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Children's Imitation of Action Sequences is Influenced by Statistical Evidence and Inferred Causal Structure

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Abstract

Children are ubiquitous imitators, but how do they decide which actions to imitate? One possibility is that children might learn which actions are necessary to reproduce by observing the contingencies between action sequences and outcomes across repeated observations. We define a Bayesian model that predicts that children will decide whether to imitate part or all of a sequence based on the pattern of statistical evidence. To test this prediction, we conducted an experiment in which preschool children watched an experimenter repeatedly perform sequences of varying actions followed by an outcome. Children's imitation of sequences that produced the outcome increased, in some cases resulting in production of shorter sequences of actions that the children had never seen performed in isolation. This behavior is consistent with our model's predictions, and suggests that children attend to statistical evidence in deciding which actions to imitate, rather than obligately imitating successful actions.

Keywords: Cognitive development; Imitation; Statistical learning; Causal inference; Bayesian inference

Introduction

Learning the causal relationships between everyday sequences of actions and their outcomes is a daunting task. How do you transform a package of bread, a jar of peanut butter and a jar of jelly into a peanut butter and jelly sandwich? Do you cut the bread in half before or after you put together the sandwich? Can you put the peanut butter on first, or does it always have to be jelly first? In order to achieve desired outcomes – from everyday goals such as eating a tasty sandwich to distinctive human abilities such as making and using tools – children need to solve a challenging causal learning problem: observing that the intentional actions of others lead to outcomes, inferring the causal relations between those actions and outcomes, and then using that knowledge to plan their own actions.

To learn from observation in this way, children cannot simply mimic everything they see. Instead, they must segment actions into meaningful sequences, and determine which actions are relevant to outcomes and why. Recent studies of imitation in children have produced varying answers to the question of whether children are capable of solving this problem. While children sometimes selectively reproduce the most obviously causally effective actions (Williamson, Meltzoff, & Markman, 2008; Schulz, Hooppell, & Jenkins, 2008), at other times they will “overimitate”, reproducing apparently unnecessary parts of a causal sequence (Whiten, Custance, Gomez, Teixidor, & Bard, 1996; Lyons, Young, & Keil, 2007), or copying an actor's precise means, when a more efficient action for accomplishing the same goal is available (Meltzoff, 1995). Sometimes children may produce both kinds of behavior in the same study. In the “rational imitation” studies by Gergely, Bekkering, and Kiraly (2002),

children saw an experimenter activate a machine with hands free or hands confined. Children both produced exact imitations of the actor (touching their head to a machine to make it go) and produced more obviously causally effective actions (touching the machine with a hand), though the proportion of such actions differed in the different intentional contexts.

We suggest that these different results reflect the multiple sources of information that contribute to a rational statistical inference about causally effective actions. Children need to balance their prior knowledge about causal relations, the new evidence that is presented to them by the adult, and their knowledge of the adult's intentions. Moreover, in the case of imitation there is often no single “right answer” to the question of what to imitate. After all, a longer “overimitation” sequence might actually be necessary to bring about an effect, though that might seem unlikely at first. The imitation problem can be expressed as a problem of Bayesian inference, with Bayes' rule indicating how children might combine these factors to formulate different causal hypotheses and produce different action sequences based on those hypotheses. It is difficult to test this idea however, without knowing the strength of various causal hypotheses for the children. Since previous studies involved general folk physical and psychological knowledge (such as removing a visibly ineffectual bolt to open a puzzle box) it is difficult to know how strong those hypotheses would be. By giving children statistical information supporting different hypotheses we can normatively determine how probable different hypotheses should be, and then see whether children's imitation reflects those probabilities.

It is also independently interesting to explore the role of statistical information in imitation. Recent studies show that children are surprisingly sophisticated in their use of statistical information such as conditional probabilities in a range of domains, from phonology (Saffran, Aslin, & Newport, 1996), to visual perception (Fiser & Aslin, 2002; Kirkham, Slemmer, & Johnson, 2002), to word meaning (Xu & Tenenbaum, 2007). Such information plays a particularly important role in both action processing (Zacks et al., 2001; Baldwin, Andersson, Saffran, & Meyer, 2008; Buchsbaum, Griffiths, Gopnik, & Baldwin, 2009) and causal inference (Gopnik et al., 2004; Gopnik & Schulz, 2007), and allows adults to identify causal subsequences within continuous streams of action (Buchsbaum et al., 2009). Varying the probabilities of events within action sequences may thus provide a way to vary the statistical evidence those sequences provide in favor of different causal hypotheses.

Statistical inference might be particularly important to

Observed Action Sequence	Potential Causal Sequences
ABC+	ABC, BC, C
DBC+	DBC, BC, C
Total Potential Causes	ABC, DBC, BC, C

Table 1: Example demonstrations, and the associated set of potential causal sequences. Letters represent unique observed actions, a + indicates a causal outcome.

imitation because it could allow children to not only determine the causal relationship between action sequences and outcomes, but to identify irrelevant actions within causally effective sequences. Imagine that I am making a peanut butter sandwich, and that between opening the jar, and spreading the peanut butter, I get peanut butter on my hands, so I wipe them on a paper towel. If this is the first time you’ve seen me make a sandwich, you might mistakenly think that hand-wiping is a necessary step. However, after watching me make a sandwich a couple of times, you might notice that while opening the jar always predicts spreading the peanut butter, it doesn’t always predict hand-wiping, and could infer that this step is extraneous. In most previous work on children’s imitation of casual sequences, children observed only a single demonstration of how to generate the outcome (e.g. Whiten et al., 1996; Lyons et al., 2007).

In this paper, we look at whether children use statistical evidence from repeated demonstrations to infer the correct causal actions within a longer sequence and imitate them. We present a Bayesian analysis of causal inference from repeated action sequence demonstrations, followed by an experiment investigating children’s imitative behavior and causal inferences. We showed preschool children different sequences of three actions followed by an effect, using our Bayesian model to guide our manipulation of the probabilistic evidence, such that the statistical relations between actions and outcomes differed across conditions in ways that supported different causal hypotheses. We then examine which sequences the children produced themselves, and compare children’s performance to our model’s predictions. We conclude by discussing our results in the context of broader work on imitation, and causal and intentional inference.

Bayesian Ideal Observer Model

In many real world situations, the causal structure of a demonstrated sequence of actions is not fully observable. In particular, which actions are causally necessary and which are superfluous may be unclear. One way children may overcome this difficulty is through repeated observations. By watching someone make a sandwich or turn on a lightbulb on multiple occasions, children can pick up on which actions consistently predict the desired outcome, and which do not.

While it is intuitively plausible that children can use the statistical evidence in repeated demonstrations to infer causal structure, we would like to verify that normative inferences from repeated observations of action sequences and their outcomes vary in a systematic way with different patterns of data. One way to derive what the normative distribution over

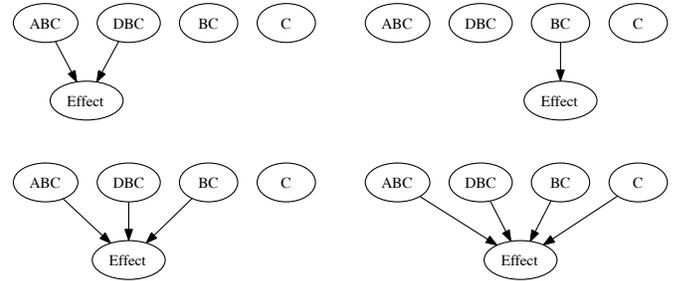


Figure 1: A subset of the hypothesis space. Each box represents a hypothesis about which action sequences are causal.

causes should be is through a Bayesian model (Gopnik et al., 2004; Griffiths & Tenenbaum, 2005). The Bayesian formalism provides a natural way to represent the roles of children’s prior assumptions and the observed data in forming their beliefs about which action sequences are likely to be causal.

Model Details

Given observations of several sequences of actions, we assume that children consider all sequences and terminal subsequences as potentially causal. These include both sequences that generate the outcome and those that do not. For instance, if the sequence “squeeze toy, knock on toy, pull toy’s handle” is observed, then squeeze, followed by knock, followed by pull handle would be one possible causal sequence, and knock followed by pull handle would be another. Given all of the observed sequences, we can enumerate the potential causes (see Table 1 for an example set of demonstrations and potential causes). As in previous work on children’s causal inference, we use a Deterministic-OR model (c.f. Cheng, 1997; Pearl, 1996), in which any of the correct sequences will always bring about the effect. To capture the intuition that there may be more than one sequence of actions that can bring about an effect, we consider all of the potential causes (such as in Table 1), as well as all disjunctions of these causes. The base causes, together with the disjunctions form the space of potential hypotheses, H (see Figure 1).

The learner wants to infer the set of causes, h , given the observed data, d , where the data are composed of an observed sequence of actions, a , and an outcome, e . Bayes’ theorem provides a way to formalize this inference. Bayes’ theorem relates a learner’s beliefs before observing the data, their prior $p(h)$, to their beliefs after having observed the data, their posterior $p(h|d)$,

$$p(h|d) \propto p(d|h)p(h), \quad (1)$$

where $p(d|h)$ is the probability of observing the data given the hypothesis is true. For Deterministic-OR causal models, this value is 1 if the sequence is consistent with the hypothesis, and zero otherwise. For example, given the hypothesis that squeeze is the cause, a consistent observation would be, knock then squeeze followed by music, and an inconsistent observation would be squeeze followed by no music. When multiple sequences of actions and effects are observed, we assume that these sequences are independent.

A key element in this inference is the learner’s prior expectations, $p(h)$. Children could have a variety of different beliefs about the kinds of sequences that bring about effects. For instance, they could believe that longer sequences, that include more of the demonstrated actions, are more likely to bring about effects. Or, they could believe that there tends to be only one correct sequence, as opposed to many possible sequences, that cause an effect. We capture these intuitions with a prior that depends on two parameters, β and p , which correspond to the learner’s expectations about the length of causal sequences and number of ways to generate an effect.

We formalize the prior as a generative model. Hypotheses are constructed by randomly choosing causal sequences, a . Each sequence has a probability p_a of being included in each hypothesis and a probability $(1 - p_a)$ of not being included,

$$p(h) \propto \prod_{a \in h} p_a \prod_{a^* \notin h} (1 - p_{a^*}) \quad (2)$$

where the probability of including causal sequence a is

$$p_a = \frac{1}{1 + \frac{1-p}{p} \exp(-\beta(|a| - 2))}, \quad (3)$$

and $|a|$ is the number of actions in the sequence a . Values of β that are greater than 0 represent a belief that longer sequences are more likely to be causes. Values of p less than 0.5 represent a belief that effects tend to have fewer causes. Together, Equations 1, 2 and 3 provide a model of inferring hypotheses about causes from observed sequences and their effects.

In our experiments, rather than probing children’s beliefs directly, we allow children to play with the toy. Therefore, to complete the model, we must specify how children choose action sequences, a , based on their observations, d . Intuitively, we expect that if we know the set of causes of the effect, h , we will randomly choose one of these actions. If we were unsure about which of several possible causes was the right one, then we may choose any of the possible contenders, but biased toward whichever one we thought was most likely. We capture these intuitions formally by choosing an action given the observed data, $p(a|d)$, based on a sum over possible hypotheses,

$$p(a|d) \propto \sum_{h \in H} p(a|h)p(h|d), \quad (4)$$

where $p(a|h)$ is one if a is a cause under h , and zero otherwise, and $p(h|d)$ is specified in Equation 1.

A Simple Modeling Example

We can now verify that the model makes distinct inferences from repeated demonstrations. In the first example, the demonstrated action sequences are ABC+, DBC+ as in Table 1. That is, a sequence of three actions A, B and C is followed by an effect. Subsequently, a different sequence of three actions, D, B, and C is followed by the same effect. In the second example, the observed sequences are ABC+, DBC. Here, the second three-action sequence is not followed by the effect.

Observed Sequences	ABC	DBC	BC	C
ABC+, DBC+	0.23	0.23	0.27	0.27
ABC+, DBC	1.0	0.0	0.0	0.0

Table 2: Example model results, $p = 0.5$ and $\beta = 0$.

Observed Sequences	ABC	DBC	BC	C
ABC+, DBC+	0.26	0.26	0.35	0.13
ABC+, DBC	1.0	0.0	0.0	0.0

Table 3: Example model results, $p = 0.1$ and $\beta = 1.0$.

Using values of $p = 0.5$ and $\beta = 0$ results in a prior that assigns equal probability to all possible causal hypotheses – a uniform prior. With this uniform prior, we can now find the probability of choosing to perform each action sequence to bring about the effect given the observed data, $p(a|d)$, as described in Equation 4. Our model infers that, in the first case, all the sequences are possible causes, with BC and C being somewhat more likely, and equally probable. Notice that the model infers that the subsequences BC and C are the most likely causes, even though neither was observed on its own. The second case is quite different. Here the model sees that DBC and its subsequences BC and C did not lead to the effect in the second demonstration, and infers that ABC is the only possible cause among the candidate sequences (see Table 2).

We now use values of $p = 0.1$ and $\beta = 1.0$ leading the model to favor simpler hypotheses containing fewer causes, and causes that use more of the observed demonstration.¹ This prior does not change results in the second case, where ABC is still the only possible cause. However, in the first case, the model now infers that the subsequence BC is the most likely individual cause, since it is the longest observed sequence to consistently predict the effect (see Table 3).

Model Predictions for Children’s Inferences

Our rational model makes differential predictions based on repeated statistical evidence, and is able to infer subsequences as causal without seeing them performed in isolation. We can now use the model to help us construct demonstration sequences that normatively predict selective imitation in some cases, and “overimitation” in others. If children are also making rational inferences from variations in the action sequences they observe, then their choice of which actions to imitate in order to bring about an effect should similarly vary with the evidence. We test our prediction that children rationally incorporate statistical evidence into their decisions to imitate only part of an action sequence versus the complete sequence in the following section.

Experiment

Method

Participants Participants were 81 children ($M = 54$ months, $Range = 41 - 70$ months, 46% female) recruited from local preschools and a science museum. An additional

¹These parameter values qualitatively fit children’s imitative behavior, as we discuss later in the paper.

“ABC” Condition	“BC” Condition	“C” Condition
ABC+	ABC+	ABC+
DEC	ADC	ADC+
ABC+	DBC+	DBC+
EDC	AEC	AEC+
ABC+	EBC+	EBC+

Table 4: The demonstration sequences for “ABC” , “BC” and “C” conditions. Each child observed the experimenter performing all 5 action sequences in their condition.

18 children were excluded from the study because of demonstration error (4), equipment failure (3), lack of English (1), unavailable birth date (1), did not try toy (6), extreme distraction (2), never performed trial termination action (1).

Stimuli There were two novel toys: a blue ball with rubbery protuberances, and a stuffed toy with rings and tabs attached to it. Six possible actions could be demonstrated on each toy. Children were assigned to one of three experimental conditions. In each condition, they saw a different pattern of evidence involving five sequences of action and their outcomes. Each individual action sequence was always three actions long. In the “ABC” pattern, the same sequence of three actions (e.g. A=Knock, B=Stretch, C=Roll) is followed by a musical effect three times, while in the “BC” pattern a sequence composed of a different first action, followed by the same two-action subsequence (e.g. A=Squish, B=Pull, C=Shake and D=Flip, B=Pull, C=Shake) is followed by the effect three times (see Table 4). In both patterns, two additional sequences that end in C and do not contain BC fail to produce the effect. Finally, in the “C” pattern the sequences of actions were identical to those in the “BC” pattern, but the outcome was always positive. The number of times each individual action is demonstrated in each sequence position is identical in all three patterns. As we show later in the paper, our Bayesian ideal observer model confirms that the statistical evidence in each pattern supports different causal inferences.

Procedure The experimenter showed the child one of the toys, and said: “This is my new toy. I know it plays music, but I haven’t played with it yet, so I don’t know how to make it go. I thought we could try some things to see if we can figure out what makes it play music.” The experimenter emphasized her lack of knowledge, so that the children would not assume she knew whether or not any of her actions were necessary. She then demonstrated one of the three patterns of evidence, repeating each three-action sequence (and its outcome) twice. The experimenter named the actions (e.g. “What if I try rolling it, and then shaking it, and then knocking on it?”), acted pleasantly surprised when the toy played music (“Yay! It played music!”), or disappointed when it did not (“Oh. It didn’t go”), and pointed out the outcome (“Did you hear that song?” or “I don’t hear anything. Do you hear anything?”). After she demonstrated all five of the 3-action sequences, she gave the child the toy and said “Now it’s your turn! why don’t you try and make it play music”. Throughout the experiment the music was actually triggered

Condition	Triplet	Double	Single	Other
“ABC”	20	1	2	4
“BC”	10	7	0	10
“C”	8	0	8	11

Table 5: Number of children producing each sequence type

by remote activation. To keep the activation criteria uniform across conditions, the toy always played music the first time a child produced the final C action, regardless of the actions preceding it, terminating the trial. Only this first sequence of actions was used in our analysis.

Children were videotaped, and their actions from the time they were handed the toy to trial termination were coded by the first author, and 80% of the data was recoded by a blind coder. Coders initially coded each individual action as one of the six demonstrated actions, or as “novel”. These sequences were then transferred into an “ABC” type representation, and subsequently coded as one of four sequence types: Triplet, Double, Single or Other (defined below). Inter-coder reliability was very high, with 91% agreement on the “ABC” type representations, and 100% agreement on sequence types.

Results and Discussion

Overall results are shown in Table 5. Children produced significantly different types of sequences across the three conditions, $p < 0.001$ (two-sided Fisher’s exact test). We will discuss results for the “ABC” and “BC” conditions first, and then return to the “C” condition.

Effect of Statistical Evidence on Imitation In their imitation, children could either exactly reproduce one of the three-action sequences that had caused the toy to activate (that is, ABC in the “ABC” condition or ABC, DBC or EBC in the “BC” condition), or they could just produce BC in isolation. We refer to these successful three-action sequences as “triplets”, and to the BC subsequence as a “double”.

Both a triplet and a double reflect potentially correct hypotheses about what caused the toy to activate in both conditions. It could be that BC by itself causes the toy to activate in the “ABC” condition and the A is superfluous, or it could be that three actions are necessary in the “BC” condition, but the first action can vary. In both conditions BC is followed by the effect three times.

If children automatically encode the adult’s successful actions as causally necessary, then they should exclusively imitate triplets in both conditions. However, if children are also using more complex statistical information, they should conclude that the BC sequence by itself is more likely to be causal in the “BC” condition than in the “ABC” condition, and that the triplet sequence is more likely to be causal in the “ABC” condition than in the “BC” condition. This is in fact what we found – the number of children producing triplets and doubles varied by condition, $p < 0.01$ (two-sided Fisher’s exact test), and differed significantly between the “ABC” and “BC” conditions $p < 0.05$ (two-sided Fisher’s exact test).

Effect of Differing Causal Outcomes on Imitation The pattern of evidence in the “BC” condition is more complex than in the “ABC” condition. This may have confused children, leading them to produce a variety of random actions, including BC. The “C” condition controls for this possibility. In this condition the sequences of actions were identical to those in the “BC” condition, but the outcome was always positive. As we show later, our Bayesian ideal observer model confirms that this provided statistical evidence for the hypothesis that C alone was sufficient to produce the effect.

In all three conditions, imitation of just the final C action in isolation was coded as a “single”. As in the “ABC” and “BC” conditions, only the subsequence BC was coded as a double in the in the “C” condition. Also consistent with the “ABC” and “BC” conditions, in the “C” condition all five demonstrated successful sequences (ABC, ADC, DBC, AEC and EBC) were coded as triplets.

The “C” condition is as complex as the “BC” condition. However in the “C” condition the final action C produced by itself reflects a likely causal hypothesis. If children selectively imitate subsequences based on the data, then children in the “C” condition should produce C more frequently than children in the “BC” condition, and children in the “BC” condition should produce BC more frequently than children in the “C” condition. Our results support this hypothesis. Children in the “BC” and “C” conditions differed significantly in the overall types of sequences they produced, $p < 0.001$ (two-sided Fisher’s exact test), and the number of children producing doubles and singles in the two conditions also varied significantly, $p < 0.001$, (two-sided Fisher’s exact test).

Performance of “Other” Actions Across all three conditions, children did not just obligately imitate one of the successful sequences or subsequences they observed – they also produced new combinations of actions. Overall, the types of “other” sequences produced did not qualitatively differ across conditions, and appear to be a mix of exploratory behavior and genuine errors. There was a trend towards children in the “BC” and “C” conditions performing more of these “Other” sequences than children in the “ABC” condition $p = 0.10$, (two-sided Fisher’s exact test). This difference becomes statistically significant when two children who imitated unsuccessful triplets are excluded from the analysis, $p < 0.05$, (two-sided Fisher’s exact test). This result is compatible with findings that children tend to increase their exploratory behavior when the correct causal structure is more ambiguous (Schulz & Bonawitz, 2007; Schulz et al., 2008). Finally, four children performed completely novel actions they had never seen demonstrated. All of these children were in the “BC” or “C” conditions, consistent with these conditions eliciting more exploratory actions.

Model Results

Supporting our experimental results, our model makes distinct predictions in each of the three experimental conditions, showing that the data lead to differential causal inferences.

Parameter values of $p = 0.1$ and $\beta = 1.0$ were chosen because they produced a qualitatively good match to children’s performances, as shown in Figure 2. The relatively high value for β suggests that children prefer longer (complete) causal sequences, perhaps representing a pre-existing belief that adults usually don’t perform extraneous actions. The relatively low value for p suggests that children employ a causal Occam’s razor, assuming that simpler hypotheses, which require fewer causes to explain the data, are more likely. Overall, these results suggest that children’s imitative choices conform closely to normative predictions.

Finally, while children performed similarly to our model’s predictions, there were some differences in performance as well. Children produced more triplets than our model predicted, especially in the “ABC” condition. One reason for this discrepancy may be that children are able to use information about the knowledge state and intentional stance of the demonstrator that our current model cannot take into account. Models that can incorporate intentional and pedagogical information, in addition to statistical evidence are an important area of future work (Goodman, Baker, & Tenenbaum, 2009; Bonawitz et al., 2009). We are currently developing such a model, and exploring the role of pedagogical cues in children’s imitation (Buchsbaum, Gopnik, Griffiths, & Shafto, submitted).

General Discussion

In this paper, we examined whether children are sensitive to statistical evidence in choosing the actions they imitate. We demonstrated that children can use statistical evidence to decide whether to imitate a complete action sequence, or to selectively imitate only a subsequence. In particular, children in the “ABC” condition imitated the complete sequence ABC more often than children in the “BC” condition, while children in the “BC” condition imitated the subsequence BC more often than children in the “ABC” condition. Children’s performance in the “C” condition demonstrated that the differential imitation in the “ABC” and “BC” conditions could not be explained as a result of task complexity.

The design of this experiment also eliminated other simple explanations for these results. There were the same absolute number of BC demonstrations followed by effects in all three conditions, but children only produced doubles in the second condition. Similarly, the absolute number of positive triplet demonstrations was the same in the “ABC” condition and the “BC” condition, and was smaller than in the “C” condition, but children produced more triplets in the first condition than in the other two conditions. Finally, the actual sequence of actions was the same in the “BC” and “C” conditions but children behaved differently in the two cases. Children appeared to selectively imitate by considering the conditional probability of the various events and outcomes, and formulating a set of causal hypotheses based on that data. They then produced responses that matched the probability distribution of the hypotheses, at least qualitatively.

It is also worth noting the information-processing com-

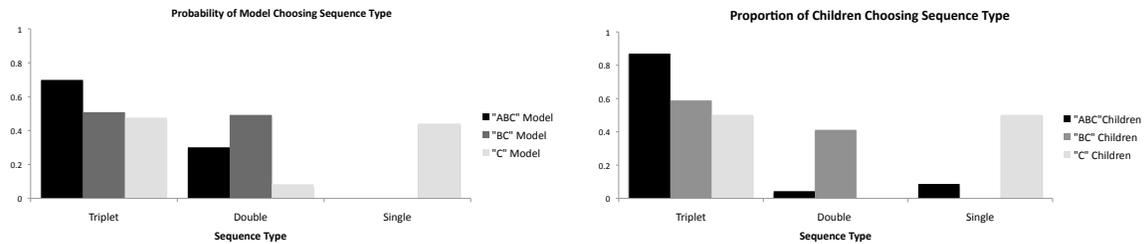


Figure 2: Left: Predictions of our Bayesian model. Right: Children's actual performance in Experiments 1 and 2.

plexity of this task. Children saw thirty similar actions and ten outcomes in each condition, and yet they appeared to track and use this information in deciding which actions to produce. This is consistent with other studies in which children and adults show surprising if implicit capacities to track statistical regularities.

These results extend earlier findings that show children take causal and intentional information into account appropriately in their imitation. They show that children also take into account statistical information about the conditional probability of events and do so in an at least roughly normative way. The studies also suggest a rational mechanism for the phenomenon of "overimitation." In particular, the "triplet" responses could be thought of as a kind of overimitation, reproducing parts of a causal sequence that are not actually demonstrably necessary for the effect. These results suggest that this behavior varies depending on the statistics of the data and the probability of various hypotheses concerning them.

Other factors may also influence the child's judgment of various causal hypotheses. For example, knowing that the adult is knowledgeable about the causal system, and is taking a "pedagogical stance" towards the evidence, may lead the child to different causal conclusions (Bonawitz et al., 2009). We are currently investigating the effect of pedagogical cues on imitation of causal action sequences (Buchsbaum et al., submitted). Similarly, seeing a repeated sequence of actions with no obvious physical causal outcome may lead children to suspect that the actions are intended to have a social or psychological rather than physical effect. Both these processes might lead to greater "overimitation" which would nonetheless be rational.

In general however, this study shows that children are sensitive to statistical information in determining which sequences of actions to imitate. Along with other studies, they support the idea that Bayesian procedures of statistical learning, procedures that allow the construction of causal models from statistical patterns, may play a significant role in many important kinds of early learning.

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