

COMMENT

Response Bias and the Process-Dissociation Procedure

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Two different approaches for treating response bias in the process-dissociation procedure were assessed: a multinomial approach proposed by A. Buchner, E. Erdfelder, and B. Vaterrodt-Plünnecke (1995) and a dual-process, signal-detection approach proposed by A. P. Yonelinas, G. Regehr, and L. L. Jacoby (1995). The authors examined data presented by Buchner et al. and found that, although the signal-detection-based model worked slightly better than the multinomial model, the data did not provide a strong test of either model. However, an examination of other recognition data showed that the multinomial model produced distorted estimates of recollection and familiarity, and it was unable to account for observed receiver operating characteristics (ROCs). In contrast, the dual-process, signal-detection model produced unbiased estimates and was able to account for the observed ROCs. The authors also provide an overview of the general controversy surrounding the process-dissociation approach.

Buchner, Erdfelder, and Vaterrodt-Plünnecke (1995) proposed a modification of the *process-dissociation procedure* that incorporates response bias. We begin this article by describing the process-dissociation procedure and then describe the multinomial model that Buchner et al. proposed, contrasting their model with a dual-process, signal-detection method that we (e.g., Yonelinas, 1994; Yonelinas, Regehr, & Jacoby, 1995) have developed to take differences in response bias into account. Next, we examine the data that Buchner et al. used as evidence to support their model and show that our model deals with those data slightly better than does their model. We argue, however, that the manipulations used in their experiments may have influenced both response bias and recollection, and thus their data may not provide a strong test of models. We assess the models further by examining changes in response criterion associated with differences in response confidence and show that the multinomial model, but not the dual-process, signal-detection model, produces distorted estimates of recollection and familiarity. Finally, we examine *receiver operating characteristics* (ROCs) and find that the model that underlies the multinomial approach is in conflict with the ROC data. In contrast, we show that our signal-detection model accounts well for observed ROCs. While considering models of response bias, we provide a “road map” for contro-

versy surrounding the process-dissociation procedure, providing references to comments made by critics of the approach and our answers to those critics.

Although the focus on differences between models emphasizes disagreement, we agree with Buchner et al. (1995) on a number of fundamental issues. We agree that the process-dissociation procedure is an advance as compared to the use of direct and indirect tests to measure conscious and unconscious memory processes. The problem for relying on indirect and direct tests is that performance on indirect tests does not reflect unconscious influences of memory alone, but rather is contaminated sometimes by conscious uses of memory (Holender, 1986; Toth, Reingold, & Jacoby, 1994). Also, performance on direct tests is sometimes contaminated by unconscious influences (Jacoby, Toth, & Yonelinas, 1993). Buchner et al. and we have agreed that the process-dissociation procedure provides a way of estimating conscious and unconscious influences within the same task and thus avoids the problems associated with equating conscious and unconscious memory processes with performance on two different types of memory test. We also agree that the original proposal of the process-dissociation approach (Jacoby, 1991) acknowledged but did not adequately deal with effects produced by differences in response bias.

The goal of the process-dissociation approach is to separately estimate the contributions of consciously controlled use of memory (recollection) and unconscious, automatic use of memory (e.g., familiarity) to the performance of a task. The problems produced by differences in response bias are similar to those encountered by models of memory that do not distinguish between recollection and familiarity but, instead, are meant to separate memory and guessing. As will be described, single-process memory models can be divided

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We thank A. Buchner for several informative discussions and for providing the raw data from the original study.

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into those taking a multinomial approach and those using signal-detection theory to account for differences in response bias. The success of a model designed to take differences in response bias into account is measured by the invariance in its estimates of memory across levels of a manipulation meant to selectively influence response bias. Both the aim of using signal-detection theory and that of using a multinomial model is to correct for differences in response bias (guessing) so as to measure true recognition memory. The measure of true recognition memory is expected to remain invariant across conditions that differ in the extent to which they encourage guessing. Returning to the process-dissociation approach, an adequate treatment of response bias within that approach can show both estimates of recollection and estimates of familiarity to be invariant across manipulations of response bias.

Buchner et al. (1995) and we have agreed on the necessity of a dual-process model of memory and that gaining true measures of recollection and familiarity is of paramount importance. However, we have disagreed in regard to ways that we favor for dealing with complications produced by differences in response bias. This disagreement is generally unimportant for conclusions that we have drawn from prior experiments using the process-dissociation procedure (e.g., Jacoby, Toth, & Yonelinas, 1993). Our interest has been in showing that experimental manipulations and individual differences can selectively influence recollection or familiarity, rather than in the absolute magnitude of estimates of recollection or familiarity. Because our main interest has not been differences in response bias, we have designed our experiments to avoid or minimize such differences. Buchner et al. made an important contribution by using designs that produce large differences in response bias and, so, force one to deal with the complications of correcting for such differences when estimating the contributions of conscious and unconscious uses of memory. Although it is important to incorporate a model of response bias into the process-dissociation procedure, we later argue that the best strategy is to avoid differences in response bias, as we have done, unless such differences are of focal interest.

The Process-Dissociation Procedure

Jacoby (1991) developed the process-dissociation procedure to derive quantitative estimates for the contributions of recollection and familiarity to recognition memory performance. Estimates for recollection and familiarity were gained by combining performance in an *inclusion condition*, in which the two bases for recognition act in concert, with performance in an *exclusion condition*, in which the bases for recognition act in opposition. As will be described, the use of these two test conditions to separate types of memory is analogous to the use of hits and false alarms to separate memory from guessing in a single-process model. Just as is true for hits and false alarms, in concert and opposition conditions can be gained in a variety of ways. As an example of the process-dissociation procedure, consider its first use by Jacoby (1991). In Phase 1 of that experiment,

participants read a list of words under incidental encoding conditions. In Phase 2, participants heard a different list of words and were instructed to remember those words for a later recognition test. At test, participants were presented with a list containing a mixture of words that were earlier seen, words that were earlier heard, and new words and were given either inclusion or exclusion instructions. In the inclusion condition, they were instructed to call a word "old" if it was in either the seen or heard list. In the exclusion condition, they were instructed to call a word "old" only if it was in the heard list. Further, they were told that if they could recollect that the word was seen they could be sure the word was not heard and thus should reject the word. That is, participants were instructed to include seen words in the inclusion condition and exclude those words in the exclusion condition.

Performance in the inclusion and exclusion conditions for the seen words was used to derive estimates of recollection and familiarity. If the two processes are independent, the probability of responding "yes" to a seen word in the inclusion (i) condition can be written as

$$P(\text{"yes"/old})_i = R + F - RF, \quad (1)$$

the probability that the item is recollected (R) plus the probability that it is familiar (F), minus the probability that the item is recollected and familiar (RF). That is, a seen item can be accepted as old if it is recollected as having been seen or if it is sufficiently familiar to be judged old. The probability of responding "yes" to a seen item in the exclusion (e) condition can be written as

$$P(\text{"yes"/old})_e = F - RF, \quad (2)$$

the probability that the item is familiar, minus the probability that it is familiar and recollected. That is, participants will only accept a seen word if it is familiar but they cannot recollect that it was seen. Recollection is calculated by subtracting the exclusion score from the inclusion score, $R + F - RF - (F - RF) = R$. Having solved for R , either of the two equations can be used to solve for familiarity; for example, $\text{exclusion}/(1 - R) = F$.

Buchner et al. (1995) used the terms *conscious* (C) and *unconscious* (U), whereas we prefer to use the terms *recollection* and *familiarity* as exemplars of the general categories of consciously controlled and unconscious, automatic processes, relevant to recognition memory (Mandler, 1980). More important, as described earlier, our use of the process-dissociation procedure has typically been based on the assumption that recollection and familiarity serve as independent bases for recognition judgments. In contrast, Buchner et al. have claimed that a merit of their modification of our approach is that they avoid making an assumption about the relationship between recollection and familiarity. To avoid the independence assumption, they have estimated the conditional probability that an item is familiar given that it was not recollected in preference to the simple probability of calling an item old on the basis of its familiarity.

A means of avoiding the independence assumption would greatly simplify our lives. That assumption has been the

most controversial assumption underlying the process-dissociation approach. Earlier, we (Jacoby, 1991; Jacoby, Toth, & Yonelinas, 1993) noted alternatives to an independence relation between recollection and familiarity and acknowledged that those alternative relations sometimes hold. Later, Joordens and Merikle (1993) favored an assumption of a redundancy relation, and we (Jacoby, Toth, Yonelinas, & Debnar, 1994) responded by defending the independence assumption as providing the most reasonable fit for data from our experimental situations. Rather than claim that independence always holds, we have aimed the design of our experiments at satisfying the assumption of independence. Curran and Hintzman (1995) followed Jacoby (1991) by noting that violation of the independence assumption can bias estimates and claimed to show that, in our experiments, we were unlikely to have satisfied the assumption of independence (see Jacoby, Begg, & Toth, in press, for a response).

Does reliance on the conditional probability of familiarity given recollection failure allow one to avoid the independence assumption? A cost of abstaining from an assumption about the relationship between bases for recognition judgments is that one can no longer estimate the contribution of familiarity. Use of the conditional probability, without an assumption about the relation between recollection and familiarity, does not allow one to show the selectivity of influences on familiarity or recollection, which is our interest. Only by assuming independence, does one have reason to expect the conditional probability of familiarity given recollection failure to remain invariant across manipulations that influence the probability of recollection. This is because with an assumption of independence, the conditional probability of familiarity given recollection failure is equal to the simple probability of calling an item old on the basis of its familiarity. The equivalence of the conditional probability and the simple probability of familiarity given the independence assumption means that consequences of violating the independence assumption are the same for the two probabilities.

Findings of selective influences in the form of dissociations provide support for the independence assumption. For example, divided, as compared to full, attention to study reduces recollection but leaves automatic influences invariant in stem-cued recall, as do age-related differences in recollection. There is substantial support for the independence assumption as it relates to stem completion performance (e.g., Cowan & Stadler, 1996; Jacoby, Yonelinas, & Jennings, in press). More relevant, however, is the evidence supporting the independence assumption in studies of recognition memory, which is the task discussed by Buchner (see Jacoby, Jennings, et al., in press; Yonelinas, 1994; Yonelinas & Jacoby, 1994; Yonelinas & Jacoby, 1995b; Yonelinas & Jacoby, 1996). In the current discussion, we assume that recollection and familiarity are independent and use the terms to represent simple probabilities, rather than use the mix of simple and conditional probabilities favored by Buchner et al. (1995). However, the arguments made for the simple probabilities hold as well for the conditional probabilities, because, given the independence assumption,

the conditional probability used by Buchner et al. is identical to the simple probability F (see Buchner et al., p. 141).

The Multinomial-Based Model Proposed by Buchner et al. (1995)

Buchner et al. (1995) propose a way of introducing response bias into the process-dissociation procedure that is based on a multinomial model (see Batchelder & Riefer, 1990). They argue that performance in the inclusion and exclusion conditions reflects not only recollection and familiarity, but also a separate guessing process. The notion is that when both recollection and familiarity fail, participants may still accept items as old on the basis of a guess. Guessing would increase the probability of accepting old items as old, but would also lead participants to incorrectly accept new items as old. This, of course, would account for the fact that participants almost always accept some proportion of new items as old (i.e., false alarms). Because the probability of a guess may differ in the inclusion and exclusion conditions, Buchner et al. have introduced different guessing terms into the inclusion and exclusion equations (G_i and G_e , respectively). They then used the false-alarm rates under inclusion and exclusion conditions as estimates of G_i and G_e and algebraically removed guessing from performance on the old items to provide a pure measure of recollection and familiarity. By their formulation, the inclusion and exclusion equations can be written as

$$P(\text{"yes"/old})_i = R + (1 - R)[F + (1 - F)G_i] \quad (3)$$

$$P(\text{"yes"/old})_e = (1 - R)[F + (1 - F)G_e], \quad (4)$$

where

$$P(\text{"yes"/new})_i = G_i \quad (5)$$

$$P(\text{"yes"/new})_e = G_e. \quad (6)$$

By solving these equations one can derive estimates for R and F .

The multinomial model that underlies this correction method has been used in studies of source memory (see Johnson, Hashtroudi, & Lindsay, 1993) and reflects a class of models known as high-threshold models. After we assess Buchner's model we discuss the use of high-threshold models in general.

The Dual-Process, Signal-Detection Model

An alternative method of incorporating response bias into the process-dissociation procedure is to use a dual-process, signal-detection model that was proposed in outline form by Jacoby et al. (1993) and further developed by Yonelinas (Yonelinas, 1994; Yonelinas et al. 1995). By that model, recollection is probabilistic just as in the model proposed by Buchner et al. (1995). However, familiarity is assumed to reflect a signal-detection process (for a discussion of signal-detection theory, see Macmillan & Creelman, 1991). The idea is that new items are sometimes accepted as old on the

basis of preexperimental familiarity. All items are assumed to have some level of familiarity that can be described by a normal distribution. Studying a list of items temporarily increases the familiarity of those items, which has the effect of shifting their familiarity distribution. The participant sets some criterion level of familiarity, and items exceeding that level are accepted as old. Participants can vary their response criterion on familiarity and thus increase or decrease their hits and false alarms.

If familiarity is a signal-detection process, then the familiarity term in the original process-dissociation equations can be replaced by a function representing the probability that an old item exceeds the response criterion: $\Phi(d'/2 - C)$. This term represents the proportion of the old-item distribution exceeding the criterion (C ; see Macmillan & Creelman, 1991). When this term is substituted into the inclusion and exclusion equations we have

$$P(\text{"yes"/old})_i = R + \Phi(d'/2 - C_i) - R\Phi(d'/2 - C_i) \quad (7)$$

$$P(\text{"yes"/old})_e = \Phi(d'/2 - C_e) - R\Phi(d'/2 - C_e). \quad (8)$$

Of course, for a given value of C , there will be some proportion of new items incorrectly accepted as old. The false-alarm rate will be equal to the proportion of the new-item distribution exceeding the criterion, and this can be written as

$$P(\text{"yes"/new})_i = \Phi(-d'/2 - C_i) \quad (9)$$

$$P(\text{"yes"/new})_e = \Phi(-d'/2 - C_e). \quad (10)$$

Thus, we have four equations (the probability of accepting old and new items under inclusion and exclusion instructions) and four variables (R , d' , C_i , and C_e). We can solve the equations to derive estimates for the four variables. However, because of the nature of the normal distributions that underlie the signal-detection model, a simple algebraic solution is not available. To solve for the unknowns, we used a gradient-descent search algorithm. However, another alternative is to assume logistic distributions, in which case there is a closed-form solution (see Appendix A). We discuss the logistic-based method in more detail in a later section. However, in keeping with the assumptions of signal-detection theory, the estimates presented in the current paper were based on normal distributions.

Because familiarity is assumed to reflect a signal-detection process, it is measured in terms of d' rather than in terms of simple probabilities. The probability that an item will be accepted on the basis of familiarity is not fixed, but will vary with the response criterion. However, to facilitate comparison to the multinomial correction method, we will provide estimates of familiarity in terms of simple probabilities by calculating the probability of accepting old items based on familiarity given a specified false-alarm rate. The signal-detection-based model and the multinomial model are similar in that they both assume that recollection and familiarity contribute to overall recognition performance. Moreover, recollection is estimated in the same way by the two models and is measured by both models as a

simple probability (i.e., the probability that an old item is recollected).

The multinomial and dual-process, signal-detection models differ in several important ways. First, we have assumed that familiarity is a signal-detection process, such that old and new items that exceed the response criterion are accepted as old. In contrast, Buchner et al. assume that some fixed proportion of old items are experienced as familiar (a high-threshold model of the class described by Snodgrass & Corwin, 1988). Buchner et al. (1995) assume that new items are never accepted as old on the basis of familiarity. Rather, false alarms arise because participants engage in a random guessing process. The guessing process is assumed to operate independently of the item's history (i.e., the probability of guessing is the same for studied and nonstudied items). Moreover, the guessing process is assumed to be independent of recollection as well as familiarity. This independence assumption is a consequence of the way Buchner et al. introduced the guessing term into the equations expressing their model. Their independence assumption can be appreciated by examining their Equations 3–6. For example, if we represent the probability that an old item is accepted on the basis of memory (i.e., recollection and familiarity) as M , then their Equation 3 can be written as: $M + G - MG$ (which is the independence equation).

Assessing the Models

We compared our model with that proposed by Buchner et al. (1995) in three ways: First, following Buchner et al., we examined how well the two models corrected for differences in response bias when bias was manipulated experimentally. We did this by applying the multinomial and signal-detection models to data from Buchner et al. Second, we applied the models to a data set from Yonelinas (1994) gained by requiring participants to make confidence judgments in an inclusion–exclusion, recognition–memory experiment. This data set allowed us to assess the models when response criterion varied as a function of response confidence. Third, the same data set was also used to examine how well the models underlying the different methods of incorporating response bias could account for ROCs.

Experimental Manipulations of Response Bias

One way of assessing a model of response bias is to find manipulations that selectively influence response bias and examine the effect of these manipulations on estimates of R and F . If the manipulations selectively influence response bias and the model adequately accounts for bias, then estimates of R and F should not be affected by those manipulations. Buchner et al. (1995) examined three potential response-bias manipulations. In Experiment 1, they varied the proportion of items in the test lists that were new. In Experiment 2, they varied the payoff schedule such that participants were reinforced to respond “yes” or “no.” In Experiment 3, they either informed the participants of the

objective probabilities that test items were old or they did not. In all three experiments, the manipulations influenced the participants' response bias, in the sense that they were more likely to accept old and new items in one condition than in another.

Buchner et al. (1995) found that estimates for both R and F gained using the original process-dissociation procedure were influenced by the response-bias manipulation. Moreover, the multinomial method led to estimates of R and F that were less affected by the response-bias manipulations than the original estimates. We examined data from their experiments and contrasted estimates gained using the multinomial method with those gained using the signal-detection method. Both procedures were found to lead to a modest decrease in response-bias effects. However, an examination of the results suggests that the experimental manipulations affected the recollection process as well as response bias, and thus the experiments did not provide a strong test of the models.

Table 1 shows the average estimates for strict and lax response-bias conditions based on the original procedure (Equations 1 and 2) and the multinomial (Equations 3 to 6) and dual-process, signal-detection methods (Equations 7 to 10). Estimates were derived for each condition in each experiment reported by Buchner et al. (1995). For simplicity, estimates for R and F were then averaged across words that were read and solved as anagrams in the study list and across the three experiments. However, the raw scores for all conditions as well as the parameter estimates are presented in Appendixes B and C, respectively. The strict conditions were those referred to as the extended, conservative, and standard conditions in Experiments 1 through 3 done by Buchner et al. Difference scores, across the response-bias manipulation, for each correction method are also presented. The difference scores reflect the effect of response bias on estimates of R and F . To the extent that the models of response bias reduce this difference, they have succeeded in accommodating the effect of the response-bias manipulation.

Estimates are presented in terms of simple probabilities for all three estimation methods. The signal-detection-based method measures familiarity in terms of d' . However, in order to facilitate comparison to the estimates from the other methods the estimates were converted into probabilities by determining the probability of accepting an old item on the basis of familiarity (d') at the average false-alarm rate (.18).

An examination of Table 1 shows that the response-bias manipulations did distort the estimates for R and F gained from the original estimation method. The response-bias manipulation led to a .07 difference in recollection and a .14 difference in familiarity. The influence of the response-bias manipulations on the process estimates suggests that a method of correcting for response bias is required. Did use of the different models decrease the effects of the response-bias manipulations? Table 1 shows that both models reduced the bias effect on familiarity but did not lead to a sizable improvement in estimates of recollection. The effect of bias (i.e., the difference score) on familiarity was reduced from .14 with the original procedure to .08 with the multinomial method. However, the signal-detection method led to a slightly more substantial reduction, decreasing the difference score to .02. In contrast, for recollection, neither model reduced the difference scores (.07 for all three estimation procedures), suggesting that neither correction method was successful at eliminating the effects of the response-bias manipulations on recollection.

Why were the estimates of recollection not greatly improved by either correction method? One possibility is that the bias manipulations used by Buchner et al. (1995) did not selectively influence response bias but, rather, also influenced recollection. That is, all three estimation procedures may have been correct in showing that the response-bias manipulations had real effects on recollection. For example, in Experiment 1, increasing the proportion of old items in the test list may have increased the probability that participants engaged in the recollection process. In the sense that recollection is a controlled memory process (Jacoby, 1991), it is likely that a participant's retrieval strategies are influenced by the proportion of trials on which the process has been successful in the past. In agreement with this possibility, Jacoby, Kelley, Brown, and Jasechko (1989) found that in a fame judgment task, participants were less likely to say "famous" to a studied nonfamous name when many of the tested names were studied, suggesting that participants were more likely to try to recollect items from the study list when many of the tested items were from that list. With the current data sets, there is no direct way of determining if the bias manipulations did influence recollection. Thus, without further experiments to determine the effects of the response-bias manipulations on recollection and familiarity, it is impossible to draw strong conclusions about the validity of the different models.

Table 1
Average Estimates for Recollection (R) and Familiarity (F) Under Lax and Strict Response Bias Conditions From Buchner et al. (1995), Based on the Original, Multinomial, and Dual-Process, Signal-Detection (DPSD) Estimation Procedures

Parameter	Estimation procedure								
	Original			Multinomial			DPSD		
	Lax (M)	Strict (M)	Mean difference	Lax (M)	Strict (M)	Mean difference	Lax (M)	Strict (M)	Mean difference
R	.63	.56	.07	.57	.50	.07	.43	.36	.07
F	.50	.36	.14	.36	.28	.08	.49	.51	.02

In summary, an examination of Buchner et al. (1995)'s data showed that, for estimates of familiarity, both correction procedures reduced the effects of the bias manipulations, but the signal-detection method led to a more complete reduction in bias effects. However, for estimates of recollection, neither correction method provided a sizable reduction in bias effects. This may have been due to the fact that the manipulations influenced recollection as well as response bias.

Differences in Response Confidence

In this section, we describe the effect of varying response criterion, observed by examining performance at different levels of response confidence. Confidence-judgment data have been used quite extensively to test models of recognition memory over the past 20 years (e.g., Murdock, 1974; Ratcliff et al., 1992). Presumably, different levels of response confidence reflect differences in response criterion. That is, high-confidence responses reflect a strict response criterion, whereas lower levels of response confidence reflect a more lax response criterion. This procedure provides a useful test of the correction methods because it does not rely on examining performance across experimental manipulations that might influence recollection.

We examined data from a recent series of experiments in which the process-dissociation procedure was used to estimate the contribution of recollection and familiarity as a function of response confidence (Yonelinas, 1994, Experiment 1). We begin by using data from that experiment to examine how well the two different models of response bias correct for differences in response bias between inclusion and exclusion conditions. In the next section we examine the ROCs from that study in more detail and contrast them with the ROCs predicted by the models underlying the two different correction procedures.

Participants rated the confidence of their recognition memory judgments in a process-dissociation experiment. They made their recognition judgments on a 6-point confidence scale from sure yes (6) to sure no (1). The data allowed us to examine inclusion and exclusion performance in the same experiment at different levels of response confidence and, thus, at different base rates. We examined estimates for R and F when the base rates for the inclusion and exclusion conditions were equivalent, as well as when the base rates differed. If the correction methods do correct for response bias, then differences in base rate should not influence estimates of R and F . That is, estimates gained using scores for which the base rates were the same should not differ from those for which base rates differed.

Table 2 presents inclusion and exclusion performance under strict response criterion conditions; we included only the most confident inclusion and exclusion judgments (5s and 6s). Also presented is performance under more lax conditions; we included 3, 4, 5, and 6 responses. As expected, the false-alarm rate was considerably higher under lax (.38) than strict conditions (.05).

Estimates for R and F were derived using the same

response-bias conditions (strict for both inclusion and exclusion) and different response-bias conditions (lax for inclusion and strict for exclusion; see Table 3). Looking first at the estimates derived using the original process-dissociation procedure (Table 3), we see that both R and F are much greater when scores from different levels of response confidence are used compared to when scores from the same level of response confidence are used. Of course, this is not surprising because the inclusion score was greater in the lax condition than in the initial condition. Increasing the inclusion score inflates R because R is calculated as the difference between inclusion and exclusion scores. Increasing the inclusion score also inflates estimates of familiarity because familiarity is calculated by dividing the exclusion score by $(1-R)$. Consequently, when base rates differ greatly between inclusion and exclusion conditions, the original estimation method cannot be relied on to produce valid estimates of R and F .

Using the multinomial model, the differences in estimates between same and different criterion conditions were slightly reduced. However, the estimates for both R and F were still inflated compared to the estimates gained using that procedure when the base rates were the same. The difference scores for R and F were .23 and .15 for recollection and familiarity respectively, showing that the multinomial model led to distorted estimates of recollection and familiarity. In contrast, the signal-detection-based correction method was not affected by differences in response bias; neither estimates of R nor F differed across the same and different response-bias conditions. Why the two models differed in their ability to correct for effects of response bias will become apparent in the next section.

Examination of the Yonelinas's (1994) data showed that differences in base rate between inclusion and exclusion conditions can lead to dramatically distorted estimates of R and F when using the original procedure. The multinomial correction did lead to a slight reduction in the effects of response bias but left estimates of both R and F greatly inflated. In contrast, the signal-detection method was successful in removing effects of response bias.

ROC Analysis

A shortcoming of the above analyses is that performance was examined only at two different levels of response criterion (strict and lax) in any one experiment. A much

Table 2
Proportion of Items Accepted From Long Lists in Experiment 1 (Yonelinas, 1994) Using Strict and Lax Response Criteria

Test condition	Response criterion			
	Strict		Lax	
	Old	New	Old	New
Inclusion	.53	.05	.84	.38
Exclusion	.15	.05	.46	.38

Table 3

Estimates for Recollection (R) and Familiarity (F) Using Inclusion and Exclusion Scores From Same and Different Levels of Response Confidence for the Original, Multinomial, and DPSD Estimation Methods

Parameter	Estimation procedure								
	Original			Multinomial			DPSD		
	Same	Different	Mean difference	Same	Different	Mean difference	Same	Different	Mean difference
<i>R</i>	.38	.69	.31	.38	.61	.23	.38	.38	.00
<i>F</i>	.24	.48	.24	.20	.35	.15	.24	.24	.00

Note. DPSD = dual-process, signal-detection.

more powerful means of testing the models is to examine performance at several different levels of response criterion in the same experiment. An ROC analysis provides just such a test, and, as we will see, it illustrates why the multinomial correction model leads to distorted estimates of *R* and *F*.

An ROC is the function that relates the proportion of hits to the proportion of false alarms. In the experiment just described, participants made their responses on a 6-point confidence scale. We can examine the ROC from that experiment by plotting performance at each level of response confidence. In Figure 1, the ROC was plotted such that the first point includes only the most confidently remembered items (i.e., items eliciting a response of 6). The second point includes all of the most confident responses plus the second most confident responses (i.e., items eliciting a response of 6 or 5, etc.) so that the 6-point response scale produces a function with 5 points.

The inclusion function begins at .35 on the *y*-axis and gradually increases in a curvilinear fashion toward the upper right corner of the graph. As is the case with most recognition ROCs, the function is curvilinear and is not symmetrical along the negative diagonal (e.g., Ratcliff, Sheu, & Gronlund, 1992). The ROCs predicted by the multinomial and signal-detection models are also presented in Figure 1. The predicted curves were generated by fitting the models to the lax inclusion score in the previous section; this is the second-most right point on the observed function.

How did the predicted and observed ROCs compare? Examination of Figure 1 shows that the model underlying the multinomial correction method provides a very poor fit to the observed ROC. In contrast to the observed data, it predicts a linear (straight line) ROC. Because the inclusion and exclusion equations are linear, increases in the false-alarm rate are accompanied by proportional increases in the hit rate, leading to straight-line ROCs.

One might argue that the curvilinear relationship between hits and false alarms may only be observed in confidence judgments under inclusion instructions and that the multinomial model might fare better under different test conditions. However, the curvilinearity that is so problematic for the model is very general. For example, curvilinear ROCs are always observed in standard studies of recognition memory (e.g., Donaldson & Murdock, 1968; Gehring, Toglia, & Kimble, 1976; Glanzer & Adams, 1990; Ratcliff et al., 1992). Moreover, curvilinear ROCs are found when

response criterion is manipulated by varying the proportion of old items in the test list (e.g., Ratcliff et al., 1992), a manipulation like that used in Experiment 1 in the Buchner et al. (1995) study. Thus, the nonlinear relationship that is observed between hits and false alarms is quite general in studies of recognition memory and is not limited to inclusion-exclusion confidence judgments.

We are not the first to argue that the curvilinear recognition ROCs are problematic for threshold models. The observed nonlinearity of ROCs was one of the primary reasons why threshold models of recognition were initially rejected as viable models for simple recognition judgments (see Murdock, 1974). Moreover, Kinchla (1994) has recently shown that these ROCs are in conflict with the multinomial models used in studies of source memory.

In contrast to the multinomial model, the dual-process, signal-detection model accounted well for the ROCs, with the observed data points falling very close to the predicted function. In agreement with the data, the model predicts a curvilinear function. The reason the dual-process, signal-detection correction method predicts such a function is that the normal distributions that underlie the familiarity com-

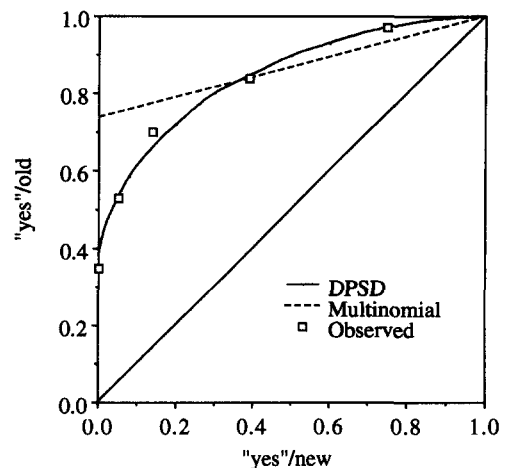


Figure 1. The observed recognition receiver operating characteristics (ROCs) from Yonelinas (1994), along with the ROCs predicted by the dual-process, signal detection model (DPSD) and the multinomial model.

ponent lead to nonlinear increases in the probability of accepting old and new items.

Although an informal examination of Figure 1 is sufficient to show that the multinomial model does not provide a satisfactory account of recognition data, we contrasted the fits of the models by calculated R^2 measures. The R^2 values for the signal-detection and multinomial models were .997 and .773, respectively, showing that the signal-detection model accounted for appreciably more variance than the multinomial model. Although a direct statistical test of the models is made difficult because of their different underlying assumptions, the R^2 measures are informative, because the two models contain a similar number of free parameters. The dual-process model fits the observed function in Figure 1 with two free parameters (R and d'). The multinomial model also fits the ROC with two free parameters (R and F). The multinomial model could be simplified to contain only one free parameter (M), but it would no longer be a dual-process model and would be of little use for interpreting inclusion–exclusion data. We have conducted similar analysis on numerous recognition and inclusion ROCs, and the signal-detection-based model always provides a sizable improvement over the multinomial model.

Although the signal-detection model does provide a reasonable fit to the recognition data, observed ROCs tend to deviate slightly from the predicted curves at the extreme levels of response confidence. For example, the left-most point on the inclusion function tends to be slightly lower than the model predicts (for further discussion of the deviations from the model, see Yonelinas et al., 1995). Such a deviation from the model might arise if participants falsely recollect that items were in a study list. False recollection could be problematic because neither the signal-detection-based model nor the multinomial model assume that false recollection occurs. That the dual-process model fit the data reasonably well suggests that false recollection was not a major problem. However, we believe that further assessments of the model must address this possibility. In any case, the deviation from the predicted curve was relatively minor and was limited to the extreme levels of response confidence. Our experience is that cases for which a correction method is required do not involve such extremes but rather fall in the middle of the function where the model fits the data quite well.

The ROC analysis showed that the multinomial model was not able to account for the curvilinear form of the observed ROC and provided a very poor fit of the data observed under inclusion conditions. Because the linear model underlying the correction method is not in agreement with recognition performance, it does not provide an appropriate method of incorporating response bias into the process-dissociation procedure. This explains why the multinomial correction method led to the distorted estimates for both recollection and familiarity described in the previous section. We should note that Wainwright and Reingold (in press) describe additional problems for the multinomial approach proposed by Buchner et al. (1995). The dual-process, signal-detection model, in contrast, provided a good fit to the observed ROC data and thus seems to

provide a reasonable method for incorporating response bias into the process-dissociation procedure.

Correcting for Response Bias in Memory Tasks Other Than Recognition

The process-dissociation procedure has been applied to numerous tasks other than recognition memory. We are currently examining the application of the dual-process, signal-detection model to stem completion performance. However, the application of the model in that domain is considerably more complex, and in some cases it may not be appropriate. ROC analysis of stem-completion performance is made difficult because, unlike recognition, participants do not have to respond to all items. In fact, the task relies on participants failing to respond correctly to many of the test items. Because of this, we cannot derive ROCs in the way we did for recognition performance and thus cannot easily assess the correction methods. However, some preliminary examinations of stem-completion performance show that the ROCs are not linear and likely involve some form of nonlinear signal-detection process. Another problem for applying correction procedures to stem-completion performance is that differences in base rate may arise for reasons different than a shift in response criterion. For example, base-rate differences arise when participants use different retrieval strategies for the inclusion and exclusion test conditions, as when they adopt a generate–recognize strategy (see Jacoby et al., 1993).

One domain in which the dual-process, signal-detection model may be useful is in studies of source memory. In a typical source-memory experiment, participants study items from two different sources. They are then given a recognition test for which they must first distinguish old items from new distracter items and then are asked to judge the source of recognized items. Batchelder and Riefer (1990) proposed several multinomial models that have been used extensively in studies of source monitoring. A problem for these theories of source monitoring is that they cannot account for the observed curvilinear recognition ROCs. Kinchla (1994) showed that ROCs generated by these multinomial models were not in agreement with a large body of data on recognition memory (however, see Batchelder, Riefer, & Hu, 1994). The difficulty is that the multinomial models are high-threshold models, like the model proposed by Buchner et al. and thus predict linear ROCs rather than the curvilinear ROCs like those observed. Performance in standard source-memory tasks may be understood using the dual-process, signal-detection model (Yonelinas, 1996). By that model, initial recognition judgments are based on a mixture of recollection and familiarity, but source judgments rely primarily on recollection. If familiarity reflects a signal-detection process that is independent of a recollection process, then one would expect to see the type of curvilinear ROCs that are so problematic for current source-memory models.

Alternative Correction Methods

Here, we contrasted Buchner et al. (1995)'s multinomial model with the dual-process, signal-detection model. There are, of course, numerous other ways in which differences in base rates could be incorporated into the process-dissociation procedure. We have examined several alternative methods and briefly describe some of those methods in the following text (for a more complete discussion of those alternative methods, see Yonelinas et al., 1995).

There are several other high-threshold correction methods that, like the multinomial method proposed by Buchner et al. (1995) assume that there is a separate guessing process that contributes to memory performance. That is, guessing terms can be added to the inclusion and exclusion equations in numerous ways. The problem with most of these methods is that the underlying models predict linear ROCs. For example, it is possible to expand the model proposed by Buchner et al. into a 2-high-threshold model by introducing an additional recollection parameter. Doing so would allow the model to vary the slope of the predicted ROC line. This would slightly improve the fit of the model to the observed data; however, an examination of Figure 1 shows that there is no straight line that provides a satisfactory fit for the entire curve.

There are more complex threshold-based models that can predict curvilinear ROCs (see Swets, 1986), and it is possible that these models can be adapted to the process-dissociation procedure. However, a problem that we have encountered when examining these models is that the number of free parameters often outnumbers the available data points. For example, in typical inclusion–exclusion experiments, one is limited to an inclusion and exclusion score for old and new items. The dual-process, signal-detection model is useful because the memory parameters (R and d'), and the two bias parameters (C_i and C_e) can be estimated on the basis of the four observed scores. However, models containing more parameters are of little use in these contexts because they are underdetermined.

There are a number of alternative ways in which signal-detection theory can be incorporated with the process-dissociation procedure. For example, one could apply signal-detection theory separately to both familiarity and recollection. That is, the two processes could be treated as separate dimensions in a multidimensional signal-detection model (see Macmillan & Creelman, 1991). In this way, both familiarity and recollection would be treated as continuous processes. Although this approach may be useful in some applications of the process-dissociation procedure, it seems unnecessary in tests of recognition memory. The reason is that recollection seems to be well described as a threshold process. For example, the recognition ROC intersects the y -axis at a point close to the estimate for recollection. That is, recollection led to very high confidence-recognition responses, and the false-alarm rate for the highest confidence responses was zero. Moreover, unlike familiarity, which increased in a continuous manner as response criterion was relaxed, estimates of recollection remained relatively constant. Such results are expected if recollection is a threshold process. However, we should note that although recollection

was well described as a fixed probability under the conditions examined in the current experiments, there may be conditions under which both processes behave in a continuous manner. We are currently exploring other tasks, using the process-dissociation procedure, for which a multidimensional signal-detection model may be appropriate.

Another alternative, mentioned earlier, is to use the dual-process, signal-detection method but to assume logistic rather than normal distributions for familiarity. An advantage of doing this is that the logistic function allows for closed-form solutions (see Appendix A). Thus, estimates of R and F can be attained with a few simple calculations rather than using a search algorithm as is required when assuming normal distributions. The logistic distributions provide a very close approximation to the normal distributions, and Snodgrass and Corwin (1988) have shown that the two distributions produce equivalent results when applied to a wide variety of recognition data. Moreover, for the current data sets, we found that the estimates based on the logistic distributions were very close to those derived using the normal distributions. Thus, the logistic-based, dual-process, signal-detection model seems to provide a relatively simple way of incorporating response bias into the process-dissociation procedure.

Avoiding Problems by Design

The model of response bias that is chosen makes little difference so long as conditions of interest do not differ in false alarms and one's interest is in the pattern, rather than the absolute magnitude, of differences (Snodgrass & Corwin, 1988). Generally, the design of our experiments has been aimed at avoiding differences among conditions in response bias because our interest has been to separate the contributions of consciously controlled and automatic processes. Our experiments have also been designed to avoid complexities that can arise from violating assumptions underlying the process-dissociation procedure. In this final section, we describe outcomes that make it necessary to correct for differences in response bias and then consider advantages of avoiding complexity by design. We end by justifying this strategy in the context of the goal of the process-dissociation approach.

If base rates do not differ across conditions, then a choice among models of response bias is not necessary, and the original inclusion–exclusion equations can be used to obtain estimates—introducing either the multinomial or the signal-detection theory correction procedure would not change the pattern of results. However, estimates of familiarity include both experimental and base-rate familiarity. If base rates differ between inclusion and exclusion conditions, then it is necessary to adopt a model of response bias to obtain true estimates of recollection and familiarity. In contrast, if base rates differ across some experimental variable, but not across inclusion–exclusion tests, only estimates of familiarity will be influenced. To compare estimates of familiarity, it is necessary to convert the measures of familiarity into a measure of sensitivity that is independent of base rate (e.g., a d' value). To do this, one can use

the false-alarm rate along with the familiarity estimate (as the hit rate) and use d' reference tables to determine the d' value. With familiarity measured in terms of d' , we can compare familiarity estimates independently of the false-alarm rate.

Buchner et al. (1995) varied inclusion versus exclusion tests among participants and observed large differences in base rates. In contrast, we think it best to manipulate the type of test within participants. Doing so makes it more likely that base-rate differences will be avoided, or at least minimized, and has the additional advantage of allowing one to compute estimates for each participant, which is important for purposes of analyses. Results reported by Dodson and Johnson (1996) illustrate pitfalls of manipulating the type of test between participants and relying on false alarms to correct for differences in response bias. To analyze their results, the inability to gain estimates for each participant led them to rely on a "macrosubjects" procedure that is analogous to randomly pairing hit rates and false-alarm rates produced by different participants to estimate d' and response bias. This approach was made even more problematic by findings of large differences in base rates that seem unexplainable. Correction for those supposed differences in response bias was largely responsible for creating the effects of manipulations on R and F that they treat as important.

Graf and Komatsu (1994) followed Jacoby (1991) by noting the assumptions underlying the process-dissociation procedure along with the consequences of violating those assumptions. One concern voiced by Graf and Komatsu is that participants may not understand instructions for an exclusion test (also see Curran & Hintzman, 1995). However, Toth, Reingold, and Jacoby (1995) noted that later experiments using the process-dissociation procedure have included ways to check the understanding of instructions. Another concern is that, contrary to an assumption underlying the process-dissociation procedure, recollection may not be equal for inclusion and exclusion tests. There is good reason to worry about such an inequality when using the particular procedure used by Jacoby (1991) and adopted by Buchner et al. (1995) and by Dodson and Johnson (1996). Later studies were designed to equate the processing demands of the inclusion and exclusion conditions (see Yonelinas, 1994; Yonelinas & Jacoby, 1994). Moreover, for more recent experiments (e.g., Yonelinas & Jacoby, 1995a; Hay & Jacoby, 1996), we have modified the procedure in ways meant to insure the equality of R across in-concert (cf., inclusion) and opposition (cf., exclusion) conditions. The later procedures have the additional advantage of insuring that response bias cannot be differential across conditions, comparable to inclusion-exclusion tests, used to estimate controlled and automatic influences, making it unnecessary to correct for differences in response bias. Yet another reason for concern is that recollection may be only partial, and partial recollection might distort estimates of F . Yonelinas and Jacoby (1996) consider potential problems produced by partial recollection and provide evidence to suggest that the problems are not serious ones, particularly

when the design of experiments is aimed at avoiding those problems.

Ratcliff, Van Zandt, and McKoon (1995) unfavorably compared the process-dissociation approach to more complete models of memory such as search of associative memory (SAM; Gillund & Shiffrin, 1984). What is overlooked in that comparison is the difference in goal between our approach and the more traditional approach. Although we appreciate the value of more complete models of memory, we center on separating consciously controlled and automatic processes. This is because a goal that is important to us is the very applied one of developing better means of diagnosing and treating different deficits of memory (e.g., Jacoby, Jennings, & Hay, in press). In pursuit of that goal, we aim for a simple model that highlights the differences that are of most interest and design procedures in ways meant to satisfy the assumptions of that simple model.

Summary

An examination of data from Buchner et al. (1995) showed that the multinomial method of incorporating response bias into the process-dissociation procedure led to a modest reduction of the effects of the bias manipulations on estimates of familiarity, but the dual-process, signal-detection method led to a more complete reduction in bias effects. However, both methods showed that the bias manipulations influenced recollection, suggesting that the manipulations may not have selectively influenced response bias and thus may not have provided a very strong test of the correction methods. When the correction methods were applied to confidence-rating data, the signal-detection-based method corrected for differences in response bias, but the multinomial method led to distorted estimates of recollection and familiarity. An ROC analysis showed that the model underlying the multinomial method was inappropriate for the process-dissociation procedure in recognition memory because it predicted linear ROCs. The dual-process, signal-detection model, on the other hand, fit the ROC data very well and thus provided a reasonable method for incorporating response bias into the process-dissociation procedure.

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Appendix A

A Logistic-Based Dual Process Model

Equations for calculating R and $F(\alpha)$ based on the dual-process, signal-detection method assuming logistic distributions for familiarity:

$$R = -(O_e - O_i - 1)/2 - \{(O_e - O_i - 1)^2 - 4[O_i(1 - O_e) - O_e(1 - O_i)N_i(1 - N_e)/N_e(1 - N_i)]\}^{1/2}/2$$

$$\alpha = \ln[(O_i - R)(1 - N_i)/N_i(1 - O_i)] = \ln[O_e(1 - N_e)/N_e(1 - R - O_e)]$$

where O_i = the probability of accepting an old item in the inclusion condition; O_e = the probability of accepting an old item in the exclusion condition; N_i = the probability of accepting a new item in the inclusion condition; N_e = the probability of accepting a new item in the exclusion condition.

The probability of accepting an item on the basis of familiarity given a false-alarm rate of x is $(xe^\alpha)/(1 + xe^\alpha - x)$.

Note that e in the preceding equation refers to the base of the natural logarithm.

Appendix B

Inclusion and Exclusion Performance From Buchner et al. (1995) for Each Condition in Each Experiment

Test condition	Item type							
	Read				Anagram			
	Lax		Strict		Lax		Strict	
	Old	New	Old	New	Old	New	Old	New
Experiment 1 (standard vs. extended)								
Inclusion	.712	.302	.595	.248	.885	.302	.822	.248
Exclusion	.192	.082	.178	.050	.082	.082	.088	.050
Experiment 2 (liberal vs. conservative)								
Inclusion	.752	.355	.690	.252	.925	.355	.850	.252
Exclusion	.278	.152	.175	.032	.172	.152	.075	.032
Experiment 3 (instructed vs. standard)								
Inclusion	.730	.342	.582	.165	.860	.342	.782	.165
Exclusion	.185	.052	.265	.080	.148	.052	.180	.080

(Appendix C follows on next page)

Appendix C

Parameter Estimates for the Data From Buchner et al. (1995), Based on the Original, Multinomial, and the Dual-Process, Signal-Detection (DPSD) Estimation Methods

Method	Parameter	Item type			
		Read		Anagram	
		Lax	Strict	Lax	Strict
Experiment 1 (standard vs. extended)					
Original	<i>R</i>	.52	.42	.80	.73
	<i>F</i>	.40	.31	.42	.33
Multinomial	<i>R</i>	.43	.31	.77	.69
	<i>F</i>	.28	.22	.29	.24
DPSD	<i>R</i>	.28	.10	.70	.59
	<i>F</i>	.43	.44	.44	.46
Experiment 2 (liberal vs. conservative)					
Original	<i>R</i>	.47	.52	.75	.78
	<i>F</i>	.53	.36	.70	.33
Multinomial	<i>R</i>	.40	.42	.73	.73
	<i>F</i>	.36	.28	.57	.25
DPSD	<i>R</i>	.29	.14	.68	.60
	<i>F</i>	.47	.57	.61	.56
Experiment 3 (instructed vs. standard)					
Original	<i>R</i>	.55	.32	.71	.60
	<i>F</i>	.41	.39	.51	.45
Multinomial	<i>R</i>	.43	.27	.65	.58
	<i>F</i>	.29	.31	.39	.38
DPSD	<i>R</i>	.17	.18	.47	.52
	<i>F</i>	.45	.49	.52	.54

Note. *R* = probability that the item is recollected; *F* = probability that the item is accepted as familiar.

Received May 9, 1995
Revision received September 19, 1995
Accepted December 6, 1995 ■