Rapid parallel processing dynamics during hierarchical category decisions

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Abstract

Objects in the world are represented at multiple hierarchical levels of abstraction. For example, you can identify a four-legged creature as an animal, or a dog, or specifically as a Cocker Spaniel. While there has been extensive work examining the relationships between hierarchical category levels, it is unclear how such representations interact during categorization. That is, do individuals process category levels serially or are category levels processed in parallel during categorization? Here, we had participants learn categorization rules for four categories of novel creatures. We examined patterns of errors that participants made in a forced response task, where we manipulated the amount of time participants had to make responses on a trial-by-trial basis. Our results indicate that participants process category levels in parallel, rather than serially resolving superordinate levels before subordinate levels. Parallel processing of category levels could underpin the remarkable flexibility with which we access and deploy category information.

Keywords: hierarchy; concepts & categories; response dynamics; representation

Introduction

As we look around the world, we are constantly dividing up the environment into different concepts and categories and using knowledge of these concepts to guide our behavior. For example, our knowledge of the concept "pets" versus "wild animals" tells you not to flee when you see an animal sitting on your couch. Concepts and categories are described as hierarchical in that we can represent category information at multiple levels of abstraction, from broad, superordinate levels (e.g., animals or dogs) to more specific categories (e.g. Chihuahuas or English Cocker Spaniels) to individual exemplars (e.g., Rover or Ruby; Grill-Spector & Weiner, 2014; Mahon & Caramazza, 2009; Mervis & Rosch, 1981; Rosch et al., 1976).

Feature-based relational rules connect hierarchical levels of category knowledge (Frank et al., 2023; Mervis & Rosch, 1981; Rosch et al., 1976; Theves et al., 2021). For example, if you have identified a dog, you might use ear or tail length (i.e., features) to further categorize that dog as a specific breed. Importantly, whether certain features are category-diagnostic for a given subcategory is critically dependent on the superordinate category. That is, while ear and tail length are important for identifying dog breeds, they are irrelevant to identifying different horse breeds. Thus, categorization involves processing of information at multiple levels of a concept to correctly identify and use category-diagnostic features.

But what are the dynamics of how hierarchical category representations are implemented in real time? Previous work has highlighted at least two possible dynamics that could emerge in a hierarchical categorization task: First, hierarchical decision making has long been thought of as a sequential, multi-step process. In this conceptualization, information is processed from "top to bottom;" processing at higher-order (i.e., more abstract) representational levels occurs before the processing of lower-order information (Braverman et al., 2014; Dux et al., 2006; Pashler, 1984). This "bottleneck" model would thus suggest that superordinate categorization is necessary for and precedes subordinate categorization. In other words, you first determine the superordinate category that an object belongs to in order to identify the relational rules necessary for subcategorization. In the context of our dog example, this view suggests that you need to first identify the superordinate category of "dog" before identifying the subordinate category of "English Cocker Spaniel." This serial model is supported by findings that suggest certain category levels are processed more quickly than others (Iamshchinina et al., 2022; Macé et al., 2009; Rosch et al., 1976). Still, such work tends to compare RTs on blocks of superordinate category judgments (e.g. animal or non-animal?) to blocks of subordinate category judgments (e.g. dog or non-dog?), rather than characterizing the category decision within individual decisions. Thus, while this previous work does indicate that representational levels might be differentially accessible, it does not address whether category levels are processed sequentially or in parallel.

In contrast to the classic serial model, research in the domain of cognitive control suggests that some hierarchical decisions are made by processing multiple levels in parallel. For example, Ranti and colleagues (2015) presented participants with a three-level hierarchical task that involved using different rules (e.g., color or shape) to determine the correct response to various visual stimuli. They analyzed participant errors to determine when decisions at each level of the task hierarchy were made. Rather than finding evidence of a serial, top-down process where participants sequentially resolved levels from top to bottom, their results indicated that participants were processing task levels in parallel. This behavioral finding has recently been supported by neural evidence that identified temporally overlapping

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representations of task information at multiple levels of a hierarchical task during task execution (Cellier et al., 2022). While these studies are not aimed at category representations, there is evidence that hierarchical levels of category information are decodable from different regions of cortex (Iordan et al., 2015; Zhuang et al., 2023). Further, there is evidence that the structure and functional organization of the ventral temporal cortex, a large region of the brain involved in visual categorization, enables simultaneous activation of category information at multiple levels of abstraction (for a review: Grill-Spector & Weiner, 2014). Thus, it is possible that category levels could be processed in parallel, echoing findings in the cognitive control domain.

In the following, we aim to characterize the decision-making dynamics of hierarchical category representations in behavior. We address our primary question here by combining a novel categorization task with a "forced response" paradigm that is designed to reveal real-time decision-making dynamics (Ghez et al., 1997; Hardwick et al., 2019; McDougle & Taylor, 2019, Trach & McDougle, 2023). Rather than focusing on natural categories where individuals might have varying expertise and represent diverse category structures, we trained participants on four novel categories of mammal-like creatures where category membership is determined by hierarchically contingent rules (Figure 1A and B; e.g., creatures with pink heads and black wings are category B and creatures with pink heads and pink wings are category A). We examined reaction times (RTs) and error rates during the categorization task to determine whether participants were representing the category structure hierarchically or with individual rules for each category. We then implemented the forced response paradigm and analyzed participant errors at different timepoints during categorization decisions to characterize decision dynamics on individual trials. This was accomplished by examining the probability of different types of errors as a function of preparation time to assess whether hierarchical category levels were processed serially or in parallel.

Our results suggest that category information at multiple hierarchical levels is rapidly and simultaneously available to the mind, even for newly-trained concepts.

Methods

Participants

We recruited 27 Yale undergraduate students (N = 16 female, mean age = 19.1; range = 18-20) to participate in this study. All participants were recruited through the Introduction to Psychology subject pool and received course credit for their participation. We planned to exclude participants who did not show adequate learning of the category structure. To do this, we inserted two exemplars in each category that only included category-diagnostic features (i.e., could not be

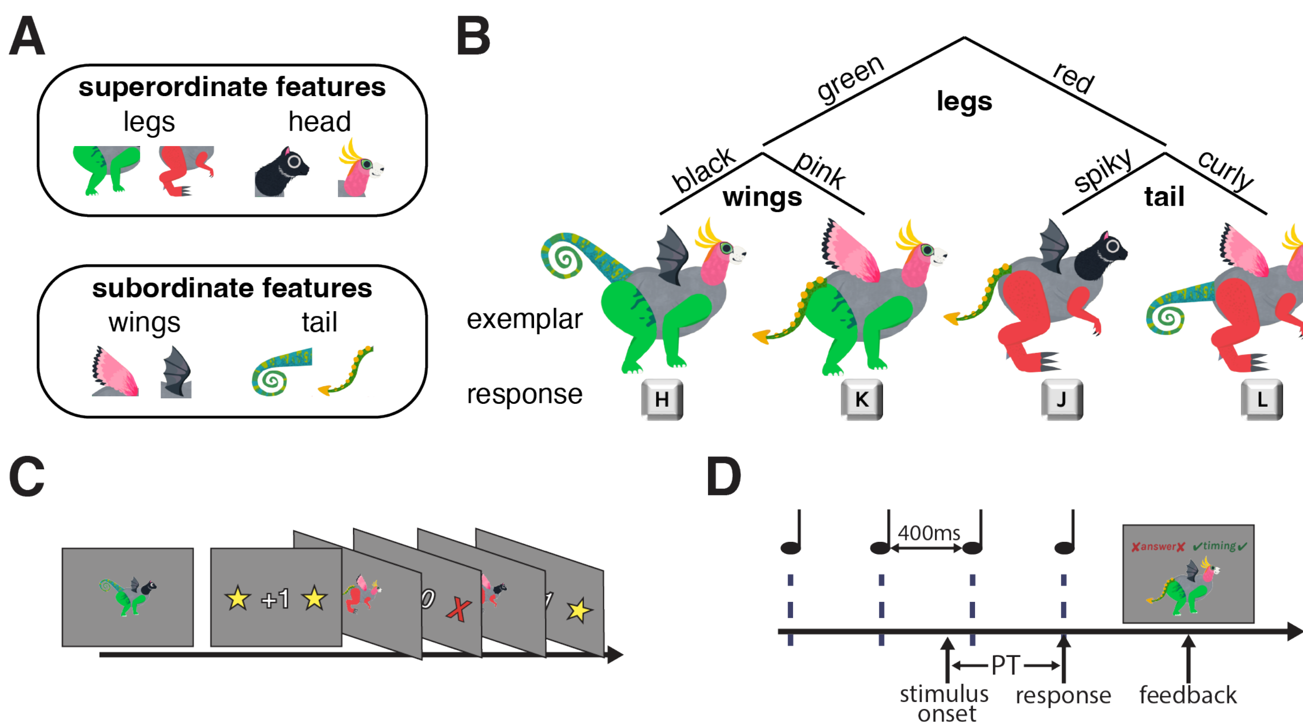

Figure 1. A) Depiction of feature values. Each of the four features had two possible values. Category structures were counterbalanced across participants. Head and legs were always used as superordinate features for each stimulus set. The unchosen feature served as the task-irrelevant feature. Wings and tails were subordinate features in the category structures. **B)** Example category structure with one exemplar per category. Superordinate feature: legs. Task-irrelevant feature: head. Subordinate features: wings and tails. Associated keyboard response is depicted under each exemplar. **C)** Illustration of category task. **D)** Illustration of forced response paradigm, adapted from Trach and McDougle (2023).

mistakenly attributed to another category based on the visible features) and excluded participants that did not reach 75% accuracy on these "easy" trials by the end of the task (N = 4 exclusions). Thus, we were left with 23 subjects (N = 13 female; mean age = 19.2; range = 18-20).

Task Design

Experimental sessions included 1) task training that familiarized participants with the creature categories and the basic procedure of the forced response task; 2) category training that consisted of two short sessions of practice with 2 categories at a time; 3) the full category task; and 4) the forced response task.

Stimulus design. Our stimuli consisted of 24 novel creatures created in "The Creature Garden" app (TinyBop, 2021). Each creature could vary in four anatomical features: the head, legs, wings, and tail (Figure 1A). Category membership was determined by two features in a hierarchically contingent manner: a "superordinate" feature (either head or leg) would dictate which other feature (wing or tail) was diagnostic of category membership (Figure 1B). We will use the term "superordinate feature" to refer to the body part that indicated which other feature was category-diagnostic and the term "subordinate feature" to refer to the other diagnostic body part for a given category. For example, Figure 1B shows a category structure where head color (black or pink) is the superordinate feature. In this arrangement, if the legs are green, then wings are the subordinate diagnostic feature and if the legs are red, then the tail is the category diagnostic feature. In addition to the task-relevant features, the remaining, unused feature (here, head) is never used for categorization. The inclusion of this feature allows for a greater diversity of exemplars. The exact category structure (i.e., which features were at the "top" versus "bottom") was counterbalanced across participants.

Each category consisted of six exemplars: four "full" exemplars that had all four features (head, legs, wings, tail) and two "core" exemplars that only included the category-diagnostic features and the task irrelevant feature (e.g., head, legs, and wings but no tail). As mentioned earlier, accuracy on these core exemplars was used to exclude participants who did not sufficiently understand the category structure (see *Participants*). The core exemplar trials were excluded from other analyses, although we note that their inclusion does not alter the key results.

Category task. Participants selected, with the right hand, the H, J, K, or L key to categorize each creature. Each key was deterministically associated with one of the four categories. We arranged category-key mappings such that categories that shared a superordinate feature were never associated with adjacent keys to limit the influence of motor clustering on responses (Collins & Frank, 2016).

Participants were introduced to two categories at a time during two short practice blocks. Before the block began, they saw one exemplar for each category and the researcher listed the diagnostic features of each category. Researchers used a script to keep instructions consistent. During the task, participants saw an exemplar, made a response, and then got binary feedback as to whether their response was correct or not (Figure 1C). Participants practiced the categories mapped to the H and J keys in the first block, and the categories mapped to the K and L keys in the second block. This design meant that categories practiced together did not share superordinate features. Importantly, participants were not explicitly told the hierarchical structure of the task and thus could have simply learned four separate rules about category membership, rather than the latent relational structure.

After participants completed the two practice blocks, they moved on to the main category task with all four categories. As in the practice blocks, they would see a stimulus on each trial, make a response, and get binary feedback on whether their response was correct or not. If they did not make a response within 2s, the next trial would begin. Participants saw 60 presentations or "iterations" of each category (i.e., 10 presentations of each exemplar, ~240 trials total) over the course of the task. Trial sequences contained all pairwise transitions between categories and transitions between categories were all equally likely.

Forced response task. We utilized a forced-response task to characterize categorization dynamics (Ghez et al., 1997; Hardwick et al., 2019; McDougle & Taylor, 2019; Trach & McDougle, 2023). In this task, we fixed trial duration by playing four beeps (400ms apart) on each trial and instructing participants to respond in synchrony with the last beep, even if they felt like they had to guess the correct action (Figure 1D). Participants received feedback on both the accuracy (i.e., correct category choice) and timing of their response. If participants made their responses within 100ms of the cued time, they received positive timing feedback. We manipulated preparation time (PT) on a trial-by-trial basis by varying the stimulus onset during the trial window. PT varied continuously between 100ms and 1.2s across trials. Thus, participants had very little time to plan responses on some trials and plenty of time on other trials. The aim of this paradigm is to force participants to make responses at different points during their deliberation process. Thus, we can examine the probability of different types of responses as a function of PT to characterize decision-making dynamics within individual trials. Participants saw approximately 180 iterations of each stimulus category in the forced response phase of the experiment (~30 iterations per exemplar; ~720 trials total). PT in all analyses and figures includes both the planned preparation time (i.e., the programmed latency between stimulus onset and response cue) and the latency between the response cue and the participant's response (i.e., their response time).

Results

Category task results. Participants learned the category structure and performed the task well (overall accuracy = 90.1%, *SD* = 6.96%). Accuracy over the course of the task is

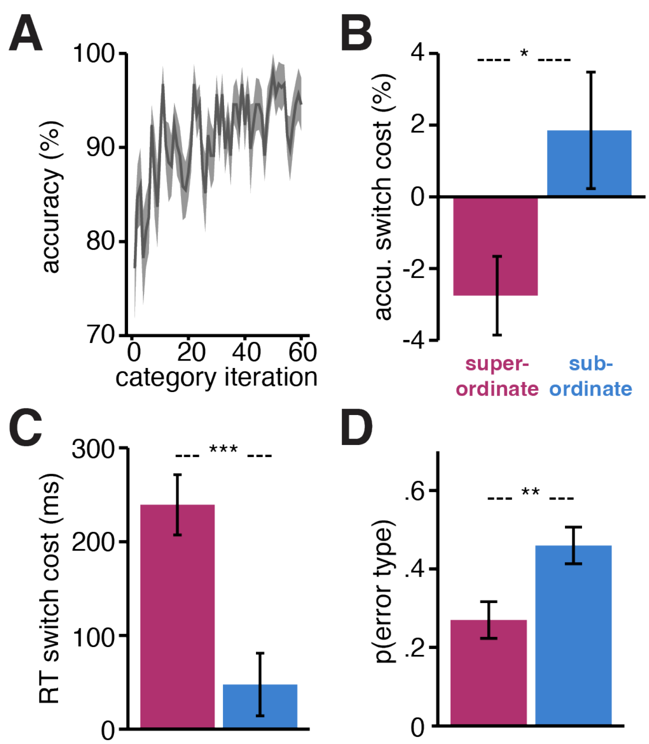

Figure 2. A) Accuracy by category iteration during the Category task. **B)** Accuracy switch cost (accuracy on switch trials – accuracy on repeat trials) for superordinate and subordinate feature switches. **C)** RT switch cost (RT on switch trials – RT on repeat trials) for superordinate and subordinate feature switches. **D)** Corrected probability of making a superordinate vs subordinate error on error trials. Probability of superordinate errors is divided by two here to correct for number of responses.
* $p < .05$, ** $p < .01$, *** $p < .001$

plotted in Figure 2A (note that this does not include practice blocks).

We examined accuracy and RT switch costs to assess whether individuals were representing the relational structure of the task or if they were simply representing individual rules for each category. We expect larger switch costs with changes in the superordinate feature (relative to subordinate feature changes) if participants are representing the hierarchical structure of the task, relative to switch costs at the subordinate feature level. Previous work has shown that changes at superordinate levels of a hierarchical task tend to incur larger switch costs than changes at subordinate levels of the task (e.g., Collins, 2017). In contrast, if participants learned individual rules for each category, switch costs should be relatively equivalent across category transitions.

We compared the magnitude of accuracy and RT switch costs for superordinate versus subordinate category switches (Figure 2B,C): Switch costs were significantly larger for trials where the superordinate feature changed (Accuracy: $M = -2.76\%$; RT: $M = 239$ms) as compared to trials where there was only a switch at the subordinate task level (Accuracy: $M = +1.85\%$; RT: $M = 48$ms; Accuracy contrast: $t(22) = 2.22$, $p = .0373$; RT contrast: $t(22) = 5.33$, $p < .001$). Thus, we have evidence that participants were representing the latent structure in the task, rather than learning four individual category rules.

We found further evidence of a hierarchically-structured task representation in the errors that participants made during the category task (Figure 2D): On trials where participants made the wrong response, they were significantly more likely to respond with the key that corresponded to the category that shared the superordinate feature with the target category ("subordinate error") than they were to make a different error ("superordinate error"; $t(22) = 2.88$, $p = .009$). If participants had learned individual rules for each category, we would not expect this difference in error rate. We note that to do this analysis, we isolated error trials for each participant and calculated the proportion of incorrect responses that were superordinate versus subordinate errors; importantly, we divided the proportion of subordinate errors by two for this analysis as there are two responses that would lead to a subordinate error on each trial and only one response that is considered a superordinate error. The error analysis provides further evidence that participants learned the hierarchical structure of the task and mentally represented it as such.

Forced response results. Participants then engaged in a forced response task with the same category structure and exemplars seen during training. Participants performed this difficult task well and frequently met the response deadline (average number of well-timed trials = 448; 64% of total trials; range = 225-543). Analyses include all trials where PT was less than 1.3s, and PT was calculated for each trial as the latency between stimulus onset and response. (We note that the key results hold when trials where the response deadline was not met within the +/- 100ms cushion were excluded.)

To characterize decision dynamics, we analyzed the probability of different types of responses as a function of preparation time (PT). Specifically, we asked whether error patterns were consistent with a serial decision-making process, where superordinate category levels are resolved prior to subordinate category levels. If participants make category judgements in a serial, top-down manner, participants should, at short PTs, make more subordinate feature errors (i.e., the superordinate category was correctly identified, but not the subordinate feature) than superordinate feature errors (i.e., superordinate category was not correctly identified), as they putatively have had time to first resolve the top level of the category structure but not yet the bottom level (i.e., p(subordinate error) > p(superordinate error), Figure 3A, top row). In contrast, if the probability of superordinate and subordinate errors decrease uniformly across PTs, the pattern of results would suggest that category judgments are executed as a unified step and task levels can be processed in parallel during decision-making (Figure 3A, bottom row).

We thus analyzed the evolving probability of different types of errors as a function of preparation time. We first coded each response as either a correct response, subordinate error, or superordinate error. Importantly, there is only one action that corresponds to a correct response and one action that corresponds to a subordinate error on each trial, while there are two responses that can considered superordinate errors on each trial (Figure 1B). Thus, we coded the two different superordinate error responses separately and include a line for each in different shades of pink in Figure 3 to retain equivalent chance probabilities for each type of error. We used a 100ms sliding window to create smoothed curves that depict the evolution of response probabilities as a function of PT (Figure 3B). Inset bar graphs depict the corrected probability of superordinate errors (rather than raw probability) to compare with subordinate errors.

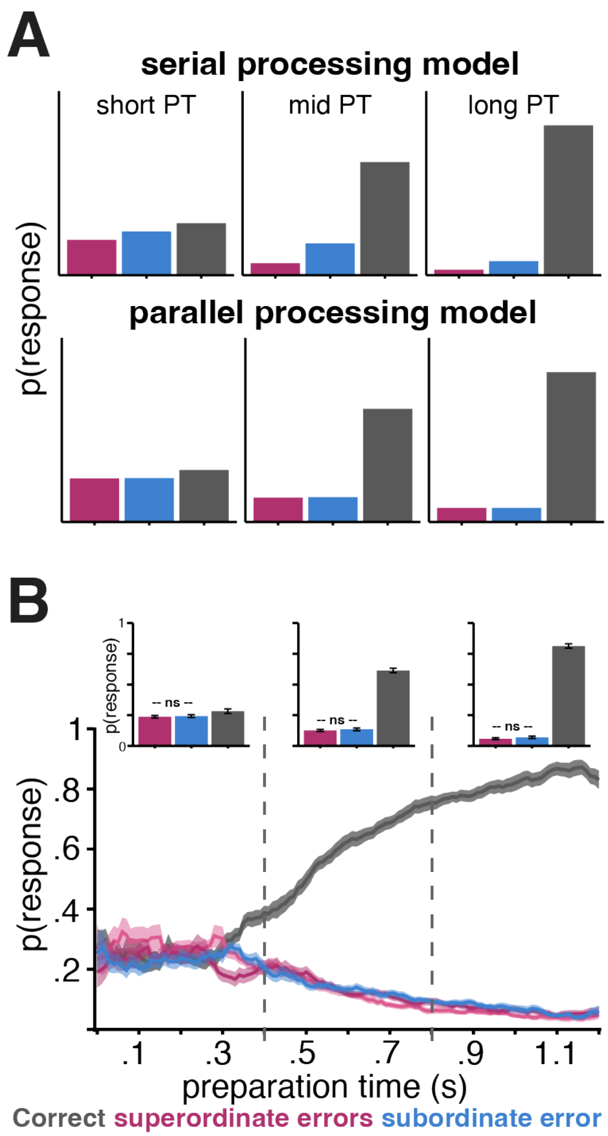

Figure 3. A) Illustration of probability of correct trials and superordinate and subordinate errors at short, intermediate, and long PT. Top row depicts expected behavior if category levels are processed serially. Bottom row depicts expected behavior if category levels are processed in parallel. Note that probability of superordinate errors is corrected (by dividing in two) to equate chance probabilities between superordinate and subordinate errors. **B)** Probability of response types as a function of PT. Inset bar graphs summarize probability of superordinate errors, subordinate errors, and correct trials in 400ms PT bins. Error shading represents 1 SEM.

Our results do not show evidence of a serial process where superordinate category features are processed before subordinate categories (Figure 3B). Instead, superordinate and subordinate errors decreased uniformly across the PT interval. We conducted t-tests between the probability of superordinate and subordinate errors in 400ms bins of short, mid, and long PTs: subordinate errors were not more frequent than superordinate errors in any bin ($t(22) < 1.87$, $ps > .05$). At very short PTs (<300ms), participants were at chance performance (25%), likely suggesting random guessing. After ~300ms of preparation, participants began to make more correct responses and the probability of both error types decreased at the same rate. At the longest PTs, accuracy was comparable to performance in the prior learning task where there was no response deadline, suggesting that the additional load of having to precisely time each response did not significantly affect participant performance. In contrast to serial models of categorical decision making that predict superordinate errors to decline more quickly than subordinate errors, our results suggest that hierarchical levels can be processed in parallel during real-time categorization decisions.

Discussion

Concepts and categories are essential to understanding the world around us and guiding behavior. The hierarchical structure of categories allows for the storage and use of category information at multiple levels of abstraction. Here, we investigated how hierarchically-structured, newly-learned category representations are implemented during decision-making in real time. Specifically, we asked whether individuals serially use information at different hierarchical levels to make categorical decisions or whether hierarchical levels are processed in parallel. We addressed our questions of interest by using a “forced response” psychophysical method to characterize categorization decisions (Hardwick et al., 2019; McDougle & Taylor, 2019). We used variation in accuracy and RT and the types of errors that participants committed during *de novo* category learning to establish that participants were mentally representing the latent hierarchical structure in the task. We found evidence across all metrics that individuals were indeed representing the relational structure of the task (Figure 2), rather than learning individual rules for each category. Next, we used a forced response paradigm to characterize within-trial decision making dynamics. Our results in this task support the hypothesis that information across hierarchical levels can be processed in parallel, rather than sequentially from superordinate to subordinate (Figure 3). That is, we did not find evidence that superordinate category features ere processed before subordinate category features, despite being relevant for determining feature-based categorization rules.

While this parallel processing dynamic might be surprising since the superordinate category determines the subordinate categorization rules, it closely resembles findings in the cognitive control domain (Cellier et al., 2022; Ranti et al., 2015). At the neural level, researchers speculate that parallel processing of task levels during cognitive control tasks is enabled by a specialized gradient of “abstraction” in the prefrontal cortex (PFC; Badre, 2008; Badre & D’Esposito, 2009; Badre & Nee, 2018). Theories concerning this “rostro-caudal abstraction gradient” in the PFC posit that the PFC is organized such that increasingly rostral areas of cortex process increasingly abstract information (Badre & Nee, 2018). For example, caudal regions of the PFC that are closer to motor hubs are involved in processing lower-order sensory-motor information, while more rostral regions might represent more abstract plans. Thus, information at different levels of abstraction can be simultaneously represented by adjacent areas of the cortex, rather than sequentially traversing each level. Similarly, there is evidence that hierarchical levels of categories are represented in different areas along the ventral visual pathway (Iordan et al., 2015) or in different regions of the brain (Zhuang et al., 2023). This organization could enable the processing of category levels simultaneously, a potentially adaptive strategy to allow flexible use of multiple levels of abstraction (Grill-Spector & Weiner, 2014).

The design of the forced response task also allows for novel computational modeling to further describe cognitive dynamics during the decision-making interval (Hardwick et al., 2019; Ranti et al., 2015) For example, Ranti and colleagues (2015) used a simple hierarchical model to formalize response dynamics in their three-level cognitive control task. The model used forced response data to estimate the time it took to reach a decision at each level of the hierarchical task during response selection. In the current study, we would expect a similar model to estimate that superordinate and subordinate task levels are resolved in parallel during categorization. This remains to be tested.

One limitation here is that the category structure was extremely simple and participants quickly achieved near-perfect accuracy in categorization after only a brief instruction. Much work has shown that expertise affects categorization performance (Johnson & Mervis, 1997; Seger & Miller, 2010), so it is unclear if we would see different results here if we used a harder task. It is possible that a serial processing strategy would be apparent earlier in learning or with a more complex category structure, pushing individuals to serially attend to relevant stimulus features to make judgments. To further this investigate this possibility, we are conducting a variant of this task where participants do not receive instruction on the categorization rules, instead using only trial-by-trial feedback to discover the category structure. This task is more difficult for participants; however, our preliminary results corroborate the findings presented here: participants appear to process hierarchical levels in parallel. Future work could incorporate learning of much more complex category structure to study more fully the dynamics of multi-level categorization decisions.

We opted to use novel categories to ensure *de novo* learning from all participants and to tightly control the category structure. However, this approach leaves some features of natural categories uninvestigated. In natural categories, hierarchical levels of categories are commonly referred to as superordinate, basic, and subordinate. Our novel categories do not have any “basic” category level, and there is no clear “prototypical” version of our stimuli. Mental representations of basic versus subordinate or superordinate category levels have received concentrated attention in the broader study of the psychology of concepts and categories. Such work often highlights a privileged role for basic category information: Basic level categories are accessed faster than sub- or superordinate categories (e.g., Macé et al., 2009) and there is evidence that neural representations of basic categories are evident earlier than representations at other levels in neural signals (in macaques: Dehaqani et al., 2016; preprint of work with humans: Greene & Rohan, 2022). While we did not find evidence of serial processing of task levels in our novel category structure, implementing our methods in a categorization task with natural categories that have a basic level as well could reveal how individuals implement structured category representation to move from basic levels to more specific or broader categories.

Overall, this work marks a novel psychophysical approach to understanding the dynamics of categorization and action selection. Our results suggest that processing across category levels likely occurs in parallel, despite participants representing a hierarchical category structure. Ongoing work with computational models or neural recordings can further characterize this fundamental cognitive process. Future investigations could also utilize the methods presented here to understand natural category representations and dissect real-time dynamics of the basic category biases that are widely documented in the field.

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