VISUAL CATEGORIZATION: THE NATURE OF CATEGORY TEMPLATES

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Declaration

I hereby declare that the matter embodied in the thesis entitled **'Visual categorization: The nature of category templates'** are the results of the investigations carried out by me at the Biology Division, IISER Pune under the supervision of Dr. S. P. Arun, Assistant Professor, Centre for Neuroscience, Indian Institute of Science, Bangalore and the same has not been submitted elsewhere for any other degree.

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Abstract:

Visual categorization is a cognitive process by which humans effortlessly and accurately identify objects that belong to a category. Conceptually, it is believed that single categorization tasks involve the use of one category template pertaining to the task (for example, animal template). The category template is a coarse shape representation of category members (like animals), and reliable match to template enables rapid categorization performance. In this study, we investigate two questions pertinent to the nature of templates underlying visual categorization. The first question concerns the features involved in categorization. In classic categorization studies, is the category template orientation dependent? Does it involve internal details or does it store contour information? We investigated this by measuring human categorization performance in an animal detection paradigm by using inverted objects and object silhouettes. We report that while categorization performance decreases on inversion, the presence of contour information is sufficient to perform categorization. The second question relates to the processing of multiple categories by humans. In a multiple category task, are two templates activated or just one? To test the presence and use of more than one classifier, we conducted three categorization tasks on human subjects – 1) animal/non-animal categorization, 2) vehicle/non-vehicle categorization, and 3) animal/vehicle categorization. We hypothesized that subjects would employ single classifiers in the single categorization tasks, and use both animal and vehicle classifiers in the animal/vehicle categorization task. We provide evidence that humans indeed activate two classifiers in the dual categorization task; even though they could have performed equally well by activating one. Thus, this contributes towards understanding the representation of features and multiple categories in a fundamental task, like visual categorization.

List of Figures

Figure No.	Caption
1	Natural image set for inverted and silhouette categorization
2	Silhouette image set for inverted and silhouette categorization
3	Comparisons between inverted and upright categorization
4	Reaction time comparisons between inverted and upright categorization
5	Comparisons between natural and silhouette categorization
6	Reaction time comparisons between natural and silhouette categorization
7	Correlations of reaction times in dual categorization task with single categorization tasks for all subjects
8	Correlations of reaction times in dual categorization task with single categorization tasks for the common images
9	Typicality effects in the three categorization tasks
10	Visual search similarity relations account for animal/non-animal categorization data
11	Visual search similarity relations account for vehicle/non-vehicle categorization data
12	Visual search similarity relations account for animal/vehicle categorization data
13	Visual search similarity relations explain dual categorization tasks: Model 1
14	Visual search similarity relations explain dual categorization tasks: Model 2

List of Tables

Table No.	Caption
1	Typicality effects in inverted and silhouette categorization
2	Summary of the different subject groups who performed the three categorization tasks, differing either in experiment order or in key press assignments.
3	Summary of categorization time predictions using different visual search models for animal/non-animal categorization using visual search data
4	Summary of categorization time predictions using different visual search models for vehicle/non-vehicle categorization using visual search data
5	Summary of categorization time predictions using different visual search models for animal/vehicle categorization using visual search data

Acknowledgements

INTRODUCTION

Visual categorization is the process by which the brain assigns objects to be equivalent on the basis of feature similarities. The ability to detect, recognize, identify and respond to the variety of objects in a matter of a few milliseconds is simply remarkable. This turns out to be an impressively difficult problem which biological visual systems have been solving efficiently. There is vast literature in visual categorization over the past few decades.

What is known about visual categorization? In general, numerous studies have assessed the importance of various features and the role of image statistics in contributing towards categorization performance. Towards this end, experimenters have removed or added visual features, modified local and global image statistics (for example, manipulate relative contrast, luminance, etc.), and manipulated category structure. For instance, categorization ability is not compromised by removal of colour (Delorme, Richard and Fabre-Thorpe 2000), or by drastic reduction in contrast (Mace, Thorpe and Fabre-Thorpe 2005). Categorization has been shown to be insensitive to in-plane rotations (Guyonneau, Kirchner and Thorpe 2006) and loss of internal detail, as in the case of outlines or line drawings (Wagemans, et al. 2008). Blurring objects to a specific spatial frequency (dependent on the category) also results in performance comparable to classical categorization tasks (Nandakumar and Malik 2009). A large number of experiments have analyzed the time course of categorization – whether detection, categorization, and recognition follow a hierarchy (Grill-Spector and Kanwisher 2005; Bowers, et al. 2008). However, no clear answer has emerged from these studies. Previous research has also examined the necessity of attention for categorization, and have shown that subjects can categorize even two objects when displayed peripherally while doing a centrally attention demanding task (Li, et al. 2002).

Studies have shown that categorization difficulty varies systematically when the composition of non-category members is varied (Mace, Joubert, et al. 2009). In fact, classic categorization studies have reported a robust typicality effect in many categories (Jolicoeur, et al. 1984; Rosch, et al. 1976). It is known that people usually take longer to categorize and recognize objects that are atypical compared to objects that are represent a category. This fits with the idea that the underlying category

template is based on the best or average category members. Given that atypical objects are visually dissimilar compared to the best example of a category, the atypical object-to-template match would not be perfect, and hence they take longer times to be categorized. For example, birds and fishes take longer times to be categorized as animals, as compared to lions or dogs. Further, atypical objects are atypical only within a context. Birds are atypical within the context of animals, and not atypical within the context of flying objects.

While some aspects of visual categorization have been studied, features that the brain uses while categorizing objects still remain unknown. Do the features pertain to overall image statistics that differ across categories or the presence of a certain diagnostic feature is sufficient to group objects into a category? What are the features underlying categorization. One way to study the underlying features is to modify natural images and assess categorization performance. An interesting manipulation is inversion. How does inversion of objects affect categorization? Many studies have used inversion as a method by which local image statistics are preserved but global processing is negatively affected (New, et al. 2007). Inversion has been extensively used in studying faces to infer the contribution of configural processing in face categorization (Maurer, et al. 2002; Yin 1969). Inversion will let us tap into the extent of orientation dependence in category templates. Another less-studied manipulation is converting objects into silhouettes. What happens to object categorization when they are silhouettes? Few studies have used outlines and boundaries to examine its role and importance in identifying various objects and performed an image-wise analysis to identify which image properties aid and hamper silhouette processing (Wagemans, et al. 2008; Torfs, et al. 2010). If categorization is orientation dependent for some objects, examining response to silhouettes of these objects would tell us if the orientation dependence is on features in the contour or in the internal features.

In addition to understanding features relevant for a category, it is interesting to understand how different categories processed simultaneously? Classic studies in categorization have used two kinds of categorization tasks interchangeably – single tasks where subjects distinguish between category members and non-category members (for example, animals vs. non-animals) (Joubert, et al. 2009; Wichmann, et al. 2010), and dual tasks where subjects distinguish between one category vs.

another category (for example, animals vs. vehicles) (Bowers, et al. 2008; Mace, Joubert, et al. 2009). Are the two tasks fundamentally different? If one category template is believed to underlie the processing of single categorization tasks, are two independent categories active during dual categorization tasks? While studies have addressed the presence of multiple category correlates in neuronal studies (Roy, et al. 2010; Rousselet, et al. 2002) and neuroimaging studies (Peelen, et al. 2009), the evidence from behaviour is not conclusive. Many studies have conducted categorization experiments using two alternative forced-choice designs (AFC). A fair number of studies have also used 4-AFC, and 10-AFC (Grill-Spector and Kanwisher 2005) and have not found significant differences in performance. Psychophysical studies (Evans, et al. 2011; VanRullen and Thorpe 2001) suggest the presence and activation of multiple categories, but the experiment design confounds the conclusion.

What can we deem as evidence of classifiers operating in parallel? A study by Evans et al. (Evans, et al. 2011) has shown that reporting presence or absence of multiple categories in a stream of images when subjects are cued before and after image display implies that observers can monitor multiple categories simultaneously. However, in this paradigm, a) subjects still report the presence or absence of only one category and not multiple categories (for example, 'is it a bird?' as opposed to 'is it a bird, or a bus?'), b) when pre-cued with a category such as birds, subjects have to monitor the images only for birds. When post-cued with a category, subjects do not know what category to monitor and have to report if they observed one particular category or not. In case they observed the category, they would have set up the classifier for that category and hence, respond correctly. However, if they set up some other classifier, they would not know if an object belonging to the post-cue condition was present, and hence, respond incorrectly. Thus, subjects could have performed both conditions (pre-cue and post-cue) using only one classifier. In this paradigm, pre-cuing subjects to a particular category (for example, dogs), followed by image display and then post-cuing subjects to a different category (for example, buses) without introducing a specific task would inform us if subjects maintain and utilize information about multiple categories simultaneously. While dual categorization tasks have been used to replace single categorization tasks, they have not been used to study if two classifiers are active in a dual task. Dual

categorization tasks can be used to understand the activation of multiple classifiers when compared with the single categorization tasks.

In this study, we investigate two questions relevant to categorization. The first question involves elucidating the features underlying the process of animal categorization. We considered two manipulations – orientation dependence of features, and the role of contour information during categorization. We conducted an animal categorization experiment involving natural upright objects. In addition, subjects also performed animal categorization on inverted objects and on silhouettes. We found that human performance on animals is compromised by inversion which suggests strong orientation dependence. On the other hand, human categorization performance is unaffected on object silhouettes. Thus, templates underlying categorization are orientation dependent and encode boundary information. The second goal of this study is to understand the processing of two categories in humans. Human subjects performed two, single, animal and vehicle categorization tasks, and one dual animal/vehicle categorization tasks. We present evidence to prove that humans activate and employ both animal and vehicle templates while performing the dual categorization task instead of using one template.

Experiment 1

In this experiment, we investigate the features that humans employ to perform animal categorization. It is thought that categorization involves the activation of a template or a classifier in a task-dependent manner. We study the importance of two features in the underlying category templates – orientation of features in the objects, and contour or boundary information, and their interaction in categorization. Subjects performed an animal vs. non-animal categorization task, in which each object was displayed in four different forms – upright, inverted, silhouette upright, and silhouette inverted.

Materials and Methods

Subjects:

6 subjects (between the ages of 20-30, with normal or corrected to normal vision) performed the animal categorization experiment. All subjects consented to participate in the experiments.

Experiment design:

All subjects were seated approximately 60 cm from a computer monitor that was controlled by customized Matlab (Mathworks, Natick, MA) programs written in Psychtoolbox (Brainard 1997). All subjects performed an animal categorization experiment. Subjects distinguished between animals and non-animals. In addition to natural, upright objects, subjects also categorized the same objects when they were inverted, upright silhouettes, and inverted silhouettes. Thus, every object could be seen either in the upright or inverted orientation, and could be either natural (with internal details visible, like texture, and features like eyes) or as a silhouette (no internal detail, only contour and shape information). All the different variants of the object were displayed within one block. We used one single task as opposed to a blocked design for each variant (inverted objects, silhouettes) to avoid ordering effects. The order in which the stimuli appeared was randomized.

Stimuli:

The animal categorization task consisted of 192 gray-scale images (48 images seen in 4 different versions). Among the 48 gray-scale images, 24 were animals and 24

were non-animals (Figure 1). Out of the 24 animals, 6 were atypical animals and 18 were typical animals. Out of the 24 non-animals, 12 were man-made and 12 were natural objects. These 48 images were then transformed to generate the three other variants.

The 48 images were transformed into silhouettes by replacing all non-zero pixels with intensity corresponding to white (Figure 2). Thus, overall shape information and external boundary were preserved in the silhouette images. We then generated the 180 degree-inverted versions of the natural and silhouette images using image processing software. Thus, in total, there were 192 images – 48 upright, natural images, 48 inverted, natural images, 48 upright silhouettes, and 48 inverted silhouettes.

All images were segmented from their original scene and displayed in a black background. All images were selected to have a profile view (head of animals pointed towards the left side). All images were equalized for luminance (including silhouettes) and were rescaled such that the longer dimension was 175 pixels. All images were presented at a size corresponding to 5.5 degrees of visual angle.
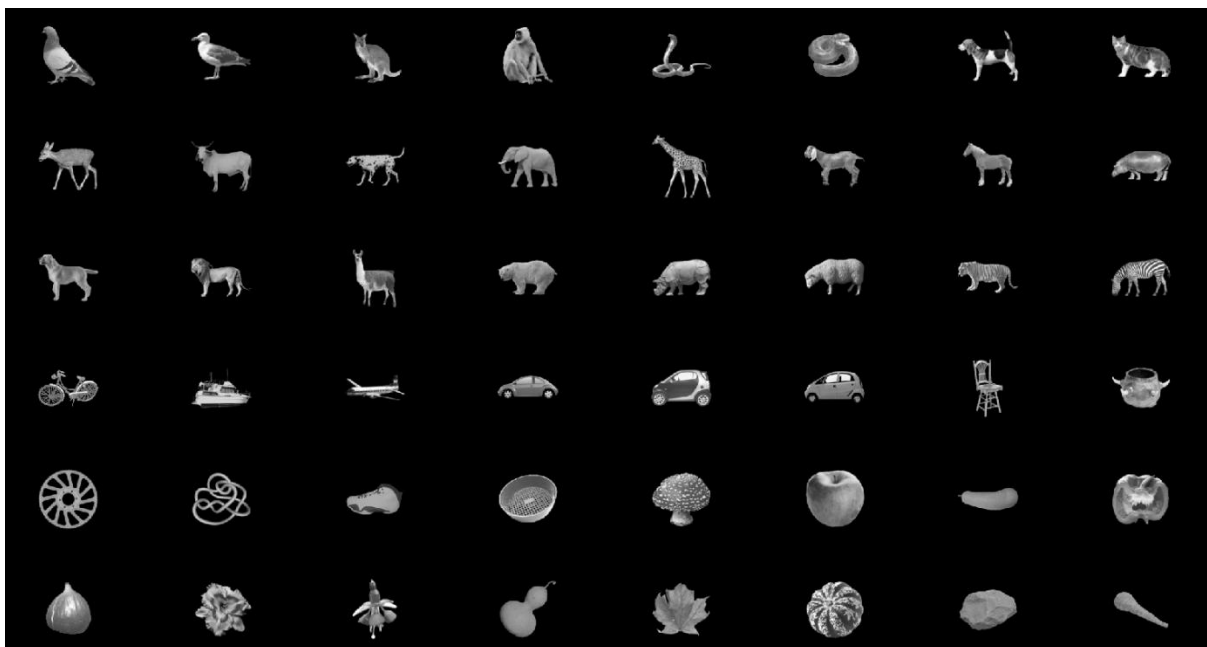

Figure 1: Natural image set for Experiment 1. Natural, upright objects – first three rows are animals, last three rows are non-animals
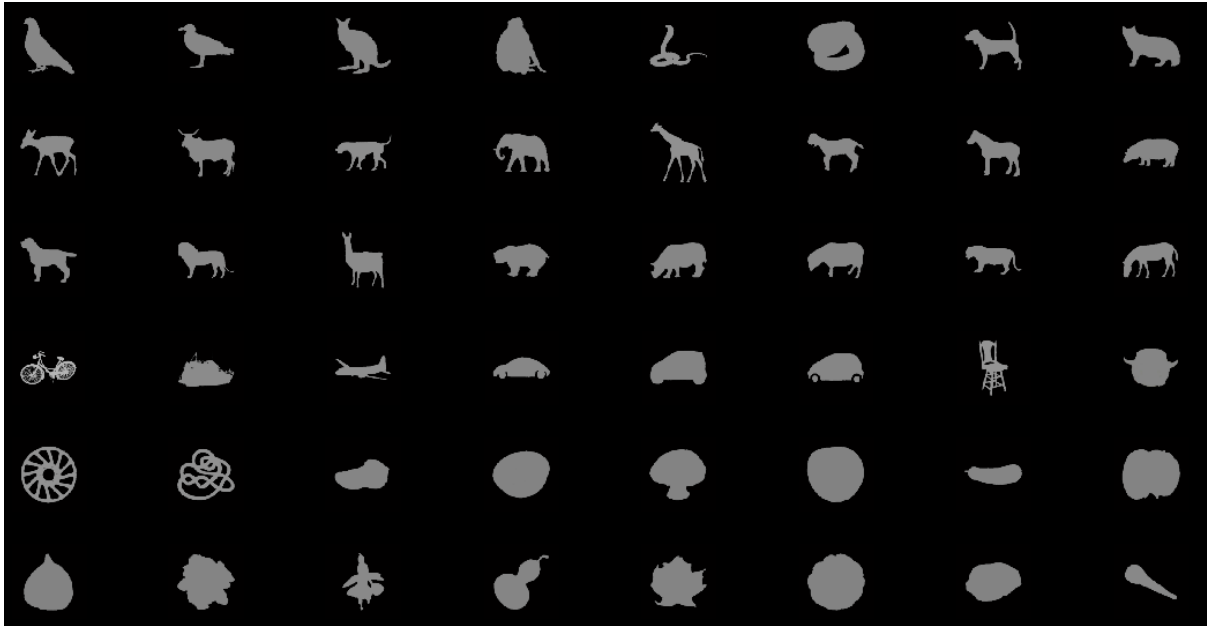
Figure 2: Silhouette image set for Experiment 1. Silhouette, upright objects – first three rows are animals, last three rows are non-animals.

Categorization task:

Each categorization task started with a practice trial in which subjects performed an animal categorization task, in which animals and non-animals (not overlapping with the image set) were displayed in all the four variations. This was followed by a snapshot of all the images that subjects were to categorize subsequently, to avoid confusion regarding object identity. Each trial began with a 750 ms fixation cross, followed by the test object displayed for 50 ms, followed by a noise mask for 250 ms. Subjects were instructed to press the "B" key to indicate that the object belonged to the animal category, and press the "Z" key to indicate that the object was not an animal. Subjects were instructed to respond correctly within 2 seconds following image display, failing which, the same image would be repeated after a fixed number of trials. The next trial started 500 ms after the subject's response. Each image was repeated 8 times within the task.

Statistical analyses:

We performed data analysis in MATLAB version 7.12.0. We compared reaction times in different conditions using ANOVA and correlation analyses.

Results

We present data from 6 subjects who performed one animal categorization task, with objects that appeared in 4 different variations – upright or inverted, natural or silhouette.

Are subjects consistent in the animal categorization task?

Subjects were highly consistent in the animal/non-animal categorization task, as indicated by the correlation in reaction times between two independent groups of subjects (r = 0.63 (p = 10^{-16}) across 48 objects in both tasks). To confirm that the correlations were significant even in the different variants of the images, we computed the correlations for all subsets of images. Subjects were highly consistent even in the individual image sets, as evidenced by the correlation in average reaction times between two independent groups of subjects (r = 0.64 (p = 10^{-5}) for natural, upright images, r = 0.59, (p = 10^{-4}) for natural inverted images, r = 0.70, (p = 10^{-6}) for upright silhouettes, and r = 0.58, (p = 10^{-3}) for inverted silhouettes. Thus, subjects seem to have used similar strategies for all the different variations in images. The consistency for inverted objects is smaller than that for upright objects, for both, natural objects and silhouettes. This could be, in part because both inverted objects and object silhouettes do not resemble upright animals, and hence, subjects may have found the task ambiguous.

Does inversion influence categorization performance?

Subjects performed the categorization of inverted objects similar to the categorization of upright objects, both for natural objects and silhouettes. We computed the correlation in average reaction times for all natural, upright objects and natural, inverted objects and found a high correlation (r = 0.78, p = 10^{-11}, Figure 3A). Similarly, we also found a high correlation between upright silhouettes and inverted silhouettes (r = 0.83, p = 10^{-13}, Figure 3B). Interestingly, the correlation in reaction times for upright and inverted animals (r = 0.6 (p=10^{-4}) for natural, r = 0.71 (p=10^{-5}) for silhouettes) is lesser than the correlation in reaction times for upright and inverted non-animals (r = 0.7 (p=10^{-4}) for natural, r = 0.75 (p=10^{-5} for silhouettes). This could be because non-animals are visually different as compared to animals or the variance within the category of non-animals is higher, and thus has high correlations.

[15]

3A   3B

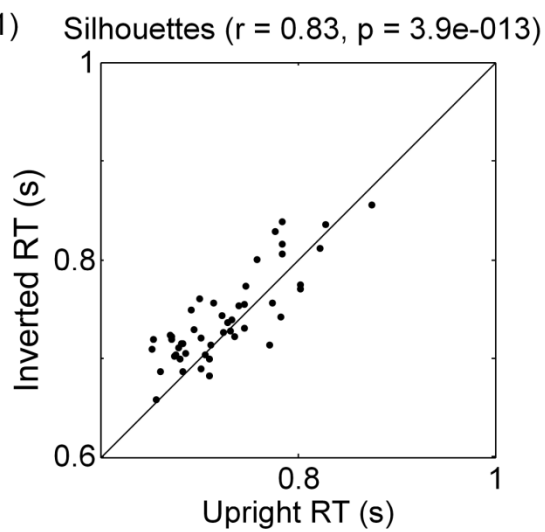Natural objects (r = 0.78, p = 7e-011)   Silhouettes (r = 0.83, p = 3.9e-013)
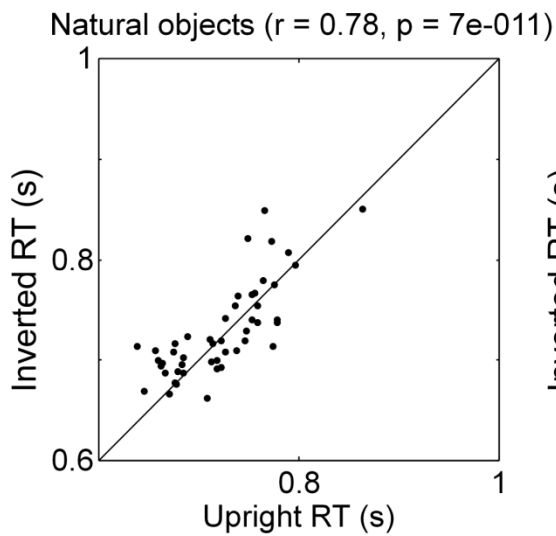
Figure 3: Comparisons between inverted and upright categorization. 3A: Correlation plot of upright vs. inverted reaction times for natural objects (r = correlation coefficient, p-value of significance); 3B: Correlation plot of reaction times for upright vs. inverted objects for silhouettes (r = correlation coefficient, p-value of significance).

Subjects took equally long times to categorize inverted objects and upright objects (730 ms for inverted, 722 ms for upright), as evidenced by a two-way ANOVA on all natural objects' reaction times with subject and condition (upright or inverted) as factors (p-value of inversion condition = 0.18). Could it be that some objects are affected by inversion, while some other are not? We tested this by doing the same analyses separately on animals and non-animals. On further analysis only on animals, we found that subjects indeed took longer to categorize inverted animals (704 ms), as compared to upright animals (685 ms), as indicated by a two-way ANOVA on animal reaction times (p-value of inversion condition = 10^{-3}, Figure 4A). A similar two-way ANOVA on non-animal reaction times of all subjects indicated that all subjects categorized upright and inverted non-animals similarly, with comparable reaction times (p-value of inversion condition = 0.65). Thus, we can conclude that categorization of natural animals is affected by inversion.

What about silhouettes of objects? Are they affected similarly by inversion? Subjects took longer times to categorize inverted silhouettes (741 ms) as compared to upright silhouettes (725 ms), as determined by an ANOVA on all silhouette reaction times

with subject and condition (upright/inverted) as factors (p-value of condition = 0.0092). To examine if this effect was solely because of animals or non-animals, we conducted the same analyses on animals and non-animal silhouettes separately. We found that subjects took longer to categorize inverted silhouettes of animals (716 ms) as compared to upright animal silhouettes (689 ms) (p-value of inversion condition = 10^{-5}, Figure 4B). In addition, subjects took equally long to categorize inverted silhouettes of non-animals and upright silhouettes of non-animals (p-value of inversion condition = 0.53) Thus, categorization performance of animal silhouettes is also affected by inversion.
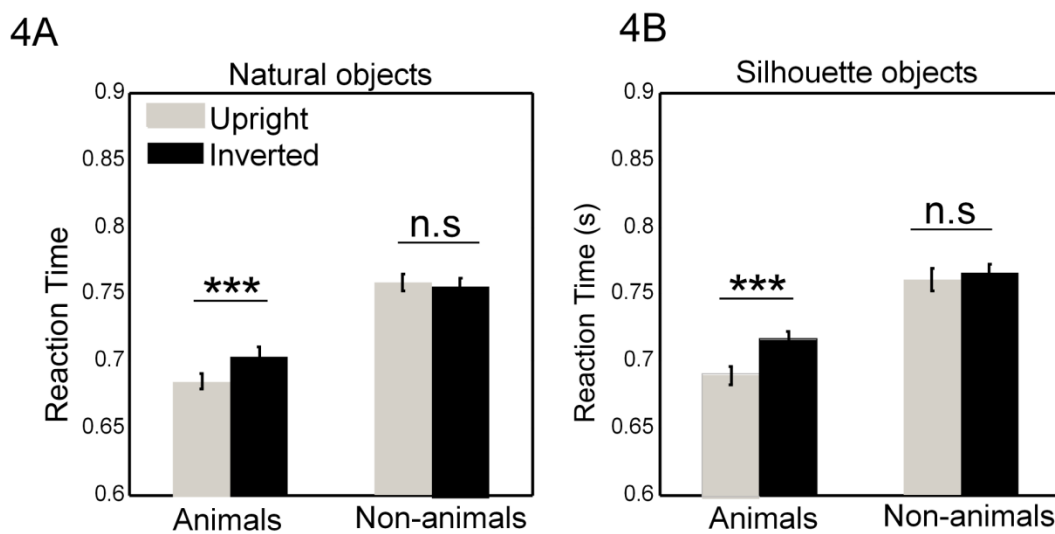

Figure 4: Reaction time comparisons between inverted and upright categorization. 4A: Comparison of reaction times for upright and inverted natural animals and non-animals; 4B: Comparison of reaction times for upright and inverted animal and non-animal silhouette objects. *** refers to p-value < 10^{-3}, and n.s refers to non-significant difference.

It is known that humans tend to take longer times to perform tasks in which they are required to be more accurate. Thus, differences in reaction times between conditions could just be because subjects were being more correct in trials where they took longer times, as opposed to arising because of the condition. To ensure that subjects did not take longer times to categorize inverted animals because they spent longer times trying to be accurate on inverted animals, we calculated the accuracies of subjects in categorizing upright vs. inverted objects, both in natural objects and in silhouettes. We found that the accuracies of subjects in categorizing upright

(96.48%) vs. inverted (96.36%) natural objects were comparable. Similarly, accuracies of subjects in categorizing upright (95.85%) and inverted silhouettes (95.62%) were also similar. Thus, subjects did not show a speed-accuracy trade-off while performing categorization. In general, we can conclude that inversion compromises human categorization performance on the category of animals. Thus, categorization of objects is dependent on the orientation of features present in the object

Is contour information sufficient for animal categorization?

Subjects performed the categorization of silhouettes similar to the categorization of natural objects, both for upright and inverted versions. We computed the correlation in average reaction times for all upright natural objects and silhouettes and found a high correlation (r = 0.78, p = 10^{-11}, Figure 5A). Similarly, we also found a high correlation between inverted natural objects and inverted silhouettes (r = 0.73, p = 10^{-9}, Figure 5B).
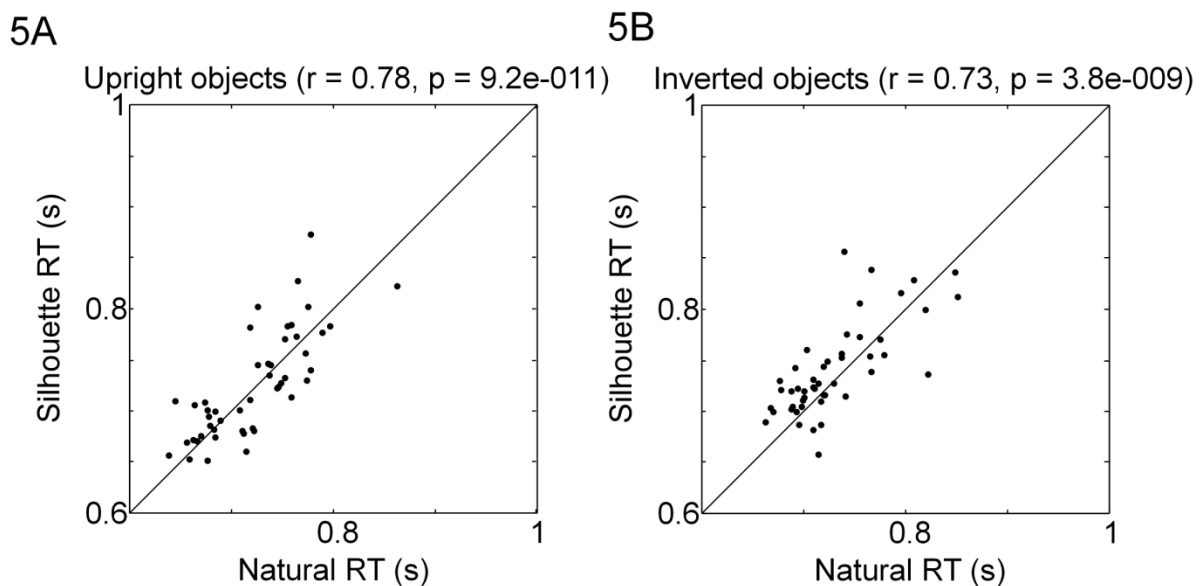

Figure 5: Comparisons between natural and silhouette categorization. 5A: Correlation plot of natural vs. silhouette reaction times for upright objects (r = correlation coefficient, p-value of significance); 5B: Correlation plot of reaction times for natural vs. silhouette objects for inverted objects (r = correlation coefficient, p-value of significance).

Subjects categorized all upright natural objects and silhouettes with similar reaction times (725 ms for silhouettes, 722 ms for natural objects), as evidenced by a two-way ANOVA on all natural objects' reaction times with subject and condition (natural or silhouette) as factors (p-value of silhouette condition = 0.56, Figure 6A). On further analysis conducted separately on animals and non-animals, we found that subjects took similar times to categorize silhouettes (690 ms), as compared to natural animals (685 ms), as indicated by a two-way ANOVA on animal reaction times (p-value of silhouette condition = 0.45). A similar two-way ANOVA on non-animal reaction times of all subjects indicated that subjects took equally long to categorize natural and silhouette non-animals (p-value of silhouette condition = 0.78). Thus, we can conclude that categorization performance is unaffected when objects are made into silhouettes.
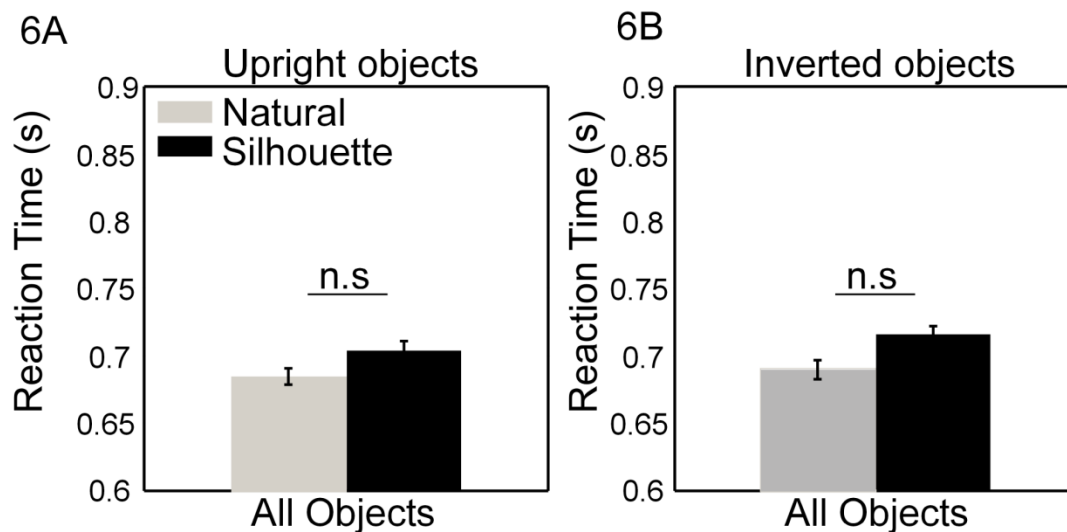
Figure 6: Reaction time comparisons between natural and silhouette categorization. 6A: Comparison of reaction times for upright natural and silhouette objects; 6B: Comparison of reaction times for inverted natural and silhouette objects. *** refers to p-value $< 10^{-3}$, and n.s refers to non-significant difference.

What about inverted objects? Are inverted silhouettes as easy to recognize as inverted natural objects? Subjects took marginally higher reaction times to categorize inverted silhouettes (741 ms) as compared to inverted natural objects (725 ms), as determined by an ANOVA on all silhouette reaction times with subject and condition (natural/silhouette) as factors (p-value of silhouette condition = 0.05, Figure 6B). To find the source of this effect, we conducted the same analyses on inverted animals

and non-animals separately. We found that subjects took slightly longer times to categorize inverted silhouettes of animals as compared to inverted natural animals as the effect is reaching significance (p-value of silhouette condition = 0.08). In addition, subjects categorized inverted silhouettes of non-animals with reaction times comparable to inverted natural non-animals (p-value of inversion condition = 0.20) Thus, categorization performance on inverted animal silhouettes is slightly decreased, but inverted non-animal silhouettes are categorized similar to inverted natural non-animals.

In general, we can conclude that removing internal details does not affect categorization performance. Thus, object silhouettes are identified as easily as the objects themselves and contour information is sufficient to perform categorization.

Feature interactions: orientation and contour information

We have analyzed the categorization performance on objects that differ in orientation and objects that have no internal detail. We proceeded to understand if one manipulation influenced the categorization on objects that differed in the other manipulation. In other words, if you invert objects, does it impact both natural objects and object silhouettes similarly? Does inversion affect natural objects or silhouettes more? To address this, we compared the difference between reaction times of natural upright and inverted objects with the difference between reaction times of upright and inverted silhouettes across all images, across subjects. We found that inversion affects natural objects and silhouettes equally, as determined by a two-way ANOVA on reaction time differences with subject, and condition (natural/silhouette) as factors (p-value of condition = 0.17). So, whether you are categorizing natural objects or silhouettes, inverting the object will decrease categorization performance equally. Could it be that the differences between the effects of inversion on natural objects and silhouettes is significantly different for some images as compared to others? To test this, we conducted a two-way ANOVA on reaction time differences between upright and inverted images for natural objects and silhouettes for every image, with subject and condition (natural/silhouette) as factors. We report that there was only one animal (giraffe) for which inversion affected the silhouette more than the natural object (p<0.05). Thus, inversion acts similarly on objects – independent of whether they are natural or objects silhouettes.

[20]

Then, what about making object silhouettes? If an object is a silhouette, does it affect the categorization of upright and inverted objects differently? In other words, does making silhouettes of objects impact upright and inverted similarly? To address this, we compared the difference in reaction times of upright natural and silhouette objects with the difference in reaction times of inverted natural and silhouette objects, across all images, across subjects. We found that making silhouettes of objects affects upright and inverted objects equally, as determined by a two-way ANOVA on reaction time differences with subject, and condition (upright/inverted) as factors (p-value of inversion = 0.21). So, whether you are categorizing upright or inverted objects, making silhouettes of objects will affect categorization performance equally. Could differences between the effects of making silhouettes on upright objects and inverted objects be significantly different only for particular images? We tested this by conducting a two-way ANOVA on reaction time differences between natural and silhouette images for upright and inverted objects, for every image, with subject and condition (upright/inverted) as factors. We report that there were 4 animals (snake, giraffe, sheep, tiger), and 2 non-animals (aeroplane, capsicum) for which making silhouettes decreased categorization performance for inverted objects more than upright objects ($p < 0.05$). While the overall trend suggest that making silhouettes of objects influences upright and inverted objects similarly, the presence of certain examples points to the fact that making silhouettes of inverted objects reduces categorization performance. Thus, making silhouettes of objects affects some inverted objects more than upright objects.

In sum, we can conclude that inverted natural objects are recognized using internal detail. If internal detail is lost, the additional loss of familiar shape contour decreased categorization times.

Does the typicality effect remain even after inversion and making silhouettes?

Subjects did not take longer to categorize atypical animals as compared to typical animals, as evidenced by an ANOVA on animal reaction with subject and typicality as a factor (p-value of typicality = 0.22). The time taken to categorize atypical animals was 695 ms, and that for typical animals was 682 ms. The effect could be because of less number of subjects, since we have reported typicality effects in the same image set (see Experiment 2), with a different group of subjects. We found a

significant typicality effect in all other variations - natural, inverted animals, upright silhouettes and inverted silhouettes. Subjects took significantly longer times to categorize atypical animals, as compared to typical animals, as determined by a two-way ANOVA with subject and typicality as factors. The reaction times and significance values are reported in Table 1.

Discussion

In this experiment, we studied the nature of the features underlying categorization. We investigated the performance in categorization tasks when objects were inverted, and when objects were made into silhouettes. Our results show that inversion leads to a significant decrease in categorization reaction times, only for animals. We also report that silhouettes of objects are categorized as easily as natural objects. Furthermore, we find that if an object is inverted, it is equally difficult to categorize the object whether it is natural or a silhouette. However, if an object is a silhouette, it is easier to identify the object when upright, than if it were inverted. In sum, category templates underlying categorization are orientation dependent, and store contour information which is informative enough to perform categorization.

Effect of inversion

We report that inversion affects animal categorization, but not non-animals. Why? We find that humans take longer times to categorize objects when inverted, and take equally long to categorize upright and inverted non-animals. We reason that, since humans are exposed to non-animals (mostly inanimate objects) in many different views, we may be adept at recognizing non-animals when they are inverted. However, we encounter animals mostly in the upright view, and hence we may take longer to categorize animals in an inverted view. Our normal visual experience would lead to a larger number of neurons tuned for upright animals than inverted animals. Alternatively, this effect could be because of structural differences between animal and non-animal images. This can be tested by studying categorization performance on non-animal objects that share the same structure as animals.

The longer times taken to categorize inverted animals can be attributed to a smaller population of neurons tuned for inverted features. This would result in a weaker activation of neurons, when compared with activation for upright objects (Perrett,

Oram and Ashbridge 1998). Studies have postulated mental rotation mechanisms to account for the longer reaction times in inverted objects (Tarr and Pinker 1989). If mental rotation were in place, we would expect all objects to be affected by the same amount, in terms of reaction times, or neuronal firing rate. The mental rotation hypothesis cannot account for the variance in the difference in reaction times for upright and inverted objects.

Effect on silhouettes

Our results show that humans can categorize object silhouettes as easily as they can classify natural objects. At the level of upright, animal categorization, internal details are not necessary. The overall shape and contour information is sufficient to make category judgments. Internal details play a role when overall shape is not informative. We see some evidence of this in the interaction effects.

Interactions between inversion and contour information

We find that inversion of objects influences natural and silhouette objects equally. However, when an object is converted to a silhouette, categorization of inverted objects is impacted more than upright objects. Here, we observe a clear order dependence of the manipulation – inversion or retaining only contour information. If a natural object is inverted, categorization becomes harder. If internal detail is removed from the inverted object, it becomes an inverted silhouette – in which case neither is the contour information familiar, nor is the orientation preserved. Thus, inverted silhouettes lose both features – orientation and familiarity of contour shape, which lead to highest decrease in reaction time. This order dependence informs us that inversion is more dominant, as it affects categorization more than the loss of internal detail.

Comparison with other studies on inversion and contour information

Our result that categorization is sensitive to inversion is in accordance with psychophysical studies that compared upright and inverted, rapid, animal categorization (Rousselet, Mace and Fabre-Thorpe 2003) and studies which show that objects rotated within the plane are harder to recognize in brief exposures (Lawson and Jolicoeur 2003). Another study that corroborates our result showed that inversion leads to lower accuracies and reaction times in categorization, but

detection remains unhindered (Mack, et al. 2008). A recent experiment used continuous flash suppression to show that inverted objects required longer times to be detected (Stein, Sterzer and Peelen 2012). A number of studies have reported the effect of inversion on face recognition. Neuroimaging studies have used upright and inverted faces and identified an early component (M100) as being sensitive to stimulus inversion (Meeren, et al. 2008; Itier, et al. 2006).

Some psychophysical studies have also reported no significant differences between reaction times for upright and inverted objects (Guyonneau, et al. 2006; New, et al. 2007). The study by New et al. report the abolition of the 'animacy' effect when stimuli are inverted, i.e. animals are categorized faster than other categories when upright, but inversion abolishes this advantage in reaction times. Both studies used objects embedded in scenes. Inverting scenes is not the same as inverting isolated objects. Scenes possess textural properties like the presence of grass, or the skyline, which may aid in categorizing objects when inverted. Thus, the said effect might not have been recovered due to the image set in consideration.

A lesser number of studies have reported the effect of categorization on object silhouettes. Experiments by Torfs et al. have used object silhouettes (more specifically, only unfilled contours), and fragmented them to understand object naming (Torfs, et al. 2010). They also found that category judgments are not affected in silhouettes as compared to natural objects. Another study considered outlines and filled-in silhouettes to detect the differences between the processing of the two stimuli (Wagemans, et al. 2008), and their basic result of how silhouette categorization is similar to natural categorization is consistent with ours.

Future work

Our study shows that animal categorization is sensitive to inversion and unaffected by loss of internal detail. First, does this result extend to other categories? What about inanimate categories like vehicles? Are they also affected by inversion, even though they are inanimate? We will conduct similar experiments on the category of vehicles. Second, what do the similarity relations between inverted, upright, and silhouette objects like? We can measure the similarity relations using visual search. We will conduct visual search experiments using upright, inverted and silhouette stimuli. If visual search of inverted objects takes longer than that of upright objects,

we will conclude that the representation underlying inverted objects is different. On the other hand, if visual search reaction times of upright and inverted objects among themselves are comparable, we would conclude that while the object representations are similar, the category templates incorporate information about visual features, like orientation and contour information.

Experiment 2

Dual Categorization

In the previous experiment, we studied the featural dependence of templates underlying categorization. In this experiment, we investigated whether multiple categories are activated in a dual categorization task. Subjects performed two single and one dual categorization task. We provide evidence that subjects indeed activate two classifiers simultaneously while performing a dual categorization task.

Subjects:

A total of 30 subjects (between the ages of 20-30, with normal or corrected to normal vision) participated in the experiments. All subjects gave written informed consent to participate in the experiments.

Experiment design:

All subjects performed three categorization experiments each – 1) animal vs. vehicle categorization, 2) animal vs. non-animal categorization, and 3) vehicle vs. non-vehicle categorization. We conducted the three experiments on different groups of subjects by varying the order of the three categorization tasks and the key presses used in the task, summarized below (Table 2).

No. of subjects	Order	Task	Key press
6	All counterbalanced orders	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	A/N V/N A/V
6	All counterbalanced orders	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	M/Z M/Z M/Z
6 + 6	Animal/Vehicle first, Animal/non-animal and Vehicle/non-vehicle tasks counterbalanced	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle (6 subjects) Animal/Vehicle (6 subjects)	M/Z M/Z M/Z Z/M
6	Animal/Vehicle last, Animal/non-animal and Vehicle/non-vehicle tasks counterbalanced	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	B/Z Z/B B/Z

Table 2: Summary of the different groups of subjects who performed the three categorization tasks, differing either in experiment order or in key press assignments.

No. of subjects refers to the number of human subjects who participated in the categorization experiment. Order of the experiment refers to the order in which the three categorization experiments were conducted (for example, all counterbalanced orders indicate that subjects performed the three experiments in all possible orders). Task refers to the three different tasks subjects performed, and key press indicates the keys on the keyboard that subjects were instructed to use.

Order-dependent variation:

12 subjects performed the three experiments in counterbalanced orders, 12 other subjects performed the animal/vehicle categorization task first, with the single animal and vehicle tasks counterbalanced across subjects. A final group of 6 subjects performed the animal/vehicle categorization task last with the order of the single animal and vehicle categorization tasks counterbalanced across subjects. We conducted these variations to ascertain whether an order dependent effect exist which determines the category template that will be activated.

Key press variation:

6 subjects were instructed to respond using the "A" key for animals, "V" key for vehicles, and "N" key for non-animals and non-vehicles. We conducted this variation to determine whether verbal labels would enable subjects to remember the key mapping without effort. 18 subjects were instructed to respond using the M and Z key presses to indicate category members (animals, vehicles) and non-category members (non-animals, non-vehicles) respectively, in the single tasks. Out of these, 12 subjects were required to respond using "M" for animals, and "Z" for vehicles in the animal vs. vehicle dual task. The remaining 6 subjects were required to respond using "Z" for animals, and "M" for vehicles to ensure counterbalanced key press assignments. However, the use of "M" and "Z" key press assignments, as outlined above, presents with two problems: 1) there is an inherent response conflict when subjects shift from a single task to a dual task or vice-versa, which may lead to increased reaction times. Specifically, if subjects performed the animal/non-animal task first using M/Z keys, and then performed the animal/vehicle task using Z/M keys, subjects who used "M" for animal will now have to switch to the "Z" key in the animal/vehicle task, and this will result in longer reaction times in the second task only due to conflict in responses between the tasks, and 2) mapping the "m" key to

animals may bias subjects to associating the key with animals (since the word 'animal' contains the letter 'm', thus inducing verbal similarity), and hence, subjects may be slower to report vehicles using the "M" key. The response conflict that subjects had while reporting the category in the last categorization task they performed did not affect the results because of the counterbalanced design of key presses. To overcome these potential confounds, we conducted the experiments with consistent key press assignments. Subjects were asked to report using the "B" key for animals, "Z" key for non-animals in the single animal task; "Z" key for vehicles, "B" key for non-vehicles in the single vehicle task; and finally, "B" key for animals, "Z" key for vehicles in the animal vs. vehicle categorization tasks. The final key press mapping had no response conflict, and eliminated any verbal association of any key with either animal or vehicle category.

A group of 16 subjects (all of them had performed the dual categorization experiments) also performed a visual search task on the set of animals and vehicles. The order of the categorization task and visual search task was counterbalanced across subjects. A different group of 12 subjects performed visual search tasks – 6 subjects on the set of animals and non-animals, 6 subjects on the set of vehicles and non-vehicles.

Stimuli:

The animal vs. non-animal categorization task consisted of 48 gray-scale images (same image set used in Experiment 1), of which 24 were animals and 24 were non-animals. Out of the 24 animals, 6 were atypical animals and 18 were typical animals. Out of the 24 non-animals, 12 were man-made and 12 were natural objects. Out of the 12 man-made non-animals, 6 were vehicles, of which 3 were typical and 3 were atypical vehicles.

The vehicle vs. non-vehicle categorization task consisted of 48 grey-scale images, of which 24 were vehicles and 24 were non-vehicles. Out of the 24 vehicles, 6 were atypical vehicles and 18 were typical vehicles. Out of the 24 non-vehicles, 12 were man-made and 12 were natural non-vehicles. Out of the 12 natural non-vehicles, 6 were animals, of which 3 were typical and 3 were atypical animals.

The animal vs. vehicle categorization task consisted of 48 grey-scale images, of which 24 were animals and 24 were vehicles. These images were the same animals and vehicles as in the animal vs. non-animal and vehicle vs. non-vehicle categorization tasks respectively.

All images were segmented from their original scene and displayed in a black background. All images were selected to have a profile view (head of animals pointed towards the left side, front of the vehicle pointing towards the left side). All images were equalized for luminance and were rescaled such that the longer dimension was 175 pixels. All images were presented at a size corresponding to 5.5 degrees of visual angle.

Categorization task:

Subjects performed three categorization tasks. Each categorization task started with a snapshot of all the images that subjects were to categorize subsequently, to avoid confusion regarding object identity. Each trial began with a 750 ms fixation cross, followed by the test object displayed for 50 ms, followed by a noise mask for 250 ms. Subjects were instructed to press one key to indicate that the object belonged to the category relevant to the task, and press a different key to indicate that the object did not belong to the category (See Experiment Design). Subjects were instructed to respond correctly within 2 seconds following image display, failing which, the same image would be repeated after a fixed number of trials. The next trial started 500 ms after the subject's response. Each image was repeated 8 times within a task.

Visual search task:

We conducted three visual search tasks using the images in the three categorization tasks – animal vs. non-animal, vehicle vs. non-vehicle, and animal vs. vehicle task. The three experiments were exactly the same, except for the images used in each visual search task. The experiment started with measurement of motor reaction time, in which a white circle appeared on the left side or the right side. Subjects were instructed to press "M" if the target appeared on the right, and press "Z" if the target appeared on the left side of the screen. This was followed by practice trials using objects that were not in any of the categorization tasks. Each trial in visual search started with a 500 ms fixation cross, followed by a 4 x 4 array of objects consisting of

one oddball target in a field of identical distractors. Subjects were instructed to locate the target and indicate the side on which it was present using the "M" key press for the right side and the "Z" key press for the left side. Subjects were instructed to respond as accurately as possible within 5 seconds, failing which, the trial repeated after a random number of trials. The sizes of the distractors were varied to avoid the influence of low level image properties like, arrangement of items along a row to affect performance. Specifically, out of the 15 distractors, 7 of them were same size as the target, 4 of them were 75% of the target size, and 4 of them were 125% of the target size. The size of the target was exactly the same as the image size used in the categorization tasks. In each visual search task, we tested all possible 1128 pairs ($^{48}C_2$ as there were 48 images per categorization task). For each image pair, subjects performed 4 trials – A or B as target (2 trials), and targets could occur on the left or right side (2 trials). The order of image pairs and target location were randomized for every trial.

Visual search similarity:

The time taken to categorize objects in a categorization task can be predicted by similarity relations as measured in a visual search task. We calculated two basic distances from visual search data – 1) Within-category similarity, and 2) Between-category similarity. Within-category similarity (CRT) is the 'distance' of an object to members of its own category. It is calculated as the mean visual search time taken to search for a test object among other objects belonging to the same category. Between-category similarity (NRT) is a measure of how distant non-category members are to the members of a category. It is calculated as the mean of visual search times taken to search for a test object among other all other non-category objects. We measure CRT and NRT for all the three visual search tasks as described above.

Statistical analyses:

We performed data analysis in MATLAB. We compared reaction times in different conditions (say, animal vs. non-animal categorization and animal vs. vehicle categorization) using ANOVA with subject and condition as factors. We used correlation analyses to compare reaction times between tasks, and multiple linear regression to model categorization times using visual search reaction times.

Results

30 subjects performed three categorization tasks – two single tasks, an animal/non-animal task and a vehicle/non-vehicle task, and one animal/vehicle dual categorization task.

Are subjects consistent in the single and dual visual categorization tasks?

Subjects were highly consistent in the single animal/non-animal and vehicle/non-vehicle categorization tasks, as indicated by the correlation in reaction times between two independent groups of subjects ($r = 0.89$ ($p = 10^{-14}$) in the animals task, and $r = 0.83$ ($p = 10^{-10}$) in the vehicles task, across 48 objects in both tasks). Subjects were consistent in the dual animal/vehicle task, but the correlation in average reaction times between two independent groups of subjects was not as high as the single task correlations ($r = 0.58$ ($p = 10^{-4}$) across 48 animals and vehicles). Thus, subjects seem to have used similar strategies in the single task. The lower consistency in the dual task can be attributed to the use of mixed strategies by subjects (for example, some subjects (mention subject number) performed the animal/vehicle task like an animal/non-animal task; some other subjects performed the dual task as a vehicle/non-vehicle task).

On repeating the analyses using 16 subjects who did the animal/vehicle categorization task first, we found similar results. Subjects were highly consistent in the single animal/non-animal and vehicle/non-vehicle categorization tasks. The correlations in average reaction times between two independent groups of subjects were 0.82 ($p = 10^{-8}$) and 0.63 ($p = 10^{-4}$) in the animal/non-animal and vehicle/non-vehicle tasks respectively. The consistency between subjects in the dual animal/vehicle task is 0.35 ($p = 0.06$), and is only marginally significant. The low consistency in the dual task can be attributed to the use of multiple strategies throughout the experiment.

Do people use multiple classifiers in the dual animal/vehicle categorization task?

In the dual animal/vehicle categorization task, subjects may either activate a single classifier (either animal or vehicle) or activate both animal and vehicle classifiers. A single classifier is sufficient to perform a dual task, where subjects can perform the

animal/vehicle task as an animal/non-animal or a vehicle/non-vehicle task, without explicitly attending to the distractor category of vehicles. Accessing a single classifier may require less neuronal circuitry or processing, as opposed to activating two classifiers. Alternatively, subjects may employ both classifiers during a dual categorization task, because it's easier compared to single categorization. An animal/vehicle task may be easier than a single category task, because the variability within each category is less (as the alternate category will contain images of only type for example: only vehicles, as opposed to non-animals). Thus, activating two independent category templates during a dual task may involve less neuronal processing as compared to processing underlying single category judgments.

We provide three lines of evidence showing that two classifiers are in operation in a dual categorization task.

Evidence 1:

If the average reaction times for common animals in the single animal/non-animal task are correlated significantly with the average reaction times for the same animals in the dual animal/vehicle task, across all subjects, it would be evidence for use of an animal classifier in the dual task. Similarly, if the average reaction times for vehicles in the single vehicle/non-vehicle task are significantly correlated with the average reaction times for the same vehicles in the dual animal/vehicle task, it would be evidence that a vehicle classifier was in use.

We found that there is a significant correlation between the reaction times of the 24 animals in the animal/non-animal task and in the animal/vehicle task (r = 0.58, p = 10^{-3}, Figure 7A). This means that subjects used an animal classifier while categorizing the animals in the animal vs. vehicle dual task. We also found a significant correlation between the reaction times of the 24 vehicles in the vehicle/non-vehicle task and in the animal/vehicle task (r = 0.73, p = 10^{-5}, Figure 7B). This means that subjects used the vehicle classifier to categorize vehicles in the animal vs. vehicle task. The implicit assumption here is that subjects indeed used a single animal classifier in the animal/non-animal task, and a single vehicle classifier in the vehicle/non-vehicle task. This is reasonable, as we do not expect subjects to activate a classifier for every non-category member as the set is too diverse. The

significant correlations between the animals and vehicles in the single and dual tasks suggest that two classifiers are being employed.
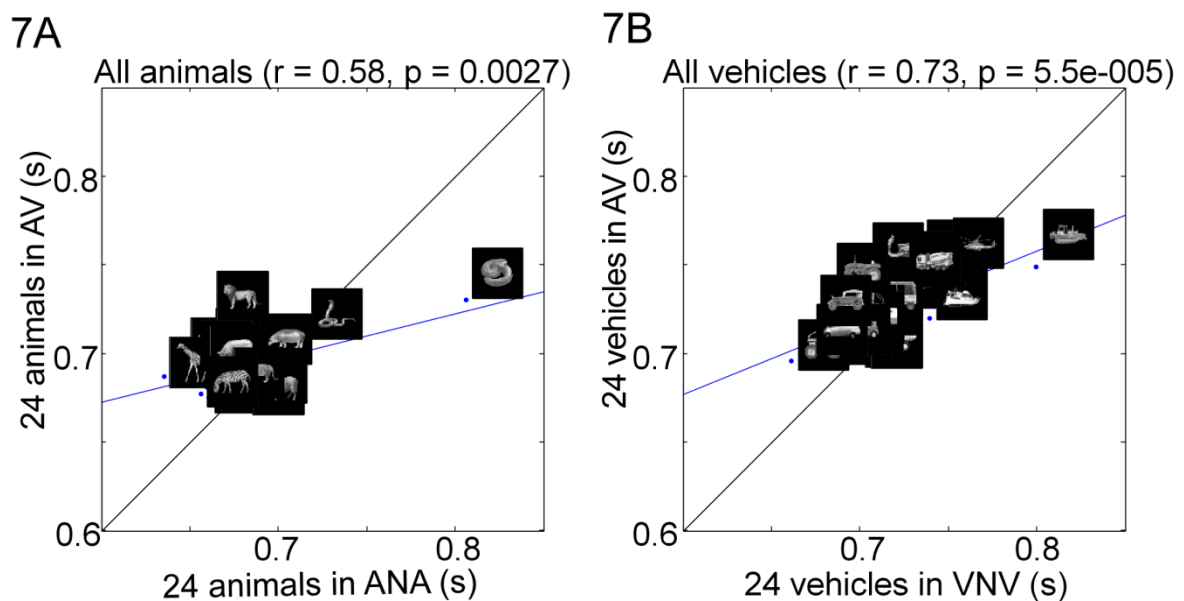

Figure 7: Correlations of reaction times in dual categorization task with single categorization tasks for all subjects. 7A: Correlation of reaction times for animals in the single animal/non-animal task and dual animal/vehicle task (r = correlation coefficient, p-value of significance; 7B: Correlation of reaction times for vehicles in the single vehicle/non-vehicle task and dual animal/vehicle task (r = correlation coefficient, p-value of significance)

Evidence 2:

A second line of evidence for the use of dual classifiers comes from non-category objects in the single tasks. The design of our experiment was such that there are 12 images common to all three categorization experiments – 6 animals and 6 vehicles. The 6 animals were animals in the animal/non-animal task, non-vehicles in the vehicle/non-vehicle task, and animals in the animal/vehicle task. Similarly, the 6 vehicles were vehicles in the vehicle/non-vehicle task, non-animals in the animal/non-animal task, and vehicles in the animal/vehicle task. To definitively confirm the use of two classifiers in the dual task, we also need to ascertain that – 1) common animals in the animal/vehicle task were not treated as non-vehicles in the vehicle/non-vehicle task, but instead treated as animals; 2) common vehicles in the

animal/vehicle task were not treated as non-animals in the animal/non-animal task, and were instead treated as vehicles.

On plotting the average reaction times of the non-animal vehicles in the animal/non-animal task and the average reaction times of the non-vehicle animals in the vehicle/non-vehicle task against the average reaction times of the same vehicles and animals in the animal/vehicle task, we found no correlation (r = 0.22, p = 0.49, Figure 4D). As a control plot, we plotted the average reaction times of the common animals in the animal/non-animal task and the average reaction times of the common vehicles in the vehicle/non-vehicle task against the average reaction times of the same animals and vehicles in the animal/vehicle task, and found a significant correlation (r = 0.77, p = 10^{-3}, Figure 4C). Thus, we can conclude that animals in the dual task were treated as animals and not as non-vehicles, and vehicles in the dual task were treated as vehicles and not as non-animals.
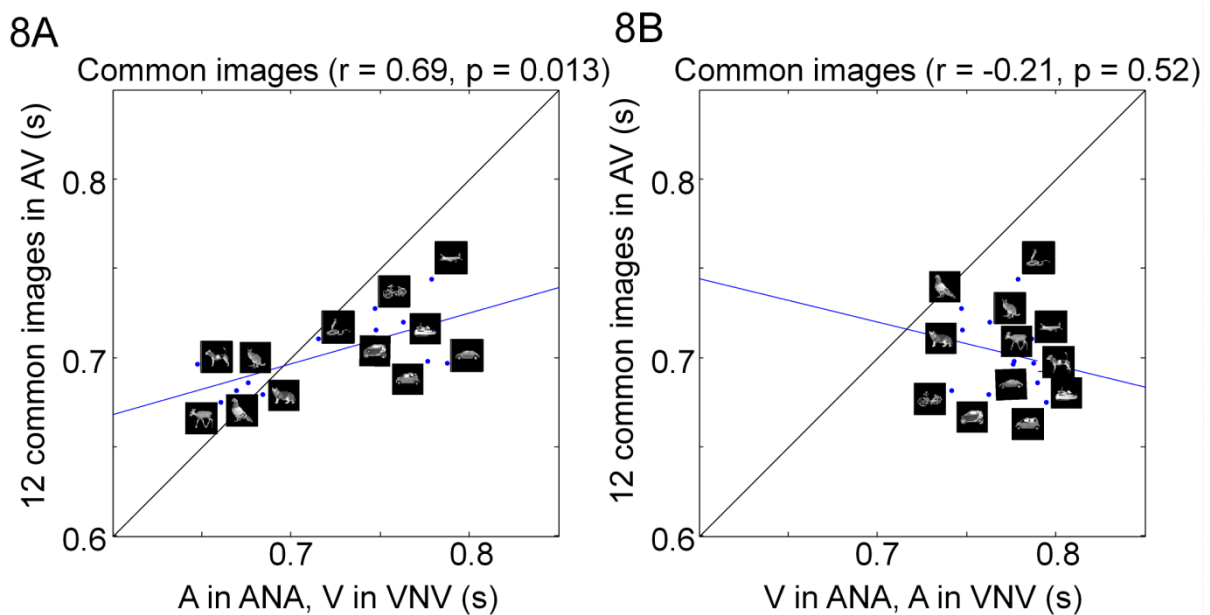
Figure 8: Correlations of reaction times in dual categorization task with single categorization tasks for the common images across the three tasks. 8A: Correlation of reaction times for animals in the animal/non-animal task, and vehicles in the single vehicle/non-vehicle task with reaction times for the same images in the dual animal/vehicle task (r = correlation coefficient, p-value of significance; 8B: Correlation of reaction times for vehicles in the single animal/non-animal task and animals in the single vehicle/non-vehicle task with reaction times for the same

images in the dual animal/vehicle task (r = correlation coefficient, p-value of significance

Evidence 3: Typicality effects

The third line of evidence for the use of dual classifiers comes from typicality effects in the categorization tasks. Classic studies in categorization have shown that it takes longer to categorize atypical objects as compared to objects that are typical of a category. For example, if you consider the category of animals, humans take longer reaction times to categorize snakes and birds as animals. It is thought that these objects are not representative of a category, as the visual similarity between atypical and typical objects is low. In this experiment, the animal/non-animal task has 6 atypical animals (2 birds, 2 snakes, 1 monkey, and 1 kangaroo) among the 24 animals. Among the 6 non-animal vehicles, there are 3 atypical vehicles (bicycle, plane, and boat). In the vehicle/non-vehicle task, we have 6 atypical vehicles (1 bicycle, 2 motor bikes, 1 plane, 1 boat, and 1 helicopter) among the 24 vehicles. Among the 6 non-vehicle animals, there are 3 atypical animals (1 bird, 1 kangaroo, and 1 snake). In the animal/vehicle task, there were 6 atypical animals out of 24 animals, and 6 atypical vehicles out of 24 vehicles.

Is there a basic typicality effect in both categories of animals and vehicles in the single tasks? Yes. In the animal/non-animal task, subjects took significantly longer to categorize atypical animals (702 ms) as compared to typical animals (664 ms), as determined by a 2-way ANOVA with subject and typicality as factors ($p = 10^{-11}$, Figure 9A). Similarly, in the vehicle/non-vehicle task, subjects took significantly longer to categorize atypical vehicles (729 ms) as compared to typical vehicles (694 ms), as determined by a 2-way ANOVA with subject and typicality as factors ($p=10^{-9}$, Figure 9B). Thus, we have established a basic typicality effect in the single categorization tasks.

Now, is there a typicality effect in the non-category members in the single categorization tasks? In the animal/non-animal categorization task, we compared the reaction times of atypical vehicles and typical vehicles that were included as non-animals. We found that atypical and typical vehicles are categorized similarly. The difference between average reaction times of atypical (772 ms) and typical vehicles (777 ms) is not significant, as determined by an ANOVA on the reaction times, with

[35]

subject and typicality as factors (p-value of typicality, p=0.59, Figure 9A). Similarly, in the vehicle/non-vehicle categorization task, we compared the reaction times of atypical animals and typical animals that were included as non-vehicles. We found that atypical and typical animals are categorized similarly. The difference between RTs of atypical (763 ms) and typical animals (771 ms) is not significant, as determined by a two-way ANOVA on the reaction times with subject and typicality as factors (p-value of typicality, p=0.42, Figure 9B). Thus, we can conclude that atypicality does not matter for objects that do not belong to a category. This means that the typicality effect is dependent on the category being judged, and does not hold for non-category members.
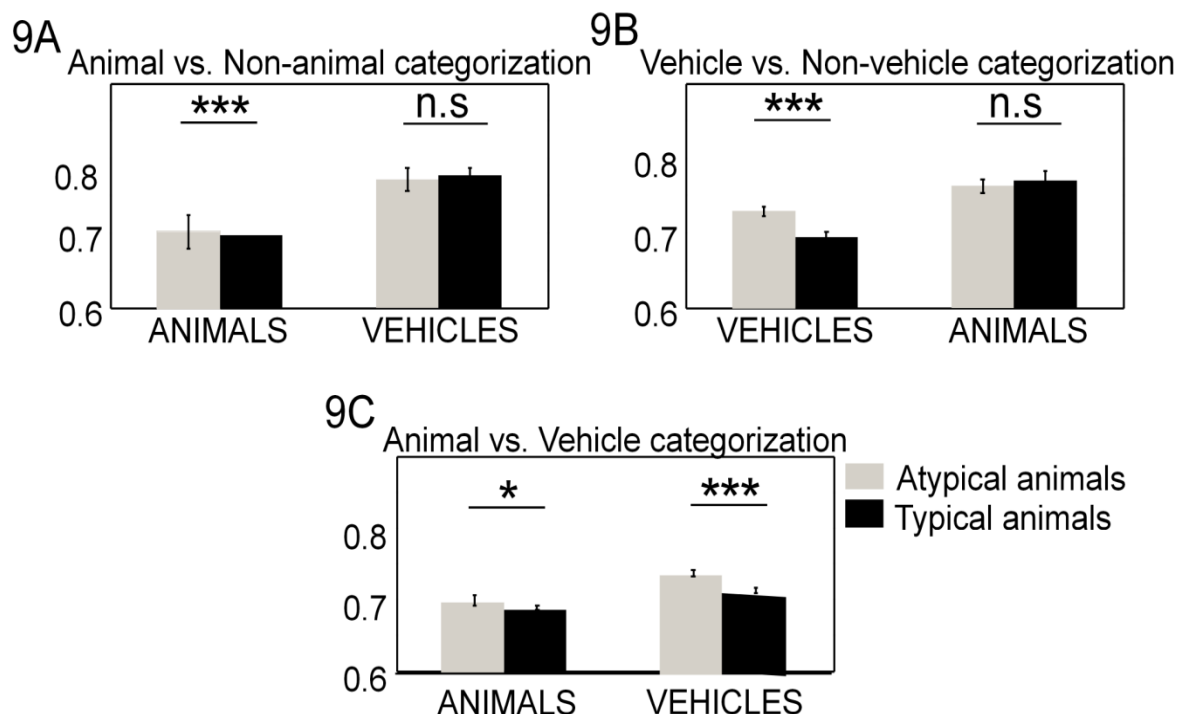
Figure 9: Typicality effects in the three categorization tasks. 9A: Comparison of reaction times between atypical and typical animals and non-animal vehicles in the single animal/non-animal categorization; 9B: Comparison of reaction times between atypical and typical vehicles and non-vehicle animals in the single vehicle/non-vehicle categorization; 9C: Comparison of reactions times between atypical and typical animals and vehicles in the dual animal/vehicle categorization. *** refers to p-value $< 10^{-3}$, * refers to p-value $< 10^{-2}$, and n.s refers to non-significant difference.

The final question is whether there exists a typicality effect in the dual animal/vehicle categorization task? In the dual task, we found that subjects take longer to categorize atypical animals (698 ms) as compared to typical (688 ms) animals. This difference is significant as verified by an ANOVA with subject and typicality (p-value of typicality = 0.0379, Figure 9C) as factors. However, there is a significant subject-typicality interaction. In addition, there is a typicality effect even in the vehicles set in the dual animal/vehicle task. Subjects took longer to categorize atypical vehicles (736 ms) as compared to typical vehicles (713 ms). This difference was also significant as determined by an ANOVA (p-value of typicality = 10^{-6}, Figure 9C). Thus, subjects were using the animal classifier while categorizing animals, and using the vehicle classifier while categorizing vehicles in the dual animal/vehicle task. This provides us with compelling evidence that human subjects are indeed using two classifiers while performing the dual animal vs. vehicle categorization task.

Can visual search similarity explain dual categorization?

We have previously shown that the time taken to categorize objects can be predicted by the visual search time taken to search for these objects among other objects that are within and outside the category (Mohan and Arun 2012). Specifically, we used two measures from the visual search task – between-category similarity and within-category similarity. We found that a linear model based on these two reaction time measures predicted the categorization reaction times for a number of categories. The categorization tasks involved subjects to make distinctions between category and non-category members. 6 subjects performed the visual search experiment involving animals and non-animals in the single animal categorization task. We computed the between-category search times and within-category search times for all objects in the animal/non-animal categorization task. We compared the average time subjects took to categorize objects with a linear sum of within-category and between-category search times and found a significant correlation between the visual search reaction times and the categorization times (r = 0.77, p = 10^{-10}, Figure 10). We fit both the within-category search times and between-category search times separately to the categorization reaction times, fit separately for animals and non-animals (Table 3). We found that the correlations and the relative contributions of the weights are consistent in all models. Interestingly, we found that within-category search times play a very important role in predicting categorization times. Addition of

between-category search times increases the correlation between categorization times and visual search times only slightly (r = 0.72 to r = 0.77).

Figure 10: Visual search similarity relations account for animal/non-animal categorization data. Full model refers to the fit of visual search reaction times to categorization reaction times on all animals and non-animals; r refers to the correlation between visual search reaction times and categorization reaction times; and p refers to the p-value of significance.

An independent group of 6 subjects performed the visual search experiment involving vehicles and non-vehicles in the single vehicle categorization task. We calculated the between-category search times and the within-category search times for all objects. We then correlated the vehicle/non-vehicle categorization times with a linear summed model of these two visual search reaction time measures. We found a high correlation between visual search predictions and categorization performance (r = 0.70, p = 10^{-8}, Figure 11). We fit the categorization reaction times separately to within-category search times and between-category search times, both together and fit separately for animals and non-animals (Table 4). We found that the correlations

and the relative contributions of the weights are comparable across all models. In the vehicle/non-vehicle categorization and visual search, we found that between-category search times play a more important role in predicting categorization times. Adding the within-category search times increases the correlation between categorization times and visual search reaction times by a small amount ($r = 0.68$ to $r = 0.70$). The best-fitting weights are such that the contribution of between-category search times is 4 times the contribution of within-category search times. The higher weights for between category search times could be because between-category search times are much smaller than within-category search times. This is obvious because searching for a category member among other objects that do not belong to the same category is much easier than detecting an object among other objects that belong to the same category. Hence, to equalize the contributing visual search reaction times, the weights for between-category search times will be higher. We can thus conclude that visual search similarity relations between category and non-category members can predict categorization reaction times for both animals and vehicles.

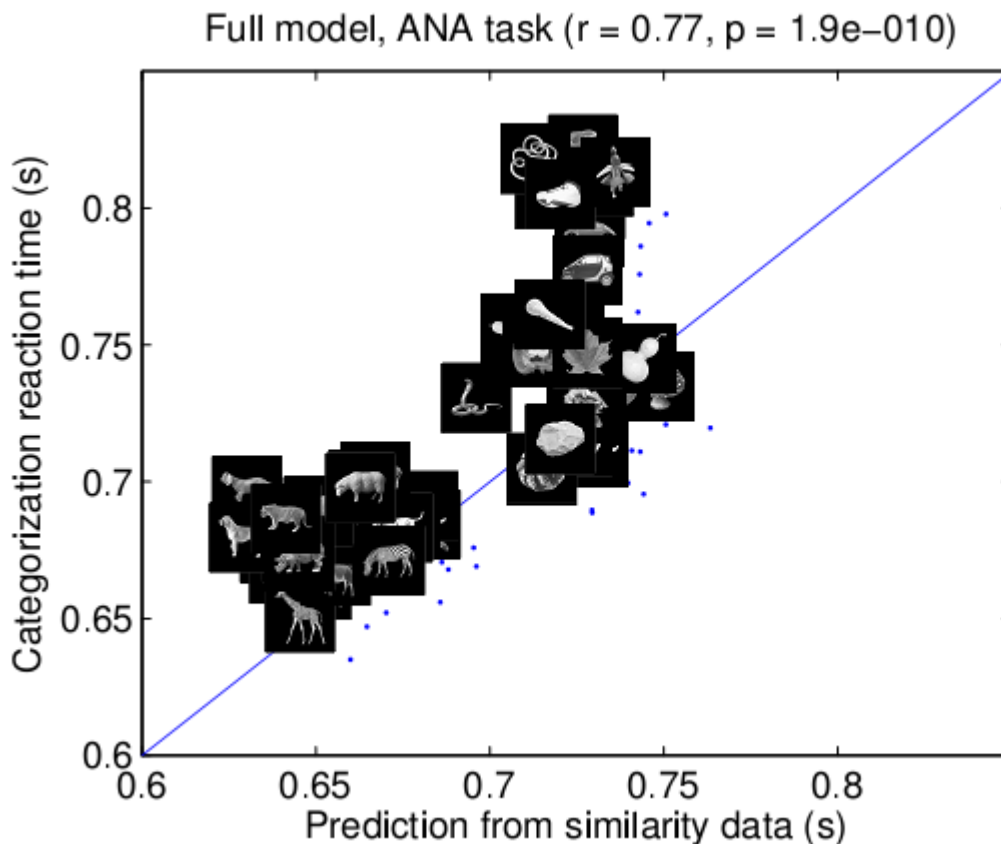Full model, VNV task (r = 0.70, p = 4e−008)

Figure 11: Visual search similarity relations account for vehicle/non-vehicle categorization data. Full model refers to the fit of visual search reaction times to categorization reaction times on all vehicles and non-vehicles; r refers to the correlation between visual search reaction times and categorization reaction times; and p refers to the p-value of significance.

Will visual search predict dual categorization times? We hypothesized that if subjects are using dual classifiers in the dual categorization task, the animal/vehicle categorization times can be predicted by the between-category search times of animals among non-animals for animals, and between-category search times for vehicles among non-vehicles for vehicles and the within-category search times for animals among animals and vehicles among vehicles. Alternatively, only the distance between animals and vehicles may play a role in the dual categorization, and the distance to other non-category members may not be relevant. If the distance between animals and vehicles contributes significantly to predicting the dual categorization times, we would conclude that the classifier underlying dual categorization is a linked classifier, where animals and vehicles interfere with each other. Such a classifier would be dependent on the context in which the task is performed. To test this, 16 subjects performed a visual search task on the animals and vehicles in the dual categorization task.

We computed within-category and between category search reaction times. We calculated two kinds of between-category search times – 1) time taken to search for animals among vehicles or vice-versa from the animal/vehicle visual search, and 2) time taken to search for animals among non-animals or vice-versa, and vehicles among non-vehicles or vice-versa. We then correlated the categorization times in the dual task with a linear model summing the contributions of between-category search times for animals among vehicles and vice-versa, between-category search times for category members among non-category members and vice-versa (for both, animals and vehicles), and within-category search times for animals and vehicles. We obtained a correlation of 0.51 ($p = 10^{-4}$). On fitting the reaction times and regressing separately on animals and vehicles, we found a significantly higher correlation of 0.78 ($p = 10^{-11}$, Figure 12). We performed more analyses to understand why a category-wise model yielded better results, as opposed to the model fit on all data. We found that categorization reaction times for vehicles were significantly greater

than the categorization reaction times for animals (both, across the animal/non-animal and vehicle/non-vehicle tasks, and within the animal/vehicle dual tasks). Thus, since the animal reaction times are different from the vehicle reaction times, it
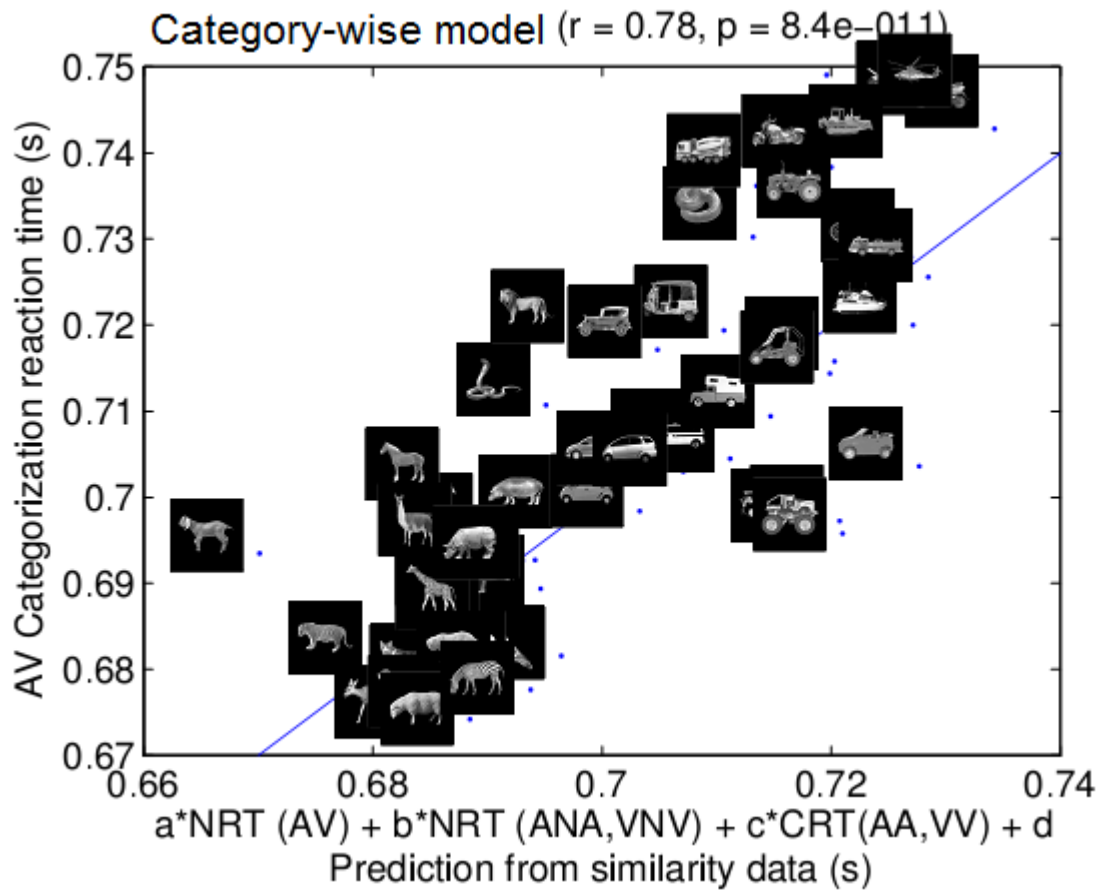

Figure 12: Visual search similarity relations account for animal/vehicle categorization data. Here, the visual search model consists of between-category animal/vehicle search times, between-category animal/non-animal and vehicle/non-vehicle search times and within-category animal and vehicle search times. Category-wise model refers to the fit of visual search reaction times to categorization reaction times on animals and vehicles separately; r refers to the correlation between visual search reaction times and categorization reaction times; and p refers to the p-value of significance. The coefficients of the contributing terms are in Table 5.

would be better to fit the visual search model separately to both categories. Hence, we report correlations obtained by using the category-wise model (Table 5). After removing the between-category search times for animals among vehicles or vice-versa, we find no change in the correlation between categorization performance and visual search predictions ($r = 0.78$, $p = 10^{-11}$, Figure 13). Thus, the distance between

animals and vehicle does not contribute to predicting dual categorization reaction times. On removing the between-category search times for animals among non-animals (or vice-versa), and vehicles among non-vehicles (or vice-versa), we found a decrease in correlation between categorization times and visual search predictions (r = 0.73, p = 10^{-9}, Figure 14). We fit different models, individually and pair-wise, to the categorization data, and we report correlations and weights for all of them (Table 5). Thus, we conclude that distances between category and non-category members matter, and distance between two categories do not matter in dual categorization. This is evidence that the classifier in operation is not linked; instead there are two independent classifiers that are active in parallel during the dual categorization task.

Figure 13: Visual search similarity relations explain dual categorization tasks. Here, the visual search model consists of between-category animal/non-animal and vehicle/non-vehicle search times, and within-category animal and vehicle search times. Category-wise model refers to the fit of visual search reaction times to categorization reaction times on animals and vehicles separately; r refers to the correlation between visual search reaction times and categorization reaction times;

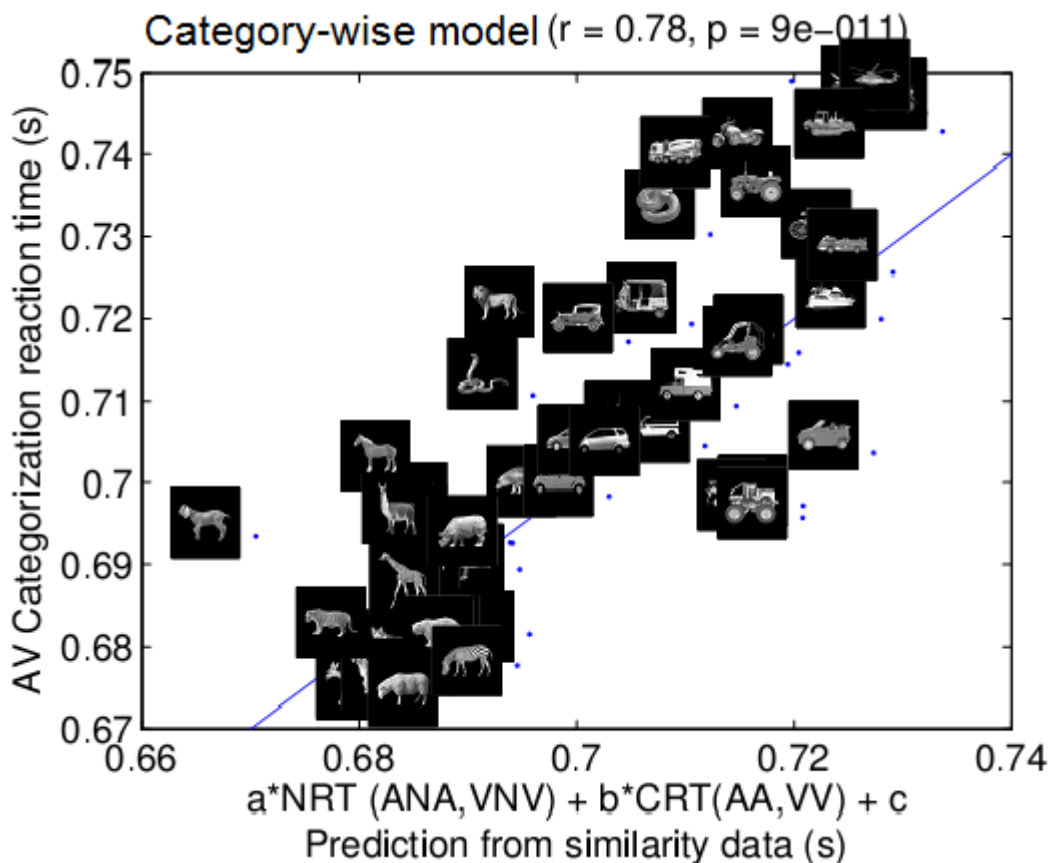and p refers to the p-value of significance. The coefficients of the contributing terms are in Table 5.

Figure 14: Visual search similarity relations explain dual categorization tasks. Here, the visual search model consists of between-category animal/vehicle search times, and within-category animal and vehicle search times. Category-wise model refers to the fit of visual search reaction times to categorization reaction times on animals and vehicles separately; r refers to the correlation between visual search reaction times and categorization reaction times; and p refers to the p-value of significance. The coefficients of the contributing terms are in Table 5.
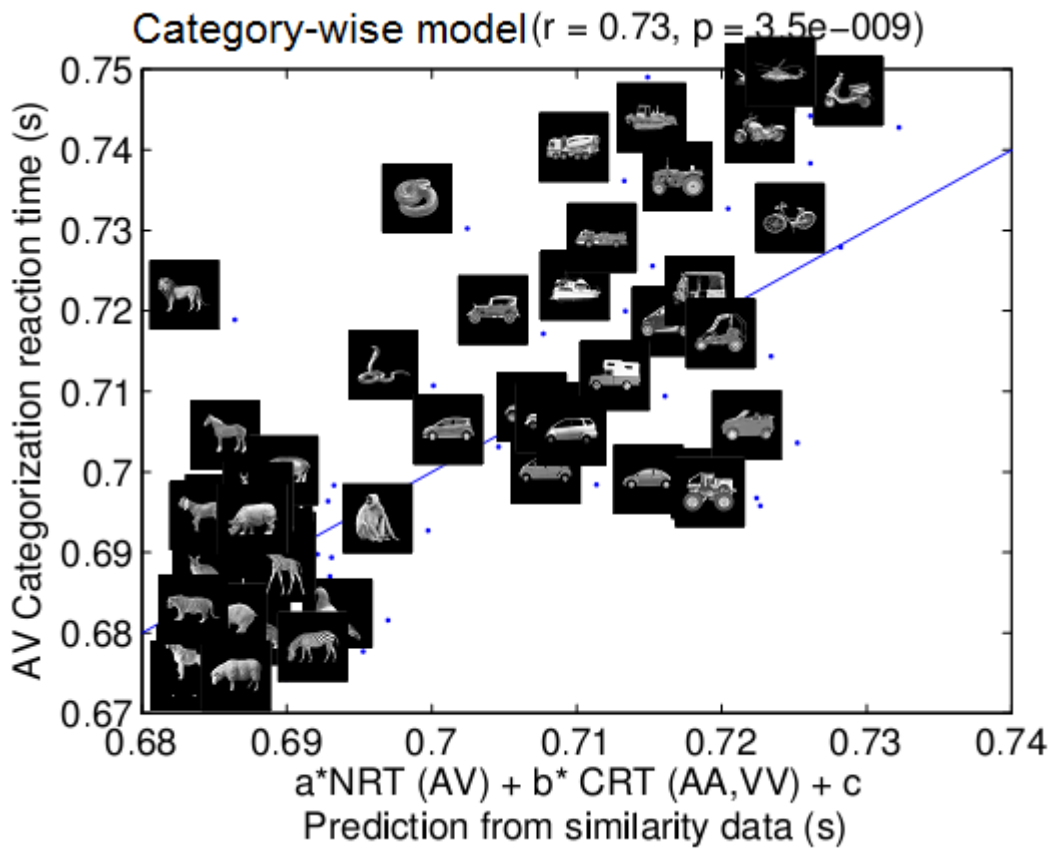
Discussion

In this experiment, we addressed how multiple categories are processed by humans in the context of categorization tasks. Here, subjects performed three different tasks – two single categorization tasks (animal vs. non-animal and vehicle vs. non-vehicle) and one dual categorization tasks (animal vs. vehicle). We hypothesized that subjects would activate and use both classifiers in a dual task paradigm as opposed to a single classifier which would also be sufficient to perform the task. We provide evidence for the use of information from two categories. We found that reaction times of animals in the single and dual tasks are correlated significantly. Similarly, we found a high correlation between reaction times of vehicles in the single and dual tasks. In addition, our results showed no correlation between – 1) the reaction times of common vehicles in the single animal and dual task, 2) the reaction times of common animals in the single vehicle and dual task, and 3) robust typicality effects are present in both animals and vehicles in the single and dual categorization tasks, but absent in the non-category objects in both the single tasks. These three lines of evidence point towards the presence of two classifiers in humans while performing the dual categorization task.

Comparison with research on dual categorization

Our findings are in accordance with psychophysical studies that have suggested the processing of multiple categories, in a different task paradigm (Evans, et al. 2011), neuroimaging studies which have shown differential activation of different categories (people vs. vehicles) suggesting the activation of distinct neuronal populations in parallel (Peelen, Fei-Fei and Kastner 2009). A number of psychophysical studies have also used categorization tasks that involve making category distinctions between one category and another (as opposed to the distinction with non-category members), and have concluded basic results about categorization (Bowers, Jeffrey and Jones 2008; Grill-Spector and Kanwisher 2005; Mace, Thorpe and Fabre-Thorpe 2005). Electrophysiological studies that agree with our basic finding include studies that measure event related potentials and show differential activity for the presence of two objects from the same category (Rousselet, Fabre-Thorpe and Thorpe 2002), and neuronal studies that have shown correlates of two categories in individual neurons in the pre frontal cortex (Cromer, Roy and Miller 2010).

Future work

We have established that humans can and activate multiple categories while doing a dual categorization task while one classifier is potentially sufficient. First, does this mean that activating two categories that are distinct and less variable makes categorization easier? This can be easily tested within the same paradigm by conducting all the three experiments in counter balanced orders to find if the dual task is easier or harder. The second question concerns the effect of prior exposure on activating classifier. If subjects did only one of the single tasks extensively, would they preferentially use that classifier in a dual task, or will the two categories be automatically activated? To test this definitively, without the involvement of a task bias, we can instruct subjects to perform a single task, and in between the task, switch images to appear only from two categories. The behaviour of subjects during this unbiased experiment will inform us about how automatic and task-independent is the activation of two categories.

Conclusion:

In this study we have analyzed the nature of category templates underlying categorization. The first experiment showed us that category templates are orientation dependent, and contour information is sufficient to perform categorization. The second experiment presents evidence that human subjects can activate two categories of objects in parallel in a dual categorization paradigm. Thus, this study will contribute towards understanding the representation of features and multiple categories in a fundamental task, like visual categorization.

TABLES

Table 1: Typicality effects in inverted and silhouette categorization.

	RT of typical animals (ms)	RT of atypical animals (ms)	p-value of typicality (ANOVA)
Natural, Upright	682	695	$0.22^{\#}$
Natural, Inverted	697	726	10^{-3}***
Silhouette, Upright	683	708	0.01**
Silhouette, Inverted	706	743	10^{-4}***

Table 1: Reaction times for typical and atypical animals in the natural/silhouette, upright/inverted categorization experiment. The image set consisted of 18 typical animals, and 6 atypical animals. The differences between atypical and typical reaction times for different categories of animals were measured and significant differences were calculated using a two-way ANOVA with subject and typicality as factors. *** refers to p-value$<10^{-3}$, ** refers to p-value $< 10^{-2}$, $^{\#}$ refers to insignificant p-values.

Table 2: Summary of the different subject groups who performed the three categorization tasks, differing either in experiment order or in key press assignments.

No. of subjects	Order	Task	Key press
6	All counterbalanced orders	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	A/N V/N A/V
6	All counterbalanced orders	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	M/Z M/Z M/Z
6 + 6	Animal/Vehicle first, Animal/non-animal and Vehicle/non-vehicle tasks counterbalanced	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle (6 subjects) Animal/Vehicle (6 subjects)	M/Z M/Z M/Z Z/M
6	Animal/Vehicle last, Animal/non-animal and Vehicle/non-vehicle tasks counterbalanced	Animal/Non-animal Vehicle/Non-vehicle Animal/Vehicle	B/Z Z/B B/Z

Table 2: No. of subjects refers to the number of human subjects who participated in the categorization experiment. Order of the experiment refers to the order in which the three categorization experiments were conducted (for example, all counterbalanced orders indicate that subjects performed the three experiments in all possible orders). Task refers to the three different tasks subjects performed, and key press indicates the keys on the keyboard that subjects were instructed to use.

Table 3: Summary of categorization time predictions using different visual search models for animal/non-animal categorization using visual search data – A) fit on all objects, and B) fit on animals and non-animals separately.

	Visual search model $b \cdot NRT + c \cdot CRT + d$			Correlation between categorization and search
Coefficients	b	c	d	
	NRT	CRT		
	0.24	-0.13	0.65	All: 0.77*** Animals: 0.7*** Non-animals: 0.11[#]
	0.20		0.54	All: 0.23[#] Animals: 0.46** Non-animals : 0.25[#]
		-0.13	0.85	All: 0.72*** Animals: 0.64*** Non-animals : -0.35[#]

Table 3A: Model performance on categorization data fit on all objects. NRT refers to the between-category visual search times (NRT of animals among non-animals), and CRT refers to the within-category visual search times (CRT of animals among animals, non-animals among non-animals). *** refers to p-value $< 10^{-3}$, ** refers to p-value $< 10^{-2}$, [#] refers to insignificant p-values.

Coefficients	Visual search model b*NRT + c*CRT + d			Correlation between categorization and search
	b	c	d	
	NRT	CRT		
	0.29 0.01	-0.12 0.22	0.59 0.55	All: 0.80*** Animals: 0.73*** Non-animals : 0.35[#]
	0.38 0.14		0.35 0.62	All: 0.74*** Animals: 0.46** Non-animals : 0.25[#]
		-0.13 0.23	0.85 0.55	All: 0.79*** Animals: 0.64*** Non-animals : 0.35[#]

Table 3B: Model performance on categorization data fit on animals and non-animals separately. Table details match conventions on Table 3A.

Table 4: Summary of categorization time predictions using different visual search models for vehicle/non-vehicle categorization using visual search data – A) fit on all objects, and B) fit on vehicles and non-vehicles separately.

	Visual search model b*NRT + c*CRT + d			Correlation between categorization and search
Coefficients	**b**	**c**	**d**	
	NRT	**CRT**		
	0.35	-0.09	0.55	All: 0.70*** Animals: 0.41** Non-animals: 0.63***
	0.30		0.50	All: 0.44*** Animals: 0.18[#] Non-animals: 0.65***
		-0.08	0.80	All: 0.46*** Animals: 0.25[#] Non-animals: -0.45*

Table 4A: Model performance on categorization data fit on all objects. NRT refers to the between-category visual search times (NRT of vehicles among non-vehicles), and CRT refers to the within-category visual search times (CRT of vehicles among vehicles, non-vehicles among non-vehicles). *** refers to p-value < 10^{-3}, ** refers to p-value < 10^{-2}, [#] refers to insignificant p-values.

	Visual search model b*NRT + c*CRT + d			Correlation between categorization and search
Coefficients	**b**	**c**	**d**	
	NRT	**CRT**		
	0.35 0.28	-0.07 0.11	0.52 0.45	All: 0.71*** Animals: 0.41** Non-animals: 0.66***
	0.17 0.32		0.57 0.51	All: 0.68*** Animals: 0.18[#] Non-animals: 0.65***
		-0.04 0.37	0.75 0.47	All: 0.61*** Animals: 0.25[#] Non-animals: 0.45*

Table 4B: Model performance on categorization data fit on vehicles and non-vehicles separately. Table details match conventions on Table 4A.

Table 5: Summary of categorization time predictions using different visual search models for animal/vehicle categorization using visual search data – A) fit on all objects, and B) fit on animals and vehicles separately.

	Visual search model $a*NRT(AV) + b*NRT(ANA/VNV) + c*CRT + d$				Correlation between categorization and search
Coefficients	**a**	**b**	**c**	**d**	
	NRT	NRT	CRT		
vsearch	AV	ANA,VNV	AA,VV		
	0.07	-0.15	-0.04	0.81	All: 0.51*** Animals: -0.03[#] Vehicles: 0.21[#]
	0.037	-0.15		0.79	All: 0.39*** Animals: -0.52*** Vehicles: -0.18[#]
	0.04		-0.03	0.72	All: 0.32* Animals: 0.37[#] Vehicles: 0.40*
		-0.13	-0.03	0.84	All: 0.45*** Animals: 0.00[#] Vehicles: 0.07[#]
	0.01			0.70	All: 0.03[#] Animals: -0.11[#] Vehicles: 0.17[#]
		-0.13		0.81	All: 0.37*** Animals: -0.47[#] Vehicles: -0.23[#]
			-0.03	0.74	All: 0.28* Animals: 0.38[#] Vehicles: 0.31[#]

Table 5A: Model performance on categorization data fit on all objects. Here, we consider three parameters and compute the model's performance on all combinations of parameters. NRT (AV) refers to the between-category visual search times of animals among vehicles (and vice-versa), NRT (ANA/VNV) is between-category visual search times of animals among non-animals, vehicles among non-vehicles, and CRT refers to the within-category visual search times (CRT of vehicles among vehicles, non-vehicles among non-vehicles). *** refers to p-value $< 10^{-3}$, ** refers to p-value $< 10^{-2}$, [#] refers to insignificant p-values.

Coefficients	Visual search model a*NRT(AV) + b*NRT(ANA/VNV) + c*CRT + d				Correlation between categorization and search
	a	b	c	d	
	NRT	NRT	CRT		
vsearch	AV	ANA,VNV	AA,VV		
	-0.02 0.01	0.16 0.24	-0.01 -0.05	0.60 0.600	All: 0.78*** Animals: 0.53*** Vehicles: 0.54***
	-0.04 0.01	0.19 0.11		0.57 0.63	All: 0.72*** Animals: 0.52*** Vehicles: 0.23[#]
	0.01 0.06		-0.03 -0.04	0.72 0.72	All: 0.73*** Animals: 0.38[#] Vehicles: 0.41*
		0.14 0.25	-0.02 -0.05	0.60 0.60	All: 0.78*** Animals: 0.54*** Vehicles: 0.53***
	-0.02 0.03			0.71 0.69	All: 0.68*** Animals: 0.11[#] Vehicles: 0.17[#]
		0.16 0.12		0.55 0.63	All: 0.71*** Animals: 0.47* Vehicles: 0.23[#]
			-0.02 -0.03	0.72 0.76	All: 0.71*** Animals: 0.38[#] Vehicles: 0.31[#]

Table 5B: Model performance on categorization data fit on animals and vehicles separately. Table details match conventions on Table 5A.

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