# EEG-based classification models reveal differential neural processing of words and images

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**Abstract**

Machine learning methods employing neuroimaging data are useful for monitoring the activation of neural representations. Specifically, they can be used to discern the brain networks engaged in processing specific categories of items. This approach has been used predominantly with functional magnetic resonance imaging data, and more rarely with electroencephalography (EEG) data. Here, we present a task, an analytical pipeline, and a stimulus dataset for investigating category representations using EEG. Participants (*N* = 30) viewed a series of images and words of objects belonging to five categories (Animals, Tools, Food, Scenes, and Vehicles) and responded when items from the same category were presented consecutively. We trained support vector machines on EEG data within participants and found that both image trials and word trials yielded significant category classification accuracy, with image trials achieving higher accuracy than word trials. When comparing categories in a pair-wise fashion, all pairs were statistically distinguishable for image trials, whereas only one pair was distinguishable for word trials. Parietal and Left Temporal electrodes contributed more to image classification than Frontal and Right Temporal electrodes. Category-specific activity patterns also generalized across participants for image trials. Our data and analytic pipeline yielded high classification accuracies, primarily for image trials, providing support for the utility of EEG data for neural decoding. These methods can be instrumental for exploring the activation and reactivation of neural representations at the category level during wakefulness and, potentially, during offline states.

## 1 INTRODUCTION

Categorization is fundamental to how the mind and brain organize semantic knowledge about the world. Children learn to categorize objects and actions as early as infancy (Owen & Barnes, 2021), and it remains an efficient way for processing information throughout life. Over years of learning, category assignment comes easily and mitigates the cognitive load of new learning. Distinct categories are represented by separable neural networks, with more similar categories (e.g., dogs and cows) having closer representation in the brain relative to more distinct items (e.g., dogs and umbrellas), which have more distinguishable representations (Bracci & Op de Beeck, 2016; Kriegeskorte et al., 2008). Research on categorical representations in the brain has revealed multiple category-specific regions, including areas that are dedicated to the processing of faces, houses, scenes, and tools (Epstein & Kanwisher, 1998; Ishai et al., 1999; Lewis, 2006).

Although early research on category representation in the brain relied primarily on lesion studies (see Gainotti, 2000, for review), recent studies employed neuroimaging techniques that capture activity throughout the brain during category processing, with most studies using functional magnetic resonance imaging (fMRI). In this study, we examined the fidelity of categorical representation using scalp electroencephalography (EEG), leveraging its high temporal resolution. Classically, studies employing EEG to examine category selectivity have used event-related potentials (ERP), the time-locked neural response in a single electrode, averaged over multiple trials. For example, Bentin and colleagues discovered the N170 ERP, a negative deviation peaking ~170 ms after the visual presentation of a face (Bentin et al., 1996). ERP analyses commonly specify a topographical location on the scalp and a specific latency at which effects are most pronounced. However, this approach does not facilitate the detection of nuanced (yet consistent) differences that are distributed across the scalp, potentially changing dynamically over time. For example, a slight lateral shift in topography may be lost when examining any single electrode due to signal-to-noise issues, but could be reliably identified when considering the pattern in a holistic way.

In recent years, methods were developed to harness these scalp-wide dynamics for examining neural representations across time and space. To achieve this, data are typically submitted to machine learning algorithms that are trained to distinguish between classes of stimuli, actions, and internal states.

For example, Bae & Luck (2018) trained classification models on EEG data across electrodes to reveal covert shifts in spatial attention. Essentially, the models examined data from all electrodes at different time points and across different attentional states to extract information regarding spatial attention. Classification accuracy was taken as a proxy for the information reflected in the neural signal, suggesting the enactment of selective neural representation. Other studies have used similar approaches to more directly examine the distinct neural representations for perceived categories (e.g., Schreiner et al., 2021). Notably, the methods used in these studies were agnostic about which electrodes contributed most, instead leveraging a data-driven approach to identify neural patterns with minimal experimenter intervention.

In our work, we build on these recent methodological advances and use support vector machines (SVMs) on high-density scalp EEG data to demonstrate EEG-decodable representation across different categories and modalities. Participants came into the lab and viewed a series of alternating images and words representing objects from five categories: Animals, Tools, Food, Scenes, and Vehicles. Participants were instructed to indicate when the currently presented item was of the same category as the one immediately preceding it, while EEG data was collected. We trained SVMs on this data to classify the presented category and modality. All SVMs were trained and tested within-subjects, except for one analysis, which trained them across subjects to identify generalizable category-specific neural patterns. All code, stimuli, and data are publicly shared to enable further exploration of category representation in the brain.

## 2 METHODS

### 2.1 *Participants*

A total of 30 participants (19 women, 11 men) were recruited for this study, with a mean age of 22.5 ± 2.86 SD years (range 18-31). Of these participants, 18 were native English speakers, and the rest were non-native fluent speakers. The majority of participants were right-handed ($n$ = 26), three were left-handed, and one was ambidextrous. The majority of our sample identified as Asian ($n$ = 20), followed by White ($n$ = 8) and Black/African American ($n$ = 1), with one participant selecting "Not Listed / Decline to State." Two people identified as Hispanic/Latino. Participants completed the study for either course credits or monetary compensation, and were recruited through flyers, emails, and social media platforms. Eligibility criteria required participants to be between 18 and 35 years of age, be fluent in English, and have no history of neurological disorders. Participants were instructed to abstain from using recreational drugs and alcohol for 24 hours prior to their lab appointment. On the day of the experiment, participants completed a consent form and a mental health questionnaire before being fitted with an EEG cap. The study protocol was reviewed and approved by the Institutional Review Board at the University of California, Irvine.

### 2.2 *Materials*

A total of 100 stimuli were used in this experiment, comprising 50 images and 50 matched words. Stimuli belonged to five categories: Animals, Tools, Food, Scenes, and Vehicles (Figure 1a). The same ten items were represented in word- and image-form for each category (e.g., for the animals category, the word "DOG" and an image of a dog were used, respectively). The image dimensions were 800 x 800 pixels, and they were sourced from the THINGS database (Hebart et al., 2019), the BOLD5000 database (Chang et al., 2019), and from online websites. The number of letters per word did not significantly differ across categories ($F(4,49) = 1.8$, $p = 0.15$; Animals: 4.2 ± 1.72 SD, Tools: 6.3 ± 2.53, Food: 6.8 ± 1.89, Scenes: 6.1 ± 1.97, Vehicles: 6.4 ± 2.61). Both stimulus types (images and words) were included to ensure that the elicited neural responses corresponded to the conceptual meaning of each stimulus rather than merely distinguishing between images and words based on their physical appearance.

Additionally, to control for potential confounds related to visual characteristics, each word stimulus was presented on an 800 x 800 pixel abstract background, which was a scrambled version of an image from the BOLD5000 database. The backgrounds were intended to match the physical features of the presented images.

### *2.3 EEG Setup and Application*

Participants were fitted with a 64-channel EEG cap (ANT Neuro, Netherlands) with electrodes positioned in accordance with the standardized 10-20 system for EEG measurements. The two mastoid electrodes served as reference electrodes, and EOG activity was measured using two electrodes positioned on the bottom-left of the left eye and the upper-right of the right eye. The behavioral task was presented on a P2418HT 1920x1080p screen (Dell Inc., Texas) and was executed using MATLAB R2022b (MathWorks Inc., Massachusetts) with the Psychtoolbox-3 toolbox (Brainard, 1997).

### 2.3 *Procedure*

After signing the consent form, participants completed a basic demographic survey, the Anxiety Sensitivity Index 3 (Taylor et al., 2007), and the Questionnaire of Unpredictability in Childhood (Glynn et al., 2019). Subsequently, they were fitted with an EEG cap and engaged in a classification task involving stimuli from five distinct categories presented as images or words on a computer screen.

Participants were first introduced to all the images and words from each category. All items for each category were simultaneously presented on the screen, along with the category title in the following sequence: “ANIMALS”, “TOOLS”, “FOOD”, “PLACES” (i.e., scenes), “VEHICLES”. Presenting all of the categories to the participants beforehand ensured that they were aware of which category each item belonged to. Participants were then presented with the instructions of the task. In the task, participants were continuously presented with images and words in succession. The stimulus type alternated from trial to trial, such that images and words never followed one another. Participants were instructed to press the spacebar if the current stimulus belonged to the same category as the preceding stimulus (e.g., an image of a dog followed by the word "COW"). Otherwise (e.g., an image of a dog followed by the word “HAMMER”), no action was required. Trials requiring a response (termed “catch trials”) were balanced

across category and stimulus type. These trials were designed to maintain participant engagement with the stimuli on the screen. There were no consecutive “catch trials”, meaning participants were not required to press the spacebar in back-to-back trials. Each stimulus was presented on screen for 2 s, followed by an intertrial interval of 1 ± 0.5 s (Figure 1b).

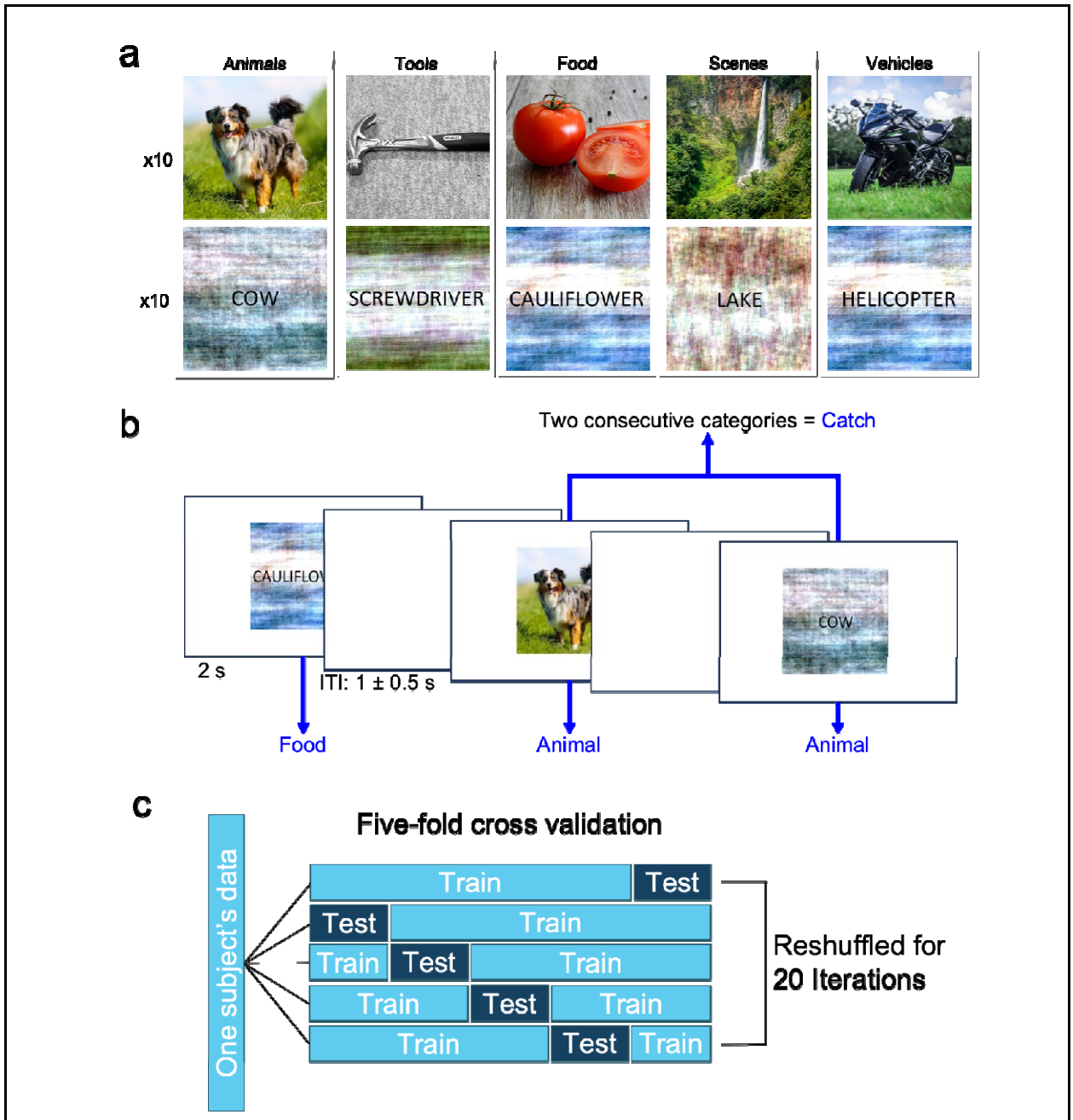



**Figure 1: An overview of the materials, behavioral task, and analyses. a**. Each category included ten images and ten words, totaling 100 items. Word stimuli were presented on a background matching

the visual dimensions of the images. **b.** To elicit categorical brain activity, participants viewed an alternating series of images and words. Each item was presented for 2 s, followed by a blank screen for 0.5-1.5 s. Participants were instructed to press the spacebar when two items of the same category appeared in sequence. **c.** We used machine learning models to identify distinguishable activity (e.g., between categories) in our EEG data. Our analysis used support vector machines. Models employed five-fold cross-validation (i.e., each model was trained on 80% of the data and tested on the remaining 20%, repeated five times). Data was reshuffled over 20 iterations.

Before beginning the task, participants completed a practice block to ensure they understood the instructions. This block consisted of 15 trials: seven images and eight words presented in alternating order, balanced across categories, with a 20% catch rate. Participants were required to repeat the practice block until they achieved a minimum score of 14/15. The main task included five blocks, each comprising 112 trials, including 10 catch trials. Blocks were planned so that 100 trials would be submitted to further analysis. The first two trials of each block were discarded, along with the catch trials. The remaining trials included all 100 stimuli, equally divided between stimulus types and categories.

Each block was completed in ~6 minutes, and participants were provided with a score upon completion to monitor their performance. To ensure optimal data quality, participants were required to achieve a threshold score of 90% in each round for their EEG data to be included in the analysis. All participants reached this threshold in all blocks, except for a single block (score: 82.14%), which was excluded from all analyses (results were qualitatively similar when including this block). In general, results indicate that participants understood the task and were focused on it throughout the experiment. Upon completion of the procedure, the EEG cap was removed, and participants were allowed to clean up and then asked to provide feedback on the task and any additional comments they wished to share.

### 2.4 *EEG preprocessing*

Data was sampled at 500 Hz. EEG recordings were pre-processed using the FieldTrip Toolbox (Oostenveld et al., 2011). The data was filtered with a bandpass filter of 0.3-35 Hz and re-referenced to the average of the mastoid electrodes. We visually inspected the data and interpolated noisy channels with the data from nearby channels. All recordings underwent independent component analysis, where components containing eyeblinks, eye movements, and related artifacts were removed. Lastly, we manually identified any artifacts in the data. The data were then segmented into trials around stimulus

onset (1.25 s, 2.75 s before and after onset, respectively). Trials that included artifacts were removed from analysis. In addition, trials that included user responses were excluded. In total, out of 500 trials of data collected, we analyzed an average of 453.5 trials (± 43.8 SD) per participant (range 341–494 trials).

### 2.5 *Support vector machine classification model*

We used support vector machines (SVM) to classify which category a participant was viewing using time-domain data from 58 preprocessed scalp electrodes as features (Fpz, Fp1, Fp2, AF3, AF4, AF7, AF8, Fz, F1–F8, FCz, FC1–FC6, FT7, FT8, Cz, C1–C6, T7, T8, CP1–CP6, TP7, TP8, Pz, P1–P8, POz, PO3, PO4–PO7, Oz, O1, O2), following the methods of Bae & Luck (2018). Separate SVMs were trained at each time point, each using data averaged over 62-ms (31-sample) windows. These windows were slid throughout each trial in 22-ms (11-sample) increments, with a 40-ms (20-sample) overlap between windows (182 time windows total over the 4-s trial duration).

We used a one-versus-all approach for our model, so that each SVM was trained to distinguish one class from the remaining classes (e.g., words vs images; images of foods vs images from all other categories). We used 5-fold cross-validation, in which an individual's data was split into five subsets, including a training set (four subsets, 80% of the trials) and a testing set (one subset, 20% of the trials) to test the model's accuracy. This resulted in five models, each tested on one subset and trained on the remaining four. This process was repeated 20 times, with a different set of trials divided into the five subsets in each iteration (Figure 1c). This process was repeated for each of the 30 participants at each of the 182 timepoints. Model accuracy was examined by comparing the predicted label to the true label at each timepoint. The accuracy rates for each timepoint were averaged across participants' 20 iterations and five subsets.

### 2.6 *Cluster-based permutation statistical analysis*

We used a set of permutation tests to determine the statistical significance of our models' performance (inspired by Bae & Luck, 2018). We generated null distributions to compare the observed models' accuracy rates. For each experimental question (see below; e.g., classifying word trials vs. image trials), we created 1,000 randomly generated permuted datasets structured similarly to our true datasets.

Permuted datasets were constructed by taking the veridical dataset and randomizing the data labels. For each participant ($N$ = 30), iteration ($k$ = 20), and fold ($j$ = 5), the true labels were shuffled across trials. We kept labels consistent across timepoints for each participant to preserve autocorrelation patterns. For each permuted dataset, we calculated accuracy by comparing the model's predictions to the shuffled labels. For both the true and shuffled datasets, accuracy rates were smoothed again across time points with an additional causal smoothing window of 9 time points (encompassing 238 ms in total), using data preceding each time point (e.g., smoothed data for time point t reflects the average of all time points between $t$-8 and $t$). Edge effects were avoided by dropping the first 8 windows, leaving 174 time windows for analyses. For both the true and shuffled datasets, we then compared the accuracy level of the model at each time point to chance levels using a two-tailed $t$-test across participants. We summed up the $t$-values for consecutive timepoints starting from trial onset that crossed $\alpha$ = 0.05 (critical $t$ = 2.045) to identify contiguous clusters in time that diverge from chance-level accuracy. Using the single largest cluster from each of the 1,000 permutation tests, we created a null distribution used to test the statistical significance of the true model's accuracy levels. The summed t-values for each contiguous cluster identified in the true dataset were compared to the distribution in a one-tailed fashion, yielding its $p$-value.

For some analyses, we determined significant differences between two different models (e.g., models that used Frontal vs Parietal electrode subgroups) and used a modified version of this approach. The approach here was to test whether the difference between two true datasets was larger than that expected by chance, as reflected by a null distribution of differences between two permuted datasets. Like before, two sets of 1,000 permuted datasets were generated based on the parameters of each true dataset. For both datasets, we followed exactly the same method as above up to calculating and smoothing accuracies, using a separate permuted dataset for each of the two contrasted models. We first computed the differences between the two true datasets for each timepoint, yielding time-series data for this difference for each participant. The same was done for the permuted data: in each permutation, for each participant, time-series data showing the differences between the models were created. The final steps of the analysis were similar to those described above: we used two-tailed t-tests across participants to compare differences in accuracy to zero for each timepoint, detected contiguous clusters, and built a

null distribution of differences using the permuted differences to determine the level of significance of the true differences in a one-tailed fashion.

2.7 *Within-Subject Classification tests*

The aforementioned SVM approach was used for most of our analyses. The overarching motivation for this project was to detect differences in brain activity when presented with stimuli from different categories. To detect modality-agnostic differences in categorical representations, we used all trials (both words and images) to classify across all five categories. We then investigated whether we could discern stimulus modalities by classifying between images and words. We further investigated whether EEG reflects modality-agnostic categorical representations in the brain by training SVMs on one modality (e.g., images) and testing on the other (e.g., words). In this case, we divided the data from each modality into five subsets for cross-validation, as described above, and used all five subsets for one modality's dataset to train the model and each of the five subsets for the other modality's dataset to test the model (e.g., image data used to train, word data used to test). This was repeated for 20 iterations of 5 blocks. Finally, we examined categorical representations for images and words separately, using image trials or word trials only.

We also examined whether different categories had more distinguishable representations by comparing categories in a pair-wise fashion (e.g., Animals vs. Food, Tools vs. Vehicles, etc.) for each modality separately. We used an alpha of 0.05 for all analyses and corrected for multiple comparisons in the pairwise analyses using the False Discovery Rate method. We next examined whether different topographical scalp regions differ in the categorical information they convey. To do this, we reran the main analyses focusing on subgroups of electrodes, examining image and word trials separately. We compared classifier accuracy between topographical regions to examine differences in representational fidelity. Since neighboring EEG electrodes tend to be strongly correlated, we repeated this analysis by sparsely selecting single representative electrodes from each of our subgroups.

Building on results from this approach, we investigated the electrodes on the left and right sides of the EEG cap separately, excluding those along the midline (odd-numbered electrodes for the left, even-numbered electrodes for the right). Classifiers were trained on each hemisphere separately for each

modality. To further assess symmetry in the information reflected on each side, we trained our models on one side (e.g., left electrodes) and tested on the other (e.g., right electrodes). For this, we matched the electrode labels for each participant's data so that the corresponding labels on each side lined up (e.g., F1 matched with F2). These models were trained over 20 iterations of 5 blocks of data shuffling, similar to our previous setup for images and words. For each block, classifiers were trained on 80% of the trials (i.e., the remaining four blocks) using data from one half of the scalp and tested on trials from the remaining block using data for the other half of the scalp.

### 2.8 *Between-Subject Classification Tests*

All analyses up to this point were done within-subject, with accuracy scores averaged across participants. To complement these analyses, we examined whether activity patterns were generalizable across the population (i.e., can models trained on multiple participants be successfully applied to a different participant). To test this, we adapted our analytic approach. Here, we used a leave-one-out approach, in which models were trained on data from 29 participants and tested on the remaining participant. This was repeated for all 30 participants, creating 30 datasets of time-dependent classification accuracy. Models were trained across all trials for each set of 29 participants and applied to each trial in the participant who was left out. As before, SVMs were used for this analysis. All individual trials within a given modality (e.g., words) collapsed across 29 participants were used for training, and all individual trials for the left-out participants were used for testing. Statistics were computed using the same approach described above - for each participant, labels were shuffled across all trials over 1,000 permutations, and a null distribution was created based on the permuted data. *t*-values were summed for each cluster of contiguous significant time points and compared to the null distribution, producing a *p*-value for each cluster.

## 3 RESULTS

### 3.1 *Participant task performance*

To investigate categorical representations reflected in EEG activity, 30 participants performed a task in which they viewed words and images depicting items from five categories (Animals, Food, Tools, Scenes, and Vehicles). In total, 100 visual stimuli (10 words and 10 images per category) were each presented once per block for 5 blocks, resulting in up to 500 trials for analysis. To maintain attention, participants had to respond when two stimuli belonging to the same category were presented consecutively, and they performed at ceiling (mean accuracy = 97.29%, SD = 0.19%, range 91.82% - 100%). Across all five blocks, the average score ranged from 97.06% - 97.55%.

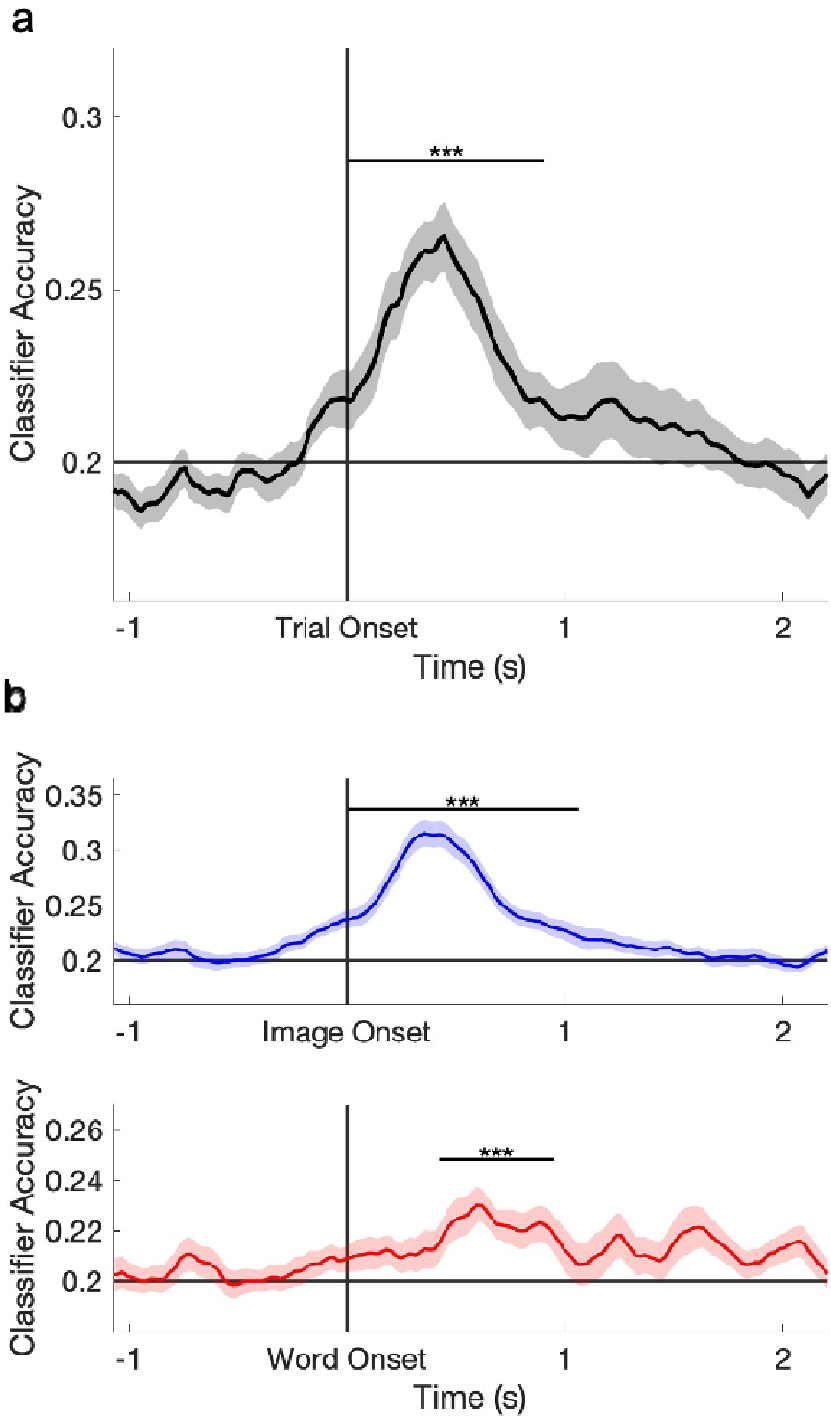
3.2 *Category information is represented in higher fidelity in images relative to words*

We first examined whether the EEG data reflect categorical information regardless of stimulus modality (i.e., words or images). We used all trials (range 341–494 across participants) to classify between the five stimulus categories and found above-chance classification accuracy between categories (cumulative $t = 170.43$, $p < 0.001$, time range = 0–0.91 s, peak accuracy = 0.27). This demonstrated that category information is reflected in EEG topographical distributions, regardless of stimulus modality. Next, we tested whether different modalities elicited distinct brain activity by training a classifier to distinguish between images and words. We indeed found above-chance classification accuracies when contrasting between modalities (cumulative $t = 1119.8$, $p < 0.001$, time range = 0–1.7 s, peak accuracy = 0.91).

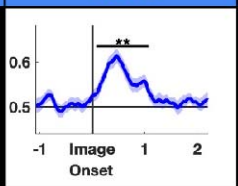
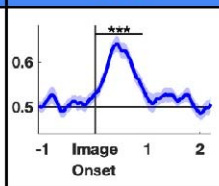
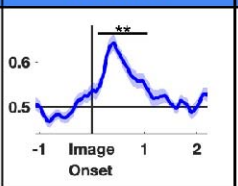
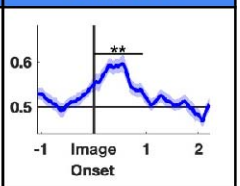
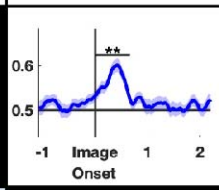
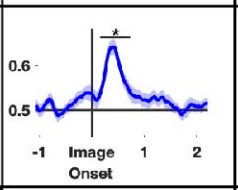
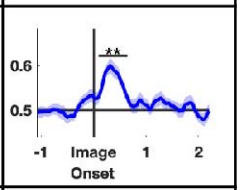
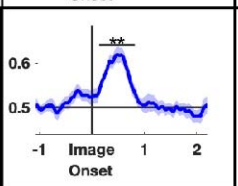
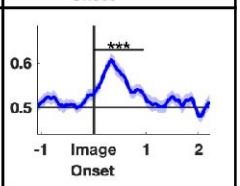
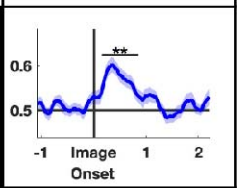
We next split our trials by modality (i.e., image and word trials separately) to examine whether modality-specific EEG data reflected category information. We found above-chance classification accuracy for images (cumulative $t = 307.8$, $p < 0.001$, time range = 0–1.06 s, peak accuracy = 0.32, trial count range = 167–247), as well as for words (cumulative $t = 81.64$, $p < 0.001$, time range = 0.42–0.95 s, peak accuracy = 0.23. trial count range = 174–247; Figure 2). Notably, the accuracy levels obtained for images were significantly higher than for words (difference between the plots: cumulative $t = 212.11$, $p < 0.001$, time range = 0–0.82 s), showing that category information is better represented in the EEG response to visual images relative to visually presented written words.

Finally, we examined whether modality-free category information is sufficiently reflected in the EEG data, allowing cross-modality classification. To do so, we trained classifiers on data from one modality and tested them on the data from the other modality. We found no evidence that classifiers

trained on EEG responses to image presentations could be used to decode category information from word trials or vice versa. Although this may mean that the EEG activity does not reflect modality-free category information, it may also be that the classification models trained for one modality overfit to certain features that are irrelevant to the other. This interpretation is supported by the results of our first classification model, showing that classifiers can be successfully applied to decode category information using data collapsed over both modalities




**<u>Figure 2.</u> EEG neural patterns reflect category information within modality and across modalities. a.** Classifiers trained on image- and word-trials are able to distinguish between categories. **b.** Classifiers trained on image trials (top) and word trials (bottom) can both distinguish between categories. Shaded areas reflect the standard error of the mean across participants. ***** *p* < 0.001**

| | Animals | Tools | Food | Scenes | Vehicles |
|---|---|---|---|---|---|
| **Animals** | |  |  |  |  |
| **Tools** | *t* = 205.09<br>***p* = 0.002**<br>peak: 0.61 | |  |  |  |
| **Food** | *t* = 234.88<br>***p* < 0.001**<br>peak: 0.64 | *t* = 151.12<br>***p* = 0.002**<br>peak: 0.6 | |  |  |
| **Scenes** | *t* = 215.68<br>***p* = 0.004**<br>peak: 0.64 | *t* = 143.67<br>***p* = 0.01**<br>peak: 0.64 | *t* = 176.81<br>***p* = 0.003**<br>peak: 0.62 | |  |
| **Vehicles** | *t* = 173.52<br>***p* = 0.002**<br>peak: 0.6 | *t* = 125.87<br>***p* = 0.003**<br>peak: 0.6 | *t* = 193.92<br>***p* < 0.001**<br>peak: 0.61 | *t* = 140.53<br>***p* = 0.004**<br>peak: 0.6 | |

**<u>Figure 3.</u> EEG data from image trials yield significant classification accuracies for all pairwise comparisons between categories.** All p-values have been adjusted with the False Discovery Rate method for multiple comparisons. Shaded areas reflect the standard error of the mean across participants.
*** *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001**

3.3 *Representation fidelity differs across categories for images*

We next sought to determine which of the five categories was most distinguishable using EEG data. To test this, we trained classifiers on EEG data to distinguish between stimuli from each pair of categories (e.g., Animals vs. Tools) separately for each modality. When examining images, our results showed that all category pairs were distinguishable from one another, yielding classification accuracies above chance level (Figure 3). Categorical representations of images between Animals and Foods, Animals and Scenes, and Scenes and Tools were most distinguishable (peak accuracy rates = 0.64), with Animals vs. Foods yielding the highest cumulative *t*-value (cumulative *t* = 234.88). When examining

words, only one pair of categories yielded neural patterns that were significantly distinguishable (Animals and Tools; Figure 4). A potential confound is that words in these categories differ in length. Indeed, words in the Animals category have a marginally lower number of average letters relative to the words in the Tools category (4.2 ± 1.72 vs. 6.3 ± 2.53; $p$ = 0.06, two-sided Wilcoxon rank sum test).

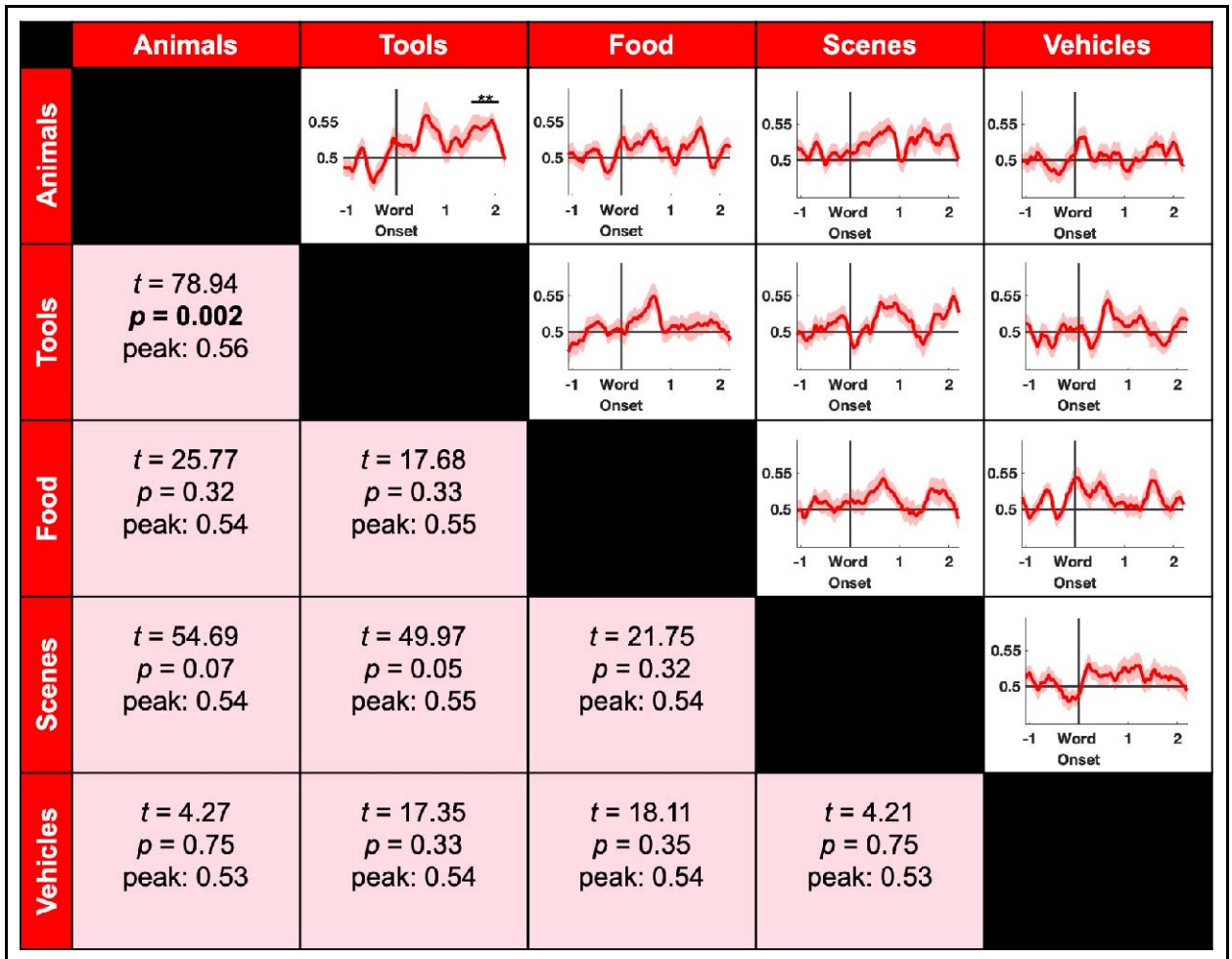



**Figure 4. EEG data from word trials yield significant classification accuracies for one pairwise comparison between categories only (Animals vs. Tools).** Non-significant *t* and *p*-values and peak accuracy values reflect the cluster closest to significance. All p-values have been adjusted with the False Discovery Rate method for multiple comparisons. Shaded areas reflect the standard error of the mean across participants.

**** $p$ < 0.01**

3.4 *Information from different scalp regions differentially distinguishes between categories across modalities*

We next examined how different scalp topographies contribute to cross-category classification. To investigate this, we divided our electrodes into different region-specific groups: occipital, parietal, temporal, and frontal (Figure 5a) and trained classifiers on each subset of electrodes across all categories, split by modality. For image trials, we found that all four groups show above-chance classification accuracies: the occipital group (cumulative $t$ = 267.97, $p$ < 0.001, time range = 0–0.93 s, peak accuracy = 0.32), the parietal group (cumulative $t$ = 308.61, $p$ < 0.001, time range = 0–1.04 s, peak accuracy = 0.32), the temporal group (cumulative $t$ = 244.47, $p$ < 0.001, time range = 0–0.95 s, peak accuracy = 0.28) and the frontal group (cumulative $t$ = 203.69, $p$ < 0.001, time range = 0–1.04 s, peak accuracy = 0.26).

Classifier trained on word trials also yielded significant accuracies for all groups: for the occipital group (cumulative $t$ = 55.18, $p$ < 0.01, time range = 0.42–0.82 s, peak accuracy = 0.23), the parietal group (cumulative $t$ = 124.18, $p$ < 0.001, time range = 0.36–0.93 s, peak accuracy = 0.24), the temporal group (cumulative $t$= 76.29, $p$ < 0.001, time range = 0.42–0.8 s, peak accuracy = 0.24), and the frontal group (cumulative $t$ = 40.16, $p$ < 0.05 time range = 0.58–0.93 s, peak accuracy = 0.22). To further examine the contributions of the electrode groups to classifying category information, we compared the groups yielding the highest and lowest accuracy rates (the parietal and frontal groups, respectively). For the image trials, we found that data from the parietal electrodes provided more discernible information regarding categories relative to the frontal electrodes (cumulative $t$ = 128.67, $p$ < 0.0011, time range = 0.11–0.69 s; Figure 5b, top). No significant differences were observed in word trials between the parietal and frontal groups (statistics for the cluster closest to significance: cumulative $t$ = 21.92, $p$ = 0.14, time range = 0.49–0.66 s; Figure 5b, bottom).

Data from adjacent EEG electrodes are typically correlated. Our approach for dividing the scalp into subgroups is, therefore, fundamentally limited, in that subgroups border each other and are therefore not truly separable. To overcome this limitation, we complemented this approach by examining five representative electrodes (one within each region, Figure 5a) to assess regional activity. Using just these five electrodes, the models are still able to classify across categories significantly above chance for both image trials (cumulative $t$ =223.92, $p$ < 0.001, time range = 0–0.91 s, peak accuracy = 0.28) and word trials (cumulative $t$ = 90.72, $p$ < 0.001, time range = 0.42–0.95 s, peak accuracy = 0.23). We next

examined the regional contribution to category classification using these single electrodes. Despite including a single feature, this analysis still yielded classification accuracies that were significant for images across all categories (frontal, electrode Fz: cumulative $t = 37.52$, $p < 0.01$, time range = 0.0.27–0.55 s, peak accuracy = 0.21; parietal, electrode Cz: cumulative $t = 53.16$, $p < 0.001$, time range = 0.27–0.58 s, peak accuracy = 0.22; left temporal, electrode C5: cumulative $t = 77.93$, $p < 0.001$, time range = 0.27–0.69 s, peak accuracy = 0.22; right temporal, electrode C6: cumulative $t = 35.59$, $p < 0.001$, time range = 0.0.33–0.58 s, peak accuracy = 0.21; Occipital electrode, Oz: cumulative $t = 55.67$, $p < 0.001$, time range = 0.25-0.55 s, peak accuracy = 0.22). While the peaks are not far above chance, this analysis shows that image stimuli elicit EEG activity that allows for category classification with even a single electrode. Word trials, however, did not produce classifiable data across all electrodes (Fz: cumulative $t = 6.95$, $p = 0.53$, time range = 0.6–0.64 s, peak accuracy = 0.21; Cz: cumulative $t = 10.19$, $p = 0.33$, time range = 1.87–1.94 s, peak accuracy = 0.21; C5: cumulative $t = 6.65$, $p = 0.59$, time range = 0.62–0.66 s, peak accuracy = 0.21; C6: cumulative $t = 18.35$, $p = 0.14$, time range = 0.53–0.66 s, peak accuracy = 0.21; Oz, cumulative $t = 9.75$, $p = 0.36$, time range = 0.58–0.64 s, peak accuracy = 0.21; all statistics for the clusters closest to significance). These results demonstrate that category classification from image stimuli is feasible even when using low-density EEG systems.

We next considered the left and right temporal subsets of electrodes separately to assess whether they asymmetrically captured category information. For images, both the right and the left temporal electrode group produced above-chance classification accuracies (left temporal: cumulative $t = 210.68$, $p < 0.001$, time range = 0.16–1.02 s, peak accuracy = 0.28; right temporal: cumulative $t = 47.06$, $p < 0.01$, time range = 0.22–0.53 s, peak accuracy = 0.21; Figure 5c, top). Interestingly, accuracy levels were significantly higher for the left cluster relative to the right one (cumulative $t = 185.18$, $p < 0.001$, time range = 0.18–1.02 s). For words, electrodes on both sides revealed above-chance classification accuracy, but there were no differences between the two subgroups (left temporal: cumulative $t = 56.21$, $p < 0.001$, time range = 0.42–0.71 s, peak accuracy = 0.24; right temporal: cumulative $t = 60.73$, $p < 0.01$, time range = 0.49–0.88 s, peak accuracy = 0.24; difference: no significant clusters; Figure 5c, bottom). Overall, results revealed varying levels of discernible EEG activity across different scalp areas. These

differences were more pronounced for image stimuli, which also elicited asymmetrical activity between the left and right temporal regions.

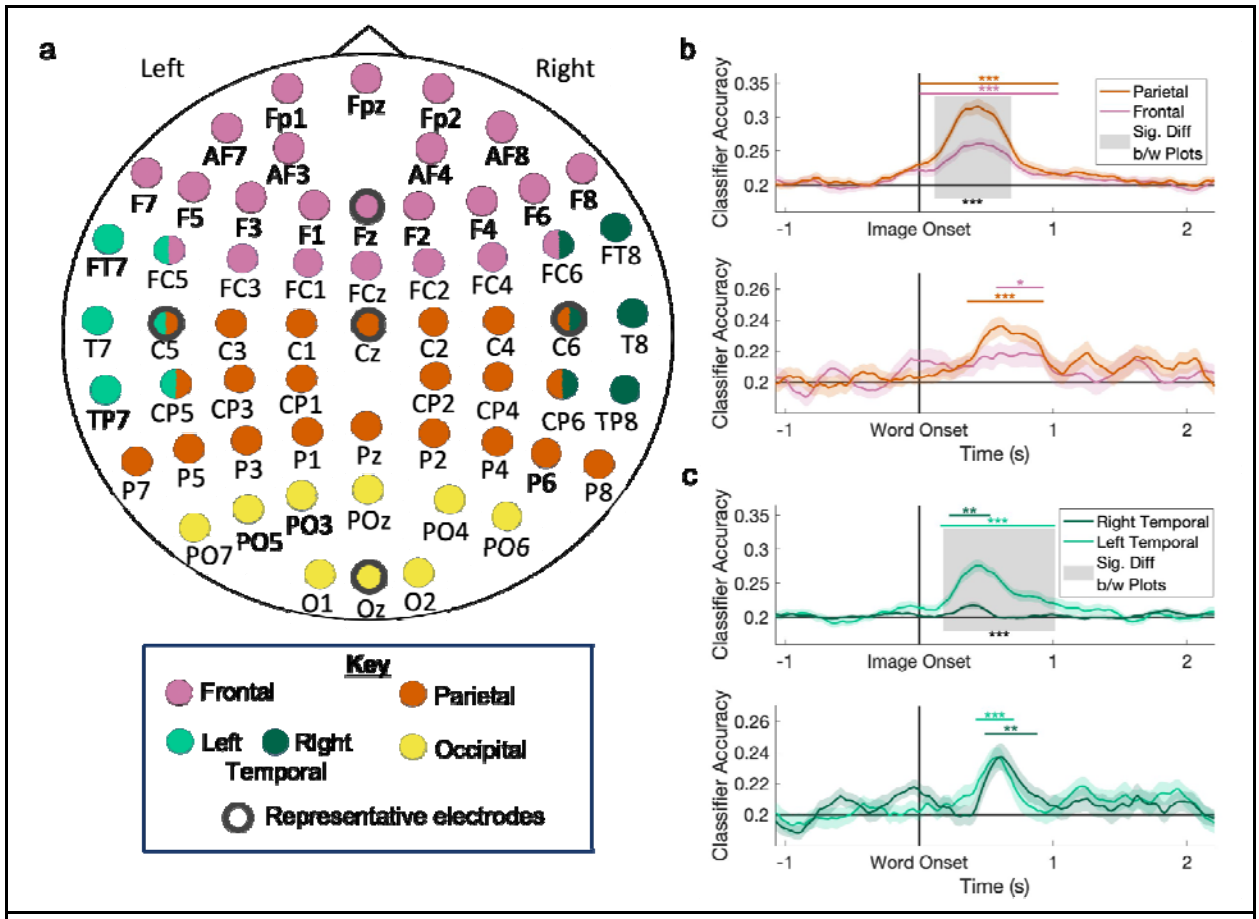



**Figure 5. Discernible topographic contributions to classification accuracy for both words and images. a**. The scalp electrodes were divided into groups, and each was used to train and test classifiers. Thick, grey outlines indicate which electrodes were selected to represent the subgroup in the representational electrode analyses (see text). Note that some electrodes were used in more than one group. **b.** Results showing the difference between accuracy levels obtained using the parietal electrode group (highest classifier accuracy) and the frontal electrode group (lowest classifier accuracy) for image trials (top) and word trials (bottom). Horizontal lines reflect significant time periods for each group; shaded areas represent significant differences between groups. **c.** Same as in (b), but comparing left and right temporal clusters. Shaded areas reflect the standard error of the mean across participants.
*** $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$**

We next examined the lateralized contributions to category classification more directly by dividing all electrodes into left- and right-scalp subgroups, omitting midline electrodes. We first tested whether each half was sufficient to classify between categories, and found above-chance accuracy levels for both left and right scalp electrodes for image trials (left scalp: cumulative $t = 295.01$, $p < 0.001$, time range = 0–

1.19 s, peak accuracy = 0.27; right scalp: cumulative $t$ = 259.44, $p$ < 0.001, time range = 0–0.99 s, peak accuracy = 0.28). For word trials, only data from the right scalp electrodes yielded accurate classifiers (right electrodes: cumulative $t$ = 69.05, $p$ < 0.001, time range = 0.44–0.93 s, peak accuracy = 0.22; left electrodes: cumulative $t$ = 27.22, $p$ = 0.05, time range = 0.49–0.66 s, peak accuracy = 0.22). Left and right scalp activity were not significantly different from each other for either modality (images, statistics for the cluster closest to significance: cumulative $t$ = 21.19, $p$ = 0.26, time range = 0.18–0.33 s; words, statistics for the cluster closest to significance: cumulative $t$ = 10.19, $p$ = 0.4, time range = 1.52–1.59 s).

We further investigated the neural symmetry of information representation by training classifiers on one group of electrodes (e.g., those over the left hemisphere) and testing on the other (e.g., those over the right hemisphere). The objective of this analysis was to determine whether category-specific information was symmetrically represented across the two sides of the scalp for images and words. Indeed, we found evidence for symmetry. For both image and word trials, we found above-chance classifier accuracy when the right electrodes were used for training and the left for testing (images: cumulative $t$ = 40.12, $p$ < 0.05, time range = 0.33–0.62 s, peak accuracy = 0.21; words: cumulative $t$ = 32.83, $p$ < 0.05, time range = 0.49–0.71 s, peak accuracy = 0.21). When left electrodes were used for training, testing on the right electrodes for image trials produced marginally significant accuracy rates (cluster closest to significance: cumulative $t$ = 26.71, $p$ = 0.06, time range = 0.36-0.55 s, peak accuracy = 0.21). The word trials, however, training on the left electrodes and training on the right ones did not yield above-chance accuracy rates (cluster closest to significance: cumulative $t$ = 4.25, $p$ = 0.72, time range = 1.5-1.52 s, peak accuracy = 0.21).

### 3.4 *Between-subjects classification*

We next tested whether the category-specific EEG topographies were generalizable across participants. Up to this point, classifiers were trained for each participant independently. Conceivably, each participant's time-dependent and category-specific neural patterns may be entirely idiosyncratic. However, there may be commonalities across participants. To test this, we examined whether classification models can be successfully applied to participants other than the one on which they were trained. Using a leave-one-out approach, we found that when the models were trained and tested on

images, we were able to generalize time-dependent models across participants, although accuracy levels were notably lower than those produced by within-participant models (cumulative $t = 62.03$, $p < 0.05$, time range = 0–0.38 s, peak accuracy = 0.211; Figure 6, top). However, models trained and tested on word trials did not generalize across participants (statistics for the cluster closest to significance: cumulative $t = 13.74$, $p = 0.33$, time range = 1.02–1.1 s, peak accuracy = 0.21; Figure 6, bottom). These results suggest that category-specific neural patterns reflected in EEG data are generalizable across the population for image representations of categories, but not for words.

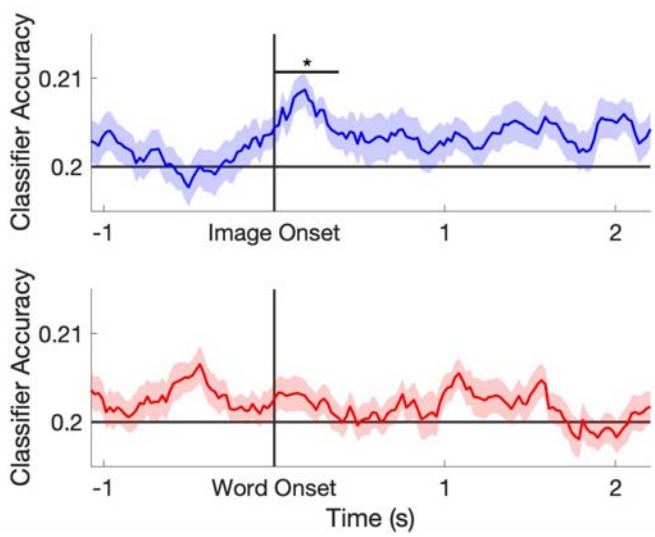



**Figure 6. Results from the cross-participant classification analysis show above-chance accuracy for images (top) but not for words (bottom).** Shaded areas reflect the standard error of the mean across participants.
*** $p < 0.05$**

## 4 DISCUSSION

The goal of this study was to build upon recent methodological advances in EEG analysis to investigate category-level neural representations across modalities. Using high-density EEG, we found discernible category representations, as well as image- and word-specific activity patterns. When comparing across modalities, EEG data following image presentation reflected more category information than data collected following word presentations, yielding higher classification accuracy. Among the five

examined categories, pairwise contrasts differed in the fidelity of the trained classifiers, suggesting that some categories are more discernible from the scalp data. We further examined whether specific topographical regions contributed differentially to classifier accuracy, and found the highest accuracy rates for electrodes positioned in parietal regions. There were also significant differences in classifier accuracy between left and right temporal electrodes, with left electrodes reflecting more category information relative to right temporal ones. Similar results were obtained using single representative electrodes, demonstrating that category classification is achievable with low-density EEG as well. Lastly, we show that category-specific EEG topography is generalizable across the population using a leave-one-out approach across participants.

A key feature of our experimental design is that we contrasted data collected in trials where images were presented and data collected in trials where words were presented. Collapsing over modalities, we were able to classify across categories, but analyzing each modality separately demonstrated that data from image trials yielded higher classification accuracies than data from word trials. More broadly, across multiple classification schemes and research questions, image trials far outperformed word trials. Notably, word trials still yielded above-chance classification accuracy, demonstrating that our models are able tap into true category representations rather than perceptual differences. However, we were unable to successfully train a classifier on one modality and apply it to the other. In this case, as in all other analyses utilizing the word trials, it is impossible to tell whether these null results are due to inherent limitations of EEG in reflecting higher-order cross-modal representations, or due to power issues borne out of the relatively low accuracy rates for word trials (peak = 0.23; chance level = 0.2).

Category representations are most typically studied using fMRI, primarily due to its superior spatial resolution and its access to neural sources throughout the brain. However, fMRI is limited due to its relatively high costs, which frequently lead to underpowered designs (Turner et al., 2018). In contrast, EEG is a more affordable neuroimaging method (especially for low-density systems). Other advantages of EEG over fMRI are that it is more tolerable to movement, facilitating more naturalistic designs and recording during sleep. Finally, EEG has better temporal resolution, which provides information about the rapid temporal dynamics of the

activity of category neural representations. Traditionally, EEG research on category representations focused on ERPs (e.g., N170 for faces; Bentin et al., 1996). In this manuscript, we leverage recently employed machine learning techniques and the unique features of EEG to demonstrate its ability to identify category-specific neural activation patterns, which could lend itself to future research on category-selective neural activity.

To determine which category pairs were more distinctly represented in the EEG signal, we conducted pairwise comparisons for each modality and found that all category pairs for image trials and one pair for word trials (Animals vs. Tools) elicited significantly distinguishable activity. Among the category pairs for images, the classifier distinguishing the Animal and Food categories performed best. Future experimental designs intended to leverage EEG for cross-category classification are therefore encouraged to use these two categories.

To examine topographical contributions to the EEG-detection of brain activity, we separated our electrodes into subgroups for classifier training. We found that all our subgroupings reflected category information for both image and word trials. Specifically, the parietal subgroup performed best in both modalities, whereas the frontal subgroup performed worst. To examine isolated electrode activity and demonstrate the feasibility of using low-density EEG setups, we reduced these subgroups to single representative electrodes and found that classification accuracy remained high when examining just five electrodes (along with the mastoid electrodes, which acted as references). Data from individual electrodes was sufficient for classifying categories in image trials but not in word trials.

Finally, we extended our results by considering across-participant category representations. All analyses mentioned up until this point were agnostic as to whether the neural representations of categories were generalizable across the population; they only considered the reliability of within-participant patterns across stimuli. For this analysis, we directly examined the generalizability of the neural representations across participants. Since different classifiers were trained at each time point, above-chance across-participant classification accuracy would require both generalized category-specific representations and common temporal dynamics. Our results demonstrate above-chance classification using data collected in image trials but not word trials. As before, it is unclear whether this null effect is due to some inherent property of words or a result of the upper bound on classification accuracy for this modality, limiting statistical power. Regardless, the findings showing above-chance classification for

images demonstrate that there are indeed some generalizable representations, although the small effect size (peak accuracy = 0.211, chance level = 0.2) demonstrates the limitations of our approach and potentially the larger contribution of idiosyncratic category-specific neural patterns.

Our study, and indeed many studies utilizing EEG, have some notable limitations. The biggest limitation is that the neural origin of the category representations is unclear. The neural underpinnings reflected in EEG signals are notoriously hard to localize, and our results are impacted by this limitation. Although data collected from the scalp indicate that there are category-specific differences in neural activity (and reveal their temporal dynamics), they leave open the question of which brain networks drive the observed differences. Another limitation is specific to our study; in some analyses, accuracy levels perplexingly seem to increase before image onset. We have confirmed that it is not due to trigger delays in our system, and therefore believe that this may be due to the zero-phase lowpass filter used in our preprocessing code, which smoothes the data in a non-causal way. To address this issue, we only considered data after image onset for all analyses.

In this manuscript, we have presented a stimulus set, experimental design, and analytic pipeline for identifying category representations using EEG data. Our data and approach could easily be adopted to address multiple research questions. Importantly, detecting category representation using EEG would allow for monitoring of neural reactivation during offline states (e.g., sleep or wakeful rest), whether accompanied by conscious perception or not (Tal & Schechtman, 2025). Our approach, therefore, supplements the current toolkit used in cognitive neuroscience to examine the manner in which covert or overt neural representations support cognitive operations.

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