Computational models of aphasia must, first, characterize the actions of the unimpaired system, and then explain how that system is damaged in aphasia. Our model of lexical deficits in aphasic speakers is based on the interactive two-step theory, an account of normal lexical access in production that associates the process with two distinct steps, word retrieval and phonological retrieval. Each step is achieved by the interactive, or bidirectional, spread of activation through a layered network of units for semantic features, words, and phonemes (Fig. 1). Deficits are created by altering parameters that affect activation. In our first model of this type, the weight-decay model (Dell, Schwartz, Martin, Saffran, & Gagnon, 1997), lesions corresponded to global decreases in the weight of connections among all units in the network (parameter $w$) and global increases in the rate with which activation decays (parameter $d$). The more recent semantic-phonological model (Foygel & Dell, 2000) also had two lesionable parameters, $s$, the weight of the connections between semantic and lexical units, and $p$, the weight of the connections between the phonological and lexical units.

Developing and testing these models involves four stages: specifying the normal model, defining the possible lesions, assigning parameters to patients based on their errors in a picture naming task, and using those parameters to test predictions about other aspects of patient behavior.

**Normal lexical access**

The word retrieval step begins with a jolt of activation to the semantic features of the target (e.g., CAT). This activation spreads throughout the network and is concluded by the selection of the most active lexical unit from the proper grammatical category (nouns for an object-naming task). The phonological retrieval step starts with an activation jolt to the selected word, which would normally be the target, CAT. Activation spreads again throughout the network, culminating in the selection of the most activated phonemes. Errors can occur during either step. During word retrieval, semantically related words (DOG), formally-related words (MAT), mixed (semantic and formal) words (RAT), or unrelated words (LOG) could be mistakenly selected. Semantic errors are promoted by shared semantic features.

**Testing predictions**

The ultimate test of a model is its ability to predict data that were not directly used in the fitting process. In our previous work, we used the parameter values derived from naming to predict: (1) the extent to which formal errors (MAT for CAT) occur during word or phonological retrieval, as indexed by whether or not these errors respect the grammatical category of the target, (2) which patients exhibit the mixed-error effect, the tendency for semantic errors to show phonological involvement, (3) the error pattern in word repetition tests and, (4) the recovery of naming ability over time. The first two of these predictions arise from the assumption that activation flows interactively from phonological to lexical units. The repetition predictions between phoneme and lexical units. Phonological retrieval provides a further opportunity for error, including the possibility of selecting nonwords (e.g., LAT).

Creating a normal version of the model involves choosing parameters and a neighborhood structure so that the model simulates normal behavior in picture naming. Specifically, we matched the model’s probabilities for correct, semantic, formal, mixed, unrelated, and nonword responses to those of 60 control subjects who were given the 175-item Philadelphia Naming Test (Roach, Schwartz, Martin, Grewal, & Brecher, 1996).

**Defining lesions**

Lesions are identified with two free parameters, $w$ and $d$, in the weight-decay model, and $s$ and $p$, in semantic-phonological model. The lesions reduce the activation of target words and phonemes, increasing the chance of errors. However, different parameters are associated with different errors. For example, reducing $s$ in the semantic-phonological model leads to lexical errors, particularly semantic, mixed, and formal errors, whereas reducing $p$ increases the chance of phonological errors such as nonwords. Because of the interactive nature of the model, though, semantic lesions impact phonological errors and vice versa.

**Assigning (‘fitting’) parameters to patients**

Patients are assigned $s$ and $p$ (or $w$ and $d$) parameter values by selecting values that make the model error proportions as close as possible to those of the patient. Specifically, the chosen values minimize $\chi^2$. The fit quality can be assessed by $\chi^2$, and by a more intuitive measure, root-mean-squared-deviation ($\text{rmsd}$).

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highlight the two-step nature of the model. Whereas naming depends both on word and phonological retrieval, we hypothesize that repetition errors occur only during phonological retrieval. Applying the model to recovery tells us whether the model explains within-patient as well as between-patient variation.

By examining the model fits for naming and by testing predictions, we can, in principle, identify the strengths and weaknesses of the general approach and determine which model of the deficit accords best with the data. Up until now, though, the models were tested only in restricted samples. Patients who make many omission errors and those whose speech is not fluent were excluded, the former because the model did not have an account of omissions, and the latter because of coding difficulties. Consequently, the relative merit of the weight-decay and semantic-phonological models and, indeed, the value of the entire approach, have not yet been determined.

Our recent work allows for all aphasic patients to be modeled. Moreover, we offer new tools (langprod.cogsci.uiuc.edu/cgi-bin/webfit.cgi) that help interested researchers use the models quickly and easily. The remaining two presentations in this symposium apply these tools to naming and repetition data from a large and diverse sample, enabling a more definitive evaluation of the interactive two-step model and its approach to aphasic lexical access.

References

