Without even Trying: How Incidental Exposure Shapes Category Learning

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Abstract

Our knowledge about the world is populated with categories like dog, chair, and cup. Yet much of what we understand about how we acquire this knowledge comes from studies of learning in circumstances that little resemble real-world experience. In the lab, category learning typically involves pursuing an explicit goal to learn categories that prompts a search for just one or a few features diagnostic of category membership. In contrast, everyday experience is full of incidental encounters that allow us to observe how features cluster together in categories, such observing the co-occurrence of four legs, tail, and snout in dogs we happen to pass on the street. Here, we investigated how incidental exposure shapes category learning using a combined behavioral, eye tracking, and computational modeling approach. We found that learners picked up on the way features clustered together in categories just from incidental exposure, with pronounced downstream consequences for category learning.

Keywords: category learning; visual attention; implicit learning

Introduction

Categories guide how we navigate, interact with, and communicate about the world around us. For example, recognizing something as a dog allows us to anticipate that it is likely to walk on the ground rather than take flight, interpret its behavior as friendly or threatening, choose whether to approach or avoid it, and discuss it in conversation. Moreover, categories provide anchors for building new knowledge, allowing us to generalize new information we learn about one dog such as is warm blooded to others. How do we learn these vital categories in the first place?

Understanding category learning has been a key focus for efforts to understand the human mind, motivating centuries of philosophy and decades of empirical research. Yet, much of what we know about category learning is divorced from everyday reality. Our day-to-day experience is full of incidental encounters with category members in which we have no goal to categorize, such as when we happen to pass a dog on the street. These encounters likely far outweigh access to explicit category information, such as observing a person pointing at a dog and saying, "This is a dog". In contrast, researchers in the lab typically study category learning that is highly explicit and goal-oriented. In a typical category learning study, learners are simply presented with items and explicitly asked to figure out how to classify them into categories. Learners might need to figure out the classification on their own (e.g., Pothos & Chater, 2005), receive the benefit of corrective feedback (e.g., Rehder & Hoffman, 2005), or alternate between the two (e.g., Bröker, Love, & Dayan, 2022). This approach is attractive because learning can be observed from the categorization decisions that learners make. However, this insight comes at a high cost because it cannot reveal how incidental encounters so commonplace in everyday experience contribute to category learning.

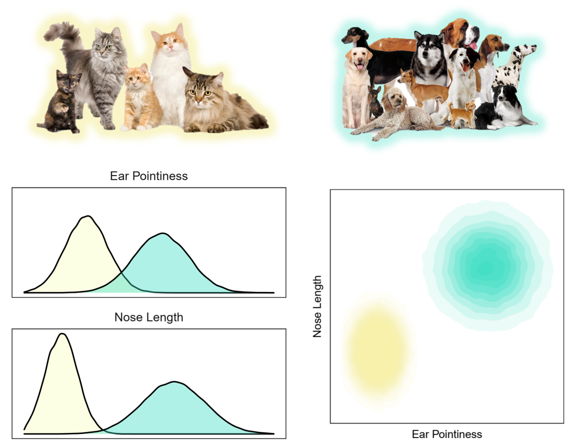

Figure 1: Example of feature clusters in cats and dogs. Feature values were generated for illustrative purposes.

Incidental encounters can potentially provide a rich source for category learning because they give us the opportunity to observe how features cluster together in categories, such as the way that fur, four legs, a snout and tail cluster together in dogs. Indeed, there is evidence from many domains for sensitivity to the regularity with which some perceptual inputs predict others (Chun & Jiang, 1998; Saffran, Johnson, Aslin, & Newport, 1999; Fiser & Aslin, 2001). In other words, even an incidental learner might be sensitive to the fact that any one dog feature tends to be accompanied by the others. As highlighted by the seminal observations of Rosch and her colleagues, such clusters of features are incorporated into knowledge about many real-world categories (Rosch, 1975;

In M. Goldwater, F. K. Anggoro, B. K. Hayes, & D. C. Ong (Eds.), *Proceedings of the 45th Annual Conference of the Cognitive Science Society*.

Malt & Smith, 1984). In contrast, category learners in the lab most readily seize upon simple criteria for making efficient categorization decisions, such as using the appearance of a single feature as the basis for determining category membership (Shepard, Hovland, & Jenkins, 1961; Rehder & Hoffman, 2005; Ashby & Gott, 1988). The efficient learning that takes place in the lab has shaped prominent accounts of category learning, which emphasize processes such as searching for simple rules to determine category membership, and selectively orienting attention to features most predictive of category membership (Nosofsky, 2011; Kruschke, 1992; Ashby, Alfonso-Reese, Waldron, et al., 1998). Thus, the picture of category learning we obtain from lab-based learners who pursue an explicit goal to categorize may miss how category learning is shaped by incidental exposure to the clusters of features characteristic of real-world categories.

The goal of the present research was to bring our understanding of category learning closer to how it may unfold from the incidental encounters ubiquitous in everyday experience. In what follows, we first discuss our currently limited understanding of the role of incidental exposure in category learning. We then present a combined behavioral, eye tracking and computational modeling study designed to shed new light on how category learning is shaped by the opportunity to pick up on clusters of features associated with category membership from incidental exposure.

Incidental Exposure in Category Learning

The most abundant source of insight into learning categories without an explicit goal to do so comes from studies with infants, who by necessity cannot be given explicit goals (Quinn, Eimas, & Rosenkrantz, 1993; Eimas & Quinn, 1994; Mareschal, Powell, Westermann, & Volein, 2005; Younger & Cohen, 1986). These studies raise the possibility that infant learners pick up on clusters of features associated with category membership. For example, one common approach has been to show infants members of a real-world category (e.g., cats) until their attention starts to drift. If attention is recaptured by images from a second category (e.g., dogs), it is taken as evidence that infants differentiate it from the first. This research has revealed that infants differentiate categories whose features form distinct clusters. For example, these studies used images of category members such as dogs and cats that varied along several dimensions, such as ear length and nose width. Importantly, infants only differentiated the categories when values along dimensions for the first category formed a cluster that was distinct from values in the second category. For example, initial exposure to cats with their consistently short ears and narrow noses was followed by successful differentiation from dogs. In contrast, initial exposure to dogs with their highly variable ear lengths and nose widths was followed by failure to differentiate them from cats. These studies suggest that infant learners may pick up on the way features cluster together in categories. However, they shed little light on how this process unfolds.

There is evidence that adults who do not pursue an explicit goal to categorize are also sensitive to the way features cluster in categories. (Note that this is distinct from ”unsupervised” circumstances in which learners pursue a goal to categorize but without corrective feedback, (Bröker et al., 2022; Pothos & Chater, 2005).) For example, in Billman and Knutson's (1996) studies, participants saw novel creatures that they were asked just to observe and remember. In one condition, several of the creatures' features clustered together. Here, as with fur, four legs and snout in dogs, each feature predicted the others in the cluster (e.g., creatures with fluffy tails were also striped, had clawed feet, and lived in the desert). In a contrasting condition, individual pairs of features predicted each other, but pairs varied independently without clustering together. Critically, participants were subsequently better at detecting violations of the predictive relationship between any two features when features were part of a larger cluster versus an independently varying pair. This finding reinforces the possibility that even without a goal to categorize, learners can pick up on feature clusters associated with category membership (for similar sensitivity in the auditory domain, see Gabay, Dick, Zevin, & Holt, 2015; Wade & Holt, 2005).

More recently, Unger and Sloutsky (2022) pioneered a novel approach to exploring the contribution of incidental exposure to category learning. Here, participants explicitly learn categories after an initial round of incidental exposure to either members of the same categories, or items composed of random combinations of features. Multiple studies revealed that incidental exposure to categories rendered people “ready to learn” - that is, it fostered rapid subsequent category learning once people were clued in to the existence of the categories and prompted to learn them. Critically, this effect only transpired for incidental exposure to categories whose features formed distinct clusters. In contrast, there was no ready to learn effect for incidental exposure to the more rule-like categories that are typically learned in the lab from pursuing an explicit goal to categorize.

Taken together, this evidence suggests that learners who are not pursuing a goal to categorize are somehow sensitive to the way features cluster in categories. Moreover, this sensitivity somehow supports category learning. At the same time, the underlying learning processes remain opaque.

Present Study

The goal of the present study was to bring our understanding of category learning closer to how it may unfold in real-world experience, which is full of incidental encounters. We studied how people learned novel categories modeled on real-world categories, in which clusters of multiple features were associated with category membership. We studied the contribution of incidental exposure following the approach pioneered by Unger and Sloutsky (2022). Participants first received a round of incidental exposure in which they completed a simple cover task that made no mention of categories, then completed an explicit phase in which they were prompted to learn the categories. Using this approach, we contrasted explicit category learning following incidental exposure to members

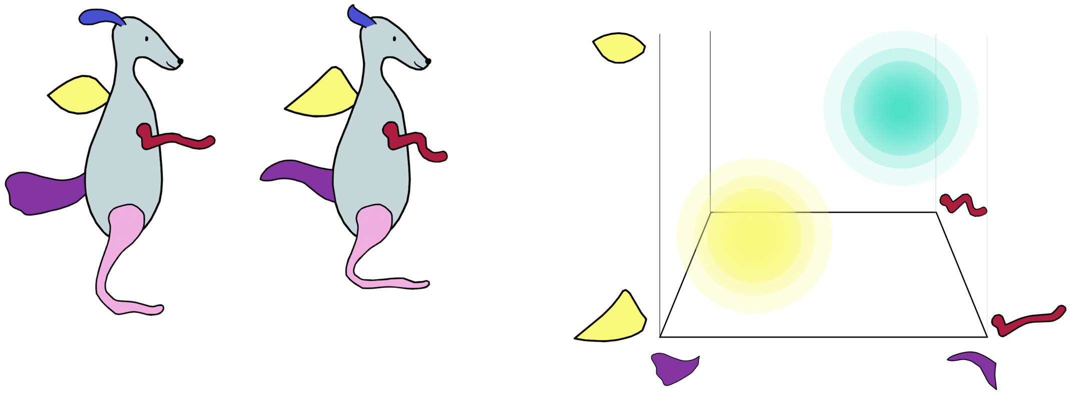

Figure 2: The left panel shows two example creatures, each with feature values characteristic of one of the two categories. The right panel visualizes the distribution of the values of three features when all values were sampled from the same mode of the bimodal distribution within a given creature.

of the categories participants were later prompted to learn, versus items composed of random combinations of features. To illuminate how incidental exposure shapes category learning, we built upon the behavioral paradigm to incorporate both eye tracking and a newly developed modeling approach that uses eye tracking data to illuminate the category representations that learners form over time (Weichart, Galdo, Sloutsky, & Turner, 2022; Turner, 2019; Galdo, Weichart, Sloutsky, & Turner, 2022).

Methods

Participants

Participants were 49 undergraduate students who participated in return for course credit.

Materials and Apparatus

We created creatures with features that we could use to divide the creatures into two categories resembling real-world categories like cats and dogs. Like cats and dogs, our creature categories possessed multiple features are associated with category membership (e.g., short snouts and narrow noses in cats versus long snouts and wide noses in dogs), and some features unassociated with category membership (e.g., long and short fur occur in both dogs and cats).

Creatures were composed of a standard body and five features: arm, ear, leg, tail, and wing (illustrated in the left panel of Figure 2. We generated 100 values for each feature by first creating two anchor versions of different shapes, then morphing continuously between them using the Blender graphics software (Blender Foundation, 2018). For all features, the frequencies of these values followed a bimodal distribution composed of two truncated normal distributions: one ranging from 0 – 50 with a mean of 25, and one ranging from 51 – 100 with a mean of 75 (SD = 24). To generate categories, we randomly selected 3 or 4 of the features to be relevant to category membership. For relevant features, all members of one category contained values sampled from one mode, and all members of the other category contained values sampled from the other mode (Figure 2, right panel). Thus, values of relevant features clustered together. Values of irrelevant features were sampled randomly from the bimodal distribution. We used an Eyelink Portable Duo eye tracker to examine attention to irrelevant versus relevant features.

Design and Procedure

The experiment consisted of two phases: an Incidental phase in which participants saw creatures in the context of a cover task, and an Explicit phase in which participants learned to categorize creatures into two categories. Participants were assigned to one of two conditions: (1) Category, in which creatures in the Incidental phase were members of the two categories they would later learn in the Explicit phase, or (2) Baseline, in which creatures in the Incidental phase possessed no category structure (all features were randomly sampled from the bimodal distribution). For each participant, we randomly selected three or four of the features to be relevant features whose values clustered together in the categories they learned in the Explicit phase (as in Figure 2B).

The Incidental and Explicit phases each contained 30 trials. In the Incidental phase, participants saw creatures appear in

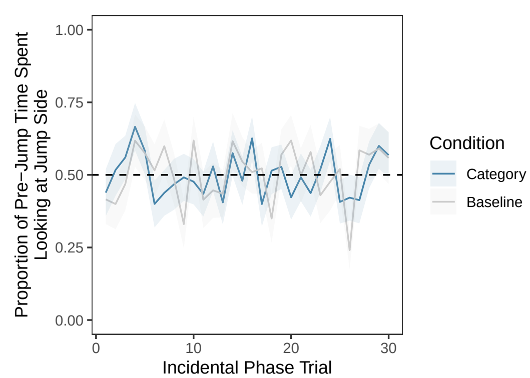

Figure 3: In the Category condition, jump location was implicitly associated with category membership. However, participants showed no evidence of learning this association. Pre-jump looking to the side of the screen where the creature jumped was at chance in Category and Baseline participants.

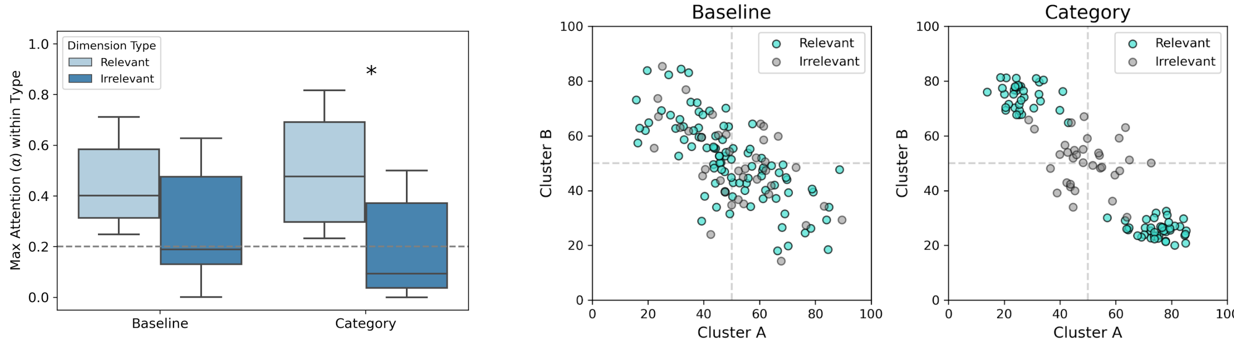

Figure 4: Left: Best-fitting values of attention to each feature were determined for each participant. Boxplots depict the distribution of attention values for each participant's most attended relevant and irrelevant feature in the Baseline and Category conditions. Right: Points represent the mean value for each feature within k-means cluster A (x-axis) and cluster B (y-axis) estimated for each participant based on the gaze-corrected values they observed. Colors represent whether each dimension was relevant or irrelevant to category membership during the Explicit phase.

the center of the screen for 80 frames (∼1,333ms), then hop to the right or left. Participants simply indicated the side to which the creature jumped using the right and left buttons on a game controller.

As in Unger and Sloutsky (2022), for participants in the Category condition, category membership was implicitly associated with jump location. This raises a potential concern that participants in the Category condition could spontaneously treat incidental exposure as an explicit category learning task, in which they try to predict jump location based on the creatures' appearance and use the observed jump location as feedback. Jump location would be readily learnable under such circumstances. However, also as in Unger and Sloutsky (2022), participants showed no evidence of such learning. Figure 3 shows that although jump location was predictable for participants in the Category condition, they did not anticipatorily look towards the category-consistent side.

In the Explicit phase, participants were instructed that the creatures belonged to two categories: Tobas and Zeemies. They were prompted to categorize creatures one at a time by saying "Toba" or "Zeemie", and given corrective feedback following each decision.

Results

The goal of analyses was to investigate whether and how sensitivity to the way features cluster together in categories contributes to subsequent explicit category learning. To accomplish this goal, we fit the data from the full experiment using the the Adaptive Attention Representation Model (AARM), which has been developed to capture categorization behavior and gaze during category learning. In-depth discussion and technical information about AARM can be found in Turner (2019); Weichart et al. (2022); Galdo et al. (2022). Here, we provide a high-level description of the application of the model to the present experiment.

In AARM, each item encountered is stored as an exemplar in memory. This memory trace consists of the set of feature values that the item possessed. Critically, AARM estimates how attention to features changes over the course of learning based on both (1) gaze and (2) categorization decisions. First, the likelihood of looking at each feature at a given point in time is treated as a function of attention. Thus, when fitting the model for a given participant, estimates of attention are based on searching for values that improve the model's prediction of the participant's pattern of looking. Second, when participants pursue an explicit goal to learn categories with corrective feedback, attention is assumed to change from trial to trial as a function of learning. Specifically, attention is assumed to increase for features whose values were useful for predicting category membership, and decrease for those that were not. Thus, when fitting the model for the Explicit phase for a given participant, estimates of attention are also based on searching for values that improve the model's prediction of participants' trial to trial categorization decisions. We next describe how we adapted this overall framework to investigate whether and how learning during the Incidental phase contributed to learning in the Explicit phase.

What is Learned from Incidental Exposure?

Previous applications of AARM exclusively focused on the conventional approach in which learners make explicit categorization decisions and receive corrective feedback. We therefore developed a novel approach to estimate what was learned from the Incidental phase (reported here) and its contribution to learning in the Explicit phase (reported below).

First, attention in the Incidental phase was freely estimated based on gaze during this phase. Based on the evidence reviewed in the Introduction, we also assumed that participants could learn the tendencies with which features clustered together in the items that they saw. Recall that each participant saw a unique set of items by sampling feature values from the bimodal distributions shown in Figure 2A. For participants in the Category condition, the values of three or four features consistently clustered together. Values of the remaining features for participants in the Category condition and for all

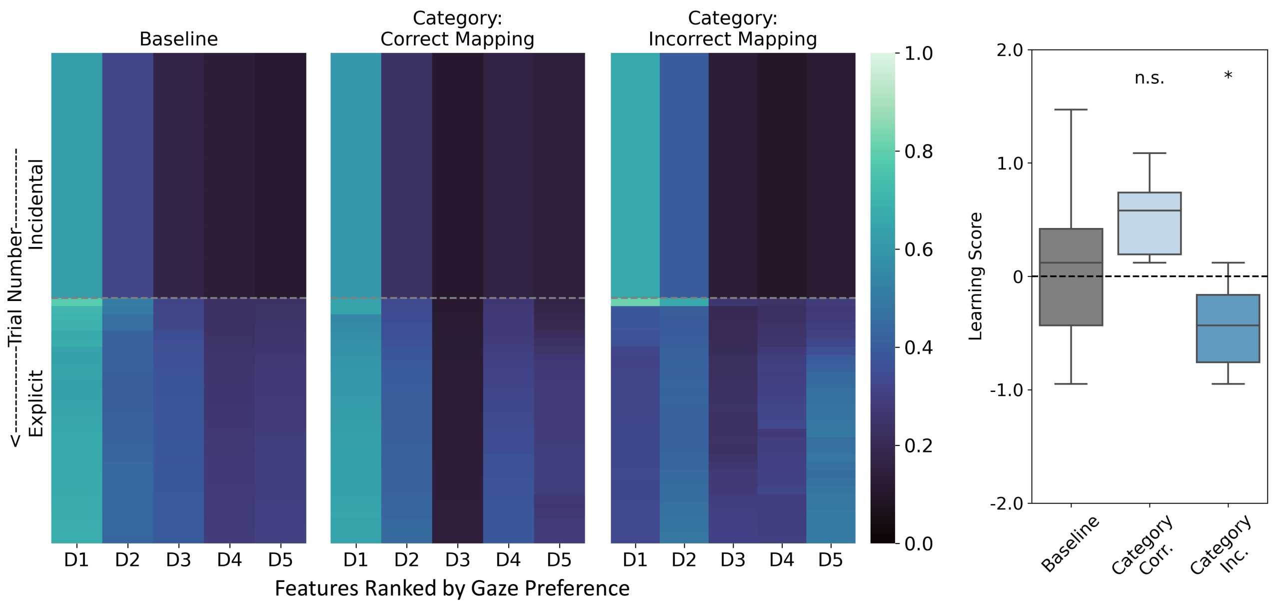

Figure 5: The panels on the left show aggregate model-predicted fixations for participants in three groups: Baseline participants (who could not form clusters from the Incidental phase), Category participants who correctly mapped clusters formed in the Incidental phase to labels, and Category participants who incorrectly mapped clusters to labels. Panel B shows that learning early in the Explicit phase was hindered by incorrect cluster mapping, and (non-significantly) aided by correct cluster mapping.

features for participants in the Baseline condition were randomly sampled from the full bimodal distribution. To capture what participants could learn from observing these items, we assumed that participants could store the items they observed as a memory trace. Critically, this memory trace only included feature values for features they actually looked at (based on a threshold of looking $\leq$ 100ms); for unobserved features, we shifted values towards the uninformative center of the bimodal distribution. We then took these estimated memory traces, and used k-means clustering to extract two unlabeled clusters from the items that each participant observed. Thus, our estimate of what participants learned during the Incidental phase consisted of: (1) these clusters, and (2) estimates of attention for each feature based on gaze data.

As shown in the left panel of Figure 4, best-fitting estimates of attention revealed that even in the Incidental phase, before the categories were even mentioned, participants in the Category condition allocated greater attention to the category-relevant features whose values clustered together. The right panel shows that the clusters estimated for participants in the Category condition from the feature values they observed neatly captured the category clusters.

Contribution of Incidental Exposure to Category Learning

Learning during the Incidental phase could contribute most strongly to learning early in the Explicit phase, before participants accumulated extensive explicit information. To capture such learning, we quantified participants' performance on the first 15 trials of the Explicit phase. We did so using a Rasch model to jointly estimate the difficulty of correct categorization on these trials and participant-level abilities to categorize correctly on these trials (Rasch, 1993). From this model, we extracted a Learning Score for each participant that captured their categorization "ability" during the first half of the Explicit phase.

Our above analysis suggests that participants in the Category condition could have a leg up on category learning early in the Explicit phase. Specifically, they could enter this phase armed with both clusters that could be mapped to category labels, and attention to features relevant to category membership. However, this prior learning could also actively harm learning in the Explicit phase if participants happened to mismap the clusters to the wrong category labels. If this occurred, a participant would be more likely to make incorrect responses and get negative feedback early on in the Explicit phase than a participant who was randomly guessing. Receiving consistently negative feedback early in the Explicit phase could lead to one of two outcomes. First, participants might be aware that they are accurately dividing creatures into categories but just mislabeling them, and therefore simply switch the labels and rapidly improve in accuracy. Second, participants may only know that they are doing *something* wrong, and shift their attention to different features in search of a new basis on which to make categorization decisions. In contrast, participants in the Baseline condition could only learn from scratch upon entering the Explicit phase.

We investigated these potential contributions of incidental

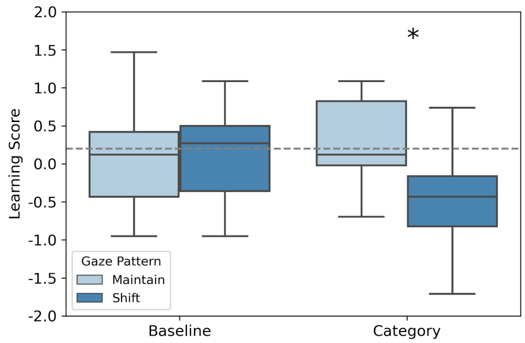

Figure 6: Higher learning scores were associated with maintaining the same pattern of attention from the Incidental to the Explicit phase in the Category condition, but not the Baseline condition.

exposure in two ways. In one approach, we used the model fits to infer whether participants in the Category condition correctly or incorrectly mapped clusters to categories, and compared these two groups to participants in the Baseline condition. For a given participant, we estimated two possible mappings of clusters estimated from the Incidental phase to labels: (1) mapping cluster A to the ”Zeemie” label and Cluster B to the ”Toba” label, and (2) the opposite mapping. During model fitting, we estimated which of the two possible mappings best captured the participant's pattern of categorization decisions during the Explicit phase. In addition, for each of these possible label mappings, we calculated the overall distance between each cluster and the members of the category with the same label, then determined which possible mapping had the smaller distance. We identified the participant's mapping as correct if it was the one with the smaller distance, and incorrect otherwise. As shown in Figure 5, we did indeed observe two divergent patterns in Category condition participants: Correct mappers learned the categories with relatively high accuracy early in the Explicit phase and maintained the pattern of attention they formed during the Incidental phase, and Incorrect mappers were actively *inaccurate* early in the Explicit phase and dramatically shifted their pattern of attention.

We corroborated this pattern with an analysis of the data itself, outside the model. To perform this analysis, we used the gaze data to divide participants in each condition into two groups: Maintainers who maintained their pattern of looking from the Incidental to the Explicit phase, and Shifters who shifted their pattern of looking. The Maintainer versus Shifter designation was based on whether the feature the participant looked most at during the Incidental phase was the same as the one they looked most at during the Explicit phase. Learning early in the Explicit phase was similar for these two groups in the Baseline condition. Critically, in the Category condition, Maintainers showed significantly better learning early in the Explicit phase than Shifters. Thus, both the data and model-based analyses provide evidence that incidental exposure built a foundation for category learning. In the present experiment, this foundation could either help or hinder once learners began to explicitly map what they learned incidentally to category labels.

General Discussion

Our minds become populated with categories that organize our experience of the world around us, such as dog, cup and chair. Here, we used a combined behavioral, eye tracking and computational modeling approach to investigate how incidental encounters that are commonplace in everyday experience may contribute to learning such categories in the first place. We particularly sought to shed light on how such incidental exposure may give learners the opportunity to pick up on the way features tend to cluster together in categories. We found that learners picked up on these features during incidental exposure, before they even knew that the items they observed belonged to categories. Once prompted to learn the categories explicitly, we found evidence that learners had formed clusters of items from incidental exposure. These clusters could either help or disrupt category learning depending on whether learners happened to map clusters onto the correct category labels. In contrast, participants who did not receive incidental exposure to the categories simply learned the categories from scratch once explicitly prompted to do so.

The present research is vital for bringing our understanding of category learning closer to how it may unfold in the real world. To date, much of what we know about category learning comes from learning under highly explicit conditions, in which learners are informed that they will encounter items from a specified number of categories, then proceed to categorize them one by one with the aid of corrective feedback. In everyday experience, access to such explicit information is likely outweighed by incidental encounters with the entities we come to perceive as members of categories. The current findings suggest that much of the heavy lifting of learning may occur during incidental exposure, as learners pick up on the way features tend to cluster together in categories. In contrast, explicit information simply gives learners the opportunity to map learned clusters onto category labels. Therefore, it is possible that instead of labels imposing category boundaries on sensory continua, many real world categories may be learned pre-verbally and mapped onto labels.

Future Directions

The present study raises multiple ways to further illuminate how incidental exposure contributes to category learning, two of which we highlight here. First, the eye tracking approach used here could be used to uncover the dynamics with which learners pick up on the way features cluster together in categories. Specifically, the appearance of any one feature predicts the appearance of others with which it clusters. Thus, gaze could be used to probe how learners detect these relationships. Second, knowledge about real-world categories often encompasses clusters of multiple features associated with membership, whereas explicit learning in the lab often fosters impoverished representations that focus on one or a few diagnostic features. Future research could thus investigate whether incidental exposure gives learners the opportunity to form richer representations that better resemble those learned from real world experience.

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