

# Non-categorical approaches to property induction with uncertain categories

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## Abstract

Three studies examined how people make feature inferences about exemplars whose category membership is uncertain. Participants studied categorized exemplars, were given a feature of a novel item and asked to make predictions about other features. Stimuli were constructed so that different inference strategies led to divergent feature predictions. Experiments 1 and 3 found that most participants used a feature association strategy where predictions were based on comparisons with exemplars similar to the test item. Experiment 2 showed that the dominance of feature association over categorical approaches to reasoning was not an artifact of stimulus complexity.

**Keywords:** Induction, Feature inference, Inductive reasoning

## Introduction

Most previous work on inductive inference has focused on how we use category membership to guide inferences about the features of category members (see Heit, 2000 for a review). Given the often unpredictable nature of the environment, however, it is inevitable that people will also have to make inferences about objects whose category membership has yet to be determined. Imagine, for example that you were a physician dealing with a patient who presents with an x-ray showing a shadow on their lung. Some diagnoses (e.g., lung cancer) would be statistically more likely given this symptom but less likely alternatives (e.g., tuberculosis) could not be ruled out. This uncertainty of diagnosis becomes particularly important when trying to predict the future disease course. Some symptoms (e.g., swelling of the neck) are reasonably likely if the correct diagnosis is cancer but unlikely if it is tuberculosis.

Previous research has focused on two possible approaches to such problems of inference under category uncertainty, both of which accord a central role to categories. One approach derived from Bayesian calculus assumes that people use information from multiple possible categories when making these kinds of inferences (Anderson, 1991). This approach assumes that people identify the categories to which an object might belong, derive the probabilities of a predicted property for each category, and then combine these conditional probabilities, weighting each according to the likelihood of the object being in that category.

Arguing against this “multiple-category” account is a body of evidence that people usually ignore category uncertainty when making inductive inferences (e.g., Murphy & Ross, 1994, 2005). According to this “single-category”

approach people base their inductive predictions only on information contained in the most likely or target category. To illustrate these induction strategies consider the geometric stimuli in Figure 1, said to have been drawn by different children. After studying these categories a participant is shown a novel instance with a given feature and asked to predict the presence of another feature (e.g., given that the object is a square, what colour is it most likely to be?). Category membership is uncertain as either Peter or Chris could have drawn a square, but Peter drew more squares and so would be considered the target category. According to the multiple category approach people would predict the feature “purple” because it is the most common colour across both categories<sup>1</sup>. Murphy and Ross (1994, 2005), however, have repeatedly found that on such tasks people ignore the less likely category and make inferences based only on feature frequencies within the target (leading to the prediction of “aqua” in this example).

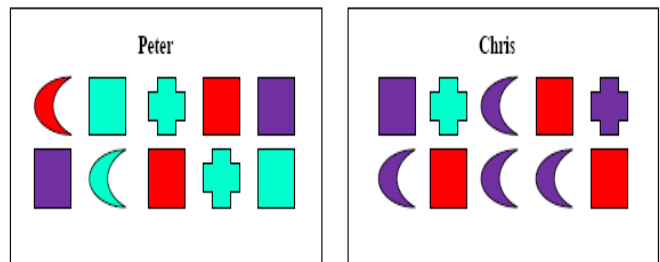


Figure 1. Example of a shape/color item from Experiment 1.

There is, however, a third way of making feature predictions under category uncertainty. People could simply ignore category-level information and examine the distribution of features in exemplars that have the given feature, an approach we refer to as “feature association”. In Figure 1 this would involve looking only at the squares and noting that they are most often “red”. In the earlier medical example it would involve the physician making a prediction about the patient based on a comparison with previous cases with the presenting symptom, without making an a priori assessment of the probable diagnostic categories.

The notion of feature association as a basis for induction seems consistent with the fact that natural categories are rich in feature correlations (Rosch & Mervis, 1975), and that

<sup>1</sup> Note that Anderson’s (1991) Bayesian model assumes that given and predicted features are conditionally independent within and between the experimental categories.

these correlations influence the way that novel instances are categorized (Crawford, Huttenlocher, & Hedges, 2006; Medin, Altom, Edelson, & Freko, 1982). Moreover, there is evidence that people are sensitive to the presence of feature correlations when making uncertain inferences (e.g., Hayes, Ruthven & Newell, 2007; Murphy & Ross, 1994, Experiments 7-8). More broadly, the feature association approach seems consistent with the notion that when learning categories people store the details of individual category exemplars and use these episodic details (in addition to category-level information) to classify new instances (e.g., Brooks & Hannah, 2006; Nosofsky, 1986; Regehr & Brooks, 1993).

What is yet to be established is the extent to which people rely on feature-association as a basis for inductive inference when alternative predictions can also be derived from category-based approaches (based on either single- or multiple-categories). In most previous studies of inference under category uncertainty feature association has been suppressed (by making it impossible for a clear prediction to be made based on this approach) or feature association predictions have been confounded with those of category-based strategies. In Murphy and Ross (1994, Experiments 1-3; 2005), for example, a feature association approach would have made the same predictions as the single-category approach favored by the authors.

Hayes et al. (2007) found some evidence that people use feature association to make property inferences even when an alternative category-based strategy is available. Participants were presented with a series of uncertain induction items where they had to predict the probability that a test object would have various features given that it had a certain feature. Feature base rates were manipulated so that, for some items, feature probabilities increased if people used feature association but remained at a baseline level if they used category-based strategies. It was found that some participants did use feature associations to guide their predictions. A major limitation of this study, however, was that use of category-based strategies led to null predictions about feature probabilities. Hence when some individuals showed no evidence of using feature association we could not be certain that they *were* using some form of category based reasoning.

The main aim of the current studies therefore was to examine the extent to which people used feature association as opposed to category-based approaches as a basis for inductive prediction when category membership was uncertain. Critically, in these studies we used a paradigm in which feature association and the two types of category-based reasoning (single- and multiple-category) led to divergent patterns of feature prediction (cf. Murphy & Ross, 2009). This meant that we were able to establish whether a participant was using feature association or a type of category based reasoning for any given item.

## Experiment 1

This study compared the predictions of three approaches for making property predictions about instances whose category membership was uncertain. The first approach was inference via feature association. The second was multiple-category-reasoning as described by Anderson (1991). The third was the single-category approach described by Murphy and Ross (1994). Based on the results of Hayes et al. (2007) we expected that a substantial proportion of participants would ignore category structure and use salient feature correlations (computed across all available exemplars) to make feature predictions.

### Method

#### Participants

Twenty five university undergraduates participated for course credit ( $M_{AGE} = 20.48$  years).

#### Design and Materials

Two stimulus sets, each containing four items, were constructed. For each item there were two categories containing ten exemplars that varied on two feature dimensions (set 1: shape and color; set 2: shape and pattern fill). Each dimension could take one of three feature values. For every item the distribution of feature frequencies across the two categories was the same as for the item shown in Figure 1. The cover story was that these were drawings done by different children (set 1) or that these were drawings done by college students in a graphic design course (set 2). At test, for each item participants were given one feature of a novel exemplar whose category membership was uncertain (e.g., a drawing of a square). They had to judge which category it was most likely to belong to and to predict what other feature it was most likely to have. As in Figure 1, all items were designed so that use of feature association, multiple-category and single-category approaches led to qualitatively different feature predictions at test. The assignment of feature dimensions to the roles of given and predicted feature was counterbalanced across items. The assignment of specific feature values to the role of predicted feature was counterbalanced across participants to control for the effects of possible differences in feature salience.

#### Procedure

Participants were presented with eight items. For each item colored pictures of the exemplars from each of the two categories were presented on a laminated A4 sheet in portrait orientation. Category labels (first name of the child or student who drew the exemplars) were positioned above the relevant category. The relative position of the target and non-target categories on the page was counterbalanced across items so that the target category appeared an equal number of items at the top or bottom. Participants were first given one minute to study the two categories and were then presented with a novel instance and six test questions (with the categories still in view). The first two test questions asked participants to identify the target category for the

novel instance (e.g., “I have a picture of a square. Which child do you think is most likely to have drawn it?”), and to rate their confidence in this judgment (0 = not at all confident; 100 = extremely confident). The next two questions were fillers that asked about the number of items in each category. The final two questions involved the key feature predictions. Participants were asked to choose what other feature would most likely be found in the novel instance together with the given feature (e.g., “What colour do you think a drawing with a square would be?”). Three feature alternatives were presented (each corresponding to a different reasoning approach) and participants circled the one they believed to be correct. They then rated their confidence in this judgment (0 = not at all confident; 100 = extremely confident). The order of presentation of the two stimulus sets was counterbalanced across participants.

## Results and Discussion

Preliminary analyses established that feature predictions did not vary across the two stimulus sets or counterbalanced versions of the task. All subsequent analyses were collapsed across these factors.

Our predictions about different approaches to inferential reasoning were based on the assumption that people could readily identify the target category for each item, and that they recognized that category membership of test instances was uncertain. Participants were extremely accurate in identifying the target category ( $M = 0.99$  correct). However, mean confidence for target category judgments was modest, ( $M = 64.85$ ,  $SD = 10.79$ ), suggesting that participants recognized that category membership was uncertain.

The most important analyses relate to feature predictions when the given feature was presented. The proportion of feature predictions consistent with each of the three approaches to reasoning (feature association, multiple-category, single-category) was calculated for each participant. Predictions were only included in the analysis for items where the target category was correctly identified. Figure 2 shows that the vast majority of responses were consistent with the feature association approach, with the proportion of such responses well above a chance value of 0.33,  $t(24) = 30.67$ ,  $p < .001$ . The proportion of multiple-category and single-category predictions was close to the floor. Confidence in feature predictions was reasonably high ( $M = 74.63$ ,  $SD = 18.69$ ) and did not vary across reasoning approaches.

We also examined the extent to which individuals showed “consistent” use of a reasoning strategy (defined as at least five predictions based on the same strategy). Twenty four participants were found to have used feature association consistently. One did not show any consistent strategy.

Unlike previous work on induction under category uncertainty, the current study allowed for a clear differentiation of the predictions based on categorical approaches (single- or multiple-category) and non-categorical feature association. When a salient pattern of co-occurrences between a given and predicted feature was

present, there was a strong tendency for people to ignore category bounds and make predictions based only on these feature associations.

These data suggest that when an object’s category membership is uncertain, people may make predictions about other object properties based on a comparison with other exemplars that share a given feature, eschewing considerations of possible category membership. To be confident in these conclusions, however, we need to first consider some alternative explanations.

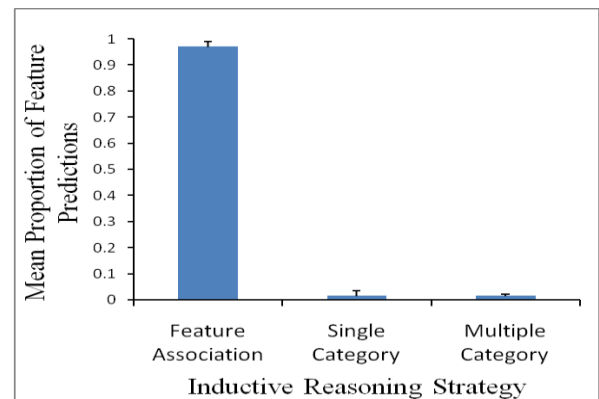


Figure 2. Proportion of feature predictions based on each reasoning approach.

The levels of single- and multiple-category reasoning shown in Figure 2 are considerably lower than those observed in previous work. Murphy and Ross (1994), for example, using geometric category stimuli, found that most participants employed single-category reasoning for most inductive predictions. Although Murphy and Ross (1994) precluded use of feature association in many of their studies, the almost complete lack of category-based reasoning in Experiment 1 remains surprising. One factor that may have contributed to this result is the complexity of our category structures. Experiment 1 used categories containing 10 bi-dimensional exemplars. By comparison, most of the Murphy and Ross (1994) studies used smaller categories (with 4-6 exemplars per category). It is possible that the larger categories made it more difficult to keep track of the distribution of features within and between each category, which in turn made it hard to generate either a single- or multiple-category prediction. If this was the case then the results of Experiment 1 would seem less interesting; in effect they would show that people use feature association only when it is very difficult for them to generate category-based predictions.

To rule out this possibility Experiment 2 used stimuli that were of comparable complexity to those used in Experiment 1 but where only category-based predictions were possible.

## Experiment 2

The aim of this study was to examine whether people were capable of making category-based predictions about

instances with uncertain category membership using category stimuli that were similar in complexity to those used in Experiment 1. As in many previous studies of induction under category uncertainty (e.g., Murphy & Ross, 1994, 2005), in this case we made it impossible for participants to make an unambiguous prediction based on feature association alone. The only way to make a feature inference was via multiple-category reasoning (Anderson, 1991) or single-category reasoning (Murphy & Ross, 1994).

## Method

### Participants

Twenty five university undergraduates participated for course credit ( $M_{AGE} = 20.48$  years). None took part in the previous study.

### Design and Procedure

The design and procedure followed Experiment 1 with the major exception that items were designed to contrast inductive predictions based on single-category or multiple-category reasoning, in the absence of feature association. An example is given in Figure 3. For this item if the given feature was “a square” then the single-category approach predicts that participants would look only at the frequency of features within the target category (Peter), leading to a prediction of “aqua”. If multiple categories were considered, however, then “red” should be predicted. Note that feature association (i.e. just looking at features that co-occur with squareness) leads to an ambiguous prediction (since there is an equal number of aqua and red squares). Eight such items were developed and administered using the same procedure as in Experiment 1.

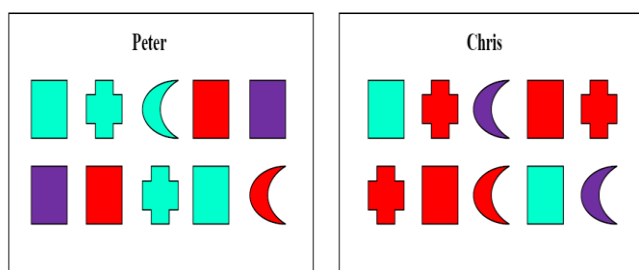


Figure 3. Example of a shape/color item from Experiment 2

## Results and Discussion

Preliminary analyses established that feature predictions did not vary across the two stimulus sets or counterbalanced versions of the task. All subsequent analyses were collapsed across these factors.

Participants always identified the target category correctly, except for one participant on one item. Again, mean confidence for target identification was modest ( $M = 58.03$ ,  $SD = 7.42$ ).

The proportion of feature predictions consistent with the two category-based approaches to induction was calculated for each participant. Predictions were only included for

items where the target category was correctly identified. The mean proportion of single-category predictions was 0.52 ( $SD = 0.25$ ) and the mean proportion of multiple-category predictions was 0.48 ( $SD = 0.25$ ). Both of these were above chance ( $t(24) = 3.81$ ,  $p < .001$  and  $t(24) = 3.06$ ,  $p < .005$ , respectively). Note that the chance value was still 0.33 because participants always had a choice between three alternatives when making a feature prediction (two alternatives corresponded to single- and multiple-category reasoning respectively, one was a feature present in both categories but not associated with any strategy). Confidence in feature predictions was modest ( $M = 49.7$ ,  $SD = 9.1$ ) and did not vary across reasoning approach.

Analysis of individual profiles (using the same consistency criterion as Experiment 1) found that 11 participants consistently used single-category reasoning, 9 used multiple-categories and 5 had no consistent strategy.

These data show that, in general, participants had little difficulty in making single- or multiple-category predictions with category items that were as complex as those used in Experiment 1. As in most previous studies of category-based approaches (e.g., Murphy & Ross, 1994, 2005), single-category reasoning was the most prevalent approach, albeit by a slim majority. These results suggest that the low levels of category-based reasoning found in Experiment 1 cannot be attributed to the complexity of the categories used in that study.

## Experiment 3

This study examined another possible explanation for the dominance of a feature association approach found in Experiment 1. It may be that feature association is only used in preference to category-based approaches when the categories in question are perceived as uninformative or lacking coherence. Past work (e.g., Patalano, Chin-Parker, & Ross, 2006) has shown that the degree to which categories are perceived as coherent influences the extent to which category membership is used as a basis for inductive prediction. It may be that participants saw the categories in Experiment 1 as ad hoc collections of instances, with category labels (names of the child or college artist) providing few clues for feature prediction. If this was the case then it is perhaps unsurprising that people used a non-categorical approach to derive feature inferences.

In Experiment 3 we re-examined feature-association reasoning with categories that varied in the extent to which category level information was salient during exemplar presentation. The categories used in the low- and high-category salience conditions had the same distribution of features as the items in Experiment 1. In the high salience condition, however, the categories were presented as different kinds of viruses, with exemplar features representing different structural parts of individual viruses. Given that categories of living things are often perceived as sharing a range of both known and unknown features (Gelman, 2003), this manipulation was intended to promote the belief that the categories were coherent and meaningful



groupings. By contrast, the exemplars in the low-salience condition were presented with little rationale for category structure and relatively meaningless category labels. The critical question was whether feature association would remain the dominant strategy when category-level information was made more salient.

## Method

### Participants

Twenty four university undergraduates participated for course credit ( $M_{AGE} = 19.34$  years). Equal numbers were randomly allocated to the low and high salience conditions. None took part in the previous studies.

### Design and Procedure

In this study the appearance and relative frequency of features within and between experimental categories was identical to the four graphic-design items used in Experiment 1. This feature distribution allowed for the same demarcation between predictions based on feature association, single-category and multiple-category reasoning as in the earlier study. The way that categories and exemplars were presented in this study, however, was quite different from Experiment 1. In the high-salience condition participants were told that they had to learn about the features of two kinds of recently discovered viruses (Sirus, Karplek). Exemplar features for each category were embedded within a “virus-shaped” outline, with different outlines used for members of the two virus categories (see Figure 4). In the low category salience condition exemplars had exactly the same shape/pattern configuration but had no outline and were given neutral category labels (Set A, Set B). In other respects the procedure for stimulus presentation, presentation of test instances and scoring of responses was identical to Experiment 1.



Figure 4. Examples of item presentation in the high salience conditions. All members of the respective categories had the same “virus-shaped” outlines as these instances.

## Results and Discussion

Preliminary analyses established that feature predictions did not vary across counterbalanced versions of the task. All analyses were collapsed across these versions.

Participants in both category salience conditions always identified the target category correctly. Both groups gave modest confidence ratings for these judgments (high

salience:  $M = 61.40$ ,  $SD = 3.70$ ; low salience:  $M = 69.90$ ,  $SD = 15.85$ ). Confidence did not differ as a function of category salience.

The proportion of predictions consistent with feature association was at, or close to, ceiling in both the low ( $M = 1.0$ ) and high salience conditions ( $M = 0.96$ ). A small number of single-category predictions were made in the high-salience condition ( $M = 0.04$ ). No predictions based on multiple-category reasoning were found. Across conditions, the proportion of predictions based on feature association was above chance,  $t(11) = 31.16$ ,  $p < .001$ , and the proportion of predictions based on single-category reasoning was below chance,  $t(11) = -14.98$ ,  $p < .001$ . Confidence in predictions based on feature association was high and did not differ across the salience conditions (high salience:  $M = 84.13$ ; low salience:  $M = 93.02$ ). Participants were classified as using a reasoning approach consistently if at least three of their four predictions were based on this approach. All 12 participants in each salience condition were found to make consistent use of feature association.

Overall these results show that even when steps were taken to highlight the significance of category-level information, feature association remained the dominant approach for making feature predictions under conditions of uncertain category membership.

## General Discussion

These studies examined how people make feature inferences when an exemplar’s category membership is uncertain. Previous work on this issue has suggested two possible reasoning strategies, a Bayesian multiple-category strategy (Anderson, 1991) and a single-category strategy (Murphy & Ross, 1994), with much of the evidence favoring the latter approach. Our studies suggest, however, that when given an opportunity to make predictions based on associations between given and predicted features across available exemplars, most participants will do so. This dominance of reasoning based on feature association was not due to the use of complex stimuli that precluded category-based inference and persisted even when category-level information was made more salient.

These results have important implications for the way that we conceptualize inferential reasoning. There is little doubt that when an object is known with certainty to be a member of a familiar category people will use category-level information to make feature predictions about the object (Heit, 2000; Osherson et al., 1990). When category membership is uncertain, however, our findings show that people will often look for alternatives to category-based reasoning. Specifically, we have shown that when someone knows at least one feature of a target object they will base their predictions about other features on the characteristics of instances that are identical (or similar to) the target, regardless of category bounds.

Previous work has shown that the specific similarity between exemplars often influences categorization judgments even when there are clear rules about category

membership (e.g., Regehr & Brooks, 1993). Our work extends these effects of exemplar similarity to the domain of inference under category uncertainty.

In the current series we found that when making inferences based on feature association people showed little respect for category boundaries, examining all available instances that were similar to the target. It is possible that people may not always ignore category bounds when making inferences based on feature association. As noted earlier, a substantial body of evidence suggests that people often focus their attention on the most likely category to which an object might belong when making feature predictions. Hence, people could make feature association inferences based on a consideration of only a subset of the available exemplars (i.e., those in the target category). This possibility could not be examined in the current study, where feature association based only on target category members did not produce a clear feature prediction. Other work, however, suggests that such “single-category feature association” is rare. Papadopoulos (2008) found that when participants had the option of making feature association predictions based on exemplars from multiple categories or only those from a target category, the overwhelming majority adopted the former approach. This shows that when people can make feature predictions based on feature correlations within specific exemplars, they prefer to use all available exemplars.

Together with Hayes et al. (2007), our data suggest that when category membership is uncertain people may use a broader range of strategies for inductive prediction than has previously been acknowledged. Future work needs to provide a clearer specification of the conditions under which people adopt either feature association or category-level approaches to uncertain inference. An obvious minimal condition for feature association is the presence of salient patterns of co-occurrence between given and to-be-predicted features. What is less clear is whether feature association would persist as a dominant approach to inference if exemplars had to be learned on a trial by trial basis and then retrieved from memory when inferences are required. Under such conditions it seems likely that some of the details of individual exemplars may become unavailable, particularly if there are extended delays between encoding and retrieval (cf. Posner & Keele, 1970). Under such conditions people may fall back on category-level information for feature predictions.

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