Sensorimotor and Linguistic Distributional Knowledge in Semantic Category Production: An Empirical Study and Model

Briony Banks, Cai Wingfield & Louise Connell (Lancaster University, UK)
b.banks@lancaster.ac.uk; c.wingfield@lanacaster.ac.uk

The human conceptual system comprises linguistic distributional and sensorimotor information, but the relative importance of each in conceptual processing is debated. We hypothesized that accessing semantic concepts during a category production task would rely on both, but particularly on linguistic distributional information which may provide a computationally cheaper shortcut. We tested this hypothesis in a pre-registered behavioral study of category production and a computational model of sensorimotor–linguistic knowledge.

In the behavioral study, 60 participants verbally named as many members of 117 concrete and abstract categories as possible, within 60 seconds per category. For each named concept and its category, we calculated a novel measure of sensorimotor similarity (based on an 11-dimension representation of sensorimotor strength across multiple perceptual modalities and action effectors; Lynott et al., 2019, *Behav. Res. Methods*), and linguistic proximity (based on large-corpus word co-occurrences within a 6-gram window). Both measures independently predicted the mean rank order (MR) and production frequency (PF) of responses (Table 1): when asked to name types of *ANIMAL*, the earliest and most frequent responses were highly similar in sensorimotor experience to the concept ANIMAL *and* often appeared close to the word “animal” in linguistic contexts. Critically, category production was better predicted when linguistic proximity was included in regression models compared to sensorimotor similarity alone, although evidence that linguistic proximity predicted first response times was equivocal. Results strongly supported our hypothesis for the offline (i.e., non-RT) measures.

Nonetheless, our predictors were limited in one critical way: they were based only on *direct* relationships between category and member concepts (e.g., ANIMAL → *hamster*), whereas activation in the conceptual system is also likely to spread *indirectly* (e.g., ANIMAL → *dog* → *hamster*). We therefore tested whether sensorimotor and linguistic information would better fit human performance if indirect relationships were considered.

To this end, we developed a computational model of linguistic distributional and sensorimotor knowledge based on the same measures of similarity as the behavioral predictors (Fig. 1; details in Definitions). The linguistic component of the model was a variant on a spreading-activation network of nodes and edges, where activation of a word node would spread out along connected edges and activate the nodes of distributional neighbors (i.e. words that occurred most often in the same linguistic contexts). The sensorimotor component was separate, and allowed activation to spread uniformly to a limited distance in an 11-dimensional sensorimotor space, activating nearby concepts (i.e. with high sensorimotor similarity). In both components, activated words/concepts could further propagate activation to neighbors.

To evaluate model performance, we compared the list of responses the model produced for each category to the responses produced by the participants in the behavioural study, and determined whether the model performed about as well as an individual human. With optimized parameters, the combined linguistic-sensorimotor model was able to perform within the human range of M±1SD 92.3% of the time for mean ranks, and 85.2% for production frequency (see Definitions). When the components were evaluated separately, both made fundamental contributions to model success, although the sensorimotor component contributed more than the linguistic component (see Figure 2). Critically, model performance was substantially worse when activation could not spread indirectly between words/concepts.

Our results provide compelling evidence for the *independent* roles of linguistic distributional and sensorimotor information during a semantic category production task, and conceptual processing more broadly. They suggest that member concepts are accessed by activation propagating from a category concept in two ways: one based on experience of how concept labels are used in language, and one based on sensorimotor experience of the referents.

Table 1. Log Bayes Factors (logBF) from Bayesian hierarchical linear regression analyses predicting the frequency, rank order and response time (RT) of category production responses.

Predictor	**Production Frequency (*N* = 2236)**	**Mean Rank (*N* = 2236)**	**1st Rank Frequency (*N* = 678)**	**1st RT (*N* = 1925)**
Step 1: Sensorimotor similarity	18.94	78.70	2.26	-3.78
Step 2: Linguistic proximity	44.21	12.51	10.09	0.41

Note: A positive logBF indicates support for H_1 (a logBF of 1.10 is equivalent to a BF of 3, i.e., moderate support for H_1). Both regression steps include word frequency as part of the null model (LgSUBTLWF; Balota et al, 2007, *Behav. Res. Methods*).

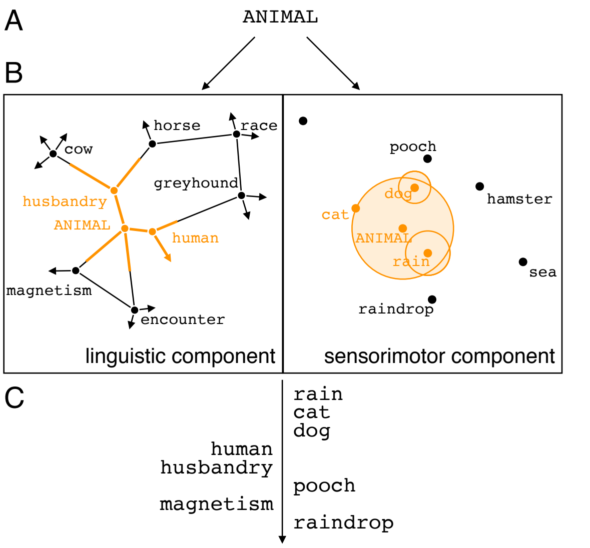

Fig. 1. Simplified example of computational model operation showing selected responses. (A) Category label is provided to the model and is initially activated in each component. (B) Activation propagates in linguistic and sensorimotor components. (C) Further words activated in either component over time, and may be produced as candidate members.

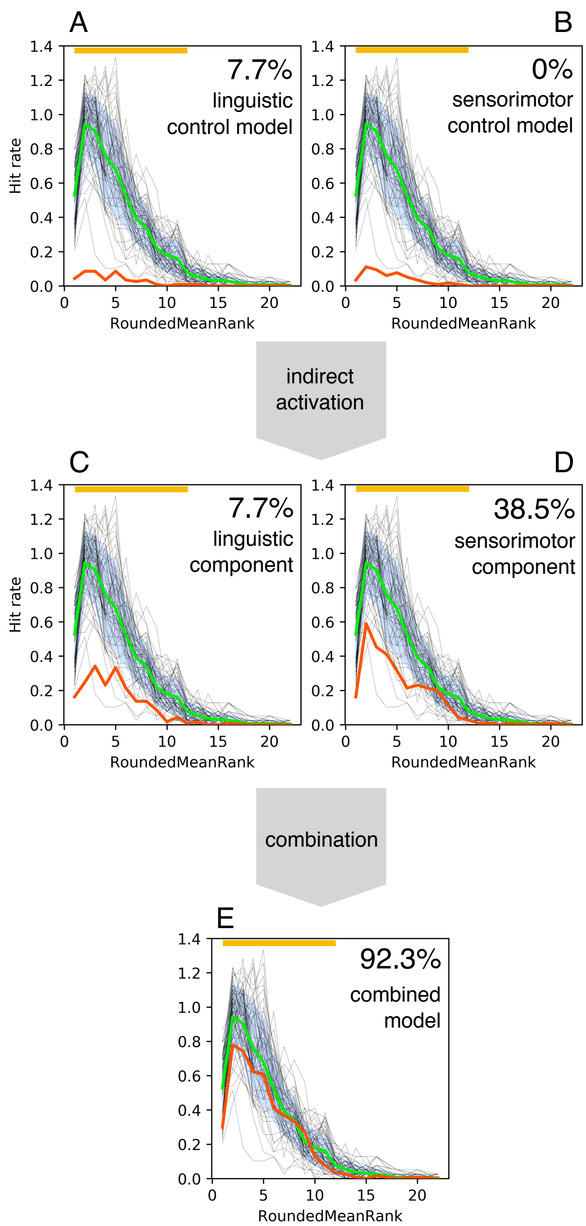

Fig. 2. Computational model fit for mean rank. Each panel graph shows hit-rates for individual participants (black lines), participant mean (green line) ±SD (light blue region) and model hit-rate (red line). Percentages show model hit-rates within 1 SD of participant mean (see Definitions). (A–B) Linguistic and sensorimotor control models without indirect activations. (C–D) Linguistic and sensorimotor separate models with indirect activations but tested individually. (E) Combined model with both linguistic and sensorimotor components allowing indirect activations and run in parallel.

Computational model definitions

Linguistic component. We built a graph from the 40,000 most common words in the linguistic corpus. A word labelled each node, with edges connecting word pairs with a non-zero PPMI score (resulting in 26,334,191 edges). The length of the edge was derived from the PPMI score so that higher scores resulted in shorter edges. When a node was activated (i.e., by seeding the model with a category label, or by incoming activation from neighbouring nodes), its activation was emitted into each incident edge if a firing threshold (0.9) was reached. Activation propagated at a fixed rate through edges according to a model clock. Activation of nodes decayed exponentially over time (1% per tick) and with a Gaussian curve (SD = 15.0) while propagating through edges. Activation reaching a node accumulated there, causing it to repropagate according to the above rule. A node could not become reactivated until its level of activation decayed below the firing threshold. Words were considered as candidate category members the first time they were activated above threshold.

Sensorimotor component. Each of the 39,707 normed concepts from Lynott et al (2019) were located in a vector space according to their mean ratings on each of the 11 sensorimotor dimensions. When a concept was activated (i.e., by seeding the model with a category concept, or by incoming activation from neighbouring concept points), its activation radiated outwards in space as an expanding "sphere" centered on the activated point, with radius (Minkowski distance with parameter 3) increasing linearly according to a model clock. Spheres which intersected other concepts before reaching a maximum radius limit (1.5) caused activation to accumulate there, attenuated linearly by the number of concurrently activated concepts (with activation ≥ 0.3, to control runaway activation in dense regions), and by the prevalence of the concept label (Brysbaert et al, 2019, *Behav. Res. Methods*). Activation of concepts decayed according to a lognormal curve (median = 5.0, σ = 0.9). Newly activated concepts were also added to a simple working memory buffer with a fixed capacity (10) if their activation cleared a threshold (0.7), potentially displacing existing members, and were considered as candidate members the first time they entered the buffer.

Model variants. Run individually, the above components constituted the *separate models* and allowed indirect activations (e.g., ANIMAL → *dog* → *hamster*). We created linguistic and sensorimotor *control models* by allowing only direct activations (i.e., between the category label and its immediate neighbours as in the behavioural study; e.g., ANIMAL → *hamster*,). Finally, in the *combined model*, a category label was activated in both linguistic and sensorimotor components, which were then run in parallel. Candidate members were produced by the combined model when they were first produced by either component. Speed of propagation in the two components were co-registered so that the same number of clock ticks were required to activate the first three members of each category in either component. In the combined model, as well as each individual component, activity was terminated after 398 ticks (chosen to maximise the hit-rate) after which time all direct activations had occurred.

Hit-rate. For both model and participants, we defined hit-rate to be the proportion of categories in which an individual produced the group's pooled responses. This was defined for mean rank (MR; excluding idiosyncratic responses) and for production frequency (PF; ranked within each category by descending frequency). In this way, hit-rate (MR = 1) essentially represented how often a participant or model produced the average earliest response in a category, hit-rate (PF = 1) represented how often they produced the most popular response in a category, and we could directly compare model and participant hit-rates in both cases. (In the case of tied ranks, hit-rate could exceed 1.0).

We further summarised the hit-rate over categories by looking at how often the model's hit-rate fell within 1 SD of the mean participant hit-rate (i.e., approximated typical human performance). To avoid the long tail of responses (in which neither participants nor model scored well) contributing positively to hit-rate, we only considered ranks before the point where 0 first lay within 1 SD of the participant mean hit-rate. These ranks are indicated by the orange bars in Fig. 2.