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OBSERVATIONS

Recognition Memory ROCs and the Dual-Process Signal-Detection Model: Comment on Glanzer, Kim, Hilford, and Adams (1999)

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An examination of recognition memory receiver-operating characteristics (ROCs) showed that large increases in accuracy often do not affect the observed asymmetry of the ROC. However, M. Glanzer, K. Kim, A. Hilford, and J. Adams (1999) reported several experiments showing that changes in accuracy do sometimes influence the asymmetry of the function. Although the observed dissociations between accuracy and asymmetry are consistent with the predictions of the dual-process signal-detection model (A. P. Yonelinas, 1994), they argued that the shape of the observed ROCs deviated from that predicted by the model and implied that the data were more consistent with an unequal-variance signal-detection model. However, they did not directly test the dual-process model, rather they conducted two indirect assessments and inferred that the original model must be inaccurate. In this article, the author directly fit the dual-process and the unequal-variance signal-detection models to Glanzer et al.'s observed data and showed that both models provided an accurate account of the ROCs, capturing more than 99.9% of the variance of the average ROCs. In agreement with previous studies, these analyses show that standard recognition memory ROCs do not clearly differentiate between these models. This article describes a broader range of ROC data that do differentiate between the two models and that provide evidence in favor of the dual-process model. A postscript responds to M. Glanzer, A. Hilford, K. Kim, and J. Adams (1999).

The study of recognition memory receiver-operating characteristics (ROCs, which plot the proportion of hits on the ordinate and the proportion of false alarms on the abscissa) has played an important role in the development of memory theory. For example, Murdock (1965) showed that recognition ROCs were curvilinear and that these results contradicted an entire class of "threshold" models that were popular at the time (see also Banks, 1970; Kinchla, 1994; Parks, 1966). These results ushered in the current era of recognition models, which were inspired by signal-detection theory (e.g., Green & Swets, 1966) and were more consistent with the curvilinear ROCs (e.g., Gillund & Shiffrin, 1984; Hintzman, 1986; Murdock, 1982; Norman & Wickelgren, 1969). However, Ratcliff, Sheu, and Gronlund (1992) found that recognition ROCs were almost always asymmetrical and that the degree of asymmetry was quite constant. For example, the upper two functions in Figure 1 are asymmetrical along the diagonal and are representative of many recognition memory experiments. Although these ROCs can be accounted for by some forms of signal-detection theory, Ratcliff et al. (1992) showed that these ROCs contradicted several global memory models—for example, theory of distributed associative memory (TODAM; Murdock, 1982); search of associative memory (SAM; Gillund & Shiffrin, 1984); and MINERVA 2 (Hintzman, 1986). More recently, Yonelinas (1994) examined recognition ROCs using Jacoby's (1991) process-dissociation procedure and found that the ROCs were consistent with a very simple dual-process signal-detection model. The model is described in more detail below, but the basic idea is that the curvilinearity of the observed ROC is due to the contribution of a *familiarity* process and the asymmetry is due to a separate *recollection* process.

Glanzer, Kim, Hilford, and Adams (1999) report a new set of ROC experiments that promise to provide important insights into the processes underlying recognition memory. They found that although it was true that in some cases increases in accuracy did not influence the degree of ROC asymmetry, there were conditions under which increases in recognition accuracy were accompanied by increases in ROC asymmetry. For example, when recognition performance was increased by manipulation of study duration, word frequency, or levels of processing, the ROCs became more asymmetrical. In contrast, increasing the number of times an item was studied led to an increase in performance with no detectable effect on asymmetry.

Glanzer, Kim, et al. (1999) draw two conclusions from these results. First, they argue that the degree of ROC asymmetry can change as accuracy increases. This follows directly from an examination of their ROCs and is supported by a large number of previous studies (e.g., Donaldson &

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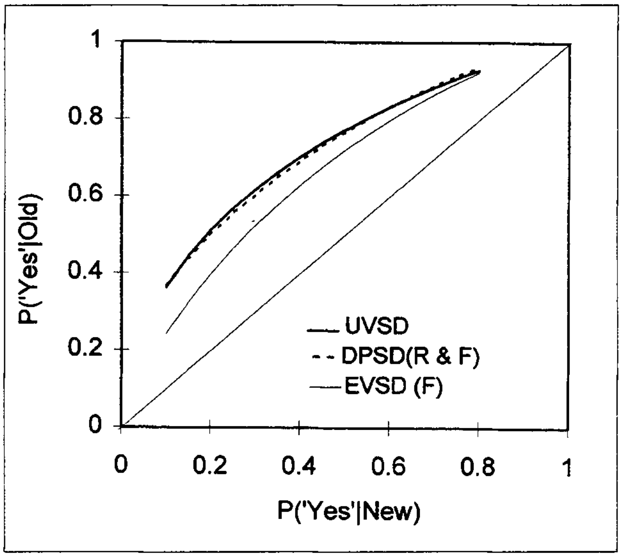

Figure 1. Recognition memory ROCs. The upper solid function represents the unequal-variance signal-detection model (UVSD). The dashed line represents the dual-process signal-detection model (DPSD) in which both recollection (*R*) and familiarity (*F*) contribute to performance. The lower function reflects familiarity alone, that is, an equal-variance signal-detection model (EVSD). Note that the upper functions approximate the average ROCs observed in Glanzer, Kim, et al. (1999).

Murdock, 1968; Gehring, Toglia, & Kimble, 1976; Glanzer & Adams, 1990; Yonelinas, 1994). However, they also conducted two indirect assessments of the dual-process model (Yonelinas, 1994) and argued that the recognition ROCs were inconsistent with that model. I first briefly describe the dual-process model and show the types of ROCs it predicts. I then discuss the shortcomings of Glanzer, Kim, et al.'s indirect model assessments. I then directly fit the dual-process and the unequal-variance signal-detection models to the ROCs, something that Glanzer, Kim, et al. did not do, and show that both models provide excellent, and very similar, accounts of the data. Finally, I describe a broader range of ROC data that argue in favor of the dual-process model.

The Dual-Process Signal-Detection Model

The dual-process model assumes that recognition memory judgments can be based either on the assessment of familiarity, a process that is well described by the classical signal-detection theory that underlies standard d' reference tables, or on recollection, a process well described by threshold theory (see Murdock, 1974, for a discussion of signal-detection and threshold theories). If performance relies exclusively on familiarity, then the model predicts a curvilinear ROC that is symmetrical along the diagonal (e.g., the lower function in Figure 1). However, if participants recollect some proportion of the studied items, then this will increase the hit rate and effectively push the ROC up, forming an asymmetrical ROC (e.g., the upper dashed function in Figure 1). The model requires two free memory parameters to generate an ROC: *R*, which represents the probability that a studied item is recollected, and d', which represents the average increase in familiarity associated with studying an item. The model equations are described in the Appendix.

The model predicts that it should be possible to find cases in which the ROC becomes more asymmetrical as recognition accuracy increases. That is, if recollection increases and familiarity remains relatively constant, then performance should increase and the ROC should become more asymmetrical. This is exactly what Glanzer, Kim, et al. (1999) report. Thus, their main findings are quite easily accommodated by the model. The model can also account for cases in which increases in accuracy do not influence the degree of asymmetry (e.g., Ratcliff et al., 1992). That is, if recollection and familiarity increase approximately equally, then the increase in asymmetry caused by recollection can be offset by the increase in symmetry caused by familiarity (see Yonelinas, 1994, for an illustration of these predictions).

The pattern of results can also be explained by an *unequal-variance* signal-detection model. This is the model that underlies all of Glanzer, Kim, et al.'s (1999) ROC analyses and is the model that they appeared to favor over the dual-process model. The model assumes that the old and new item distributions are Gaussian and that the variance of the old item distribution can differ from that of the new item distribution. For example, the upper solid function in Figure 1 reflects an asymmetrical ROC generated by the unequal-variance signal-detection model when the variance of the old item distribution is greater than that of the new item distribution. Like the dual-process model, the unequal-variance model requires two free memory parameters to generate an ROC: d', which represents the average increase in familiarity or memory strength associated with studying an item, and V_o, which represents the variance of the old item distribution (assuming the variance of the new item distribution is equal to 1).

Both the unequal-variance model and the dual-process model can account for the accuracy and asymmetry findings reported by Glanzer, Kim, et al. (1999). Moreover, as Figure 1 illustrates, they can produce very similar ROCs. However, a careful examination of Figure 1 shows that the dual-process model tends to predict a slightly flatter function than does the unequal-variance model. It is this subtle difference that Glanzer, Kim, et al. focused on in testing the dual-process model.

Glanzer, Kim, et al.'s (1999) ROC Analyses

To assess the dual-process model, Glanzer, Kim, et al. chose not to directly fit the model to the data, rather they conducted two indirect assessments: First, they *z*-transformed the ROCs and tested for U-shaped *z*-ROCs. Second, they developed and tested a new dual-process regression equation. However, there are important limitations with both of these indirect assessment methods. Moreover, when the dual-process model is actually fit to the observed ROCs, it becomes clear that the model is in good agreement with the recognition data.

U-*Shaped z-ROCs*

Replotting the ROCs in z-space and assessing linearity provides a way of contrasting the dual-process and the unequal-variance signal-detection models. Because the unequal-variance model assumes Gaussian confidence distributions, it predicts a perfectly linear ROC in z-space (this is referred to as a z-ROC). Thus, finding a deviation from linearity would show that the Gaussian assumption was violated. The dual-process model can also produce a linear z-ROC, but when recollection contributes to memory performance, it begins to produce a slightly U-shaped function. Figure 2 shows the ROCs from Figure 1 replotted on z-coordinates and shows that the z-transformed function predicted by the dual-process model exhibits a very slight U shape compared with the straight line predicted by the unequal-variance model.

Glanzer, Kim, et al. (1999) examined the z-ROCs from the four experiments they conducted, as well as from five previously reported experiments from Glanzer and Adams (1990). They found that in two of the experiments, the z-ROCs were significantly U shaped, but in the remaining experiments the functions did not deviate significantly from linearity. In fact, the function in one of the experiments appeared to show an *inverted* U shape (see Experiment 4 [GK4] in Table 5, p. 511, from Glanzer, Kim, et al., 1999). Although the curvilinearity of the latter z-ROC was not significant, when included with the other experiments it was apparent that *on average* the z-ROCs were not U shaped. Thus, on average, the ROCs are fit quite well by the unequal-variance signal-detection model, and this led Glanzer, Kim, et al. to conclude that the ROCs must contradict the dual-process model.

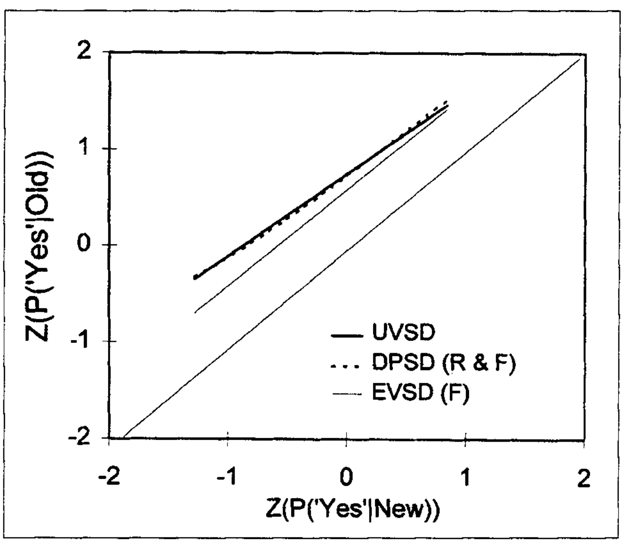

Figure 2. Recognition memory ROCs plotted on z-coordinates. The upper solid function represents the unequal-variance signal-detection model (UVSD). The dashed line represents the dual-process signal-detection model (DPSD), in which both recollection (*R*) and familiarity (*F*) contribute to performance. The lower function reflects familiarity alone, that is, an equal-variance signal-detection model (EVSD). Note that the upper functions approximate the average ROCs observed in Glanzer, Kim, et al. (1999).

Do these results contradict the dual-process model as Glanzer, Kim, et al. (1999) propose, or do the results support it? The results from the two experiments in which the z-ROCs exhibited a significant U shape clearly *support* the dual-process model and are problematic for the unequal-variance model—these results show that the Gaussian assumption underlying the unequal-variance model was violated in these two experiments. Less clear are the results from the remaining experiments. As Glanzer, Kim, et al. concede, the results of these experiments amount to null effects; they failed to find significant curvilinear components associated with the z-ROCs. Besides the usual difficulties associated with interpreting null effects, these findings are particularly uninformative because in standard recognition memory tasks, the dual-process model predicts ROCs that are very similar to those of the unequal-variance model (e.g., see Figures 1 and 2). Thus, Glanzer, Kim, et al.'s failure to find significantly U-shaped z-ROCs in some of their experiments should not be surprising from the perspective of either model. In sum, the results of the linearity analysis of the z-ROCs are not problematic for the dual-process model. Moreover, the significantly U-shaped z-ROCs observed in two of the experiments contradict the unequal-variance model.

Glanzer, Kim, et al.'s (1999) Dual-Process Regression Equation

As a second way of assessing the dual-process model, Glanzer, Kim, et al. developed a new dual-process regression equation. They found that this new equation failed to accurately account for the ROCs and argue that the original dual-process model must also be inadequate. However, the success or failure of their new equation must be interpreted cautiously because the new equation is not equivalent to the original model.

To derive the new equation, Glanzer, Kim, et al. (1999) first generated a set of ROCs based on the dual-process model by selecting parameter values for recollection ranging from 0.1 to 0.8 and d' parameter values ranging from 0.1 to 2.0. Having generated a set of theoretical ROCs, they plotted them on z-coordinates and conducted a linearity analysis on each function. They determined the slope and intercept of the best fitting linear function and measured the curvilinearity by introducing a quadratic component to the linear function and determining its contribution. Finally, they conducted a regression analysis on these three derived measures to determine the average relationship between slope, intercept, and curvilinearity. They argue that the "regression equation tells us what the quadratic constant should be, according to dual-process theory" (Glanzer, Kim, et al., p. 511). Thus, on the basis of the finding that the regression equation did not accurately capture the observed relationship, they concluded that the original dual-process model must also be inaccurate.

However, the regression equation is not identical to the dual-process model, and thus testing the regression equation is not the same thing as testing the model. As an illustration, I assessed the original dual-process model in the same way that Glanzer, Kim, et al. (1999) assessed their new regression equation,[1] and found that the regression equation often predicted a different curvilinear component than did the dual-process model. For example, using the algorithm described in the Appendix, the dual-process model was fit to the average ROC in Experiment 2 (Glanzer, Kim, et al., 1999), then the predicted z-ROC was assessed for curvilinearity, as described by Glanzer, Kim, et al. For that experiment, Glanzer, Kim, et al.'s equation predicted a quadratic component (.09) that was significantly greater than the observed quadratic, $t(29) = 2.85$, $p < .01$. In contrast, the dual-process model predicted a quadratic component (.07) that did not differ significantly from the observed quadratic, $t(29) = 1.88$, $p > .05$. Although the regression equation overpredicted the expected curvilinearity by about 20% only, the example shows that the regression equation can lead to predictions that differ from those of the dual-process model. Note that I have examined a large number of data sets and found that there are cases in which the regression equation does make predictions that are very close to that of the dual-process model. However, given that the regression equation is not identical to the dual-process model, direct tests of the original model would be more informative than tests of the regression equation. Moreover, as I show, when the dual-process model was directly fit to the ROCs reported by Glanzer, Kim, et al., it became clear that it provided an accurate account of their data.

Why did Glanzer, Kim, et al.'s (1999) regression equation lead to different predictions than that of the dual-process model? First, the regression equation attempts to capture the predicted relationship between the slope, intercept, and curvilinearity of the z-transformed ROCs. However, an examination of the dual-process model showed that the relationship among these three factors should not be as simple as the regression equation suggests. That is, the dual-process model predicts that the degree of curvilinearity will be dependent on the specific response criteria that the participant adopts. For example, an examination of the functions generated by the dual-process model showed that the z-ROCs became more curvilinear as one moved to the left of the function. Thus, the fit of the regression equation might be improved if some measure of response criterion were also included in the regression analysis. Second, the regression equation was based on a specific set of theoretical ROCs that the authors used as a basis for their regression analysis. They derived the regression equation on the basis of a sample of ROCs that included recollection estimates of up to 80% correct and familiarity estimates for d' of up to 2.0. Such parameter values lead to recognition performance that is almost perfect. An examination of the ROCs from Glanzer, Kim, et al. (see Figure 3) showed that the ROCs they observed did not come close to this level of performance. If the theoretical ROCs were more representative of the ROCs that actually were observed in their studies, then their equation may have provided a better fit for the observed data.

Directly Testing the Dual-Process and Unequal-Variance Models

Glanzer, Kim, et al.'s (1999) ROCs

To assess directly how well the dual-process and unequal-variance models accounted for the ROCs reported by Glanzer, Kim, et al., I simply fit the two models to the observed ROCs. Figure 3 presents the average ROCs for the four experiments reported by Glanzer, Kim, et al. (1999). The solid line represents the fit of the unequal-variance model and the dashed line represents the fit of the dual-process model. Both models were regressed to the observed data by reducing the sum of the squared differences along the x- and y-dimensions (see Yonelinas, Dobbins, Szymanski, Dhaliwal, & King, 1996). Note that a maximum likelihood estimation method was also used, but because it led to very similar fits, only the results of the regression analyses are shown.

An examination of the ROCs in Figure 3 showed that the two models produced very similar ROCs and that both provided extremely accurate accounts of the data. On average, the dual-process model accounted for 99.91% of the variance, and the unequal-variance model accounted for 99.97%. These results converge with those of previous studies in showing that the two models provided excellent accounts of standard recognition ROCs. In fact, previous attempts to discriminate between the two models have shown that both models provide such good fits of the recognition data that it is extremely difficult to differentiate between them (see Yonelinas, 1994; Yonelinas et al., 1996). For example, Yonelinas et al. (1996) compared the fits of the two models for standard recognition ROCs and found that although the dual-process model sometimes provided a significantly better fit than the unequal-variance model, both models accounted for more than 99.9% of the variance. Because both models provided such good fits and one model did not always provide a better fit than the other, suggests that recognition ROCs do not prove very useful in contrasting the two models.

Although both models provide a very good account of the recognition ROCs, neither model is perfect. For example, Glanzer, Kim, et al.'s (1999) analysis of the z-ROCs showed that the ROCs sometimes deviated significantly from the unequal-variance model. Moreover, a careful examination of Figure 3 shows that the middle point in the ROC often sits slightly above the ROCs predicted by both models (Ratcliff, Van Zandt, & McKoon, 1995, reported a similar finding).

Why the ROCs sometimes differ from the predictions of these two models is not entirely clear. However, Ratcliff, McKoon, and Tindall (1994) have provided a potential explanation. They found that in recognition memory tests, some participants consistently exhibited U-shaped z-ROCs, some participants exhibited linear z-ROCs, and some exhibited inverted U-shaped z-ROCs. They then went on to show

[1] I thank Murray Glanzer, Kisok Kim, Andy Hilford, and John Adams for providing the data from the four experiments in their article.

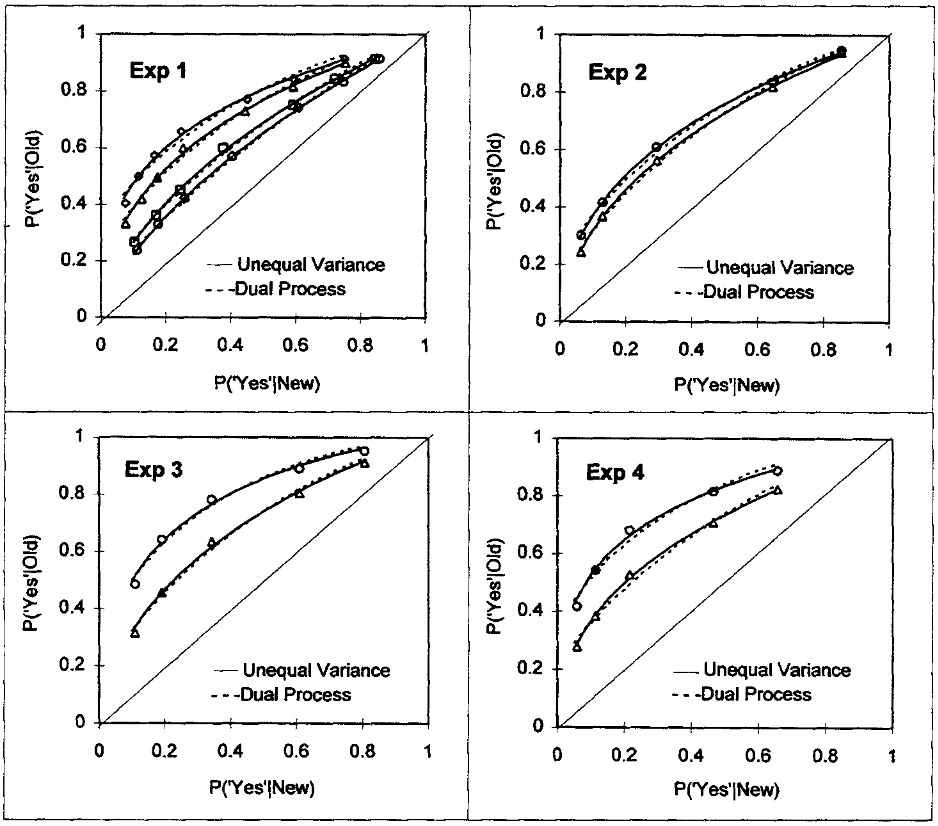

Figure 3. Recognition ROCs from Experiments (Exp) 1–4 (from Glanzer, Kim, et al., 1999), fit to the unequal-variance and dual-process signal-detection models.

that noise could lead z-ROCs to exhibit an exaggerated inverted U shape. That is, when as few as 5% of the participants' responses were random the observed z-ROC would begin to exhibit an artifactual inverted U shape. Given that hundreds of responses are collected from each participant in most ROC experiments, it is likely that some proportion of the responses do reflect noise. Thus, the observed z-ROCs may sometimes exhibit a slightly more inverted shape than our models would predict. For example, the unequal-variance model produces linear z-ROCs, but if noise is introduced to the model, it produces slightly *inverted* U-shaped z-ROCs. Note, however, that noise would not allow the unequal-variance model to account for the observed U-shaped z-ROCs. In contrast, the dual-process model can account for the U-shaped z-ROCs; adding a small amount of noise could lead to linear z-ROCs, and adding additional noise would be expected to produce inverted U-shaped z-ROCs.

Although it is impossible to determine whether noise contributed to the observed ROCs in the current studies, future studies examining this issue will be useful in evaluating these models. If noise is found to play an important role in the ROCs, then it may be necessary to incorporate additional model parameters to reflect this. Given that both of these models require only two memory parameters, it is quite likely that additional parameters eventually will be required.

Are there ways of testing the models further? Over the past few years my colleagues and I have taken several different approaches to address this issue. One strategy has been to use the dual-process model to generate novel predictions and conduct experiments to directly test those predictions. A second strategy has been to directly contrast the dual-process model with the unequal-variance model under conditions in which they make different predictions. The results of these two approaches are briefly described below.

Predicting the Shape of the ROC

If the shape of the ROC is determined by the contribution of recollection and familiarity, then it should be possible to predict the shape of the function on the basis of estimates of these two processes. Yonelinas (1994) showed that estimates of recollection and familarity derived by using the process-dissociation procedure (i.e., Jacoby, 1991) could be used to accurately predict the slope and intercept of the z-ROCs. Moreover, Yonelinas et al. (1996) showed that participants' reports of remembering and knowing (i.e., Tulving, 1985) also accurately predicted the shapes of the observed ROCs. Prior to these studies, there was no way of predicting what the shape of the ROC would be for a given experiment. These results show that ROC data are closely related to the results of the process-dissociation and remember–know procedures, and they show that the processes underlying the dual-process model are psychologically real in the sense that they serve as a basis for intentional control and are available to subjective experience.

Linear ROCs

A direct way to contrast the dual-process and unequal-variance models is to examine ROCs under conditions in which they predict substantially different ROCs. Although, as I showed earlier, the two models predicted very similar ROCs under standard recognition memory conditions, they should diverge under conditions in which performance relies primarily on recollection. Under these conditions, the dual-process model predicts relatively linear ROCs that should exhibit a noticeable U shape in *z*-space. In contrast, the unequal-variance model predicts linear *z*-ROCs.

These predictions have been evaluated in tests of associative recognition in which participants studied pairs of items and were then required to discriminate between previously presented pairs and rearranged pairs. Because all of the studied and rearranged pairs consisted of familiar items (i.e., they have been studied), familiarity should be less useful than in tests of single-item recognition in which the lure items are novel. If associative recognition relies primarily on recollection, then the ROCs should be relatively linear. Figure 4 presents the average ROC for associative recognition from Experiment 1 in Yonelinas (1997). The associative ROC was relatively linear, and further analyses showed that the function was significantly U shaped when plotted in *z*-space. Similar results were found in two other experiments in that study (see also Kelley & Wixted, 1997; Yonelinas, Kroll, Dobbins, & Soltani, 1998). The results provide strong support for the dual-process model and show that the unequal-variance model is not consistent with the ROC data.

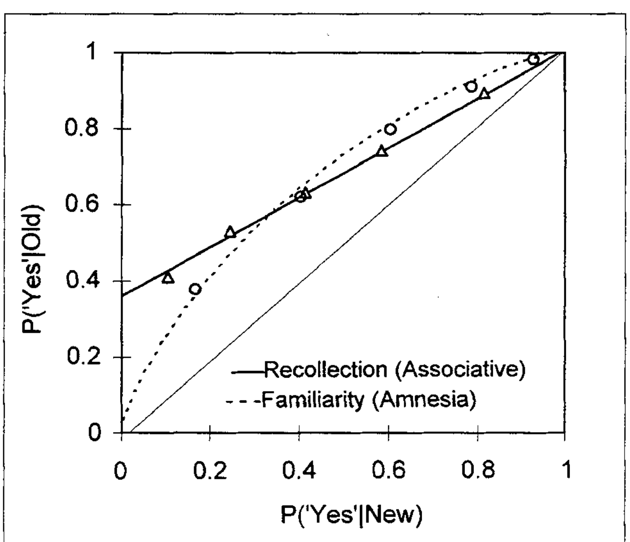

Figure 4. A linear recognition ROC observed for associative recognition (from Experiment 1, Yonelinas, 1997) and a symmetrical ROC for amnesics (from Yonelinas, Kroll, Dobbins, Lazzara, & Knight, 1998).

The dual-process model's predictions were further verified in tests of source memory (Yonelinas, 1996), in which participants had to discriminate between items that had originated from two different sources (e.g., words spoken by two different experimenters). Under test conditions in which the familiarity of items from the two different sources did not differ, the ROCs were relatively linear and exhibited a significant U shape in *z*-space (Donaldson & Mackenzie, 1996, have also reported similar results). The results of the associative and source recognition studies have provided strong evidence that recollection is well described as a threshold process. Moreover, given that the unequal-variance model does not predict U shaped *z*-ROCs, the results show that the unequal-variance model is inconsistent with the data.

Symmetrical ROCs

One of the more appealing aspects of dual-process theories of memory is that they are compatible with the notion that different memory processes may be differentially disrupted by brain injury. For example, early proponents of dual-process theory (e.g., Huppert & Piercy, 1976; Mandler, 1980) argued that amnesics (i.e., patients with damage to the medial temporal lobes) were no longer able to recollect previous events, but they could make recognition memory judgments based on familiarity. If the current dual-process model is correct and amnesics are making their recognition judgments on the basis of familiarity alone, then their recognition ROCs should be curvilinear and symmetrical, in contrast to the asymmetrical functions observed in healthy participants. This prediction was tested by examining recognition memory for words in amnesics (Yonelinas, Kroll, Dobbins, Lazzara, & Knight, 1998). In contrast to healthy control participants who exhibited curved asymmetrical recognition ROCs, the amnesics' functions were curved and symmetrical. The average ROC for the amnesics is presented in Figure 4. Similar results were also observed when recognition memory for faces was tested (Dobbins, Yonelinas, Kroll, Soltani, & Knight, 1998). The results provide support for the claim that familiarity is well described as an equal-variance signal-detection process and demonstrate that the dual-process model is useful in understanding the memory performance of healthy and memory-impaired populations.

Conclusion

The results of Glanzer, Kim, et al. (1999) are important in showing that recognition accuracy and ROC asymmetry can dissociate. Their ROC results were found to be consistent with two very simple recognition memory models: the dual-process model and the unequal-variance signal-detection model. Although neither model perfectly predicted the ROCs, both of these models were found to account for over 99% of the observed variance in the average ROCs by using only two free memory parameters. Hence, Glanzer, Kim, et al.'s ROCs are not particularly problematic for either model. However, an examination of a broader range of recognition ROC data provided strong support in favor of the dual-process model by showing that the predictions of that model were verified and that the assumptions of the unequal-variance model were violated under conditions in which recollection played a large role in recognition performance.

Glanzer, Kim, et al.'s (1999) results join a growing body of research that uses ROC analysis to examine recognition memory. Like the process-dissociation and remember–know procedures, the ROC procedure provides much more constraining information than do traditional recognition measures. Taken together with the study of patients who have brain damage, ROC results are providing important insights into the processes that underlie recognition memory and are playing an essential role in testing our theories of human memory.

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Appendix

Fitting the Dual-Process Model

In the dual-process signal-detection model, recognition is assumed to reflect the contribution of recollection and familiarity. It is assumed that an old item will be correctly accepted as old if it is recollected (R) or if it is not recollected ($1 - R$) but is accepted on the basis of familiarity. Familiarity is assumed to reflect a Gaussian equal-variance signal-detection process such that the probability that an item is accepted on the basis of familiarity is a function of sensitivity (d') and response criterion (c). The probability that the familiarity of an old item exceeds the response criterion is equal to ϕ $(d'/2 - c)$: the proportion of the old item distribution exceeding the response criterion (c). Thus, the probability of a hit can be written as $P(\text{"yes"}|\text{old})_i = R + (1 - R)\phi[(d'/2) - c_i]$. The probability that a new item will be incorrectly accepted as old will be equal to the probability that the familiarity of the new item exceeds the response criterion, and this can be written as $P(\text{"yes"}|\text{new})_i = \phi[(-d'/2) - c_i]$. These equations represent performance at one point on the ROC. Continuously varying c will produce a continuous ROC. The equations can be fit to ROCs in the following way. An ROC with 5 points will have a set of 10 equations. Assuming that memory (R and d') remains constant across the ROC and only c_i varies, then the set of equations can be solved to derive estimates of R and d'. For the current article, the solver in Excel 5.0 (1994) was used to find the best fitting parameters for these equations by reducing the sum of squared errors between the predicted and observed data (see Yonelinas, 1997).

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Postscript

Glanzer, Hilford, Kim, and Adams (1999) make two points in their response to this article. First, because z-ROCs in many recognition experiments are fit quite well by linear functions, they conclude that recognition z-ROCs are linear in general. However, this is an oversimplification. Indeed, other researchers (e.g., Ratcliff et al., 1994; Yonelinas, 1994) have been concerned with the significant and *systematic* deviations from linearity that are observed (e.g., U-shaped z-ROCs). Glanzer, Hilford, et al. treat these deviations as tangential because these deviations are often observed under conditions they consider to be unusual (e.g., when participants are required to process the meaning of each word during the study phase or when participants are required to determine in which of two study lists, rather than one, an item was presented). But, even if one excludes all of these studies, there are numerous other recognition experiments, including Glanzer's, in which significantly U-shaped z-ROCs are observed (e.g., Glanzer & Adams, 1990; Glanzer, Kim, et al., 1999; Ratcliff et al., 1994; Yonelinas et al., 1996). Limiting the range of experiments examined, or considering only the average pattern, as Glanzer et al. (Glanzer, Kim, et al., 1999; Glanzer, Hilford, et al., 1999) do, simplifies the story, but at the cost of obscuring the theoretical implications of the ROC data. A close examination of the data shows that recognition memory models must be able to account for both linear and significantly U-shaped z-ROCs.

Glanzer, Hilford, et al.'s (1999) second point is that in two of their original experiments the dual-process model deviated significantly from the observed data. As I discussed earlier in this article, this reflects the fact that the middle points on the ROC were sometimes slightly higher than the dual-process model and the unequal-variance model predicted. Glanzer, Hilford, et al. argue that this means that the dual-process model is in need of a "major revision" (p. 522). However, their conclusion is premature for two reasons. First, the observed deviation was extremely small. For example, in both of those experiments the model accounted for over 99.9% of the observed variance, and at the very worst point on the function, the predicted hit rate differed from the observed hit rate by only .01. Second, one must be particularly cautious when interpreting this result because this type of deviation can be created if even a small proportion of the participants' confidence judgments are random (see my earlier discussion). Whether random responding plays an important role in ROC experiments, or whether better models can be developed, are important questions for future studies. However, until then, it appears that we must be content with a model that accounts for only 99.9% of the variance.