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Context-dependent and Dynamic Effects of Distributional and Sensorimotor Distance Measures on EEG

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Abstract

An important issue in the semantic memory literature concerns the relative importance of experience-based *sensorimotor* versus language corpus-based *distributional* information in conceptual representations. Here we examine how each sort of information is associated with the EEG response to words in a property verification task in which participants indicated whether or not a property term (such as "red") is typically obtained for a concept term (such as "APPLE"). To define and measure each type of information, we operationalized distributional and sensorimotor information using cosine distance measurements derived from GloVe Embeddings and Lancaster Sensorimotor Norms respectively. We then modeled single-trial EEG responses to property words in a property verification task using regression models. Our findings indicate that semantic processing in this task simultaneously incorporates distributional and sensorimotor information, and their contribution is shaped by task-relevant linguistic context. We aim for our study to contribute to a critical examination of such information operationalizations and also encourage a systematic evaluation of their performance across tasks, particularly for EEG measurements.

Keywords: semantic memory; distributional semantics; embodied semantics; Lancaster sensorimotor norms; EEG

Introduction

Theories of human semantic processing often contrast the assumptions and predictions of embodied or *grounded* approaches to meaning with those of *distributional* accounts. Distributional theories propose that the meanings of words can be derived in part from their linguistic distributions, i.e., the words with which they tend to co-occur (Harris, 1954). The cognitive feasibility of these distributional proposals is supported by decades of research demonstrating that metrics derived from language co-occurrence data align with human behavioral performance on semantic tasks (Harris, 1954; Mandera, Keuleers, & Brysbaert, 2017). Embodied or *grounded* frameworks, on the other hand, underscore the significance of sensorimotor or experiential information in our conception of meaning. In these models, comprehension involves activating sensorimotor representations of the events described in language (Barsalou, Simmons, Barbey, & Wilson, 2003). However, in recent years, a number of "hybrid" proposals have attempted to reconcile these approaches, arguing that both sources of information contribute to our semantic knowledge. Among hybrid accounts, there is agreement that embodied and distributional information both play a role in semantic representations, though claims differ regarding the importance and extent of these contributions (Kemmerer, 2019; Binder & Desai, 2011; Louwerse, 2011).

A key question concerns how these theories are *operationalized*, i.e., which representations are used (and how) as proxies for distributional, grounded, or hybrid accounts. Crucially, any operationalization must also be validated against human behavioral and neural data. In the distributional semantics literature, a common method of operationalizing semantic content is in the form of multidimensional vectors that have been derived from large text corpora (Mikolov, Chen, Corrado, & Dean, 2013). More recently, a vector-based approach has been adopted to capture sensorimotor features of words, typically obtained using crowd-sourced human judgments (Lynott, Connell, Brysbaert, Brand, & Carney, 2020). Models created from these vector representations are taken as stand-ins for either distributional or sensorimotor semantic information structures depending on their sources. (Andrews, Vigliocco, & Vinson, 2009; Fernandino, Tong, Conant, Humphries, & Binder, 2022; Fernandino & Conant, 2023; Davis & Yee, 2021; Trott & Bergen, 2021).

Importantly, validating these models (and the theoretical claims they are used to test) requires assessment of their performance across various tasks and diverse neural and behavioral measures (Yarkoni, 2020). In line with this, this paper presents an investigation into how well the operationalizations of sensorimotor and distributional relationships between concept-property pairs predict electroencephalogram (EEG) activity during a property verification task.

In a property verification task, participants are presented with pairs of concepts ('APPLE') and properties ('red') and they must make rapid decisions about whether the property is typically true for the concept. Although the property verification task is designed to encourage the use of sensorimotor information, the distributional information could plausibly influence online processing during task performance as well. For example, verifying "red" is a property of "apple" might involve *simulating* the sensory properties of apples, but it might also reflect the associative strength between these two words, e.g., how frequently 'APPLE' and 'red' co-occur in linguistic contexts (Solomon & Barsalou, 2004). This task with high-temporal EEG measurements is therefore well suited to investigate whether and to what extent the distributional and sensorimotor information measurements simultaneously inform conceptual processing.

We operationalize the distributional distance between concept-property pairs using the GloVe embeddings (Pennington, Socher, & Manning, 2014), and sensorimotor distance using the Lancaster Sensorimotor Norms (Lynott et al., 2020), and assess their explanatory power in predicting

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EEG variance using linear mixed-effects regression models. To our knowledge, this is the first study testing measurements based on Lancaster norms on EEG activity. Further, using multivariate modeling for evaluating the distributional and sensorimotor measurements, our work aims to provide a time course of their simultaneous and relative contribution to semantic processing in this task.

Data Collection and Preprocessing

Materials The material included 576 concept–property pairs for the property verification task. Each trial consisted of a presentation of the concept (”APPLE”) and the potential property (”red”) word consecutively. Out of the total trials, 480 included pairs used sensory property words, including visual (e.g., ”red”), tactile (e.g., ”prickly”), and auditory (e.g., ”loud”) words. These 480 pairs are referred to as **PROPERTY** trials. Half of those elicited a **TRUE** response (e.g., ”APPLE-red”) and the other half a **FALSE** response (e.g., ”APPLE-loud”). The rest of the 96 trials were lexical associates that were included to discourage participants from shallow processing relying on word association. Half of the associated trials elicited TRUE responses (ESSAY-written), and half FALSE (BUFFALOS-winged). Only **PROPERTY** trials were included in the analysis presented in this paper.

Procedure The experimental paradigm is shown in Fig 1. Each trial began with the presentation of a fixation cross for 250ms. Between 200 and 400ms later, the CONCEPT term was displayed in the center of the screen for 150ms, followed by 250ms of blank screen. The property term was then presented for 200ms. The 2600ms inter-trial interval allowed plenty of time for participants to make their decision and press the button with their right hand to indicate TRUE and their left hand for FALSE. Analyses in this paper were based on data recorded from eighteen undergraduate participants. All participants were aged between 18 and 40 years old, reported normal or corrected-to-normal vision, and had no history of neurological or psychiatric disorders.

EEG Preprocessing EEG was recorded at 250Hz using a cap with 29 electrode sites. Electrodes were referenced online to the left mastoid. Blinks and horizontal eye movements were monitored using EOG electrodes under and on the sides of both eyes. The EEG data was later filtered using an FIR bandpass filter from 0.1 to 40 Hz and re-referenced to the mean of both mastoid sites. Maximum likelihood ICA was used to identify components with artifacts and subtract them from the data. Following artifact correction, epochs with residual artifacts were manually rejected. All epochs were baseline corrected using a 100ms window before the word onset. Data preprocessing was performed using implementations in the MNE package in Python (Gramfort et al., 2013).

Analysis

Our primary goal was to investigate the explanatory power of distributional and experiential information in predicting EEG elicited by words. For our analysis, we utilized a subset (n=384) out of the unique 480 concept-property pairs for which word frequency scores from SUBTLEX-US (Brysbaert, New, & Keuleers, 2012), GloVe embeddings, and Lancaster norms were all available for both of the words in the trial. To control for the confounds introduced by using different hands for responding to TRUE versus FALSE trials, separate single-trial EEG analyses were conducted for the Property-TRUE (n = 2836) and the Property-FALSE (n = 3093) trials, after removing the trials with wrong responses. In this section, we first describe how these sources of information were operationalized and then detail our statistical modeling approach.

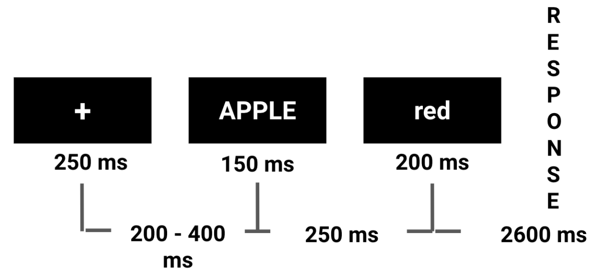


Figure 1: Study Paradigm: Participants were presented with two words in a row. The concept (e.g., APPLE) appeared in capitals, followed by the property (red) in lowercase. The task of the participant was to verify whether the property (e.g., ’red’) was typically true of that concept (e.g., ’APPLE’). Participants had 2600ms to respond before being presented with another trial.

Operationalizing distributional and sensorimotor distance

Distributional Distance GloVe word embeddings were used to operationalize *distributional information* (Pennington et al., 2014). Specifically, we used embeddings from the pre-trained 6B (Wikipedia 2014 + Gigaword 5) GloVe model with 200 dimensions. These are pre-trained representations of a word’s distributional pattern in a large corpus of text. In general, words with more similar meanings tend to cluster together in vector space. As a measure of *dissimilarity*, we calculated the *cosine distance* for the pairs of words (e.g., concepts and properties) in our stimuli (Trott & Bergen, 2021). Cosine distance is defined as $1 - \frac{A \cdot B}{\|A\| \cdot \|B\|}$, where A and B are vector representations of two words. Intuitively, a larger cosine distance corresponds to more dissimilar vectors (and thus more distinct distributional patterns). Note that for the Property-TRUE trials, the distributional semantic distance varied from 0.4 to 1.0 (M = 0.78, SD = 0.14), and for the Property-FALSE trials, it ranged from 0.5 to 1.2 (M = 0.89, SD = 0.12).

Sensorimotor Distance Following recent work in the literature on grounded meaning (Wingfield & Connell, 2023), we used the same principle of cosine distance measurement to capture Sensorimotor Distance using the Lancaster Sensorimotor Norms database (Lynott et al., 2020). The Lancaster norms consist of average human ratings by 3,500 participants for 39,707 words across 11 dimensions of sensorimotor information - six perceptual modalities (vision, auditory, gustatory, olfactory, tactile, and interoception) and five action effectors (foot/leg, hand/arm, torso, mouth/throat, and head excluding mouth). As we use all 11 dimensions of the Lancaster norms, it is important to note that all of them may not represent independent information as the perceptual and action scores were collected from distinct sets of participants. We converted the norms for each of our words into vectors in an 11-dimensional space to measure the cosine distance between word pairs. For the Property-TRUE trials, the sensorimotor semantic distance varies from 0.0 to 0.5 (M = 0.21, SD = 0.13), and for the Property-FALSE trials varies from 0.0 to 0.7 (M = 0.28, SD = 0.16). The Spearman correlation coefficient between the distributional and sensorimotor cosine distance for the Property-TRUE trials was rho = 0.32 ($p < 0.001$), and for Property-FALSE trials was rho= 0.18 ($p < 0.001$) indicating that for both subsets of the data, the two semantic distance measurements had a weak positive association.

Modeling Approach

We first constructed linear mixed-effects regression (LMER) models for each 100 ms averaged dataset. Conceptualizing EEG channels as either random or as different levels of a fixed effect poses challenges due to correlations between adjacent channels. Therefore, our approach involved modeling predictor interactions with scalp topography dimensions, instead of individual channels, to enhance interpretability (Winsler, Midgley, Grainger, & Holcomb, 2018). Toward the same goal, all predictors were z-scored. Further, with high subject- and item-level variance in EEG data, LMER models afforded an excellent means of controlling for these random effects. Regression models were fit using the lme4 package in R (Bates, Mächler, Bolker, & Walker, 2015). We also conducted a post-hoc exploration of the effects of these distance measurements at each time point and channel level using regression Event-Related Potentials (ERPs) as outlined by Smith and Kutas (2015).

LMER Models From each single trial EEG epoch, we measured the mean EEG voltage at each electrode for every 100 ms window starting 0-100 ms post-word onset to 600-700 ms. We also captured the three-dimensional (X, Y, and Z axes) location information of each scalp channel. For both Property-TRUE and Property-FALSE trials, we fit four competing models on the 100ms averaged voltage. The predictors in these four models are described below. To further aid the interpretability of model estimates, the three predictors of interest (word frequency, distributional distance, & sensorimotor distance) were normalized by z-scoring across both the trial subsets. The distribution of these scaled measurements can be observed in Fig 2.

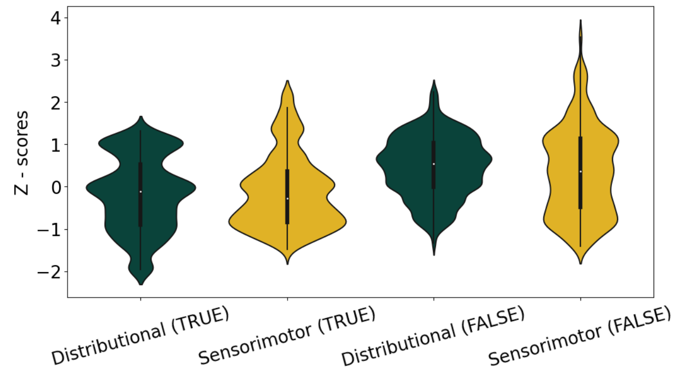


Figure 2: Distributions of distributional and sensorimotor cosine distance measurements (scaled) for both TRUE and FALSE properties

1. **Base model (B)**: The Base model includes the logarithmic word frequency (WF) measurement as the only predictor. Its description in the LMER structure would be:

Voltage = Intercept + (Word Frequency) * (X + Y + Z) + (1 | subject) + (1 | word).

Word Frequency is then included as a control predictor in the rest of the three models of theoretical interest, and all models have the same random effects structure.

2. **Distributional model (D)**: Base model + Distributional Semantic Distance

3. **Sensorimotor model (S)**: Base model + Sensorimotor Semantic Distance

4. **Distributional + Sensorimotor model (DS)**: Base model + Distributional Semantic Distance + Sensorimotor Semantic Distance

Each lmer model included an interaction between each predictor of interest with the scalp topography variables (X, Y, and Z positions of the channels), and two random intercepts - subject, and word (Winsler et al., 2018). Interactions of each predictor with scalp topography variables inform whether and how the effect varies across channels arrayed in these three spatial dimensions. For example, interaction with the X-axis indicates how the effect changes from the left hemisphere channels to right hemisphere channels. Similarly, the Y-axis interaction refers to posterior to anterior channels, and the Z-axis refers to changes from central channels at the top of the head to peripheral channels closer to the ears.

For model comparison, we primarily use the Akaike Information Criterion (AIC) scores, but also employ log-likelihood ratio tests to compare nested models. AIC scores are $(-2\ln(\mathcal{L}) + 2k)$ where $\mathcal{L}$ is the likelihood of the model and k the number of parameters, and thus penalize models for complexity. Consequently, AIC scores are suitable both to evaluate model fit and visualize it over time (Burnham & Anderson, 2004). We also use the significant beta values from interactions between scalp topography variables and our predictors to estimate the topographic distribution of their effects. While this approach offers stable and robust insights into coarse topographic patterns, it is limited for detecting nuanced spatiotemporal dynamics that EEG can offer. To address that, we did an exploratory rERP model fitting with our best models.

rERP exploration rERP is a regression modeling approach where EEG measures at each timepoint and channel across trials is fit by an ordinary least squares regression (OLS) (Smith & Kutas, 2015). These regressions yield a time series of estimated coefficients $\beta_n(t,c)$, for each regressor X_n, time t, and channel c. This time series of β values (dubbed the rERP) can then be visualized just as ERPs are. Using the implementation in MNE-Python, we applied the rERP approach to the best models from the LMER analysis for the Property-TRUE and Property-FALSE trials, respectively.

Results

EEG LMER Model Comparison

We compared the four models we constructed for each time window using the AIC measurements. Log-likelihood ratio tests (LRT) were performed for the nested models. Burnham and Anderson's (2004) heuristics suggest that AIC differences above 4 are considered as robust evidence for a model with more complexity. Figure 3 compares the AIC values for **D**, **S**, and **DS** models scaled to the Base model; the comparisons are presented for all seven 100ms time windows. Here, a more negative value indicates a better model fit relative to the baseline model.

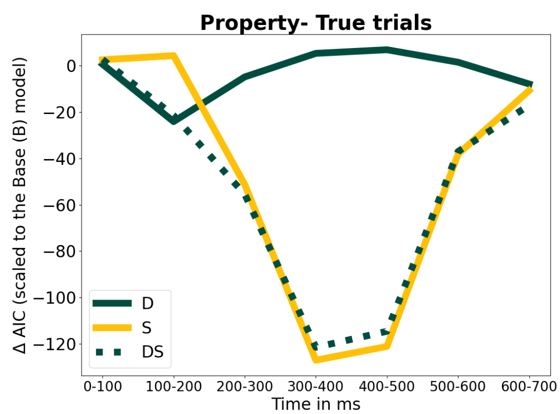
For the Propety-TRUE trials, AIC comparison (Fig 3a) shows that none of the models perform better than the Base model in the first 100 ms window. Both the AIC and LRT statistics (Table 1) indicate that from 100 to 300 ms, (**DS**) model, which includes both distributional and sensorimotor distance offers a better fit than the other three models. Subsequently, however, the sensorimotor (**S** model) provides the overall best account of EEG measurements until 600 ms. From 600-700 ms, (**DS**) again exhibits a marginally better fit than the **S** model. For the Propety-FALSE trials (Fig 3b, and Table 1), the **DS** model offers the best fit across six of the seven time windows, i.e. from 100 to 700 ms post word onset. This suggests that the addition of the sensorimotor predictor in **DS** leads to significant improvement over the **D** model for most of the processing, except the first 100 ms.

Topographies of the effect

Table 2 reports the significant effects from the best models post FDR correction with the Benjamini & Yekutieli (2001) procedure. For the Property-TRUE trials, the sensorimotor distance has a significant main effect from 200-600 ms windows and a significant interaction with the Y axis during 300-400 ms. This indicates that the greater sensorimotor distance

Time (ms)	LRT {Chi}^2 (df, p-value)	
	Property- TRUE S vs DS	Property- FALSE D vs DS
0-100	7.87 (4, ns)	8.79 (4, ns)
100-200	**33.81 (4, <0.001)**	**19.44 (4, <0.001)**
200-300	**12.21 (4, <0.05)**	**65.60 (4, <0.001)**
300-400	2.43 (4, ns)	**28.44 (4, <0.001)**
400-500	1.47 (4, ns)	**26.31 (4, <0.001)**
500-600	6.9 (4, ns)	**20.96 (4, <0.001)**
600-700	**14.3 (4, <0.05)**	**61.05 (4, <0.001)**

Table 1: Likelihood Ratio Tests (LRT) Results: Each row presents a consecutive time window of 100 ms. The second and third columns have LRTs comparisons with the full model (**DS**). For Property-TRUE the comparison is with the overall best model for most time windows (**S**). And for Property-FALSE trials comparison is with the second-best model for most time windows (**D**).



(a) AIC comparison for Property-TRUE trials

(b) AIC comparison for Property-FALSE trials

Figure 3: Scaled AIC values across all time windows. AIC is scaled by subtracting the base (word frequency) model's AIC from each of **D**, **S**, and **DS** models for better visualization. Lower the scaled AIC value, better the model fit.

Time	Property- TRUE	Property- FALSE	
	Sensorimotor	Distributional	Sensorimotor
0-100		D*Y (1.3), D*Z (-2.8)	
100-200		-0.5	
200-300	-0.55	-0.5	-0.3
300-400	-0.92, S*Y (3.0)	-0.5	
400-500	-1.0		-0.2
500-600	-0.6		
600-700		0.3	S*Y (-3.2)

Table 2: FDR corrected significant ($p < 0.05$) regression coefficients for Distributional and Sensorimotor predictors from the overall best models- **S** for TRUE and **DS** for FALSE trials. For each predictor, the corresponding regression coefficient (β, in μV) for main effects as well as for interactions with specific axes are listed.

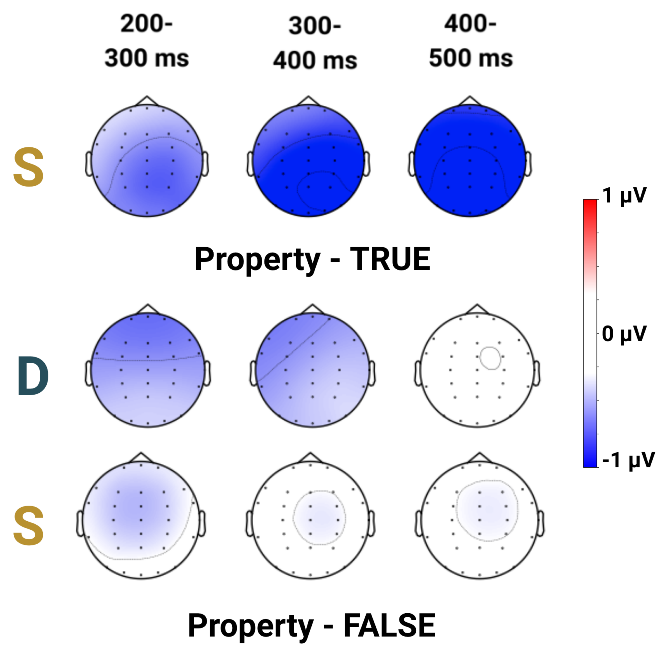


Figure 4: Topographic distribution of beta values from the LMER models. β_i for channel (i) is estimated as $\beta + \beta_x \cdot X_i + \beta_y \cdot X_i + \beta_z \cdot Z_i$, where β is the coefficient of the main effect for a predictor, β_x the coefficient of interaction of the predictor with topography axis X, and (X_i, Y_i, Z_i) are the coordinates i.

between the concept and the property words, ERPs to property words elicited a negativity larger over posterior than anterior channels. For the Property-FALSE trials, both distributional and sensorimotor distance measurements had significant main effects across the entire processing window. In the first 100 ms, the distributional distance interacts with the Y and the Z dimension showing that greater distances were associated with more negative anterior and peripheral ERPs.

We use the lmer models to estimate the coefficient value for each predictor at each channel to better visualize the magnitude and topographic distribution of the effects described. Fig 4 shows estimated betas for sensorimotor and distributional distances in three time windows between 200 and 500 ms. Fig 5 shows rERP (β time-series), along with topographies from the central time point from the 200-500 ms interval to ease comparison to the LMER estimates in Fig 4. Both analyses show that distributional and sensorimotor distance in Property-FALSE trials elicits more anteriorly distributed negativities compared to sensorimotor distance in Property-TRUE trials, which elicits more posterior negativity that resembles the N400 (Kutas & Federmeier, 2011).

Discussion

In the present study, we operationalized distributional and sensorimotor information as cosine distances measured from GloVe embeddings and the Lancaster sensorimotor norms, and modeled the single-trial EEG elicited by property words in a property verification task. While there have been previous suggestions about the role of both kinds of information in property verification, the extent to which either explains neural measurements has not previously been investigated (Solomon & Barsalou, 2004). Our results broadly demonstrate that both distributional and sensorimotor distance measures account for unique variance in the EEG, and their contributions vary not only across semantic processing time course but also between trials contingent on whether the property relation was TRUE. This finding that both of the distance measures impact the real-time recruitment of conceptual knowledge on the property verification task aligns with accounts that reconcile embodied and distributional approaches to meaning (Andrews et al., 2009).

In the early ERP, from 100-200 ms, while the model with both distributional and sensorimotor information offers the best fit, AIC comparisons for both types of trial show that the distributional distance contributes more to the EEG variance than the sensorimotor distance. This observation is consistent with a proposal of distributional information peaking earlier than sensorimotor information in some of the prominent *hybrid* accounts such as the Symbol Interdependency Hypothesis, Linguistic Shortcut Hypothesis, and Language and Situated Simulation (LASS) theory (Louwerse, 2011; Barsalou et al., 2008; Connell, 2018). The occurrence of property terms during the processing of concepts poses a challenge as EEG amplitudes likely reflect overlapping processing of both. However, the objective here was analyzing *contextual* representations of property terms and it is aligned with that objective that the concept and property terms are processed close in time. Further, given the human reading rate of approximately 3 words per second (Brysbaert, 2019), contextual processing serves as a more natural reflection of cognitive processes than if it were artificially slowed down. The early ERPs associated with property terms signify access to property information within the context of its relationship with the concept term and the task.

The interval of 200-500 ms is classically associated with semantic processing effects on ERPs (viz. the N400 win-

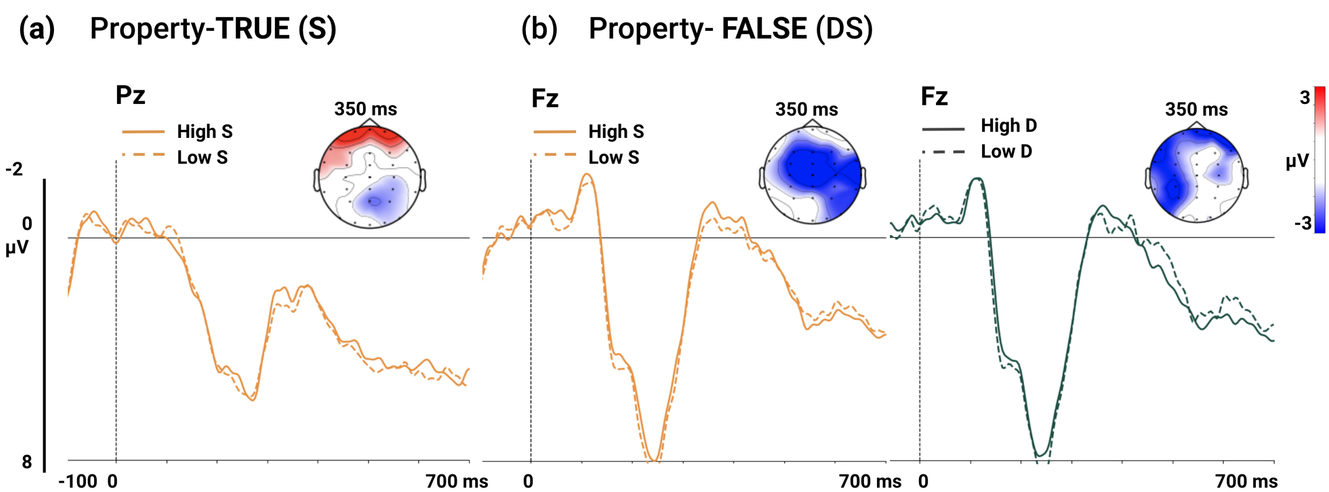


Figure 5: The rERP (β timeseries) for high vs low distributional and sensorimotor distance measurements from the best models (in bracket) for (a) TRUE and (b) FALSE trials. Topographies from the central time point in the 200-500 ms window, i.e. at 350 ms, are presented to make them comparable to LMER beta estimates in Fig 4.

dow). Our analyses suggest that, for the TRUE pairs, both sensorimotor and distributional distances are associated with systematic effects on EEG amplitude in the earlier phase of this window (200-300ms), and exclusively with sensorimotor distance in the later phases of the brain response (300-600ms). By contrast, for the FALSE pairs, distributional and sensorimotor distance were both associated with EEG effects throughout the window. This observation is in keeping with prior analyses of behavioral measurements such as response times and accuracy rates that suggest distributional and sensorimotor information contribute variably to word processing, depending on the features of stimuli and the task (Louwerse & Jeuniaux, 2010). We find that the task relevance of the linguistic context impacted the relative importance of our measures of distributional versus sensorimotor information on neural measures of word processing. That is, while sensorimotor distance was the prevailing influence on ERPs elicited in the property TRUE pairs, both distributional and sensorimotor distance influenced ERPs to the property FALSE pairs. In line with dynamic accounts of semantic memory (Kumar, 2021; Kemmerer, 2019), the differing pattern of effects observed here in property TRUE versus property FALSE pairs may indicate the greater engagement of perceptual resources during the property TRUE trials.

Both distributional and sensorimotor distance were associated with larger negativities in EEG during the N400 window, suggesting that a larger semantic distance of either kind leads to greater demands on semantic retrieval processes indexed by EEG in this time window (Kutas & Federmeier, 2011). Interestingly, however, topographical distributions of the sensorimotor distance effects found here differed between the types of trials. The sensorimotor distance effects in the TRUE trials exhibit the posterior scalp distribution of the classic N400 response to words in sentences (Kutas & Federmeier, 2011), whereas those in the FALSE trials exhibit a more frontal response akin to that of the FN400 linked to conceptual priming (Voss & Federmeier, 2011). However, in both cases, the negative-going brain response is reduced in amplitude as property terms are preceded by words with lower sensorimotor distance.

This topographic divergence between sensorimotor distance effects in TRUE versus FALSE trials suggests that sensorimotor distance as a construct may not map onto a consistent set of neural resources. Recent fMRI work also demonstrated that models derived from experiential information explain the representational code for semantic knowledge stored in sensory-motor cortical regions, as well as in high-level transmodal regions (Fernandino et al., 2022). As the latter are major contributors to the scalp-recorded N400 component, the results of the present study are in line with such suggestions regarding the importance of experiential information in the organization of semantic memory.

In summary, this work suggests that semantic processing in a property verification task simultaneously engages both distributional and sensorimotor information, rather than relying exclusively on a single source of information. Both measures account for unique EEG variance, suggesting distinct, if not entirely independent, contributions of neural mechanisms sensitive to the statistics of language and those that maintain some connection to the sensorimotor origins of conceptual structure. Additionally, our findings indicate the task-relevant linguistic context can impact the relative importance of distributional versus sensorimotor semantic distance in word processing. In keeping with the hybrid models reviewed above, results suggest semantic memory recruits both distributional and sensorimotor information associated with words in a dynamic fashion.

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