Fuzzy learning can decouple language and odor representations: Associative memory loss in a computational model

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Abstract:

Odor naming is considered as a particularly challenging test of olfactory ability. It is common that in free naming scenarios people fail to respond with any linguistic label to certain odors they smell, resulting in an omission (i.e., a blank response in a test). The cognitive demands and the nature of interactions between olfactory memory and language related brain's neural resources are not well understood. Here with the support of a computational model we offer some hypotheses regarding the neural network-level mechanisms underlying the phenomenon of omissions in a free odor naming task. The available behavioral data suggests that odors with numerous language associations (one-to-many mapping) lead to elevated blank responses. To simulate the task and examine whether the trends observed in the behavioral data can be reproduced and mechanistically analyzed, we developed a memory model consisting of two networks that are reciprocally connected with Bayesian-Hebbian plasticity [1]. We stored and associated distributed, overlapping odor percept and odor label language representations in this model network. Overall, we suggested and evaluated a hypothesis that associative Bayesian-Hebbian plasticity for the connections between the two networks results in weak coupling for odors paired with multiple different labels during the odor-label encoding (one-to-many mapping), thereby increasing the subthreshold network responses (omissions) for these odors.

Motivation

Naming odors constitutes a complex cognitive phenomenon that relies on reciprocal interactions between olfactory memory and language related cortical networks [2]. Most of research on odor identification, recognition and naming has traditionally relied on behavioral, psychophysical and neuroimaging studies, which offer rather limited insights into neural and network-level underpinnings of these phenomena. In this work, we employed a computational approach with the intention to cast more light on mechanistic underpinnings of odor-language cortical interactions. In particular we aimed to explain why certain odor percepts tend to result in omissions more often than others in a free odor naming task.

Methods

Behavioral data: The data that we used to compare our model output was collected from a Swedish National Study on Aging and Care in Kungsholmen (SNAC-K), where ~2500 subjects underwent an odor naming test of 16 odors [3]. After presenting each individual odor, the SNAC-K participants were asked to freely identify and name the presented stimulus (odor naming).

Model: The model architecture, inspired by a previous work on item-context episodic memory binding [4], rests on two reciprocally connected modular associative memory networks: one that accounts for an olfactory memory system and the other one that corresponds to a language reservoir of odor labels at the given level of abstraction (Fig. 1A). Unlike previous detailed spiking models [4], here we utilized a less detailed non-spiking implementation with population rate based coding units. The sparse distributed representations of odor percepts and odor labels, embedded in the memory model, were first obtained using a greedy optimization scheme [5] matching the pairwise similarities between, respectively, odor percepts (collected in another dedicated behavioral study on odor similarity ratings [6,7]), and Word2Vec odor label embeddings (Word2Vec assesses the semantic similarity between words based on contexts they appear within a large corpus of text [8], here: the Swedish blog corpus). The resulting average similarity matrices were used as the target for building distributed overlapping odor and language representations. The connectivity between the two networks was trained by associative Bayesian-Hebbian learning [1] through paired stimulations of odor percepts and corresponding odor labels. These associative pairs were typically made to reflect inherent variability in naming the same odor. In particular, four groups of odors were identified based on the Simpson diversity index [9], which quantified heterogeneity in SNAC-K participants' responses in a free odor naming paradigm. The odor groups reflected the number of odor percept associations with different labels (from one-to-one to one-to-four mappings).

Results

In line with the SNAC-K memory test, we cued each of the 16 stored odors for 100 ms with an inter-stimulus interval of 1 s. To avoid biased learning due to varying number of label associations per odor, the stimulation protocol was balanced so that each odor was cued the same number of times. Following the learning protocol, each odor percept was probed with a cue and the evoked activation in the language network was reported as the label response allowing for the quantification of the model's odor naming performance. We found evidence that odors forming associations with many different labels tended to generate omissions, i.e. blank responses, in the language network (Fig. 1B, Model). We observed a similar trend in behavioral responses, where the variability of odor names partly explained the omission rates in SNAC-K data (Fig. 1B). A key mechanism underlying this odor-label decoupling process in the network model was attributed to the weakening of the between-network connectivity for the case of one-to-many mappings (Fig. 1C). We concluded that the diversity of labels associated with an odor percept renders the associative strength rather weak, which counteracts a meaningful response in the language network when the odor percept is cued.

Next, we evaluated the importance of the bi-directional network connectivity with a focus on different origins of omissions hypothesized in the experimental literature [7], i.e. those stemming from perceptual issues (missing odor percept), and those caused by a missing language response once the odor itself was perceived. By gradually removing the language to odor network connectivity (Fig. 2A, α,β), or all the associative between-network connections (Fig. 2A, γ), we noticed a dramatic increase in the omission rate (Fig. 2B). A high percentage of omissions were caused by lack of odor perception (Fig. 2C, α), mainly due to high odor overlap (indicative of perceptual similarity among odors), which introduces confusion and diminished odor recognition. Eliminating the connections from the language to odor network slightly increased the language omissions and lowered the perceptual failure (Fig. 2C, β). Further removal of all the connections between the two networks resulted in omissions in all cases primarily due to language network's failure in generating any response (Fig. 2C, γ).

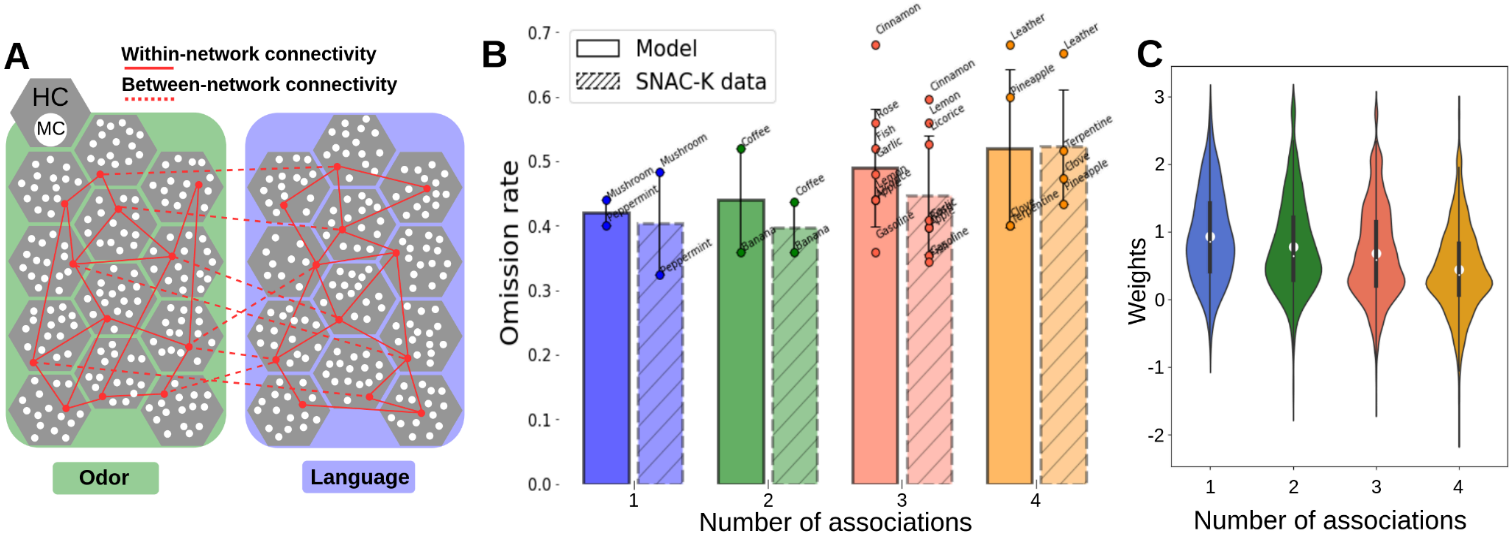

Figure 1: A) Schematic of the odor (green) and language (blue) networks. Within-network connectivity reflects local connections across hypercolumns (HCs) in the same network, and between-network connectivity represents associative connections. **B)** Mean omission rates in the language network for the model (25 simulations) and behavioral SNAC-K data. The bar diagram reveals progressive loss of language information over the number of odor-name associations (i.e., mushroom forms one association whereas leather is associated with four different descriptors). **C)** Distribution of the between-network connectivity. Weights are weaker for items which participate in multiple associations (e.g. one vs. four associations).

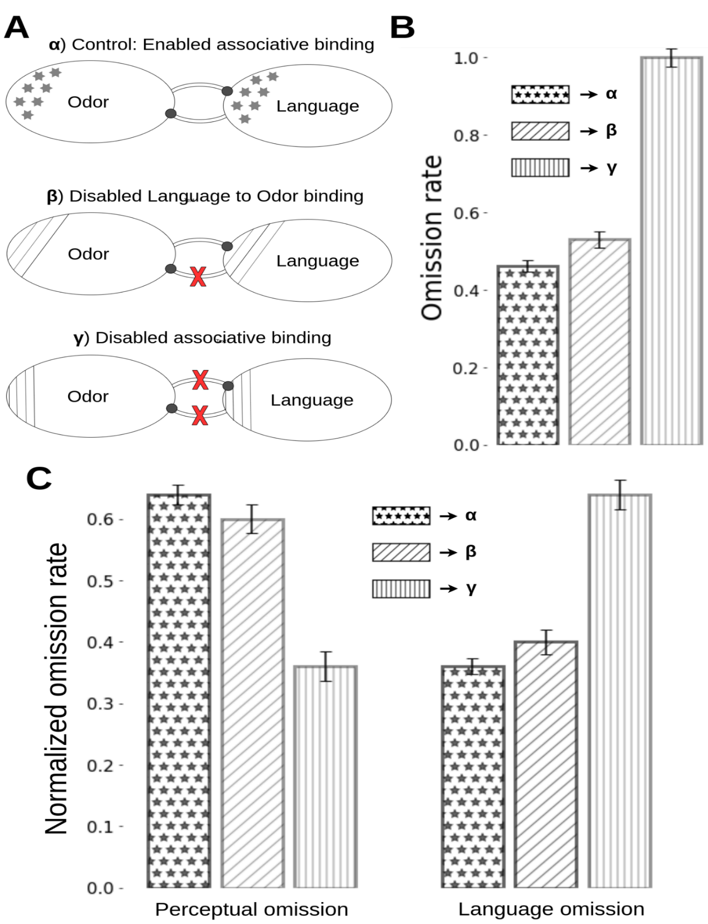

Figure 2: A) Gradual removal of the binding connecting the two networks. **B)** Omission rate increases with gradual removal of associative binding. **C)** Classification of normalized omission rates to odor (perceptual) vs. language failure, for the three scenarios α,β,γ in A.

Conclusion

We have developed a computational model consisting of two reciprocally connected and interacting recurrent networks storing long-term olfactory and language memory representations, respectively, to study mechanistic underpinnings of odor naming. Our main objective was to propose a hypothesis about the origins of omissions in a free odor naming scenario reported in the SNAC-K study. As a result, the simulations offered computational insights into synaptic and network-level factors possibly underlying the odor specific distribution of blank responses observed in the experimental data. In essence, odor percepts associated with multiple odor labels (one-to-many mapping) in the memory pre-encoding phase, prior to the simulated free naming test, were more susceptible to omissions due to weaker odor-label synaptic coupling than odors with more selective (one-to-few) label pairings. We consider this work as an embryo for further computational investigations into the complex dynamical interactions between the brain's perceptual and language resources during object naming.

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