Relational Concept Learning via Guided Interactive Discovery

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Abstract

A key goal in both education and higher-order cognition research is to understand how relational concepts are best learned. In the current work, we present a novel approach for learning complex relational categories – a low-support, interactive discovery interface. The platform, which allows learners to make modifications to exemplars and see the corresponding effects on membership, holds the potential to augment relational learning by facilitating self-directed, alignably-different comparisons that explore what the learner does not yet understand. We compared interactive learning to an identification learning task. Participants were assessed on their ability to generalize category knowledge to novel exemplars from the same domain. Although identification learners were provided with seven times as many positive examples of the category during training, interactive learners demonstrated enhanced generalization accuracy and knowledge of specific membership constraints. Moreover, the data suggest that identification learners tended to overgeneralize category knowledge to non-members – a problem that interactive learners exhibited to a significantly lesser degree. Overall, the results show interactive training to be a powerful tool for supplementing relational category learning, with particular utility for refining category knowledge. We conclude with implications of these findings and promising future directions.

Keywords: relational categories; structural alignment; discovery learning; category learning; generalization

Introduction

A key aim of higher-order cognition research is to understand the mechanisms that undergird the ability for humans to acquire and use abstract, complex categories. The literature in concepts and categories research has primarily been devoted to the study of *attribute categories* – categories whose members possess a set of independent features by which they can be classified. Research on attribute category learning has unequivocally advanced our understanding of human concept acquisition and its many facets.

However, much of the category knowledge we possess is not reducible to knowledge of specific attributes – myriad concepts such as *positive feedback loop* are abstract, attribute-agnostic, and dependent on relationships rather than features. Fittingly, an increasing amount of empirical attention has been granted to the study of *relational categories* (Gentner & Kurtz, 2005; Markman & Stilwell, 2001). Relational categories are rule-like categories whose members share a common relational structure characterized by extrinsic relationships between objects and/or attributes (e.g., protection, sibling, reciprocity). Because relational categories need only share a relational structure to belong, members of a category can be quite featurally disparate (e.g., your sibling and your dog's sibling hopefully don't look alike). In this way, relational category members share analogical similarity. It should be noted that relational categories are not an idiosyncratic facet of category learning - roughly half of the 100 highest frequency nouns are relational (Asmuth & Gentner, in press). Thus, to understand human category learning generally, it is critical to understand relational category learning.

A question that bears both theoretical and applied import is: how do we come to acquire relational category knowledge? Previous research has explored the potential for comparison to promote relational discovery and transfer. This work follows from a large body of research showing the benefits of comparison to analogical transfer (Gick & Holyoak, 1983; Loewenstein, Thompson, & Gentner, 1999; see also Alfieri, Nokes-Malach, & Schunn, 2013 for a meta-analysis and review). Studies of comparison with relational categories have largely corroborated findings from the analogical transfer literature; presenting same-category pairs (Patterson & Kurtz, 2015) or a mixture of same- and different-category pairs (Kurtz, Boukrina, & Gentner, 2013) during training leads to enhanced learning and transfer over sequential item presentations. The power of comparison can be understood through a process of structural alignment (Markman & Gentner, 1993). Comparing instances facilitates the alignment of their parallel relational predicates. This serves to highlight common relational structure that is not salient when either instance is considered in isolation. Additionally, comparison facilitates abstraction, which promotes later analogical retrieval and transfer.

As many of the core concepts taught in educational settings are relational in nature (e.g., evolution by natural selection, Newton's laws), relational categories represent a key bridge between cognitive and educational research (Goldwater & Schalk, 2016). Thus, investigating how relational categories are best learned can both palpably advance educational techniques and further basic, theoretical understandings. In the present work, we draw on an innovative area of education research that serves as a promising avenue for enhancing relational category learning: discovery learning. Discovery learning generally refers to unsupported learning where the learner actively constructs their understanding of some target information using only a set of materials or a task environment. Though many flavors of discovery have been the subject of study, a

common theme in the literature is that completely unassisted discovery approaches are not effective for learning (Mayer, 2004; for a meta-analysis see Alfieri, Brooks, Aldrich, & Tenenbaum, 2011). Among other reasons, the large cognitive load incurred by needing to generate and explore hypotheses (Sweller, 1988) while metacognitively maintaining an idea of what is known and what needs to be known (Kirschner, Sweller, & Clark, 2006) can present challenges for the approach. However, when some guidance is introduced (such as direct instruction – e.g., Chen & Klahr, 1999), discovery learning can be a highly effective tool (Alfieri et al., 2011).

Discovery learning has the clear potential to augment the learning of complex relational concepts in educational settings – particularly when the target category is abstract or when classroom instruction is subpar. With a basic understanding of the target category, an interactive environment that enables learners to freely create or modify category exemplars and receive dynamic category membership feedback ought to enhance category knowledge, notably through three mechanisms. First, it would allow learners to engage in self-directed exploration that is specifically catered to what they do not understand or need further clarification on. The opportunity to select exemplars for study has been shown to confer benefits on rule-based category learning (e.g., Markant & Gureckis, 2014). Second, the dynamic membership feedback provided by the task interface would implicitly encourage explanations about the causes underlying the effects of learners' modifications. Such self-explanation has been demonstrated to be a powerful facilitator of concept acquisition (e.g., Chi, de Leeuw, Chiu, & LaVancher, 1994). Third, critically, a learning environment such as this should strongly engage analogical processing faculties. In modifying an exemplar and receiving membership feedback, the learner effectively creates a temporally juxtaposed comparison between the item's new state (*s*) and *s-1*. Modifications that do not break membership create alignably-different, same-category comparisons. These comparisons should promote highlighting of common relational structure and facilitate abstraction. Conversely, modifications that do break membership create alignably-different different-category comparisons, which critically should serve to highlight membership-relevant relations.

In the present work, we explore the efficacy of a low-support, interactive discovery learning tool to promote the learning of complex relational categories. To avoid effects of domain knowledge, we created an artificial, multi-constraint category that served as the target of learning. Advised by the discovery learning literature and pilot data, we gave participants some support to reduce cognitive load. This support was a clear, but quite abstract, definition of the category that was given to all learners immediately prior to the learning phase. In the *interactive* condition, participants were given a computerized interface where they could engage in self-directed exploration of three examples of the category. We contrasted interactive training with an *identification* learning control in which learners were exposed to a larger number of exemplars in the context of a member identification task. To evaluate the effectiveness of the interactive learning mode, we compared the two learning conditions on their ability to generalize category knowledge to novel exemplars. We predicted interactive learning would lead to enhanced generalization performance.

Method

Participants

Seventy undergraduates from Binghamton University participated to partially fulfill a course requirement.

Materials

The training and generalization stimuli consisted of arrangements of blocks that varied in their size (small, medium, or large), color (white, gray, or dark brown), border color (black or distinctive blue), and spatial location (see Figure 1 for examples). The 'matched containment' concept instantiated by these blocks was quite complex. Category members were characterized by the presence of three or more blocks that obeyed all of the following constraints: (1) the blocks were aligned vertically or horizontally, (2) two of the involved blocks were *special* by sharing a distinctive blue border color, (3) the special blocks were exactly matched in their attributes, (4) the special blocks contained/flanked at least one additional 'normal-bordered' block in the lineup, and (5) all of the contained, normal blocks matched the special blocks on at least one attribute (i.e., color, size, or both).

Twenty-one category members and 21 non-members were used as the stimuli for the identification condition. All members contained the category-defining core – constituted by either three (*Length 3 [Len3]*; two flanking, one flanked) or four (*Length 4 [Len4]*; two flanking, two flanked) objects – and one additional distracter block, such that all examples had length + 1 blocks. The category core and distracter block were varied in their attributes (i.e., orientation of core [vertical, horizontal], spatial location, color, size) across examples to ensure an attribute-based solution was not available.

The members were comprised of six item types, each which instantiated the special-normal match constraint in a unique way. For both Len3 and Len4 stimuli, there were items whose flanked object(s) matched based on (1) color, (2) size, (3) or *both* color and size. For Len4 stimuli there were also items whose flanked objects consisted of (4) one color and one size match, (5) one *both* and one color match, or (6) one *both* and one size match. The item breakdown can be seen in Table 1. Since the Len4 stimuli included matching types that were distinct from those present in the Len3 stimuli, the Len4 examples were weighted on types 4-6 to ensure comprehensive coverage of the category for identification learners. The non-member set used was programmatically generated by randomly sampling and arranging blocks, with the constraint that two of the blocks

had to possess the distinctive border. Number of blocks was matched between the members and non-members. The interactive condition was given considerably fewer examples: one Len3 color match and two Len4 examples, each which had one color match and one size match.

To evaluate participants' ability to generalize their knowledge, a distinct set of 30 members and 30 non-members was created. The members were sampled from several match types. Critically, non-members consisted of items that violated the constraints of membership in several focal ways (see Table 2 for generalization item breakdown). As knowledge of the specific constraint that was violated was necessary to get each of these items correct, they served as a stringent test of category knowledge.
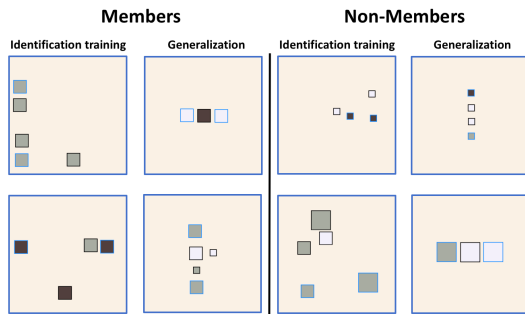

Figure 1: Eight example stimuli from the training (identification) and generalization phases.

Design and Procedure

Participants were randomly assigned to either identification (n = 39) or interactive (n = 31) learning conditions in a between-subjects design. Due to a spreadsheet error, condition assignments were slightly imbalanced.

In the pre-training instructions, all subjects were first informed they would be learning about something called a 'Togging situation' – the arbitrary category label – before being provided with an abstract definition of the category: "A Togging situation occurs when (1) there are two matching special objects with other objects in the space between them; and (2) all the objects in the space between have at least one thing in common with the special objects." Subjects were then told they were to gain a full and clear understanding of Togging situations by engaging in the upcoming learning experience.

Table 1: Number of category members by length and type for identification training.

Special-Normal Match Type	Length 3 Items	Length 4 Items
Color	3	1
Size	3	1
Both Size and Color	3	3
One Both, One Color	--	2
One Both, One Size	--	2
One Size, One Color	--	3
Total	9	12

Condition-specific instructions for the interactive group informed learners they would receive (1) an 'exploration zone' that would tell them if the objects inside were currently in a Togging situation and (2) a set of 'exploration tools' that could be used to modify the objects/attributes in informative ways. They were then told they could gain an understanding by paying attention to modifications that break the Togging situation and by trying to create novel Togging situations. To combat confirmation bias – as piloting revealed this to be a considerable impediment to learning – subjects were also told to try to prove their ideas about Togging wrong by fully testing them. Lastly, subjects were informed they would be tested later and that they would have seven minutes with the learning task. Following these general task instructions, interactive learners then read a brief tutorial that described the ways they could modify the examples with the exploration tools.

Table 2: Number of exemplars by length, type, and membership in the generalization assessment.

Members: Special-Normal Match Type	Length 3 Items	Length 4 Items
Color	8	1
Size	7	2
Both Size and Color	4	0
One Both, One Color	--	1
One Size, One Color	--	7
Total	19	11
Non-member Type		
No Special-Normal Match	8	3
No Special-Special Match	4	3
Only One Special Block	3	0
Special Objects not Aligned	2	0
Only One Special-Normal Match	--	7
Total	17	13

Instructions in the identification condition informed learners they would receive a series of frames with objects inside, some of which would have a Togging situation. They were told they could gain an understanding by paying attention to the frames and feedback they received and by learning to identify which frames contained a Togging situation. The identification learners also received an analogous instruction to try to prove their ideas about Togging wrong by fully considering the frames and feedback on each trial. Finally, identification learners were informed of the upcoming test.

To remind participants, and guide learning, both conditions were again given the abstract category definition immediately prior to the learning task.

Training – Interactive Condition The training interface can be seen in Figure 2. In the center of the interface was an 'exploration zone' that dynamically checked whether the constraints of category membership were met by the objects inside. The zone's border color turned green if the constraints were met, and red if not. A textual notification above the zone regarding membership mirrored the color feedback. The exploration zone started with a positive example of the category, randomly selected from the three

positive examples that were provided to the interactive group.

Participants could freely engage the training interface in five distinct ways. First, clicking the 'new' button cycled through the three positive examples. The button allowed learners to reset the exploration zone to a positive example if they became lost with their current discovery path and also get experience with the three different instantiations of the category. Second, double clicking a block would change its color – cycling in order through the three colors with each double click. Third, clicking and dragging the bottom right corner of a block diagonally allowed participants to stretch or shrink it to one of the three discrete sizes. Fourth, clicking and dragging elsewhere on a block allowed participants to change its spatial location. Lastly, participants could add or remove objects from the exploration zone. To the left of the zone was a space containing additional normal blocks that varied in their size and color. Participants could bring additional blocks into the exploration zone or remove any of the blocks from the zone to this space. This allowed participants to: (1) swap blocks to change attributes, (2) simplify the example in the exploration zone, and (3) create more elaborate examples of the category that involved more objects.
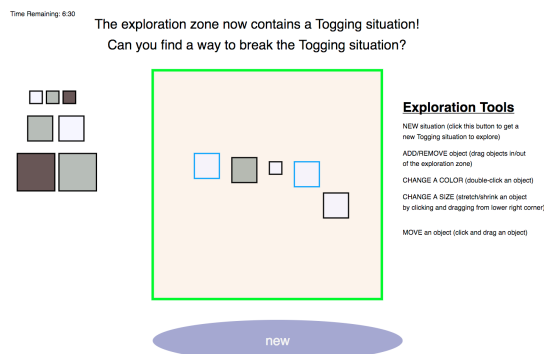

Figure 2: Visual of the interactive workspace.

Since there were many ways participants could interact with the interface, they were provided with a 'how to' cheat-sheet to the right of the exploration zone. During the task, participants had seven minutes for self-directed investigation of the category. A timer in the upper left corner of the interface showed how much time remained. To encourage participants to stay on task, a query was presented below the text notification of membership. The query corresponded to the current state of the objects in the exploration zone. When category constraints were met, the query asked participants if they could, "find a way to break the Togging situation." When the constraints were not met, it asked if they could "find a way to make a Togging situation again." Besides this general query, no additional direction was given during the task.

Training – Identification Condition Learners in the identification group were directly provided with 21 examples of the category – seven times as many as were provided to interactive learners. These 21 positive cases were combined with the 21 negative cases in a random order for each participant. Participants made one pass through the set. On each trial, the participant was presented with an item and two response buttons ("Togging situation", "Not a Togging situation"). The amount of time to study the example and make a response was unconstrained. Participants selected their response using the mouse and were given feedback indicating if they were (in)correct and whether the item was (not) an example of a Togging situation. Feedback was presented for 2.5s before moving on to the next trial.

Generalization Assessment Following the learning phase, all participants were given a generalization assessment to assay their ability to both identify category members and correctly reject near-miss non-members. The 60 generalization items were presented in a randomized order for each participant. The trial structure of the generalization phase was identical to that of identification training, except no feedback was given.

Results

Training

All except three learners in the identification condition ($M = .83$, $SE = .02$) performed reliably above chance. Data from these non-learners were retained in the subsequent analyses for two reasons: (1) the general pattern of results did not change when their data were excluded, and (2) there was not a comparable basis for excluding interactive learners. Identification training took 3-8 minutes ($M = 3.89$ minutes, $SE = .14$). Though there was a wide range, time spent during training did not predict generalization accuracy in a trial-wise logistic regression ($\beta = -0.005$, $SE = 0.01$, $Z = -.44$, $p = .66$).

Interactive learners made between 151 and 321 manipulations ($M = 227.21$, $SE = 6.60$). Number of manipulations, however, did not predict generalization accuracy ($\beta = -0.0001$, $SE = 0.001$, $Z = -.12$, $p = .91$), suggesting that the quantity of manipulations was not critical. However, higher rates of crossover – the proportion of the manipulations that switched the state from member to non-member (or vice versa) – were associated with higher generalization accuracy ($\beta = 3.05$, $SE = 0.86$, $Z = 3.54$, $p < .001$), suggesting that generating alignably-different different-category comparisons is key for getting the most out of the platform.

Generalization Accuracy

Trial-wise accuracy data were modeled with logistic regressions. Using condition as the lone predictor, the main analysis yielded the key finding that interactive learning ($M = .73$, $SE = .01$) significantly augmented generalizable category knowledge over identification learning ($M = .67$, $SE = .01$); $\beta = 0.29$, $SE = 0.07$, $Z = 4.27$, $p < .001$.

To further probe the effect of condition, we conducted a follow-up analysis to see how each condition performed on members and non-members. To this end, we used condition, item membership (1, 0), and their interaction as predictors. Interestingly, the regression revealed a highly reliable cross-over interaction between condition and item membership (see Figure 3; $\beta = 1.35$, $SE = 0.18$, $Z = 7.70$, $p < .001$). The interaction was marked by a reliable enhancement for the identification group on category members (*identification*: $M = .93$, $SE = .01$; *interactive*: $M = .87$, $SE = .01$; $\beta = -0.63$, $SE = 0.15$, $Z = -4.20$, $p < .001$), but a reliable enhancement for the interactive group on non-members (*identification*: $M = .41$, $SE = .01$; *interactive*: $M = .59$, $SE = .02$; $\beta = 0.72$, $SE = 0.09$, $Z = 8.01$, $p < .001$). It should be noted that average accuracy on non-members was generally low. This is directly attributable to their more challenging nature. Contrasted with the member set, on which it was possible to successfully identify all items using knowledge of any single relational constraint, the non-member set consisted of items that each focally violated a constraint of membership. To perform successfully on these, participants required knowledge of the specific constraint that was violated in each instance. Thus, performance on the non-members serves as a proxy for learners' understanding of the category's composite constraints. While learners still had much to learn about the category, low means should not be interpreted to mean that performance was at chance or random in nature. Rather, the high accuracy observed for members suggests that learners took a limited understanding of the constraints of membership and overgeneralized it to non-members.

Given the curious reversal in the effect of condition between levels of item membership, we were prompted to explore the possibility that identification learners were more likely to overgeneralize category knowledge, which ostensibly would explain this pattern of results. We used two signal detection theory measures to this end: *d'* and *β*. *d'* is a measure of sensitivity to the signal when present that reflects hit rate on signal trials while adjusting for false alarm rate on noise trials. A higher *d'* indicates a greater sensitivity to the underlying signal (category members). *β* is a likelihood ratio that reflects response bias. A *β* of 1 indicates learners were neither biased towards nor against extending the category label, whereas *β* below or above 1 indicates a bias towards extending or not extending the label, respectively. *d'* and *β* were computed for each subject and the values for each were then predicted by condition in separate linear regressions. Despite showing increased accuracy for members, identification learners were not more sensitive, owing to a significantly increased false alarm rate (*identification*: $M = 0.58$, $SE = .04$; *interactive*: $M = 0.41$, $SE = .04$; $\beta = -0.17$, $SE = 0.05$, $t(68) = -3.19$, $p < .01$). In fact, a numerical advantage in *d'* favored interactive learners but did not reach significance (*identification*: $M = 1.46$, $SE = .09$; *interactive*: $M = 1.71$, $SE = .21$; $\beta = 0.24$, $SE = 0.21$, $t(68) = 1.16$, $p = .25$). Additionally, identification learners were found to be significantly more biased towards endorsing items as members – showing lower *β* than their interactive counterparts (*identification*: $M = 0.34$, $SE = .06$; *interactive*: $M = 0.61$, $SE = .09$; $\beta = 0.27$, $SE = 0.11$, $t(68) = 2.50$, $p < .05$). Collectively, these measures indicate that the identification group's enhanced accuracy for members was not the result of greater sensitivity. Instead, it appears to be a byproduct of a liberal extension of a limited understanding of the category, relative to interactive learners.
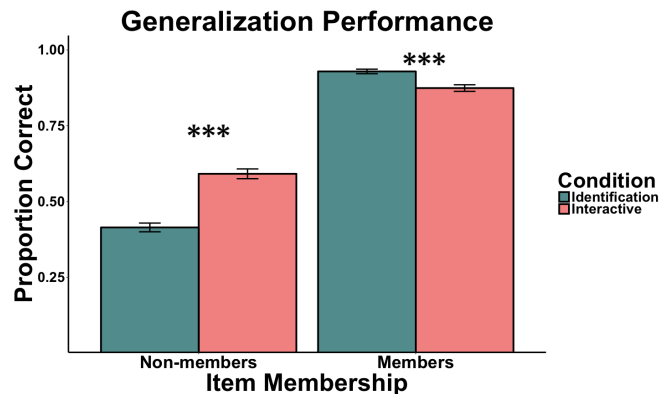

Figure 3: Generalization performance by condition and item membership. Error bars represent +/- 1 SE.

Discussion

The primary goal of this study was to evaluate the potential for a novel, interactive discovery platform to facilitate the acquisition of a complex relational concept. Consistent with our hypothesis, our findings resolutely show that interactive training is an effective way to affect relational category knowledge. Compared to identification training – a learning mode organic to both category learning experiments as well as common educational practices – interactive learners exhibited an enhanced ability to generalize and enriched knowledge of specific membership constraints.

The results of this study inform both basic and applied interests. Our data suggest that our interactive platform can aptly supplement learning when complex, abstract relational categories are the target of learning. On an intriguing note, this paradigm appears to possess a distinct utility for combating overgeneralization by helping learners to explore and refine the boundaries of membership. It should be noted these advantages accrued despite the minimalistic support that was given (compared to other guided discovery approaches; e.g., Chen & Klahr, 1999), the short amount of time allotted for learning, and the transfer appropriate processing advantage granted to identification learners in the shared task between training and test.

A limitation of this study is the use of randomly generated non-members in the identification training condition. As a function of the random generation, they tended to be slightly more entropic than the positive examples. This exposes a possible deflationary account of these findings – that identification learners may have simply learned to differentiate more and less entropic examples from each

other, which might explain poorer generalization performance. However, this account is unlikely for two main reasons. First, learners were provided a definition of the relational concept not once, but twice, prior to training. A basic understanding of the category should have guided learners to seek information that extended that understanding, not part with it altogether. Second, if learners acquired and used an entropy strategy during training, the effects of this should have been notable in the generalization data. Unlike the training set, non-members in the generalization phase were orderly. If learners adopted an entropy strategy, they would likely use it before realizing, later in the generalization phase, that there were not any entropic cases – at which point they might shift to the principle-relevant knowledge they acquired through the definition and learning experience. If this occurred, we should expect better performance later in the generalization phase. To investigate this possibility, we compared performance on the first 30 trials to the second 30 trials of generalization for identification learners. The difference was non-significant (p = .81), suggesting identification learners engaged the task the way we intended. Nevertheless, planned research using yoked controls will provide more definitive evidence.

Further work will be necessary to specify the cognitive processes behind the benefits of interaction in relational category learning. Consistent with Markant & Gureckis (2014), the effect of actively selecting modifications that supplement one's current understanding is likely to be critical. However, our next main pursuit in developing this platform is to more deeply explore the potential for analogy and comparison to serve as the engine for interactive relational category learning. Much of the power of this learning paradigm likely follows from its facilitation of informative, user-created comparisons with alignable differences – a possibility echoed by the higher generalization accuracy associated with higher rates of category crossover. To the extent that this underlies its utility, providing learners with co-presented exemplars that are dynamically linked in their manipulations should promote enhanced generalization and transfer, and possibly serve to shorten acquisition time. Contrasting this interactive approach with static comparisons and other educational tools, such as the explicit elicitation of self-explanations, will be integral to the evaluation of this tool's potency in upcoming research.

Acknowledgments

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