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# Eyetracking as an Implicit Measure of Category-Based Induction

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## Abstract

Category information is used to predict unknown properties of category members. Previous research has found that when categorization is uncertain, property predictions do not reflect integration of information across categories as normative principles and Bayesian models would suggest. Rather, people often base their predictions on only the most likely category and disregard information from less likely ones. Research in category-based induction tends to elicit explicit, verbal responses which may not readily allow for integration of information across categories. This paper explores whether changing response mode can promote more normative use of category information in induction. Experiment 1 used an implicit measure of prediction: eye movements. The results suggest that when making predictions implicitly people integrate information across categories. The results of Experiment 2 suggest that the integration of information found in Experiment 1 were not a result of explicit strategies.

**Keywords:** category-based induction; reasoning; implicit processes.

## Introduction

The ability to use category-level information to infer information about novel objects aids our reasoning, social interactions, communication and predictions. By placing an object into a category, we can make predictions about it even though we have never encountered that particular object before. Because you know about the category of Chinese food in general, when you see some Chinese food cartons in your refrigerator you know that there is some chance that the food is spicy, but it's likely not. For our purposes, *category-based induction* refers to a process like the one described above (the extension of category information to a new item in that category). This process becomes more complicated when you are unsure what category an item belongs to. Imagine that your roommate has left unmarked cartons of leftover food in the refrigerator, and you can't tell whether they hold bland Chinese or spicy Indian food. Do you take an acid reducer before eating? You must make a prediction about the food's spiciness based on the characteristics you can observe.

To decide whether the food will be spicy, you should take into account both the possibility that it is Chinese food and the possibility that it is Indian food. This type of reasoning

is consistent with Bayesian approaches to classification and prediction in which people weight different possibilities by their prior likelihoods. Anderson (1991) proposed such a model of category-based induction<sup>1</sup> in which the probability that an object with observed features,  $F$ , has an unobserved feature,  $j$ , is the weighted sum of the probabilities across all categories,  $k$  (assuming they are mutually exclusive):

$$P(j | F) = \sum_k P(k | F) \times P(j | k). \quad (1)$$

Thus, if you were a Bayesian food thief you would take the probability that the unknown food is Chinese food and multiply that by the probability that Chinese food is spicy. Next you would take the probability that the food is Indian food and multiply that by the probability that Indian food is spicy. The sum of the two products is the probability that the food is spicy. This appears normatively correct, since it takes into account your uncertainty and weighs the strength of the prediction accordingly. If very certain that the food is Chinese food you should make a moderate prediction about the likelihood of it being spicy; if uncertain, you should make a stronger prediction. Surprisingly, however, previous research on induction with uncertain categories has provided evidence using both real-life and artificial categories that people usually base their induction on only a single category (Hayes & Newell, 2009; Malt, Ross, & Murphy, 1995; Murphy, Chen, & Ross, 2012; Murphy & Ross, 1994).

These findings are in contrast to those of perception and motor control research that often find that people integrate information across possibilities in a Bayesian manner (Kersten, Mamassian, & Yuille, 2004; Tassinari, Hudson, & Landy, 2006; Trommershäuser, Landy, & Maloney, 2006; Trommershäuser, Maloney, & Landy, 2008). In perception, Bayesian models are used to explain how the visual system takes ambiguous inputs and returns percepts that are most

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<sup>1</sup> In all our experiments, the categories are novel and equally probable, so we omit the prior probability component of Bayesian reasoning. We continue to use the term *Bayesian* because of the common feature of Bayesian models of induction that predictions are integrated across multiple categories, weighted by their likelihood.

likely. People use knowledge about prior probabilities of states of the world and the likelihood of each state given the visual stimulus to arrive at the most probable interpretation of the stimulus (Kersten et al., 2004). In motor control, one action may be best suited to achieve a goal, given the state of the world. But since perception is not perfect, the state of the world is uncertain. Models of action propose that people integrate information about the likelihood of the possible states of the world to make near optimal actions (Haruno, 2001). These actions are sensitive to the payoff structure of the task: Subjects make motor decisions that minimize costs, given the uncertainty of different motor outcomes and the costs and benefits associated with each action (Trommershäuser, Landy, & Maloney, 2006; Trommershäuser, Maloney, & Landy, 2008).

Why might people be unable, or unwilling, to combine information about two categories in category-based induction tasks, but are able to integrate across possibilities and weigh costs and benefits in seemingly more complex perception-action tasks? We suggest that this discrepancy can, in part, be explained by the distinction between implicit and explicit processes (Sloman, 1996). Explicit processes are conscious and rule-based, while implicit processes are unconscious and associative. Explicit reasoning is subject to a reasoning heuristic called *the singularity principle*, which states that people generally only consider one possibility at a time (Evans, 2007). More specifically, we suggest that response mode is critical to whether information is integrated across categories. In category-based induction tasks, subjects often explicitly report what category they think an item belongs to prior to making a prediction. In contrast, perception and motor control experiments tend to depend on implicit responses. Subjects in these experiments are not asked to explicitly consider the potential possibilities (states of the world) but are instead prompted to act on this information (often, but not always, with a motor response).

Chen, Ross, & Murphy (in press) provided evidence that implicit and explicit responding lead to different use of category information during induction. In one experiment, subjects learned artificial categories of moving geometric figures defined by two features: shape and direction. At test, subjects were presented with a shape and asked to predict its direction either implicitly or explicitly. The implicit test was a novel, game-like motor task that elicited a speeded prediction, and the explicit test was a formally identical verbal task that elicited a conscious, unspeeded prediction.

The categories consisted of eight moving geometric figures (see Table 1). There were two critical shapes of interest: squares and hearts. Each of these shapes belonged to one of two categories, the *target* or *secondary* categories. The target category is the category that the shape is most likely to be in given its distribution in the categories. For example, there was a 66% chance that a square belonged to Category 1, the target category, and a 33% chance that it belonged to Category 2, the secondary category (that is, there were eight squares in Category 1 and four in Category 2). In the target category, half of the squares moved in the 1

o'clock direction and half moved in the 5 o'clock direction. In the secondary category, the critical shapes moved in only one direction. In Condition 1, the squares moved to 1 o'clock; in Condition 2, which served to counterbalance the direction of the secondary category, they all moved to 5 o'clock. Therefore, if people only attend to the target category in predicting the direction of a new square, they should be indifferent between predicting movement toward 1 and 5 o'clock, and thus their average prediction should be around 3 o'clock. If they attended to both the target and alternative categories, they should have a preference, because the alternative category (Category 2) would break the tie (in different directions in the two conditions).

This design was replicated for another stimulus and other directions: For hearts, the target category was Category 4, and half of the hearts moved in the 11 o'clock direction and half moved in the 7 o'clock direction. The secondary category was Category 3, and its hearts moved either toward 11 or 7 o'clock, depending on condition (see Table 1). Thus, if people integrated information across categories they would shift their predictions depending on what condition they are in, that is, depending on the less likely, secondary category. All subjects went through an identical learning phase in which they learned all four categories, based on the objects' shapes and direction of movement.

For the implicit test, subjects saw each shape presented briefly in the center of the screen before it rapidly moved off the screen in one of the learned directions. The subjects' task was to catch the shape with their cursor before it disappeared from the screen. Subjects were unable to catch the shapes in the middle of the screen, so they had to place their cursor towards the edge of the screen. Subjects controlled cursor placement and movement with the mouse.

For the explicit test, subjects were presented with static shapes and asked three questions about them: what category the shape was most likely to belong to, the probability their categorization was correct, and what direction the shape was most likely to travel in.

Subjects performed both the implicit and explicit induction tasks (order of tasks was counterbalanced). The results revealed that the exact same category knowledge led to significantly different inductions. Implicit inductions were, on average, shifted towards the secondary category, showing evidence of integration of information across categories. Explicit inductions showed no evidence of normative integration across categories. This pattern of results suggests that response mode is critical in determining how category information is used in induction. This is not to say that all things that make categories implicit lead to integration across categories. In Experiment 4 of Chen et al. (in press), subjects learned categories implicitly and made predictions explicitly. These predictions showed no evidence of integration of information across categories.

While these results suggest that implicit response promotes integration of information across categories, they are in contrast to much research on category-based induction under uncertainty which has consistently found

Table 1: Category Structure used in Experiments 1 and 2 (and Chen et al., in press)

Exemplar	Category 1 (target for squares)		Category 2 (secondary for squares)		Category 3 (secondary for hearts)		Category 4 (target for hearts)	
	Shape	Direction	Shape	Direction*	Shape	Direction*	Shape	Direction
1	Square	1	Square	1/5	Heart	7/11	Heart	7
2	Square	1	Square	1/5	Heart	7/11	Heart	7
3	Square	1	Square	1/5	Heart	7/11	Heart	7
4	Square	1	Square	1/5	Heart	7/11	Heart	7
5	Square	5	Rectangle	1/5	Diamond	7/11	Heart	11
6	Square	5	Rectangle	1/5	Diamond	7/11	Heart	11
7	Square	5	Rectangle	1/5	Diamond	7/11	Heart	11
8	Square	5	Rectangle	1/5	Diamond	7/11	Heart	11

Note. The direction entries are clock directions (1 = 1 o'clock, etc.).

\*The first number refers to the direction in condition 1, the second to condition 2.

that most people based their inferences on only a single category. In Experiment 1, we seek to replicate this result with a different implicit measure of induction: eye movements. In Experiment 2, we provide evidence that subjects are not consciously aware of the strategies used in this implicit induction task.

### Experiment 1

To examine whether subjects would integrate information across categories when making predictions implicitly, Experiment 1 used a cover task, in which predicting movement was incidental. Subjects learned the four categories of moving shapes used in Chen et al. (in press). During test they performed a cover task (same/different task) in which they saw the shapes appear in the center of the screen. The shapes were the same as the ones subjects had learned, except they now had diagonal stripes that were either tilted right or left. After their initial presentation in the center, the shapes moved towards the edge of the computer screen but momentarily disappeared behind an annulus that was on the test screen such that subjects were unable to tell which direction the shape was going to move. Shapes briefly reappeared from behind the annulus and then disappeared off the edge of the screen. When the shapes reappeared from behind the annulus, their stripes may have reversed their tilt (e.g., from left to right). Subjects' task was to report whether the tilt of the stripes was the same or different from when it appeared in the center of the screen.

Thus, subjects were never asked to predict direction or category as they were only questioned about the stripes. However, since the shapes only reappeared briefly, looking close to where they reappeared improved performance (e.g., for squares, it would be beneficial to look near 1 o'clock or 5 o'clock depending on where you thought it would go). Position of eye gaze just prior to the shape's reappearance is the dependent measure as it is a proxy for subjects' prediction of shape direction. If subjects integrate information across categories, fixations should, on average, be shifted towards the direction of the secondary category.

### Method

**Design** Subjects were randomly assigned to one of two between-subjects conditions. The conditions served to counterbalance the direction of the secondary categories.

**Participants** Subjects were 32 undergraduates at New York University who participated for course credit. Data from eight subjects were dropped for not fixating prior to the shape's reappearance on at least five trials. One subject was dropped for not reaching the performance criterion during learning.

**Materials** Stimuli for each category were 8 black shapes approximately 1.75 to 2.5 cm in length, as shown in Table 1. The same shapes were used during test except they had stripes (see Figure 1). The category structure was the same as that used in Chen et al. (in press). See Table 1 for details.

All stimuli were presented on the background of a light gray circle 30 cm in diameter centered on a black computer screen. Stimuli started in the center of the screen and then moved off the screen disappearing once they moved beyond the border of the circle. Eye movements were monitored with the SR Research (Ontario, Canada) EyeLink 1000.

**Procedure** The experiment consisted of three phases: 1) observation, 2) learning, and 3) test. A Macintosh computer presented the instructions and controlled all three phases. Eye movements were recorded during the test phase only.

Subjects were told that they would view four categories of moving shapes and were to learn what combination of shapes and directions belonged to each category for a memory test. During observation, all shapes from each category were presented singly. Each shape appeared in the center of the screen for 1 s, then moved horizontally (towards 3 o'clock for shapes in Categories 1 and 2, towards 9 o'clock for Categories 3 and 4) for .4 s, and then moved towards its assigned clock direction for .95 s until it disappeared off the edge of the gray circle (see Table 1 for directions). Each shape's category name appeared in the center of the screen for the entire time it was on the screen. All exemplars from Category 1 were presented, then all exemplars from Category 2, and so on.

Subjects were next told that they would see the same items as in the observation phase. They were to classify

each shape into one of the four categories by pressing a number key on the keyboard. At the beginning of each trial, a white fixation cross appeared in the center of the screen for 1 s. The shape then moved as they did in the observation phase. There was no time limit on responding. After answering, the correct answer appeared for 1.25 s. After an error, subjects viewed a repeat display (without responding) of the moving shape with the correct category displayed. There were four learning blocks in which each of the 32 items was tested in random order. Because of the category uncertainty of the critical items (e.g., a square could be in Categories 1 or 2), subjects could get no more than 75% correct, assuming they chose the most likely category for all presented stimuli. In all experiments subjects had to reach at least 50% correct during the final block of learning to be included in analysis.

The final phase of the experiment consisted of a 64-trial test in which subjects had to perform the same/different task while their eye movements were tracked by the EyeLink 1000. Subjects saw the same items they had seen in the previous phases except that the shapes would now move a little bit faster and have diagonal stripes on them. These shapes would appear in the center of the screen (for 1 s) and continue to move along the same path as in previous phases. However, there was now a black annulus on the screen such that the shape would move horizontally (for .25 s) and then disappear behind the annulus for .7 s. The shape would then reappear from behind the annulus just before it disappeared from the screen. (After the shape's reappearance from behind the annulus it was visible for .15 s before it disappeared.) Recall that all stimuli were presented on a gray circle 30 cm in diameter. The annulus (24 cm in diameter) was centered on this image. Its center hole had a diameter of 8 cm (see Figure 2).

The stripes on a test object were either tilted left or right when the shape initially appeared (see Figure 1). The subjects' task was to report whether the direction of the stripes was the same or different when it reappeared. The direction of stripes remained the same for half of the trials and changed for the other half. Subjects saw a 1.25 s feedback message. There were five practice trials prior to the test phase. As shapes only briefly reappeared from behind the annulus, looking close to where shapes reappeared was beneficial. Thus, fixation location just prior to the shape's reappearance was used as a proxy for prediction of direction and as the dependent measure. (Recall that horizontal movement for the critical shapes did not indicate its category as the horizontal direction was the same for Categories 1 and 2, and Categories 3 and 4.)



Figure 1: Example of stimuli used in the test phase of Experiments 1 and 2.

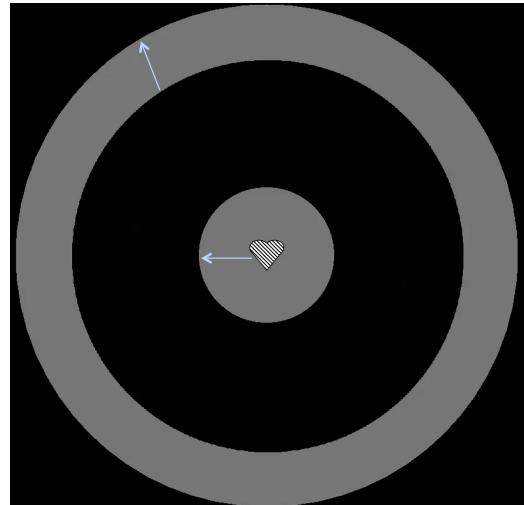


Figure 2: Illustration of the implicit induction task. The shape appeared in the center of the screen for 1s. It then moved horizontally for .25 s and disappeared behind the annulus while traveling on its path (learned in phase 1). Subjects reported whether the diagonal lines had changed when it reappeared. Arrows indicate the shape's path when it was visible and did not appear in the experiment.

**Data Analysis** Responses for critical shape trials were coded such that a position exactly in between the two possible directions of the shape was 0 degrees, and a shift from that point towards the direction reinforced by the secondary category was coded as positive. For example, for the squares in Condition 1 (which might move to 1 o'clock or 5 o'clock), the 3 o'clock position was 0 degrees, the 1 o'clock position (the direction of the secondary category) was 60 degrees, and the 5 o'clock position was -60 degrees. In Condition 2, the latter values were reversed. We obtained the mean fixation position for each subject by averaging the mean fixation position for squares and hearts. Thus, use of a single category (i.e., use of only the target category) is evidenced by an average prediction of 0 deg. Normative use of categories is evidenced by a positive average prediction, as this represents a shift from 0 deg in the direction of the secondary category.

Trials in which the fixation position was greater than 100 degrees or less than -100 degrees were not included in the analysis because the subject was fixated on the opposite side of the screen from where the shape traveled, indicating that the subject either forgot where the shapes went, or did not see the shape correctly prior to its movement. Additionally, trials where fixation was within the hole of the annulus were excluded from analysis. When subjects looked at the center of the screen while doing the task, they were effectively not making a prediction about direction.

## Results & Discussion

Subjects were on average 66.4% correct (chance = 25%) during their last training block, suggesting that they learned the categories quite well. (Recall that maximum performance was 75%, if subjects always classified

ambiguous items into the most likely category.) Performance on the same/difference task averaged 72%.

As explained above, integration of information across categories is evidenced by a shift from 0 deg in the direction of the secondary category, which we coded as positive. This is indeed what we found. The mean fixation position for the critical shapes, ( $M = 7.5$  deg,  $SD = 8.9$ ), was significantly greater than 0 deg,  $t(23) = 4.1$ ,  $p < .01$ ,  $d = .84$ , indicating that people's predictions of direction were integrated across the two categories. The mean fixation position was positive for 21 of the 24 subjects. These results are consistent with those of Chen et al. (in press) and suggest that implicit induction promotes integration of information across categories. A question for future research will be to examine how categories are used during implicit induction. The multiple category use found in Experiment 1 may be a result of a feature-level strategy (e.g., using information about only squares when making a prediction about where a square will go) rather than a category-level strategy like that described in Eq 1 (see Griffiths et al., 2011, for similar ideas).

Perhaps subjects did not truly induce the objects' direction but learned to change their eye movements via practice in doing the task. To examine this possibility we compared the mean fixation position for the first and second blocks of testing. The difference between the mean fixation positions for the first and second blocks was not significant ( $M_s = 6.2$  and  $8.8$  deg,  $SD_s = 9.1$  and  $11.9$ ),  $t(23) = 1.0$ ,  $p > .05$ ,  $d = .25$  suggesting that subjects' normative use of categories was not a result of learning during test. The positive shift in eye movements was significant in block 1,  $t(23) = 3.3$ ,  $p < .01$ ,  $d = 6.8$ , and in block 2,  $t(23) = 3.6$ ,  $p < .01$ ,  $d = .76$ .

## Experiment 2

Experiment 1 revealed that people use information from multiple categories when making inductions implicitly. However, it is possible that the placement of eye fixation was not the result of implicit processes but instead the result of a conscious strategy (i.e., after practice subjects could have realized that they would perform better when they looked closer to the direction reinforced by the secondary category). Experiment 2 tested this explanation. Subjects completed the full learning procedure of Experiment 1. They then saw a few example trials of the same/different task and then reported (using feedback from the eyetracker) where they would look to best perform the task. This question sampled subjects' explicit beliefs about where they would look. If the results match those of Experiment 1, this would suggest that the fixations were the result of an explicit strategy.

### Method

**Participants** Subjects were 21 New York University undergraduates who participated for course credit. Data from four subjects were dropped for not fixating on at least

three trials. One more subject was dropped for not reaching the performance criterion during learning.

**Materials and Design** Identical to Experiment 1.

**Procedure** The procedures of the observation and learning phases were identical to those used in Experiment 1. As with Experiment 1, eye movements were only recorded during the test phase. The test phase consisted of a 16-trial test in which subjects were asked to report where they would look in order to best do the same/different task that subjects in Experiment 1 performed. Subjects saw the same five practice trials used in Experiment 1 and then were told that they would not be doing the task but rather reporting where they would look just prior to the shape's reappearance from behind the annulus to best do the task. In order to keep the dependent measures of the two experiments similar, we used eye position to indicate this prediction. A white dot on the display indicated where the subjects were looking. The task was to look at the location on the screen that they thought would be best to do the same/different task they had just observed. They then saw a test screen (gray circle with the annulus) and were instructed to look around the screen to get a sense of how the white dot corresponded to their eye gaze.

The test phase consisted of four blocks in which each shape was tested once in random order (except that shapes were not queried twice in a row). Each test trial started with the presentation of the shape in the center of the screen for 1 s. It then moved horizontally for .25 s until it disappeared behind the annulus (the shape never reappeared). Subjects then saw the white dot that marked their eye gaze on the screen. To report their location, subjects moved their eyes until they were satisfied with the location of the white dot and then pressed the enter key. The white dot stayed on the screen for 1.25 s so that the subjects could see their answer.

### Results & Discussion

Subjects were on average 68.2% correct (chance = 25%) during their last training block, near the 75% maximum, suggesting that they learned the categories quite well.

As in the analysis of Experiment 1, subjects' responses for the critical shapes were coded such that the time corresponding to the point exactly in between the two possible directions of the shape was 0 degrees (3 o'clock for squares and 9 o'clock for hearts, and a shift towards the direction reinforced by the secondary category was positive). To find the mean prediction (the amount of shift from 0 deg towards the secondary category) for each subject, we calculated the mean prediction for each shape and took the average of the two. The mean prediction ( $M = 0.2$  deg,  $SD = 2.9$  deg) was not significantly different than the average observed direction for the shapes in their target category only (0 deg),  $t(15) = 0.2$ ,  $p > .05$ ,  $d = .07$ , suggesting that subjects were not basing their responses on multiple categories. Subjects chose locations around 0 deg the majority of the time. In fact, 84% of all responses were within 10 deg of 0 deg. In contrast, in Experiment 1, only 25% were in this range.

These predictions from this experiment show no integration of information across categories. This suggests that the integration of information across categories found in Experiment 1 was not the result of a conscious decision or strategy and provides further evidence that response mode is critical to how category information is used in induction.

### General Discussion

The results of Experiment 1 suggest that people integrate information across categories when making inductions implicitly. The results of Experiment 2 revealed that explicit prediction of eye fixation position in the same/different task showed no evidence of integration of information, suggesting that subjects were unaware of the strategies used to perform the task. Taken together, these results suggest that response mode is critical in determining when people integrate information across categories when making inductions and that the single category focus found in previous research on category-based induction may result from conscious reasoning strategies. These results are consistent with the findings of Chen et al. (in press), that speeded catching of a stimulus also showed integration across categories, but verbal predictions did not. These results also help explain the discrepancy between studies of induction in reasoning vs. perception and action.

Our findings suggest that implicit responses can, at least sometimes, lead to greater use of available information than our conscious, explicit responses do. This is particularly important because many everyday predictions are about items whose categorizations we may be unsure of. Doctors may have to predict which treatment is most likely to work even though they are not certain what the correct diagnosis is. A person who is walking alone at night and sees an unknown person approaching may have to decide whether to avoid the person despite being unsure whether that person belongs to the category of mugger or pedestrian. The results of the present experiments help in understanding which situations and contexts people are most likely to consider alternative possibilities and make predictions based on relevant information from them.

Additionally, many of these inferences can be made either implicitly or explicitly (e.g., one might run upon seeing an unknown person approaching, but given more time, one may exclude less likely possibilities and act as if certain that the unknown person is a pedestrian). In fact, in social psychology, a similar distinction has been made between automatic and controlled processes in prejudice. Automatic processes are often associated with stereotype activation (a type category-based induction) which, in low-prejudice people, conflicts with explicit attitudes and is inhibited in favor of explicit beliefs (Devine, 1989). Thus, the explicit system's bias to disregard or avoid information from alternative categories (that made it less normative in our task) could, in other cases, lead to more normative responses. Our research shows that this distinction is crucial for understanding when category-based predictions are more likely to be accurate or inaccurate.

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