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Toward a Neurolexicology: A Method for Exploring the Organization of the Mental Lexicon by Analyzing Electrophysiological Signals

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Abstract

This article analyzes the organization of the mental lexicon based on neurophysiological data. The neuroscience literature has devoted many studies to the semantic processing of words. However, the research remains specific to certain categories, studied separately, and does not address the lexicon as a system. In order to provide further insight into the neuronal organization of the lexicon, we conducted an EEG-based semantic decision experiment using words from eight categories (four living and four nonliving categories) as the material. A data-analysis method (correspondence analysis or CA) commonly used in computational linguistics was applied to the electrophysiological signals. The results revealed a two-factor structure: an ontological organization separating the living from the nonliving, and an organization with a human referential structured by proximity to the person. A comparison of the ERP-CA and the linguistic-CA data revealed organizational analogies. Lastly, a tomography software (Loreta®) was used to estimate the cerebral sources associated with the ERP signals.

Keywords: mental lexicon, ERP-derived semantic distances, NLP-derived semantic distances.

Since ancient times, the lexicon and its organization have been studied from various angles: philosophical, linguistic, psychological, computational, and neurological. Without looking in depth at these different points of view, which are far beyond the scope of the present article, we will first briefly recall that a key element interrelating these different points of view is the notion of system.

In a philosophical perspective, the classic approach (also called Aristotelian) posited an ontological system of categories of the world that was founded on logic. This system derives its hierarchical organization from the transitive inheritance of properties, a logical process that applies to all categories. The psychological approach breaks away from the purely theoretical point of view. It no longer attempts to account for all categories, taken to be objects of the world, but looks instead at how they are acquired and processed. This change of paradigm from objects of the world, to objects of human cognition, has ushered in new approaches. The experimental approach has replaced the *a priori*, solely theoretical approach, and the results of experiments have cast doubt –from the standpoint of human cognition– on the purely logical and hierarchical Aristotelian organization. Accordingly, Rosch and Mervis (1975), who take a cognitive approach, suggest that categories are organized around prototypes by a membership gradient. The proposals of Rosch and her colleagues, along with those of many studies dealing with this issue (Smith, Shoben, and Rips (1974), Collins and Quillian (1969), etc.), have been tested using behavioral protocols essentially founded on the analysis of subjects’ reaction times on tasks involving verbal or graphic stimuli. In the present study, we worked on neurophysiological data. Although the debate opposing a hierarchical, logical organization to a similarity- and difference-based organization has divided many researchers over the years, it is still a current issue both from the philosophical point of view and in terms of its cognitive relevance (Reboul (2007) Chapter 2, Caplan (1992)). In this debate, the systemic aspect remains a key element shared by the various different approaches.

Finally, we will not discuss the large body of research on the question of lexical se-

mantics from the language standpoint. Most of these studies have attempted to describe the multifaceted relationship between words and concepts, and have found context effects in the construction or selection (depending on the school of thought) of word meanings. The issue of lexical polysemy will not be addressed here because the experiment reported in this paper uses isolated words and does not look at the differential effects of context. Note, however, that, as we have just recalled for the philosophical and psychological approaches, the notion of system remains important for those linguists who, following Saussure (1972), think that the meaning of any word in a language is given by its difference from the meanings of all other words and not solely by its own characteristic(s).

Recently, researchers in two domains have begun to use new technologies to study concepts and their links with words: computers and brain imaging. The computer has enabled the development of computational linguistics through the automatic analysis of corpora (see, for example, Mitkov (2005)); words and their meanings are analyzed via a large sampling of their uses in the language. Neuroimaging techniques have enabled the study of the neuronal processing of the semantics of words and concepts, by way of experiments whose results are no longer based on behavioral data alone but now include neurophysiological signal analysis. While automatic language processing seeks to track down the organization of the lexical system as a whole by studying links between words (co-occurrence, synonymy, homonymy, etc.), the debate about lexical semantics in the neurosciences focuses on locating the brain regions where specific categories are processed. Various hypotheses are proposed to explain category processing location, several of them are based on semantic-category deficits among brain-damaged patients (see Forde and Humphreys (2002)). The question most often raised in this domain concerns whether neuronal processing is modular and encapsulated, or on the contrary, distributed across neural networks specific to the concept referred to by a given word. In a historical literature overview, Jeannerod (2008) reminds us that according to a mainstream traditional view¹, the brain areas involved in word processing, and in particular, word semantics are located in the left hemisphere (along the sylvian fissure), whereas more recent studies using brain imaging have shown that word processing

is distributed across regions extending beyond the "classical" language areas. Color words, for instance, additionally engage visual areas, and action words activate motor areas. Hauk, Johnsrude, and Pulvermüller (2004) showed that brain activation patterns are closely tied to word content, in such a way that the part of the motor and premotor areas associated with hand movement, for instance, is activated for processing the verb *to pick*, whereas for the verb *to kick*, the authors noted activation of the parts of the areas associated with foot movement.

The present article presents a method of automatic language processing aimed at studying concepts and their processing, not in a category-by-category fashion, but as a system taken as a whole. We use correspondence analysis (CA), developed by Benzécri (1980), which is a multivariate statistical technique typically applied to lexicology, where it produces maps of semantic proximities among words based on their use in text corpora. CA differs from other data-analysis techniques in that it establishes a correspondence between two types of variables, e.g., words and sociodemographic variables (sex, age, etc.) as in survey analyses (Lebart, Piron, and Steiner (2003)), or words and semantic subunits (Ploux and Victorri (1998)), etc. Here we will use it to uncover a correspondence between semantic categories of words and event-related potentials (ERPs) associated with the processing of these words.

Below, we will set forth a few arguments justifying the choice of this method to meet the objectives set for this study. Note to begin that Mitchell et al. (2008) used functional magnetic resonance imaging (fMRI) to locate individual noun processing and showed that it could be deduced from a limited set of 25 verbs most typically found in the context in which the noun was used. Their simulation system gives a good approximation of the pattern of brain activity involved in processing the word *celery*, for example, when the verbs *eat*, *taste*, and so forth are used as factors. The authors compared the real brain activity obtained for processing the word, to that simulated by a combination of activities for the processing of associated verbs. This model connects data obtained via automatic language processing (the method employed is LSA (Landauer, Foltz, and Laham (1998))), a statistics-

based corpus-analysis method), which reflects language production, to neurophysiological data, which reflect semantic processing in the brain. The present study was also aimed at interrelating these two domains (computational linguistics and language production on the one hand, neurophysiology and the study of the neural substrates of language processing on the other), which until very recently have been blind to each other. As stated above, however, our approach stands apart from others by the fact that it searches for a global organization describing the semantic processing of the whole lexical system.

Why use correspondence analysis? CA (see (Benzécri, 1980)) assesses the extent of matching between two variables. It determines the first n factors of a system of orthogonal axes that capture the greatest amount of variance in the matrix. The first axis (or factor) captures the largest variations, the second axis captures the second largest, and so on. The basic underlying idea is to eliminate redundancy in the original data while trying to capture the variation with a smaller number of factors that combine the original variables. This method was chosen for several reasons. Firstly, it is a data-analysis technique that automatically detects the greatest differences between the conditions, which frees one from dependency on human expertise likely to be subjected to the forgetting or ignoring of important phenomena. Secondly, as its name indicates, this method can be used to establish a correspondence between two types of variables, e.g. ERPs and the experimental conditions, by systematically computing the greatest variations between the electrophysiological signals associated with those conditions. This is an advantage over other data-analysis methods –such as principal component analysis (see Dien and Frishkoff (2005) for an introduction to its use on ERPs)– which also reveal the internal structure of the data in a way that best explains the variance, but they do not establish this correspondence. Thirdly, unlike in most studies which are either spatial or temporal, CA as applied here reveals networks organized by electrode location, and by location in time. Although Pulvermüller and his colleagues (Pulvermüller (2005)) demonstrated networks that are both time-based and location-based, their approach (which applies to electrophysiological EEG or MEG signals, or is based on

fMRI) differs from ours because it does not directly and automatically supply a summary of the similarities and differences between the various conditions. This point brings up a fourth argument in favor of using CA: conditions are processed as a whole, which as we shall see below, helps in understanding the organization underlying the whole set of conditions rather than simply studying differences taken two at a time, as in most current work. Finally, CA has already been used in computational linguistics to analyze the meanings of word in terms of how they are employed (e.g. (Ploux & Victorri, 1998), Ji, Ploux, and Wehrli (2003)). Applying one and the same method to word-usage data and neurophysiological word-processing data should enable the researcher to compare the organizations revealed by these two processes.

Method: General Description

Without going into mathematical details, which are more precisely specified in the *Recording and Data Processing* section, the CA will reveal electrodes and time windows within which the amplitude difference between the eight tested categories is maximal. Figure 1 schematically illustrates this approach to the ERPs of three hypothetical conceptual categories, measured from 0 ms to 500 ms after stimulus onset. The grey frames in the figure indicate time slots within which a specific pattern of relation between the three conditions becomes repeatedly evident. The amplitude extrema for the category are indicated by red and blue lines; intermediate amplitudes, by green lines. The black arrows point to another such pattern (*[blue, red, green]*). The CA, as applied here, identified these patterns over the time window (0 ms – 500 ms) at all electrodes, and classified these patterns from the most to the least significant in terms of magnitude and frequency. The theoretical assumption underlying this analysis is that systematic ERP variation on the different word categories (e.g., *[red, green, blue]*) is caused by the same factors. For instance, if red lines are observed while participants process words referring to fish, green during the processing of words referring to birds, and blue during the processing of words referring to apes, the factor that might underlie the depicted ERP variations in the identified frames could code for something that

relates to modes of animal locomotion. With this method, we can thus detect –and follow over time and in terms of head location (electrode position)– the evolution of a specific ERP pattern that indexes the processing of a variable.

In parallel, the CA will also uncover semantic relations between the words used in the ERP experiment, as defined by synonymy (and parasynonymy) and co-occurrence in corpora. This analysis was applied to databases of synonyms Ploux and Ji (2003) and databases of associated words Ploux and Ji (2003). Associated words are the most specific co-occurrences of a word in a sentence (e.g., *wings* is an associated word of the word *bird*). These two types of data have complementary linguistic characteristics since synonyms (and parasynonyms) specify categories while associated words specify syntagmatic links. For instance, one can substitute the synonym *wildcat* for *feline* in the sentence *The feline caught its prey*, without significantly modifying the meaning, whereas the words *feline* and *prey* –which are closely associated semantically– cannot be interchanged without modifying the sentence’s meaning. As with the ERP data, CA applied to word corpora was used to determine the first n factors that capture the greatest amount of variance in the data. Comparing CA applied to ERPs with CA applied to word corpora will thus allow us to link the neural processes underlying semantic classification, with the semantic relations between words as defined by their use.

Insert Figure 1 about here

Experiment

Experimental Task

The experiment conducted here involved a semantic decision task. The words presented to subjects were nouns belonging to eight conceptual categories: four containing living entities and four containing nonliving entities. The living-nonliving distinction is known to be significant from both the philosophical and experimental angles. In addition, all eight categories (*clothing*, *parts of a house*, *tools*, *vehicles*, *fruits/vegetables*, *animals*, *body parts*, and *people*) have often been studied in the literature.

Materials and Methods

Participants. Sixteen native-French-speaking students (14 women and 2 men) between the ages of 20 and 29 (mean age 23) attending Lyon 2 University participated in the experiment. All were right-handed and were tested on the Edinburgh Handedness Inventory (mean 0.8). None had any known neurological disorders or were taking any medication. They all reported having normal or corrected-to-normal vision. All subjects signed an informed consent form before the experiment.

Stimuli. The stimuli were nouns, divided into two categories: living and nonliving entities. Each category had four subcategories of 30 nouns each, making for a total of 240 nouns. The stimuli in the nonliving category were chosen from the *clothing* (*dress*, etc.), *parts of a house* (*kitchen*, *staircase*, etc.), *tools* (*hammer*, etc.), and *vehicles* (*plane*, etc.) categories; those in the living category were chosen from the *fruits/vegetables* (*lemon*, etc.), *animals* (*cow*, etc.), *body parts* (*neck*, etc.), and *people* (*brother*, *novelist*, etc.) categories. The words were selected from the *Lexique* lexical database (New, Pallier, Brysbaert, and Ferrand (2004)). The following features were controlled for the set of words as a whole, and for each of the eight categories: lexical frequency (mean($\log_{10}$) = 0.9, std = 0.9), number of letters (mean = 6.4, std = 1.6), number of syllables (mean = 1.8, std = 0.6), number of phonemes (mean = 4.7, std = 1.3), grammatical gender (equal number of masculine as feminine nouns), and frequency of orthographic (mean = 2.9, std = 3.6) and phonological (mean = 8.0, std = 8.3) neighbors.

Experimental Procedure. The subjects had to state whether the words presented referred to biological or non-biological entities. This terminology seemed preferable to living vs nonliving things because it is less semantically ambiguous (Is a piece of fruit a living thing or not?). The subjects were seated 60 cm from the screen and had to right-click or left-click on the mouse held in their right hand if they thought the displayed word fell into the biological category, and click on the opposite side (right or left) if they thought the word fell into the non-biological category. The clicking sides for the biological and non-biological categories

were assigned randomly to each subject. The experiment included an initial training phase during which words from each category were presented. None of these words belonged to the material used during the signal-recording phase. In the experiment proper, the stimuli were presented in three blocks lasting an average of eight minutes each. During a given block, all 240 words were presented once, in random order. The display timing was as follows: a mid-screen fixation cross was displayed for 250 ms, followed by a word for 800 ms, then a fixation cross until the subject responded. Subjects were explicitly instructed to respond only after the second fixation cross appeared. A black screen lasting 500 ms followed the offset of the second fixation cross. Subjects were asked not to blink their eyes until the end of a trial.

Recording and Data Processing. E-prime software was used to program the experimental task. The EEG signals were recorded by a Brainvision Recorder connected to 30 electrodes placed on a Fast'n Easycap helmet in which the impedances were kept under 10 k Ω . The electrodes were positioned according to the 10/20 system. The sampling frequency was 500 Hz. To detect ocular artifacts, electro-oculograms (EOGs) were recorded using two electrodes, one located on the outer corner the left eye and the other approximately 1 cm under the left eye.

EEG data were analyzed with Brainvision Analyser software. Phase shift-free Butterworth filters were applied (high-pass: 0.1 Hz; low-pass: 40 Hz; slope: 48 dB/octave). EEG channels were re-referenced offline to the average reference², and then segmented to extract the portions of the signal containing a marker for each of the eight categories. Segmentation windows started 250 ms before and ended 1600 ms after the appearance of the word. Segments containing an amplitude greater than ± 100 mV were rejected. The mean of the segments was then calculated for each of the eight conditions and for each subject, along with the grand mean per condition for all subjects. A baseline correction was applied using a [-250 ms, 0 ms] window before stimulus onset.

CA and subsequent analyses were performed using a dedicated software platform written in Matlab® (source code is available upon request to the corresponding author).

Purely statistical tests, on the other hand, were done in Statistica®. Since lexical access has been estimated to occur within the first 500 ms after word onset (Friederici (2002)), our analysis focused a time window from 150 ms to 500 ms after word onset. The CA was performed on the matrix denoted $M_{150-500}$, which has eight lines, one per condition (i.e., category), and 900 columns. The columns correspond to a sampling done every 11.5 ms (see below) of the amplitude of the grand means of the ERP signals between 150 and 500 ms after stimulus onset, on the series of 30 electrodes. Wavelet decimation was used to reduce the size of the matrix³ while avoiding sampling noise. The sampling period is calculated automatically by applying this procedure; it was equal to 11.5 ms in the present study.

$$M_{150-500} = \begin{pmatrix} A_{150-150+\delta, \text{Fp}_1}^{\text{Tools}} & \cdots & A_{500-500+\delta, \text{Fp}_1}^{\text{Tools}} & \cdots & A_{150-150+\delta, \text{O}_2}^{\text{Tools}} & \cdots & A_{500-500+\delta, \text{O}_2}^{\text{Tools}} \\ A_{150-150+\delta, \text{Fp}_1}^{\text{Vehicles}} & \cdots & A_{500-500+\delta, \text{Fp}_1}^{\text{Vehicles}} & \cdots & A_{150-150+\delta, \text{O}_2}^{\text{Vehicles}} & \cdots & A_{500-500+\delta, \text{O}_2}^{\text{Vehicles}} \\ \vdots & & & \ddots & & & \vdots \\ A_{150-150+\delta, \text{Fp}_1}^{\text{People}} & \cdots & A_{500-500+\delta, \text{Fp}_1}^{\text{People}} & \cdots & A_{150-150+\delta, \text{O}_2}^{\text{People}} & \cdots & A_{500-500+\delta, \text{O}_2}^{\text{People}} \end{pmatrix}$$

where

$$A_{\text{time,elec}}^{\text{cond}} = V_{\text{time,elec}}^{\text{cond}} - \min_{t,e,c} V_{t,e}^c$$

and

$$V_{t,e}^{\text{cond}} = \text{ERP}_{t,e}^{\text{cond}} - \frac{1}{8} \sum_{c=1}^8 \text{ERP}_{t,e}^c$$

and δ is the sampling period; Fp_1 and O_2 are electrodes.

Note that the CA involved normalization of the ERP amplitudes, similar to that proposed by McCarthy and Wood (1985), without which an analysis of variance (ANOVA) of the scalp distribution of ERPs by condition could be erroneous. A matrix of row profiles was calculated by dividing the rows (conditions) in $M_{150-500}$ by their respective row sums. In the same manner, a matrix of column profiles was calculated by dividing the columns (electrode, time) in $M_{150-500}$ by their respective column sums. The profile matrices are thus based on normalized data. The CA calculated a low-dimensional approximation of the

original data matrix $M_{150-500}$ representing both the row and column profiles.

From the CA map to neural spatio-temporal networks. The principal plane output by the CA leads to a map on which categories are plotted as a function of their coordinates on the first two axes, i.e. the two variables that capture the greatest amount of variance in the data. The first step was to test the significance of the maps (ERP map and linguistic data maps) and their topology. Recall that the CA identified spatiotemporal patterns of ERPs (or patterns of interest, PI) (see Figure 1) that made a significant contribution to calculating the main axes and coordinates, and thus the location, of each semantic category of words on the principal plane. The next step was to compute the organization revealed by the axes, from the standpoint of the PIs involved and the PIs correlated with the different categories. The last step was to provide support for the hypothesis that the underlying semantic processing is distributed across specific networks. This was done using Loreta® source-reconstruction software (Pascual-Marqui, Michel, and Lehmann (1994)), which made it possible to compute the differences between the activation levels of the cortex regions for the time windows associated with the previously detected PIs.

Testing the Significance of the ERP Map and its Topology. The significance of the map's typology was tested for all subjects by projecting the ERP CA results (category means, by subject) on the principal plane. The method consisted of determining the coordinates, on this plane, of the categories for each subject. The coordinates (output by the CA) were calculated by multiplying matrix $M_{subject_i,150-500}^T * Coord_{elec,time}$ (where $M_{subject_i,150-500}$ is the matrix of the mean signal amplitudes for subject i , generated in an analogous way to matrix $M_{150-500}$ of the grand means) and $M_{subject_i,150-500}^T$, its transpose. $Coord_{elec,time}$ is the matrix of the coordinates of the column vectors of matrix $M_{150-500}$ on the principal plane. An ANOVA was conducted to test the category from the values of the category's coordinates associated with the first (variable denoted x) and second (variable denoted y) axes, for all subjects pooled.

Comparing the ERP Map and Maps Computed from Linguistic Data. The map obtained from the electrophysiological signals was compared to maps obtained from word usage in the language. Two types of linguistic data were used as input: a database of synonyms or parasynonyms compiled by merging seven published dictionaries of synonyms (Ploux & Victorri, 1998), and a database of associated words (Ji et al., 2003) (the most frequent and specific co-occurrences of a word in a sentence). The associated words were compiled from co-occurrences taken from a 10-year journalism corpus containing 77 million words. The exact procedure used to compile these databases is described in the two publications cited above, which can be browsed freely on our website <http://dico.isc.cnrs.fr>. The two corpus-based maps were constructed by applying the geometric model called Semantic Atlases (Ploux & Ji, 2003) –generated from the above databases by a CA– to the set of words presented to the subjects in the experiment, for each data type (synonyms and associated words). The semantic space retained for each map was the one containing the greatest number of words. The coordinates on the two linguistic data maps of each of the eight categories under study were calculated by taking the mean of the coordinates of the words belonging to that category. The method is described in detail in (Ji et al., 2003). This method was chosen rather than a vector model (like LSA (Landauer et al., 1998) used by (Mitchell et al., 2008), as mentioned above) on the basis of an earlier study (Ji, Lemaire, Choo, & Ploux, 2008) showing that the geometric model was better than the vector model at simulating association-task execution by subjects.

Results

The Maps

Figure 2a below gives the map of the categories on the principal plane of the ERP CA. Figure 2b pertains to synonyms and parasynonyms and Figure 2c, to co-occurrences of words in word corpora.

Insert Figure 2 about here

Visual inspection of the maps immediately reveals a clear separation between living and nonliving categories (i.e. the second axis) in the ERP data as well as in the synonym data. However, for the ERPs, the greatest variations in the data are those separating the living entities from each other, especially *people* from *fruits/vegetables*. In fact, the first axis for ERP data exhibits a gradient ranging from *people* to *fruits/vegetables* for living entities, and from *clothing* to *tools* for nonliving entities, suggesting that this gradient brings out an opposition between person-related categories and attributes, and categories that are farther removed from the human referential. Accordingly, the categories closest to the *people* category are *clothing* (for nonliving entities) and *body parts* (for living entities) and the farthest categories are *tools* (for nonliving entities) and *fruits/vegetables* (for living entities). We can also see a greater dispersion for living categories as opposed to nonliving ones, in both the ERP and the synonym data. However, discrepancies in the category distribution can also be seen between the ERP and synonym maps. This could be due to the following: given that the words in the language have a primary sense but also many figurative senses, and that the map was built from all synonyms corresponding to a diversity of senses, it is reasonable to assume that subjects in the experiment favored the primary sense (*mug* = *cup* and not *mug* = *face*) because the words were presented in isolation here. The results of the tests conducted on this organization are presented below. Three points will be examined: the ERP map's topology, the relative dispersion of the living and nonliving categories, and a comparison with maps resulting from applying a CA to lexicographic data obtained by automatic corpora processing.

Significance of the ERP Map's Topology. The result of this test was significant (ANOVA, Wilks' Lambda = .351, $F(14, 238) = 11.682$, $p < .001$, Figure 3). A post-hoc within-category analysis (Duncan's test) for each of the variables x and y showed that the second axis (Table 2) indeed distinguishes the living from the nonliving entities, and that the first axis (Table 1) significantly separates *clothing* from *tools*, and *people* from *fruits/vegetables*. Also along this axis, we can also see that the *clothing* category differs significantly from *fruits/vegetables*, and from *tools*, and that the *body parts* category differs

from *tools* and from *fruits/vegetables*.

Insert Figure 3 about here

Insert Table 1 about here

Insert Table 2 about here

The second point tested was the dispersion on the map of the categories associated with the living vs the nonliving entities. This was done by comparing, for all subjects pooled, the area on the principal plane of the smallest rectangle containing the living categories and the area of the smallest rectangle containing the nonliving categories. The results indicated a significant difference (t-test for matched values, $t = 2.668$, $df = 15$, $p < .02$). Given that CA is a linear model, the greater dispersion of the living categories reflects a greater dispersion of the amplitudes of the ERP signals more specifically involved in living-category processing, than of those involved in nonliving-category processing.

Comparing the ERP Map and Maps Computed from Linguistic Data. Tests on the synonym data (Figure 2b) showed (1) a separation into two living-nonliving clusters (ANOVA, $F(2, 124) = 9.9$, $p < .001$), as on the ERP map, and (2) a greater dispersion of living categories than of nonliving ones (t-test on the distances between the living-cluster nouns and the distances between the nonliving-cluster nouns, $t = 9.9$, $df = 4077$, $p < .001$). The map generated from the co-occurrence data did not preserve the separation between the living and nonliving categories, but did indicate that the greatest distances between pairs of categories were between *people* and *fruits/vegetables*, and between *people* and *tools* (ANOVA, $F(6, 8825) = 77.222$, $p < .001$; probabilities of Dunnett post-hoc tests ($M < control$), Error: $MSE - inter = 2.258$, $df = 8825.0$, $p < .01$).

For a better understanding of the relation between that categories captured by the CA, we compared the map generated from the ERP data to the maps generated from the synonym data and the word co-occurrence data. Figure 2d provides linear regression and correlation coefficients for the principal axes of the ERP and word-corpus maps. Two correlations stand

out. The first is the correlation between ERP Axis 2 and synonym Axis 2, which distinguishes living and nonliving entities; the second is between ERP Axis 1 and co-occurrence Axis 1. The ERP-synonym correlation reveals that the separation into living and nonliving entities is not categorical but continuous. With the exception of the *fruits/vegetables* category, which appears as an outlier in this figure (and was thus excluded from the analysis), word categories span from *animals* to *parts of houses*, along a gradient that could depict the degree of animateness of the entities described by the words ($y = .087 + 2.021 * x$, $R = .813$, $p < 0.05$). Figure 2d (bottom), which gives the correlation between the ERPs and the co-occurrence data, reveals another aspect of the data ($y = .471 + 2.037 * x$, $R = .724$, $p < 0.05$). The co-occurrence statistics provide an estimation of how likely it is that a given word occur in association with another word in a sentence. The correlation depicted in Figure 2d, which spans from *people* to *fruits/vegetables*, thus suggests that ERP amplitudes capture aspects of how words relate to each other in language usage.

The ERP Patterns of Interest

Analysis by axis. The CA ordered the PIs by their relative contributions to defining each axis. For each axis, the results were then sorted and all PIs whose $\cos^2$ to the axis was greater than 0.7 were retained (this value makes sure that the contribution of a PI is greater for the axis under study than for the other axis). Below is the list of the PIs found and tested.

Axis 1 The four main PIs –the ones that contributed the most to the gradient in question (first axis) seen in Figure 2a– were as follows: Fp1 (383-477 ms), Fpz (383-477 ms), Fp2 (383-477 ms), and F7 (383-418 ms). The values in parentheses give the corresponding time window, which was concatenated whenever the regions were contiguous. For these four electrodes, which contributed strongly to the calculation of this axis, the figure 4 plots the amplitude of the signal for each condition, minus the mean amplitude of all conditions. We can see that in the 383-476 ms window calculated by the CA, there are differences between the conditions, that are similar to the differences between their coordinates along the first

axis. However, the CA detected the entire spatiotemporal network used in calculating this axis. The same figure (lower) gives the linear combination of the amplitudes of all electrodes, with their coefficients output by the CA for the first axis, and of each electrode-time unit. Compared to the individual graphs of the four main PIs, this graph offers a clearer picture of the analogy between the values of the linear combinations of the ERPs, and the values of the first-axis coordinates calculated by the CA. In order to test the validity of the four PIs' contributions for all subjects, the coordinates on the principal plane generated solely from the contribution of these PIs were computed for each subject and each category. These coordinates were obtained by taking the vector containing the amplitudes of the PIs (and zero for the other electrode-time units), and multiplying it by the $Coord_{elec,time}$ matrix containing the coordinates of the column vectors of matrix $M_{150-500}$. An ANOVA yielded a significant result ($F(14, 238) = 11.192, p < .001$). The upper part of the Table 3 gives the results of a post-hoc test (Duncan) on the eight categories compared with the value of the linear combination of the Axis-1 PIs. The results showed that those categories located at the extremities of the axis were differentiated by this test. That is, the *people* and *clothing* categories differed from the *fruits/vegetables* and *tools* categories on all four PIs. There were also some significant differences between certain more centrally-located categories like *animals*, which differed from the more off-centered categories *people*, and *fruits/vegetables*. As a whole, the results of this test are in line with the topology of the ERP axis-1 gradient, insofar as the categories that are the most clearly differentiated (based on the $p - level$ obtained on the test) were also the farthest away from each other on this gradient.

Insert Tab 3 about here

Axis 2 The PIs that contributed the most to this axis, which reflects the living/nonliving opposition, are clustered around two areas: left occipital-parietal O1 (267-325 ms), P7 (278-325 ms), and Oz (267-313 ms), and frontal Fp2 (290-325 ms), Fpz (290-325 ms), Fp1 (290-325 ms), and F7 (290-325 ms). The distinction revealed by this second axis thus seems to have occurred earlier (about 270 to 320 ms after stimulus presentation) than it did in the

organization detected by the first axis (about 380 to 470 ms after stimulus presentation), but it was not as great insofar as it was ranked as the second factor by the CA. Axis 2 indicated a categorical type of differentiation between the living and the nonliving entities. In order to test the significance of this distinction, the result for Axis 2 of the linear combination given by the CA on the grand means of these PIs was calculated for each subject and each category. An ANOVA showed that the living/nonliving distinction was significant ($F(1, 126) = 51.355, p < .0001$). Figure 5 shows the amplitude curve for the detected PIs, along with the linear combination of the amplitudes for the entire set of electrode signals, with the second-axis coefficients computed by the CA.

Analysis by Semantic Category of Words. Although the CA showed that the set of electrode-time units discriminated every category from every other category except for the pairs *tools-parts of a house*, *vehicles-parts of a house*, and *vehicles-clothing*, as demonstrated in the first analysis, it seemed interesting to try to determine which PIs participated the most in distinguishing each category. This was done by calculating the contributions to χ^2 , in the manner described previously (see *Analysis by axis* paragraph). For each category, the vector containing the contribution to χ^2 of each electrode-time unit was computed, and the values were ranked in decreasing order in view of retaining only the largest ones. The cutoff point was set at 0.5. Note that for *vehicles* and *parts of a house*, the set of PIs was empty because all the electrode-time units had χ^2 contributions below 0.5. For each of the other six categories, Table 4 gives the set of PIs, along with the result of comparisons with the other categories. The same procedure was applied for each category: a repeated-measures ANOVA on the combinations of PIs associated with the coefficients on Axis 1 (first variable) and Axis 2 (second variable) and a post-hoc test (Dunnet) between the category and each of the other categories.

Insert Tab 4 about here

Lastly, for the *animals* and *people* categories, Figures 6 and 7 present the linear combinations of the PIs most strongly involved in differentiating these categories (see Table 4).

The linear combination given for the *animals* category was obtained from the CA coefficients along the second axis, which best discriminates this category; the linear combination for the *people* category was obtained from the CA coefficients of the first axis, which discriminates it the best.

Insert Figures 6, 7 about here

In sum, for six of the eight categories tested, the method detected a network of PIs that participated in their differentiation. We can conclude from the results of these tests that the map adequately depicts the combination of PI networks that determine both the organizing factors, and also the finer differentiations between the categories themselves.

Analysis by Detection of Sources

Despite the distribution of ERP-based PIs uncovered by these results, it was not possible on this step of the study to answer the question about the distribution of networks of regions that might be differentially involved in category processing. Indeed, Urbach and Kutas (2002) showed that differences in ERP signals do not necessarily involve differences between the brain areas activated. In an attempt to gain further insight into this issue, we used the Loreta source-reconstruction software. In this system, ERP signals are entered as the input, and a linear method (Pascual-Marqui et al., 1994) is applied to compute the corresponding activity levels in the cortex for each value of the time variable. It is important to note that Loreta puts out calculated solutions, not measured ones. Like all source-reconstruction models, it must solve problems that have multiple solutions and the results must therefore be taken with caution. However, many studies –Pascual-Marqui, Esslen, Kochi, and Lehmann (2002) cited about forty such studies published between 1998 and 2002– have made it possible to validate the areas calculated by Loreta by showing that they are similar to those measured on the same tasks by brain imaging (fMRI, PET), even when there is a limited number of electrodes, as in our protocol. Accordingly, next to the results obtained by Loreta in our study, we show the results we found (when available) in the literature on the localization of processing for the categories examined here. Thus, even

though they are calculated, our results provide a useful indication for finding out whether this method –despite its lack of resolution– can support the hypothesized distribution of regions, and thus, the link between the semantic processing of a word and its conceptual content.

Reconstruction method The matrix of cortical activity was reconstructed for the living and nonliving conditions, for each of the six categories selected above on the basis of their signal contributions in the CA, and for the corresponding time windows (given above). Then the voxels for which the difference between the condition tested and the overall condition mean was the greatest (more than 0.9 times the maximum difference) were selected. Once the selected voxels were classified according to the Brodmann area that Loreta associated with each voxel, the significance of the activity differences between the conditions in these areas was tested. The width of the time windows for calculating the differences was set at 30 ms.

Sources associated with the principal factors of the organization output by the CA The anatomical correlate of the gradient associated with ERP Axis 1 was not directly testable using a method based on the difference-of-means between groups of conditions since it exhibited a gradual variation rather than a categorical difference. Thus, no statistical results are available for this axis⁴.

Comparison of the second axis associated with the living/nonliving difference The results indicated a significant difference (sign test for matched samples) between the means of the activity amplitudes for the living and nonliving categories in left middle temporal gyrus (BA21) (C. -55, -10, -20; S. 77)⁵ ($Z = 2.25$, $p < .05$), and in the left inferior temporal gyrus (BA20) (C. -45, -20, -30; S. 91) ($Z = 2.25$, $p < .05$) between 280 and 310 ms after stimulus onset. In these connected areas, the calculated activity was greater for living entities than for nonliving ones. This result can be linked to the data obtained for patients with temporal lobe lesions and deficits in living-category processing and whose left inferior

temporal lobe (Brodmann's area 20) is damaged (Moss, Tyler, Durrant-Peatfield, and Bunn (1998)). More generally and as stated by Caramazza, Hersch, and Torgerson (1976), given that "most of the patients with selective impairment of the living category had sustained damage to (at least) the left temporal lobe, it might be further surmised that the latter neural structure is part of a neural network specifically dedicated to representing conceptual knowledge about living objects."

Sources associated with the tested categories For the remaining results, a matched-sample ANOVA was applied and whenever the result was significant ($p < .05$), a post-hoc Dunnett test was applied.

Animals. The results indicated greater activity for the *animals* condition than for the other conditions (except *fruits/vegetables*) in the occipital lobe (BA19) (C. +/-25, 50, -5; S. 22 on the right; S. 16 on the left) between 240-270 ms on the right and 250-280 ms on the left. This zone is located in the lower part of the occipital lobe and in the fusiform gyrus, which is consistent with studies on the localization of areas involved in the semantic processing of concepts in the *animals* category (Chao, Martin, and Haxby (1999) and Tyler et al. (2003)). The results also showed greater activation of the *animals* category in perirhinal temporal areas (BA30) between 260 and 290 ms after stimulus onset (C. +/-10, -45, -5; S. 27 on the left; S. 8 on the right), in the limbic lobe (parahippocampal gyrus) (BA35) between 250 and 290 ms (C. 25, -25, -20; S. 12 on the right), and in BA36 between 250 and 290 ms (C. 30, -30, -20; S. 24 on the right). The post-hoc test on these areas differentiated this category from all others except *tools* and *fruits/vegetables*. This result is consistent with the Chao et al. (1999) and Tyler et al. (2003) studies.

People. The *people* condition differed from all others on left occipital areas (middle and inferior occipital gyri) (BA18) (C. -30,-90,-5; S. 38), (middle occipital) (BA19) (C. -40, -80, 5; S. 82), and left occipitotemporal area (BA37) (C. -50, -60, -5; S. 35) at 390-420 ms, and from all conditions except *animals* and *body parts* in parietal lobe (BA39) (C. -50,-70,

20; S. 48). The activity mean for the *people* condition in these areas was greater than for the other categories.

Tools. The *tools* condition differed from the *people*, *body parts*, and *vehicles* conditions in left frontal lobe (inferior frontal gyrus) (BA47) (C. -30,-20, -15; S. 54) at 350-380 ms. It also differed from *vehicles*, *fruits/vegetables*, and *body parts* in dorsolateral prefrontal lobe (medial frontal gyrus) (BA9) (C. -10, 50, 39; S. 48) at 400-430 ms, from *fruits/vegetables*, *body parts*, and *people* in left anterior temporal lobe (BA38) (C. -40, 10, -30; S. 71) at 360-390 ms, and from *clothing*, *fruits/vegetables*, *body parts*, and *people* in left superior temporal area (BA34) (C. -20,0,-20; S. 16) at 340-370 ms. In each of these areas, the activity level calculated by Loreta for the tools category was below that of the other categories.

Clothing. *Clothing* differed from *body parts* and *people* in left insular cortex (C. -40,-40, 20; S. 21) at 270-300 ms. The computed activity level for the clothing condition in this area was lower than for these other two conditions.

Discussion

In the first step of this study, subjects performed a specially designed semantic decision task and the ERP signals obtained were analyzed using a correspondence analysis. The results revealed that the lexical concepts tested are structurally underlain by two principal axes. The first axis, which detected the greatest differences, seems to be the organizing principle of a human referential opposing person-centered entities –i.e., relations or social positions, which were included here on the stimulus list for the *people* category (*brother*, *novelist*, etc.), and also *clothing*– from entities that are farther removed from this referential (*tools*, *fruits/vegetables*). Processes characterized by this axis occurred approximately 380 ms after stimulus onset and showed up mainly on frontal electrodes. The elements situated at the extremities of this axis are two living categories, *people* and *fruits/vegetables*. The second axis, which can be called ontological, separates categories associated with living entities from those associated with the nonliving. The underlying processing occurred sooner

after stimulus onset (at around 270-320 ms) and involved left occipital-parietal electrodes as well as frontal ones. The topology of the map output by the CA proved significant for the subjects as a whole, and the greater dispersion of living categories than of nonliving ones was also validated. This greater spread reflects larger within-category differences for living entities on the ERP signals. The living vs nonliving distinction, and the more scattered processing of living entities, echoes the proposal of Caramazza and Shelton (1998) of a categorical organization structured by the phylogenetic past of our species. Indeed, the ability to discriminate congeners from predators, and also from prey and edible things, is thought to be essential to the survival of the species and would thus necessitate a differentiation faculty that is both deep (fine-grained) and broad. The ability to discriminate artifacts and tools would come later on the scale of human evolution. For this reason, it would give rise to a lesser degree of specialization but could nevertheless be selectively damaged, as shown by the handful of cases described in the literature. Furthermore, differentiating living from nonliving entities has been observed very early in childhood (at the age of 4 years for Gelman and Wellman (1991)).

Note that while the task required a categorization that may have underlain the observed differentiation between the living and the nonliving, this differentiation was not the greater one detected in the signal analysis. In addition, the results obtained are more precise and more complex than a simple binary categorization (living-nonliving). The *animals* category, for instance, stands well apart from the others on Axis 2. One can interpret this difference as a more clear-cut, more prototypical attribution of aliveness to *animals* as opposed to *fruits/vegetables*, *body parts*, or *people* (this last category's attributes being at least as social as biological).

The map derived here from ERP signals is analogous to maps obtained from lexical links in the language. As on the ERP map, the synonym-based map preserves the ontological separation between the living and the nonliving. The map generated from contextual links preserves a maximal distance between *people* and *fruits/vegetables*, and to a lesser degree, between *people* and *tools*. Thus, the ERP map seems to retain the distances rep-

representing the categorical links and the contextual links presented as the two main axes of the linguistic analysis of texts. These results therefore support the idea of an organizational resemblance between the neurophysiological processing of categories and the semantic structure of language productions. It corroborates an ontological and hierarchical⁶ organization of categories, while adding an organization underlain by a gradient of proximity and distance from the person. The next step in this study was to find the networks most highly correlated with the various categories in order to define networks of PIs that participate in differentiating certain categories from others, and the last step was to use Loreta source-reconstruction software in order to compute the source networks at play in these different ways of processing and organizing categories. Although this method gives computed results, not measured ones, and remains imprecise when applied to EEG signals from only 30 electrodes, it was nevertheless able to detect some differences and point out some dynamic category-specific source networks that are in line with the findings of fMRI and PET studies.

All of the present results argue in favor of a conceptual approach to word semantics. In this view, the neuronal processing of word meaning is not encapsulated solely in the language areas but involves more extensive spatiotemporal patterns linked to the processing of categories designated by words.

In sum, the map obtained here directly from the automatic processing of electrophysiological signals, without electrode pre-selection, provides a relatively rich synthesis. It should also be stressed that, while the data in the literature are congruent with the present ERP map analysis, the categorical organization and differentiation detected by the CA are not composed of networks of areas but of patterns of spatiotemporal differences. This last point goes against some widely acknowledged hypotheses according to which the semantic processing of words or concepts is attributed in an absolute and non-relative fashion to the consistently positive activity of certain areas of the brain. On the other hand, it aligns with Ferdinand de Saussure's structural view whereby language is a system of differences. The topology defined by the CA for this "system of differences" makes it possible to detect proximities and major distinctions between word categories. (Ploux, Dabic, Paulignan, Cheylus,

& Nazir, 2012)

Footnotes

¹Note, however, that this prevailing point of view, which came out of Broca and Wernicke's work, triggered immediate rejection by opposers such as Hughlings Jackson (1835-1911), who cast doubt on the hypothesized language-specific area of the brain.

²This procedure was justified by the uniform distribution of the electrodes Junghöfer, Elberta, Tuckerb, and Braun (1999) (Bertrand, Perrin, and Pernier (1985)). Note, however, that since the calculation of the reference value and the CA are linear, this procedure did not cause a distorting effect.

³The signals were smoothed in advance by applying the *wavedec* and *wrcoef* functions of Matlab. The *wavedec* function processes the signal's wavelets. The family of wavelets retained was daubechies (*db1*) on 5 levels, $[C, L] = \text{wavedec}(\text{signal}, 5, \text{db1})$. The function *wrcoef* uses the coefficients calculated by *wavedec* to reconstruct the smoothed signal. The signal was reconstructed at level 3.

⁴Note, however, that the greatest differences, shared by the category pairs *people-fruits/vegetables* and *clothing-tools*, are located in right areas BA47 between 420 and 450 ms, and BA38 between 460 and 490 ms after stimulus presentation. The activity calculated by Loreta was greater for *people* than for *fruits/vegetables*, and for *clothing* than for *tools*. This intermediate result, which needs further evaluation, can nevertheless be compared to the Zahn et al. (2007) study, which showed that Brodmann's area 38 is selectively activated when participants "judge the meaning relatedness of social concepts (e.g., honor-brave) as compared with concepts describing general animal functions (e.g., nutritious-useful)", and also to the Gerretsen et al. (2010) study suggesting that area BA47 is involved in establishing and maintaining social links.

⁵C. stands for the coordinates of the zone's barycenter in the Loreta software; S. stands for its area in Loreta units, measured in 5-voxel steps.

⁶Here, the hierarchy is two-tiered: the first tier is the level of the superordinate categories "living" and "nonliving"; the second is the level of the 4x2 categories used in the experiment.

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Table 1: Dimension 1, Duncan Post-hoc test ($\ast 10^{-3}$) on the coordinates for all subjects pooled (repeated-measures ANOVA).

Categories	Vehicles	Tools	Clothing	House	Animals	Fruits Veg.	Body Parts	People
Vehicles								
Tools	<i>9.185</i>							
Clothing	72.274	<i>0.044</i>						
House	337.291	71.032	<i>9.458</i>					
Animals	603.331	<i>27.962</i>	<i>30.488</i>	610.203				
Fruits	<i>1.623</i>	533.660	<i>0.022</i>	<i>21.124</i>	<i>6.502</i>			
Veg.								
Body	813.229	<i>14.954</i>	54.152	437.698	748.860	<i>2.961</i>		
Parts								
People	<i>0.256</i>	<i>0.020</i>	<i>35.920</i>	<i>0.029</i>	<i>0.065</i>	<i>0.017</i>	<i>0.149</i>	

Table 2: Dimension 2, Duncan Post-hoc test ($\ast 10^{-3}$) on the coordinates for all subjects pooled (repeated-measures ANOVA).

Categories	Vehicles	Tools	Clothing	House	Animals	Fruits Veg.	Body Parts	People
Vehicles								
Tools	302.365							
Clothing	393.762	804.462						
House	229.586	818.212	655.818					
Animals	<i>0.028</i>	<i>0.020</i>	<i>0.025</i>	<i>0.017</i>				
Fruits/Veg.	<i>39.936</i>	<i>2.881</i>	<i>5.134</i>	<i>1.610</i>	<i>0.561</i>			
Body	<i>41.594</i>	<i>2.816</i>	<i>5.188</i>	<i>1.530</i>	<i>0.522</i>	958.337		
Parts								
People	<i>46.216</i>	<i>4.044</i>	<i>6.744</i>	<i>2.375</i>	<i>0.397</i>	86.683	837.511	

Table 3: Duncan Post-hoc test significance ($\ast 10^{-3}$) (repeated-measures ANOVA) between the eight conditions and the linear combination of PIs whose contribution to Axis 1 was greater than 0.7. The four main PIs were frontal: Fp1 (383-477 ms), Fpz (383-477 ms), Fp2 (383-477 ms), and F7 (383-418 ms).

Categories	Vehicles	Tools	Clothing	House	Animals	Fruits Veg.	Body Parts	People
Vehicles								
Tools	<i>6.109</i>							
Clothing	110.850	<i>0.049</i>						
House	228.558	92.236	<i>7.914</i>					
Animals	358.049	53.856	<i>17.593</i>	724.895				
Fruits/Veg.	<i>0.517</i>	411.318	<i>0.021</i>	<i>17.393</i>	<i>8.209</i>			
Body	865.693	<i>8.435</i>	95.564	275.105	416.673	<i>0.794</i>		
Parts								
People	<i>1.072</i>	<i>0.020</i>	64.070	<i>0.037</i>	<i>0.069</i>	<i>0.017</i>	<i>0.768</i>	

Table 4: Main PIs associated with category distinctions.

Categories	PIs with χ^2 contribution > 0.5	Repeated-mesures ANOVA ($F(14, 238), p$)	Post-hoc (Dunnet)($p < .05$) test
Tools	Fpz (325 – 360ms, 383 – 407ms), Fp2 (325 – 360ms), Fp1 (325 – 360ms, 372 – 383ms).	(2.0, < .05)	<i>people</i>
Clothing	Fp2 (407 – 418ms), Fp1 (430 – 453ms), Fpz (407 – 418ms), P7 (267 – 278ms).	(2.4, < .05)	<i>tools, animals, fruits/vegetables, body parts</i>
Animals	O1 (267 – 313ms), Oz (267 – 278ms), O2 (243 – 278ms), P7 (278 – 290ms, 313 – 325ms), Fp1 (313 – 325ms), Fpz (290 – 325ms).	(2.1, < .02)	Each of the other categories except <i>fruits/vegetables</i>
Fruits/Veg	Fp1(418 – 500ms), Fpz(465 – 500ms), Fp2(477 – 500ms), O1(243 – 267ms, 278 – 290ms).	(2, < 0.05)	<i>vehicles, clothing, part of a house, people</i>
Body Parts	P8 (243 – 267ms).	(3.35, < .01)	<i>vehicles, tools, animals</i>
People	O1 (232 – 243ms), Oz (232 – 243ms), Fp2 (383 – 407ms), F7 (372 – 407ms), Fp1 (383 – 407ms), Fpz (383 – 407ms), P4 (407 – 418ms).	(3.4, < .01)	Each of the other categories except <i>clothing</i> and <i>animals</i>

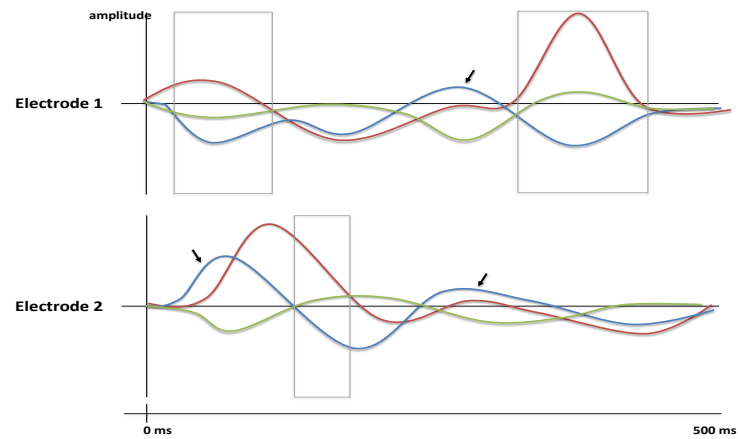


Figure 1. Hypothetical ERP curves for words referring to three categories (fish = red; birds = green; apes = blue). Grey frames delineate time slots within which a specific relational pattern between the three conditions is evident (i.e., the amplitude extrema for the category are indicated by red and blue lines, intermediate amplitudes are shown as green lines). The black arrows point to another such pattern (i.e., *[blue, red, green]*). The CA identified these patterns over a defined time window at all electrodes, and classified them from the most to the least significant in terms of magnitude and frequency.

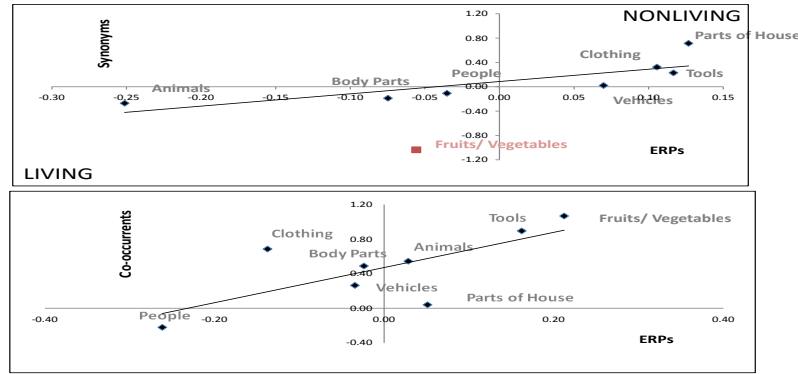
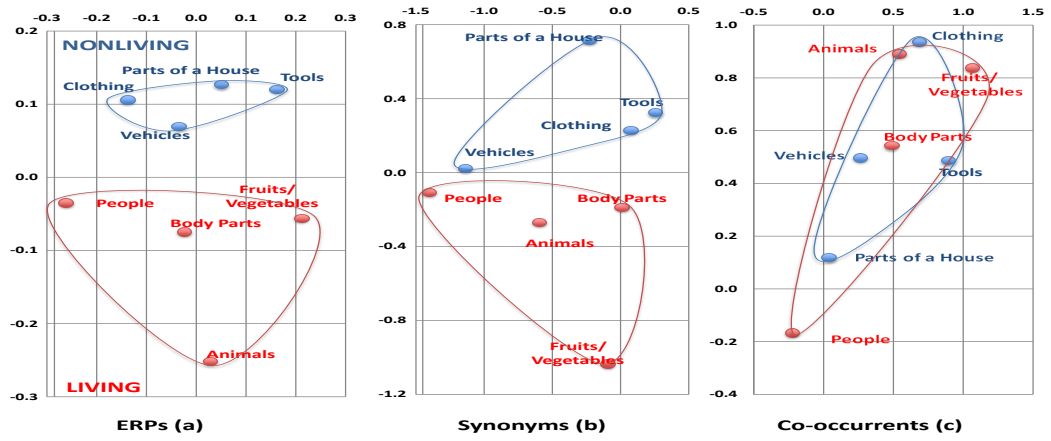


Figure 2. (a) ERP map obtained from grand average signals 150-500 ms after stimulus presentation. These two axes account for 65.12% of the total inertia of the initial matrix: 37.6% for Axis 1, 27.5% for Axis 2, and 10% for Axis 3, which is not represented here. (b, c) Maps based on synonym and co-occurrence links. For the corpus-based maps, the principal axes account for less than 10% of the total inertia, in line with analogous results obtained from linguistic data whose axes have a slowly decreasing variance. (d) Regression lines between ERP Axis 2 and Synonym Axis 2 (upper), and ERP Axis 1 and Co-occurrence Axis 1 (lower).

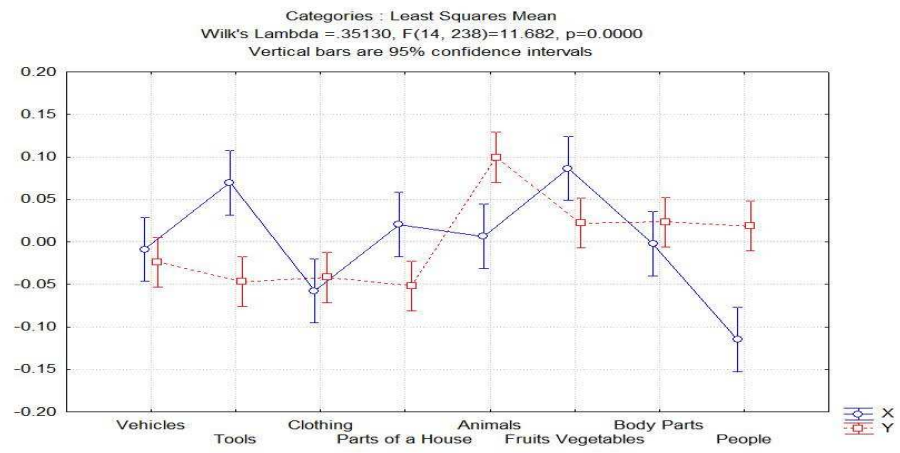


Figure 3. Repeated-measures ANOVA on categories. The dependent variables are the coordinates on the two dimensions.

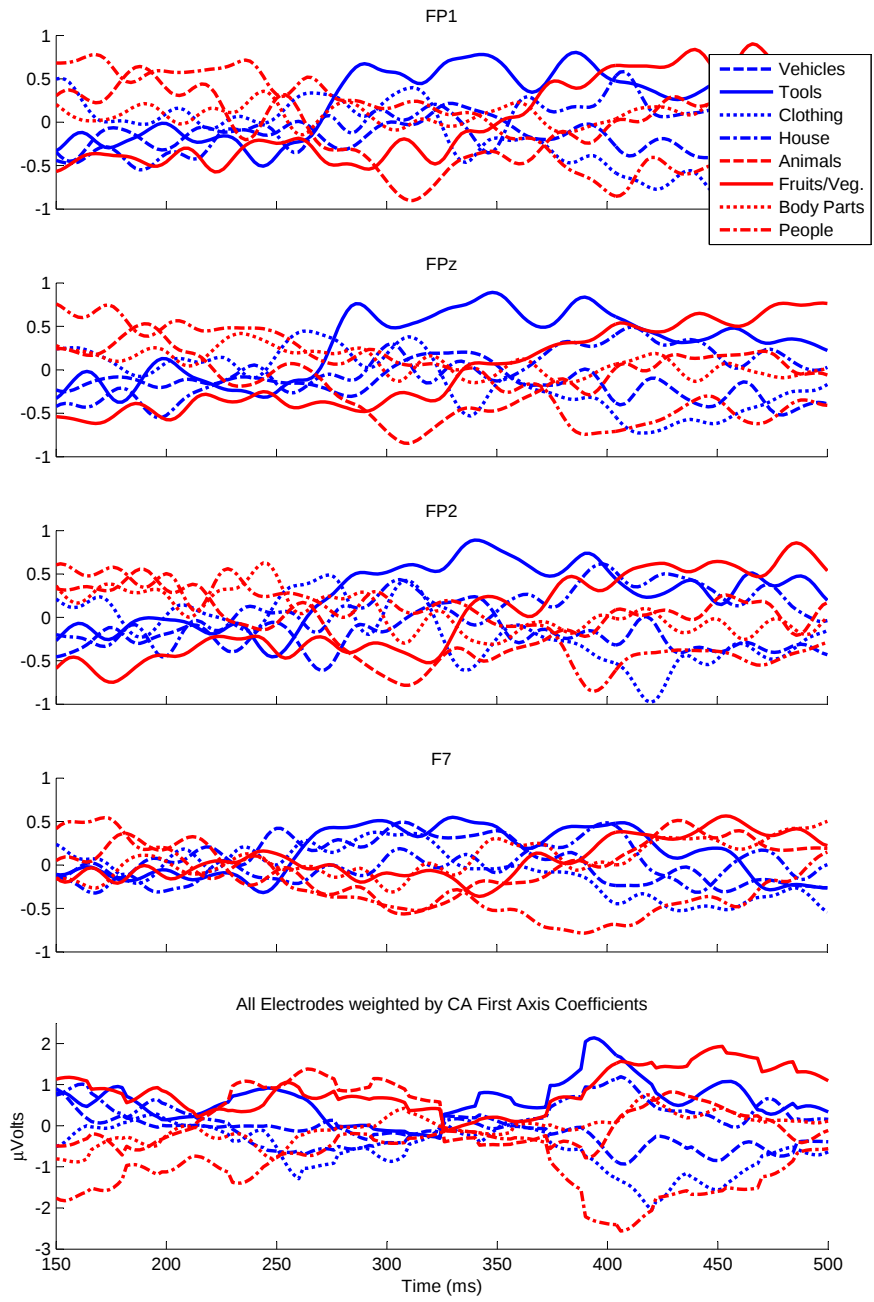


Figure 4. Axis 1. Signal amplitude on the electrodes with the greatest contributions to defining Axis 1. The mean amplitude of all conditions was subtracted from the amplitude of each condition. Bottom graph: linear combination of signals for the whole set of electrodes, with first-axis coefficients calculated by the CA.

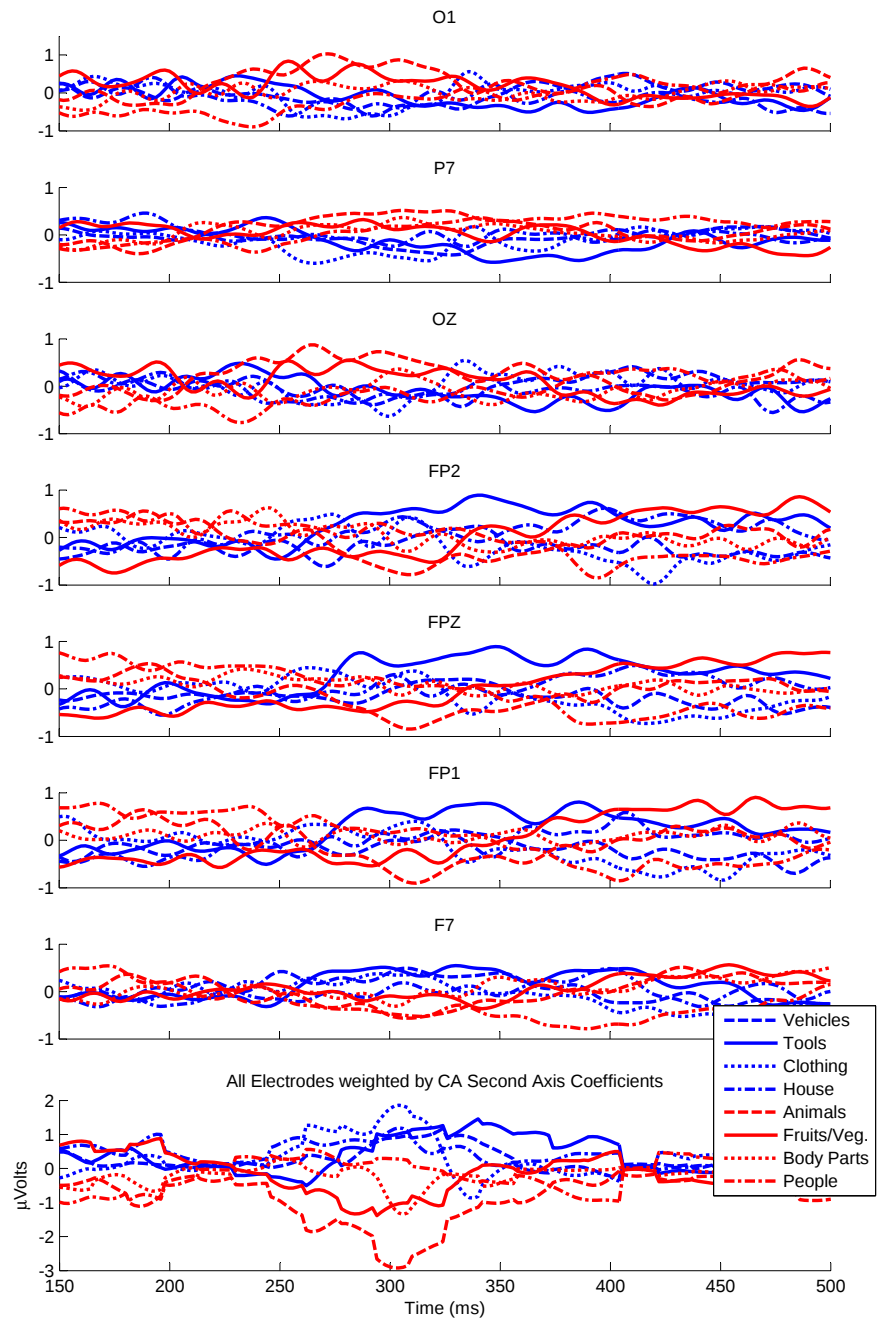


Figure 5. Axis 2. Signal amplitude on the electrodes with the greatest contributions to defining Axis 2. The mean amplitude of all conditions was subtracted from the amplitude of each condition. Bottom graph: linear combination of signals for the whole set of electrodes, with second-axis coefficients calculated by the CA.

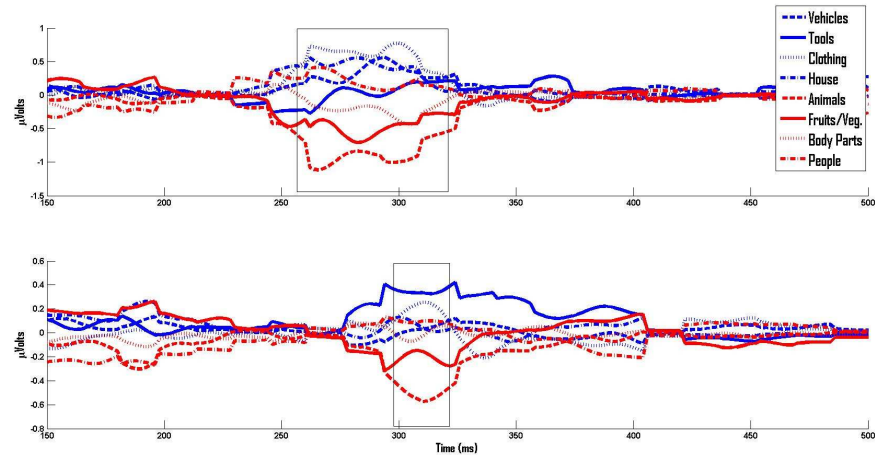


Figure 6. Main PIs for *animals*. Combination of signals from occipito-parietal electrodes O1, Oz, O2, and P7 (upper) and frontal electrodes Fp1 and Fpz (lower), according to the second-axis coefficients calculated by the CA.

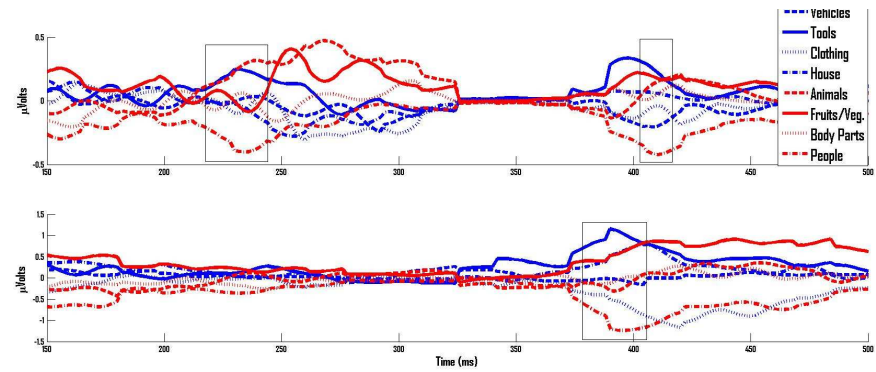


Figure 7. Main PIs for *people*. Combination of signals from occipito-parietal electrodes O1, Oz, and P4 (upper) and frontal electrodes Fp2, Fp1, F7, and Fpz (lower), according to the first-axis coefficients calculated by the CA.