AN INTERACTIVE TEST TO STUDY THE RELEVANCE OF ANALOGICAL REASONING AND CONCEPT SEPARABILITY IN CATEGORY LEARNING

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ABSTRACT

Previous studies have shown that Analogical Reasoning is used to learn categories with similarities between them, but has not addressed the question of whether similarities or separability are preferred in categorization. We describe an innovative interactive and multimedia test designed to answer this question. In this test some categories are defined by two different criteria, one of which is similar across categories while the other one differs. Participants have to click to discover the relevant features, and their clicks are analyzed to understand which of the two criteria they prefer to use. Partial results suggest that similarity-based criteria are preferred.

Keywords: Analogical Reasoning; Category Learning; Concept Separability.

INTRODUCTION

The many models already existing in Category Learning range from those which assume generalization through the identification of salient features (e.g. Nosofsky's Generalized Context Model - 1986, 1991); the creation of prototypes (Smith & Minda, 2002); the creation of boundaries in the representation space, identifying zones corresponding to different concepts (Ashby and Gott, 1988; Ashby et al., 1998); the creation of abstract rules for attribution to different categories (Ashby et al., 2003); and other various theories that use these approaches to different extents. But the common denominator of these theories is that they need a sharp divisibility between concepts.

In a previous experiment (Bianchi & Costello, 2008), briefly explained below, we found that in a category learning task in which some categories had similarities between them, those similarities were exploited to transfer knowledge between the partially understood concepts, so that the two similar categories were learned almost simultaneously.

Although it has already been suggested that Analogical Reasoning has a role in Category Learning (Kuehne et al., 2000; Gentner and Medina, 1998; Gentner and Namy, 1999; Sloutsky and Fisher, 2004), this research stressed the role of analogy in the use of similarities between exemplars of the same category, andhas not focused on the role of analogies between different categories during learning.

On the contrary our interest is to investigate the case in which two (or more) categories with similar structures are learned simultaneously, and discover if and how analogical reasoning is used in this case, and whether the use of similarities and analogical reasoning, or the separability of concepts, is preferred.

This point can also be explained in terms of alignable and non-alignable differences (Gentner & Markman, 1994; Markman & Gentner, 1993, 1996). As Gentner and Markman found, the alignable differences can be easier spotted than the non-alignable ones, although this "runs against the commonsense view - and the most natural prediction of feature-intersection models - that it should be easier to list differences the more of them there are to list - that is, the more dissimilar the two items are." (Gentner & Markman, 1997)

In this experiment there are alignable and non-alignable differences, as will be shown below, and we expect the alignable differences to be the ones that will be exploited to more easily learn to classify the objects.

Previous Experiment

In previous research (Bianchi and Costello, 2008) we investigated how Analogical Reasoning can help learning similar categories. Participants were asked to learn to classify examples taken from four different categories. The examples were composed by colored geometric shapes, and were produced by the computer accordingly to four different rules, similar two by two. Two rules had a more complex structure, based on the quantities of the elements (e.g. same number of yellow and red circles in category A, different number in category B); the other two rules had a simpler structure (presence of a distinctive element - e.g. a blue triangle in category C, a green triangle in D).

The analysis of learning times in the different categories showed that learning of one category is quickly followed by learning of the other similar category, but is completely unrelated to the learning of the other two. Moreover, the analysis of errors highlighted that even before any category is learned, it is more frequent to give the incorrect answer remaining in the correct macrocategory (i.e. answer A instead of B, C instead of D), than being totally wrong (e.g. A instead of C). These two facts show that Analogical Reasoning is used not only to transfer knowledge from a well known concept to another less known one, but also during the learning of completely new concepts, thanks to the mutual completion of partial understood concepts, which are sensed to have similar structures.

Limits. Nevertheless, due to its design, this experiment is limited and can only show that analogical reasoning is used but cannot clarify in what extent its use is spontaneous. Actually, the fact that analogies are used might be determined just by the task structure itself, that gives no other choice, while in more flexible conditions people might instead prefer a strategy based on the identification of rules that are possibly very distant from each other.

Moreover, the extremely abstract nature of the relational rules (ratio between number of elements), besides making the test very difficult to solve, could also create a bias towards the use of analogical reasoning.

To confirm the results of this first experiment and overcome its limits we decided to design a new experiment, that is shown in this paper.

Limits of other experiments

It must be also added that the use of geometric shapes, if on the one hand guarantees that previous knowledge is not used, on the other hand doesn't respect ecological plausibility, as well as the presentation of static stimuli. A vast literature has been produced in the last years about analogical reasoning experiments that use static figures (e.g. Kokinov et al, 2007; Mutafchieva & Kokinov, 2007; Thibaut et al., 2008; Goswami & Brown, 1989, 1990; Rattermann et al., 1990; Lipkens & Hayes, 2009), yet the limits of such approach are manifest, considering both the little ecological plausibility they have, and the little interest and poor attention they cause in participants.

To partially overcome these limits, in this new experiment we decided to use interactive and multimedia figures, so that the movement and sound dimensions could be introduced, and with them the possibility to use causal and synchrony relations. This choice is also supported by several studies (Seitz, 2005; Goswami et al, 2008) that propose that the basis of analogical reasoning could lie exactly in the cross-modal sensory mapping.

Given the benefits of this novel experimental design (most notably: attention of the participants and richness of the collected data and possible analyses) we suggest it as a new paradigm that can be adopted also in other experiments both in the field of analogical reasoning and category learning, and we are willing to share the implementation of the test and give advice for its use in other experiments.

DESIGN

Constraints

To design the current test various constraints have been considered, deriving both from the will to go beyond the limits of our previous experiment, as well as the limits of the other experiments done in this field, and from the need to test multiple hypotheses at the same time.

Alternative Solutions. One of the main questions that are asked with this experiment is whether people prefer to use analogical reasoning, and so the similarities between categories, or the separability of concepts, thus preferring rules that are the least possible similar to each other. To obtain this, the only choice was to provide some of the categories with more than one membership rule, and then to observe which rule is learned for each category and which is instead ignored. The solution that has been found for this problem is summarized in Table 1, where A1, A2 and A3 represent rules similar to each other, whilst B, C and D are rules that have little similarities between them and to the "A" rules.

***Table 1**. Rules defining the different categories.*

<table>
<tr><th>Category</th><th>1</th><th>2</th><th>3</th><th>4</th><th>Wrong</th></tr>
<tr><td rowspan="2">Rules</td><td>A1</td><td>A2</td><td rowspan="2">A3</td><td rowspan="2">D</td><td rowspan="2">Only Distractors</td></tr>
<tr><td>B</td><td>C</td></tr>
</table>

Consequently if participants learn as a classification criterion the rules A1, A2, A3 and D, it can be deduced that the push to use analogical reasoning is stronger than the one to use the concept separability.

Having categories defined by more than one rule makes hard to test the difficulty of each single rule (in order to have baselines), therefore the categories 3 and 4 have been introduced: category 3 gives the baseline for the "A" rules, while category 4 provides the baseline for rules B, C and D, that are swapped between three distinct groups of participants.

Avoid Elimination. In order to avoid that the participants learned only 3 of the 4 categories and answered by elimination, the "Wrong" category has been introduced, that has only distractors randomly selected, which can recall the criteria for the other categories, but don't coincide with them.

Insight of learning process and learned rules. A problem that arose at this point was how to discover which rules were learned to classify the objects: in a task in which participants are asked only to observe the figures it is almost impossible to tell what criteria they use. Some hints could come from eye-tracking system, but one should greatly rely upon the debriefings.

Complex Relations. Another problem that arises from this complex experimental design is to ideate four different kinds of classification rules, with at least one kind ("A") declinable in multiple versions, very similar to each other but distinguishable. And because the focus is on analogical reasoning, the rules shouldn't be based on the single features but on relations between them. Also in this case a task with fixed, only observable figures puts too many limits on the kind of relations that can be used.

Easiness. An equally important constraint is then the easiness of learning. The numerical relations used in our previous experiment (equal or different number of elements with the same shape and different colours) were already too abstract and complex for some participants, and the present test with all these new constraints risked of having classifying criteria not learnable by average people.

Pleasantness and Entertainment. A last but not less important element to consider is the boringness and repetitiveness of the task, that makes the attention fall quickly. If increasing the easiness can reduce the time needed to complete the task, it is nevertheless useful to intervene also on pleasantness and entertainment, in order to make the task more similar to a game and hold the participants' attention.

Resulting Design

The solution to all these constraints was to create a task in which the figures are not static but interactive: thus the number of possible relations between the elements increases (e.g. clicking on an element makes some other move in the same way or different ways, synchronically or one after the other, possibly playing a sound or music at the same time, etc.), and it is also possible to record which elements the participants click on, in order to discover which are the learned classification criteria. A task so structured also gains in ecological plausibility, and becomes more entertaining, resembling more a game.

Composition of objects. As in our previous experiment, every object is made up of various geometric coloured figures (in this experiment they are always 16, disposed in a 4x4 grid) that can be of five different shapes and seven different colours, for a total amount of 35 combinations. Differently from the previous experiment, the specific shapes and colours have no meaning, nor the number of identical elements.

Inside the objects 3 groups of figures are created: every element in each group shares the same shape and colour (chosen randomly for each object) and is near the other elements of the group (Figure 1). The groups are formed by a number of elements varying from 3 to 5, and the remaining elements, randomly disposed on the grid, have colours and shapes different from each other. This allows to exploit a visual hint to suggest that the elements so grouped could also share other features. In fact one of the groups (or two for the categories 1 and 2 - see Table 1) is also the key to correctly classify the object: clicking on the group's elements elicits some reactions, and these reactions make the difference between the categories. Also some other elements can elicit reactions, but being randomly chosen they are only distractors. These randomly chosen distractors, finally, are the only components of the "Wrong" group.

The participants thus learn that all the elements of one of the three groups, when clicked, produce the same reaction (different in each category), and on the basis of that reaction they choose the correct label. Since the group isn't characterized by any fixed visual feature through the different examples (colour and shape change at every example, only the reaction remains the same), when the participants see a new example they need to randomly click until they find the right group with the distinguishing reaction, and only then they will know to which category the example pertains. This allows, analyzing the last clicks before the correct answer, to know which criterion (in case of categories 1 and 2 that have 2 active groups, each for the two usable criteria) participants use to classify the objects. In fact it is reasonable to expect that after searching randomly the "good" group, when they find the one that tells what category the object is, they stop searching and give the

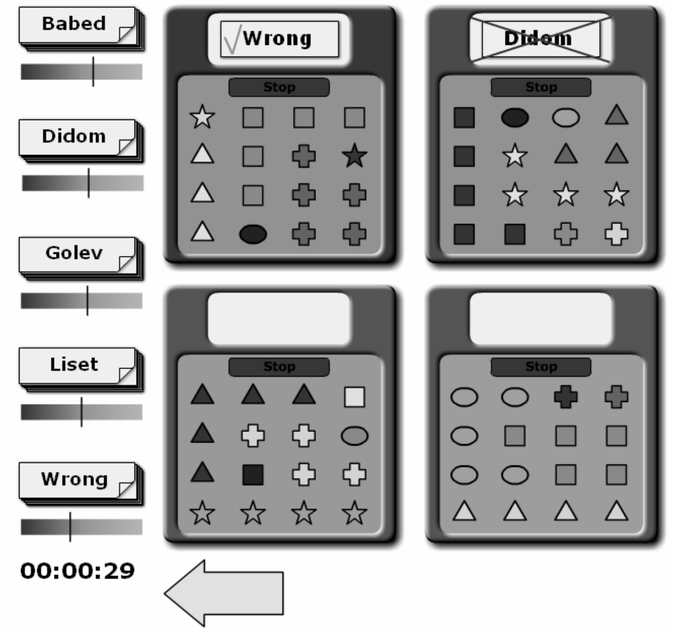

Figure 1. *On each screen four objects are presented, composed by 16 elements (some of which are interactive). Each object must be labeled with one of the 5 available labels, and then a feedback (positive or negative) is given. After all 4 objects are correctly labeled, a button allows to go on to the next 4 objects. Another button allows to go back and see again the already labeled objects. A clock shows the elapsed time.*

answer: the last clicks are therefore on the "good" group, whichever it is they found (i.e. whichever the rule of its behaviour).

Since all the clicks are recorded, it will be also possible to make more complex analyses of the learning patterns.

Rule Definitions. The actions that objects can do in reaction to the click are of different kinds: jump, rotate, tremble, flash to black or to white, blur, change shape, change colour, zoom in or out, and/or play a music or a tone (which can also change its volume in synchrony with the elements' action). The elements associated with rules A1, A2 and A3, when clicked, play only a music (always the same music for the same category, but different between the categories), without any movement (Table 2). Other distractor elements can also play music, but pieces different than those used for these three rules. The elements of the group for rule B, when clicked, make the same group react in synchrony with the same action (randomly chosen for each example) without any music or tone. The elements associated with rule C also react all together, but each with a different action. Finally, for rule D, the click on an element makes all the elements of the group react with the same action but in turn, and in the meantime a tone changes its volume in synchrony with the actions.

As can be easily seen, the rules A1, A2 and A3 have alignable differences (they all play music, different for each rule), while the rules B, C and D are non-alignable. Although the common sense and the majority of the categorization models suggest that non-alignable differences should be found more easily, Gentner and Markman (1994, 1997) already proposed that it is the opposite, and this experiment can demonstrate that it is true also in the specific case of categories with similarities between them.

Table 2. *Rule Definitions*

Click on each element of the associated group causes:	
A1	play music 1
A2	play music 2
A3	play music 3
B	do same action all together
C	do different actions all together
D	do same action in turn + tone change volume in synchrony

Running of the Test. At the beginning of the test (that has been implemented with Adobe Flash and is done on normal computers with 15" screen and professional headphones) the participants are asked to read the instructions, that contain a cover story about a toy firm that was experimenting a new machine to produce interactive toys. The machine unfortunately didn't work well and produced also broken toys, and moreover didn't label them. The task is thus to learn how to correctly label the good toys and reject the broken ones, and during the test there are in fact 5 different labels (with invented names) that must be dragged and dropped on the toys. If the correctlabel is chosen, a positive feedback is given, whilst if it is incorrect there is a negative feedback, and the participant can try again, until the correct label is found. This answering mechanism allows also to study which doubts participants have, that is if they confuse systematically some categories.

On each screen of the test four objects are shown, that can be all of different categories or some of them of the same category. When all of them are correctly labelled, an arrow appears to go on to the next four objects. At any time it is possible to click to another "back" arrow to go back to the already labelled objects, to review them. The test finishes when, for each category, the participant gives 4 corrects answers (first shot) out of the last 5. At the end of the test the participants are asked to write a brief report to teach a worker how to classify the "toys".

PRELIMINARY RESULTS

Although this kind of task diverges from standard classification tasks, this experimental design also allows more complex analyses, such as studying the clicks both in the learning phase (to see what the participants focus on and their adopted strategies) and after the learning of the criteria, to find out what rules they use. It is possible to analyze the errors produced when answering, to ascertain the doubts and confusion of the participants. Some other standard analyses can be done, such as to compare the learning times (and number of examples) for the different categories, and the learning order.

Because we are still doing the experiment and only a little amount of data (17 people) is available, the analysis we present here is limited both in its importance and in its extent. We present it only to show the trends that are already visible, and as an example of the kind of analyses that will be done. For this reason we focus only on the analysis of the last 3 clicks done before answering, after learning of that category has already occurred (i.e. when the participant gives always 4 first-shot correct answers out of the last 5). This is the main novelty of this experiment: only with an interactive test of this kind it is possible to have this kind of data, and it is encouraging the fact that the data supports our theory, also corroborating the usefulness of this new experimental design.

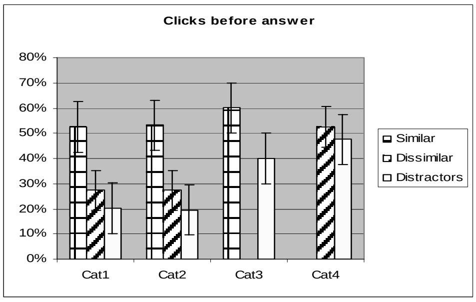

Figure 2. *Last 3 clicks before answer in each group for each category. Error bars are 5% C.I.*

As shown by the graph (Figure 2), the clicks on the elements of the "A" groups, for categories 1 and 2, are almost two times the clicks on "B" and "C" groups. Although no statistical analysis has been done, the shown trend suggests that similarities are greatly used and have a strong push in which criteria are found, and this contrasts with many of the actual theories of category learning, that would predict that the most different criteria would be found.

CONCLUSIONS

In our previous work we discovered that Analogical Reasoning is used in a Category Learning task in which some categories have a common structure, but the question whether analogy or separability is preferred remained open.

We decided to overcome this problem designing this new experiment, that also lays the bases of a new experimental paradigm, one with richer stimuli that enthrall the participants' attention, more data available for new analyses, and a better ecological plausibility. A paradigm that we suggest can and should be also used in other experiments both in the field of analogical reasoning and category learning.

This new experiment is therefore able to answer the question whether analogy or separability is preferred in category learning, and the preliminary results suggest that analogical reasoning has a stronger effect than the separability of concepts: when there are similarities between one or more categories, instead of create confusion and make the task more difficult, they are exploited to more easily learn the other categories. The heuristic used in this case could be described as: "if something has already worked, let's try to use it again", and this would give a renewed importance to analogies even in a field (category learning) in which has been always suggested that similarities between categories are detrimental to learning.

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