

**Understanding the effect of social context on learning:**

**A replication of Xu and Tenenbaum (2007b)**

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### **Abstract**

Does the source of a piece of data—the process by which it is sampled—influence the inferences that we draw from it? Xu and Tenenbaum (2007b) measured a large effect of sampling process on learning: When a category exemplar was presented from a knowledgeable teacher, learners generalized more narrowly than when it was presented from an unknowledgable source. In five experiments, four online and one in-person, we attempt to reproduce this result. We replicate the original finding of sensitivity to the sampling process, but with a smaller effect size than the original. We discuss these findings in the context of new research on sampling processes and questions about reproducibility more generally.

**Keywords:** word learning, induction, Bayesian inference

## Introduction

Imagine you're hiking up a trail and come to a junction. You see a large branch leaning on the trail, partially blocking one path. Most likely the branch is a bit of random debris that shouldn't affect your decision of which way to hike. But if you know that a friend walked up the trail in front of you just a few minutes before, you might interpret the branch as a signal, intended to point you in the right direction and help you follow her. The intuition underlying this example is that an observation can have a very different meaning depending on its source.

Xu and Tenenbaum (2007b, 2007a) (XT, below) examine this phenomenon—sensitivity to the sampling process for data—in the context of a particularly difficult inductive problem: concept generalization in word learning. Faced with a novel word and its referent, children must decide between an infinite number of hypotheses about the concept extension of that word. For example, consider a child who hears the word “apple” in the context of a single apple on a table. While the referent of that object is clear in the moment of language use (i.e., the particular apple on the table), the broader concept is highly ambiguous: “apple” could refer to the category of apples, the category of fruit, that particular kind of apples (e.g., granny smith), green things, or any number of other ad-hoc categories. As a possible solution to this problem, XT proposed a model of word learning as inductive concept learning. In their model, learners observe data as word-object pairs and make inferences about the concept associated with that word from a hypothesis space of all possible meanings. Critically, their model predicts that a learner should generalize more broadly when the exemplar for learning is sampled from the full hypothesis space of meanings (*weak sampling*), and should generalize more narrowly when the exemplar is sampled from only those true exemplars of the word (*strong sampling*).

In the study we focus on here, Xu and Tenenbaum (2007b) asked whether adults and children are sensitive to these differences in sampling process. In their experiment, they altered the strength of the sampling process by manipulating the source of the observed data. Learners in their study were presented with three labeled exemplars from a target category, either provided by a

knowledgeable teacher or via the learners' own (presumably uninformed) guesses. Importantly, in both conditions, the data that the participants observed was the same: three exemplars from the same subordinate-level category. What differed between conditions was only the sampling process for these exemplars: Since the teacher knew the true concept, the data were presumed to be sampled strongly from the true concept. But in the learner-generated condition, the learner was naïve about the true underlying concept and the data were thus sampled weakly from the full hypothesis space.

Participants observed these samples in the context of a display of possible novel category members that showed hierarchical structure such that it could easily be clustered into subordinate, basic level, and superordinate categories. Participants were then tested on how broadly they generalized from the exemplars they observed. The key prediction was that participants in the teacher condition should be more likely to generalize tightly to the subordinate level, while participants in the learner condition should generalize more broadly at the basic level. The observed data supported this prediction in both adults ( $N = 14$ ,  $d = 1.49$  [0.01, 2.97]) and children ( $N = 24$ ,  $d = 1.21$  [.19, 2.23]).

The theoretical question addressed by XT—how the source of information influences learning—has far-reaching implications for our understanding of human learning. Every datum is observed in some context, and social aspects of that context can radically change the interpretation of that datum. Evidence for sensitivity to sampling assumptions is thus critical in constraining theories about language learning, concept learning, and the social transmission of information more generally. The reproducibility of XT's results is therefore of broad import.

In addition to its theoretical relevance, there are a number of other reasons to conduct a replication of this study. First, other related empirical findings predicted by XT's model have been challenged ("suspicious coincidence effect"; Jenkins, Samuelson, Smith, & Spencer, 2015; Spencer, Perone, Smith, & Samuelson, 2011). Thus, testing the empirical foundations of XT's model has additional importance due to this controversy. Second, recent work has revealed large

individual variability across participants in the strength of sampling assumptions (Navarro, Dry, & Lee, 2012), making the strength and consistency of XT’s original finding somewhat surprising. Third, the original study relies on a social manipulation that is grounded in the interaction between experimenter and participant; such social manipulations tend to have a lower reproducibility rate (Open Science Collaboration, 2015), perhaps due to difficulties in consistently creating the same context and interaction.

Motivated by these concerns, in the current work we conducted a series of five replications of Xu and Tenenbaum (2007a), four online (Experiments 1, 2, 4 and 5) and one in-person (Experiment 3). The last of these studies (Experiment 5) was a large-sample, exact, pre-registered replication of Experiment 4. Our data are consistent with XT’s original report, but suggest an effect substantially smaller in magnitude than the original estimate. In the General Discussion, we reflect on this replication attempt and how it can be connected to the broader literature.

## Experiment 1

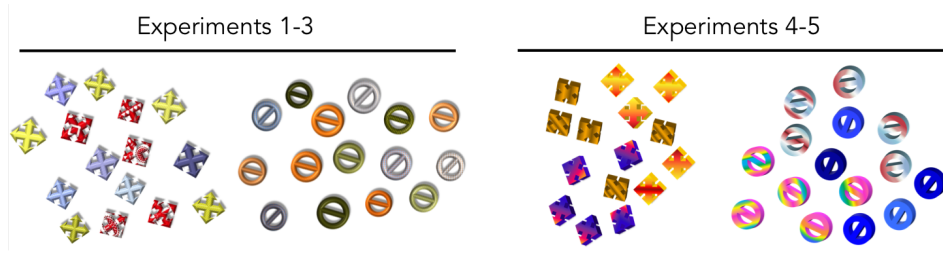
In Experiment 1, we attempted to replicate XT’s original design in an online paradigm.

### *Methods*

*Participants.* XT’s original sample with adults included 14 participants. We recruited 294 adult participants online through Amazon Mechanical Turk. Participants were paid US \$0.25.

We excluded participants from our analysis who responded “yes” to the basic non-match question (see Procedure below;  $N = 8$ ) or who did not select subordinate matches in the learning condition ( $N = 21$ ) because this pattern of response indicated a misunderstanding of the task. No participant missed the attention check question.

In addition, we found that not all participants responded consistently across questions of the same type within a trial, unlike in the original report (for example, a participant might respond “yes” to one subordinate match and “no” to another). In all five of our experiments, we adopt two different criteria for categorizing participants’ response pattern to deal with this variability: liberal



*Figure 1.* Sample stimuli used in Experiments 1-3 (left) and Experiment 4 and 5 (right). The Experiment 4 and 5 stimuli are intended to be maximally similar to the original Xu and Tenenbaum (2007b) stimuli, with lower subordinate-level variability than the stimuli used in Experiments 1-3. All stimuli can be accessed here: <https://github.com/mllewis/xtSamp/tree/master/experimentMaterials/stimuli>.

and strict. Under our liberal criteria, we categorized a participant as a basic-level generalizer if they responded “yes” to both the subordinate matches and *at least one* basic-level match. Under our strict criteria, we categorized a participant as a basic-level generalizer if they responded “yes” to both the subordinate matches and *both* basic-level matches. Under both criteria, a participant was categorized as a subordinate-level generalizer if they responded “yes” to only the subordinate level matches. We excluded participants from our analysis who could not be categorized under either criterion. We report the results using the liberal criterion in the Main Text and describe the results using the strict criterion in Appendix A. In no case does the statistical significance of the results depend on the criterion we used. Under the liberal criteria, 79 participants could not be categorized as either basic or subordinate-level generalizers, and thus were excluded. With all exclusions, our final sample for Experiment 1 included 195 participants ( $N_{\text{learner}} = 101$ ;  $N_{\text{teacher}} = 94$ ).

*Stimuli.* We created four sets of objects similar to the original stimuli (Figure 1, left).<sup>1</sup> There were four basic level categories that included 15 unique objects each. Within each basic level category, there were three subordinate categories, with 5 unique objects each. The same novel

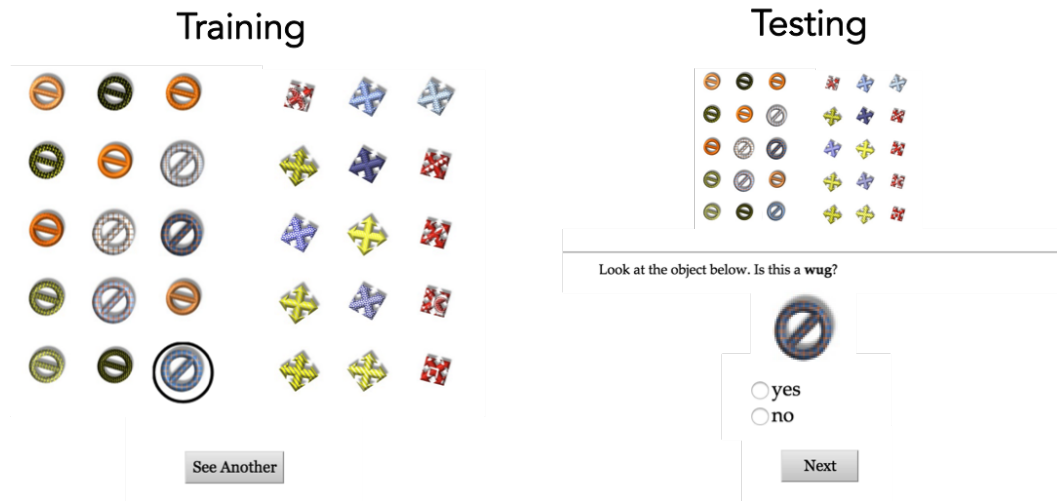


Figure 2. Screen shots of the training (left) and testing (right) phases in Experiment 1.

words were used as the original experiment: “wug,” “tupa,” “blicket,” and “fep.”

*Procedure.* Participants first viewed an instruction page that described the task. In the teacher condition, the instructions read:

In the first part of the experiment, you will see pictures of objects. Some of the objects are called *wugs*. In order for you to learn which objects are *wugs*, I will circle three of them for you. After you learn about the *wugs*, you will be asked questions about them.

In the learner condition, the instructions were identical except the second sentence above was replaced with: “In order for you to learn which objects are *wugs* you will try to find two of them. I will tell you whether you are right or wrong.”

Participants then viewed a screen showing all the objects from two basic level categories. Within each basic-level category, the shapes were arranged in a 5 x 3 grid, and the two categories were spatially separated (Figure 2). One of the objects in the category on the left was circled. In

<sup>1</sup>All stimuli, experiments, raw data and analysis code can be found at <https://github.com/mllewis/xtSamp>. The analyses can be viewed directly here: <http://rpubs.com/ml1/xtSampAnalysis>.

the teacher condition, the instructions read: “Find the object that is circled below. That object is a *wug*. When you click on the ‘See Another’ button, I will show you another *wug*.” The participant was then asked to press a button which caused a circle to appear around one of the exemplars from the same subordinate category as the initially circled object. The participant clicked the button twice in total.

In the learner condition, the instructions were identical, except the last sentence was replaced with: “The object circled below is a *wug*. Click on two more *wugs*.” Participants were then asked to click on two more objects. After each click, a pop-up window appeared with the text “You’re correct! That’s a *wug*.” This text appeared regardless of the object the participant clicked on. The display then showed the object with a circle around it to indicate that it had been selected. Critically, in both the teacher and the learner conditions, the final display was identical: Thirty objects from two basic level categories, with three circled exemplars.

Participants then advanced to the test phase. On the test screen, the objects from the training phase were shown at the top of the page in an identical format to the training phase, but without the exemplars circled. Below these objects was a horizontal line, and a generalization question (Figure 2). There were five generalization questions presented sequentially in the same order as in the original report (subordinate match, basic non-match, basic match, subordinate match, basic match). In each test question, the following text appeared, with one of the exemplars below: “Look at the object below. Is this a *wug*?” Participants responded by marking “yes” or “no” using radio buttons.<sup>2</sup> Finally, we asked an attention check question where participants had to select the label they previously learned from four alternatives.

Object categories and word items were randomized across participants. The order of presentation of the individual objects on the screen was also randomized, as was the placement of the first circle. Sampling condition was manipulated between-participants. This and all subsequent online paradigms can be viewed directly here:

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<sup>2</sup>After these questions, we asked several questions related to an additional manipulation irrelevant to the current work.



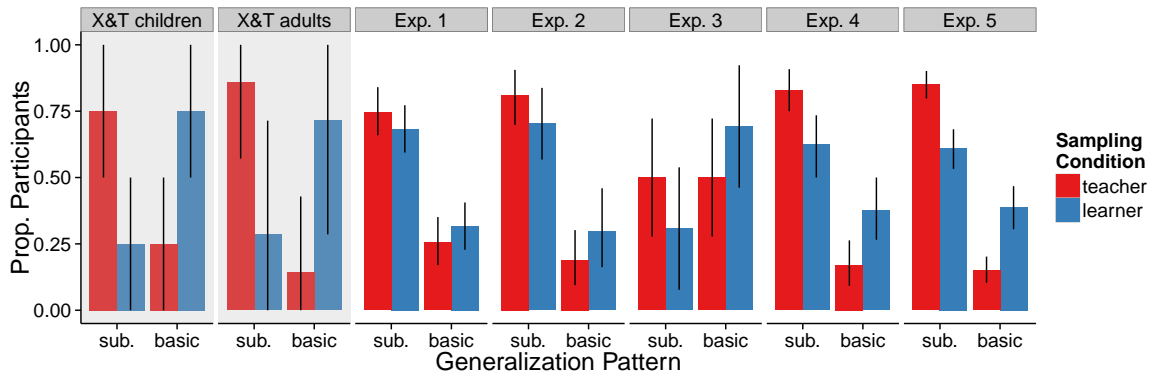


Figure 3. Proportion participants generalizing to the subordinate (sub.) or basic level category in the original child ( $N = 24$ ) and adult experiment ( $N = 14$ ), and in our five replication attempts ( $N_1 = 294$ ;  $N_2 = 150$ ;  $N_3 = 41$ ;  $N_4 = 200$ ,  $N_5 = 500$ ). Experiments 1, 2, 4 and 5 were conducted online, and Experiment 3 was conducted in-person. Error bars reflect 95% confidence intervals, calculated via non-parametric bootstrapping. Note that we report the Xu and Tenenbaum data by aggregating across participants, rather than trials (the method in the original report).

<https://mllewis.github.io/projects/xtSamp/xtSampindex.html>.

## Results and Discussion

While participants' generalizations were numerically more biased towards basic level generalization (as in XT's original study), the difference between sampling conditions was much smaller and was not statistically reliable ( $\chi^2(1) = 0.63$ ,  $p = .32$ ; Figure 3). The effect size was also much smaller than the original finding ( $d = 0.17 [-0.17, 0.51]$ ; Figure 4).

## Experiment 2

Given that Experiment 1 did not fully replicate XT's original effect, we attempted to alter our paradigm in Experiment 2 to more closely reflect the original in-person experiments. One critical difference between the in-person and online paradigms was the salience of the experimenter. In the in-person version, the teacher was an actual person interacting with the participant, while in Experiment 1, the reality of the teacher had to be inferred based only on first

person text (“I will show you...”). Thus, one reason we might have observed a smaller effect in Experiment 1 is that participants might not have assumed strong sampling in the teacher condition. In Experiment 2, we tried to strengthen this manipulation by introducing a teacher character using a picture.

We also made several other changes to our design. Because many participants in Experiment 1 did not generalize at all (answered “no” to all generalization questions), we added questions that queried the original three exemplars that participants learned about. These “proper name” trials allowed us to more directly understand these participants’ generalization strategy. We also reduced memory demands between the training and testing phases by circling the training exemplars in the testing phase, allowing participants to reflect back on their training data during test.

### *Methods*

*Participants.* In Experiment 2, we recruited 150 participants from Amazon Mechanical Turk. Participants were paid US \$0.25 for their participation.

As in Experiment 1, we excluded participants who responded “yes” to the basic non-match question ( $N = 15$ ) or who did not select subordinate matches in the learner condition ( $N = 22$ ). We also excluded participants who missed any of the attention check questions ( $N = 9$ ).

The criteria for categorizing a participant’s generalization strategy were identical to Experiment 1, except for the inclusion of the additional questions. To be categorized as either a subordinate or basic-level generalizer, a participant had to respond “yes” to all training items. To be categorized as a basic-level generalizer, a participant had to respond “yes” to one of the three basic-level questions under the liberal criteria, and “yes” to all three under the strict criteria. Twenty-eight participants were excluded because they could not be categorized as a subordinate or basic-level generalizer. Our final sample included 90 participants ( $N_{\text{learner}} = 53$ ;  $N_{\text{teacher}} = 37$ ).

*Stimuli.* The object and word stimuli were identical to Experiment 1.

*Procedure.* The procedure was identical to Experiment 1, with the exception of several key changes described below.

First, we increased the saliency of the experimenter by adding a clipart image of a woman. In the initial instructions, we introduced her by saying, “Hi, my name is Natalie.” The image of the teacher was also present in the training and testing phases. These changes were made in both the teacher and learner conditions.

Second, we slightly altered the language of the experimenter to sound more natural. In the learner condition, the instructions in the training phase read: “Click on two more objects that you think might also be called wugs.” We also changed the feedback in the training phase to be more conversational, “Yeah, that’s a wug.” In the testing phase, we added the following text above the training items: “You identified the objects below as wugs” (the training exemplars were circled, see below). In the teacher condition, the instructions in the training phase read: “Find the object that is circled below. That object could be called a wug. When you click on the “See Another” button, I will show you another wug.” In the testing phase, we added “I showed you these objects were wugs” above the training items. We also changed the critical question to be “Could this be called a wug?,” instead of “Is this a wug?” in both conditions. This was done to increase the number of basic-level interpretations of the generalization question.

Third, we added more generalization questions and randomized their order. Each participant was queried about 10 objects in total: The three training exemplars, two objects from the same subordinate level category as the training exemplars, three basic matches, and two basic non-matches.

Fourth, we reduced memory demands between the training and testing phases by showing the full set of training items during testing (as in Experiment 1) but leaving the selected exemplars circled. This change ensured that participants remembered which objects had been identified as examples of the target category.

Finally, we added three additional check questions. We showed participants an object from

the target category, as well as two objects from never-seen categories. For each of these objects, we asked “Did you learn about this kind of object?.” Participants responded by indicating “yes” or “no” on a radio button.

### *Results and Discussion*

There was not a reliable effect of sampling on generalization ( $\chi^2(1) = 0.89, p = .34$ ;  $d = 0.33 [-0.22, 0.88]$ ). Proportions and effect sizes are shown in Figures 3 and 4, respectively.

## **Experiment 3**

Despite increasing the saliency of the teacher, we did not replicate the original effect in Experiment 2. We remained concerned that the teacher was less salient in our version, however, relative to the original. To address this possibility, we next conducted an exact replication of the original study in the laboratory with a real experimenter.

### *Methods*

*Participants.* In Experiment 3, we recruited 41 undergraduate participants. Participants received either course credit or payment (US \$5.00) for their participation.

We excluded one participant who did not select subordinate-level matches in the training phase. We also excluded nine participants because they could not be categorized as a subordinate or basic-level generalizer. Our final sample included 31 participants ( $N_{\text{learner}} = 13$ ;  $N_{\text{teacher}} = 18$ ),

*Stimuli.* The object and word stimuli were identical to Experiments 1 and 2.

*Procedure.* The procedure in Experiment 3 closely followed the original. The experimenter presented 15 objects from two basic-level categories on two pieces of paper. On each paper, the objects were spatially unstructured. As in the original, the experimenter asked five generalization questions (see Experiment 1) and each participant completed two trials such that they were trained

and tested on two different categories. Participants were incentivized in the training phase with a sticker. The exact script used by the experimenter is given in Appendix B.

### *Results and Discussion*

There was not a reliable effect of sampling condition on generalization ( $\chi^2(1) = 0.49$ ,  $p = .48$ ;  $d = 0.45 [-0.38, 1.28]$ ). One notable difference in this experiment, however, was the rate of generalizations to the basic level: In Experiment 3, there were overall more basic level generalizations compared to the online versions. We return to this difference in the General Discussion.

## **Experiment 4**

Given that the observed effect in Experiment 3 was only slightly larger than the two previous studies, we inferred that the smaller effect sizes we observed were not due primarily to the decreased saliency of the experimenter. In the next replication, we explored another possible difference between our experiments and the original: the object stimuli. While similar to the original, our objects had slightly more variability within each subordinate level than the original. This increased variability may have led participants to be less likely to generalize to the basic level. Thus, in Experiment 4, we conducted an online replication using the same procedure as Experiment 2, but with less variable objects at the subordinate-level.

### *Methods*

*Participants.* We recruited 200 participants from Amazon Mechanical Turk. Participants were paid US \$0.30 for their participation.

As in the previous experiments, we excluded participants who responded “yes” to the basic non-match question ( $N = 17$ ) or who did not select subordinate matches in the learning condition ( $N = 27$ ). We also excluded participants who missed an attention check question ( $N = 10$ ). An additional twenty-one participants were excluded from our analyses because they could not be

categorized as a subordinate or basic-level generalizer. Our final sample included 140 participants ( $N_{\text{learner}} = 64$ ;  $N_{\text{teacher}} = 76$ ).

*Stimuli.* The objects contained less subordinate-level variability than that used in Experiment 1–3, and were highly similar to the original (Figure 1, right).

*Procedure.* The procedure was identical to Experiment 2.

### *Results and Discussion*

There was a reliable effect of sampling on generalization: Participants in the teacher condition were more likely to generalize to the subordinate category, while participants in the learner condition were more likely to generalize to the basic-level ( $\chi^2(1) = 6.42$ ,  $p = .01$ ;  $d = 0.59$  [.15, 1.03]). This dataset thus replicates the pattern seen in the original XT report, though with a much smaller effect size.

## **Experiment 5**

In our final experiment, we repeated Experiment 4 with a pre-registered sample size based on the effect size estimated from Experiments 1–4 and the XT adult experiment.

### *Methods*

*Participants.* To determine the sample size for Experiment 5, we conducted a power analysis based on the effect size estimated from our four replications attempts and the original adult experiment. Using this effect size, a sample size of 355 was required to achieve 95% power on the chi-squared test. Given approximately 35% data loss in the previous online experiments, we decided on a sample size of 500 participants. We pre-registered our sample size on Open Science Framework (<https://osf.io/5xg96/wiki/home/>). Due to an initial error in power calculations, the final sample was collected in two separate groups. As in Experiment 4, participants were recruited on Amazon Mechanical Turk and paid US \$0.30 for their participation.

We used the same exclusion criteria as in Experiment 4. We excluded participants who responded “yes” to the basic non-match question ( $N = 40$ ) or who did not select subordinate matches in the learning condition ( $N = 63$ ). We also excluded participants who missed an attention check question ( $N = 21$ ). An additional sixty-one participants were excluded from our analyses because they could not be categorized as a subordinate or basic-level generalizer. Our final sample included 347 participants ( $N_{\text{learner}} = 154$ ;  $N_{\text{teacher}} = 193$ ).

*Stimuli.* The stimuli were identical to Experiment 4.

*Procedure.* The procedure was identical to Experiment 4.

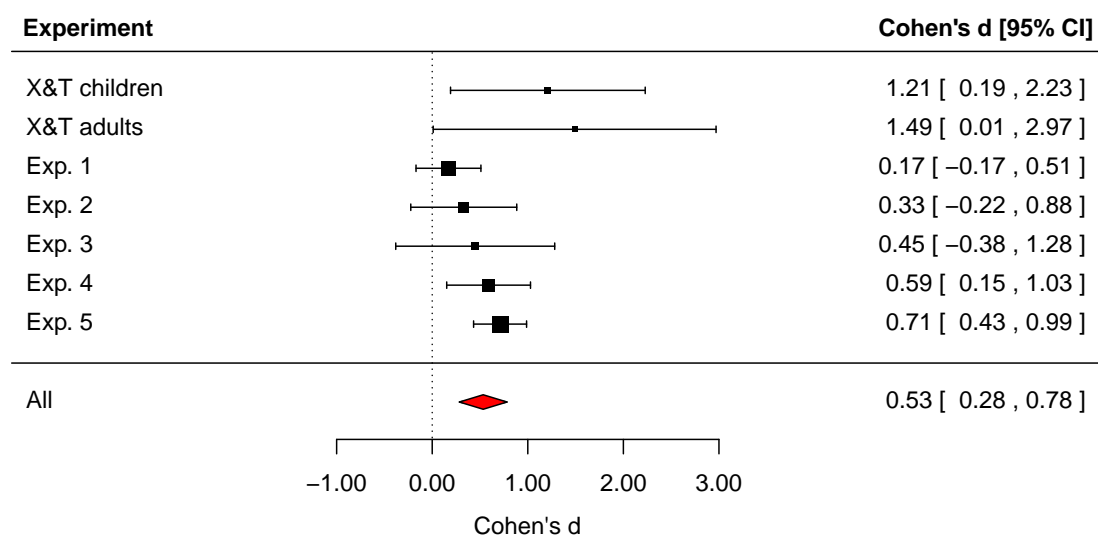
### *Results and Discussion*

As in Experiment 4, there was a reliable effect of sampling on generalization: Participants in the teacher condition were more likely to generalize to the subordinate category, while participants in the learner condition were more likely to generalize to the basic-level ( $\chi^2(1) = 24.49$ ,  $p < .001$ ;  $d = 0.71$  [.43, .99]).

### **Meta-analytic Synthesis**

To obtain the best estimate of the underlying effect size, we used meta-analytic methods to aggregate across estimates from each study. We defined a random effects model based on the estimates from all seven studies (Viechtbauer, 2010). The random effect model treats each effect size estimate as an estimate of an underlying population effect size, and weights it by the precision of the estimate (sample size).

Across all seven studies, the estimated effect size was .53 ([.28, .78]; Figure 4). This estimate was only slightly reduced when the original experiment with children was excluded ( $d = .50$  [.24, .75]). Thus, we replicate the original effect of sampling on generalization ( $d = 1.49$  [0.01, 2.97]), but with an effect size approximately one-third as large as the original.



*Figure 4.* Effect sizes for the original experiment with children and adults, and our five replication attempts. Effect size estimates are calculated by transforming log odds ratio into Cohen's  $d$  (Sánchez-Meca, Marín-Martínez, & Chacón-Moscó, 2003; Del Re, 2013). The red diamond indicates the estimate based on a random effect model of all seven studies. Error bars are 95% confidence intervals.

## General Discussion

We attempted to replicate a theoretically-important effect first reported by Xu and Tenenbaum (2007a): sensitivity to sampling process in inductive generalization. Across five replication attempts, we found a statistically significant effect in the same direction as the result in two; the other three attempts found results that were numerically congruent though weaker. To obtain an estimate of the overall effect size, we used meta-analytic methods to aggregate across estimates from each study. Aggregating across all studies, we found strong evidence of a real effect, albeit one with an estimated size approximately one-third the magnitude of the original. We



discuss this estimate with respect to general issues in replication and with respect to its consequences for studies of sensitivity to sampling.

### *Reflections on replication*

Although we attempted to reproduce XT's original paradigm as closely as possible, there were a number of differences both across studies and within each individual study that differed. Some of our studies were online (1, 2, 4, and 5), while one was in person; some of our studies used less variable stimuli (4, 5) while others used stimuli with slightly more variability (1, 2, 3); some of our online studies pictured the teacher (2, 4, 5), while one did not (1). Examining our estimated effect sizes, it is tempting to try and synthesize these variations with the different magnitudes of our estimated effects and assume that each of these factors is a moderator of effect size. Such a conclusion is unwarranted by our data however.

It is of course *possible* that the .14 effect size difference between Experiments 1 and 2 was *caused* by the addition of the teacher's face and the text modifications that we made. But the difference between these studies is of course not statistically reliable. And nearly the exact same difference in effect size (.12) is observed between Experiments 4 and 5, where there is no difference whatsoever. More generally, it is virtually impossible to gain empirical traction on moderators whose effects are in the range of  $d = .1$ . Measuring such effects with appropriate statistical power requires thousands of participants, and will not be a fruitful exercise in a case where many such tiny moderators could exist.

There may also be larger moderators that were responsible for the difference between the large effect observed by XT and the smaller effects we observed. Social paradigms like XT's likely are sensitive to the details of the social interaction between teacher and participant, the incentive structure in the task, the visual variability of the stimuli, and the spatial layout of the stimuli, to name a few factors. Indeed, the larger degree of basic-level generalization that both we and XT observed in the lab (compared with our online samples) may suggest that online participants felt

compelled to be overall more conservative in their generalizations. They may have placed greater value on “getting it exactly right,” and therefore been less likely to generalize more broadly to the basic level under uncertainty.

It may also be the case that there are *no* moderators that explain the difference between XT’s original result and ours, and that the observed difference is due instead to chance variation. Most effect sizes in psychology are in the range we estimated for XT’s effect (Richard, Bond Jr, & Stokes-Zoota, 2003), and often the first measurement of an effect is larger than a replicated effect size, even if the replication is successful (Open Science Collaboration, 2015). Recall that XT’s original theory made no prediction about the size of the effect, and that  $d = .5$  is generally classified as a medium effect (Cohen, 1992). In this context, we believe that the most appropriate conclusion is that our data support an effect of statistical sampling process on generalization. We next turn to corroboratory demonstrations of related effects, and attempt to place XT’s original result in context.

### *Sensitivity to sampling*

Although no experiments that we are aware of have used XT’s precise paradigm, following the original demonstration, a host of related experiments have provided evidence for effects of sampling process on learning and inference. For example, Bonawitz et al. (2011) showed that children interpret evidence about the functionality of a toy differently depending on how the function was demonstrated. In their experiments, children discovered fewer additional functions of a toy when its primary function was demonstrated by a knowledgeable teacher, compared with when this demonstration was accidental. This finding suggests that children in the knowledgeable teacher condition assumed that there were no additional functions associated with the toy, and thus generalized more narrowly than those in the accidental condition (much like the narrower generalizations found by XT). And a number of other findings with both adults and children provide evidence for some form of “strong sampling” in social contexts (e.g. Navarro et al., 2012;

Frank & Goodman, 2012; Gweon, Tenenbaum, & Schulz, 2010).

More broadly, the social context of human learning has practical consequences for the interpretation of data collected in psychological experiments. Experimental data are often consistent with at least two accounts—an account that relies on reasoning about the intention of the experimenter, and an account that relies on context-independent reasoning. Consider two examples. A well-known phenomenon in word learning is that children are biased to select a novel object for a novel word, given the presence of both a familiar and novel object (often referred to as *mutual exclusivity* in the literature; Markman & Wachtel, 1988). On the one hand, this result could be due to a context-independent bias to assume that lexicons are structured with one word mapping to one concept, and one concept mapping to one word. But another possibility relies on reasoning about the intentions of the experimenter (Why would the experimenter use a strange word to refer to the familiar object if she meant the familiar one?; Clark, 1987, 1988). Both of these accounts make similar predictions, and are therefore difficult to disentangle empirically.

Another example of this interpretative ambiguity is the Heider and Simmel (1944) study. In this task, participants viewed a short movie showing several geometric shapes moving in a way that appeared to be contingent. Nearly all participants spontaneously interpreted the video as depicting animate beings, rather than as simple shapes moving around. Like in the case of mutual exclusivity, there are at least two ways to interpret this result. One possibility is that participants rely on low-level features of the scene to infer animacy (e.g., contingency), but another possibility is that participants infer the intention of the *experimenter* to be the creation of the videos in order to depict an animate scenario.

These two cases—mutual exclusivity and animacy projection—illustrate a pervasive theoretical issue in experimental psychology. Experimental data are almost always consistent with both social and asocial accounts. There is no simple solution to this empirical challenge: it is impossible to eliminate social context from experimental paradigms, because experiments are social interactions between participant and experimenter. Our best bet is to try and understand the

influence of social context on learning. On this view, then, XT’s paradigm provides one robust datapoint that informs this project.

## Appendix A

Table ?? give results of all five experiments using the strict categorization criteria.

	N excluded	$\chi^2$	$p$	$d$
Exp. 1	94	0.08	.78	0.09 [−0.30, 0.48]
Exp. 2	36	0.07	.79	0.19 [−0.46, 0.85]
Exp. 3	14	0.63	.43	0.53 [−0.35, 1.41]
Exp. 4	31	4.13	.04	0.54 [0.06, 1.02]
Exp. 5	92	17.20	.00	0.70 [.36, 1.04]

Table 1

*Results of all five experiments using the strict categorization criteria, described in Experiment 1. “N excluded” refers to the number of participants excluded from analyses because they could not be categorized as either basic or subordinate-level generalizers. All  $\chi^2$  tests have 1 degree of freedom.*

## Appendix B

Below is the script used by the experimenter in Experiment 3. “[word]” denotes a randomly selected novel label. Different labels and objects were used in Trial 1 and Trial 2.

*Thank you for participating in this study. We’re going to play a game that was initially designed for preschoolers, so it may seem a little silly, but just play along. Are you ready to begin?*

### Training

Teacher Condition: *See this? It’s a [word]. See this one? It’s a [word]. See this one? It’s a [word]. Thank you for paying attention. Would you like to choose a sticker?*

Learner Condition: *See this? It’s a [word]. Can you point to two other [word]s? If you get both of them right you get a sticker! You’re correct! You’re correct! Would you like to choose a sticker?*

### Testing

*Alright, now I'm going to ask you some questions about [word]s. Are you ready?*

⟨point to subordinate⟩ *Is this a [word]?*

⟨point to basic non-match ⟩ *Is this a [word]?*

⟨point to basic match⟩ *Is this a [word]?*

⟨point to subordinate⟩ *Is this a [word]?*

⟨point to basic match⟩ *Is this a [word]?*

*Alright, now I'm going to show you some new shapes. Are you ready?*

⟨repeat Training and Testing for Trial 2⟩

*All done! Thank you for participating!*

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