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Representing Categorical Knowledge: An fMRI Study

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Abstract

This paper investigated the nature of mental representation of categorical knowledge by examining the neural substrates that support classification and feature inferences. The results from one experiment suggest that frontal lobe regions were activated when an inference task was given, while temporal lobe regions, especially the fusiform gyrus, became active when a classification task was given. These results are consistent with the view that categorical knowledge is mediated by two separate neural structures, and further indicate that two interrelated functions of categories – classification and feature inference – are processed by distinct brain regions.

Human knowledge is organized largely by categories that we form in everyday situations. Many of man-made names, such as “terrorists,” “fundamentalists” or names of natural objects such as dogs and cats are all categorically arranged. Perhaps, because of this generic characteristic of knowledge representation, we are able to carry out many complex and abstract tasks such as communication, reasoning, and solving math problems relatively easily.

How do we represent categorical knowledge in our brain? In this paper, we examined the neural structures that support the representation of categorical knowledge. We addressed this problem by comparing two basic functions of categories – classification and feature inference. Classification and inference are two of the most important functions of categories (Smith, 1994). The very reason why human concepts are organized categorically is said to license inferential predictions (Anderson, 1990; Rosch, 1978). In this regard, we consider that scrutinizing the underlying neural structures of these two functions would provide a crucial clue to understand the nature of mental representations of categorical knowledge.

Despite the close relationship between classification and feature inference, much research in concept formation in the last 40 years has focused on the investigation of classification (see Murphy 2002 for review). These studies suggest that subjects acquire some form of “category-level knowledge” after extended training of classification (see Medin & Schaffer, 1978; Posner & Keele, 1968). That is, (1) subjects are able to classify new items accurately even though they have never seen exactly the same items during a learning phase; (2) their accuracy of classification transfer depends on the degree of feature overlap between a transfer item and studied items; (3) subjects generally classify non-studied prototypes (average instances) as accurately as studied items.

A dominant theory of category learning explains that the aforementioned effects of category learning arise because participants in an experiment make classifications by measuring similarities between a new target item and old exemplars that were stored in memory. In this theory, the mental representation of category-level knowledge consists of the episodic memory trace of the instances that were experienced during learning (Medin & Schaffer, 1978; Nosofsky, 1986; Kruschke, 1992).

Although this theory has received an impressive amount of support from a variety of studies, this view has met serious challenge from two sources: (A) Patients who have severe damage to hippocampus and the medial temporal lobe learn to classify new items as accurately as normal control subjects, while their recognition memory for training items is severely impaired (Knowlton & Squire, 1993; Squire & Knowlton, 1995; but see also Nosofsky & Zaki, 1998; Palmeri & Flanery, 1999; for an alternative explanation); (B) The extent to which specific exemplar information affects category-level representations depends on the task and the structure of categories that are employed in a category learning task (Smith & Minda, 1998; Maddox, et al., 2003; Markman & Ross, 2003; Ross, 1997; Smith, Patalano, & Jonides, 1998; Strange et al. 2001; Yamauchi & Markman, 1998). For example, recent neuroimaging studies have reported increased activities in the vicinity of the frontal lobe during categorization tasks that require an application of abstract rules (Smith et al. 1998; Strange et al. 2001), while the temporal lobe is responsible for object recognition and classification (e.g., Haxby et al. 2001)

These findings indicate that the mental representation of categorical knowledge is likely to consist of multiple neural substrates – one that processes similarity-based associative information, and the other that assesses rule-based abstract information (Ashby, et al., 1998; Erickson & Kruschke, 1998; Smith et al., 1998).

Consistent with this suggestion, our studies have indicated that different types of information are used for classification and feature inference: Subjects often rely on the information about concrete instances to make classifications, while they use abstract rule-like information to make feature inferences (Yamauchi & Markman, 2000).

On the basis of these findings, we reasoned that if categorical knowledge in general is represented by multiple neural substrates, then the category information acquired by a particular single learning task should generate a mental representation that encompasses separate brain regions;

Table 1: Category Structure

stimulus	category	form	size	color	position
A0	A	1	1	1	1
A1	A	1	1	1	0
A2	A	1	1	0	1
A3	A	1	0	1	1
A4	A	0	1	1	1
B0	B	0	0	0	0
B1	B	0	0	0	1
B2	B	0	0	1	0
B3	B	0	1	0	0
B4	B	1	0	0	0

Note. A “correct” response in an inference question is defined as those consistent with the feature value of the corresponding prototype stimulus (i.e., values 1 in Set A, and values 0 in Set B).

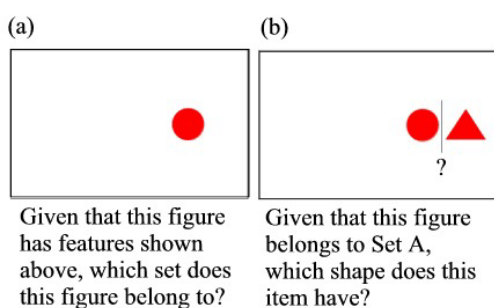


Figure 1: Samples of a classification trial and an inference trial

furthermore, such a representation should be selectively accessed by a classification test and an inference test. We tested this hypothesis in the following experiment.

In our experiments, participants learned two arbitrary categories incrementally either in a classification task or in a feature inference task (Nosofsky, 1986; Medin & Schaffer, 1978; Yamauchi & Markman, 1998). Stimuli were geometric figures similar to those used in the Medin and Schaffer study (1978) (Figure 1). In a classification task, participants predicted the category membership of a stimulus on the basis of the information about other four features; in an inference task, participants predicted an unknown value of a feature on the basis of the information about the other three features and the category membership of the stimulus. After each trial, participants received feedback.

Our main focus of investigation was concerned with the characteristics of the mental representation thus formed after classification learning or inference learning. Given the hypothesis that category representation incorporates two types of information – similarity-based exemplar information and rule-based abstract information, we hypothesized that two different brain regions should become primarily active in the same subjects. More specifically, we predicted that, *irrespective of the format of learning*, the frontal lobe region that supports rule-based abstract information becomes active when an inference transfer task is given; in contrast other

cortical areas such as the medial temporal lobe should become primarily active when a classification task is given.

Experiment

Participants & Materials Participants were 34 students at Rutgers University who participated in this experiment for course credit. The data from 2 participants were lost for fMRI analyses. In total, there were 16 participants in a classification learning condition and 16 participants in an inference learning condition.

The stimuli were geometric figures that were differentiated with 4 feature dimensions of binary values – form (circle/triangle), color (red/green), size (large/small), and position (left/right). Each stimulus was bound by a rectangular frame drawn with a solid black line on the computer screen. These stimuli were equivalent to those employed in the Medin and Schaffer (1978) study.

Table 1 shows the structure of the two categories. A single stimulus set was produced from two prototypes by changing one of the four feature values. For example, the prototype of Category A was arbitrarily determined with the values of (1, 1, 1, 1) = (form=circle, color=red, size=large, position=left), and the prototype of Category B was defined with values of (0, 0, 0, 0) = (Form=square, color=green, size=small, position=right). To produce a training stimulus, A1 (1, 1, 1, 0), the feature value of position in A0 was replaced with that of B0. In this manner, no single feature deterministically divides the two categories, and every stimulus used in training possessed three features consistent with the prototype of the corresponding category and one feature consistent with the prototype of the opposite category. Hereafter, the feature values that were consistent with the opposite prototypes were called “exception-features.”

Procedure The basic procedure of the experiment consisted of three phases – a learning phase, a filler phase, and a transfer phase, which were given in sequence. The learning phase was further subdivided into two between-subjects conditions – the classification learning condition, and the inference learning condition. The filler phase and the transfer phase were identical in all participants.

Learning Phase In the classification learning condition, participants were shown one of the eight training stimuli and were asked to indicate the category to which it belonged by pressing a specified response key (Figure 1a). In the inference learning condition, participants made inferences of one of four features while its category label and the remaining three feature values were depicted in the stimulus frame. For example, in Figure 1b, participants were presented with a stimulus frame depicting the size, color, and position of the item as well as its category label, and the form of the item was left unspecified. Participants were asked to select one of the two values of the unspecified feature. For each stimulus, the location of the correct choice was determined randomly.

Initially, no information about the category was given, and participants had to guess. Following each response, feedback was provided together with the entire display of a stimulus and its category label. The stimulus frames for feedback were

identical in the two learning conditions. In classification learning, participants saw all eight exemplars except for the two prototypes (i.e., A0 (1, 1, 1, 1), B0 (0, 0, 0, 0)). In inference learning, participants answered all feature questions for each stimulus except for the feature questions associated with the two prototypes (e.g., A0 (? , 1, 1, 1, 1, 1)). This arrangement was made to equate the two learning conditions as much as possible (see Yamauchi & Markman, 1998).

In the classification learning condition, each block consisted of 8 different classification questions that corresponded to 8 exemplar stimuli of the two categories. In the inference learning condition, each block had 4 different feature questions (form, color, size, and position) associated with 8 different exemplars of the two categories. In this manner, all 24 inference questions excluding exception-feature values of individual stimuli were carried in three consecutive blocks of the inference learning condition. These three blocks were presented in the same order throughout the learning phase. Within each block, the order of presenting individual questions was determined randomly.

The stimulus presentation schedule in the two learning conditions was as follows: (1) a fixation point appeared for 2 seconds, (2) a stimulus (either a classification question or an inference question) was presented for 6 seconds, (3) a response frame, in which a response was solicited, appeared for 4 seconds, (4) a feedback frame was shown for 4 seconds. All participants carried out the learning phase with this presentation schedule.

The learning phase consisted of a total of 96 trials (12 blocks). The learning phase was divided into four sessions of 24 trials. All participants received a short break after each session.

Filler Phase Immediately at the completion of the learning phase, all participants were given an anatomical scanning (i.e., MP-RAGE) trial, in which the anatomical images of individual participants were registered. This phase lasted approximately 10 minutes.

Transfer Phase The stimulus presentation schedule of the transfer phase, which was identical in all participants, was as follows: (1) a fixation point appeared for 2 seconds, (2) a stimulus (either a classification question or an inference question) was presented for 6 seconds, (3) a response frame appeared for 4 seconds. No feedback was given for the transfer tasks.

Participants were first given 10 classification transfer questions and then 32 inference questions. The 10 classification questions consisted of 8 classification questions of the 8 exemplars of the two categories and 2 prototypes. These 8 classification questions were “old” in the sense that these stimuli were presented during the learning phase. The 2 other classification questions were “new” in the sense that these stimuli were never presented during the learning phase. The order of presenting classification transfer questions was determined randomly. Immediately after completing all the classification transfer questions, participants answered 32 inference transfer questions. These questions encompassed all possible feature inferences of 8 stimuli (4 feature questions

for 8 stimuli). The order of presenting inference transfer questions was determined randomly. The instructions specifically asked participants to make their decisions based on the categories learned during the learning phase.

fMRI data acquisitions The data consisted of 32 axial slices (3.0mm thick, no gap) BOLD collected from a Siemens 3T Allegra using a gradient echo EPI (TR = 2000ms, TE = 30 3.0mm thick axial images, field of view = 220mm, matrix size = 64 x 64). We collected five BOLD data sets (four during the learning phase and one during the transfer phase) and two anatomical images were recorded twice for each subject before the Learning phase and during the Filler phase. All BOLD data collections lasted for the entire session for the learning phase or the entire session for the transfer phase. No data was acquired during 4 short breaks in the learning phase.

Design The experiment employed an one-between-factor (learning condition: classification learning vs. inference learning) repeated measure (transfer task: classification transfer vs. inference transfer) design. The dependent measure for the behavioral analyses was the proportion of “correct classifications” and “correct inferences” (see Table 1 for the definitions of “correct” responses). In order to account for meaningful differences in brain activities associated with classification and inference tasks, we screened out participants who performed less than 80% accuracy in the last 3 blocks of the training trials. In addition, in order to find the differences in brain activities associated with classification and inference of category, but not particular learning strategies, we were only concerned about within-subject differences in those tasks and thus analyze only BOLD data from the transfer session.

Our analysis was carried out using FEAT Version 5.4, part of FSL (FMRIB’s Software Library). The following pre-statistics processing was applied; motion correction using MCFLIRT (Jenkinson 2002); non-brain removal using BET (Smith 2002); spatial smoothing using a Gaussian kernel of FWHM 5mm; mean-based intensity normalization of all volumes by the same factor; highpass temporal filtering (Gaussian-weighted LSF straight line fitting, with $\sigma=12.5s$). Low-level time-series statistical analysis for individual subjects was carried out using FILM with local autocorrelation correction (Woolrich 2001) with Gamma convolution ($SD = 3$ and mean lag = 3.0s) for the hemodynamic responses. Registration to high resolution and standard images was carried out using FLIRT (Jenkinson, 2001 & 2002). Higher-level analysis was carried out using FLAME (FMRIB’s Local Analysis of Mixed Effects) (Beckmann, et al. 2003; Woolrich, et al., 2004).

Results

Behavioral Analyses We first report the results from behavioral data (see Table 2), and then form the fMRI data.

Learning Performance We first discuss participants’ learning performance for the last 24 trials (3 blocks) of the learning tasks and examine whether or not participants in the two learning conditions reached approximately the same level of

learning performance. This analysis showed that participants in the two learning conditions were equally accurate; $t(30) = 0.15, p = 0.88$. Cohen's $d = 0.05$. Overall, 10 out of the 16 participants in the inference learning condition reached an accuracy level of 80% or above ($M = 0.83, SD = 0.20$), and 10 out of the 16 participants in the classification learning condition reached an accuracy level of 80% or above ($M = 0.82, SD = 0.19$). For our fMRI analyses we used the data taken from these 20 participants (10 participants in each condition) to make sure that the two groups of participants were equivalent in their learning performance. The accuracy of these selected sets of participants was statistically indistinguishable; Inference condition, $M = 0.958, SD = 0.071$; Classification condition, $M = 0.930, SD = 0.061$; $t(18) = 0.95, p = 0.36, d = 0.43$.

Transfer Performance Table 2 shows the transfer performance of the participants in the two learning conditions. Because our fMRI analyses were applied only to the data obtained from the 20 selected participants (see above), we will report behavioral results obtained from these participants alone. First, participants in the two conditions were generally able to generalize one mode of learning procedure to another; yet their transfer performance was better when their learning task and their transfer task matched than when these two tasks miss-matched.

Overall, participants in the two conditions were able to perform the classification transfer tasks and the inference transfer tasks better than a chance level; $t(9) > 4.28, p < 0.01$ for all four dependent measures. A 2 (learning condition) \times 2 (transfer task) ANOVA revealed that the two learning conditions were not different in their overall transfer performance, $F(1, 18) = 1.07, MSE = 0.035, p = 0.31, \eta^2 = 0.056$; most importantly, the main effect of transfer task was not significant; $F(1, 18) = 2.50, MSE = 0.009, p = 0.13, \eta^2 = 0.122$, suggesting that the overall accuracy of the two transfer tasks was not statistically different. An interaction effect of the two factors was significant; $F(1, 18) = 18.03, MSE = 0.009, p < 0.01, \eta^2 = 0.500$. Given the inference transfer task, participants in the inference condition were more accurate than participants in the classification condition; $t(18) = 3.02, p < 0.05, d = 1.13$. In the classification learning condition, participants were significantly better in classification transfer than inference transfer; $t(9) = 4.13, p < 0.05, d = 1.31$.

Taken together, these results suggest that (1) the two categories learned by one task (either classification or inference) can give rise to a representation that can handle both the classification transfer task and the inference transfer

task; (2) in general, transfer performance was better when the learning task and the transfer task matched.

fMRI Analyses Table 3 shows the areas that exhibited significant and differential activations for the classification or inference tasks. Since the numbers of data points differ in the two sets of transfer data, we used different threshold values for those data sets. The voxels with Z-values larger than 3.50 and Z-values larger than 2.00 were plotted for the classification and inference, respectively. Figure 2 shows the areas that exhibited higher activations during the classification transfer task as compared to the activations observed during the inference transfer task. Most notable activations occurred in the fusiform gyrus, Brodmann's area 37 (BA37), the superior parietal gyrus (BA7); and the cuneus (BA18) in the occipital lobe. In contrast, Figure 3 shows the areas that exhibited higher activations during the inference transfer task as compared to the classification task. These areas include the right inferior frontal gyrus (BA47), the medial

Table 3: List of activation areas

Task	Region of activation	BA	L/R	Z
CL	Fusiform Gyrus	37	L&R	6.17
CL	Cuneus	18	L&R	4.33
CL	Superior Parietal	7	L&R	4.26
INF	Inferior Frontal	47	R	3.13
INF	Medial Frontal	10	L&R	2.60
INF	Cingulate & Anterior Cingulate	24/31	L&R	3.40
INF	Superior Temporal	22/38	R	2.88

Note: CL=classification transfer task, INF=inference transfer task, BA=Brodmann's area, L/R=Left/Right hemisphere

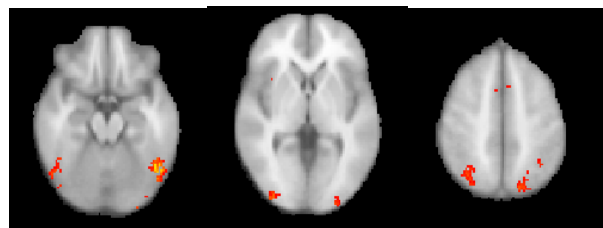


Figure 2 Brain areas that have more activation in classification tasks than inference tasks. The areas include fusiform gyrus (left), cuneus (middle), and superior parietal gyrus (right)

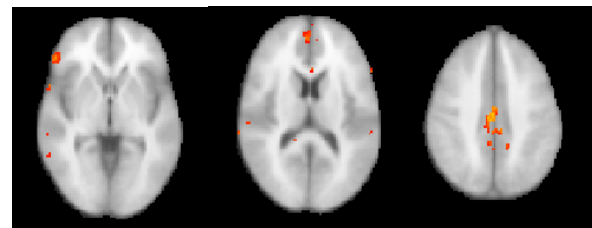


Figure 3 Brain areas that have more activation in inference tasks than classification tasks. The areas include, right inferior gyrus, right superior temporal lobe (left), medial prefrontal gyrus (middle), and cingulate (right).

Table 2: Transfer Performance - Means and standard deviations (enclosed in parentheses)

Training Condition	Transfer Task	
	Classification	Inference
Classification	0.882 (0.153)	0.703 (0.109)
Inference	0.827 (0.145)	0.911 (0.124)
Average	0.854 (0.149)	0.807 (0.171)

frontal gyrus (BA10), the right superior temporal gyrus (BA38), the cingulate (BA 24, BA31) and the anterior cingulate (BA24).

Interpretations - Classification Task: It is widely accepted that the fusiform gyrus is associated with object recognition (e.g. Haxby et al., 2001). This may indicate that the classification process was driven by some concrete identification mechanism related to the recognition of individual stimuli. The increased activity in the cuneus may be explained by its role in memory retrieval. That is, in the classification task participants probably tried to compare a target stimulus (to be categorized) with previously encountered exemplars in order to classify the target stimulus correctly. This indicates that the classification process indeed requires some form of memory-based process (e.g. Smith et al., 1998; Nosofsky, 1986). However, it is uncertain what sort of memory was retrieved in this process (e.g., exemplars vs. prototypes). It is, however, as discussed below, less likely to be a retrieval of rules. Another important function of the cuneus is visual and spatial attention. A number of studies have shown that classification learning increases attention to the features that divide between categories (Goldstone, 1995). The observed activation in the cuneus is likely to reflect this attentional shift in classification. Similarly, the superior parietal lobe is known to mediate selective attention. Although, this observation is not consistent with the results of a neuroimaging study by Smith et al. (1998), in which increased activities in the superior parietal lobe was observed during rule application, but not in memory based processes, we find our result (involvement of attention process in classification) to be consistent with the results of several recent computational modeling studies; Some computational models incorporating selective attention process (Nosofsky, 1986; Kruschke, 1992) have been successful in accounting for many psychological phenomena, and thus it is highly possible that this memory-based process requires selective tuning of attention processes. However, we do not have a clear interpretation why the classification task requires a “greater” amount of (spatial) selective attention than the inference task, given that the stimuli used in the present experiment were qualitatively identical. Our hypothesis is that classification tasks and inference tasks require or induce different types of attention mechanisms recruited while examining either stimulus features or category label.

Interpretations - Inference Task: We found that several different brain areas were activated during the inference task, namely the right inferior frontal gyrus (BA47, a part of Broca’s area), medial frontal gyrus (BA10), superior temporal lobe (BA38), cingulate (BA24 & BA31) and anterior cingulate (BA24). In particular, increased activities in the right inferior frontal gyrus and the medial frontal gyrus agree with previous neuroimaging findings on rule-applying categorization tasks. For example, Smith et al. (1998) observed an increased activity in right dorsolateral prefrontal cortex (BA46), which is also part of Broca’s area. In addition, Strange et al. (2001) observed an involvement of the Fronto-

polar prefrontal cortex (BA10) during rule learning. In general these frontal lobe areas are suggested to be important for executive functions. In addition, the right inferior frontal gyrus is known to be related to language processing, including abstract grammar computation (Sahin et al., 2004), and the medial frontal gyrus is associated with working memory (e.g., buffering & retrieval)

In addition to those “rule” areas, we observed a significant activity in the right superior temporal lobe, which can be considered as a part of Wernicke’s area, another area for language processing. This area has further interesting functions; for example, a study indicates that this area is involved when a difficult exploratory search through feature items was required (Ellison, et al 2004); and Jung-Beeman et al. (2004) reported that this area is involved in solving verbal problems insightfully (e.g., “aha!” moment)

Finally, we observed an increased activity in the cingulate and anterior cingulate cortex (ACC), probably playing an important role as an executive attention system by relegating tasks to achieve efficient usage of brain areas (Posner & Raichle, 1994). The cingulate and ACC might have been involved in switching attentional targets between category label and visual features of stimuli during inference task.

In sum, for the inference task, we observed several brain areas that are associated with language processing. This finding perhaps indicates that despite their visual presentation the stimuli were semantically processed as participants made feature inferences.

General Discussion

Discussion on fMRI results: Our findings suggest that multiple neural circuits mediate the representation of categorical knowledge – one that supports abstract rule-like information and the other that records concrete exemplar information. The results from the present neuroimaging study indicate that classification requires a process that is oriented to perceptual information, while feature inference relies on more abstract and semantically oriented processes. Previous research showing distinctive neural circuits involved in memory-based and rule-applying processes may be described by these two differences-

Our findings further suggest there are more than one attention systems involved in categorization processes. It is, however, unclear what triggered different attention processes. That is, it might have been the differential processes of category label and stimuli feature, differences in memory-based and rule-applying processes, and/or difference in perceptual and semantic processes.

This distinction between semantic and perceptual information reflects the verbal and nonverbal distinction suggested by Ashby et al. (1998). Category labels are most typically expressed verbally, while other features are most typically expressed visually. Furthermore, category labels, which specify category membership, correspond to an object as a whole, while features correspond to specific parts of an object. Processing an overall aspect of an object and parts of objects may require different neural mechanisms.

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