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Using Multivariate Pattern Analysis to Identify Conceptual Knowledge Representation in the Brain

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Using Multivariate Pattern Analysis to Identify Conceptual Knowledge Representation in the Brain

by

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Dedication

To my mother

Abstract

Representation of semantic knowledge is an important aspect of cognitive function. The processing of concrete (e.g., *book*) and abstract (e.g., *freedom*) semantic concepts show systematic differences on various behavioral measures in both healthy and clinical populations. However, previous studies examining the difference in the neural substrates correlating with abstract and concrete concept representations have reached inconsistent conclusions. This dissertation used multiple novel data analyses approaches on functional magnetic resonance imaging (fMRI) data, to investigate representational differences of abstract and concrete concepts and to provide converging evidence that the representations of abstract and concrete semantic knowledge in the brain rely on different mechanisms.

Study 1 used meta-analysis method on a combined sample of 303 participants to quantitatively summarize the published neuroimaging studies on the brain regions with category-specific activations. Results suggested greater engagement of working memory and language system for processing abstract concepts, and greater engagement of the visual perceptual system for processing of concrete concepts, likely via mental imagery. Study 2 showed successful identifications of single trial fMRI data as being associated with the processing of either abstract or concrete concepts based on multivoxel activity patterns in widespread brain areas, suggesting that abstract vs. concrete differences were represented by multiple mechanisms. Study 3 investigated the classification based on condition-specific connectivity patterns. Results showed successful identifications of the

connectivity patterns as abstract or concrete for an individual based on the connectivity patterns of other individuals, both by the connectivity for *a priory* selected seed regions as well as by the whole-brain voxel-by-voxel connectivity patterns. The results indicated the existence of condition-specific connectivity patterns that were consistent across individuals on a whole-brain scale. Moreover, the results also suggested the representation of abstract and concrete concepts differs from the semantic association perspective in addition to differences on coding forms. Study 4 illustrated the application of MVPA as a cross-modal prediction approach, which is a promising method for further investigation of semantic knowledge representation in the brain, by investigating the role of general semantic system on person-specific knowledge.

Overall, the work described in this dissertation provides converging evidence of the representational difference between abstract and concrete concepts. The differences are suggested to occur at various levels, including the dependence on modality-specific perceptual systems, the organization of associations among different semantic-related systems, and the difficulty and strategy of retrieving contextual information.

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List of Abbreviations

ATL .... Anterior temporal lobe

EEG .... Electroencephalography

fMRI .... Functional magnetic resonance imaging

IFG .... Inferior frontal gyrus

MEG .... Magnetoencephalography

MVPA .... Multivariate pattern analysis

PET .... Positron emission tomography

pSTS/MTG .... Posterior temporal sulcus / middle temporal gyrus

TMS .... Transcranial magnetic stimulation

Chapter 1

Introduction

Representations of concrete and abstract concepts in the brain are relevant to understanding language function in both healthy and clinical populations (Eviatar, Menn, & Zaidel, 1990; Kuperberg, West, Lakshmanan, & Goff, 2008; Mervis & John, 2008). The concreteness of a semantic concept is commonly defined as the extent to which a word refers to features of objects that can be sensually experienced. Concepts that are associated with physical entities are regarded as concrete, while those associated with mental events are regarded as abstract.

Neuropsychological studies have motivated important proposals on the organization principles of concepts, while the introduction of neuroimaging techniques has largely facilitated the investigations on the functional architecture of conceptual representations. The large body of neuropsychological and neuroimaging literature treats the two categories of concepts separately, investigating either the organizations of knowledge about concrete concepts, or the overall difference between abstract and concrete concept representations. The main studies reported in this dissertation focused on the latter aspect. The current chapter will first selectively review several prevailing theories and the empirical neuroimaging evidence on both the representation of concrete concepts and its difference from the representation of abstract concepts, to offer a context of the following chapters in this dissertation.

1.1. Organization of concrete concepts in the brain

1.1.1. Neuropsychological motivations and theories

The conceptual knowledge about objects constitutes a significant proportion of the concrete concepts. Our knowledge about objects is largely acquired through direct experience of the material world (Bloom, 2000). The organization of these concepts is unlikely to be the mere mapping of taxonomies based on definitions (Rosch, 1975).The way we perceive, interpret, or interact with objects during knowledge acquisition or later daily experience may influence the representations of object concepts in the brain. Studies on the neural representation of object concepts have been largely motivated by cases of brain-damaged patients with category-specific semantic deficits (e.g., Warrington & McCarthy, 1983; Warrington & Shallice, 1984). The development of theories on concept organization is tightly linked to the observations of selective impairments of object knowledge in either living or nonliving (mostly manmade objects) domain. These theories fall into several classes, as is discussed below.

Domain-based views

Since the first reported cases of living/nonliving dissociation (see Forde & Humphreys, 1999 for an overview), the straightforward account that concepts for different categories are represented in separate components of the conceptual knowledge system has been one of the mostly studied proposals. The domain-specific hypothesis (Caramazza & Shelton, 1998) assumes that object domain provides the first-order principle of the organization of information in conceptual system. Moreover, the category-specificity should be observed not only in the semantic but also in the perceptual areas in the brain (Mahon & Caramazza, 2009). Natural selection pressure has

been reflected in the specialized neural circuits for processing evolutionarily significant semantic categories, such as living animate, living inanimate, conspecifics, and tools. This view has been found to be compatible with a large number of cases of category-specific deficits (Capitani, Laiacona, Mahon, & Caramazza, 2003). A limitation of this theory lies in the criticism of not being panoramic: because the candidate semantic categories are limited to those with evolution-related history, and because further hypotheses are needed to specify the rules governing information within these broad semantic domains (Caramazza & Shelton, 1998), the domain-specific model cannot be the exclusive constraint on conceptual knowledge representation in the brain.

From property-based to modality-specific views

A second line of theories assumes the category-specific deficits reflect the relative importance of different attributes to different objects. The sensory/functional hypothesis assumes sensory and functional properties are stored separately in the brain (Warrington & Shallice, 1984). If knowledge of sensory features is critical to concepts in the living domain, whereas knowledge of functions is more important to the nonliving domain, the disproportionate impairments can be attributed to the disruption of one of the modalities. Neuropsychological predictions according to this hypothesis will be (1) selective impairments for knowledge of certain type of property will be observed; (2) the knowledge impairments for a type of property will co-occur with the impairments of selective categories of objects that are most reliant on that type of property; and (3) category-specific deficits may also occur in the categories across living/nonliving boundaries as long as the impaired property knowledge is supposedly critical to the category, for example, the sensory knowledge impairments may result in the loss of

knowledge about musical instruments or food in addition to the broad classes of living things (Warrington & Shallice, 1984).

Supportive neuropsychological evidence for this hypothesis has been found (e.g., Basso, Capitani, & Laiacona, 1988; De Renzi & Lucchelli, 1994). However, the observed relations between the knowledge about property and about category are not always as predicted. For example, Lambon Ralph et al. (1998) reported a patient with impaired visual knowledge across living and nonliving domains but without a category-specific deficit for living things. Such case suggests the existence of sensory/functional dissociation, but it is at least insufficient to predict the living/nonliving dissociation. On the other hand, knowledge of different properties within the same modality have been found to be unequally damaged in some patients, such as the impairments of perceptual knowledge only for living things (Sartori, Job, Miozzo, Zago, & Marchiori, 1993). As another line of challenging evidence, some patients with category-specific deficits showed evenly impaired sensory and functional knowledge (Barbarotto, Capitani, & Laiacona, 1996; Samson, Pillon, & De Wilde, 1998). Moreover, patients with category-specific deficits may not present selective impairments for the knowledge types that are assumed to be critical (Lambon Ralph, et al., 1998). Such evidence might be a falsification to the sensory/functional hypothesis, because the impairment of property knowledge is shown to be unnecessary to the occurrence of category-specific impairment. However, it is also possible that the critical property to a given category has been incorrectly assumed in these studies (for example, representing the concept of fruit does not mostly depend on color information). This alternative explanation mirrors the questioning about the premise of sensory/functional hypothesis: is it really the case that

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knowing living things mainly depends on sensory information while knowing nonliving things relies on their functions? Although behavioral studies such as Cree and McRae (2003) have identified the most salient knowledge type for a given category of object based on features produced by participants, the explicitly verbalized features may not reflect the properties, if they exist, that guide the concept representation. Moreover, it is unclear how the "importance" of a property is defined. The definitive properties for a category are not necessarily the most featured properties for identifying its members.

Despite these questions, the hypothesis of a sensory/functional dissociation reflects a general view of property-based organization of semantic knowledge. It assumes the meaning of a word referring to an object is learned by associating the symbol with other symbols referring to sensory and motor properties (Humphreys & Forde, 2001; Warrington & Shallice, 1984). This hypothesis is theoretically suggestive in that it relates the higher-level conceptual processing to the primary perceptual processes that are well defined, finite in number, and have relatively clearly understood processing centers in the brain. The hypothesis of property-based organization has been further associated with the embodied cognition view (Barsalou, 1999; Glenberg, 1997) by virtue of the emphases on perceptual and motor information in representing knowledge about objects. The recent interests to embodied cognition are inspired by a large body of behavioral evidence from healthy participants. For example, a cost of reaction time has been found when various semantic tasks required processing of object properties of different sensory modalities (Pecher, Zeelenberg, & Barsalou, 2004). Another example is the interference between perceptual and semantic information. The implied positions and spatial relations of

objects in sentences affect the performances in subsequent tasks about objects depicted by pictures (Stanfield & Zwaan, 2001).

In subsequently developed hypotheses of conceptual representation along the line of property-based organization, the role of specific sensory modalities has been emphasized over the sensory vs. functional dichotomy. According to the sensory-motor model (Martin, 2007; Martin & Chao, 2001), knowledge about properties that comprise an object is stored close to the sensorimotor systems. Object properties that are invariant to viewpoint, size, and orientation, such as visual form, color, motion, or actions, guide the organization of concrete concepts. Instead of being explicitly represented, concepts arise from weighted activity in brain regions for processing properties.

The connectionist approach

A common approach of the two views discussed above is to identify functionally and anatomically distinct substrates for different types of semantic knowledge. An alternative approach is investigating concept representation from the internal structure of a concept, or in other words, the statistical relations between a concept and certain features of it. Some of the theories taking the connectionist approach (e.g., Farah & McClelland, 1991) draw on a multiple semantics assumption, while most of them suggest a unified conceptual system (Devlin, Gonnerman, Andersen, & Seidenberg, 1998; Gonnerman, Andersen, Devlin, Kempler, & Seidenberg, 1997; Tyler & Moss, 2001). This group of theories assumes that important aspects of conceptual knowledge are represented by semantic features. Concepts are the expressions of how various features are intercorrelated and how they are connected to the concepts. Therefore, the overlap of features can account for various relationships between concepts, such as the similarities

between concepts, the typicality of category membership, etc. (McClelland & Rogers, 2003; Rips, Shoben, & Smith, 1973).

In the context of a connectionist approach, the category-specific deficits are derived from differences in the structures or patterns of these feature contents. For example, Tyler and Moss (2001) addressed the living/nonliving dissociation by focusing on the facts that (1) deficits for living things are more frequently observed than those for nonliving things (mainly artifacts), and that (2) brain areas activated for processing living and nonliving concepts have considerable overlap, with arguably inconsistent regions of domain-specific activations. Living things have more properties, which are overall more intercorrelated but less distinctive than artifacts. Moreover, the relations between perceptual and functional properties in living things are either loose or generic across categories, whereas artifacts have distinctive and consistent associations between form and function. Therefore (and based on lesion simulations), compared to artifacts, the distinctive properties of living things are more vulnerable to damage, whereas the shared properties of living things are more resilient. This model further suggests that the organized conceptual system may emerge from the randomly distributed network, with well-defined structure for similar concepts and less so for concepts with fewer and loosely intercorrelated properties. The conceptual structural models have shown great successes in explaining the graded deficits in patients with widespread cortical damage (e.g., Almor et al., 2009; Silveri, Daniele, Giustolisi, & Gainotti, 1991).

Convergence zones and hierarchical processing

The connectionist view has provided a critical part for the models that suggest a distributed representation, namely how object concepts arise from the separately

represented knowledge about properties or features. It should be noted that the connection-only account is not the only group of models that attempts to address this question. For example, McClelland and Rogers (2003) have proposed that representation units that bind object properties may lie in the temporal pole.

The convergence zones theory (Damasio, 1989; Tranel, Damasio, & Damasio, 1997) appeals to distinct modules, i.e., convergence zones, which function as mediational association cortices to bind sensorimotor information and introspective states from various sources. The convergence zones are distributed from the posterior to the anterior cortical regions in a hierarchical style, with the lower-level association areas near the modality-specific sensorimotor areas and the higher-level association areas in the more anterior regions that conjoin information from the lower-level regions. These assumptions are in line with the research with nonhuman primates that suggests hierarchically structured systems for visual and auditory perceptual feature processing, with the more anterior regions responsible for the more complex feature conjunctions (Bussey, Saksida, & Murray, 2005; Tian, Reser, Durham, Kustov, & Rauschecker, 2001).The convergence zones hypothesis has been extended and revised by Simmons and Barsalou (2003) to make it more compatible with the neuropsychological evidence, such as proposing sub-types of convergence zones that have more specialized functions for feature integration.

Interim summary

A number of theories of concrete concept representation derive from research on category-specific deficits. The domain-specific hypothesis assumes the local representation of objects by object domains. The modality-specific hypothesis assumes

distributed representation by sensory and motor modalities. The connectionist view

assumes the distributed representation by semantic features. The hierarchical processing

view assumes additional module that binds increasingly complex features. These views

comprise the starting points of numerous empirical functional imaging studies and the

catalysts of new hypotheses.

1.1.2. Current understanding of conceptual representation of objects: neuroimaging

evidence

The existence of category-specific deficits not only tells about the deficits

themselves in individual cases, but also inspires investigation of the general process of

concept representation in the healthy brain. Functional neuroimaging studies on healthy

participants have become an important complementary approach in offering evidence for

testing and modifying the hypotheses. Compared to neuropsychological studies,

functional imaging is less restricted by explicit behavioral performance, thus more

straightforward to interpretation, and useful in identifying regions automatically involved

in a given task or stimuli. Over the last decade, functional magnetic resonance imaging

(fMRI) has become a primary tool for identifying the neural correlates of mental activity.

Lesion and neuroimaging studies have identified a number of foci for the perception of

object-related properties in the brain, i.e. the modality-specific areas. For example,

besides the centers for primary processing of visual, auditory, olfactory, gustatory, tactile,

and motor information, recognizing colors of objects has been associated with the

posterior ventral temporal area, including the fusiform gyrus (Beauchamp, Haxby,

Jennings, & DeYoe, 1999; Zeki & Marini, 1998). The posterior lateral part of the

superior temporal sulcus and middle temporal gyrus is the center for integrating local

motion signals into the visual perception of the motion of objects (Dupont, Orban, De

Bruyn, Verbruggen, & Mortelmans, 1994; Watson et al., 1993). Is the semantic

knowledge about object-related properties stored in corresponding sensorimotor areas?

Does the concept of an object emerge from these property-based regions, as the

sensorimotor model has predicted; or are the concepts of objects organized by domains

regardless of the sensorimotor properties? The following sections will discuss these

questions based on evidence from neuroimaging studies.

Modality-specific systems in semantic knowledge representation

The relation between the sensorimotor system and object concept representation is

one of the most critical aspects to the view of modality-specific processing. The

intentional retrieval of sensory and motor information that is related to objects has been

associated with brain areas that are close to or overlapping with the sites for the

corresponding primary sensory and motor processing, including color (e.g., Hsu,

Kraemer, Oliver, Schlichting, & Thompson-Schill, 2011; Kellenbach, Brett, & Patterson,

2001; Martin, Haxby, Lalonde, Wiggs, & Ungerleider, 1995; Simmons et al., 2007),

sound (Goldberg, Perfetti, & Schneider, 2006; Kellenbach, et al., 2001), touch (Goldberg,

et al., 2006), taste (Goldberg, et al., 2006), motion and manipulation (see Martin & Chao,

2001 for a review). These experiments have used tasks that intentionally require the

processing of sensory or motor information, such as property verification (*Is a banana

yellow?*), judgment (*Choose the item whose color is most similar to the color of a

banana*), or generation (participants respond to *banana* with *yellow*). Moreover,

unintentional but explicit tasks, such as reading words denoting object properties, also

activated modality-specific areas, such as activations in motor cortices for action verbs

(Hauk, Johnsrude, & Pulvermuller, 2004) and ventral temporal cortex for words referring to forms and colors (Pulvermüller & Hauk, 2006).

Although these results are often considered as supporting the view of the embodied representation of semantic knowledge, the exact contribution of activation in the modality-specific areas has been under debate. For one, the correspondence between sensorimotor areas and semantic stimuli is not always specific enough (see Chatterjee, 2010 for a critical review). Second, it is not clear whether sensorimotor systems engage in semantic processing in an undifferentiated way. Is their involvement necessary for all levels of processing? Passive reading of single words may still generate additional processing, especially in laboratory conditions. Does the embodiment occur regardless of the internal context of a subject? In fact, the activations in action-related areas during semantic processing have been found to rely on personal motor experience (Beilock, Lyons, Mattarella-Micke, Nusbaum, & Small, 2008; Lyons et al., 2010).

A related question is whether the representation of object concepts requires the modality-specific information that is assumed to represent object-related properties. For most of us, vision is perhaps the modality we rely on most to acquire information about and interact with the physical world. The posterior portion of the ventral temporal cortex along the vision pathway from the occipital cortices is involved in object recognition and conceptual representation. Within this area, different categories of object have been related to different activity profiles, as discussed below.

Domain-specificity in the posterior ventral temporal visual stream

The ventral stream of visual processing pathways that extends from the occipital lobe to the temporal lobe has been recognized to be engaged in object identification.

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Numbers of studies have identified "category-specific regions" in the ventral temporal areas. The landmark study by Kanwisher and colleagues (1997) first named an individual-specific region in the fusiform gyrus that selectively responded to faces as the fusiform face area (FFA). The FFA has been found to show greater activations in the presence of faces, regardless of the viewpoints, than in the presence of exemplars of nonliving common objects, other parts of human body, and scrambled faces (generated by partitioning the original picture of face and shuffling the pieces to different locations). One remaining question is that despite the rigid controls over a number of low-level visual features, neither objects such as buildings and hands, nor scrambled faces that serve as the control condition have a similar contour or layout, thus it is possible that the activation in FFA results from the response toward certain types of shape and structure. In fact, a shape with these features is very likely to be perceived as a face, which makes a clear dissociation in experiment manipulation between the concept of face and the visual structure difficult. This question has been addressed by a subsequent study investigating the relationship between inverted face and FFA (Kanwisher, Tong, & Nakayama, 1998). The FFAs of some of the participants showed reduced activation for inverted faces, which had the same visual features as upright faces except the position but were more difficult for face recognition. This effect of inversion was stronger and more consistent across individuals on two-tone face, which disrupted face detection when it was placed upside-down. Moreover, another study (Yovel & Kanwisher, 2004) clearly demonstrated that the FFA is selective for face, as a semantic category, rather than for configural processing. These results dissociated the processing of the face per se from the processing of low-level visual features.

The interpretations on the role of the face-specific areas have reached no consensus. The existence of FFA may indicate a mechanism with qualitatively different kinds of computation for a particular domain (Kanwisher, et al., 1997), but alternative explanations are also available. A prominent argument is that the seemingly face-specific effect reflects the expertise of processing faces compared to other objects, while the mechanisms are not category-specific (Gauthier & Tarr, 1997). The debate between the FFA hypothesis and the expertise hypothesis is highly relevant to the general question of domain-specificity of object representation (for a critical review, see McKone & Kanwisher, 2005).

A comparison of activation for faces and for another domain of object, which requires the same level of expertise to detect and recognize, but physically different and unrelated to faces, will provide key information to the question. Neuroimaging studies using words as stimuli (Puce, Allison, Asgari, Gore, & McCarthy, 1996), training participants to become experts to a laboratory-made object (Gauthier, Tarr, Anderson, Skudlarski, & Gore, 1999), or recruiting participants who were real-world experts to certain objects (Gauthier, Skudlarski, Gore, & Anderson, 2000; Rhodes, Byatt, Michie, & Puce, 2004) have revealed inconsistent results. Crucially, none of these findings indicate that objects other than faces engage FFA to the same degree as faces do.

In addition to the consistently found face-specific effect (Haxby et al., 1999; McCarthy, Puce, Gore, & Allison, 1997), selective responses to other categories of objects have also been identified in distinct regions in the ventral temporal area. These categories include scenes or spatial layouts (Epstein, Harris, Stanley, & Kanwisher, 1999), houses (Aguirre, Zarahn, & D'Esposito, 1998), tools (Chao, Haxby, & Martin, 1999), and

body parts (Downing, Jiang, Shuman, & Kanwisher, 2001). These findings have jointly suggested domain-specific organizations for the pre-semantic representation of objects in ventral temporal areas.

Whether this interim conclusion is also applicable to the representation of conceptual knowledge of objects? The key to such a question is to dissociate the higher-level conceptual processing from the object perception or mental image generation. This can be achieved by using tasks demanding deep processing, presenting stimuli in symbolic format, investigating concepts that are detached from physical objects, i.e. concepts related to objects but with higher abstractness, such as the knowledge about broader domains (living vs. nonliving things) or object-related properties, etc. Chao and colleagues (1999) found the medial areas of the right fusiform gyrus that were more active in categorical judgment on the names of tools were also more active in picture naming of tools compared to animals. Similarly, voxels in the right lateral fusiform gyrus that were significantly more active in categorical judgment of animals also showed a greater response in naming animal pictures. This suggests the spatial overlap between perceptual and conceptual processing of objects. A study using the semantic priming paradigm showed that a pair of words referring to two related objects elicited reduced activity compared to a semantically unrelated word pair in several areas, including the bilateral ventral temporal cortex (Wheatley, Weisberg, Beauchamp, & Martin, 2005). This provides support for the hypothesis that the ventral temporal area is sensitive to conceptual processing in the absence of explicit sensory processing. This study also identified the distinction between living and nonliving things: the lateral part of left fusiform gyrus responded more greatly to animals than to artifacts. Martin (2007)

reviewed studies using various tasks and stimuli and argued that the lateral area of fusiform gyrus is consistently associated with animals and human bodies, whereas the medial part has been associated with manmade objects. This has been argued to be consistent with the spatial dissociation of face vs. place perception in terms of the living vs. nonliving distinction (Martin, 2007; Martin & Caramazza, 2003).

The finding of domain-specific areas for animate and inanimate objects does not explain the organization principles by itself. For example, Rogers et al. (2005) asked participants to verify the category of pictures of animals and vehicles. When the task required basic-level categorization (*dog* or *car*), the lateral posterior fusiform gyrus responded more strongly to animals as expected. However, the preferential response to animals disappeared when the task required categorization on more specific level (*Labrador* or *BMW*). These results may indicate that the lateral fusiform gyrus represents object concepts at coarse levels, as the domain-specific hypothesis suggests, but it may also indicate that the role of this area is detailed discrimination of visual or semantic features, as the authors concluded.

A study (Wheatley, Milleville, & Martin, 2007) that indicated the role of fusiform gyrus in the interpretation of object animacy shed light on this issue. In this experiment, participants watched or imagined moving shapes that could be inferred as either animate or inanimate objects according to two types of biasing backgrounds. When the shapes were interpreted as animate objects, the lateral portion of left fusiform gyrus as well as other areas related to social cognition showed increased activity compared to the condition when the same shapes were inferred as inanimate. Although it is logically possible that the lateral fusiform activation was due to additional imagery of real living

objects, this study provides strong suggestion that the organization of a living vs. nonliving distinction is at least partly driven by the conceptual level dissociations.

The role for central properties in object concept representation

Evidence discussed above shows the subareas in the ventral temporal cortex that preferentially respond to several categories of objects. However, the representations of object-related knowledge are not restricted to the ventral temporal stream. The category-specific activations are found in more than one continuous area. For example, in addition to the fusiform gyrus, the superior temporal sulcus has been associated with face and animal processing. A more prominent example is the activation of the left posterior middle temporal gyrus in response to artifacts, particularly tools (e.g., Chao, et al., 1999; Martin, Wiggs, Ungerleider, & Haxby, 1996; Mummery, Patterson, Hodges, & Price, 1998). Does domain-specificity hold when taking other relevant systems into considerations? Parallel to the topography based on animacy in the ventral stream, activation in the visual motion area has been suggested to be modulated by object category. The pSTS has been shown to preferentially respond to biological motion (see Allison, Puce, & McCarthy, 2000 for a review) while the pMTG and the premotor cortex respond more to the movement of manipulable objects (Beauchamp, Lee, Haxby, & Martin, 2002, 2003). These studies suggest the left posterior lateral temporal cortex also represents objects, but only for those with motion as an important or salient property, such as animals and tools.

Regions in the pSTS/MTG for sound perception showed stronger activation to visually presented words denoting objects with salient acoustic features (e.g., *telephones*) than to those without such features (Kiefer, Sim, Herrnberger, Grothe, & Hoenig, 2008).

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Generating words denoting objects or events that were characterized by visual (e.g., animal), motor (e.g., transportation), or somatosensory (e.g., body parts) features were found to elicit corresponding sensorimotor areas (Hwang, Palmer, Basho, Zadra, & Müller, 2009). Processing of words referring to objects with strong and unique smells is found to activate olfactory cortices compared with control words (Gonzalez et al., 2006). The embedding of certain categories of objects in certain modality-specific areas suggests the role for critical sensorimotor modalities in the neural representation of objects.

Multimodal areas and hierarchical semantic processing

The above sections argue that only part of the object concept is represented modality-specifically. Although the representations of objects rely on different modality-specific systems to different extents, our knowledge about objects comprises information from multiple properties within and across modalities. How does the brain bind various properties to form meaningful object representations?

The above section also showed that in the posterior ventral visual stream, the fine-grained category-specific effects presented in the pre-semantic processes are blurred but merged into the coarse living vs. nonliving distinction during concept retrieval. If the posterior ventral stream shows the distinction by domains, how does the brain represent the knowledge about objects on the basic level or even individual level?

As described before, the intercorrelations between features of different modalities, such as appearance and function, are recognized to be important to the object representation (Tyler & Moss, 2001). How is it realized in the brain?

According to the convergence zone and hierarchical processing models, additional to the modality-specific areas, the semantic knowledge representation also requires

certain supramodal systems that are responsible for the complex feature discrimination and the combination of information across modalities. Two sites in the brain, one at the pSTS/MTG and the other at the anterior temporal cortex, have been proposed to perform these functions in different ways.

The left pSTS/MTG. The left pSTS/MTG has been associated with integrating object-related information from multiple modalities. Pictures of objects or sounds typically generated by certain categories of objects have found to elicit stronger activations than meaningless complex stimuli (Beauchamp, Lee, Argall, & Martin, 2004). Presenting visual and auditory stimuli simultaneously elicited stronger activations than presenting unimodal stimuli of the same objects (Beauchamp, Argall, Bodurka, Duyn, & Martin, 2004; Beauchamp, Lee, et al., 2004; Taylor, Moss, Stamatakis, & Tyler, 2006). By using high-resolution fMRI, Beauchamp et al. (2004) revealed heterogeneous architectures in the STS bilaterally: within the functionally defined multisensory STS areas based on a standard-resolution fMRI, they found patches that responded preferentially to auditory or visual stimuli compared to stimuli of the other modality, and in-between patches that responded equally to both modalities. The authors proposed that such organization within the multisensory area suggested separate patches for the arrival of visual and auditory inputs and an integration in the intervening regions.

Although this area was selectively activated for object recognition, it seemed insensitive to the semantic congruency between inputs from different modalities. Activations for processing congruent (*picture of cat + sound of "meow"*) vs. incongruent (*picture of dog + sound of "meow"*) stimuli were not different in either an implicit task (one-back same/different judgment, Beauchamp, Lee, et al., 2004) or an explicit task

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(congruency judgment, Taylor, et al., 2006). This area was also found to respond indifferently to the living and nonliving domains (Taylor, et al., 2006). Therefore, the left pSTS/MTG area may serve as a center receiving semantically meaningful visual and auditory information without binding the information to form integrated concepts.

The left anteromedial temporal cortex. On the other hand, in spite of the insensitivity of fMRI measures to the activities in the anterior temporal areas due to the susceptibility artifacts (Devlin et al., 2000; Lipschutz, Friston, Ashburner, Turner, & Price, 2001), functional imaging studies have provided converging evidence suggesting a role of the left anterior temporal cortex in multimodal processing of concrete concepts. Tyler et al. (2004) used a picture naming task that either asked for the name at a basic level (*tiger*) or at a domain level (*living thing*) to manipulate the level of specificity in differentiating among similar objects. First, when compared to a fixation baseline, both the basic-level and domain-level naming tasks activated bilateral areas in the inferior occipital cortex to fusiform gyrus, more prominently in the left hemisphere. When more lenient thresholding methods were applied, a trend of anteriorly and medially extended activation, including the perirhinal and entorhinal cortices, additional fusiform areas, amygdala, and hippocampus, was found in the left hemisphere, only for the basic-level naming. Second, the direct comparisons between the two conditions showed greater activations in the left entorhinal and perirhinal cortices for the basic-level than domain-level naming, while the domain-level naming elicited greater activations in the right middle frontal gyrus. Third, the differences of percent signal changes between the basic-level and domain-level tasks progressively increased from no difference along the anteriorly extended stream. These results suggested the anteromedial temporal area was

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critical for differentiating detailed features in object knowledge retrieval, and also suggested a posterior-to-anterior stream for processing increasingly fine-grained semantic features.

The role of the left anteromedial temporal cortex has been further confirmed by a study using finer-grained categories of objects (Moss, Rodd, Stamatakis, Bright, & Tyler, 2005). Moreover, this study also found that during the basic-level naming, living things elicited stronger activations than artifacts, which was not shown during the domain-level naming. In the context of the identified functions for this area, these results were in line with the assumption that living things share more features, thus requiring more complex combinations of multimodal features for discrimination.

In addition to the fine-grained semantic processing, the anteromedial temporal cortex has also been associated with integrating cross-modal perceptual properties into conceptual representation. This proposal mirrors nonhuman primate studies showing that the perirhinal cortex receives inputs from multiple sensory modalities (e.g., Suzuki & Amaral, 1994). The functional difference between the anteromedial temporal cortex and the pSTS/MTG was identified in a study by Taylor et al. (2006), showing that activities of the left perirhinal cortex were modulated by object domains and probably semantic congruency.

Interim summary

Semantic knowledge of an object is at least partly represented within the modality-specific systems that represent the central properties of the object. Within the visual processing stream in the posterior ventral temporal cortex, pre-semantic conceptual representation presents domain specificities for both coarse- and fine-grained categories

that are likely to be evolutionarily significant (as fine as faces and body parts, and as coarse as living things). This area is also sensitive to the semantic information of objects. Objects in the living domain tend to evoke stronger activation in the lateral areas compared to nonliving objects while the medial areas are more responsive to nonliving objects. Domain-specific activation profiles are also found in the visual motion area that represents knowledge about movements that indicate biological or instrumental functions. The convergence of multisensory information, particularly from the visual and auditory modalities occurs in the anteromedial temporal cortex and pSTS/MTG. The more anterior portion of the temporal cortex is sensitive to the more fine-grained semantic discrimination.

1.2.   Representational differences and relations between abstract and concrete concepts

1.2.1. Motivations and theories

Compared to the object-related concepts, the representation of abstract entities are less investigated and understood in the empirical studies as well as in the traditional cognitive theories. By definition, the more abstract a concept is, the more detached it is from physical entities. In practice, language is arguably the most commonly used vehicle to convey abstract knowledge. Although research on the organization of concrete concepts in the brain is closely linked to object perceptions, this approach meets apparent difficulty in understanding the representation of abstract concepts. Therefore, the amodal vs. modality-specific debate on the format of conceptual representation has been unsurprisingly dominated by the former.

Abstract concepts are typically acquired later in development and more vulnerable to brain degeneration. The concreteness effect, which refers to the observations in a

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variety of cognitive tasks that words representing concrete concepts are processed faster

and more accurately than words representing abstract concepts (see Paivio, 1991;

Schwanenflugel, 1991 for reviews), also suggests a disadvantage for our brain to process

concepts with increased abstractness. The concreteness effect has become an important

clue for the early theories about the representation of abstract knowledge. The dual-

coding theory (Paivio, 1991) assumes two independent processes are central to concept

processing. The representations of both concrete and abstract concepts rely on a common

verbal symbolic system, but representation of concrete concepts also involves a process

based on mental imagery, resulting from the high imageability of concrete concepts in

comparison to abstract concepts (*book* is more easily visualized than *freedom*). In

contrast, the context availability hypothesis (Kieras, 1978) attributes the concreteness

effect to the assumption that it is easier to assign a context to concrete concepts. This

theory states that only one system is required for the brain to process semantic

information (Schwanenflugel, Harnishfeger, & Stowe, 1988), indicating the difference

between abstract and concrete concepts is that contextual information is more readily

available to concrete concepts because they are associated with more representational

information and have stronger connections to semantic knowledge than abstract concepts.

The disadvantage of abstract concepts was found to be compensated when both concrete

and abstract words were presented in a sentence context (Schwanenflugel & Stowe,

1989).

After the first paragraph indent: According to both theories, abstract concepts are by nature more vulnerable to

brain damage, thus will always be more severely affected if a disproportionate

impairment occurs. This is incompatible with findings of the reversal of concreteness

effect, i.e., better performances on abstract than concrete concepts in some patients with brain damage (see the introduction of Papagno, Fogliata, Catricalà, & Miniussi, 2009 for a review). The dissociation suggests the existence of neural substrates exclusively involved in the representations of concrete or abstract concepts, challenging the traditional theories only accounting for the representational advantages for concrete concepts.

Furthermore, the organization principles of abstract concepts have been argued to be fundamentally different from those of concrete concepts. Crutch and Warrington (2005) reported a series of experiments on a patient with semantic refractory access dysphasia, with which the performance on semantic task is facilitated if the interval between a response and the subsequent stimulus is increased. A ubiquitously observed effect on refractory access disorders is the sensitivity to semantic similarities in the concrete domain: refractoriness occurs not only in the processing of individual concepts, but also in concepts similar to the previously presented ones. However, such an effect was not observed for abstract concepts in a spoken word – written word matching task: the refractoriness remained at the same level whenever the presented abstract words were synonyms or unrelated, suggesting that abstract words with similar meanings were not necessarily presented in similar neural spaces as the concrete words do. By contrast, abstract but not concrete words with associated meanings (*exercise, healthy, fitness, etc.*) presented significant interferences with each other, suggesting abstract concepts are represented in an "associative neural network".

1.2.2.   Implications from activational differences: neuroimaging evidence

Neuroimaging studies that compare the activation profiles of abstract and concrete words processing have reached few conclusions on how the underlying mechanisms are different. Supporting evidence exists for either theory (Binder, Westbury, McKiernan, Possing, & Medler, 2005; Kiehl et al., 1999; Martin-Loeches, Hinojosa, Fernandez-Frias, & Rubia, 2001), while other studies show results that are inconsistent with both theories (Kiehl, et al., 1999; Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007). One reason of this confusion is the discrepancies in explaining the theories with neuroimaging language. The cognitive theories explaining the concreteness effect were raised before the time when functional neuroimaging techniques were widely available. The neuroanatomical predictions of the theories were derived from early observations in patients with verbal or imagery deficits. The translations of different theories to neuroanatomical predictions are sometimes vague and not exclusive from each other. For example, the dual-coding theory makes few inferences of the activities in the left hemisphere for concrete compared with abstract concepts, while the context-availability theory does not predict the activation comparison between concrete and abstract concepts in the right hemisphere, thus leaving room for post-hoc explanations.

Moreover, some predictions from the original theories have been shown to be incompatible with the more recent functional neuroanatomical findings. For instance, a shared prediction of the dual-coding and the context-availability theories is that greater activation should be observed for concrete concepts in comparison to abstract concepts. A number of studies only identified regions selectively involved in processing abstract concepts (Friederici, Opitz, & von Cramon, 2000; Grossman et al., 2002; Jessen et al., 2000; Kiehl, et al., 1999; Noppeney & Price, 2004; Perani et al., 1999; Pexman, et al.,

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2007). For another example, the dual-coding theory assumes that representation of abstract concepts is restricted to the language-dominant hemisphere, while concrete concepts rely on both hemispheres because the image-based system is known to be bilateral (Paivio, 1986). Although some neuroimaging studies use the hemispherical asymmetry as a criterion of the involvement of mental imagery process (e.g., Binder, et al., 2005), the laterality of image generation has been controversial. Compared to listening passively to abstract words, imagining the appearance of the objects when concrete nouns were aurally presented was found to activate the inferior temporal lobe, premotor area and the anterior cingulate gyrus in the left hemisphere (D'Esposito et al., 1997). Based on the current understanding of the neural machineries for both mental imagery and concrete object representation (Ganis, Thompson, & Kosslyn, 2004; Kosslyn, Ganis, & Thompson, 2001), simply using the hemispheric asymmetry as the criterion has been argued to lack specificity (Scott, 2004).

Similarly, different studies have offered different explanations on the predictions of context-availability from a neural view. Some studies emphasize the difference in the strength of association with the context between abstract and concrete concepts. For example, Binder et al. (2005) stated that according to context availability hypothesis, the neural substrates of abstract and concrete concepts are identical, while activations correlating with concrete concepts are stronger than those of abstract concepts. Other studies emphasize the accessibility to context, or the retrieval difficulty. For example, Fiebach and Friederici (2004) interpreted its prediction as stronger activity for abstract words in brain regions associated with the retrieval of semantic information, mainly in the left posterior superior temporal region. The lack of correspondence between early

theories and neuroimaging language suggests revisions on the theories and cautions on interpreting the results.

1.3. Multivariate pattern analysis

1.3.1. Motivation

The sections above review studies using neuroimaging techniques to infer how conceptual knowledge is represented in the brain based on statistical parametric mapping (SPM),which characterizes region-specific responses by performing statistical analysis on individual voxels (Friston et al., 1994). Despite the tremendous effectiveness in dealing with questions of locating brain areas whose activities systematically vary with specific cognitive process, SPM has its limitation as a univariate approach. Because SPM treats individual voxels independently with separate general linear models, it is unable to capture the joint activity patterns grounded in multiple areas. Also, the mass-univoxel modeling is accompanied by multiple comparisons in statistical contrasts. Stringent control on the increasing familywise type I error rate impairs the power of studies further. One of the conventional ways to rescue power in SPM approach is focusing on specific regions, such as the small volume comparison or regions of interest analysis, instead of fishing within the whole brain data. However they are not suitable when a clear anatomical hypothesis is lacking, or when the cognitive processes are not concentrated in a small number of areas.

With the motivations of detecting spatially distributed information content beyond single voxels as well as gaining power, multivariate pattern analysis (MVPA) has been introduced as a complementary approach to SPM. In a pioneering work, Haxby and colleagues (2001) were able to decode the functional architecture during viewing pictures

of eight commonplace categories of objects in human ventral temporal cortex. This study

showed the ability of MVPA in detecting the difference in distributed response patterns

toward different stimuli in the same region, verifying a theoretical hypothesis that is

difficult to be tested by merely investigating the maxima of single voxels. Follow-up

studies have found consistent evidence that the ventral temporal cortex provides critical

information to accurately identify the categories of object a person is viewing (Hanson &

Halchenko, 2007; Hanson, Matsuka, & Haxby, 2004). A number of MVPA studies (e.g.,

Cox & Savoy, 2003; Haynes & Rees, 2005; Kamitani & Tong, 2005) and reviews (e.g.,

Haynes & Rees, 2006; Norman, Polyn, Detre, & Haxby, 2006; O'Toole et al., 2007;

Pereira, Mitchell, & Botvinick, 2009) following this early exploration have shown the

effectiveness of this method on various topics.

Considering the ways of addressing questions by using MVPA are different from

those using the canonical approach, I will temporally deviate from the topic of concept

representation and briefly overview MVPA methodology. MVPA has prominent

applications in various neuroimaging and neurophysiological data. The following section

will illustrate its application on fMRI data.

1.3.2. A brief introduction on MVPA procedure

The research question and procedure of an MVPA study are different from those

of conventional SPM approach on several aspects due to the differences in goals and

rationales. MVPA deals with the representational content of brain regions while SPM

considers the magnitudes of activity as dependent variable. Therefore, instead of

demonstrating the involvement of brain areas in a particular process, MVPA addresses

questions in two directions: (1) to directly establish a temporary computational models

characterizing the activity patterns (the reason of being temporary will be discussed later); and (2) to reversely decipher the neural response patterns in order to relate them to specific cognitive processes. The latter is sometimes also referred to as decoding, prediction, classification, or "mind-reading", as it includes the procedure of indicating what type of information is being processed given a specific response profile. In practice, the two directions are often coexistent for the following reasons. If the goal of a study is to model the activity patterns of different conditions, the classification procedure will provide a validation that the models are productive, or distinguishable. If the goal is to decode mental states, the modeling, although being an implicit procedure, is necessary to achieve the successful decoding. Both the block and event-related designs have been used in MVPA studies. The greater sensitivity of MVPA enables it to decode the mental states based on activities in a short period of time, i.e. one or two scans for each event trial. The features of MVPA have been discussed by far in the frame of comparing to univoxel approaches. MVPA is apparently not the only multivariate statistical method that has been applied to neuroimaging data. An important reason for MVPA to be more welcomed than other multivariate approaches is MVPA directly connect the data pattern to conditions of a study (which will be referred to as categories) as SPM does. Compared to exploratory, descriptive, data-driven multivariate methods, such as principal component analysis or independent component analysis, MVPA is more compatible with the hypothesis testing paradigm (see O'Toole, et al., 2007 for more detailed and insightful discussions).

A "typical" procedure of MVPA is usually constituted of the preprocessing, feature extraction, cross-validation, and significance testing (Figure 1.1). The
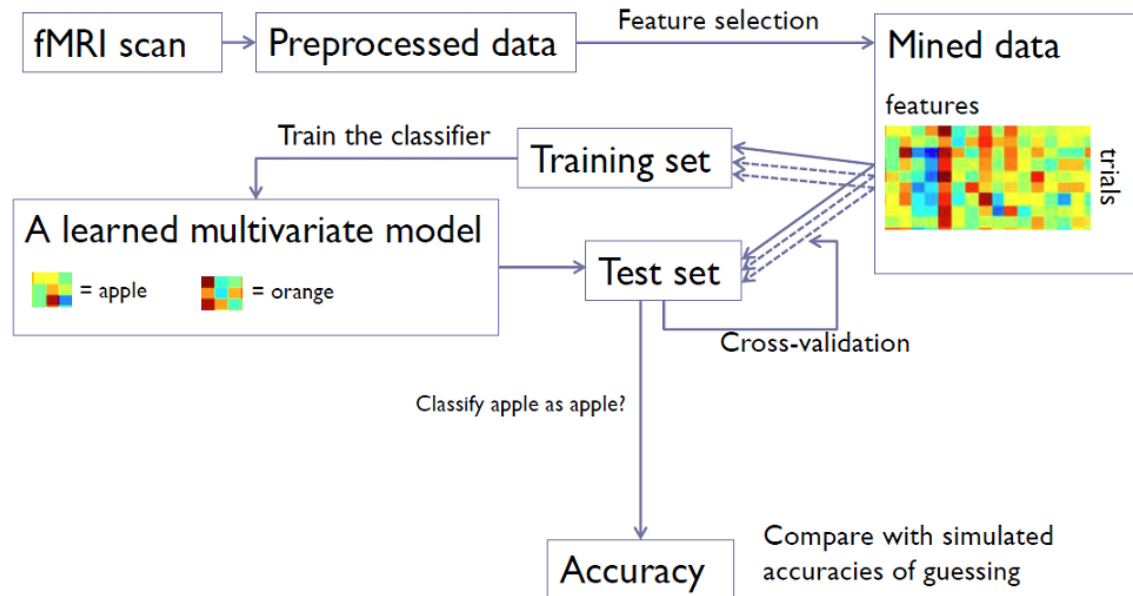
Figure 1.1   Example of the procedure of multivariate pattern analysis.

preprocessing approach is very much the same as in SPM except that spatial smoothing is

not always necessary: Without averaging across neighboring voxels, the data will retain

the joint, fine-grained spatial patterns which may carry important condition-specific

information. However, MVPA may require extra data mining processing before data

enter the major analyses step. Temporally, unlike the SPM which may model a whole

block of scans, MVPA uses a single time point of data by averaging scans in a block, or

selecting single scan with estimated peak of activity in an event-related trial. Spatially, a

feature selection procedure may be included to remove the measures that are unlikely to

carry information. The *feature*, corresponding to the multivariate in MVPA, can refer to a

subset of voxels as in most cases, independent components (e.g., Douglas, Harris, Yuille,

& Cohen, 2011), connections between pairs of regions, or other variants that are extracted

to represent the data. This procedure is usually important for two main reasons. First,

there are numbers of occasions that not the whole brain is engaged in condition-specific

activities. Second, from a computational perspective, a better estimate of model requires a large number of observations (trials) and a small number of variants (voxels or other features), which is hard to achieve in fMRI studies by nature. Thus, feature selection is helpful to unburden the computational difficulties. Analogous to the functional localizer in SPM approach, in order to avoid circular reasoning, feature selection procedure should never be based on an ad hoc rationale to the categories.

The training and test phases are the modeling and hypothesis-testing procedures. They are also the estimate and validation of a *classifier*. Analogous to the general liner model towards SPM, classifier is a structured algorithm applied to represent the multivariate data. Before classifier training, the overall dataset will be partitioned in parallel and assigned to the two phases. Conceptually, the training dataset is constructed in a high-dimensional space, in which the dimensions correspond to the features. A classifier training phase is to insert a hyper-plane to separate data of different categories apart as much as possible. In the test phase, the new, unseen set of data will be mapped onto the space so that the hyper-plane (classifier) can decide which category each data point belongs to, based on their locations. Because the actual categories of the test set are known from the experiment, the classification performance by the hyper-plane can be compared with the true categories, and evaluated in terms of accuracy.

The above training and test procedure as a whole is called cross-validation. To make full use of the data and to reduce variability, cross-validation is very often performed in a recycling way: different subsets of the whole data will be assigned to training or test sets iteratively, and the overall accuracy will be evaluated across iterations.

The feature selection should be performed only on the training set in each iteration, then apply to the test set. This ensures that the classifier modeling is blind to the test set.

A data-specific, random-permutation-based method is usually used to statistically evaluate the classification accuracy. The null hypothesis is that labels (categories) of the observations (trials) are meaningless, thus the classifier is trained on nonsense "patterns", and the classification procedure is essentially guessing. To simulate the distribution of this null hypothesis, the same dataset will be trained and tested in the same procedure for multiple times, but with randomly permuted labels. Therefore, the significance level of the real accuracy can be estimated by comparing it to the guess distribution.

MVPA procedures may have lots of variations in the specific steps or overall frame, for example, the analysis of representational similarity may replace the classification procedure according to the purpose, as long as they present the two definitional components: the multivariate data analysis approach, and the direct link between analysis results and experiment conditions.

The advantages of examining information content and high sensitivity hold promise for addressing questions that are difficulty to deal with by SPM approach, as is discussed below.

1.3.3. Previous application of MVPA on conceptual representation

Revisiting evidence for category-specificity of concept representation in the ventral temporal stream

It should also be noted that the category-specificity is a relative effect: category-specific regions are also responsive to other categories, with smaller magnitudes. For example, the FFA is specialized for face perception in terms of the consistent response

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with the largest magnitude over other categories, but it also significantly responds to

objects other than faces (Haxby, et al., 1999; Ishai, Ungerleider, Martin, Schouten, &

Haxby, 1999). Similarly, Chao et al. (Chao, Weisberg, & Martin, 2002) found that

naming pictures of familiar animals or tools elicited reduced activities compared to novel

animals or tools in the ventral occipitotemporal cortices that were not limited to the

corresponding category-specific region of each.

Moreover, the domain-specificity within modality-specific areas as shown in the

previous section is not consistently found by other studies. A review on twenty studies

that used pictures as stimuli to localize the category-specific activities showed

considerable inconsistencies (Gerlach, 2007). Tyler et al. (2003) examined the

representation of domain and property information using words denoting object names

(animals or tools) or actions (biological actions or tool-related actions). Participants were

asked to quickly judge whether each target word was semantically related to (essentially,

whether the object belongs to the same semantic category as) the two cue words. The left

fusiform gyrus, superior and middle temporal cortices were found to be activated by both

object names and their associated actions when compared to the baseline task of letter

string judgment, suggesting words referring to tool and animal implicitly activate the

actions associated with them. The activities in the fusiform gyrus for objects and actions

were largely overlapped, while the activities in the superior and middle temporal cortices

were more extensive for actions than objects. However, this study did not find a domain-

specificity for either object words or action words. In another study (Marques, Canessa,

Siri, Catricalà, & Cappa, 2008), participants were required to make judgment of living

and nonliving things on the same sets of visual and motion properties (*"cut trees"* for

both *Beaver* and *Saw*). Results showed the visual- and motion-specific effects

respectively in expected areas, but no domain-specific main effect or interaction between

domain and properties was found. Mechelli et al. (2006) argued that the greater activation

in the medial fusiform gyrus for artifacts than animals could be at least partly explained

by the different semantic relevance for the two domains: when semantic relevance were

matched for stimuli in the two domains, the effect of artifacts > animals was greatly

reduced. In short, the domain-specific hypothesis has been questioned that the overlap

between categories is much more significant than the difference, and the exact location of

"object area" is not consistent. The discrepancies across studies may be partly due to the

analysis details. Studies identifying category-specific regions have relied heavily on a

functional localizer by using lenient threshold, followed by region-of-interest analysis

which avoids the stringent correction for familywise error rate. It is also possible that the

locations of category-specific areas lack cross-individual consistency.

Distributed activity patterns in domain-specific ventral temporal areas

　　　　Canonical neuroimaging studies based on univoxel activation have identified a

domain-based dissociation in the ventral temporal vision pathway, but left the question of

how numerous categories and individual objects are recognized unanswered. MVPA

studies have contributed to this question by showing distinguishable multivoxel patterns

for different categories within the ventral temporal cortex. Haxby et al. (2001)

investigated the response patterns when participants viewed pictures of living and

manmade objects in seven categories. They hypothesized that the unique representation

of each category was associated with a distinct pattern represented by strong and weak

responses in multiple voxels in the general object cortex. If such category-specific

patterns exist, it should be possible to distinguish which category of stimuli a participant was viewing from the data. A correlation-based similarity measure was used to test this hypothesis, i.e. by measuring whether the response patterns of two independent observations from the same category were more similar than the patterns evoked by stimuli from different categories. The patterns for each of the categories were found to be significantly distinguishable, even when the voxels with maximal response to each category were excluded from the analyses, suggesting that patterns of non-maximal responses carry category-related information. On the other hand, in regions with maximal responses to a certain category, the patterns of response to other categories were still distinguishable. Thus, the pattern-specificity of an object category is reflected to a much greater extent than simply maximal response in the object-selective cortex. Specifically, the representation of faces and objects in the ventral temporal cortex are widely distributed, with spatial overlapping across categories.

Since this first report of using MVPA to decode the perception of objects, the functional topographies in the occipital and ventral temporal cortices have been investigated in more details. A closer looking at the confusability of categories in classification reveals a primary distinction between animate and inanimate objects, and a further distinction between small artifacts and houses (Hanson, et al., 2004; O'Toole, Jiang, Abdi, & Haxby, 2005). Viewing or imagining categories and even objects such as individual faces, scenes, and numbers have been found to activate overlapped voxels, but with category- or object-specific patterns (Downing, Wiggett, & Peelen, 2007; Weil & Rees, 2010 p.651).

The response patterns in the ventral temporal cortex have been further demonstrated to be structured by the degree of animacy. By measuring the similarity of multivoxel response patterns toward six animal species from birds, insects, and primates, Connolly et al. (2012) showed a hierarchical category structure corresponding to the biological class structure, with insets and primates at the two ends of this continuum. Bugs elicited cortical activity patterns similar to artifacts, and primates elicited activity similar to living things in previous studies. Moreover, the cortical representational similarity was also correlated with participants' similarity judgment on these species. These results suggest an animate-to-inanimate gradation represented in the ventral temporal cortex.

Content-specific representation in early sensory and perceptual cortices

An interesting finding by Connolly et al. (2012) is that the between-species dissimilarity in the ventral temporal cortex is correlated with the response patterns in V1 cortex but not retinotopic visual cortex. Despite the extensive studies on the primary sensory systems, the recognized processes can only account for small properties of activity variances. Recent MVPA studies have identified the roles beyond early sensory processing in these areas.

Harrison and Tong (2009) showed successful classifications on which of the two orientations of gratings was held in working memory from activity patterns in the visual cortex V1 to V4,suggesting the early visual regions contain memorized information of visual features. Ester and colleagues (2009) demonstrated that the areas showing differential patterns to visual details held in working memory were not limited to cortices that corresponded to the retinotopic position of the remembered item. Meyer et al. (2010)

found content-specific patterns in primary auditory cortex in the absence of auditory input. Participants watched muted videos of short events that implied sounds of animals, musical instruments or other ordinary artifacts. In the anatomically defined unimodal auditory cortices, they were able to identify which content of the videos the participants saw with accuracies above chance based on the multivoxel patterns but not based on the mean magnitudes of activities across voxels. Moreover, the significant correlation between participants' ratings on how evocative the video was and the classification performance suggested that the activities at the very early stage of sensory processing were associated with conscious perceptual experience.

In addition to the information within the same sensory modality, sensory cortices have also been found to respond to information of other modalities. For example, different types of natural sounds elicited distinguishable patterns in early visual cortex, even when the participants were performing an orthogonal word memorizing task to constrain mental imagery (Vetter, Smith, & Muckli, 2011). Ethofer and colleagues (2009) found that the voxels sensitive to voices also presented distinguishable patterns for different categories of emotions conveyed by aurally presented pseudowords. Based on the voxel-by-voxel correlations of the responses to different stimuli, Peelen et al. (2006) found similar responses to body parts and biological motion in the body-selective regions in posterior fusiform gyrus and posterior inferior temporal sulcus.

Overall, these findings suggested the sensory cortices might serve a function in the representation across modalities. Such implication challenges the traditional view on the meaning of activity in primary sensory cortices, and further indicates the link between perceptual and conceptual processing.

Focusing on semantic knowledge

A large body of MVPA literatures on object representation has focused on the pre-semantic conceptual representation in the ventral temporal visual stream. These studies have contributed to addressing the specific questions based on findings and debates from the univoxel studies. Mitchell and colleagues (2008) tackled the question of semantic knowledge representation from a different perspective. They hypothesized that the representational patterns of word meanings in the brain could be associated with the use of words in large text corpus. The semantic features that distinguish a target word could be represented by the co-occurrence of certain other words with it in the text corpus; therefore, the brain activity associated with the target word could be modeled by these featural words. In this study, a set of 25 verbs representing sensorimotor events related to objects (e.g. *taste, enter, wear, clean*) were chosen as the semantic features to represent 60 nouns referring to various categories objects, forming a model for each noun by linear combination of these features. These models were then trained with the fMRI activity patterns of a subset of the nouns, thus a brain signature could be inferred for each of the features. The predicted activity patterns for the left-out nouns based on the trained computational model were found to successfully match the actual patterns for these words. This study builds the link between the brain activities with computationalist approach and shows the possibility of establishing predictive models for the brain activities associated with arbitrary words.

Another study combining MVPA and text corpus analysis method was able to generate relevant text from fMRI data when participants were viewing object pictures (Pereira, Detre, & Botvinick, 2011). In this study, the researchers collected fMRI data

when participants viewed 60 categories of objects during a semantic processing task. Meanwhile, they collected 3500 Wikipedia articles relevant to the objects, and extracted a topic model from the text for each article, which modeled a probability distribution of words for each topic. The relations of topic models and corresponding brain activity patterns were then learned by regression model, thus establishing functions of the probability for different topic models to be predictive for a target brain image. Finally in the test phase, a set of new brain images that were unseen during the learning phase were applied to the established models, to reversely generate words that have high probability of associating with the brain images. Results showed high matches between the fMRI stimuli category and the generated words, which were also quantitatively validated by accuracies of classifying brain images into the articles. As the authors proposed, further development of this approach may offer a new perspective of decoding brain activities into language outputs.

The representational patterns of words denoting objects have been found decodable in a widely distributed pattern. Chan et al. (2011) recorded simultaneous EEG and MEG when participants were asked to judge whether the presented words referred to a living or nonliving object larger than one foot in any dimension. The representation of each of the five words could be decoded from EEG and MEG recordings. Moreover, the patterns that were informative to the discrimination were found in data from the bilateral anterior temporal, bilateral inferior frontal, and left inferior temporal-occipital sensors, which was more distributed than the areas localized by univoxel analysis.

Interim summary

The application of multivariate pattern analysis on neuroimaging studies has provided new perspectives to understand conceptual representation in the brain. The representations of various objects have been found to elicit identifiable distributed response patterns in the ventral temporal cortex. In line with the finding of locational differences of the peak activations for living and nonliving objects, the semantic similarities on animacy between objects are likely to be encoded in the multivoxel patterns in the posterior ventral temporal cortex. Multivariate patterns in certain early sensory systems also present cross-modal content-specific information, suggesting that conceptual representation may occur at early stages of processing. Another important implication from multivariate studies is that the brain areas conveying informative patterns associated with semantic concepts are more widely distributed than thought.

1.4.   Motivations for the current work

The critical new findings on the perpetual and semantic representations of concrete concepts have provided important insights and challenged some of the traditional perspectives on neural representation of concepts to a great extent. By contrast, how abstract concepts are represented in the brain is less studied. As a preliminary step, using the current findings on the representation of concrete concept as a scaffold to understand abstract concepts appears to be an effective approach and has been implemented in previous studies. What conclusion can we draw from the extant literature examining the representational differences between abstract and concrete concepts? How would MVPA offer further information on this question, and what would be the implications on previous findings? How could MVPA, combined with other data analysis methods, answer questions that are difficult to be tested by the canonical methods? The

general goal of this dissertation was to provide converging evidence that the neural

representations of abstract and concrete semantic knowledge rely on multiple different

mechanisms. Specifically, it aimed to address the following four questions:

Chapter 2: According to previous neuroimaging studies, what brain regions

consistently show activational differences for representing abstract and

concrete concepts?

Chapter 3: Can multivoxel activity patterns be used to decode fMRI data associated

with abstract or concrete concept processing on a single trial basis? How

will the results inform us about the mechanisms of abstract and concrete

concept representation?

Chapter 4: Does the functional connectivity associated with abstract or concrete

concept processing show distinguishable patterns that are consistent across

individuals?

Chapter 5: How can MVPA be applied as a cross-modal prediction approach to

investigating the role for semantic memory in other cognitive process?

Chapter 2

Meta-analysis of neuroimaging studies on the representational differences

between abstract and concrete concepts

2.1.   Introduction

The review of neuroimaging evidence on the representational difference between

abstract and concrete concepts (section 1.2.2) suggests considerable discrepancies across

studies (also see Figure 2.1). Typically, a single neuroimaging experiment does not have

enough power to reveal the neural substrates of a cognitive process, partly due to the

limited sample size. Desmond and Glover (2002) have found that to detect a signal

change of 0.5% with 80% power, approximately 25 participants are necessary, and many

studies have far fewer participants than that (Thirion et al., 2007). A number of studies

examining the neural representation of abstract and concrete concepts have been

conducted, and it is possible to examine the consistency among results using a

quantitative approach. Two studies (Fiebach & Friederici, 2004; Pexman, et al., 2007)

reviewed the reported activity coordinates in relevant studies; Fiebach and Friederici

(2004) also offered an integrated visualization of these peaks in one brain template.

Binder et al. (Binder, Desai, Graves, & Conant, 2009) performed a meta-analysis of

functional neuroimaging studies on semantic processing, and identified representational

differences in abstract and concrete concepts. The aim of the current study is to clarify
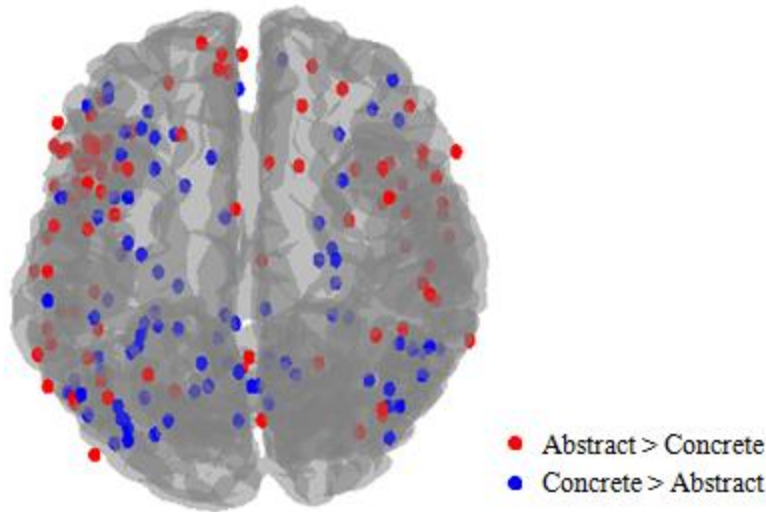
Figure 2.1   Activation peaks for abstract vs. concrete representation from 19 studies (Table 2.1) are shown on the brain template. © 2013 Human Brain Mapping

the differences in neural representation of abstract and concrete concepts by integrating existing neuroimaging evidence through meta-analysis. Multilevel kernel density analysis (Etkin & Wager, 2007) was applied to evaluate the activation consistency across published neuroimaging studies of abstract and concrete concept representation.

2.2.   Methods

2.2.1. Study selection

Peer-reviewed journals in *PsycARTICLES, PsycCRITIQUES, PsycINFO, Web of Science* and *Psychology & Behavioral Sciences Collection* databases were searched for neuroimaging studies of abstract and concrete concepts. In addition, we searched the reference lists of identified studies to ensure inclusion of all relevant studies fitting our criteria. To compare abstract and concrete concepts directly, the criteria for study inclusion were (1) participants were healthy adults; (2) the selected studies reported the peak activations in Montreal Neurologic Institute (MNI) or Talairach coordinates (Talairach & Tournoux, 1988) in either condition, i.e., brain regions where concrete

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concepts showed greater activations compared to abstract concepts (*concrete > abstract*) or the reverse (*abstract > concrete*); (3) contrasts were performed at a whole brain level (i.e., not at a region-of-interest level). These criteria resulted in a total of 303 participants across nineteen studies eligible for inclusion in the meta-analysis (Table 2.1).

2.2.2. Multilevel kernel density analysis (MKDA)

The multilevel kernel density analysis is a coordinate-based meta-analysis method where the statistical indicator is the probability of activation of a given voxel in the brain (Kober et al., 2008; Wager, Lindquist, & Kaplan, 2007; Wager, Lindquist, Nichols, Kober, & van Snellenberg, 2009).The general null hypothesis is that peak coordinates of activated regions are randomly distributed. If the number of nearby active peaks for a peak coordinate is greater than the number expected by chance, the null hypothesis is rejected. A number of meta-analysis methods are available; the MKDA method was selected for its several advantages. First, MKDA emphasizes the multi-level hierarchy of the data: multiple peaks are nested in a contrast, and multiple contrasts are nested in a study. Second, MKDA allows weighting contrasts by study sample size and quality.

Compared with other commonly used meta-analysis methods in brain imaging (e.g., ALE, Turkeltaub, Eden, Jones, & Zeffiro, 2002), this method prevents the result from being dominated by any single study with a large number of reported activations. It has the ability to weight the included studies by the number of participants and the quality of analysis based on random or fixed effects designs, such that studies with fewer participants or fixed effects designs are given less weight while studies with a larger numbers of participant or random effects designs are given more weight. Finally, the

Table 2.1   Studies included in the meta-analysis

Study	Imaging modality	Number of participants	Random or fixed effect	Materials	Input modality	Task
Mestres-Miss éet al., 2008	3T fMRI	15	Random	Sentence pairs	Visual	Recognition
Tettamanti et al., 2008	3T fMRI	18	Random	Sentences	Auditory	Passive listening
Pexman et al., 2007	3T fMRI	20	Random	Words	Visual	Semantic categorization (consumable or not)
Fliessbach et al., 2006	1.5T fMRI	21	Random	Words	Visual	Recognition
Harris et al., 2006	1.5T fMRI	20	Random	Words	Visual	Semantic judgment (positive or negative)
Binder et al., 2005	1.5T fMRI	24	Random	Words	Visual	Lexical decision
Sabsevitz et al., 2005	1.5T fMRI	28	Random	Word triads	Visual	Semantic similarity decision
Wallentin et al., 2005	1.5T fMRI	18	Random	Sentences	Visual & Auditory	Sentence comprehension
Fiebach&Friederici, 2004	3T fMRI	12	NA	Words	Visual	Lexical decision

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Noppeney& Price, 2004	2T fMRI	15	Random	Word triads	Visual	Semantic similarity decision
Whatmough et al., 2004	PET	15	NA	Word pairs	Visual	Semantic similarity decision (read aloud if the pair is similar in meanings)
Grossman et al., 2002	4T fMRI	16	Fixed	Words	Visual	Semantic judgment (pleasant or not)
Friederici et al., 2000	3T fMRI	14	NA	Words	Visual	Semantic categorization (syntactic task: noun or function word; semantic task: concrete or abstract)
Jessen et al., 2000	1.5T fMRI	14	Fixed	Words	Visual	Memory encoding
Wise et al., 2000*	PET	18	Fixed	Words	Auditory	Passive listening
			Fixed	Word triads	Auditory	Semantic similarity

			Fixed	Words	Visual/	decision sample
					Auditory	Passive listening/viewing
Kiehl et al., 1999	1.5T fMRI	6	Fixed	Words	Visual	Lexical decision
Perani et al., 1999	PET	14	Fixed	Words	Visual	Lexical decision
Mellet et al., 1998	PET	8	Fixed	Words with definitions	Auditory	Mental image generation (concrete)& passive listening (abstract)
D'Esposito et al., 1997	1.5T fMRI	7	NA	Words	Auditory	Mental image generation (concrete) & passive listening (abstract)

* Relevant results taken from multi-study analysis conducted by Wise at al. (2000)

MKDA test statistic offers a straightforward interpretation as the weighted proportion of activated contrasts in a kernel around each voxel (Kober, et al., 2008).

For this meta-analysis, relevant study variables were sample size, analysis type (fixed or random effects), and peak coordinates in the contrasts *concrete > abstract* and *abstract > concrete*. We retained significance criteria set by individual studies. For those studies using multiple tasks for one contrast, data from only one task were retained to avoid inclusion of data from the same participants more than once (however, we cannot guarantee against data from the same participants being reported in different studies). Analyses were performed in Matlab (Mathworks, Naticks, MA) based on the MKDA tool package created by Wager and colleagues (http://wagerlab.colorado.edu/tools). Peaks from each study were convolved with a spherical kernel of 10 mm radius (kernels of 5 mm and 15 mm were also investigated). The studies were weighted by the number of participants (*N*) and type of analysis (*δ*):

$$P = \sum_c I_c \frac{\delta_c \sqrt{N_c}}{\sum_c \delta_c \sqrt{N_c}}$$

where *c* is the index factor for the number of comparison maps *I* (Kober, et al., 2008). Studies that used random effects analysis had an adjusted weight of 1.0 and studies that used fixed effects, or when analysis type was unknown, had an adjusted weight of .75 (Kober, et al., 2008). The test statistic *P* represents the proportion of studies that found significantly active voxels within the 10 mm radius of each voxel. The threshold for statistical significance was determined using a Monte Carlo simulation procedure with 5000 iterations; increasing the number of iterations to greater than 5000 did not change the results. The significance threshold was set at the proportion exceeding 95% of the

Monte Carlo simulation maxima and controlled by familywise error (FWE) rate. In addition, we examined FWE-corrected results based on cluster extent.

2.3. Results

Meta-analysis results indicated different neural representation patterns for abstract and concrete concepts (Figure 2.2). Regions with significant proportions of stronger activation for abstract compared to concrete concepts were in the inferior frontal gyrus (IFG) and middle temporal gyrus (MTG) in the left hemisphere. Regions that showed stronger activation for concrete concepts were found in the left precuneus, parahippocampal gyrus, posterior cingulate, and fusiform gyrus (Table 2.2). These results were robust to changes in kernel size. Additional activated foci corrected on cluster extent at the 10 mm kernel were located within these regions. Applying a 15 mm kernel resulted in additional regions for each of the contrasts. Abstract concepts elicited greater activation in the left precentral gyrus, whereas concrete concepts were more strongly activated in left superior occipital gyrus, angular gyrus and culmen.

2.4. Discussion

This study used a multilevel kernel density method to conduct a meta-analysis on nineteen neuroimaging studies to investigate the neural representation of abstract and concrete concepts. Although the results of these studies were varied, the meta-analysis presented a consistent tendency for representational difference. Results suggest a greater engagement of the verbal system for processing of abstract concepts, and a greater engagement of the perceptual system for processing of concrete concepts.
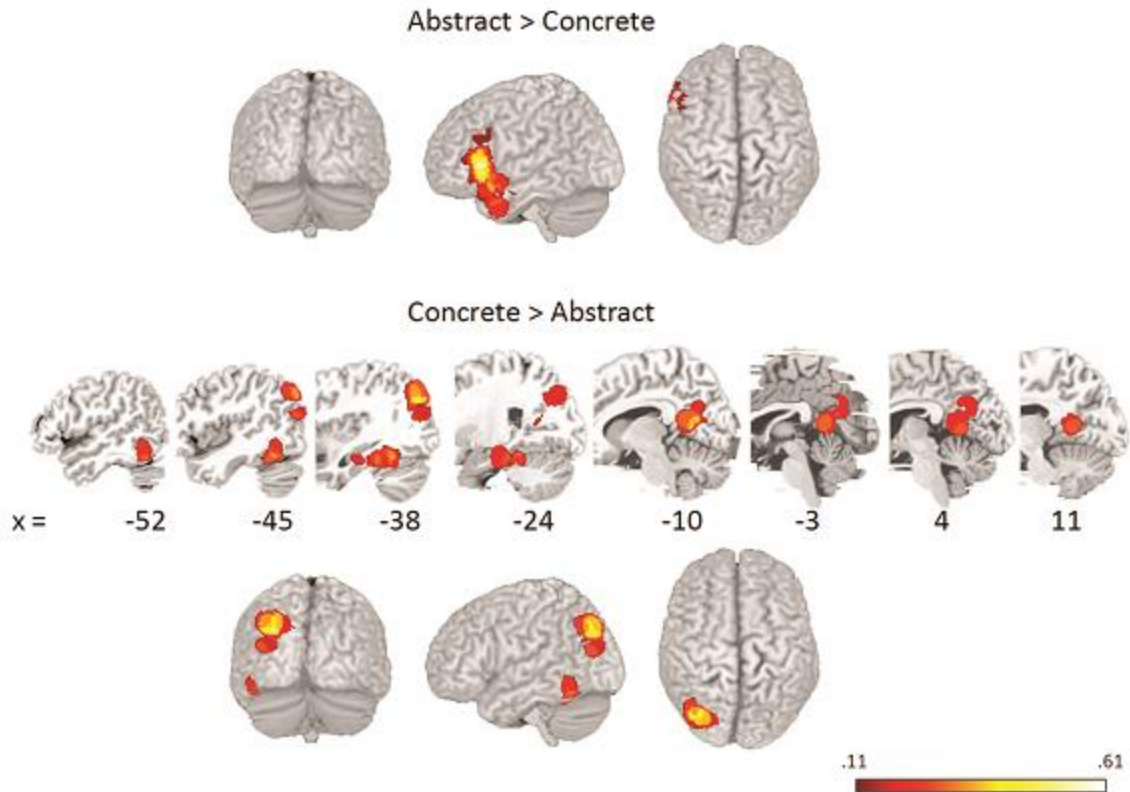
Figure 2.2   Meta-analysis of neuroimaging studies on abstract and concrete semantic concept representation. Color map indicates the weighted probability of activation for a given area across individual studies. © 2010 Human Brain Mapping

Concrete > Abstract

The comparison of concrete > abstract concepts showed significant consistent activation in the left precuneus, posterior cingulate, parahippocampal gyrus, fusiform gyrus and culmen, with a trend toward the left temporal, occipital and parietal regions that are around the angular gyrus (Figure 2.2). These results imply greater engagement of object and mental imagery processing in concrete compared to abstract concept representation.

The left fusiform and parahippocampal gyrus have been found to contribute to the processing of visual, imageable spatial property knowledge during explicit semantic tasks

Table 2.2   Consistently activated foci across studies ($p \leq 0.05$, FWE corrected)

Region		MNI			Number of
		x	y	z	voxels
Abstract > Concrete					
Left	Inferior Frontal Gyrus	-48	18	-2	738
	Inferior Frontal Gyrus	-50	20	4	373
	Inferior Frontal Gyrus	-42	20	-4	138
	Middle Temporal Gyrus	-52	10	-18	68
	Superior Temporal Gyrus	-48	18	-10	117
	Superior Temporal Gyrus	-48	10	-8	42
	Middle Temporal Gyrus	-52	8	-32	37
	Middle Temporal Gyrus	-58	-42	-4	7
Concrete > Abstract					
Left	Precuneus	-34	-76	34	147
	Posterior Cingulate	-12	-58	12	111
	Posterior Cingulate	-14	-56	12	45
	Posterior Cingulate	-10	-62	14	41
	Posterior Cingulate	-12	-56	6	25
	Fusiform Gyrus	-40	-52	-22	16
	Parahippocampal Gyrus	-32	-32	-20	8
	Parahippocampal Gyrus	-28	-34	-20	1

(Sabsevitz, Medler, Seidenberg, & Binder, 2005; Wallentin, Østergaard, Lund, Østergaard, & Roepstorff, 2005). Although the increased activation of the left fusiform gyrus for concrete concepts might be confounded by task differences rather than the concreteness difference in some studies (D'Esposito, et al., 1997; Mellet, Tzourio, Denis, & Mazoyer, 1998), this left fusiform activation effect was also found in the *concrete > abstract* comparison by using a precisely controlled semantic similarity task (Sabsevitz, et al., 2005). Moreover, the anterior fusiform gyrus was associated with the activation of several competing alternatives associated with the target concrete word in looking for the matching concept (Mestres-Missé, Münte, & Rodriguez-Fornells, 2008), which was compatible with the findings of this area in retrieving complex knowledge about objects (p19, section 1.1.2).

The left parietal lobe is predominant in generating mental images, and activation in parietal and occipital lobes has been attributed to different mental imagery tasks (Kosslyn, et al., 2001; Sack, Camprodon, Pascual-Leone, & Goebel, 2005). Specifically, the precuneus has been associated with memorizing verbally described scenes which requires mental image generation (Mellet et al., 2000). The comparison of concrete concepts to abstract concepts also elicited activity in the left supramarginal gyrus and posterior cingulate. The posterior cingulate has been associated with mental imagery processes (Johnson et al., 2006; Kilts, Gross, Ely, & Drexler, 2004). This region has also been linked with episodic and visuospatial memory function (Aggleton & Pearce, 2001; Epstein, Higgins, Jablonski, & Feiler, 2007; Rudge & Warrington, 1991), possibly because mental imagery plays a role in those processes. However, others have suggested that the bilateral posterior cingulate is semantically more engaged in abstract information

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processing (Pexman, et al., 2007; Tettamanti et al., 2005). This opposite effect may be due to the deactivation of this region in response to concrete concepts (Ghio & Tettamanti, 2010).

Abstract > Concrete

Consistently greater activities for processing abstract than concrete concepts were found in the left inferior frontal gyrus and left anterior temporal lobe (ATL) centering at the middle temporal gyrus (Figure 2.2). The anterior inferior portion of IFG has been linked to verbally-mediated semantic knowledge processing (Goldberg, Perfetti, Fiez, & Schneider, 2007; Petersen, Fox, Posner, Mintun, & Raichle, 1988). Semantic task requirements have been shown to alter activity in this area (Zatorre, Evans, Meyer, & Gjedde, 1992). Fliessbach et al. (2006) posited that the increased left IFG activation associated with abstract words reflects more strategic retrieval of semantic knowledge. This effect on semantic processing in the IFG has been dissociated from the effect of task difficulty, and it has been argued that IFG may act as a specialized central executive area for semantic retrieval (Demb et al., 1995; Noppeney & Price, 2004). The crucial role of the left inferior frontal area for abstract words processing has been further confirmed in a TMS study (Papagno, et al., 2009): task performances were hurt after the stimulation in left inferior frontal areas only when the participants were making lexical decision on abstract words.

The left IFG has also been implicated in phonological processing during working memory tasks (Fiebach & Friederici, 2004). Lesions to the left IFG produce deficits in phonological and syntactic processes (Bookheimer, 2002). Sabsevitz et al. (2005) proposed that activation in the more posterior parts of the frontal lobe by abstract

concepts may represent phonological working memory processing, while the more anterior regions of the inferior frontal gyrus may play a role in the putative verbal semantic system. Binder et al. (2005) suggested that the stronger left IFG activation reflects the additional semantic processing for abstract words compared to concrete words during a lexical decision task, as abstract words are held in working memory in phonological form to a greater degree than concrete words. These inferences suggest that neural representational differences between abstract and concrete concepts might also be ascribed to phonological processing differences caused by processing difficulty. Such difficulty is likely to be intrinsic to the representation of abstract concepts rather than driven by task.

The role for ATL in abstract concepts processing presented in neuroimaging studies has also been demonstrated in a TMS study (Pobric, Lambon Ralph, & Jefferies, 2009). Although the preferential response to abstract concepts in this area has been argued to reflect the difference in retrieval strategies (Noppeney & Price, 2004), this effect has been found in studies requiring superficial or deep processing in the tasks using fMRI or PET scans (Table 2.3), suggesting the activational differences were due to the difference in neural representations per se, rather than in the retrieval processes. Pexman et al. (2007) found the greater activation in this area for abstract concepts, however, when the words with more than one meaning were excluded from the test, the difference were only found in the posterior area of the brain, which mirrored the findings in object concept representation that the anterior temporal area is responsive to detailed discrimination of object (e.g., Tyler, et al., 2004. See section 1.1.2 for detailed discussion).

Table 2.3   Studies that found preferential activations in the left anterior temporal lobe for processing abstract compared to concrete concepts.

Study	Imaging modality	Task	Laterality of activations
Noppeney & Price, 2004	fMRI	semantic similarity judgment	Left
Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007	fMRI	semantic categorization	Left
Tettamanti et al., 2005	fMRI	passive listening	Left
Binder, Westbury, McKiernan, Possing, & Medler, 2005	fMRI	lexical decision	Left
Perani et al., 1999	PET	lexical decision	Bilateral
Sabsevitz, Medler, Seidenberg, & Binder, 2005	fMRI	semantic similarity judgment	Bilateral
Wallentin, Østergaard, Lund, Østergaard, & Roepstorff, 2005	fMRI	sentence comprehension	Bilateral
Mellet, Tzourio, Denis, & Mazoyer, 1998	PET	silent reading or mental imagery generation	Right

Taken together, the consistent activation across studies resulting from processing of concrete compared to abstract concepts suggest the representation of concrete concepts relies more heavily on the visual perceptual and mental imagery system. The greater involvement of left IFG and ATL in processing abstract concepts is likely to suggest that the processing of abstract concepts is more demanding in retrieving relevant knowledge and discriminating among the competitors.

Potential factors influencing results discrepancies among studies

The meta-analysis results revealed the consistent difference between the neural representation of abstract and concrete concepts across studies. However, not all studies used in meta-analysis reported activations in regions identified by the meta-analysis. For instance, the most consistently reported region, the left IFG in *abstract > concrete* comparison, was found only in ten out of the nineteen studies. On the other hand, some other brain regions that were reported by several studies were not identified by the meta-analysis results. Some of these regions were in close proximity to the consistently activated regions or were right hemisphere homologues, such as the inferior temporal gyrus (Mellet, et al., 1998; Sabsevitz, et al., 2005; Tettamanti, et al., 2008), or the right MTG for *abstract > concrete* comparison (Mellet, et al., 1998; Pexman, et al., 2007; Wallentin, et al., 2005). Additional regions were not identified by the meta-analysis, including the superior frontal gyrus for the *abstract > concrete* comparison (D'Esposito, et al., 1997; Pexman, et al., 2007; Sabsevitz, et al., 2005; Wallentin, et al., 2005), or the precentral gyrus for the *concrete > abstract* comparison (Mellet, et al., 1998; Sabsevitz, et al., 2005; Wallentin, et al., 2005). The effects of task and stimuli may have contributed to the discrepancies in results, as discussed below.

Effects of task. One might argue that the type of task used to elicit semantic processing can affect neural activation. For example, the relation of the left IFG activation to working memory (Binder, et al., 2005; Fiebach & Friederici, 2004; Sabsevitz, et al., 2005) makes it reasonable to assume a moderation effect of task load on this region. To determine the effect of task on the representation of concepts, we conducted additional meta-analyses examining the above contrasts according to task type. We divided tasks into superficial (passive listening and lexical decision on words and pseudowords) or deep processing (semantic categorization, semantic judgment and semantic similarity) categories. Several studies using tasks, such as recognition, were not included in this additional analysis because they did not fit our selection criterion as either superficial or deep processing tasks. However, the numbers of studies in the two groups were too small (7 and 8 respectively out of 19 studies) to detect consistent effects of task across the included studies.

Effects of stimuli. The materials were similar across studies, so the form of the stimuli was unlikely to have an effect on our results. The stimuli used in individual studies were single words (real and pseudo), word groups or sentences. Sixteen studies used words while three used whole sentences as stimuli. Most studies presented the stimuli visually; also six studies presented auditory stimuli, some of which used both presentation modalities (Table 2.1).

The effects of organizations of semantic categories in the brain have long been discussed (Bookheimer, 2002). The semantic categories selected to represent abstract or concrete concepts varied among studies. Most studies had one general abstract and one general concrete concept category, whereas some others used more specific subcategories.

For example, Noppeney et al. (2004) used one semantic category for abstract concepts and three (sound, visual or hand motion) for concrete words; Harris et al. (2006) used one category for concrete and two (metaphysical or mental state) for abstract words. Regions identified by the current meta-analysis, such as the fusiform gyrus, have been associated with object recognition and naming (Bookheimer, Zeffiro, Blaxton, Gaillard, & Theodore, 1995). The evidence raises the question of whether the representational differences between abstract and concrete concepts are content specific, in which case the change of specific word category would change the patterns of representational difference (Martin and Chao 2001). This question could be tested by including diverse subcategories in both abstract and concrete conditions.

Stimuli characteristics such as the word frequency, length, familiarity, and phonological or orthographic match between abstract and concrete words can also be critical. A lower average word frequency of abstract words might activate additional regions not associated with semantic differences. In some studies the stimuli were not balanced on these factors, possibly due to the difficulty in finding semantically suitable words. As a consequence, the differences in activation may be attributed to missing controls. One example is the debate concerning the role of the superior temporal gyrus. The left superior temporal gyrus was consistently activated across studies for *abstract > concrete* concepts, but not all studies reporting this region controlled for phonological factors. In fact, it recently has been argued that the superior temporal gyrus may be engaged in phonological processing rather than semantic comprehension(Bradley & Mark, 2008; Graves, Grabowski, Mehta, & Gupta, 2008).

Meta-analysis methodology

Meta-analysis combines data from multiple studies, resulting in a large total number of participants. The total number of participants included in the current analysis was 303, a number far beyond what is feasible within a typical neuroimaging study. MKDA was selected because it has several advantages suited to the investigation of representational differences for abstract and concrete concepts. It allowed weighting studies by the sample size and analysis type, and the results of MKDA provided an intuitive interpretation, representing the proportion of studies activating within the chosen radius of a voxel (Kober, et al. 2008).

Despite its clear advantages, meta-analysis has some inherent limitations. Because the meta-analysis was based on spatial coordinates from neuroimaging data, it was limited to PET and fMRI studies, and excluded EEG/ERP studies despite the large body of literature in that field. In addition, coordinate-based meta-analysis methods such as MKDA incorporate information only from published coordinates. Thus, these methods do not account for different within-study variability and cannot model random variation across studies (Salimi-Khorshidi, Smith, Keltner, Wager, & Nichols, 2009).

2.5.   Conclusion

This experiment has identified meaningful and consistent differences in the neural representation of abstract and concrete concepts by using meta-analysis to combine data from 303 participants across nineteen published studies. Abstract concepts elicit greater activity in the left inferior frontal gyrus and anterior middle temporal gyrus compared to concrete concepts, while concrete concepts elicit greater activity in the posterior cingulate, precuneus, fusiform gyrus and parahippocampal gyrus compared to abstract concepts. These results suggest greater engagement of the working memory and verbal system for

processing of abstract concepts and greater engagement of the perceptual system for

processing of concrete concepts, likely via mental imagery.

Chapter 3

Decoding abstract and concrete concept representation based on single-trial

fMRI data

3.1. Introduction

Although the meta-analysis results offer reliable evidence of the cross-study

consistency, the considerable disagreements of results among these studies are still

alarming: visualizing peak activations from nineteen studies recruited in the meta-

analysis revealed distributed locations for the processing differences (Figure 2.1). The

neural representational differences of abstract vs. concrete concepts were interpreted with

various factors. The difference may occur during concept learning or semantic memory

encoding (Jessen, et al., 2000), or is driven by the semantic retrieval strategy rather than

the representation per se (Fiebach & Friederici, 2004; Thompson-Schill, D'Esposito,

Aguirre, & Farah, 1997). The explicit task requirement of thinking of concrete concepts

may call for a more imagery-oriented retrieval approach, while representing abstract

concepts may introduce more verbal associations. Intrinsic difficulty of processing

abstract compared to concrete concepts may also contribute to the neural representational

differences. Because abstract concepts are less imageable, representing abstract concepts

may occupy the working memory to a larger degree (Binder, et al., 2005). Whether these

discrepancies are due to study idiosyncrasies, or whether they in fact do reflect the

abstract vs. concrete processing differences as well, is unclear.

Using multivariate pattern analysis to identify category-specific concept representation

MVPA is an ideal approach for investigating if the content of concept representation can be accurately inferred from individual trials of data. Most MVPA studies on concept representation used pictorial stimuli (Carlson, Schrater, & He, 2003; Cox & Savoy, 2003; Hanson & Halchenko, 2007; Hanson, et al., 2004; Haxby, et al., 2001; O'Toole, et al., 2005; Polyn, Natu, Cohen, & Norman, 2005; Shinkareva et al., 2008). Only a few studies have applied MVPA to decode semantic concept representations of concrete objects based on verbal stimuli (Chan, et al., 2011; Just, Cherkassky, Aryal, & Mitchell, 2010; Shinkareva, et al., 2011). Compared to visual depictions of objects, verbal stimuli are more independent of visual perception and can refer to abstract concepts. Whether representation of abstract concepts can be distinguished from concrete concepts using MVPA methods is unclear. In this work we extend the previous MVPA findings on concept representation by including the abstract category that is less dependent on perceptual or motor experiences. The purpose of this study was twofold. First, we explored whether MVPA methods could be used to identify single trials as abstract or concrete within each individual by decoding functional patterns of whole brain activity, thus extending previous MVPA studies of concept representation to abstract concepts. We also examined where the discriminating information between abstract and concrete concepts is located in the brain by focusing at the spatially localized anatomical brain regions that contained sufficient information for identification of abstract or concrete concepts on average across participants. Second, we investigated whether the representations of abstract and concrete concepts are similar across

individuals by training the classifier on all but one participant and then predicting single trials as abstract or concrete in the left out participant.

<div align="center">3.2. Methods</div>

3.2.1. Participants

Thirteen participants (six female) from the University of South Carolina community participated in this experiment and gave written informed consent in accordance with the Institutional Review Board at the University of South Carolina. Participants were right-handed, healthy adults and native English-speakers.

3.2.2. Materials

Stimuli were word triplets comprised of semantically similar nouns from two concrete (*tools* and *dwellings*) and two abstract (*cognition* and *emotion*) categories. Each category contained four exemplars, with four different words in each exemplar. For instance, the words *knife, scalpel, razorblade* and *cutlass* composed the exemplar *cutting object* within the concrete category *tools*. For each exemplar, six different triplets were selected from all possible permutations of the four words. Because the six triplets in each exemplar referred to the same semantic concept, these triplets were regarded as repetitions of the same exemplar. The sixteen exemplars were each presented six times, with each repetition composed of a unique list of triplets, generating 96 triplets in total (4 categories $\times 4$ exemplars $\times 6$ repetitions). Triplets were balanced between the abstract and concrete categories on word frequency ($M_{Abstract} = 27.86$ and $M_{Concrete} = 31.98$, $t(94) =$ -0.53, $p = .60$) and word length ($M_{Abstract} = 7.25$ and $M_{Concrete} = 6.83$, $t(94) = 1.84$, $p = .07$).

3.2.3. Procedure

While being scanned, the participants were asked to make judgments on

semantically similar written words, analogous to the synonym judgment paradigm (Breedin, Saffran, & Coslett, 1994; Noppeney & Price, 2004; Sabsevitz, et al., 2005). In each trial, a word triplet was presented for three seconds, followed by a seven-second fixation period. For each triplet, participants were asked to decide during the three-second triplet presentation which of two words at the bottom of the display was more similar to the word shown at the top. During the presentation of the seven-second fixation, the participant was instructed to clear the mind and fixate on the cross at the center of the screen. The task was designed to prompt careful evaluation of each item and its properties, thus implicitly eliciting the semantic representation of the presented exemplar. A long fixation trial of 24 seconds was presented after each repetition of the sixteen exemplars. Participants were prompted by the word "Ready?" following the long fixation to indicate the beginning of the next repetition. The whole experiment was completed in two scanning sessions, with three repetitions in each session.

3.2.4. MRI acquisition

Functional images were acquired with gradient echo EPI on a Siemens 3T Trio scanner at the McCausland Brain Imaging Center at the University of South Carolina with the following parameters: TR = 2200 ms, TE = 30 ms, flip angle = 90 °, voxel size = $3 \times 3 \times 3.6$ mm^3.

3.2.5. FMRI data preprocessing

The data were processed using SPM5 (www.fil.ion.ucl.ac.uk/spm). Data for each participant were corrected for head movement by aligning images to the first volume based on a six-parameter rigid body transformation. The head movement in any direction of any participant was smaller than 1.5 mm. The motion-corrected images were then

normalized to Montreal Neurological Institute (MNI) template and re-sampled to $3\times3\times3$ mm^3 voxels.

3.2.6. MVPA methods

The MVPA analysis steps employed in this work are similar to those that have been successfully used in other MVPA studies (Mitchell, et al., 2008; Shinkareva, et al., 2008). Classifiers were trained on the mean percent signal change (PSC) of functional activity for each word triplet in the training set to identify the cognitive states associated with processing abstract and concrete concepts. For each participant's data, the mean PSC of each voxel was the ratio of signal difference between word triplets and the baseline to the baseline signal. The baseline was computed from the averaged signal in the long fixation trials. The signal of each triplet was computed by averaging two volumes offset 4.4 s away from the stimulus onset (the third and fourth volumes of one trial) to account for the delay of hemodynamic response function. Furthermore, the PSCs in each voxel were normalized across triplets to have mean 0, and variance 1, to equate variations in different voxels (Pereira, et al., 2009).

Feature Selection. To reduce the size of the data, relevant features were extracted by using voxels with the most consistent responses toward different conditions across cross-validation folds (Pereira, et al., 2009). Response stability was computed by averaging pairwise correlation coefficients between vectors of repetitions of all exemplars (Shinkareva, et al., 2011). The voxels with lowest response stability were removed. The rationale of stability-based feature selection was that if a voxel responded unsystematically between repetitions across conditions, it was unlikely to contain information that is associated with different conditions. This procedure was based on

training data only to avoid over-fitting. We explored different numbers of voxels retained by feature selection instead of deciding upon an arbitrary threshold.

Classification within participants. A logistic regression classifier was used for *abstract vs. concrete* two-way classification. As a commonly used classifier, logistic regression directly estimates its parameters from the training data (Bishop, 2006). This classifier was chosen because it is simple, less likely to generate overfitting compared to non-linear classifiers, and has been successfully applied in previous studies (Mitchell et al., 2004; Pereira, et al., 2009). To ensure the evaluation of classification performance was unbiased, classification accuracy was evaluated using six-fold cross validation procedure, where each fold corresponded to one repetition of all exemplars. The repetitions were separated by the long fixation period, thus the independence between training and test sets was ensured.

In each cross-validation fold, the trained classifiers were applied to each trial in the test set to classify it as abstract or concrete. The accuracy was the proportion of trials that were correctly classified. For each participant, the obtained accuracy was compared to an empirically generated null distribution, formed by 1000 classification accuracies obtained from the same dataset, but with randomly permuted labels.

In addition, the multinomial logistic regression classifiers were also trained to identify each of the 16 exemplars. For simplicity, the number of voxels from a feature selection step in this analysis was set to 400. The rest of the procedures of feature selection, cross-validation, and significance test were the same as in the main two-way classification.

Region of interest (ROI) analysis. To investigate how the discriminating information is distributed in the brain, the classifiers were trained on data from one of the 90 anatomically defined regions at a time (Shinkareva, Malave, Just, & Mitchell, 2012). ROIs were defined by the automated anatomical labeling (AAL; Tzourio-Mazoyer et al., 2002). Mean PSC in all gray matter voxels in each ROI was used to train the logistic regression classifiers. To access if an anatomical region contained sufficient information to decode abstract or concrete concepts on average across participants, the classification accuracy for each region was compared to a binomial distribution *B(n, p)*, where *n* was the number of triples, and *p* is the probability of successfully identifying a triple as abstract or concrete under the hypothesis that triples are randomly assigned into the two categories (Pereira, et al., 2009). P-values (computed using a normal approximation) were obtained for the mean classification accuracy, computed across participants for each region. The p-values were compared to significance level at *p* = .05, corrected for multiple comparisons.

Classification across participants. To test for a commonality in the neural representation of abstract and concrete concepts across individuals, classifiers were trained on data from all but one participant to identify trials as abstract or concrete in the left-out participant. An entropy-based feature selection was applied to retain the voxels containing most stable information across individuals. For each voxel, the Shannon entropy was computed from the data of twelve individuals in the training set ordered by individual exemplars within abstract and concrete categories. Entropy-based feature selection has been validated as an efficient index of the voxel sensitivity toward the variation of conditions (Poldrack, Halchenko, & Hanson, 2009). For simplicity, the top

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20% of most stable voxels, i.e., voxels with the lowest entropy values, were selected. For each cross-validation fold, the classifier was trained on the PSC data from all but one participant, which was the test dataset. This procedure was repeated for all participants. Classification accuracy was compared to the empirically generated distribution, formed by 1000 classification accuracies obtained from the same dataset, but with randomly permuted labels. Accuracies with p-values smaller than .05 were considered significant.

3.3.   Results

3.3.1. Behavioral results

There were no significant differences in the mean reaction times across participants between judgments on abstract and concrete triplets ($M_{Abstract}$ = 1.66 and $M_{Concrete}$ = 1.69, $t(12)$ = -0.85, p = .41). Moreover, none of the individual participant showed significantly different reaction times between abstract and concrete triplets (p ranged from .08 to .94). These results suggest making judgments on abstract or concrete triplets did not differ in difficulty.

3.3.2. Within-participant classification based on the whole brain

When classifiers were trained to identify word triplets as abstract or concrete, the mean accuracies across participants were significantly greater than chance ($p \leq .05$) for all threshold levels (Figure 3.1). Classification accuracies for one participant were as high as 90.62% (87 out of 96 triplets correctly identified as abstract or concrete). The classification accuracies were highest when the numbers of voxels used for classification ranged from 50 to 3000. The accuracies were reliably above chance for most participants even when all the voxels were included in the analysis.

- — Median accuracy across 13 participants
- ● Mean accuracy across 13 participants
- ✳ The most conservative critical value across 13 participants (p = .05) for a given feature selection threshold. The last column is using all the voxels, i.e., no feature selection applied.
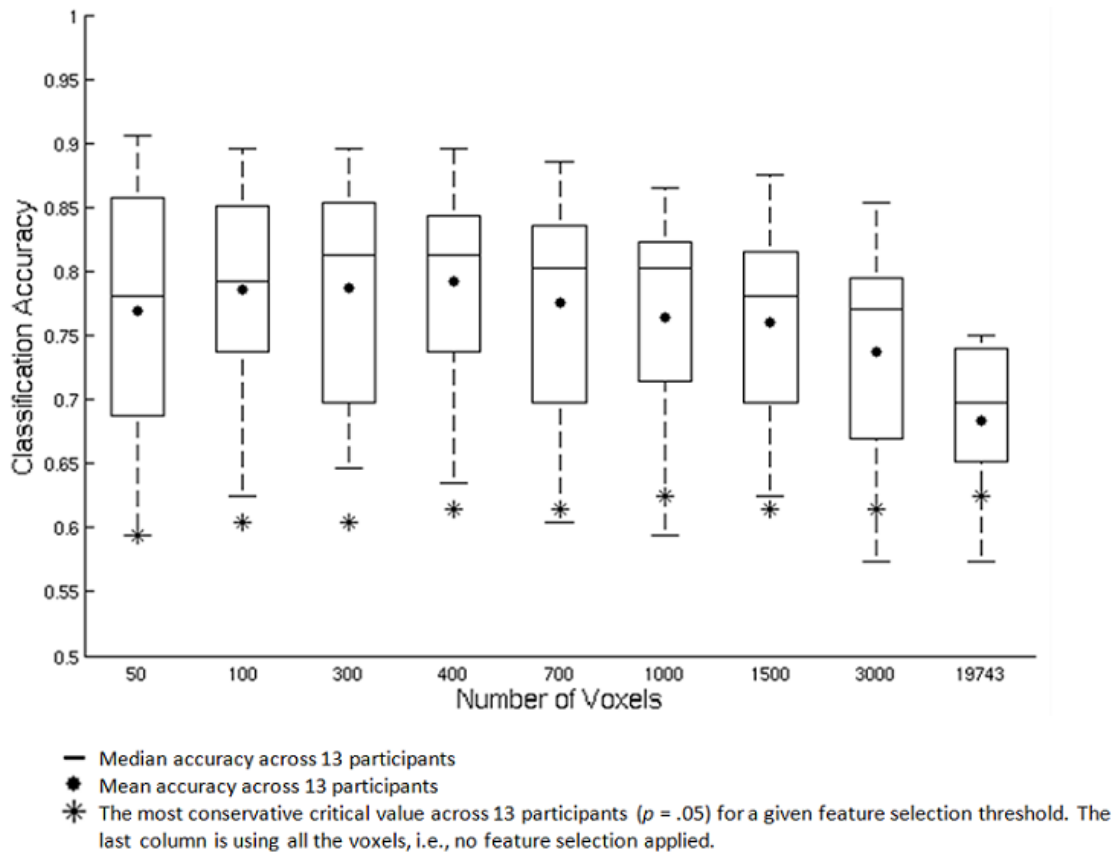
Figure 3.1   Within-participant classification accuracies for identifying trials as abstract or concrete, summarized across 13 participants by box plots, are shown as a function of different number of voxels. © 2013 Human Brain Mapping

The locations of voxels with largest classifier weights for identifying trial as abstract or concrete were distributed in multiple areas in the brain (Figure 3.2). When feature selection retained 400 voxels, the most informative voxels for identifying abstract concepts that were consistently identified across participants were located in the left inferior frontal gyrus, middle temporal gyrus, and posterior cingulate cortex; the most consistent informative voxels for identifying concrete concepts were located in the left angular gyrus, fusiform gyrus, inferior temporal gyrus, middle frontal gyrus, posterior cingulate cortex, and precuneus.

Participant	400 Voxels	1000 Voxels	3000 Voxels
1			
2			
3			
4			
5			
6			
7			
8			
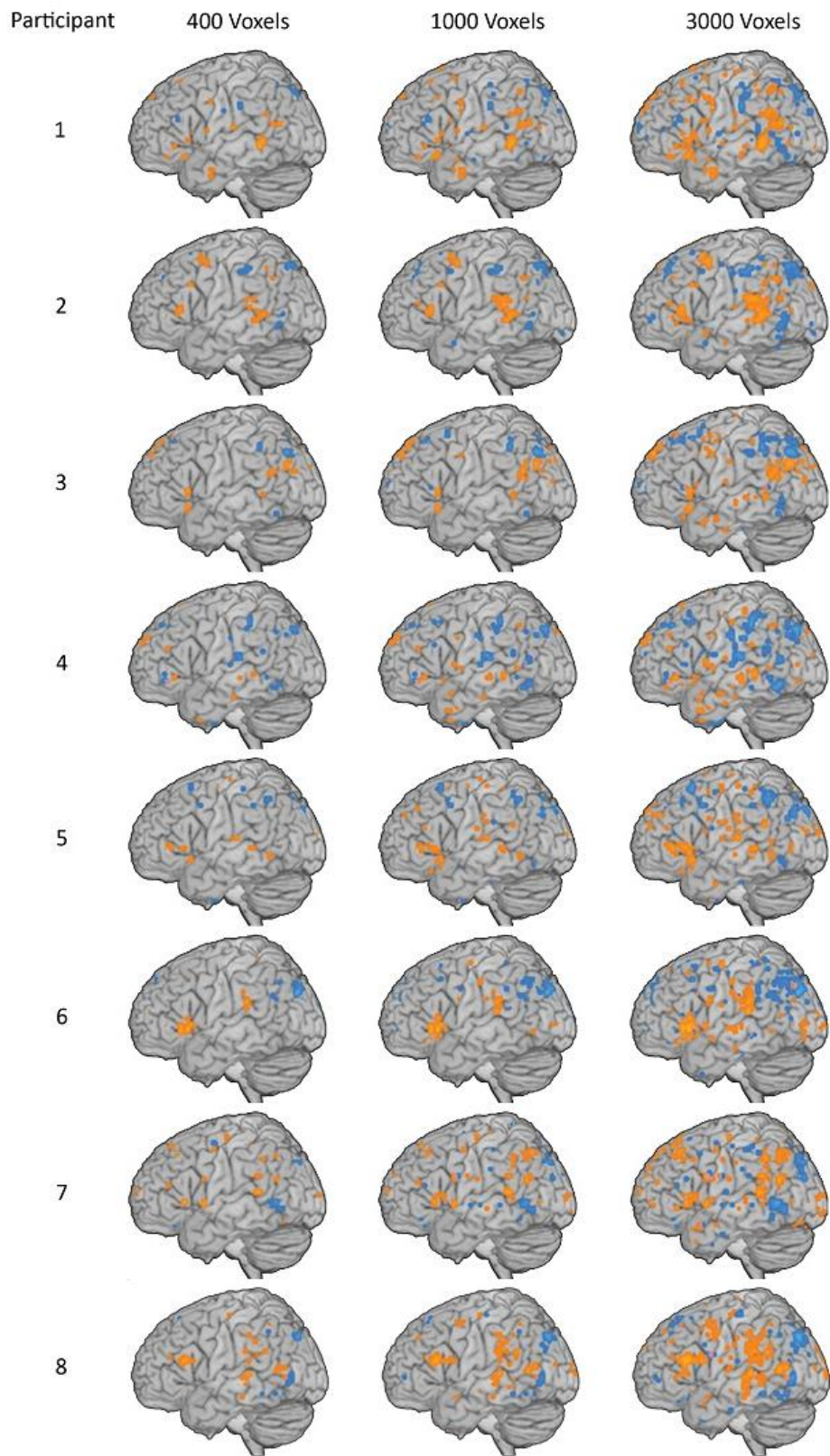
(Figure continued)
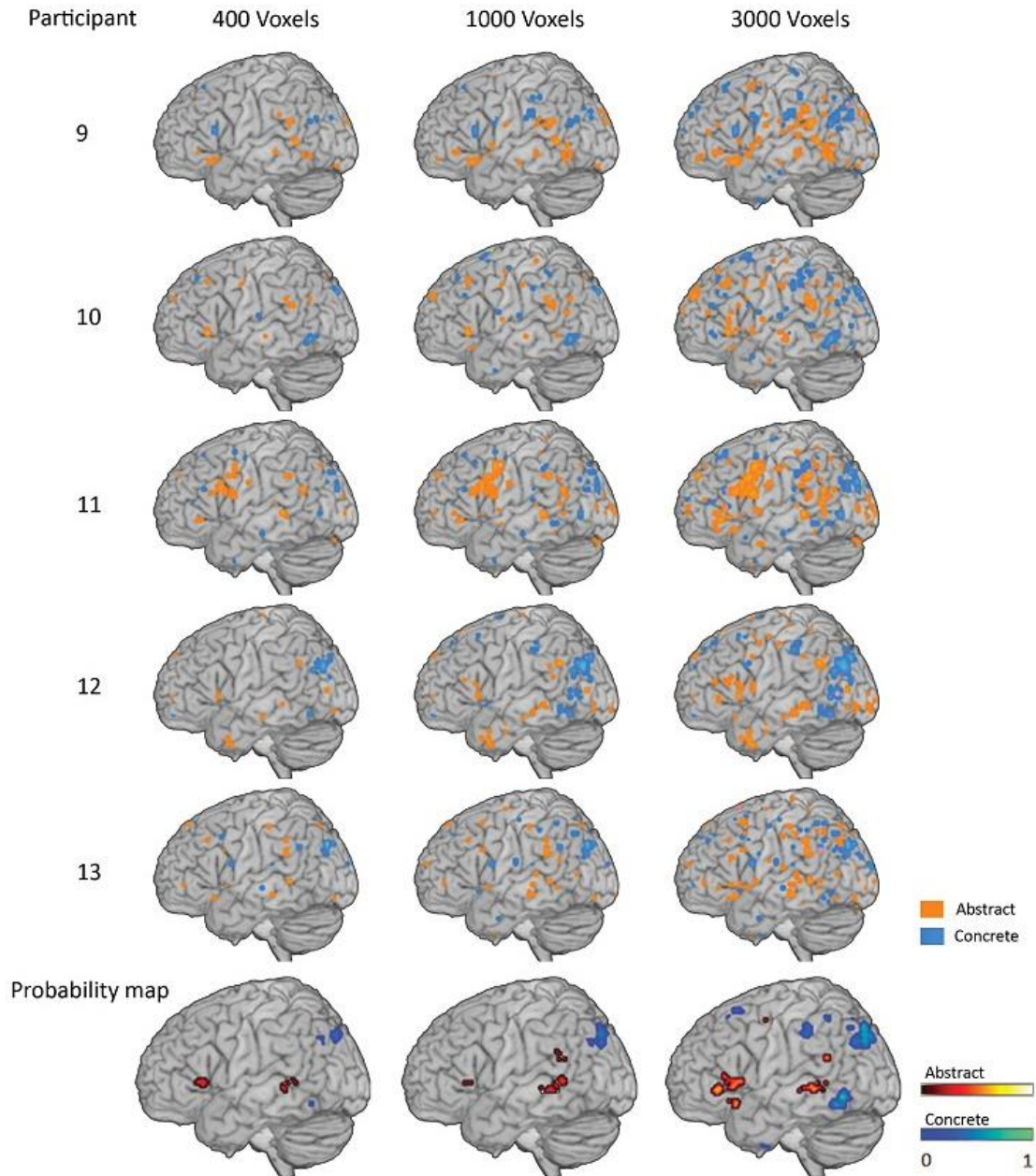
Figure 3.2   Consistency of informative voxels across participants. The most informative voxels for decoding abstract vs. concrete concepts representation within participants were shown on a surface rendering at three feature selection thresholds: retaining 400, 1000, or 3000 voxels. Participants were ordered by within-participant classification accuracy. The warm color indicates the top 5% of voxels that were most informative for identifying abstract trials. The cool color indicates the top 5% of voxels that were most informative for identifying concrete trials. The last row displayed the thresholded probability maps ($p = 0.05$, FWE corrected) of the informative voxels that were consistently identified across all 13 participants.

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In addition, classifiers were trained to identify which specific exemplar a participant was making similarity judgments on. Classification reached mean accuracy of 14.4% across participants for classifying an exemplar into one of the 16 categories (compared to 9.38% at $p = 0.05$ level of significance). Exemplars were reliably ($p \leq .05$) identified for 11 out of 13 participants. Most of the mistakes that the classifier was making were within the same abstract or concrete category (Figure 3.3). Thus, the mental states associated with making similarity judgments with either abstract or concrete concepts can be decoded on a single trial basis, suggesting the distinct representations of abstract and concrete concepts.

3.3.3. Within-participant classification based on single ROIs

To investigate whether individual regions contain sufficient information for decoding abstract and concrete concepts, classifiers were trained using voxels from only one anatomical region at a time. Fifty-two out of the 90 ROIs showed reliable ($p \leq .05$) classification accuracies on average, across participants. These regions were distributed across temporal, frontal, parietal and occipital lobes bilaterally, while the regions with the highest accuracies were mostly in the left hemisphere (Figure 3.4). Out of the 52 informative ROIs, 30 were in the left hemisphere, including the top 15 ROIs with highest average accuracies across participants. The left homologues of all the informative right-hemisphere ROIs also contained information for successful identification. Among these bilateral region pairs, the average classification accuracies across participants were higher in the left hemisphere, with an exception of the lingual gyrus. Five ROIs, including left middle temporal gyrus, left precuneus, left angular gyrus, left middle occipital gyrus and
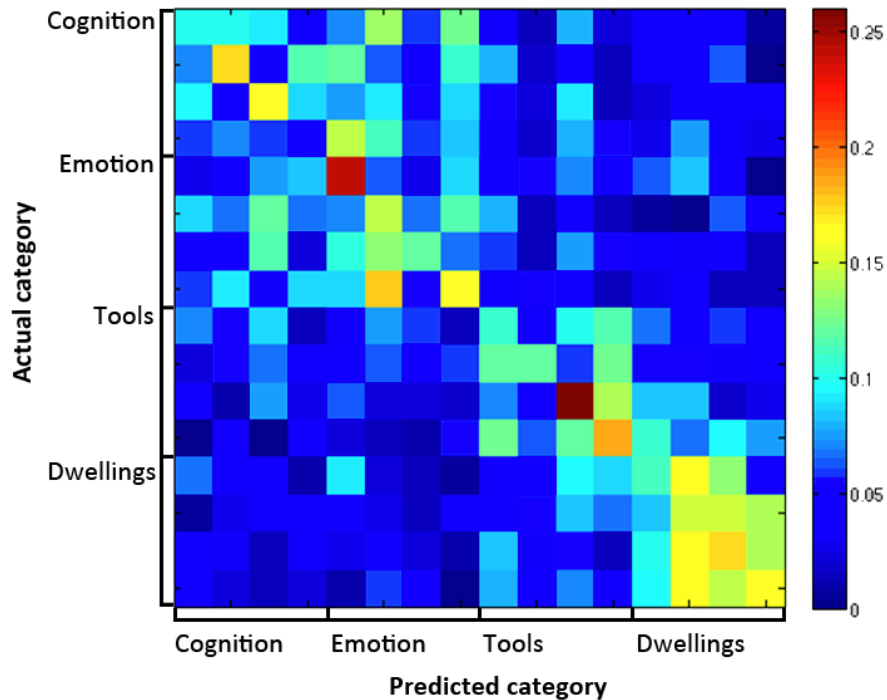
Figure 3.3   Exemplar classification confusion matrix averaged across participants. The value of each element indicates the proportion of exemplars identified as the corresponding label. © 2013 Human Brain Mapping

left precentral gyrus, showed significant accuracy for all of the participants (Figure 3.5).

These results were highly comparable to the location of the informative voxels weighted by the classifier (Figure 3.2). Thus *abstract vs. concrete* processing can be successfully decoded from multiple single brain regions.

3.3.4.   Across-participant classification based on the whole brain

Classifiers were trained on data from 12 participants to determine if it was possible to identify individual trials as abstract or concrete in the left-out participant. The average accuracy across participants of identifying triples as abstract or concrete when the classifier was trained on data from other participants was 84.13% ($p \leq .001$). Word triples for all 13 participants were reliably ($p \leq .05$) identified, with the accuracies

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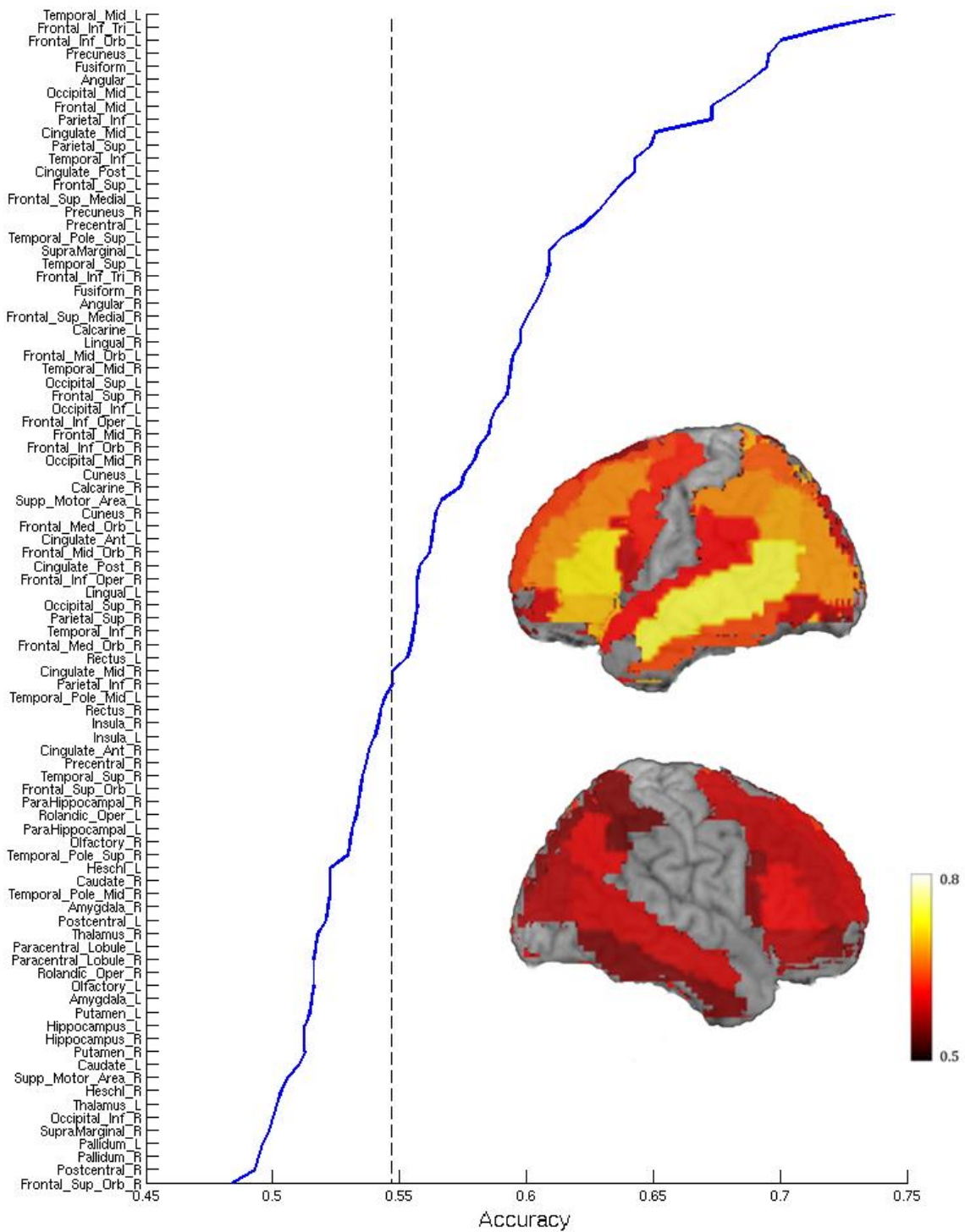
Figure 3.4   Mean classification accuracies across participants, for trial identification as abstract or concrete, are shown for each anatomically defined ROI. Regions with significant mean accuracy across participants (p = .05) are shown on a brain template. © 2013 Human Brain Mapping
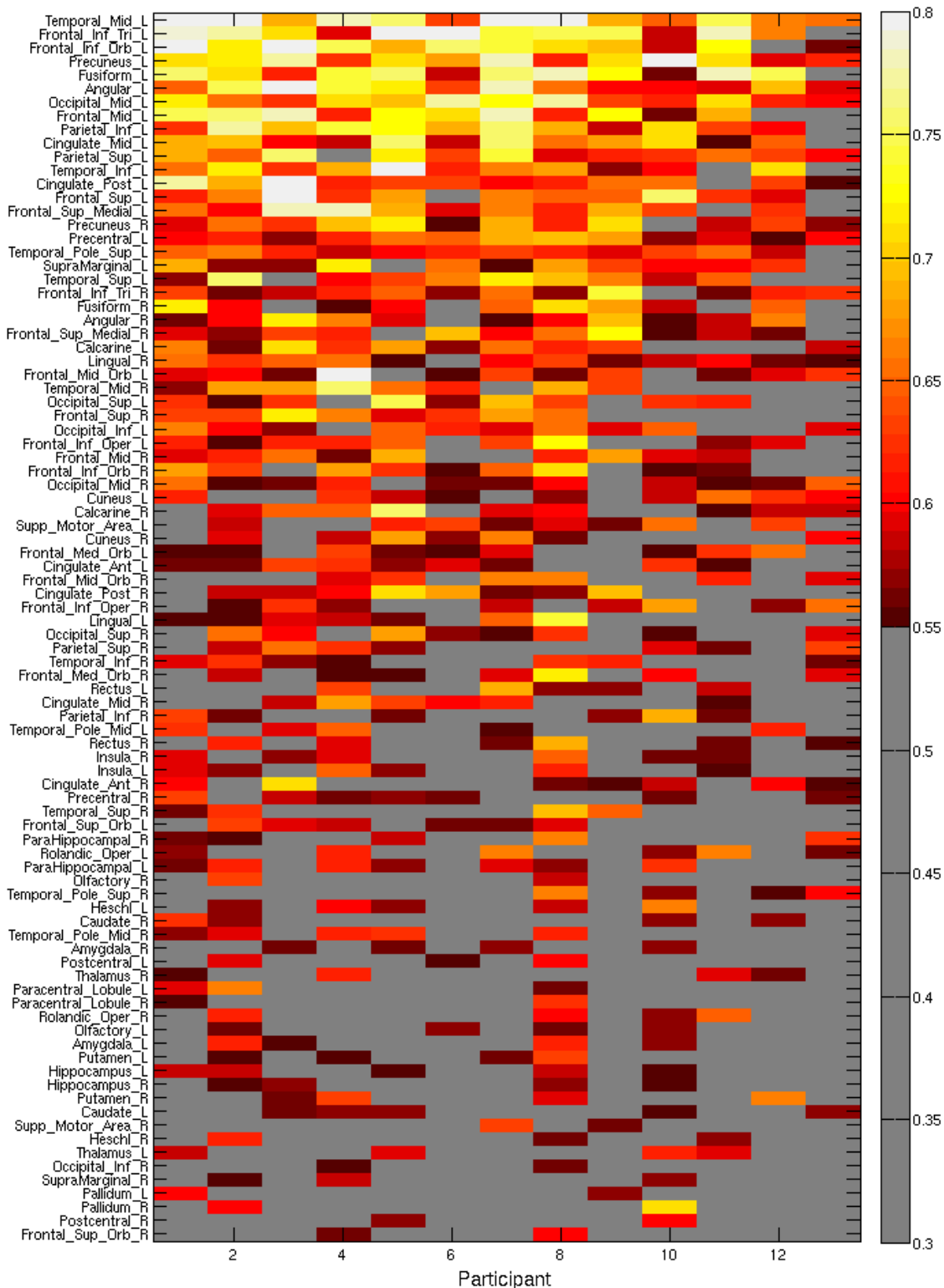
Figure 3.5   Classification accuracies for identification of trials as abstract or concrete are shown for each ROI and each participant. Significant accuracies ($p = .05$) are shown in color. © 2013 Human Brain Mapping

ranging from 62.50% to 93.75% (Figure 3.6). This result indicates the commonality of *abstract vs. concrete* representation across individuals.

3.4.   Discussion

We were able to successfully identify brain activity patterns as abstract or concrete based on single trial data. This study has extended previous results on concrete words representation to abstract concepts. Compared with studies that examined activation differences in abstract and concrete concept representation, this study suggests participants' mental states during processing of abstract and concrete semantic concepts were identifiable from distributed patterns of activity on an individual trial basis.

Moreover, whether a participant was making similarity judgments on abstract or concrete concepts was identifiable solely based on data from other participants, in spite of the anatomical and functional variability across individual brains (Fedorenko & Kanwisher, 2009). It supports the cross-individual principles of processing semantic concept. Classification of mental states across individuals has been previously shown for visually depicted objects (Shinkareva, et al., 2008), concrete nouns referring to physical objects (Just, et al., 2010; Shinkareva, et al., 2011), lie detection (Davatzikos et al., 2005), attentional tasks (Mourao-Miranda, Bokde, Born, Hampel, & Stetter, 2005), cognitive tasks (Poldrack, et al., 2009), and voxel-by-voxel correspondence across individuals has been demonstrated during movie-watching (Hasson, Nir, Levy, Fuhrmann, & Malach, 2004). The current study for the first time demonstrates the ability to identify the mental states of a participant as processing abstract or concrete concepts based on neural activation data from other participants.

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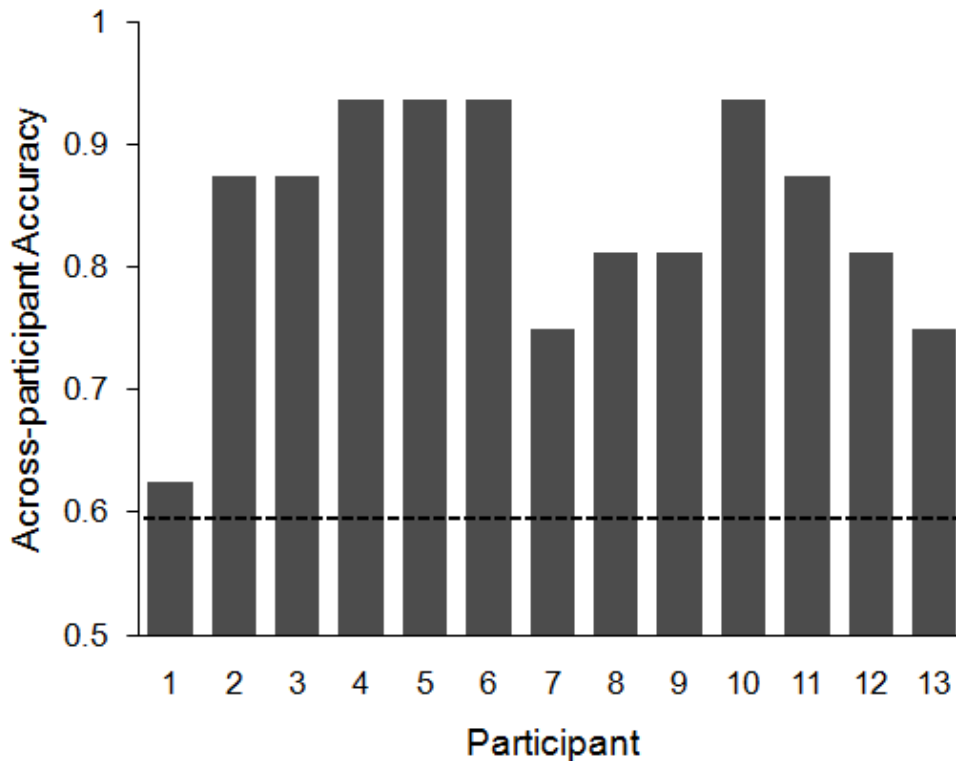
Figure 3.6   High across-participants classification accuracies for identifying single trials as abstract or concrete based on data from other participants. Dashed line indicates *p* = .05 level of significance. © 2013 Human Brain Mapping

Classification within individual anatomically defined regions showed that activity patterns in even single regions were sufficient for identifying trials as abstract or concrete. The present results of regions with discriminating information show considerable overlap with the meta-analysis results based on previous statistical parametric mapping studies locating the differences of abstract vs. concrete semantic concept representation (Binder, et al., 2009; Wang, Conder, Blitzer, & Shinkareva, 2010). Most regions that were previously identified by the meta-analysis were also found to contain information sufficient for identification of trials as abstract or concrete in the current study (Table 2.2; Figure 3.4). The top six ROIs with the highest average accuracy were also identified by the meta-analyses results. However, this single study identified more informative areas

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compared to the combined results of early lesion studies and neuroimaging. In fact, the current results are more comparable to the collection of previous univariate results (Figure 2.1). The extensive spatial distribution of discriminating information may reflect the lack of semantic context restriction during single word processing. Compared to the word specified in a meaningful sentence, single word processing in a semantics-related task may stimulate the rich contexts of the word more extensively (Price 2010).

Although the left ATL is one of the areas that consistently show activational differences for abstract > concrete concept processing, activity patterns in the temporal pole only result in chance-level accuracies for identifying the two conditions. Considering the ATL has been associated with a number of functions related to knowledge representation (Simmons & Martin, 2009), we attribute the lack of information for the temporal pole in Chapter 3 to the low signal-to-noise ratio of fMRI measures at this area due to the susceptibility artifacts (Devlin, et al., 2000; Lipschutz, et al., 2001). A possible solution is adjusting MRI acquisition parameters to reduce signal loss.

The left hemisphere was engaged in the *abstract vs. concrete* concept identification to a very large extent. Thirty out of the 45 left hemisphere ROIs showed significant accuracies on average across participants. A number of right hemisphere regions also held information of *abstract vs. concrete* differentiation. Previous studies have found the activation differences in some of these right hemisphere regions, but with low cross-study consistency (Binder, et al., 2005; D'Esposito, et al., 1997; Fliessbach, et al., 2006; Grossman, et al., 2002; Harris et al., 2006; Jessen, et al., 2000; Mellet, et al.,

1998; Perani, et al., 1999; Sabsevitz, et al., 2005; Tettamanti, et al., 2008; Wallentin, et al., 2005; Whatmough, et al., 2004).

The extensive spatial distribution of discriminating information may reflect the lack of semantic context restriction during single word processing. Compared to the word specified in a meaningful sentence, single word processing in a semantics-related task may stimulate the rich contexts of the word more extensively (Price 2010). Even though, this is the first time that such a large number of informative brain areas for abstract vs. concrete concept representation were identified in a single experiment. It is quite striking that single regions contain, on their own, enough information to decode the presented concepts. It is likely to be the case that sufficient information for category identification is represented in several different regions, lending a somewhat different interpretation to the notion of a distributed representation. Different areas may contribute to differences in *abstract vs. concrete* representation in various ways, for example in terms of the richness of semantic context, coding system, retrieval strategy, or working memory. A number of regions identified in the current study have been shown in previous studies using statistical parametric mapping, but not in the same experiment, with a limited number of stimuli in a single task. One of the reasons, based on the current results, may be the lack of sensitivity in detecting the differences. These results suggest that the representation of abstract and concrete concepts were differentiated on various aspects rather than a single mechanism. Further studies may help illuminate the representational content in regions that support category identification across stimulus formats, such as studies using item-repetition priming (Grill-Spector, Kushnir, Edelman, Avidan, & Itzchak, 1999; James,

Humphrey, Gati, Menon, & Goodale, 2002; Vuilleumier, Henson, Driver, & Dolan, 2002) or Dynamically Adaptive Imaging (Cusack, Veldsman, Naci, Mitchell, & Linke, 2012).

3.5.   Conclusion

By using multi-voxel pattern analysis, this study successfully identified brain activity patterns as abstract or concrete based on single trial data, suggesting participants' mental states during processing of abstract and concrete semantic concepts were identifiable from distributed patterns of activity on an individual trial basis. The ability to identify whether a participant was representing abstract or concrete concepts solely from other participants' data suggests the cross-individual principles of organizing this type of knowledge are similar.

Chapter 4

Using functional connectivity patterns to identify abstract and concrete

concept representations

4.1. Pattern classification beyond localized information

4.1.1. Context availability hypothesis and functional connectivity

Semantic memory relies on anatomically widespread and functionally complex neural components with high interactivity (Binder, et al., 2009; Bookheimer, 2002). The review and experiments in the previous sections have clearly indicated that category-specific information is represented in a more distributed pattern than previously thought. Specifically, the successful multivoxel classification on a whole brain level suggests that co-activation patterns across various brain regions carry information that distinguishes between the abstract and concrete categories. Do the patterns of interaction among regions differ for processing abstract and concrete concepts? From a theoretical perspective, this question pertains to some aspects in the context-availability hypothesis that remain unanswered by the previous studies. Both the univoxel and multivoxel studies have strongly suggested the recruitment of modality-specific, visual sensory and imagery systems in processing concrete concepts, supporting the hypothesis that the representation of concrete concepts can resort to the additional modality-specific systems. By contrast, the context availability hypothesis has been examined in indirect and limited ways, partly due to its focus on the extensiveness of semantic associations instead of

identifying separate processing systems. The findings that verbal semantic system is involved in the processing of abstract and concrete concepts to different extents do not directly inform about the variety or density of the associated semantic content. To address these questions, a method that directly measures the intercorrelation among brain regions for different conditions is more suitable than the approach that investigates the information localized in segregated spatial units. The presumptions for mapping context-availability theory onto the spatial correlation between brain regions are the modularity of brain function, and the distribution of brain regions involved in semantic processing. The structure or pattern of the semantic association is assumed to be reflected in the patterns of connectivity among brain regions, even though the units of observation, namely voxel and between-voxel correlation, do not represent the node or link in the hypothetical semantic space. The current work aimed to test the context-availability hypotheses by examining whether the patterns of functional connectivity associated with processing abstract concepts are different from the patterns associated with concrete concepts.

We translated the context-availability hypothesis to functional connectivity language from two perspectives. First, the hypothesis of retrieval difficulty predicts different patterns of functional connectivity of the semantic executive functioning area with other regions for processing abstract and concrete concepts. We assumed the difference of intrinsic difficulty between the two categories of concepts was associated with different retrieval strategies and efforts. The connectivity between the semantic executive functioning area and other systems involved was expected to reflect such category-specific differences. Based on rationale discussed in the previous chapters, we considered the left inferior frontal gyrus as the semantic executive functioning area.

Second, the hypothesis of contextual constraints predicts difference in the large-scale connectivity across multiple regions involved in the semantic processing. Abstract concepts were considered having greater variety or looser constraints on semantic contexts, therefore we expected the patterns of whole-brain voxelwise connectivity for processing abstract and concrete concepts to be different. In addition, we also investigated the voxelwise connectivity patterns within the left middle temporal gyrus and angular gyrus, which were considered supramodal semantic areas based on a comprehensive quantitative review on semantic memory (Binder, et al., 2009).

4.1.2. Classification based on patterns of condition-specific connectivity

Functional connectivity in the brain refers to the temporal correlations in neural activity among distinct brain regions (Friston, 1994). Although the majority of applications of functional connectivity to resting-state network in the brain, some studies have illustrated possible methods that allow the investigation of connectivity patterns associated with experimental conditions (Dodel et al., 2005; Rissman, Gazzaley, & D'Esposito, 2004). However the condition-specific differences were not statistically evaluated in these studies, likely due to the lack of sensitivity of univariate tests. The present study used the MVPA framework to test whether the condition-specific connectivity patterns learned from a group of individuals can be applied to identify the condition of data from a new individual. The temporal resolution of fMRI measures limits the examination of connectivity differences within individuals, whereas the cross-individual classification allows investigating the condition-specific differences for each individual based on the data of others. We used the same experimental paradigm as in

Chapter 3, with twelve additional participants to reach a sample size of 25 for cross-individual classification.

Previous studies have applied MVPA approach to classify connectivity-based fMRI data for different mental states, such as movie watching vs. resting (Richiardi, Eryilmaz, Schwartz, Vuilleumier, & Van De Ville, 2011), or tasks associated with episodic memory, music lyrics, and mathematical operation (Shirer, Ryali, Rykhlevskaia, Menon, & Greicius, 2012). These studies were able to use relatively small numbers ($\leq$ 100) of nodes on a whole-brain level to identify fundamentally different cognitive states. The present study aimed to detect the comparatively subtle differences in category-specific semantic processing. Therefore, we investigated the voxel-by-voxel connectivity patterns both at a whole-brain level and with pre-defined regions of interests. The rationale of the procedure is that if connectivity patterns are different for the representations of abstract and concrete concepts, and such differences are consistent across individuals, we should be able to identify whether an individual is processing an abstract or a concrete concept based on the connectivity patterns from other individuals.

4.2.   Methods

4.2.1. Participants

Twenty-five participants (thirteen female) from the University of South Carolina community participated in this experiment and gave written informed consent in accordance with the Institutional Review Board at the University of South Carolina. Participants were right-handed, healthy adults and native English-speakers. Thirteen of these participants were included in the study reported in Chapter 3.

4.2.2 – 4.2.4

See section 3.2.2 – 3.2.4 for *Materials, Procedure* and *MRI Acquisition.*

4.2.5. FMRI data preprocessing

The data were processed using SPM5 (www.fil.ion.ucl.ac.uk/spm). Images for

each participant were corrected for head movement by aligning images to the first

volume based on a six-parameter rigid body transformation. The linear trend in images

for each participant was then removed to correct the signal intensity drift. The images

were normalized to Montreal Neurological Institute template and re-sampled to the voxel

size of $3 \times 3 \times 3$ mm^3 for examining the connectivity within the general semantic systems,

or re-sampled to $10 \times 10 \times 10$ mm^3 voxels for computing the whole-brain connectivity

matrix and connectivity seeded in the left IFG.

4.2.6. Preliminary test: SPM on seed-based connectivity

We first examined if the condition-specific difference of the connectivity to the

left IFG could be located in any region. This approach was analogous to the univoxel

SPM approach on the activity maps. We first examined whether the connectivity of any

voxel to the seed region showed significant response to the abstract or concrete condition.

The correlation maps at the resolution of $3 \times 3 \times 3$ mm^3 voxel for the seed region with the

other voxels for abstract and concrete conditions were converted to the z-maps by

Fisher's Z transformation. Random-effect group level analyses were performed on the z-

maps for each condition respectively (Rissman, et al., 2004).

4.2.7. Connectivity-based MVPA

The cross-participant MVPA was performed on three types of connectivity

matrices as indicated by the hypotheses: the whole-brain voxel-by-voxel connectivity, the

connectivity between the seed of left IFG and other voxels in the brain, and the voxel-by-voxel connectivity within the semantic areas. The regions of interests were defined by the anatomical masks from Anatomical Automatic Labeling (Tzourio-Mazoyer, et al., 2002). The measurement of connectivity was the Pearson correlation coefficient of weighted time series between pairs of regions. The condition-specific weight was estimated by convolving the vector of onsets for abstract or concrete condition with the canonical hemodynamic response function. To ensure the real-valued correlation all the values in the weight vector are made positive by taking the absolute value (Dodel, et al., 2005). Preprocessed time series were weighted for each condition to generate two correlation matrices that represented the connectivity patterns for abstract and concrete conditions.

The pattern classification procedure was performed to test the cross-individual consistencies of the patterns for abstract and concrete conditions. A similarity-based classifier was trained on data from all but one participant, to identify the test data, i.e. connectivity matrices for the left out participant. This procedure was implemented iteratively, leaving out each of the participants once. Classifications were performed either on all the unique connections in the matrix or with feature selection. To select connections that responded to the experimental conditions, matrices in the training set were first transformed to Fisher's Z score. One sample t-tests against the null hypothesis of no response were then performed for each connection across all the participants in the training set, for abstract and concrete matrix respectively. The connections with the highest t values in either condition were selected jointly for both conditions, so that the feature selection was orthogonal to the classification categories. Because there is no one

preferred way to choose the threshold, we have studied abstract and concrete condition-specific matrices at multiple threshold levels.

For the training set, weighted average matrices for abstract and concrete conditions were generated by weighting each participant's matrix by how similar they were to each other (Abdi, Dunlop, & Williams, 2009; Shinkareva, et al., 2011; Shinkareva, Ombao, Sutton, Mohanty, & Miller, 2006). Pairwise similarity between participants was measured by the RV coefficient (Robert & Escoufier, 1976), a multivariate generalization of the Pearson correlation coefficient to matrices. Each participant's data were weighted by the first eigenvector of the similarity matrix which was scaled to sum up to one.

For each test matrix, the cosine similarity scores with abstract and concrete training matrices was computed, and the test matrix was labeled according to the training condition with the higher similarity score (Mitchell, et al., 2008). Classification was evaluated based on whether the hit score was higher than the miss score across the two conditions. The overall classification accuracies were averaged across participants.

To determine the significance of classification accuracy, the distribution of accuracies under the null hypothesis of no condition-specific distinction was empirically generated. This distribution was formed by 1000 accuracies obtained from the same dataset and procedure, except that the elements in training matrices were randomly reordered in each of the 1000 iterations.

4.3.   Results

4.3.1. Seed-based connectivity: SPM

Before testing the hypotheses by using MVPA, we localized the condition-

specific connectivity differences for the left IFG. First, regions that were significantly connected to the left IFG in the two conditions across participants were found to be considerably overlapping (Figure 4.1).

We then tested condition-specific difference on the connectivity maps. The difference z-maps were obtained respectively for concrete > abstract and abstract > concrete comparisons. The comparisons between the two conditions did not reveal any voxel whose connectivity to the seed region showed significant difference, even at a liberal threshold of uncorrected $p \le .001$, cluster size = 2 voxels. Nevertheless, the maps of the t tests implicated several regions with a trend of condition-specific connectivity strengths to the seed. Compared to abstract concepts, concrete concepts tended to elicit greater connectivity to the seed IFG region in the bilateral inferior temporal gyrus, from the posterior lateral to the medial anterior portion. The bilateral angular gyrus also appeared to show stronger connectivity to the seed region for concrete concepts. The left medial superior frontal gyrus, a lower portion of the left postcentral gyrus, the right lateral globus pallidus, a cluster at the posterior cingulate cortex and retrosplenial region, and the anterior prefrontal cortex also tended to associate with the seed region to a greater extent for concrete concepts (Figure 4.2). In contrast, the regions showing a tendency of stronger connectivity to the seed region for processing abstract concepts included a stream from the supramarginal gyrus down to the pSTS and the relatively medial section of middle temporal gyrus, a cluster around the lower portion of the precentral gyrus, and the middle occipital gyrus. The cross-individual commonality of connections that responded to both of the conditions and the trend of univariate differences between conditions suggested that the connectivity-based MVPA was promising to identify

condition-specific connectivity patterns.
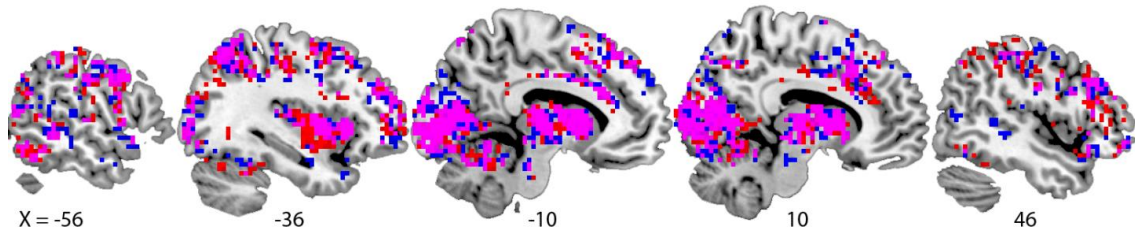
Figure 4.1   Voxels with significant (FWE corrected, $p \leq .05$, cluster size = 5) connectivity to the left IFG for concrete (red) and abstract (blue) concept processing; spatial resolution at $3 \times 3 \times 3$ mm^3. The overlapped voxels of the two conditions are shown in magenta.
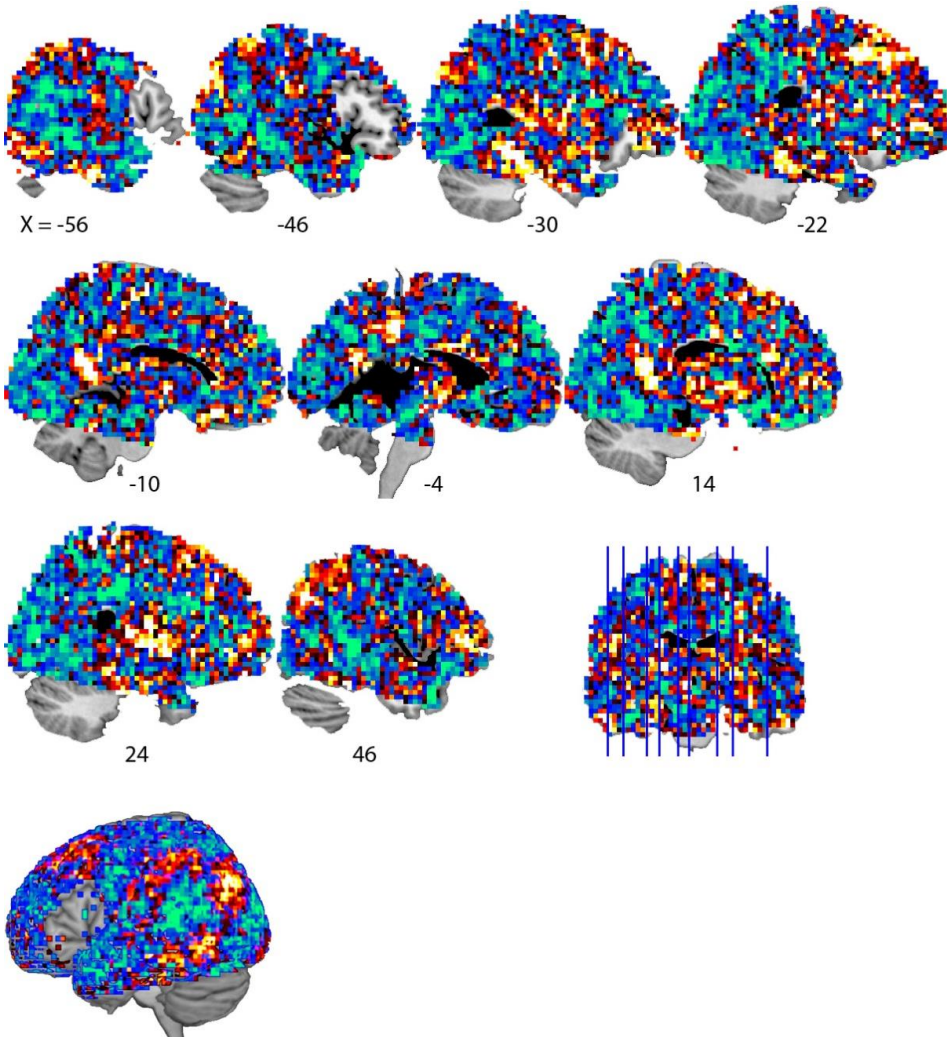
Figure 4.2   The map of t-values for contrast concrete > abstract (hot) and abstract > concrete (cold) on MNI template of multiple slices and a rendered brain surface.

4.3.2. Classification on connectivity between the left IFG with other regions

We were able to identify abstract or concrete concepts associated with connectivity patterns of the left IFG with other brain areas with accuracies that were significantly above chance at multiple threshold levels (Table 4.1). The classification accuracy based on all the connections in the brain was 72%. Using the connections that significantly responded to either condition (FWE corrected) increased the classification performance to an accuracy of 80%. To investigate the connections that were included in the thresholded connectivity maps, the same one-sample t-tests used for feature selection were performed on all the participants and thresholded at p of .05 (FWE corrected). First, the selected voxels were distributed in multiple regions (Figure 4.3), comparable to the results of the analyses performed on the resolution of $3 \times 3 \times 3$ mm^3 (i.e., Figure 4.1). Second, the voxels selected by the data from abstract and the concrete conditions also largely overlapped. These findings indicated that (1) the selections of voxels by the feature selection for classification were not dominated by either of the two conditions, and (2) the selected voxels were not discriminative to the conditions at univoxel level. In other words, the successful classifications were unlikely to be driven by the bias in voxel selection or the univariate differences.

4.3.3. Classification on voxel-by-voxel connectivity

The whole-brain group mask for the current experiment consisted of 1509 voxels common to all 25 participants. Classification based on the whole-brain connectivity patterns with no further feature selection resulted in 84% accuracy. The above-chance classification accuracies were stable at a range of numbers of connections (Table 4.2).

In addition, we investigated the voxel-by-voxel connectivity pattern at the voxel

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Table 4.1   Classification accuracies at multiple feature selection threshold levels based on connectivity to the left IFG

Threshold of feature selection	1	.05, FWE corrected	.1	.05
Accuracy	0.72*	0.8*	0.84*	0.72*
Averaged number of connections	1401	484.48	212	112.16

*: $p \le .05$.

Table 4.2   Classification accuracies at multiple feature selection threshold levels based on whole-brain voxel-by-voxel connectivity.

Threshold of feature selection	1	0.05	0.01	0.001
Accuracy	0.84*	0.92*	0.72*	0.56
Averaged number of connections	2277081	179144.40	39122.80	5447.68

*: $p \le .05$.
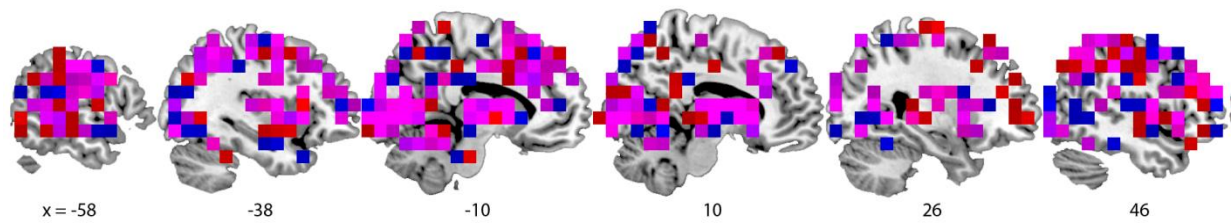
Figure 4.3   Voxels with significant (FWE corrected, $p \le .05$) connectivity to the left IFG in concrete (red) and abstract (blue) concept processing; spatial resolution at $10 \times 10 \times 10$ mm^3. The overlapped voxels of the two conditions are shown in magenta.

size of $3 \times 3 \times 3$ mm^3 within the left MTG and angular gyrus. Classification accuracies were significant when feature selection was used (Table 4.3).

4.4.   Discussion

The present study examined the cross-individual consistencies of the connectivity patterns for abstract and concrete concept representations based on fMRI data.

Table 4.3   Classification accuracies at multiple feature selection threshold levels based on voxel-by-voxel connectivity in the left MTG and angular gyrus.

Threshold of feature selection	1	0.05	0.002	0.001	0.0001	0.00001
Accuracy	0.56	0.64*	0.68*	0.76*	0.52	0.6
Averaged number of connections	1615503	10382.44	4066.68	2093.28	253.24	26.32

*: $p \le .05$.

The findings indicated systematic differences in functional connectivity between abstract and concrete conditions. The commonality across participants in the connectivity patterns elicited by abstract and concrete words enabled the cross-participant classification.

Context-availability theory attempted to interpret the representational difference between abstract and concrete concepts by the difference in a single mechanism. Although it has been shown that the modality-specific systems are involved in category-specific concepts to different degrees, these findings have not ruled out the possibility of predictions about the context-availability. The current evidence was consistent with the hypothesis that the representation of abstract and concrete concepts also differs from the semantic association perspective. First, the successful classification on seed-based connectivity indicated that the property of retrieved information or retrieval strategy for processing abstract and concrete concepts were different, even though the regions involved were considerably overlapping. Although the seed-based SPM test did not reveal any statistically meaningful difference between abstract and concrete concepts, the clustering of voxels with a difference between conditions suggested the possibility for the connectivity of those regions to the left IFG to be condition-specific. Consistent with the

findings of locating activational differences, the inferior temporal gyrus was found to be more involved in the processing of concrete concepts whilst the middle temporal gyrus was found to engage more in the processing of abstract concepts. The results also suggested that various regions in the temporal-parietal junction area were involved in conceptual representation in different ways, with the posterior area being involved more in processing concrete concepts and the anterior area in abstract concepts. Similarly, the anterior temporal lobe, particularly the medial section, presented complex patterns for representing the two categories of concepts. In addition, condition-specific differences appeared to present at the lateral area in the posterior and medial area in the anterior section in the temporal lobe. The overall patterns of connectivity suggested that the retrieval of knowledge about concrete concepts was more localized in several regions, whereas retrieving abstract concepts was associated with a more distributed network.

Second, the patterns of intercorrelations among regions involved in semantic processing showed category-specific differences. The successful classification based on all the voxels in the brain indicated such differences were represented in widespread areas. Future study is required to characterize the differences in connectivity patters by using network analyses approaches. The unstable performance of identifying connectivity patterns of the supramodal semantic areas as abstract or concrete could be attributed to several factors, including the lack of distinguishable patterns between the two conditions, the lack of cross-individual consistency, and the vulnerability to noise at relatively smaller voxel size. It is possible that the functional organization represented by the connectivity was different from that by the activation-based results. Hence model-free

network extraction methods would be useful to explore the functional structure for further investigation.

4.5. Conclusion

The condition-specific connectivity patterns across the whole-brain were distinguishable between abstract and concrete concept representations, and these differences were consistent across participants. Our findings provided supporting evidence for two aspects of the context-availability theory that accounted for the representational difference between abstract and concrete concepts, namely the differences of retrieval difficulty and strategy, and the differences of semantic contextual constraints.

Chapter 5

The role of general semantic systems in the representation of person-specific

knowledge: An application of cross-modal MVPA

5.1.   Introduction

In research of semantic knowledge representation in the brain, one long-standing

question is whether common neural responses exit between different stimuli presentation

formats of the same concept. For instance, processing pictures of animate vs. inanimate

objects results in systematically different brain activities, and reading words referring to

these two categories of objects also causes a difference in brain activities, how do we test

whether the differences are dependent of presentation format, or due to supramodal

representations? Such questions are highly compatible with MVPA's framework of

prediction, and can be translated to MVPA languages, such as, "given that the response

patterns of animate vs. inanimate object processing are identifiable in picture or words, is

it possible to predict which categories of words the participant is reading based on data of

viewing pictures?" Accurate classifications will suggest a commonality of distinguishable

animate vs. inanimate representations between words and pictures. A recently study used

this method to verify the identifiable common neural states across pictorial and verbal

stimuli of tools and dwellings by successful classification in both directions (Shinkareva,

et al., 2011).

This cross-format prediction approach, characterized by using heterogeneous data for training and test sets, is a useful tool to demonstrate the representational commonality across formats or modalities of stimuli. The current experiment aimed to illustrate the application of this approach on examining the role of general semantic system on person-specific knowledge.

The biographical knowledge about familiar people is a significant component of semantic memories and plays important roles in various aspects of life. Neuropsychological cases of semantic deficits on person-specific knowledge suggest the possibility that such information is represented separately from other domains of knowledge (Ellis, Young, & Critchley, 1989; Evans, Heggs, Antoun, & Hodges, 1995; Thompson et al., 2004). The reports of cases with relatively preserved person-specific knowledge in the context of impaired general semantics further suggest a dissociation of person-specific and general semantic memory (Lyons, Kay, Hanley, & Haslam, 2006; Thompson, et al., 2004). However, this hypothesis is subject to questionings at multiple levels. First, certain confounders may exist in the tasks used for person-specific vs. general semantics and the stimuli per se in these studies, such as the strength of semantic association among stimuli within the same condition (e.g., the overall semantic distance for a stimulus pool with names of musicians and politicians can be different from that for a stimulus pool with animals and artifacts), the salience of the given property to the object in property verification tasks (e.g., the function as to objects can be of different importance from the occupation as to people), the semantic density of each stimulus, etc. The activity of regions for processing person-specific information has been found to relate to the amount of knowledge associated with the concept (Desai, Tadimeti, &

Binder, 2012), suggesting the possible alternative interpretation of the role for these areas. Second, the localization of neural substrates for person-specific knowledge has revealed discrepancies in both neuropsychological and functional imaging literatures (Ellis, et al., 1989; Gorno-Tempini et al., 1998; Hodges & Graham, 1998; Leveroni et al., 2000; Miceli et al., 2000). It is noteworthy that the reported areas have considerable overlap with the neural circuits for general semantic memory, such as ATL, pSTS/MTG, the precuneus, etc. (e.g., Desai, et al., 2012; Gorno-Tempini, et al., 1998; Leveroni, et al., 2000). Third, the impairments of person-related knowledge in some reported cases co-occurred with impaired knowledge of other domains, such as living things (Hanley, Young, & Pearson, 1989) or concepts with high uniqueness, such as geographical shape or famous products and buildings (Ellis, et al., 1989; Saetti, Marangolo, De Renzi, Rinaldi, & Lattanzi, 1999). These findings are compatible with the argument that deficits on person-specific knowledge essentially reflect impaired general semantic memory system, to which the knowledge with low semantic density, or high uniqueness, is more vulnerable.

We hypothesized that the representation of person-specific knowledge partly relied on the general semantic system. The current study examined whether the multivoxel activations in the brain areas that were associated with semantic memory showed distinguishable patterns for processing familiar vs. unfamiliar items on a single trial basis. Furthermore, we used a cross-modal MVPA to examine whether the activity patterns associated with general semantic processing can be applied to identify the processing of familiarity.

5.2. Methods

5.2.1. Participants

Five right-handed, native English-speakers with no history of neurological illness participated in this study. Written informed consents were obtained from the participants prior to the experiment in accordance with the protocol sanctioned from Medical College of Wisconsin and Marquette University Institutional Review Boards.

5.2.2. Materials

The stimuli for the semantic task were 100 real words and 100 pseudowords matched on various low-level properties. The real words condition contained 50 abstract words and 50 concrete words. These three categories of stimulus (concrete, abstract and pseudowords) were matched on letter length, phoneme length, mean positional bigram frequency (MPBF) and orthographic neighborhood size using phonological data and frequency counts from English Lexicon Project database (Baayen, Piepenbrock, & Van Rijn, 1993; Balota et al., 2007).

The stimuli for the person-specific knowledge task included names of known (famous or personally familiar) or unknown persons and places. Each category of stimuli (famous person, famous places, personally familiar person, personally familiar places, unfamiliar person, or unfamiliar places) consisted of 40 items. The famous people and places list which was used for all subjects was constructed such that most items were familiar to the subjects. The personally familiar people and places list was provided by the subjects a few days before the experiment. The unknown people and places were

which were also common for all the subjects were collected from the telephone directory and the web and were verified using ratings.

5.2.3. Procedures

While being scanned, participants were instructed to make lexical decisions on words or pseudowords in the semantic task, and to make familiarity judgments on names of items in the person-specific knowledge task. Both tasks were implemented in event-related design, with each item presented for 1 s in pseudo-random order with jittered intervals of 2.5 - 12 seconds. Each of the tasks consisted of 4 imaging runs.

5.2.4. MRI acquisition

MR images were acquired on a 3T long bore scanner (GE Medical Systems, Milwaukee, WI). Functional data consisted of gradient echo planar images, with TR = 2500 ms, TE = 20 ms, voxel size = $1.5 \times 1.5 \times 2$ mm3. Structural T1 weighted images were collected using a spoiled gradient-echo sequence , with TR = 8.2 ms TE = 3.2 ms, flip angle = 12 °, FOV = 240 mm, 256×224 matrix, slice thickness = 1 mm. Images were collected with oblique partial brain acquisition, which covered the temporal lobe, inferior frontal and the supramarginal gyri in 34 slices.

5.2.5. FMRI data preprocessing

The AFNI software package (Cox, 1996) was used for image analysis. Images were despiked by replacing the extreme value in a voxel based on those of its neighbors using interpolation. Motion artifacts were minimized by with-in-participant registration of echo planar image volumes. Estimates of the three translation and three rotation movements at each point in each time-series were computed during registration. The mean signal in the ventricles, white matter areas and regions outside the brain were

estimated to be included as covariates of noise in the general linear models along with the head motion parameters. The mean and linear trends across time in each imaging runs were removed on a voxel basis.

5.2.6.   MVPA methods

Data extraction

The data for MVPA were the beta estimate of the general linear model for each of the trials in a task at each voxel. Trials on which errors occurred were excluded from the model. For each individual trial, event-related deconvolution analysis of the time-series was used to estimate the hemodynamic response at each voxel. The head motion parameters and noise parameters were included in the regression model as covariates. The resulting maps for each participant were linearly resampled in standard stereotaxic space to a voxel size of $1 \times 1 \times 1$ mm^3 and spatially smoothed with a 6 mm full-width-half-maximum Gaussian kernel to compensate for variance in anatomical structure.

Feature selection

Discriminative feature selections were used for both the within-modal and cross-modal classification. For the within-modal classifications (training and testing sets were from the same task), to select voxels with different responses between conditions in each task, two-sample t-tests were performed in a leave-one-trial-out cross-validation procedure, so that the selected voxels were blind to the test set.

For the cross-modal classifications, we used the group level contrast map to select voxels for each task. Event-related deconvolution analyses were used to estimate the hemodynamic response to each condition, i.e. word and pseudoword for the semantic task, and familiar and unfamiliar items for the person-specific knowledge task. The head

motion parameters and noise parameters were included in the regression model as covariates. Contrasts between conditions were then performed under the general linear model for each task to identify the differences of response between conditions within each voxel. The contrasts for the two tasks were word – pseudoword and familiar – unfamiliar respectively. The resulting contrast maps for each participant were linearly resampled in standard stereotaxic space to a voxel size of $1 \times 1 \times 1$ mm^3 and spatially smoothed with a 6 mm full-width-half-maximum Gaussian kernel to compensate for variance in anatomical structure. The normalized and smoothed maps were then subject to a random effects analysis comparing the coefficient values to a null hypothesis mean of zero across participants.

Voxels with highest absolute values of the contrast were selected for the training and testing. We examined the classification performance on a range of numbers of voxels to examine the reliability of classification.

Classification 1: Within- modal classification

The purpose of within-modal classifications was twofold. The first purpose is to validate the MVPA procedure for decoding information content in this dataset for further analyses. The second purpose is to test the hypothesis that regions included in the semantic processing contained sufficient information to identify stimuli as being familiar or unfamiliar. Within-modal classification was conducted to identify word vs. pseudoword trials in the semantic task. Logistic regression classifiers were trained on all but one trial per condition to identify the left-out one as being word or pseudoword.

Classification 2: Familiarity and semantic processing

Classifiers were trained on the beta estimate in the semantic task to identify the

conditions of processing familiar and unfamiliar items in the person-specific knowledge

task within each participant, and vice versa. Logistic regression classifier was used within

each participant's data. Classification accuracies were the average performance across all

the test trials.

Significance tests

The chance accuracy for the two-way classification was expected to be 50%. To

determine the significance of accuracy, the obtained classification accuracy was

compared to a binomial distribution $B(n, p)$, where n was the number of triples, and p is

the probability of successfully identifying a triple as abstract or concrete under the

hypothesis that triples are randomly assigned into the two categories. P-values (computed

using a normal approximation) were obtained for the mean classification accuracy,

computed across participants for each region. The p-values were compared to

significance level at $p = .05$.

5.3.   Results

5.3.1. Within-modal classification

Within-modal classification was conducted to identify word vs. pseudoword trials

in the semantic task. We were able to identify individual trials as word or pseudoword

with above-chance accuracies for all of the participants by using a large range of numbers

of voxels. Using fewer or more voxels resulted in a steady decrease in the classification

performances for some participants (Figure 5.1).

We were also able to identify individual trials as being associated with familiar or

unfamiliar people or places for most of the participants with above-chance accuracies.

Figure 5.1   Classification accuracies for identifying trials as word or pseudoword, summarized across all the participants by box plots, are shown as a function of different number of voxels.

The numbers of voxels included in successful classifications were in a smaller range compared to that for identifying word vs. pseudoword (Figure 5.2).

5.3.2. Cross-modal prediction

To test the hypothesis that the activity patterns processing of person-specific knowledge relies on the semantic system, classifiers were trained on semantic tasks and tested on person-specific knowledge tasks, and vice versa. Classification accuracies were significant for one or two out of five participants in both directions (Figure 5.3 and Figure 5.4). The mean accuracies suggested that training on semantic task and testing on person-specific knowledge task resulted in higher accuracy than training on person-specific knowledge task and testing on semantic task.
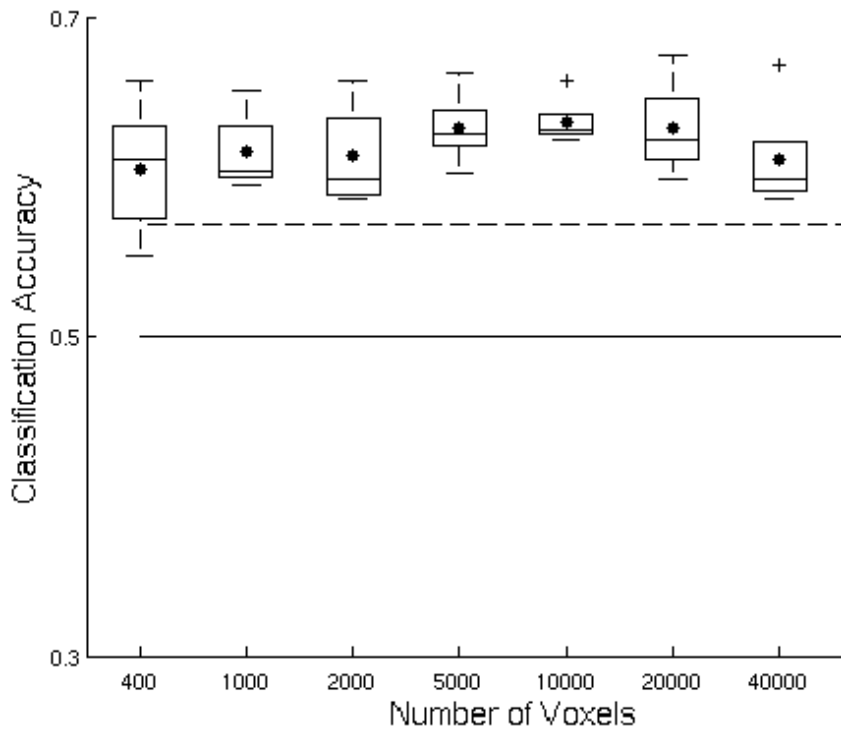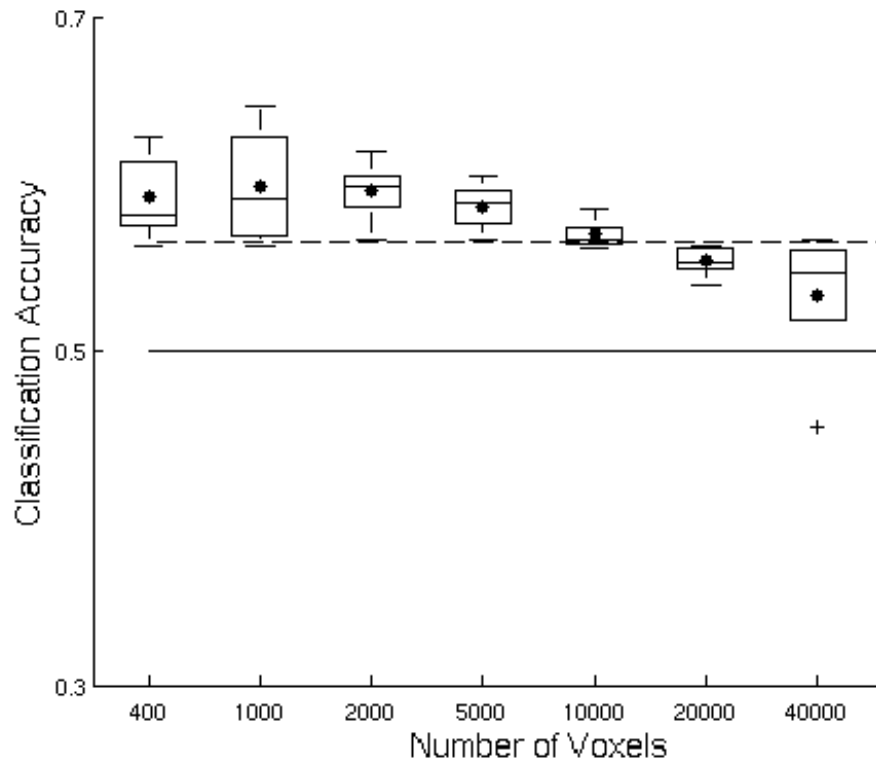
Figure 5.2   Classification accuracies for identifying trials as familiar or unfamiliar items, summarized across all the participants by box plots, are shown as a function of different number of voxels.

5.4.   Discussion and summary

The current study investigated the role of the general semantic systems in representing person-specific knowledge. By using the activity patterns in the temporal lobe, inferior frontal and the supramarginal gyri, we were able to distinguish not only between word and non-word, but also between the names of people and places that were familiar and unfamiliar to the participants. The successful identification of familiarity in the brain regions associated with semantic memory indicated shared neural substrates for processing person-specific knowledge and semantic knowledge. Moreover, this study illustrated the application of MVPA as a cross-modal prediction approach by
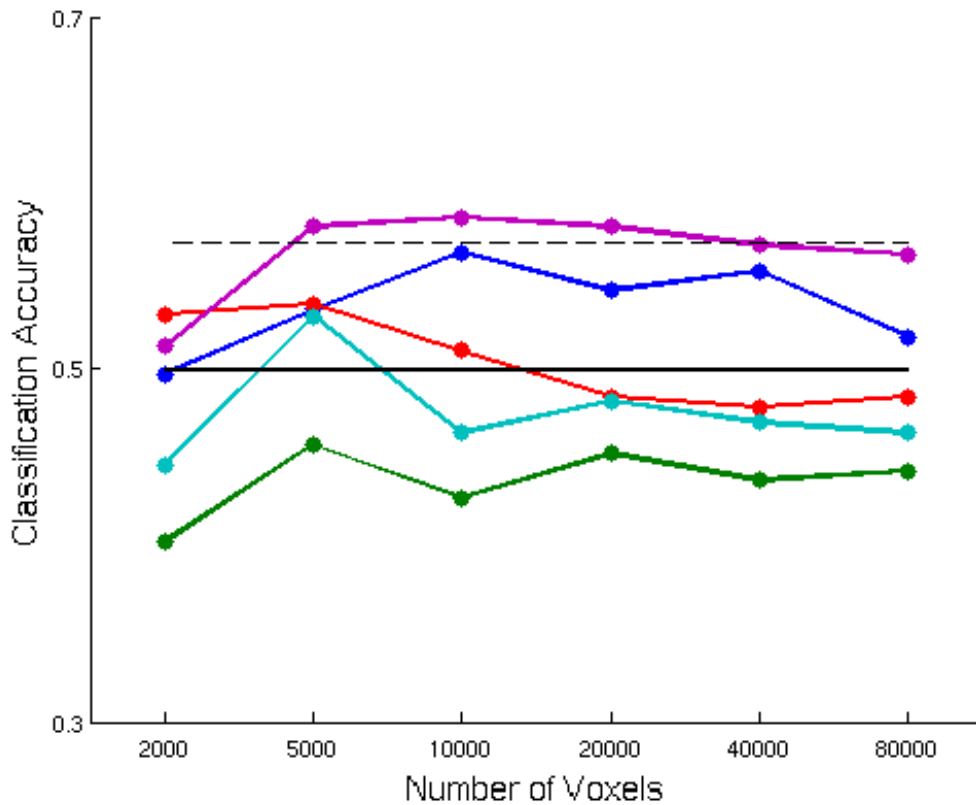
Figure 5.3   Classification accuracies for identifying trials as familiar or unfamiliar items based on patterns distinguishing words and pseudowords are shown for each participant as a function of different number of voxels. Each line represents a participant.

investigating the role of general semantic system on person-specific knowledge. Results suggested the possibility that person-specific knowledge was represented partly using the general semantic systems (see section 6.2.2 for discussion on further application of this approach). On the other hand, the trend that training on semantic task and testing on person-specific knowledge task resulted in a trend of higher accuracy than training on person-specific knowledge task and testing on semantic task suggested that the representation of person-specific knowledge also relied on unique activity patterns that were not shared with the representation of semantic knowledge.
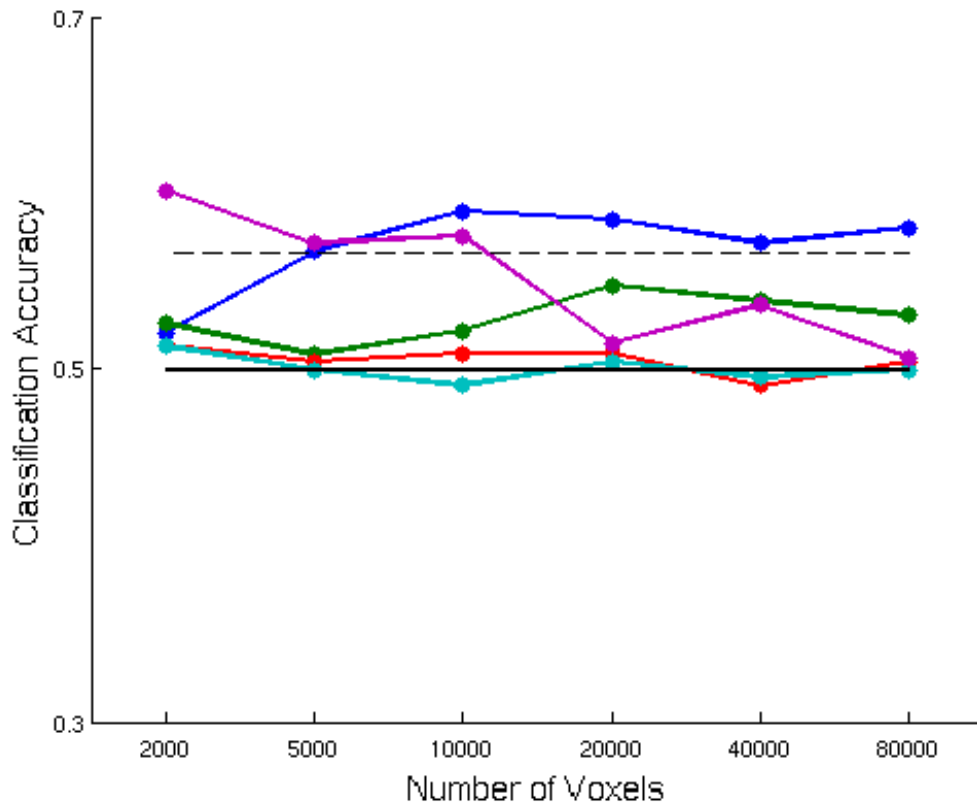
Figure 5.4   Classification accuracies for identifying trials as word or pseudoword based on patterns distinguishing familiar and unfamiliar items are shown for each participant as a function of different number of voxels. Each line represents a participant.

It should be noted that the current experiment with rapid presentation was designed for other purposes, which was not ideal for MVPA. The accuracies for word vs. pseudoword identification were not as high as expected, suggesting the noisy feature of this dataset. Future studies may use optimized slow event-related design to separate signals from contiguous trials.

Chapter 6

General discussion

6.1.   Summary and implications

The representation of semantic knowledge in the brain is an important aspect of the cognitive functioning. Neuroimaging studies not only validate the hypotheses derived from lesion studies, but also provide further information about the localization problem and implications to the organizational principles of semantic knowledge in the brain. The development of novel methods for analyzing fMRI data allows utilizing the rich information to investigate a broad research question from various complementary perspectives. This dissertation focused on two perspectives, namely the representational difference between concrete and abstract concepts, and the application of multivariate analyses to semantic processing in the brain. A joint examination at the results suggested that when the processing difficulty was controlled, the concreteness of a concept affected the neural mechanisms involved in the processing. These differences were presented on multiple aspects. Different regions were activated to different degrees for the representations of abstract and concrete concepts. Concrete concepts relied more on the perceptual and imagery systems, whereas the processing of abstract concepts was more demanding in retrieving relevant knowledge and discriminating among the competitor and relied more on the supramodal verbal systems. Besides the activational differences localized in specific regions, the category-specific effects were found in widely distributed areas, in terms of both the activity patterns in segregated sites and the

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intercorrelations among regions. It is unlikely that the effects of concreteness can be attributed to single isolated cognitive process.

6.1.1. Implications on the theories accounting for the concreteness effects

The work in this dissertation indicated that the original, strong versions of both the dual coding and context availability theories are insufficient to account for the concreteness effect. On the one hand, the selective involvement of posterior ventral temporal area, the precuneus and posterior cingulate cortex implicated that the representation of concrete concepts drew on modality-specific, particularly visual perceptual and imagery systems. On the other hand, the distinct patterns of inter-regional correlations at a scale of whole brain suggested the associational contextual differences for processing abstract and concrete concepts. Using the left IFG as the executive functioning area for semantic processing, the distinguishable pattern of its connection to other regions indicated that the online processing of abstract and concrete concepts also differed in the way of how the semantic information was retrieved. In summary, the results reported in this dissertation suggested that the representational differences between abstract and concrete concepts occur at various levels: the dependence on modality-specific perceptual systems, the organization of associations among different semantic-related systems, and the difficulty and strategy of retrieving contextual information.

6.1.2. Implications on the functional anatomy of semantic processing

The large body of literatures on the representation of object-related concepts has provided crucial information of the roles of various brain areas in semantic processing. Combining these findings with the current results suggested some trends of the perceptual

to semantic representation of concepts (Figure 6.1). The anterior temporal lobe and the left angular gyrus and surrounding areas, which were identified in the meta-analyses, are located adjacent to, if not overlapping with, the areas that converge multimodal inputs and represent supramodal conceptual knowledge about objects. Considered as two supramodal centers, the anterior temporal lobe is thought to process integrative fine-grain object discrimination, while the pSTS/MTG is thought to hold the multisensory information, as is discussed in section 1.1.2. Considered as two semantic processing areas, the left angular gyrus has been associated with complex information integration, general semantic knowledge retrieval (Binder, et al., 2009), and the anterior temporal area has been argued to be a supramodal hub for the processing of word meaning (Lambon Ralph & Patterson, 2008; Patterson, Nestor, & Rogers, 2007) based on neuropsychological and neuroimaging findings. It is possible that the information from modality-specific systems is converged and abstracted away from the perceptual or motoric symbols to form supramodal symbols along two streams. This might explain why the left middle temporal gyrus and superior temporal sulcus, which are located between the two terminals, play important roles in distinguishing abstract and concepts (Chapter 3), and are suggested to be more associated with the retrieval of concrete or abstract knowledge respectively (Chapter 4).

The two terminals of the two streams are likely to serve different functions. The left angular gyrus binds semantic information from multiple sensorimotor modalities, whereas the roles of left anterior temporal lobe can be multifold: this area is crucial for the triggering of detailed properties of concepts, and it may also "captures the semantic similarities among concepts" (McClelland & Rogers, 2003), both of which facilitate the
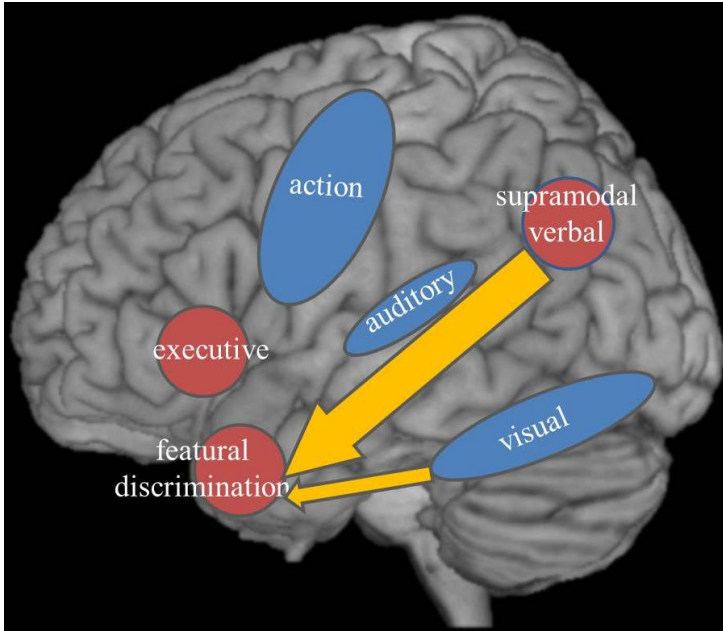
Figure 6.1   An illustrative hypothetical model of neuroanatomical systems involved in conceptual representation. The blue circles indicate systems processing modality-specific information. The yellow arrows indicate the streams along which information from various sources are abstracted away from the original modalities or formats. The red circles indicate supramodal systems severing different roles as labeled.

representation of semantically abstract concepts.

It should be noted that the inferences of the localization of semantic categories were about the net, averaged effects on a coarse scale, rather than localizing semantic concepts onto anatomy. Neural activity occurs on a scale that is not measureable by the functional imaging techniques discussed in this dissertation, but multivariate patterns strongly suggest that concept-sensitive regions are widespread and overlap across different concepts. The preference of an area to certain categories of concepts does not indicate the exclusiveness of either the function of the area, or the neural substrates of the concepts.

In general, the current findings suggest widespread involvement of multiple systems in conceptual representation. Modality-specific systems are the integral parts for

semantic representation. The extent to which modality-specific systems are involved in conceptual representations depends on the importance or salience of properties. The supramodal processing is critical for representing abstract concepts. Perceptual and motor information may also receive fine-grained processing and is abstracted to supramodal symbols, depending on the task requirements.

6.2.   Future directions

6.2.1. From association to necessity

The MVPA approaches avoid the problem of reverse inference (Poldrack, et al., 2009) while being powerful to detect small effects. However, as a neuroimaging data analysis method, MVPA per se does not answer the question of the necessity for the neural substrates to task performances. This leaves some issues about representational differences of abstract vs. concrete concept unanswered, for example, whether the concreteness effect will be diminished if the modality-specific representation is unavailable? Behavioral measurements combined with techniques such as TMS may add important further information to the necessity question and the specific roles of neural correlates for conceptual representation.

6.2.2. Mechanisms underlying the fine-grained conceptual representation

Research on the organizational patterns of concepts may inspire the investigation on the causes of such organizations. For instance, in the context of overlapping and distributed patterns of conceptual representation, what drives objects from the same domain to be close together is a question worth pursuing. The domain-specificity found in certain regions has been proposed to emerge from their connectivity to other systems that may play a critical role in the representation of the concepts (Mahon & Caramazza,

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2011). Further investigation on both the anatomical and functional connectivity associated to conceptual representation will help testify these assumptions.

In spite of the progress in functional localization of knowledge representation, how individual concepts, particularly concepts in the abstract domain, are processed in the brain is far from clear. Based on the findings from multivariate pattern analysis, the distinct patterns of activation within certain cortical regions may partly account for the representation of various concepts. Behavioral and neuropsychological studies have shown that our knowledge about objects or abstract entities can also be organized by themes such as goals, plans, and situations (Crutch and Warrington 2005). The similarity-based multivoxel pattern analysis is a powerful tool to establish the representational neighbors of concepts, which may further offer implications to the organizational principles of concepts in the neural space. These approaches may also help the investigation of the specific roles of supramodal areas in concepts processing.

Previous studies have focused on the differences between abstract and concrete concepts by contrasting the processing of concepts with extreme high and low concreteness. This approach is effective to locate the representational differences, but insensitive to how the differences occur. Abstractness and concreteness are by definition two ways to express the same continuum based on the two ends of it. The explanation of identified areas relies on reverse inference, which is vulnerable to misinterpretation in the face of multiple plausible options and the insufficient understanding about the identified brain regions.

One alternative is to rethink the relations between abstract and concrete concepts based on the general views on conceptual knowledge representation as a whole. For

example, the strong embodied view suggests the grounding nature of conceptual knowledge including the abstract concepts. Considering the relatively better understood neural substrates of concrete objects and modality-specific systems, it might be informative to investigate whether and how these systems function or disconnect to the concepts with increasing abstractness.

Introducing the amodal conceptual system has been considered as uninformative expedients by proponents of radical embodied cognition. A possible approach to the representation of abstract concept along the embodiment view is through conceptual metaphor (Lakoff & Johnson, 1999). Recent behavioral studies have found supporting evidence on concepts with medium abstractness. For example, processing verbs such as *rush* and *respect* is found to activate image schemata of horizontal or vertical spatial relations (Richardson, Spivey, Barsalou, & McRae, 2003). The speed of processing sentence describing object or information transfer has been found to be modulated by the consistency of the direction of physical movement of participants with the direction of transfer implied in the sentence, and the sentence processing has also been found to be affected by activity in the hand muscles (Glenberg & Kaschak, 2003; Glenberg et al., 2008), suggesting the association between the concept *transfer* and literal movement is not merely the structural similarity between domains of concepts. However, the grounded representations may not be applicable to other abstract concepts, and the core of concepts like *respect* is more than a vertical relation.

The cross-modal MVPA, as was illustrated by the study in Chapter 5, is a suitable tool to map the abstract concepts to concrete ones. For example, in research on numerical-spatial concept relations, the role of spatial patterns in number coding was

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demonstrated by a recent study that predicted the numerosity of dot sets based on fMRI data in symbolic digits processing task (Eger et al., 2009). Another study showed the possibility of predicting mental addition vs. subtraction by training the classifier on data from a task of right vs. left eye movement (Knops, Thirion, Hubbard, Michel, & Dehaene, 2009). The authors suggested the results as evidence in align with the conceptual mapping of small-to-large numbers onto left-to-right spatial patterns. Etzel and colleagues (2008) trained the classifier on activity patterns in the premotor cortex when participants heard sounds relating to hand or mouth actions, to predict the data when participants performed hand or mouth actions. These examples suggest a potential approach to addressing theoretical debates on embodied vs. amodal nature of cognitive processing. In summary, combining the new approaches of measurement and analysis with theoretical perspectives of linguistics and general cognitive models will be promising future directions to further understand the representation of semantic knowledge in the brain.

6.3.   General merits and contributions

This dissertation provided new and converging evidence for the representational differences between abstract and concrete concepts from multiple perspectives. The differences in the representation of abstract vs. concrete concepts were found to be represented in a large number of single anatomical regions, as well as on the whole-brain level, and voxelwise connectivity patterns. The representational differences were suggested to occur at various levels, including the dependence on modality-specific perceptual systems, the organization of associations among different semantic-related systems, and the difficulty and strategy of retrieving contextual information.

Methodologically, this dissertation illustrates the applications of MVPA to investigating representation of semantic knowledge, based both on activation and condition-specific functional connectivity data. The findings could inform theories of semantic knowledge representation and understandings of functional anatomy of human brain.

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