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Cumulative semantic interference as learning

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Introduction

When aphasic individuals name pictures in a blocked-cyclic naming paradigm, they produce more semantic and omission errors when the repeatedly named items come from a single semantic category, relative to when the items are from different categories, an effect known as *cumulative semantic interference*. This effect is magnified in Broca's aphasics and increases as patients repeatedly cycle through the pictures in each block (Schnur, Schwartz, Brecher, & Hodgson, 2006). A similar phenomenon manifests in non-aphasic populations as comparatively increased naming latencies for pictures from a single category (e.g. Howard, Nickels, Coltheart, & Cole-Virtue, 2006; Schnur et al., 2006).

We propose a model in which incremental learning occurs during naming and is realized as weight change within the lexical system (e.g. Gordon & Dell, 2003), thereby producing cumulative semantic interference. To test our hypothesis that incremental learning alone could produce interference, we built a two-layer neural network with a distributed semantic input layer and a lexical output layer (Fig. 1a). We simulated blocked-cyclic naming as repeated access of lexical representations through semantic features with continued application of the error-based learning algorithm by which we initially trained the network.

Methods

The network's input represented semantic features (e.g. MAMMALIAN), and these were directly connected to each lexical output (e.g. DOG), with no feedback. Within the nine-word lexicon, each lexical output was uniquely specified by two of the six semantic features (e.g. DOG's features were MAMMALIAN and TERRESTRIAL).

Initial connection weights were determined from 150 naming training trials. For each trial, two inputs were activated and the correct output was specified; connection weights were then adjusted according to the delta rule, an error-based learning algorithm. Fig. 1a shows the learned weights associated with the inputs, MAMMALIAN and AQUATIC.

The simulation of blocked-cyclic naming proceeded in the same manner as the training, except that pictures were named in blocks of three items that were either semantically-related (e.g. DOG, WHALE, and BAT share the MAMMALIAN feature) or semantically-unrelated (e.g. DOG, WATER LILY, and AIRPLANE have no features in common). Crucially, the model continued to learn during the simulation, so that the only difference between training and testing trials was the blocking.

In order to map activation patterns onto observable behaviors (such as errors, omissions, and response times), the model relies on a noisy activation function, a difference threshold (for selection decisions), an amplification of activations if the threshold is not reached (which affects RTs) and a timeout function (which creates omissions). When semantic features are activated, they transmit that activation to the lexical units, which also receive a certain amount of normally-distributed noise. This noise leads to semantic and omission errors, and the difference between aphasics and non-aphasics was modeled simply as an increase in standard deviation of the noise. The most activated lexical output is then selected if its activation is sufficiently greater than the mean of its competitors. If no lexical item exceeds this difference threshold, a "booster mechanism" kicks in, amplifying all activations by repeatedly multiplying them by a constant. If this amplification succeeds in determining a "winner" within a certain a number of multiplications, then that winner is selected. Otherwise, an omission is recorded (i.e. the word selection process simply *times out*). Response time is assumed to be directly proportional to the number of multiplications required to pick the winner.

Results and discussion

Simulations of Schnur et al.'s Experiment 1 (concerning nonaphasics' naming latencies) and Experiment 2 (errors in aphasic participants) closely mirrored the major qualitative effects. In both the model and the data, naming latencies in the semantically-related (or *homogeneous*) condition increased with each cycle, relative to the mixed-block baseline.

In the simulation of Experiment 2, more semantic errors were produced in the homogeneous condition than in the mixed condition, and this effect increased across cycles (Fig. 1b). Similar patterns held true for omissions. All of these findings are also present in the data (Fig. 1c). Furthermore, the simulation produced a significant perseverative tendency in the homogeneous condition, consistent with the findings of Lee, Schnur, and Schwartz (this symposium). Because there is no temporal decay built into the model, this perseverative tendency results from the "unlearning" that occurs for each previously produced item when a similar item is named. For example, the model's learning algorithm weakens DOG when the model produces BAT, and then further weakens DOG when it produces WHALE next. The resulting perseverative gradient is independent of time and the occurrence of unrelated items, as in the data.

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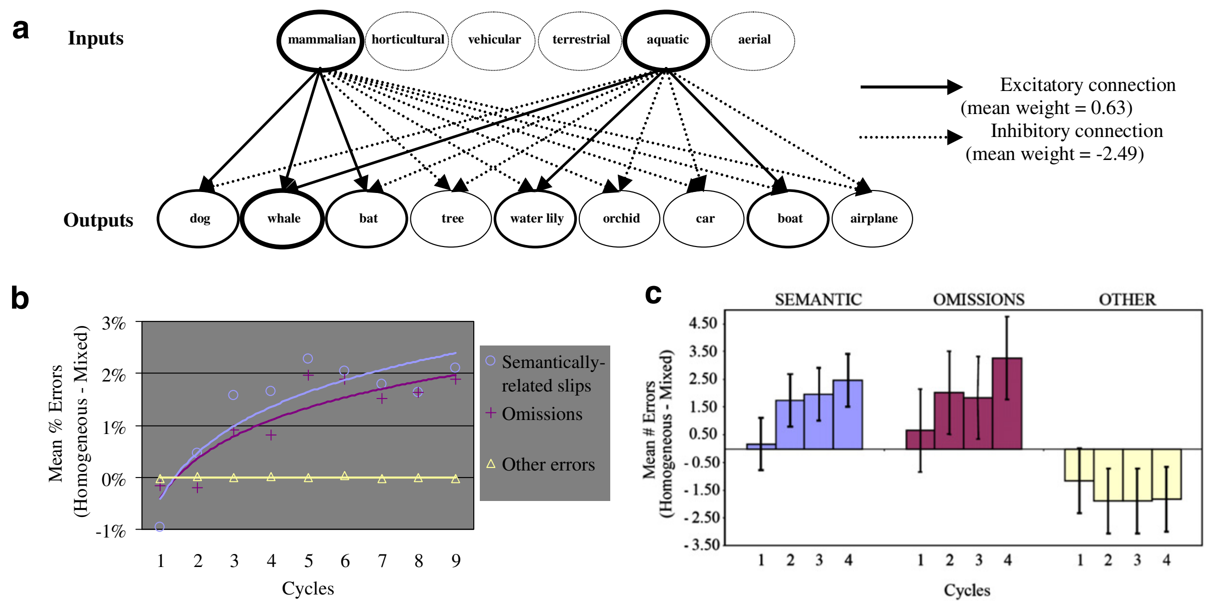

Fig. 1. The network (a) contains feedforward connections from a distributed semantic input lay to a lexical output layer. This figure illustrates how activation of the inputs MAMMALIAN and AQUATIC in a trained network primarily activates WHALE, but also activates semantic relatives to a lesser extent; model data (b) shows that the blocking effect (i.e. the difference between naming performance on items in homogeneous and mixed blocks) manifests in both semantic and omission errors, and increases with each naming cycle, echoing the Schnur et al. (2006) patient data (c).

Conclusion

The model instantiates the processes that Howard et al. (2006) identified as necessary for any account of cumulative semantic interference: shared activation, competition, and priming. *Shared activation* arises from the model's distributed semantic features; *competition* comes from its having to surpass a difference threshold to achieve selection; and *priming* involves the continuation of incremental, error-based learning on each naming attempt. The model also has mechanisms for response selection that simulate an executive process that compares activation among potential outputs (e.g. Thompson-Schill, D'Esposito, & Kan, 1999), and then continually amplifies this difference until one output is clearly the most active. Its mechanisms for learning and selection also enable it to explain semantic errors, omissions, and perseveratory tendencies. The simulation demonstrates that cumulative semantic interference can result from the same learning processes that would normally effect improvements in accuracy, without recourse to specific inhibition mechanisms or persistence of activation.

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