Signal detection theory analyses of semantic priming in word recognition

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Abstract

Evidence concerning the nature of the processes underlying word recognition and semantic priming, as well as general questions of cognitive impenetrability, has come from metaanalyses, empirical studies, and computer simulations of models. In this research, various Signal Detection Theory (SDT) measures have been used to separately evaluate perceptual effects and post-perceptual decision changes. The Norris (1986) checking model of semantic priming, and the Norris (1995) simulation of this model, are often cited both as strong existence-proof that purely post-perceptual criterion changes can alter perceptual sensitivity and as the definitive statement that SDT is inappropriate for the investigation of complex cognitive processes. According to the model, priming alters only post-perceptual criteria for word decisions: priming the stimulus-related word reduces uncertainty, which increases sensitivity; priming stimulus-unrelated words increases false alarms more than hits, resulting overall in a reduction in sensitivity. In contrast to these two claims, our Norris simulation analyses indicate that related word priming does not directly alter sensitivity, and unrelated priming only increases false alarm rate, which reduces sensitivity. In developing the framework for our analysis, we describe the derivation of SDT from statistical decision theory. This background allows new perspectives on concepts of decision processing as used in SDT, the Norris model, and the more traditional word recognition literature.

[End of Abstract]
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One component to the often-heated debate about whether perceptual systems are cognitively impenetrable (e.g., Pylyshyn, 1999) is the conjecture of a modular semantic system, with an encapsulation of perceptual processes. If the semantic system is modular, then the input analyzers would be “informationally encapsulated from the central, semantic system . . . (this) encapsulation allows the perceptual modules to be fast and reflex like (i.e., obligatory). . . and insulated from top-down influences” (Rhodes, Parkin, & Tremewan, 1993, p. 155). Based on a meta-analysis of relevant research studies, Farah (1989) argued that the mechanism responsible for perceptual priming is encapsulated and qualitatively different from the mechanism responsible for semantic priming. To refute this claim, Rhodes et al. (1993) presented empirical findings that were argued to demonstrate perceptual priming “based upon semantic properties of a stimulus” (Rhodes et al., 1993, p. 154), with the clear implication that the perceptual input mechanism is influenced by more central semantic processes. With the explicit goal of separating perceptual sensitivity from post-perceptual decision processes, both Farah (1989) and Rhodes et al. (1993) used descriptive statistics from two models of Signal Detection Theory [d’ and β; A’ and B’]; with these statistics computed from single data points (Hits, False Alarms).

Norris (1995) took strong issue with the use of “unidimensional” Signal Detection Theory (SDT) to address questions about perceptual encapsulation and the nature of priming effects in Lexical decisions. To support his position in favor of perceptual encapsulation, Norris presented simulation results claimed to demonstrate changes in a SDT sensitivity measure caused solely by post-perceptual changes in criteria. The simulation was based upon his checking model of semantic priming (Norris, 1986). This model posited a simple, automatic, encapsulated perceptual process, with priming acting as purely post-perceptual, decision-level changes in criterion or bias. Specifically, changes in criterion were claimed to alter uncertainty, and changes
in uncertainty were claimed to alter sensitivity. The goal of the simulation was to demonstrate that criterion changes could produce the pattern and magnitude of changes in sensitivity reported by Rhodes et al.

In subsequent debates about cognitive impenetrability and the nature of the Lexical priming processes, several major position papers (Masson & Borowsky, 1998; Pylyshyn, 1999; Norris, McQueen, & Cutler, 2000; Goldinger, 1998) have cited Norris (1995) both as the definitive statement on the relevance of SDT to this debate and as an existence-proof that purely post-perceptual criterion changes can alter measures of perceptual sensitivity. In this literature, SDT analyses are sometimes not consistent either with interpretations of research using other descriptive statistics (e.g., RT, where underlying assumptions are usually, at best, implicit) or with the researcher’s notions about the operation of components to the priming process (e.g., different levels of priming). In this context, the Norris criticisms, and his model simulation, have become a basis for dismissing the use of SDT measures (e.g., Goldinger, 1998; Masson & Borowsky, 1998). Some aspects of the Norris (1995) criticisms of SDT are valid, but many reflect modern, widely held misconceptions about that theory; these broad misconceptions are addressed elsewhere (Pastore, Crawley, Berens, & Skelly, in press). Although our current focus is on the validity of the Norris (1995) simulation as the stated existence-proof, parts of the arguments about the existence-proof are based upon assertions about SDT. We thus begin with a brief summary of assertions by Norris (1986, 1995) and others about SDT, and a brief description of the actual nature of SDT. With this background, we will be able to provide a careful analysis and understanding of the Norris (1995) simulation. Our analysis will demonstrate that the version of the Norris (1995) model in the simulation and, by generalization, the Norris (1986) model, operates in a manner that is very different than the purely post-perceptual manner described by Norris (1986, 1995).
Assertions about SDT. Several important, but inaccurate, working premises are sometimes found in both the Lexical decision literature and the debate about cognitive impenetrability. One premise is that traditional SDT measures of sensitivity and bias are independent of each other, with sensitivity (i.e., d’ and A’) and bias or criterion (i.e., β or B”) respectively reflecting only separable perceptual or input effects and post-perceptual effects. For example, Rhodes et al. (1993) explicitly assume that changes in SDT measures of sensitivity reflect perceptual changes, whereas changes in SDT measures of criterion reflect post-perceptual changes. A second, often encountered, premise is that A’ and B” are nonparametric measures that, in contrast to the Gaussian Equal-Variance assumptions underlying traditional SDT (i.e., d’ and β), make no assumptions about the nature of underlying distributions. Although not immediately obvious, it is also relevant that, in both Lexical priming research and the modularity debate, measures of sensitivity and bias are always computed for single data points (hits and false alarms). Finally, Norris (1986; 1995) asserted that the unidimensional nature of the SDT decision variable makes SDT inappropriate for use in analyzing complex, multidimensional processes, such as semantic processing.

Norris (1995) specifically argued that the conclusions of Rhodes et al. (1993) reflect invalid assumptions about traditional Signal Detection Theory (SDT) and the inappropriateness of traditional unidimensional SDT for analyzing complex, multidimensional processes. In essence, Norris is credited with the assertion that “standard signal detection theory has no means of capturing the selective reduction in response criteria and therefore misrepresents a criterion shift as a change in sensitivity” (Masson & Borowsky, 1998). Furthermore, “the claim that changes in measured sensitivity are a direct reflection of changes in the sensitivity of some early perceptual process is only true under the specific set of assumptions made by signal detection theory” (Norris, 1995, p. 936). The importance of the Norris (1995) simulation, then, is the claimed demonstration that changes in purely decision-level criteria or bias, specifically the “selective
lowering of logogens criteria[,] could produce an increase in sensitivity as measured by signal
Because it is a simulation, Norris (1995) has provided sufficient detail to allow a careful analysis
of the operating behavior of the components of his model simulation. Our analysis will
demonstrate that the Norris model is essentially a threshold model. More important, when
criterion changes in the model alter measures of sensitivity, they do so, almost exclusively,
through unrelated priming that increases the effectiveness of noise in the processing system. In
essence, the model operates by amplifying some of the noise, with the resulting increase in False
Alarm rate causing a reduction in sensitivity.

Summary of relevant aspects of SDT.

Pastore, Crawley, Berens, and Skelly (in press) provide a detailed discussion of problems with
these and other aspects of modern conceptualizations of SDT. Several basic, briefly stated points
from this other work are needed for the current discussion. First, the too common modern
conception of traditional SDT is actually a limited and distorted version of one SDT model, the
Gaussian Equal-Variance model. SDT is a specific instantiation of statistical decision theory
(Wald, 1950; 1952). Both theories model the processes that achieve a decision based upon the
statistical properties of the available evidence.¹ Thus, as a broad theory, SDT posits a
statistically-based evaluation of the evidence relevant to each decision alternative. Because
evidence is rarely assumed to be unidimensional, the alternative decision categories can be
represented as having a distribution of evidence in multidimensional space. We will consider the
common task that has two decision alternatives. Although one can conceptualize a set of
hierarchical processes that first evaluates the two alternative decisions for each dimension of the
evidence, then combines the initial decision outcomes across the many dimensions, the best
statistical decision model for this set of hierarchical processes is one that represents the combined
distribution of evidence along a unidimensional decision axes that transects the two decision
alternatives (Wald, 1952). In simple terms, even though the evidence is assumed to be multidimensional (an assumption common to Statistical Decision Theory, SDT, and most models in psychology), the functional decision variable for each binary decision is unidimensional. Because a Lexical (word-nonword) decision, such as the one modeled by Norris (1986, 1995), is a binary decision, the functional decision variable is unidimensional. Thus, whereas adding the label “unidimensional” to SDT may be a creative strategy to dismiss research findings that one wishes to refute, the basis for the label is the task used by the researcher (e.g., Lexical decision), and applies equally well (or poorly) to any model or theory used to analyze the results of such a task, including the Norris model.

Decision versus process models. All decision theory (including SDT) measures of sensitivity [e.g., $d'$, $A'$, $\ln(\alpha)$] reflect the statistical separability of evidence for the two decision alternatives (this is equivalent to the power of an inferential statistical test), whereas the various SDT and other decision theory measures of criterion or bias [e.g., $\beta$, $\ln(\beta)$, $c$, $B''$] reflect the decision rule (this is equivalent to the criterion for significance in inferential statistics). SDT and inferential statistical tests are models of decisions based upon the available evidence, and NOT models of the processes that obtain and evaluate the available evidence. Like inferential statistics, SDT does NOT make any assumptions about the nature of the evidence or the evidence processes (i.e., perceptual, post-perceptual, memory, semantic, or all of these). SDT, and inferential statistics, can be used to evaluate the decision outcome of actual or modeled behavior (e.g., current analyses; Tanner, 1961).

Uncertainty. Knowledge about the relationship between evidence and the decision alternatives is important in the evaluation of the available evidence. The degree of accuracy, precision, or uncertainty in the observer’s knowledge therefore plays a role in determining both the variability and degree of separation of the statistical distribution of evidence for the alternative decision categories. Uncertainty therefore should be a factor in determining any
descriptive statistic that reflects the observer’s decision-making ability (e.g., d’, A’). The observer’s knowledge or beliefs about the relative likelihood that the alternative decisions will be valid (e.g., signal probability) or about costs and benefit of each decision alternative should not alter the distribution of evidence for the alternative decisions, but should be a factor in determining the decision criterion used by the observer. Such uncertainty about decision outcomes should be reflected in the placement and stability of the criterion. Therefore, uncertainty is not a universal construct whose reduction will result in increases in descriptive statistics for accuracy (e.g., percent correct) or sensitivity (e.g., d’ or A’). Uncertainty reflects the quality, precision, and accuracy of a specific type of knowledge, and the nature of the knowledge determines whether the change in uncertainty will alter sensitivity or criterion (e.g., Green & Swets, 1966; Swets & Sewall, 1961). Thus, a change in criterion may reflect a change in a specific type of uncertainty, but, unless that change improves the separation of the statistical distribution of evidence, the change in uncertainty should not result in an increase in d’ or A’.

Independence. In the Gaussian Equal-variance model of SDT, the measures of sensitivity and criterion are independent when the underlying assumptions are valid. This independence, however, is not symmetric (Pastore et al., in press). If the available evidence is constant, then changes in criterion should not alter the statistical distributions of evidence for the alternatives, and thus should not change sensitivity. A change in the statistical distribution of evidence, however, should alter the ability to decide between the alternatives, but has no implications for the criterion; there is nothing in SDT that requires a fixed decision criterion when the evidence changes. Therefore, criterion changes should not alter sensitivity, but sensitivity changes can alter criterion.

Nonparametric measures. Finally, when A’ and B” are computed from a single data point (hits, false alarms), these descriptive statistics are definitely NOT nonparametric (Macmillan & Creelman, 1990, 1996; Pastore et al., in press). Specifically, because a multipoint ROC curve
reflects the underlying distribution that exist (and thus does not require assumptions about the nature of those distributions), the area under a multipoint ROC curve approximates a nonparametric measure of ability. In contrast, the area under a single point ROC curve can be estimated only by making assumptions about the shape of the ROC curve, and thus cannot be nonparametric. More generally, any measure of ability, when computed for a single data point, is based upon explicit (or implicit) assumptions about the underlying distributions. If the assumptions about the underlying distributions are not valid, then the measures of ability and bias (e.g., d’ and \( \beta \), A’ and B”) will not be independent and each will be a distorted representation of the underlying processes. If there is a reasonable approximation to the underlying assumptions of a descriptive statistic (e.g., d’ and \( \beta \)) or inferential statistical test (e.g., Student-t, ANOVA), however, then the properties of the measurement theory will be reasonably valid.

*SDT in current analysis.*

Based solely upon the points we have summarized, there clearly are a number of serious problems with the Norris (1986, 1995) criticisms of SDT as well as with modern attempts to use SDT to support different views on encapsulation of the perceptual processes (e.g., Rhodes, et al, 1993). Both the Rhodes et al. (1993) empirical study and the Norris (1995) computer simulation are typical of these more traditional approaches to research, where descriptive statistics (e.g., A’ or d’ and B” or \( \beta \)) are measured under specific conditions, with inferences made about the nature of the intervening processes. Our analysis will demonstrate how SDT can be used effectively to analyze complex decision models, identifying the behavior or operating characteristics of the component processes and the interactions of these processes. These operating characteristics allow us to understand the effects of changes in parameters or conditions on each internal component stage in the decision processes that determine the final descriptive statistics. This understanding provides meaning to the concepts of sensitivity and bias that are associated with the descriptive statistics.
Our current analysis employs basic, but seldom used, SDT procedures to evaluate the nature and the behavior of processes that Norris (1986, 1995) proposed to describe the perceptual and the post-perceptual components of semantic processing and priming. One major goal in the development of SDT was the ability to evaluate the performance of different ideal observer models by plotting the pattern of results as a function of different conditions, different underlying assumptions, and changes in the decision criteria (e.g., Tanner, 1961; Swets, 1964, 1996; Swets, Tanner, & Birdsall, 1961). In these analyses, the processing models specify the nature of information processes and SDT provides the model for optimal decisions, with the results typically plotted in ROC space. ROC space is simply the mapping of the probabilities of alternative decision outcomes (hits versus false alarms) as a function of criterion. The advantage to the ROC-based approach is that the researcher and the scientific community can observe the general performance characteristics of the model and its component stages, usually without having to make strong assumptions, such as those required for drawing broad inferences from individual data points (e.g., Egan, 1975). This basic approach does not impose any assumptions other than those of the model being evaluated. Unfortunately, the use of this powerful approach to model evaluation requires a specification of the underlying processes that is more detailed than the general concepts described in most of the semantic priming literature. The Norris (1995) simulation of critical aspects of the Norris (1986) checking model provides the needed detail. Because a goal for Norris (1995) was to demonstrate that the Norris checking model could replicate the findings of Rhodes et al. (1993), Norris (1995) used the descriptive statistics of $A'$ and $B''$ as measures of sensitivity and bias. We will demonstrate that known problems with $A'$ result in a somewhat distorted perspective on the performance of components to the Norris simulation. We therefore analyze the performance of the Norris model simulation in terms of isosensitivity contours for both $d'$ and $A'$. Finally, although the Norris (1986) model and (1995) simulation may be atypical of the organizational structure of processes usually conjectured to be
important for priming in a Lexical decision task, understanding the actual functioning of the components in his model simulation can provide insight into the functioning of these components in a more typical organizational structure (e.g., Neely, 1991; Farah, 1989; Rhodes et al, 1993; Masson & Borowsky, 1998).

Norris Checking Model and Simulation.

We begin our analysis with a brief description of the elements of the Norris (1986) checking model that are specifically relevant to the Norris (1995) simulation, followed by a brief description of the nature of the simulation and the reported findings. These descriptions are especially important because, even with a careful reading, it is not simple to understand the exact nature of the simulation conditions. Once we describe the nature of the simulation and the assumed properties of the processing mechanisms in the model, we will analyze the functional behavior of the model’s component processes for each of the conditions in the simulation. Finally, we will use our analyses not only to re-evaluate the Norris simulation, but also to address central premises in the debate about whether there is perceptual encapsulation for a modular semantic system.

In the Norris (1986) model, each word in the Lexicon is represented as a collection of features, and each of these words has a criterion or threshold number of features required for a match. When a word or nonword stimulus is presented, only some of the stimulus features are perceived. The perceived features are compared with the features of each word in the Lexicon. If the number of matched feature meets or exceeds a word’s threshold, the presented stimulus is identified as that word. If the perceived stimulus fails to meet or exceed the threshold for a match to any word in the Lexicon, the stimulus is identified as a nonword. Priming and context effects are conceptualized in terms of changes in word thresholds; specifically, priming a word lowers the threshold for the primed word in the Lexicon. This type of priming is based upon the relationship between a stimulus presented for identification and the primed word in the Lexicon.
being evaluated for a match. Each nonword is derived from a word stimulus and this related stimulus pair shares a maximum number of features. The presentation of either (word or nonword) member of a related stimulus pair defines the related word; specifically the word from that pair. Related priming is defined by the priming (lowering of threshold) of that related word. Unrelated priming is defined as the priming of other (unrelated) words in the Lexicon. Because related and unrelated priming are based upon different words in the Lexicon, it is possible to simultaneously have both related and unrelated priming.

In the Norris model, the perceptual system operates in a simple, automatic, imperfect fashion, without any top-down influence. Another problem with the Norris model is that strictly feature-based, logogen type models have long been known to be too limited to account for many factors (e.g., word frequency, word repetition, meaningfulness) that affect Lexical decisions (e.g., Balota & Chumbley, 1984). As already noted, semantic context and priming effects are attributed to strictly post-perceptual changes in the decision criteria or thresholds for word recognition. In the Norris model, the effects of semantic priming on SDT descriptive statistics are based upon two relatively imprecise arguments. First, “although the effects of context in the checking model are mediated by changes in recognition criterion, these changes operate in a manner which leads to changes in $d'$ as well as beta. This is due to the fact that the priming word in a Lexical decision experiment will almost inevitably lead to a reduction in stimulus uncertainty which will allow even a criterion bias system to effect an increase in $d'$ on validly primed trials” (Norris, 1986, p. 126). Thus, related (or valid) priming will produce increases in $d'$. In addition, “so long as the context effects are associated with an increase in the nonword error rate it might seem that context should alter beta and not $d'$. But, Lexical decision provides a rather imperfect approximation to the ideal signal detection task” (Norris, 1986, p. 127). Unrelated priming is later described as having a greater effect on nonword (as opposed to word) matches to words, which translated into a greater effect on false alarm than hit rate (Norris, 1995). Thus, according
to the model, the criterion changes due to related and unrelated priming will have opposite effects on sensitivity. These are very broad, relatively imprecise statements about why aspects of the checking model will alter descriptive SDT statistics. From a general SDT perspective, a greater effect on false alarm rate can result in a reduction in SDT measures of sensitivity (as well as any other reasonable measures of sensitivity), but (as noted earlier) there is no reason to assume that a change in sensitivity will not be accompanied by a change in criterion. Our current analysis of the Norris (1995) simulation of his checking model will demonstrate that the criterion changes described in the model will directly produce either no change or a decrease, but not an increase, in sensitivity (i.e., $A'$ or $d'$). Furthermore, the statistical properties of the Norris (1995) Lexical decision simulation provide a very good approximation to the assumptions of the Gaussian Equal Variance model of SDT.

*Norris simulation details.* In the Norris (1995) simulation, there was a simple Lexicon of 500 words. Each word was defined by a unique set of 20 features that have been sampled from a population of 30 possible features, with each word in the Lexicon differing from every other (thus, unrelated) word by at least 4 features. Each of the 500 words had a *related* nonword that differs from that word by exactly 4 features. There thus were 500 *related* (word-nonword) *stimulus pairs*. Specifically, each related word-nonword pair shared exactly 16 of their 20 features. [Although not stated, it seems implicit that each nonword differed from each of the 499 unrelated words by at least 4 features. Furthermore, because each stimulus has 20 out of the 30 possible features, any pair of stimulus must share a minimum of 10 features (10 unique features for each plus 10 shared features $= 30$ features).] Based upon the sampling statistics, each (word or nonword) stimulus shared between 10 and 16 features with every other stimulus. The full set of 500 word-nonword pairs represented the corpus of 1000 stimulus items that were used in the simulation.
A Lexical decision task requires a decision about whether a word or a nonword stimulus was presented. In Norris (1986, 1995), a word decision reflected a match between the presented stimulus and a word in the Lexicon, and each of the 500 words in the Lexicon had a “criterion” or “threshold” number of feature matches required for recognition; in Norris (1986, 1995) criterion and threshold were synonymous. In the Norris (1986) model, the threshold varied across words, in the Norris (1995) simulation, the thresholds could have only one of two values: the unprimed or the primed value. In the simulation, priming of a word nominally lowered that word’s threshold by 1 feature; our analysis will demonstrate that the unprimed and primed threshold values were, respectively, 14 and 13 feature matches. In the simulation, the equivalent priming effect was actually produced by adding one to the count of perceived feature matches for each comparison with a primed word. In this way, Norris (1995) implicitly acknowledged a functional equivalence between lowering a threshold and increasing information channel gain (i.e., weight of perceived feature matches) for comparisons with a primed word.

Functionally, each trial in the simulation involved the selection of one of the 500 related (word-nonword) stimulus pairs. That stimulus pair then defined both the possible presented (word or nonword) stimulus and the related word in the Lexicon. For all related priming conditions, the word from that selected stimulus pair was primed. For all unrelated priming conditions, there was priming of some words unrelated to the presented stimulus.

In the simulation, a rudimentary initial “perceptual” process was represented by an automatic, statistically-based (thus imperfect or noisy) feature recognition process. This dumb front-end process accurately recognized each of the 20 features in the presented stimulus with an independent probability of 0.7. The perceived features were then compared with the features in each of the 500 words. If the number of perceived matching features exceeded an individual word’s threshold, the presented stimulus was judged to be that word. Therefore, the match of a presented (word or nonword) stimulus to a word required that a supra-threshold number of
presented features were perceived and that a supra-threshold number of the perceived stimulus features matched the features present in that word. The specific threshold or criterion value depended upon whether or not the Lexical word was related to the stimulus and whether or not the word had been primed. Judgment of the stimulus as a nonword required a failure to match any of the 500 words in the Lexicon. A hit (H) was the identification of a word target as being a word; a false alarm (FA) was the identification of a nonword target as being a word. The values of P(H) and P(FA) from the simulations were used to compute A' and B”, the “nonparametric” measures of sensitivity and criterion (Pollack & Norman, 1964; Grier, 1971).

The full simulation consisted of 100,000 trials for each of five conditions that were defined by the nature and number of words that were primed. The five basic conditions of the Norris simulation are summarized in Table 1. The conditions differ in whether or not the one related word had been primed and also in the number of the 499 unrelated words that had been primed. The second column in Table 1 lists the symbols used in plotting the condition results in Figures 1 and 2. In the Neutral (or Zero-Word Priming) condition, there was no priming, with performance in this condition defining a baseline standard for evaluating increases or decreases in sensitivity due to priming in the other four conditions. In the 1-Word Related Priming condition, the word from the (related word-nonword) selected stimulus pair was primed. [In our description, the presented stimulus is either the word or nonword from the selected (related) stimulus pair.] In the 1-Word Unrelated Priming condition, one word again was primed, but that word was not the word in selected stimulus pair, but rather one of the 499 other (or unrelated) words. Skipping to the last of the listed conditions, the 50-Word Unrelated Priming condition was equivalent to the 1-Word Unrelated Priming condition, but now there was priming of 50 words that were unrelated to the presented stimulus. The final condition was a hybrid that of the 1-Word Related Priming
and (a 49 word approximation to) the 50-Word Unrelated Priming conditions; this Hybrid 50-Word Related Priming condition was the only condition with both related and unrelated priming.

Norris simulation results. The results originally reported in the Norris (1995) simulation are presented in Table 2A. For each condition, the basic data were expressed as \( P(H) \) and \( P(\text{FA}) \). [In Figure 1, these same \( P(H) \) and \( P(\text{FA}) \) results are plotted in ROC space using the symbol listed in the second column of Tables 1 and 2.] In Table 2, the column labeled “Reported” summarizes the “Nonparametric” descriptive SDT statistics reported in Norris (1995) to reflect sensitivity (\( A’ \)) and criterion or bias (\( B” \)). As noted above, the Neutral condition provides a baseline for evaluating the effects of priming. In the Norris model, related priming is said to reduce uncertainty, which, in turn, increases sensitivity (\( A’ \)). Based upon the values of \( A’ \) reported by Norris (1995), the 1-Word Related Priming condition did exhibit a small increase in sensitivity. In the Norris model and simulation, unrelated priming was described as reducing sensitivity by inflating \( P(\text{FA}) \) more than \( P(H) \). There was a small decrease in \( A’ \) for the 1-Word Unrelated Priming condition and a significant decrease in \( A’ \) for the 50-Word Unrelated Priming condition. Finally, the Hybrid 50-Word Related Priming condition, which combined the priming that separately defined the 1-Word Related Priming and the 50-Word Unrelated Priming conditions, did seem to exhibit a cancellation of the increase in sensitivity from related priming and the decrease in sensitivity for the large degree of unrelated priming. These reported \( A’ \) and \( B” \) results appear to be consistent with the effects of Related and Unrelated priming described in the Norris model and the empirical results reported by Rhodes et al. (1993), but at least one \( A’ \) value seemed at variance with the raw data.

Because the \( \text{FA} \) rate relative to the \( H \) rate for the Hybrid 50-Word Related condition seemed too high to result in the reported value of \( A’ \), we recomputed the descriptive statistics from the reported \( H \) and \( \text{FA} \) results. These recomputed values of \( A’ \) and \( B” \) are listed in the “Computed”
column of Table 2A. The major discrepancy is for the hybrid 50-Word Related Priming condition, where the Related and Unrelated priming effects appear to cancel each other. The actual values of \( A' \) indicate that sensitivity is identical to the 50-Word Unrelated Priming conditions. Thus, the reported data actually demonstrate that, in the context of a large amount of unrelated priming (i.e., approximately 50-Word Unrelated Priming), related priming has no effect on sensitivity. We contacted Norris about this discrepancy in the value of \( A' \). In his reply, he provided alternative H and FA data from a different run of his simulation. With his permission (Norris, 1999 personal communication), we have listed these alternative data in Table 2B [New Results from Norris], along with the values of \( A' \) and \( B'' \) that we computed from the new data. [We also have plotted these new P(H) and P(FA) values in Figure 2 (along with isosensitivity contours for \( d' \))]. We will address the expected and unexpected nature of the original results, as well as the new results, after we develop a conceptual basis for understanding the Norris (1995) simulation.

**Analyses of Norris Simulation**

*Initial broad examination.* The nature of the Norris simulation can be understood in terms of Equation 1, which describes the traditional single high threshold model (e.g., Green & Swets, 1966; Macmillan & Creelman, 1991). This threshold model posits two discrete states: a supra-threshold and a sub-threshold state. When a stimulus is presented, \( p \) is the probability that the threshold has been exceeded, and this condition always leads to a positive response. When, with probability \((1-p)\), the threshold is not exceeded, a positive decision still can be reached with the probability \( q \) via a secondary route. Although this model traditionally has been used to derive a correction for guessing,\(^6\) this model is quite appropriate for the Norris simulation. In the current application, \( p \) is the probability that the presented stimulus is recognized as the related word (the probability of exceeding the related word threshold) and \( q \) is the probability of matching at least one unrelated word after a failure to recognize the stimulus as the related word.
Equations 2A and 2B are identical to Equation 1, but we have changed our symbols to define the formula in terms of the Norris simulation. Based upon the number of shared features, there is a difference in the probability of the stimulus matching a related and an unrelated word. The symbol $R$ is probability of word recognition from a match to the related word. The symbol $U$ is the probability of word recognition from a match to at least one unrelated word, conditional upon the failure to match the related word. The subscripts $W$ and $N$ define whether a word or a nonword stimulus is presented. Eq. 2A defines $P(H)$, the probability of a hit (a word decision to a presented word). We have substituted $R_W$ for $p$, to represent the probability that the word stimulus is accurately recognized, and thus the probability that it has exceeded the threshold for a match to its related word (itself) in the Lexicon. We also have substituted $U_W$ for $q$, to represent the probability that the word is recognized as a different word, and thus the probability that it has exceeded the threshold for a match to one or more unrelated words (after having not exceeded the threshold for a related match). Eq. 2B is equivalent to Eq. 2A, except that the presented stimulus is a nonword; Eq. 2B thus defines $P(FA)$, the probability of a false alarm.

\[
\begin{align*}
P(\text{“Word”}) & = p + (1 - p) * q \\
P(H) = P(\text{“Word”} | W) & = R_W + (1 - R_N) * U_W \\
P(FA) = P(\text{“Word”} | N) & = R_N + (1 - R_W) * U_N
\end{align*}
\]

*Anticipating our analysis findings.* Our analysis evaluates the relative values of $R$ and $U$ for word and nonword stimuli under the conditions of the Norris simulation, thus indicating both the role of related and unrelated word matching processes in defining the ability to perform the Lexical decision task and the effects of priming on these processes. Norris had rejected the use of $d'$, and instead used the supposedly nonparametric measures of $A'$ and $B''$ to reflect ability and criterion. Our analysis used both $A'$ and the more traditional $d'$ statistics for sensitivity, comparing the results with these two measures. The general patterns of our analysis results are
illustrated in an ROC space (Figure 3). Before turning to our analysis, however, we will summarize expectations based upon the Norris model and what our analysis will demonstrate.

According to the Norris model, related priming (R in our equations) reduces uncertainty, which causes an increase in sensitivity. Thus, related priming should shift the operation of the model from one isosensitivity contour for A’ or d’ to a different, higher isosensitivity contour that reflects better performance. As illustrated in Figure 3, our analyses will demonstrate that related processing (comparison of the perceived features of the presented stimulus and its related word) causes a direct change only in the location (a bias change) along a single isosensitivity contour for d’ or A’. Since the ROC curve reflects related word-matching performance for all possible criteria, and since related priming is only a criterion change, our analysis also demonstrates that related priming does not have a significant direct effect on sensitivity.

The Norris model also states that Unrelated Priming has a greater impact on FA rate than H rate, causing a reduction in sensitivity. Our analysis will demonstrate that unrelated word processes (comparison between the perceived features of the presented stimulus and the features of each of the unrelated words), only increases P(FA), and thus will always reduce sensitivity. Specifically, we will demonstrate that, when a word stimulus has been presented, comparisons to unrelated words will not alter P(H); Uw in Eq. 2A is always essentially zero. We also will demonstrate that, when a nonword stimulus has been presented, Un in Eq. 2B will always greater than zero (and larger than Rn), and thus unrelated word comparisons always increase P(FA). The increase in P(FA) due to nonword matches to unrelated words is the second major trend summarized in Figure 3. In essence, the only important component in the Norris simulation that alters sensitivity is the magnitude of false positive word decisions due to comparisons with unrelated words. Therefore, in the simulation, related priming only changes the criterion and unrelated priming only reduces sensitivity.
Analyzing the Probability of Related Word Decisions.

We define $C_R$ as the threshold or criterion number of feature matches, the minimum number that must occur for the decision that the presented stimulus is the related word (i.e., a criterion of 14 requires that 14 or more perceived feature matches have occurred). Because all 20 features are common between a word and its own Lexical entry, $R_W$ is the probability that the number of perceived features in the presented word equals or exceeds $C_R$. The Binomial distribution defines the sampling of exactly $n$ out of $N$ possibilities (features), where each feature has an independent probability, $p$, of being sampled (e.g., Hayes, 1963). For the Norris simulation, the value of $p$ is 0.7 (the independent probability of correctly perceiving each feature) and the total number of possible features, $N$, is 20. The probability, $R_W$, of perceiving $C_R$ or more features is the area in the tail of this Binomial distribution equal to or above $C_R$. $R_W$ defines the P(H) at each value of $C_R$, and thus defines the ordinate value of related comparison operating characteristic (the ROC curve in Figures 1 & 2 below) at each criterion value.

The “related” parameter, $R_N$, is, the probability that a nonword stimulus matches its related word (the word from which it was derived). The presented nonword stimulus has only 16 features in common with its related word. Therefore, $R_N$ must be zero when $C_R$ is 17 or higher, as there simply are too few common features to achieve a match. When $C_R$ is 16 or lower, a match to the related word requires only the accurate perception of $C_R$ or more of the 16 shared features (the 4 features in the stimulus that are not shared with the related word are completely irrelevant to the match to related word match). Following the logic for Word stimuli, the probability of accurately perceiving $n$ of the shared features is defined by a Binomial distribution, again with $p = 0.7$, but now with $N = 16$. $R_N$ is the area under the tail of this Binomial distribution that equals or exceeds $C_R$. $R_N$ defines P(FA) at each value of $C_R$, and thus defines the abscissa value of the related feature ROC curve at each criterion (Figures 1 and 2).
Related process ROC curve. The diamond symbols in Figures 1 and 2 plot the ROC curve for related word comparisons over the full range of reasonable criteria (i.e., 10 to 16). The number beside each symbol indicates the value of \( C_r \), the criterion number of related word feature matches. Because Norris (1995) computed \( A' \) and \( B'' \) as descriptive statistics, we first compare the related word ROC curve with isosensitivity \( A' \). The two bold solid curves in Fig. 1 are the isosensitivity contours for \( A' \) values of .68 and .84. These \( A' \) isosensitivity curves were generated by holding \( A' \) constant and solving for \( P(H) \) as a function of different \( P(FA) \). Each theoretical isosensitivity curve for \( A' \) maps the location of all possible values of \( B'' \) for a single, constant value of \( A' \). The theoretical isosensitivity contour for \( A' = .68 \) was selected to intersect the data point representing the Norris simulation results for the Neutral condition. The location in ROC space of the results for the other conditions is an indication of the sensitivity relative to this isosensitivity curve and bias relative to the Neutral condition.

The other theoretical isosensitivity contour, at \( A' = .84 \), was selected to correspond to the related word process operating characteristic at criterion 13, where \( A' \) is maximum and \( B'' \) is approximately zero (at the negative diagonal). The related word operating characteristic falls on the .84 isosensitivity contour at \( C_r = 13 \) and \( C_r = 14 \), which means that a change between these two criteria will not alter \( A' \); we soon will demonstrate that these are the primed and unprimed criteria used in the Norris simulation. All other points in the related word processing ROC curve fall below the \( A' \) contour, indicating lower values of \( A' \). When sensitivity is measured in terms of \( A' \), a priming change from criterion value 15 to 14 will appear to cause a slight increase sensitivity. In contrast, when priming reduces the criterion from any value between 13 and 11, there will appear to be a small decrease in sensitivity. These deviations from isosensitivity for related matches in the simulation can be attributed, in part, to a known problem with \( A' \); specifically, when there is bias, \( A' \) underestimates sensitivity (the tails of \( A' \) isosensitivity
contours are too high). Furthermore, the magnitude of underestimation is a direct function of the magnitude of both bias and sensitivity (McNichol, 1972; Snodgrass and Corwin, 1988). Because $d'$ avoids this characteristic of $A'$, the discrepancy between the related processing operating characteristic and isosensitivity for $d'$ only reflects other characteristics of the simulation.

Figure 2 compares the same related process ROC curve with isosensitivity for $d'$. The two values of $d'$, 1.43 and .56, correspond to the values of $A'$ plotted in Figure 1 at the unbiased criterion. Comparing Figures 1 and 2, we find a much closer relationship between the related process ROC curve and isosensitivity for $d'$ than for $A'$. This closer relationship with $d'$ allows us to see the small, systematic asymmetry in the related process ROC curve. This asymmetry reflects some small degree of inequality in variance for the distribution of Hits and False Alarms in the related process decisions. The asymmetry of variance that characterizes the simulation means that any decrease in criterion will always result in a small reduction in $d'$; since related priming is a small reduction decrease in criterion, related priming in the model will cause a small decrease in sensitivity. Anticipating our later, more detailed discussion, however, this small inequality of variance is a characteristic of the simulation, and not a characteristic of Lexical processing. Therefore, related priming does not alter ability sensitivity for Lexical decision.

Before we began our analysis, we used the ROC space in Figure 3 to summarize the anticipated impact of related and unrelated word processing in the model on sensitivity. Based upon our analysis of the Norris simulation to this point, we now have demonstrated that related word processing and priming in the Norris simulation accomplishes nothing more than a shift in bias along an isosensitivity contour. This related processes property is depicted in Figure 3 by the curved arrow along the isosensitivity contour. We next will demonstrate that evaluation of possible matches to unrelated words can only increase $P(FA)$, with any priming of unrelated words only further increasing $P(FA)$. This property of unrelated processing is depicted in Figure 3 as a shift to the right from the isosensitivity.
Analyzing the Probability of Unrelated Word Decisions

$C_U$ and $C'_U$, respectively, are the unprimed and primed criteria or thresholds for matching an unrelated word (likewise, $C_R$ and $C'_R$ are the unprimed and primed criteria, respectively, for matches to the related word) In the Neutral condition, because no words are primed, the value of $C_U$ is both identical for all unrelated words and is equal to $C_R$. Earlier, we indicated that our analysis will demonstrate that $C_R = 14$, and this (yet to be demonstrated) assertion means that $C_U = 14$. In the 1-Word and 50-Word Unrelated Priming conditions, because priming reduces by 1 feature the criterion for either 1 or 50 of the unrelated words respectively; the decision criterion for a match to these (1 or 50) primed words is $C'_U$, thus 13. The decision criterion for a match to the remaining 498 or 449 unprimed words is still $C_U$, or 14. In Equation 2, the probability of a match to unrelated words is easiest to understand when the presented word ($U_W$ in Eq. 2A) and nonword ($U_N$ in Eq. 2B) stimuli are considered separately.

Unprimed, unrelated word decisions for word stimuli $\{U_W = 0\}$. For reasons that soon will become clear, in three of the simulation conditions, there cannot be a match to an unrelated word following the failure to match the related word. This is because the presented word shares all 20 features with its related Lexical representation (i.e., with itself). Thus, a failure to match the related word means that the number of perceived features is less than the criterion for a related word match (i.e., $n < C_R$, where $n$ is the number of perceived features). A word stimulus shares a maximum of only 16 features with any other word in the Lexicon. Except in the conditions where $C_U < C_R$, the failure of a related word match also means that too few features were perceived to achieve a match to any unrelated word (i.e., $n < C_U$ when $C_U = C_R$). This relationship is found in the Neutral, the 1-Word Related Priming, and the Hybrid 50-Word Related Priming conditions of the simulation. In the Neutral (No Priming) condition, $C_U = C_R$. In the 1-Word Related Priming condition, the priming of the related word means that $C_U > C'_R$. In the Hybrid 50-Word Related Priming condition, the related word and 49 of the 499 unrelated
word are primed, meaning that $C_U > C'_U$ and, more important, $C'_U = C'_R$. Therefore, in these three conditions, $U_W$ is zero, and $P(H)$ is determined exclusively by $R_W$, the probability that the presented word achieves a match to its related word (i.e., its own representation in the Lexicon).

_Determination of simulation criterion values_ \{C = 14; C' = 13\}. We now have sufficient information to prove our earlier assertion that the unprimed criterion in the simulation corresponds to 14 features. In the three conditions we have just considered, $P(H)$ is determined exclusively by $R_W$, and the value of this parameter is the ordinate of the Related process ROC curve. The value of the unprimed related word criterion therefore can be determined by matching the value of $P(H)$ reported by Norris (1995) for the Neutral condition and the ordinate of the Related process ROC curve at the possible criterion. $P(H)$ for the Neutral condition corresponds to the ordinate of the related process ROC curve at a criterion value of 14 (see Figure 1 or 2). The new results from Norris (1999) report the identical value of $P(H)$ for the other conditions in which there is an absence of related priming (1-Word and 50-Word Unrelated Priming conditions); these conditions should, and do, reflect the identical unprimed criterion. For the Hybrid 50-Word Related Priming condition, the value of $P(H)$ corresponds to a criterion value of 13, which is consistent with the 1 feature reduction in criterion that defines related priming. The 1-Word Related Priming condition also should have a value of $P(H)$ that corresponds to a criterion value of 13, and we do see this in the new results from Norris (1999) (see Figure 2). In the originally published results, $P(H)$ for this 1-Word Related Priming condition corresponded to a criterion of 12, and thus a related priming change of 2 features, rather than the single feature specified for the simulation. This explains why the original published values of $P(H)$ and $P(FA)$ for the 1-Word Related Priming appeared inflated. This result for the wrong criterion, however, adds information to our analysis. Specifically, the results for a related criterion of 12 (original results for this condition) and a related criterion of 13 (new results for this condition) have
identical values of A'. This lack of change in A' between simulations adds support to our conclusion that related word processing in the simulation does not directly alter sensitivity.

*Primed unrelated word decisions for word stimuli* \( \{U_W \equiv 0\} \). In the remaining two conditions, \( U_W \), the probability of a match to an unrelated word, is sufficiently small to be considered as essentially zero. In the 1-Word Unrelated Priming condition, the 1 related word and the 498 unrelated words have unprimed recognition thresholds of \( C_R \) and \( C_U \) (and \( C_U = C_R = 14 \)), but the one primed unrelated word has a criterion of \( C'_U \) (where \( C'_U = (C_R - 1) = 13 \)). There thus is an extremely small possibility of a match to the one primed unrelated word, with that probability close to zero (i.e., \( U_W \equiv 0 \)). Specifically, with a low probability \( (p = 0.11) \), exactly \( C'_U \), or 13, features will be perceived; any more than 13 features would result in a match to the related word \( (C_R = 14) \) and any less than 13 features would be too few to achieve a match to the one primed unrelated word (i.e., less than \( C'_U \), or 13, perceived features). In this case, with an exceedingly low probability\(^9\), every one of the 13 perceived features will be shared with the one unrelated word that has been primed; if any of the perceived features is not shared with that primed word, the matching threshold will not be exceeded. The joint probability of (1) perceiving exactly 13 features and (2) having all of these perceived features present in the one primed word is exceedingly small, and essentially zero. Therefore, in the 1-Word Unrelated Priming condition, \( U_W \equiv 0 \), and \( P(H) \) is defined by the related process ROC curve at criterion 14. Thus, \( P(H) \) should be identical for the 1-Word Unrelated and the Neutral conditions; we see this relationship in the new results (Figure 2).

The 50-Word Unrelated Priming condition can be evaluated by comparison with the 1-Word Unrelated Priming condition. In the former condition, only 1 unrelated words has been primed, whereas in the latter condition 50 unrelated words have been primed. In the latter conditions, there thus is 50 times the probability of a match to an unrelated, but primed, word. However, 50 times an exceedingly small probability still results in a very low probability (definitely less .01)
of a match to an unrelated word. Thus, in the 50-Word Unrelated Priming condition, the value of \(U_w\) is also essentially zero. This conclusion is consistent with the fact that, in the new Norris simulation results (Table 2B), identical values of \(P(H)\) are reported for 1-Word Unrelated Priming condition, the 50-Word Unrelated Priming condition, and the Neutral condition. In all of these conditions, there is an identical unprimed related criterion, \(C_R\), and in the latter two conditions \(U_w = 0\). Thus, although the 50-Word Unrelated Priming condition has the greatest probability of a match to an unrelated word, that probability is essentially zero (\(U_w \approx 0\)). Our analysis of the five conditions in the Norris (1995) simulation indicates the comparison of presented words with unrelated word in the Lexicon has no effect on \(P(H)\). \(P(H)\) is defined solely by the value of \(C_R\) or \(C'_R\), the unprimed or primed criterion for related word matches; unrelated word comparisons do not contribute to \(P(H)\).

Unrelated word decisions for nonword stimuli \(\{U_n = k^* R_n, \text{ where } k \text{ is 2.5 to 3}\}\). The value of \(U_n\), the probability of a nonword matching an unrelated word, is always greater than zero. Norris (1995) does not provide quite enough detail for a precise determination of \(U_n\), but we can estimate the magnitude of \(U_n\) relative to the magnitude of \(R_n\). We begin with an examination of the Neutral condition, where there is no priming. Because the nonword shares only 16 features with the related word, the failure to match the related word means that less than \(C_R\) of these 16 features has been perceived (i.e., \(n < 14\)), but this tells us nothing about the perception of the 4 features of the nonword that are not shared with the related word. Thus, the failure of a match to the related word means that up to \((C_R - 1) + 4\) of the 20 stimulus features have been perceived [i.e., \((C_R + 3) \geq n, \text{ or } 17 \geq n\)]. Since \(C_U = 14\), a match to an unrelated word requires (1) that 14 to 17 of the 20 stimulus features are perceived and (2) that at least 14 of these features are shared with one of the 499 unrelated words. The probability that exactly 14, 15, 16, or 17 of the 20 features in the nonword stimulus are perceived is specified by the Binomial distribution and equals .57. We cannot easily estimate the probability of the second requirement (the probability that the 14 to 17
perceived features are shared with at least one of the 499 unrelated word), but we know that this probability is not inconsequential. In order to produce the P(FA) results reported by Norris for this condition, however, this probability would be 0.56. Having estimated the values of the variables in Eq. 2B, we conclude that P(FA) at C_U = 14 is almost three times as likely to occur from a match to an unrelated than to a related word (i.e., U_N = 2.9*R_N). Therefore, unrelated word matches are far more important for P(FA) than are related word matches.

Because the analyses are fairly complicated and we seek only to demonstrate that unrelated word decisions constitute the major determination of P(FA), we will not analyze the remaining nonword conditions in the same detail as the Neutral condition. In the 1-Word Unrelated Priming condition, one of the 499 unrelated words has been primed, but this priming of only one word should result in only a very small increase in U_N, and therefore should have essentially no measurable effect on P(FA). Thus, in Figure 2 and in Table 2B, the results for the Neutral (N) and the 1-Word Unrelated (U1) conditions should be, and are, identical. [We have no explanation for the discrepant original results for the latter condition (Table 2A), but the difference between the original and new results are relatively small (.02).]

The 50-Word Unrelated Priming condition was created by priming ten percent (50 out of 499) of the unrelated words. Priming (lowering of the recognition threshold) for this number of words is not inconsequential, and thus should increase the value of U_N, which again translates into an increase in P(FA). We see this expected change in the new results in Figure 2, where the data point for this condition is shifted to the right of the common location for the data points from the Neutral and 1-Word Unrelated conditions. This 50-Word Unrelated Priming condition should exhibit the poorest performance or the lowest level of sensitivity in the Lexical decision task.

In the Related Priming conditions of the simulation, the related-word recognition threshold or criterion has been decreased (C'_R = C_R – 1). There thus is an increased probability of a match between the presented nonword and its related word (as discussed above in our analysis of R_N).
As a result, there is a decreased probability [lower value of \((1-R_N)\)] for an additional match based upon the comparison with unrelated words. The lower value of \(C'_R\) also means that, when there is a failure to match the related word, fewer total features may have been perceived [because \((C'_R+3)\) or fewer features were perceived, the maximum number of perceived features must now be 16, instead of 17, when the related word was not primed]. The fewer number of possibly perceived features will decrease the probability, \(U_N\), of a match from a comparison with unrelated words. For the specific conditions in the simulation, however, this decrease was not very large. The value of \(R_N\) is defined by the abscissa of the related processing ROC curve (Figure 1 or 2) at the appropriate criterion. The respective values of \(R_N\) for the unprimed and primed criteria (\(C_R = 14\) and \(C'_R = 13\)) are only .10 and .15 (the ordinates of the related process operating characteristic in Figure 1 or 2 at these criteria). Using the analysis employed earlier for the Neutral condition, we find that, for the 1-Word Related Priming condition, \(P(FA)\) is over 2½ times as likely to be determined by matches of the presented nonword to unrelated words than to the related word in the Lexicon (i.e., \(U_N = 2.6*R_N\)). With the addition of significant unrelated priming in the Hybrid 50-Word Related Priming condition, this ratio will be considerably larger. Thus, at least for the conditions of the Norris simulation, even in the presence of related priming, unrelated word decisions are the major factor in determining \(P(FA)\) [i.e., \(U_N = k*R_N\), where \(k\) is 2.5 to 3].

Summary of primary analyses of Norris simulation. This completes our primary analysis of the Norris simulation. Before we began this analysis, we used Fig. 3 to summarize our anticipated findings. Our analysis has now demonstrated that related word comparisons or processes directly alter \(P(H)\) and \(P(FA)\) in a manner that essentially represents isosensitivity for \(d'\). Specifically, the criterion change that defines related word priming simply moves the operating point along an isosensitivity contour for \(d'\). Therefore, related priming does not directly alter sensitivity. Unrelated word comparisons do not contribute to the recognition of word stimuli,12 but are a major factor in word recognition errors (false alarms) for nonword
stimuli. Specifically, in the simulation conditions, the \( P(FA) \) is \( 2\frac{1}{2} \) to 3 times as likely to be due solely to a match to an unrelated than to a related word. In the Norris simulation, unrelated word matches and unrelated word priming manipulate \( P(FA) \), and this manipulation of \( P(FA) \) is the only manner in which sensitivity, as measured by \( d' \), is directly altered. Therefore, the direct changes in sensitivity are only decreases in \( d' \), and never the increase that is described in Norris (1986, 1995). Finally, the statistics of the Norris simulation are quite consistent with the assumptions underlying the use of \( d' \), the sensitivity statistic of the Gaussian Equal-Variance model of SDT.

**Finer Analysis Issues**

In the remaining sections of our analysis of the Norris simulation and model, we address several additional, but less central, issues about the relationship between the statistical properties of the Norris simulation and aspects of SDT analyses and measures. The first additional analysis will indicate that the small inequality of variance in the related processing ROC curve (see Figure 2) is due to the small number of sampled features in the simulation, and is not characteristic of complex Lexical processing. The second analysis will explain why a known problem with \( A' \) accounts for the poorer relationship of the related processing ROC curve with isosensitivity for \( A' \) than with isosensitivity for \( d' \). The third analysis will demonstrate the close correspondence between our analyses and the new results from Norris, and also will account for the major discrepancies between the original and new results from Norris. We then will examine a small, secondary interaction between related and unrelated processing that we include for completeness. Finally, we will end our analysis with an evaluation of whether the simulation has actually examined solely post-perceptual criterion changes for a multidimensional decision variable.

*Inequality of variance for related word processing.* During our analysis of related word processing in the Norris simulation, we indicated that we would discuss the small degree of inequality of variance in the related processing ROC curve. The two major issues about this
inequality of variance concern the identification of its source and an evaluation of its importance. The inequality of variance for related word decisions stems from the limited feature sampling of the simulation. Our analysis for the middle range of criteria is based upon comparisons to \(d'\). In the use of the Gaussian Equal Variance model of SDT, the more tenuous assumption is for equality of variance (Green & Swets, 1966). Like a z-score or t-statistic, \(d'\) is a ratio that reflects the difference in distribution means scaled in terms of some measure of variability (the standard deviation or standard error is the denominator for these statistics). In typical discussions of the equality of variance assumption for \(d'\), the focus is on the ratio of the standard deviations, which is the slope of the normalized (z-score) ROC curve (Green & Swets, 1966). The slope of the normalized ROC curve thus indicates the direction and magnitude of variance inequality; a slope or ratio of 1 reflects equal variance.

The related processing ROC curve for the simulation is based upon Binomial sampling distributions. The Binomial distribution has a mean and variance respectively equal to \(Np\) and \(Np(1-p)\), where \(p\) (defined for Eq. 1) in the simulation has a constant value of 0.7. Note that the difference in means is proportional to the difference in \(N\), the number of features shared between the presented (word or nonword) stimulus and the related word in the Lexicon (i.e., \(20-16 = 4\)). Our focus is on standard deviations for the word and nonword stimulus presentations that determine whether a positive word decision reflects a hit or a false alarm. Our focus thus is on the variability in \(R_W\) and \(R_N\), the portion of \(P(H)\) and \(P(FA)\) that is based solely on matches to the related words in the Lexicon. The ratio of standard deviations for \(R_W\) and \(R_N\) is defined by Equation 3a:

\[
\frac{\sigma_W}{\sigma_N} = \left\{ \frac{p(1-p) \cdot N_W}{[p(1-p) \cdot N_N]} \right\}^{1/2} \quad (3a)
\]

\[
\frac{\sigma_W}{\sigma_N} = (N_W/N_N)^{1/2} \quad (3b)
\]

The standard deviations for word and nonword stimuli differ only in the value of \(N\), the number of features shared with the related word in the Lexicon \((p = .7, a constant)\). Eliminating
the common, constant component, \( p(1-p) \), we obtain Eq. 3b. Thus, the ratio of standard
deviations is proportional to the square root of the ratio of the number of features shared between
the related word in the Lexicon and the word (\( N_w \)) and nonword (\( N_N \)) stimuli. In the simulation,
each stimulus had only 20 features, with word and nonword stimuli respectively sharing 20 and
16 features with the related word (thus, \( N_w = 20 \) and \( N_N = 16 \)). The ratio of standard deviations
therefore is \( 1.15 \left(\frac{20}{16}\right)^{1/2} \). This ratio deviates from 1 because of the magnitude of inequality of
relevant features [i.e., \( (N_w - N_N) = 4 \)] relative to the number of features being sampled (i.e., 20).
If word and nonword stimuli still differ by 4 shared features (thus, the difference in means is
constant), but each stimulus has a larger number of features, the ratio of standard deviations
would quickly converge on 1 or equal variance. In fact, with increasing sample size, the
Binomial distribution (and many other distributions) approximates or becomes a Gaussian
distribution and the standard deviation ratio approximates a value of 1; this is the basic central
limit theorem that is fundamental to modern inferential statistics (e.g., Hayes, 1963). In the
broader context, this same inequality of variance is a problem for both inferential and descriptive
statistics when the sampling size is small. It thus should be clear that the small degree of
asymmetry in the related word processing ROC curve is only a reflection of a simulation based
upon a small number of possible features. The small asymmetry in the ROC curve identified by
our analysis of the Norris model and simulation thus is not an inherent characteristic of what
Norris (1986; 1995) describes as the complex, multidimensional Lexical decisions processes that
he claimed are reflected in his model.

A major goal of the Norris simulation, and of our analyses of that simulation, is to draw
inferences about the impact of the underlying processes on performance of the Lexical decision
task. What is the relative magnitude and direction of sensitivity change associated with priming
that is due to the inequality of variance under the limited sampling conditions of the Norris
(1995) simulation? In the simulation, priming lowers the decision threshold or criterion by 1
In Figure 2, the ROC curve for related word processing (the operating characteristic for the \( R \) term in Eq. 2) is plotted along with an isosensitivity contour for \( d' = 1.43 \). A lowering of the related word criterion from 14 to 13 reduces \( d' \) by 0.13, whereas a change in criterion from 13 to 12 reduces \( d' \) by 0.10. These are quite small, really inconsequential changes in \( d' \), and represent changes in \( P(c)_{\text{max}} \) of .02 or less. Furthermore, by comparing these two ROC curves in Figure 2, it should be obvious that, beginning with a criterion of 16 [the highest criterion with a nonzero \( P(FA) \)], any reduction in criterion will result in a reduction in the value of \( d' \). However, according to Norris (1986), related priming reduces uncertainty, and this reduction in uncertainty will result in an increase (not a decrease) in sensitivity. Therefore, although very small, the change in \( d' \) is always in the wrong direction for the claims in the Norris model and simulation.

We also indicated earlier that part of the asymmetry of the related word processing operating characteristic is due to threshold-like characteristics of the simulation for the more extreme criterion values. For criterion values greater than 16, \( P(H) \) increases with decreasing criterion value, but \( P(FA) \) is always zero. This FA threshold is because a nonword in the simulation cannot share more than 16 features with any word. Therefore, there is an upper limit or threshold for the \( P(FA) \). At the other extreme, every stimulus in the simulation must share a minimum of 10 features with every other stimulus (each stimulus has 20 of the 30 possible features). Therefore, the probability of a related word match [\( P(H) \) and \( P(FA) \)] is 1.0 when the related word criterion for the condition is less than 11. This represents a threshold for maximum performance.

Putting the components of our immediate analysis of the simulation together, we see that the related word processing operating characteristic is a vertical line [\( P(FA) = 0 \)] for \( C > 16 \), is constant [\( P(H) = P(FA) = 1 \)] for \( C < 11 \), and, with some small inequality of variance, has a rough approximation to isosensitivity for \( d' \) between these two thresholds.

Poorer correspondence to isosensitivity of \( A' \). Much of our immediate discussion of related priming has been based upon \( d' \). Norris (1995), however, rejected the use of \( d' \), using, instead,
A’. We therefore turn to Figure 1 that compares the ROC curve for related word processing and isosensitivity for A’. The A’ statistic, in addition to being inappropriately labeled as nonparametric (for explanations, see Macmillan and Creelman, 1990; Pastore et al., in press), has the known problem of underestimating sensitivity when there is significant bias (e.g., McNichol, 1972; Pastore et al., in press; Snodgrass & Corwin, 1988). This underestimation (caused by limits of the geometric principles that are used to estimate an average value of A’) can be seen as elevated tails of the isosensitivity contour for A’. As a result, we see in Figure 1 that, as the criterion is reduced, the ROC curve for related word processing first systematically rises to intersect the A’ contour (the upper threshold discussed in the previous paragraph), then falls below the A’ contour. Thus, when compared to isosensitivity for A’, related priming would appear to alter sensitivity, first increasing, then decreasing the value of A’. Clearly, there is no systematic, monotonic increase in sensitivity due to priming-reduced uncertainty, as described in the Norris model. More to the point, however, the major change in sensitivity observed with criterion change is due to a known problem with the A’ measure when there is a bias in the criterion, and are not due to some aspect of the Norris simulation or model.

Comparison of our analysis with Norris results. How does our analysis relate to the original (Figure 1) and new (Figure 2) results from the Norris simulation? According to our analysis, P(H) is defined solely by the value of the related processing ROC curve at the applicable value of C_R, the related word threshold or criterion. The Neutral (N), 1-Word Unrelated (U1) and 50-Word Unrelated (U50) all have the same unprimed criterion for related word comparisons (C_R), and thus should have the identical value of P(H) that corresponds to the value of C_R selected by Norris. Based upon the value of P(H) for the Neutral condition, C_H is 14 feature matches. For the new results (Figure 2 and Table 2B), the related processing ROC curve at criterion 14 has a P(H) value that is identical to P(H) for these three conditions. Related priming in the simulation reduces C_R to 13 (C_R’). For the new simulation results (Figure 2), P(H) for the 1-Word Related
Priming condition (R), and the Hybrid 50-Word Related Priming condition (H) are identical to P(H) for the Related process ROC curve at criterion 13. Thus, our analysis accurately predicts P(H) for the new simulation results.

There are several discrepancies between the originally reported results (Figure 1 and Table 2A) and our analyses (as well as the new results). In the original results, there is a discrepancy from the expected value of P(H) of 0.61 for the 1-Word Unrelated condition (where P(H) = .59) and the Hybrid 50-Word Unrelated condition (where P(H) = .62). These discrepancies are quite small; we believe that a change in probability of .02 or less could be dismissed as behaviorally inconsequential, and possibly due to rounding error. The new P(H) values for these conditions (Table 2 and Figure 2), however, are identical to each other. The original value of P(H) for the 1-Word Related Priming condition (R), thus, is clearly too high. As noted earlier, it also is clear that P(H) corresponds to the ordinate for the related word ROC curve at a criterion (C’R) value of 12, representing a priming criterion change of 2, rather than 1 feature. Although not of direct importance for interpreting the simulation results, this error is indicative of the accuracy of our analysis of related priming, and the new Norris simulation results (Table 2B) correct this error.

Our analyses indicated that P(FA) should be identical for the Neutral and the 1-Word Unrelated Priming conditions, with the 50-Word Unrelated Priming condition exhibiting a higher P(FA); we see this relationship in the new results (Figure 2 and Table 2B). In the original results (Figure 1 and Table 2A), the 1-Word Unrelated Priming condition exhibits a small discrepancy (.02) that, like the small discrepancy with the P(H) value for this condition, is probably inconsequential. Because P(FA) in the related priming conditions is increased by the related criterion change, P(FA) should be greater than the conditions we have just discussed. Finally, with greater unrelated priming in the Hybrid 50-Word Related Priming condition (symbol “H”), P(FA) should be somewhat higher than the 1-Word Related Priming condition (symbol “R”), and thus should exhibit the highest value of P(FA) of the conditions investigated. We see precisely
these relationships in the new results. In considering the original results (Table 2A), we need to ignore the 1-Word Related Priming condition results (that were based upon the incorrect criterion). In these original results, P(FA) for the Hybrid 50-Word Related Priming condition has a higher value than in the new results; we would guess that there is a typographical error in the original results (the value of P(FA) in the new results is .56, but is originally reported as .66), since the new value of P(FA) yields the originally reported value of A’. Again, the error in the originally reported results is not of importance in interpreting the model. Therefore, our analyses are quite consistent with the new results from Norris (Table 2B) and can explain the discrepancies between the original and new Norris results.

One final loose end in analysis results. Overall, our analyses of the Norris simulation are consistent with the exact values of P(H) and the general trend in values of P(FA) in the new results provided by Norris (Table 2B). There is one small aspect of the results that we have not yet directly addressed. In both the original (Table 2A) and new (Table 2B) results, the value of A’ (.70) for the 1-Word Related Priming condition (R), is slightly higher than the value (A’ = .68) for the Neutral (N) condition. Although the discrepancy (.02) is small [we dismissed equivalent discrepancies in our discussion of P(H) and P(FA) for the original Norris simulation results], we now address this discrepancy. The value of A’ is identical for the original, erroneously reported results (i.e., related criterion of 12) and the correctly reported (related criterion of 13), and is greater than the value for the Neutral condition (related criterion of 14). Is this small discrepancy a problem for our analysis?

Our analysis did not indicate that unrelated processing will increase P(FA) by a constant amount (i.e., by an amount that is independent of criterion). Decreasing the value of the related criterion increases the probability that a nonword stimulus matches the related word, and this is expressed as an increase in the first term \( R_{SN} \) of Eq. 2B. An increase in \( R_{SN} \) is, by definition, a reduction in \( (1 - R_{SN}) \). In Eq. 2B, \( (1 - R_{SN}) \) sets the limit on the possible contribution of unrelated
word matches to \( P(FA) \). [For example, when the probability of a related word match is unity (\( R_n = 1 \)), and the value of \((1 - R_n)\) is zero, which means an absence of any unrelated word contribution to \( P(FA) \), no matter what the value of \( U_n \).] Related priming also means that there is a reduction in the total number of possibly perceived features. Specifically, in our earlier analysis, we demonstrated that a failure to achieve a match to a related word means that a maximum of \( C_R + 3 \) of the presented nonword’s features were perceived. Related priming reduces the criterion by 1 feature (\( C_R = 14, C'_R = 13 \)), and thus reduces the maximum number of perceived features from 17 to 16. With fewer perceived features, there is a reduction in the probability of matching one or more unrelated word, which is \( U_n \) in Eq. 2B. The change in \( P(FA) \), as defined in Eq. 2B, depends upon the magnitude of changes in both \( R_n \) and \((1 - R_n)U_n\). These changes represent an interaction of related and unrelated word processing, and are not a direct result of either process. Furthermore, the magnitude of these changes depends upon the value of the original unprimed criterion, \( C_R \). Therefore, change in \( d' \) depends upon the size of changes in \( P(H) \) and \( P(FA) \) relative to their values in the absence of priming. Specifically, the value of \( d' \) will not always increase, but rather can increase, be constant, or decrease, depending upon the original value of \( C_R \). Finally, the magnitude of change in \( d' \) due to this interaction will be small (i.e., a change of no more than .02 in \( P(c)_{MAX} \)). Analogous changes will be seen in \( A' \), but those changes that involve strict or lax criteria will interact with the problems (discussed above) with the \( A' \) measure. Thus, the small increase in \( A' \) seen for the simulation results for 1-Word Related Priming condition is relatively inconsequential, is not a direct consequence of either related or unrelated word comparisons, and is certainly not the consistent, monotonic increase in sensitivity that the checking model described for reduced uncertainty associated with related priming.

Unidimensional versus multidimensional decisions. In developing Statistical Decision Theory, Wald (1952) demonstrated that the evaluation of multidimensional evidence to reach a binary decision is functionally achieved by using a unidimensional decision axis. In the Norris
simulation, one can argue that, on each trial, there are 500 separate evaluations of the evidence, with each evaluation being a comparison between the perceived features of the stimulus and the features present in one word in the simulation’s Lexicon. From this perspective, each word in the Lexicon can be considered a dimension of evidence. Each of these word comparisons is functionally a unidimensional threshold evaluation that leads to a binary outcome. The ultimate simulation decision variable for the Lexical decision task, however, is the “number” of matches to words in the Lexicon, and the final decision is also a threshold evaluation, with the threshold set to a single word match. Thus, the evidence evaluated may have 30 possible features and 500 word dimensions, but the decision variable for the simulation is unidimensional.

_Criteria, threshold, or both._ In standard use of the concept, changes in the costs and benefits of the decision outcomes, and changes in the probability that each decision outcome is valid, are assumed to alter the decision criterion without altering the distribution of evidence on which the decision is based. In the Norris (1986) model, these traditional manipulations of bias only can be accommodated by changing the criteria that are alter by priming. This premise then leads to two important questions. First, is it reasonable to equate the functional consequences of changes in payoff, stimulus probability and priming? The idea that priming results in changes in criterion is at least nominally equivalent to typical conceptualizations of priming in the SDT literature. Second, is the Norris conceptualization of criterion or bias change equivalent to the standard definition? All changes in criterion in the simulation are achieved by an increase in the number of perceived feature matches. The changes in criterion, however, differ in relationship to the presented stimulus (specifically, related versus unrelated, as well as the number of unrelated criterion changes). For related stimulus comparisons considered in isolation, the addition of 1 to the perceived feature matches is either present (related priming) or absent (no priming). For these comparisons, the priming does alter the decision criterion without altering the underlying distributions of evidence. Thus, for stimulus related comparisons (and therefore accurate word
recognition), priming does involve a true change in what is the typical decision criterion. In keeping with expectations for traditional criteria (except for the small inequality of variance due to properties of the simulation), we have demonstrated that these criterion changes are isosensitive. For unrelated stimulus comparisons, the addition of 1 to the number of perceived feature matches for a portion of the stimulus comparisons does manipulate the statistical distribution of evidence. Specifically, when the stimulus is a nonword, unrelated priming adds meaningful “evidence” (adds 1 perceived feature match) to the comparison some words in the Lexicon. In contrast, when the target is a word, the comparison with the related word filters out, or makes meaningless, comparisons with unrelated words. It is this non-criterion property of the Norris (1995) word thresholds that manipulates sensitivity. Thus, what are claimed to be purely post-perceptual criterion changes requires a blurring of the distinction between criterion changes and altering the distribution of evidence being evaluated by a threshold processes. The changes in sensitivity reported in the Norris (1995) simulation are simply not accomplished in the manner described by Norris (1986; 1995).

Broader Implications

There were two reasons that the Norris (1995) simulation had been considered to be important. First, it was argued to be a demonstration that a very simple, purely post-perceptual criterion change model of related word priming can increase perceptual sensitivity. Second, it provided a strong argument that SDT is inappropriate for the analysis of complex, multidimensional processes, such as those involved in semantic processing and lexical decisions. We now understand why both of these claims are invalid. In developing our analyses of this specific model, we have provided the basis for a better understanding of SDT and the conceptualization of complex processes.

Modern approaches to lexical processing, priming, and the broader question of modularity, all posit an initial perceptual processing stage and later cognitive processing stage(s). Farah (1989)
had implied, and Rhodes et al. (1993) were explicit in positing, that the independent SDT measures of sensitivity and criterion reflect initial perceptual processing and later cognitive processing respectively. This conceptual relationship between SDT measures and stages of processing is not uncommon in the modern cognitive research (for discussion, see Pastore et al., in press). By adopting this working premise, researchers appear to have a powerful research tool to separately investigate perceptual and post-perceptual processing effects. Norris (1995) correctly challenged this working premise, asserting that SDT measures reflect the behavior of the whole system. Unfortunately, his criticism of SDT was incorrectly based upon his argument that SDT is unidimensional, whereas cognitive behavior is multidimensional. It is correct that any dependent measure (d', P(c), RT, etc) used to evaluate behavior must reflect the combined action of all of the processes between stimulus and response. This statement is not unique to SDT; it is valid for both the processing of information that is multidimensional and for processes that are complex and multidimensional. We have seen that SDT models decision-making based upon the distributions of available, evaluated information, but does not model the processes intervening between the presentation of information and the decision. That is, SDT does not model the processes that either obtain or evaluate information. To evaluate the intervening processes, the researcher must develop both models for these intervening processes (and their interrelationships) and research strategies evaluate the contributions of the process models (e.g., Tanner, 1961). SDT measures may be valuable to the researcher, but the simple use of SDT measures is not a substitute for solid research design.

Major problem in the modern literature are due to differences in the meaning and interpretation of conceptual processes assumed in SDT. When describing the attributes of any model in SDT-relevant terms, it is important that one views the components of the model in a manner that corresponds to the basic distinctions made by SDT. SDT evaluates two aspects of information processing, sensitivity and criterion or bias (typically reflected respectively by the
values of $d'$ or $A'$ and $\beta$, $c$, or $B$). The SDT definitions for sensitivity and bias, however, often differ in subtle, but critical ways, from typical usage.

For SDT, sensitivity reflects the statistical separation of evidence for the alternative decisions, whereas criterion or bias reflects the decision rule that, when applied to the evidence distributions, determines the response. The determination of statistical distributions of evidence can be attributed to Evidence processes, whereas the determination of criterion can be attributed to Decision processes. The Evidence processes must reflect both (1) the quantity and quality of information obtained and (2) the extent and accuracy of the knowledge used to evaluate the available information. Certainly, a perceptual system that fails to accurately pick up information will have less separation of evidence for the alternative decisions than a perceptual system that accurately acquires information. The quantity and quality of acquired information definitely sets an upper limit on the degree of separation of evidence, but the simple acquisition of information does not specify the distribution of evidence for the decision alternatives. Rather, the evidence must be evaluated in terms of relevance to the decision alternatives, and this evaluation must require knowledge about the relationship between the information and the decision alternatives.

An ideal “Signal Known Exactly” (SKE) observer (e.g., Green & Swets, 1966) has perfect knowledge; for the SKE observer, the statistical distributions are determined only by the acquired information, and sensitivity is limited only by the information acquired. For a real observer with more limited knowledge (i.e., uncertainty), the statistical distributions are determined by an imperfect interpretation of the acquired information; sensitivity is limited by the ability to accurately acquire and interpret information. Thus, sensitivity reflects the properties of both types of Evidence processes; the acquisition and evaluation of information. Whether the acquisition and the evaluation processes are either serially-connected and modular or interactive, both types of processes are components of Evidence processing that determines sensitivity. Furthermore, higher-level cognitive processes are just as important in determining sensitivity as
perceptual processes. In contrast, differences in the costs / benefits for alternative decisions, or in
the probabilities that the alternative decisions are valid, do not affect the acquisition or
interpretation of evidence, and thus do not alter the statistical distribution of evidence. Instead,
differences in probability and payoff alter the rule used to determine the decision based upon the
available evidence. The Decision processes determine the criterion or decision rule.

The distinction we have drawn between Evidence and Decision processes has some strong
implications. For example, the Evidence versus Decision process contrast is functionally
equivalent to a perceptual versus post-perceptual process contrast only when one can assume an
SKE observer where (instead of the more typical assumption of an automatic, but noisy,
perceptual system) one assumes an automatic, omniscient evaluation system, with the post-
perceptual processes only altering the decision criterion. A less extreme example is the two stage
model of Balota and Chumbley (1984) for Lexical decisions, which is a variant of the model
developed by Atkinson and Juola (1973) for memory search. This Lexical decision model
accounts for a broad range of effects, especially when RT is the dependent measure. In the
model, there is a low and a high criterion along the Lexical decision axis that reflects familiarity
/meaningfulness (FM). “The first stage of the decision process involves a global computation of
the FM value of the letter string” (Balota & Chumbley, 1984, p. 352). If the FM value fails to
exceed the lower criterion (or exceeds the high criterion), the subject quickly makes a nonword
(or word) response. “If this FM value falls between the upper and lower criteria, then the subject
needs more information before a decision is made” (Balota & Chumbley, 1984, p. 352). The
“decision stage” of this model thus does more than set criteria. The decision stage both evaluates
the initial letter string information and, when needed, expands the information being considered;
these are attributes of Evaluation processes, rather than Decision processes.

Our argument here is not about the basic mechanisms that were proposed in the classic Balota
and Chumbley(1984) model, but whether one conceptualizes the mechanisms as contributing to
sensitivity (distribution of evidence) or bias (criterion or decision rule). Consider, then, an equivalent, continuous (rather than discrete) conceptualization of the Balota and Chumbley model. In the original model, each of the serially-organized stages fully processed a type of information before making a decision. Suppose, instead, that evidence is evaluated in a systematic macroscopic to microscopic manner and that decisions do not require a full, exhaustive completion of evidence evaluation. For some stimuli, the initial macroscopic analysis will produce very strong evidence for one decision, such that the distribution of evidence would not be altered in any meaningful way by the more microscopic analysis. In this alternative version of the model, the observer will respond without waiting for the evaluation to run to completion. Adding high and low decision criteria to this terminating decision process makes this alternative conceptualization equivalent to the first stage of the Balota and Chumbley model. When the initial aspects of the information evaluation has failed to produce overwhelming support for one decision alternative, the evaluation will continue, with the decision delayed, possibly until a full evaluation of all evidence is completed. Functionally, this is equivalent to a decision that requires the second stage of the Balota and Chumbley model. In our conceptualization, however, there are not a rigid structure of two discrete, serial stages of information evaluation, each providing a full evaluation of a specific type of information, and each incorporating a decision component. Instead, we have maintained a separation of evaluation and decision processes. From an SDT perspective, the factors that contribute to the Evaluation processes (and reflected as sensitivity) are separated from factors that alter the decision rules (as reflected in criterion). Furthermore, as in the original description, differences in RT reflect the extent of analysis required before a decision, with RT roughly reflecting the distance along the decision variable between the current evidence and the final decision criterion.

From a strictly SDT perspective, the important contrast is between Evidence and Decision processes, and not between perceptual and post-perceptual processes, or the question of whether
these latter processes are modular. We still can contrast perceptual and cognitive processes as the
difference between the acquisition of evidence about the immediate stimulus conditions and the
use of knowledge to evaluate the available evidence. Furthermore, careful research design can
separate these two types of Evidence processes. In doing so, however, care is needed to avoid
confounding attributes of processes that evaluate available evidence and those that determine the
decision rule applied to the evaluated evidence. The Norris (1995) simulation is an example of
this not uncommon confounding of attributes.
References


Footnotes

1 Norris (1995), thus, is correct in asserting that SDT descriptive statistics reflect the behavior of the whole system (see also, Pastore & Scheirer, 1974). This statement is not unique to SDT, but rather is true for essentially all descriptive and inferential statistics.

2 In Wald (1952), when there are more than two decision alternatives, the decision variable for each pair of alternatives is the distribution of evidence for each alternative across the unidimensional decision variable that transects the statistical evidence distribution for the two alternatives under consideration.

3 SDT decision statistics for sensitivity reflect separation of central tendency of evidence relative to pooled variance. Therefore, criterion variability does have a small, inverse effect on measures of sensitivity (Pastore & Scheirer, 1974; Macmillan & Creelman, 1991).

4 Evaluating performance of the Norris model simulation in terms of A’ is logical because a central goal of our evaluation is to understand the processes that produced the Norris results. Evaluating ROC performance in terms of A’ does add implicit assumptions about A’ to our analysis. We should note that the behavior of A’ and d’ are equivalent when sensitivity is low and bias small (Pastore et al., in press), as in the Norris results.

5 In contrast to this assertion, an increase in false alarm (nonword error) rate should alter both d’ and β, and this has nothing to do with how well Lexical decisions approximate the conditions of SDT.

6 In the traditional threshold model, p is the true probability that the stimulus exceeds the detection or recognition threshold and q is the probability of a false positive response when in the subthreshold state.
The alternative definition of criterion value is the number of matches that must be exceeded (i.e., under this alternative definition, a criterion of 13 would require 14 or more matches). Other than the specific nominal value of criteria, our analysis is independent of which definition we use.

Since, for A’ computed from a single point to be constant, every value of P(FA) can have only one value of P(H), there is a single isosensitivity contour for A’. The distinction between A’ computed from the computational formula for a single point and d’ is not whether the assumed underlying distributions posit equal variance (thus ROC curves that are symmetric around the negative diagonal, as is the case for A’ and d’), but rather whether or not the nature of the underlying distributions are explicitly specified (e.g., Macmillan and Creelman, 1995; Pastore et al., in press).

We cannot easily estimate this probability. However, 30 features, when sampled in groups of 20 that define a word, yield approximately 30 million possible words. This large number of words needs to be reduced because of the restriction that each word is distinguished from every other word by at least 4 features. This still leaves millions of possible words. A given word is defined by a specific set of 20 features. Assume that exactly 12 of these features are perceived; there are approximately 126,000 unique combinations of those 12 features. Therefore, the possibility that a specific set of those 12 perceived features is shared with a word has to be extremely small.

Using the results reported by Norris for this condition and the P(FA) for related word decisions at criterion 14 as the value for R_N, we solve Eq. 2b for U_N. The P(FA) of 0.39 for this Neutral condition reflects a probability (R_N) of 0.10 for a related word match and a probability (U_N) of .32 for an unrelated word match. From Eq. 2b, \( (1- R_N)U_N = \left[ (0.90)(0.32)/(0.10) \right] R_N \), \( U_N = 2.9 \times R_N \).
11 P(FA) will be determined more by unrelated word decisions for both strict and moderate criterion values, and thus the range of criteria employed in the Norris simulation.

12 We acknowledge that the combination of related word priming with very large amounts of unrelated word priming will have a small (thus nonzero), but inconsequential effect on P(H).
Table 1: Summary of Conditions and Priming in Norris (1995) simulation

<table>
<thead>
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<th>Condition</th>
<th>Symbol</th>
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<tr>
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<tr>
<td>50-Word Unrelated</td>
<td>U50</td>
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<td>50</td>
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Table 2: Summary of Original and New Results and “Nonparametric” Statistics from Norris Simulation

A. Norris (1995)

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<th>Condition</th>
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<th>Computed</th>
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<td>.68</td>
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</table>

B. New Results from Norris

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<td>Neutral</td>
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<td>U50</td>
<td>.61</td>
<td>.49</td>
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</table>

* Hybrid Condition that combines Related and Unrelated Priming
Figure Captions

Figure 1: ROC analysis of related word processing and original results from the Norris (1995) simulation. The operating characteristic of related word processing is plotted as diamond symbols, with the number next to each symbol indicating the criterion or threshold value for matching the related word. The ordinate and abscissa at each diamond symbol is the values of $R_W$ and $R_N$ in Equation 2 at each criterion. The bold lines are the isosensitivity contours for $A'$ values of 0.84, 0.68 and 0.50 (chance), with the $A' = 0.84$ curve allowing comparison of the related word ROC curve with isosensitivity for $A'$. The letter symbols plot the results for the five conditions in the Norris simulation: Neutral (N), 1-Word Related (R), Hybrid 50-Word Related (H), 1-Word Unrelated (U1), and 50-Word Unrelated (U50).

Figure 2. New Norris simulation results and ROC analysis of Norris simulation compared with isosensitivity for $d'$. The solid lines now plot isosensitivity for $d'$, and the symbols are the new results provided by Norris for each of the five simulation conditions (see Figure 1 for details).

Figure 3. Illustration in ROC space of the behavior of word decisions based upon comparison of presented stimuli with the related word in the Lexicon (related process) and comparison with unrelated words in the Lexicon (unrelated process) following the failure to match the related word. The behavior of the related and unrelated processes is derived in the analyses developed in the body of this paper.
Figure 1
Figure 2