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OBSERVATION

Process Dissociation and Mixture Signal Detection Theory

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The process dissociation procedure was developed in an attempt to separate different processes involved in memory tasks. The procedure naturally lends itself to a formulation within a class of mixture signal detection models. The dual process model is shown to be a special case. The mixture signal detection model is applied to data from a widely analyzed study. The results suggest that a process other than recollection may be involved in the process dissociation procedure.

Keywords: process dissociation, mixture signal detection, source processing, dual process, recognition memory

Jacoby (1991) argued that memory tasks involve a blend of processes, such as automatic and intentional processes, and offered the process dissociation procedure as a means to tease the processes apart. The logic of the procedure was to place the different processes in opposition so that their separate effects could be solved for. This was done by presenting participants with a test consisting of two lists of words and then telling them to treat one of the lists as old and the other as new. This procedure creates opposition by requiring one of the studied lists to be treated as new: The words on it were previously seen, which would tend to make participants respond to them as old; however, the instructions are to respond to them as if they are new.

The crux of the process dissociation procedure clearly has do to with whether a participant has information about the source of a word (cf. Buchner, Erdfelder, Steffens, & Martensen, 1997), that is, information about which list the word was on, because this is necessary to perform the task. For example, if a participant has no information about the source of a word, then his or her response will depend solely on the familiarity of the word, and so he or she should tend to respond "yes" to words from both lists when asked whether the word has been seen before. However, if a participant has information about which list the word was on, then he or she can say "no" to words that are from the list that was designated as new.

Whether a participant has information about the source of a word has typically been conceptualized in terms of recollection (e.g., Jacoby, 1991; Yonelinas, 1994; Yonelinas & Jacoby, 1996); that is, the view has been that participants respond "no" to a word from the list designated as new if they recollect that the word was from that list, whereas if they do not recollect the word's source, then their response depends solely on the word's familiarity. Thus, there are two processes assumed, familiarity and source recollection, giving a dual process model. The process dissociation procedure and the dual process model have been examined in many studies; there has also been some controversy about assumptions (e.g., Buchner, Erdfelder, & Vaterrodt-Plünnecke, 1995; Cowan & Stadler, 1996; Curran & Hintzman, 1995, 1997; Dodson & Johnson, 1996; Erdfelder & Buchner, 1998; Jacoby, Begg, & Toth, 1997; Jacoby & Shrout, 1997; Joordens & Merikle, 1993; Ratcliff, Van Zandt, & McKoon, 1995; Yonelinas & Jacoby, 1996).

Here it is shown that the second process does not have to be conceptualized as recollection, and, in fact, the evidence presented below, as well as previous evidence (DeCarlo, 2007), suggests that the second process is not simply recollection. A more general view recognizes that the crucial aspect is simply whether a participant has any information about the source of a word, regardless of whether he or she recollects the source. This, in turn, is consistent with an interpretation in terms of latent classes of words (i.e., there is source information for some words, whereas there is only partial or no source information for other words), which in turn is the idea underlying mixture extensions of signal detection theory (SDT). Mixture SDT (DeCarlo, 2000, 2002, 2003a, 2007) offers a general way to recognize the role of different processes in memory tasks and has been applied to recognition memory, source memory, and the mirror effect.

In the present article, I show that the process dissociation procedure lends itself quite readily to a theoretical interpretation in terms of mixture SDT, given that the basic idea underlying the process dissociation procedure has to do with a mixture or blending of processes. A mixture SDT model for the process dissociation procedure is formally presented. The dual process model, as presented by Yonelinas (1994), is shown to be a special case of the mixture SDT model, which clarifies relations between the models and shows how recollection can be viewed within the framework of SDT. It is also shown that mixture SDT, as applied to the process dissociation procedure, is consistent with receiver operating characteristic (ROC) curves that go below the diagonal. An application of the mixture SDT model is illustrated using data from a widely analyzed study (Yonelinas, 1994); the analysis reveals some new and interesting results.

The Process Dissociation Procedure

As noted by Yonelinas, Regehr, and Jacoby (1995), the process dissociation procedure has been implemented in several ways;

Sample programs and links to software are available at http://www.columbia.edu/~ld208.

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considered here is a version of it as used in the study of Yonelinas (1994). Participants were first presented with two lists of words. After the lists were presented, the participants' task was to detect words from one of the lists (e.g., the first or second list) and to treat words from the other list as new. The list with words to be detected is referred to as the *inclusion* list and the list with words to be treated as new is referred to as the *exclusion* list, in line with terminology used by Yonelinas (1994) and others. During the test, words from both lists were presented, along with new words, and participants used a 1 (*sure no*) to 6 (*sure yes*) rating scale to indicate their confidence, with *sure yes* indicating that they were sure that a word was from the inclusion list and *sure no* indicating that they were sure that a word was new, that is, that it was either from the exclusion list or was a new word.[1]

As noted above, the performance of participants on the task clearly depends on whether they have information at the test about the source of a word (i.e., which list the word was on). This is consistent with the view that there are two or more latent classes of words, corresponding to the level of processing of a word's source.[2] Thus, for the application of mixture SDT presented here, the process dissociation procedure is conceptualized as involving two latent classes, which can be viewed as consisting of words with source information versus words without source information.

Figure 1 illustrates an application of mixture SDT to the process dissociation procedure. To simplify notation, I use *A* to denote words from the inclusion list and *B* to denote words from the exclusion list. The task is to detect inclusion (A) words, with exclusion (B) words treated as new, and so with respect to the 1–4 responses shown in the figure, a response of 1 indicates *sure no* (i.e., sure the word is not an inclusion word), 2 indicates *slightly sure no*, 3 indicates *slightly sure yes*, and 4 indicates *sure yes* (i.e., sure the word is an inclusion word); c_1, c_2, and c_3 in Figure 1, shown as vertical lines, represent the response criteria used by a participant to choose his or her responses.

First, suppose that a word's source was not processed. In that case, the participant bases his or her judgment on the familiarity of the word, shown in Figure 1 as the solid distributions labeled *A* and *B* (with no assumptions about their relative locations); the N distribution represents new words. Note that the effect of studying a word is to simply shift the distribution's location (i.e., A and B are to the right of N), and so an equal variance version of SDT is used, as in other developments of mixture SDT (DeCarlo, 2000, 2002, 2003a, 2007): This reflects an important aspect of mixture SDT, in that it accounts for results that appear to indicate unequal variances in terms of a mixture of equal variance distributions (see DeCarlo, 2007, for some graphical illustrations). In the equal variance approach, an increase in memory strength is conceptualized as a simple shift in the location of an underlying distribution (i.e., it is a main effect), and so *d* has a simple interpretation, whereas this is not the case for the unequal variance approach (where there is both a change in location and a change in the variance; see DeCarlo, 2002).

Second, suppose that a word's source was processed or that there is at least some information available about the word's source. In that case, it is assumed that the participant bases his or her judgment on two different distributions, which are shown in Figure 1 as dotted distributions labeled *A*′ and *B*′; that is, it is assumed that the presence of source information leads to a different set of familiarity distributions. The A′ distribution is for source-processed inclusion words and is to the right of the new item distribution; it is also to the right of the A distribution, because if a participant has information about the source of a word (i.e., he or she believes it is from the inclusion list), then he or she can be fairly sure that the word is old, and so it seems reasonable to assume that the A′ distribution will be to the right of the A distribution. Similarly, if the participant has information about the source of a word being the exclusion list, then he or she can be fairly sure to treat the word as new, and so the B′ distribution should be to the left of the B distribution and close to (or to the left of) the new word distribution. These ideas are also consistent with those underlying the dual process approach to the process dissociation procedure, with similarities and differences noted below.

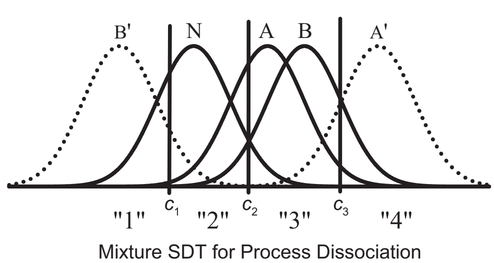

Figure 1. Signal detection theory (SDT) with mixture distributions as applied to the process dissociation procedure. A and B denote the inclusion and exclusion familiarity distributions, respectively; N denotes new words; A′ and B′ denote distributions for source-processed words; c_1 to c_3 are response criteria.

A Mixture Signal Detection Model for the Process Dissociation Procedure

Figure 1 leads directly to a mixture SDT model. Let the *K* response categories be denoted by *k* and the $K - 1$ response criteria be denoted as c_k. As shown earlier, an SDT model for rating responses recognizes the underlying distributions and the ordinal nature of the response by using cumulative response prob-

[1] Another approach would be to ask for a separate response to each component, that is, a confidence rating as to whether the word is old or new (a familiarity response) and a confidence rating as to which list it was on (a source response). In that case, a multivariate signal detection model can be applied (DeCarlo, 2003b); this model allows one to study the separate processes (familiarity and source recognition) and also allows one to examine their interrelationship (e.g., there is some evidence that source information strength is greater when recognition memory strength is greater). Using separate responses is likely more informative about the different processes than using one response, as in the process dissociation procedure.

[2] As shown here and earlier, two latent classes appear to suffice, which is consistent with the view that the level of processing can be usefully conceptualized as consisting of discrete classes, such as full versus partial processing. By using more latent classes with the sizes restricted appropriately, one can also approximate a continuous distribution (if one wants to think of the level of processing as being continuous), although the discrete view is just as (if not more) plausible. Some arguments for viewing variables that are often assumed to be continuous as instead being discrete are given in DeCarlo (2005).

abilities, $p(Y \leq k|X$; see DeCarlo, 1998). The mixture SDT model for the process dissociation procedure that follows from Figure 1 can be written as

$$p(Y \leq k|\mathrm{A}) = \lambda_{\mathrm{A}'}\Phi(c_k - d_{\mathrm{A}'}) + (1 - \lambda_{\mathrm{A}'})\Phi(c_k - d_{\mathrm{A}})$$

$$p(Y \leq k|\mathrm{B}) = \lambda_{\mathrm{B}'}\Phi(c_k - d_{\mathrm{B}'}) + (1 - \lambda_{\mathrm{B}'})\Phi(c_k - d_{\mathrm{B}})$$

$$p(Y \leq k|\mathrm{N}) = \Phi(c_k), \tag{1}$$

for $1 \leq k \leq K - 1$, where $p(Y \leq k|\mathrm{A})$ is the probability of a response of k or less given that an A item was presented, with similar meanings for B and N items; Φ is the cumulative distribution function for the normal distribution; d_{A} is the distance of the A distribution from the new item distribution (the new item distribution is used as zero); $d_{\mathrm{A}'}$ is the distance of the A′ distribution from the new item distribution, with similar meanings for B and B′, where the prime is used to indicate the distributions associated with the second latent class (e.g., source information); $\lambda_{\mathrm{A}'}$ and $\lambda_{\mathrm{B}'}$ are mixing parameters, which can be interpreted as the proportion of words with source information.

Equation 1 shows that, for A and B words, the decision is based either on a word's familiarity, with probability $1 - \lambda$ (for A or B), or, in the presence of source information, on the second set of familiarity distributions, with probability λ, as shown in Figure 1. The Appendix shows that, with respect to fitting Equation 1, the three components can be written as a single probit regression model with latent categorical variables (also see DeCarlo, 2002, 2003a, 2007). Further notes and details on fitting the model are given in the Appendix.

Relation of the Dual Process Model to Mixture SDT

It has previously been shown that recollection can be thought of in SDT simply as high familiarity (DeCarlo, 2007). This applies here as well. In particular, note that if the source-attended distributions are far to the right for A′ and to the left for B′, then the sources are, in essence, recollected, in that participants are quite sure that they have seen the word (and so respond in the end categories). In particular, note that for large values of $d_{\mathrm{A}'}$, $\Phi(c_k - d_{\mathrm{A}'})$ approaches 0, and for large negative values of $d_{\mathrm{B}'}$, $\Phi(c_k - d_{\mathrm{B}'})$ approaches 1, and so Equation 1 approaches

$$p(Y \leq k|\mathrm{A}) = (1 - \lambda_{\mathrm{A}'})\Phi(c_k - d_{\mathrm{A}})$$

$$p(Y \leq k|\mathrm{B}) = \lambda_{\mathrm{B}'} + (1 - \lambda_{\mathrm{B}'})\Phi(c_k - d_{\mathrm{B}})$$

$$p(Y \leq k|\mathrm{N}) = \Phi(c_k), \tag{2}$$

which is the dual process model. Thus, the mixture SDT model, in essence, reduces to the dual process model if it is assumed that the source-attended familiarity distributions are far from 0. In practice, it appears that Equation 2 can be closely approximated by using Equation 1 with values of d of about 8 or larger; for the current data, the results were the same regardless of whether values of d of 10 or 100 were used.

To see the relation to the dual process model as commonly written (where the probability of a "yes" response is modeled), note that the above can be rewritten in terms of $p(Y > k)$ as follows:

$$p(Y > k|\mathrm{A}) = \lambda_{\mathrm{A}'} + (1 - \lambda_{\mathrm{A}'})\Phi(-c_k + d_{\mathrm{A}})$$

$$p(Y > k|\mathrm{B}) = (1 - \lambda_{\mathrm{B}'})\Phi(-c_k + d_{\mathrm{B}})$$

$$p(Y > k|\mathrm{N}) = \Phi(-c_k). \tag{3}$$

Equation 3 is the dual process model as applied to the process dissociation procedure, as given by Yonelinas (1994) and Yonelinas and Jacoby (1996; in this case with equal criteria across the inclusion and exclusion lists; see their Equations 7–10).[3] This shows that recollection can be conceptualized in a mixture signal detection framework simply as high familiarity. The mixture SDT model and dual process model are compared below for the data of Yonelinas (1994).

Also considered is the unequal variance normal SDT model (Green & Swets, 1966), which for the process dissociation procedure can be written as

$$p(Y \leq k|\mathrm{A}) = \Phi[(c_k - d_{\mathrm{A}})/\sigma_{\mathrm{A}}]$$

$$p(Y \leq k|\mathrm{B}) = \Phi[(c_k - d_{\mathrm{B}})/\sigma_{\mathrm{B}}]$$

$$p(Y \leq k|\mathrm{N}) = \Phi(c_k),$$

where d_{A} and d_{B} are the distances of the A and B distributions from the new item distribution (which are scaled differently from d in the dual process or mixture model; see DeCarlo, 1998), and σ_{A} and σ_{B} are the standard deviations of the A and B distributions (see DeCarlo, 2003c, for some notes on fitting the model).

An Application: Yonelinas (1994)

The data are from a widely cited study of Yonelinas (1994);[4] the data have previously been analyzed in several articles (e.g., Erdfelder & Buchner, 1998; Macho, 2002; Ratcliff, Van Zandt, & McKoon, 1995; Yonelinas & Jacoby, 1996). In Experiments 1 and 2, either short or long study lists were used and participants gave confidence rating responses on a 1–6 scale; in Experiment 3, words were presented for either 1 s or 3 s. For Experiment 1, the short and long lists consisted of 10 and 30 words, respectively, with a test of 10 inclusion words, 10 exclusion words, and 10 new words. The procedure consisted of study–test blocks with two tests per block. In one test, the first list was designated the inclusion list; in the second test, the second list was designated the inclusion list (with the order balanced across blocks).[5] In Experiment 2, the short and long lists consisted of 6 and 18 words, with a test of 6 inclusion words, 6 exclusion words, and 6 new words (the test was divided into three sections of 2 inclusion words, 2 exclusion

[3] Note the difference that Yonelinas and Jacoby (1996) parameterized the model using effect coding, whereas dummy coding is used here (see DeCarlo, 1998).

[4] I thank A. Yonelinas for making the original data, in terms of response frequencies, available.

[5] Note that in both cases, the task is to detect inclusive words, only the labeling of the response categories is changed (reversed). For example, for a 1–4 response, a response of 1 indicates *sure List 2* and 4 indicates *sure List 1* in one condition, whereas a response of 1 indicates *sure List 1* and 4 indicates *sure List 2* in the other condition. Pooling across the conditions, as done by Yonelinas (1994), assumes a symmetry in the response criteria locations; this assumption could be examined in future research.

words, and 2 new words, and the instructions were varied across the sections); Experiment 2 also differed in that it included recognition trials (see Yonelinas, 1994). Because the short and long lists were tested in different blocks in Experiments 1 and 2, it is possible that the response criteria differed across the short and long lists, which is allowed for in the analyses below. Experiment 3 consisted of study–test blocks of two lists that each consisted of eight pairs of words, with half of the word pairs presented for 1 s each (weak) and the other half presented for 3 s each (strong); the test included the 32 studied words and 16 new words, where each word was presented by itself. Because the strong and weak words were each presented together during the test block, one set of response criteria is assumed. As in all previous analyses of this data, the data pooled across participants are analyzed, although it would be of interest in future studies to examine individual data (with more extensive testing of individual participants).

The mixture SDT model can be fit with several software packages. Used here were Lemwin (Vermunt, 1997), a prerelease version of Latent Gold 5 (Vermunt & Magidson, 2007), and Mplus Version 5 (Muthén & Muthén, 1998–2007). The results were generally identical to at least two decimal places across the packages; the results from Latent Gold are reported here. With respect to fitting the dual process model, the model can be approximated, as shown above, by incorporating parameter restrictions in the mixture SDT model; this was done using Latent Gold (and Mplus). Links to the software, as well as sample programs, are available at http://www.columbia.edu/~ld208.

Table 1 shows, for all three experiments, results for maximum likelihood fits of the mixture SDT model (Equation 1), the dual process model (approximated as in Equation 2), and the unequal variance SDT model. A likelihood ratio (LR) goodness-of-fit statistic is shown, along with the degrees of freedom and probability value; also shown are information criteria, namely Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Information criteria can be used to compare the relative fit of different models (such as the nonnested models considered here), with smaller values indicating a preferred model, whereas the LR statistic assesses the absolute fit of the model (see DeCarlo, 2003c).

Table 1 shows that the fit of the mixture SDT model is acceptable for all three experiments, in that the LR statistics are not significant (at the .05 level), whereas the unequal variance SDT model and the dual process model are rejected by the LR test, and so they show some lack of fit, with the exception of the unequal variance SDT model in Experiment 3. Thus, the mixture SDT model adequately describes the data in all cases, whereas the unequal variance SDT model and the dual process model do not. With respect to relative fit, note that the mixture SDT model has more parameters than do the other two models, which is shown in Table 1 by the fact that the LR statistic has fewer degrees of freedom. This should be taken into account when comparing the relative fit of the models; information criteria do this by including a penalty term for additional parameters (the penalty is heavier for BIC than for AIC). Table 1 shows that AIC favors the mixture SDT model over the dual process model and the unequal variance SDT model for both conditions of Experiments 1 and 2; for Experiment 3, AIC favors the mixture and unequal variance SDT models (which have about the same value of AIC) over the dual process model. BIC favors the mixture SDT model over the dual

Table 1
Goodness-of-Fit Statistics and Information Criteria for Experiments 1, 2, and 3 of Yonelinas (1994)

Model	LR	*df*	*p*	AIC	BIC
Experiment 1					
Short list (N = 4,320)					
Mixture SDT	3.84	4	.43	12265	12335
Dual process	52.62	6	<.01	12309	12367
Unequal variance SDT	15.28	6	.02	12272	12329
Long list (N = 4,320)					
Mixture SDT	6.89	4	.14	13638	13708
Dual process	27.51	6	<.01	13654	13712
Unequal variance SDT	57.13	6	<.01	13684	13741
Experiment 2					
Short list (N = 3,456)					
Mixture SDT	0.36	4	.99	9153	9221
Dual process	72.06	6	<.01	9221	9276
Unequal variance SDT	17.18	6	<.01	9166	9221
Long list (N = 3,456)					
Mixture SDT	7.13	4	.13	10690	10758
Dual process	40.09	6	<.01	10719	10775
Unequal variance SDT	28.94	6	<.01	10708	10764
Experiment 3					
1 s and 3 s (N = 7,040)					
Mixture SDT	7.07	8	.53	23712	23828
Dual process	36.49	12	<.01	23733	23822
Unequal variance SDT	15.34	12	.22	23711	23801

Note. LR = likelihood ratio goodness-of-fit test; AIC = Akaike's information criterion; BIC = Bayesian information criterion; SDT = signal detection theory.

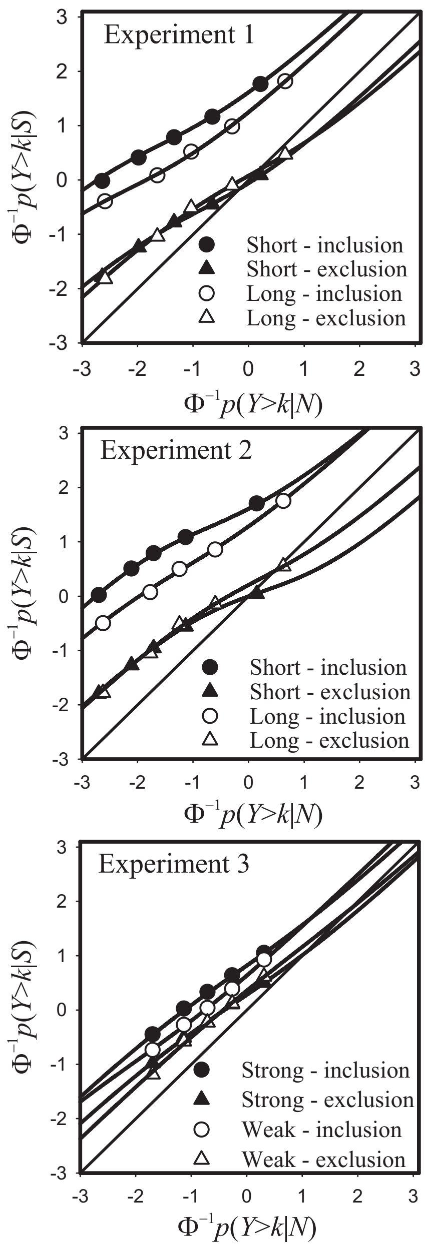

Figure 2. Data and fitted mixture signal detection theory receiver operating characteristic curves on inverse normal coordinates for all three experiments of Yonelinas (1994).

process model in the long list conditions of Experiment 1 and 2 and favors the unequal variance SDT model in Experiment 3 and the short list condition of Experiment 1.

ROC plots provide a useful supplement to the fit statistics. Figure 2 shows, on inverse normal coordinates, the data for all of the experiments and conditions, along with fitted *z*-ROC curves from the mixture SDT model of Equation 1. Figure 2 shows that the *z*-ROC curves from the mixture SDT model are consistent with the data, as expected in light of the fit statistics. The figure also clearly shows why the unequal variance SDT model generally does not fit, in that the data are not well described by straight lines but rather show some curvilinearity. The figure shows that the dual process model fails to fit because it predicts upward curvature in the *z*-ROC curves (i.e., a U shape; see Yonelinas, 1994), whereas the data instead suggest more of a kinked or reversed S shape (particularly in Experiments 1 and 2), which is a characteristic (for recognition memory experiments) of *z*-ROC curves for mixture SDT (see DeCarlo, 2002).

Model fit is, of course, of interest, but of greater importance are the parameter estimates and their behavior across experimental manipulations. Table 2 shows the parameter estimates and standard errors for maximum likelihood fits of the mixture SDT model to the data from the three experiments. A consistent and important finding across all three experiments is that the estimates of the proportion of source-processed words ($\lambda_{A'}$ and $\lambda_{B'}$) are larger for the short and strong lists than for the long and weak lists (.70 and .66 for short vs. .46 and .47 for long in Experiment 1, .86 and .49 for short vs. .65 and .40 for long in Experiment 2, .67 and .46 for strong vs. .27 and .26 for weak in Experiment 3). The interpretation is that source information was available for a greater proportion of words when the lists were shorter or the words were presented for a longer time. Thus, the mixture parameter appears to vary in a systematic way in response to experimental manipulations, as has also been found in other studies (DeCarlo, 2002, 2003a, 2007). With respect to a comparison across inclusion and exclusion words, $\lambda_{A'}$ and $\lambda_{B'}$ are about equal in magnitude for both conditions of Experiments 1 and 3. However, $\lambda_{A'}$ tends to be larger than $\lambda_{B'}$ in Experiment 2; this could be due to the differences in the procedure in Experiment 2.

The next two rows of Table 2 show the detection parameters for the source-processed words, $d_{A'}$ and $d_{B'}$. For all three experiments, the estimates (taking into account their standard errors) are about equal in magnitude across the short–long and strong–weak conditions (and 95% confidence intervals clearly overlap). Thus, the experimental manipulations did not appear to affect the memory strength of source-processed words. Table 2 also shows that the estimates for exclusion words are to the left of the new item distribution, that is, $d_{B'}$ is less than zero for all three experiments. This indicates that participants have greater certainty that exclusion words are "new" as compared with new words, which is a sensible finding because (source-processed) exclusion words contain information about source that is not available for new words (i.e., if one believes a word is from the exclusion list, then one can reject the word, whereas additional information of this sort is not available for new words).

The fifth and sixth rows of Table 2 show results for the distributions without source information. For each experiment, there are no apparent differences in either d_A or d_B across the short–long and strong–weak conditions (and 95% confidence intervals overlap). Thus, the list length manipulation did not appear to affect memory strength for words without source information, as also found above for words with source information. With respect to a comparison across inclusion and exclusion words, it is interesting to note that d_A tends to be smaller than d_B, which could reflect a difference in familiarity for inclusion versus exclusion words without source processing. More evidence on this is needed, but it could reflect an effect of processes activated during the test, a limitation of the process dissociation procedure, a limitation of the mixture model, or a combination of these.

Another result in Table 2 is that the response criteria differ across the short and long lists in Experiments 1 and 2, in that the criteria for the long list are to the left of those for the short list. This means that for the long lists, participants were more likely to judge

Table 2
Parameter Estimates for the Mixture Signal Detection Model for Experiments 1, 2, and 3 of Yonelinas (1994)

	Experiment 1		Experiment 2		Experiment 3	
Parameter	Short	Long	Short	Long	Strong	Weak
$\lambda_{A'}$	.70 (0.04)	.46 (0.05)	.86 (0.03)	.65 (0.06)	.67 (0.10)	.27 (0.12)
$\lambda_{B'}$	.66 (0.04)	.47 (0.05)	.49 (0.07)	.40 (0.06)	.46 (0.11)	.26 (0.17)
$d_{A'}$	3.23 (0.17)	3.16 (0.21)	2.97 (0.13)	2.56 (0.17)	1.64 (0.16)	1.99 (0.45)
$d_{B'}$	−0.69 (0.11)	−1.02 (0.16)	−1.47 (0.58)	−1.06 (0.24)	−0.54 (0.26)	−0.63 (0.61)
d_A	0.93 (0.13)	0.87 (0.09)	0.35 (0.20)	0.60 (0.16)	−0.04 (0.27)	0.38 (0.13)
d_B	1.54 (0.16)	1.10 (0.12)	1.28 (0.17)	1.15 (0.14)	1.17 (0.18)	0.74 (0.16)
c_1	−0.22 (0.03)	−0.66 (0.03)	−0.15 (0.04)	−0.62 (0.04)	−0.31 (0.02)	−0.31 (0.02)
c_2	0.66 (0.03)	0.31 (0.03)	1.13 (0.05)	0.61 (0.04)	0.27 (0.02)	0.27 (0.02)
c_3	1.32 (0.04)	0.99 (0.04)	1.71 (0.06)	1.20 (0.05)	0.71 (0.03)	0.71 (0.03)
c_4	2.02 (0.07)	1.68 (0.05)	2.12 (0.08)	1.84 (0.06)	1.11 (0.03)	1.11 (0.03)
c_5	2.74 (0.10)	2.61 (0.08)	2.74 (0.10)	2.65 (0.09)	1.72 (0.04)	1.72 (0.04)

Note. A represents inclusion words, B represents exclusion words. Standard errors are shown in parentheses.

that a word was from the inclusion list than from the exclusion list (and they were less confident that a word was from the exclusion list). To my knowledge, this is the first time differences in the response criteria across the short and long lists have been noted for the data of Yonelinas (1994).

In sum, the results suggest that the experimental manipulations had a consistent effect on the source memory proportions ($\lambda_{A'}$ and $\lambda_{B'}$), in that they were smaller for long lists and short presentation times in all three experiments, but did not affect memory strength, either for source-processed words ($d_{A'}$ and $d_{B'}$) or non-source-processed words (d_A and d_B). Thus, the experimental manipulations appear to have affected only source processing and not memory strength. Note that these results are consistent with those found by Yonelinas (1994), in that Yonelinas found an effect of list length on the recollection parameter of the dual process model (similar to the effect on $\lambda_{A'}$ and $\lambda_{B'}$ found for the mixture SDT model) but did not find an effect on the memory strength parameters (Yonelinas claimed a difference in Experiment 3, but the standard deviations shown in his Table 5 do not support that claim). In terms of mixture SDT, the results suggest that less source information is available for words from longer lists or with shorter presentation times, whereas familiarity is about the same across short–long lists and weak–strong words. It was also found that the unmixed solution gave an exclusion distribution for source-processed words that was clearly to the left of the other distributions; this result suggests that the mixture SDT model captures the opposition that is a basic part of the process dissociation procedure.

Conclusions

The present article provides a theoretical model, based on a mixture extension of SDT, for the process dissociation procedure. The mixture SDT model attempts to separate different processes and provides a detailed picture of process dissociation data. The results for an analysis of Yonelinas's data (1994) show that the mixture SDT model accounts for curvilinearity that appears in *z*-ROC curves for the process dissociation procedure. The results also show that mixture SDT is consistent with exclusion ROC curves that go below the diagonal, which provides an answer to a recent question of Yonelinas and Parks (2007) about how the mixture SDT model would account for "negative-going exclusion ROCs" (p. 828). More important, the theoretical reason for this result is quite clear: As shown in Figure 1, the exclusion *z*-ROC curves go below the diagonal because the distribution for source-processed words (B′) is to the left of the new word distribution (N, which is used as the zero point); for another example of negative ROC curves, see DeCarlo (2007). It was also found that the mixture parameter, which can be interpreted as indicating the proportion of words with source processing, varied as expected in response to experimental manipulations.

It was also shown that the dual process model does not fit the data of Yonelinas (1994). Because of problems of this sort, several authors have introduced generalizations of the dual process model. For example, Sherman, Atri, Hasselmo, Stern, and Howard (2003) introduced a generalization that allows for "variable recollection"; the model has also recently been noted by Yonelinas and Parks (2007) and is referred to here as the *var DP model*. Recollection in the var DP model is represented by a probability distribution on the familiarity dimension, with a free location and variance, in which case the model simply becomes a mixture SDT model, with a different interpretation (note that the present results show that assuming unequal variances is not necessary, because the equal variance mixture model fit quite well).

Here it is noted that the var DP model raises some issues because, in contrast to the original DP model, recollection is no longer necessarily viewed as a (high) threshold process. More specifically, as shown here and elsewhere (DeCarlo, 2007), recollection within the SDT framework can be viewed as a probability distribution with a large value of *d*. By relaxing this assumption, as in the var DP model, the interpretation in terms of recollection is potentially lost (e.g., if the recollection distribution is close to or to the left of the familiarity distribution).[6] That is, if one recollects the source of a word, then one should say "sure yes": That is the basic idea of the original formulation of the DP model as a threshold model, and so, by relaxing this assumption, the var DP

[6] One could place constraints on the mean in the var DP model, but difficulties then arise with respect to rationalizing a particular value for the constraint.

model changes the conceptualization in a major way. Why one would use less than sure response categories (as also done in other extensions of the DP model, such as in Macho, 2002) if the source of a word is recollected remains to be explained.

Another problem is that the var DP model is basically an ad hoc empirical generalization and is not theoretically motivated. This was, in fact, recognized by Sherman et al. (2003): "An assumption of the Yonelinas High Threshold model is that recollection always results in a high-confidence 'yes' response. Perhaps by relaxing this assumption, we can accommodate the broadened recollective peak apparent in the scopolamine subjects' old-item distribution" (p. 532). This is clearly an empirical motivation and not a theoretical one, just as Green and Swets (1966) noted that the unequal variance SDT model is simply an empirical generalization of the equal variance SDT model (see DeCarlo, 2002). This is also true of other generalizations of the dual process model, such as simply allowing the familiarity distributions to have unequal variances (e.g., Healy, Light, & Chung, 2005), which again is an empirical generalization and not theoretical.

In contrast, the mixture SDT model does not simply introduce parameters to improve fit; an important aspect of the approach is that all of the parameters are theoretically grounded, in that they represent either memory strength (for inclusion and exclusion words) or the proportion of words with source information. Of course, one could generalize the mixture SDT model by introducing additional parameters, such as by allowing the variances of the distributions to vary, but that would defeat a basic purpose of mixture SDT, which is to uncover a simple shift in strength (with constant variance), and would also be an empirical generalization, not a theoretical one.[7] In short, the mixture SDT model does not introduce parameters in an ad hoc fashion to improve fit; all of the parameters have specific theoretical interpretations, which is not the case for recent generalizations of the DP model.

In the current article, I show that the process dissociation procedure is similar to other recognition memory procedures in that it involves a mixture of processes. The article also raises questions as to whether the process dissociation procedure really helps to separate different processes or instead complicates the situation (given that mixture SDT shows that the processes can be separated in simple recognition experiments). A mixture SDT model for process dissociation is offered as a starting point for further development and study.

[7] It also raises estimation issues, in that there is a partial confounding of effects of mixing and the variance.

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Appendix

Some Notes on Fitting the Model

The model can be implemented in different ways, depending on the software used. Here, the approach used for Lemwin (Vermunt, 1997) and Latent Gold (Vermunt & Magidson, 2007) is shown.

First, note that it is convenient to rewrite the equation for new items in Equation 1 as

$$p(Y \leq k|\mathrm{N}) = \lambda_{\mathrm{N}}\Phi(c_k) + (1 - \lambda_{\mathrm{N}})\Phi(c_k), \qquad \text{(A1)}$$

which reduces to $\Phi(c_k)$ for a given value of λ_{N} (e.g., it can be set to any value when fitting the model). Next, let X be a (dummy) variable that takes on a value of $x = 1$ when an A item is presented and 0 otherwise, Z be a variable that takes on a value of $z = 1$ when a B item is presented and 0 otherwise (and so $X = 0$ and $Z = 0$ indicates a new item), V be a latent variable with values of 0 and 1, and W be a latent variable with values of 0 and 1. Equation 1 is then part of a restricted latent class model; the signal detection part of the model is

$$p(Y \leq k|X, Z, XV, ZW) = \Phi(c_{k\cdot} - d_{\mathrm{A}}\mathrm{x} - d_{\mathrm{B}}z - d_{\mathrm{A'A}}xv - d_{\mathrm{B'B}}z\mathrm{w}), \qquad \text{(A2)}$$

where $d_{\mathrm{A'A}}$ is the distance of the A′ distribution (the source-processed familiarity distribution) from the A distribution (the non-source-processed familiarity distribution) and $d_{\mathrm{B'B}}$ is the distance of the B′ distribution from the B distribution; note that the interaction terms allow the source-processed distributions to have different locations from the non-source-processed distributions.

Next, Equation A2 is incorporated into a restricted latent class model, which models the cumulative response probabilities for the observed variables,

$$p(Y \leq k|X, Z) = \Sigma_V \Sigma_W p(V)p(W)p(Y \leq k|X, Z, XV, ZW), \qquad \text{(A3)}$$

where the summation is over the possible values of V and W (each coded as 0 or 1) and the second term on the right is given by Equation A2. Multinomial (binomial in this case) models are used for the source probabilities of Equation A3,

$$p(V = 1) = \exp(a)/[1 + \exp(a)]$$

$$p(W = 1) = \exp(b)/[1 + \exp(b)],$$

where exp is the exponential function.

For the model as parameterized in Equation A2, the parameters $d_{\mathrm{A'}}$ and $d_{\mathrm{B'}}$ are obtained by addition, specifically, $d_{\mathrm{A'}} = d_{\mathrm{A'A}} + d_{\mathrm{A}}$ and $d_{\mathrm{B'}} = d_{\mathrm{B'B}} + d_{\mathrm{B}}$, where $d_{\mathrm{A'A}}$ is the distance of the A′ distribution from the A distribution and $d_{\mathrm{B'B}}$ is the distance of the B′ distribution from the B distribution. The standard errors of the parameters can be obtained by using the estimated covariance matrix of the parameters (which can be printed out in Lemwin [Vermunt, 1997] by using the command *wse*) and the relation $\mathrm{var}(d_{\mathrm{A'}}) = \mathrm{var}(d_{\mathrm{A'A}}) + \mathrm{var}(d_{\mathrm{A}}) + 2\mathrm{cov}(d_{\mathrm{A'A}}, d_{\mathrm{A}})$; $\mathrm{var}(d_{\mathrm{B'}})$ may be derived similarly.

Note that for the fitted model, two equivalent solutions can be obtained, because it is arbitrary whether, for example, $V = 1$ indicates Class A or Class A′ or $W = 1$ indicates B or B′ (see DeCarlo, 2002). The log likelihood (and fit) is identical across the labelings and the estimates for one solution can be obtained from the other, because one solution is simply a reparameterization of the other; the different solutions will usually appear over repeated runs of Latent Gold or LEM. This comes under a more general issue referred to as *label switching* in mixture models in statistics (e.g., McLachlan & Peel, 2000); the use of starting values in Latent Gold allows one to gain some control over which solution is obtained. For the application to process dissociation, there are four solutions, given by the possible combinations of values of V and W, that is, 00, 01, 10, or 11 (which creates some complexities in the analysis). Note that it was assumed here that the distributions that were the furthest to the right or left were for words with source information.

As noted earlier (e.g., DeCarlo, 2002), it is also important to run the analysis repeatedly using different starting values because local maxima are often encountered.

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