Process Dissociation, Single-Process Theories, and Recognition Memory

Roger Ratcliff  
Northwestern University

Gail McKoon  
Northwestern University

Trish Van Zandt  
Johns Hopkins University

According to the assumptions of L. L. Jacoby's (1991) process dissociation method, performance in recognition memory is determined by the combination of an unconscious familiarity process and a conscious intentional recollection process. The process dissociation method is used to produce estimates of the contributions of the 2 components to recognition performance. This article investigates whether the method provides the correct estimates of components if performance actually depends on only a single process or on 2 processes different from those assumed by the method. The SAM model (G. Gillund & R. M. Shiffrin, 1984) was used to produce simulated data based on a single process. Variants of SAM with 2 processes and R. C. Atkinson and J. F. Juola's (1973) 2-process model were used to produce data based on 2 processes.

The hallmark of memory research over the past 25 years has been the development of models: theoretical accounts of how people perform when they are given tasks for which previously learned information is used or required. The goal has been to devise concise theoretical frameworks that will explain experimental data and lead to new predictions. With the development of theories has come the realization that memory processes are not fully open to introspection. Intuitions about how retrieval from memory operates are certainly incomplete and probably often wrong. Even the most appealing of insights needs to be accompanied by tests of falsifiability and validity.

One of the newest contributions to the effort to understand memory is a method developed by Jacoby and his colleagues (Jacoby, 1991; Jacoby & Kelley, 1992; Jacoby, Yonelinas, & Jennings, in press; Yonelinas, 1994). They have proposed the process dissociation procedure as a method by which two components of retrieval—one a conscious recollection process and the other an unconscious familiarity process—can be separated from each other. The method is defined by the two simple assumptions that exactly these two processes are always present and that they operate independently of each other. Given a task for which performance depends on information from memory, the method is said to allow determination of what part of performance is due to conscious recollection and what part is due to unconscious familiarity.

The question addressed in this article is whether application of the process dissociation method necessarily provides a correct analysis of memory processes. Application of the method will always produce measures of exactly two components, but is this always correct? Could process dissociation produce estimates of two components of processing when, in fact, there was only one? Could it produce estimates of recollection and familiarity when performance was actually determined by two other processes? To answer these questions, we constructed situations for which we knew what the components of retrieval were and then applied process dissociation to determine whether it correctly reproduced those components. To construct these situations, we generated simulated data from two models, a single-process model (SAM; Gillund & Shiffrin, 1984) and a two-process model with processes different from recollection and familiarity (Atkinson & Juola, 1973); for each, we examined whether process dissociation correctly estimated the processes from which the data were generated.

Without some guidance, the data simulated from the models might not be anything like the data usually obtained in recognition memory experiments, and the data might not be anything like the data observed in the experiments to which process dissociation has been previously applied. To make sure that the simulated data did provide a fair test of process dissociation, we constrained the simulations to produce the patterns of data that had been observed in previous experiments (e.g., Jacoby, 1991; Yonelinas, 1994; Yonelinas & Jacoby, 1994). For each simulation, we knew the parameters of the retrieval processes for the model on which the simulation was based, and we could compare the processes implied by these parameters with the estimates of retrieval processes produced by process dissociation. If process dissociation works correctly, the estimates should match the processes of the model.

It is possible that the process dissociation method might
be seen as a theory-free method for uncovering conscious and unconscious components of information processing. The research presented in this article shows that the method depends on the validity of the assumptions underlying it (see Jacoby, 1991) and that the estimates produced by the method for its two processing components are not meaningful if the underlying assumptions are incorrect. It is important to make these points because the method has such intuitive appeal and such wide potential applicability and because it can be applied without careful thought being given to the underlying assumptions. In the first section that follows, we provide background on the method to show its strengths in the contexts in which it was developed. Then, in later sections, we proceed to describe several different tests of the method. First, we simulated data from a single-process model (SAM) and showed that process dissociation does not recover an accurate description of this model. Second, we produced hypothetical data from two processes different than those assumed by process dissociation and again showed that process dissociation does not, in general, recover the underlying processes correctly. We generated hypothetical data from SAM's single familiarity process plus an added recall process and also from Atkinson and Juola's (1973) two-process model. Finally, in the last section of the article, we investigate how Jacoby and Yonelinas have combined the process dissociation assumptions with signal detection theory and show that this combination cannot correctly predict the z-ROC (receiver operating characteristic) functions that have been obtained for recognition memory.

The Process Dissociation Method

Background

A recent challenge to research in memory has been the proliferation of demonstrations that memory can affect performance in the absence of awareness (e.g., Jacoby & Wirthspon, 1982; Schacter, Bowers, & Booker, 1989; Warrington & Weiskrantz, 1968). Amnesic patients show effects of prior learning without being able to remember the learning episode itself. Normal participants also appear to show memory without awareness when their performance on "indirect" memory tasks (tasks that do not ask for or require the use of previously learned information) reflects that information. Indirect tasks have therefore been suggested as offering the possibility of investigating unconscious processes.

Jacoby proposed that the way to begin to understand memory without awareness is to assume that performance on both direct and indirect tasks is a mixture of the same two processes—conscious recollection and unconscious familiarity—with indirect tasks relying more heavily on unconscious processes than direct tasks. This proposal stands in opposition to proposals by which memory systems are divided into implicit systems that mediate performance on indirect tasks and explicit systems that mediate performance on direct tasks (see Hintzman, 1990; Jacoby & Wirthspon, 1982; McKoon & Ratcliff, in press; Nosofsky, 1988; Ratcliff & McKoon, in press; Tulving & Schacter, 1990; Squire, 1992).

If unconscious processing is to be investigated, it must be separated from conscious processing. The process dissociation procedure is one proposal for how to do this. This potential for separation of conscious from unconscious processing is one basis for the prominence and popularity of the process dissociation procedure in recent research. It is therefore important to understand the strength of the reasoning that underlies the procedure, and so we outline that reasoning here. Others (see Schacter & Tulving, 1994) have attempted to split conscious from unconscious processes with task dissociations, that is, with findings that show that performance on indirect tasks is affected by different variables than performance on direct tasks. However, task dissociations cannot necessarily accomplish a clean separation. Jacoby (1991) pointed out that research using task dissociations to investigate unconscious processes has relied on the assumption that there is a one-to-one mapping between a task and a process; the methods that have been used require that a task be "factor pure" for the process it is designed to measure. But indirect tasks do not necessarily provide pure tests of implicit memory; they can be contaminated by participants' explicit recall of earlier experiences (cf. Ratcliff & McKoon, in press; Richardson-Klavehn & Bjork, 1988). Moreover, Jacoby argued, performance on direct tests can also be the result of a mixture of conscious and unconscious processes.

In Jacoby's view, unconscious influences in direct tests can take either of two forms. Usually, the effect of unconscious influences is to facilitate performance. In recognition, for example, the unconscious familiarity of a test item can lead to a correct positive response even when conscious attempts to recognize it fail. But unconscious influences can also interfere with performance on direct recollection. In this regard, Jacoby (1991) cited the early Warrington and Weiskrantz (1968) finding that when amnesics were asked to recall or recognize words from a studied list, incorrect responses were often intrusions from earlier lists. Normal participants' performance can also show decrements from unconscious influences. In a study conducted by Jacoby, Woloshyn, and Kelley (1989), participants were asked to judge whether or not each name in a list was the name of a famous person. The judgments were preceded by study of some of the nonfamous names. Participants were told that previously studied names were all nonfamous, so they could use retrieval of names from the studied list to reduce their likelihood of making the error of judging a nonfamous name as famous. But when direct recollection was made difficult by adding a concurrent task to be performed during the fame judgments, the familiarity produced by prior study led to an increased probability of judging previously studied nonfamous names to be famous.

With results like these, Jacoby has motivated his claim that conscious and unconscious processes can never be separated through task manipulations because performance can always reflect a mixture of conscious and unconscious processes. Instead, the separation of conscious and uncons-
scious processes must be accomplished theoretically. Jacoby has assumed that there is one conscious intentional recollection process and one unconscious familiarity process and that they combine independently to produce performance. These assumptions define the process dissociation procedure by which the contributions of the two processes can be separated and identified. The aim is to eventually understand the two processes by examining how they are independently affected by different variables. Jacoby has used process dissociation to examine the effects of a number of variables across a range of both direct and indirect tasks (Jacoby & Kelley, 1992; Jacoby, Toth, & Yonelinas, 1993; Jacoby et al., 1989, in press), in each case finding interpretable patterns by which variables affect the two processes differentially.

Implementation

The process dissociation method is said to use a “commonsense approach of measuring intentional control (recollection) as the difference between performance when one is trying to as compared with trying not to engage in some act” of memory retrieval (Jacoby et al., 1993, p. 141). In other words, performance on a task for which recollection facilitates the production of some class of responses is compared against performance on a task for which recollection facilitates the suppression of those responses. It is assumed that recollection alone is responsible for the difference between performance in the two cases, so the difference provides a measure of conscious recollection, from which a measure of unconscious familiarity can be calculated through equations based on the assumptions underlying the method (as explained later). Process dissociation has been applied to cued recall (Jacoby et al., 1993), fame judgments (Jacoby et al., 1989), stem completion (Jacoby et al., in press), and perception of briefly flashed stimuli (Jacoby & Kelley, 1992). It has also been applied to recognition (Jacoby, 1991; Yonelinas, 1994), the task that is the focus of tests of process dissociation in this article.

For recognition, process dissociation can be exemplified by an experiment in which participants study two lists of words (e.g., List 1 and List 2; Yonelinas, 1994). In one condition, they are instructed to respond positively to words from List 1 and negatively to words from List 2 and to new words. In a second condition, they are instructed to respond negatively to words from List 1 and to new words and positively to words from List 2. Thus, participants are to try to respond positively to words from List 1 in the first condition (the “inclusion” condition) and to try not to respond positively to words from List 1 in the second condition (the “exclusion” condition). In the inclusion condition, both the unconscious familiarity process and the conscious recollection process contribute to the probability of a correct yes response for words from List 1:

\[
P(\text{Include}) = P(I) = P(R) + P(F) - P(R) \times P(F)
\]

\[
= P(R) + P(F) \times [1 - P(R)], \quad (1)
\]

where \(P(R)\) is the probability of successful recollection, \(P(F)\) is the probability that the familiarity of a test item is higher than the criterion value that is necessary for a positive response, and the two processes are assumed to be independent (and recollection is not in error). Both processes also influence performance in the exclusion condition. A yes response in the exclusion condition (an incorrect response) is due to familiarity exceeding the positive response criterion when there is a failure of the recollection process:

\[
P(\text{Exclude}) = P(E) = P(F) \times [1 - P(R)]. \quad (2)
\]

Equations 1 and 2 are based on the assumption that recollection and familiarity are independent. It is also assumed that recollection is never in error. The probability of recollection is calculated as the difference between the include and exclude scores (i.e., the difference between when a participant is trying to respond positively and when he or she is trying not to respond positively):

\[
P(R) = P(I) - P(E). \quad (3)
\]

Then familiarity is

\[
P(F) = P(E)/[1 - P(R)]. \quad (4)
\]

Equations 3 and 4 represent the assumptions of the process dissociation method as applied to recognition memory. They show the statistically independent influences of recollection and familiarity on memory. That is, whether an item’s familiarity is high or low has no bearing on its likelihood of recollection, and vice versa. An item’s familiarity does not change across tasks. Once encoded, an item’s familiarity value is the same in any memory retrieval task; there is no mechanism by which it can vary with task or retrieval context. Jacoby et al. (in press) presented support for the independence assumption in contrast to some other possible assumptions that might be made about the relation of the two factors (see Curran & Hintzman, in press).

In addition to the assumptions that there are exactly two processes and that they operate independently, Jacoby (Jacoby et al., 1993; Yonelinas, 1994) adopted signal detection theory as an account of the familiarity process. Values of familiarity are assumed to be distributed across a continuum from high to low, and participants are assumed to respond according to whether the familiarity value of a test item is above or below a criterion amount of familiarity. To the standard signal detection theory assumptions, Jacoby and Yonelinas added the assumption that the distributions of previously studied and nonstudied items have equal variance, an assumption for which tests are described in the last part of this article.

In summary, process dissociation has been proposed as a method of dealing with difficult issues that have plagued research on conscious versus unconscious processes, issues recently brought into sharp focus by findings of dissociations between tasks and effects that intuitively seem to involve conscious recollection and effects that intuitively seem to involve memory without awareness. The
process dissociation method is designed to allow investigation of the separate influences of conscious and unconscious processes on performance toward the eventual development of an understanding of how they work.

Support for the assumptions embodied in the process dissociation procedure comes in two forms. First, when the procedure is applied, it appears to separate the effects of a number of variables into conscious versus unconscious influences in intuitively predictable ways that are invariant across a range of tasks (see Jacoby et al., in press, for an overview). For example, the variable of full versus divided attention during a test has a large influence on conscious processing but little influence on unconscious processing, and this is true for item completion, cued recall, recognition, and fame judgments (Jacoby et al., in press). The process dissociation assumptions themselves do not predict which of the two processes should be influenced by dividing attention; independent notions about how attention interacts with unconscious processes do that. The second form of support for the assumptions of process dissociation is that the measure of unconscious processing that is derived from process dissociation is affected in generally the same ways by experimental manipulations as performance on indirect tests of memory. This would be predicted because indirect tests are thought to rely mostly on unconscious processes.

In this article, the main domain of investigation is recognition memory. Jacoby (1991) found support for the assumptions of process dissociation in recognition by comparing the contributions of recollection and familiarity to performance as estimated from process dissociation (by the preceding equations) with their contributions as measured directly by manipulation of full versus divided attention. According to Jacoby's account, dividing attention at test should severely reduce recollection and give a relatively pure measure of familiarity. This amount of familiarity should match the estimate of familiarity derived for a full attention test from the process dissociation equations and, as predicted, the two values, observed and estimated, were nearly equal (Jacoby, 1991).

Single-Process Models for Recognition Memory

When the process dissociation method is applied to data from a recognition memory experiment, it produces an estimate of the influences on performance of familiarity and recollection. The question we address is whether these estimates necessarily represent a correct analysis of performance. In doing so, we generate data from models for which the estimates might not provide a correct analysis. In the global memory models (Gillund & Shiffrin, 1984; Hintzman, 1988; Murdock, 1982; Ratcliff & McKoon, 1988), recognition is typically modeled by a single process. We simulated recognition data from one of these models, SAM (Gillund & Shiffrin, 1984), using only a single process, and we applied process dissociation to those data. The correct analysis of the data would be that performance was determined by only the single process. The question was whether process dissociation would provide that analysis. In the sections that follow, we describe the simulations and the application of process dissociation to them, beginning with an overview of the SAM model.

For the purposes of this article, we used SAM to exemplify single-process models. Like all of the global memory models, SAM assumes that learned items are stored in long-term memory and that a test item is matched against all of the items in long-term memory in parallel (hence the label global). For SAM, long-term memory stores associative strengths between items in memory and items that might be presented as tests of memory (cues). An item to be learned is encoded into a working memory buffer. While in the buffer, the strength of the item as a possible future test item is increased by strengthening the association between the item as a cue and the item itself in long-term memory, strengthening the association between the item as a cue and other items in the buffer at the same time, and strengthening the association between the item and the context in which it is learned. The association between the item as a cue and the item itself in memory is called self-strength, the strength between the item and the other items in the buffer at the same time is called interitem strength, and the strength between an item and its context is called context strength. An item that is never encoded into the buffer (a "new" item on a recognition test) is assumed to have some preexperimental, residual strength. The strength values for learned items are a function of the time spent in the buffer, and the values are variable: with a .33 probability a value is multiplied by 0.5, multiplied by 1.5, or left unchanged. This assumption about variability leads to normally distributed familiarity values by the central limit theorem once all of the strength values are multiplied and summed (see Equation 5).

Table 1 shows a part of the association structure that might be built when two lists of words are learned, as in the Yonelinas (1994) experiment described earlier. Item 2 from List 1, for example, is encoded with some value of strength between itself as a test item and itself as an item in memory and some value of strength between itself and other items in memory that were in the buffer at the same time (e.g., Items 1 and 3 in List 1; here the values of self-strength and interitem strength were set to the same value, 5, for simplicity). There is also some value of strength (C) between the list context in which an item was studied and the item in memory. For the two-list situation, it is assumed that, for an item encoded in one list, there is some small residual context strength between the context of the other list and the item (RC), because there is some overlap in general context between the two lists. There is also some residual strength (R) from an item as a cue to all items in memory that were not encoded in the buffer at the same time as the item.

For recognition, there is a single retrieval process: A test probe is matched against all of the items in memory. The probe is made up of a test item and the relevant context(s). The match process produces a global value of familiarity: A value above a criterion leads to a positive response, and a value below the criterion leads to a negative response. For the situation in which two lists of words were studied, a test probe is made up of the test item and the contexts of the two
Table 1

<table>
<thead>
<tr>
<th>Cue</th>
<th>Item 1 in List 1</th>
<th>Item 2 in List 1</th>
<th>Item 3 in List 1</th>
<th>Item 1 in List 2</th>
<th>Item 2 in List 2</th>
<th>Item 3 in List 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Context List 1</td>
<td>C</td>
<td>C</td>
<td>C</td>
<td>R_C</td>
<td>R_C</td>
<td>R_C</td>
</tr>
<tr>
<td>Context List 2</td>
<td>R_C</td>
<td>R_C</td>
<td>R_C</td>
<td>C</td>
<td>C</td>
<td>C</td>
</tr>
<tr>
<td>Item 1 in List 1</td>
<td>S</td>
<td>S</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>R</td>
</tr>
<tr>
<td>Item 2 in List 1</td>
<td>S</td>
<td>S</td>
<td>S</td>
<td>R</td>
<td>R</td>
<td>R</td>
</tr>
<tr>
<td>Item 1 in List 2</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>S</td>
<td>S</td>
<td>R</td>
</tr>
<tr>
<td>Item 2 in List 2</td>
<td>R</td>
<td>R</td>
<td>R</td>
<td>S</td>
<td>S</td>
<td>S</td>
</tr>
</tbody>
</table>

Note. An example is as follows: Using Equation 3 (see text) and assuming that all Ss are equal, all Rs are equal, all Cs are equal, and all R_Cs are equal (in general, these will vary from item to item and trial to trial) the familiarity of Item 1 in List 1 is $C^{w1}R_C^{w2}(2S^{w3} + R^{w4}) + 3R_C^{w5}C^{w6}R^{w7}$ (i.e., the sum of the weighted products of the first three entries in each column). $C =$ context strength; $R_C =$ residual context strength; $R =$ residual strength; $S =$ item strength (determined by self-strength, interitem strengths, and encoding time).

The contributions to familiarity are weighted to allow the relative contributions of the two context strengths and the item strength to vary across different experimental situations. If, for example, items from List 1 were to receive a positive response and items from List 2 a negative response, then the context strength for List 1 would be weighted more heavily than the context strength for List 2. The three weights are assumed to sum to one. Familiarity for a test item $j$ with contexts $C_1$ and $C_2$ (for List 1 and List 2) is computed by summing over all items in memory (all $i$):

$$F_j = \sum_i S_{C_1,i}^{w1}S_{C_2,i}^{w2}S_{ij}^{w3},$$

where $w1$, $w2$, and $w3$ are the weights; $S_{C_1,i}$ is the strength of the List 1 context to item $i$; $S_{C_2,i}$ is the strength of the List 2 context to item $i$; and $S_{ij}$ is the strength of test item $j$ to item $i$. The computation of familiarity for Item 1 from List 1 is shown in Table 1.

The equation for familiarity represents a single process for recognition, a process by which responses are determined by the sum over items in memory of joint multiplicative functions of the strengths of association between the test context and items in memory, and the test item and items in memory. Summing over values obtained from the multiplicative function leads, by the central limit theorem, to normally distributed familiarity values. The choice of a positive versus negative response is made by comparing the familiarity value for a test item in context to a criterion.

The single process stands in opposition to the two processes assumed by Jacoby's (1991) process dissociation method. An essential point about the difference between the two models is that the single familiarity process in SAM is influenced by list context so that the value of familiarity for a test item in an include condition $P(F_i)$ can be different from its value in an exclude condition $P(F_{ij})$. In fact, context was originally (Gillund & Shiffrin, 1984) made part of the test probe to allow the recognition process to focus on recently learned items, and so it is exactly the mechanism to deal with list discrimination effects. The familiarity process that is assumed in the process dissociation procedure is not dependent on list context; the value of familiarity for a test item is the same in an include test condition as in an exclude test condition. Therefore, the two familiarity processes, one in SAM and the other in process dissociation, are quite different from each other.

The Gillund and Shiffrin (1984) model, like Hintzman's (1988) and Murdock's (1982) models, is supported by a wide range of data over a number of experimental variables and tasks. For recognition, SAM successfully accounts for the effects of variables such as study time, list length, encoding context, and word frequency. With the same memory structure but different processing assumptions, it has been applied to recall and cued recall (see also a related categorization model; Nosofsky, 1988). Other global memory models have been similarly successful with various independent variables in tasks assessing frequency judgment, recency judgment, categorization, serial order, and so on. The global memory models have also been successfully applied to priming phenomena in recognition and lexical decision (Doser & Rosedale, 1989; McKoon & Ratcliff, 1992; Ratcliff & McKoon, 1988, 1994). In most cases, the models provide not only qualitative accounts of data but also close quantitative fits to data arising from systematic variations of experimental variables. The assumptions of process dissociation are supported by a number of intuitively compelling and interesting dissociations and decompositions of data, but the global memory models likewise can marshal a range of successful applications to data and interpretations of empirical findings.

In the following section, we describe the simulations by which SAM was used to produce recognition data, data that were based on SAM's single familiarity process. The process dissociation method was then applied to those data. As mentioned in the introduction, we needed to be sure that the simulated data were comparable to real data to provide a fair test of process dissociation. To accomplish this, we constrained the simulations to produce data that matched those from the Yonelinas experiment described earlier and those from two other experiments (Yonelinas, 1994; Yonelinas & Jacoby, 1994).
It is important to note that producing data to match those of Yonelinas' and Jacoby's experiments is not a strong test of SAM. To provide serious test of SAM, one would need to collect more data over a large range of conditions (Gillund & Shiffrin, 1984) or examine more detailed aspects of the data (e.g., Ratcliff, Clark, & Shiffrin, 1990; Ratcliff, Sheu, & Gronlund, 1992; Shiffrin, Ratcliff, & Clark, 1990). The data discussed here do not provide the range of manipulations that would be necessary to seriously test the global memory models. We stress that the goal in this article is not to test SAM but, rather, to use SAM to simulate data with which to test process dissociation.

Simulations of Recognition Data From the Single-Process Model SAM

In Yonelinas's (1994) Experiment 1, participants were given two lists of words to study. There were two conditions: At test, participants were either instructed to respond yes to words from the first list and no to words from the second list (and no to new words) or instructed to respond no to words from the first list (and no to new words) and yes to words from the second list. The first list was included in the first condition and excluded in the second condition, and the second list was included in the first condition and included in the second. Yonelinas asked participants to make their responses on a 6-point confidence judgment scale; for our purposes, however, we used the positive-negative split he reported to produce two response categories, grouping high-, medium-, and low-confidence positive responses into one category and high-, medium-, and low-confidence negative responses into the other category. Yonelinas used both short study lists (10 items each) and long study lists (30 items each).

Yonelinas's (1994) data are shown in the first two rows of Table 2. The probability of a positive response to items when they were in the include condition is shown in the second column, the probability of a positive response to items when they were in the exclude condition is shown in the third column, and the probability of a positive response to items that were not from either list is shown in the fourth column. The probabilities of recollection and familiarity can be calculated from Equations 1–4, and these probabilities are shown in the remaining columns. The probabilities exhibit the kind of separation of two processes that has been claimed to support the process dissociation assumptions: List length affects recollection but not familiarity. The support for the assumptions comes only from the existence of a dissociation of the list length effect for familiarity versus recollection. The assumptions do not specify why list length should affect recollection and why it should not affect familiarity, so the actual form of the dissociation provides no particular support for the assumptions.

Yonelinas and Jacoby (1994) reported a second experiment in which list length was manipulated. Participants were given one list of words to study, with the words on the list alternating in presentation modality between visual and auditory. At test, they were instructed to respond positively to words that had been presented in one of the modalities and negatively to words that had been presented in the other modality and to new words. The length of the studied list was either 60 words or 30 words. Results of the experiment are shown in the first two rows of Table 3, along with the probabilities of recollection and familiarity as calculated from the process dissociation. The results again show a dissociation between recollection and familiarity, with list length affecting recollection but not familiarity.

To allow the SAM model to produce data that matched Yonelinas's and Jacoby's real data, we assumed the size of SAM's encoding buffer to be four words (the same assumption as was made by Gillund & Shiffrin, 1984, for study lists in which single words were presented individually). From SAM's assumptions about how strengths are built up during encoding and the equation for the calculation of the global familiarity of a test probe, explicit expressions can be derived for the mean and variance of each of the necessary distributions of familiarity values: the mean and variance for included test items, the mean and variance for excluded test items, and the mean and variance for new items. Because the distributions are approximately normal, standard signal detection theory can be used to compute the probabilities of positive responses in the different conditions. A

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability of positive response</th>
<th>Process dissociation estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Include</td>
<td>Exclude</td>
</tr>
<tr>
<td>Data, short lists</td>
<td>.78</td>
<td>.22</td>
</tr>
<tr>
<td>Data, long lists</td>
<td>.70</td>
<td>.30</td>
</tr>
<tr>
<td>Model, short lists</td>
<td>.78</td>
<td>.23</td>
</tr>
<tr>
<td>Model, long lists</td>
<td>.70</td>
<td>.29</td>
</tr>
</tbody>
</table>

Note. The parameters of SAM were as follows: interitem strength, 0.24; self-strength, 0.90; context strength, 2.00; residual strength, 0.14; residual context strength, 0.02; short list familiarity criterion, 9.58; long list familiarity criterion, 20.62; included list context weight, 0.41; excluded list context weight, 0.05; and item weight, 0.54. P(R) = probability of recollection; P(F) = probability of familiarity.
least squares minimization routine was used to estimate the values of the parameters of the model that would best lead to a match with Yonelinas’s and Jacoby’s data. 

Tables 2 and 3 show the results of the SAM simulations. The differences between the real and simulated data are within the bounds of experimental error. The parameter values used to produce the simulated data are listed in the tables. The parameter that varies to simulate the include versus exclude conditions is the weight assigned to their contributions to familiarity; the weight given to the strength for a list context is high if the items from the list are to be included, and the weight is low if items from the list are to be excluded. Unlike the assumptions for process dissociation, the familiarity value of a test item is not constant across these two conditions; instead, it is a function of the include versus exclude task requirements as represented in SAM by a change in context weighting. In SAM, the single retrieval process focuses on different information in the include versus exclude conditions, in contrast to process dissociation, for which there are different contributions from two processes in the include versus exclude conditions.

The only parameter free to vary to produce the effect of list length is the familiarity criterion (see Gillund & Shiffrin, 1984). Because there are more studied items in memory contributing to familiarity for a test item from a long list than a test item from a short list, familiarity is higher, on average, for items from a long list, and familiarity is more variable for items from a long list. This is true for both old test items and new test items. It is true for new test items because they are matched against a larger number of studied items from a long list than from a short list (see Gillund & Shiffrin, 1984). Because of the higher and more variable familiarity values for both old and new test items, the criterion familiarity value is higher for long lists than for short lists. The relative values of the other parameters (the learning parameters) are typical of other situations in which SAM has been fit to empirical data (Gillund & Shiffrin, 1984): Self-strength is higher than item strength, which in turn is higher than residual strength, and context strength is higher for the list in which an item was learned than residual context strength for the other list.

To provide generality to experimental variables other than list length, we also used SAM to simulate the data from Yonelinas’s (1994) Experiment 3, which used a strength manipulation. In this experiment, there were again two lists of words. The words were studied in pairs, either for 1 s or for 3 s, with study time a within-list variable. At test, participants were instructed, as in Experiment 1, either to exclude the first list or to exclude the second list. The data are shown in Table 4, along with the probabilities of recollection and familiarity derived by the process dissociation method.

Simulations from SAM were produced in the same way as for Yonelinas’s (1994) Experiment 1, except that the encoding buffer was assumed to hold two words (i.e., one pair) at a time instead of four words. The simulated data in Table 4 show that, again, SAM matches the real data well. The include versus exclude difference comes from shifting weight from one list context to the other, as with the other experiments. The difference between strongly and weakly encoded items (long and short study time) involves no changes in values of the parameters of the model and occurs because the encoding strength values (self, item, and context) are multiplied by study time multiplied by 0.41. The scaling factor, 0.41, allows the model to match the empirically observed rate at which d’ increases with study time (see Shiffrin et al., 1990).

It should be stressed again that the simulations reported here are not a test of SAM. It is relatively easy for SAM to simulate the data because the data provide few constraints. The point is that SAM provides simulated data that are known to be generated from a single process so that one can proceed to test process dissociation.

Testing the Process Dissociation Method

The simulated data from SAM look almost identical to the real data from Yonelinas’s and Jacoby’s experiments. Therefore, process dissociation yields almost the same estimates of processing components for the simulated data as for the real data. The estimates of process dissociation familiarity and recollection are shown in Tables 2, 3, and 4.
Even though the simulated data were produced from a single retrieval process, the process dissociation method attributes the data to two processes. The conclusion from this demonstration is that the estimates given by process dissociation are valid only under process dissociation’s assumptions. Process dissociation equations have two parameters (the probability of recollection and the probability of familiarity being above a criterion), and the equations are applied to only two data points in each experimental condition. This means that the method will always produce estimates of two components, even if the data were actually generated from a single process. This point is illustrated by the simulations from SAM. Furthermore, the interpretations of the components are valid only under the process dissociation assumptions. According to process dissociation, the results of Yonelinas’ and Jacoby’s experiments show that list length affects recollection, a conscious process, but not familiarity, an unconscious process. According to SAM, the correct interpretation of the results is that list length affects familiarity. Therefore, what is learned about conscious versus unconscious processes in recognition is theory dependent, and process dissociation does not provide a theory-independent means of examining memory processes. The same conclusion holds for Yonelinas’ (1994) Experiment 3, for which process dissociation and SAM both interpret the results to show that strength of encoding affects familiarity; however, process dissociation also has strength affecting recollection. Again, what is learned about retrieval depends on the choice of model.

When a Single Familiarity Process Is Not Enough

We argued in the preceding sections that it is possible for process dissociation to attribute data to two processes even though the data were actually generated by a single process (i.e., generated from the SAM model). In this demonstration, a single-process model was found to adequately simulate the data from real experiments to which process dissociation had been applied. The issue raised in this section is how the process dissociation method fares when a single-process model cannot adequately simulate the relevant data, that is, when it appears that the data require the assumption of two processes. We attack this issue in the same way as before: We produce data from a model for which the underlying processes are known and then examine whether process dissociation produces correct estimates of those processes.

The data that appear to require more than a single process come from an experiment conducted by Jacoby (1991, Experiment 3). In this experiment, participants heard the words of one study list, and, in another list, they read some of the words and they were asked to solve anagrams to produce some of the words for themselves. In the include condition, participants were asked to respond positively to all of the studied words. In the exclude condition, they were asked to respond positively only to the words that they had heard; they were warned to respond negatively to words that were studied in their normal form (the “read” words) and to words that were presented as anagrams.

Table 5 shows Jacoby’s (1991) data. The difference between the probabilities of responding positively in the include and exclude conditions is much larger for the anagram words than the read words, in accord with the expectation that the extra work required for the anagrams at study would lead to better memory at test. Table 5 also shows estimates of familiarity and recollection derived from process dissociation. Jacoby assumed that the difference between the include and exclude conditions was a measure of the probability of recollecting the anagram and read words (Equation 3). He also assumed that familiarity sometimes led participants to respond positively to read and anagram words when they were supposed to be excluded, so that familiarity could be calculated from Equation 4. The probability of recollecting an anagram word, as derived from process dissociation, is much higher than the probability of recollecting a read word, and familiarity is also higher for an anagram than for a read word.

These data appear to be likely candidates for a situation in which more than a single process is required. To test process dissociation in this situation, we needed to find a model that could produce these data using processes other than the familiarity and recollection processes assumed by process dissociation. We chose to use SAM’s familiarity process with a recall process added to it. This is a reasonable choice:
Table 5
Experimental Data and SAM Predictions for Experiment 3 of Jacoby (1991)

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability of positive response</th>
<th>Process dissociation estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Anagram</td>
<td>Read</td>
</tr>
<tr>
<td>Data, include</td>
<td>.80</td>
<td>.48</td>
</tr>
<tr>
<td>Data, exclude</td>
<td>.29</td>
<td>.37</td>
</tr>
<tr>
<td>Model, include</td>
<td>.48</td>
<td>.18</td>
</tr>
<tr>
<td>Model, exclude</td>
<td>.37</td>
<td>.22</td>
</tr>
</tbody>
</table>

Note. The parameters of SAM were as follows: context, 1.20; interitem, 0.58; heard self-strength, 1.51; read self-strength, 1.01; residual strength, 0.26; residual context strength, 0.06; include familiarity criterion, 33.04; exclude familiarity criterion, 39.04; heard list context, include condition weight, .37; read and anagram list context, include condition weight, .43; item, include condition weight, .20; heard list context, exclude condition weight, .47; read and anagram list context, exclude condition weight, .37; and item, exclude condition weight, .16. \( P(F) \) = probability of recollection; \( P(R) \) = probability of familiarity.

The global match process by which SAM calculates familiarity has never been expected to apply to all memory retrieval situations, and, in the SAM framework, free recall is modeled not with familiarity but with a different process, a repeated sampling and recovery process (Gilhund & Shiffrin, 1984; Raaijmakers & Shiffrin, 1981). Our intuition was that SAM's familiarity might account for performance for the read and heard words but that there might be some recall contributing to performance for anagram test words. Following this intuition, we first simulated the data for the read and heard words with only the single familiarity process and then investigated what further was needed to produce the data for the anagram words.

To simulate performance on the read and heard test words in the include and exclude conditions, we used the SAM model much as for the experiments described in the previous sections. The encoding parameters were kept constant except that self-strength was allowed to be different for the two kinds of words (it might also be reasonable to allow interitem strength to vary, but it was unnecessary because SAM was able to simulate the real data without this; also, decoding of anagrams probably suppressed interitem rehearsal). The criterion value of familiarity for dividing positive from negative test responses was different for the include and exclude conditions because the include and exclude items were presented in different test lists. The context weights were set to differentiate the lists: Items from the read and anagram list required positive responses in the include condition and negative responses in the exclude condition, so the weighting of the read–anagram list context had to be high in the include condition and lower in the exclude condition. The weighting of the heard context, correspondingly, had to vary in the opposite way (higher when read–anagram words were excluded than when they were included partly because the read–anagram, heard, and context weights sum to one). The parameter values are shown in Table 5, and they are reasonable in comparison with previous tests of SAM against data. The simulated probabilities of positive responses for read, heard, and new words exactly match the real data.

It is important to note, once again, the difference between SAM's account of the include versus exclude conditions and process dissociation's account. In SAM, the familiarity of a test word in the include condition is different than in the exclude condition \( F_r \) for read items is different from \( F_e \) for read items, and \( F_i \) for heard items is different from \( F_e \) for heard items. In process dissociation, the probability of a yes response based on familiarity is the same in the include and exclude conditions.

Given that SAM could simulate the data for the read and the heard test words, we checked to see whether it could simultaneously simulate the data for the anagram test words. (As stated earlier, we suspected that it could not.) In Jacoby's (1991) experiment, all four kinds of test words were mixed within a test list, so there was no way for participants to change the positive–negative criterion from one kind of test word to another. Also, the weights for the list contexts could not be different for the read words than for the anagram words because they were studied in the same list. Thus, all of the test parameters were fixed. In addition, the interitem strength parameter could not vary between read and anagram words, again because they were studied in the same list. The only parameter free to vary between the anagram and read words was the self-strength parameter.

To find out whether there was a value of anagram self-strength that could allow SAM to simulate the real data, the value was varied over the range shown in Figure 1. Figure 1 shows how the probability of a positive response to an anagram test item varies as a function of anagram self-strength and displays the probability that the familiarity value is above the criterion for a positive response in the include condition \( P(F_i) \) and in the exclude condition \( P(F_e) \). It also gives the empirical probabilities of a positive response in the include and exclude conditions (.80 and .29). As the figure shows, there is no value of anagram self-strength that allows SAM to simulate the empirical values. SAM cannot simultaneously simulate the read, heard, anagram, and new test items in the include and exclude conditions with its single familiarity process. In SAM's terms, the anagram manipulation must do more than simply change the familiarity of the anagram versus read items.
The goal, then, is to estimate how much recall SAM would have to produce to account for the anagram data. Figure 1 shows that what needs to be added to familiarity to match real data varies as a function of anagram self-strength. One can choose the anagram self-strength value by choosing assumptions about whether recall is used in both the include and exclude conditions and whether recall and familiarity are independent processes or have some degree of dependence. These assumptions fix the value of anagram self-strength, which in turn allows estimation of what recall needs to add to familiarity. One can then compare this estimate with the estimate of recollection obtained from process dissociation.

**Familiarity Plus Recall in SAM**

We considered three sets of assumptions that could fix the value of anagram self-strength in SAM. First, recall was assumed to contribute independently from familiarity to the probability of a response for anagram test words, and it was assumed to make a contribution in both the include and exclude conditions; second, recall was assumed to contribute independently and only in the exclude condition; and, third, recall and familiarity were assumed to be dependent processes, with recall contributing only to the exclude condition. In each case, the contribution recall had to make to produce the data accurately was the difference between what the familiarity process contributed and the real data. That is, the recall process must subtract from the probability of a positive response in the exclude conditions for anagrams, and it must add to the probability of a positive response for anagrams (in the case in which it contributes to the include condition).

It should be stressed that the goal is only to provide tests of process dissociation. In the real SAM model, familiarity and recall are dependent processes, with some positive degree of dependence that is not complete dependence. In our test case to follow, we assumed complete dependence; that is, when an item is recalled, its familiarity value is above the criterion for a positive response. With the independence assumptions on the one hand and the complete dependence assumption on the other, the cases we explored bracketed the estimates of the recall process that a real version of SAM would produce. A full implementation of SAM would require manipulations of multiple variables and decisions about whether and how recall should be involved in the include and exclude conditions, whether the contribution from recall should be the same in the exclude and include conditions, and so on.

**Independence: Recall Contributes to Both the Include and Exclude Conditions**

In each test case, we used the difference between the real data and SAM’s best predictions based on familiarity alone to provide an estimate of what the recall process needed to contribute to performance. The first case was that the familiarity and recall processes are independent and both contribute in the include and exclude conditions. The probability of a positive response to an anagram test word in the include condition is given by

\[ P(I) = P(R) + P(F) - P(R)P(F), \]

where \( P(R) \) is the probability of a positive response based on recall and \( P(F) \) is the probability, in the include condition, that the familiarity value exceeds the criterion for a positive response.

In the exclude condition, the probability of a positive response to an anagram test word is given by

\[ P(E) = P(F) - P(R)P(F), \]

where \( P(F) \) is the probability in the exclude condition that the familiarity value exceeds the criterion for a positive response. In essence, recall adds to the probability of a positive response in the include condition and subtracts from the probability of a positive response in the exclude condition so as to make up the difference between the real data and the probabilities of positive responses based on familiarity alone. Solving for \( P(R) \),

\[ P(R) = [P(F) - P(E)]/P(F), \]

and, eliminating \( P(R) \) from the preceding equations,

\[ P(E)/(1 - P(I)) = P(F)/(1 - P(F)). \]
is fixed by the experimental data \(P(E) = .29\) and \(P(l) = .80\) in Jacoby’s (1991) experiment fix the ratio in Equation 9 to be 1.45, and this in turn determines the self-strength parameter for anagrams (because it is the only parameter free to vary for anagram familiarity values). Across the possible values of the self-strength parameter (Figure 1), the only value of self-strength that produces the correct ratio is 4.91 [where \(P(F_E) = .68\) and \(P(F_{E}) = .46\)]. Using these values in Equation 8 yields a value for \(P(R) = .37\).

It turned out that the probability of extra information contributing to performance for anagram test words estimated from SAM \(P(R) = .37\) was about the same as the probability of extra recollection for anagram test words over read text words for process dissociation. Thus, for the assumptions that recall and familiarity are independent and that recall contributes to both the include and exclude conditions, the process dissociation method provides about the right estimate of recall’s contribution for SAM (although recall contributes only for anagrams in SAM, whereas it contributes for all types of test items in process dissociation).

**Independence: Recall Contributes Only to the Exclude Condition**

The assumption made in the preceding section, that recall is used in both the include and exclude conditions, is the same as that made by process dissociation. It might be just as plausible to assume that recall is used only in the exclude condition. In the include condition, all highly familiar test words should be given a positive response, so it is reasonable to assume that responses in this condition are based only on familiarity and that participants adopt a strategy of attempting to use or using recall only to exclude anagram words in the exclude condition.

In the exclude condition, participants are instructed to respond positively only for words that were heard. Jacoby (1991) assumed that participants do not rely entirely on recollection to do this, that they still respond positively to highly familiar words when recollection fails (see Equation 1; see also discussion by Curran & Hintzman, in press). We followed that assumption for the exclude condition here.

With these assumptions, the probability of a positive response for an anagram test word in the inclusion condition is simply \(P(l) = P(F_{E})\). The probability of a positive response for an anagram in the exclude condition is the same as Equation 7, \(P(E) = P(F_{E}) - P(R)P(F_{E})\). The probability of recollection can be estimated from Equation 8, where the value of \(P(F_{E})\) is obtained from Figure 1. In Figure 1, the function for inclusion familiarity \(P(F_{E})\) reaches the value .8 [i.e., \(P(F_{E}) = P(l) = .8\) from the data] at the point at which \(P(F_{E}) = .533\). With \(P(E) = .29\) (from the data), \(P(R)\) is estimated, with Equation 8, to be .45. This value of recollection from two processes based on SAM is about 15% lower than the value of extra recollection for anagram over read test words estimated from the process dissociation equations. Again, as for the case in which recall contributes to both the include and exclude conditions, process disso-

Ation provides an approximation of the contributions of the underlying processes.

**Dependence: Recall Contributes Only to the Exclude Condition**

So far, the computations we have used to find how much the recall process needs to contribute to account for the data have assumed independence of recall and familiarity. In this last case, we assumed complete dependence; that is, if an item is recalled, its familiarity value must be greater than the criterion for a positive response. This means that the recall process contributes nothing additional to familiarity in the include condition [Equation 6 reduces to \(P(l) = P(F_{E})\)] and recall is used only in the exclude condition. The equation for the probability of a positive response to an anagram in the exclude condition is \(P(E) = P(F_{E}) - P(R)\). Then the value of \(P(R) = .23\). This value is about half the process dissociation estimate for recollection.

**Conclusions**

In summary, we first showed that the single familiarity-based process from SAM could not account for the data for anagram test items in Jacoby’s (1991) Experiment 3. To the familiarity process, we added a recall process, in three different ways. We found that the contribution of recall to performance varied from .23 to .46 with different assumptions about the independence or dependence of the two processes and whether both processes applied to both the include and exclude conditions. These values bracket a range of possible valid estimates for SAM. SAM assumes a common memory structure for familiarity and recall and, therefore, requires a moderate degree of dependence (neither the complete independence nor the complete dependence assumed for our test cases). Thus, process dissociation’s estimate of what recollection contributes to anagram test items relative to read test items (.40) is not an accurate and unique estimate of recall for SAM, because different possible versions of SAM would require different contributions from the recall process.

The assumptions that we have discussed for adding a recall process to SAM to produce Jacoby’s (1991) include-exclude data do not, of course, exhaust all possibilities. For example, there might be a recall process operating for the heard and read test words, instead of just the anagram test words, especially in the exclude condition (for a discussion of the possible roles of recall in recognition and evidence against the use of recall in standard experiments, see Gil-lund & Shiffrin, 1984). Or there might be no recall process at all, and the data might be explained by a two-stage familiarity process in which high familiarity for a test item might initiate a response (an include response in the include condition and an exclude response in the exclude condition) and lower familiarity test items would be matched against memory a second time with a different response criterion.

However, our goal was only to use SAM to produce data that would match real data and therefore allow tests of
process dissociation. Our concern was to show that there exist plausible explanations of the data that are different from those provided by process dissociation and that what is learned about retrieval processes is different under the different assumptions of SAM versus process dissociation. The general conclusion is the same as that reached for the Yonelinas and Jacoby experiments for which SAM’s single familiarity process was a sufficient account of the data: What is learned about memory processes from the process dissociation procedure depends on the validity of the underlying assumptions. Different underlying assumptions, like those for SAM, lead to different interpretations of data. The picture given by process dissociation of conscious versus unconscious retrieval is not necessarily the same picture that would be given of retrieval processing by SAM.

Process Dissociation Tested by Atkinson and Juola’s Two-Process Model

The often compelling intuition that the retrieval of information from memory involves two processes, even for recognition tasks, is not new (Atkinson & Juola, 1973; Jacoby & Dallas, 1981; Mandler, 1980). For example, Mandler (1980) postulated a familiarity process and a recollection process and proposed that familiarity was a fast retrieval process running in parallel with the slower recollection retrieval process. Mandler’s model was applied to explain a range of recognition and recall data, and the hypotheses about the time course of the two processes have also been tested (e.g., Mandler & Boek, 1974). The model would apply to data from Jacoby’s (1991) include versus exclude manipulation in the same way as process dissociation because it makes the same assumption about the independence of the two processes.

A different two-process model was developed by Atkinson and Juola (1973) for recognition. In their model, there are two processes of retrieval, but both processes are not always executed. If the familiarity of a test item is above some criterion value or below some second criterion value, then a response is made directly. The second process, a “search” process, is initiated only if the value of familiarity falls between the two criteria. This model was successfully applied across a range of mean reaction time data (Atkinson, Herrmann, & Westcourt, 1974; Atkinson & Juola, 1973).

Both the Mandler (1980) and the Atkinson and Juola (1973) models have been explicitly tested, and it has been argued that data do not, in general, support their assumptions about two processes (e.g., Gillund & Shiffrin, 1984; Monsell, 1978). The issue of concern here was whether the process dissociation method is compatible with the general assumption of two retrieval processes in recognition or is limited by its particular assumptions. More specifically, the question is whether the process dissociation method can uncover correct estimates of the two processes assumed by other two-process models. To address this question, we followed the same logic as with SAM: We used the Atkinson and Juola model to simulate include-exclude data and then compared the parameter estimates from the simulation with the parameter estimates recovered by process dissociation.

The data chosen for simulation were those from Yonelinas’s (1994) Experiment 1 (repeated from Table 2 and shown in Table 6). The first step for the simulation was to find parameters of the model that would produce Yonelinas’s data. The model was originally intended to deal with retrieval of words from lists that were so highly memorized that the search process would always result in perfect performance. That was not the case in Yonelinas’s experiment, and so we assumed some lesser degree of learning. We assumed that study led to a higher degree of learning for words from short lists than for words from long lists; thus, the distributions of values of familiarity used by the familiarity retrieval process were ordered with the mean of the new word distribution set at zero, the mean of the distribution for words from long lists above zero, and the mean of the distribution for words from short lists farther above zero. These distributions were assumed to be normal, each with associated variance.

At test, the familiarity retrieval process determines whether the familiarity of a test word is above the positive criterion or below the negative criterion, and, if it is, a response is executed. If familiarity is between the two criteria, then in the original model the result of the search process determines the response (always accurate). In our

<table>
<thead>
<tr>
<th>Condition</th>
<th>Probability of positive response</th>
<th>Process dissociation estimate</th>
<th>Atkinson and Juola estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Include</td>
<td>Exclude</td>
<td>New</td>
</tr>
<tr>
<td>Data, short lists</td>
<td>.78</td>
<td>.22</td>
<td>.09</td>
</tr>
<tr>
<td>Data, long lists</td>
<td>.70</td>
<td>.30</td>
<td>.14</td>
</tr>
<tr>
<td>Fit 1 short lists</td>
<td>.78</td>
<td>.21</td>
<td>.08</td>
</tr>
<tr>
<td>Fit 1 long lists</td>
<td>.70</td>
<td>.31</td>
<td>.15</td>
</tr>
<tr>
<td>Fit 2 short lists</td>
<td>.78</td>
<td>.22</td>
<td>.09</td>
</tr>
<tr>
<td>Fit 2 long lists</td>
<td>.70</td>
<td>.30</td>
<td>.14</td>
</tr>
</tbody>
</table>

Note. \(P(R)\) = probability of recollection; \(P(F)\) = probability of familiarity.
application, we assumed that the search process would not always succeed. We added two parameters: \( p \), the probability that the search process successfully finds a word in a studied list, and \( q \), the probability of a positive response if the search fails (see Atkinson et al., 1974, p. 113, Footnote 5). We also assumed that the probability of successful search was independent of familiarity.

In the include condition, a positive response can occur if the familiarity of a test item is (a) above the positive criterion or (b) between the two criteria and the search process is successful or (c) there is a positive guess:

\[
P(I) = P(F > C_{\text{high}}) + [p + (1 - p)q]P(C_{\text{low}} < F < C_{\text{high}}).
\]

(10)

In the exclude condition, a positive response can come about if the familiarity of a test item is (a) above the positive criterion or (b) between the two criteria and the search process fails and there is a positive guess:

\[
P(E) = P(F > C_{\text{high}}) + (1 - p)qP(C_{\text{low}} < F < C_{\text{high}}).
\]

(11)

The number of parameters is greater than the number of data points, and the model can easily simulate the data (the model was designed to deal with reaction time data in addition to the accuracy data considered here). In the course of investigating the model, we discovered that the guessing process could trade off against the familiarity process so that the same level of performance could be obtained from a few positive responses resulting from high familiarity and a high positive guessing rate, or many positive responses resulting from high familiarity and a lower guessing rate. To illustrate this, we simulated the data twice. Table 6 shows the results of the two different simulations, and Table 7 shows the values of the parameters that were used.

The first conclusion is that the simulations reproduce the data quite well. The second issue is the test of process dissociation. Process dissociation produces the estimates of the contributions of familiarity and recollection shown in Table 6 for the Jacoby (1991) model. Are these also accurate estimates of familiarity and the search process for the Atkinson and Juola (1973) model? From Equations 10 and 11, one can derive estimates of familiarity and search directly from the Atkinson and Juola model and compare them with the estimates derived through process dissociation. The probability of a yes response based on the search process is the probability of executing a search multiplied by the probability of the search being successful: \( P(S) = pP(C_{\text{low}} < F < C_{\text{high}}) = P(I) - P(E) \).

For both simulations of the data, the estimate of the contribution of the search process for the Atkinson and Juola (1973) model is the same as the estimate of the contribution of the recollection process from process dissociation. But the estimates of familiarity are different. In Jacoby's (1991) model, the unconscious familiarity process is not affected by list length. In the Atkinson and Juola model, familiarity is affected by list length in either direction: In the first simulation, familiarity is greater for a long list than for a short list; in the other simulation, it is less. This occurs because of the trading off mentioned earlier between the different components of the model (search, familiarity, and guessing). In the two simulations we present, familiarity and guessing trade off against each other. This is not a positive aspect of the simulations, but it is to be expected when a limited range of data is modeled relative to the range of data for which the model was designed.

The conclusion offered by these simulations is that the include–exclude data do not support estimates of two components that are the same for all two-process assumptions. This is similar to the situation when process dissociation was compared with SAM. The picture given of conscious versus unconscious processing is different when it is drawn from Atkinson and Juola's (1973) model than when it is drawn from process dissociation.

### Slopes of z-ROC Functions and Process Dissociation Assumptions

The main two assumptions of process dissociation are that there are two processes, recollection and familiarity, and that they are independent. However, Jacoby and Yonelinas (Jacoby et al., 1993; Yonelinas, 1994) assumed, in addition, that familiarity could be described by signal detection theory with the distributions of the familiarity values of studied (old) and nonstudied (new) items having equal variances. From this latter assumption, it is possible to predict the slopes of the z-ROC functions that can be obtained with confidence judgment procedures. This is particularly salient because it has become clear from recent research that the global memory models make predictions inconsistent with the slopes of the z-ROC curves obtained in recognition memory experiments. If it turned out that process dissociation:

### Table 7

**Parameters for the Atkinson and Juola (1973) Model**

<table>
<thead>
<tr>
<th>Condition</th>
<th>( C_{\text{low}} )</th>
<th>( C_{\text{high}} )</th>
<th>New ( \mu )</th>
<th>New ( \sigma )</th>
<th>Old ( \mu )</th>
<th>Old ( \sigma )</th>
<th>( p )</th>
<th>( q )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fit 1 short lists</td>
<td>1.69</td>
<td>9.69</td>
<td>0.0</td>
<td>4.35</td>
<td>5.72</td>
<td>4.81</td>
<td>0.96</td>
<td>0.2</td>
</tr>
<tr>
<td>Fit 1 long lists</td>
<td>0.51</td>
<td>6.28</td>
<td>0.0</td>
<td>4.35</td>
<td>3.73</td>
<td>4.85</td>
<td>0.86</td>
<td>0.2</td>
</tr>
<tr>
<td>Fit 2 short lists</td>
<td>0.56</td>
<td>6.76</td>
<td>0.0</td>
<td>2.27</td>
<td>4.53</td>
<td>2.45</td>
<td>0.73</td>
<td>0.2</td>
</tr>
<tr>
<td>Fit 2 long lists</td>
<td>1.66</td>
<td>9.03</td>
<td>0.0</td>
<td>2.27</td>
<td>4.53</td>
<td>2.47</td>
<td>0.48</td>
<td>0.6</td>
</tr>
</tbody>
</table>

*Note: \( C_{\text{low}} \) and \( C_{\text{high}} \) are the lower and upper familiarity criteria, \( \mu \) and \( \sigma \) are the means and standard deviations of the familiarity distributions, \( p \) is the probability of a successful search for an old item, and \( q \) is the probability of a positive guess if the search process fails.*
The problem with z-ROC curves for the global memory models arises because of the models’ assumptions about the relative variability in familiarity values for old versus new test items. Empirically, the ratio of the standard deviation of new-item familiarity values to the standard deviation of old-item familiarity values can be obtained from signal detection theory by means of confidence judgment data. This is done by plotting the z transforms of the hit and false alarm rates against each other for each level of confidence to produce a z-ROC curve. For the global memory models, the underlying distributions of familiarity values are normal (either directly or by the central limit theorem applied to sums of discrete values), so the slope of the z-ROC is the ratio of the new-item standard deviation to the old-item standard deviation, \( \sigma_x/\sigma_e \). The data presented by Ratcliff et al. (1992) showed a roughly straight-line z-ROC function with a slope of about 0.8 for both weakly encoded items and strongly encoded items. The constant value of the slope across different strengths of encoding is difficult if not impossible for the current global memory models to accommodate. For example, SAM predicts that the standard deviation of old-item familiarity should increase relative to the standard deviation of new-item familiarity as a function of overall level of familiarity. The predicted increase comes from the way variability of encoding is introduced into the model. Increasing the mean value of strength that results from encoding (e.g., by increasing study time) increases the variance in the encoded strength values. This assumption lies at the heart of the model; changing the assumption to fit the z-ROC data would be tantamount to proposing a new model requiring new fits to all experimental data. The difficulties presented by the z-ROC data are similarly critical for the other global memory models (Hintzman’s [1988] model also predicts that the standard deviation for old-item familiarity increases with strength, and Murdock’s [1982] model predicts almost equal standard deviations for old-item and new-item familiarity values; see Ratcliff et al., 1992).

In Yonelinas and Jacoby’s account, the distributions of familiarity values for old and new test items are assumed to be normal with equal variance; thus, if responses were based on familiarity alone, the slope of empirical z-ROC functions should have a value of one. The empirical slope is less than the value of one, by their account, because of the recollection process. When participants make high-confidence positive responses, some of them are based on familiarity and some on recollection. The addition of the recollection-based responses in the high-confidence category causes an increased standard deviation for old items, which in turn makes the slope of the z-ROC less than one. With this assumption about recollection contributing to high-confidence positive responses, Yonelinas (1994) attempted to show that process dissociation assumptions were consistent with z-ROC functions observed in his experiments.

Yonelinas and Jacoby’s proposal provides a test of an inherent prediction of process dissociation assumptions. Previous support for the assumptions has stemmed from the intuitive reasonableness of their accounts of patterns of dissociations and patterns of the relative contributions of recollection and familiarity to processing. For example, although it might be reasonable that list length affects recollection but not familiarity, as in the experiments discussed earlier, the process dissociation assumptions themselves do not make that prediction. The assumptions alone would be equally consistent with the opposite outcome. In contrast, if Yonelinas and Jacoby’s proposal about z-ROC curves fails, then their signal detection assumptions fail. In the sections that follow, we present the results of several different evaluations of their proposal and show that the proposal is not consistent with empirical z-ROC curves.

**z-ROC Curves Based on Familiarity Plus Recollection**

For our first analysis, we calculated what the shape of z-ROC curves should be according to process dissociation assumptions. We assumed that the assumptions were correct and that recognition performance in confidence judgment tasks is based on familiarity and recollection, and we then examined the forms of predicted hypothetical z-ROC curves.

We began with data from an experiment conducted by Ratcliff, McKoon, and Tindall (1994, Experiment 4). In that experiment, participants studied lists of words that were of either high or low frequency and were encoded either strongly or weakly (i.e., studied for a short time or a long time). At test, participants were instructed to respond positively to any word that had been studied, using a 6-point confidence scale. This corresponds to an include condition in that participants were instructed to respond positively to all studied words. From the z transform of the hit and false alarm rates at each confidence level, z-ROC curves were produced (as described at the beginning of the Appendix). The experiment did not use an exclude condition, so we could not calculate an empirical measure of recollection by using the process dissociation method. But performance in an include condition must, by the process dissociation assumptions, depend on both recollection and familiarity. We examined a range of possible values of recollection, looking for a value that would result in the empirically obtained z-ROC functions being consistent with the process dissociation assumptions.

The methods by which we examined process dissociation predictions for z-ROC functions are described in detail subsequently. Figure 2 shows the results for one experimental condition (weakly encoded high-frequency words). The z-ROC curve obtained directly from the data is shown by the diamonds, and it has the slope of less than one that is characteristic of recognition memory. The other z-ROC
curves are predictions from process dissociation, each based on a different hypothetical value of recollection [with the probability of a yes response based on recollection, \( P(R) \), varied from 0 to .45]. Not all of these values for recollection are actually possible for the process dissociation assumptions. What we show in the following analyses is that, in general, there are no values for recollection that are consistent simultaneously with the assumptions and the empirical z-ROC functions.

Generating the curves in Figure 2 and testing the process dissociation assumptions requires a multistep algorithm (given in detail in the Appendix). The algorithm begins with data from confidence judgments with include instructions; that is, participants are instructed to respond positively to all studied items. The algorithm first uses confidence judgment data to obtain a \( d' \) value for the familiarity process (see Appendix, Steps 1–3). This is done by collapsing over the positive half of the confidence categories to obtain one hit rate and one false alarm rate. From this hit rate, this false alarm rate, a hypothetical value of \( P(R) \), the process dissociation equations, and the assumption that familiarity distributions are normal with equal variance, a \( d' \) value can be calculated for the familiarity process alone, separate from the hypothetical recollection process. Once \( d' \) is obtained, it can be used with the empirical false alarm rates for the different confidence judgment categories to obtain a familiarity-based hit rate for each confidence category.

The algorithm gives the familiarity-based hit rate for each confidence category, and the data give the false alarm rate for each category. To generate the predicted z-ROC curve for familiarity plus recollection, one can add the hypothetical value of \( P(R) \) back in at each confidence category to obtain predicted hit rates for familiarity and recollection combined (see Appendix, Step 4). These predicted hit rates

---

**Figure 2.** Hypothetical familiarity-based z-ROC functions derived from data for weakly encoded high-frequency words from Experiment 4 of Ratcliff, McKoon, and Tindall (1994). The diamonds show the z-ROC function for the data from the experiment. (Standard errors in the z scores for the data are between 0.05 and 0.03 [see Kendall & Stewart, 1976, for standard errors in quantiles].) The recollection scores used to generate the curves are ordered from 0 to .45 going from bottom to top for the lowest \( z_m \) value; \( fa = \) false alarm. ROC = receiver operating characteristic.
and the empirical false alarm rates are then used to obtain the predicted z-ROC curve. The z-ROC curves for the 10 hypothetical values of \( P(R) \) shown in Figure 2 were generated in this way. Not all of the 10 values of \( P(R) \) are actually possible; values of .35 and above (very high values of recollection) give \( d' \) values for the familiarity-based process that are not greater than zero. None of the remaining predicted z-ROC curves match the shape of the real z-ROC curve from the data (large diamonds in Figure 2). That curve overlaps the curve for the third lowest value of recollection at lower \( z_d \) values, and it overlaps the fourth highest value of recollection at higher \( z_d \) values.

The method just described for generating predicted z-ROC curves uses the same hypothetical value of \( P(R) \) for all confidence categories to predict the hit rates for recollection and familiarity combined. Another way of generating predicted z-ROC curves is to use the empirical hit rates to predict what the values of \( P(R) \) should be for each confidence category (see Appendix, Step 5). The hit rates and the false alarm rates from the data and the familiarity-based hit rates from the algorithm are used to predict what the probability of recollection should be at each confidence interval \([P(R)]\). These values must all be positive (at no confidence level can the probability of a yes response resulting from recollection be zero or negative). If any value of the hypothetical \( P(R) \) that was used to generate the familiarity \( d' \) does lead to a negative or zero value of any \( P(R)_n \) then it must be rejected as inconsistent with process dissociation. Values of \( P(R) \) less than or equal to .15 in Figure 2 must be rejected for this reason.

Rejecting these values and those for which \( d' \) for the familiarity-based process was not greater than zero (.35 and above) leaves only the hypothetical \( P(R) \) values of .2 to .3. For these values, the bend of the ROC curve (the U shape) is quite large, large enough to be empirically detectable (see Figure 2). Examination of empirical z-ROC functions (including many from single participants tested over many sessions) from the experiments described by Ratcliff et al. (1994) shows only a small fraction of the total cases for which the z-ROC functions have this shape, so data do not, in general, support this prediction of the process dissociation assumptions.

The values of \( P(R) \) can be submitted to a further constraint. The predicted probabilities of recollection \([P(R)]_i\) at each confidence category must never decrease from the highest confidence positive category to lower confidence categories. This is because hit rates come from cumulating correct positive responses from the highest confidence category down to the lower confidence categories, so the number of responses based on recollection can increase across these categories but cannot decrease. To test this, we used data from Experiment 4 of Ratcliff et al. (1994). Moving from most extreme positive to most extreme negative confidence categories is equivalent to increasing the false alarm rate, and so the predicted probabilities of recollection can be plotted against the false alarm rate as it changes across confidence categories. This was done for all of the conditions of the experiment (the conditions involved strongly and weakly encoded low-frequency and high-frequency words) for all values of \( P(R) \) that did not yield \( d' \) zero or negative or recollection less than zero. The results are displayed in Figure 3; each panel shows a subset of the different \( P(R) \) values for different conditions of the experiment. The value of \( P(R) \) used to generate the \( P(R)_i \) is always the same as the middle value of \( P(R)_i \) [because the middle split is used to obtain \( d' \) and \( P(R) \) in the algorithm presented in the Appendix]. The panels show that there are almost no values of \( P(R) \) that are consistent with the process dissociation assumptions; instead of holding constant or perhaps increasing across confidence categories, the \( P(R)_i \) generally decrease from the midpoint to the most confident negative category (39 of 44, significant by sign test).

Yonelinas (1994) also obtained \( P(R)_i \) values that decreased like those in Figure 3. He attributed the decrease to floor and ceiling effects on accuracy. However, most of the data in Figure 3 are not subject to floor and ceiling problems and so do present a contradiction of process dissociation assumptions.

The Present Experiment

The preceding analyses were based on data from an experiment in which there were only include conditions. Without an exclude condition, there is no way to estimate recollection directly from the data. All of the analyses were based on hypothetical values of recollection. To pursue the analyses, we collected include–exclude data using the list discrimination procedure that Yonelinas (1994) used in his experiments. Participants studied two lists of words, and then they were cued as to whether the words of the first list

![Figure 3](image-url)
or the words of the second list were to be given positive responses.

To provide the strongest test of process dissociation assumptions, we chose experimental conditions for which the slope of the z-ROC curve would be farthest from predictions of process dissociation assumptions for the familiarity process alone (i.e., a slope as much below one as possible). This is a strong test because the recollection process has to be assumed to move the slope far from one. We also picked conditions in which recollection seemed most unlikely to be able to do this. If recollection could move the slope far from one, under conditions in which recollection was intuitively unlikely, then process dissociation assumptions would have passed a strong test. The conditions we used were low-frequency words studied at a fast presentation rate. These conditions give low z-ROC slopes and a low probability of recall, which suggests a low probability of recollection (see Glanzer & Adams, 1990; Glanzer, Adams, Iverson, & Kim, 1993; Ratcliff et al., 1994).

Method

Participants. The participants were 8 undergraduates from Northwestern University paid to participate in the experiment. Each student participated in one 50-min session.

Materials. The pool of 865 low-frequency words used by Ratcliff et al. (1994) was used for this experiment. For the experimental study and test lists, only words from this pool were used. There was also a pool of high-frequency words used only for practice lists.

Procedure and design. All stimuli were presented on the screen of a personal computer, and the computer keyboard was used to record responses. Each block of the experiment consisted of two lists of words to be studied, followed by a single test list. There were 16 words in each study list presented at a rate of 750 ms per word. The beginning of each list was signaled to the students by the instruction to press the space bar on the keyboard. At the end of the second list, students were given an instruction to tell them for words of which list they were to give a positive response. They were also instructed to flip an index card to show which was the positive list; the card was used to make sure students noted the instruction and to serve as a reminder if they needed one. There were 48 words in the test list: 16 from the first studied list, 16 from the second, and 16 new words that had not appeared on either studied list. The words of the test list were presented 1 at a time, each remaining on the computer screen until a response key was pressed. A 250-ms blank screen followed each response, and then the next test word was presented. Students were instructed to respond on an 8-point confidence scale ranging from extremely sure negative to extremely sure positive. For the positive end of the scale, the m, comma, period, and ?/keys were used. For the negative end, the keys were z, x, c, and v. Labels for the response keys were shown on the index card that students flipped to show which list required positive responses. Students were instructed to try to use the full range of response keys.

There were 20 blocks in an experimental session, the first 2 used only for practice. For half of the blocks, a positive response was required for the first study list; for the other half of the blocks, a positive response was required for the second study list. Words for the study lists, new words for the test lists, the orders of presentation of words in the study and test lists, and the order of the two kinds of blocks were determined randomly, and the randomization was changed after every second student.

Results

For test words that were from the study list designated for positive responses (the include condition), the proportion of positive responses was .553. For test words from the other study list (the exclude condition), the proportion of positive responses was .418. For new test words, the proportion of positive responses was .147, leading to d' values (based on the equal variance assumption) of 1.18 for the include condition and 0.84 for the exclude condition. There were more than 2,000 responses in each of the include, exclude, and new test word conditions, giving good stability to the data.

Figure 4 shows the z-ROC curve for test words in the include condition. According to Yonelinas's (1994) application of d' to process dissociation, responses to these test words should be based on both familiarity and recollection.  Using process dissociation, we plotted the z-ROC curve for familiarity alone. Following Yonelinas (1994), we estimated the probability of recollection \( P(R) \) by calculating a hit rate for the exclude condition and a hit rate for the include condition and subtracting the exclude hit rate from the include hit rate (Equation 1). The hit rates were calculated by summing the numbers of responses in each of the high positive, high medium positive, low medium positive, and low positive confidence categories and dividing by the total number of responses across all confidence categories for the

![Z ROC curves for Group for Include and Familiarity](image-url)
class of items (include or exclude). From \( P(R) \) and the hit rate at each confidence category in the include condition, a familiarity-based hit rate was calculated for each confidence category (Equations 1 and 2). The familiarity-based z-ROC was obtained from these hit rates and the false alarm rates from the data.

The estimates of the slopes of the z-ROC curves and their intercepts, along with the standard errors in those estimates, are shown in the first three rows of Table 8. As expected from process dissociation assumptions, the recovered familiarity slopes are nearer one than the slopes for the include or exclude condition. But they are still significantly different from one. The slopes for the include and exclude conditions are approximately 0.7 (in the range of those found by Glanzer & Adams, 1990, and Ratcliff et al., 1994). The derived familiarity-based z-ROC has a slope of 0.857 and a standard error of 0.045, which means that it is significantly different from one.

Discussion

According to process dissociation assumptions, the slopes of z-ROC curves from recognition memory experiments are generally less than one because a recollection process contributes to high-confidence positive responses. Removal of this process should leave only familiarity, and the z-ROC should be linear with a slope of one. The data and analyses presented in Yonelinas (1994) provided support for this prediction. However, our aim was to provide a more stringent test, and to do this we chose conditions that were the least favorable for the process dissociation method. The results contradicted process dissociation’s predictions. For our experimental conditions, designed to produce a slope much less than one and a low probability of recollection, the familiarity slope was significantly different from one.

The failure of process dissociation to predict the data raises the issue of how process dissociation uses signal detection theory as a basis for familiarity. Process dissociation assumes that the old item and new item distributions of familiarity have equal standard deviations. This assumption is questionable. What it means is that study adds no variability to the representations of items in memory. For example, an item originally with a familiarity one standard deviation below the mean of the new item familiarity distribution will have, after study, a familiarity exactly the same distance below the mean of the old item distribution. This implies that, for the familiarity-based process, there will be no item effects in learning—all items are learned to exactly the same degree—and this seems to contradict what is known about item effects. The assumption of equal standard deviations comes from the classical application of signal detection theory to perception in which a fixed signal is added to noise and so the z-ROC is expected to have a slope of one. It is not obvious that the assumption should transfer to memory, and it appears that it does not work when combined with process dissociation’s other assumptions. Unfortunately, if the assumption of equal standard deviations in old and new item familiarity is dropped from process dissociation, then the assumptions have no way to predict either the shapes or the slopes of z-ROC curves.

**Process Dissociation and the Shape of z-ROC Functions**

According to the assumptions, z-ROC curves should have slopes equal to one after process dissociation is applied. In general, if the slope of the empirical z-ROC curve is less than one, application of process dissociation is guaranteed to increase the slope, bringing it nearer one. Therefore, finding that the estimated slope of the recovered familiarity z-ROC slope does, in fact, increase and become nearer one than the slope of the data is not a strong test of the assumptions.

As a more detailed illustration of this point, assume that recognition confidence judgment responses come from a single underlying strength process, such as in the SAM model, with no second recollection process. Also assume that there are three different distributions of strength values: one for new items \((M = 0, SD = 1.0)\), one for items to be excluded \((M = 1.0, SD = 1.25)\), and one for items to be included \((M = 1.5, SD = 1.25)\). Distributions such as these are what the z-ROC data from Ratcliff et al. (1992) imply if the familiarity distributions are normal. The distributions are shown in Figure 5, with seven confidence judgment criteria. If this were a true description of underlying processing arising from a single familiarity-based process (e.g., one of the global memory models), there would be no recollection component, but the process dissociation equations could still be applied to the data. For the purposes of this illustration, the estimate of recollection is taken to be the difference between the include and exclude distributions at the highest confidence response category; the difference is 0.12. Then the slope of the recovered z-ROC for the hypothetical familiarity process is 1.0 (obtained as for the preceding experimental data). Both the original z-ROC curve for the include data and the recovered familiarity z-ROC are shown in Figure 6. The slope of the recovered curve is nearer one than the slope for the original data. The bottom two lines in Table 8 show the linear regressions for the include condition (the slope is the ratio of the standard deviations, 1.0:1.25, and the intercept is the difference in means, 1.5, divided by the included distribution standard deviation, 1.25) and the “familiarity” z-ROC regression slopes and intercepts.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Slope</th>
<th>Intercept</th>
<th>Slope SE</th>
<th>Intercept SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1: include</td>
<td>0.687</td>
<td>0.847</td>
<td>0.019</td>
<td>0.026</td>
</tr>
<tr>
<td>Experiment 1: exclude</td>
<td>0.724</td>
<td>0.509</td>
<td>0.030</td>
<td>0.040</td>
</tr>
<tr>
<td>Experiment 1: familiarity</td>
<td>0.857</td>
<td>0.852</td>
<td>0.045</td>
<td>0.060</td>
</tr>
<tr>
<td>Three normals: include</td>
<td>0.800</td>
<td>1.200</td>
<td>0.0002</td>
<td>0.0003</td>
</tr>
<tr>
<td>Three normals: familiarity</td>
<td>1.000</td>
<td>1.246</td>
<td>0.046</td>
<td>0.059</td>
</tr>
</tbody>
</table>

Note. ROC = receiver operating characteristic.
This example illustrates that the process dissociation method is guaranteed to increase the slope of the z-ROC. It does so because it removes probability density from the upper-right-hand tail of the observed distribution, which reduces the standard deviation for the old items.

Figure 6 also shows a bend at the high-confidence end of the recovered z-ROC curve similar to that illustrated in Figure 2. If process dissociation assumptions were correct, the z-ROC curve would be linear, with no bend. For a single-process model, if the original distributions are normal, then removing probability density from the high end necessarily results in the bend in the z-ROC function. In other words, the bend indicates a nonnormal distribution in familiarity after process dissociation, a contradiction of process dissociation assumptions but consistent with single-process models. The appearance of a bend in the recovered familiarity z-ROC is a strong pointer to a failure of process dissociation under the assumption of normal distributions (see also the familiarity z-ROC function in Figure 4).

Finally, a subsidiary question is whether a recall plus recollection process might be able to repair the failure of the familiarity-based global memory models to predict empirical z-ROC functions (see Ratcliff et al., 1992, 1994). The TODAM model of Murdock (1982) could be augmented by adding a recall process in much the same way as Yonelinas (1994) added recollection because TODAM predicts that the old and new item distribution variances are approximately equal. In detail, the model would not be able to account for results found in Ratcliff et al. (1992) and Ratcliff et al. (1994) because, with variations of list length or strength, the slope of the empirical z-ROC function remains constant. The TODAM model predicts that the contribution from recall would increase with increasing strength or decreasing list length. The SAM model (Gillund & Shiffrin, 1984) and the MINERVA 2 model (Hintzman, 1988) predict that, with increasing strength or decreasing length, the variance of the familiarity distribution for old items increases. Thus, increasing recall with increasing strength or decreasing list length would make the z-ROC slope decrease even more than the models predict without recall.

**Conclusion**

The process dissociation method is very appealing. It appears to offer a method of separating conscious from unconscious components of processing, with the hope that such a separation will lead to better understanding of both. If correct, the method would begin to solve age-old questions about the relative contributions of conscious and unconscious components to processing in any task. But the method is built on specific assumptions about processing (as noted by Jacoby, 1991), and it must be considered in that context, not as an assumption-free procedure and not as a purely empirical procedure.

The potential strength of the process dissociation method lies in the include versus exclude manipulation. In recognition memory, for each of the sets of data we considered, the account of include-exclude data given by process dissociation was different than that given by theories based on other assumptions. It follows that the explanation of how unconscious processing is affected by experimental variables will be different for process dissociation than for other assumptions. For example, consider the experimental results...

---

**Figure 5.** Hypothetical distributions of strength for new, exclude, and include conditions.

**Figure 6.** ROC functions for the include condition and the estimated familiarity derived from the process dissociation procedure for the distributions in Figure 5. ROC = receiver operating characteristic.
discussed in this article. If the SAM account of recognition is correct, then the estimates from process dissociation of how familiarity and recollection are affected by experimental variables are incorrect; conversely, if the process dissociation estimates are correct, then the SAM account is wrong.

The strongest form of the logic of our argument is as follows: Suppose SAM is the correct description of underlying processing and one generates data from SAM; then, if one applies process dissociation to produce estimates of the contributions of two processes, those estimates will be incorrect because the data came only from one process. We used SAM to simulate real experimental data to ensure that this argument was valid in the range of normal performance on recognition with include and exclude instructions.

The obvious challenge that arises from this situation is to find some way of choosing which theoretical account is correct. A traditional method is falsifiability. For recognition memory, SAM (and the other models like it) can potentially fail in a multiplicity of ways internal to itself by making predictions that are incorrect. In contrast, process dissociation has just two assumptions that can lead to internally generated predictions. One is the assumption that familiarity is described by signal detection theory with equal variance in old and new item values of familiarity. We discussed this assumption in earlier sections of this article and showed that it can be falsified. However, it can also be viewed as an auxiliary assumption unnecessary to the basic process dissociation procedure. Process dissociation can still be applied to data, with or without the signal detection theory assumptions. The second potentially falsifiable assumption is that the recollection and familiarity processes are independent. This assumption has been criticized by Curran and Hintzman (in press) and Joordens and Merikle (1993). However, whatever the result of those critiques, the process dissociation method can remain intact. Even if there is dependence between the two components of retrieval, their relative influences on performance can still be computed from data (see Joordens & Merikle, 1993). Process dissociation is applied to exactly two performance measures (probability of a positive response in the include condition and probability of a positive response in the exclude condition), and two measures can always be fit by two parameters, so the model is not falsifiable at this level.

A question that can be raised at this point of the debate is whether the mechanisms by which SAM simulates data are equivalent in some sense to the processes assumed by process dissociation. For example, in the first set of simulations considered, SAM simulated the include-exclude data by using context weights to focus on one list context versus the other list context. Might this be equivalent to process dissociation’s assumption of two processes? The answer to this question is no, for several different reasons. First, manipulation of one parameter or factor in one model does not necessarily have a one-to-one correspondence with manipulation of a parameter or factor in the other model. For example, changing a link strength in a semantic network model would have no one-to-one correspondence with changing a single parameter in a distributed connectionist model. Second, even some partial equivalence (e.g., two parameters having equivalent effects over some restricted range) would not change any of our conclusions. The two sets of assumptions are very different in terms of how they view representation of information in memory and the processes that operate on that information. Third, it may be claimed that the assumptions underlying process dissociation make it better than SAM because they have fewer parameters. The problem with this argument is that, as pointed out earlier, the process dissociation method does not provide any account of relationships between the familiarity and recollection parameters across experimental conditions; the familiarity values for different conditions can be different or the same, and this also holds for the values of recollection. In contrast, SAM’s parameters are constrained across conditions, sometimes allowing no change in parameter values and sometimes allowing only one parameter to change. Thus, when data from a large number of conditions (e.g., a range of study times) are examined, SAM will sometimes have fewer parameters than process dissociation.

The SAM model has been very successful with recall phenomena (Raaijmakers & Shiffrin, 1981) and with recall and recognition interactions (Gillund & Shiffrin, 1984). With relatively few assumptions, it affords a reasonably coherent view of the effects on performance of a large number of independent variables in terms of the behavior of underlying parameters. It might seem that the model has enough freedom and enough parameters to deal with any pattern of experimental results. This would be correct if there was a one-to-one correspondence between parameters and empirical effects, such that adjustments to one parameter completely controlled predictions for one variable, or if all of the parameters varied in unprincipled ways to account for the effects of every variable. However, this is not the case. There are many situations in which the model is tightly constrained, and it requires insight into the structure of the model to determine what situations provide such constraint. One way in which predictions have been falsified is SAM’s failure to predict the behavior of the z-ROC data discussed earlier in this article (see Ratcliff et al., 1992, 1994). SAM fails, in part, because of the way variability is introduced into the encoding process, and changing this would result in a new and different model (see also Ratcliff et al., 1990; Shiffrin et al., 1990).

The point is that there are potentially multiple ways (some not intuitively apparent) in which SAM can be falsified by failures of predictions generated from its assumptions. In fact, however, the model has been remarkably successful in its predictions, both qualitatively and quantitatively, as exemplified by the following factors:

1. **List length:** In the typical experiment, participants do not know whether a list of words they are given is going to be a long list or a short list, so the encoding parameters of SAM remain constant across different list lengths (the self, interitem, and residual strength parameters). Increasing list length simply increases the number of items encoded into memory. The result is larger values of familiarity for items from longer lists and larger variability in their familiarity
values. For example, for a new item presented as a test
word, familiarity is twice as large for a list twice as long.
This means that the familiarity criterion that separates pos-
itive from negative responses has to be moved as list length
changes so as to keep it between the old and new item
distributions (Gillund & Shiffrin, 1984, p. 64; also see
preceding sections above in which SAM was fit to Yoneli-
nas and Jacoby's data). The familiarity criterion is the only
parameter that can vary to accommodate list length changes.

When test items are presented, they must enter the
short-term memory buffer, just as study items do. They add
to the items from the study list to increase the total number
of items in the experiment. Therefore, their effects are
modeled in the same way as variations in list length, and
effects resulting from the position of a test word in the test
list are accurately predicted.

2. Study time: The only change as a function of study
time is the amount of strength that accumulates during
encoding for each studied item. The encoding strength pa-
rameters are fixed, and the cue to item strength values
accumulated during study are the product of these param-
eters and the amount of time an item spends in the encoding
buffer (with some scaling factor). As with list length, the
criterion has to be adjusted to keep it between the old and
new distributions because both old and new items have
higher familiarity values for lists with longer study times
(see Gillund & Shiffrin, 1984, p. 64, and earlier discussion).

3. List context effects: The context parameter in SAM
was designed to allow retrieval to focus on subsets of
information in memory, such as items from studied lists
versus all other items in memory and items from one studied
list versus another. In modeling of list context effects, none
of the encoding parameters can vary. The only parameter
that can be adjusted is the weight placed on the context
parameter for each context in the retrieval cue.

4. Rehearsal instructions: With maintenance instruc-
tions, participants are instructed to rehearse each item dur-
ing its entire presentation time and not to rehearse any other
items during that time. With elaboration instructions, they
are instructed to use the presentation time for an item to
relate it to other items in the study list. The only parameters
adjusted to fit data for this manipulation are the self-strength
and interitem strength encoding parameters (Gillund &
Shiffrin, 1984, p. 25).

5. Item effects: Similarity of distractor test words is mod-
eled by varying the residual strength parameter (with small
adjustments to the criterion). Word frequency effects are
also explained with the residual strength parameter: Lower
frequency distractors have a lower residual strength, so they
are farther from the distribution of studied items than would
be higher frequency distractors (for a complete discussion of
word frequency and its interactions with other variables,
see Gillund & Shiffrin, 1984).

Demonstrations of the kind just summarized show how
SAM accounts for empirical data in principled ways and
point to the most salient contrast between the global mem-
ory models and process dissociation. The global memory
models' goal is to simultaneously and quantitatively explain
the effects of a number of different variables on recall and
recognition (and other tasks for some of the models). The
goal of process dissociation is to explore possible dissocia-
tions between a conscious retrieval process, recollection,
and an unconscious process, familiarity. If global memory
models are ultimately found wanting, it will probably be
because they are falsified by their own predictions. If pro-
cess dissociation ultimately comes to be viewed with sus-
picion, it will probably be because its explanations of data
are implausible for external reasons. Of course, both models
should provide reasonable interpretations of data across a
range of variables and tasks. But this kind of evaluation is
difficult because what is reasonable must be defined from
outside the theories. If one hypothesized that some variable
would affect familiarity in process dissociation and residual
strength in SAM but this turned out to be wrong—the
variable affected process dissociation's recollection and
SAM's focusing weights—then it would not be the theories
that failed but one's intuitive hypotheses. Failure of one's
intuitions is not necessarily grounds for rejection of a mod-
el; the model might be correct and one's intuitions wrong.
However, at the same time, process dissociation gains con-
siderable strength from the consistency of its estimates of
familiarity and recollection across a range of tasks. The
prediction of this consistency and the evaluation that the
prediction is a reasonable one come from not from process dis-
sociation's assumptions but from other sources external to
the theory.

Our conclusions apply to recognition memory, the do-
main of testing in this article. We believe that testing can be
especially provocative in this domain because there exist
several well-developed models. But for many tasks to which
process dissociation might most fruitfully be applied, such
as those that have been used to postulate implicit memory
systems, there are no other well-developed models against
which to test process dissociation's assumptions. For those
domains, process dissociation will serve as the default
model against which future models will be tested.

References
Search processes in recognition memory. In R. L. Solso (Ed.),
Theories in cognitive psychology: The Loyola Symposium (pp.
Atkinson, R. C., & Juola, J. F. (1973). Factors influencing the
speed and accuracy of word recognition. In S. Kornblum (Ed.),
Attention and performance IV (pp. 583–612). New York: Aca-
demic Press.
Curran, T., & Hintzman, D. (in press). Violations of the indepen-
dence assumption in process dissociation. Journal of Experimen-
tal Psychology: Learning, Memory, and Cognition.
a mechanism for priming in retrieval from memory. Journal of
Experimental Psychology: General, 2, 191–211.
Glanzer, M., & Adams, J. K. (1990). The mirror effect in recogni-
tion memory: Data and theory. Journal of Experimental Psy-
chology: Learning, Memory, and Cognition, 16, 5–16.
Appendix

Algorithm to Generate z-ROC Curves and $P(R)_i$ From Process Dissociation Theory Assumptions

A hit rate and a false alarm rate for each of six confidence categories can be calculated from data as follows: Assume that the numbers of responses for old items in each category are $n_1$ through $n_6$ for the high-confidence negative to the high-confidence positive categories and that the numbers of responses for new items in each category are $m_1$ through $m_6$ for the high-confidence negative to the high-confidence positive categories. Then the hit and false alarm rates are computed as follows: If $N = \sum_{i=1}^{6} n_i$, and $M = \sum_{i=1}^{6} m_i$, then the hit rate for a category $i$ is $h_i = \frac{\sum_{j=1}^{6} m_i}{N}$ and the false alarm rate for a category $i$ is $f_i = \frac{\sum_{j=1}^{6} n_i}{M}$. (An empirical z-ROC curve can be generated from the $z$ scores for these hit and false alarm rates for each of the categories; the z-ROC for one experimental condition from Ratcliff, McKoon, and Tindall [1994] is shown by the diamonds in Figure 2.)

To test process dissociation, assume some value of $P(R)$, between 0 and .45, and then complete the following steps:

1. Assume that the top half of the confidence judgment categories is composed of all positive responses to calculate the hit rate $hF_3$, the probability based on familiarity alone of a yes response to an old test item. [If the data involve include and exclude conditions as in Experiment 1, $P(R)$ can be estimated from the difference in hit rates for the two conditions.] Through process dissociation (Equation 1), $P(F) = [P(I) - P(R)]/[1 - P(R)]$; thus, $hF_3 = \{h_f - P(R)\}/[1 - P(R)]$.

2. In process dissociation, distributions of familiarity for old and new items are assumed to be normal with equal variance, so $d'$ tables can be used to calculate $d'$ for the familiarity process from $hF_3$ and $f_3$.

3. With $d'$ for the familiarity process, one can then calculate hit rates based on familiarity alone for all of the confidence categories ($hF_i$) using the $d'$ and the false alarm rates for those categories ($f_i$).

(Two alternatives, 4 and 5, can follow from this point, and both have been used in this article.)

4. Using process dissociation again, one can add the assumed value of $P(R)$ back to the familiarity process at each confidence level to generate the predicted empirical z-ROC curve for familiarity and recollection combined, plotting the predicted hit rates $(hP_i)$ against false alarm rates $(f_i)$: $hP_i = hF_i + P(R) - hF_i P(R)$. Curves obtained in this way for 10 values of $P(R)$ are plotted in Figure 2.

This way of generating a predicted z-ROC function assumes that $P(R)$ is constant across confidence categories. $P(R)$ was calculated by summing across the positive response categories; most of the recollection-based responses should have come from the highest confidence positive category, but it is possible that some recollection-based responses would occur in the medium- and low-confidence categories. If so, then the predicted hit rates might be a little too large in the upper-right-hand corner of the z-ROC function. However, allowing the recollection amounts at each of the positive confidence levels to be free parameters would weaken the predictive power of the model.

5. The values of $hP_i$ represent hit rates based on familiarity alone, obtained by assuming that the value of $P(R)$ is constant across confidence categories. An alternative is to use the empirical $h_p$, the familiarity-based $hF_i$, and the process dissociation equations to calculate $P(R)_i$, for each confidence category: $P(R)_i = (h_p - hF_i)/(1 - hF_i)$. These values of $P(R)_i$ can be plotted for each of the $f_i$ (i.e., for each confidence category), as shown in Figure 3.

Received October 31, 1994
Revision received March 20, 1995
Accepted March 22, 1995

1996 APA Convention Call for Programs

The Call for Programs for the 1996 APA annual convention appears in the September issue of the APA Monitor. The 1996 convention will be held in Toronto, Ontario, Canada, from August 9 through August 13. The deadline for receipt of program and presentation proposals is December 1, 1995. Additional copies of the Call are available from the APA Convention Office, effective in September. As a reminder, agreement to participate in the APA convention is now presumed to convey permission for the presentation to be audiotaped if selected for taping. Any speaker or participant who does not wish his or her presentation to be audiotaped must notify the person submitting the program either at the time the invitation is extended or before the December 1 deadline for proposal receipt.