

EEG searchlight decoding reveals person- and place- specific responses for semantic category and familiarity

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Uncorrected accepted version

Abstract

Proper names are linguistic expressions referring to unique entities, such as individual people or places. This sets them apart from other words like common nouns, which refer to generic concepts. And yet, despite both being individual entities, one's closest friend and one's favourite city are intuitively associated with very different pieces of knowledge - face, voice, social relationship, autobiographical experiences for the former, mostly visual and spatial information for the latter. Neuroimaging research has revealed the existence of both domain-general and domain-specific brain correlates of semantic processing of individual entities; however, it remains unclear how such commonalities and similarities operate over a fine-grained temporal scale. In this work we tackle this question using EEG and multivariate (time-resolved and searchlight) decoding analyses. We look at when and where we can accurately decode the semantic category of a proper name, and whether we can find person- or place-specific effects of familiarity, which is a modality-independent dimension and therefore avoids sensorimotor differences inherent among the two categories. Semantic category can be decoded in a time window and with spatial localization typically associated with lexical semantic processing. Regarding familiarity, our results reveal that it is easier to distinguish patterns of familiarity-related evoked activity for people, as opposed to places, in both early and late time windows. Second, we discover that within the early responses, both domain-general (left posterior-lateral) and domain-specific (right fronto-temporal, only for people) neural patterns can be individuated, suggesting the existence of person-specific processes.

1 Introduction

Proper names refer to individual entities, also called unique entities or individual concepts— personally and socially relevant entities such as people, places, pets, or works of art (Jeshion, 2009; Semenza, 2009, 2022). In cognitive neuroscience, people and geographical places are the two semantic categories whose proper names seem to most clearly involve entity-specific semantic processes in the brain, differing from those involved with generic (non-individual) entities (Martins & Farrajota, 2007; Desai, Tadimeti, & Riccardi, 2022).

Theories of individual entities proposed in cognitive neuroscience, building on decades of results (reviewed in (O’Rourke & de Diego Balaguer, 2020; Semenza, 2022; Kaminski, Bowren Jr, Manzel, & Tranel, 2022)), state that all proper names, no matter whether they refer to people or places, involve the same kind of semantic processing in the brain, specific to unique entities - ‘individual semantics’ (Semenza, 2009) - as opposed to words referring to generic semantic knowledge such as common nouns. This proposal links back to a tradition in philosophy of language and semantics which emphasizes that, whereas common nouns refer to classes of entities, proper names refer to individual members of those classes and therefore involve special referential processes (Cumming, 2019; Murez & Recanati, 2016; Michaelson & Reimer, 2022). For instance, the common noun *philosopher* refers to the generic concept “a person who studies or writes about philosophy”¹. Such a concept can apply to many referents, such as the individuals called Plato, William of Ockham, Gilles Deleuze. By contrast, the proper name *Socrates* in a context such as “Socrates is the protagonist of many of Plato’s dialogues” only refers to the one and only original Greek philosopher.

However, other semantic theories in neuroscience have proposed that, when processing semantic information related to people, the brain makes use of dedicated and possibly priority processes, pathways or resources, different from those employed for individual entities from other domains such as places. Such accounts are rooted in evolutionary (Miceli et al., 2000; Mahon & Caramazza, 2011) or social (Olson, McCoy, Klobusicky, & Ross, 2013) considerations: neural pathways specific to people would have emerged in the brain from the need to quickly and accurately bind together multimodal (the physical traits of a person, their voice), affective (the emotions they generate), and social (the relationship in which they stand with you) information, as well as episodic (shared autobiographic experiences) and other (e.g. what they like doing, where they worked) memories.

We can find functional magnetic resonance imaging (fMRI) evidence compatible with both views: some studies report common neural bases for people and places (Kaminski et al., 2022) whereas others report differences (Morton, Zippi, Noh, & Preston, 2021). The brain areas that appear to be activated for individual entities of both types are mainly the temporal poles and orbital prefrontal cortex (O’Rourke & de Diego Balaguer, 2020). These locations have been

¹Definition retrieved from <https://www.oxfordlearnersdictionaries.com/definition/american.english/philosopher>

associated with entity-level, amodal, domain-general semantic representations (Gorno-Tempini et al., 1998; Leonardelli, Fait, & Fairhall, 2019). Category-specific areas have been explained as reflecting access to domain-specific knowledge. For people, they consist of an anterior temporal network including the inferior temporal and orbitofrontal cortices, as well as the amygdala. For places, by contrast, it’s a posterior medial network involving the angular gyrus, the precuneus and the parahippocampal cortex (Morton et al., 2021).

A temporal perspective on individual entity processing One gap common to most existing literature is the lack of evidence about the temporal aspect of individual entity processing. Most studies employed fMRI, which offers great spatial but little temporal detail. Therefore, at the moment it is unclear to what extent temporal processing of entity-level semantic information shows similar patterns for the two semantic categories. Filling this gap was one of the main objectives of this study. In order to study the temporal characteristics of neural processing of individual concepts, in this work we used high-density 128-channels electroencephalography (EEG), because of its excellent temporal resolution and insightful spatial detail. Furthermore, we employed multivariate pattern analyses (time-resolved and searchlight Representational Similarity Analysis decoding), which provide excellent sensitivity without requiring to fit a model (Anderson, Zinszer, & Raizada, 2016; Morton et al., 2021).

We also used names instead of images, in contrast with previous work on individual entities. In the vast majority of cases (an exception is, for instance, (Leonardelli et al., 2019)), pictures are used as input to activate semantic processing. This is usually done to ensure a stronger signal in the brain data than the one elicited by written text (Shinkareva, Malave, Mason, Mitchell, & Just, 2011; Simanova, Hagoort, Oostenveld, & Van Gerven, 2014). However, as pointed out for instance in (Just, Cherkassky, Aryal, & Mitchell, 2010; Simanova et al., 2014), this choice in experimental design has the main disadvantage of capturing entity representations biased towards a given modality. By using pictorial stimuli, the recorded brain activity will inevitably represent specific instances of the picture presented, with strong dominance of its visual features. What’s more, this effect is particularly strong for EEG signals. First, notable differences in timing of semantic activation across the written and the pictorial modality emerge (Simanova, Van Gerven, Oostenveld, & Hagoort, 2010; Leonardelli et al., 2019). Secondly, low-level categorical differences in visual features across distinct categories, such as people and places, are particularly salient - in other words, processing a face and a scene are quite different processes (de Beeck, Pillet, & Ritchie, 2019). Therefore, we decided to use names as inputs, in order to be able to capture semantic information about individual entities whose activation is independent of sensory modalities.

Familiarity We investigated temporal and spatial commonalities and differences within brain processing for different types of individual concepts through the lens of familiarity, which is considered to be a fundamental component

of semantic representations of individual entities in the brain (Gainotti, 2015; Schweinberger & Neumann, 2016). Familiarity is an ideal dimension to compare brain processing of people and places for two reasons. First of all, it is not modality-specific - that is, it allows to compare semantic processing for people and places without the inevitable confounds which are related to sensorimotor differences in the representation of the two categories (Morton et al., 2021). Secondly, it is an open question whether there exist person-specific familiarity effects on ERPs, given their special cognitive salience (Scott, Tanaka, Sheinberg, & Curran, 2006; Pierce et al., 2011; Ross & Olson, 2012; Devillez et al., 2019; Klink, Kaiser, Stecher, Ambrus, & Kovacs, 2023). Tackling this question lets us, in turn, provide original evidence with respect to which elements of entity representations in the brain are domain-specific (Gorno-Tempini et al., 1998; Fairhall, Anzellotti, Ubaldi, & Caramazza, 2014; Leonardelli et al., 2019).

To this aim, we collected and analyzed evoked responses to a balanced set of famous and personally familiar people and places from thirty-three subjects. We chose to use famous entities as counterparts to personally familiar entities, instead of completely unknown entities, because of our focus on semantic processing. For semantic processing to take place, subjects need to be able to retrieve some previously acquired knowledge about the entity - something which would be impossible with unknown entities. At the same time, we wanted to ensure enough quantitative differences could emerge between personally familiar and famous stimuli. As a consequence of this, we selected for our set of stimuli famous entities which are moderately, but not extremely well known (see Section 2.1). In this respect we build on (Wiese et al., 2021) . There, it was shown that even if ERPs for personally familiar and famous faces show *qualitatively* similar responses (i.e. they affect the same ERP components), they can be successfully teased apart *quantitatively* (i.e. in terms of response magnitude). In other words, we assume, after (Wiese et al., 2021) , that familiarity effects on ERPs are graded. In this view, in terms of familiarity, entities are placed along a continuum from completely unknown to personally familiar entities - and ERP correlates of familiarity reflect this gradient. Selecting famous entities with whom subjects are only moderately familiar allows to elicit semantic processing, while maintaining a clear quantitative distinction with a subject's closest personally familiar people and places.

More specifically, we looked at the first 800 milliseconds after stimulus presentation, where previous work on identity recognition from faces, as well as lexical and memory retrieval, has found significant effects. We also consider time frames previously associated with face processing, despite using names as stimuli, for two reasons. First of all, these are ERP components where non-visual, higher level semantic processing is thought to take place. If this is the case, then we can expect to find brain activity related to person semantic knowledge in those time ranges, even when using as stimuli person names instead of faces. Secondly, as it is not clear whether effects in such components are domain-specific or not - i.e. whether they hold also for other types of individual entities such as places, our experiments allow to test this hypothesis.

The first effect is the **N250**, happening between 200-300ms, which has been

proposed as the main early marker of face familiarity (Tacikowski, Jednoróg, Marchewka, & Nowicka, 2011; Schweinberger & Neumann, 2016).

The second is the **N400**, found between 300 and 500ms. The N400 has been found to be reliably modulated by a large number of semantic phenomena. These can be linguistic (among others: word expectancy, priming, repetition, frequency, concreteness - both for words in isolation and within sentences) as well as non-linguistic (e.g. images, sounds) (Kutas & Federmeier, 2011) . Since the range of semantic phenomena affecting the N400 is extremely broad, a unified theoretical account of the N400 as a marker of semantic processing is still missing (Rabovsky, Hansen, & McClelland, 2018; Delogu, Brouwer, & Crocker, 2019; Eddine, Brothers, & Kuperberg, 2022; Šoškić, Jovanović, Styles, Kappenman, & Ković, 2022) . However, crucially for our focus, a number of previous studies found that the time range of the N400 can be modulated by various types of aspects of semantic processing of individual entities - including the ones modulated in our experiment: categorical information (Bruera & Poesio, 2022) ; face familiarity, since a familiarity-induced counterpart of the N400, the **FN400**, has also been observed (Curran & Hancock, 2007) (although it's not clear whether the two are actually functionally identical or not (Voss & Federmeier, 2011; Bridger, Bader, Kriukova, Unger, & Mecklinger, 2012; Leynes, Bruett, Krizan, & Veloso, 2017)) ; and additionally, the difference between proper names and common nouns (Proverbio, Lilli, Semenza, & Zani, 2001; Proverbio, Mariani, Zani, & Adorni, 2009; Adorni, Manfredi, & Proverbio, 2014; Sulpizio & Job, 2018) .

In a later time window (500-800ms) two ERP components have been observed. First, the Sustained Familiarity Effect (**SFE**), peaking at around 600ms (Wiese et al., 2019; Dalski, Kovács, & Ambrus, 2022; Li, Burton, Ambrus, & Kovács, 2022), which has been put forward as the most solid effect for face familiarity. Secondly, the late positive component (**LPC**), between 500-800ms, has been consistently associated with explicit access to semantic information, such as access to episodic memory (Rugg & Curran, 2007; Renoult et al., 2016; Dimsdale-Zucker, Maciejewska, Kim, Yonelinas, & Ranganath, 2022).

Decoding analyses We ran two sets of decoding analyses.

First, we wanted to obtain direct indication of the spatio-temporal loci where the two semantic categories can be distinguished. To do so, we looked at when and where we can decode whether a brain response was evoked by the name of a person or a place. Furthermore, we did so separately for famous and personally familiar entities, providing initial evidence with respect to the interplay between familiarity and categorical information.

We expected, according to previous literature (Proverbio et al., 2001; Bruera & Poesio, 2022) , to be able to decode information about semantic categories for both people and places within the N400 time range, distributed over centro-temporal electrodes.

Then, we delved deeper into the interaction between semantic category and familiarity by flipping the direction of the decoding. In this second analysis

we tried to correctly classify responses according to whether they were evoked by personally familiar or famous entities, comparing decoding performance for people and places.

We predicted that we would be able to find information related to stimulus familiarity across all time ranges for the components described in the ERP literature, with varying spatial distributions over the scalp - right fronto-temporal and occipito-temporal for the N250 (Tacikowski et al., 2011; Schweinberger & Neumann, 2016) ; centro-temporal for the F/N400 (Curran & Hancock, 2007) ; posterior-temporal for the SFE/LPC (Rugg & Curran, 2007; Wiese et al., 2019) . Based on (Tanaka, Curran, Porterfield, & Collins, 2006) , and consistently with cognitive theories regarding proper names and individual entities(Kaminski et al., 2022; Semenza, 2022) , we further hypothesized that people and places should exhibit similar patterns in terms of decoding across all time ranges.

In this respect, such similarities in decoding patterns of familiarity among people and places would support the existence of domain-general (irrespective of semantic category) responses to familiarity; on the contrary, differences would highlight domain-specific (either person- or place-) processing related to familiarity with the stimuli.

Results Our decoding analyses reveal both domain-general and domain-specific markers of processing of familiarity.

Regarding the former, information related to familiarity can be decoded in all time windows, and in overlapping spatial clusters of electrodes, from both people and places.

For the latter, easier processing of individual identity for people is indicated by two factors: consistently higher decoding scores and more wide-spread spatial clusters where decoding is significantly above chance. Furthermore, person-specific clusters are found in right fronto-temporal and temporo-parietal areas, especially in the early N250 time range.

Such interaction between familiarity and semantic categories in brain representations of individual entities is also confirmed when decoding information related to semantic categories.

The semantic category of a stimulus can be decoded from ERPs within time and spatial ranges where processing of lexical semantics has been shown to take place (300-800ms, in centro-parietal and bilateral fronto-temporal electrodes). We nevertheless find that the less familiar the individual entities, the harder it is to carry out the decoding. In particular, exploiting spatially distributed patterns is crucial to find categorical semantic information in brain activity for famous entities - something which is not required for personally familiar entities.

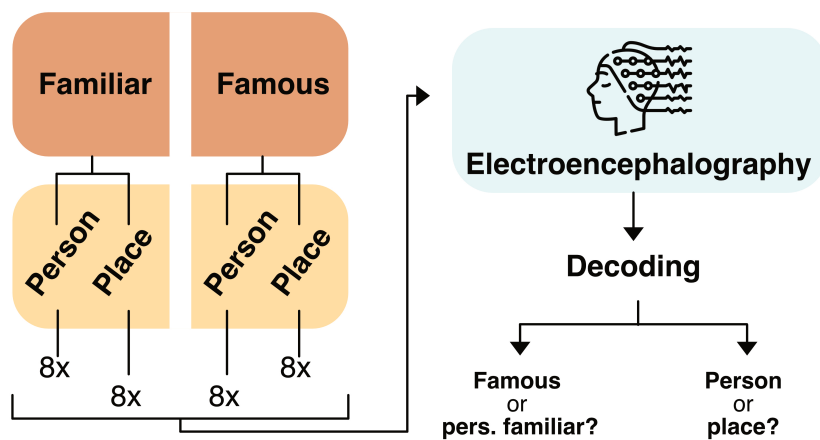


Figure 1: **Schematic diagram of the experimental setup.** Our stimuli were divided into two sets. The first set were proper names for sixteen famous individual entities (eight people and eight places), selected by controlling for familiarity, imageability and name length. The second set were sixteen proper names for personally familiar people and places (eight names for each category), which were obtained by asking each participant to provide the names themselves. Then we collected the EEG data, and carried out separately for each participant two decoding analyses - first, decoding semantic category (person vs place) and then decoding familiarity (personally familiar vs famous).

2 Methods

2.1 Stimuli

Famous entities We selected eight famous people and eight famous places to be used as stimuli across all participants (see Figure 1, left). These stimuli are balanced in terms of name length, familiarity, and imageability. We selected them from a larger set of 100 stimuli for which we obtained familiarity and imageability ratings from separate sets of subjects (33 subjects for familiarity and 30 for imageability). All subjects for the norming experiments were native speakers of Italian, and none of them took part to the EEG experiment. The final list of famous stimuli, as well as the familiarity and imageability norms, can be found together with the publicly available code.

Name length is overall 13.5 on average; average person name length is 14.1, while average place name length was 13, and the difference across categories is not significant ($t = 0.68, p = 0.5$). Before the EEG experiment took place, we ensured that, for all famous entities, our subjects had not either personally known the person or visited the place. Only two subjects had visited one of the famous places selected as experimental stimuli. In those cases we substituted the names with other place names matched for length, familiarity and imageability.

Familiarity with an entity was defined in the same way as in (Moore & Valentine, 2020) - a quantification on a scale from 1 to 5 of the number of cumulative encounters with an individual entity, across time and media. The average familiarity overall is 3.59; average familiarity for people is 3.75, while for places it is 3.44, and the difference across categories is not statistically significant ($t = 1.42, p = 0.18$). As discussed above (see Section 1) we decided to select as stimuli entities which are moderately well known, but not extremely so. This was done in order to ensure a clear-cut quantitative difference in familiarity between personally familiar and famous individual entities.

Imageability was measured in a separate norming experiment. Following (Paivio, Yuille, & Madigan, 1968), imageability was defined as the ease or difficulty of arousing a mental image. We chose to control imageability since, during the experiment, subjects were asked to read a name and picture their referent mentally (see Section 2.2). We used a scale from 1 to 7, which is the most common one in imageability rating experiments (Rofes et al., 2018). The average imageability across all entities is 4.97. Average imageability for people is 5.17, while average imageability for places is 4.78. The difference between the two is not statistically significant ($t = 0.88, p = 0.39$).

Personally familiar entities Before starting the EEG experiment, we asked participants to provide the names for eight people and eight places (see Figure 1, left). For people, we followed research on social circles (Dunbar, 1998; Zhou, Sornette, Hill, & Dunbar, 2005) and focused, in our definition, on members of the so-called ‘support clique’, which consists of people with whom one has a positive relationship, is in touch regularly, and from whom one would seek personal advice or help (Hill & Dunbar, 2003). For places, given a lack of

relevant literature, we tried to mirror as closely as possible the definition given for people – in this sense, ‘support places’ are places with which an individual has a special, positive relationship, and where one would (if possible) return to when in a situation of distress.² Notice that participants were not only asked to provide names, but also to provide either the person’s occupation or the type of place (i.e. monument, city, river, etc.), to be used during the experimental paradigm (see below). Also, subjects were asked to respond to a questionnaire, that will be analyzed in future work.

In the case of personally familiar names, we could not control name length, since participants came up themselves with the names. Therefore, we implement in the analyses a procedure for explicitly removing all variance associated with name length from the EEG data, described below in Section 2.4.

Additionally, we were not able to control for familiarity and imageability for personally familiar names. For both variables, we assumed that no significant differences would be present within such small sets of personally familiar entities and we decided not to remove the variance associated with them from the data. We took this choice because of two reasons. First of all, we reckoned that the way in which we elicited the stimuli would act as a ‘soft’ way of controlling these variables: having only eight exemplars ensures that only the participants’ closest - and therefore extremely imageable and familiar - people and places belong to these sets. This reduces dramatically their variance in both imageability and familiarity, both within and across semantic categories, without enforcing a ‘hard’ confound control procedure. In other words, we assume that, because of this ‘soft’ confound control, for both personally familiar people and places, imageability and familiarity scores would be around the ceiling value. Secondly, the confound removal procedure should be limited as much as possible since it is extremely aggressive, in that it removes *all* information correlated with each variable (Snoek, Miletic, & Scholte, 2019; More, Eickhoff, Caspers, & Patil, 2021), thus also inadvertently cancelling non-confounded parts of the signal. Therefore we chose to limit our confound removal procedure to word length. The variance for the names’ lengths would inevitably be much bigger than the variance for imageability or familiarity, as it could not be controlled at all (neither in a ‘soft’ nor in a ‘hard’ fashion). Also, the effect of word length on ERPs is notoriously dominant when left uncontrolled (Hauk, Davis, Ford, Pulvermüller, & Marslen-Wilson, 2006).

2.2 Experiment

Thirty-three right-handed subjects (age from 20 to 31 years old, with 21 female participants) took part to the experiment. No participant was excluded from the analyses, since task accuracy was always extremely high (see Section 3.1). As the experiment was conducted in Italian, all the subjects were native Italian speakers. All experimental procedures were approved by the Ethical Committee

²We provide together with the code the text of the specific instructions given to the subjects, translated to English

of the institution where the data were collected, and subjects gave their written informed consent.

2.2.1 Sample sizes

The number of subjects (thirty-three) was chosen following (Boudewyn, Luck, Farrens, & Kappenman, 2018) . There, the authors investigated the effects of the amount of subjects in a study on the power to detect a significant effect in an ERP study. Considering thirty-two participants as their upper limit, they found that as the amount of subjects increased, statistical power dramatically improved. Therefore, we took their upper limit as our estimated required sample size (thirty-three). Additionally, as reported in (Šoškić et al., 2022) , only 2.27% of all the EEG studies investigating the N400 had more than 31 subjects - making our sample size very high when contrasted to similar studies.

The number of stimuli and the number of trials for each stimulus were chosen following recommendations relevant for our multivariate analyses (decoding using a model based on Representational Similarity Analysis - see Section 2.4).

Regarding the number of trials, as described in (Grootswagers, Wardle, & Carlson, 2017) , in EEG a higher number of trials per stimulus entails higher decoding performance. This is because trial-specific random noise can be effectively cancelled out by averaging multiple trials together. As indicated in (Grootswagers et al., 2017) , optimal increase in performance against increase in the number of trials is obtained by using between sixteen and thirty-two trials. Therefore we opted for twenty-four trials.

The remaining choice was the number of stimuli, which we set to thirty-two in total, having eight stimuli per sub-category (personally familiar people, personally familiar places, famous people, famous places). This number had to be limited because of three factors. First, we could not run multiple sessions per participant, thus forcing us to limit as much as possible the amount of stimuli per condition. Secondly, we wanted to have a set of personally familiar individual entities with whom a subject would have little variability in terms of familiarity. As an empirical guideline to estimate the size of this set, we looked at research on social circles (Dunbar, 1998; Hill & Dunbar, 2003; Zhou et al., 2005) . There it was found that the two closest social circles for individuals, the so-called support circle and the sympathy group, whose definitions we employed to elicit the personally familiar names (see Section 2.1), count on average respectively 5 and 12 persons. This provided us with approximate boundary sizes for each set of personally familiar entities (people and places) . Finally, for Representational Similarity Analysis, the minimum recommended number of stimuli per experimental condition is seven (Nili et al., 2014) . Considering all these constraints, we chose to have eight stimuli for each of the four conditions (subcategories), resulting in thirty-two stimuli per subject overall.

2.2.2 Experimental paradigm

Before the EEG experiment, participants provided names and occupations or types of places for sixteen personally familiar people and places (eight names for each category). These names were then used as one half of the experimental stimuli, the other half being the set of sixteen names for famous people and places previously selected (see Section 2.1). While recording EEG data, participants took part to twenty-four experimental runs, during which each name would appear once, in randomized order.

Within each run, names were preceded by a fixation cross. They appeared on screen for 500 milliseconds, followed by a fixation cross lasting 1 second. Subjects were instructed to think about the referent of the proper name, as in (Pereira et al., 2018), and mentally picture it. As in (Bruera & Poesio, 2022), mental imagery was added to the task in order to improve entity-specific signal across trials in recorded brain activity. Making subjects focus on visual features, which are crucial in mental representations of individual entities (Anzellotti & Caramazza, 2017; Tsantani, Kriegeskorte, McGettigan, & Garrido, 2019; Semenza, 2022), makes subjects avoid mind wandering and allows to capture more coherent entity representations. Importantly, this (thinking of a name’s referent and picturing it) is the only evoked response (ERP) which is being analyzed in decoding: $t = 0ms$ is the time where the fixation cross appears after the name has been presented, and the last time point considered, $t = 800ms$, still falls within the fixation cross’ time on screen.

After this, a randomized binary yes/no question appeared on screen, to which subjects had to answer using two keys (‘k’ for yes, ‘d’ for no; this mapping was used for the whole experiment). Questions were added to keep subjects attentive to the stimuli and on their meaning, while collecting additional data regarding semantic processing of individual entities (see Section 3.1 for the results). To avoid systematic confounds in the ERPs that could be due to both strategic preparation from the participants and motor activity triggered by pressing a key, questions were randomly sampled. Also, participants were instructed to respond as accurately as possible, and that there was no time pressure. The randomization procedure involved two types of questions – coarse-category questions such as ‘is it a person/place?’, and fine-grained questions such as ‘does the name refer to a student?’ or ‘does the name refer to a city?’, a methodology previously used in (Leonardelli et al., 2019; Bruera & Poesio, 2022). In the case of fine-grained questions, also the occupation or place type was randomized. Questions were balanced between yes/no answers.

At the end of the experiment, each name had been repeated twenty-four times, and twenty-four ERPs for each individual entities had been obtained. Before entering the analyses, all the ERPs for each individual entity were averaged to improve the signal-to-noise ratio - following common practice in decoding studies for EEG, as discussed above (Grootswagers et al., 2017).

2.3 EEG data collection and preprocessing

The EEG data was collected using a BIOSEMI ActiveTwo system with 128 channels, recording unfiltered signals at a sampling rate of 2048Hz. We also collected signals from two electro-oculogram channels (EOG) so as to be able to use them later for artifact rejection with Independent Component Analysis (ICA; details below). For preprocessing, we adapted an automated procedure using MNE (Gramfort et al., 2013), which was validated in (Jas et al., 2018) and whose main steps we briefly report here. The full implementation is available together with the code provided.

First, we set the montage to the MNE default for the 128-channel BIOSEMI system.³ Then we applied a low-pass filter to the ERP data to 80Hz, we epoched the data and subsampled it to 256hz (Luck, 2014). To remove eye-movement artifacts, we used the ICA-based artifact rejection procedure of (Jas et al., 2018). We computed the independent components from the evoked data, and then removed the components with the highest correlation with the EOG channels. We applied baseline correction computing the average of the signal between -100 and 0 ms before stimulus appearance. Finally, we identified bad epochs and interpolated bad channels using the autoreject algorithm (Jas, Engemann, Bekhti, Raimondo, & Gramfort, 2017). Before entering the analyses, we set the reference for the EEG data to the grand average.

The final preprocessing step was removing all the variance associated with word length from the EEG signal using cross-validated confound regression, which was validated in (Todd, Nystrom, & Cohen, 2013; Snoek et al., 2019) and whose implementation is publicly available.

2.4 Decoding

We ran two decoding analyses – namely, two classification tasks where the target labels are two sets of binary categories. We learned to classify evoked responses into patterns of brain activity related to 1. people as opposed to places, then 2. famous as opposed to personally familiar entities. We also looked at the interaction between familiarity and semantic category by running the classification separately within each subset of stimuli (for instance, learning to classify responses to personally familiar entities only into person- or place- related).

Following customary practice in EEG decoding (Grootswagers et al., 2017), analyses were carried out separately for each individual subject (within-subject decoding analysis). In this framework, a measurement of the overall accuracy is obtained by averaging subject-level average accuracies. Measures of accuracy for decoding analyses can be interpreted as reflecting non-standardized effect sizes (Hebart & Baker, 2018). Since no procedure for the standardization of effect sizes for multivariate decoding is available, it is important to underline that decoding scores are not directly comparable across studies.

³A visualization of the montage, together with the codes for the channels, is included in the publicly available code and can be retrieved at https://www.biosemi.com/pics/cap.128_layout_medium.jpg.

Representational Similarity Decoding

As a methodology for decoding we used the **Representational Similarity Analysis (RSA) decoding** approach of (Anderson et al., 2016). RSA decoding does not require fitting a model: it just relies on pairwise similarities among representations, as in the more general RSA framework (Kriegeskorte, Mur, & Bandettini, 2008). This methodology has many advantages when compared to approaches requiring to fit a model: it is computationally extremely lightweight, it avoids the risk of overfitting, it is straightforwardly interpretable within the general RSA framework and it provides excellent performance (Anderson et al., 2016). The goal of RSA is to compare, given a set of stimuli, the so-called ‘representational structures’ or ‘spaces’ (Kriegeskorte et al., 2008; Diedrichsen & Kriegeskorte, 2017) of brain and model representations, quantifying how similar the two are with one another. The fundamental intuition behind the original RSA is that the representational structures of both brain and model representations can be captured in a common way by looking at *pairwise similarities between stimuli*.

To provide an example for our case, in our model based on semantic categories each stimulus is associated with a set of discrete and mutually exclusive labels (e.g. either *person* or *place*). Such labels can be transformed into numbers via numerical coding ($person = 1, place = 0$). This allows to represent numerically distances (and similarities) straightforwardly: if two stimuli both refer to a person, their distance will be 0 (because $dist = abs(1 - 1) = 0$), and their similarity 1 (because $sim = 1 - dist = 1$); and *vice versa*. In the terminology of RSA presented above, this can be used to define the *representational space* for a set of stimuli in terms of all possible pairwise similarities/distances. Suppose we take a toy example involving as stimuli $a = Marseille$, $b = Trieste$, $c = Lise Meitner$, $d = Toni Morrison$. Its representational space in terms of semantic categories ($person = 1, place = 0$) would be given by $[sim(a, b), sim(a, c), sim(a, d), sim(b, c), sim(b, d), sim(c, d)] = [1, 0, 0, 0, 0, 1]$. An equivalent approach can be taken for ERPs. The only difference is that each pairwise distance/similarity is then defined as Pearson correlation among responses evoked by different stimuli (for example, using fictional similarities, $[0.8, 0.1, 0.15, 0.2, 0.08, 0.75]$).

RSA decoding (Anderson et al., 2016) expands on this hunch by adapting it to a machine learning approach (Pereira, Mitchell, & Botvinick, 2009). In this framework, the goal is learning to classify multivariate brain patterns evoked by experimental stimuli into their categories (e.g. learning to recognize whether a given ERP was evoked by a person or a place). The ability to carry out such classification (decoding) is interpreted as indicating the presence of the relevant information in patterns of brain activity - for instance, information regarding specific semantic categories (Naselaris, Kay, Nishimoto, & Gallant, 2011). Such a multivariate classification approach, therefore, is naturally suited to our research question - finding out where and when different types of semantic information about individual entities can be found in ERPs.

In RSA decoding, given a set of stimuli of size N for which matched ERPs and labels are available, first they are split them into a train set of size $N - i$ and

a test set of size i . In a typical brain decoding setting, a decoding model (e.g. a regularized linear regression model) would be trained to learn, based on the items in the training set, a linear transformation from the brain responses to the corresponding labels for the items in the test set (Pereira et al., 2009; Naselaris et al., 2011). By contrast, in RSA decoding all that is used to decode information from the brain are *pairwise similarities between a test item and all items in the training data* (Anderson et al., 2016). Each item from the test set (both in the input space - the brain - and the target space - the labels) is transformed to the vector of its pairwise similarities to all items in the train set. In the example above, if a is a test item, and the training set is made of $\{b, c, d\}$, then the transformed representation of a would be $\hat{a} = [sim(a, b), sim(a, c), sim(a, d)]$ - both in the input and target spaces. This allows to compare directly the transformed test items in the input (brain) and target (label) spaces through Pearson correlation, as now they have the same dimensionality (in our example, 3). In turn, the results can be interpreted in terms of success at decoding, and evaluated using an appropriate evaluation metric (in our case we used a pairwise metric; see below for details).

Leave-two out pairwise evaluation As an evaluation metric, we employed a **leave-two-out pairwise evaluation**, which is the original metric validated in (Anderson et al., 2016) and that is often used in brain decoding settings with limited training data such as ours (Mitchell et al., 2008; Pereira et al., 2018). In this evaluation, the size of the test set is 2, and the size of the training set is therefore $N - 2$. Suppose splitting our toy training/test sets in a leave-two-out fashion as follows: $test = \{a, c\}$, training: $train = \{b, d\}$. Given the two test items, they are first transformed to their pairwise similarities to all items in training set, as described above, both in input (brain; $\hat{a}_{input}, \hat{c}_{input}$) and target (labels; $\hat{a}_{target}, \hat{c}_{target}$) spaces. In our example, $\hat{a} = [sim(a, b), sim(a, d)]$, and $\hat{c} = [sim(c, b), sim(c, d)]$. Then, Pearson correlations among all possible pairs of transformed input and target test items are computed: $sim(\hat{a}_{input}, \hat{a}_{target})$; $sim(\hat{a}_{input}, \hat{c}_{target})$; $sim(\hat{c}_{input}, \hat{a}_{target})$; $sim(\hat{c}_{input}, \hat{c}_{target})$. Finally, decoding is considered correct ($accuracy = 1$) if the sum of the correlations between the correctly matched brain and labels vectors: $match = sim(\hat{a}_{input}, \hat{a}_{target}) + sim(\hat{c}_{input}, \hat{c}_{target})$ is bigger than that of the mismatching vectors: $mismatch = sim(\hat{a}_{input}, \hat{c}_{target}) + sim(\hat{c}_{input}, \hat{a}_{target})$ -i.e. $accuracy = 1$ if $match > mismatch$, else $accuracy = 0$.

This evaluation is carried out for all possible pairs of stimuli (all possible leave-two-out test sets), and results are averaged in order to provide an evaluation for within-subject decoding accuracy. Since the evaluation is binary (either 1 or 0), the random baseline, which would reflect absence of information relevant for decoding in the brain, is 0.5.

As anticipated in Sections 2.1 and 2.3 we employed a cross-validated confound regression procedure, validated and shown to be unbiased in (Snoek et al., 2019), in order to control for name length for personally familiar people and places. This method computes, for each train-test split, the variance associated

with the confound variable from the train set, and removes it from both the train and the test data.⁴.

Time-resolved decoding First we looked at the temporal development of brain processing using a time-resolved approach. Time-resolved decoding for EEG consists in running the decoding analyses using all of the electrodes, once for every time point (Grootswagers et al., 2017). Time points where decoding is above chance with statistical significance contain information relevant for decoding (e.g. information about the semantic category of a stimulus). In doing so, it exploits large-scale, distributed patterns among electrodes – affording excellent sensitivity, at the expense of local spatial information.

Spatio-temporal searchlight

We also implemented a searchlight decoding analysis in order to look at where on the scalp categorical and familiarity information can be found. The searchlight approach in cognitive neuroscience was introduced as a data-driven, bottom-up approach for multivariate analyses to find clusters of brain activity selectively associated with a certain experimental condition. The main intuition was that of treating brain activity as data over which minimal assumptions should be done: since stimulus-related brain activity is smoothed across recorded units, this could be exploited to find out, without recurring to regions of interest defined on the basis of human anatomy, which clusters of recorded units reflect activity evoked by a given stimulus. The searchlight approach was originally proposed for fMRI, where the investigated clusters are spatial (voxels). However, since brain activity is also smoothed in time, it was recently adapted to EEG data (Su, Fonteneau, Marslen-Wilson, & Kriegeskorte, 2012), where clusters of brain activity can take into account both the spatial and the temporal dimensions. In this approach, spatio-temporal clusters include multiple electrodes and time points, effectively allowing to account for interactions across these two dimensions. The searchlight approach is in fact rather simple: it consists of running the multivariate analysis (in our case, decoding) multiple times, once for every cluster of recorded units (here, spatio-temporal clusters of electrodes and time points) in the brain. Clusters affording higher decoding scores can be said to be associated with processing of the given experimental condition.

This approach provides two main advantages. First of all, it allows to discover clusters of brain activity which may not be predictable in advance. This overcomes the limitations of the top-down analytical approach looking only at regions of interest defined *a priori* – that can be either spatial (an anatomical brain area) or temporal (e.g. an ERP component). Secondly, by running a multivariate analysis within a cluster, it offers more sensitivity than univariate analyses. A univariate approach considers only the difference in intensity of the signal for a single variable (e.g. brain or time location), which may result in

⁴We use the original python implementation retrieved from <https://github.com/lukassnoek/MVCA>

missing or obscuring important pieces of information (Etzel, Zacks, & Braver, 2013; Kriegeskorte, Goebel, & Bandettini, 2006).

Notice that the size of the clusters is arbitrary and is derived from previous work. Here we used a temporal radius of 50ms (considering 100ms at a time) and a spatial radius of 30mm, following (Collins, Robinson, & Behrmann, 2018).⁵

Statistical testing and corrections for multiple comparisons For both the time-resolved and searchlight decoding we first computed t- and p-values using one-tailed t-tests. We tested the hypothesis that scores are reliably above chance (0.5) across subjects. We compared decoding scores for each time-point (time-resolved decoding) and spatio-temporal cluster (searchlight) against chance, for all time points between 0ms and 800ms. Given that we ran numerous statistical significance tests, incurring in the risk of false positives, we controlled the risks of multiple comparisons using the TFCE procedure (Smith & Nichols, 2009; Latinus, Nichols, & Rousselet, 2015; Grootswagers et al., 2017). TFCE accounts for temporal (time-resolved) and spatio-temporal (searchlight) clusters in the computation of the corrected p-values, providing strict control while maximizing sensitivity.

3 Results

3.1 Behavioural results

3.1.1 Accuracy

Participant accuracy on the behavioural task (randomized semantic categorization using yes/no questions, with chance performance at 50%; see Section 2.2) was extremely high: overall accuracy was 98.2%, and with very little variation across categories and levels of familiarity (people: 98%, places: 98.3%, personally familiar: 98.8%, famous: 97.4%).

3.1.2 Response times

We also measured choice response times (RTs), corresponding to the amount of time occurred between the appearance of the semantic categorization question and the pressing of a response key. It is important to underline that this task comes *after* the ERP time window, when participants were carrying out a different task (thinking about and picturing a name’s referent). Therefore, analyzing response times provides an additional, but different perspective into semantic processing of individual entities when compared to the evoked responses. RTs are traditionally taken to be measures of cognitive processing, reflecting multiple overlapping processing stages and inviting different interpretations depending

⁵The average number of electrodes included in each cluster was 9.6. This is in accordance with previous work (Graumann, Ciuffi, Dwivedi, Roig, & Cichy, 2022) where an average of 5 channels (half of the cluster size) was used for a 64-electrodes montage (half of the electrode density).

on the task at hand (Luce, 1991) . Since our task involved semantic categorization, we interpret RTs as reflecting ease of access to stimulus-related categorical information - i.e. shorter response times indicate easier categorization and easier processing of entity-specific information (Carlson, Ritchie, Kriegeskorte, Durvasula, & Ma, 2014) . While RTs are not central to our investigations, they can provide additional evidence that relevant differences in semantic processing exist across levels of familiarity and categories.

Significant differences in RTs emerged depending on the type of stimulus. Since RTs are not normally distributed (Balota & Yap, 2011) , we follow the methodological recommendation of (Lo & Andrews, 2015) of reporting also results for RTs after logarithmic transformation. RTs were higher on average for places (average raw RT: 1.636s; average log-transformed RT: 0.311s) than for people (average raw RT: 1.583s; average log-transformed RT: 0.279s), and the difference between the two was statistically significant (non-parametric permutation test on raw RTs: $T = 4.88, p = 0.0139$; on log-transformed RTs: $T = 9.217, p = 0.002$). RTs were also significantly quicker for personally familiar as opposed to famous (for personally familiar, raw RTs: 1.575s, log-transformed RTs: 0.247s; for famous, raw RTs: 1.644s, log-transformed RTs: 0.317s; non-parametric permutation test on raw RTs: $T = -6.37, p = 0.004$, on log-transformed RTs: $T = -13.08, p = 0.002$).

Overall, behavioural results thus indicate that, while accuracy was not affected by familiarity or semantic categories, response times were. That is, relevant differences in semantic processing could be retrieved already at a behavioural level. In particular, processing of entity-specific categorical information was easier for people and personally familiar entities as opposed, respectively, to places and famous entities.

3.2 Decoding semantic category

First, we report in Figure 2 the decoding scores when classifying ERP according to their semantic category - i.e. predicting whether a given ERP refers to a person or a place. We do so separately for personally familiar and famous stimuli, so as to obtain preliminary evidence with respect to the interaction between information regarding semantic category and familiarity.

Personally familiar entities Regarding the time-resolved decoding analysis for personally familiar stimuli (upper portion of Figure 2), we could decode with accuracy significantly above chance in the 330-800ms time range (peak between 400 and 540ms, $p < 0.001$). This indicates the presence of reliable category-related information in distributed patterns in the ERP signal, as expected, within the time range usually found to be associated with semantic processing (the N400 and LPC - see (Rugg & Curran, 2007; Kutas & Federmeier, 2011; Dimsdale-Zucker et al., 2022)). Searchlight decoding revealed the presence of clusters of electrodes affording statistically significant decoding in centro-parietal and bilateral areas of the scalp (peak decoding $p < 0.001$) - this

is again compatible with previous results on lexical semantic processing (Kutas & Federmeier, 2011).

Famous entities Decoding semantic category for famous stimuli in a time-resolved fashion, by contrast, provided accuracy significantly above chance only in the time window (330-430ms; peak decoding at 360ms, $p = 0.0156$) typically associated with the N400 semantic response (Šoškić et al., 2022). Overall time-resolved decoding scores were lower than for personally familiar stimuli, indicating that familiarity affects the way in which category-related information is processed in the brain (Gobbini, Leibenluft, Santiago, & Haxby, 2004). Furthermore, no spatial cluster where decoding was significantly above chance was found in the searchlight analysis (lower portion of Figure 2; peaks per time window: between 400 and 500ms: electrode D17, $p = 0.310$, D28 and A17, $p = 0.321$; between 700 and 800ms, electrodes D14 and D16, $p = 0.283$). This indicates that, in the case of famous individual entities, looking at spatially distributed patterns is critical to find the distinction between semantic categories.

Personally familiar > famous In the lowest row of Figure 2 we compared directly the decoding performance for personally familiar and famous entities. We subtracted their decoding scores obtained in the searchlight analyses (personally familiar-famous) and then we computed statistical tests (as described in Section 2.4). Specifically, we looked at spatio-temporal clusters where the difference was significantly above 0, thus indicating significantly superior decoding performance for personally familiar entities. We found that significant differences in decoding performance emerge in limited clusters already after 200ms (e.g. B12, $p = 0.04785$), and become clearer between 400ms and 700ms. In terms of spatial location, they revolve around a central set of electrodes (peak between 400-700ms at A1, $p = 0.00195$), reaching to right fronto-temporal (peak between 600-700ms at C3, C4, $p = 0.00292$) and left frontal (peak between 600-700ms at C24, $p = 0.0019$) and posterior (peak between 500-600ms at A17, $p = 0.0097$) clusters.

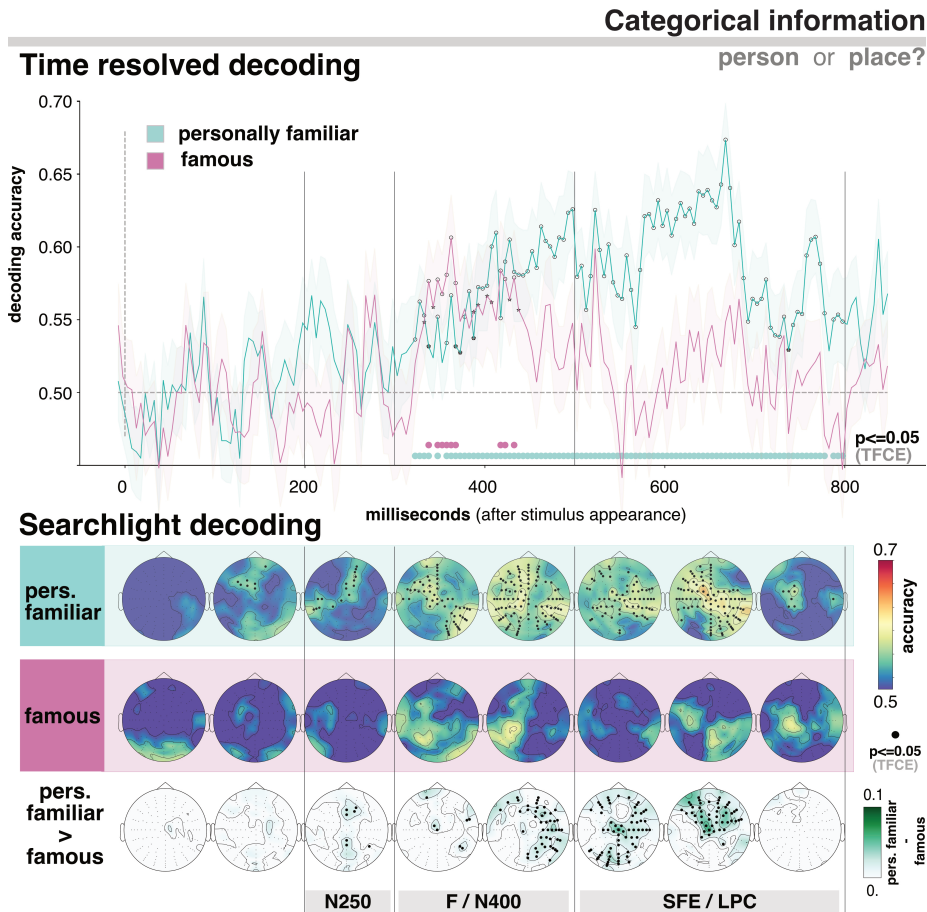


Figure 2: **Visualization of the results for time-resolved and searchlight decoding of semantic category (people vs places).** In the top portion of the figure we report decoding scores, averaged across subjects (y axis), against time points (x axis). Here we used all electrodes, thus looking at whole-brain patterns. The standard error of the mean is reported as a shaded area around the decoding performance lines. In the lower section, we report searchlight decoding performance – i.e. scores for clusters of electrodes within a 30mm radius – which indicate localized presence of information relevant for decoding. In order to compare personally familiar and famous entities more easily, we also plot in the last row the difference maps, showing electrodes where performance for personally familiar stimuli is better than for famous stimuli. Statistically significant performance ($p <= 0.05$ after TFCE correction) in both cases is indicated by solid colour dots. Semantic category information could be reliably decoded between 300ms and 500ms for both personally familiar and famous entities, and, specifically for personally familiar entities, until 800ms. Overall, performance was significantly better and more extended, both temporally (upper portion) and spatially (bottom part, last row), for personally familiar as opposed to famous entities.

3.3 Decoding familiarity

In Figure 3 it is possible to compare time-resolved performance and spatio-temporal decoding maps for people and places, understanding when and where familiarity information is domain-specific – i.e. selectively present for people or places.

People For people, statistically significant time-resolved decoding performance was reached in a very large time window (230-800ms; with an extended peak where $p < 0.001$ between 400ms and 590ms). In searchlight, between 200 and 400ms decoding was statistically significant in right fronto-temporal and left posterior-parietal clusters ($p < 0.001$). Between 400 and 700ms familiarity could be decoded in a larger set of clusters, first on the left-right temporo-parietal axis and then developing frontally and posteriorly along the central midline ($p < 0.001$). Finally, between 700 and 800ms only right temporo-parietal electrodes were statistically significant (peak at B23 $p < 0.001$).

Places Regarding places, time-resolved decoding was significantly above chance only in the range between 360-560ms (N400 and SFE ranges, peak cluster with $p < 0.001$ between 400-450ms), but not in the N250 range (200-300ms). In searchlight, statistical significance in the N250 range was achieved only in left posterior-parietal electrodes (peaks at D24, D25, $p = 0.0029$); later the distribution of statistically significant electrodes largely followed the one described above in the case of people. Notice, however, that overall statistically significant decoding performance for places was temporally and spatially more constrained when compared to people.

People > places We also looked at whether the difference between people and places was statistically significant (lower section of Figure 3). We subtracted the decoding scores for places to those for people (people-places) obtained in the searchlight analyses, as previously done for categorical information (see Section 3.2). Clusters where the difference is significant emerge diffusely after 200ms, indicating that familiarity information is more easily decoded for people than for places. Importantly, the difference between the two categories is statistically significant during the N250 time window, whose person-specificity is debated (Tanaka et al., 2006), in most, but not all, clusters. Significant differences emerge in fronto-temporal (peaking at C5, C6, C7, $p = 0.00292$) and in left posterior-parietal clusters (peaking at A10, A11, $p = 0.02148$), but not in left temporal electrodes (e.g. D21, $p = 0.96$). There, familiarity information could be decoded for both places and people. This is compatible with the existence of both domain-general and domain-specific ERP effects in the N250 range.

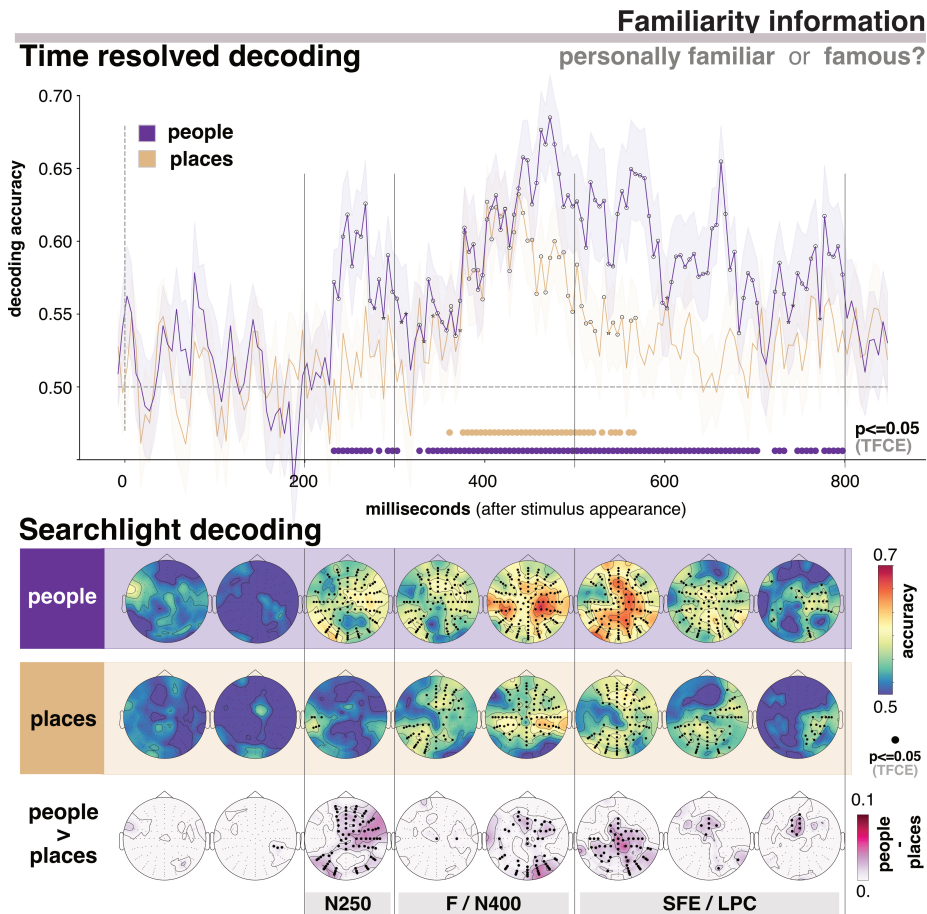


Figure 3: Visualization of the results for time-resolved and searchlight decoding of familiarity (personally familiar vs famous). In the top portion of the figure we report decoding scores, averaged across subjects (y axis), against time points (x axis). Here we used all electrodes, thus looking at whole-brain patterns. The standard error of the mean is reported as a shaded area around the decoding performance lines. In the lower section, we report searchlight decoding performance – i.e. scores for clusters of electrodes within a 30mm radius – which indicate localized presence of information relevant for decoding. In order to compare people and places more easily, we also report in the last row the difference maps, showing electrodes where performance for people is better than for places. Statistically significant performance ($p \leq 0.05$ after TFCE correction) in both cases is indicated by solid colour dots. Familiarity information could be reliably decoded between 300ms and 600ms for both people and places, and, specifically for people, between 230-800ms. Responses to people afforded, overall, significantly better decoding performance as opposed to places: in the early time window (200-300ms) one domain-general cluster was revealed in left posterior-parietal areas, and a person-specific cluster in right fronto-temporal electrodes.

3.4 Univariate ERP analysis

The ERP components relevant to familiarity and semantic processing described above (N250, F/N400, LPC/SFE) were first individuated using a univariate approach, as opposed to the multivariate decoding used here. As it has been pointed out recently in both the fMRI and EEG literature (Davis et al., 2014; Hebart & Baker, 2018; Wang & Kuperberg, 2023), univariate and multivariate analyses can sometimes provide complementary evidence. Therefore, in addition to the multivariate decoding results of Sections 3.2 and 3.3, we also computed the grand average ERPs. Furthermore, we ran statistical tests to find out at which time points differences in voltage are statistically significant across levels of familiarity and semantic categories. This makes it possible to obtain a more complete picture regarding the differences in evoked activity for the types of stimuli considered in our study.

Results are reported in Figure 4. While ERPs start to show some differences in voltage starting from around 250ms (earliest peak difference for famous vs personally familiar is at 0.3075ms - $p = 0.635$, for people vs places at 0.3925ms, $p = 0.288$), comparisons reach statistical significance only in a later time frame (500-800ms, LPC/SFE). The difference between ERPs for people and places is statistically significant from around 630ms to 800ms (peak at 0.732ms, $p = 0.02832$), and between personally familiar and famous entities between 500ms and 750ms (peak at 0.5575ms, $p = 0.00586$). This adds to the evidence emerging from multivariate decoding in showing that, in a later time window in the evoked activity, both familiarity and semantic category can be reliably distinguished. Regarding the directionality of such effects, in the LPC/SFE the activity evoked by names of people and famous entities has overall lower voltage than the one elicited by names of places and personally familiar entities.

Univariate comparisons thus offer more conservative estimates of the differences in ERPs when contrasted with the multivariate decoding results reported above. Despite not adding new information, these results confirm recent reports that, in the case of EEG (Wang & Kuperberg, 2023) as well as fMRI (Kuhnke, Kiefer, & Hartwigsen, 2023), multivariate analyses afford higher sensitivity as opposed to univariate analyses. Importantly, this validates a multivariate decoding approach such as ours, as it allows to detect pieces of evidence that would be otherwise ignored.

4 Discussion

In this work we have shown that familiarity interacts with semantic categories in shaping representations of individual entities. Crucially, we have done so using, as stimuli, names instead of pictures. This allowed us to sidestep low-level visual recognition processes which are usually intertwined in face- and scene-recognition studies. As a framework for the analyses, we have used a multivariate decoding approach. This method affords additional sensitivity when compared to univariate ERP techniques. To look at the differences between the

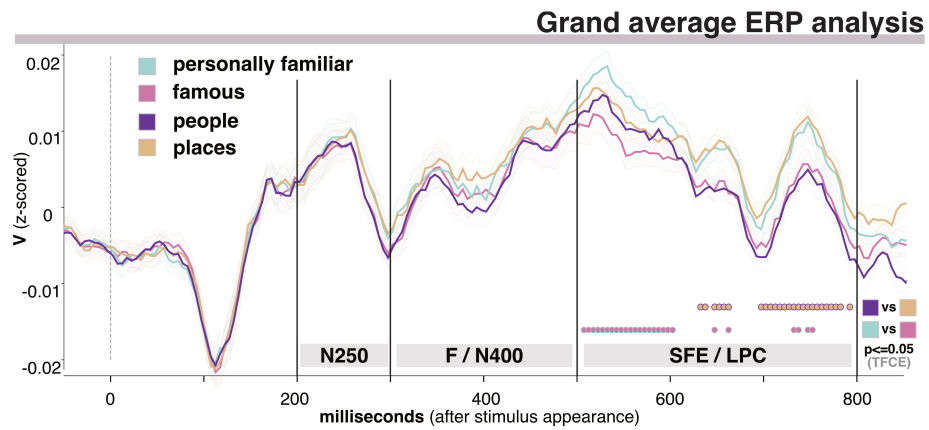


Figure 4: **Visualization of the grand average ERPs, separately for people and places as well as personally familiar and famous entities.** We report changes in voltage averaged across all electrodes (y axis) for all time points (x axis). We also run statistical tests, comparing ERP voltage for people vs places and for personally familiar vs famous entities. Statistically significant differences ($p \leq 0.05$ after TFCE correction) in both cases are indicated by solid colour dots. Although some differences can be visually detected already from 250ms on, the only time window where differences between different ERPs are statistically significant is the LPC/SFE range.

two approaches, we also reported time-resolved univariate ERP results (Figure 4), which did show less sensitivity than decoding. Also, we employed a searchlight decoding procedure to find in a bottom-up fashion spatio-temporal clusters containing relevant categorical and familiarity information. Overall, clusters were broadly distributed, concurrently covering electrodes and time ranges traditionally associated with multiple separate ERP components. This confirms the high sensitivity afforded by our approach, while suggesting that information related to semantic processes such as those investigated here well outside of traditional regions of interest. Not only familiarity-related information was found in person-specific spatial clusters, but our results also suggest easier processing of person identity as opposed to places. Despite such differences, our work reveals domain-general loci of processing of familiarity - and how familiarity with a person or a place makes it easier to process identity-specific information. In the following, we will look at these points in two steps. First, we will discuss separately results for the three time windows described in the Introduction (N250, F/N400 and SFE/LPC). Then, we will look at what such evidence can tell us about the role and the interactions of familiarity and categorical information in brain representations of individual entities.

4.1 The timing of individual entities processing

4.1.1 200-300ms: the N250 range

In this early time window, mainly information related to familiarity, and not to semantic categories, appears to be available. This was expected, based on previous literature (cf. predictions in Section 1).

Figure 2 shows that categorical information could be decoded only for personally familiar entities, in reduced clusters of electrodes. By contrast, we see from Figure 3 that familiarity could be classified in this interval with accuracy significantly higher than chance both for people (in both time-resolved and searchlight analyses) and for places (using the searchlight approach).

In particular, people and places shared statistically significant clusters in the left posterior-parietal part of the scalp. These locations are consistent with localization previously associated with the familiarity effect for faces (Tanaka et al., 2006; Kaufmann, Schweinberger, & Burton, 2009; Sommer et al., 2021). Therefore, our results seem to suggest that the N250 may not be a component specific to person recognition, but a marker of recognition of domain-general representations of individual entities. This is consistent with our expectations, that were based on the image recognition results reported in (Pierce et al., 2011; Klink et al., 2023). There, it was shown that not only faces, but also images of other important types of entities (personal car, own dog, rooms from one's apartment) elicited differences in N250 depending on familiarity. The novelty of our results comes from the fact that by using names as stimuli, instead of pictures, we could avoid capturing responses evoked by specific instances of images or visual features - thus being able to look more closely at domain-general correlates of familiarity.

Finally, we expected to be able to decode, during the N250, familiarity information similarly for both people and places. With respect to this, our analyses revealed a more complex picture. A domain-general cluster where decoding performance was comparable emerged in left temporal areas. However, for people only, familiarity information was strongly represented in right fronto-temporal areas (lowest row of Figure 3, people > places), indicating the presence of domain-specific information. This person-specific role of frontal areas is to be expected, as frontal areas were proposed as being part of the person-specific network (Morton et al., 2021).

Also, overall, decoding performance was higher for people than places. In this sense, although the N250 in general may not be person-specific, identity-specific patterns may be more distinguishable for people than for places. This result is novel in the literature for familiarity on EEG, as far as we know. It is nevertheless in accordance with the results of a fMRI decoding experiment reported in (Ragni, Lingnau, & Turella, 2021), which found that when decoding familiarity from mental imagery for places and people, the former always provide lower decoding scores. We discuss why this may happen below, in Section 4.2.

Therefore, our results seem to indicate that, when processing individual entities within the N250 range, different neural processes happen simultaneously - some being domain-general and reflected in left posterior-parietal areas of the scalp and other being person-specific, in right fronto-temporal clusters.

4.1.2 300-500ms: the F/N400 range

In this time window, which is the one most typically associated with lexical semantic processing (Hauk et al., 2006; Kutas & Federmeier, 2011; Šoškić et al., 2022), both categorical and familiarity information could be decoded in time-resolved and searchlight analyses. This reflects our expectations, with only one partial exception. We were not able to find any localized cluster where categorical information could be reliably decoded for famous individual entities in searchlight - which was only possible when looking at whole-scalp distributed patterns. We discuss this exception in Section 4.2 in light of our general results.

When comparing how familiarity information was encoded in evoked responses for people and places (Figure 3), spatial patterns were largely similar, nevertheless showing the same effect reported for the N250 range - namely, that decoding scores are higher overall for people (again, see Section 4.2 for a discussion).

Other than that, the emerging topography is compatible with that typically found to be involved in the semantic processing of individual entities (Semenza, 2022).

Temporo-parietal clusters are compatible with traditional accounts of proper name processing which have implicated both anterior and posterior temporal areas (Semenza, 2011; O’Rourke & de Diego Balaguer, 2020; Desai et al., 2022). Frontal and posterior midline clusters, where decoding provided higher scores especially when looking for familiarity (Figure 3), may reflect the activity of the Default Mode Network, which is involved in social cognition and episodic (self-

related) memory retrieval (Raichle, 2015; Campbell, Louw, Michniak, & Tanaka, 2020; Smallwood et al., 2021; Kaefer, Stella, McNaughton, & Battaglia, 2022).

4.1.3 500-800ms: the SFE/LPC range.

In this time range, as predicted, decoding accuracy was significantly above chance for all of our distinctions (with the usual exception of famous entities) until 700ms, which is when categorical and familiarity information began to fade away from the ERP signal.

In this time range, people and places could be distinguished in left fronto-temporal and right posterior-parietal clusters (see Figure 2), showing spatial patterns which are quite similar to the ones found in the previous time window (300-500ms). In time-resolved decoding of familiarity (Figure 3), however, the difference between people and places was quite stark: familiarity could be accurately decoded for places starting from around 550ms, whereas for people decoding was significant until 800ms. Searchlight, however, revealed that, in fact, spatially circumscribed clusters still carried information regarding familiarity for both people and places up until 800ms. Once more, the main difference among the two types of entities seems to be in terms of how much information is carried in the ERPs. Decoding was significantly better for people than for places in widely distributed clusters (Figure 3, lowest row). Given that this is a relatively late time window, this could reflect differences in the ease of processing identity-specific information, as proposed in (Wiese et al., 2021); we discuss this below, in Section 4.2.

In general, the familiarity-related effects that we found between 500-800ms, which involved consistently posterior-parietal clusters, are compatible with the recent proposals of a SFE (Wiese et al., 2019; Dalski et al., 2022; Li et al., 2022) and with previous accounts of LPC focusing on its role as a marker of activation of episodic memory related to personally familiar stimuli (Rugg & Curran, 2007; Renoult et al., 2016; Dimsdale-Zucker et al., 2022). Nevertheless, it seems impossible to distinguish among the two - which may in fact reflect similar brain processes.

4.2 Ease of identification

Overall, decoding scores were higher when considering information related to familiarity, for people as compared to places ; and, when decoding semantic category, for familiar compared to famous stimuli (Figure 2 and 3; direct comparisons with statistical tests are reported in the lowest row). We interpret such differences in decodability between categories as reflecting differences in the ease of processing identities, which is a widely used perspective to look at semantic processing of individual entities (Ramon & Gobbin, 2018; Wiese et al., 2021). In other words, our assumption is that the easier the identification and processing of the identity of a person or a place for a subject, the easier it will be to correctly classify the evoked response to that individual entity with a decoding analysis, in turn obtaining higher scores. This perspective is also

supported by the response times results for the categorization task, that took place independently from the time window of the analyzed ERPs (see Section 3.1). Responses were significantly faster for people as opposed to places, and for personally familiar as opposed to famous entities. These results, showing that categorization - a crucial part of processing individual identities - is easier for people and personally familiar entities, converge with the picture emerging from EEG decoding.

4.2.1 People > places

The first gradient, people > places, is the most relevant with respect to our research question - looking for differences in evoked responses among the two semantic categories. The spatio-temporal dynamics of access to familiarity, in particular, provide an amodal indicator of the ease of identity processing. Our key finding is that, in all time windows, information regarding the familiarity of people was easier to decode with respect to that of places, being both temporally and spatially more extended; in the crucial N250 range, clusters specific to people were revealed in right fronto-temporal electrodes, and, in the LPC/SFE time range, time-resolved decoding performance for places reduced drastically.

While it has been shown in previous neuroimaging studies that processing people and places involves partially distinct brain areas which can be selectively impaired, it is an open question why decoding, whose success can be interpreted as reflecting ease of processing individual identities in the brain, should be easier when considering people instead of places.

(Kaminski et al., 2022) and (Desai et al., 2022) discuss some reasons why this could be the case. People identity could be easier to process because richer semantic knowledge involving multiple modalities is available about people (voice, face, autobiographical experiences), while places only involve visual and less autobiographical knowledge (Kaminski et al., 2022); or they could involve a larger set of secondary meanings and associations with other concepts (Desai et al., 2022).

Another possible explanation could be the peculiar relevance of conspecifics in human brain processing, be it because of evolutionary (Mahon & Caramazza, 2011) or social (Olson et al., 2013) factors. Both our results and this theoretical view seem to be consistent with the analysis of BOLD activation in (Desai et al., 2022), where it is shown that, when comparing areas selectively activated by either people or place names, the former involve a substantially larger amount of brain voxels ($23768mm^3$ vs $7035mm^3$), whereas the latter mostly seem to involve a subset of areas associated with processing of people names.

Finally, a number of semantic and linguistic variables may affect brain processing, which makes it difficult to properly measure differences among the two categories.

Our analyses address these concerns by controlling name length, familiarity and imageability. Familiarity and imageability were controlled by design. Both were controlled during stimuli selection in order to avoid confounds across categories for the famous stimuli. Also, familiarity was controlled with the aim

obtaining two clearly separated levels - famous and personally familiar entities (see Section 2.1). Notice that neither name length nor imageability, on the other hand, could be controlled *a priori* for personally familiar entities - names provided by individual participants could not be matched with word lengths or the imageability of famous entities. Therefore, we chose to remove the variance associated with word length, whose effect is particularly pervasive on EEG responses, out of our data.

Our results show that, after having ruled out low-level distinctions between people and places such as name length, people evoked more clearly distinguishable patterns of activity in terms of individual identity, and that in early access to familiarity information (200-300ms) people-specific processes, reflected in right fronto-temporal activity, emerged.

4.2.2 Familiar > famous

The second gradient (familiar > famous) is less surprising. Behavioural results from the face recognition literature, reviewed in (Ramon & Gobbini, 2018), have consistently shown that identity recognition of people is much easier when personally familiar stimuli are used. Previous neuroimaging studies have shown that familiar stimuli entail greater brain activation, linked to access of richer entity-related semantic knowledge, stronger social and emotional response (Gobbini et al., 2004; Donix et al., 2010; Cloutier, Kelley, & Heatherton, 2011; Desai et al., 2022).

Our results suggest that this seems to hold for places too. There is less literature on familiarity for this type of entity, but our results are consistent with previous results. In (Klink et al., 2023), pictures of one’s apartment elicited stronger category-specific representations as opposed to somebody else’s. In (Penaud et al., 2022), using scene exploration in virtual reality, it was shown that first-person experience improves encoding and subsequent recall of semantic information.

Our finding that discriminability of neural patterns is easier when personally familiar stimuli are used thus converges with previous results suggesting that personal familiarity with any type of experimental stimuli makes processes related to identity recognition easier, or at least qualitatively different as proposed in (Renoult, Davidson, Palombo, Moscovitch, & Levine, 2012; Renoult et al., 2016).

We nevertheless acknowledge that our experiment has a clear limitation, when it comes to understanding in detail how different levels of familiarity affect semantic processing. Namely, our approach is coarse-grained: we decided to look at a binary set of familiarity labels (personally familiar / famous), and we did not collect individualized familiarity ratings for each participant. Therefore, we are unable to investigate fine-grained variations in brain responses modulated by small-scale differences in familiarity across stimuli within each of the categories (cf. Section 2.1). We believe that this could be a fruitful future direction to better understand semantic processing of individual entities.

5 Conclusions

In this study we used EEG and multivariate decoding analysis to investigate similarities and differences between temporal *and* spatial evolution of the evoked responses to proper names of individual entities of different semantic categories (people and places). In particular, we looked at how the two semantic categories access familiarity information, which is amodal and therefore should not involve the sensorimotor differences between the two categories.

In terms of spatial locations, our results about individual entity processing are consistent with those of previous studies. The key novelty of this work is our analysis of temporal processing. Our results suggest that semantic category can be reliably distinguished in a time window and with spatial localization typically associated with lexical semantic processing (300-800ms, with peaks in centro-parietal and bilateral temporo-parietal areas). With respect to familiarity information, two main findings emerge. First, we find that people seem to be easier to identify than places, in both early (N250) and late (SFE) time windows. Second, we discover that within the early time window, both domain-general (left posterior-lateral) and domain-specific (right fronto-temporal, only for people) neural patterns can be individuated, suggesting the presence of person-selective processes during the N250 time range.

Author Contributions

Andrea Bruera: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Software, Validation, Visualization, Writing - Original Draft; **Massimo Poesio:** Conceptualization, Funding Acquisition, Project Administration, Resources, Supervision, Writing - Review and Editing.

Data Availability Statement

The dataset used in this study (preprocessed ERPs in BIDS format), together with the code necessary to run the analyses, can be found at this page: https://osf.io/sjtmn/?view_only=49dcdbf7aa2649fa9e376f07c26ee417

Acknowledgments

We would like to thank prof. Davide Crepaldi, head of the Language, Learning and Reading lab at SISSA, who provided the facilities for collecting the EEG data while the first author was visiting, and Marjina Bellida for helping out with subject preparation procedures.

Diversity in Citation Practices statement

We used the Gender Citation Balance Index (GCBI) tool available at <https://postlab.psych.wisc.edu/gcbialyzer/> to calculate the likelihood that the first and the last author for our references self-identifies as woman (W) or man(M). In the following, the first letter refers to the first author, the second to the last (e.g. WW means both first and last authors likely identify themselves as woman). To interpret results, they are scaled around 0, where 0 is the Journal of Cognitive Neuroscience (JoCN) base rate: negative and positive values indicate respectively below-JoCN and above-JoCN rates. Results are as follows: MM=0.284, WM=-0.183, MW=0.285, WW=-0.571.

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