Can we improve how we learn? Investigating learning and transfer of abstract relational principles

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ABSTRACT

Evidence from both educational and cognitive psychology shows that people have trouble learning abstract relational principles and applying them to different contexts. Participants (*N*=84) learned to categorise stimuli consisting of abstract coloured patterns organised within either a classification or an inference presentation. They could do so using similarity of features or a relational principle, but only the latter was applicable to the transfer task. Results suggest that inference learning suppressed the ability to consistently encode features and lead to more consistent use of the relational rule and subsequently higher transfer performance, in spite of unchanged contextual richness.

Keywords

Learning, categorisation, relational principle, abstraction, transfer

INTRODUCTION

The ability to see deep relational similarities between superficially different situations has been marked as a property of expertise (Goldwater, & Gentner, 2015). A famous example is the invention of Velcro by the Swiss inventor George de Mestral: during an alpine hike, he discovered that burrs were stuck in his dog's fur. In contrast to many hikers who have been in the same situation, De Mestral was able to abstract the functional principle of small hooks catching into loops, which allowed the burrs to stick so quickly and so pervasively, and to apply it to another setting, creating the most convenient fasteners.

There is indeed evidence that experts, as opposed to novices, focus on causal patterns rather than features (Goldwater, & Gentner, 2015). In addition, it has been shown that experts describe tasks in more abstract and less concrete statements than novices do. When applied to learning a novel task, the instructions given by experts were more difficult to follow than more concrete ones given by non-experts. However, having been exposed to the more abstract expert instructions facilitated transfer to a related task, even though the initial learning progress has been slower (Hinds, Patterson, & Pfeffer, 2001). Thus, it seems that more abstract representations, which are typically associated with experts, facilitate transfer and are thus more readily applicable to new contexts, but are much harder to grasp for non-experts.

Two important modes of stimulus presentation for learning categories can be distinguished: classification and inference. Despite being similar, these paradigms require different strategies and can lead to different learning outcomes (Anderson, Ross & Chin-Parker, 2002; Yamauchi & Markman, 1998). In classification, participants are presented with stimuli and then asked to assign a category, while in inference, participants are given incomplete stimuli that they have to complete in some way in order to suit a category that is already given. Thus, in classification participants have to make predictions of the (usually binary) category label, while in inference they have to predict any missing feature of the stimulus. Erickson, Chin-Parker and Ross (2005) have shown that inference learning leads to better understanding of relational coherence in abstract categories than classification learning does.

Category learning experiments often measure transfer of a category to novel stimuli. However, successful transfer of a relational rule to a novel task is notoriously difficult to achieve (Sloutsky, Kaminsky & Heckler, 2005). According to widely held beliefs in education, learning is facilitated by providing concrete instructions and examples. Indeed, when superficial features contain useful aspects of what is to be learned, perceptually rich stimuli can facilitate the learning of complex representations (Goldstone & Sakamoto, 2003). On the other hand, there is comprehensive evidence that concrete representations hinder relational transfer. For instance, Son and Goldstone (2009) showed that a context-dependent understanding of signal detection theory led to lower levels of application of SDT principles, and therefore hindered its functional understanding.

Drawing from the literature of both cognitive and educational psychology, the present study investigates the learning and application of an underlying relational rule in a categorization task. The ultimate objective was to to gain theoretical insight into learning conditions facilitating the acquisition and transfer of relational knowledge that could eventually be applied to improving educational materials. Specifically, participants were tasked to learn to categorize novel visual stimuli into two categories within either a classification presentation mode or an inference presentation mode that was implemented as a pattern completion task.

Hypotheses

- H1: In line with the literature on inference learning, it was hypothesized that participants in the pattern completion (PT) condition would rely primarily on the relational rule for assigning categories, while those in the classification condition (CL) were expected to rely on surface features. Specifically, cross-mapped and relation score were expected to be significantly higher in PT, while feature score would be higher in CL.
- H2: Furthermore, PT participants were expected to be able to employ rules for categorisation on a more abstract level and thus perform significantly better in the transfer task, as indicated by transfer score.

METHOD

A total of 84 participants took part in the experiment in exchange for partial course credit or 15AUD. Ethical approval was granted through the Human Ethics Administration at Sydney University prior to testing. The computer-based part of the experiment was implemented using Psychtoolbox for Matlab (Brainard, 1997; Pelli, 1997). Stimuli were presented on 17'' CRT monitors with 1280 x 1024 pixels resolution, attached to Apple Mac Mini computers. Stimuli size was 300 x 300 pixels.

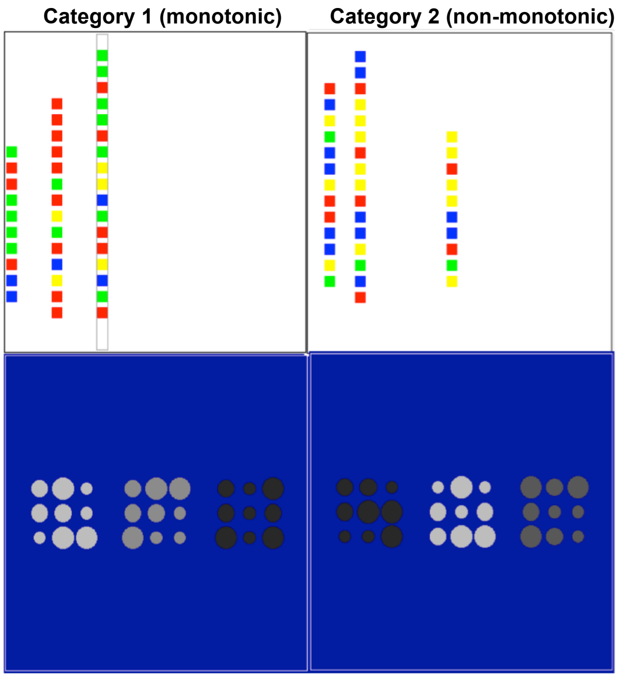

Figure 1. *Array of stimuli used for the monotonic and non-monotonic categories during the categorisation task (top) and the transfer task (bottom). In category one, line length or luminance would monotonically ascend or descend, while in category 2 the middle line or patch would be either the longest/brightest or shortest/darkest.*

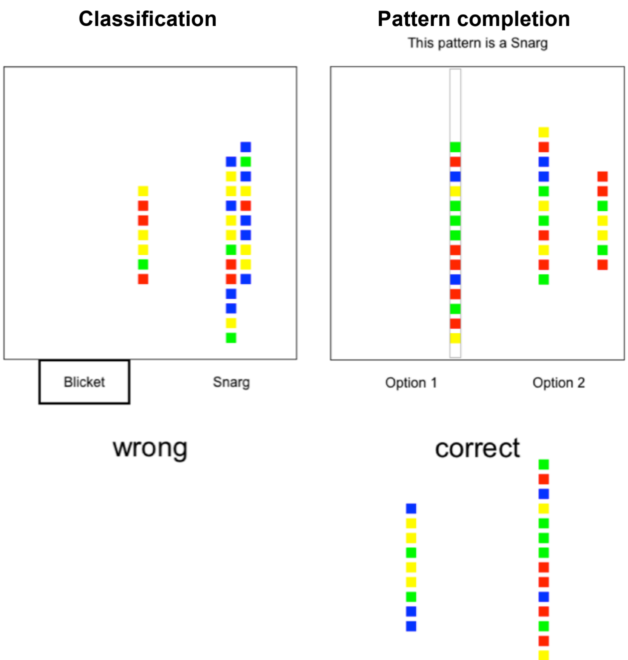

Figure 2. *Different presentation modes during the training phase for the classification and pattern completion conditions. In the classification condition, participants decided which category a given stimuli would best fit into, while in the pattern completion condition, participants were asked to complete a pattern so that it best fits a given category. Participants in both conditions received feedback throughout the learning phase.*

Categorisation task

Stimuli consisted of coloured (red, green, yellow, blue) squares that were organized in three vertical lines in a grid of 20 x 20 squares. Line length varied from 6 to 18 squares, with a minimum difference of two squares between any two lines (Figure 1). Lines were centred vertically, while horizontal placement was probabilistic, with a maximum distance of four squares between lines. Two categories of stimuli could be distinguished based on either feature (colour composition) or relation (line length). Category one always had a strictly *monotonic* relationship (ascending or descending), between line lengths, while for category two the middle line would strictly be either the longest or the shortest. The stimuli's colour composition was determined probabilistically and was predominantly (70 to 30) red-green for category one and blue-yellow for category 2. Categories were randomly named either "Snargs" or "Blickets", as these terms relate to no known meaning (Chomsky & Halle, 1968).

Transfer task

Stimuli used the same relational principle (*monotonic vs. non-monotonic*), but, in order to simulate a different context, were designed to look superficially vastly different (Figure 1). An array of three square patches in three different shades of grey (drawn from 5 luminance values), was shown against a blue background. Each patch consisted of 3x3 circles of three different sizes (3 of each size). The positioning of the array was always the same, and circle size was determined randomly and was non-informative. Correct classification could only be achieved through the order of grey shades, which was either *monotonically* brightening or darkening for category one, while the middle patch was either the brightest or the darkest for category two (see Figure 1 for examples).

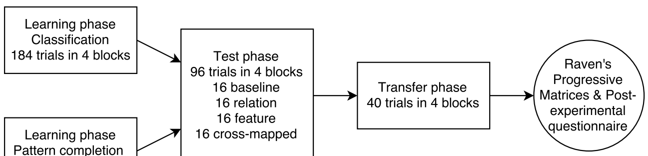

Figure 3. *Flowchart visualising the different stages of the experiment. Only the learning phase was different across conditions. After the main experiment, participants completed Raven's Progressive Matrices on screen and filled in the questionnaire on paper.*

Procedure

The experiment consisted of several phases (Figure 3). Apart from the training phase, these were identical for both conditions. Starting with the learning phase of the categorisation task, CL participants were given a complete array of three lines and presented with the answer options "Blicket" and "Snarg". PT participants were presented with an incomplete array, in which one line of squares would be missing, the display was labelled as either a "Snarg" or a "Blicket", and participants were presented with two options of lines which they could select to complete the pattern (Figure 2). The test phase consisted of four blocks (*baseline, feature, relation, cross-mapped*) of 16 trials each (8 per category). The *baseline* block was identical to the CL training task, but with the omission of feedback; the *feature* block employed stimuli that could only be classified using colours, as the lines were all of identical length. Next, the *relation* block presented stimuli that could only be categorized using line lengths, as all colours were drawn from an equally sampled pool. Finally, the *cross-mapped* block employed stimuli that pitched feature-based against relation-based categorization, i.e. lines would be *monotonic* in order, but squares mostly blue and yellow in colour and vice versa. Directly following the test phase, participants engaged in the transfer task. Participants received feedback throughout the learning and transfer phase, but not in the test phase. After the main experiment, participants completed Raven's Progressive Matrices and a questionnaire. These measures are not further considered in this paper due to space considerations.

RESULTS

Responses during the categorisation and transfer tasks were generally scored as either correct or wrong and averaged over blocks, with a chance level performance of 50%. A notable exception was cross-mapped score in the testing phase. In this case, a feature-based strategy was pitted against a relational strategy, thus score indicated strategy preference rather than accuracy. Cross-mapped trials were scored for the relational strategy, thus employing a feature-based strategy would lead to an expected score significantly below zero.

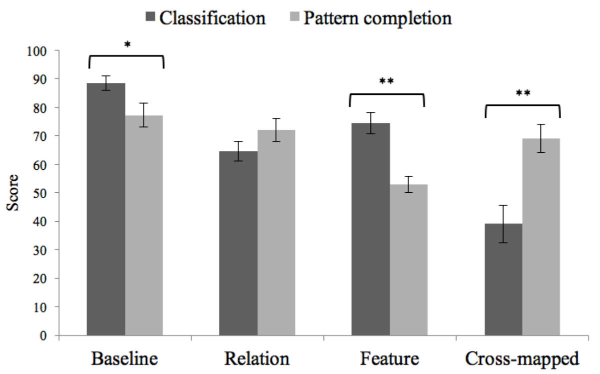

Figure 4. *Mean accuracy scores (+/- SEM) per group for the baseline, relation, feature and cross-mapped blocks assessed during the test phase. Baseline was similar to the learning phase in the classification condition, while relation and feature probes strategy use; cross-mapped pitted both strategies against each other. Participants in the classification condition scored higher in baseline and feature, but lower in cross-mapped.*

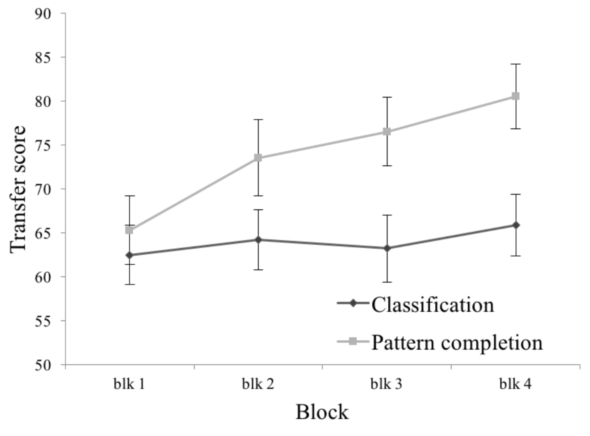

Figure 5. *Mean transfer score (+/- SEM) per block of 10 trials for each condition. Participants in the pattern completion condition showed markedly stronger transfer performance from block 2 onwards.*

Categorisation task.

Figure 4 shows the mean scores in the four blocks of the test phase per condition. Testing H1, a split-plot ANOVA with condition as between-subjects factor and baseline, feature, relation and cross-mapped score as within-subjects factors was conducted. The interaction between test phase and condition was significant, yielding $F(1.31)=18.36$ and $p<.001$ under Greenhouse-Geisser (*epsilon*=.436) correction. CL outperformed PT in the baseline block with $M=88.41$, over $M=77.19$, ($t(65.27)=2.3$, $p=.03$, 95% CIs [83.20, 93.63], [68.76, 85.61]). Relation score was higher in PT with $M=72.03$ compared to $M=64.48$ for PT, however this difference was not significant ($t(76.72)=-1.43$; $p=.16$, 95% CIs [57.54, 71.42], [63.87, 80.19]). Differences in feature score were larger with $M=74.39$ in CL and $M=52.97$ in PT and significant ($t(74.76)=4.56$, $p<.001$, 95% CIs [66.91, 81.87], [47.17, 58.77]). Finally, cross-mapped score was significantly ($t(74.55)=-3.66$, $p<.001$) lower for CL ($M=39.02$, 95% CI [25.93, 52.12]) than for PT ($M=69.06$, 95% CI [58.98, 79.14]), indicating a preference for a feature-based strategy in CL and a relational strategy in PT.

Transfer task.

As predicted, performance in the transfer task was higher in PT and this difference increased over time (Figure 5). The mean transfer score was $M=63.90$, 95% CI [58.12, 69.67] for CL and $M=73.93$, 95% CI [66.89, 80.99] for PT, while in the final, fourth block this difference was larger at $M=65.85$ compared to $M=80.05$. Testing H2, another split-plot ANOVA was performed with the four blocks of the transfer phase as within-subjects factor. There was a significant effect for group ($F(1)=4.98$, $p=.03$, while the interaction between group and transfer was significant ($F(2.9)=2.69$, $p=.049$) using Huynh-Feldt correction (*epsilon*=.97).

DISCUSSION

As shown by the significant interaction in the test phase, strategy use did differ between conditions. While no difference was found for relation score, feature score was significantly higher in CL and cross-mapped score significantly higher in PT, the latter two in line with predictions. It should also be noted that feature score in PT was at chance level, suggesting that features did not serve as valid predictors of category for this condition. In addition, cross-mapped score differed significantly from chance level only for PT, but not for CL. Likewise, even though relation score in CL was indistinguishable from PT, cross-mapped score in PT was much higher than in CL. Taken together, this indicates that participants in CL showed a preference towards a feature-based strategy, but they could also encode line length. Participants in PT, however, seem to have been unable to successfully implement a feature-based strategy and could thus only rely on a relational strategy. This suggests that the inference stimulus presentation in PT inhibits the use of a feature-based strategy.

As predicted, mean transfer score was significantly higher in PT. Additionally, participants in PT improved throughout the 4 blocks in the transfer tasks, whereas those in CL did not, as shown by the significant interaction between conditions (Figure 6). In block 4, PT scored almost 15 points higher than CL (80,5 vs. 65,85), while the mean difference was about 10 points (73,93 vs. 63,90). Given the often documented difficulty of learning underlying relational principles and transfer to superficially different tasks, the results from PT are somewhat remarkable. Nonetheless, performance in category learning was much lower than what is custom in categorisation experiments. For instance, Rein and Markman (2010) reported an accuracy rate of 96%, albeit with much less complex stimuli.

There is research indicating that a frustratingly high difficulty level can lead to greater levels of insight. Goal-setting theory (Locke, 1996) argued that specific and difficult goals lead to higher performance, and that specifically difficult of attaining a goal would be linearly related to performance. However, setting goals is dependent on internal motivation, while the difficulty level in this task arose through the condition imposed upon participants. Perhaps more applicable, in the domain of education, Kapur (2008) demonstrated the phenomenon of productive failure; that ill-structured problem-solving processes associated with lower performance can lead to greater insight. Specifically, 309 high-school students were tasked to solve problems related to a car accident that were either scaffolded through additional instructions or not. Despite the fact that the scaffolded group had better-structured, more solution-oriented group discussions, they performed lower than the un-scaffolded group on two follow up individual tests. Thus, students arguably reached a deeper understanding despite apparent failure in the main task. Again, concrete, structured information was associated with higher performance originally, but but much harder to use in different contexts (cf. Hinds, Patterson, & Pfeffer, 2001; Sloutsky, Kaminski & Heckler, 2005).

The findings outlined are subject to a number of limitations. Especially concerning is the high task difficulty and the large variance within the PT condition compared to much lower variance and difficulty in CL. Presenting the stimuli in the classification mode for assessing baseline performance may have disadvantaged participants in PT, however there was no sizeable difference between performance in the last part of the training phase and baseline performance. Furthermore, many studies employing the classification vs inference comparison in category learning have assessed learning outcome with a classification task (e.g. Erickson, Chin-Parker & Ross, 2005); this seemed not to have substantially disadvantageous despite being an unfamiliar mode of stimulus presentation at the time.

CONCLUSION

It was demonstrated that learning abstract relational principles and application to superficially very different contexts can be influenced by stimulus presentation. The higher transfer performance demonstrated in the inference condition may be due to the learning condition inhibiting the adoption of a feature-based strategy, and thus forces participants to engage deeper in the line-length criterion, instead on judging intuitively on similarity in shape. Likewise, due to a relational strategy being inherently harder, participants in the inference condition show higher variance and lower learning outcomes on average and find the task more difficult. Inference learning may thus have a similar effect as varying degrees of contextual richness, even though the stimuli in both conditions were the same in this experiment. The fact that this seems to be related to using a relational strategy and learning in inference gives hope that educational materials may be structured to facilitate knowledge abstraction.

ROLE OF THE STUDENT

This research was carried out by Moritz Krusche under the Supervision of Evan Livesey and Micah Goldwater at the University of Sydney, within the Marble Abroad programme of Maastricht University. The research question was chosen by the student within a research line suggested by the supervisors. The design and implementation of the study were set up by the student in dialogue with the supervisors. Evan Livesey programmed the task in Matlab. All testing, data analysis and all writing were performed solely by the student. The study was partly funded by a research grant to Micah Goldwater.

REFERENCES

Anderson, A. L., Ross, B. H., & Chin-Parker, S. (2002). A further investigation of category learning by inference. *Memory & Cognition*, 30, 119-128.

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision, 10*, 433-436.

Chomsky, N., & Halle, M. (1968). *The Sound Pattern of English*. New York: Harper and Row

Erickson, J. E., Chin-Parker, S., & Ross, B. H. (2005). Inference and classification learning of abstract coherent categories. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 31, 86-99.*

Goldwater, M., & Gentner, D. (2015). On the acquisition of abstract knowledge: Structural alignment and explication in learning causal system categories. *Cognition, 137*, 137-153.

Goldstone, R. L., & Sakamoto, Y. (2003). The transfer of abstract principles governing complex adaptive systems. *Cognitive Psychology, 46*(4), 414-466.

Hinds, P. J., Patterson, M., & Pfeffer, J. (2001). Bothered by abstraction: the effect of expertise on knowledge transfer and subsequent novice performance. *Journal of Applied Psychology, 86*, 1232-1243.

Kapur, M. (2008). Productive failure. *Cognition and Instruction, 26*, 379-425.

Locke, E. A. (1996). Motivation through conscious goal setting. *Applied and Preventive Psychology, 5*, 117-124.

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision, 10*, 437-442.

Rein, J. R., & Markman, A. B. (2010). Assessing the concreteness of relational representation. Journal of Experimental Psychology: Learning, Memory, and Cognition, 36, 1452.

Sloutsky, V. M., Kaminski, J. A., & Heckler, A. F. (2005). The advantage of simple symbols for learning and transfer. *Psychonomic Bulletin & Review, 12*, 508-513.

Son, J. Y., & Goldstone, R. L. (2009). Contextualization in perspective. *Cognition and Instruction, 27*, 51-89. doi:10.1080/07370000802584539

Yamauchi, T., & Markman, A. B. (1998). Category learning by inference and classification. *Journal of Memory and Language, 39*, 124-148.