

Word Production: Behavioral and Computational Considerations

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What happens when a person names a picture? To a first approximation, the answer to this question is uncontroversial. The speaker must identify the pictured object, determine that object's name, and say it. Putting it more formally, the production of a word in a task such as picture naming involves conceptualization, linguistic formulation, and articulation (Levelt, 1989). The controversy begins when we try to spell out these components in any detail. In this chapter, we discuss data that are informative about the linguistic formulation of single-word utterances, and focus on attempts to simulate its inner workings with computational models.

Behavioral data for word production models

Errors or response time? For many production researchers, that is the question. Is word production best illuminated by the errors that the process generates, or by careful measurement of the time that it takes to correctly retrieve words while speaking? The field's Hamlet-like indecision on this issue reflects its history. The first analyses of production from a psycholinguistic perspective were based on naturally occurring speech errors (e.g. MacKay, 1970; Nooteboom, 1969). Slips were viewed as a "window into linguistic processes [that] provides...the laboratory data needed in linguistics" (Fromkin, 1973, pp. 43-44). Natural errors can be divided into those in which whole meaningful units, such as words or morphemes, slip, and those in which the phonological parts of those units slip, thus echoing the fundamental duality of linguistic patterns: Phonological units combine to make words and morphemes, and these then combine to make sentences. Slips can involve substitution ("knee" for "elbow", a word substitution), exchange ("lork yibrary" for "York library", a phonological exchange), shift, addition, or deletion of a linguistic unit or

sequence of units. Moreover, errors are influenced by numerous linguistic, contextual, and psychological factors, even leaving aside potential “Freudian” influences on errors. The systematicity of the slip data provided the field with its first good look at the production process, and inspired its first true theory, that of Garrett (1975). Moreover, error analyses led to the development of methods for generating slips in the laboratory (e.g. Baars, Motley, & MacKay, 1975), thus providing a degree of experimental control that was lacking in the natural error collections.

Speech errors show how the production process breaks down. But such data are limited by the tautological fact that a slip is the product of a system that, at that time, did *not* work correctly. Given this, perhaps normal production is better studied by measuring the properties of error-free, rather than erroneous, production. As Levelt, Roelofs, and Meyer (1999, p. 2) put it, “the ultimate test [of production models] cannot lie in how they account for infrequent derailments of the process but rather must lie in how they deal with the normal process itself.” This perspective has led to many studies in which the response time to generate single-word utterances is measured. For example, picture naming times can be measured as a function of lexical variables such as frequency (e.g. Oldfield & Wingfield, 1965). To fractionate the lexical-access process, though, researchers have enhanced naming tasks in several ways. An enhancement that is widely studied is the *picture-word interference paradigm* (Glaser & Dünghoff, 1984; Schriefers, Meyer, & Levelt, 1990), in which a distractor word (either spoken or printed) is presented along with a target picture. The participant must name the picture as quickly as possible while ignoring the distractor. The distractor, which can be related in

meaning or form to the picture's name and can be presented at different times before or after the picture, affects the naming time. For example, a semantically related distractor presented closely before or at the same time as the picture will slow naming more than an unrelated distractor will. There are several other response-time paradigms for studying single-word production, including *implicit priming* (e.g. Meyer, 1990), *blocked-cyclic naming* (e.g. Damian et al., 2001), *symbol-cued naming* (e.g. Cholin, Levelt, & Schiller, 2006), *translation* (e.g. Jescheniak & Levelt, 1994), *repetitive recirculation* (e.g. O'Seaghdha, & Marin, 2000) and *multi-task paradigms* in which the participant must do some other task in addition to naming a picture (e.g. Ferreira & Pashler, 2002). In all of these methods, the participant retrieves a target word from a cue that points to that word so effectively that error is unlikely, and the time to begin speaking is influenced by manipulation of the target's properties or the task context. The experimental procedures can get pretty complicated, but the payoff is that one can measure systematic differences in the time it takes to successfully produce the target.

Pathological language production. The error- vs. RT-data debate becomes more pointed when language pathology is considered. Single-word production tasks, such as picture naming or auditory word repetition, are common clinical and research tools for aphasia. Moreover, some of the most important theories of single-word production rely on data from speakers with production deficits (e.g. Caramazza, 1997; Rapp & Goldrick, 2000). These theories, like the speech-error based theories of production, are based on the probability and the form of production errors, that is, they are based on episodes in which production failed in some way. On top of this, though, the production systems

that generated these errors are themselves impaired. So, if the goal is to understand successful production, then the data from aphasic speakers suffer from a double whammy, at least from the perspective of researchers who focus on response times for correct productions.

The neuropsychological community has long been concerned by the fact that their data consist of erroneous responses generated by damaged brains. Consequently, theorists in this area have developed guidelines for inference from impairment patterns to conclusions about the unimpaired system, guidelines that they continue to debate and refine (e.g. Caramazza, 1984; Harley, 2004). Nonetheless, those who question the empirical value of slips made by unimpaired speakers have even more reason to be skeptical about aphasic data. One of our goals for this chapter is to show how computational models can allay this concern. Models can make error mechanisms concrete thus showing how errors reflect the structure of the normal system. Furthermore, models can reveal the relationship between errors generated by a normal system and those that arise from a damaged one. If a model can simulate both the normal and the abnormal, that is, if it can explain the properties of erroneous and correct utterances *and* damaged and intact production systems, then error data can usefully add to the picture.

Theoretical issues in word production models

Representational levels and production steps. We have introduced the conceptualization, linguistic formulation, and articulation components of production and said that our focus is on single-word lexical access within the formulation

component. Can we further subdivide lexical access? All researchers agree that lexical access involves multiple levels of representation, including representations of word meaning or semantics, and representations of word form, or phonology. A stronger claim, which is accepted by most researchers, is that lexical access has steps, specifically two of them (Dell & Reich, 1981; Garrett, 1975; Levelt, 1989; Rapp & Goldrick, 2000). The first step (lemma access, word-access, L-access) consists of mapping a semantic representation onto an abstract lexical unit (*lemma* or *word node*), and the second of mapping that abstract unit onto a representation of the lexical unit's pronunciation (word-form access, phonological access).

Evidence for two steps comes from several sources. First, slips can profitably be divided into those that might have arisen during the first step (e.g. semantic errors such as “dog” for “cat”) and those that could have happened in the second step (e.g. “cap” for “cat”). Later, we shall see how the two steps achieve this division using a model. Furthermore, the tip-of-the-tongue (TOT) state that speakers experience when they cannot retrieve a word's phonology can be characterized as getting stuck between the steps. When speakers are stuck in this way, they can retrieve lexical properties that are associated with the first step—grammatical features such as gender for nouns—providing support for the view that the first step has been taken (Badecker, Miozzo, & Zanuttini, 1995; Miozzo & Caramazza, 1997; Vigliocco, Antonini, & Garrett, 1997). Response-time data can also be interpreted within the two-step framework. For example, in the picture-word interference paradigm, both semantically related and phonologically related distractors affect the time to name a target picture. But the

strongest influences of these two distractor types occur at different stimulus-onset-asynchronies (SOAs) relative to the picture onset; the semantic effect is earlier than the phonological effect (e.g. Schriefers et al., 1990). Thus, the time course of the influence is consistent with an earlier semantic step and a later phonological step (Levelt et al., 1991; Peterson & Savoy, 1998).

Stages, cascading, and interaction. The two-step idea implies discreteness—step one, *then* step two—rather than a continuous evolution from semantics to phonology. There is, however, an even stricter form of discreteness, *modular stages*. If the two steps are modular stages, the information that is accessed during each step is restricted to that which is appropriate for the step. Specifically, in the *WEAVER++ model* of Levelt et al. (1999; Roelofs, 1997; 1992) described below, while lemma access is occurring, there is no activation of word-form information, and during word-form access, no semantic information is activated. We can relax this modularity by allowing for *cascading*. In a cascaded lexical access system, activation can flow to word-form information before lemma access finishes. To make this concrete, imagine that in an attempt to access the lemma CAT, there is also activation of the lemma DOG from either shared semantic features or other connections between their concepts. If lemma access is a modular stage, there would be no activation of word-form information until the stage is finished. But, if cascading happens, phonological properties of both CAT and DOG could become active before lemma-access completion. We can relax modularity even more by admitting a bottom-up flow of activation (feedback) from phonological information to words and from words to semantics. If bottom-up feedback and

cascading are present, the system is said to be *interactive*: Activation flows in both directions during both steps. The *interactive two-step model* described below (Dell, Schwartz, Martin, Saffran, & Gagnon, 1997) is interactive in this sense. During lemma access, phonological information becomes active (cascading) and can influence lemma selection (through feedback). During phonological access, activated phonological units can feed back to the lexical level, which in turn can affect which phonological units are chosen.

The question of the discreteness of lexical access thus boils down to whether the access steps are modular, cascading, or interactive. Support for cascading has largely come from response-time studies (but see Ferreira & Griffin, 2003). Peterson and Savoy (1998) asked participants to name pictures and, on some trials, interrupted the naming process by presenting printed probe words that the participant must read aloud as quickly as possible. They found that probes that were phonologically related to an alternate name of the picture, such as the probe “soda” related to the alternative name SOFA for a picture of a COUCH, were read faster than when the picture name was unrelated. Furthermore, when “count” (related to COUCH) was a probe, it was also associated with a comparable speed up. The facilitation for both “soda” and “count” occurred with a picture-probe SOA of 150 ms, but not with an SOA of 50 ms. These findings suggest that, during the first step of lexical access, the lemmas for both COUCH and SOFA were activated. Critically, the phonological properties of both words were also activated, even though for these participants, the pictured piece of furniture is nearly always referred to as a couch. If lexical access were modular, only the phonology of the

selected item (couch) would be active. Consequently, the data indicate cascading from step one to step two. Step two information becomes active before step one has made its selection. Since the Peterson and Savoy study, several other response-time experiments have obtained findings consistent with cascading and it is now generally agreed that there is some degree of cascading during lexical access (e.g. Costa, Caramazza, & Sebastian-Galles, 2000; Cutting & Ferreira, 1999; Jescheniak & Schriefers, 1998) and in later phonetic processes (Goldrick & Blumstein, 2006).

What about interaction? Some speech-error findings have been interpreted as evidence for a bottom-up flow of activation during lexical access. The *mixed-error effect* is the tendency for semantic word substitutions to share phonological information. For example, U.S. Vice President Joe Biden once referred to the pope as the “president.” Both *pope* and *president* designate powerful offices and so clearly the slip is semantic. But it is tempting to conclude that both words beginning with /p/ helped the error happen. In fact, analyses of natural slips (e.g. Dell & Reich, 1981; Harley, 1984) and picture-naming errors from both control and aphasic speakers (e.g. Martin et al., 1996; Rapp & Goldrick, 2000) show that semantic word substitutions exhibit phonological effects in excess of what would be expected by chance. The mixed-error effect is a natural consequence of interaction. During the first step of access, activation cascades to phonological units (e.g. to /p/ for the target POPE). This activation then feeds back to all /p/-initial word units including those that were already activated by virtue of their semantic relations to the target (e.g. PRESIDENT). This extra phonological activation gives these mixed semantic-phonological neighbors a boost over purely semantic

neighbors, thus increasing the chance of the slip. Another speech-error phenomenon that can be explained by interaction is the *lexical-bias effect*—the tendency for phonological errors to create words, and particularly words related to the context, over nonwords (Baars et al., 1975; Motley & Baars, 1976). For example, saying “darn bore” instead of “barn door” would be more likely because “darn” and “bore” are words. An interactive (two-way) flow of activation between word and phonological units can increase the activation of phonological units that correspond to words, thus creating lexical bias.

Although the mixed-error and the lexical-bias effects suggest some kind of interaction between processing levels, whether these effects are achieved by an automatic bottom-up spread of activation is controversial. Both the lexical bias and mixed-error effects can, instead, be explained by postulating that the lexical access system also includes a pre-articulatory editor—a system whose function is to detect and weed out errors before they are spoken (Baars et al., 1975). The lexical bias effect would require an editor that detects that the speaker is about to say a nonword and prevents articulation. Hence, errors that are nonwords become less likely. The mixed-error effect requires that the editor preferentially weed out semantic errors that are phonologically dissimilar to the target (Levelt et al, 1999). For example, when trying to say “cat”, the editor can detect that “dog” is not “cat”, better than it can tell that “rat” is not “cat”. Hence, the mixed error, “rat,” is more likely to be spoken. Although pre-articulatory editing may require time and effort (e.g. Nozari & Dell, 2009) and existing theories of editing are poorly specified, there is little doubt that speakers monitor planned speech

for purposes of error detection (Levelt, 1983; Hartsuiker & Kolk, 2001) and that at least some of the lexical bias effect can be attributed to this process (Hartsuiker et al., 2005; Nootboom & Quene, 2008; Oppenheim & Dell, 2010). Note, however, that editorial explanations of these error effects do, in fact, involve bottom-up processing. Representations at a lower level (e.g. phonological level) are evaluated for their higher level (e.g. lexical) properties before articulation. In this way, the editorial explanations and the bottom-up feedback explanations are similar, with both asserting that production is not strictly top down (Dell & Reich, 1980; Rapp & Goldrick, 2004).

Competition in lexical selection. The first lexical-access step culminates in the selection of an abstract lexical item. In all of the models that we review below, the activation levels of the word or lemma units are the basis for selection. The interactive two-step model simply selects the most active word unit which, as explained below, could be the wrong one thus creating a lexical error. Since this model is concerned with explaining errors rather than lexical selection time, the time at which the selection happens is a fixed parameter of the model. In contrast, the WEAVER++ model directly explains response times through its selection mechanism. The key property of this mechanism is that it is *competitive*. Not only does a more active target decrease selection time, but more active competitors have the opposite effect. So, if CAT is highly active and nothing else is, selection is rapid. But if DOG is activated, even if less so than CAT, CAT's selection time increases with DOG's activation level.

Competitive lexical selection is both intuitive and consistent with general cognitive theory (e.g. Miller & Cohen, 2001). Moreover, competition is a natural

explanation for why a semantically related distractor word slows naming times in the picture-word interference paradigm (Schriefers et al., 1990). It nicely explains other phenomena such as the fact that naming pictures from the same semantic category gets progressively slower (Damian, Vigliocco, & Levelt, 2001; Howard et al., 2006): The activation of the semantic competitor(s) increases the time taken to settle on the correct lexical item during the first access step, because it is harder to “see” the right answer when there are activated wrong answers in front of you. What could be simpler? In the last several years, though, some anomalous findings have surfaced. For example, Miozzo and Caramazza (2003) varied the frequency of an unrelated distractor word in the picture-word interference paradigm and found that low-frequency distractors retarded naming more than high-frequency ones. If selection were competitive, one would expect that the more active distractors, presumably the high-frequency ones, would be more potent. Instead, Miozzo and Caramazza suggested that the distractor’s power to slow naming arises because it blocks the naming process at some point and that this block must be removed. Presumably, it is easier to latch onto a high-frequency distractor during this disposal process. Later on, other findings contrary to the competitive hypothesis emerged, such as instances in which related distractors actually speeded naming (e.g. Costa, Alario, & Caramazza, 2005). These findings have inspired alternative accounts of interference in the picture-word interference paradigm—accounts that deny that the first step of lexical access is competitive (e.g. Mahon et al., 2007).

Whether lexical selection is competitive thus remains controversial. And resolving the issue is turning out to be more difficult than expected. As a case in point, we will later present a model of semantic interference, a model that simulates response time effects in picture naming by using competitive selection. However, we will then show that the assumption of competitive selection is not necessary to explain the data.

Connectionism and word production

Before we turn to specific models, it is useful to review the principles that are common to those models. In general, the influential computational models of lexical selection in production are *connectionist* or at least have many connectionist properties. In fact, word production—like word recognition (e.g. McClelland & Rumelhart, 1981)—was one of the first domains to be simulated through connectionist modeling.

A connectionist model contains a network of units. Like neurons, these units or “nodes” possess an *activation* value (often a real number between -1 or 0, and 1), and this value changes as activation passes from unit to unit through weighted links or *connections*. Processing in a connectionist model is carried out by *spreading activation*. The model is given an input by setting the activation levels of its *input units* to particular values. The input for a word production model might consist in setting the activations of units representing the word’s concept to positive values. Then the activation spreads throughout the network via the connections. This spread is governed by the *activation rule*, which specifies how each unit’s activation changes when it receives activation from its neighboring units. Finally, the output of the model is determined by examining the activation levels of a set of *output units*. In a model with two clear steps, there would

first be a determination of the output for the first step, and the relevant output units would correspond to the selected lexical item. This selection would then affect the input to the next step, the output of which would be units representing that lexical item's phonological or phonetic form.

Many connectionist models, such as the model of cumulative semantic interference reviewed later on, include a learning component that determines the weights of the connections. Such a model is trained by giving it many trials, each of which consists of an input activation pattern and (typically) a desired output activation pattern. After the activation has spread on a trial, each connection's weight may be changed by the model's *learning rule*, an equation that computes the weight change as a function of the activation and/or feedback associated with the units on the ends of the connection. For example, a model of word production might receive an input suitable for the CAT concept. But if the model has not yet been well trained, the activation might spread to the output units for RAT instead of CAT, resulting in an error. The learning rule might then change the connection weights so that the retrieval of /k/ is favored over the retrieval of /r/, when the CAT concept is input, thus decreasing the chance of this error in the future. If the model's learning rule is doing its job and the training regimen is a good one, then the network's weights will eventually become well adapted to its task, and its words will be accurately retrieved.

The next two sections summarize two models of lexical access in production, the interactive two-step model of Dell et al. (1997; Dell & O'Seaghdha, 1992), and the WEAVER++ model of Levelt et al. (1999). These models are over 10 years old, but are

still influential. Together, they embody the two empirical traditions of the field; the interactive two-step model simulates speech errors, while WEAVER++ accounts for unimpaired speakers' response times in experimental studies. Then, we present two newer computational models: an application of the interactive two-step model to aphasia, and a learning-based model of semantic interference during lexical access.

Interactive two-step model

The interactive two-step model is succinctly described by its name. It has two clear steps, *word retrieval* and then *phonological retrieval*, but the interactive spread of activation allows for phonological information to influence the first step, and lexical-semantic information to affect the second one.

Both steps of lexical retrieval are carried out by the spread of activation through a network of semantic, word, and phonological units (See Figure 1). Each network connection conveys activation between two units, according to a noisy linear activation rule. The activation sent to a unit is directly proportional to the sending unit's activation and the connection's weight, and the sent activation is just added to that of the receiving unit. Also, every unit's activation decays exponentially toward zero. In this model, all of the connection weights are positive and so decay is the only means by which activation levels are reduced. Importantly, every connection from one unit to another is associated with a connection that runs in the reverse direction. For example, there is a top-down connection from the word unit CAT to the phoneme /k/, and a bottom-up connection from /k/ to CAT. The influence of the bottom-up connections makes the model's retrieval process interactive.

During word retrieval, the semantic units of the target, say, CAT, are given a jolt of activation and this activation spreads through the network for a fixed period of time. This activates the word unit for CAT and potential error units as well. Semantically related word units such as DOG or RAT also get activation from semantic units shared with CAT, and phonologically related words such as MAT or RAT gain activation as well from the bottom-up spread of activation from shared phonemes (e.g. the /ae/ and /t/ units.). Word retrieval is concluded by the selection of the most activated word node of the proper grammatical category. Thus, the model assumes that the selection system 'knows' that the system is looking for, for example, a noun. In this way, the selection process is affected by the anticipated syntactic structure of the sentence. For a task in which pictured objects are named, singular nouns are selected. Because of the noise in the activations, there is some chance that a semantic (DOG), mixed (RAT), formal (MAT), or in extreme cases, an unrelated word may be selected instead of the target. Thus, the model provides a simple mechanism for these lexical level errors.

Phonological retrieval begins by giving an activation jolt to the selected word (e.g. CAT), with all other nodes retaining their residual activation from the first step. The size of the jolt is large relative to the residual activation, thus providing a degree of discreteness to this interactive model. After the jolt is provided, activation spreads again through the network in both directions—up toward semantics and down toward the phonemes—for a fixed period of time. After that, the most activated phonemes are selected. Errors in this step would most likely create nonwords (CAG) or phonologically related words (MAT).

The interactive two-step model accounts for the kinds of errors that occur during lexical retrieval and particularly effects that suggest interaction between representational levels. For example, the model explains the mixed error effect, the tendency for semantic substitution slips to also exhibit phonological similarity. During the model's first step, word nodes for potential mixed errors such as RAT (for CAT) gain activation from shared phonemes via bottom-up spreading activation as well as shared semantic features. Thus, mixed errors are especially likely in the model, as they are in the data. The tendency for phonological errors to create words, or lexical bias, is also due to activation feeding back from phonemes to words. During the second step, an activation pattern that corresponds to a word error (e.g. MAT for CAT) has an advantage over one that corresponds to a nonword (e.g. CAG for CAT). If the phonemes /m/, /ae/, and /t/ are highly activated, they will activate the word node for MAT, which will, in turn, further activate the phonemes, making the error even more likely. Patterns that correspond to nonwords do not have a corresponding word node and hence do not get this extra boost. Thus, slips tend to make words over nonwords. The model also explains other error phenomena through interaction including the repeated phoneme effect (Dell, 1984), the error-proneness of words with few phonological neighbors (Vitevitch, 2002), and the tendency for phonological slips to be semantically related to their contexts (Motley & Baars, 1976). Furthermore, as we show below, the model can account for aphasic error patterns.

To summarize, the interactive two-step model has two clear steps. But its assumption of bi-directional spreading activation makes its retrieval processes both

cascaded and interactive. Because the model assumes a fixed period of time for activation to spread, it does not simulate any response-time phenomena. Moreover, given its lack of sensitivity to time, the model does not take a stand on the question of whether lexical selection is competitive. In one sense, selection is competitive in that the most active word node is always chosen. But the time that passes before such selection is possible is not a factor in the currently implemented model.

WEAVER++

The WEAVER++ model of lexical access was based on Levelt's (1989) general theory of production and was formally developed in Roelofs (1992; 1997) and Levelt et al. (1999). It is similar to the interactive two-step model in that it, too, has a clear distinction between a lemma-access step and subsequent word-form encoding steps, and it retrieves lexical information through a linear spreading activation process that includes decay. In other respects, though, it differs, sometimes fundamentally.

The nodes in WEAVER++'s lexical network (Figure 2) represent lexical concepts (as single nodes, not collections of features), lemmas, morphemes, segments (analogous to phoneme nodes), and syllable programs. The connections between the nodes convey activation, but also represent information about the relation between the connected nodes. For example, the connection between the lexical concept **CAT** (lexical concepts are in bold) and the lemma for CAT indicates that the latter is the name of the former. So, it is not just a conduit for activation; it has a symbolic function as well.

During lemma access, the lexical concept (**CAT**) is flagged as the goal concept and activation spreads from this concept to related concepts (e.g. **DOG**) and lemma

nodes (CAT and DOG). Because the lexical access steps in WEAVER++ are discrete, it does not allow cascading to word form levels during lemma access. Spreading continues until lemma selection is achieved, subject to two requirements. The first is that the lemma-to-be-selected realize the goal concept (e.g. that the selected lemma CAT is the *name* of **CAT** and that **CAT** is the *goal* concept). The second is that the lemma's activation be sufficiently greater than the activation of all the other lemma nodes. This latter requirement makes selection competitive because selection time will increase if other lemma nodes are active for whatever reason.

The semantic relations among the lexical concepts and the assumption of competitive selection enable WEAVER++ to give a good account of basic semantic interference effects in the picture-word interference effect. If a picture of a cat is to be named in the presence of an auditory or visual distractor, this distractor is a source of activation to the lemmas and concepts. In particular, a distractor such as “dog” will enhance the activation of the lemma DOG beyond what is gets from the lexical concept **CAT**, thus slowing the access of the CAT lemma. This semantic interference effect will only arise if the presentation of the distractor is timed so that it impacts lemma access, thus explaining the effects of distractor timing on naming RTs.

WEAVER++ is distinct from other production models in that it takes pains to have a fairly complete account of word-form retrieval, the processes that occur after lemma access, but before articulation. So, it is not just concerned with the retrieval and selection of phonological segments; it deals with how segments are organized into syllables, and how the syllabified phonological representations are used to retrieve

phonetic programs (e.g. Cholin et al., 2006). The model has been specifically applied to many studies using the implicit priming paradigm (Meyer, 1990; Roelofs & Meyer, 1998). In this paradigm, participants produce words from associative cues as quickly as they can (e.g. cue=INFANT, target response="baby"). The critical trials are blocked based on phonological properties; for example, all the words in a block may begin with /b/. The RT's in these blocked trials are compared to those in control trials in which the targets in a block are not phonologically similar. The advance knowledge of the word form associated with the phonologically blocked trials can speed retrieval thus creating priming. It turns out that this only happens when the shared phonological material comprises an initial section of a word. For example, words sharing initial /b/ would benefit from blocking. Moreover, greater similarity leads to greater priming. Sharing initial /bey/ as in a block of "baby" "bacon", and "basin" would reduce RT's more than sharing just /b/ (Meyer, 1991). These findings were neatly explained in WEAVER++ by assuming that word-form encoding can be suspended at various points prior to articulation, and then resumed from that point. (This suspend-resume mechanism is motivated by the incremental nature of production, Levelt et al., 1999.) For example, in a block of words beginning with /b/, the production system can retrieve a /b/ and place it in a syllable-initial position, suspending planning at that point. This is all before the trial even begins. Then once the trial starts and the word to be spoken becomes known, the system resumes word-form encoding. The head start from the advance knowledge makes the response occur more quickly, thus explaining the priming.

In summary, the WEAVER++ model, in contrast to the interactive two-step model, treats lemma access and word-form encoding as discrete steps. Moreover, in both its treatment of lemma access and word-form encoding, it emphasizes accounting for performance in tasks in which production is accurate. In fact, the model's use of labeled relations to verify that what it selects correctly realizes its production goal makes it 100% accurate, unless assumptions about errors in the verification process are introduced. (WEAVER stands for Word Encoding by Activation and *VER*ification.) Hence, WEAVER++ focuses on response-time studies, and it has achieved a high degree of success in explaining effects in the picture-word interference and implicit priming paradigms in particular. The model's ability to explain RT effects stems from its assumption that the selection times for both lemmas and word forms depend on the activation of competing representations as well as target ones. Thus, competitive selection is an important property of WEAVER++.

The final two models that we present are chosen because they represent recent developments in the study of single-word production, but more importantly, because they attempt to confront the challenges associated with studying production using error data, and particularly error data from brain damaged speakers.

Modeling aphasic lexical access

We mentioned earlier that studying speech errors to gain insight into production is not unanimously accepted. If the goal is to understand how the system functions, why look specifically at cases where it malfunctions? The objection only grows stronger when errors are generated by a damaged brain, for now an abnormal system is studied

during a failed attempt at producing a correct utterance. In response, we claim that error data could in fact be quite informative, if two assumptions hold:

(1) *If the nature of speech errors is systematic rather than arbitrary.* This assumption clearly holds, as it is universally accepted that speech errors, even those from aphasic speakers, follow systematic patterns. The errors respect grammatical and phonological constraints and are often quite similar to the target (Dell, 1986; Garrett, 1975). In short, slips are more right than wrong. Moreover, speech error probability is sensitive to the properties of the target word such as frequency, age of acquisition, length and neighborhood density (e.g. Kittredge et al., 2008), all of which have been shown in response-time studies to be indices of lexical retrieval. The error data thus clearly fit with other linguistic and psycholinguistic facts.

(2) *If speech errors produced by brain-damaged patients (aphasic errors) are qualitatively similar to those produced by normal speakers.* Freud (1891/1953) asserted that aphasic errors differ in degree rather than in kind from the blunders of normal speakers. If Freud is right, then a model of lexical access in unimpaired speakers must accommodate errors of aphasic speakers without a need for a change in the structure of the model, provided that one has an accurate characterization of dimension(s) that suffer damage in aphasia. Schwartz, Dell, Martin, Gahl, and Sobel (2006) employed the interactive two-step model of word production (Figure 1) to empirically test Freud's idea, which they called the 'continuity thesis'. The model simulates picture naming by generating responses in six categories: correct response, semantic error, formal error, mixed error, unrelated word error and finally, nonword error. When applied to aphasia,

the model has two free parameters: the strength of the connections between the semantic and word nodes, called s (semantic), and the strength of the connections between the word and phoneme layers, called p (phonological). To illustrate how the model simulates picture naming, let us first consider a normal speaker. Since picture naming is a simple task, an unimpaired speaker would respond correctly on most trials (around 98% correct responses), with occasional errors, almost exclusively of semantic nature (2% semantic errors, 1% mixed errors). To get the model to generate a similar pattern, parameters s and p are varied until an acceptable fit is obtained. At $s=p= 0.04-0.06$, the model exactly mimics these proportions, thus successfully characterizing an unimpaired speaker.

Now, if the continuity thesis is correct, the model must be able to characterize a variety of aphasic patients under the same framework as an unimpaired speaker. Schwartz et al. tested this prediction by ‘lesioning’ the model, or decreasing the values of the s and p parameters and therefore weakening the connectivity between the layers of the production system. They tested a sample of 94 aphasic patients on the 175-item Philadelphia Picture Naming Test and registered the proportion of their responses in each category. For each patient then, the model was lesioned to best simulate the response pattern of that patient by tweaking the s and p parameters. As an example, consider a patient from the Moss Aphasia Psycholinguistic Project Database (Mirman et al., submitted). This patient’s naming profile comprised 58% correct responses, 2% semantic errors, 3% formal errors, 1% mixed errors, 1% unrelated errors and 35% nonword errors. With $s =0.034$ and $p =0.011$ the model closely simulated this pattern

(.55, .02, .06, .02, .01, .34, for the six response categories, respectively). When comparing these values to those of an unimpaired speaker (s and p greater than 0.04) it becomes evident that the model characterizes this patient as having a more pronounced impairment in phonological retrieval rather than in word retrieval, as evidenced by the relatively larger discrepancy between the values of the normal and lesioned p weights.

This fitting procedure was completed for each of the 94 patients, with the fitted models accounting for 94.5% of the variance in the response-category proportions across the sample. The mean patient RMSD (unadjusted root mean squared deviation) was .024. (The RMSD for the patient above is .018, and so the mean fit for the study was slightly worse). Hence, the model can, for the most part, simulate the naming response patterns of a variety of aphasic patients, regardless of the depth of their impairment or clinical syndrome. The model shows a spectrum of graceful degradation from normal to profoundly impaired on the two dimensions of word retrieval and phonological retrieval, indexed by the decreasing values of the s and p parameters respectively. The continuity thesis was thus supported.

In summary, speech errors show systematic and informative patterns even when they are generated by a damaged brain, making an error-based approach a reasonable and complementary companion to the response-time-based approach for studying normal production. This systematicity was made particularly apparent by the use of a computational model, one that could simulate both the normal and the abnormal using the same system. In the remainder of this section, we will briefly discuss two other capacities in which modeling aphasic errors has been used.

Making predictions. Schwartz et al. (2006) showed that the interactive two-step model successfully simulates the picture naming pattern of a variety of aphasic patients. But a model is most useful when it not only fits the data, but is capable of making predictions. Can the interactive two-step model do this? Dell, Martin, and Schwartz (2007) showed that once the model characterizes patients based on their naming performance, it can predict their scores on an auditory word repetition task, without any additional pieces of information. Based on the studies showing the influence of lexical properties such as frequency on repetition, Dell et al. predicted that, at least in some cases, once the word to be repeated is recognized (i.e. selected at the word level), repetition could be accomplished simply by completing the phonological step of lexical access (the 'lexical-route' model; see Figure 3). Therefore, by keeping the s and p parameters recovered from a patient's naming performance, the lexical-route repetition model can predict the patient's repetition score just by running the parameterized model on the phonological retrieval step alone. For example, for the patient with $s = 0.034$ and $p = 0.011$, the lexical-route model predicts 57% correct responses in word repetition. When compared to the actual performance of the patients in an auditory word repetition version of the 175 pictures used for naming, the lexical-route model was successful in predicting repetition accuracy of the majority of patients. However, in some cases it underestimated the accuracy.

Investigation of the alternative models of repetition. The fact that some aphasic patients outperformed the prediction of the lexical-route model in word repetition is hardly surprising. This model has no mechanism to accommodate repetition of a

nonword, a task that normal speakers, at least, accomplish without much difficulty. When a 'nonlexical route', or direct mapping from input to output phonology, is added to the lexical-route repetition model, a 'dual-route' model of repetition is created (Hanley, Dell, Kay, & Baron, 2004; see Figure 3). As an example, recall the patient with $s = 0.034$ and $p = 0.011$, whose predicted accuracy in repetition, as estimated by the lexical-route model, was 57%. In reality, this patient repeated 74% of the words correctly. So, in this case, the lexical-route model underestimates accuracy. Let us now attempt to fit the patient to the dual-route model. To characterize the patient's nonlexical route, the patient's ability to repeat nonwords, a task that must be carried out through the nonlexical route, is tested. This patient repeats only 15% of nonwords correctly. Then the strength of the patient's nonlexical route (nl) is estimated by determining what value of nl would lead to 15% correct repetition of nonwords in an implementation of the nonlexical route. A strength of 0.013 does this. Now, a dual-route model consisting of a lexical part (with parameters s and p determined through the naming simulation) and a nonlexical part (parameter $nl = 0.013$) is run with both lexical and nonlexical sources of activation adding together to yield the model's repetition output. This model predicts 75% accuracy on word repetition, quite close to the patient's actual performance.

Although the dual-route model solved the problem in cases where the lexical-route model failed, the nature of the model remained unspecified. Is labor divided equally between the two routes or is one route used by default? Which route is the default route? Nozari, Kittredge, Dell, and Schwartz (2010) addressed this question by

comparing the effect of the frequency of the target word on repetition errors generated by different repetition models. It is well known that errors are more probable on low-frequency targets in both picture naming and word repetition. Furthermore, studies of naming have shown that frequency affects phonological retrieval more than word retrieval (e.g. Kittredge et al., 2008). Recall that Dell et al.'s (2007) lexical-route model of repetition is simply the phonological step of naming, the step in which frequency exercises most of its influence. Now, if only the errors specific to that step are considered, then the structural overlap between naming and repetition through the lexical-route predicts a *similar-sized frequency effect* in the two tasks. To keep the focus on the phonological retrieval step instead of the word retrieval step, only errors that created nonwords were chosen. According to the model, nonword errors occur at the phonological step; errors in the previous step are necessarily words. Given this, the prediction from the lexical-route model of repetition is as follows: As the frequency of the target word increases, the probability of making a nonword error on that item should decrease by the same amount in naming and repetition. More formally, the slope of the logistic regression relating nonword error probability to the log of target-word frequency should be similar for the two tasks.

To examine this prediction more closely, Nozari et al. first simulated the interactive two-step model of naming, as well as three models of repetition: the lexical-route, dual-route and a pure-nonlexical route model. Specifically, they measured the effect of target-word frequency on the probability of making a nonword error (regression slopes) generated by each model. As expected, the lexical route model

showed a strong frequency effect, similar to that produced by the naming model, and the pure nonlexical-route model, which directly maps input onto output phonology, showed very little frequency effect. Crucially, the frequency effect generated by the dual-route model was no different in magnitude from that of the lexical-route model and both were similar to that generated by the naming model. The simulated predictions for both the lexical-route and dual-route models were confirmed by real patient data. A comparison between the frequency effect in naming and repetition in a sample of 59 aphasic patients showed comparable and sizable effects in both tasks.

The fact that the frequency effects were equally strong in naming and repetition shows that word repetition is as heavily influenced by lexical information as naming is. This finding is consistent with the dual-route model as well as the lexical route model because the dual-route model's nonlexically generated activation is added on top of activations generated through the lexical route; any lexically sensitive differences in activation remain. So, which of these two repetition models is correct? Recall that, aside from frequency effects, the dual-route model predicts that there will be fewer nonword errors in repetition than there are in naming (because activation from the nonlexical route prevents these errors), and that this prediction is not made by the lexical-route model, which lacks the nonlexical route's contribution. In most patients, there were fewer nonword errors in repetition than in naming, even though the frequency effects on these errors were similar for the two tasks. Together, these findings support a dual-route model of word repetition. There is a default lexical route to which the nonlexical route is added by some patients to boost repetition's accuracy.

In summary, computational modeling of aphasic errors is useful for a variety of purposes, including understanding each patient's condition (e.g., fitting to naming data), making predictions about the patient's performance in other tasks (e.g., predicting repetition accuracy from naming) and even studying the architecture of the lexical access system (e.g., investigation of the alternative models of repetition).

Incremental learning during lexical access – the Dark Side model

According to Levelt (1989), unimpaired speakers successfully retrieve 2-3 words per second from an active vocabulary of 40,000. How is this feat of information processing possible? Much of the research on lexical access that we have reviewed represents an attempt to answer this question. This research, however, neglects a key fact: The production system benefits from an extraordinary amount of practice; speakers retrieve an average of 16,000 words per day (Mehl et al., 2007). We claim that the production system learns from every one of these retrieval events, and generally that the system is continually tuned by an implicit-learning process.

The models that we have described until now have all approached speech production as a stable process. But mounting evidence suggests that production constantly adapts to new experience. This point has recently been emphasized for syntactic (e.g. Bock & Griffin, 2000; Chang, Dell, & Bock, 2006; Ferreira, Bock, Wilson, & Cohen, 2008) and phonotactic (e.g. Warker & Dell, 2006) information, but it has long been known that lexical access in production is sensitive to word frequency, repetition priming, and other effects of experience (e.g. Damian & Als, 2005; Howard et al., 2006). Word production models should be incorporating mechanisms for learning and

adaptation. To illustrate, we next describe a recent model of lexical retrieval in speech production that learns through use.

Oppenheim, Dell, and Schwartz's (2010) Dark Side model of lexical access incorporates an incremental learning process to continually tune its semantic-to-lexical mappings. The model's name reflects a claim that incremental lexical learning has a light side and a dark side that work together in this tuning process. The light side learns a target mapping by strengthening connections from activated semantic features to a target word. The dark side unlearns competing mappings by weakening connections from the same semantic features to other activated words. Thus lexical learning is sensitive to activated competitors, a point that we will return to later in this section.

The Dark Side model follows a tradition of division-of-labor models (including MacKay, 1982, the interactive two-step model, and more recently Gordon & Dell, 2003, and Chang, et al., 2006) in characterizing lexical retrieval as emerging from the interaction of semantic activation and syntactic selection. Although the model only deals with the first step of lexical retrieval (lemma or word retrieval), that step has two distinct phases, activation and selection, and a third process associated with learning. In the activation phase, words are activated through their associations with conceptual information, a process that we can tentatively localize to the left anterior/middle temporal lobe (*e.g.* Schwartz *et al.*, 2009). The mapping is implemented as a two-layer feedforward network, where an input of semantic features (*e.g.* MAMMAL,

TERRESTRIAL) activates an output of localist word nodes (*e.g.* DOG; see Figure 4).¹

Noise in the lexical activations reflects a modicum of input from externalities and, as in the interactive two-step model, such noise provides a basis for lexical selection errors, particularly when the model is simulating brain damage.

The second phase entails selecting a single syntagmatically appropriate word for production, a process that we can associate with neural activity in the left inferior frontal gyrus (*e.g.* Schnur *et al.*, 2009). As in the WEAVER++ model (and unlike the interactive two-step model), lexical selection in the Dark Side model unfolds over time, allowing it to account for response time data. Selection is implemented via a booster mechanism, which repeatedly floods the lexical layer with additional activation, combining nonlinearly with the existing lexical activations.² Boosting continues until the activation of one of the lexical nodes is sufficiently greater than that of other nodes, at which point that node is considered to be selected. Thus, selection latencies reflect target and competitor activations, as in WEAVER++. However, unlike WEAVER++, the Dark Side model is not bound to select the correct word. Omission errors occur when boosting continues for too long without producing a clear winner and, since the selection process is blind to the desired outcome, noisy activations can even lead to selecting an undesired word (*e.g.* BAT instead of DOG). Thus, the model predicts response time as well as errors.

¹ While the implemented model only contains forward-spreading activation, this merely reflects the limited scope of the model, rather than a theoretical claim against cascading activation or feedback.

² Although the constraint is not implemented in the model, it is assumed that the booster activation is limited to words that are syntagmatically appropriate for the current context. So, for example, selecting DOG would not entail boosting BARKED.

Crucially, the model assumes that while people may rapidly acquire new vocabulary, they never truly stop learning the words that they already know. To understand how this works, we can imagine a trial in which the model attempts to retrieve the word DOG. As discussed earlier, two factors might make it difficult to quickly and accurately retrieve DOG: first, if DOG is too weakly activated, and second, if other words (*e.g.* BAT, WHALE) are too strongly activated. The Dark Side model addresses both of these problems by employing an error-based connectionist learning algorithm (specifically, the delta rule) to continually adjust each connection as a consequence of its use. The light side of incremental learning addresses the first problem by strengthening the connections that support retrieving the target word (*e.g.* MAMMAL→DOG), and dark side addresses the second problem by weakening the connections that would support retrieving its competitors (*e.g.* MAMMAL→BAT, MAMMAL→WHALE). With its stronger connections, retrieving DOG a second time will become faster and more accurate. But since its connection from the shared MAMMAL feature (*i.e.* MAMMAL→BAT) is now weaker, retrieving BAT will become slower and more error prone. Moreover, since the connections supporting DOG have just been strengthened, with a little noise in the lexical activations, DOG will be more likely to emerge as a semantic error on the BAT trial. Similarly, a subsequent attempt to retrieve WHALE will be even slower and more error prone because its connection from the shared MAMMAL feature will have been weakened twice. A further point to note is that, because learning is driven by relevant experience, any connection changes should persist indefinitely unless other learning overwrites them.

The Dark Side model offers an integrated account of effects in both speech errors and correct naming latencies that arise from persistent changes to semantic-to-lexical mappings, such as cumulative semantic interference. Cumulative semantic interference refers to the phenomenon that meaning-based lexical retrieval becomes increasingly difficult when speakers retrieve a series of semantically related words. For instance, when naming pictures from a single semantic category, like DOG, BAT, WHALE, the typical finding is that unimpaired speakers take slightly longer to name each picture (*e.g.* Howard *et al.*, 2006; Navarrete, Mahon, & Caramazza, 2010), and speakers with aphasia make increasing numbers of semantic errors and omissions (*e.g.* Schnur *et al.*, 2006). In the model, increasing response times chiefly reflect the dark side of incremental learning: previous competitors have weaker connections from shared semantic features, so they have weak activations that are more similar to those of their competitors, thus leading to slower retrieval. Retrieving multiple words from the same semantic category therefore elicits slower responses because each word from that category has previously acted as a competitor. Noise in the lexical activations—as one might expect to increase with brain damage—can turn these slow responses into omission errors. Semantic errors also require noisier activations in the model, but they further reflect the light side of incremental learning: competitors that have more recently served as targets retain stronger connections from shared semantic features and thus are more likely to emerge as errors. Semantic errors from aphasic patients particularly support this interpretation, because the words that speakers produce in error tend to match their most recent responses, irrespective of timing manipulations

(Hsiao et al., 2009). In fact, all of the interference effects are robust to short timing manipulations (Howard et al., 2006; Schnur et al., 2006) and persist when same-category pictures are interspersed with unrelated ones (*e.g.* Damian & Als, 2005; Howard *et al.*, 2006; Oppenheim, in prep), suggesting that they reflect relatively persistent changes to the lexical access system. Indeed, there is some indication that the semantic interference that accumulates from naming a series of related pictures remains detectable even an hour later (Oppenheim, in prep), strengthening the model's claim that cumulative semantic interference reflects the mechanisms by which people learn and maintain their vocabularies.

The Dark Side model can also inform the question noted earlier of whether lexical selection is competitive in the sense that having an activated competitor slows down target retrieval. Although cumulative semantic interference has been claimed as support for a competitive selection process (*e.g.* Howard, et al., 2006), Oppenheim et al. (2010) demonstrated that using a competitive algorithm for lexical selection did not contribute to the model's account of any aspect of the phenomenon. Instead, the model's performance indicated that the dark side of learning (*i.e.* weakening connections to activated competitors on previous trials) implemented sufficient 'competition' to carry the effects. Thus, while there may be other reasons to hypothesize a competitive mechanism for lexical selection (as noted earlier), competitive selection may in practice be difficult to distinguish from competitive (error-based) learning.

Finally, we note that the Dark Side model is the only production model to simulate normal and aphasic speech errors, as well as response times, in the same task. By explaining all of these data, it addresses the quandary described at the beginning of this chapter. There is no longer any debate about whether one should explain errors or response times, if the same model can explain both. It should be recognized, however, that the model is purchasing its ability to explain a variety of data types by focusing on just a single step of the lexical access process and a specific set of phenomena that occur during this step, those associated with cumulative semantic interference.

Conclusion

Computational models of word production have achieved some success in explaining both the normal and the abnormal products of production. Also, through the models, we better understand theoretical notions such as stages and steps, cascading and interaction, competitive selection, and implicit learning, and even have achieved a degree of consensus on some points, such as the role of cascading in a multi-step production process. Much has been discovered since Garrett (1975) and Levelt et al. (1999) demonstrated the power of speech-error analysis and experimental methods, respectively, and, although many issues are far from settled, lexical-access theory is in pretty good shape. Now, that theory needs to transcend object-picture naming and other single-word methods and measures, and link up with the wider world of production-- with theories of utterance generation in multi-speaker interactions (see CHAPTER W), acquisition (see CHAPTER X), speech articulation (see CHAPTER Y), and with the cognitive neuroscience of language (see CHAPTER Z).

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Figure 1. Interactive two-step model of lexical access

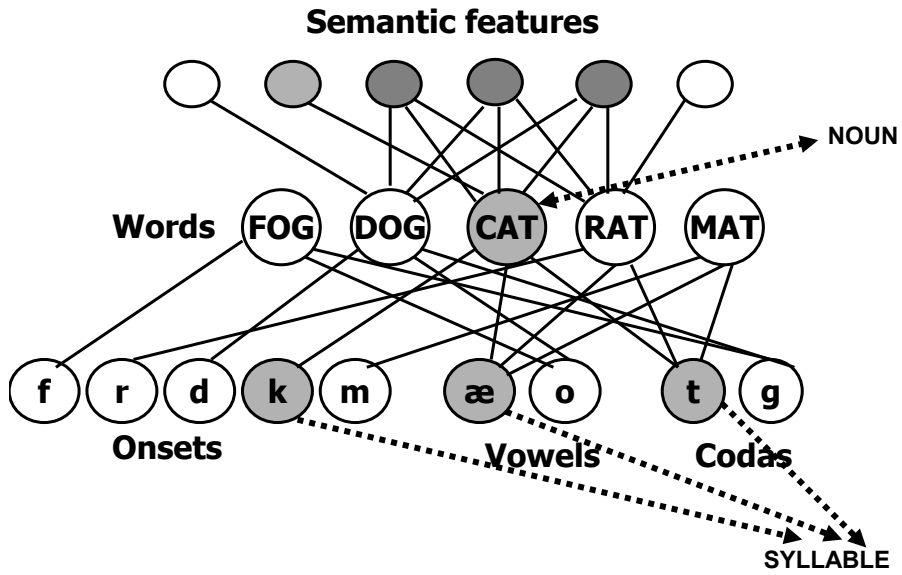
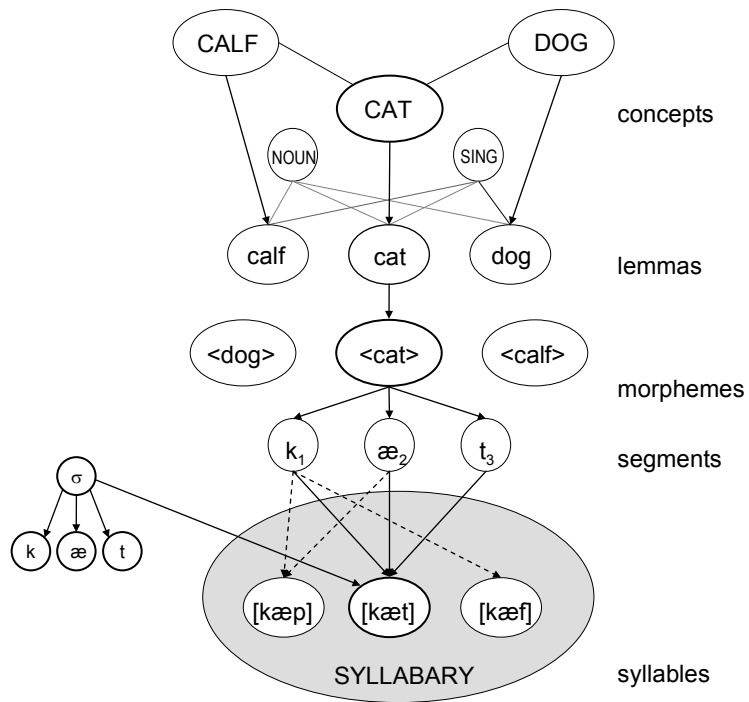


Figure 2. The WEAVER++ model of lexical access in production.



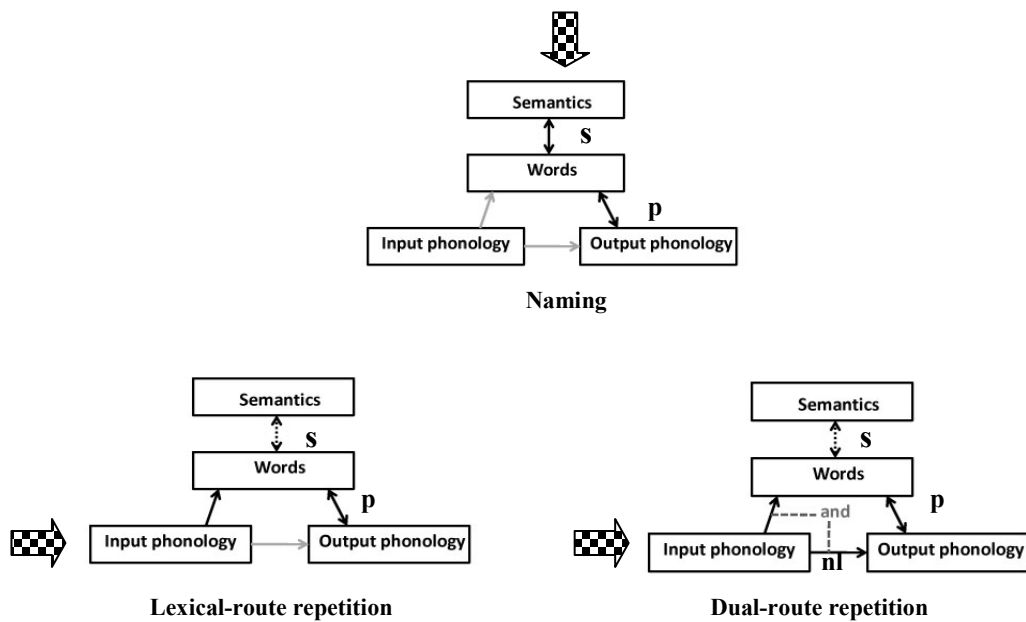


Figure 3- Models of naming, lexical-route and dual-route repetition with their relevant parameters. Dashed arrows represent involvement through feedback only. Gray arrows represent an inactive route. Patterned arrows represent the source of input to the model. Output phonology is always the output of the model. In the naming model, semantic (parameter s) and phonological (parameter p) connections operate bidirectionally. In the lexical-route repetition model, phonological connections are bidirectional, but semantic connections are employed only through feedback. In the dual-route model the nonlexical route (parameter nl) is added to the lexical-route model.

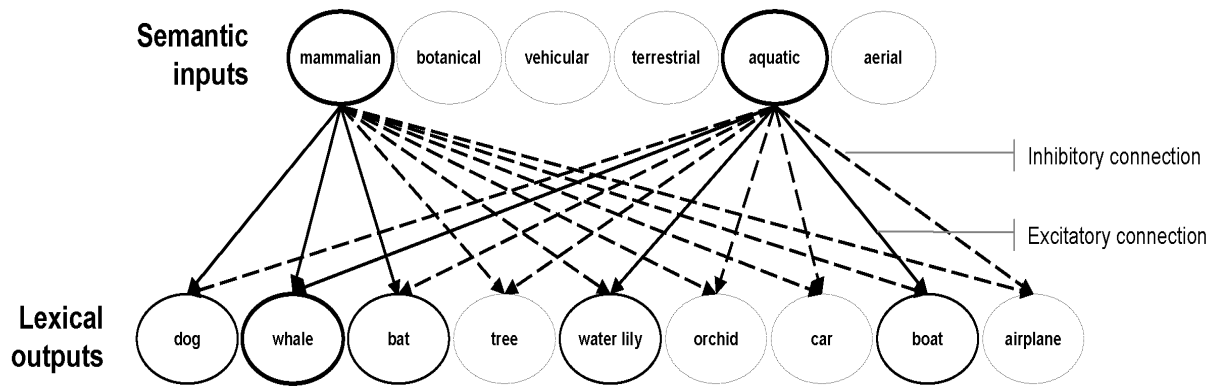


Figure 4. The lexical activation component of Oppenheim, Dell, and Schwartz's (2010) Dark Side model of lexical retrieval.