Category Specificity in Normal Recall: Investigations of the Verbal and Visual Domain

by

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Abstract

Patients with category-specific agnosia (CSA) of the biological type have a disproportionate deficit in recognizing objects from biological categories. Bukach et al. (in press) have shown that a similar pattern of category specificity (CS) arises in normal subjects due to the interaction of structural and conceptual knowledge in the episodic retrieval of object knowledge. The current set of studies extends these findings in two ways: The first series of 4 experiments uses the newly learned attribute recall developed by Bukach et al. to investigate CS in the verbal modality. When word reading is mediated by meaning, recall of newly learned attributes assessed in the verbal modality showed a CS pattern, just as it does in patients with CSA of the biological type. The second series of 3 experiments examines recognition of object form and the nature of structural similarity by using novel stimuli that vary in the number of structural dimensions that are required to uniquely identify an object. I demonstrate that structural similarity can be understood as the proximity of exemplars in a multidimensional space defined by the diagnostic structural features that have been integrated in the current task. Competition of retrieved episodes based on their structural similarity comes from 2 sources: When the values of diagnostic dimensions are poorly specified, errors reflect competition from exemplars that are close (*dimensional proximity)*. When an insufficient number of diagnostic dimensions are integrated, errors reflect competition from exemplars that share values on diagnostic dimensions (*dimensional paucity)*. I also present preliminary evidence that conceptual relatedness modulates the structural integration process. These results are related to CSA of the biological type, and are discussed in terms of an episodic model of object recognition in which object information is retrieved and integrated from distributed episodic memories.

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It is good to have an end to journey towards; but it is the journey that matters in the end.

\- *Ursula K. Le Guin*

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GENERAL INTRODUCTION

Theories of object recognition have in large part been based on studies of the retrieval of established knowledge in normal adults, and its failure in adults with neurological damage. The study of *category-specific* breakdown in object recognition following brain injury has been particularly useful in generating theories of how object knowledge is stored and organized in the brain. This phenomenon is known as category-specific agnosia (CSA). The majority of cases with CSA are disproportionately impaired for biological categories such as mammals, birds, and fruits and vegetables (though performance on other non-biological object classes such as musical instruments and cars are frequently impaired as well). Far fewer cases have been reported with the reverse pattern, CSA for non-biological objects. (For a recent review of CSA cases, see Bukach, Bub, Masson & Lindsay, in press; Capitani, Laiacona, Mahon, & Caramazza, 2003; Humphreys & Forde, 2001). Although this phenomenon imposes useful constraints on theories of object recognition, it has been difficult to provide convincing evidence for category-specific breakdown in the retrieval of established object knowledge for neurologically normal individuals.

A possible reason for the failure to model category-specific breakdown in normal performance is the conceptualization of object knowledge as a stable, abstract entity. An alternative approach views object knowledge as episodically based and posits that object concepts are computed on-line through retrieval and integration of relevant stored aspects of past episodes. According to this episodic account, object concepts are both temporal and dynamic (Barsalou, 1993), and are therefore easily modified by experience. This episodic approach has the advantage of employing paradigms that study the retrieval of newly acquired object knowledge, a methodology commonly employed by the related field of object categorization. My colleagues and I (Bukach et al., in press) have established the utility of this approach in providing an analogue of CSA in normals. In a paradigm that tests normal adults' memory for newly learned object attributes, participants' pattern of recall errors was similar both quantitatively and qualitatively to the recognition deficits seen in patients with the most common form of CSA (a disproportionate impairment of biological categories). Through this paradigm, we provided evidence that the retrieval and integration of newly learned object attributes from across prior episodes is susceptible to interference from objects that are structurally similar and conceptually related, a pattern consistent with that found in CSA (Arguin, Bub, & Dudek, 1996; Dixon, Bub, & Arguin, 1997).

The present research further investigated the nature of the object recognition system and category specificity from within this episodic framework. In Part 1, I explain how an episodic framework for object recognition differs from the more traditional approach. I also explain more fully how recall of newly learned attributes can capture category-specific patterns of performance most typically found in CSA and how this paradigm provides a useful tool for examining underlying mechanisms of category specificity in normal object recognition. In Part 2, I review the different patterns found among patients with CSA of the biological kind when presented with words versus the visual form of objects. In a series of four experiments, I broaden the application of the newly learned attribute recall (NLAR) paradigm to examine the nature of category specificity induced by words, and examine the role of structural and conceptual similarity in the confusions produced by word targets. In Part 3, I explore the nature of category specificity in visual form recognition. In particular, I examine the nature of structural knowledge and the type of competition that occurs between objects that are structurally similar when information from prior episodes is retrieved. In a series of 3 experiments, I manipulate the structural and conceptual properties of objects directly by using novel object forms that vary in the number of structural dimensions[1] that are required to uniquely identify an object. I demonstrate that structural competition (confusions due to recruitment of episodes involving exemplars that are structurally similar to the target) can be understood as a function of *proximity* in a space defined by multiple diagnostic dimensions. In addition, I provide evidence that failure to retrieve and integrate (i.e., conjoin) the full set of diagnostic dimensions necessary to disambiguate exemplars from a set leads to errors that can be explained on the basis of competition from exemplars that share diagnostic features. I refer to this effect as *dimensional paucity.* Finally, I show preliminary support for the modulation of structural integration by conceptual information.

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[1] By *dimension* I mean attributes of a set of stimuli that may be varied such that an item possesses only one value of a particular dimension (Arguin & Saumier, 2000). I refer to the dimensions necessary to disambiguate an exemplar from others in its set as *diagnostic dimensions* and the values of the diagnostic dimensions belonging to a particular object as *diagnostic features.*

PART 1: AN EPISODIC FRAMEWORK AND PARADIGM FOR UNDERSTANDING OBJECT RECOGNITION

The Traditional Fixed Architecture Framework for Object Recognition

In the traditional approach to object recognition, which I shall refer to as the *fixed architecture* approach, object information is stored in distinct memory systems (e.g., semantic memory and pre-semantic structural description systems), separate from perceptual systems and memories for individual episodes (e.g., Cohen & Squire, 1980; Tulving, 1972). These object stores contain information that has been *abstracted* from the original episodes, and are in this sense independent of contextual variations between individual episodes. This approach has been used to explain why amnesics can retain knowledge about the meaning of objects, while being unable to recall specific encounters with objects. Although fixed architecture theorists differ as to whether these abstract representations are integrated or distributed, most consider them to be fairly stable and invariant over time.

Explanations of CSA from within a fixed architecture framework have taken a variety of forms. Some accounts propose that multiple semantic systems exist and that they can be damaged in isolation. For example, Caramazza and colleagues (Capitani et al., 2003; Caramazza & Shelton, 1998) have proposed that due to evolutionary pressures, different categories of knowledge (e.g., animals, plants, tools) are represented in distinct neural regions. Warrington and colleagues (see also Farah & McClelland, 1991; Warrington & McCarthy, 1983; Warrington & McCarthy, 1987; Warrington & Shallice, 1984) proposed different semantic systems for functional and sensory knowledge types.

Category-specific effects arise because of the differential salience of functional versus sensory knowledge for identifying biological versus non-biological objects. Other theories emphasize the degree to which form (e.g., has wings) and function (e.g., can fly) are correlated across exemplars within a category (Tyler & Moss, 1997). Whereas biological categories tend to have form-function correlations that are shared among exemplars (e.g., has legs, can walk), non-biological categories tend to have distinctive correlations that are more diagnostic for object recognition (e.g. has blade, used for cutting). According to this explanation, retention of the information that a dog has legs will not contribute to the disambiguation of dog and cat, whereas the retention of the information that a knife has a blade will help disambiguate knife from spoon. Yet other theories emphasize the importance of interactions between structural and conceptual knowledge and the combined effects of similarity between exemplars within these two knowledge domains (Arguin et al., 1996; Dixon et al., 1997; Humphreys & Forde, 2001). According to this account, biological categories are more vulnerable to brain damage because they share a high degree of structural and conceptual similarity.

Although it is clear from the brief review given above that fixed architecture accounts can be quite diverse in the way that object knowledge is organized and stored, all of the accounts listed above suffer from a common limitation in that they deal only with pre-established knowledge, and do not provide an explanation of how object representations are developed to begin with (O'Reilly & Munakata, 2000). The acquisition of object knowledge is an important issue not only on theoretical grounds, but also because patients with CSA are unable to relearn the object knowledge they have lost. As a result of this missing component, fixed architecture accounts are limited in the methodologies that are employed to investigate category-specific effects and to model it in the behaviour of neurologically intact participants. Paradigms are restricted to modifying input to, or output from, the knowledge stores.

For example, Gaffan and Heywood (1993) presented perceptually degraded pictures to normal subjects in a picture-naming experiment, and found that more errors were made to biological (42%) than non-biological (34%) items, in concordance with the pattern most commonly found among patients with CSA. However, Laws and Neve (1999) found the reverse pattern with briefly presented pictures when categories were matched for visual complexity, concept familiarity, and name frequency. Other researchers have used speeded naming paradigms to elevate naming errors in normal subjects (Vitkovitch & Humphreys, 1991; Vitkovitch, Humphreys, & Lloyd Jones, 1993), and found evidence for lower accuracy for biological categories relative to nonbiological categories.

The difficulty with experiments that rely on degraded stimuli, brief presentations, or speeded naming is that they tap encoding and response processes that are presumed to be intact among patients with CSA. Rather, patients with CSA have difficulty with *retrieval* of object knowledge (attributes as well as names). Modelling retrieval deficits in normal subjects whose object knowledge is well established poses a difficult challenge for fixed architecture theories.

An Episodic Framework for Object Recognition

In contrast to a fixed architecture approach in which object knowledge is stored in a separate semantic system, object knowledge can be thought of as based on a collection of memories of previously experienced episodes (Jacoby, Baker, & Brooks, 1989; Kahneman & Miller, 1986). In such a system, relevant object features and associations are encoded with each instance, and maintained in memory through subsequent encounters in which they are actively processed or retrieved. During recognition, information present in the current stimulus and relevant to the current task (such as the object's shape) evokes a modality-specific representation that then acts as a retrieval cue for stored structural and conceptual features of an object, contingent on the similarity of prior episodes to the current task constraints. The recruited features (some subset of past experiences) are integrated at the time of recall, resulting in a temporally created unified concept. When the stimulus consists of the object's form, for example, structural information will first be recruited because of its similarity to the cue, and other nonstructural information relevant to the current episode will then be retrieved and integrated.

Thus semantic memory is conceptualized as an episodically based system involving retrieval and integration of information over multiple episodes and multiple features of an object. The dynamic reconstruction of object knowledge through the retrieval and integration of episodic traces has been successfully instantiated in a number of exemplar-based models of object recognition and categorization (Hintzman, 1984; Kahneman & Miller, 1986; Kruschke, 1992; Lamberts, 2000, 2002; Logan, 2002; McClelland & Rumelhart, 1985; Medin & Schaffer, 1978; Nosofsky & Palmeri, 1997).

An episodic theory of object recognition differs in several important ways from the traditional approach. First, the content of stored object information is not distinct from memories of the episodes themselves, but rather represents activation of memories across stored episodes. Second, the content of object representations is not abstracted from the original episodes, but rather involves partial reactivation of processing that occurred during prior episodes. Third, the content of dynamically created object representations depends on contextual variables such as the current goal and the similarity of the present cue to prior episodes, and in this sense dynamic object representations are variable and temporary, rather than fixed (Barsalou, 1993; Simmons & Barsalou, in press). Finally, because stored object information is distributed across features encoded in various episodes, integration of retrieved information plays a necessary role in creating a unified concept.

One benefit of the episodic framework for object recognition is that it easily accounts for the influence of prior episodes on retrieval of object information, particularly when the prior episodes share similarities with the current situation. A number of researchers have shown that perceptual and categorical processes are as vulnerable to alterations in context and task as is memory for individual episodes. For example, Jacoby and Brooks (1984) found that a single prior encounter with an object or word can substantially affect the speed or accuracy with which that item is later classified or identified. Similarly, Whittlesea (1987) demonstrated the influence of prior episodes on perceptual identification: He found that perceptual identification of briefly presented pseudowords was dependent on similarity of the test items to previously studied instances of other pseudowords. Furthermore, the perception of the test stimuli was dependent on whether the previously studied instances were encoded in an analytic or nonanalytic (holistic) fashion. Waszak, Hommel and Allport (in press) also showed that part of the response time costs associated with switching between word reading and picture naming in a Stroop task is due to item-specific interference from prior episodes. They showed that task switch costs were larger for stimuli presented for both tasks than for stimuli presented in only one task, and that a single prior episode was sufficient to produce this item-specific slowing, even after several intervening trials.

The fixed architecture account explains the influence of prior episodes on retrieval of abstract information primarily from a priming perspective, in which abstract representations are more easily or quickly activated due their prior activation in a previous episode. While this lasting or spreading activation explanation may be able to explain short-term effects of prior episodes, it has a more difficult time explaining the influence of a prior event when a longer time (e.g. days) or many trials have intervened. The episodic account, in contrast, claims that recognition occurs when prior episodes are recruited as a function of their similarity to the current encoding conditions, no longer how long the delay.

A second advantage of an episodic account is that it incorporates an explanation of how object knowledge is developed from experience. As a result, a wider variety of laboratory paradigms can be utilized to study the normal object recognition system and to model the category-specific patterns of performance typically found among patients with CSA. A dynamic framework allows episodic manipulations that go beyond the input/output level to examine retrieval of object knowledge as it is developed and modified through episodes in which new attributes are associated to objects (Jacoby et al., 1989). This is possible because in a dynamic framework, object knowledge is not fixed, but momentarily reconstructed from relevant aspects of past episodes that are similar to the current situation. The contents of object concepts can therefore be modified by episodes that occur within the laboratory setting. In support of this idea, Lewis and Anderson (1976) found that attributes learned in the laboratory setting are integrated with pre-existing conceptual knowledge, and that retrieval of pre-existing attributes is influenced by the acquisition of the new knowledge.

Recall of Newly Learned Attributes as a Method for Studying Object Recognition

In an episodic framework, successful object recognition can be considered as the retrieval of a set of diagnostic features that is sufficient to distinguish a particular object from other potential competitors. The competitors are typically members of the object's category, but may be limited by task constraints, such as in a forced-choice experiment. The diagnostic features necessary to specify an object may include information from across multiple knowledge domains, including information about the object's structure, colour, texture, sound, taste, function, etc. Retrieval of an object's name is also an indication of successful recognition, and in this sense, an object's name can be considered another diagnostic feature. In the special case where a single diagnostic feature outside of the name domain exists (say, for example, a unique colour assignment), retrieval of this single attribute is functionally equivalent to retrieval of the object's name. The ability to retrieve such a unique diagnostic feature is therefore evidence for correct object identification.

As alluded to earlier, it is difficult to study the normal retrieval of familiar object attributes independently of input and output processes, as normal subjects are unlikely to produce many errors if the stimuli are not degraded or if the subjects are not required to give speeded responses. However, normal subjects are likely to be less accurate in retrieving *newly learned* attributes of familiar objects. The findings of Lewis and Anderson (1976) suggest that principles derived from studying the retrieval of newly learned attributes can be applied to recall of more familiar attributes. Therefore, the confusions generated in the retrieval of newly learned attributes should be indicative of competition that occurs as a result of normal object recognition procedures. Because a dynamic theory poses that object attributes are stored in a distributed fashion across episodes and are integrated only at the time of retrieval, errors are expected to reflect competition from exemplars that share diagnostic features, or whose values are very close on diagnostic features. The nature of these confusions should therefore be informative as to how object information is stored, and should also provide clues as to why certain categories are more vulnerable than others in the context of brain injury, as is the case in CSA.

Bukach et al. (in press) developed a paradigm that required the retrieval of newly learned diagnostic features to investigate category specificity in normal object recognition. Subjects first learned to associate arbitrarily assigned colours or textures to the visual forms of familiar objects in a training phase, and then attempted to report the diagnostic feature of each object in a recall phase. For example, for colour recall experiments, each trial in the training phase consisted of a briefly presented pair of arbitrarily coloured objects, followed by a mask, and a single white line drawing of one of the previously presented items. Participants were required to name the colour of the cued item as quickly as possible. Objects were consistently coloured across the training blocks. After several blocks of training, participants were given a recall task. In the recall task, a white line drawing of each object was presented for an unlimited exposure duration, and participants attempted to recall the colour that had been assigned to that object in the training task. The pattern of recall errors across a number of experiments using a variety of categories was similar to the pattern of recognition errors produced by patients with the most common form of CSA, that for biological objects. Recall was poor for living things such as mammals, birds, and fruits and vegetables, and relatively better for nonliving categories such as utensils, furniture and clothing. In addition, musical instruments clustered with mammals, as is often the case in CSA. Moreover, the pattern of errors tended to reflect interference from objects that were both structurally and conceptually similar, as is also seen among patients with CSA for living things (Arguin et al., 1996). The striking resemblance of recall performance in the NLAR paradigm to the recognition deficits most commonly found in patients with CSA suggests that the NLAR paradigm taps object recognition processes affected by CSA for biological kinds. This paradigm is therefore a useful tool for examining the normal object recognition system and the underlying determinants of category specificity, and will help to constrain theories of object recognition derived from studies of brain-damaged individuals.

PART 2: CATEGORY SPECIFICITY IN RETRIEVAL OF OBJECT INFORMATION CUED BY THE WORD FORM

The central defining feature of CSA of the biological type is the disproportionate impairment in recognizing the visual form of objects from categories such as animals or fruits and vegetables (and often musical instruments), typically demonstrated through category-specific performance in object naming and picture-word matching tasks. Many patients, however, also have difficulty retrieving object information from the verbal modality. Recognition via the verbal modality is typically tested by tasks such as naming to definition, producing definitions to words, or attribute verification.

The specificity of CSA in terms of modality of input is important for determining the nature of the object recognition processes or components that are responsible for category-specific breakdown in retrieval of object knowledge. In the same way that some have interpreted category-specific recognition deficits as evidence for independent category-specific semantic systems (Caramazza & Shelton, 1998), Warrington and Shallice (1984) interpreted modality specific patterns of CSA as evidence for separate modality-specific semantic systems. They based this claim on the finding that consistency of responses within a modality was greater than the consistency of responses between verbal and visual (object form) modalities for CSA patients JBR and SBY. Because both of these patients nonetheless exhibited a deficit in recognition of verbal and picture stimuli, Warrington and Shallice concluded that for these cases, both the verbal and visual semantic systems were damaged. According to an episodic account, however, differences in retrieval of object information from words versus object forms are due to the nature of the cue that is used to access a *common* memory store. Object forms necessarily activate information based initially on visual appearance, but words need not do so, and may initially activate non-visual information. Thus, visual information likely plays a more important role in determining the type of competition that arises from object forms than it does from words. However, to the extent that tasks involving words versus pictures share common goals, similar information will be recruited from prior episodes. Thus, when there is a deficit in knowledge retrieval procedures, words and objects forms should both show impairments to the extent that the recognition task requires retrieval of similar information.

To determine the frequency with which both verbal and object form recognition is impaired in CSA of the biological type, I examined 60 of the 61 cases reported in the recent review by Capitani and colleagues (Capitani et al., 2003, case CA was excluded as the original paper was published in Italian). A list of the cases and their references can be found in Appendix A. No information regarding recognition performance on verbal tasks was reported for 12 of the 60 cases with CSA of the biological type. Two cases, HJA (Riddoch & Humphreys, 1987a; Riddoch, Humphreys, Gannon, Blott, & Jones, 1999) and NA (Funnell, 2000), showed modality-specific impairment for object form. However, both of these cases had perceptual deficits, and thus the modality-specific nature of the impairment can be attributed to difficulty deriving a percept of the object, and cannot be used as evidence for separate modality-specific semantic systems. All of the remaining 46 cases showed a deficit in retrieving object information from both words and object forms. Some cases reported a verbal deficit for retrieval of structural information only, as assessed by tasks such as verbal definition and attribute judgments (DM97 - Humphreys, Riddoch & Price, 1997; ELM – Arguin, Bub & Dudek, 1996; KR - Hart & Gordon, 1992;

Michaelangelo - Sartori & Job, 1988), indicating that for these cases the recognition deficit may be limited to retrieval of stored *structural* aspects of prior episodes. (But see Caramazza & Shelton, 1998, for criticisms regarding equality of level of difficulty for perceptual versus non-perceptual attribute judgments.)

In light of the evidence presented above, it is very unlikely that separate verbal and visual semantic systems exist. Rather, it is more likely that a common source of object knowledge exists, as proposed by the episodic account, thus explaining why CSA for biological objects affects both verbal and object form modalities when the deficit affects *retrieval* of object information.

The frequency with which deficits co-occur for verbal and object form modalities in CSA for the biological type provides a strong constraint for tasks designed to model CSA in normal recall performance: Both word and picture cues in such a task should elicit a category-specific pattern of response in normal observers. The ability of object forms to produce category-specific patterns in normals analogous to deficits of patients with CSA of the biological type was well established by Bukach et al. (in press) using the NLAR paradigm. As discussed earlier, in this paradigm, observers learned to associate arbitrary colours or textures to line drawings of familiar objects. Retrieval of these newly learned attributes showed a category-specific pattern of response similar to that shown by patients with CSA of the biological type. Bukach et al. found that performance in this task was sensitive to both conceptual and structural similarity within the categories. For example, in the first three experiments mapping colour to line drawings, recall accuracy was worse for mammals and musical instruments (39% and 36%) than for structurally similar, conceptually unrelated objects (70%) or structurally dissimilar, conceptually unrelated objects (81%). When words were used instead of pictures (Bukach, 1999) however, the category differences disappeared, contrary to what would be expected if this task were an analogue of CSA of the biological type (mammals 41%; instruments 45%; structurally similar 51%; unrelated 48%).

One important difference in the NLAR paradigm and the tasks typically used to assess the retrieval of object knowledge from the verbal modality in CSA is that the NLAR paradigm used words in both the study phase and the recall phase, whereas studies of patients are concerned with words only at the recall stage (the patients having had a life-time of experience associating object knowledge with the visual form of the objects). Thus, it may be that using line drawings in the colour training phase but cueing with words at the recall phase may be a better analogue of verbal deficits in CSA.

A related explanation for the failure to find a category specific effect using words in this paradigm is that participants may have used a non-semantic reading route (see Funnell, 1983; Marshall & Newcombe, 1973; Schwartz, Saffran, & Marin, 1987; Shallice & Warrington, 1987; Shallice, Warrington, & McCarthy, 1983; for evidence of the existence of non-semantic reading routes). Thus, participants may not have accessed any conceptual or structural information during the task, but simply mapped colour to the word form. The equally poor performance in colour recall accuracy supports this hypothesis. If the failure to find category-specific recall in the verbal domain was due to a non-semantic reading strategy, it might be possible to find category-specific differences in attribute recall using words in the NLAR paradigm if participants are encouraged to think about the meaning of the words while performing the task.

The following series of experiments were designed to investigate the conditions under which category specificity emerges in normal recall of newly learned attributes when tested in the verbal modality. To facilitate comparisons to studies that included object form only, all of the experiments presented here used identical items to those used in Experiments 1-3 of Bukach et al. (in press). The items included exemplars from the following four categories: mammals, musical instruments, structurally similar (but conceptually unrelated), and unrelated (both structurally and conceptually). Experiment 1 and 2 were designed to determine whether the failure to obtain category-specific recall patterns in the verbal versions of the NLAR paradigm could be attributed to the use of words in a particular phase of the experiment. Experiment 1 used words in training only, while Experiment 2 used words at recall only. The methodology in Experiment 2 is closer to the assessment of access to object knowledge from the verbal modality in CSA, and therefore I expected attribute recall to show category specificity in Experiment 2, but not Experiment 1. Experiment 3 and 4 investigated whether evoking a semantic word-reading strategy in the training phase would result in category specificity in recall. The training phase of Experiment 3 used black and white line drawings to indicate which of the two coloured words was the target, ensuring that encoding of the coloured word forms would be mediated by semantic information (including the structural form of the object). The training phase of Experiment 4 used category labels as cues to indicate which of the two coloured words was the target (items were paired across categories). This manipulation was intended to evoke a level of semantic processing during word reading that required some conceptual processing of the words, but did not necessarily require retrieval of object form information.

Experiment 1: Word Training and Picture Recall

Experiment 1 used words in the training phase and line drawings at recall. In the previous word-only version of the task (where words were used during training and recall, Bukach, 1999), it appeared that participants bound colour to the word form only, and did not engage in semantic processing. I expected participants to use a similar strategy during training in Experiment 1. Recall should therefore be equally poor for all categories.

Method

Participants

Participants in Experiment 1 and subsequent experiments were students from the University of Victoria who volunteered for optional course extra credit. A total of 16 students participated in Experiment 1.

Materials

Both line drawings and word stimuli were used in Experiment 1. The line drawings were the same as those used in Experiment 1-4 of Bukach et al. (in press), the majority of which were edited from Snodgrass and Vanderwart's (1980) set of normalized pictures. A total of 40 line drawings were used, 8 from each of four categories, and 8 practice items. The categories were mammals, musical instruments, structurally similar objects (these items were conceptually unrelated), and unrelated objects (both conceptually and structurally dissimilar). The structurally similar objects were long, narrow implements oriented at a 45-degree angle for maximal contour overlap. All pictures were edited to fit a presentation box 4.52 cm X 4.52 cm. Word versions of the stimuli were presented in lower case in 30 point font, and coloured using

Adobe Photoshop. The colours used in this experiment were red, green, blue, pink, yellow, brown, gray, and turquoise. A complete list of stimuli can be found in Appendix B. The pictures and words were presented with a black background on a Macintosh computer using Psychlab™ (Bub & Gum, 1990) software. A voice key was used to collect response time measures.

Design and Procedure

A within-subjects experiment design was used, with word-colour associations within categories counterbalanced across subjects. Events in the training phase proceeded as follows: a central fixation for 250 ms, and inter-stimulus interval (ISI) of 500 ms, a pair of differently coloured words from one of the four categories for 500 ms, an ISI of 100 ms, a white patterned mask for 50 ms, and ISI of 250 ms, a cue consisting of a word in white colour that matched one of the previously viewed words. Participants were given only 1500 ms to respond with the colour in which the cued word had appeared in the preceding pair of stimuli, after which the cue disappeared and a beep indicated that the trial was over. The next trial began after a 500 ms pause.

Participants first completed an initial practice block of 32 trials with a practice set of stimuli that changed colour every time they were presented. Prior to the start of the training phase, all of the words were briefly presented one at a time in white and named by the experimenter, to familiarize the participant with the stimuli. Participants then completed four training blocks, in which each word was presented twice per block, once as a target and once as a distractor. Thus they viewed each coloured word eight times. Unknown to the participants, the words in the training phase were consistently coloured. Word pairs were assigned randomly within categories across blocks, such that a word was never paired with another word from a different category. Word pairs were presented randomly to right or left of a central fixation dot. Targets and distractors appeared equally often in the right and left positions. Latencies of the participant's verbal responses were recorded by a voice key, following which the experimenter recorded the participant's response on the keyboard.

After completing the 128 training trials, the participant was informed that all of the 32 items were consistently coloured. The participant then completed a surprise colour recall task. In the recall task, white line drawings of the 32 objects were presented randomly one at a time in the middle of the computer screen, and the participant named the colour associated with each item. Participants were encouraged to guess if they did not recall a colour. No deadline was used in this recall test, and the stimuli stayed on the screen until a response was given.

Results and Discussion

Results will be presented throughout the paper in graphic form, using 95% confidence intervals based on analyses of variance and appropriate contrasts to interpret data patterns (Loftus & Masson, 1994; Masson & Loftus, in press). The 95% confidence interval is related by a factor of $\sqrt{2}$ to the confidence interval of the difference between condition means, and thus can be used to infer differences between conditions. When comparing the means of two conditions, a significant difference between two conditions can be inferred (at alpha = .05) providing the confidence intervals do not overlap by more than a factor of .4 on one side of the mean. For figures presenting a condition mean relative to a value expected by chance, a significant difference can be inferred if the confidence interval around the observed mean does not include the chance value. Finally, for figures presenting effect magnitudes based on specific contrasts, a significant difference can be inferred if the confidence interval around the effect magnitude does not include 0.

For Experiment 1 and subsequent experiments, the results of the training phase will be discussed separately from the recall phase. The training phase was expected to reflect pairwise similarity between items due to the pairwise presentation of stimuli, while the recall phase was expected to reflect competition across the entire category as participants in this phase of the experiment had to retrieve colour information from across all of the training episodes. A 60% accuracy level on the last block of the training phase was established as a criterion for inclusion in the study. All subjects met criterion for this and subsequent experiments.

Training Phase

For Experiment 1 and subsequent experiments, training trials in which participants failed to respond within the 1500 ms deadline were coded as errors. Trials in which response times fell below 300 ms were excluded from all analyses. Response time analyses were based on the remaining correct trials only.

By Block 4, accuracy was quite high for all four categories, ranging from 91.4% for mammals to 95.2% for musical instruments. As Figure 1 shows, there were no category differences in either accuracy or response time measures.

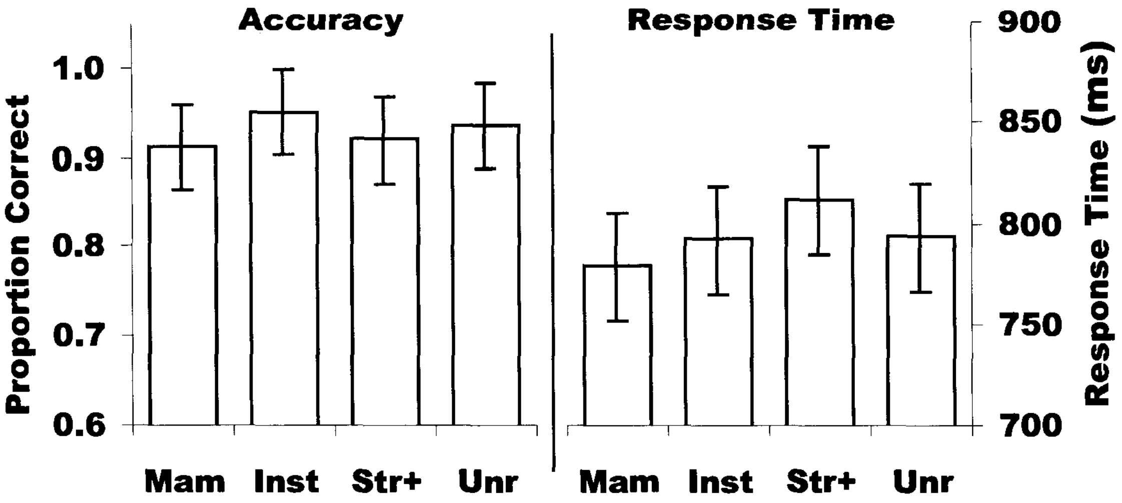

Figure 1. Mean accuracy and response times for Block 4 of the colour training phase of Experiment 1. Error bars represent 95% within-subject confidence intervals.

Recall Test

Figure 2 shows the recall accuracy of the four conditions in Experiment 1. As was expected, all conditions had equally poor colour recall (mammals = 25.0%; musical instruments = 24.2%; structurally similar = 26.6%; unrelated = 21.9%). The poor recall of word form colour is consistent with the hypothesis that participants did not engage in a semantic word reading strategy during training. This strategy would result in a rather shallow binding of colour to word form, and competition during recall of colour associations would come primarily from confusability of the word forms, rather than confusability of the word referents. Further evidence for this interpretation will be presented in Experiments 3 and 4, in which I manipulated reading strategy during the training phase.

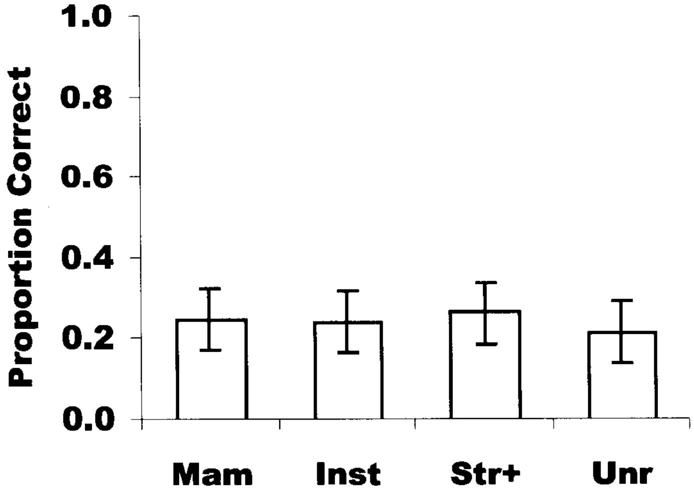

Figure 2. Mean accuracy for the recall phase of Experiment 1. Error bars are 95% within-subject confidence intervals.

Experiment 2: Picture Training and Word Recall

As mentioned above, tests of the ability to retrieve object knowledge from the verbal modality in patients with CSA are tests of verbally cued recall of *object* attributes, not *word form* attributes. In real life, we learn attributes of common objects primarily through engaging with the objects themselves or pictorial representations of the objects. Experiment 2 therefore used line drawings of familiar objects during training, and used words to cue retrieval of the object attributes. Because this is more similar to the testing situation for patients with CSA, I expected that normal participants would show a category specific pattern of colour recall similar to what was found when line drawings were used exclusively (Experiments 1- 3 of Bukach et al., in press). That is, I expected colour recall of mammals and musical instruments to be the most difficult, and colour recall for the structurally similar category to be worse than for the unrelated category.

Method

Participants

Sixteen participants took part in Experiment 2.

Materials and Procedure

The materials and procedure were the same as those in Experiment 1, with the exception that line drawings were used in the training phase, and words were used during the recall phase.

Results and Discussion

Block 4

By Block 4, accuracy was quite high for all four categories. As Figure 3 shows, Block 4 accuracy was significantly higher for unrelated items relative to mammals (97% vs. 87%). Response times showed a marginally significant advantage for unrelated items relative to musical instruments (796 ms vs. 847 ms). This advantage for unrelated items is consistent with that found in the studies of Bukach et al. (in press), and supports the idea that the training phase is highly sensitive to perceptual factors, as the unrelated category was the only category for which items were structurally distinct.

Recall Test

Figure 4 shows the recall accuracy of the four conditions in Experiment 2. As the figure shows, all conditions were significantly different from one another. The colours of unrelated items were most accurately recalled (79%), followed by those of structurally similar objects (66%), instruments (34%), and mammals (21%). Importantly, the two patterns of interest that were previously found in Bukach et al. (in press) using line

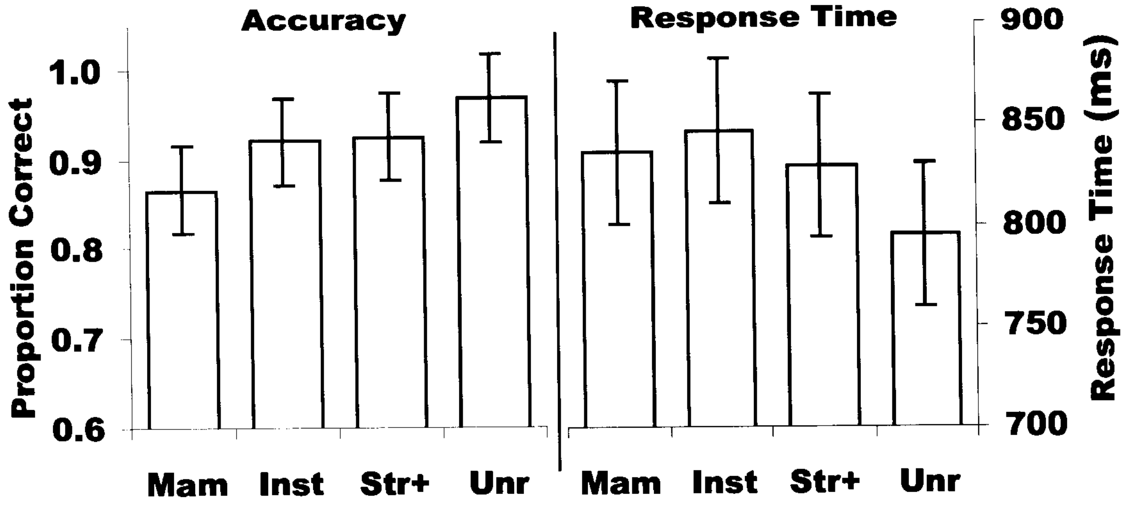

Figure 3. Mean accuracy and response times for Block 4 of the colour training phase of Experiment 2. Error bars represent 95% within subject confidence intervals.

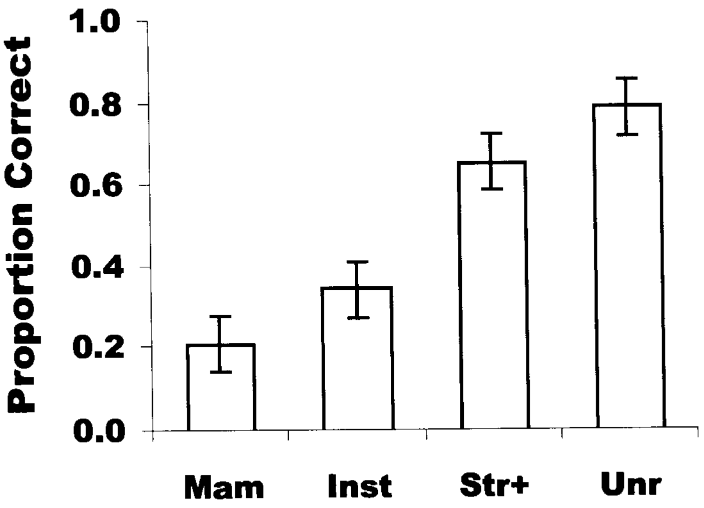

Figure 4. Mean accuracy for the recall phase of Experiment 2. Error bars are 95% within-subjects confidence intervals.

drawings exclusively were also found when memory for object colour was probed in the verbal modality: colour recall for both instruments and mammals was significantly worse than for visually similar and unrelated items, and colour recall of structurally similar items was poorer than that of unrelated items. These results, in combination with those found by Bukach et al. (in press), provide strong support for the NLAR paradigm as a model of CSA of the biological type, and demonstrate the utility of conceptualizing object knowledge as retrieval of information from past episodes.

Experiment 3: Word Training with Picture Cue and Word Recall

Experiment 1 and 2 demonstrated that a category-specific pattern of attribute recall is found when attributes are associated with object forms during training, but not when the attributes are associated with words during training. Thus, an important determinant of category specificity in normal recall is the nature of associations that are initially learned and later retrieved. A possible explanation for the failure to find category specificity when words were used during training is that a non-semantic reading route was used, such that colour was bound to the word form, rather than to the meaning of the words. It is possible, therefore, that if participants were encouraged to use a semantic reading strategy during colour training with words, a categroy-specific pattern of colour recall may be found. To encourage participants to think of the meaning of the coloured words during the training phase of Experiment 3, the coloured word target was cued with the object form in the learning trials. This prevented a simple word-form matching strategy during colour training, ensuring that colour would be bound to word meaning and not simply the word form.

Method

Participants

Twenty four participants took part in Experiment 3.

Materials and Procedure

The materials and procedures were similar to those of Experiment 1, with the following exceptions: During the training phase, a line drawing was used to cue the word target. That is, after a brief presentation of two coloured words, a white line drawing appeared to indicate which of the two coloured words required a response. During the recall phase, words presented in white were used to cue memory for the colour of each of the studied items.

Results and Discussion

Training Phase

The results of the fourth block of training are presented in Figure 5. Accuracy measures showed an advantage of unrelated items (93.2%) relative to mammals (81.5%) and musical instruments(79.1%). Similarly, response time measures revealed an advantage for unrelated items (785 ms) relative to all other categories (mammals: 871 ms; musical instruments: 923 ms; structurally similar: 862 ms). Musical instruments were

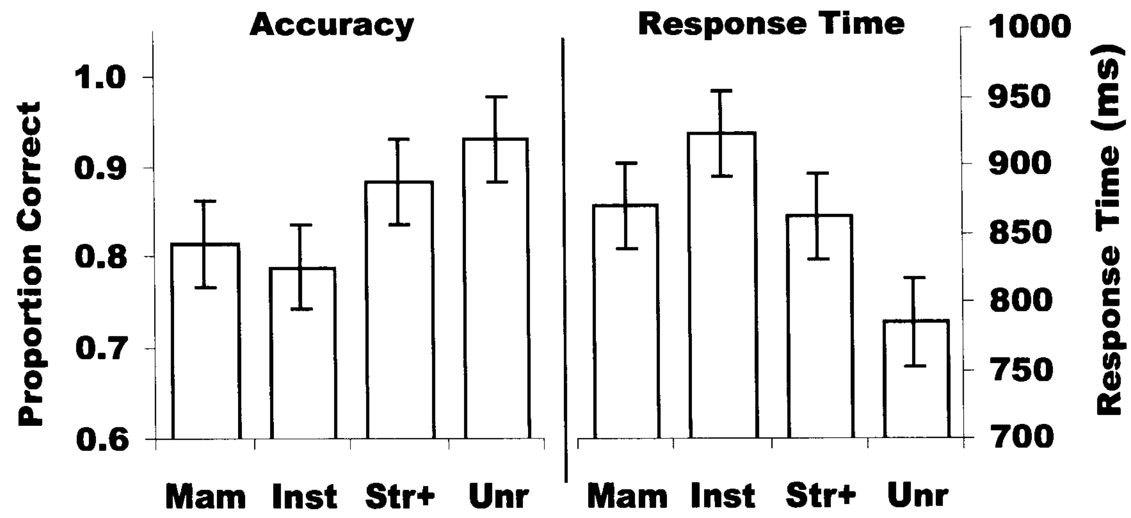

Figure 5. Mean accuracy and response times for Block 4 of the colour training phase of Experiment 3. Error bars represent 95% within-subject confidence intervals.

significantly slower than mammals.

Recall Phase

The results of the recall phase are presented in Figure 6. As predicted, colour recall showed a category-specific pattern similar to that found when pictures were used exclusively (Bukach et al., in press), and all conditions were significantly different from one another. Colour was recalled most poorly for musical instruments (31.8%), followed by mammals (41.1%), structurally similar items (58.9%), and unrelated items (73.4%). As was the case in Experiment 1, the important findings are that mammals and musical instruments were more poorly recalled than the other two categories, and structurally similar items were more poorly recalled than unrelated items. Thus, it can be concluded that during training, colour was bound to the meaning of the words, and that this meaning was evoked by words in the recall phase when the colour of the words was retrieved.

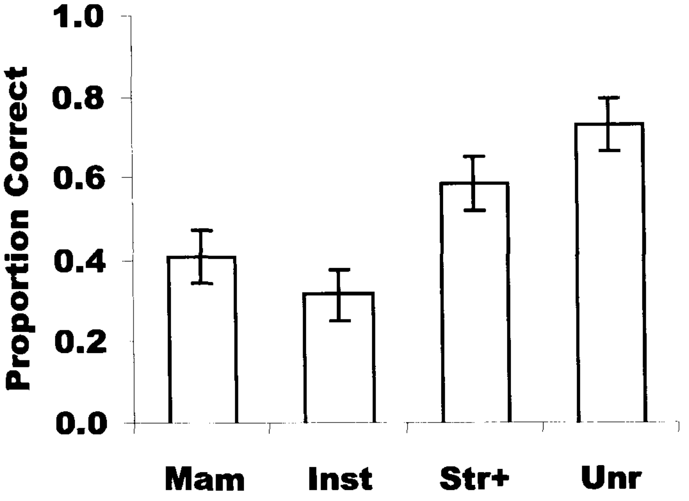

Figure 6. Mean accuracy for the recall phase of Experiment 3. Error bars are 95% within-subject confidence intervals.

It is interesting to note that in Experiment 2, when coloured pictures were used during training, mammals were more poorly recalled than musical instruments. However, in Experiment 3, when coloured words were read semantically during training, instruments were more poorly recalled than mammals. This reversal suggests that words and pictures do not evoke *identical* meaning. Indeed, according to an episodic approach, the contents of meaning evoked by words and forms will vary depending on the similarity of the cue to past episodes. For example, the saliency of structural form information may vary between verbal and object form modalities. Structural information will be strongly retrieved by an object form because of its similarity to the cue, whereas the degree to which structural information is retrieved from a verbal cue will depend on the requirements of the task, and the frequency with which the word has been associated with structural information in past episodes. This hypothesis is investigated further in Experiment 4.

Experiment 4: Word Training with Category Cue and Word Recall

The purpose of Experiment 4 was to determine whether the saliency of structural form evoked by words could be manipulated in the NLAR paradigm. In Experiment 3, the difference between structurally similar and unrelated items provided evidence that the meaning evoked by the word form in the recall phase included structural information, and that this information was relatively salient. The saliency of structural form during colour recall was likely due to the fact that the colour of words were learned in the context of line drawing cues. However, structural form may not always be as salient an aspect of retrieved meaning, particularly if the task does not evoke structural form during the learning phase. To test this hypothesis, Experiment 4 cued colour words during training with category labels. This manipulation requires the words to be read semantically, but structural information may not be as strongly evoked in the training phase as it was in Experiment 3 when pictures were used to cue the target in the training phase. The critical comparison in Experiment 4 is the structurally similar and unrelated conditions, which differ only in whether the items are structurally similar.

A second method of testing the hypothesis that structural information may be less salient in word tasks that do not involve a picture cue is by determining whether the nature of confusions produced in the recall phase can be predicted by independent structural and conceptual similarity ratings. This method was used by Bukach et al. (in press) to show that colour confusions generated to objects were related to both structural and conceptual similarity of the items within a category. If structural information is less salient when words are cued by category labels, confusions should not be related to the pairwise structural similarity ratings.

Method

Participants

Sixteen participants took part in Experiment 4.

Materials

In addition to the word stimuli used in Experiments 1 – 3, three category labels were also used: mammal, instrument, and object.

Procedure

To allow items to be cued by their category label, stimuli were paired across categories during training. Bukach et al. (in press) found no difference in recall performance between within-category and between-category pairing in the training phase. Items in Experiment 4 were paired such that musical instruments and mammals were always presented with items from either the structurally similar or unrelated category, in a counterbalanced fashion between blocks. In this way, the label "object" cued both structurally similar and unrelated items, which were never paired together. Participants were told that the experiment contained three categories of stimuli: mammals, musical instruments, and objects. Prior to beginning the experiment, participants were shown each word and told the appropriate category for that object. During the training phase, subjects briefly viewed two coloured words on the screen, and then were cued with the label "mammal," "instrument." or "object." During the recall phase, items were cued with words in white ink. In all other respects, the procedure was similar to Experiments 1-3.

Results and Discussion

Training Phase

By Block 4, accuracy was quite high for all four categories, ranging from 90.4% for mammals to 92.8% for unrelated items. As Figure 7 shows, no significant differences were found in the training phase for either accuracy or response time measures.

Recall Phase

The results of the recall phase of Experiment 4 are displayed in Figure 8. As was the case in Experiment 3, musical instruments were most poorly recalled (29.7%), followed by mammals (45.3%), both of which were more poorly recalled than the other object categories, indicating sensitivity to some conceptual factors during recall.

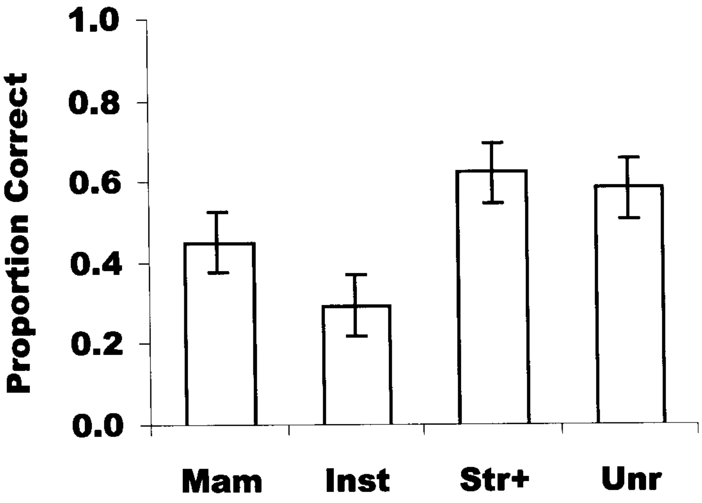

Figure 7. Mean accuracy and response times for Block 4 of the colour training phase of Experiment 4. Error bars represent 95% within-subject confidence intervals.

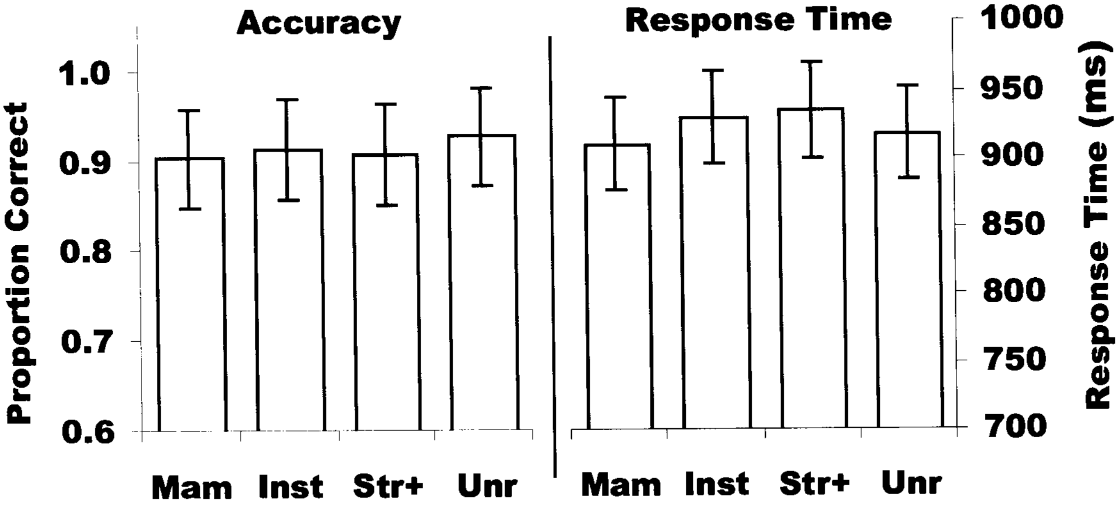

Figure 8. Mean accuracy for the recall phase of Experiment 4. Error bars are 95% within-subject confidence intervals.

Interestingly, there was no difference in the accuracy of colour recall between structurally similar (62.5%) and unrelated (58.6%) categories, suggesting less sensitivity to structural components of object meaning than was derived in Experiment 2 (where participants associated colours to pictures) or Experiment 3 (when coloured words were cued with pictures during training).

In the experiments reported by Bukach et al. (in press), both structural and conceptual factors were found to be important in the pattern of recall errors. This was confirmed by a regression analysis of independent ratings of pairwise structural and conceptual similarity on pairwise confusion probabilities computed from errors in the colour recall phase of the first three experiments. The similarity ratings were collected by asking independent participants to rate the similarity (on a scale of 1 to 7) of all possible pairs of items within each of the four categories. The pairwise confusion probabilities of the colour recall task were calculated by recoding each incorrect colour response to the name of the object (within the same category) that was associated with that colour during training. From these data the probabilities of confusing any two particular items from the same category can be computed (for more details, see Experiment 4 of Bukach et al.). To further determine the relative saliency of structural and conceptual factors when word-colour associations were learned in the context of line drawings versus category labels, I regressed these same pairwise similarity ratings on the pairwise confusion data produced in Experiment 3 and 4 of the current study, using a forward stepwise regression procedure. This procedure enters each predictor in a stepwise fashion providing it meets the criterion for entry (alpha = .05), starting with the predictor that is most strongly correlated with the dependent variable.

The results of this regression analysis are displayed in Table 1. For Experiment 3, a model including both conceptual and structural similarity best predicted colour recall, as was found by Bukach et al. (in press). For Experiment 4, however, adding structural similarity to the model did not significantly improve prediction over and above a model including conceptual similarity alone. Because structural similarity and conceptual similarity

Table 1

Summary of the Step-wise Forward Regression Analysis of Structural and Conceptual Pairwise Similarity Ratings on Pairwise Colour Confusion Probabilities in the Recall Data of Experiments 3 and 4.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Experiment 3						
Model 1	48.8	<.001	.307			
Conceptual Similarity				.554	7.0	<.001
Model 2	28.5	<.001	.343			
Conceptual Similarity				.474	5.6	<.001
Structural Similarity				.206	2.4	.016
Model 1 vs. Model 2	6.0	.016	.036			
Experiment 4						
Model 1	20.6	<.001	.157			
Conceptual Similarity				.397	4.5	<.001
Model 2	10.8	<.001	.166			
Conceptual Similarity				.435	4.6	<.001
Structural Similarity				-.10	1.0	.306
Model 1 vs. Model 2	1.1	.306	.008			

Note. Statistics for Model 1 and for Model 2 represent tests of the overall model. Predictors included in the respective models and their associated statistics are listed directly below each model. Statistics for Model 1 vs. Model 2 represent change statistics, and are a test for the improvement of a model including only conceptual similarity to one that includes both conceptual and structural similarity (F change, R^2 change, and their associated probability value).

ratings were significantly correlated (r (110) = .34), one cannot conclude that no structural information was retrieved in Experiment 4. However, it is clear that the structural information was not salient enough to produce a difference between structurally similar and unrelated categories in the recall task.

It is interesting to note that colour recall of mammals was superior to that of musical instruments in both Experiment 3 and 4, a reversal of the pattern seen in Experiment 2 where colour recall of object form was investigated. Although highly speculative, this reversal may be related to the relative saliency of structural information across the three experiments. The saliency of structural information is likely to be highest when learning to associate colours to pictures, somewhat salient when colours are associated to words in the context of a picture cue (Experiment 3), and less salient when associated to words in the absence of a picture cue (as evidenced by the regression analysis of recall data from Experiment 3 and 4). However, for this to account for a reversal of relative performance for the two categories, one must also assume that the mammals were more susceptible to structurally based confusions than were the instruments (which included both string and brass instruments). While this hypothesis is not directly tested here, unpublished data support this conjecture: Objective measures of the visual confusability of the mammals and musical instruments (as assessed by a forced-choice speeded perceptual matching task) revealed that the mammals were more confusable than the instruments as a category. Category-wise visual similarity ratings also showed that mammals were rated as more highly visually similar than were the instruments (8.5 vs. 6 on a scale of 1 – 10 for mammals and instruments, respectively).

General Discussion

The results of the experiments presented above reveal the conditions under which category-specific patterns of attribute recall can be found in normal episodic recall when assessed in the verbal modality. Experiments 1 and 2 showed that category effects emerged in colour recall when words were used to cue colour associated with object form (Experiment 2), but not when object form was used to cue colour associated to word forms (Experiment 1). Experiment 3 and 4 showed that the failure to produce category specificity in Experiment 1 was due to a non-semantic word reading strategy, and that when colour is bound to a semantically mediated word, category specific effects re-emerge. The category-specific pattern produced by semantically mediated words varied depending on whether structural form was more salient (Experiment 3) or less salient (Experiment 4). These findings have implications for the NLAR paradigm as a model of CSA, and for the normal object recognition system.

Validation of the NLAR Paradigm

The validation of the NLAR paradigm as a model of CSA of the biological type was substantially established in the work of Bukach et al. (in press), who examined attribute retrieval in the context of object forms. In this body of research, we showed that the NLAR paradigm was able to produce a category-specific pattern of recall for which retrieval of object information was disproportionately worse for categories such as mammals, fruits and vegetables, and musical instruments, than it was for categories such as tools, clothing, and furniture. Furthermore, the pattern of recall errors reflected the same types of confusions as were produced by the CSA patient ELM (Arguin et al., 1996; Dixon et al., 1997); that is, errors reflected both conceptual and structural similarity. Failure to retrieve object information from the verbal modality, however, remained to be successfully modeled using the NLAR paradigm.

The importance of establishing a category-specific pattern of object retrieval deficits from the verbal modality is clearly seen in the frequency with which patients with CSA of the biological type exhibit verbal modality deficits. All 46 of the cases reviewed that provided reports of performance in verbal tasks, and that also demonstrated a retrieval deficit as opposed to a perceptual deficit, showed impairment in the verbal modality. The version of the NLAR paradigm that was most similar to the testing procedure (i.e., coloured line drawings during training and words at recall – Experiment 2) exhibited the same pattern of category specificity that was found in the studies using line drawings exclusively. The combined results of this word study and the line drawing studies conducted by Bukach et al. provide strong evidence for the validity of the NLAR paradigm as a way to model CSA of the biological type, and to investigate normal object recognition processes and their breakdown in the presence of neurological damage.

Multiple or Single Semantic Systems?

The review of the CSA literature and the findings of Experiment 2 also bear on the debate of whether a separate semantic system exists for the verbal and visual modality. Warrington and Shallice (1984) proposed that separate semantic systems exist for visual and verbal modalities, and that patients with CSA who demonstrate impairments for both verbal and visual modalities have damage to both systems.

However, the review of the CSA literature showed that all relevant cases for which data were reported showed impairments for both modalities. A more parsimonious explanation would be that both modalities access a common knowledge source. The NLAR paradigm provides converging evidence from normal observers. The similarity of the recall pattern produced in Experiment 2 when words were used to cue memory of object colour to the recall pattern produced when object form was used to probe memory (Experiments 1- 3 of Bukach et. al, in press) indicate that both words and object forms access a common object knowledge system.

Variability in the Object Representations Activated by Words

Although the evidence suggests that a common knowledge source is contacted from words and from object forms, it is also clear that there is variability in the representations that are constructed when cued by different input types and when cued in different task contexts. First, as Warrington and Shallice (1984) pointed out, some patients with CSA show more consistency in item responses within as opposed to between visual and verbal modalities. Second, Experiment 1 demonstrated that it is possible that words may activate very little or no semantic information if the task does not require it. Third, it is clear from the difference in recall patterns between Experiment 3 and 4 that words may activate different levels of structural information.

The variability in retrieved information from words in different task contexts is not a novel phenomenon, but the implication of this variability is the subject of some debate. Tulving and Thomson (1973), for example, interpreted variability in information retrieval as the effect of encoding specificity, and claimed that this was a property of episodic, but not semantic, memory. Whereas this explanation may account for the findings of the NLAR task, which can be argued to be "episodic", it cannot account for the greater consistency of *semantic* knowledge retrieval within, as opposed to between, verbal and visual modalities in CSA. Other researchers claim that differences in memory retrieval reflect different cognitive procedures required by the different tasks, rather than different memory systems. For example, Roediger (1990) proposed that differences in retrieval patterns across various tasks reflect the degree to which the processes required in the study phase match those required in the test phase.

Barsalou (1982) also proposed that the contents of concepts vary depending on the context of the particular task. He proposed that these differences were due to context dependent properties as opposed to context independent properties. Context independent properties are retrieved in all tasks and contexts, and represent the core meaning of an object. Retrieval of context dependent properties, in contrast, is variable, and these properties are activated only by the appropriate task context. Although this distinction might at first glance be interpreted as proposing separate memory systems for context dependent and independent properties, Barsalou points out that the status of context independent properties is not fixed, but is itself dependent on one's personal history. He proposed that the factors that determine when properties become context independent are their diagnosticity, frequency, and recency in prior processing episodes. The concept of context independent properties in an interesting one, and suggests that as well as variability, there should also be some consistency in the information retrieved across situations, providing the input is processed for meaning.

Many aspects of these theories fit well with the episodic framework for object recognition. According to the episodic framework, variability in retrieval of object information occurs because the type of information retrieved on different occasions is dependent on the similarity of the cue to prior episodes, as well as the goal and general context of the task. These principles encapsulate elements of encoding specificity, transfer appropriate processing, and context dependent properties.

The Importance of Structural Information to Category Specificity

According to an episodic framework, biological objects are more vulnerable to confusions because of their joint structural and conceptual similarity. Evidence for the influence of structural similarity in CSA comes from patient ELM, whose confusions to fruits and vegetables were determined by the amount of structural overlap between exemplars. Using coloured line drawings, the NLAR paradigm showed the same pattern of specificity for biological categories, and structural factors were also shown to be important in this task (Bukach et al., in press). In the present study, structural information was also found to be important when recall was tested in the verbal modality, both when colours were associated to line drawings (Experiment 2), and when colours were associated with words in the context of line drawings (Experiment 3).

Pictures are said to be worth a thousand words, but it appears from Experiment 4 that words are not *always* worth a thousand pictures. When colours were associated with words in the context of a category cue, category specificity in retrieval of colour as assessed by the verbal modality was not determined by structural similarity, as evidenced by equivalent colour recall for structurally similar and unrelated items, and by the failure of the regression analysis to show an effect of structural similarity over and above that of conceptual similarity alone. Thus, structural information is not necessarily a salient aspect of word meaning.

This raises the question of how the pattern of category specificity might be affected when structural knowledge does not play an important role. Would biological items be disproportionately impaired relative to non-biological items? Unfortunately, the results of the Experiment 4 are not informative as to how this lack of a structural similarity effect would impact the pattern of category specificity for biological versus non-biological categories, as its design did not include non-biological natural categories. This question could easily be addressed, however, by substituting the categories of furniture and clothing for the structurally similar and unrelated categories.

Conclusion

From the above studies, it is clear that the NLAR paradigm can successfully model category specificity of the type found in patients with CSA of the biological kind, and thus shed light on the normal object recognition processes that are damaged in CSA in both the visual and verbal modality. The results point to an object recognition system that is flexible in the information it recruits in different situations. This episodic approach of examining recall of newly learned attributes should prove useful in investigating the types of knowledge that are recruited by word and picture cues in different task contexts.

PART 3: INTEGRATION OF PERCEIVED AND RETRIEVED STRUCTURAL FEATURES

Specification of the nature of structural representations is fundamental to the development of a theory of object recognition. Although other sources of information, both from the visual modality (texture, colour, motion) and from other modalities (haptic, auditory, olfactory, taste) may contribute to an object's identification, much of the information necessary to identify an object is carried by the details of the object's form. Bukach et al. (in press) showed that a primary source of competition in retrieval of object information arises from structural similarity and its interaction with conceptual information, and that this interaction results in a pattern of category specificity that resembles that of CSA for living things. This interaction was also evident in retrieval of object information from words (Experiment 2 of the present study). Understanding how this interaction produces category specific effects necessitates specifying the manner in which structural information is processed, stored, and retrieved, as this will determine the way objects are structurally similar to one another.

Arguin et al. (Arguin et al., 1996) suggested that diagnostic structural dimensions are themselves stored in a distributed fashion and require integration during recall. Thus, information may be distributed not only across information domains, but within information domains. In the context of a dynamic framework, object recognition should therefore depend on the retrieval and integration (from across prior episodes) of the particular structural features that are diagnostic for the immediate context. Competition in such a system should occur at the level of diagnostic features, and should lead to two types of error patterns: a) When there is poor specificity of values or noise in the system, confusions should reflect *dimensional proximity:* objects that are close in value on diagnostic dimensions should be confused. b) When integration of structural dimensions fail, errors should reflect *dimensional paucity:* objects that share diagnostic features should be particularly susceptible to confusions. The following sections examine evidence for the integration of structural features both in normal perception and normal recall, and the modulation of this process by conceptual similarity.

Integration of Structural Features in Perception

The need for integration of object features during perceptual processing is well established. Indeed, many conventional theories of object representation assume that perceptual processes extract structural features such as object parts, shape primitives, or structural dimensions (Biederman, 1987; Biederman & Gerhardstein, 1993; Marr & Nishihara, 1978; Palmer, 1977). Biederman, for example, suggested that structural attributes of objects are represented across a distributed network of neurons in a hierarchical system of increasing complexity. During perception, structural attributes are temporally integrated through synchronous firing. At the lowest levels, structural attributes derived from the visual input such as edges, vertices and axes of elongation are conjoined to represent one of a limited number of shape primitives called geons. As information is passed forward in the system, the geons become specified in terms of their global properties and their relation to other geons belonging to the same object, and finally, at the highest level, this information is conjoined to represent a unified and integrated object structure.

More controversial, however, is the nature of structural features that become integrated during perception. Conventional theories emphasize a set of fixed dimensions or features by which objects are characterized, such as Biederman's alphabet of geons. Implicit in these theories is the idea that all available features are fully specified and integrated in the perceptual shape representation (although attention to different features may vary). Other research emphasizes the flexibility of the perceptual system by showing that the structural elements of perception depend upon task demands. For example, Feldman and Richards (1998) found that the dimensions by which rectangles were characterized (length and width vs. area and shape) depended on the orientation of the rectangles to be compared. Likewise, Schyns (1998) proposed that perceptual analyses and object representations depend not only on feature availability, but also on the diagnosticity of features for a particular task. In support of this view, Schyns and Rodet (1997, see also P. Schyns, Goldstone, & Thilbaut, 1998) found that the type of features used to represent a set of novel cell-like objects depended on the categorization history of the individual and the diagnosticity of the features for the categorization task. Thus the diagnostic structural features used to represent objects may not be "hard-wired," but rather seem to be determined by the demands encountered as we experience objects. This second view is more consistent with an episodic approach to object recognition, in which the current goal and task constraints determine the particular features that become integrated both in perception and in retrieval of stored information.

The integration of diagnostic object features during perception has been studied extensively by Treisman and colleagues, and their *Feature Integration Theory* (FIT, Treisman & Schmidt, 1982; Treisman & Gelade, 1980) is perhaps the most well known theory of perceptual integration. According to FIT, certain object attributes are processed independently and require an additional process of integration to be conjoined as a unified percept. Several factors can influence the accuracy with which these features are conjoined, including top down processes, task demands, and time constraints. Importantly, Treisman demonstrated that focused attention is necessary to properly integrate features when stimuli share values along multiple dimensions, and when these dimensions are also necessary to differentiate the stimuli from one another. For example, extra time is necessary to find a green T in a background of green X's and brown T's relative to finding a blue T or a red S in the same background. When there is insufficient time to focus attention to each item in a multi-item display, participants produce errors in which features "migrate" and become incorrectly conjoined (for example, in a briefly presented display containing a green X and brown T, participants might report seeing a green T). These errors are called *illusory conjunctions*, and can be considered evidence for dimensional paucity within perception.

Most often, FIT is associated with the integration of features from different visual domains, such as the integration of colour and form investigated in the visual search experiment described above. However, Treisman also demonstrated the need for feature integration of structural dimensions, a finding that is sometimes overlooked (e.g., by Arguin & Saumier, 2000). Treisman, Sykes, and Gelade (1977) demonstrated illusory conjunctions with local facial features (eyes and mouths) in a sequential match paradigm using pairs of schematic faces that shared features. Illusory conjunctions were also demonstrated with letter fragments (Treisman & Gelade, 1980): In a display containing P's and Q's, participants sometimes incorrectly conjoined the tail of the Q to the letter P, incorrectly reporting the presence of the letter "R". Both of these tasks demonstrated a serial search pattern whenever the possibility of illusory conjunctions existed (i.e., when targets or test stimuli shared values on multiple diagnostic dimensions with the distractors or study stimuli), indicating that attention to individual stimuli was necessary to conjoin multiple diagnostic features.

Arguin and Saumier (2000) provided further evidence for the integration of structural form during perception using a visual search paradigm. They showed that integration occurs not only between discrete object parts, but also between structural features that define a single part[2]. They used simple, blob-like stimuli that differed along three structural dimensions: tapering, elongation, and curvature (stimuli similar to those used originally by Arguin et al., 1996). They created two types of object triplets consisting of a search target and two distractors: In 1D sets, targets differed from distractors along a single structural dimension (each item in the triplet had a unique value on the diagnostic dimension). 1D sets therefore required specification of only a single feature to differentiate the target from the distractors. In 2D sets, the target shared a value with distractors along two diagnostic dimensions, such that the target could only be differentiated from the two distractors by the conjunction of two structural diagnostic features. Figure 9 shows the structural relationships within 1D and 2D sets. Importantly, 1D and 2D sets were matched on the pairwise similarity of the target to each of the distractor types so that they could test whether single part stimuli are perceived holistically or whether they also require integration of structural features. They reasoned

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[2] Parts can be defined as "divisible, local components of an object that are segmented at points of discontinuity, are perceptually salient, and are usually identified by a linguistic label" (Tanaka & Gauthier, 1998, p. .5).

that if object form is encoded holistically, search times should be equivalent for 1D and 2D sets across an increasing number of distractors. Contrary to the holistic encoding hypothesis, they found that search rates were significantly longer for the 2D sets. Arguin et al. interpreted this longer latency as the time necessary to integrate the two diagnostic structural features of each object in the 2D set.

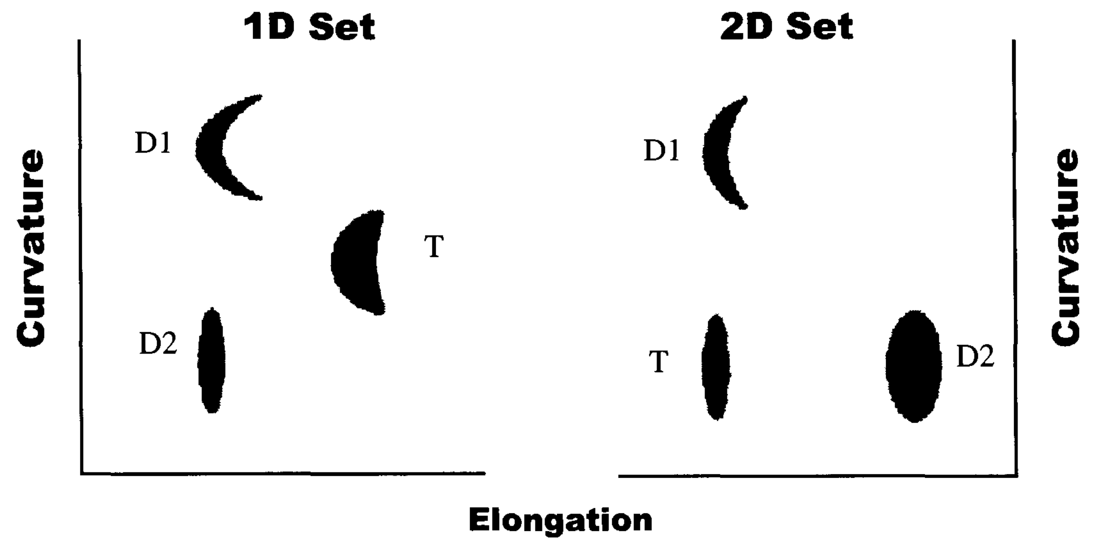

Figure 9. Sample stimuli from the visual search task of Arguin and Saumier (2000) showing the structural relationships between targets (T) and distractors (D) for the 1D and 2D sets. In this example, the target in the 1D set has a distinctive value on the curvature dimension, whereas the target in the 2D set does not have a distinctive value on either curvature or tapering dimensions.

Integration of Stored Structural Features in Recall

Whereas many theories of object recognition acknowledge the need for integration or binding of structural features in perception, the role of feature integration in memory is notably less developed. Generally, stored structural representations are depicted as exhaustive and fixed. Using Biederman's Recognition-by-Components model as an example (Biederman, 1987; Hummel & Biederman, 1992), recognition occurs when the geon description derived by temporal binding of the perceptual input is matched to the stored geon description of a known object. According to Biederman's model, the stored structural description of each object is represented as a single node containing within it the full specification of the object's geons and their relations. Thus, implicit in this theory is the assumption that structural features are a fixed and invariable part of the object representation.

Not only do most fixed architecture models of object recognition ignore the question of structural integration of stored features, they also lack a mechanism whereby stored structural representations can give rise to even the simplest form of recognition: the knowledge that a particular object has been encountered before. Biederman's model is no exception. Although Biederman calls his theory "*Recognition* by components," the theory primarily explains perceptual mechanisms, and leaves recognition processes substantively underspecified. Biederman's theory essentially deals with how structural information derived from the retina is combined to form a geometrical description of an object, but has little to say about how mapping this percept to stored 3D structural descriptions results in the recognition of an object as one that was previously encountered. Indeed, the stored structural descriptions in Biederman's model are devoid of any episodic component that places the objects in a context of time and place such that information learned from previous experiences can be contacted. According to Gallistel (1990), it is precisely this spatio-temporal information that allows perceptual records of prior episodes to be interrelated and bound during recall so that a unified concept can be formed.

In contrast to the fixed architecture account, the components of stored structural descriptions within an episodic framework are themselves distributed across different past encounters with an object, and thus spatio-temporal information is an integral aspect of memory for objects (though the precise time and location of the distributed memory components may not be consciously accessible). Furthermore, within the episodic framework, it is possible that only a subset of the structural features may be recruited at the time of retrieval. In this case, the type of structural dimensions defining an object on a particular occasion will depend on the history of prior episodes and the similarity of processing in these previous encounters to those necessary in the current situation. This principle is similar to Barsalou's (1993) idea of flexibility in conceptual representations: A person's cognitive representation of a category or object on a particular occasion is not a stable entity but is constrained by the goal and the similarity of the current context to past episodes. Like Treisman's FIT, Barsalou's theory also posits a central role for selective attention to diagnostic dimensions. According to Barsalou, selective attention to diagnostic information determines the perceptual features that are recorded in a particular episode, as well as the nature of the perceptual cue that is used to retrieve information from memory. In this way, selective attention also determines the features that are retrieved and integrated during recall on each occasion. This theory can be applied not only to integration of features from across domains such as colour and shape, but to separable structural features from within the shape domain.

Evidence for distributed structural descriptions and the need for structural integration comes from studies of ELM (Arguin et al., 1996), who had difficulty recognizing the visual form of biological objects. An analysis of ELM's errors to fruits and vegetables in an auditory-word/picture matching paradigm revealed that confusions were driven by structural similarity between items, such that object foils were incorrectly accepted when they partially matched the structural properties of the word referent. Because errors occurred for all of the objects tested, Arguin et al. concluded that the deficit was unlikely to be due to selective damage to the visual properties themselves, as fixed architecture accounts usually propose. Rather, ELM's deficit appeared to be due to impaired *integration* of the retrieved structural properties, resulting in an impoverished shape representation that integrated only a subset of the diagnostic structural features necessary to differentiate an object from the other category members, and leading to massive competition from other exemplars with shared diagnostic features.

Arguin et al. (1996) found further support for an integration deficit of stored structural features in a task that required the association of four novel shapes to four locations on a computer screen. Arguin et al. attempted to capture the natural variation in the global structure of fruits and vegetables by constructing novel blob-like shapes that differed along three structural dimensions: tapering, elongation, and curvature (structural dimensions that were later used by Arguin & Saumier, 2000, in the study mentioned above). Sets were constructed such that exemplars varied either along one diagnostic dimension (1D sets) or along two diagnostic dimensions (2D sets). The exemplars in the 2D sets shared values on the two relevant dimensions, so that differentiation of the exemplars within 2D sets depended on the conjunction of values of both diagnostic dimensions. The structural relationships between the exemplars in 1D and 2D sets are displayed in Figure 10. Importantly, ELM's performance on the shape-location task depended on the number of structural dimensions that were necessary to disambiguate the

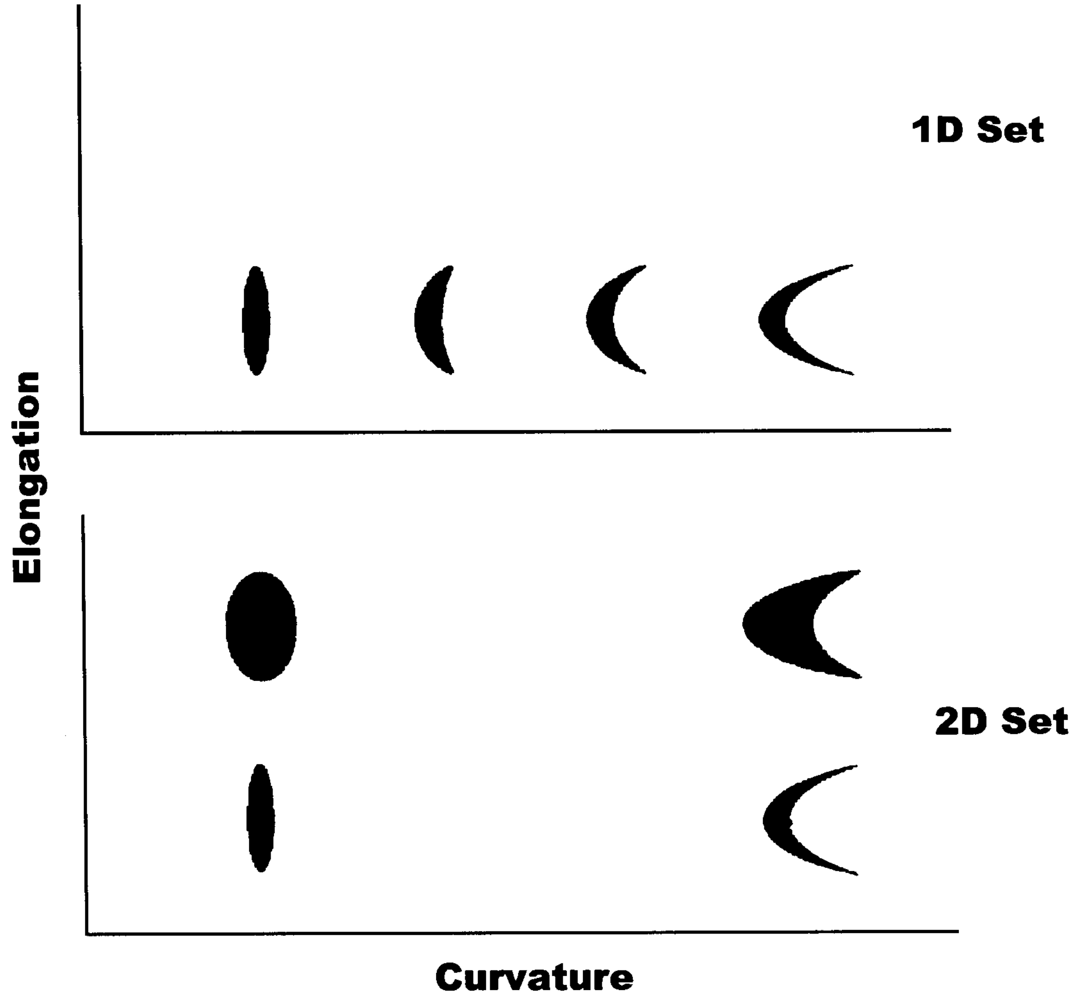

Figure 10. Sample stimuli from Arguin et al. (1996) showing the structural relationships between stimuli in the 1D and 2D sets. In this example, items in the 1D set vary only on curvature, whereas the items in the 2D set vary on both curvature and elongation.

stimuli. ELM made many more errors with 2D sets (56.7%) than with 1D sets (29.2%), even though the values along a particular dimension were closer in the 1D sets than in the 2D sets, thereby ruling out a loss of resolution as an explanation for the deficit. Nor could the deficit be attributed to an inability to process a particular shape dimension, as ELM was able to process all three dimensions in a categorization task that required him to classify stimuli according to each of the three dimensions separately. Moreover, in the shape-location task, errors revealed that ELM based his responses on only one of the necessary diagnostic dimensions and rarely confused exemplars in the 2D sets that did not share a value on one of the critical dimensions (i.e., with respect to the layout of 2D stimuli in Figure 10, he made very few diagonal confusions). This pattern constitutes strong evidence for dimensional paucity in retrieval of structural dimensions.

Arguin et al. proposed that stored structural descriptions could be considered as organized according to a multidimensional psychological space, in which global properties such as tapering, elongation and curvature serve as the structural dimensions that define the space. Competition during recall is determined by proximity of exemplars in this space. Importantly, if multiple structural dimensions recruited from past episodes are unable to be integrated during recall, competition from exemplars that share values on diagnostic dimensions will be particularly problematic, resulting in many errors whenever a task involves memory of object structure. The diagnostic dimensions that are integrated define the similarity space and therefore determine the likelihood that any two objects will be confused with one another.

Arguin et al. (1996) distinguished two possible loci for integration processes in the recognition of objects from their visual form: a) the encoding stage at which a percept is created from a visual input, and b) the recall stage at which stored information is recruited. Whereas ELM showed a clear deficit for 2D stimuli sets when *memory* for shape-location associations was tested, he showed no such deficit in an immediate match-to-sample task where memory requirements were minimized, demonstrating that the locus of ELM's integration impairment was at the retrieval stage rather than the encoding stage. It is also interesting to note that the perceptual match task, although minimizing the need for long-term memory, nonetheless requires retention of information over a short period of time, as the task involves a sequential presentation of a single study item followed by a one-second delay before the four simultaneously presented test stimuli appeared. Thus ELM's ability to integrate structural dimensions could also be dissociated in working memory versus long-term memory tasks. His deficit appeared to affect integration of structural dimensions only when retrieval from long-term memory was required.

Modulation Of Structural Integration By Conceptual Proximity

According to an episodic framework for object recognition, the type of information recruited from past episodes will depend on the nature of the cue. A line drawing of an object will therefore preferentially recruit information about objects that share similar stored structural features, and this structural information acts as a further cue to recruit other conceptual information that has been associated with the form in past episodes. However, as Humphreys, Riddoch and Quinlan (1988; see also Humphreys & Forde, 2001) pointed out, these procedures, even in a fixed architecture account, are not strictly serial nor are operations within each stage completely isolated from one another. Rather, recruitment of conceptual information is likely to occur concurrently with resolution of competition within the structural description system. Feed-forward and feedback projections between stored structural knowledge and other types of conceptual knowledge allow interactions between structural and conceptual knowledge.

The interaction between structural and conceptual knowledge has been proposed as an account for the prevalence of CSA for biological categories. Humphreys et al. (1988) had normal observers rate the structural similarity of exemplars within several natural categories and found that biological categories were rated as more structurally similar than non-biological categories, and also were judged to have more attributes in common. They also measured the contour overlap of line drawings from the Snodgrass and Vanderwart (1980) corpus and found that biological categories shared a higher degree of contour overlap than did non-biological categories (but see Laws & Neve, 1999). Furthermore, Riddoch and Humphreys (1987b) demonstrated the interaction of visual and conceptual similarity in the object recognition deficits of JB, a patient with CSA of the biological type. In a picture/word-matching task, JB made many errors when distractor pictures were both visually and conceptually similar to the target, but performed normally when distractors were either visually similar and conceptually unrelated or visually dissimilar and conceptually related to the target. Humphreys and colleages (Humphreys & Forde, 2001; Humphreys, Lloyd Jones, & Fias, 1995) suggested that biological objects are particularly vulnerable to brain damage because of the hierarchical and cascading nature of the object recognition system and the need for top-down re-entrant processing to help resolve competition at the structural description level during object naming.

Dixon, Bub, and Arguin (1997; see also Arguin et al., 1996) also proposed that resolution of competition at the structural description level can be modulated by conceptual proximity. Their account of CSA differs from that proposed by Humphreys and colleagues in that structural similarity is defined in terms of shared values along multiple diagnostic dimensions as opposed to contour overlap (a more holistic measure of similarity). Dixon et al. showed that ELM's ability to associate concepts to novel shapes that varied on multiple dimensions (stimuli similar to those used by Arguin et al.) depended on the conceptual relatedness of the concepts. Whereas ELM was able to learn labels for objects that did not require integration of diagnostic features (1D sets) regardless of the conceptual similarity of the labels, ELM's error rates for 2D sets showed a strong positive correlation with normal ratings of the conceptual similarity of the labels ($r = .84$). When labels were conceptually disparate (e.g., plate, door, stapler, kite), ELM's error rate for 2D sets was quite low (3.13%), lower even than that for 1D sets (15.63 %). When labels were highly related (e.g., mustang, camaro, corvette, trans am) ELM's error rate was quite high for 2D sets (65.63%), substantially higher than for 1D sets (16.67%). Thus, for ELM, structural confusions due to shared diagnostic features could be overcome if the exemplars were separated along conceptual dimensions. ELM's performance provided evidence that competition of exemplars within a category is determined by both conceptual and structural factors, and that object knowledge can be thought of as a multidimensional psychological space in which the dimensions are defined by both structural and conceptual properties.

Bukach et al. (in press) used the NLAR paradigm described earlier to investigate whether the poor performance for biological items in normal retrieval of object attributes could also be explained by the interaction of conceptual and structural knowledge in a dynamic model of object recognition. They provided three sources of support for this hypothesis: First, attribute recall for mammals and musical instruments was worse than for objects that were structurally similar but conceptually unrelated, and was also worse than for objects that were both structurally and conceptually unrelated (Experiments 1-3). Second, a regression of pairwise ratings of structural and conceptual similarity on pairwise confusion data from the recall phase revealed that a model including both structural and conceptual similarity better predicted attribute recall than either of these factors alone (Experiment 4). Third, an examination of the confusion matrix of colour recall for fruits and vegetables (Experiment 7) revealed that objects that shared structural (long vs. round) and conceptual (fruit vs. vegetable) values were confused more often than would be expected by chance. The results of Bukach et al. provided converging evidence from normal observers for the interaction of structural and conceptual factors in the retrieval of object knowledge.

Summary

The research presented above demonstrates several important aspects of structural representations and raises several questions for further investigation. First, research on integration within perception indicates that diagnostic elements of structural form are perceived as discrete structural features, and require additional time to be integrated to form a unified percept. Furthermore, the evidence demonstrates that participants can allocate attention to the relevant structural dimensions by which stimuli sets vary (i.e., to diagnostic dimensions). When attention needs to be allocated across several diagnostic structural dimensions, more time is necessary to form a unified percept that specifies the values of multiple features. When insufficient time is available, only a subset of the necessary diagnostic features may be fully specified and conjoined, resulting in errors that reflect dimensional paucity in perception – competition from *perceived* exemplars that share values on diagnostic dimensions.

The studies of ELM provide evidence that structural descriptions are also stored in a distributed fashion, and require integration at the time of retrieval. Competition in this system will be determined by the proximity of exemplars to one another in the space defined by the retrieved structural dimensions. When an insufficient number of diagnostic structural features are retrieved and integrated, errors reflect dimensional paucity in recall: competition from *retrieved memories* of previously encountered objects that share stored values on diagnostic dimensions. Additional evidence from ELM suggests that the integration of structural features in recall can be modulated by conceptual similarity. Bukach et al. (in press) presented converging evidence from normal observers for the interaction of structural and conceptual factors in attribute recall. However the use of natural stimuli, while providing a clear link to CSA, prevented the direct manipulation of structural and conceptual dimensions in the NLAR paradigm. This study was therefore able to provide only indirect support for structural similarity defined in terms of distributed structural representations.

Finally, some tentative conclusions may also be drawn regarding the relationship between structural integration processes during perception and recall. The evidence across the studies suggests that the type of features retrieved from memory are similar to the type of structural features that are extracted and attended during perception, and moreover, that the selection of features is related to their diagnosticity for particular tasks. However, the experiments described above did not explicitly address the relationship between the integration processes during perception and retrieval, thus further research is necessary to support these conclusions.

In the following experiments I extended the study of Bukach et al. (in press) by using the NLAR paradigm with novel stimuli that have clearly defined structural differences, so that evidence for confusions based on dimensional proximity and dimensional paucity may be examined. The use of novel stimuli allows manipulation of the number of structural dimensions that are necessary to uniquely identify an object (stimuli within sets differed by either one or two dimensions), and enables a factorial design in which structural dimensionality and conceptual similarity can be fully crossed to determine whether conceptual relatedness can modulate the resolution of structurally-based competition. Experiment 5 was intended to determine the nature of confusions produced when perceptual integration of structural features is interrupted in a match-to-sample task (involving both perceptual and working memory processes across a single episode). Experiment 6 and 7 was intended to establish the nature of confusions for the same stimuli in the colour recall task (involving retrieval from long-term memory across several episodes). Both the match-to-sample task of Experiment 5 and the recall task in Experiments 6 and 7 were designed to allow competition from the entire stimuli set, so as to reflect the kind of within category competition evident in category specific failures of object identification. Experiment 7 was also designed to examine whether associating conceptual labels with the novel objects influences resolution of competition from structurally proximate exemplars.

The rationale for determining whether the identification of visual forms can be described as the integration of distributed structural dimensions relies heavily on the analysis of confusions in the various tasks according to their proximity in a multidimensional space defined by the diagnostic structural dimensions that I manipulated. For 1D stimuli sets, confusions were expected to reflect proximity along the single diagnostic dimension – more confusions were expected between targets and their closest neighbour than expected by chance. For 2D sets, errors were also expected to reflect dimensional proximity and, in addition, where integration of multiple diagnostic dimensions failed, dimensional paucity. The analyses for dimensional paucity in the current experiments are based on the finding that ELM rarely confused exemplars that had a diagonal relationship with one another according to their distribution in a multidimensional space (i.e., exemplars that had no diagnostic property in common, Arguin et al., 1996). Rather, his errors were primarily parallel to the dimensional axes, indicating an impairment of feature integration. To determine whether, under the constraints of brief presentation or recall of newly-learned attributes, normal participants sometimes also fail to integrate structural dimensions, errors for 2D sets in the following three experiments were therefore coded as either diagonal and parallel, and their observed frequencies were compared to what would be expected by a chance distribution.

Experiment 5: Perception of Novel Objects from 1D and 2D Sets

Experiment 5 was a match-to-sample task in which participants identified a single briefly displayed object from a template of six exemplars. This task is similar to the one used to demonstrate intact perceptual integration in patient ELM, with the exception that this task was designed to disrupt perceptual processing in normal observers before diagnostic features could be integrated, so that evidence for dimensional proximity and dimensional paucity could be observed. Because the exposure duration was very brief (60 or 75 ms) and stimuli were followed immediately by a pattern mask, I expected that perceptual processes would be interrupted such that participants would have only enough time to specify one diagnostic feature. Because specification of one diagnostic feature is sufficient for 1D sets, errors for these sets should mainly reflect the proximity of competitors on the relevant structural dimension. Specification and conjunction of two diagnostic features are necessary for 2D sets; therefore errors for these sets should reflect dimensional paucity (that is, errors should predominantly involve competitors that share a value on one of the diagnostic structural dimensions). Although matching a briefly displayed single stimulus to one from an array of six objects produces a different measure of dimensional paucity than the conventional illusory conjunctions that are found in briefly presented multi-stimulus displays, the match-to-sample experiment is more analogous to conventional identification tasks used to test for object recognition deficits such as CSA in that it allows competition from the entire category.

Method

Participants

A total of 24 participants from the University of Victoria participated in return for optional course credits.

Materials

Stimuli were generated using Ulead COOL 3.0. Two basic forms were created (cylinders and cubes) allowing participants in Experiment 6 and 7 to be assigned both a 1D and 2D object set with minimal interference between sets. Objects within sets varied on either one shape dimension (tapering *or* pinching) or two shape dimensions (tapering *and* pinching). 1D sets were created by varying the width of the upper edge (tapering) or by varying the width of the middle (pinching), such that each object within a set had a unique value on the relevant shape dimension. Similarly, 2D sets were created by varying the width of both the upper edge and the width of the middle, such that all values of tapering and pinching were shared by two objects within a set. Six objects were generated in each set. The resulting six object sets (four 1D sets and two 2D sets) are shown in Figure 11. Four masks were created from rearranged and overlapping segments of a subset of these objects. A practice set was created by including one object from each of the six sets. The experiment was run on a Macintosh computer using RSVP 4.0.5 software.

Design and Procedure

The experiment was a single factor (1D vs. 2D) within-participants design, and each participant was tested on all six of the object sets. Trials were blocked by object set, and order of blocks was counterbalanced across participants. Each experimental block consisted of 24 trials. Order of trials was pseudo-randomized within each block, such that a complete cycle of the six objects was shown before beginning the next cycle. At the beginning of each block, participants were given a sheet of paper depicting all six objects from the appropriate object set for that block. On each trial, one object was shown on the screen briefly, followed immediately by a mask at the same exposure duration. All four masks were used within each block to avoid adaptation to the masks. Participants indicated which of the six items from a particular set was presented by pointing to the appropriate object on the object sheet. The experimenter recorded the responses on the keyboard.

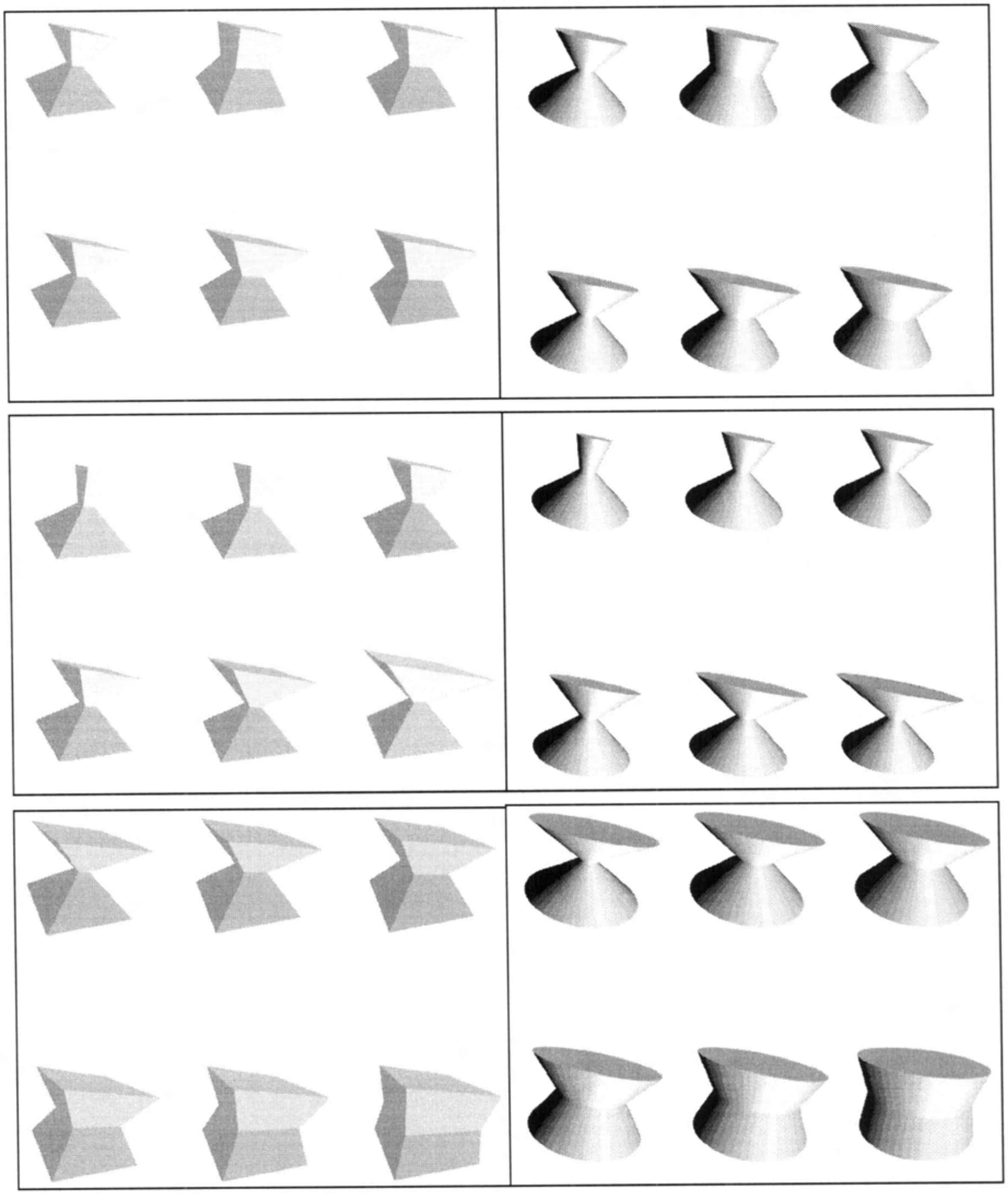

Figure 11. Stimuli used in Experiment 5 through 7. The top panels show 2D sets that vary on both tapering and pinching; the middle and bottom panels show 1D sets that vary on tapering only (middle panel) or pinching only (bottom panel).

The experiment began with six trials of the practice set presented for decreasing exposure durations (180, 120, and 90 ms). Next, participants completed two blocks of additional practice trials, with 12 trials in each block. In the first block, practice objects were presented for 75 ms, and in the second block, practice objects were presented for 60 ms. Exposure duration of the remaining experimental blocks was based on accuracy levels in the practice blocks. Stimuli were displayed for 60 ms if the participant's accuracy was at least 10/12 for the 60 ms practice block. Otherwise, stimuli were displayed for 75 ms.

Results and Discussion

The results of the match-to-sample task are presented in two sections: The first section compares the overall accuracy rates between 1D and 2D sets. The second section examines the role of structural proximity and paucity in the type of confusions made in 1D sets and 2D sets. In addition to examining the observed rates of various error types (close vs. distal and diagonal vs. parallel), I employed an analysis regressing pairwise confusion data on the distances between exemplar pair, a dummy variable coding whether the confusions are parallel or diagonal, and an interaction term. This analysis reveals what proportion of variability in the errors can be accounted for by proximity, paucity, and their interaction.

Overall Accuracy Rates

Figure 12 displays the accuracy results of the match-to-sample task for 1D and 2D sets. Identification of the briefly presented stimuli was not trivial, as is evidenced by the

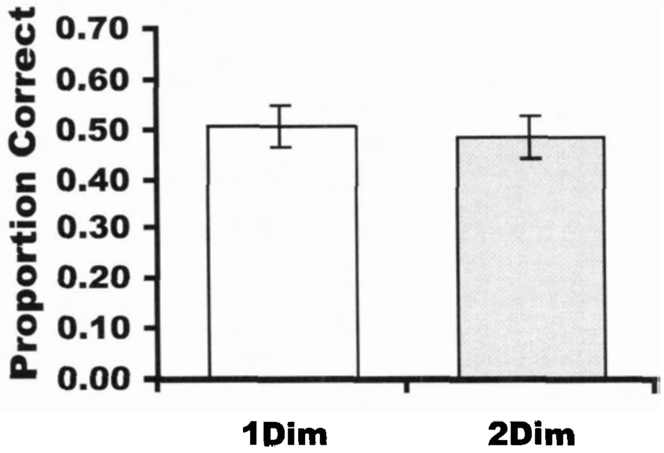

Figure 12. Mean accuracy and 95% within-subject confidence intervals for 1D and 2D object sets in the match-to-sample task (Experiment 5).

relatively low accuracy rates (*M* = .51 and .49 for 1D and 2D sets, respectively). Although accuracy rates of most of the stimuli within object sets were equivalent, one particular stimulus in the 2D sets had very high accuracy rates (74% vs. 44% for the others), and thus may have inflated the overall accuracy rate for the 2D set. This object had a value of 30 units on both tapering and pinching (see Figure 13).

There are two possible reasons for higher accuracy for this particular stimulus. First, this is the only stimulus that has no *close* competitor with shared features (placing the stimulus in a more sparse region of the stimulus space, as can be seen in the bottom panel of Figure 13, which shows the structural relationships between stimuli in the 2D sets according to their physical unit values). The second reason is that the stimulus sides are almost parallel, and parallel sides may facilitate integration of the tapering and pinching dimensions. In support of this idea, several participants commented that this stimulus "popped out" from the rest. Although the idea of emergent integration due to

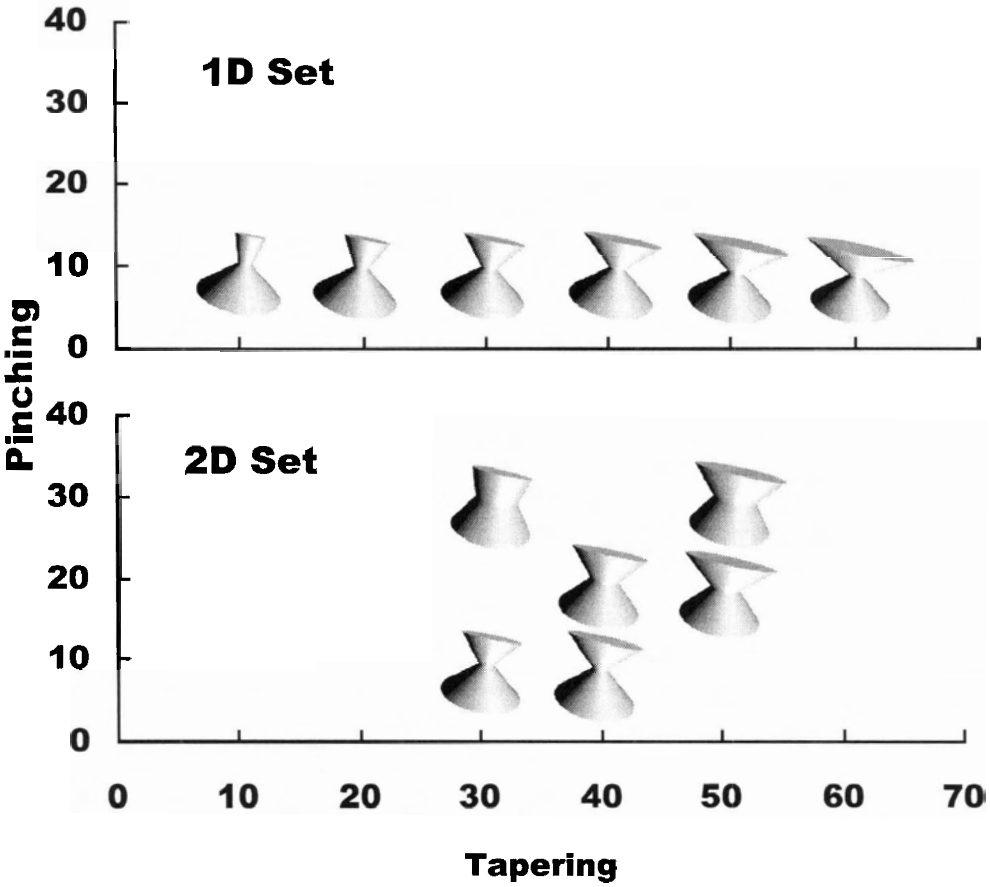

Figure 13. Stimuli showing the structural relationships between objects in the 1D and 2D sets of novel stimuli.

parallel sides is interesting, the distinctiveness of this stimulus could potentially reduce the ability to find evidence for dimensional paucity. A replication of the current studies should therefore endeavor to avoid stimuli with parallel or almost parallel sides.

Confusions in the 1D and 2D Object Sets

Confusions in the 1D and 2D sets should reflect the structural relationships between stimuli as described by a multidimensional psychological space. Figure 13 shows a graphic presentation of the structural relationships between sample stimuli from the 1D and 2D object sets, as defined by the *physical* distances between stimuli. I use the physical measurements here to approximate the psychological distances, and although there may not be an exact correspondence between psychological and physical distances, (see results below for more discussion on the validity of using physical distances as estimates in this case) this physical representation nonetheless demonstrates some of the relevant differences between structural relationships in 1D and 2D sets (e.g., shared dimensions and relative spread of the two types of sets).

Objects in the 1D sets varied along only a single dimension, with values ranging from 10 to 60 units (see the top panel of Figure 13). I hypothesized that confusions for these sets would reflect the proximity of competitors to the target along this single diagnostic dimension, with closest neighbours providing the most competition. To test for the effect of dimensional proximity, I coded the errors as either close (differing by only 10 units from the target) or as distal (differing by more than 10 units). As can be seen in Figure 13, there were more possibilities for distal errors (20) than for close errors (10), resulting in different chance probabilities for the two conditions. Figure 14 shows the observed error rates for the close error type with 95% confidence interval based on the standard error of the mean, relative to the error rate expected by chance for this condition (equivalent to a one-sample t-test). Of the 35.4 errors made by participants on average to the four 1D sets, the 84.2% were close neighbours, significantly more than would be expected by chance (33.3%).

Another way of testing for the effect of proximity on recall is to regress the observed confusion frequencies between stimuli pairs on the distances between exemplars. I used the reciprocal of the distances because according to the analysis above,

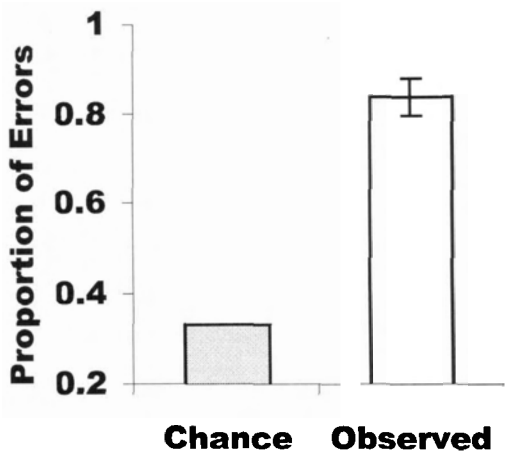

Figure 14. Mean proportion of observed errors for the close error type in the 1D condition of Experiment 5, relative to the number expected by chance. 95% confidence interval is based on the standard error.

the majority of competition should come from closest neighbours. It should be noted that I used the reciprocal of the *physical* distance between pairs in this analysis, and that it cannot be assured that equal intervals in physical space correspond to equal intervals in psychological space. Nonetheless, the reciprocal of the physical proximity between exemplars was able to account for 81% of the variance in the confusion data, as Table 2 shows. These results are consistent with competition based on structural proximity, and also suggest that physical distance is a good estimate of psychological distance for these stimuli.

Unlike objects in the 1D set, objects in the 2D set varied along two structural diagnostic dimensions. If participants had time to specify only one structural feature due to the limited exposure duration, exemplars that shared values on diagnostic dimensions should be particularly confusable. My primary interest in the 2D set was therefore to

Table 2

Summary of the regression analysis in which proximity (the reciprocal of the distance between exemplars) was used to predict the observed pairwise confusion data for 1D sets in the match-to-sample task of Experiment 5.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Model	118.4	<.001	.809			
Proximity				.899	10.9	<.001

determine whether the error pattern would reflect dimensional paucity. Errors that reflect dimensional paucity will have a structural relationship to the target that is parallel to one of the axes, as opposed to target-error relationships that are diagonal to the two axes. As can be seen in Figure 13, there are fewer possibilities for parallel errors (12) than diagonal errors (18), resulting in different chance error rates for the two conditions. To test for the effect of dimensional paucity, I coded errors as either diagonal or parallel. The proportion of parallel errors and the chance error rates are depicted in Figure 15. Of the 18.5 errors made by participants on average to the two 2D sets, 58.5% were parallel, significantly more than would be expected by chance (40%).

However, this analysis does not control for the proximity of the exemplars, a factor that is also likely to constrain error probabilities, and to interact with dimensional paucity should participants fail to integrate the dimensions. Arguin et al. (1996) controlled for proximity by choosing exemplars from the 1D sets that had the greatest distance separating them to include in the 2D sets. In their recall task, they found that for ELM, parallel errors were frequently observed even though these same stimuli were rarely confused in the context of the 1D set. Unfortunately, this control was not incorporated in the design of the current experiments, and dimensional paucity and dimensional proximity were therefore confounded. That is, exemplars that shared diagnostic features also tended to be most proximate. In an attempt to separate these factors I further subdivided the diagonal and parallel errors into the following categories: a) DiaC: diagonal errors in which both dimensions were close to the target; b) DiaCD: diagonal errors in which one dimension was close and the other distal to the target; c) DiaD: diagonal errors in which both dimensions were distal to the target; d) ParC: parallel errors in which one dimension was shared and the other close to the target; e) ParD: parallel errors in which one dimension was shared and the other was distal to the target.

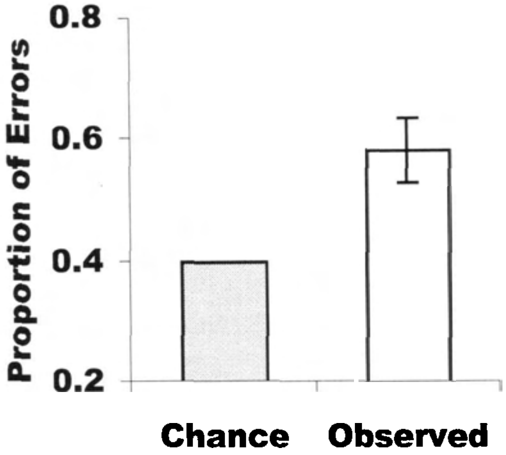

Figure 15. Mean proportion of observed errors for the parallel error type in the 2D condition of Experiment 5, relative to the number expected by chance. 95% confidence interval is based on the standard error.

The left panel of Figure 16 shows the observed proportion of errors in each condition relative to what would be expected by chance. Close errors were more likely for both diagonal and parallel error types than what was expected by chance. To test whether dimensional paucity had an effect over and above proximity, I directly compared the observed values for close diagonal and close parallel error types, as both error conditions had equal expected mean proportions. This comparison is shown in the right panel of Figure 16. When expected proportions for proximity were matched, significantly more errors were parallel than diagonal (*M* = 52.2% and 35.5% respectively), indicating that the effect of dimensional paucity remained significant over and above the effect of proximity.

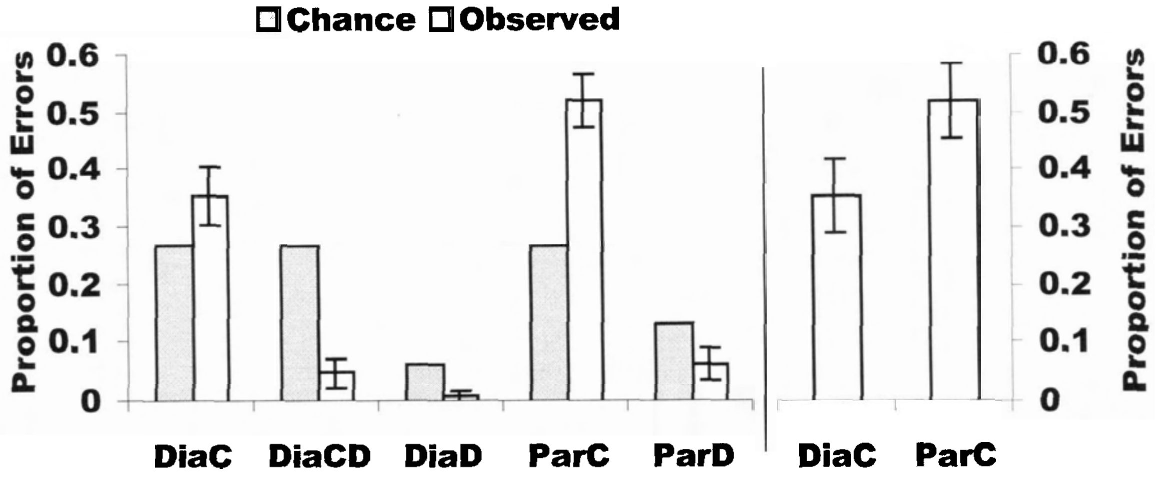

Figure 16. The left panel shows the mean proportion of observed errors for the various error conditions in Experiment 5, relative to the number expected by chance. DiaC = diagonal with values on both dimensions close to target values; DiaCD = diagonal with values on one dimension close and the other distal to target values; DiaD = diagonal with values on both dimensions distal to target values; ParC = parallel with the second dimension close to target value; ParD= parallel with second dimension distal to target value. 95% confidence intervals are based on the standard error of each condition. The right panel is a direct comparison of diagonal and parallel errors for the close condition. Error bars for this comparison are 95% within confidence intervals based on the MS from the repeated measures ANOVA.

Unfortunately, this analysis is also open to criticism, as parallel "close" and diagonal "close" are not strictly equivalent in terms of their physical distance. According to Pythagorean theorem, diagonal errors will always be more distal than the corresponding parallel errors. To take both physical distance and shared features into account, I performed a step-wise forward regression in which the pairwise confusion data were regressed onto physical proximity (reciprocal of physical distances), paucity (coded as diagonal = 1 and parallel = 2), and their interaction. The results of this analysis are presented in Table 3. The only significant predictor in this model was proximity, which accounted for 59% of the variance. It should be noted, however, that proximity and the interaction term were highly correlated (r = .91), making it unlikely for the interaction to account for variance over and above that accounted for by proximity alone.

Table 3

Summary of the step-wise forward regression analysis in which the pairwise confusion data of the 2D sets of Experiment 5 was regressed onto proximity (reciprocal of physical distances), paucity (coded as diagonal = 1 and parallel = 2), and their interaction.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Model 1	39.6	<.001	.586			
Proximity				.765	6.294	<.001
Excluded Variables						
Paucity				-.051	.330	.744
Proximity X Paucity				-.148	.514	.611

Note. Statistics for each significant model represent tests of the overall model. Predictors included in the respective models and their associated statistics are listed directly below each model. Statistics for variables that failed to meet the inclusion criterion are listed following the last significant model.

Although analysis of the practice trials was not planned as participants were learning the task at this point, I noted a surprising pattern in participant's responses that indicated they frequently failed to integrate the geometric shape of the stimuli with the values of tapering and pinching. The practice trials differed from experimental trials in that the practice set included a mixture of cubes and cylinders. The practice stimuli were chosen so that within a geometric shape (cylinder vs. cube), values on pinching and tapering were both diagnostic (that is, there were no shared structural values on pinching or tapering between stimuli within a given geometric shape). However, these values were shared across geometric shape such that cube-cylinder pairs shared values on both tapering and pinching. Participants showed a tendency to confuse cubes and cylinders when the values on both tapering and pinching matched: of the 141 errors made on practice trials, 40% represented confusions of geometric shape alone, compared to an expected rate of 20% by chance alone. This result is surprising given that the cylinder/cube dimension seems intuitively quite salient. The evidence nonetheless suggests that participants failed to integrate this aspect of the stimuli when specifically attending to the dimensions of pinching and tapering. Variation of geometric shape within stimuli sets may be an avenue to pursue in future experiments examining integration of structural dimensions.

The pattern of errors in Experiment 5 suggests that given brief exposure durations, normal observers' perception and maintenance of structural information in working memory is susceptible to competition from exemplars that are proximate as defined by a multidimensional space consisting of the diagnostic structural dimensions of pinching and tapering. Evidence for whether participants failed to integrate structural dimensions in the 2D set, although suggestive, was somewhat mixed. On the one hand, several findings support the notion that shared features are particularly problematic: a) accuracy for stimuli in the 2D sets (with the exception of one particular stimulus) was less accurate than for stimuli in the 1D sets; b) parallel errors occurred more often than expected by chance; and c) practice errors showed a tendency to reflect confusions across shared values on the geometric shape dimension. On the other hand, the regression analysis failed to show an effect of dimensional paucity or an interaction of paucity with proximity. Unfortunately, the confounding of dimensional proximity and dimensional paucity both inflates the chance of finding parallel errors and reduces the ability to find an interaction of proximity and paucity in the regression analysis. To properly control for proximity in this analysis, the experiment should be redesigned so that overall accuracy in the 2D set could be compared with that of a 1D set in which the exemplars are more proximate, as was done in Arguin et al (1996).

Experiment 6: Colour Recall of Novel Objects from 1D and 2D Sets

Experiment 6 used the NLAR paradigm developed by Bukach et al. (in press) in conjunction with novel stimuli shapes used in Experiment 5 so that the pattern of errors for 1D and 2D sets could be examined for effects of dimensional proximity and dimensional paucity in recall. Participants first completed an incidental colour-training phase for two sets of objects: a 1D set and a 2D set. Participants then attempted to recall the colour of each object in a surprise recall test. Because each object within a set was assigned a unique colour, correct colour recall is analogous to successful object recognition. According to an episodic framework, correct colour recall requires the retrieval and integration of diagnostic structural features and colour information. If structural dimensions are stored in a distributed fashion so that retrieved structural dimensions must be integrated during recall, then errors in the 1D and 2D sets should reflect competition from exemplars that are proximate in the defined space. If normal participants fail to integrate dimensions in the colour recall phase of the NLAR paradigm, 2D sets should be more prone to errors in recall than 1D sets because 2D sets require two diagnostic dimensions to uniquely specify an object. In addition, errors in the 2D set should reflect confusions between stimuli that share values on diagnostic dimensions, as was the case with CSA patient ELM.

It is important to note that the training phase differs in two substantial ways from the recall phase. First, the training phase involves a brief exposure duration and immediate report, whereas the recall phase is a long-term memory task with unlimited exposure duration. The training task therefore reflects perceptual and working memory processes, whereas the recall task reflects retrieval from long-term memory. Second, the training task involves pairwise comparisons, limiting the interference to a single distractor, whereas the recall task involves set-wise comparisons. Performance in the training phase will therefore depend not on setwise differences, but on pairwise differences between stimuli.

Method

Participants

A total of 24 participants from the University of Victoria participated.

Materials

The stimuli were the same as those used in Experiment 5, with the exception that stimuli were coloured using Adobe Photoshop 5.0. The colours used in the training phase were red, green, blue, yellow, pink and brown.

Design and Procedure

The experiment was a within-subject design, manipulating the number of structural dimensions along which an object set varied (one vs. two). Participants first completed an incidental learning phase in which each object was associated with a particular colour. Each participant was trained to associate colours to a one-dimension and a two-dimension set of stimuli (one cube and one cylinder set). Assignment of sets was counterbalanced across participants. Following training, participants were administered a posttest in which they were asked to recall the colours of each of the objects.

Training Phase. The training procedure was similar to that of Experiments 1 – 4. Details are as follows: a central fixation for 250 ms, two differently coloured objects presented randomly to the right or left of fixation for 750 ms, two masks in the locations of the previously presented stimuli for 500 ms, a single grayscale object presented centrally for 1500 ms. Participants were given 1500 ms to report the colour of the cued object. Objects were always paired with another object from the same set, and order of trials was random. Each object in a set was assigned a unique colour, and assignment of colour to objects was constant for all participants. Participants completed 15 blocks of trials in which each of the 12 objects appeared once as a target and once as a distractor.

Recall Phase. Following the training phase, participants were told that all of the objects were consistently coloured. They then completed a surprise recall test in which they viewed each of the 12 objects in grayscale one at a time in random order, and attempted to report the colour that was assigned to the object in the training phase. Participants were given unlimited time to respond.

Results and Discussion

The results of Experiment 6 will be presented in two sections: the training phase in which errors are expected to reflect pairwise competition, and the recall phase, in which errors are expected to reflect setwise competition.

Training Phase

Trials in which participants failed to respond within the 1500 ms deadline were coded as errors. In addition, trials in which response times fell below 300 ms were excluded from all analyses. Response time analyses were based on the remaining correct trials only. The results of the training phase for 1D and 2D sets are displayed in Figure 17. Accuracy was quite high for both object sets (M = 85% and 86% respectively), indicating that for the majority of trials, attention was directed to the diagnostic structural dimension that differentiated the pair of stimuli. Responses for 1D trials were significantly faster than for 2D trials (M = 679 and 694 ms, respectively), indicating a slight advantage for 1D objects.

Performance in the training phase was expected to vary because of pairwise differences between stimuli. There are two possible sources of pairwise differences between objects in 1D and 2D sets that could potentially lead to differential performance

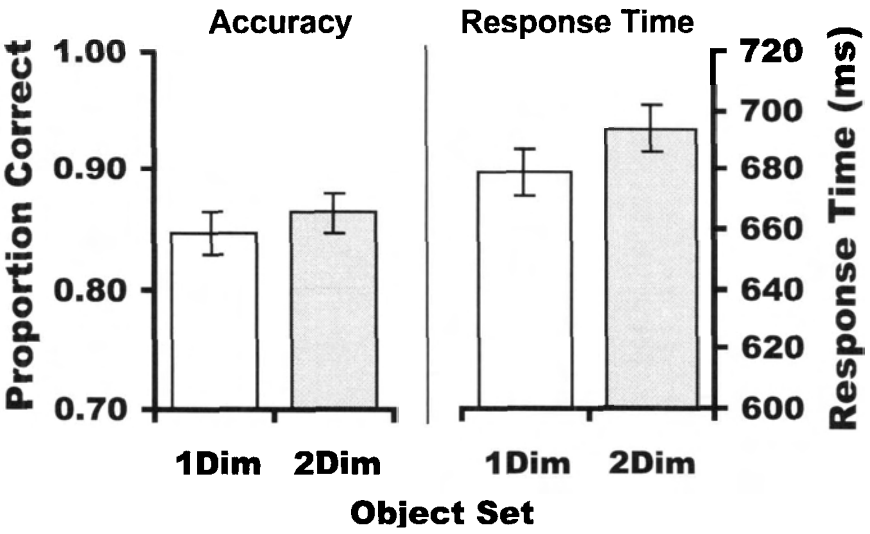

Figure 17. Mean accuracy and response times for 1D and 2D sets in the colour training phase of Experiment 6. Error bars represent 95% within-subject confidence intervals.

in this task. First, object pairs in 1D sets may be more easily discriminated because they have a greater range in the amount by which pairs differ from one another (up to 50 units for 1D sets vs. only 20 units for 2D sets; see Figure 13). This difference should lead to better performance for 1D sets, at least for those trials in which the distance between pairs along the relevant dimension is greater than 20 units.

The second difference between 1D and 2D sets is that only 2D sets contain trials in which stimuli pairs differ by both relevant structural dimensions (equivalent to diagonal relationships in Figure 13). Stimulus pairs that differ by both dimensions have an advantage in the training task in that binding colour to any one structural dimension would lead to a correct response. Accuracy for stimulus pairs that differ by only one dimension, on the other hand, depends on the binding of colour to the particular structural dimension that is diagnostic for that pair. If, due to the time constraints, participants engage in a strategy whereby colour is bound to a single structural dimension only, performance should be better for 2D sets, at least for trials in which target-distractor pairs could be differentiated by either dimension (66.7% of the 2D trials).

Because these two factors (discriminability and the number of dimensions that differentiate objects in a pair) act in opposition for 1D and 2D object sets, the analysis of overall accuracy and response times may have masked differences between object sets. I therefore separated trials in the 1D set into two bins: those trials in which targets differed from the distractors by 20 units or less (the maximum difference between pairs in the 2D sets) and those trials in which targets differed from their distractors by more than 20 units. All of the stimulus pairs in these conditions differed by one dimension (1Diff). I also separated the trials in the 2D set into two bins: those for which pairs differed by only one dimension (1Diff), and those that differed by both dimensions (2Diff). All of the stimulus pairs in the 2D object sets differed by 20 units or less.

The results of this analysis are displayed in Figure 18. As predicted, 1Diff pairs that varied by more than 20 units were more accurate than 1Diff pairs that varied by 20 units or less (whether they came from 1D or 2D object sets), confirming the first hypothesis that colour-binding is more successful when stimuli pairs are more discriminable.

The second hypothesis was also supported: Of the trials in which pairs varied by 20 units or less, 2Diff pairs were more accurate than 1Diff pairs (whether they came from 1D or 2D sets). This cannot be attributed to a speed-accuracy trade-off, as response times for 2Diff pairs were also faster than 1Diff pairs from the 2D sets, and moreover, did not differ from 1Diff pairs in 1D sets. An examination of the errors in the current task

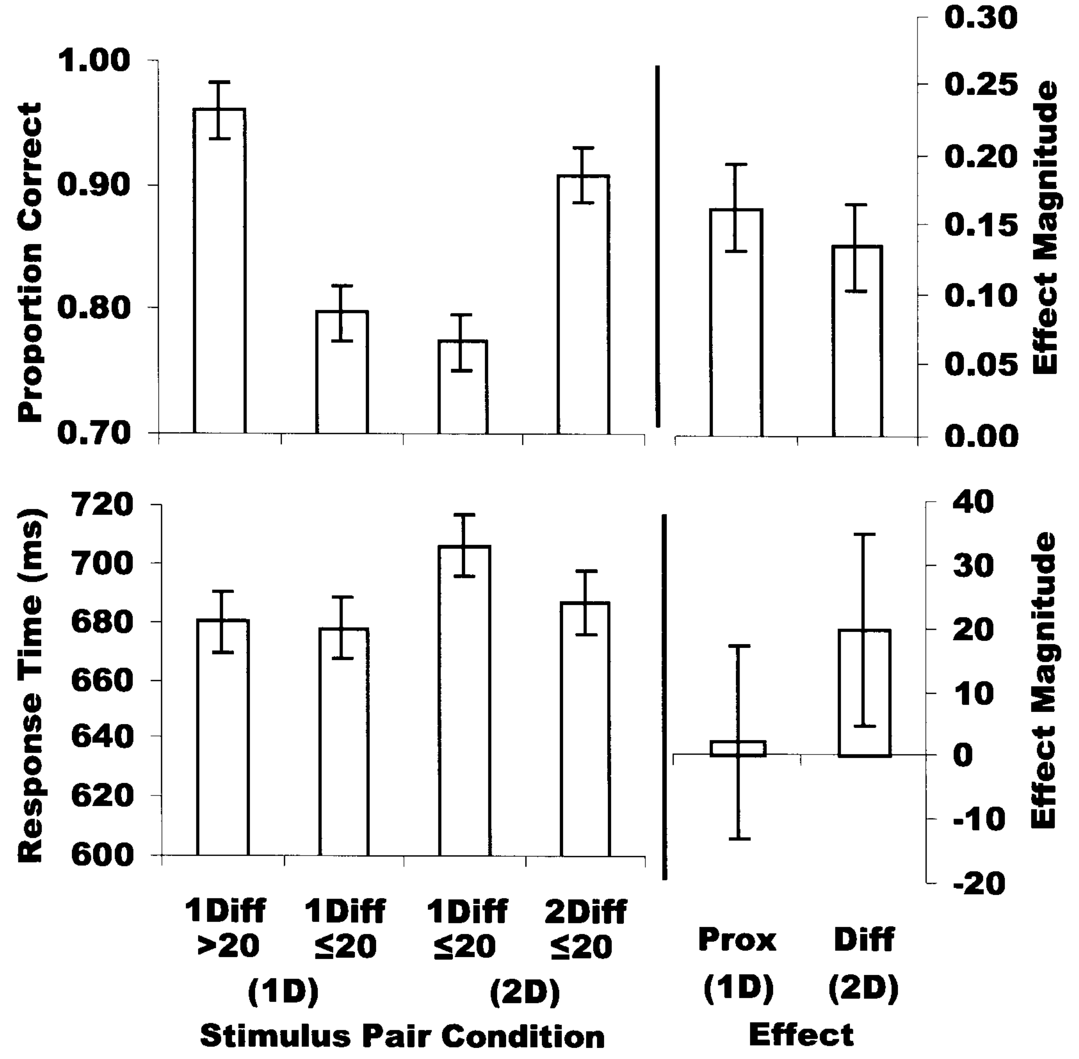

Figure 18. Left panels show accuracy and response times for stimulus pair conditions in the colour training phase of Experiment 6. Trials are grouped according to both the proximity of stimuli along the diagnostic dimensions (>20 vs. ≤20), as well the number of dimensions that differed between stimuli (1diff vs. 2diff). Error bars represent 95% within subjects confidence intervals.Right panels show contrasts for proximity (1D set only) and number of dimensional differences (2D sets only). Contrasts are plotted as positive values for convenience. Error bars are 95% confidence intervals for the contrasts.

confirmed that the majority (88%) were due to report of the distractor colour rather than the target colour. Critically, many more illusory conjunctions were made when stimuli pairs differed by one structural dimension than when they differed by two. This pattern of results is consistent with the hypothesis that participants may have bound colour to only one structural dimension, and suggests an alternative interpretation to illusory conjunctions in perception. That is, illusory conjunctions may arise not only because of a complete failure to bind colour to form, but also under certain circumstances, may occur because colour is bound to structural dimensions that are non-diagnostic for the task. In support of this argument, Arguin et al. (2000) demonstrated that under challenging task constraints, participants selectively attended to only one structural dimension if integration of structural dimensions is unnecessary (e.g., in the 1D search condition). Because a single structural dimension may differentiate any *pair* of stimuli, integration of structural dimensions was unnecessary in the colour-training task as well. The implication of binding of colour to a single dimension in the training phase has implications for setwise recall, and will be discussed further, below.

Recall Phase

Overall Accuracy. Unlike the training phase, the recall phase is susceptible to setwise competition, such that two dimensions are necessary to differentiate stimuli in the 2D set. I therefore expected that if dimensions are stored separately in memory, colour should be better recalled for 1D than for 2D sets. The results of the colour recall phase of Experiment 6 are displayed in Figure 19. As predicted, colours of 1D objects were better recalled than the colours of 2D objects.

Figure 20 contrasts the results of the setwise recall task with the results of the pairwise training task (with accuracy converted to a standardized scale), showing a significant interaction between task and the dimensionality of the set. This rules out the possibility that poor recall for 2D sets is merely due to poor performance in the colour training phase.

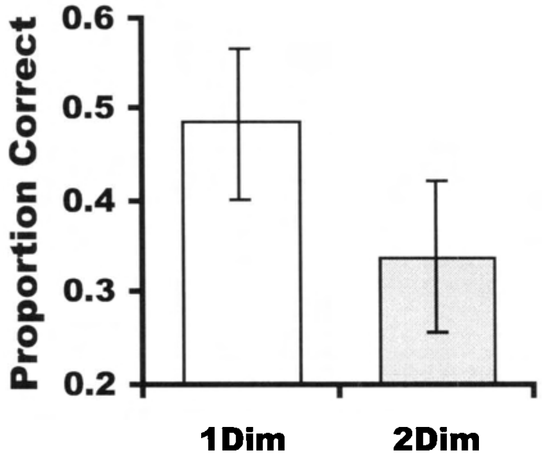

Figure 19. Mean accuracy for 1D and 2D stimuli sets in the recall phase of Experiment 6. Error bars are 95% within-subject confidence intervals.

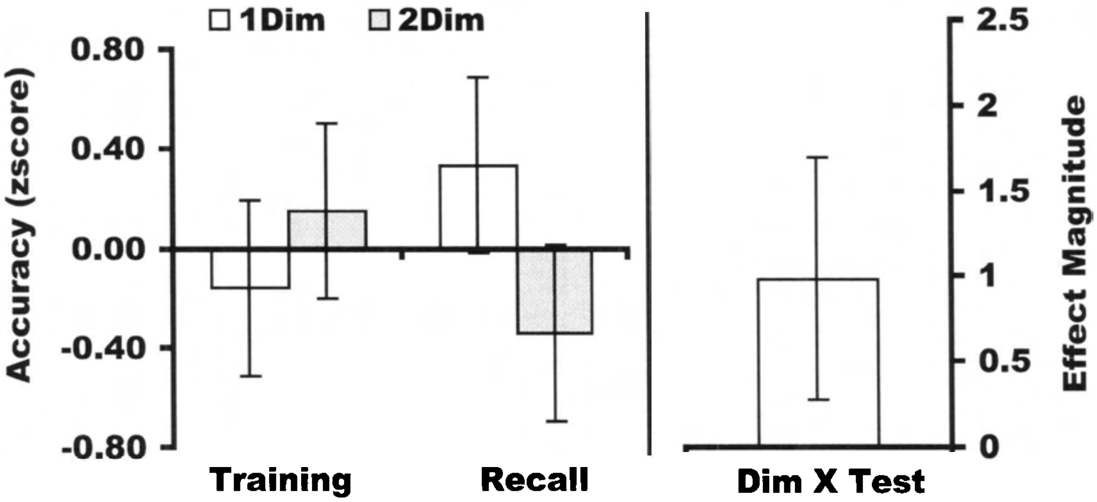

Figure 20. The left panel shows the condition means (converted to z-scores) for training and recall tasks of Experiment 6, with 95% within-subject confidence intervals. The right panel shows the contrast for the interaction between task and dimensionality, with 95% confidence interval for the contrast.

Error Pattern for 1D and 2D sets. To examine the nature of colour confusions, incorrect colour responses were recoded according to the structural form that the colour was associated with in the training phase. I predicted that pattern of errors in the recall phase would reflect the structural relations between stored exemplars as defined by a multidimensional space of diagnostic structural dimensions. I therefore expected that errors in the 1D set would reflect competition from close neighbours. I classified errors from the 1D set as either close (10 units away) or distal (20 or more units away) to the target, as I did in Experiment 5. The results of this analysis are shown in Figure 21. As predicted, significantly more errors were due to confusions with close neighbours (69.8%) than expected by chance (33.3%).

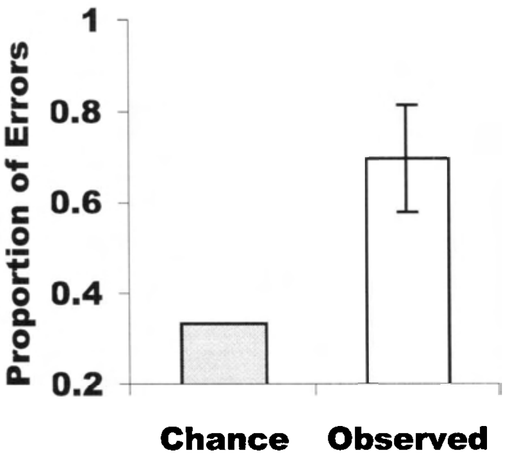

Figure 21. Mean proportion of observed errors for the close error type in the 1D condition of the recall phase of Experiment 6, relative to the number expected by chance. 95% confidence interval is based on the standard error.

I also regressed observed pairwise confusion frequencies of 1D sets onto pairwise proximity values as defined by the reciprocal of the physical distance between items in a pair. As Table 4 shows, proximity was able to account for 46% of the variability in the pairwise confusion data. Thus for objects that differ on one diagnostic dimension, the ability to disambiguate retrieved structural features is determined by the proximity of exemplars along the single structural dimension that is diagnostic for the set.

Table 4

Summary of the regression analysis in which proximity (the reciprocal of the distance between exemplars) was used to predict the observed pairwise confusion data for 1D sets in the recall task of Experiment 6.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Model	23.5	<.001	.456			
Proximity				.676	4.848	<.001

Recall errors for 2D sets were expected to reflect a combination of dimensional proximity and dimensional paucity. The analyses will proceed in the same fashion as those for Experiment 5, first examining the likelihood of observing parallel versus diagonal errors. If structural features are stored in a distributed fashion in memory, errors reflecting dimensional paucity should also arise during recall of newly learned attributes. The result of this analysis is shown in Figure 22. Contrary to what was predicted, no evidence was found for dimensional paucity in recall of colour associations.

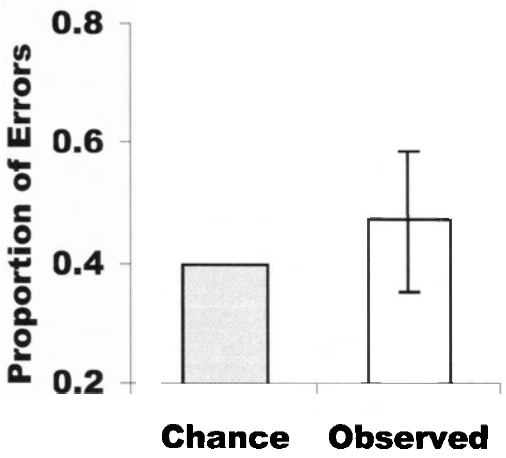

Figure 22. Mean proportion of observed errors for the parallel error type in the 2D condition of the recall phase of Experiment 6, relative to the number expected by chance. 95% confidence interval is based on the standard error.

To examine the joint contributions of dimensional paucity and proximity, I coded errors as close and distal in addition to whether they were diagonal or parallel as was done in Experiment 5. These results are displayed in Figure 23. The only condition that had more errors than would be expected by chance was the parallel and close condition. Consistent with the lack of evidence for dimensional paucity in the previous analysis, there was no difference between the number of mean errors for diagonal and parallel errors in the close condition.

The 2D recall results were also submitted to a regression analysis in which pairwise confusion frequencies were regressed onto dimensional proximity, paucity, and their interaction, as was done in Experiment 5. As is evident from Table 5, none of these predictor variables had a reliable relationship to pairwise recall confusions.

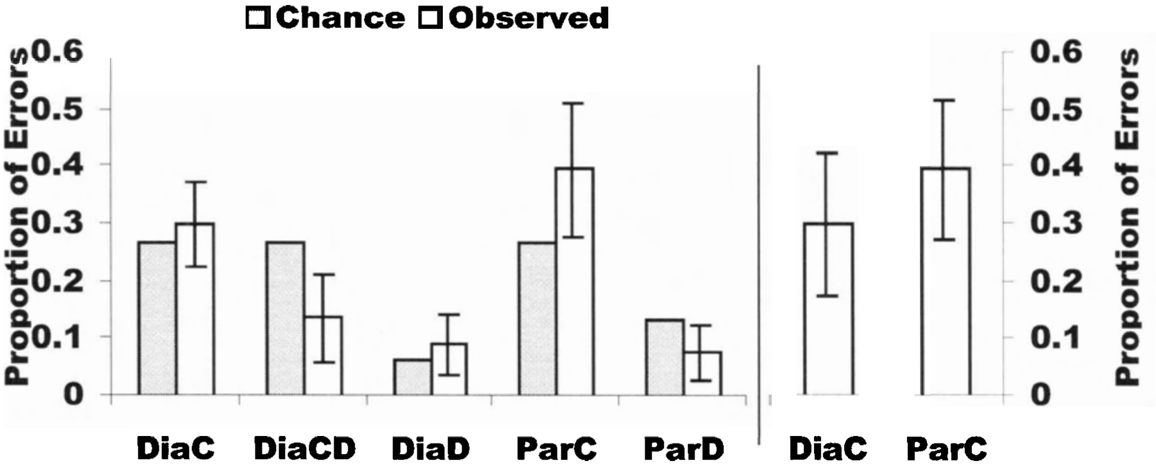

Figure 23. The left panel shows the mean proportion of observed errors for the various error conditions in the recall phase of Experiment 6, relative to the number expected by chance. DiaC = diagonal with values on both dimensions close to target values; DiaCD = diagonal with values on one dimension close and the other distal to target values; DiaD = diagonal with values on both dimensions distal to target values; ParC = parallel with the second dimension close to target value; ParD= parallel with second dimension distal to target value. 95% confidence intervals are based on the standard error of each condition. The right panel is a direct comparison of diagonal and parallel errors for the close condition. Error bars for this comparison are 95% within-subject confidence intervals based on the MS from the repeated measures ANOVA.

Table 5

Summary of the step-wise forward regression analysis in which the pairwise confusion data of the 2D sets in the recall task of Experiment 6 were regressed onto proximity (reciprocal of physical distances), paucity (coded as diagonal = 1 and parallel = 2), and their interaction.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Excluded Variables						
Proximity				.028	.033	.794
Paucity				-.285	.402	.691
Proximity X Paucity				.500	.376	.710

Whereas proximity was a significant predictor for 1D colour recall, neither proximity nor paucity appeared to have any effect on the pattern of recall errors for 2D sets. The overall pattern of errors as displayed in Figure 23 suggests that colour was simply poorly bound to stimuli in 2D sets. This hypothesis was confirmed when accuracy for individual stimuli within the 2D set were examined. As was the case in Experiment 5, performance for the distinctive stimulus was highly accurate (79%), but accuracy for the other five stimuli was very low (25% on average).

Why might recall confusions be randomly distributed for the majority of 2D stimuli? One possibility is that the small number of errors (M = 3.96) in combination with the distinctive stimulus reduced the ability to detect patterns in the recall errors. Another possibility is that poor colour recall was due to inconsistency in the structural dimension to which colour was bound in the training phase, resulting in overall weak colour bonds. For 1D sets, the structural dimension that is diagnostic for a particular stimulus is the same across all potential target-distractor pairings. Thus for correct 1D training trials, participants consistently bound a colour to a particular diagnostic dimension, and this dimension was also diagnostic for recall. In contrast, for 2D sets, the diagnostic structural dimension in training depended on the particular pairing of target and distractor, and thus participants may have bound colour to one structural dimension of a stimulus on some training trials, and to the other structural dimension on other training trials. This would have resulted in fewer training trials per diagnostic dimension, and a weaker colour bond relative to colour bonds for 1D stimuli. The effect of dimensional proximity and dimensional paucity is dependent on a certain level of learning of colour associations. If colours were too well learned, then performance would be at ceiling (as it is with normal recall of known attributes for familiar stimuli). If the colours were not adequately learned in the first place, selective competition cannot occur. The question of dimensional paucity in recall will be further addressed in Experiment 7.

Experiment 7: Label Recall of Novel Objects from 1D and 2D Sets

Experiment 7 was originally designed as a replication of Experiment 6 with the addition of a label-training phase prior to colour training, so that the effect of conceptual relatedness on structural integration in colour recall could be investigated. Participants were trained to associate either conceptually related or conceptually unrelated labels to the stimulus sets before beginning colour training. However, Experiment 6 failed to provide evidence for confusions based on the structural relationships between stimuli in the colour recall phase, possibly because of the pairwise nature of the colour-training task. In addition, the extensive label training of Experiment 7 also provides an opportunity for participants to overcome difficulties disambiguating the visual forms of the objects in recall, making it less likely to find evidence of dimensional paucity for colour recall following two days of label training. The results of the label-training phase of Experiment 7 are nonetheless of interest, because the label training tasks utilized a setwise rather than a pairwise procedure, requiring subjects to attend to both diagnostic dimensions in the 2D set while learning the object labels. This setwise training procedure avoids some of the problems inherent in the pairwise colour-training paradigm, and therefore provides a better opportunity to observe evidence for structural integration in recall. Therefore, the report of Experiment 7 is limited to the label recall phase. The results of colour training and recall phases are presented in Appendix C.

Recall of newly learned labels should be sensitive to the structural relationships between stimuli, providing the labels are adequately learned. I therefore expected that confusions in the label learning tasks would be sensitive to structural proximity as defined in a multidimensional space. Furthermore, I expected that retrieval of newly learned labels might show a failure to integrate multiple diagnostic dimensions, resulting in a pattern of errors for 2D sets that reflect both dimensional paucity and proximity. Finally, according to an episodic framework in which conceptual and structural information interact, conceptual relatedness should also modulate the ability to recall colour attributes for 2D sets. That is, competition from exemplars that share structural dimensions should be more easily resolved when values on the conceptual label dimension are more distinct (conceptually unrelated).

Method

Participants

Twenty-four participants from the University of Victoria participated for optional course credit.

Materials

The stimuli were the same as those used in Experiment 6. Sets of semantically related object labels were generated from 12 natural categories (6 living, 6 nonliving), with 6 exemplars in each set (see Appendix D). Sets of unrelated object labels were generated by recombining labels from across each of the 6 different living or nonliving categories. The experiment was run on a Macintosh computer using RSVP 4.0.5 software.

Design and Procedure

The experiment was a 2 X 2 mixed factorial design, manipulating structural dimensionality (1D vs. 2D) and semantic proximity (related vs. unrelated), with structural dimensionality as the within-subject factor. Each subject was trained on a 1D and a 2D set of stimuli (one cube and one cylinder set), using labels from one living and one non-living category (either related or unrelated). The experiment was counterbalanced with respect to the assignment of label categories to object sets. The experiment took place over two sessions, scheduled twenty-four hours apart. The first session involved label training and verification in which each grayscale object was associated with a unique label. In the second session, after a brief review of the labels and further verification trials, participants were given an incidental learning phase in which each object was associated with a particular colour. Following colour training, participants were administered a posttest in which they were asked to recall the colours of each of the objects. The details of the colour training and recall phases can be found in Appendix C.

Label training was accomplished with four different tasks, and the first three tasks were completed with one set of objects (either the 1D or 2D set) before beginning training on the second set of objects. The fourth task was administered after training on the first three tasks was completed for both object sets.

Passive Viewing. The first task was a passive viewing task in which participants passively viewed each of the six objects with their labels for six cycles. Each cycle included a trial in which all six objects and labels were presented together, and a further six trials in which each of the objects appeared individually with the appropriate label.

Passive viewing trials remained on the screen for 5 seconds, and were randomly ordered. Participants were instructed to carefully examine each object and to learn the labels.

Word-Picture Matching. In the second phase, participants were required to match a label to the appropriate object. All six objects appeared on the screen together in random order, and a single label appeared in the center of the screen, making this a setwise recall task. Participants used the mouse to click on the object that matched the label. Participants had unlimited time to respond. If an incorrect object was chosen, a beep indicated an incorrect response and the correct object was then shown with its label for two seconds. All participants completed an initial practice block consisting of 24 trials. Following the practice block participants continued to complete blocks of 24 trials each, until they made no more than one error in a block.

Picture-Word Matching. The third phase was a picture-word matching task, in which participants matched an object to the appropriate label. The procedures were similar to the word-picture matching task, with the exception all six labels appeared on the screen in random order with one of the objects in the center of the screen. When all three phases were completed with one set of objects, they were repeated with the second set. The order of sets was counterbalanced across subjects.

Label Verification. A verification task was used to provide additional practice so that labels would be well learned for both 1D and 2D sets before colour training began. Trials from both object sets were randomly mixed. On each trial, participants were shown an object with a label from either the 1D or 2D set. In half of the trials the object was correctly paired with its label and in half the trials the object was paired with a label belonging to another object within its set. Participants responded by pressing the “m” key if the label matched the object and the "z" key if the label did not match the object. An initial practice block consisted of 24 trials in which each object appeared with its correct label once and an incorrect label once. Test blocks consisted of 48 trials in which each object appeared with its correct label twice and an incorrect label twice. Feedback in which the object appeared with the correct label was provided for incorrect responses. Subjects completed 12 test blocks and were shown their mean accuracy and reaction time for the two object sets at the end of each block. This ended the first session.

During the second session (Day 2), subjects first completed two cycles of the passive viewing phase for each of the object sets, followed by one cycle of passive viewing in which the objects from the two sets were randomly mixed. Subjects then completed a practice block and an additional 12 blocks of the verification task.

Results and Discussion

The results of the label-training phase of Experiment 7 will be presented in three sections: Word-Picture Matching, Picture-Word Matching, and Label Verification.

Word-Picture Matching.

The word-picture matching task required subjects to choose the correct picture from six exemplars that matched a single label, such that recall was open to competition from the entire set. Figure 24 presents the overall accuracy for 1D and 2D sets in the conceptually unrelated and related conditions. There was no effect of dimensionality or conceptual relatedness in overall accuracy rates.

If structural dimensions are stored in a similar fashion as they are perceived, then the nature of confusions for 1D sets in the word-picture matching task should reflect proximity as it did in Experiment 5 . To test the proximity hypothesis for 1D sets, I coded

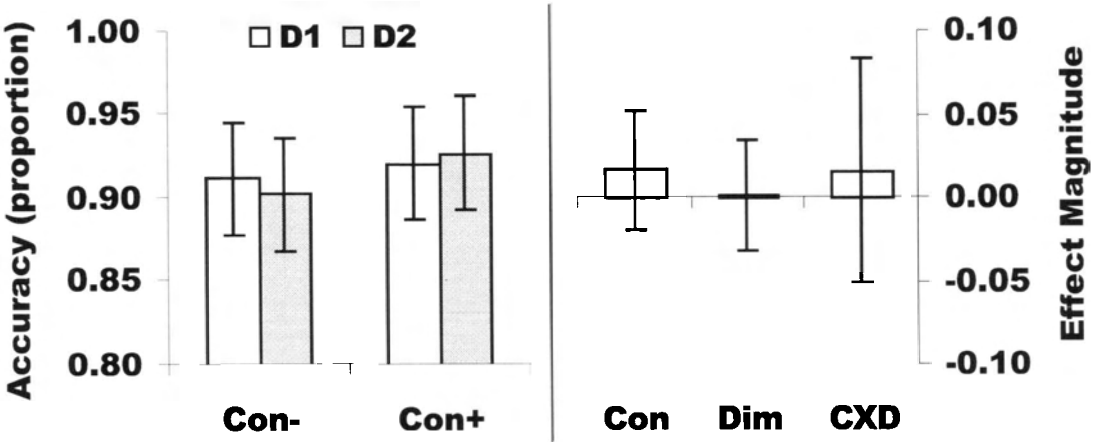

Figure 24. The left panel shows mean accuracy for 1D and 2D sets in the conceptually unrelated (Con-) and conceptually related (Con+) conditions of the word-picture match phase of Experiment 7. The right panel shows the contrasts for the main effects and interaction. Error bars represent 95% confidence intervals.

errors as either close or distal as I did in Experiment 5. The results are displayed in Figure 25. The percentage of close errors did not differ between conceptually unrelated and related errors (92% and 95% respectively), and both percentages were much higher than expected by chance alone (33.3%).

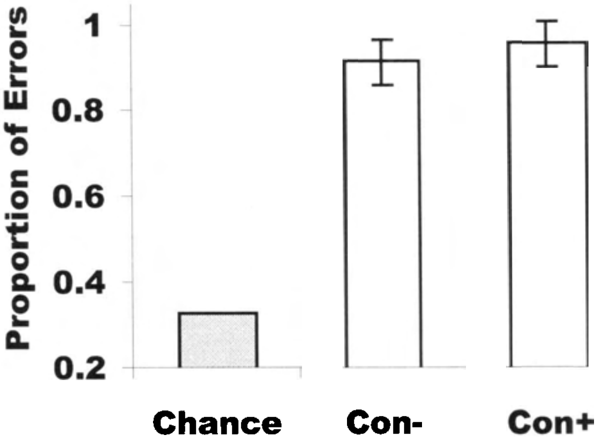

Figure 25. Mean proportion of observed errors for the close error type in the conceptually unrelated (Con-) and related (Con+) conditions for 1D sets in the word-picture match phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

An analysis regressing the pairwise confusion frequencies on the pairwise proximity of items within a pair confirmed the importance of the role of proximity in determining the nature of confusions in the 1D set. As Table 6 reveals, proximity was able to account for 69% of the variability in the error pattern in the conceptually unrelated condition, and 44% of the variability in the conceptually related condition.

Table 6

Summary of the regression analysis in which proximity (the reciprocal of the distance between exemplars) was used to predict the observed pairwise confusion data for 1D sets in the word-picture matching task of Experiment 7 for the conceptually unrelated and related conditions.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Unrelated Model	61.7	<.001	.688			
Proximity				.829	7.855	<.001
Related Model	21.8	<.001	.438			
Proximity				.662	4.670	<.001

To test for dimensional paucity in word-picture matching for 2D sets, I coded errors as either diagonal or parallel. The results of this analysis are displayed in Figure 26. The percentage of parallel errors was similar for conceptually unrelated and related conditions (77% and 81% respectively), and percentages for both conditions were much higher than expected by chance (40%).

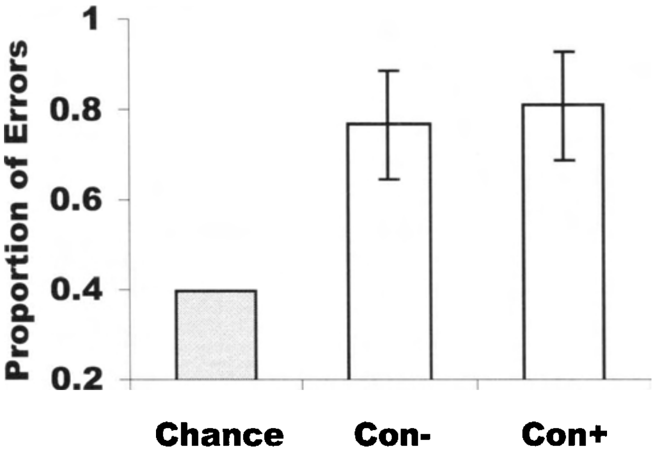

Figure 26. Mean proportion of observed errors for the parallel error type in the conceptually unrelated (Con-) and related (Con+) conditions for 2D sets in the word-picture matching phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

To examine the combined effect of proximity and shared dimensions in the 2D sets, diagonal and parallel errors were further coded as either close or distal. The left panels of Figure 27 shows the observed proportion of each error condition relative to what would be expected by chance in the conceptually unrelated (upper panel) and related (lower panel) conditions. For both unrelated and related conditions, more errors were parallel and close than expected by chance. Furthermore, as the right panels of Figure 27 show, a direct comparison of diagonal and parallel errors for the close error types shows that there were significantly more parallel than diagonal errors for both unrelated and related conditions, by a ratio of approximately four to one.

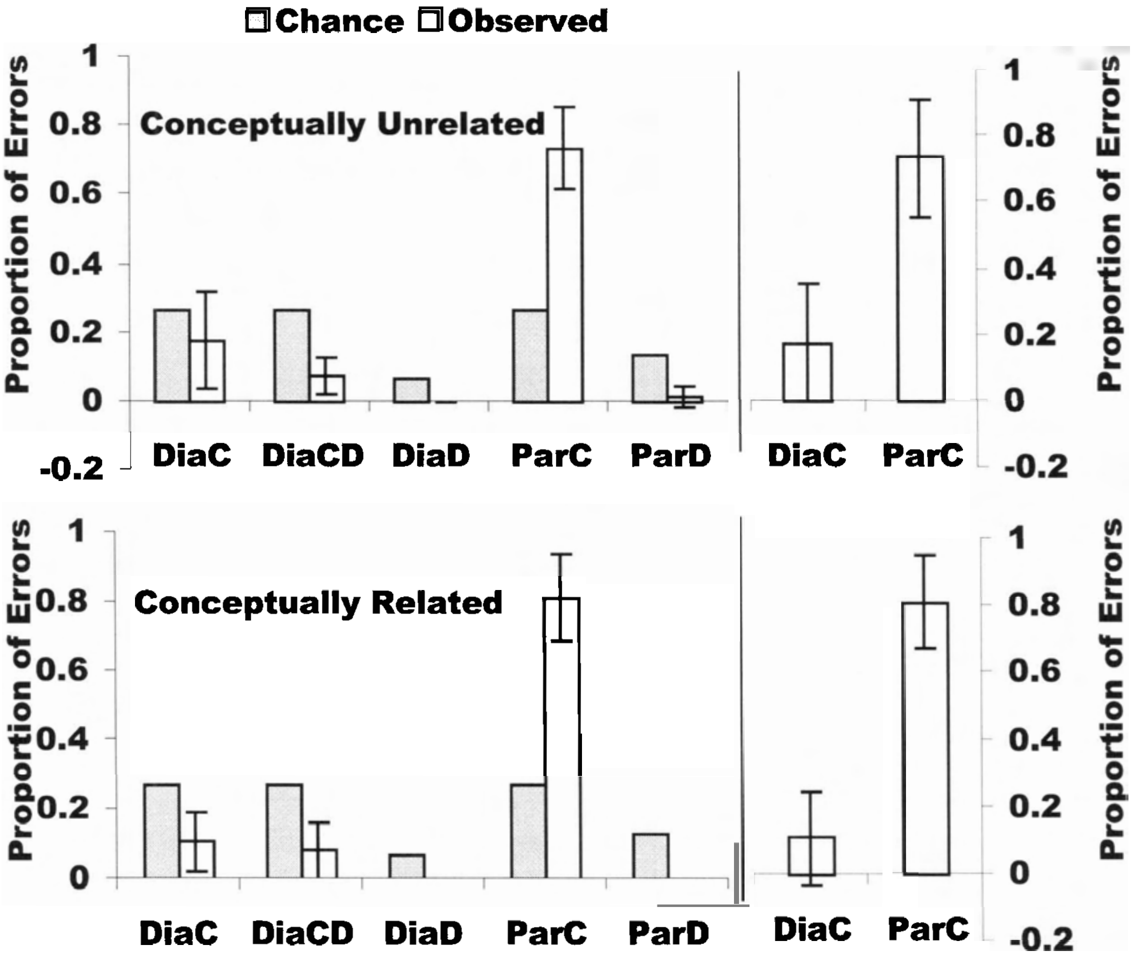

Figure 27. The left panels show the mean proportion of observed errors for the various error types in the conceptually unrelated (upper panel) and unrelated (lower panel) conditions of the word-picture match phase of Experiment 7, relative to the number expected by chance. DiaC = diagonal with values on both dimensions close to target values; DiaCD = diagonal with values on one dimension close and the other distal to target values; DiaD = diagonal with values on both dimensions distal to target values; ParC = parallel with the second dimension close to target value; ParD= parallel with second dimension distal to target value. 95% confidence intervals are based on the standard error of each condition. The right panels are a direct comparison of diagonal and parallel errors for close errors. Error bars for this comparison are 95% within confidence intervals based on the MS from the repeated measures ANOVA.

As Figure 28 shows, the conceptual relatedness of the labels did not modulate the magnitude of the dimensional paucity effect.

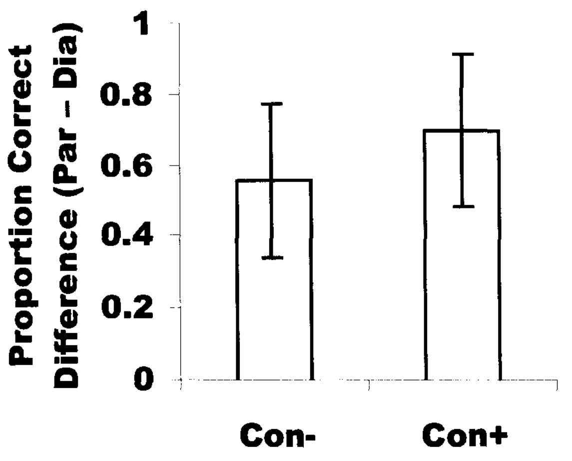

Figure 28. Mean difference in proportions of observed errors (parallel – diagonal) for close errors only in the conceptually unrelated (Con-) and related (Con+) conditions of the word-picture match phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

A stepwise forward regression of 2D pairwise confusion frequencies on proximity, paucity and their interaction was applied separately to the unrelated and related conditions. The results are displayed in Table 7. For both related and unrelated conditions, the recall of 2D labels was significantly related to the interaction of proximity and paucity. This interaction accounted for 60% and 58% of the pairwise confusion data for the unrelated and related conditions, respectively. Thus competition during label recall for 2D sets was related to the proximity of the exemplars, with exemplars that shared dimensions particularly susceptible to confusions.

Table 7

Summary of the step-wise forward regression analysis in which the pairwise confusion data of the 2D sets in the word-picture matching task of Experiment 7 were regressed onto proximity (reciprocal of physical distances), paucity (coded as diagonal = 1 and parallel = 2), and their interaction, for the conceptually unrelated and related conditions.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Unrelated Model 1	41.5	<.001	.597			
Proximity X Paucity				.773	6.444	<.001
Excluded Variables						
Proximity				.272	.971	.340
Paucity				-.411	1.788	.085
Related Model 1	39.2	<.001	.583			
Proximity X Paucity				.764	6.260	<.001
Excluded Variables						
Proximity				.245	.855	.400
Paucity				-.424	1.818	.080

Note. Statistics for each significant model represent tests of the overall model. Predictors included in the respective models and their associated statistics are listed directly below each model. Statistics for variables that failed to meet the inclusion criterion are listed following the last significant model.

Picture-Word Matching. The picture-word matching task is similar to the word-picture matching task in that both are open to competition from the entire object set. Confusions in this task should therefore also reflect both proximity and competition from shared diagnostic structural dimensions. The accuracy for 1D and 2D sets in the conceptually unrelated and related conditions is displayed in Figure 29. Unlike the word-picture matching task, the picture-word matching task revealed a main effect of dimensionality, with 2D sets less accurate than 1D sets. Whereas the word-picture task displayed all six objects and one label, the picture-word task displayed only the target picture with six labels. In the picture-word task subjects therefore had to identify the structural form of the target relative to the other five exemplars stored in memory, thus this task may have been more sensitive to structural dimensionality because it had a stronger structural *memory* component. This effect was not modulated by conceptual proximity, however.

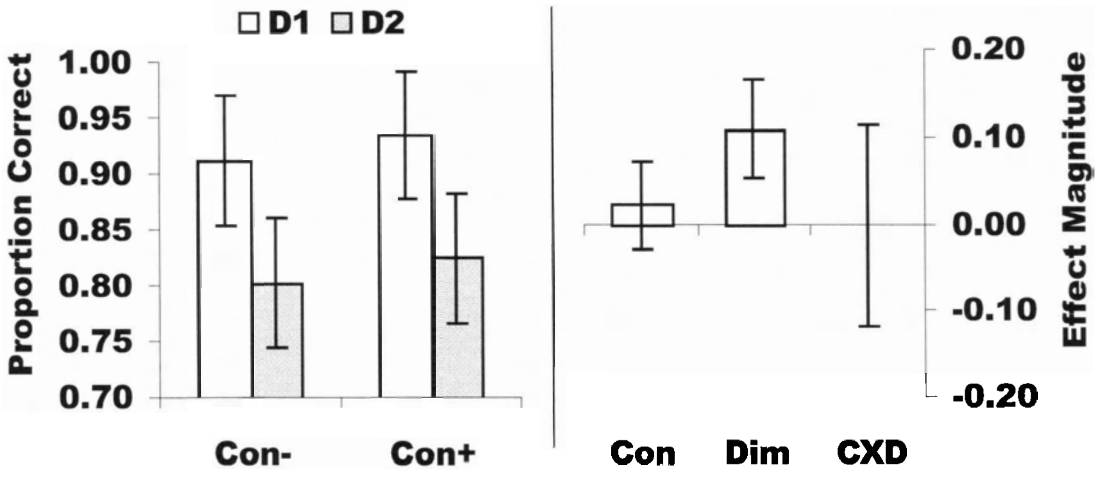

Figure 29. The left panel shows mean accuracy for 1D and 2D sets in the conceptually unrelated (Con-) and conceptually related (Con+) conditions of the picture-word matching phase of Experiment 7. The right panel shows the contrasts for the main effects and interaction. Error bars represent 95% confidence intervals.

Errors for 1D sets were coded as either close or distal to examine the effect of proximity. The proportions of observed close errors for the conceptually unrelated and related conditions are displayed in Figure 30, along with chance levels. As was the case for the picture-word matching task, the percentage of close errors did not differ for conceptually related and unrelated conditions (91% and 86% respectively), and both were greater than expected by chance alone (33%).

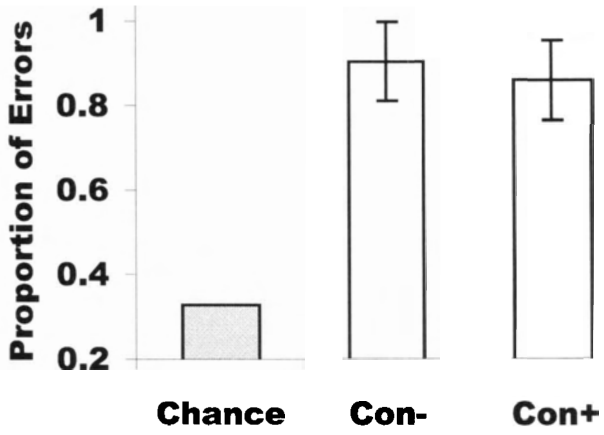

Figure 30. Mean proportion of observed errors for the close error type in the conceptually unrelated (Con-) and related (Con+) conditions for 1D sets in the picture-word matching phase of Experiment 7. Error bars represent 95% between-subjects confidence intevals.

The results of the regression of pairwise confusion frequencies on proximity (as defined by the reciprocal of the physical distance between items in a pair) is displayed in Table 8. Proximity accounted for 32% of the variability in the 1D pairwise confusion data for the unrelated condition, and 24% of the variability in the related condition.

Table 8

Summary of the regression analysis in which proximity (the reciprocal of the distance between exemplars) was used to predict the observed pairwise confusion data for 1D sets in the picture-word matching task of Experiment 7 for the conceptually unrelated and related conditions.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Unrelated Model	13.2	.001	.321			
Proximity				.566	3.636	.001
Related Model	8.6	.007	.236			
Proximity				.486	2.939	.007

Errors for 2D sets were coded as either parallel or distal to examine the effect of dimensional paucity. The proportions of observed parallel errors are displayed in Figure 31, relative to what would be expected by chance. Conceptually unrelated and related conditions had an equivalent distribution of errors (72% parallel), which was significantly greater than expected by chance alone (40%).

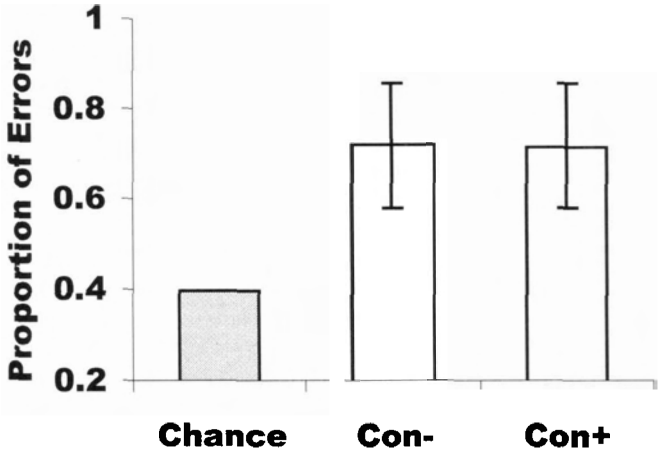

Figure 31. Mean proportion of observed errors for the parallel error type in the conceptually unrelated (Con-) and related (Con+) conditions for 2D sets in the picture-word match phase of Experiment 7. Error bars represent 95% between-subjects confidence intervals.

To examine the combined effects of dimensional paucity and proximity, the errors in the 2D sets were further coded for proximity along the dimensions that differed. The left panels of Figure 32 show the observed proportion of each error condition relative to what would be expected by chance. For both unrelated and related conditions, more errors were parallel and close than expected by chance. Furthermore, a direct comparison of diagonal and parallel errors for the close error types shows that there were significantly more parallel than diagonal errors for both unrelated and related conditions, by a ratio of over three to one (right panel of Figure 32).

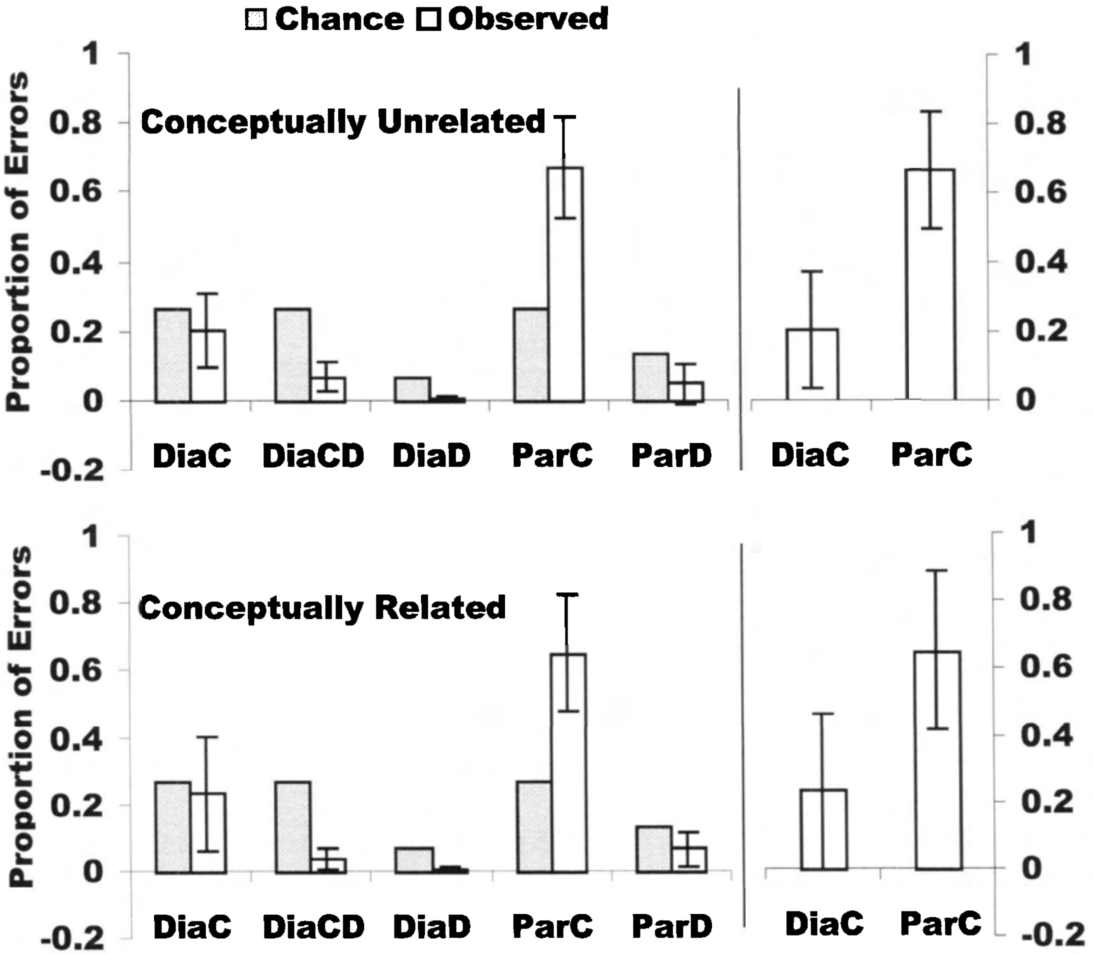

Figure 32. The left panels show the mean proportion of observed errors for the various error types in the conceptually unrelated (upper panel) and unrelated (lower panel) conditions of the picture-word matching phase of Experiment 7, relative to the number expected by chance. DiaC = diagonal with values on both dimensions close to target values; DiaCD = diagonal with values on one dimension close and the other distal to target values; DiaD = diagonal with values on both dimensions distal to target values; ParC = parallel with the second dimension close to target value; ParD= parallel with second dimension distal to target value. 95% confidence intervals are based on the standard error of each condition. The right panels are a direct comparison of diagonal and parallel errors for close errors. Error bars for this comparison are 95% within-subject confidence intervals based on the MS from the repeated measures ANOVA.

As was also the case for word-picture matching, the magnitude of the dimensional paucity effect for close errors was not modulated by the conceptual relatedness of the labels (see Figure 33).

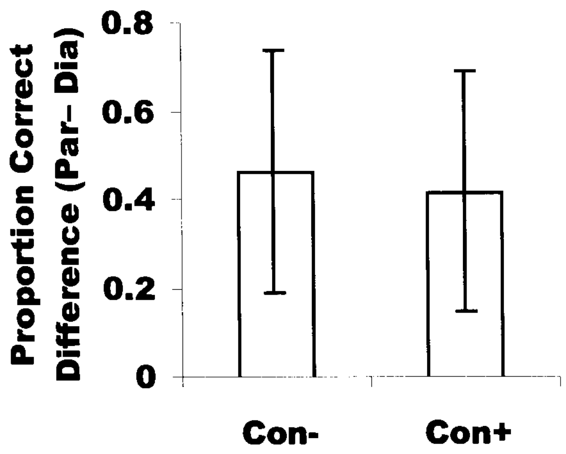

Figure 33. Mean difference in proportions of observed errors (parallel – diagonal) for close errors only in the conceptually unrelated (Con-) and related (Con+) conditions of the picture-word matching phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

The results of the stepwise forward regression of 2D pairwise confusion frequencies on proximity, paucity and their interaction are displayed in Table 9. For both related and unrelated conditions, the recall of 2D labels was significantly related to the interaction of proximity and paucity. This interaction accounted for 67% and 40% of the pairwise confusion data for the unrelated and related conditions, respectively. As was the case in the word-picture matching task, competition for 2D sets in the picture-word matching task was also related to the proximity of the exemplars, and exemplars that shared dimensions were particularly susceptible to confusions.

Table 9

Summary of the step-wise forward regression analysis in which the pairwise confusion data of the 2D sets in the picture-word matching task of Experiment 7 were regressed onto proximity (reciprocal of physical distances), paucity (coded as diagonal = 1 and parallel = 2), and their interaction, for the conceptually unrelated and related conditions.

	Model Statistics			Standardized Coefficient Statistics		
	F	p	R^2	β	t	p
Unrelated Model 1	55.5	<.001	.665			
Proximity X Paucity				.815	7.451	<.001
Excluded Variables						
Proximity				.383	1.533	.137
Paucity				-.415	2.006	.055
Related Model 1	18.9	<.001	.403			
Proximity X Paucity				6.35	4.345	<.001
Excluded Variables						
Proximity				.288	.839	.409
Paucity				-.264	.906	.373

Note. Statistics for each significant model represent tests of the overall model. Predictors included in the respective models and their associated statistics are listed directly below each model. Statistics for variables that failed to meet the inclusion criterion are listed following the last significant model.

Label Verification. Several blocks of the label verification task were administered over Day 1 and Day 2 to ensure that labels were well learned for both 1D and 2D sets before colour training began. Differences between 1D and 2D sets are most likely to be evident in normal individuals during the first day of training, however, before label-shape associations were well established. I therefore present the results of the label verification separately for Day 1 and Day 2. In addition to response times, sensitivity (d') was chosen as a dependent variable, as this measure controls for individual differences in response bias.

Figure 34 displays the mean sensitivity and response times for 1D and 2D sets on Day 1. Although sensitivity and response times were statistically equivalent across all conditions, certain effects approached significance, and because of the low sample size (n=12), are worth noting. First, participants in the conceptually related condition tended to have higher sensitivity than participants in the semantically unrelated condition for both 1D and 2D sets. Importantly, response times showed a trend for longer response times in the conceptually related 2D condition relative to all other conditions, as revealed in a nearly significant main effect of dimensionality and interaction between dimensionality and conceptual relatedness. Thus, the slightly higher sensitivity for conceptually related conditions came at a cost of much longer response times (over 100 ms) for the 2D, but not the 1D sets.

This difference in response times between conceptually related and unrelated 2D sets can be interpreted as the extra time necessary to resolve competition from exemplars with shared structural dimensions when they are also conceptually related. When exemplars can be easily distinguished along conceptual dimensions (unrelated condition), competition between exemplars that share values on structural dimensions is more quickly resolved. These conclusions require further support from a larger sample size. Verification of newly-learned labels nonetheless appears to be a promising paradigm for showing the modulation of structural integration by conceptual relatedness.

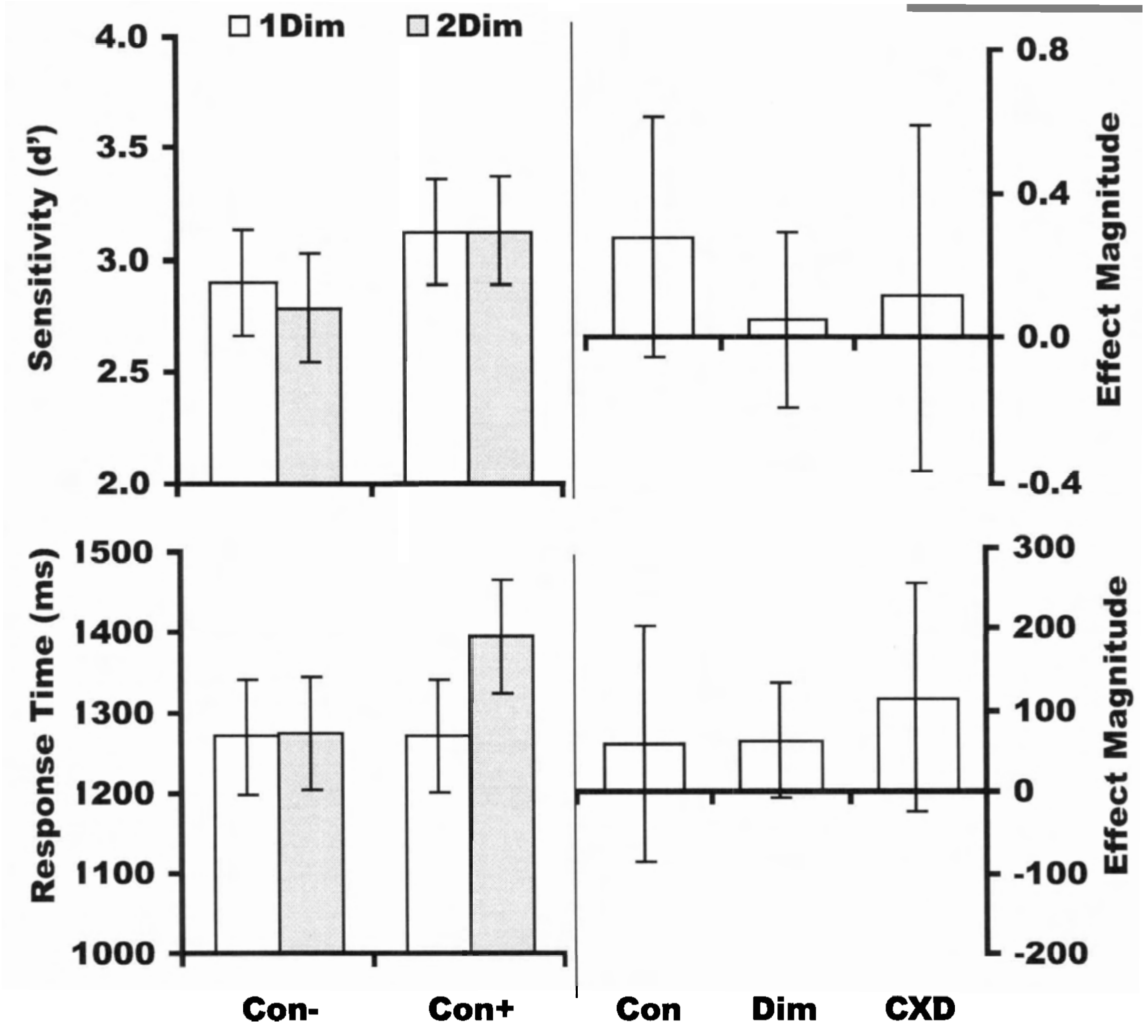

Figure 34. Mean sensitivity and response times with contrasts for the first day of label verification in Experiment 7. Error bars represent 95% confidence intervals.

The results of the Day 2 label training are presented in Figure 35. Sensitivity increased for all conditions, and there was a significant sensitivity advantage for the conceptually related condition. Response times also decreased, and were statistically equivalent for all conditions. Thus continued training was able to reduce the effect of dimensionality, as it was intended to do before colour training began.

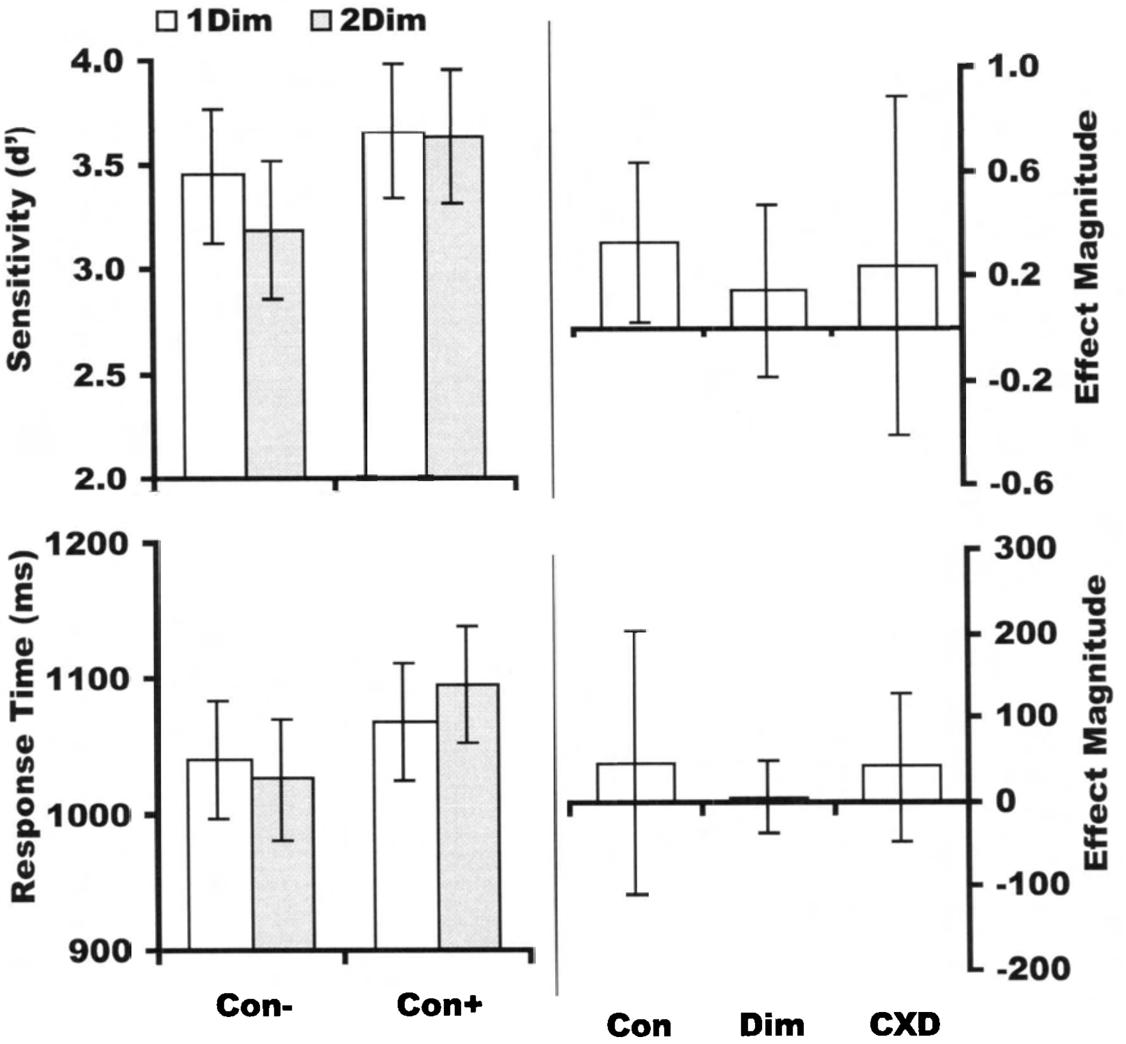

Figure 35. Mean sensitivity and response times with contrasts for the second day of label verification in Experiment 7. Error bars represent 95% confidence intervals.

General Discussion

Experiments 5 – 7 sought to find evidence, across a variety of tasks, for distributed structural dimensions in normal perception/short-term memory and long-term recall by using novel stimuli sets that varied on either one or two dimensions. Error patterns in 1D and 2D sets were examined for competition based on proximity of exemplars in the multidimensional space defined by the diagnostic dimensions of the sets. In addition, these experiments attempted to induce a pattern of dimensional paucity in normal observers similar to that found in patient ELM, whereby errors would reveal strong competition from exemplars that shared values on diagnostic dimensions, indicating a failure to integrate all of the diagnostic dimensions necessary to disambiguate the exemplars in a set. The final experiment also sought evidence for the modulation of structural integration by conceptual labels.

Evidence for competition based on dimensional proximity was clear for 1D sets across all tasks. For both perception/short term memory (Experiment 5), and long-term recall (Experiment 6 and 7), incorrect responses were most likely to be a close neighbour, and regression analyses of the reciprocal of the physical distance between pairs were able to account for significant proportions of the variance in the pairwise confusion data. The more important test of dimensional proximity was the error pattern for 2D sets, for which proximity depended on the values of two diagnostic dimensions. Here again, both the likelihood of close neighbour errors and the regression analysis showed that proximity was a significant factor in the confusions made in match-to-sample task of Experiment 5, assessing perception/short-term memory. In recall, proximity also was important in determining error patterns in the label recall task of Experiment 7, as revealed by a significant interaction between proximity and the number of dimensions by which pairs varied.

Evidence of dimensional paucity for 2D sets was difficult to obtain in the current design, owing to the significant correlation between proximity and the number of dimensions by which stimuli sets varied. For the match-to-sample task of Experiment 5, several sources of evidence nonetheless suggest that integration of dimensions during perception did not always succeed. First, with the exception of the one distinctive stimulus, accuracy for stimuli in the 2D sets was lower on average than accuracy for stimuli in the 1D sets. Second, parallel errors (indicating confusion of stimuli that shared dimensions) occurred more often than expected by chance. Third, during practice participants often made confusions across the geometric shape of stimuli (cylinder vs. cube), indicating that attention to the tapering and pinching values of stimuli sometimes came at a cost of this third geometric dimension. However, because the regression analysis failed to show a significant effect of dimensional paucity over and above dimensional proximity, this evidence should be interpreted with caution.

More relevant to modeling the behavior of CSA patient ELM, however, is evidence for dimensional paucity during recall. Although colour recall for the majority of stimuli in the 2D sets in Experiment 6 was too poor to provide evidence for dimensional paucity, the recall of newly learned labels in Experiment 7 showed that competition from exemplars that shared structural diagnostic dimensions was particularly strong: Accuracy for 2D sets was poorer than for 1D sets in the picture-word matching task; parallel errors occurred more often than expected by chance in both word-picture and picture-word matching tasks; and a regression analysis of proximity and paucity on the pairwise confusion data showed a significant interaction of the two factors for both matching tasks.

Experiment 7 also provided preliminary evidence for the modulation of processes involved in the integration of structural dimensions by conceptual information:

Verification of conceptually related labels for 2D sets took longer than verification of unrelated labels for 2D sets, whereas there was no difference in response time between related and unrelated labels for 1D sets. Although this interaction of dimensionality with conceptual relatedness only approached significance, it is nonetheless highly suggestive given an sample size of only 12.

The Nature of Structural Similarity in Recall

The theoretical approach to object recognition taken here is that semantic knowledge can be conceived as an episodic system, whereby relevant aspects of prior episodes are recruited as a function of at least three factors: the demands of the current task, the frequency with which the features have been processed or recruited in past episodes, and of similarity to the cue. The present experiments have focused on the latter factor, in an attempt to more precisely define what is meant by similarity in the context of an object form cue. The findings suggest that structural similarity can be conceptualized as a function of the distance between exemplars in a multidimensional space, where the structural dimensions that define the similarity space are those structural dimensions that have been dynamically recruited. There are two possible sources of error in such a system: dimensional proximity and dimensional paucity. Confusions due to proximity occur in situations where values on a diagnostic dimension have been insufficiently specified. In this case, competition between close neighbours in the similarity space cannot be resolved. Confusions due to dimensional paucity occur in situations where an insufficient number of diagnostic dimensions have been retrieved. In this case, competition between exemplars that share values on diagnostic dimensions cannot be resolved.

Krushke (1992) has implemented an episodic model of distributed diagnostic features with a similar conception of similarity space in an exemplar-based connectionist model. According to the ALCOVE model, exemplars are represented as points in a multidimensional psychological space. Input nodes represent a single psychological dimension, with activation levels of the node corresponding to the value of the exemplar on that dimension. These feed forward to hidden input nodes representing a point in the multidimensional space. These hidden nodes in turn feed forward to category nodes that represent the output for a particular categorization task, and are mediated by learned association weights. Importantly, the model includes an attentional gating mechanism whereby attention can vary the relevance of a particular input node for a particular task. The attentional strengths of the various dimensions are determined by experience, with dimensions that have a history of diagnosticity across past episodes having greater attentional strengths. This model can accommodate the two types of errors described above: Specificity is represented by the width of the activation profile of the hidden exemplar nodes, determined in the Alcove model by a specificity constant C. It should be noted, however, that because specificity is determined at the exemplar level, it is assumed that all dimensions defining that exemplar have equal specificity. This may not necessarily be true of human observers, but is a question worth pursuing. Dimensional paucity, although not mentioned explicitly by Krushke, could be accommodated in this model via the strengths of the attentional weights. An extremely low attentional weight could shrink the input space along a particular dimension such that values on that dimension are practically overlapping, and are captured within the specificity fields of multiple exemplars. In Krushke's model, the attention weights are determined by the diagnosticity of the dimension in the current and past episodes. However, one can also imagine that other factors, such as display time and overall attentional capacity or load might also influence the attentional weights in such a system.

The implication of an episodic system is that similarity between two stimuli is not fixed, but is the outcome of processes in which the structural dimensions that define the similarity space are dynamically and variably retrieved. This notion is consistent with that proposed by Medin, Goldstone, and Gentner (1993). They pointed out that similarity judgements are constructive in that the outcome is dependent on the selection of features that are integrated to make the judgement. The selection of features, they maintain, is dependent on such factors as stimulus context, task, and past experience.

The Relationship Between Structural Similarity in Memory and Perception

According to the episodic approach, structural dimensions retrieved in a memory task will be the same as those selected in a perceptual task when the goals and context of the tasks are the same. This was demonstrated in the error patterns of the match-to-sample task and the label recall tasks, which both required setwise disambiguation of stimuli. Not only did the same proximity measures account for significant variance in both the match-to-sample task and the recall task, the same stimuli were distinctive in both tasks. The episodic framework maintains that this relationship between memory and perception exists because semantic memory is not abstracted from perceptual episodes, but is a subset of the actual processes that occurred in prior episodes. It should be noted here that the records of any episode would of course include not only the perceptual processing of the stimulus, but also include whatever retrieval processes were operating at the time. In any case, it is clear that perceptual and memory processes are not strictly separated in the episodic framework that I propose.

Simmons and Barsalou (in press) have similarly conceptualized the relationship between memory and perception as one of partial reenactment or simulation, based upon Damasio's (1989) theory of retroactivation through convergence zones. According to this theory, perception involves the activation of feature detectors distributed across sensory-motor areas. Guided by selective attention, features become bound via conjunctive cells in association areas that encode patterns of coactivated features. These association areas, referred to as convergence zones (CZ's), are hierarchical in nature, with higher-level CZ's binding lower-level CZ's. Memory operates via the conjunctive neurons, which partially reactivate lower-level conjunctive neurons and ultimately the feature maps in the sensory-motor areas active in the original processing episodes (unless the task is highly automatized through experience, in which case the CZ's themselves may feed forward to a response area without first having to reactivate the feature maps). This theory is compatible with the episodic approach in that semantic information is not abstracted from the original episodes, but rather is retrieved from records of prior episodes.

Imaging studies support the notion that subsets of neural areas involved in encoding are reactivated during retrieval. For example, in a functional magnetic resonance imaging study, Wheeler, Petersen, and Buckner (2000) found that vivid remembering of studied pictures and sounds differentially activated areas of the auditory and visual cortex, and that these areas represented a subset of those activated during perception. Similarly, in a positron-emission tomography study, Nyberg, Habib, McIntosh, and Tulving (2000) found that auditory brain regions involved in encoding of visual word-sound associations were activated in a later recognition task that involved presentation of the visual word stimuli alone.

Multidimensionality: Within and Between Knowledge Types

Although the discussion thus far has been limited to multidimensionality within structural representations, it is clear from the verification task in Experiment 7 that conceptual and structural processes are not strictly separated, but interact. This is consistent with the finding that retrieval of newly learned attributes depended on both structural and conceptual factors when stimuli consisted of familiar objects (Bukach et al., in press) and words (Experiment 2). Rather than including stored structural knowledge as a pre-semantic stage, therefore, the episodic approach includes structural knowledge as one of many types of knowledge that can be recruited to contribute to the meaning of a perceived object. Because Experiments 5 - 7 have emphasized structural knowledge, I have for convenience lumped these other sources of knowledge together and labeled them "conceptual" knowledge. However, as Cree and McRae (2003) point out, there are likely many types of knowledge that contribute to an object's meaning, and thus "semantic representations" can be conceived as a multidimensional at two levels: both *within* and *between* knowledge types. At a micro level, independent dimensions within a knowledge type exist and are subject to integration processes. Thus, principles that apply to competition within the structural domain may also be applied to competition within other knowledge domains as well. At the macro level, each knowledge type may also be conceived as one of several independent dimensions that could potentially be integrated to achieve a coherent representation. Because the dimensions that define a stimulus include multiple information types, resolution of competition within one information domain may be modulated by the proximity of exemplars within other retrieved information domains. Objects that are structurally similar, but have very different functions, for example, will be less susceptible to confusions than objects that are both structurally similar and share similar functions.

In the verification task of Experiment 7, the relatedness of conceptual labels modulated response times to 2D, but not 1D stimuli sets. This implies that inter-domain modulatory effects may target integration processes specifically. This result was based on a very small sample size, however, and should be subjected to more vigorous testing.

Applications to CSA of the Biological Type:

Previous studies taking an episodic approach to object recognition have supported the idea that biological categories are particularly susceptible to confusions because these categories tend to be highly similar both conceptually and structurally (Bukach et al., in press). The present study extends these findings by providing a clearer understanding of what is meant by structural similarity. These experiments show that an important determinant of structural similarity is the proximity of exemplars to one another in a multidimensional space that is defined by diagnostic structural dimensions that are recruited from past episodes. When exemplars within a category share many diagnostic features across structural and conceptual domains, the exemplars cluster close to one another, and are susceptible to confusions. The implication of such a system is that category-specific patterns in object recognition that disproportionately affect conceptually and structurally similar categories will occur whenever: a) there is low specificity of the values of the structural dimensions (this can also be conceived as noise in the system), or b) an insufficient number of structural dimensions are integrated during recall.

The case of ELM appears to be of the latter type, in that he tends to confuse conceptually similar items from categories that must be disambiguated by a conjunction of diagnostic features. Interestingly, ELM has difficulty retrieving structural information from word cues as well, though he can accurately retrieve other types of conceptual information from word cues. His deficit, therefore, appears to be limited to integration of stored structural features, although this deficit is modulated by intact conceptual processing.

Not all cases of CSA of the biological type need have a structural integration deficit, however. Although yet to be tested, I would predict that other cases may have problems specifying the values on the relevant structural dimensions. These patients should show an error pattern that reflects primarily structural proximity rather than paucity, and they may even have difficulty learning conceptually similar labels to one-dimensional sets as well.

Specification and integration problems need not be limited to the structural domain. Potentially, these kinds of deficits may affect any knowledge domain. In fact, some patients may have a problem integrating information from across knowledge domains. This possibility is suggested by patients with CSA of the biological type who have problems recruiting both conceptual and structural information from word cues.

Simmons and Barsalou (in press) also propose that deficits may occur at different levels in the object recogntion system, giving rise to different patterns of category specificity. They developed an object recognition theory called conceptual topography theory (CTT) that incorporates a hierarchical system of CZ's (described above) with two principles that instantiate the concept of similarity by proximity. The *similarity-in-topography* (SIT) principle states: "The spatial proximity of two neurons in a CZ reflects the similarity of the features they conjoin." The *variable dispersion* principle states: "In a CZ, the proximity of the non-contiguous clusters for a category reflects the similarity of its instances. As the instances of a category decrease in similairty, its non-contiguous clusters of conjunctive neurons become increasingly dispersed in the CZ's spatial topography." These two proximity principles result in different kinds of emergent organizations at different levels in the CZ hierarchy. Lower level CZ's within a modality are organized by the similarity of the properties they encode, whereas high level CZ's within a modality and cross-modal CZ's conjoin properties at the exemplar level, and therefore have an emergent organization that reflects similarity within and between categories. These higher-level CZ's capture property correlations between exemplars. Importantly, the proximity principles is hypothesized to result in a differential level of dispersion for biological and non-biological categories in higher-level CZ's that can explain the frequency for which CSA of the biological type is found. Biological categories, such as mammals, have a very concentrated representation at higher level CZ's, relative to non-biological categories such as tools, which are more dispersed.

Simmons and Barsalou propose that damage to different levels of the system will result in specific patterns of conceptual deficits. For example, damage to the feature maps will result in a modality-specific deficit that affects both perception and conceptual processing for that modality, particularly when strategic (non-automatic) conceptual processing is required (e.g., cortical blindness, colour agnosia). Damage to lower-level

CZ's will affect knowledge of properties represented in the area of damage, and therefore will affect recognition of any category for which those properties are relevant, though perception will remain intact (e.g., patients with multiple category loss in the absence of perceptual deficits). Damage to modality CZ's will result in a modality-specific recognition deficit for categories represented in the area of topographical damage, though knowledge from other modalities will remain intact. ELM would likely be classified as having damage to modality-specific CZ's in the visual domain. Damage to cross-modal CZ's will affect all knowledge types for the affected categories, and the patient will be unable to recognize an object from any modality.

Although not the only possible instantiation of the episodic framework, CTT captures many of the concepts proposed in the episodic framework, including dynamic reactivation of knowledge across episodes, the need for integration or conjunction of features within and between knowledge types, and category specificity determined by proximity. It also has the ability to account for a variety of semantic deficits.

Improvements to the Current Design

Although the findings of Experiments 5 – 7 were informative as to the nature of structural descriptions and the processes involved in perceiving and retrieving structural information, the tasks could be improved in several ways. First, stimuli should be chosen so as to avoid distinctive emergent qualities such as parallel sides that could lead to differential accuracy among the stimuli within a set. Second, investigations of dimensional paucity should provide better control for dimensional proximity, so that integration failures can be investigated more independently from confusions based on competition from proximal values. One way of doing this is to compare confusion probabilities for parallel stimuli pairs in the context of 2D sets to confusion probabilities for the same stimuli pairs in the context of 1D sets where there are intervening stimuli between the exemplars of interest. This is similar to the design of Arguin et al. (1996). A second possibility is to choose exemplar pairs of interest for 2D sets such that parallel errors can be compared to diagonal errors of equal or lesser physical distance (see Figure 36).

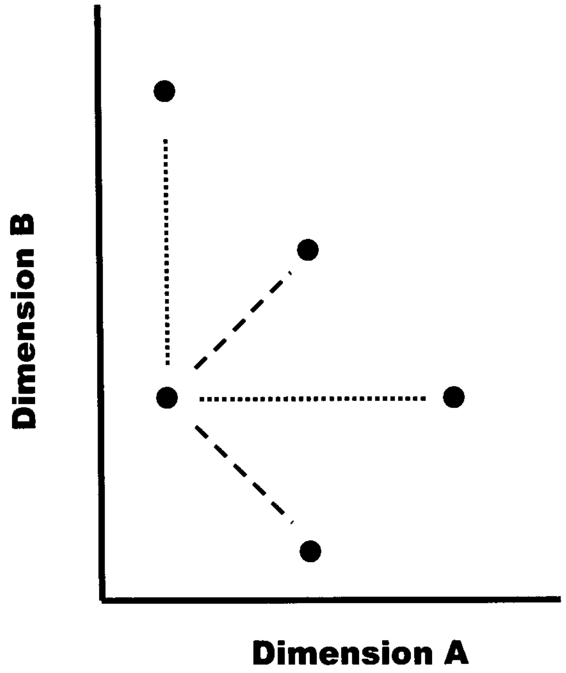

Figure 36. Structural relationships between stimuli pairs of interest, showing parallel relationships of greater distances than diagonal relationships.

The failure of Experiment 6 to show error patterns reflecting dimensional proximity or paucity may be due to inadequate learning of colour associations. Colour learning may be improved if participants were given intentional learning instructions, and if more learning blocks were administered.

Several changes could be made to improve the design of Experiment 7. The manipulation of conceptual relatedness for novel stimuli should be limited to label training and recall, as the label itself can be considered retrieval of a newly learned attribute. Also, the research design may be more powerful if the related categories were restricted to those that have been shown to be most vulnerable in studies using familiar words (e.g., mammals and musical instruments). A follow-up study should double the number of participants. A new study could also manipulate conceptual relatedness through assignment of conceptual properties, as opposed to labels.

Conclusion

The experiments presented here demonstrate the utility of an episodic approach to questions of category specificity and object knowledge retrieval. In particular, using novel stimuli for which structural and conceptual relations can be operationally defined and controlled provides insight regarding object recognition processes that are otherwise assumed in studies examining recognition of familiar objects. These studies have shown that structural similarity in recall may be conceptualized as the proximity of exemplars across diagnostic structural dimensions that have been retrieved and integrated from prior episodes, and that competition within this system can arise due to poor specificity or dimensional paucity. The structural features that are retrieved during recall therefore have a direct relationship to those that were processed during perception. These principles may be applied to other domains of knowledge as well. These studies have also shown that resolution of competition within the structural domain can be modulated by conceptual knowledge, and therefore object knowledge can be conceptualized a multidimensional space that includes diagnostic dimensions from multiple knowledge types that have been retrieved from prior episodes.

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Appendix A

Classification of Cases with CSA of the Biological Type According to Whether or Not They Show a Deficit in the Verbal Modality

Case	Reference	Deficit in Verbal Modality?
BD	(Hanley, Young, & Pearson, 1989)	Yes
C (CW97)	(Wilson, 1997; Wilson, Baddeley, & Kapur, 1995)	Yes
Dante	(Sartori, Job, & Coltheart, 1993)	Yes
DB	(Lambon Ralph, Howard, Nightingale, & Ellis, 1998)	Yes
DM94	(Breedin, Saffran, & Coslett, 1994)	Yes
DM97	(Humphreys, Riddoch, & Price, 1997)	Yes[a]
EA	(Barbarotto, Capitani, & Laiacona, 1996; Laiacona, Capitani, & Barbarotto, 1997)	Yes
EC	(Carbonnel, Charnallet, David, & Pellat, 1997)	Yes
ELM	(Arguin et al., 1996; Dixon, 1999; Dixon & Arguin, 1999; Dixon et al., 1997; Takarae & Levin, 2001)	Yes[a]
Emma	(Gentileschi, Sperber, & Spinnler, 2001)	Yes
EW	(Caramazza & Shelton, 1998)	Yes
FA	(Barbarotto et al., 1996)	Not Reported
FB	(Sirigu, Duhamel, & Poncet, 1991)	Yes
Felicia	(De Renzi & Lucchelli, 1994)	Yes
FI	(Barbarotto et al., 1996)	Not Reported
FM	(Laiacona, Barbarotto, & Capitani, 1993)	Yes
FS	(Dixon, Piskopos, & Schweizer, 2000)	Not Reported
GC	(Cardebat, Demonet, Celsis, & Puel, 1996)	Not Reported
Giulietta	(Sartori, Job, Miozzo, Zago, & Marchiori, 1993; Sartori, Miozzo, & Job, 1994)	Yes
GP97	(Gonnerman, Andersen, Devlin, Kempler, & Seidenberg, 1997)	Not Reported
GR	(Laiacona et al., 1993)	Yes
Helga	(Mauri, Daum, Sartori, Riesch, & Birbaumer, 1994)	Yes
HJA	(Riddoch & Humphreys, 1987a; Riddoch et al., 1999)	No
IL	(Lecours et al., 1998)	Not Reported
ING	(Warrington & Shallice, 1984)	Not Reported
JB	(Humphreys et al., 1988; Riddoch & Humphreys, 1987b)	Yes
JBR	(Bunn, Tyler, & Moss, 1997; Funnell & De Mornay Davies, 1996; Warrington & Shallice, 1984; Wilson, 1997)	Yes
Jennifer	(Samson, Pillon, & De Wilde, 1998)	Yes
JH	(Swales & Johnson, 1992)	Not Reported

Case	Reference	Deficit in Verbal Modality?
JMC	(Magnie, Ferreira, Giusiano, & Poncet, 1999)	Yes
JV	(Pietrini et al., 1998)	Yes
KB	(Warrington & Shallice, 1984)	Not Reported
KG	(Wilson, 1997)	Not Reported
KR	(Hart & Gordon, 1992)	Yes
LA	(Gainotti & Silveri, 1996; Silveri & Gainotti, 1988)	Yes
LF	(Barbarotto et al., 1996; Laiacona et al., 1997)	Yes
LH	(Etcoff, Freeman, & Cave, 1991; Farah, Hammond, Mehta, & Ratcliff, 1989; Farah, Meyer, & McMullen, 1996; Takarae & Levin, 2001)	Yes
MB	(Farah et al., 1996; Takarae & Levin, 2001)	Not Reported
MC	(Teixeira Ferreira, Giusiano, & Poncet, 1997)	Yes
MD	(Hart, Berndt, & Caramazza, 1985)	Yes
MF	(Barbarotto, Capitani, Spinnler, & Trivelli, 1995)	Yes
Michelangelo	(Mauri et al., 1994; Sartori, Coltheart, Miozzo, & Job, 1994; Sartori & Job, 1988; Sartori, Job, & Coltheart, 1993; Sartori, Miozzo, & Job, 1993; Sartori, Miozzo et al., 1994)	Yes[a]
MS	(Mehta, Newcombe, & De Haan, 1992; Young, Newcombe, Hellawell, & De Haan, 1989)	Yes
MU	(Borgo & Shallice, 2001)	Yes
NA	(Funnell, 2000)	No
NR	(De Haan, Young, & Newcombe, 1992)	Not Reported
NV	(Basso, Capitani, & Laiacona, 1988)	Yes
PR	(Teixeira Ferreira et al., 1997)	Yes
PS	(Hillis & Caramazza, 1991)	Yes
RC	(Moss, Tyler, Durrant Peatfield, & Bunn, 1998; Tyler & Moss, 1997)	Yes
RM	(Pietrini et al., 1998)	Yes
SB	(Sheridan & Humphreys, 1993)	Yes
SBY	(Warrington & Shallice, 1984)	Yes
SE	(Laws, 1998; Laws, Evans, Hodges, & McCarthy, 1995; Moss, Tyler, & Jennings, 1997)	Yes
SRB	(Forde, Francis, Riddoch, Rumiati, & Humphreys, 1997; Humphreys et al., 1997)	Yes
TOB	(McCarthy & Warrington, 1988; McCarthy & Warrington, 1990; Parkin & Stewart, 1993)	Yes
TS	(Wilson, 1997)	Yes
TU	(Farah & Wallace, 1992)	Yes
VG	(Teixeira Ferreira et al., 1997)	Yes
Mr. W	(Farah, 1997; Rumiati & Humphreys, 1997; Rumiati, Humphreys, Riddoch, & Bateman, 1994)	Yes[a]

[a] verbal deficit for structural knowledge only

Appendix B

Stimulus List for Experiments 1-4.

Practice Items	Mammals	Instruments	Structurally Similar	Unrelated
cap	cow	bass	knife	wagon
sailboat	buffalo	tuba	cigarette	garbage can
tree	sheep	saxophone	nail file	bell
candle	horse	trumpet	toothbrush	umbrella
kite	donkey	trombone	screwdriver	traffic light
bird	bear	guitar	pencil	snowman
fish	deer	banjo	needle	glasses
book	goat	violin	baseball bat	chair

Appendix C

Colour Training and Recall Phase of Experiment 7

Because the colour recall phase of Experiment 6 failed to display effects of either proximity or dimensional paucity (possibly because of the pairwise nature of the colour training), I no longer expected the design of the colour training and recall phase of Experiment 7 to be suitable for examining the interaction of conceptual relatedness with dimensional paucity, as it was originally intended. Furthermore, the label-training phase requires participants to overcome dimensionality effects, and strategies employed by participants in the label-training phase may be carried over to the colour-training phase, another aspect that was not considered in the original design of the Experiment. This portion of Experiment 7 is presented in the appendix for the reader's interest.

Method

Colour Training. Procedures for the colour-training task were similar to those used in Experiments 6, with the exception that objects were cued with the label rather than the grayscale version of the object. Subjects completed 10 blocks of trials in which each of the 12 objects appeared once as a target and once as a distractor.

Colour Recall. Following the colour-training phase, subjects were told that all of the objects were consistently coloured. They were then given a surprise recall test in which they viewed each of the 12 objects in grayscale one at a time in random order, and reported its colour. As in previous experiments, subjects were given unlimited time to respond.

Results and Discussion

Colour Training

Overall Accuracy and Response Times. Figure C1 shows the overall mean accuracy and response times for 1D and 2D sets in the conceptually unrelated and related conditions. Accuracy was statistically equivalent for all conditions. Although the conceptually related conditions were more than 60 ms longer than conceptually unrelated

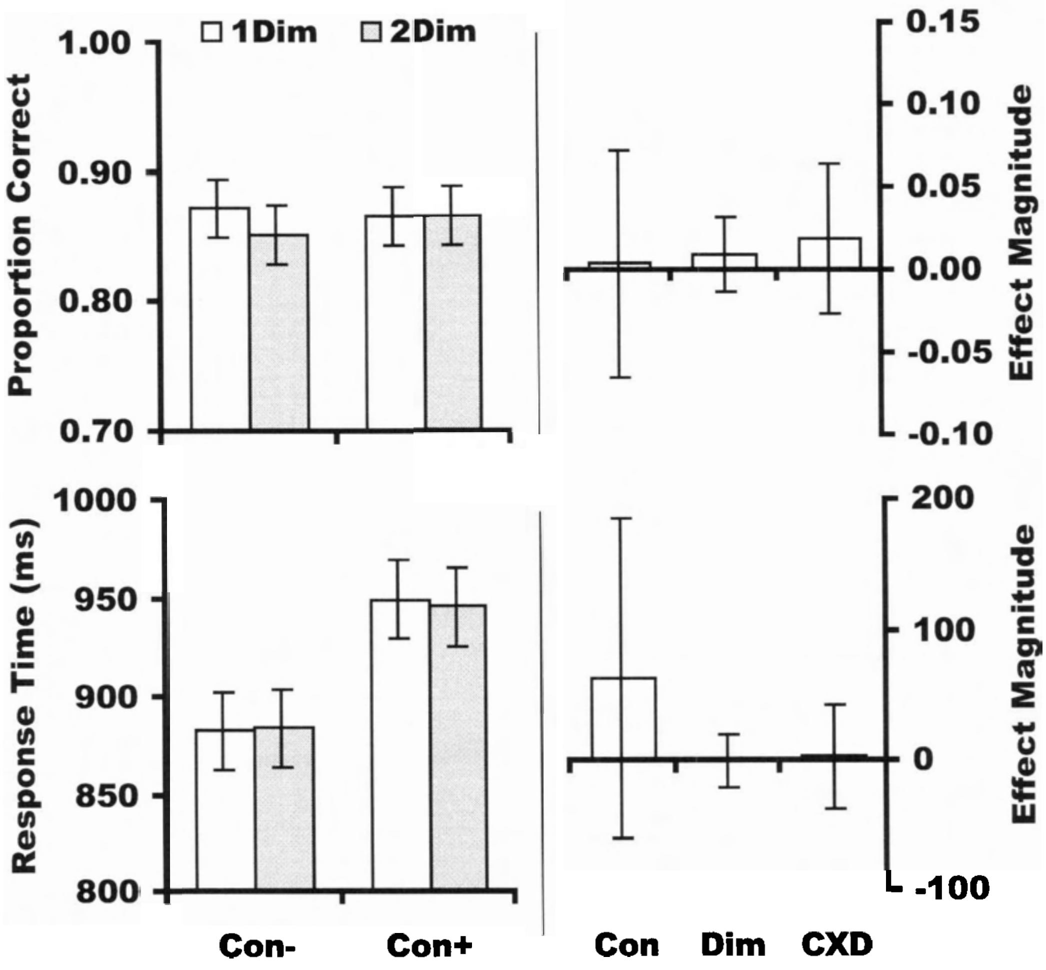

Figure C1. Mean accuracy and response times with contrasts for the colour-training phase of Experiment 7. Error bars represent 95% confidence intervals.

conditions on average, this difference was also not statistically reliable (probably due to the small number of subjects in each condition).

As was the case in Experiment 6, 1D and 2D sets in the colour-training phase of Experiment 7 differed in how distal pairs were from one another, as well as in the number of dimensions by which pairs varied. Trials in1D sets for which pairs differed by more than 20 units (> 20) were therefore grouped separately from trials for which pairs differed by 20 units or less (≤ 20). Likewise, trials in 2D for which pairs differed by two dimensions (2Diff) were grouped separately from those for which pairs differed by only one dimension (1Diff). The mean accuracy and response times for the various trial conditions are presented in Figure C2 for both conceptually unrelated and related conditions. The effect of proximity in 1D sets in the conceptually unrelated condition was similar to that found in Experiment 6: pairs that differed by more than 20 units were more accurate than those that differed by 20 units or less. The effect of proximity for the conceptually unrelated condition, however, was present for both accuracy and response times, with the >20 trials being both more accurate and faster than ≥ 20 trials.

The interaction between proximity and conceptual relatedness for response times was significant, as the left panels of Figure C3 displays. Thus associating the stimuli with conceptually related labels exacerbated the effect of proximity along structural dimensions.

The effect of number of dimensional differences between pairs for 2D sets in the conceptually unrelated condition was also similar to that found in Experiment 6: trials that differed by two dimensions were both more accurate and faster than trials that differed by only one dimension. For the conceptually related condition, there was a

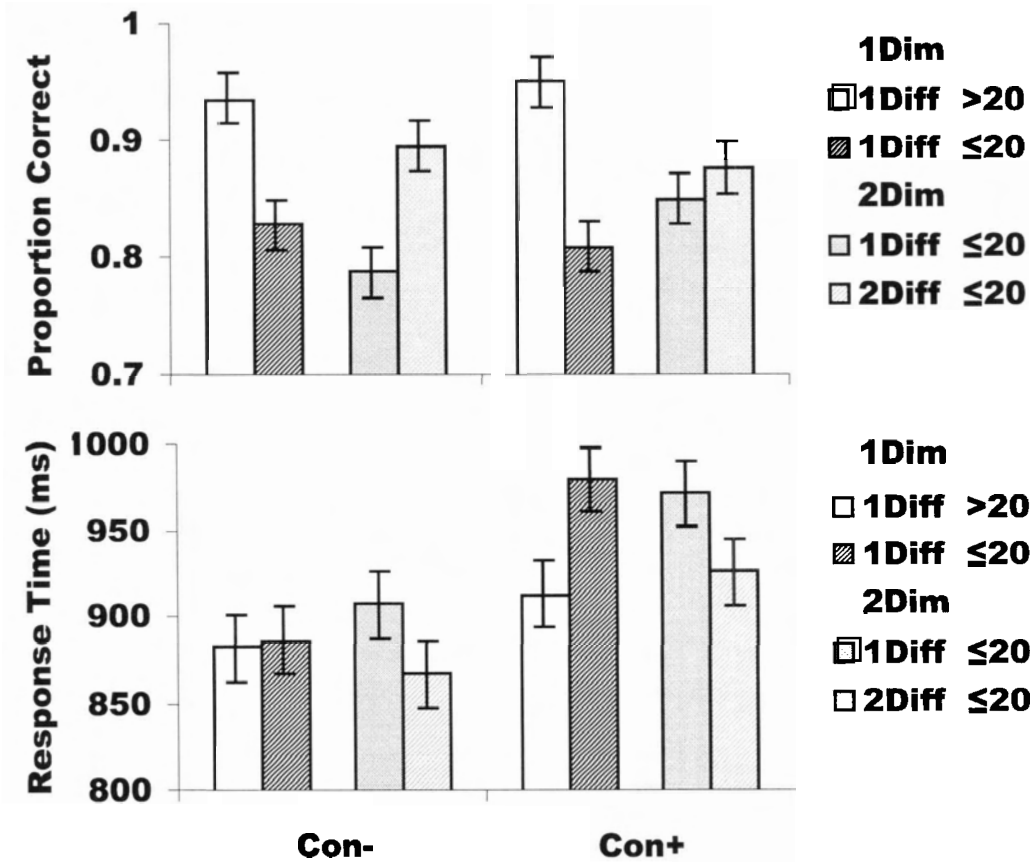

Figure C2. Mean accuracy and response times for stimulus pair conditions in the colour training phase of Experiment 7 across conceptually unrelated (Con-) and conceptually related (Con+) conditions. Trials are grouped according to both the proximity of stimuli along the diagnostic dimensions (>20 vs. ≤20), as well as the number of dimensions that differed between stimuli (1Diff vs. 2Diff). Error bars represent 95% within-subjects confidence intervals.

significant difference between 1Diff and 2Diff pairs for response times only. The modulation of the dimensional difference effect by conceptual relatedness for accuracy can clearly be seen in the upper panel of Figure C3. This pattern of results suggests that subjects in the conceptually related condition were more likely to bind colour to integrated structural dimensions than subjects in the unrelated condition.

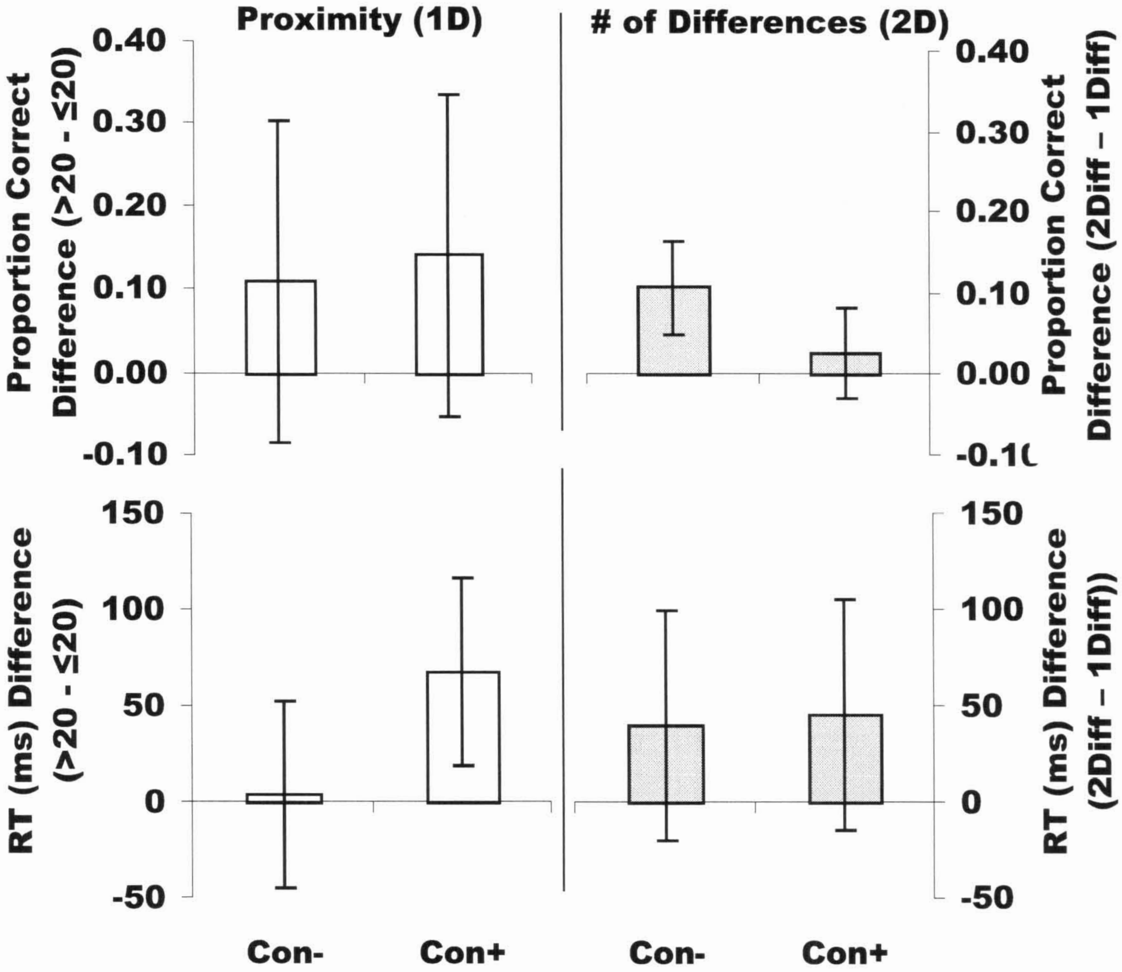

Figure C3. Mean differences in accuracy and response times for proximity conditions (1D sets) and # of differences conditions (2D sets) across conceptually unrelated (Con-) and conceptually related (Con+) label conditions in the colour-training phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

This difference in processing between conceptually related and unrelated conditions may originate from prior experience in the label-training phase. While subjects in both conditions received practice integrating structural dimensions in the word-picture and picture-word matching tasks, the results of the verification task for Day 1 showed that integration of structural dimensions in the conceptually related condition was effortful and required more time than integration of structural dimensions in the conceptually unrelated condition. However, over the course of label training, subjects in the conceptually related condition became very efficient at integrating the structural dimensions: by Day 2 conceptually related conditions had significantly higher sensitivity than unrelated conditions, and response times were statistically equivalent for conceptually related and unrelated 2D sets. This acquired skill of integrating the structural dimensions in the label-training phase may have transferred to the colour-training phase. The interaction of the dimensional difference effect with conceptual relatedness in the colour-training phase may impact the likelihood of finding evidence for dimensional paucity in colour recall, and will be discussed further below.

Colour Recall

Overall Accuracy. The results of the colour recall phase of Experiment 6 showed that colour recall for 2D sets was poorer than colour recall for 1D sets. In the colour recall phase of Experiment 7, I predicted that colour recall would also be poorer for 2D than for 1D sets, and that the added conceptual dimension would modulate the retrieval of colour attributes such that retrieval of colour information for 2D sets would be more accurate for the conceptually unrelated condition than the related condition. The mean accuracy rates of colour recall for 1D and 2D sets are displayed in Figure C4. Contrary to what was expected, accuracy was statistically equivalent between 1D and 2D sets for both related and unrelated conditions . Furthermore,. there was no difference in mean recall accuracy for conceptually related and unrelated 2D sets (56% and 58% respectively).

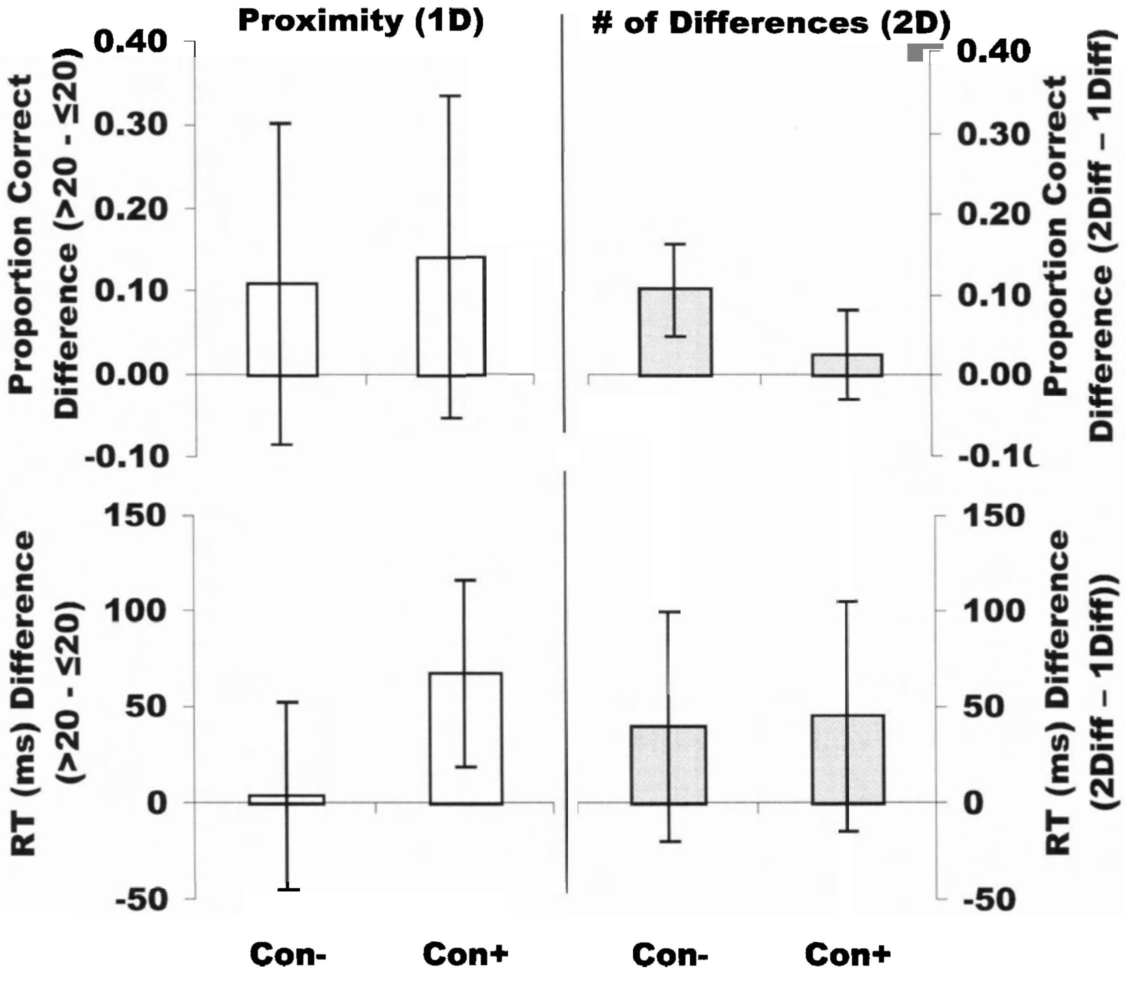

Figure C4. Mean differences in accuracy and response times for proximity conditions (1D sets) and # of differences conditions (2D sets) across conceptually unrelated (Con-) and conceptually related (Con+) label conditions in the colour training phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

Although I did not find evidence for the modulation of structural integration by the relatedness of conceptual labels, a comparison of colour recall for Experiment 6 and 7 nonetheless provides support for the modulation of structural integration by conceptual information. Figure C5 compares the colour recall results of Experiment 6, which had no label training, with those of Experiment 7 (collapsed across conceptual relatedness). This comparison reveals a main effect of adding a conceptual label, and a significant interaction with label learning and dimensionality. Whereas colour recall was better for 1D sets than 2D sets in Experiment 6, there was no difference between 1D and 2D sets for Experiment 7. Adding a conceptual label (related or unrelated) to the stimuli selectively improved colour recall for 2D sets (34% in Experiment 6 vs. 57% in Experiment 7), even though subjects in Experiment 6 received 15 blocks of colour training, whereas subjects in Experiment 7 received only 10 blocks.

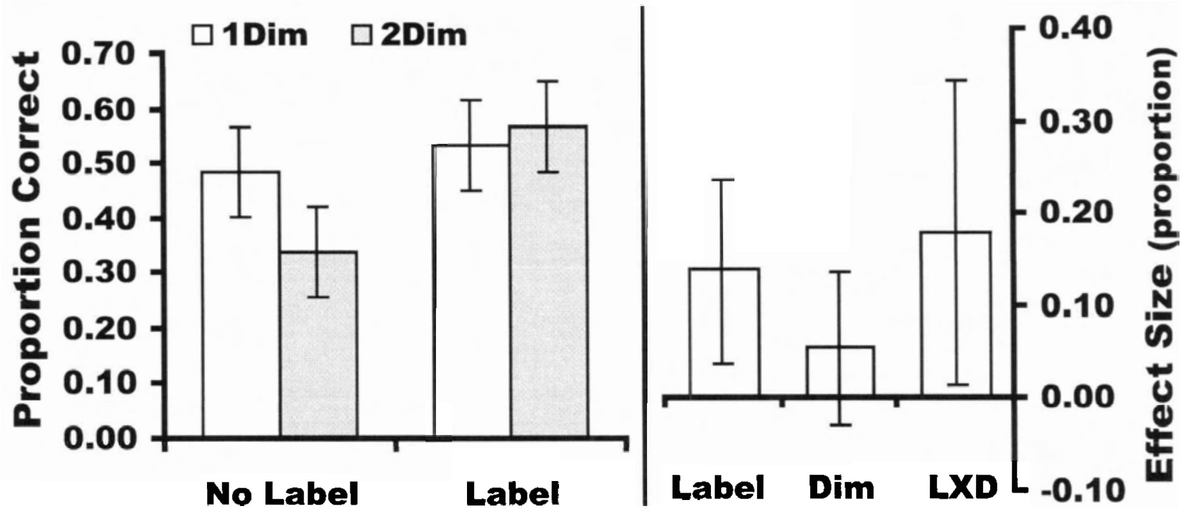

Figure C5. Mean accuracy with contrasts for the colour recall phase of Experiment 2 (No Label) and Experiment 7 (collapsed across unrelated and related label conditions), with contrasts. Error bars represent 95% confidence intervals.

Error pattern for 1D and 2D sets. The pattern of colour recall errors in the 1D and 2D sets were explored for factors underlying recall performance as they were in Experiment 6, with the exception of the regression analysis, for which the number of errors was deemed too sparse. For 1D sets, I expected that errors would reflect proximity along the single diagnostic structural dimension, as they did in Experiment 6. Errors in the 1D set were therefore coded as either close or distal. The chance and observed error proportions for close error types in the conceptually unrelated and related conditions are displayed in Figure C6. The percentage of close errors did not differ for conceptually related and unrelated conditions (63% and 59% respectively), and both were greater than expected by chance alone (33%).

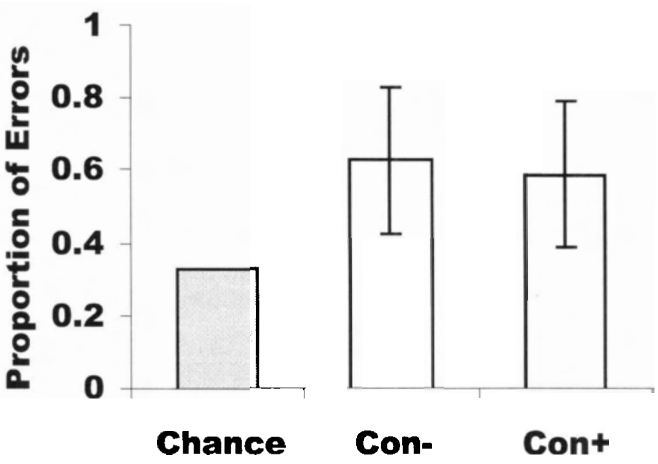

Figure C6. Mean proportion of observed errors for the close error type in the conceptually unrelated (Con-) and related (Con+) conditions for 1D sets in the colour recall phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

I hypothesized that conceptually related 2D sets would be more likely to show evidence of dimensional paucity than unrelated 2D sets, because the distinctiveness of unrelated labels was expected to help resolve competition from exemplars with shared structural dimensions. To investigate this hypothesis, colour recall errors for 2D sets were coded as either parallel or diagonal. The chance and observed proportions of parallel errors are displayed in Figure C7. The probability of an error being parallel to the target was indeed dependent on conceptual relatedness of the labels, but in the opposite direction to what was predicted: The conceptually unrelated condition, not the related condition, had a greater proportion of parallel errors than was expected by chance (63% vs. 38% for unrelated and related conditions respectively, compared to a chance rate of 40%).

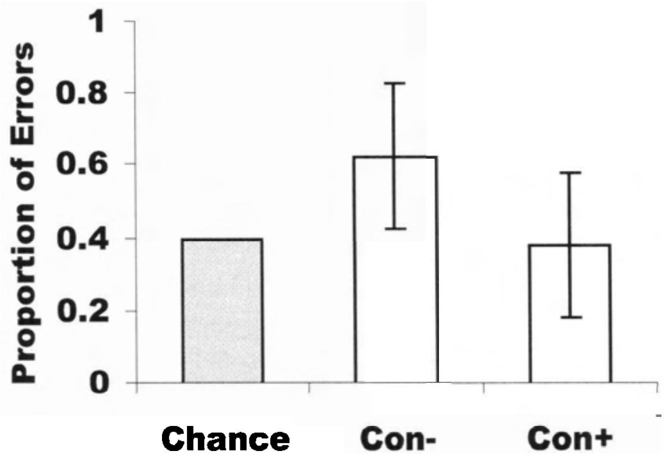

Figure C7. Mean proportion of observed errors for the parallel error type in the conceptually unrelated (Con-) and related (Con+) conditions for 2D sets in the colour recall phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

The combined effects of dimensional paucity and proximity in colour recall errors are displayed in Figure C8. For the conceptually unrelated condition (upper panel), only errors that were both parallel and close were more frequently observed than expected by chance. A direct comparison of diagonal and parallel close error types for the conceptually unrelated condition also revealed a significant effect of dimensional paucity. For the conceptually related condition (lower panel of Figure C8), only errors that were diagonal and close were observed more frequently than expected by chance. A direct comparison of diagonal and parallel close errors for the conceptually related condition shows no difference in the observed proportions for these two types of errors.

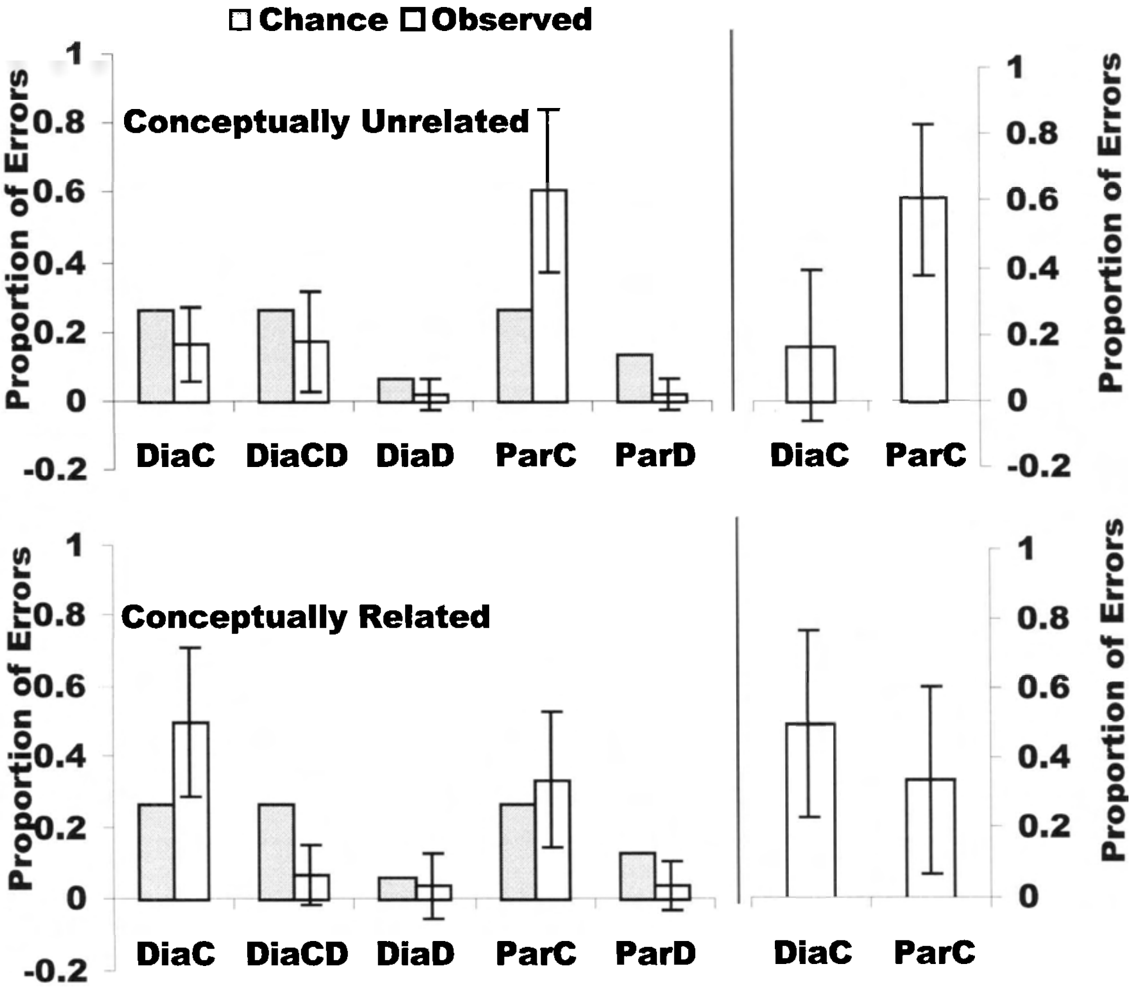

Figure C8. The left panels show the mean proportion of observed errors for the various error types in the conceptually unrelated (upper panel) and unrelated (lower panel) conditions of the colour recall phase of Experiment 7, relative to the number expected by chance. DiaC = diagonal with values on both dimensions close to target values; DiaCD = diagonal with values on one dimension close and the other distal to target values; DiaD = diagonal with values on both dimensions distal to target values; ParC = parallel with the second dimension close to target value; ParD= parallel with second dimension distal to target value. 95% confidence intervals are based on the standard error of each condition. The right panels are a direct comparison of diagonal and parallel errors for close errors. Error bars for this comparison are 95% within confidence intervals based on the MS from the repeated measures ANOVA.

Figure C9 displays the significant interaction of dimensional paucity with conceptual relatedness as measured by the difference between proportions of parallel and diagonal errors in the close condition.

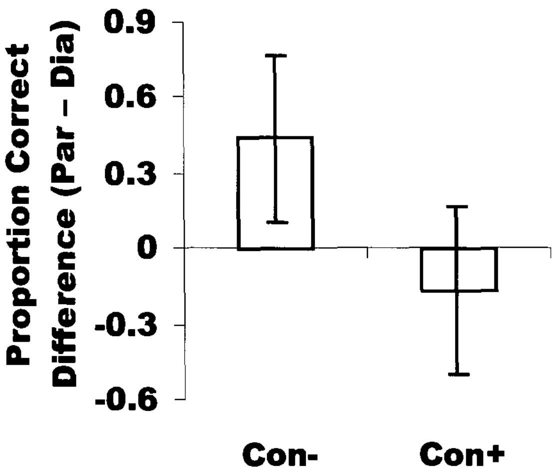

Figure C9. Mean difference in proportions of observed errors (parallel – diagonal) for close errors only in the conceptually unrelated (Con-) and related (Con+) conditions of the recall phase of Experiment 7. Error bars are 95% between-subjects confidence intervals.

Although these findings are contrary to what was originally expected, they are consistent with the results of the colour-training phase: Only the conceptually unrelated condition showed evidence for dimensional paucity in colour training errors. The combined results of Experiment 6 and 7 suggest that for the NLAR paradigm as it is currently designed, competition from shared structural dimensions are evident in normal colour recall only when colour is bound to a single dimension in the colour training phase, and when these bonds are strong enough to affect retrieval of colour information. In Experiment 6, subjects appeared to bind colour to only one dimension during training, but colour bonds were not strong enough to show evidence for competition from shared structural dimensions in colour recall. In Experiment 7, the colour bonds were stronger as evidenced by the higher recall accuracy, but only the conceptually unrelated condition showed evidence for colour binding to a single dimension in the colour-training phase, and only this condition showed evidence for competition from shared dimensions during recall.

Why were participants in the conceptually related condition less susceptible to the effect of structural dimensionality in the colour training and recall phases? As pointed out in the discussion of the colour-training phase, these subjects had previously overcome the difficulty of integrating structural dimensions for conceptually related stimuli by the end of the label-training phase. In fact, the label-training phase may have encouraged participants in the conceptually related condition to utilize a strategy whereby structural dimensions are perceptually integrated to overcome competition from the conceptual domain. Consistent with this idea, participants in the conceptually related condition had longer response times in the colour-training phase. If this is indeed the case, then testing for colour recall after extensive label training is unlikely to be sensitive to the interaction of conceptual relatedness and structural dimensionality, and in this sense is an unnecessary addition. The label-training phase itself is sufficient to address this question.

Appendix D

Labels Used in Experiment 7

Insects	Mammals	Vegetables	Birds	Shellfish	Fruits
spider	cow	carrot	eagle	lobster	apple
beetle	horse	potato	crow	crab	banana
fly	goat	onion	pigeon	clam	pear
ant	sheep	cucumber	duck	mussel	strawberry
wasp	cat	corn	chicken	oyster	plum
grasshopper	dog	lettuce	goose	shrimp	lemon

Garden Tools	Clothes	Desktop	Carpentry	Transport	Utensils
shovel	hat	eraser	screwdriver	train	fork
spade	scarf	paperclip	hammer	airplane	knife
pitchfork	mittens	ruler	chisel	van	spoon
rake	skirt	pen	drill	helicopter	tongs
hoe	socks	stapler	pliers	bus	ladle
pick	pants	scissors	wrench	motorcycle	whisk