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Is there Evidence of Specialised Semantic Subsystems from Normal Processing?

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Abstract

Category-Specific Disorders are frequently explained by suggesting that living and non-living things are processed in separate subsystems (e.g. Caramazza & Shelton, 1998). If subsystems exist, there should be benefits for normal processing, beyond the influence of perceptual similarity. However, no previous study has separated the relative influences of similarity and semantic category. We created novel examples of living and non-living things so category and similarity could be manipulated independently. Pre-tests ensured that our images evoked appropriate semantic information and were matched for familiarity. Participants were trained to associate names with the images and then performed a name-verification task under two levels of time pressure. We found no significant advantage for living things alongside strong effects of similarity. Our results suggest that similarity rather than category is the key determinant of speed and accuracy in normal semantic processing. We discuss the implications of this finding for neuropsychological studies.

Is there Evidence of Specialised Semantic Subsystems from Normal Processing?

The existence of selective semantic deficits for living or non-living objects has been used to argue that semantic knowledge about objects is processed by distinct neural subsystems, specialised for living and nonliving concepts (e.g. Caramazza & Shelton, 1998). Two of the original cases reported by Warrington and Shallice (1984) remain among the best examples. Their patient J.B.R. recognised only 3 out of 48 pictures of animals and plants, but he recognised 43 out of 48 pictures of inanimate objects. Patient S.B.Y. did not recognise any of 48 pictures of animals and plants, but he recognised 36 of 48 pictures of inanimate objects. The strength of the dissociation, the fact that similar dissociations have been reported in a series of patients (e.g. Caramazza & Shelton, De Renzi & Luccelli, 1994; Farah & Wallace, 1992; Kurbat & Farah, 1998; Warrington & Shallice), and the existence of a dissociation in the opposite direction (an advantage for nonliving over living, e.g. Hillis & Caramazza, 1991; Turnbull & Laws, 2000) are the phenomena which underpin the hypothesis that the semantic system is divided into specialised subsystems.

We argue that these data alone do not force one to assume that semantic information is processed in separate subsystems because it is possible for category specific deficits to occur within a range of semantic organisations, including those that are unitary and unspecialised. Different organisations are not distinguished by whether or not selective deficits are possible at all, but by how often they should occur, and this can be difficult to assess. However, the structure of semantic organisation should also have an effect on processing in the undamaged brain. Converging evidence from intact participants should, therefore, form part of the case used to support a particular theory of semantic organisation. Our study is designed to investigate whether participants without brain damage show evidence of semantic subsystems specialised for living things.

Alternative Semantic Organisations

To motivate the necessity of converging evidence from intact participants, we will describe several possible semantic organisations, and the kinds of neuropsychological deficits they allow. We will describe these organisations in explicitly topological terms. However, it is important to emphasise that this is a functional, and not a neural topology. Cats and dogs are likely to be closer to each other than cats and airplanes in a functionally described semantic space. They may also be closer to each other in neural space, but this is an independent issue. Specialised neural mechanisms may be more likely to be localised (Caramazza & Shelton, 1998), but if they were not, this would not change the functional issues.

When describing how brain damage may affect a system that has a functional topology we make a few general assumptions. We assume that representations that are substantially independent are more likely to be selectively impaired than representations that overlap. We assume that damage can affect regions of functional space, such that adjacent functional regions are likely to be affected together. Finally, we assume that damage that is not contiguous is also possible (i.e. damage that affects independent regions of functional space, or damage that affects the space in a scattershot fashion). While these assumptions allow all the organisations that we describe to produce selective deficits in single patients, they do limit how often different patterns should occur across patients.

We describe alternative semantic organisations in terms of a continuum of increasing specialisation. The semantic organisation that is least structured is a homogeneous semantic space, with all objects equidistant from each other. In a homogeneous space, damage can be specific to categories of objects, but only by chance. There are infinitely many subsets of objects that could be damaged together, and most subsets would not adhere to category boundaries. Therefore, category-specific deficits should occur very rarely, and only draw attention because they appear systematic.

However, a homogeneous space is just a baseline and we do not consider it to be a likely organisation. A structured unitary system, where related things are “near” each other, is much more plausible. In the neuropsychological literature this is the “lumpy” semantic space of the Organised Unitary Content Hypothesis (OUCH, Caramazza, Hillis, Rapp & Romani, 1990; Tyler, Moss, Durrant-Peatfield & Levy, 2000, also argue for a structured unitary system). A “lumpy” space allows deficits to affect just living things or artefacts, but also more specific categories if appropriate dimensions define the space. Damage to a category as specific as *aquatic animals*, for example, is possible in principle. The frequency of different kinds of deficits will be determined by the specific features and processes involved in semantic representation (and, as always, by anatomical considerations that are orthogonal to functional organisation, e.g. brain regions near vascular pathways that are more vulnerable to stroke).

A specialised subsystems account is the final organisation of semantic space that we consider. Two alternative subsystems accounts have been proposed. The system could be organised into separate subsystems for processing different categories of object or separate subsystems dedicated to the processing of different types of information. Farah and McClelland (1991), Warrington and McCarthy (1987), Warrington and Shallice (1984) have all proposed that semantic memory is organised according to subsystems processing sensory or functional information.

Category specific disorders arise because certain categories depend disproportionately on one kind of information. Sensory information is though to be particularly important for the recognition of living things and functional information for the recognition of non-living things. More recently, Martin, Ungerleider and Haxby (2000) have proposed a variant of the original sensory/ functional theory, called the sensory/ motor theory, emphasising that the identification of manipulable artefacts relies heavily on knowledge about how to use the object. Although the sensory/functional or sensory/motor division has been supported by evidence from imaging studies on intact participants (e.g. Chao & Martin, 2000; Damasio, Grabowski, Tranel, Hichwa & Damasio, 1996; Martin, Wiggs, Ungerleider & Haxby 1996; Thompson-Schill, Aguirre, D'Esposito, & Farah, 1999), the evidence from patients is less clear (Caramazza & Shelton, 1998; Kolinsky et al., 2002; Lambon Ralph, Howard, Nightingale & Ellis, 1998; Pillon & Samson, 2003; Samson, Pillon & De Wilde, 1998; Sheridan & Humphreys, 1993). Capitani, Laiacona, Mahon, and Caramazza (2003) review the category-specific literature and find that the majority of patients do not present with a disproportionate deficit for types of knowledge. In fact, the pattern of deficits is more consistent with divisions along category lines, specifically: animals, fruit/ vegetables and artefacts. Since a division along category lines reflects the pattern of deficits more closely than a sensory/ functional division, the current study will focus on the evidence for separate subsystems for different categories of object.

Caramazza and Shelton (1998, see also, Kolinsky, Fery, Messina, Peretz, Evinck, Ventura & Morais, 2002) propose that specialised mechanisms for the processing of living things exist and are prone to damage because they are highly localised. They speculate that evolutionary pressures led to the development of dedicated neural circuits for responding to and recognising animal and plant life. Animals may be classified as predators or a potential source of food. Plants must also be recognised accurately in order to ascertain their use as food or medicine. Caramazza and Shelton argue that these specialised circuits can account for the fact that the categories of animals, plants (including fruits and vegetables) and non-living things can be damaged independently of one another. More recently, Mahon and Caramazza (2003), specify a range of categories for which rapid and efficient identification could have survival and reproductive advantages. In addition to animals, and plants, there may be specialised neural circuits dedicated to the processing of conspecifics and tools. However, the patient data reviewed in Capitani et al. (2003) provides strongest support for divisions between animals, plants (fruit/ vegetables) and artefacts.

Two kinds of subsystems accounts are possible. One includes specialised subsystems for living and nonliving things, with a homogenous space within each subsystem. The other allows “lumpy” spaces within each subsystem. These accounts make different predictions, but both prioritise the living/nonliving distinction.

Caramazza and Shelton (1998) are equivocal about subsystem structure. They suggest that the only truly categorical deficits are those specific to animals, plants, and artefacts, a position that could be taken to favour homogenous subspaces, but they also say that their account is silent about subspace organisation, so that within the three fundamental categories, “lumpy” organisation is possible. Specialised subsystems prioritise the categories *animal*, *plant* and *artefact*, so selective deficits for these categories should be among the most common deficits. If the subsystems are homogenous, more specific systematic deficits will only happen by chance, and should be rare. If the subsystems are structured, more specific deficits are also possible. Both accounts allow deficits to affect both living and nonliving things when lesions affect subsystems independently.

In sum, a homogeneous space will rarely produce deficits that conform to category boundaries. Deficits that affect both living and nonliving objects should be common. A structured unitary system allows selective deficits more frequently than a homogenous system, but only prioritises living/nonliving categories if this constitutes one of the basic divisions in semantic space. Selective deficits for the categories of animal, plant and artifact could occur, but deficits would *not* be restricted to these domains. Dissociations across a much wider range of category boundaries would be expected.

A separate subsystems architecture will frequently produce selective deficits for the categories that define the subsystems: plants, animals and artefacts. Deficits that cross these category lines are possible, but should occur more rarely. In fact, most deficits should affect the subsystems unequally.

Clearly, a structured unitary system and separate subsystems will be very difficult to distinguish. A fundamental difference, but one that has received little attention, should be that a structured unitary system is governed by set of principles that apply to all semantic knowledge, while subsystems are governed by domain-specific principles (which motivate the division).

Investigations of Normal Processing

We have noted that the simple presence of category-specific deficits cannot distinguish alternative semantic organisations, since category-specific deficits are possible in any architecture. However, the frequency with which living/non-living deficits occur, and the specificity of damage, would differ for each type of organisation. Theoretically, it should be possible to distinguish between these organisations by assessing the frequency with which different types of deficit occur. However, this assessment would be complicated by anatomical factors (e.g. not all functionally-equivalent processes will be equally susceptible to damage by stroke), by reporting bias, and by the effort necessary to assess sufficient numbers of patients in enough detail to exclude non-semantic influences on their error patterns.

The difficulty in assessing frequency of occurrence provides a strong motivation for underpinning patient results with convergent results from normal processing. A separate subsystems architecture should influence normal processing in a way that is qualitatively different from the other two organisations. A specialised subsystems architecture should give a measurable advantage to the categories for which it is specialised (i.e. living things). A homogenous architecture or a structured unitary system do not require categorical effects in normal processing over and above the influence of factors that affect retrieval (e.g. familiarity, similarity, visual complexity). Our experiments are designed to look for evidence of specialised subsystems in intact adults. If independent subsystems for living things have developed because of evolutionary pressures, the subsystems should improve the speed and accuracy with which novel living images are learned, recognised and/or named.

Although Caramazza and Shelton (1998) and Mahon and Caramazza (2003) make no specific predictions for normal processing, they invoke an evolutionary explanation for the development of selective semantic subsystems. However, for evolutionary pressures to act, there must be benefits for normal processing. In fact, Mahon and Caramazza argue that evolutionary pressures have resulted in specialised subsystems, only for, “those categories for which rapid and efficient identification could have had survival and reproductive advantages” (p434). Thus, the following prediction is implicit: If evolutionary pressures caused separate subsystems for animals and fruit/vegetables to develop, objects from these categories (i.e. living things) should be processed faster and more accurately than objects from categories with no dedicated sub-system (i.e. non-living things).

Previous experiments that have investigated category differences in naming or recognition in intact participants have produced conflicting results. For example, Laws (2000) and Laws and Neve (1999) found an advantage for living things over nonliving things, consistent with the existence of specialised subsystems for living things. In contrast, Humphreys, Riddoch and Quinlan (1988) and Lloyd-Jones and Humphreys (1997) found that living things were named more slowly than nonliving things.

Several dimensions have been identified as possible sources for differences between categories other than the category difference itself. Firstly, intrinsic characteristics of real objects such as visual complexity, familiarity, frequency and name agreement have all been considered potential confounding variables (Funnell & Sheridan, 1992, Stewart, Parkin & Hunkin, 1992). Humphreys et al. (1988) controlled name agreement, but not familiarity or visual complexity. Laws (2000) and Laws and Neve (1999) controlled visual complexity and familiarity, but not name agreement (which had an influence when assessed by linear regression).

Secondly, since groups of animals usually share a basic body plan, animals have been considered more structurally similar than artefacts, and this “visual crowding” may make animals more difficult to name and recognise. For example, Humphreys, et al. (1988) attributed slower naming of living things to the structural similarity of animals. Gaffan and Heywood (1993) drew the same conclusion from their study, in which they showed living and nonliving things to monkeys and to people. More errors were made to pictures of living things. Since monkeys showed the same pattern as people, Gaffan and Heywood argued that the pattern was due to the visual characteristics of the stimuli, and not the semantic characteristics. Object decision is also slower for living things (Lloyd-Jones & Humphreys, 1997; Vitkovitch & Tyrrell, 1995) but category decision is faster (Riddoch & Humphreys, 1987). Gerlach (2001) found that the disadvantage living things suffer in object-decision at unlimited exposure durations reversed when objects were presented in the periphery for 150 milliseconds. He argued that global shape gave more information about living things when brief exposure limited processing, but when internal detail is available at unlimited exposure duration, the similarity of living things caused slower response times. Lloyd-Jones and Luckhurst (2002) also found that performance for living things was impaired less than performance for nonliving things by the presentation of silhouettes rather than full objects. In addition, same/different judgements take longer for pairs of animals than pairs of artefacts, and similarity ratings are higher (Lamberts & Shapiro, 2000). All of these results are expected if the structural similarity of animals allows quicker classification into the category *animal*, but slower identification, and, therefore, slower naming.

Finally, time demands can potentially change the outcomes of experiments with living and nonliving objects. Humphreys, Lloyd-Jones and Fias (1995) found that an advantage for nonliving (dissimilar) objects at unlimited exposure durations disappeared when living and nonliving objects were presented for only 500 milliseconds in a cued-naming paradigm. Unlike other experiments mentioned above, Laws and Gale (2002) found better results for living things when they used a speeded presentation paradigm.

In sum, these studies have produced mixed results. Some found an advantage for living things and some found a disadvantage. In most studies (apart from Laws, 2000), these effects have been attributed to intrinsic characteristics of the stimuli, which affect processing differently according to task demands, and not to the category difference. A common problem for these investigations was that all stimulus characteristics could not be controlled simultaneously. In particular, these studies did not isolate the relative influence of perceptual similarity and semantic category. Since Humphreys et al. (1988) and Lamberts and Shapiro (2002) claim that living things are intrinsically more similar to each other, it may be impossible to find sets of real living and non-living that are matched for similarity, without resorting to highly unusual members of each category.

The Current Study

In our experiment we address the three sets of issues that we have highlighted from the current naming literature. Artificial sets of stimuli have been successfully used to test detailed mathematical models of categorisation processes (e.g. Lamberts, 1995; Lamberts & Brockdorff, 1997; Lamberts & Freeman, 1999; Medin & Schaffer, 1978; Nosofsky, 1992). Borrowing from these paradigms, we constructed an artificial set of animals and vehicles in order to avoid some of the confounds inherent in research with real objects. Artificial objects also allowed us to manipulate category and structural similarity independently. Finally, evolutionarily important advantages that are not apparent under unlimited time conditions may become apparent when there is pressure to respond quickly. We asked people to respond under long and short deadlines to ensure that we did not miss categorical differences that only become apparent when responses must be made quickly.

We will focus on whether a separate subsystem for animals exists, since the survival value in quickly recognising animals provides the most compelling evolutionary argument. Caramazza and Shelton (1998) claim that a specialised subsystem for animals has evolved because of the importance of making quick decisions (while non-living things are processed in the more generic and, presumably, less efficient system). We will compare normal processing of animals with vehicles, a category for which evolutionary pressures could not have resulted in a specialised system. We created novel examples of animals and vehicles in order to manipulate semantic category and structural similarity independently. One set of animals and vehicles were perceptually similar and one set of animals and vehicles were perceptually dissimilar. We used vehicles, because, like animals, vehicles involve a hierarchical domain with a substantial degree of internal structure (e.g. different classes of vehicles: boats, cars, trucks, trains; different kinds in each class: boats, sailboats, motor boats, dinghies etc.). We trained participants to associate our novel objects with nonsense names. It was not necessary to control name agreement or frequency because the names were novel and counterbalanced across all conditions. We also systematically controlled the familiarity of living and nonliving objects. It was not possible to control visual complexity at the same time, but we did measure it in order to assess its ability to influence our results.

When using novel images, it is important to ensure that participants do not treat them as purely abstract designs without semantic content. With abstract designs, no difference would be expected between what we have chosen to call “animals” and “vehicles” because the category labels would be arbitrary. However, if our images come to be seen as animals and vehicles during the learning process our design should allow category differences to emerge. We checked that participants categorised the images appropriately, using questionnaires to assess whether participants made appropriate assumptions about the semantic content of the images both at first sight, and after training.

Manipulating category and similarity independently allows the following outcomes. If only semantic category affects name-verification, this provides converging evidence for the subsystems account, and indicates that similarity is unlikely to confound results from patients. If only similarity affects name-verification, perceptual similarity is also likely to affect patient performance. This implies that some category-specific results from patients may be explained by structural similarity instead. If both category and similarity affect performance, this is consistent both with a specialised subsystems account, and with the potential for similarity to confound patient results.

Stimulus Construction and Pre-tests

We used a graphics package that allows three-dimensional rendering of shaded objects (POV-Ray™, Persistence of Vision Development Team, 1991) to create five dissimilar animals and five dissimilar vehicles that had some resemblance to real examples of each category (e.g. mammals, dinosaurs, reptiles, insects; trains, boats, airplanes, rockets), but the objects also sometimes involved novel combinations (e.g. a rocket with wheels, a dinosaur with wings). Four of the animals and four of the vehicles made up the two dissimilar sets (labelled AD and VD respectively). The remaining animal image and vehicle image were used as the basis for two sets of similar images. Three single features were changed on the animal to create three related images, resulting in a set of four similar animals (labelled AS). The same procedure was used to create four similar vehicles (labelled VS). All images were the same colour to avoid any differences in salience. Green was chosen because it was plausible for both animals and vehicles but not predominantly associated with one category. Figure 1 shows greyscale versions of the full set of images.

(Figure 1 about here)

Participants

Undergraduate and postgraduate students from the University of Birmingham, aged between 18 and 32, participated in the pre-tests used to assess the properties of the stimuli. Psychology undergraduates received course credits for taking part in the experiment and other students received cash payments. New participants were recruited for each pre-test.

Pre-test 1: Similarity, Visual Complexity, Familiarity and Category Membership

15 participants rated similarity and visual complexity first and then familiarity and category membership second, in counterbalanced order. It was important to ask for similarity and visual complexity ratings first because these tests required participants to ignore what the images represented whereas semantic attributes were necessarily involved in the familiarity and category pre-tests.

For the similarity pre-test, all within-condition pairs of images (48 pairs) were presented in random order. Participants were instructed to rate each pair on a scale from 1 for a pair of images that looked nothing like each other to 5 for a pair of images that were almost identical. The similarity pre-test was used to ensure that similar animals and vehicles were rated as significantly more similar than the dissimilar animals and vehicles, but also to check that similarity did not interact with category.

For the familiarity, category membership and visual complexity pre-tests, all 16 images were presented one at a time in a random order. When rating each image for familiarity, participants were instructed to use a scale from 1 for a very unusual image to 5 for a very familiar image. The familiarity pre-test was used to check that animals and vehicles were equally familiar, that similar and dissimilar images were equally familiar, and that there were no interactions between category and similarity.

For the category membership pre-test, participants were asked whether the image looked like a vehicle, an animal, or neither. This test was used to ensure that the images evoked the intended category.

When rating the images for visual complexity, participants were instructed to use a scale from 1 for a very simple image to 5 for a very complex image. It was desirable to have images with a similar level of visual complexity in each condition, but this could not be systematically controlled along with the other factors. However, measuring complexity allowed us to assess its affects mathematically.

Pre-test 1 Results

The data were analysed by participants and by image (F1 denotes the analysis by participants and F2 denotes the analysis by image). There was no significant effect of category on similarity rating, F1(1,14) = 0.84, MSE = 0.12, F2(1,44) = 0.71, MSE = 0.12. As expected, there was a significant main effect of similarity on similarity rating, F1 (1,14) = 474.29, MSE = 0.16, $p < 0.001$, F2 (1,44) = 488.86, MSE = 0.12, $p < 0.001$. There was no interaction between category and similarity on similarity rating, F1(1,14) = 0.17, MSE = 0.10, F2(1,44) = 0.10, MSE = 0.12. Table 1 shows that, as expected, the similar conditions were rated as much more similar than the dissimilar conditions.

Table 1 also shows were no significant effects of category or similarity on familiarity ratings, category: F1(1,14) = 0.01, MSE = 0.88, F2(1,12) = 0.004, MSE = 0.28; similarity: F1(1,14) = 0.51, MSE = 0.82, F2(1,12) = 0.40, MSE = 0.28. There was also no significant interaction between category and similarity on familiarity rating, F1(1,14) = 0.004, MSE = 0.004, F2(1,12) = 0.004, MSE = 0.28.

As shown in Table 1, the category membership results were nearly always in the expected direction.

There was a significant main effect of category on visual complexity rating and a significant interaction between category and similarity, category: F1(1,14) = 9.33, MSE = 0.20, $p < 0.01$, F2(1,12) = 7.58, MSE = 0.06, $p < 0.02$, interaction: F1(1,14) = 10.14, MSE = 0.42, $p < 0.01$, F2(1,12) = 17.61, MSE = 0.06, $p < 0.001$. As shown in Table 1, animals were more complex overall, but the dissimilar animals were rated as less complex than the similar animals while the dissimilar vehicles were rated as more complex than the similar vehicles. There was no significant main effect of similarity on visual complexity rating, F1(1,14) = 0.20, MSE = 0.52, F2(1,12) = 0.43, MSE = 0.06. If visual complexity affects naming, the unequal complexity should give an advantage to vehicles over animals. In addition, it could make dissimilar animals faster or more accurate than similar animals, but similar vehicles faster or more accurate than dissimilar vehicles.

(Table 1 about here)

Pre-test 2: Nearest-Neighbour Questionnaire

Ten participants completed the nearest-neighbour questionnaire. The entire set of 16 images was displayed on a computer screen. The experimenter pointed to each image in turn and asked the participant, “What real-world thing does this look like?” The order of the images on the display was the same for each participant.

Pre-test 2 Results

Responses to each image are reported in Appendix A. On average, half of the participants associated each image with the same real object. Only one response for each category was inconsistent with its designated category (‘teddy bear’ for animal and ‘cake on wheels’ for vehicle). This task showed that participants readily associated the novel images with existing categories of real objects, and, more importantly, that participants almost always put the objects in the same superordinate category within the animal and vehicle domains.

Pre-test 3: Semantic Properties Questionnaire

The results from the nearest-neighbour questionnaire reflect the assumptions people make when viewing our images for the first time. However, we only asked for a nearest neighbour and not how far away the neighbour is. An image may look most like a bird without resembling birds very much, if no closer real object comes to mind.

Another problem is that the question only probes the surface properties of each novel image. The response “teddy bear” exemplifies the problem. A teddy bear looks like a real bear but does not share the properties that make living things distinct from artefacts (internal organs, independent movement, etc). To get a better idea of the inferences that people naturally developed regarding the objects, we created a set of questions tapping semantic knowledge that should generate different answers for animals and vehicles. In order to examine the semantic content ascribed to the images in the context of a name-learning experiment, these questions were given to 15 participants after they had completed training and testing for a set of images. These were not the same participants that undertook the main experiment reported here.

Their training sessions were designed to address questions regarding the influence of similarity under different learning conditions and are reported elsewhere (Shapiro, Lamberts & Olson, 2004). However, results for learning and name verification were consistent with those reported below.

Participants completed the questionnaire immediately after they had completed all tests for a set of images. When answering the questions, participants were not shown the images again. Instead, they were given the name of each of the eight images in random order and asked to answer the following questions: 1. Is it living or non-living? 2. What category does it best fit in? 3. What is its normal environment? 4. What parts does it use to move? 5. What does it use to get its energy? 6. What terrain does it move on? 7. What kind of surface does it have? 8. If you opened up the outer surface, what would it have inside?

Participants were asked to respond with 1-word answers wherever possible and were given example answers to help with interpretation of the questions.

There were six questions that were designed to be appropriate to both animals and vehicles, but elicit different responses according to the category into which each object was placed (questions 1,2,4,5,7 and 8). Two questions (3 and 6) were fillers designed to make participants think about each image individually. The filler questions were not analysed because responses do not provide information specific to animals or vehicles.

Two naive participants acted as judges. They were shown the answers to the six distinguishing questions and were asked to judge whether each response indicated that the participant was considering an image of an animal, vehicle, either or neither. The judges rated all responses for one question before proceeding to the next question. This ensured that each response was rated separately, i.e. the responses for any one image could not be combined to build up a picture of that image. The judges had not seen any of the images so the only information they had was the participants' responses.

Pre-test 3 Results

Responses were appropriate to animals and vehicles and consistent across participants. For example, responses for VD4, to question 8 were: engine (x11), people, lots of seats, a place for people to sit and drive it (all x1). Responses for AD3, to question 5 were: food (x13), plants (x1). However, one participant systematically responded to the similar vehicles as if they were animals. We have separated her data from the following analyses because it was a systematic misclassification. Although this one participant was anomalous, we acknowledge that there may be a slight ambiguity in the classification of the similar vehicles.

We present data from 14 participants. Scores for each category (animal/vehicle) are out of 224 (14 participants x 2 judges x 8 images). The results are shown in Table 2. Responses falling in the intended category are in bold.

(Table 2 about here)

Some participants described the surfaces of the fish and reptiles as "smooth." This was coded as a vehicle characteristic but could also be used to describe aquatic animals or reptiles. Some participants responded, "wings" when asked what parts were used to move for the planes and these were coded as "animal" responses. This method of coding the responses is conservative, since the response "wings" is obviously not limited to the animal category and had the judges known that the image could be an airplane, they may have coded the response, "wings", as appropriate to either animals or vehicles. Nevertheless, this conservative coding resulted in 97% of animal responses and 94 % of vehicle responses falling in the intended category, indicating that participants retrieved information appropriate to animals and vehicles.

Main Experiment

The pre-tests demonstrated that our images evoked the intended semantic properties, that they manipulated similarity independent of category, and that familiarity was matched across conditions. We trained participants to associate nonsense names with these images and then conducted a name verification task.

Method

Participants

15 new participants who had not participated in the pre-tests undertook the main experiment. All were undergraduate or postgraduate students from the University of Birmingham, aged between 18 and 32. Psychology undergraduates received course credits and other students received cash payments.

Training

Participants completed the experiment in two sessions. In each session, they learned either four similar animals and four dissimilar vehicles or four dissimilar animals and four similar vehicles. In the training session, an image was randomly selected and presented with a choice of eight possible names, arranged in random order beneath the image. The participant selected the appropriate name using the mouse. If the answer was incorrect, the correct name was displayed. All eight images continued to be displayed until participants responded with 100% accuracy to the entire set of eight images, eight times in a row.

The names were all pronounceable English letter sequences, matched for consonant-vowel structure and N-count (N-count is the number of real words that can be created by changing 1 letter at a time in the target and was based on the CELEX corpus, Baayen, Piepenbrock & van Rijn, 1993). One group of names was assigned to each condition, counterbalanced across participants. The names are presented in Appendix B. The number of correct and incorrect responses participants gave for each image was recorded during training. If specialised subsystems enable the identities of animals to be acquired more rapidly we would expect animal objects to be learned more quickly than vehicles.

Name verification

Name verification was used to measure speed and accuracy of identification. Name-verification is often used as a test of object recognition because response latencies can be measured much more precisely than in a naming task using a voice key (e.g. Lawson and Jolicoeur, 1998). A name verification task also allows the response deadline to be manipulated (as in Brockdorff & Lamberts, 2000 and Lamberts, 1995). After training, participants were given a name verification task under time pressure. A name was presented for 800ms followed by an image, presented either for 600ms (long deadline) or 400ms (short deadline). Participants had to decide as quickly as possible whether or not the name for the image was correct. Caramazza and Shelton (1998) suggest that specialised subsystems evolved for processing living things because recognizing and responding quickly to animals has survival and reproductive value. Even if the effects of a specialised subsystem are not apparent normally, they could emerge when the time allowed for a decision is limited. For each session, the participant completed training and then the long deadline task followed by the short deadline task. The order was consistent across participants to ensure that worse performance in the short deadline task was due to the greater difficulty of the task rather than practice effects. Each task was preceded by a practice session, identical to the test. Participants were asked to respond before the image disappeared, using a button box to indicate whether the name preceding the image was correct or incorrect. When the response was too slow, a buzzer sounded and the message “Too slow- Try to respond before the beep”, appeared. No feedback was given in the test phase of the experiment. There were 56 trials that tested every possible incorrect combination of an image and a name (non-matching trials) and 56 trials of correct combinations (matching trials). RTs and errors were recorded. One week after their initial training and name-verification session, participants returned to complete the experiment with the remaining eight images.

Results

Training

A specialised subsystem could either allow greater efficiency in the acquisition of new representations, or allow faster processing of existing information. The training data was analysed to see if category differences were evident during the learning process. The percentage of correct responses made to each image before criterion was reached was subjected to a repeated-measures analysis. There was a significant main effect of similarity, $F1(1,14) = 40.02$, $MSE = 47.02$, $p < 0.001$, $F2(1,12) = 44.06$, $MSE = 20.14$, $p < 0.001$, but no effect of category, $F1(1,14) = 2.86$, $MSE = 55.49$, $F2\ (1,12) = 1.08$, $MSE = 20.14$. There was no interaction between category and similarity, $F1\ (1,14) = 0.14$, $MSE = 50.75$, $F2\ (1,12) = 0.16$, $MSE = 20.14$. As shown in Table 3, participants performed more accurately for dissimilar items than similar items but performance was equivalent for animals and vehicles.

(Table 3 about here)

Name verification

Matching and non-matching trials were analysed separately. Non-matching trials were only analysed when both images came from the same condition (e.g. both dissimilar vehicles), since only these give unambiguous information about the effects of category and similarity. All incorrect and missed responses were removed before analysing the data. Extreme RTs, defined as more than 3 times the interquartile range from the upper or lower quartiles, were excluded from each participant’s data.

Matching Trials

The response deadline had the intended effect. There was a significant main effect of deadline in both RT and accuracy. RT: $F1(1,14) = 182.05$, $MSE = 870.48$, $p < 0.001$, $F2(1,12) = 433.75$, $MSE = 94.75$, $p < 0.001$, accuracy: $F1(1,14) = 14.40$, $MSE = 6.02$, $p < 0.002$, $F2(1,12) = 14.21$, $MSE = 22.88$, $p < 0.003$. Figures 2 and 3 show that RTs were faster for the short deadline test, but accuracy was poorer.

Manipulating similarity and category produced a strong effect of similarity, but not category. There was a significant main effect of similarity in both RT and accuracy, RT: $F1(1,14) = 49.05$, $MSE = 355.26$, $p < 0.001$, $F2(1,12) = 12.14$, $MSE = 326.99$, $p < 0.01$, accuracy: $F1(1,14) = 4.96$, $MSE = 13.61$, $p < 0.04$, $F2(1,12) = 5.68$, $MSE = 44.54$, $p < 0.04$. As shown in Figures 2 and 3, performance was faster and more accurate for the dissimilar conditions. There was also a significant interaction between similarity and deadline on RT by participants, $F1(1,14) = 5.99$, $MSE = 242.18$, $p < 0.03$. However, this interaction was not significant on RT by image, $F2(1,12) = 2.65$, $MSE = 94.75$ or on accuracy, $F1(1,14) = 0.01$, $MSE = 3.43$, $F2(1,12) = 0.01$, $MSE = 22.88$. Figure 3 shows that the effect of similarity on RT was larger for long deadline trials than short deadline trials. Participants were responding very close to the short deadline, bringing all RTs much closer together. RT differences between conditions were therefore reduced for the short deadline but accuracy differences remained.

There were no significant main effects of category, RT: F1(1,14) = 3.68, MSE = 104.77, F2(1,12) = 0.44, MSE = 326.99, accuracy: F1(1,14) = 4.06, MSE = 7.89, F2(1,12) = 2.70, MSE = 44.54. However, the effect of category on accuracy did approach significance in the by-participants analysis ($p = 0.06$). Figure 2 indicates a trend towards more accurate responses to animals than vehicles. The accuracy advantage for animals was 1.33 at the 600ms deadline and 0.73 at the short deadline. The similarity difference was greater: 1.53 at the 600ms deadline and 1.47 at the 400ms deadline. These data, therefore, provide weak evidence for effects of category, and certainly do not provide evidence that category differences emerge as time pressure is increased.

The interaction between category and similarity was non-significant, RT: F1(1,14) = 0.03, MSE = 1032.48, F2(1,12) = 0.01, MSE = 326.99, accuracy: F1(1,14) = 0.002, MSE = 14.89, F2(1,12) = 0.003, MSE = 44.54. The interaction between category and deadline was non-significant, RT: F1(1,14) = 1.41, MSE = 189.32, F2(1,12) = 1.21, MSE = 94.75, accuracy: F1(1,14) = 0.41, MSE = 2.70, F2(1,12) = 0.44, MSE = 22.88. The 3-way interaction was also non-significant, RT: F1(1,14) = 0.16, MSE = 494.67, F2(1,12) = 0.34, MSE = 94.75, accuracy: F1(1,14) = 0.71, MSE = 10.6, F2(1,12) = 1.23, MSE = 22.88.

(Figures 2 and 3 about here)

Non-matching Trials

The effect of the deadline was also evident in non-matching trials. Again, RTs were faster, but accuracy was poorer for the short deadline task (Figures 4 and 5), RT: F1(1,14) = 118.39, MSE = 2208.37, $p < 0.001$, F2(1,12) = 292.20, MSE = 240.93, $p < 0.001$, accuracy: F1(1,14) = 125.72, MSE = 1.32, $p < 0.001$, F2(1,12) = 82.72, MSE = 7.51, $p < 0.001$.

Non-matching trials also showed a strong effect of similarity, but no effect of category. All main effects of similarity were significant, RT: F1(1,14) = 25.44, MSE = 432.64, $p < 0.001$, F2(1,12) = 33.54, MSE = 113.65, $p < 0.001$, accuracy: F1(1,14) = 23.68, MSE = 5.33, $p < 0.001$, F2(1,12) = 13.67, MSE = 34.59, $p < 0.003$. Performance was faster and more accurate for dissimilar images. There was a significant interaction between deadline and similarity on RT, F1(1,14) = 13.73, MSE = 450.77, $p < 0.002$, F2(1,12) = 9.76, MSE = 240.93, $p < 0.01$, but not on accuracy, F1(1,14) = 0.52, MSE = 3.63, F2(1,12) = 0.94, MSE = 7.51. As before, RT differences between conditions were reduced for the short deadline but accuracy differences remained (Figures 4 and 5).

No effects of category were significant, RT: F1(1,14) = 0.05, MSE = 746.67, F2(1,12) = 0.36, MSE = 113.65, accuracy: F1(1,14) = 0.51, MSE = 1.97, F2(1,12) = 0.11, MSE = 34.59. The trend towards an advantage for living things that was observed for matching trials was not present in the non-matching data. There was no significant interaction between category and deadline, RT: F1(1,14) = 0.02, MSE = 738.21, F2(1,12) = 0.03, MSE = 240.93, accuracy: F1(1,14) = 0.14, MSE = 1.46, F2(1,12) = 0.10, MSE = 7.51.

The interaction between category and similarity approached significance in RT for non-matching trials by image, F2(1,12) = 4.49, MSE = 113.65 ($p = 0.06$). This interaction was non-significant in all other analyses, RT: F1(1,14) = 2.11, MSE = 1833.93, accuracy: F1(1,14) = 0.11, MSE = 3.69, F2(1,12) = 0.04, MSE = 34.59. As shown in Figures 4 and 5, the disadvantage for the similar images was greater for the animals than vehicles. As we discussed in the Introduction, real living things have been shown to be more similar to one another than non-living things. If a specialised subsystem for processing of living things existed, one would expect it to afford greater sensitivity in distinguishing between highly similar items. However, this effect goes in the opposite direction.

There was no 3 way interaction, RT: F1(1,14) = 0.07, MSE = 1956.01, F2(1,12) = 0.03, MSE = 240.93, accuracy: F1(1,14) = 0.02, MSE = 3.86, F2(1,12) = 0.04, MSE = 7.51.

(Figures 4 and 5 about here)

Visual Complexity

The results from Pre-test 1 indicated that visual complexity was not matched across conditions. Vehicles were rated as less complex than animals. If vehicles were processed more efficiently because they were less complex, but animals were processed more efficiently because they engaged a specialised system, visual complexity could be masking an advantage for animals that would otherwise be apparent. In order to assess the influence of visual complexity on our results, an ANCOVA (analysis of co-variance) was conducted on the data by image. Category and similarity were between-item factors, deadline was a within-item factor and visual complexity (using ratings from Pre-test 1) was a covariate. The pattern of results obtained from the ANCOVA was the same as reported above. No main effects or interactions involving category were pushed closer to significance. In fact, the interaction between category and similarity on RT for non-matching trials by image was non-significant, F2(1,12) = 2.20, MSE = 123.32. The status of all other effects was the same.

Discussion

If category specific subsystems exist, category effects should be observable in normal processing over and above the influence of confounding factors such as similarity and familiarity. Although familiarity is routinely controlled, previous studies have failed to isolate the relative influences of similarity and semantic category on naming performance. We manipulated similarity and category independently by using a set of novel animals and vehicles as stimuli.

Category

We found little evidence that category was important but strong effects of structural similarity. Similarity had a significant effect on learning and on name verification, in both RT and accuracy, for matching and non-matching trials. Out of all analyses, we only found one set of results where category appeared to have any influence. Animals showed a trend toward slightly higher accuracy in matching trials with a long deadline.

As expected, the short deadline decreased RTs and increased error rates. Putting participants under increased pressure, however, did not exaggerate differences that were apparent at the longer deadline. In particular, effects of category did not emerge when faster processing or a quicker decision was required.

Our learning and name verification paradigms obviously do not exhaustively test the advantages that a specialised system might offer. However, we have shown that the images were not just treated as visual patterns, and that participants made inferences that clearly indicated contact with semantics appropriate to their intended categories. In addition, the tasks cover a range of processing—including object recognition, storing new exemplars, associating objects with names, and retrieving name and object information from memory—that constitutes a considerable sample of what might have been expected to reveal the impact of evolutionarily important advantages. Therefore, these results are inconsistent with a specialised semantic system than confers an evolutionarily important behavioural advantage to the processing of animals. We concede that these results are not problematic for a theory in which specialised subsystems have no functional consequence. However, semantic specialisation is defined in functional terms (i.e. the animal/artefact distinction is not an anatomical distinction). An account that invokes functionally defined differences with no functional consequence for normal processing (i.e. brain damage reveals organisational structure that must be described functionally, but has no impact on the undamaged brain) would create a very general problem for neuropsychological reasoning. Although these results are preliminary, in the sense that they set the scene for a search for category effects using a range of tasks and stimuli, they are also most consistent with a structured unitary semantic system rather than one that makes a fundamental distinction between living and non-living categories.

Similarity

The idea that similarity exerts a different influence in the category of animals and artefacts has taken various forms in the literature (e.g. Sacchett & Humphreys, 1992; Sartori, Miozzo & Job, 1993; Tyler et. al 2000, Tyler & Moss, 2003), but the variations all have an underlying theme. Categories of animals have a basic body plan that is essentially the same. Therefore, distinctions among types of animals within broad groupings (e.g. mammals, birds) are based on variations in size or surface features that are subordinate to the similarity of the overall structural description. Furthermore, features that distinguish one animal from its neighbours are often uncorrelated with the functional information we have about the animal (e.g. has eyes : sees; chicken : lays eggs). Conversely, artefacts do not share a common form, but there is a strong connection between structure and function (e.g. the tools *screwdriver*, *hammer* and *saw* have different shapes, but there is a connection between their differently shaped parts—blades, heads, handles—and their function).

Animals may be more difficult for patients to identify because there is competition among similar exemplars (Sacchett & Humphreys, 1992). This competition may arise either because distinctive information is represented at a level lower in the hierarchy used for object representation that is more susceptible to damage (Sartori et al., 1993; based on Marr, 1982), or because distinctive features are not supported by form/function relationships (Tyler et al., 2000). Nevertheless, all accounts agree that information about the basic form of the object is stronger and/or better preserved because it is held in common across animals, while identifying features are weaker because they are distinctive and/or not supported by links to function. Our results make it clear that identification is slower and more difficult for items with distinctive features imposed on a common overall structure than items with a distinctive overall structure. Crucially, we found that animals and artifacts were affected equally by this structural difference.

Implications for Neuropsychology

The clear role for similarity in our results from normals has consequences for the neuropsychology literature. In fact, there are neuropsychological studies in which similarity appears to play a role in category-specific effects (e.g. Arguin, Bub & Dudek, 1996; Dixon, Bub & Arguin, 1998; Forde, Francis, Riddoch, Rumiati & Humphreys, 1997; Humphreys et al., 1998; Moss et al., 1998). However, we do not suggest that structural similarity could explain all cases of patients who show selective differences between categories. There are cases where similarity does not provide an alternative explanation (Caramazza & Shelton, 1998; Funnell & de Mornay-Davies, 1996; Turnbull & Laws, 2000). For example, Caramazza and Shelton’s patient was impaired at recognising animal sounds in addition to pictures, and her deficit affecting knowledge of living things was evident in verbal knowledge that did not tap structural descriptions. Selective deficits for nonliving things (Hillis & Caramazza, 1991; Sacchett & Humphreys, 1992; Warrington & McCarthy, 1983, 1987) are also inconsistent with similarity-based explanations (assuming living things are more structurally similar; for an opposing view, see Turnbull & Laws, 2000).

Nevertheless, our results add to the evidence that structural similarity can cause processing differences between animals and man-made objects. Since similarity has such a strong effect on normal naming, it will inevitably influence the performance of *some* patients, and must, therefore, be controlled in studies that attempt to rule out non-semantic sources of animal/artefact differences. We noted in the Introduction that the frequency of neuropsychological cases showing genuine selective deficits was one factor that distinguished unitary and subsystem accounts. If controlling for similarity reduces the number of selective deficits originating in semantics, the weight of evidence supporting a subsystems account will be reduced accordingly.

Ultimately, the problem that the neuropsychological literature presents is not only to do with stimulus control or procedure, but a lack of theoretical commitment regarding semantics. Without further theorising about how specialised and/or generic semantic systems function, and without hypotheses detailing how the principles that govern the systems are different, alternative accounts will remain difficult to evaluate, and the consequences of adopting a specialised or unitary hypothesis will remain obscure.

However, research in related fields may be useful to neuropsychologists. We have borrowed a paradigm from the literature devoted to categorisation and category learning (see Murphy, 2002, for a summary). This literature is characterised by formally specified mathematical models, which might be used to help explore the category dimensions that patient errors reveal.

Likewise, linguists and psycholinguists developing accounts of the relationship between semantic and lexical or syntactic knowledge have proposed that a relatively small number of distinctions are at the heart of the combinatorial system that produces the richness of human conceptual structure. For example, Jackendoff (1990) defines a small set of major ontological categories (thing, event, state, action, place, path, property and amount). Pustejovsky (1991) defines a small number of event types (initial, internal, final) and rules of event composition that underlie word structure. Miller and Fellbaum (1991) specify a limited number of categories (26) that are the basis for the hierarchy of noun concepts. These kinds of distinctions should influence semantic processing and the distribution of errors that arise after brain damage, and they give an independently motivated starting point for exploring patterns of deficits.

We have reported that learning and name verification with novel objects failed to provide clear support for category-specific semantic organisation, but revealed a strong influence of structural similarity. We have noted that neuropsychological dissociations are not proof of semantic specialisation. Although it is a plausible hypothesis, the evidence for specialised semantic subsystems limited to the domains *animal, plant* and *other* remains weak. Our results demonstrate that structural similarity is an important factor in the processes involved in object learning, recognition and naming, and must be controlled in patient studies. We remain optimistic about the contribution of neuropsychology to the understanding of semantic structure, if it makes use of the theoretical development offered by other domains, and examines the patterns of neuropsychological deficits more fully, in the context of more explicit claims about semantic representation.

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Appendix A

Pre-test 2. Frequencies of Nearest Neighbour Responses

AD1: Fly (4), Ant (3), Bee (2), Bug (1).

AD2: Fish (8), Aquatic animal (1), Crab (1).

AD3: Bear (8), Dog/cat (1), Teddy bear (1).

AD4: Dinosaur (4), Dragon (3), Flying mammal (1), Loch-ness monster (1), Bird (1).

AS1-4: Lizard (5), Worm (2), Centipede (1), Snake (1).

VD1: Tractor (5), Lorry (1), Bulldozer (1), Truck (1), Building-work-vehicle (1), Farm-machine (1).

VD2: Boat (8), Land boat (2).

VD3: Tank (5), Car (3), Pod (1), Cake-on-wheels (1).

VD4: Train (5), Rocket (2), Rocket-missile (1), Tanker (1), Tank (1).

VS1-4: Plane (8), Spaceship (1), Kite (1).

Appendix B

Names for Images

Group 1	Group 2	Group 3	Group 4
Bruka	Shoni	Dronu	Flipi
Zidle	Kimba	Vulsa	Jutle
Denil	Pukid	Fulag	Gigip
Trolb	Glond	Chask	Skung

Table 1

Pre-test 1. Mean similarity, familiarity and visual complexity ratings and category membership classifications (Standard deviations, S.D.s, in parentheses)

	Similarity (/5)	*Familiarity (/5)*	*Visual complexity (/5)*	*Category Membership classifications (% correct)*
Dissimilar Animals	2.07 (.45)	3.05 (.98)	3.17 (.75)	97
Similar Animals	4.26 (.56)	3.23 (1.27)	3.62 (.68)	98
Dissimilar Vehicles	1.95 (.66)	3.08 (.81)	3.35 (.99)	98
Similar Vehicles	4.21 (.48)	3.23 (.92)	2.73 (.62)	95

Table 2

Pre-test 3. Judges scoring of responses to novel animals and vehicles.

Response appropriate for:	*Total scores for responses to Animals (%)*	*Total scores for responses to Vehicles (%)*
animal	**97**	2
either	3	3
vehicle	.2	**94**
neither	.1	1

Table 3

Mean Accuracy in the Training Session (S.D.s in parentheses)

Condition	Mean % correct
Dissimilar Animals	87.43 (5.94)
Similar Animals	75.55 (13.15)
Dissimilar Vehicles	83.50 (6.91)
Similar Vehicles	72.98 (11.40)

Figure Captions

Figure 1. Dissimilar and similar novel animals and vehicles (labelled AD1 to VS4).

Figure 2. Name-verification accuracy for matching trials (95% confidence intervals as described by Loftus & Masson, 1994).

Figure 3. Name verification RT for matching trials (95% confidence intervals as described by Loftus & Masson, 1994).

Figure 4. Name verification accuracy for non-matching trials (95% confidence intervals as described by Loftus & Masson, 1994).

Figure 5. Name verification RT for non-matching trials (95% confidence intervals as described by Loftus & Masson, 1994).

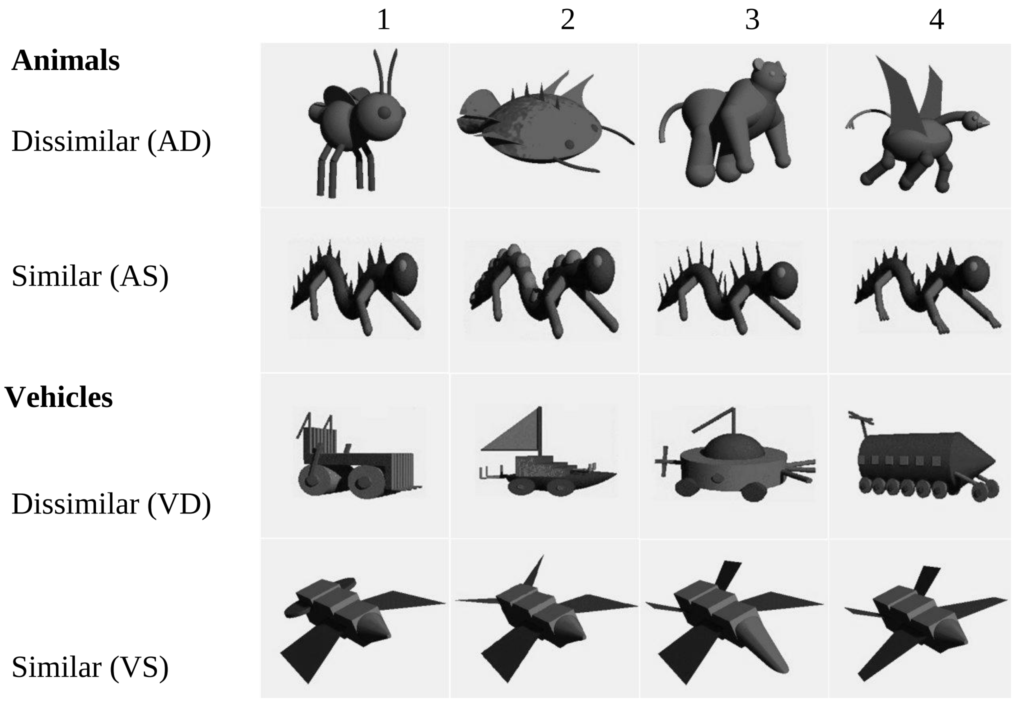
1
2
3
4
Animals
Dissimilar (AD)
Similar (AS)
Vehicles
Dissimilar (VD)
Similar (VS)

Figure 1

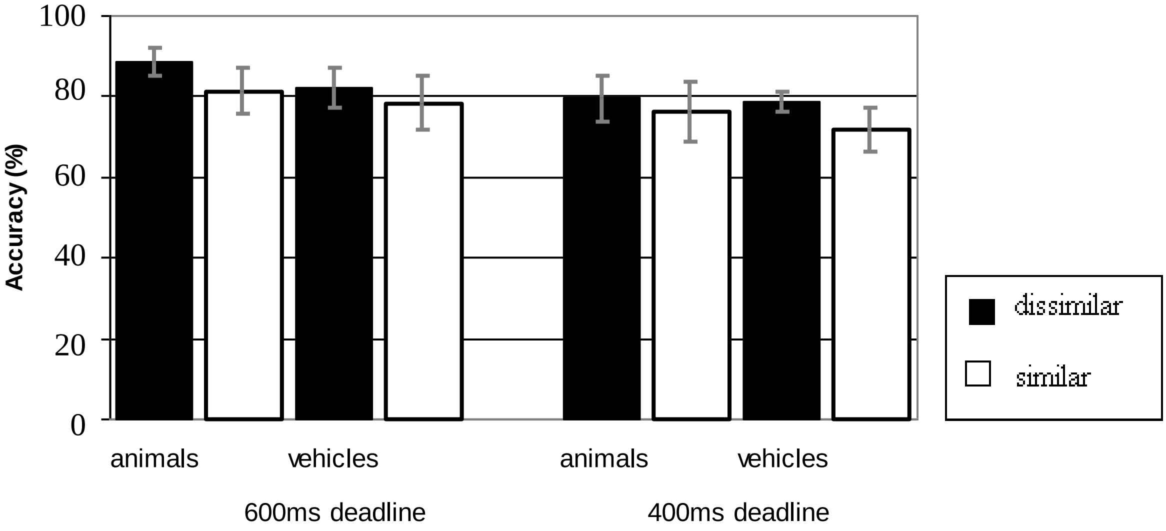
100
80
60
40
20
0
Accuracy (%)
animals
vehicles
animals
vehicles
600ms deadline
400ms deadline
dissimilar
similar

Figure 2

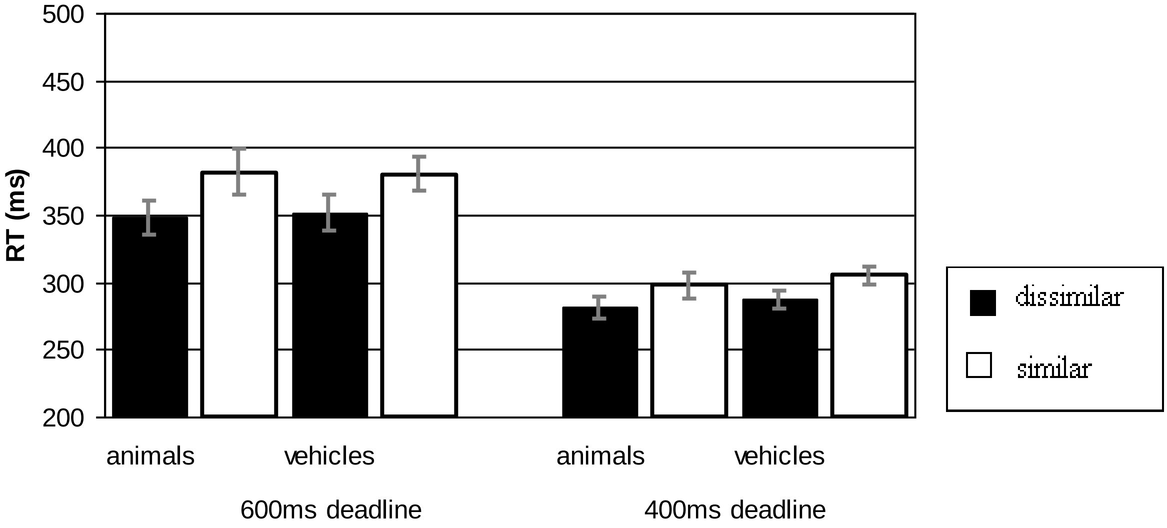
500
450
400
350
300
250
200
RT (ms)
animals
vehicles
animals
vehicles
600ms deadline
400ms deadline
dissimilar
similar

Figure 3

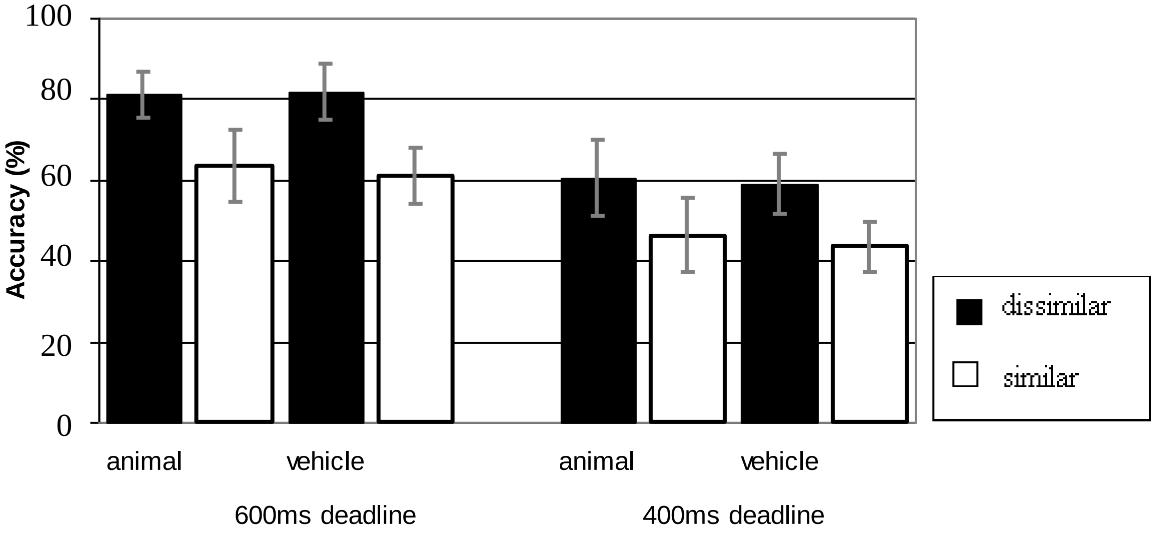
100
80
60
40
20
0
Accuracy (%)
animal
vehicle
animal
vehicle
600ms deadline
400ms deadline
dissimilar
similar

Figure 4

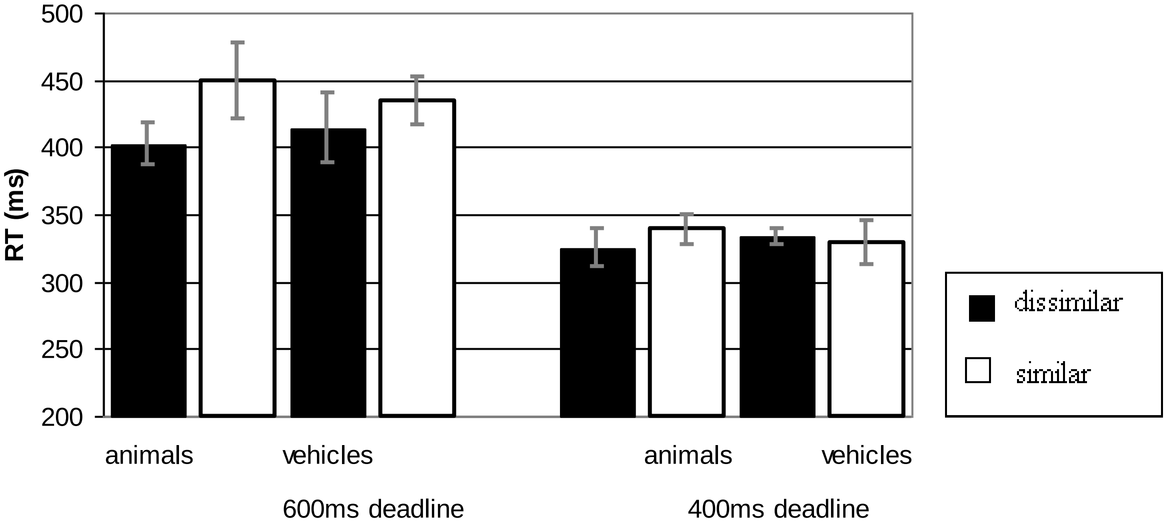
500
450
400
350
300
250
200
RT (ms)
animals
vehicles
animals
vehicles
600ms deadline
400ms deadline
dissimilar
similar

Figure 5