Ready to Learn: Predictive Exposure to Category-Relevant Regularities Facilitates Novel Category Learning

Layla Unger (unger.114@osu.edu)
Ohio State University, Department of Psychology, 1835 Neil Avenue
Columbus, OH 43210 USA

Vladimir Sloutsky (sloutsky.1@osu.edu)
Ohio State University, Department of Psychology, 1835 Neil Avenue
Columbus, OH 43210 USA

Abstract

Prior evidence suggests that category learning can occur implicitly by detecting regular co-occurrences of features within categories. Less studied is whether regularities wherein category membership predicts other events or actions also foster category learning. Moreover, we know little about whether, and to what degree, exposure to these regularities facilitates subsequent supervised learning. Here, participants were pre-exposed to exemplars from two categories during a cover task, while uninformed of their category membership. Pre-exposure occurred under conditions in which category membership did (Predictive Mapping) or did not (Mere Exposure) predict task events to which participants responded. Baseline participants completed the same task with category-irrelevant stimuli. Subsequently, all participants were taught the categories (using pre-exposure exemplars) under explicit supervision. Whereas neither Predictive Mapping nor Mere Exposure influenced cover task performance (vs. Baseline), Predictive Mapping substantially improved subsequent supervised category learning. These findings point to latent category learning given pre-exposure to Predictive Mapping regularities.

Keywords: category learning, latent learning, implicit learning, supervision

Introduction

Learning to group distinct perceptual experiences into categories is a fundamental cognitive ability that manifests itself in perception, memory, reasoning, and language. Much of research on category learning conducted to date has investigated how we accomplish this feat under explicit supervision conditions (e.g., Ashby, Maddox, & Bohil, 2002; Smith et al., 2014). For example, participants are often informed that the stimuli they will experience belong to categories whose composition they must try to determine, often provided with category labels, and given explicit feedback following their categorization decisions. During real-world category learning, access to such explicit information is often very limited. In the absence of explicit supervision, how does implicit category learning unfold? Moreover, does implicit learning (or even mere exposure to stimuli) help learners capitalize on the relatively small amount of explicit category information they may receive? Here, we investigate how exposure to to-be-learned stimuli influence category learning, with an emphasis on whether such exposure heightens the readiness with which categories may be learned under explicit supervision.

Category Membership and Perceptual Features

In comparison to research on category learning under explicit, supervised conditions, the body of research conducted on implicit or incidental category learning is relatively small, and has focused primarily on learning that is driven by sensitivity to regularities in the perceptual characteristics of category members. Moreover, this research has treated learning from such regularities as entirely separate from learning from explicit category-relevant information.

Research in this field is motivated by the observation that, in many naturalistic categories, members of the same category often resemble each other more strongly than they resemble members of other categories (Rosch, 1975). Such family resemblances may be thought of as resulting from reliable co-occurrences of perceptual features with each other within exemplars from the same category, but not with features that occur in exemplars from other categories. As an example, consider the category of “birds”: In this category, perceptual features such as feathers, wings, and beaks reliably co-occur, and rarely occur with features characteristic of other categories, such as fur.

Evidence from research in infants (Quinn & Johnson, 2000; Younger & Cohen, 1983), children (Kloos & Sloutsky, 2008) and adults (Clapper & Bower, 1994; Nelson, 1984) suggests that a sensitivity to these perceptual feature regularities contributes to category learning from an early age. Moreover, learners who are given implicit or incidental exposure to category exemplars are more likely to learn family resemblance categories, in contrast to learners given explicit supervision, who are more likely to learn rule-based categories. (Love, 2002; Nelson, 1984). Accordingly, in many accounts of implicit category learning, sensitivity to such regular co-occurrences of perceptual features plays a key role (Quinn & Eimas, 1997; Sloutsky, 2010; Smith & Heise, 1992). In prior empirical research, implicit, unsupervised learning from perceptual feature regularities has been treated as distinct from learning under explicit supervision. The possibility that such implicit learning might help learners take advantage of information about category membership provided by explicit supervision remains largely unexplored (though see Folstein, Gauthier, & Palmeri, 2010 for an investigation with equivocal results).

Category Membership and Prediction

Beyond regularities in the features of category exemplars themselves, the environment may also convey regularities with which category membership predicts other perceptual experiences or goal-related actions. With respect to perceptual experiences, an exemplar's category membership may predict the location in which it is seen (e.g., dogs typically appear on the ground, whereas birds often appear in the sky), the other entities with which it is seen (e.g., a dog is often seen with a leash), the type of motion it will exhibit (e.g., birds often fly, whereas dogs do not), the words that are heard when it is seen (e.g., the words "dog", "furry", etc. are more likely to be heard when seeing a dog than a bird, even in the absence of explicit labeling events), and so on. Similarly, with respect to goal-related actions, an exemplar's category membership may predict whether it is an entity to approach or avoid, the appropriate way in which to interact with it (e.g., a nail should be hammered, whereas a screw should be turned with a screwdriver), and so on. Importantly, these prediction regularities are often implicit: We typically do not receive explicit feedback when we make a correct or incorrect prediction. Instead, when predicting a perceptual experience, we might see what we expect or be surprised, and when predicting a goal-related action, we might accomplish or fail at our goal. Both the possibility that such implicit prediction regularities contribute to category learning, and how category learning that is fostered by prediction regularities unfolds, remain relatively unstudied.

To our knowledge, the only research in which implicit, prediction-driven category learning has been studied to date consists of a handful of studies conducted in the auditory domain (e.g., Gabay, Dick, Zevin, & Holt, 2015). In these studies, participants completed a task in which they made different responses to visual stimuli that were different from each other either in appearance, or in the location in which they appeared. For example, in one version of this task (Gabay et al., 2015), participants indicated in which of 4 possible locations an X appeared, but were not given feedback about whether they responded correctly. Critically, the different visual stimuli were each preceded by task-irrelevant exemplars from the same number of acoustic or speech sound categories. The absence of corrective feedback during the task rendered the predictive mapping between auditory category and perceptual events/visuomotor responses implicit. Across studies, when the category membership of the sounds predicted the location or identity of the stimulus to which participants respond, participants showed evidence of having learned both this predictive mapping, and the relevant auditory categories. Moreover, the category learning that took place in versions of this paradigm generalized to novel category exemplars.

The success with which category learning took place in these studies provides initial evidence that predictive relationships between category membership and perceptual events/goal-related actions fosters category learning. However, this evidence consists of a small number of studies conducted within the auditory domain, which recruits different brain systems (Ley et al., 2012; Seger & Miller, 2010) and contains qualitatively different categories (e.g., ones that are temporally dynamic) from those in the otherwise more extensively studied visual domain. Moreover, as in research on implicit category learning from perceptual feature regularities, this line of research has not investigated whether implicit learning from prediction regularities facilitates subsequent learning from explicit supervision.

Present Experiment

As described above, category learning may be facilitated implicitly by sensitivities both to the reliable co-occurrence of perceptual features in category exemplars, and the reliability with which category membership predicts perceptual events or goal-directed actions. However, the effects on category learning of the latter are comparatively unstudied. Moreover, we know little about whether either sensitivity improves the readiness with which categories are learned under explicit supervision. These gaps in our current understanding of category learning led to our two aims. First, we aimed to compare category learning under conditions in which participants were either only exposed to category-relevant perceptual feature co-occurrences, or additionally exposed to regularities in which category membership predicted visual events and goal-related actions. Second, we aimed to test whether learning under either condition facilitated subsequent supervised category learning.

To accomplish these aims, we exposed participants to stimuli that, unbeknownst to them, were members of two categories within which perceptual features reliably co-occurred. We accomplished this exposure in the context of a speeded cover task, which we manipulated such that the category membership of an exemplar did or did not predict task events and appropriate responses. Specifically, in the cover task, participants were given a short period of time (<500ms) during which to indicate whether a stimulus that first appeared in a central location had then "jumped" to the left or right. In the "Predictive Mapping" condition, category membership perfectly predicted the location to which stimuli jumped, whereas in the "Mere Exposure" condition, category membership and jump location were unrelated. As a control, participants in a Baseline condition completed the same task with stimuli unrelated to the categories in the former two conditions. Importantly, participants were not asked to *predict* where the stimulus jumped, nor were they given explicit corrective feedback about whether their responses were accurate (they were only informed when they had failed to respond within the time allowance given). Accordingly, the predictive regularities in the Predictive Mapping condition were incidental to task performance. After completing the cover task, all participants then were taught the two categories under traditional explicit supervised conditions with corrective feedback.

Using this approach, we investigated: 1) Whether participants showed evidence of learning the Predictive Mapping, as indexed by more rapid improvements in RT over the course of the cover task, and 2) Whether Mere Exposure, Predictive Mapping, or both facilitated subsequent supervised category learning.

Method

Participants

Participants were 72 adults (M_{age}=34.21 SD_{age}=11.89) recruited from Amazon Mechanical Turk who received $1 for participation for this ~15min study. Participants were randomly assigned to one of three conditions (*N*=24): Predictive Mapping, Mere Exposure, and Baseline.

Stimuli

Category Exemplars The primary stimuli used in this experiment were exemplars from two categories: Flurps and Jalets. These exemplars were colorful images of "creatures" similar to those used in prior category learning research conducted by Deng and Sloutsky (e.g., Deng & Sloutsky, 2012). Creatures were composed of 7 binary-valued features including a head, antennae, body, hands, feet, tail, and button. Category membership was based on a combination of deterministic and probabilistic features, such that each category had a family resemblance structure. Specifically, one feature (antennae) was perfectly associated with category membership, and therefore deterministic, whereas five were

Table 1: Category Structure

		Feature						
	Exemplar	D	P1	P2	P3	P4	P5	I
Flurps	E1	1	0	1	1	1	1	2
	E2	1	0	1	1	1	1	3
	E3	1	1	0	1	1	1	2
	E4	1	1	0	1	1	1	3
	E5	1	1	1	0	1	1	2
	E6	1	1	1	0	1	1	3
	E7	1	1	1	1	0	1	2
	E8	1	1	1	1	0	1	3
	E9	1	1	1	1	1	0	2
	E10	1	1	1	1	1	0	3
Jalets	E1	0	1	0	0	0	0	2
	E2	0	1	0	0	0	0	3
	E3	0	0	1	0	0	0	2
	E4	0	0	1	0	0	0	3
	E5	0	0	0	1	0	0	2
	E6	0	0	0	1	0	0	3
	E7	0	0	0	0	1	0	2
	E8	0	0	0	0	1	0	3
	E9	0	0	0	0	0	1	2
	E10	0	0	0	0	0	1	3

Note: The "D" feature is deterministic, "P"s 1-5 are probabilistic, "I" is irrelevant.

associated with membership in a given category in 80% of exemplars, and therefore probabilistic. The remaining feature occurred equally often in exemplars from both categories, and was therefore irrelevant to category membership. This category structure is summarized in Table 1.

Baseline Exemplars An additional set of creatures dissimilar in appearance from the Category Exemplars were adapted from stimuli created by Badger and Shapiro (2012) for use in the Baseline Condition only. Like the Category Exemplars, these stimuli were composed of binary-valued features. Unlike the Category Exemplars, the set of Baseline Exemplars included all possible combinations of feature values, and was not divided into categories.

Procedure

Participants followed a link on Amazon Mechanical Turk to the experiment, which was presented using the Gorilla™ platform. During the experiment, participants proceeded through three phases: A Practice Phase, an Exposure Phase, and a Supervised Category Learning Phase.

Practice Phase The purpose of the Practice Phase was to accustom participants to the task in the subsequent Exposure Phase (see below). The task in this phase was introduced as the "Color Jump Game". A schematic of this task as used in both the Practice and Exposure Phases is provided in Fig. 1.

In the task, participants watched a star that initially appeared on the center of the computer screen in between a red panel on the left, and a blue panel on the right. The star then disappeared, and reappeared on the left red panel or the right blue panel. Participants were instructed to hit the "q" key if the star reappeared on the left, and "p" if it reappeared on the right. Participants were informed that they would have only a short amount of time to respond, and that they would receive feedback indicating whether they were correct, incorrect, or too slow. (As noted below, corrective feedback was not provided in the Exposure Phase version of this task.)

Participants then completed the task, which consisted of 20 trials. The star reappeared equally often on the left and right, in a pseudorandomized order. The amount of time

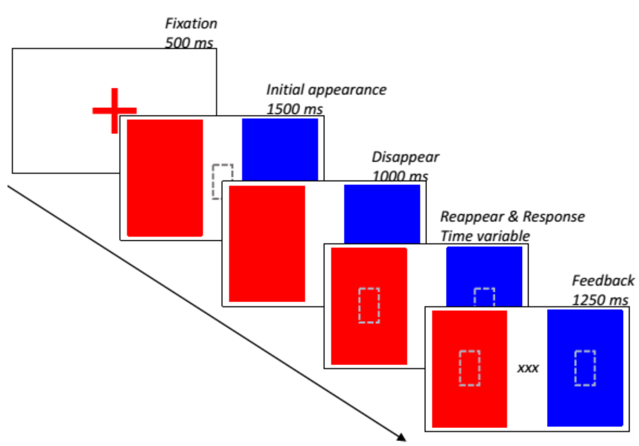

Fig 1: Color Jump Game schematic. Dotted boxes denote stimulus locations; "xxx" denotes feedback.

participants had in which to respond after the star reappeared started at 500ms, then decreased in 25ms increments every 5 trials such that the allowance for the last 5 trials was 425ms.

Exposure Phase In this phase, participants continued to play the Color Jump Game. However, the star that appeared in the Practice Phase was replaced by: 1) Category Exemplars whose category membership perfectly predicted whether they reappeared on the left red or right blue panel in (Predictive Mapping Condition), 2) Category Exemplars whose category membership was *unrelated* to their reappearance locations (Mere Exposure Condition), or 3) Baseline Exemplars in the Baseline Condition. Participation in each of these conditions was randomly assigned between subjects. To keep any predictive mapping between category membership and reappearance location implicit, participants were only given feedback when they responded too slowly, but were not told whether their responses were correct or incorrect.

In all conditions, participants completed 80 trials (8 blocks of 10 trials) of the Color Jump Game. To increase the potential speed and accuracy benefits of detecting any predictive mapping between category membership and reappearance location, the difficulty of the task was increased every two blocks by reducing the RT allowance. Specifically, the RT allowance began at 425ms, then decreased by 25ms every 2 blocks, such that the allowance was 350ms for the final 2 blocks. Participants were alerted to this reduction in RT allowance at the beginning of each block in which it occurred. The outcome measure of interest in this phase is the rate at which participants' RTs for accurate trials improved.

Supervised Category Learning Phase The purpose of this phase was to investigate how well participants in each of the conditions learned to classify the Category Exemplars into two categories under traditional supervised learning conditions. In this phase, participants in all conditions completed the same task with the same stimuli. First, participants were informed that they would be learning about two kinds of creatures: Flurps and Jalets. Participants were told that for each creature, they should identify whether they think it is a Flurp or Jalet using onscreen buttons, after which they would receive corrective feedback.

Participants then proceeded through 30 trials of this task (3 blocks of 10 trials each). On each trial, participants were presented with a Category Exemplar, and asked whether it was a Flurp or Jalet. After responding, participants received a message saying "That's a [Flurp/Jalet]! preceded by a green checkmark if they had responded correctly, or a red X if they had responded incorrectly. The outcome measure of interest in this phase was participants' accuracy at categorizing Category Exemplars over the course of the 3 blocks.

Results

Analyses were conducted in the R environment (R Development Core Team, 2008) using functions in base R, the lmer function for mixed effects regression from the lme4 package (Bates, Maechler, Bolker, & Walker, 2015), and the Anova function for deriving F-statistics and p-values for regression models from the car package (Fox & Weisberg, 2011).

Exposure Phase Overall, RT decreased over the Exposure Phase. Specifically, in a mixed regression model with RT on accurate trials as the dependent variable, Trial Number as a fixed effect, and participant as a random effect, Trial Number had a significant, negative coefficient (β = -0.65 ms, SE = 0.03, $p < .0001$).

To test whether exposure to Category Exemplars in either the Predictive Mapping or Mere Exposure conditions concurrently influenced performance on the Color Jump Game during the Exposure phase, we fit regression models for each participant in which Trial Number predicted RT on accurate trials. We then used the regression coefficient for Trial Number as a measure of the rate of change in RT over the course of this phase. Finally, we analyzed whether rate of change in RT varied across the three conditions. To conduct this analysis, we fit a regression model in which Condition predicted rate of RT change. This model revealed no significant relationship between Condition and rate of RT change ($F(2,69)=0.10$, $p=.90$)[1] (Fig. 2).

Supervised Category Learning Phase The purpose of this phase was to test whether the success with which participants learned to categorize the Category Exemplars given explicit supervision varied according their preceding experience in the Exposure Phase. We therefore first tested whether participants in each condition were able to learn the categories under explicit supervision. We found that participants in the Predictive Mapping and Mere Exposure conditions achieved above-chance performance in Block 1 of the Supervised Category Learning Phase (both ps < .01); by Block 2, participants in all three conditions achieved above-chance performance (all ps < .01).

To investigate whether experience in the Exposure Phase influenced the *degree* to which participants successfully learned the categories, we took as our outcome variable the accuracy with which participants categorized Category Exemplars in each of the 30 trials in this phase, and tested whether accuracy varied with Condition (Predictive Mapping, Mere Exposure, and Baseline). Because the 30 trials were organized into three blocks, over which categorization accuracy may improve, we also tested whether accuracy varied across blocks. Specifically we fit an omnibus mixed regression model with accuracy as the dependent variable, Condition, Block, and their interaction as fixed effects, and participant and trial number within a block as random effects. We then derived F-statistics and p-values for each of the fixed effects. This analysis revealed significant main effects of both Condition ($F(2,69)=5.22$, $p=.008$), and Block ($F(1,2076)=20.82$, $p<.0001$), which did not interact ($p=.16$) (see Fig. 2).

[1] Analysis of accuracy also yielded no condition differences.

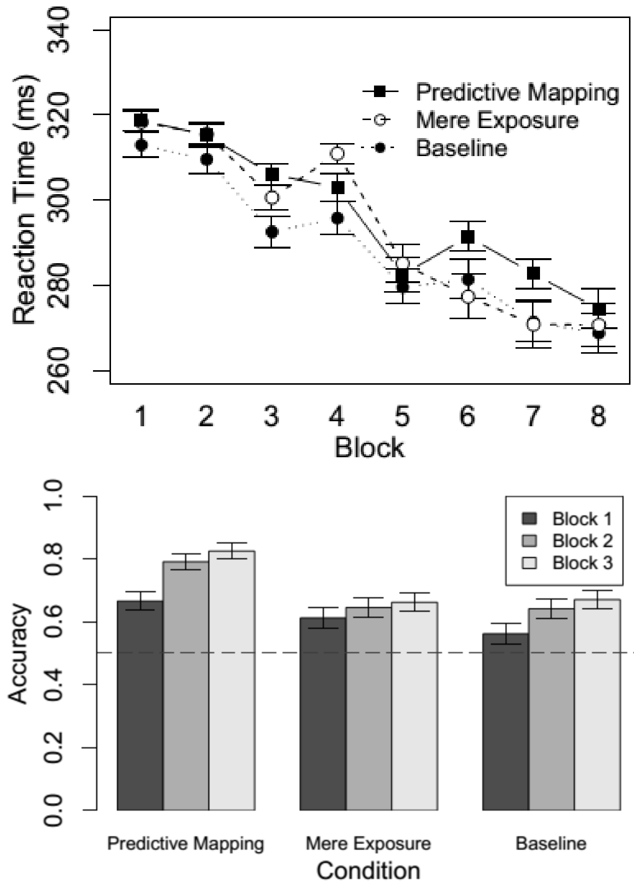

Fig 2: RTs during Exposure Phase (top) and Accuracies during Supervised Category Learning Phase (bottom)

To further investigate these main effects, we compared each pair of Blocks or Conditions using three fixed effects models. These models included the same components as the omnibus model, but each used data from only one pair of Blocks or Conditions. The pairwise comparisons of Blocks revealed that Block 1 accuracy was significantly lower than in Blocks 2 or 3 (both ps $< .01$), but that accuracies in Blocks 2 and 3 did not significantly differ (p=.22). More importantly, the pairwise comparisons of Conditions revealed that the Predictive Mapping condition exceeded both the Baseline ($F(1,46)=8.51$, $p=.005$) and Mere Exposure ($F(1, 46)=6.55$, $p=.014$) conditions. In contrast, accuracies in the Mere Exposure and Baseline conditions did not significantly differ ($F(1,46)=.118$, $p=.733$). In sum, participants in the Predictive Mapping condition learned the categories more successfully than either participants in the Mere Exposure or those in the Baseline conditions, whereas the success of category learning for participants in the latter two conditions did not differ.

Discussion

Prior evidence has revealed that exposure to regularities in which perceptual features co-occur in category exemplars can implicitly facilitate category learning. However, we know little about whether exposure to regularities in which category membership predicts other perceptual events or goal-directed actions can similarly facilitate category learning. Moreover, we know little about how either form of exposure may allow us to more readily learn categories under explicit supervision.

In this experiment, we exposed participants to exemplars of two categories that possessed distinct perceptual feature co-occurrence regularities. This exposure took place within a cover task, under conditions in which category membership did (Predictive Mapping) or did not (Mere Exposure) predict task events to which participants responded. Importantly, this exposure was implicit: Participants were neither informed that the stimuli they viewed were members of two categories, nor alerted of any relationship between stimulus appearance and task events, or given corrective feedback about their responses to task events. For comparison, Baseline participants completed this task with other, non-categorized stimuli. Subsequently, all participants were taught the two categories under traditional, explicitly supervised conditions.

Although we found no variation across exposure conditions in performance on the cover task, participants who were exposed to the category exemplars under Predictive Mapping subsequently learned the categories under explicit supervision substantially more successfully than participants in either the Mere Exposure or Baseline conditions. In contrast, participants in the Mere Exposure condition were not measurably more accurate than those in the Baseline condition. These findings suggest that exposure to category exemplars under conditions in which category membership predicts other perceptual events and goal-directed actions improves the readiness with which categories are learned given explicit supervision. Exposure to predictive regularities may therefore promote *latent learning* (e.g., Kimble & BreMiller, 1981), in which such exposure promotes the formation of mental representations that render learners more receptive to explicit instruction.

Open Questions

The present experiment sets a foundation for further investigation into both the influence on category learning of category-relevant prediction regularities, and how exposure to category-relevant regularities may facilitate subsequent supervised category learning.

One question to explore in future research is raised by the superiority of the Predictive Mapping condition during supervised category learning, despite the lack of condition effects during the Exposure Phase. Specifically, the superiority of supervised category learning in the Predictive Mapping condition suggests that participants were sensitive to the regularity with which category membership predicted Exposure Phase task events and appropriate responses. Such sensitivity could, in principle, have allowed participants to increasingly anticipate events in the Exposure Phase task, and therefore improve more rapidly than participants in the other conditions. However, we observed no such effect, as evidenced by comparable RT decreases across conditions in the Exposure Phase (the Color Jump Game). We therefore do not have evidence of sensitivity to predictive regularities *while they were being experienced*. One possible explanation for the lack of condition differences during the Exposure Phase is that the rate at which we shortened the RT allowance in the Exposure Phase task pushed participants to the limit of the rate at which they were able to speed up. Future research might address this issue in multiple ways. For example, a future version of this experiment might include "guess" trials interspersed within the Exposure Phase, in which participants are asked to predict task events. Sensitivity to predictive regularities could therefore manifest as the gradual achievement of above-chance performance on guess trials in the Predictive Mapping, but not the Mere Exposure condition.

Another key direction for future research is to illuminate the nature of *what* is learned via implicit sensitivity to category-relevant regularities. For example, does exposure to these regularities increase attention to category-relevant features, and away from those that are irrelevant?

Conclusion

In this experiment, we found that supervised category learning was facilitated when preceded by implicit exposure to exemplars from family resemblance categories under conditions in which category membership predicted other perceptual events and goal-directed actions. This facilitation occurred above and beyond the effect of mere exposure to the exemplars themselves. These findings point to implicit learning due to exposure to category-relevant predictive regularities that in turn helps learners capitalize on explicit information about category membership.

Acknowledgements

This work was supported by National Institutes of Health Grants R01HD078545 and P01HD080679 to Vladimir Sloutsky.

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