positive linear function anytime soon, due to the saliency of the rule coding $x < 1/3$ its maximum length = maximum y. It seems likely, however, that this function could converge to a fully discrete function, which might be just as stable as the positive linear function.

5. Discussion

These experiments elicited a wider variety of behavior in than has been previously demonstrated in an iterated function learning experiment. This is probably due to an under specification of the nature of the function to be learned, resulting in subjects entertaining, on average, more hypotheses than subjects in Kalish et al. (2007). These results show that some aspect of human subject's hypotheses can be reached by manipulating their expectations of the processes which generate the data they see. The more expectations they have toward a particular class of functions (such as continuous, one-to-one mappings), the less they will entertain hypotheses which do not conform with those expectations. However, this result could very well be explained by a change in subjects' prior distribution over hypotheses between the original and present experiments. And thus, serves as evidence that the distribution of prior probabilities over hypotheses can be manipulated through instructions or context. Additionally, it is quite likely that the biases which subjects bring to a specific task can be directly manipulated, perhaps by changing the domain or reasoning in which the task is couched. For example, if the two bars were said to represent the volume of two cups (linear) or the speed and stopping distance of vehicles (exponential), the corresponding ranking of biases might be altered.

This variance in behavior obtained in the present experiments, coupled with a small number of chains, makes it unclear whether there was a difference in convergence rate between conditions 1 and 2. Perhaps collecting more chains could provide a clearer picture. There is some evidence, though, that the purported noise facilitated subjects in choosing their first hunch. In particular, subject C2-1-3 reported entertaining a wide variety of possible relationships to no success during the training phase, but then "remembered reading something about the noise added and I decided to stick to my original idea…" which was inverse proportionality of the two bars.

Although individual variation in ILMs may obscure differences between experimental manipulations, these differences shouldn't necessarily be controlled for, but instead studied in greater depth. These experiments demonstrated that experimental ILMs offer a very incomplete picture of individual learning biases. Looking back at the results, a wide variety of responses are obtained in the first generation of each chain, to initializations of the same class; random (x,y) pairs. Although we can see different responses from different people to similar stimuli, there is not way to tell, from such an ILM, what range of responses to this stimuli any particular subject is capable of.

Despite an unclear difference between conditions, this experiment largely replicates the results of Kalish et al. (2007). This helps to establish this relatively new task as a reliable paradigm for revealing the inductive biases of human function learning. As Kalish et al. assert, the experimental ILM may be a good tool for revealing human inductive biases for tasks where they are unknown or where researches have few a priori hypotheses about what they might be. Additionally, the human subjects ILM may lend itself well to the experimental manipulation of convergence patterns or the biases themselves. Such manipulations could be useful in testing hypotheses informed by computational modeling, as explained in this paper's introduction.

In general, an experimental ILM can inform us more about human iterated learning behavior than a computational ILM and the relevant psychological studies combined. However, it will provide the strongest results when coupled with these other methodologies. It is possible that certain psychological pre-tests could be conducted with experimental ILM participants to ascertain subject-specific biases. Subjects could be grouped into ILMs according to differences in biases and this could be correlated with differences that are obtained in the dynamics or resulting communication systems in each ILM. It is also possible that the actual trajectory which a particular chain takes can be explained by the particular biases of the individuals at each generation. Using experimental and computational ILMs in combination can help us to infer unknown behaviors (such as hypothesis choice strategy) from observed behavior (such as sensitivity to data likelihoods). Because the models provide us with insights into what behaviors are typically associated with what parameter settings, we may be able to infer certain underlying relationships in the human subject, when particular behaviors are obtained. Eventually, it may be possible to read off the biases of individuals from the properties of the languages they develop in an experimental ILM. Until then, experimental ILMs will still serve as good tools for revealing the general, shared biases in a population of human learners.

Acknowledgments

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Appendix

Experiment instructions for condition 1:

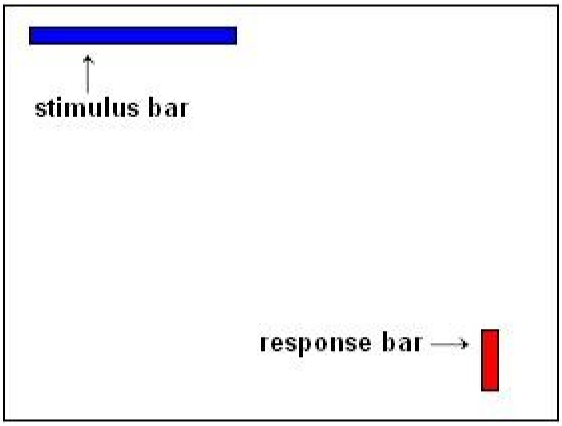
Instructions:

Thank you for your participation! This experiment consists of 2 parts. In the first part, you will be taught the relationship between the sizes of two different bars. In the second part, you will be tested to see how well you learned this relationship.

Part 1 Instructions:

Part 1 will teach you the relationship between the sizes of a blue and a red bar. During this part of the experiment, pay attention and try to learn this relationship the best you can.

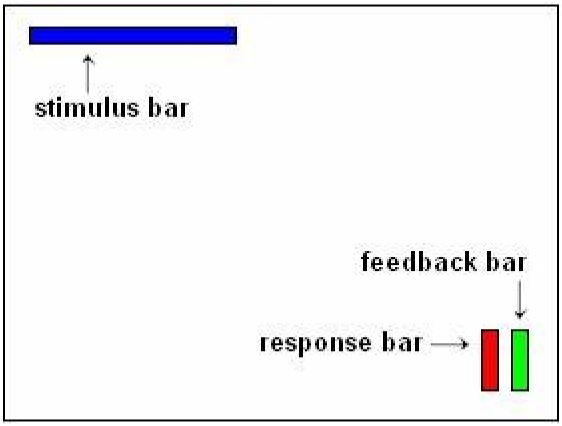
Here's what will happen in Part 1:



1. At the top of the screen, a blue bar will be shown at a particular size. Each trial, it will be a different size. Your job is to adjust the red bar (by rolling your mouse) so that the red bar has the size you want. You will learn, over the course of Part 1, what the correct response is.

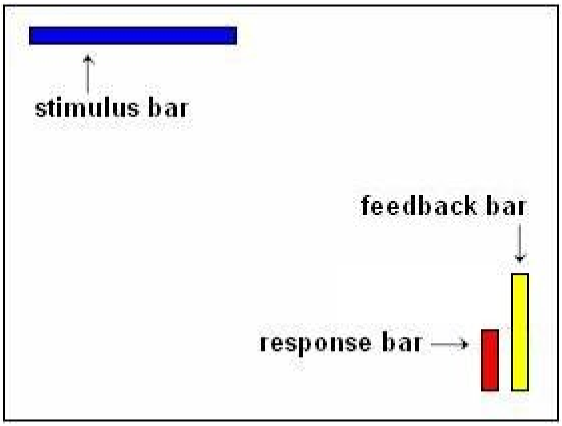
2. Once the red bar is the size you want, press the **space bar** on your keyboard to record your response.

When your response is correct:



If your response was correct, a green bar will appear to the right of the red bar for a 1-second study period. (If your answer is very close, but not exact, it will be accepted). Then the next trial will begin.

When your response is *not* correct.



If your response was incorrect, a yellow bar will appear to the right of the red bar and show you the correct answer. You must re-adjust the red bar to the exact height of the yellow bar and press the **space bar**. There will be a 2-second study period and then the next trial will begin.

Part 1 consists of 50 trials. There is no time constraint.

Part 2 Instructions:

Part 2 will test how well you have learned the relationship between the blue and the red bar. This part is identical to Part 1 except that **the feedback bar will not appear**. Once you record your response with the **space bar**, the next trial will begin.

Try your best to indicate the correct size of the red bar during this part of the experiment!

Part 2 consists of 50 trials. There is no time constraint.

Good Luck!

Click here to run the experiment.

Experiment instructions for condition 2:

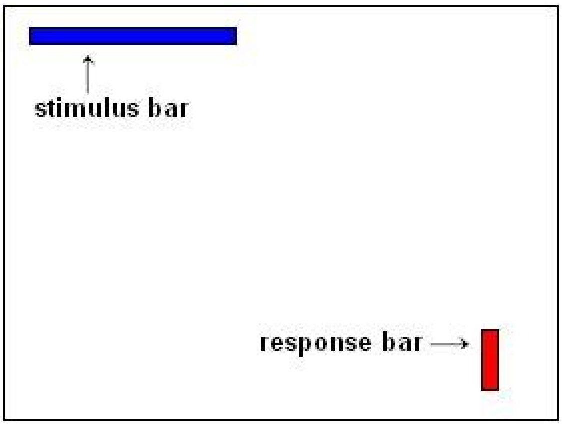
Instructions:

Thank you for your participation! This experiment consists of 2 parts. In the first part, you will be taught the relationship between the sizes of two different bars. In the second part, you will be tested to see how well you learned this relationship.

Part 1 Instructions:

Part 1 will teach you the relationship between the sizes of a blue and a red bar. For most of the trials in Part 1, the blue and red bar sizes will correspond to this relationship. However, in some trials the blue and red bar sizes will be random – this adds a small level of noise. During this part of the experiment, pay attention and try to learn the underlying relationship the best you can.

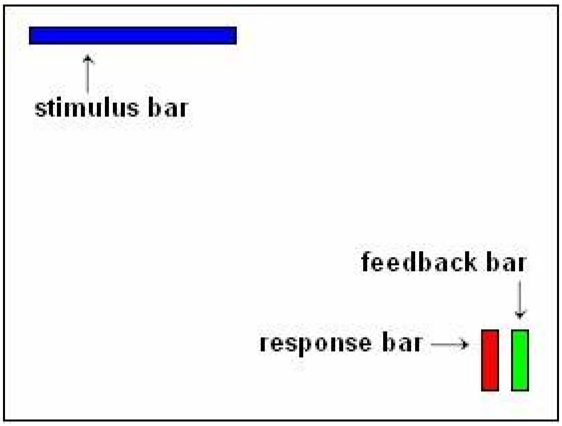
Here's what will happen in Part 1:



1. At the top of the screen, a blue bar will be shown at a particular size. Each trial, it will be a different size. Your job is to adjust the red bar (by rolling your mouse) so that the red bar has the size you want. You will learn, over the course of Part 1, what the correct response is.

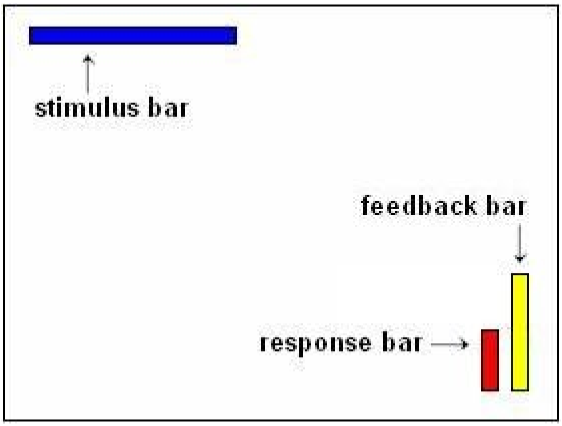
2. Once the red bar is the size you want, press the **space bar** on your keyboard to record your response.

When your response is correct:



If your response was correct, a green bar will appear to the right of the red bar for a 1-second study period. (If your answer is very close, but not exact, it will be accepted). Then the next trial will begin.

When your response is *not* correct.



If your response was incorrect, a yellow bar will appear to the right of the red bar and show you the correct answer. You must re-adjust the red bar to the exact height of the yellow bar and press the **space bar**. There will be a 2-second study period and then the next trial will begin.

Part 1 consists of 50 trials. There is no time constraint.

Part 2 Instructions:

Part 2 will test how well you have learned the underlying relationship between the blue and the red bar. This part is identical to Part 1 except that **the feedback bar will not appear**. Once you record your response with the **space bar**, the next trial will begin.

Try your best to indicate the correct size of the red bar during this part of the experiment!

Part 2 consists of 50 trials. There is no time constraint.

Good Luck!

Click here to run the experiment.

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