Open-Ended Category-Based Induction: The Influence of Associative Strength and Structured Knowledge Representations

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Abstract

Accounts of category-based inductive reasoning can be distinguished by the emphasis they place on associative retrieval processes versus structural knowledge representation. Using an open-ended category-based induction task with a secondary task manipulation, we explored whether the relative importance of these two processes in determining the reasoning output depends upon the availability of mental resources. Regressing indices of strength of association and measures of structured relation against reasoners' inferences showed that people's inductions generated under cognitive load were more strongly predicted by associative strength between base and conclusion category. In contrast, inferences made under no load were best predicted by the measure of the existence of structural relations between base and conclusion category. This suggests that people make use of associative processes and recruit structured knowledge to make inductive inferences, and that the relative importance of these two forms of reasoning is determined by the availability of mental resources.

Keywords: Category-Based Induction; Knowledge; Categorical Inferences; Reasoning.

Knowledge and Category-Based Induction

Generalizing properties from one category to another is known as category-based inductive reasoning. If people learn that carrots have a certain disease, they might infer that rabbits could also be affected. However, if people are reasoning about shared cells, they might prefer to generalize from carrots to parsnips rather than to rabbits. Understanding how people select relevant knowledge has become central to explaining the mental processes that underlie category-based inductive reasoning (Shafto, Baldwin and Coley, 2007). But is knowledge selection based on a single process, such as the activation of automatic associations in semantic memory (Rogers & McCllelland, 2004) and the calculation of similarity (Sloman, 1993; Sloutsky & Fisher, 2004) or the explicit representation of structural relations between categories (Osherson et al., 1990; Tenenbaum, Griffiths & Kemp, 2007), or does it depend on an interplay between such processes? In this paper, we argue that how people reason is determined by more domain-general factors, such as available cognitive resources.

Associative Processes in Inductive Reasoning

Associative processes can explain a host of phenomena in category-based inductive reasoning. For example, Sloman's (1993) feature-based induction model assumes that similarity represented by the degree to which premise and conclusion categories activate common features determines the strength of the conclusion. Similarly, Roger and McClelland's application of the parallel-distributed processing model to category-based inductions assumes that generalizations from one instance to another will be strong to the extent that the activated distributed representations of the two instances overlap via their shared attributes. Several predictions follow from the way in which the connectionist model acquires semantic knowledge and makes generalizations. As it acquires knowledge gradually based on experiential input, the internal representations should mirror the structure of the learning environment. For example, if one repeatedly encounters two species in the same context, the internal representations ought to reflect this statistical co-occurrence. Inductive inferences between categories should be stronger to the extent that the categories have repeatedly been simultaneously activated in semantic memory, forming strong associations

Structural Knowledge Representations

In contrast to models that emphasize associative processes, structured knowledge representations might be necessary to draw accurate inferences where the categories have complex ecological, causal or taxonomic relations. The seminal study by Heit and Rubinstein (1994) demonstrated that people recruited differential knowledge depending upon the type of property they were asked to generalize. Similarly, structured Bayesian models (e.g., Kemp & Tenenbaum 2009; Shafto et al., 2008) successfully explain phenomena that arise from paying attention to the higher-order interrelationships between categories. For example, reasoning about causal transmission is best predicted by inferences computed over a theoretical model of food web relations, whereas inferences about physiological properties seem to be based on an understanding about taxonomic interrelationships. Use of structural representations can also explain phenomena such as the causal asymmetry effect.

Thus, people believe that diseases are more likely to be transmitted from prey to predator than vice versa (Medin, Coley, Storms & Hayes, 2003; Shafto et al., 2008).

An interesting question is what factors determine the use of such structural representations. Cross-cultural work and research on experts (e.g. Lopez, Atran, Coley, Medin & Smith, 1997; Proffitt, Coley & Medin, 2000) suggests that to some extent, use of structural representations in inductive reasoning depends upon having the appropriate background knowledge. For example, Shafto and Coley (2003) compared commercial fishermen's inductive inferences about marine life to those of US undergraduates. When reasoning about novel diseases, only the fishermen drew on causal/ecological relations between premise and target categories to inform their inference. The undergraduates tended to base all their inferences on similarity. However, while such studies illustrate that people vary in the sophistication of the structural representations they have across different domains, the underlying mental processes that prompt people to draw on these or instead fall back on simple similarity during the reasoning process remain unclear.

Two Types of Reasoning?

One possibility is that drawing on structural representations is an effortful process, whereas the use of simple associations and similarity requires fewer mental resources. The relative importance of each strategy might be determined by domain-general factors, such as available time and mental resources. Support for this position comes from a study looking at reasoning in music experts (composers and musicians) and novices (Baraff & Coley, 2003; Coley & Barraff, 2003). Compared to novices, experts tended to use more elaborate context-dependent relational knowledge. However, when the induction task was carried out under time pressure, thus decreasing available cognitive processing time, experts' reasoning was indistinguishable from novice reasoning. This change in expert responding suggests that drawing on structured knowledge representations during reasoning is slow and effortful. Thus, under time pressure, experts had to rely more on associative similarity, the default for novices who lack relevant structural knowledge representations.

A study by Bright and Feeney (2010) lends further support to the suggestion that people reason differently depending upon available mental resources. Thus, when people made speeded inferences, argument strength was predicted by associative strength between the two categories, whereas causal and biological knowledge predicted inference strength when people were not under time pressure.

However, Coley et al. (2005) have argued that some phenomena may be task-specific, especially if people are unaware of the nature of the relation between categories. Most findings are based on experimental paradigms in which people evaluate the strength of an inductive argument (*Rabbits have property X, therefore, Foxes have property X*), evaluate a series of conclusions (*Rabbits have property X. How likely is that Foxes have property X? Eagles? Hares?*), or are forced to choose between two alternative conclusion categories (*Rabbits have property X. Is it more likely that Hares or Foxes have property X?*). When people are presented with pre-determined base and conclusion categories, lack of structural knowledge representations that highlight relevant relations between categories might force people into adopting a default associative reasoning strategy that they wouldn't normally use. In contrast, open-ended methodologies allow people to use background knowledge in a more flexible manner. For example, Baker and Coley (Baker & Coley, 2005; Coley & Baker, 2004) gave their participants two related category pairs and asked them to make inferences about which other categories might also have a novel property. People tended to make inferences based on complex ecological relations rather than on taxonomic similarity, suggesting that they were recruiting whatever relevant structural knowledge representations were available to them.

In the following experiment, people were told that a base category had a property and were asked to infer which other category was most likely to also have that property. We predicted that people who generated categories under cognitive load would use a strategy that placed less demand on cognitive resources, such as similarity or strength of association. In contrast, we expected people to make use of diverse structural knowledge representations when they were not under cognitive load. Previous work using a speeded response paradigm (Shafto, Coley & Baldwin, 2007) has suggested that taxonomic knowledge is more available to reasoning processes than is ecological knowledge. When they have sufficient time, people tend to bring taxonomic knowledge to bear when reasoning about intrinsic properties such as cells and ecological knowledge to bear when reasoning about extrinsic properties such as diseases (see Shafto et al., 2007). So that we could attempt to replicate Shafto et al's finding that taxonomic knowledge is more available to reasoning processes, we asked people to reason about cell and disease properties expecting that only under light load would there be evidence of use of ecological relations when people reasoned about diseases.

Methods

The experiment had three phases, the induction generation phase 1, the associative rating phase 2 and the structured relation rating phase 3.

Induction Generation Phase

The first phase had a 2 (*load: heavy or light*) by 2 (*property: infection or cells*) mixed design, with load as the between-subjects manipulation.

Twenty-three students (*M* age = 24.2 years) from Durham University (the reasoners) were presented with 20 base categories and told that each category had a novel property, either an infection (e.g. has infection 5y5u) or cells (e.g. has 3-yu-cells). There were equal numbers of each property type and the combination of property type and base category was counterbalanced. Participants were then asked to generate ONE other category that they believed was most likely to also have the property. For example, people would read the following generative induction problem:

Weasels have 4Ou-cells / infection 4Ou.
Which other category is most likely to also have 4Ou-cells/ infection 4OU?

Once people had written down their response, they rated how likely they thought it was that the two categories shared the property on a scale from 1 (*very unlikely*) to 9 (*highly likely*).

Preceding each of the induction trials was a secondary memory task. People were presented with a 4*4 dot matrix with 4 randomly placed black dots for 2000 ms. Participants remembered the location of the dots, completed the induction task and then recalled the location of the dots in an empty matrix. The configuration of the dots was different for each of the 20 trials.

In the heavy load condition, the dots were completely randomly placed, with the restriction that they could never appear in a straight or diagonal line. In the light load control condition, the dots always appeared in a straight or diagonal line, placing minimal burden on working memory.

Association Rating Phase

In the second phase each individual reasoner's 20 category pairs were transcribed onto an association rating sheet and interspersed with 15 weakly associated distracter items. A group of 92 participants (the raters) who had not taken part in the first phase received one of 23 different sheets (approximately 4 participants per sheet) and were asked to rate the strength of association on a scale from 1 (*unrelated*) to 9 (*very highly associated*) between the 35 category pairs. They were instructed to respond as fast as possible, based on the first intuitive answer that came to mind.

Structured Relation Ratings

In order to determine the underlying structural relations between the base and conclusion categories generated by reasoners in phase 1, the experimenter and a second blind coder rated whether there was a taxonomic and/or interaction-based relationship between the 20 category pairs. Table 1 below contains examples of the different types of relation.

Thus, category pairs were awarded 0 if there was no discernible link between the base and the generated category (e.g. alligator → soil), 1 if they were taxonomically related (e.g. zebra → horse), 1 if they were related through a causal link or ecological interaction (e.g. hawk → mouse) and 2 if there was both a taxonomic and interaction-based relation between the categories (e.g. cod → shark). Concordance rate across the two primary coders was 67%. Disagreements were resolved through discussion with two further colleagues.

Table 1: Coding Scheme for Structured Relations

Taxonomic Relationship	
Category Membership	Both categories belong to the same class or category (e.g. carrot & parsnip)
Physiological Similarity	Both categories are similar with respect to specific organs or systems (e.g. bat & bird)
Interaction-Based Relationship	
Similar Habitat	Both categories share similar or the same habitat (e.g. trout & shrimp)
Behavioural Interaction	Both Categories interact via some aspect of behaviour (e.g. monkey & tree)
Food Chain Interaction	Both categories interact with respect to diet or eating, i.e., one category eats or is eaten by the other (e.g. heron & fish)

Results

Association Ratings

We averaged association ratings made by raters in phase 2 across all 20 category pairs generated by reasoners in phase 1. One rater in phase 2 failed to complete more than 50% of the association ratings and was excluded from the analysis.

The mean association scores were analyzed with a 2 (*load: heavy or light*) by 2 (*property: cells or infection*) mixed-design ANOVA, with load as the between-subjects variable.

There was no main effect of property, $F_{(1, 89)} = 1.08$, p = .30, effect size d = .22. People gave a mean association rating of 6.23 (SE = 0.12) for category pairs which had been generated about shared cells, and a mean association rating of 6.15 (SE = 0.13) for category pairs generated about infections.

As predicted though, there was a main effect of load, $F_{(1, 89)} = 4.03$, p = .048, effect size d = .42, such that categories generated under conditions of heavy load (M = 6.42, SE =.16) were rated as more strongly associated than categories generated by reasoners whose resources were minimally taxed (M = 5.96, SE = .16).

Finally, there was no interaction between property and load condition $F_{(1, 89)} =$ .55, p = .46, effect size f = 0.08.

Types of Structured Relations

We summed the taxonomic relationship ratings and the interaction-based relationship ratings across the categories for which reasoners had made inferences about diseases, and likewise across the 10 category pairs that were generated for shared cells. These were analyzed with a 2 (*type of relationship: taxonomic or interaction-based*) by 2 (*load: heavy or light*) by 2 (*property: cells or infections*) mixed-design ANOVA, with load as the between subjects variable. The crucial result was a three-way interaction between property, relation and load, $F_{(1, 21)} = 5.43$, *p* = .03, effect size f = 0.51, illustrated in Figure 1 below.

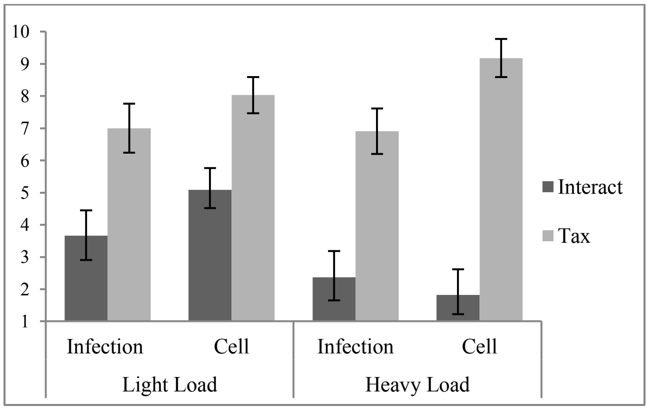

Figure 1: Number of interaction-based and taxonomic relations (and standard errors) across the two types of property for heavy and light load conditions

Heavy Load

In the heavy load condition, there was a main effect of property, $F_{(1, 10)} = 26.94$, $p < .0005$, d = 3.3. Thus, when people reasoned about cells, the conclusion categories they generated shared more structural relations with the base categories (M = 5.50, SE = 0.19) than when they generated categorical inferences about infections (M = 4.64, SE = 0.18).

There was also a significant main effect of type of relation, $F_{(1, 10)} = 68.15$, $p < .0005$, d = 5.3. Thus, people seemed to generate more taxonomically-related categories (M = 8.05, SE = 0.41) than conclusion categories which were related via an interaction (M = 2.09, SE = 0.39).

Finally, there was a significant two-way interaction between property and relation $F_{(1, 10)} = 8.27$, *p* = .017, effect size f = 0.91. Bonferroni post-hoc tests showed that there were no property effects for interaction-based responses. Interaction-based responses were similarly low when reasoning about cells (M = 1.82, SE = 0.38) and infections (M = 2.36, SE = 0.53, *p* = .29). In contrast, property effects arose for taxonomic responses, showing that people gave more taxonomic responses when reasoning about cells (M = 9.18, SE = 0.30) than when reasoning about infections (M = 6.91, SE = 0.63, *p* = .002).

Light Load

The pattern of results was different in the light load condition. Here, the only significant effect was for property, $F_{(1, 11)} = 33.0$, $p < .0005$, effect size d = 3.5. When people reasoned about cells, the conclusion categories they generated shared more structural relations with the base categories (M = 6.58, SE = 0.20) than when they generated categorical inferences about infections (M = 5.33, SE = 0.09).

Although the pattern of means suggests that people generate more taxonomically related conclusion categories (M = 7.54, SE = 0.77) than interaction-based conclusions categories (M = 4.38, SE = 0.89), this main effect of type of relation was not statistically significant, $F_{(1, 11)} = 3.69$, *p* = .08, effect size d = 0.4. Finally, the most important difference compared to the heavy load condition was an absence of an interaction between property and type of relation, $F_{(1, 11)} = 0.128$, *p* = .73, effect size f = 0.38.

Generative Inductive Strength Ratings

Inductive strength ratings for the categories the reasoners had generated were analyzed with a 2 (l*oad*) by 2 (*property*) mixed-design ANOVA with load as a between-subjects variable. Inductive strength ratings did not differ between the load conditions, $F_{(1, 21)} < .001$, *p* = .99, effect size d < .01. Reasoners under heavy load gave a mean inductive strength rating of 5.55 (SE = .40) whereas those under minimal load rated the strength of their induction at 5.56 (SE = .42).

There was also no main effect of property, $F_{(1, 21)} = 2.1$, *p* = .16, effect size d = .63. Inferences about cells (M =5.68, SE = .32) were rated as strong as inferences about infections (M =5.42, SE = .29).

The interaction between load and property was not statistically significant, $F_{(1, 21)} = 2.68$, *p* = .12, effect size f = .35.

Relations between Inductive Strength Ratings, Structured Relations and Associative Strength

To explore whether reasoners place different emphasis on associative processes and reasoning based on structured knowledge representation in the two load conditions we used an associative strength measure and the index of structured relations described above to predict their inductive strength ratings.

To create the associative strength measure we averaged the mean strength of association scores attached to each reasoner's 20 category pairs across the four raters from phase 2. We then calculated Cronbach's Alpha for each of the 23 reasoners across the association ratings. The mean Cronbach's Alpha across all reasoners was .71 (SD = .13), showing that the association ratings had good inter-rater reliability.

To create the structured relation measure, the experimenter and a second blind coder assessed in how many ways the generated target could be related to the base. 0 was attached if there was no obvious structured link, 1 if there was either a taxonomic or an interaction-based connection, and 2 if they were related in more than one way.

For each reasoner who had taken part in phase 1, we used the associative strength and structured relation measures to predict his/her inductive strength ratings. The beta weights were then subjected to a 2 (*load: heavy or light*) by 2 (*type* *of beta weight: associative versus structured relation*) mixed-design ANOVA, with type of beta weight as the repeated-measures variable.

There was no significant main effect of type of beta weight, $F_{(1, 21)} = .068$, p = .80, effect size d = .11 and no main effect of load, $F_{(1, 21)} = 3.22$, p = .09, effect size d = .78. However, there was a significant interaction between beta weight type and load, $F_{(1, 21)} = 6.53$, p = .018, effect size d = 1.1. This is illustrated below in Figure 2.

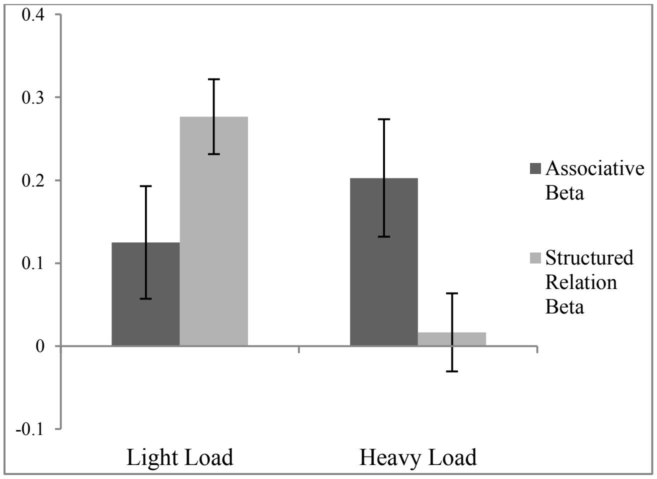

Figure 2: Beta weights (and standard errors) across the two load conditions

Bonferroni posthoc tests showed that when reasoners were under heavy memory load, the associative strength beta weight (M beta= .20, SE = .07) was larger than the structured relation beta weight (M beta = .02, SE = .02), although this difference was not quite statistically significant due to the small number of participants in this condition (p = .065, effect size d = 1.2). A one-sample t-test confirmed that associative strength beta weight was significantly above zero, $t_{(10)} = 3.79$, $p = .004$, but that the structured relation beta weight was not significantly above zero, $t_{(10)} = 0.45$, $p = .66$.

The pattern was reversed when reasoners were not under a heavy memory load. Thus, the structured relation beta weight (M beta = .28, SE = .05) was slightly but not significantly larger in magnitude than associative strength beta weight (M beta = .11, SE = .07, p =.11, effect size d = .62). However, the one-sample t-test showed that whereas the structured relation beta weight was significantly above zero, $t_{(11)} = 5.24$, p <.0005, the associative strength beta weight was not statistically different from zero, $t_{(11)} = 1.56$, $p = .15$.

Across the two load conditions, the associative strength beta weight was slightly but not significantly larger for reasoners who generated their inferences under load compared to those who were not cognitively compromised ($p = .44$, effect size d = .32). In contrast, the mean structured relation beta weights were significantly larger for reasoners who generated their inferences under minimal cognitive load compared to reasoners who were cognitively burdened by the complex dot matrix task ($p = .001$, effect size d = 1.6).

The results suggest that the reasoning process used to arrive at a particular inference depends to some extent on available cognitive resources. Whereas structured knowledge representations were influential when reasoners were only under minimal cognitive load, associations seemed to be more important to reasoners under a heavy cognitive load.

Discussion

Our results suggest that the process people adopt to generate category-based inductive inferences depends upon available cognitive resources. Categories produced under heavy load were rated as more strongly associated than categories generated under a light load. Furthermore, under heavy load conditions, those association ratings were better predictors of inductive strength than an index of structured relations. In contrast, in the light load condition the index of structured relations was the better predictor of inductive strength ratings. Furthermore, under heavy cognitive load, people were less likely to generate categories that shared more complex interaction-based relationships, whereas generating taxonomically related categories was unaffected by cognitive load.

The advantage of the open ended paradigm is that we can be sure that participants possess knowledge about structured relations between base and conclusion categories. Despite using this more flexible reasoning paradigm, people who were under cognitive load seemed less able to make use of complex structural representations, and instead relied more strongly on associative processes. This suggests that while people do seem motivated to base their reasoning on domain-specific knowledge representations such as ecological/ causal structures, this comes at a cognitive cost. If necessary, people can shift towards a more associative strategy that might result in an inference that is different to the one that would have been generated through the activation of more complex structural knowledge representations. Sloutsky and colleagues (2008) suggest that structured knowledge can arise from simple associative processes and co-occurrence. Thus, it is conceivable that even once people possess more elaborate knowledge structures, they may use associative strength as a useful heuristic short-cut during reasoning, especially when time and/or cognitive resources are sparse.

Interestingly, we found no differences in people's inductive strength ratings across the two load conditions, suggesting that people were equally confident about inferences generated using associative reasoning or a reasoning strategy based on more complex structural knowledge.

As well as allowing us to disentangle the relative effects of associative and structured knowledge on reasoning, our results replicate Shafto et al's finding that taxonomic knowledge is more available to reasoning processes than is ecological knowledge. Although our results clearly show that associative knowledge was a better predictor of reasoning when participants were under load, they also show that participants were much more likely to generate conclusion categories that were taxonomically rather than ecologically related to the base category when under load. This was regardless of the property they were asked to reason about. Large numbers of ecologically related conclusion categories were seen only when participants reasoned about disease properties under light load.

Conclusion

Our results suggest that apparently contradictory theories of category-based inductive reasoning best explain inference strategies under different domain-general processing conditions. People's reasoning might best be explained by associative approaches such as parallel-distributed processing connectionist accounts (Rogers & McClelland, 2004) and featural similarity (Sloman, 1993) when they do not have time or available mental resources to engage in more elaborate reasoning.. In contrast, people with plenty of time and cognitive capacity might recruit complex structural knowledge representations (e.g. Kemp & Tenenbaum, 2009) to derive their inferences.

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