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Predicting Reasoning from Visual Memory

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Abstract

This work examined the relationship between recognition memory and inductive reasoning for a common set of visual stimuli. Adults were shown pictures of large dogs and then asked whether test pictures were old or new (memory task) or whether they shared a target property with old items (reasoning task). Although more positive responses to test stimuli were made in the reasoning task, there was a strong correlation between memory and reasoning judgments. Simulations confirmed that both sets of judgments could be explained by a single exemplar-based model with variations in the parameter corresponding to the generalization gradient for each task.

Keywords: Inductive reasoning, Recognition memory

Introduction

By tradition, reasoning and memory are kept separate. On average, reasoning and memory are six chapters apart in cognitive psychology textbooks (see Table 1, with comparison to perception as well). Each topic is most often studied with its own experimental paradigms, addressing different questions and resulting in reasoning phenomena and memory phenomena being addressed by separate theories. Of course, there are exceptions to this generalization. For example, research on meta-cognition sometimes addresses how people reason about their own memories (e.g., Finn & Metcalfe, 2008), and research has shown false memories can be created through reasoning (Brainerd & Reyna, 1993; Sloutsky & Fisher, 2004). Modeling frameworks such as Bayesian models (Chater & Oaksford, 2008) and connectionist models (e.g., McRae, 2004) have been applied to both reasoning and memory. Still, the usual conception is that reasoning and memory are very different cognitive activities.

Despite the apparent differences there are some good reasons for thinking that reasoning and memory may share underlying cognitive processes. At a very general level, reasoning and memory, like many other perceptual and cognitive tasks, involve the generalization of existing knowledge (about familiar stimuli and their properties) to a novel set of stimuli (cf., Shepard, 1987). A more specific point of overlap is the central role accorded in each task to the similarity between familiar targets and test items in determining test responses. In recognition the probability that an item is recognized as "old" is a positive function of its similarity to previously studied items (Jones & Heit, 1993). In inductive reasoning the probability that a novel item is judged to have some property depends on its similarity to known

instances that have that property. This overlap goes beyond the level of task description; models of both recognition memory (Gillund & Shiffrin, 1984; Hintzman, 1988; Ratcliff, 1990) and induction (Feeney & Heit, 2007; Osherson et al. 1990; Sloman, 1993) view similarity computation as a core process that determines performance.

Table 1: Chapter Numbers for Perception, Memory, and Reasoning in Cognitive Psychology Textbooks

Textbook	Perception	Memory	Reasoning
Anderson (2004)	2	6	10
Eysenck (2005)	3	7	16
Galotti (2008)	3	6	12
Goldstein (2007)	3	6	12
Hunt & Ellis (2003)	2	5.5	12
Kellogg (2007)	2	5	10
Matlin (2004)	2.5	6	12
Medin, Ross, & Markman (2004)	3	6.5	11
Solso, MacLin, & MacLin (2007)	3.5	6	13
Sternberg (2005)	4	6.5	12
Mean	2.80	6.05	12.00
Standard Deviation	0.67	0.55	1.70

Note: When a topic is covered in multiple chapters within a textbook, the average chapter number is reported.

Our own approach therefore is to investigate the similarities between memory and reasoning rather than treat them differently. We developed a new experimental paradigm that makes reasoning and memory tasks as comparable as possible. In particular, people were either asked to make recognition judgments about a set of pictures they had studied, or make property inferences about the same set. We examined whether the overgeneralization errors that people make in visual recognition predict the pattern of generalization that other people show in inductive reasoning. When memory and reasoning tasks differ only in the nature of judgments being made at test, we predicted that there will be a reasonably close correspondence between them in performance on individual items. Items that are more likely to be identified as old should generally be judged as stronger candidates for property inference.

On the other hand, by making the tasks comparable, it could be the case that dissociations between memory and reasoning are made more salient, interpretable as revealing the deeper nature of memory and reasoning as opposed to just task differences. For example, a visual recognition memory task may be more perceptually driven, whereas a reasoning task might tap into deeper conceptual knowledge. Sloutsky and Fisher (2004), for example, argued that children use the same information (perceptual similarity) for memory and reasoning, but that adult reasoning is particularly influenced by conceptual (taxonomic) information. Other researchers have emphasized the role of more complex conceptual knowledge, such as beliefs about causal mechanisms, in property induction (e.g., Medin, Coley, Storms & Hayes, 2003; Rehder, 2006). Although such conceptual knowledge could conceivably affect picture memory, one might expect a greater influence on a reasoning task.

One form of conceptual knowledge that might affect induction but not recognition is knowledge about the relationships between a particular stimulus (and the category to which it belongs) and the kind of property that is to be inferred. Previous work has shown that varying the nature of the property can strengthen or weaken property generalization between the same target and test items. Heit and Rubinstein (1994), for example, found that anatomical properties were more likely to be generalized from sparrows to hawks than from tigers to hawks, but that this pattern reversed when the property was predatory behavior. One interpretation is that different properties cause people to compute similarity between target and test instances in different ways (e.g., inferences about anatomical properties may be based on taxonomic similarity while inferences about predation may be based on similarity between ecological roles). This work suggests that the relationship between recognition and induction performance might vary with the type of property being inferred. This possibility was tested in the current study by varying the target property for induction; people doing induction made inferences about either anatomical or behavioral properties.

A second important goal of this work was to examine whether reasoning and memory performance could be accommodated within a single computational model. As noted by Heit and Hayes (2005), previous, successful models of recognition memory have not addressed reasoning and likewise previous models of inductive reasoning have not addressed memory. The key assumption of our model was adapted from exemplar models of categorization (Medin & Schaffer, 1978; Nosofsky, 1988); namely that the tendency to make a positive response to a test stimulus is a positive function of the total similarity between that stimulus and all studied items. Exemplar models have been successful in accounting for patterns of categorization and recognition of the same stimulus sets (e.g., Nosofsky, 1988; Shin & Nosofsky, 1992) but have only rarely been applied to reasoning data (e.g., Estes, 1994). A strength of these models is that they can account for apparent dissociations between tasks without assuming multiple cognitive systems. Nosofsky

and Zaki (1998), for example, were able to account for past dissociations in recognition and categorization among amnesic patients and normal controls using a single, exemplar-based model, allowing a sensitivity parameter to vary from the categorization task to the recognition task. The key idea was that categorization involves broader generalization and recognition involves more sensitivity to exact matches between studied items and test items. In the current work we followed the same logic assuming that, all things being equal, inductive judgments would show a broader pattern of generalization across test items than recognition judgments.

Method

Participants

Ninety-seven students were recruited individually in quiet, public places, such as the library, on the University of California, Merced campus. Subjects were randomly assigned to one of three conditions: memory (n=31), reasoning-anatomical property (n=32), reasoning-behavioral property (n=34).

Materials

The stimuli were color photographs of dogs, 280 pixels square, adapted from a compendium of dog breeds (American Kennel Club, 2006) and other internet sources. The same stimulus set was used for all three conditions. The study list consisted of 10 pictures of large dogs. The test list consisted of 45 pictures of dogs. There were 10 old items (the large dogs originally studied), 15 lure items (other large dogs, not previously studied), and 20 new items (10 small dogs and 10 medium dogs).

Procedure

The experiment was run using a program on a laptop computer. In the memory condition, subjects were instructed to memorize the initial set of pictures. They were shown the 10 pictures on the study list, in a different random order for each subject. Each 10 cm^2 picture was presented for 2 s, with a 0.5 s interstimulus interval during which the screen was blank. There was a 60 s unfilled retention interval before the test phase. Subjects were instructed to judge whether or not they had seen each test picture, by selecting either a yes or no button on the computer screen. During the test phase, the 45 test pictures were shown sequentially, in a different random order for each subject.

The reasoning-anatomical property condition was like the memory condition, except for the following. Before the study phase, subjects were told they would see a set of animals with "beta cells" in the blood. Before the test phase, subjects were told to judge whether or not each animal has "beta cells."

The reasoning-behavioral property condition was like the reasoning-anatomical property condition, except for the following. Before the study phase, subjects were told they would see a set of animals which had been observed to perform "behavior X." Before the test phase, subjects were

told to judge whether or not each animal performs "behavior X."

Results and Discussion

Across the 45 items on the test list, responses in the three conditions were very strongly correlated. The correlation between the memory condition and the reasoning-anatomical property condition was .83, the correlation between the memory condition and the reasoning-behavioral property condition was .88, and the correlation between the reasoning-anatomical property condition and the reasoning-behavioral property condition was .86. In other words, memory was a very good predictor of reasoning, and the correlations between memory and reasoning were approximately the same as the correlation between two reasoning tasks. This relation is illustrated in Figure 1, showing a scatter plot of memory responses versus reasoning on anatomical properties, for the 10 old items, 15 lure items, 10 new, medium dogs and 10 new, small dogs. Note the curvilinear relation between memory and reasoning, falling above the main diagonal, indicating a greater level of generalization for reasoning than for memory.
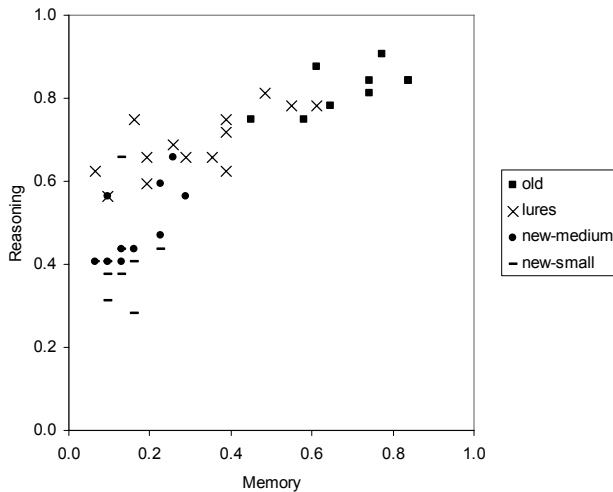

Figure 1: Relationship between memory and reasoning judgments (axes show probability of a "yes" response)

The key descriptive results are shown in Table 2. In the memory condition, recognition performance was good, with a hit rate of .68 on old items (large dogs) and a false alarm rate of .15 on new items, with discrimination measured as 1.64 in d' units based on these averages. The false alarm rate was slightly higher on pictures of medium dogs than pictures of small dogs. For the lure items (large dogs not studied), the average false alarm rate was .30, with a corresponding d' (old compared to lures) of 1.09.

Table 2: Results (proportion of "yes" responses and d') and Model Predictions

	Old	New Medium	New Small	All New	Lure	d' (Old-New)	d' (Old-Lure)
Results							
Memory	0.68	0.13	0.17	0.15	0.30	1.64	1.09
Reasoning-Anatomical	0.82	0.41	0.49	0.45	0.68	1.15	0.39
Reasoning-Behavioral	0.79	0.39	0.42	0.40	0.57	1.21	0.66
Model							
Memory	0.68	0.18	0.10	0.14	0.30	1.55	0.99
Reasoning	0.81	0.48	0.42	0.45	0.68	0.99	0.38

Compared to the memory condition, subjects in the reasoning-anatomical property condition were more likely to give positive responses. On old items, they inferred beta cells .82 of the time, and on new items, .45 of the time, with discrimination measured as 1.15 in d' units. Hence discrimination between old and new items was poorer in the reasoning-anatomical property condition than in the memory condition. As in the memory condition, there were more positive responses to medium dogs than to small dogs. For the lure items, the rate of positive response was high, .68, with a corresponding d' (old compared to lures) of .39. Overall, compared to the memory condition, in the reasoning-anatomical property condition, there was a high rate of generalization, with subjects particularly likely to extend the property to the lure items, other large dogs. The results for the reasoning-behavioral property condition were similar to the reasoning-anatomical condition.

These observations were confirmed by ANOVAs on responses for individual subjects. The probability of responding "yes" to old items, new items (small and medium dogs) and lures was higher in the induction conditions than in the recognition condition ($F(1, 91) = 7.97$, $p<.01$, partial $\eta^2 = 0.08$; $F(1, 91) = 23.52$, $p<.001$, partial $\eta^2 = 0.21$; and $F(1, 91) = 21.934$, $p<.001$, partial $\eta^2 = 0.19$; respectively). Sensitivity (d') was higher for recognition judgments than induction judgments for both old vs. lure items, $F(1, 91) = 6.69$, $p<.05$, partial $\eta^2 = 0.07$ and old vs. new items, $F(1, 91) = 3.98$, $p<.05$, partial $\eta^2 = 0.05$ No differences between the two reasoning conditions were found in yes responding or sensitivity (F's < 0.5)[1].

Simulations

We used an exemplar model framework, applied to the recognition memory task as in Nosofsky and Zaki (1998) as well as Heit (1993) and Estes (1994). We modeled the overall pattern of results, rather than the actual stimuli used in the experiment. Hence, predictions were made for four types of

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[1] Data from three participants who responded "yes" to all test items were not analyzed.

stimuli, assigned by simulations to randomized positions in hypothetical two-dimensional stimulus space.

The study list contained 10 large dogs. Their X-Y positions were drawn randomly from a bivariate normal distribution with mean of (0, 0) and a standard deviation of 1. The test list included these 10 old items as well as 15 lure items, additional large dogs also drawn randomly from a bivariate normal distribution with a mean of (0, 0) and a standard deviation of 1. There were 10 new items that were medium dogs, in the simulations drawn randomly from a bivariate normal distribution with an origin of (A, A) and a standard deviation of 1. Finally, there were 10 new items that were small dogs, in the simulations drawn randomly from a bivariate normal distribution with an origin of (B, B) and a standard deviation of 1. Note that A and B were estimated as free parameters—these values would reflect the average positions in psychological space of the large, medium, and small dogs. It was expected that B>A, reflecting the notion that large dogs are more similar to medium dogs than large dogs are to small dogs.

The model was embodied by two equations. Equation 1 shows the familiarity rule. The familiarity of each test stimulus equals its summed similarity to the 10 studied items. Similarity is assumed to be an exponential function of distance between the test item and the studied item, calculated according to the standard Euclidean formula. The parameter c is a free parameter reflecting sensitivity-lower values of c correspond to broader generalization and higher values of c correspond to steeper generalization gradients.

$$fam(test) = \sum_{i=1}^{10} \exp(-c\, dist(test, study_i)) \quad (1)$$

The response rule is shown in Equation 2. Essentially, the probability of a positive response is a monotonic function of a test item's familiarity. The response rule has a single scaling parameter, β. In effect, a lower value of β corresponds to a greater overall bias to respond positively.

$$resp(test) = \frac{fam(x)}{fam(x) + \beta} \quad (2)$$

The model was used to make predictions on 45 test items, for memory and for reasoning with anatomical properties. (Although not reported here, it was also straightforward to fit the model to reasoning with behavioral properties). These predictions were compared to the main 8 data points shown in Table 2, namely the average response rates on old, lure, new medium, and new small items. The c parameter was allowed to vary between the memory and reasoning conditions, but otherwise the model was the same for the two conditions, hence there were 5 free parameters: A, B, c for memory, c for reasoning, and β. The free parameters were estimated using the Solver function in Microsoft Excel, minimizing the root mean squared error (RMSE) of prediction. The model was

applied to 20 different random stimulus configurations. The average estimated parameter values of A, B, c for memory, c for reasoning, and β were as follows: 1.22, 1.49, 4.10, 1.65, and 0.53. The estimated A and B values indicate that the medium dogs were somewhat closer in psychological space to the large dogs than were the small dogs. Notably, the c value was considerably higher for memory than for reasoning, reflecting steeper generalization for memory and broader generalization for reasoning.

Overall, there was a good fit between model and data, with an average *RMSE* of .0554. Table 2 shows average predictions of the model. This table shows that the main trends in the data have been captured, such as differences between the memory and reasoning conditions, and differences between old, lure, new medium, and new small items. Likewise the predicted d' measures are close to the original results. Note that the simulation had actually made 45 predictions for the memory and reasoning conditions, for 45 test items. Thus it was possible to calculate the predicted correlation between memory and reasoning, just as the original data had shown a .83 correlation between memory and reasoning with anatomical properties across the 45 test items. In the simulations, the average predicted correlation between memory and reasoning was .84. This result was simply an emergent property of the model, that is, the correlation results were not fitted directly by the model. Figure 2 shows representative predictions from one simulation.
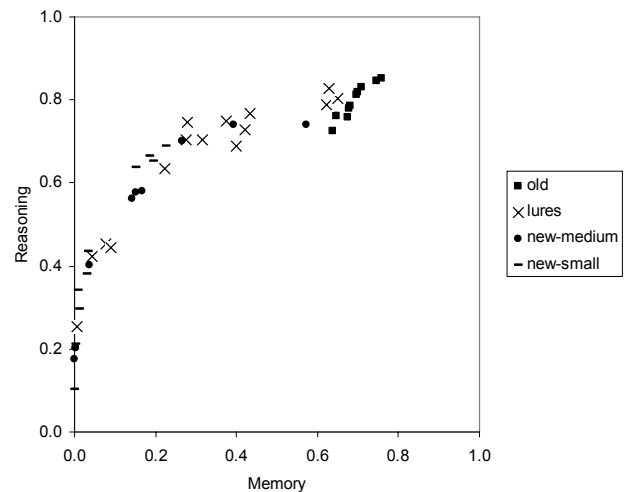

Figure 2: Simulated Predictions (axes show predicted probability of a "yes" response)

To summarize, it was possible to simulate both recognition memory and inductive reasoning within a single modeling framework. Only the steepness of the generalization gradient varied between memory and reasoning. Although the fit of the model was good, in this initial exercise we did not engage in comparative model fitting. It would not surprise us if alternative models could be developed, such as a connectionist model along the lines of McRae (2004). Even in absolute terms, this model could be subjected to stronger

tests, e.g., by having a greater number of data points relative to free parameters, or by actually fitting each individual test item rather than making general predictions for types of stimuli based on a simulation of random stimuli. This latter approach would require more detailed data about each test stimulus, namely its perceived similarity to each studied item.

General Discussion

Our aim was to examine the relationship between memory and inductive reasoning judgments about the same set of visual stimuli. The main empirical finding was that when procedural differences between these tasks were kept to a minimum there was a close correspondence between the two kinds of judgments. Judgments about whether a novel property would generalize to a given test item was positively related to the probability of responding "old" to that item in recognition. The strength of this relationship supports the view that recognition and induction share some underlying component processes. (For related results, showing high correlations between categorization and induction, see Rehder and Hastie, 2004, and Sloutsky and Fisher, 2004.)

There were also some interesting differences between recognition and induction. People doing induction were more likely to make positive responses to both familiar and novel test stimuli (and hence showed lower sensitivity) than those doing recognition. Induction instructions promoted a broad generalization of the novel property across the dog category, whereas recognition instructions led to more of a focus on whether the test pictures were identical to previously studied items.

Reasoning and memory judgments could be accounted for by a single model in which positive test responses were determined by the total similarity between a test item and previously studied items. Differences between recognition and induction in the rate of "yes" responding were captured by changes in a sensitivity parameter that increased or decreased the overall psychological distance between study and test stimuli.

The most straightforward implication of these findings is that reasoning and memory are not as different as has often been assumed. Our work provides some preliminary evidence that exemplar similarity plays a major role in both kinds of tasks. Differences in patterns of recognition and inductive responding may be explained in a relatively straightforward way by altering similarity parameters in the respective decision rules and do not require the postulation of multiple systems of representation or processing, or even different sources of information affecting the two tasks.

Although similarity has been long been acknowledged as a key component in models of induction and recognition, ours is the first attempt to explain recognition and induction judgments for a common stimulus set using a single theoretical model.

As noted earlier, there is evidence that inductive judgments are sometimes influenced by complex knowledge that goes well beyond the visual or taxonomic similarity of old and new items (e.g., Medin et al., 2003). So at least some kinds of property induction may involve additional cognitive processes (e.g., access to knowledge about causal relations) that are unlikely to be central to visual recognition. Having said that our work underscores the pervasive influence of similarity in ostensibly "conceptual" tasks like inductive reasoning. Broadly, these results resemble those of studies which have examined the role of the specific similarity between old and new items in classification. Even when people are asked to classify novel instances on the basis of an abstract and perfectly predictive rule old-new similarity still has a potent influence on classification judgments (e.g., Allen & Brooks, 1991).

An important question for future work is whether there are any conditions where memory performance does not predict reasoning. One factor that we thought would affect the relationship between memory and reasoning but was not found to do so was the type of property that people were asked to infer. Unlike previous studies (e.g., Heit & Rubinstein, 1994), changing the property had little effect on patterns on induction. The anatomical and behavioral properties used in this study, however, may have been so abstract that participants judged them as equally likely to apply to most study and test items. Stronger effects are likely with properties that more clearly prime different kinds of relations between stimuli. One possibility might be to contrast the generalization of a novel anatomical property of dogs with generalization of an evaluative property like "makes a good pet." The anatomical property is likely to be generalized along taxonomic lines while the evaluative property might lead to much broader generalization with positive responses to test items from very different taxonomic categories (e.g., cats, goldfish).

More broadly, both the memory and reasoning literatures suggest other factors that might lead to more divergent response patterns (e.g., Gentner, Ratterman, & Forbus, 1993). Recognition judgments, for example, are influenced by both the similarity of old and new items, and the context in which they are encoded and retrieved (Tulving, 1983). Hence, the addition of a distinctive contextual cue (e.g., different photographic backgrounds) for familiar and unfamiliar items is likely to enhance recognition sensitivity but may have little effect on property induction. Alternately, if items from different basic categories were used during study and properties were correlated with category membership, this should lead to a broader generalization of the property at test (to new items from the same categories) but have little effect on item recognition (cf., Sloutsky & Fisher, 2004).

We suspect that these kinds of manipulations may reduce the strong contingency that was found between responses in memory and reasoning tasks. It remains to be seen though whether such task dissociations can be explained within a unitary model or require multiple processing systems to be invoked. In principle, neither single nor double dissociations between the factors affecting memory and reasoning provide conclusive evidence for the operation of distinct underlying processes (Dunn, 2004). Moreover, in a related line of research, Nosofsky (1988) has shown how dissociations

between responding in categorization and recognition can be accommodated by a singe exemplar model using modest variations of the decision-rules used in each task. This leads us to be guardedly optimistic about the prospect that a single modeling framework might be used to explain a wide variety of memory and reasoning phenomena.

Acknowledgments

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