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Is source memory continuous or discrete? : an Roc analysis.

Item Type	Thesis (Open Access)
Authors	Wong, Mungchen
DOI	10.7275/7765813
Download date	2026-03-13 13:51:38
Link to Item	https://hdl.handle.net/20.500.14394/45984

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312066 0275 4107 2

IS SOURCE MEMORY CONTINUOUS OR DISCRETE?
AN ROC ANALYSIS

A Thesis Presented

by

MUNGCHEN WONG

Submitted to the Graduate School of the
University of Massachusetts Amherst in partial fulfillment
of the requirements for the degree of

MASTER OF SCIENCE

September 2003

Cognitive Psychology

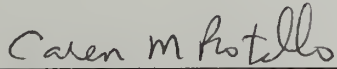
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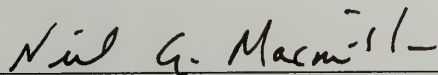
by

MUNGCHEN WONG

Approved as to style and content by:



Caren M. Rotello, Chair



Neil A. Macmillan, Member



Neil E. Berthier, Member



Melinda A. Novak, Department Chair
Psychology Department

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CHAPTER 1

INTRODUCTION

Imagine you walk down the street and see a familiar face. Immediately, you try to recall who the person is, where and when you met him before. Source memory refers to memory for the origin of information, or the memory for the context in which the event was acquired (e.g., the spatial, temporal, and social context of the event; Johnson, Hashtroudi, Lindsay, 1993). Source memory is an important cognitive function in our everyday life. It helps us differentiate fact from fantasy (e.g., whether you really met the celebrity in a park or it only occurred in a dream), reliable from unreliable information (e.g., whether you heard from someone personally that he hates dogs or you heard a rumor), and action from intention (e.g., whether you really punched the guy or only thought about doing it). Sometimes our recollection for the source information is effortless and accurate, but other times it is not.

The big question raised in this paper is: How is source memory processed? More specifically, what is the underlying representation of source memory, or what is the basis of information we use to decide that an event was associated with one source versus another?

Introspection provides two possible clues: Sometimes you can recall the specific source information (e.g., you met the familiar person at a party), but the memory is weak (because you can not recall which party it was or when it took place). This example implies a continuous memory state underlying source recollection such that the memory strength of source information can vary from weak to strong continuously. Other times, the recollection for the source (that you met him in a party) is clear even though other

memories about him may be vague. For example, you either remember that you met him at a party or you do not, regardless of how confidently you recall that he was introduced to you by your roommate, or how unsure you are that he had a tattoo on his neck the first time you met him. This second example implies a discrete mechanism (threshold-like process) underlying source recollection such that the memory reflects one of the two discrete states: either recall or not recall.

Several models of source memory have been proposed in the literature. In general, they can be grouped into two types of models corresponding to their assumption about the underlying representation: *Continuous-state models* and *Discrete-state models*.

Here I will briefly review the two types of assumption from their representative models, starting with Continuous-state models (including *Source Monitoring Framework (SMF)*, a *single-dimensional signal-detection model (SDT)* and a *multi-dimensional SDT*), and then a Discrete-state model (the *dual-process model*; Yonelinas, 1999).

Continuous Assumption

Source-Monitoring Framework (SMF)

First of all, the source-monitoring framework is not a computational model of memory. Instead, it is a framework developed by Johnson et al. (1993) for understanding the empirical findings about source monitoring, or the set of cognitive processes involved in making attribution about the origin of memory. According to the SMF, source memory is not an “either-or” concept. Instead, it can be specified to differing degrees because the features of an event (its visual, auditory, temporal, spatial, emotional characteristics) are bound together as a result of encoding processes. Therefore, during source monitoring different subsets of these characteristics are retrieved and evaluated, with different

degrees of confidence. For example, you may remember that Mary introduced you to the familiar person and where and when that took place. Or you may only remember that *someone* introduced the person to you sometime recently. Or you may remember virtually no information about the person, regardless of how familiar he or she seems.

Because learning is imperfect with regard to the binding of features or attributes, and retrieval cues can also be imperfect, it is possible that source recollection can be based on *partial information* (Hicks, Marsh, Ritschel, 2002). Partial information varies in a continuum such that the amount of retrieved information can range from a “vague detail” (e.g., visual or auditory; Hicks et al., 2002, pg. 503) to a very vivid sense of recollecting such details. Hicks et al. tested this claim with the *remember-know* paradigm. Participants studied a list of words from two sources (seen or heard) and performed a source memory task in which they had to decide whether words had been seen, heard, or were new. If they gave a “seen” or “heard” judgment, they also made a binary remember-know judgment. It was assumed that when a “remember” response was given, it was associated with clear and vivid details about the source information. If a “know” response was given, it was assumed that the source recollection constitutes only partial information that lacks the same clarity of a “remember” response. Since items from the two sources were randomly intermixed during the study trials, an undifferentiated familiarity process was assumed not to be helpful for source identification. Therefore the correct “know” response would suggest that source judgments could be based on partial information that was nonetheless sufficient enough to distinguish one source from another. The result was consistent with the claim that high proportions of correct source judgments were associated with “know” responses.

Single-Dimensional Signal-Detection Model

Single-dimensional signal-detection model is a Continuous-state model that has been widely applied in the domain of recognition memory. The model assumes that the underlying distributions of the Old and New items are Gaussian and overlapping on a continuous dimension (e.g., familiarity or memory strength), with old items having a greater average strength (see Figure 1). To discriminate between Old and New items, a response criterion is placed along this continuum so that the items whose strength is above the criterion are called “old”, and below the criterion are called “new”. The observer’s performance is characterized by a sensitivity measure termed d' , assuming the two distributions are equal variance¹. The estimate of d' is obtained by subtracting the z -transformed *false-alarm* rate (proportion of incorrect “old” response) from the z -transformed *hit* rate (proportion of correct “old” responses). Figure 1 shows that d' is simply the mean distance in standard deviation units between the two underlying distributions.

The model can well account for recognition memory tasks in which participants are to discriminate a list of Studied items from New items. This model can also be generalized to a source memory task in which participants are asked to discriminate between items studied from Source A and Source B.

Multi-Dimensional Signal-Detection Model

Extending the Single-dimensional SDT model, Banks (1999) developed a multi-dimensional signal-detection model that can well account for recognition performance,

¹ The sensitivity estimate of d_o is preferred for unequal variance distributions; for details see Macmillan & Creelman (1991).

source discrimination performance, and exclusion performance². The central claim of his model is that we make various decisions about items in memory by giving different types of memory information (e.g., visual or auditory details) different weight, and making memory decisions along a single-dimensional decision axis derived from the combined influence of multiple types of information. Source memory is assumed to vary continuously in a single multi-dimensional representation.

To understand why a multi-dimensional representation is needed, first recall that the memory sensitivity estimate (d') is the distance between the means of two distributions in standard deviation units. Next consider a memory task in which participants are asked to accept words that were Seen on the computer as “old”, while rejecting both words that were Heard on the tape recording and New words. Suppose that d' for discriminating Seen items from New items is 1.5, and d' for discriminating Heard items from New items is 1.25. As shown in Figure 2(a), a single dimension is enough to account for the data if the distance between the Heard Mean and Seen Mean is 0.25. If the source d' is not 0.25, then a two-dimensional space is needed, as illustrated in Figure 2(b).

Figure 3 illustrates the multi-dimensional representation for seen-heard source judgments. The distributions (Heard list, Seen list, and New list) are assumed to be bivariate normal, with the seen distribution located at the higher end of the ‘seen’ axis and the lower end of the ‘heard’ axis; New items are distributed around the origin (0,0). During a memory judgment, all information is projected onto a single dimension--a

² A memory test in which participants accept an item as positive if and only if it comes from a specific list. For example, accept items spoken in a male voice only while reject items spoken in a female voice and new items, see (Jacoby, 1991 & Banks, 1999).

decision axis³, and a response criterion is placed along this decision axis. Once the three distributions are projected onto the decision axis they are treated exactly the same as the single-dimension of signal-detection model (see Figure 3). Therefore, source memory in the two-dimensional model varies continuously, just as it is in the single-dimensional model.

Threshold Assumption

Dual-Process Model

While the continuous-state model assumes that source memory can vary continuously, an alternative view has been offered by Yonelinas (1999). He claims that source memory relies primarily on the process of *recollection*, which is a discrete mechanism that produces a few discrete states: sources are either recalled, not recalled, or uncertain. According to the model, accurate source recollection is always associated with clear and vivid details, and if a false-alarm (misidentification of one source for another) occurs, it is due to guessing. Such model is equivalent to the double-high threshold model⁴.

The threshold assumption can be better understood with a state diagram. Figure 4 presents a state diagram for a seen-heard source task. As the diagram indicates, there are three discrete detection states. Seen items can only be detected in the Seen State or in the Uncertain State, with probabilities of q and $(1-q)$, respectively. Analogously, Heard items can only lead to the Heard State or the Uncertain State, with probabilities of q and $(1-q)$,

³ For the largest *Source d'*, the decision axis should parallel the line connecting the centers of the seen and heard distributions, see (Banks, 1999) for details.

⁴ Dual-process model is originated designed for item recognition memory, in which 2 types of process: *recollection* and *familiarity* are assumed to contribute to the judgment. When the model is extended to source task in which the two sources do not differ in familiarity, it reduces to a double-high threshold model, assuming a threshold process—recollection underlying source judgment.

respectively. Items in the Uncertain State lead to a “seen” response with probability p , and to a “heard” response with probability $(1-p)$. Therefore, the *hit* rate is $P(\text{“seen”} | \text{Seen item}) = q + p(1-q)$, and the *false-alarm* rate is $P(\text{“seen”} | \text{Heard item}) = (1-q) * p$. The sensitivity measure in this model is a “true” detection rate: the proportion of Seen items leading to Seen State or the proportion of Heard items leading to Heard State; $q = 2p(c) - 1$ ⁵. For example, if $p(c)$ equals 0.8, the proportion of items entering in Seen and Heard states is 0.6 (i.e., $q = 0.6$).

For the purpose of direct comparison with the continuous-state model, the underlying rectangular distributions consistent with the double-high threshold model are also shown in Figure 5. The center of decision space (the region of overlap) is set to zero, and the decision criterion is measured with respect to this origin. So $H = p(c) - k$, and $F = [1 - p(c)] - k$, $H - F$ is simply $2p(c) - 1$ in the model. In contrast to having a range of *likelihood ratio*⁶ values in the Continuous-state model (Figure 1), the double high threshold model only has three values of likelihood ratio: zero, infinity, and one value in between (Figure 5). The boundaries among the three areas are the two “high” thresholds, the first boundary can only be crossed by Seen items, and the second boundary can only be crossed by Heard items (Macmillan, Creelman, 1991).

Implied Source ROCs

The two types of model offer two fundamentally different assumptions about the memory states underlying source memory: a continuous state versus a discrete state. One

⁵ Proportion of correct response, $P(c)$, is $[H + (1 - F)] / 2$ in conditions with equal numbers of items from two sources; q equals $2p(c) - 1$, which is the x-intercept and y-intercept in Figure 7 (see Macmillan & Creelman, 1991).

⁶ In a continuous decision space like Figure 1, each point x on the decision axis has two associated “likelihoods”, the height for each distribution. The likelihood ratio at a given criteria is the ratio of the two heights, which is used as one measure of the response bias, see (Macmillan & Creelman, 1991).

of the most direct ways to compare the two types of model is by examining receiver operating characteristics (ROC) curves implied by the models.

ROC curves describe the relationship between hit and false-alarm rates at different levels of response bias or confidence. ROC data can be collected in several different ways, and one typical way is to ask participants to make confidence ratings in memory task (Macmillan & Creelman, 1991). In a standard recognition memory task, for example, after studying a list of words, participants judge whether or not the test items had been studied and make their confidence response on a 6-point rating scale, ranging from “sure new” (1) to “sure old” (6). Recognition memory ROCs tend to look like those presented in upper panel of Figure 6a. Sometimes, they look like the upper panel of Figure 7. Theoretically, the lowest point (first pair of hit- and false-alarm rates) on the curve reflects the most strict response criterion that includes only the proportion of the most confident old responses (i.e., “sure old”). The second lowest point reflects a slightly relaxed response criterion, which sums the proportion of the most confident old responses and the proportion of the second most confident old responses. The procedure is repeated until 5 (false-alarm, hit) pairs are plotted. The last response category is not plotted because its cumulative hit and false-alarm rates are equal to 1.0. Therefore, a confidence scale with N ratings produces a ROC curve with N-1 points. All (false-alarm, hit) pairs on the curve represent the same sensitivity, and differ only in terms of response bias.

The analysis of the ROC shapes can be generalized to source memory performance and source memory ROC curves can be plotted. For example, after studying a list of words spoken by either a man or a woman, participants perform *male-female voice* source judgment on a 6-point confidence scale, ranging from “sure male”(1) to

“sure female” (6). To construct a source ROC curve when *male voice* serves as the target source, the hit rate (proportion of male spoken items correctly accepted as spoken by male) is plotted against the false-alarm rate (proportion of female spoken items incorrectly accepted as spoken by male) as a function of response confidence.

The shape of source ROCs informs us about the underlying representation of source memory. It serves as a useful tool for evaluating the two types of source memory models because each model makes different predictions about the form of source ROC. By comparing the predicted source ROCs with the observed source ROCs, the theoretical statements about the source memory made by the two models can be assessed.

Continuous state model predicts source memory ROCs increase gradually in a curvilinear manner as a function of response confidence. If the two underlying distributions (e.g., items seen or heard) are normal with equal variance, the source ROCs will be curvilinear and symmetrical along the minor diagonal, as show in Figures 6a. Asymmetrical ROCs occur when the distributions have unequal variances (see Figure 6b). To measure the asymmetry we can plot the ROC on *z-coordinates* (z-ROCs) and estimate the *slope* of the function. The slope is the ratio of the standard deviations of the two distributions, so a perfectly symmetrical ROC, like that in Figure 6(a), will have a unit slope; asymmetrical ROC, like that in Figure 6(b), will have a slope other than 1.0. Continuous-state models with normal distributions predict a linear z-ROC regardless of what the slope is.

In contrast, the discrete-state model predicts that the source ROCs should be relatively linear in probability space (Figure 7). It intercepts the boundaries of ROC space at $[q, 0.0]$ and $[1.0, (1-q)]$. The linear ROC is predicted on the assumption that items in

the Seen State (D_{seen}) or Heard State (D_{heard}) are always given the most extreme levels of confidence ratings, the highest (“sure seen”), and the lowest (“sure heard”), respectively, and guessing items (in $D_{\text{uncertain}}$) are randomly distributed across all the rating scales⁷.

The corresponding source z-ROC is somewhat U-shaped, as shown in Figure 7.

Empirical Source ROCs

Four studies have been done to examine source memory ROCs. Among the 4 studies, one found that source ROCs were linear, favoring the discrete-state model; one found that the source ROCs were curvilinear, consistent with the continuous-state model; and the other 2 found that the source ROCs were in-between-shape (nonlinear with a small degree of curvature), which were not well-described by neither of the models. Next I will briefly review the 4 studies and their findings under different conditions.

Linear source ROCs

Yonelinas (1999) tested the dual-process model of source memory under various study conditions. In his Experiment 1, participants studied a list of common words, in which half of the words were presented on the left side of the screen and the other half on the right side. Because items from the two sources (left vs. right) were randomly intermixed, they were assumed to be equally familiar. Thus, the *familiarity* process would not be useful for source judgments, and the source judgments should be primarily based on the threshold-like *recollection* process, leading source ROCs to be relatively linear.

The study instruction was explicit in the experiment. Participants were instructed to remember all the words that were presented to them and to try to remember the side of the screen on which they were studied. To improve source memory, participants were taught to use an encoding strategy to associate words from the two sources with two

⁷ Other mappings of the Internal States to responses are possible (e.g., Malmberg, 2002).

distinctive people. During the source test, participants performed left-right judgment on a 6-point confidence scale, ranging from *sure left* to *sure right*. Consistent with the dual-process model, linear source ROCs were observed.

According to the Yonelinas' view, source ROCs should exhibit more curvature if a familiarity process contributes to source judgments in addition to the recollection process. He tested this hypothesis in his Experiment 4. Participants studied one list of words (spoken by a male voice) on day 1, and a second list (spoken by a female voice) 5 days later so that items on the second list should be much more familiar to participants. The same rating scale was used, and participants judged whether the test items were spoken by a man (list 1) or a woman (list 2). Yonelinas claimed that under conditions in which familiarity is clearly indicative of an item's source (list 2), participants should be willing to attribute an item's high level of familiarity to the occurrence of that item in the most recent list (i.e., female spoken list). Therefore source ROCs should be curvilinear, resulting from the contributions of both familiarity and recollection process. The findings were consistent with the predictions of dual-process model.

Curvilinear source ROCs

Qin, Raye, Johnson, and Mitchell (2001) claimed that source ROCs are typically curvilinear because source information can vary qualitatively in a continuum, and that the curvilinearity is not simply due to the influence of undifferentiated familiarity process. To make their point, Qin et al. analyzed source performance data collected in the study of Mather et al. (1999)⁸. In that experiment, participants viewed a videotape of two women reading statements (half read by each woman) about various facts and feelings, for

⁸ The Mather et al. (1999) study was not conducted specifically for source ROC analyses, but the data were collected in a way that allowed source ROCs to be plotted and examined.

example, “Classical music is soothing” and “Children should never be physically disciplined”. The study instruction was implicit in this experiment. Participants were not told about subsequent memory test on the source, instead they were instructed to either focus on their own feelings about the statements (Self-focus condition), or focus on the speakers’ feelings (Other-focus condition)⁹. In the unexpected source memory test that included both studied sentences and new sentences, participants first performed binary old-new judgments for each test item. For items that they judge “old”, they also made a source judgment (speaker identity) and rated their confidence from 1 (lowest) to 6 (highest). Curvilinear Source ROCs were observed in both conditions. According to Qin et al., because the statements from the two sources were presented only once and were randomly intermixed, the familiarity process was assumed not contributed to source judgments. Therefore the observed curvature in source ROCs was resulted from the differences of the qualitative memory characteristics (e.g., visual, auditory information, emotion, etc), supporting the assumption of continuity for source memory.

Qin et al. further tested this claim in another experiment, in which the study materials were similar to those in Mather et al.’s experiment, except that there were no new test items included and the study instruction was limited to “focus on the speakers’ feelings”. Two test conditions were used. In the Confidence-only condition, participants made source identity judgments on a rating scale identical to the one used in the Mather et al.’s experiment. In the MCQ (Memory Characteristics Questionnaire) condition, participants performed 4 additional judgments: after giving a source rating for a test item, they also described the quality of their memory in terms of visual detail, auditory detail,

⁹ Their main hypothesis was not of interest here; suffice it to say, both study conditions received implicit instruction and performed the same source test.

information about their own feelings and reactions, and information about the speakers' feelings and reactions. Each memory characteristic was rated on a 6-point scale, ranging from "least information" to "most information". Consistent with their predictions, curvilinear source ROCs were observed in both test conditions with no significant differences in source sensitivity. Furthermore, the MCQ ROCs for all 4 types of information were also found to be curvilinear, providing evidence that source judgments were based on qualitative memory characteristics because individual characteristic could also vary in a continuum.

In-between-shaped source ROCs

Slotnick, Klein, Dodson, and Shimamura (2000) compared the unequal-variance single-dimensional SDT model with the two-high threshold model by examining source ROCs in 3 experiments. The 3 experiments were similar to one another in both study and test phase, with only minor changes (see Slotnick et al., 2000 for further details). The two sources were a male voice and a female voice. Participants studied a list of nouns that were presented both visually (on the center of the screen) and auditorily (half spoken by a man and another half by a woman, in a random order). The study instruction was implicit; participants were not told that there would be a subsequent memory test. Instead, they were asked to rate each word according to the "difficulty of covertly reproducing or imaging the quality of the voice". The unexpected source memory test included both studied words and new words. For each test item, participants made two kind of rating judgments: old-new judgment ratings from *sure old* to *sure new*, and source judgment ratings from *sure male voice* to *sure female voice*. In all three

experiments, Slotnick et al. observed an in-between-shaped source ROCs¹⁰ that neither the continuous model nor the two-threshold model could account for.

Hilford, Glanzer, Kim, & DeCarlo (2002) also reported a similar pattern of source ROCs in 3 experiments. The 3 experiments were similar to one another except for some minor changes. In Experiment 1, the two sources were male voice and female voice, and participants were told to remember who said what. Participants listened to a series of nouns spoken either by a male or female voice, and then performed a source memory test that included both studied nouns and new nouns. For each test item, participants first performed a binary old-new judgment. For items that they judged old, they also performed source judgment on a 6-point confidence rating scale, ranging from *very sure male* to *very sure female*. Experiment 2 was similar to Experiment 1 except that there were no new items, so the source judgment was not conditioned on an old-new judgment. Experiment 3 differed from the earlier 2 experiments in the modality of the source. Instead of male voice versus female voice, the two sources were two different positions: items presented on the top or the bottom of the screen. All three experiments observed that the source ROCs were slightly convex, the z-ROCs slope was unity, and the z-ROCs were concave. These findings led to the rejection of both the threshold model and the simple 2-dimensional signal-detection model (2D-SDT). Hilford et al. revised the 2D-SDT model and proposed a mixture normal SDT model that could better account for the observed source ROCs. The mixture model keeps the continuity assumption and captures

¹⁰ Slotnick et al. also reported analysis from 'Top-source' data, which only included proportion of items that received the highest confidence rating of old responses. This is not equivalent to the common rating responses reported in the literature. We only address their Collapsed source data, which collapsed over old-new ratings (see Slotnick et al. 2000, for details).

the role of attention. We will discuss the model and its implications in the General Discussion section.

Major differences of the 4 Studies

The findings of the source ROCs were not consistent in the literature: Yonelinas (1999) observed linear source ROCs that supports the Discrete-state model, Qin et al. (2001) observed curvilinear source ROCs that supports the Gaussian SDT model, Slotnick et al. (2000) and Hilford et al. (2002) observed in-between-shaped source ROCs that were not well accounted for by neither model. Next I will discuss the major differences among the 4 studies, including the study materials and the study instructions.

Study material

The study materials in the 4 studies were different in terms of the number of features or details associated with the source, and the level of predictive value the features have for one source versus another. In Qin et al.'s experiments, the study materials were statements about various facts and feelings made by 2 women in the videotape. Compared to the common nouns used in the other 3 studies, Qin et al.'s statements were much richer in that they provided multiple features or information associated with each source during study phase. For example, when watching the two women reading statements about feelings in videotape, participants presumably encoded multiple types of information associated with each speaker. The types of information include visual characteristics (e.g., facial expression, clothing, and demeanor of the speakers), auditory characteristics (e.g., tone of voice and pauses of the speakers), the semantic content of the statements that influenced participants' emotions, the contextual information (e.g., the physical background behind the speakers), etc. According to the

source-monitoring framework, all of the features are bound together during encoding. In the source memory test, a cue is likely to activate different subsets of those encoded features. As a result, source judgment can be based on different kinds of retrieved information, ranging from “least information” to “most information or vivid details”. Therefore, memory states underlying source judgments should be continuous under such condition, leading to curvilinear source ROCs. In contrast, source ROCs should exhibit less curvature or is linear under the condition in which source information available for most items is impoverished.

It is also possible that the shape of the source ROCs were driven by another aspect of the study materials: If the features associated with one source varied systematically from the features associated with another source, each feature could have predictive value. That is, when a feature served as a perfect predictor of the source, the source judgment was threshold-like. For example, when the study materials were simple nouns that differed from one another *only* in position of the screen they were presented on (left versus right in Yonelinas, and top versus bottom in Hilford et al.), and only this feature (the source itself) served as perfect predictor of the source. Source judgments under such condition were likely to vary in a discrete manner because the position was either recalled or not recalled; there were no other features available for making the source judgment. In Qin et al.’s experiment, the two speakers (two sources) might differ in terms of visual characteristics (e.g., facial expression, clothing and demeanor), auditory characteristics (e.g., tone of voice and pauses when they speak), the semantic content of the statements brought out by their tone, etc. If these features varied systematically between the two sources, these features could have predictive value. For

example, although participants may not recollect exactly which speaker said the statement, they remembered there was a pause in the sentence, and this is more compatible with the way speaker A talks than speaker B. Therefore they would likely to give a “speaker A” response. However, the features in Qin et al.’s studies were rich and were not perfectly correlated with the speakers. So when each feature was not a perfect predictor of the source, source judgment could be based on different kinds of combined information that ranges from “vague detail” (partial information, discussed earlier) to vivid detail, leading to curvilinear source ROCs.

Study Instruction

Lastly, study instruction might play a factor, too, in that different study instructions would lead to different learning strategies, which would influence the basis of information for source judgment. An explicit study instruction might lead participants to adopt an atypical learning strategy. For example, knowing they would be tested on the left-right source memory, participants might try to encode that, and *only*, that specific source information for each item. Therefore, source recollection was discrete—either recall or not recall—resulting a relatively linear source ROC (e.g., Yonelinas). In contrast, not knowing that they would be tested on the specific source memory (e.g., Qin et al. and Slotnick et al.), participants may have encoded aspects of materials and sources more generally. Recall that participants in Slotnick et al. were asked to rate each word according to the difficulty of covertly reproducing or imaging the quality of the voice, and participants in Qin et al.’s experiments were asked to pay attention on their own emotions or the speakers’ emotions when watching the videotape. Therefore, source

recollection could be based on many aspects of the combined information, ranging from least information to vivid details, resulting a relatively continuous source ROC.

However, Hilford et al. observed nonlinear source ROCs under a same explicit study instruction, contradict with the linear source ROCs observed by Yonelinas. What was different between the two studies was that participants in Yonelinas were instructed to use a learning strategy to remember the source: by making association of words from the two sources (left-right) with two distinctive people (e.g., left side is dad, and right side is mum). This association strategy would likely to induce a discrete process because the association was either remembered or not. The difference in source ROCs between Yonelinas and Hilford et al. might very well be just the degree to which the source judgment is based on a discrete mechanism.

The Present Study

The empirical findings about source ROCs are inconsistent. Among the four studies, one observed linear source ROCs, supporting the discrete-state model; one observed curvilinear source ROCs, supporting the Gaussian SDT model; the other two observed in-between-shaped source ROCs, showing that neither models was accurate. Therefore, the primary purpose of the present study was to identify a variety of conditions under which source memory is best described as continuous or discrete, as reflected by the shape of the source ROCs. If a study condition produces curvilinear source ROCs in probability space and relatively linear z -ROCs, such source memory is best described as continuous, supported by the Continuous-State theory. In contrast, if a study condition produces relatively linear source ROCs in probability space and U-

shaped z-ROCs, source memory under that condition is best described as discrete, favoring the Discrete-State theory.

I will examine two hypotheses: 1). When the number of features associated with the source increases, source ROC will be relatively curvilinear; 2). When the predictive value of the features associated with the source decreases from perfect level, source ROC will be relatively curvilinear. The rationale and details of each hypothesis will be discussed in the next section.

Two experiments were run to examine the source ROCs under different study conditions. Experiment 1 manipulated the number of features associated with one source versus another. In the Single-feature condition, study items from two sources were exactly the same in terms of their font type (*Arial*), color (*white* on a black background), and font size (*60*). Participants were to distinguish words presented on the left side from words presented on the right side in a source memory test, in which the test items were printed exactly in the same font, color and size as it was in the study phase. So the only feature associated with each source is the position (i.e., left-right), which is the source itself. In the Multiple-feature condition, the study items from the two sources differed not only in their positions, but also in terms of font type (*Courier New* on the left and *Broadway BT* on the right), color (*Green* on the left and or *Blue* on the right), and font size (*40* on the left and *70* on the right). As in the Single-feature condition, participants performed the same type of *left-right* source memory judgment. If an increase of features associated with a source influences source recollection, we should observe a relatively curvilinear source ROC in the Multiple-feature condition relative to the Single-feature condition. This is predicted because recalling two features associated with a source

should elicit a higher confidence than recalling only one, therefore source recollection could vary from weak to strong in a continuum, as reflected by a relatively curvilinear source ROC. In contrast, single features should lead to a threshold-like process, as reflected by a relatively linear ROC.

The second experiment manipulated the level of predictive value of features associated with one source versus another. Three conditions were run in this experiment: One Perfectly-predictive condition and two Imperfectly-predictive conditions. The Perfectly-predictive condition was identical to the Multiple-feature condition in Experiment 1, in which the study items from the left side were always associated with same set of features (*Courier New, Green, and font size 40*) and items from the right side with another set of features (*Broadway BT, blue, and font size 70*). In one Imperfectly-predictive condition, study items from the left side were associated with the same three binary-valued features, but one value of feature independently had a predictive value of 0.85 for the source, and another value of feature had independently had predictive value of 0.15. That is, items on the left side were printed in *Courier New* 85% of the time, in *green* 85% of the time, in a small font size (*size 40*) 85% of the time, in *Broadway BT* 15% of the time, in *blue* 15% of the time, and in a large font size (*size 80*) 15% of the time. In this way, three features each independently had a predictive value of 0.85 for the source, and another three features had a 0.15 predictive value for the source. Items studied on the right side had the opposite pattern of predictive values. In another Imperfectly-predictive condition, the same three binary features were associated with each source but the predictive values were 0.75 and 0.25. If the predictive value of the associated features influences the source recollection, the source ROC would vary across

three conditions. An increased curvature of source ROC is predicted in the Imperfectly-predictive conditions, relative to the Perfectly-predictive condition. This is predicted because when the associated features have a predictive value of less than 1.0, all features have some chance of occurring on either side, so recalling two features associated with a source should elicit a higher confidence than recalling only one feature. Therefore, source recollection under such Imperfectly-predictive conditions could vary greatly from weak to strong. In contrast, when each feature serves as a perfect predictor of the source, recalling one associated feature is enough to lead you to identify the source; so recalling two associated features would not necessarily elicit a higher confidence. Source recollection under such condition should reflect a threshold-like process, as reflected by a relatively linear source ROC.

Both experiments consisted of the same study phase and test phase. Participants studied a list of words presented either on the left or right side of the screen, and then performed a source memory test in which they were required to rate their confidence on the source judgment. The group ROCs were plotted in probability space as a function of response confidence and several analyses were conducted. Firstly, a Gaussian analysis was conducted to determine whether the observed data was well accounted for by the Gaussian Signal-detection model. Then, a linearity analysis was then conducted to determine whether the observed functions were consistent with the predictions of the Threshold model. To further assess the data, we replotted the group ROCs in z -space, and a second linearity analysis was conducted to determine if the z -ROCs were linear or U-shape. Statistical analyses of individual participants ROCs' was also conducted to complement the group data, and to compare the experimental conditions.

CHAPTER 2

EXPERIMENT 1: NUMBER OF FEATURES ASSOCIATED WITH THE SOURCE

In Experiment 1, we examined the hypothesis that when the number of features associated with the source increases, the resulting source ROCs will be relatively curvilinear. The Single-feature condition was the replication of Yonelinas' Experiment 1 (Yonelinas, 1999), with only a few changes (study list contained 40 words from each source, as opposed to 60 each, and study instruction did not include using the association learning strategy). A relatively linear source ROC is predicted in the Single-feature condition as a result of threshold-like recollection process. In a Multiple-feature condition, the study items from each source were associated with multiple features (font type, font color, and font size). A relatively curvilinear source ROC is predicted in the Multiple-feature condition because when there are multiple features associated with a source, recalling two associated features could elicit a higher confidence than recalling only one feature. Therefore, source recollection can vary from strong to weak in a continuum.

Method

Participants

Fifty-three undergraduate students at the University of Massachusetts participated in Experiment 1 for extra credit in their psychology courses. All participants were native English speakers. Two participants who did not follow the instruction and 2 participants who had negative d' were excluded from the analysis. The remaining participants were randomly assigned to one of the 2 conditions.

Stimuli

Eighty English nouns were selected from the MRC Psycholinguistic Database (Coltheart, 1981) to serve as study items. The words were divided equally into 2 sets that were closely matched on the number of syllables (mean = 1.45), number of letters (mean = 5.18), and linguistic frequency (mean = 63.93 per million; Kucera & Francis, 1967). One set of words was presented on the left side of the screen and the other on the right side. Fourteen additional words were drawn from the same pool to serve as practice, primacy, and recency items, thus creating study lists of 94 total words. Presentation order of the critical words was randomized for each participant.

The stimuli in the Single-feature condition were constructed such that all the stimuli from both sources were in the same font type, font color and font size. The stimuli in Multiple-feature condition were constructed such that stimuli from the left side were printed in the font type of *Courier New*, in *green*, in a smaller font size (40), and stimuli from the right side were printed in *Broadway BT*, in *pink*, in a bigger font size (70).

Procedure

Both conditions consisted of a study phase, a practice phase, and a final test phase. Participants studied a list of 80 words presented one at a time either on the left side of the screen or the right side in a random order. Each word stayed on the screen at a 3-s rate, with a 750 ms interval between words. Participants were instructed to remember all the words and the side of the screen each word was presented on. They were also instructed to pay attention to the 3 features of the word- font type, font color and font size- because those features might help them remember which side the word was studied on. During the test, all participants made source judgments on a 6-point scale, ranging from 1 (sure left) to 6 (sure right).

All participants were told to try to use the entire range of the scale for the source judgment. They were also told that reaction time was not collected. The entire experiment took about 30 minutes to complete.

Analysis

The ROC data in this experiment and the one that follows are analyzed in the following way. A *group* ROC was generated for each condition by summing across the responses of the participants, and the Gaussian Signal-detection model was applied to the group data. The fit of model to the data was done by maximum likelihood estimation (analyses were done with SYSTAT). Individual analysis was also conducted to complement the group data by fitting the model to each individual ROC.

Then, we tested the threshold model. A standard linear regression was conducted on the group ROCs to determine whether there is a significant linear function. A quadratic term was then added to the linear function to determine whether it leads to a significant improvement in the fit. Significant curvature would contradict the predictions of the Threshold model and conform to the Continuous model. To further assess the data, the group ROC was then replotted in *z*-space, and the same linear regression analyses were conducted to determine if the *z*-ROC is linear or U-shape. The threshold model predicts U-shaped *z*-ROCs, and the continuous model predicts linear *z*-ROCs. All fitting done with linear regression analyses was using least squared estimation. This method gives results that are essentially the same as those derived with maximum likelihood estimation (Ratcliff, McKoon & Tindall, 1994; Glanzer, Kim & Hilford, 1999; Hilford et al, 2002).¹¹

¹¹ ROC data present an unusual statistical problem in that both axes represent dependent variables. Therefore, least squared estimation is technically inappropriate for such data because it minimizes the

Although the group ROC data are more stable than individual data, they may not be representative of the trends for the individual participants whose data are combined. Therefore, we also analyzed individual participants' ROC data to complement the group analyses. Each participant's ROC and z-ROC were generated and the same linear regression analyses were performed so that each individual participant was associated with a set of statistics (e.g., a quadratic constants for both the ROC function and z-ROC function, and a z-ROC linear slope). For each condition, a one-sample t-test was performed to determine whether the mean quadratic constant for both ROC and z-ROC was significantly different from zero. The continuous model predicts a negative quadratic constant in the ROC and a close to zero quadratic constant in the z-ROC; the threshold model predicts a close to zero quadratic constant in the ROC and a positive quadratic constant in the z-ROC.

Finally, to compare the experimental conditions, a two-sample t-test or ANOVA was performed to determine whether the difference in mean statistics across conditions were significant. All analyses are performed with $p < .05$.

Results

Receiver operating characteristics (ROCs)

The rating responses summed across participants for Experiment 1 and Experiment 2 are presented in the Appendix. The group ROC data for the Single- and Multiple-feature conditions are shown in Figure 8, along with the best-fitting function generated by the Gaussian Signal-detection model (broken line). The ROCs plot the

deviations between model and data along the y-axis, and assumes that the x-axis is error free. A more appropriate method is maximum likelihood estimation because it assumes that both axes are dependent variables and are subject to error.

probability of responding “left” to an item studied on the left side against the probability of responding “left” to an item studied on the right side as a function of response confidence¹². As can be seen, neither condition was well-described by the Gaussian Signal-detection model, $\chi^2(3) = 17.353$ ¹³, $p < 0.001$ for the Single-feature condition, and $\chi^2(3) = 19.373$, $p < 0.001$ for the Multiple-feature condition.

Individual analyses were conducted and the results were consistent with the group data. In the Single-feature condition, the Gaussian SDT model could be rejected for 26% of the participants. Out of the remaining data that were well fit by the model, 59% of them had relatively low memory accuracy indexed by d' ($d' < 1.0$)¹⁴. In the Multiple-feature condition, 12% of the participants' data did not conform to the Gaussian model; and out of the remaining data that were well fitted by the model, 61% had low d' . So far, the data indicated that the simple Gaussian SDT model is inadequate to account for the source ROCs. Next let us move on to the linear regression analyses, which tested the fit of the threshold model.

The best-fitting linear functions generated from linear regression analyses are shown superimposed on the data in Figure 8 (straight line). For the Single-feature condition, a linear function fits the group ROC well ($R^2 = 0.984$). However, adding the quadratic component led to a significantly better fit than that found with the linear

¹² ROCs generated from plotting hit rate for *right* items against false-alarm rate for right items as a function of response confidence led to similar shapes and statistics. This was consistent with the linear *z-slope* being close to 1.0, which indicates the symmetry of the ROC along the negative diagonal.

¹³ The significant chi-square statistic here indicates that the null hypothesis that the model fits is not rejected (i.e., the model does not fit well).

¹⁴ When d' is low, Gaussian model predicts a relatively linear source ROC, which is indistinguishable from the threshold model. So the fits were not very informative about the superiority of either model.

function [$R^2 = 0.999$, $\chi^2(1)^{15} = 14.311$, $p < 0.001$], indicating that the function was curvilinear. The best fitting function was $P(\text{Hit}) = 0.245 + 1.478 * P(\text{false-alarm}) - 0.691 * P(\text{false-alarm})^2$.

Now we turn to the individual data¹⁶. The same linear regression analysis was also conducted on each of the individual ROCs so that each individual was associated with a set of statistics. The means of the statistics for each condition are presented in Table 1. In the Single-feature condition, the mean of the quadratic constant, -0.355 (16 out of 23 were negative), was not significantly different from zero, $t(22) = -0.956$, $p = 0.350$, inconsistent with the group ROC statistic. However, there was one extremely positive quadratic constant, 6.263. Excluding this outlier gave a mean quadratic constant -0.656, and its difference from zero was now significant, $t(21) = -2.883$, $p = 0.009$, consistent with the group data (the adjusted statistics are presented in Table 2).

For the Multiple-feature condition, there was a significant linear component ($R^2 = 0.987$), but adding a quadratic component led to a significant improvement over the linear function [$R^2 = 0.999$, $\chi^2(1) = 14.017$, $p < 0.001$], showing that the function was curvilinear. The best fitting function was $P(\text{Hit}) = 0.207 + 1.517 * P(\text{false-alarm}) - 0.655 * P(\text{false-alarm})^2$. Now we turn to individual data¹⁷. Seventeen out of 26 quadratic

¹⁵ A likelihood test procedure was used for testing nested model. The likelihood ratio statistic is $\lambda = [SS_{\text{residual, nonlinear model}} / SS_{\text{residual, linear model}}]^{n/2}$, where $n = \text{number of data points}$. A simple transformation gives $-2 \ln(\lambda) \sim \chi^2$, with $df(\text{nonlinear model}) - df(\text{linear model})$.

¹⁶ In the Single-feature condition, 21 out of the 23 individual ROCs exhibited a significant linear component, but adding a quadratic component only led to a better fit for 2 individual ROCs. Two individual ROCs exhibited an abnormal function: both the linear and quadratic components were insignificant. These results should be interpreted cautiously because the individual data have fewer trials and therefore associated with greater variability (Macmillan, Rotello, & Miller, in preparation).

¹⁷ In the MF condition, 23 individual ROCs exhibited a linear component, but adding a quadratic component only led to a better fit for one individual ROC. Two individual ROCs exhibited an abnormal function that was neither linear nor quadratic.

constants were negative. The mean ROC quadratic constant, -0.877 , was significantly different zero, $t(25) = -2.753, p = 0.011$ ¹⁸, indicating that the group source function was representative of most of the individual participants' ROCs. To examine if there was averaging effect of test items, ROCs were also examined as a function of test position (i.e., first versus second half of the test list, as well as quartile of the test list). The observed ROC functions were not found to be greatly influenced by test position.

Overall, the experimental manipulation was not supported: the mean ROC quadratic constant in the Multiple-feature condition was essentially the same as the Single-feature condition (-0.877 vs. -0.355), $t(47) = -1.074, p = 0.288$, with a comparable memory sensitivity indexed by d' between the conditions, (0.922 vs. 1.002), $t(47) = 0.514, p = 0.610$. The outcome of the analysis remained the same after excluding the outlier of the quadratic constant (6.263) in the Single-feature condition: no significant effect was observed between the two conditions in both the mean quadratic constants (-0.877 vs. -0.656), $t(46) = 1.037, p = 0.593$, and the d' 's (0.921 vs. 1.007), $t(46) = 0.596, p = 0.237$.

Normal-normal receiver operating characteristics (z-ROCs)

To further assess the source data, the group ROCs were replotted on z -coordinates for each condition (see Figure 8, the right panels). In the Single-feature condition, the group z -ROC was u-shaped, consistent with the ROC data (see the top right panel of Figure 8). Although there was a significant linear component ($R^2 = 0.982$), adding a quadratic component led to a significant improvement in fit (i.e., the best fitting function was $Z(\text{Hit}) = 0.887 + 1.198 * Z(\text{false-alarm}) + 0.219 * Z^2(\text{false-alarm})$, $R^2 = 0.999, \chi^2(1) =$

¹⁸ There was also one outlier in the MF condition (quadratic constant = -6.357), but excluding it did not change the outcome.

13.724, $p < 0.001$), showing that the source z -ROC was u-shaped. The group result was supported by the individual analysis. The mean quadratic constant, 0.297, was significantly differently from zero, $t(22) = 2.466$, $p = 0.022$. The mean linear slope, 0.983, was not significantly different from 1.0, $t(22) = -0.438$, $p = 0.666$, indicating that the underlying distributions of the two sources were equal in variance, or that the items from the two sources were equally attended to by the participants¹⁹.

For the Multiple-feature condition, the group z -ROC was also U-shaped (see the bottom right panel of Figure 8). The linear component was significant ($R^2 = 0.980$), but adding a quadratic component led to a significant improvement in fit, $R^2 = 0.999$, $\chi^2(1) = 17.035$, $p < 0.001$. The best-fitting function was $Z(\text{Hit}) = 0.859 + 1.272 * Z(\text{false-alarm}) + 0.238 * P(\text{false-alarm})^2$. The individual analysis supported the group result, the mean quadratic constant, 0.198, was significantly differently from zero, $t(25) = 2.686$, $p = 0.013$. The mean linear slope, 1.016, was not significantly different from 1.0, $t(25) = 0.407$, $p = 0.688$.

The z -ROC was essentially the same in the two conditions: the difference in mean z -ROC quadratic constant was 0.099, $t(47) = -0.723$, $p = 0.474$, and the difference in mean linear slope was 0.017, $t(47) = 0.267$, $p = 0.791$.

Discussion

The results of Experiment 1 do not support the hypothesis that when the number of the features associated with a source increases, source recollection varies continuously, leading to a relatively curvilinear source ROC. The source ROC data observed in the

¹⁹ Because the departure from linearity of z -ROC was small, the slope value was still informative.

Multiple-feature condition was not different from that in the Single-feature condition, in which studied items were relatively impoverished.

Surprisingly, we did not replicate Yonelinas's data (1999) in the Single-feature condition, despite an experimental design that was essentially identical to his Experiment 1. In contrast to the linear source ROC he observed, we found significant curvature, and therefore we can reject the double-high threshold model that he proposed. The data also contradict the simple Gaussian SDT model even though the best-fitting function of the source ROC included a significant quadratic component. The source ROC observed in the Multiple-feature condition was essentially the same as that in the Single-feature condition. A pattern of data similar to ours was also found by Slotnick et al.'s, Hilford et al.'s experiments and in the experiment that follows.

The Multiple-feature condition was designed in an attempt to provide with richer study materials, a possible factor responsible for the curvature of source ROC observed in Qin et al.'s experiment. However the findings in the Multiple-feature condition was inconsistent with Qin et al.'s in that the data were not well described by the Gaussian signal-detection model.

The null effect of ROC shapes between the two conditions suggests that participants in the Multiple-feature condition did not use the extra features associated with the source and based their judgments on solely one feature. The fact that the memory accuracy (d') in the Multiple-feature condition was no better than the Single-feature condition supported this speculation. Then why would not participants in the Multiple-feature condition take advantage of those extra features? Maybe it was because the associated features were perfectly correlated with the source. Recall the study

materials in the Multiple-feature condition. Words studied on the left side were always associated with the same set of features (i.e., *Courier New* font type, *green* font color and *smaller* font size), and words on the right side were associated with a different set of features (i.e., *Broadway BT*, *blue* and *bigger* font size). Thus, each feature served as a perfect predictor of the source. Since one piece of information was enough to make a *left-right* source judgment, participants might not have made any effort to recall additional details of the study experience. The nature of the predictive value of a feature associated with a source was explored further in the next experiment.

CHAPTER 3

EXPERIMENT 2: PREDICTIVE VALUE OF FEATURES FOR THE SOURCE

In Experiment 2, we examined the hypothesis that when the predictive value of a feature for a source decreases from perfect level, source recollection should vary to a greater extent, leading to more curvature in the source ROC. Three conditions were designed. In the Perfectly-predictive condition (PP), items from one side were always associated with the same type of three features, and another side with another type of three features (exactly identical to the Multiple-feature condition from Experiment 1). In one Imperfectly-predictive condition (IP85), the features are not perfectly correlated with the source: the predictive values of each of the three binary features are assigned such that value one of the features has an independent probability of 0.85 and value two has a probability of 0.15 of being assigned to the items on the left side. The opposition pattern of predictive values was assigned to the items on the right side. A second Imperfectly-predictive condition (IP75) was similar, but the predictive values of the associated features were now either 0.75 or 0.25. We predicted that the source ROCs would show increased curvature in the Imperfectly-predictive conditions compared to the Perfectly-predictive condition, and that the less predictive case (IP75) would show the most curvature. When the associated features have a predictive value of less than 1.0, all features have chances of occurring on either side, so recalling two features associated with a source should elicit a higher confidence than recalling only one feature, and therefore source judgment based on two features should lead to a higher confidence than one feature, leading to a relatively curvilinear source ROC. In contrast, when each feature serves as a perfect predictor of the source, recalling two associated features would not

necessarily elicit a higher confidence than one feature, therefore source recollection in the Perfectly-predictive condition should reflect a threshold-like process, leading to a relatively linear source ROC.

Method

Participants

Ninety-one undergraduate students at the University of Massachusetts participated in Experiment 2 for extra credits in their psychology courses. All participants are native English speakers. One participant who did not follow the instruction and 2 participants who had negative memory sensitivity indexed by d' were excluded from the analysis. The remaining participants were randomly assigned to one of the 3 conditions.

Stimuli

The same 80 English nouns as that in Experiment 1 were used and were divided into 2 study sets as in Experiment 1. The Perfectly Predictive condition was exactly the same as the Multiple-feature condition in Experiment 1. That is, items from the left side were always in printed in *Courier New*, *green*, and a small font size (40). Items from the right side were always in printed in *Broadway BT*, *blue*, and a large font size (70). Therefore each feature was serves as a perfect predictor of the source. There were two Imperfectly-predictive conditions: IP85 and IP75, each condition included 40 items from the left side. For the IP85 condition, 85% (randomly chosen) of the items were presented in *Courier New*, 85% in *green*, and 85% in small font size; each of these feature values was 85% predictive of the source and each worked independently. Fifteen percent of the items were presented in *Broadway BT*, 15% in *blue*, and 15% in large font size (70); each value was 15% predictive of source. The associated features on the right side were

assigned an opposite pattern of the predictive values. For the IP75 condition, items from two sources were assigned to a predictive value in the same way, except that the predictive value now was either 0.75 or 0.25.

Procedure

The procedure was identical to that of Experiment 1.

Results

Receiver operating characteristics (ROCs)

The group ROC data for the three conditions are shown in Figure 9, along with the best fitting functions generated from the Gaussian signal-detection model (broken line). As can be seen, the group data from all three conditions were not well accounted for by the model, same as the Experiment 1. For the PP condition, $\chi^2(3) = 13.234$, $p = 0.004$; for the IP85 condition, $\chi^2(3) = 26.733$, $p < 0.001$; and for the IP75, $\chi^2(3) = 43.498$, $p < 0.001$. Individual analyses were conducted and the results, despite showing more variability, were generally consistent with the group data. For the PP conditions, 11% of the participants rejected the Gaussian model; and out of the remaining data that were well fitted by the model, 58% of them had relatively low d' ($d' < 1.0$). For the IP85 condition, 7% of the participants rejected the Gaussian model, and out of the remaining data that were well fitted by the model, 64% of them exhibited low d' . For the IP75 condition, 9% of the participants rejected the Gaussian model; and out of the remaining data that were well fitted by the model, 71% of them exhibited low d' . It is clear that the Gaussian SDT model did not adequately account for the observed source ROCs.

Figure 9 also presents the best-fitting linear functions generated from regression analyses (straight line). The group ROC in the Perfectly-predictive condition should

replicate that in the Multiple-feature condition in Experiment 1, and as can be seen in the top left panel of Figure 9, this is exactly the case. A linear regression analysis showed that there was a significant linear component ($R^2 = 0.980$), but adding a quadratic component significantly improved the fit ($R^2 = 0.999$, $\chi^2(1) = 16.479$, $p < 0.001$). The best fitting function was $P(\text{Hit}) = 0.197 + 1.625 * P(\text{false-alarm}) - 0.819 * P(\text{false-alarm})^2$. Now we turn to the individual data²⁰. The means of the statistics for each condition are presented in Table 3. In the Perfectly-predictive condition, the mean ROC quadratic constant, -0.981 (20 out of 27 exhibited a negative constant), was significantly different zero, $t(26) = -2.536$, $p = 0.018$. In the two Imperfectly-predictive conditions (IP85 and IP75), the group ROCs were essentially the same as in the Perfectly-predictive condition (see the left panels of Figure 9). The best-fitting function for IP85 group data included a significant quadratic component: $P(\text{Hit}) = 0.196 + 1.543 * P(\text{false-alarm}) - 0.700 * P(\text{false-alarm})^2$, $R^2 = 0.999$, $\chi^2(1) = 13.105$, $p < 0.001$. For IP75 group data, $P(\text{Hit}) = 0.198 + 1.374 * P(\text{false-alarm}) - 0.467 * P(\text{false-alarm})^2$, $R^2 = 0.999$, $\chi^2(1) = 10.184$, $p < 0.005$. The group data for these two conditions were supported by individual analysis (see Table 3). The mean quadratic constant for IP85 was -0.688 (22 out of 30 exhibited a negative constant), and its difference from zero was significant, $t(29) = -2.888$, $p = 0.007$. The mean quadratic for IP75 was -0.562 (22 out of 31 exhibited a negative constant), and its difference from zero was also significant, $t(30) = -3.548$, $p =$

²⁰ In the PP condition, 24 individual ROCs exhibited a linear component, but added a quadratic component did not led to a better fit. Three individual ROCs exhibited an abnormal function that was neither linear nor quadratic. In the IP85 condition, 29 individual ROCs exhibited a linear component, but added a quadratic component only led to a better fit for 4 individual ROCs. One individual ROC's function was neither linear nor quadratic. In the IP75 condition, 31 individual ROCs exhibited a linear component, but added a quadratic component only led to a better fit for 3 individual ROCs.

0.001. As in the previous experiment, the functions of the ROCs for all three conditions were not found to be greatly influenced by the test position.

The main hypothesis was not supported: the ROCs were essentially identical across conditions. The mean quadratic constant for the PP, IP85 and IP75 was -0.981, -0.688 and -0.562, respectively, $F(2, 85) = 0.629, p = 0.536^{21}$, indicating that the ROC shape was essentially identical across conditions. There was also no difference in memory sensitivity (mean d' was 0.940, 0.909 and 0.875 for PP, IP85 and IP75, respectively), $F(2, 85) = 0.094, p = 0.910$. Although it was expected that the memory performance (d') in the Perfectly-predictive condition should be better than the two Imperfectly-predictive conditions simply because when the features were correlated with the source, it was less confusing and therefore should be easier to encode the materials. The null effect here suggests that participants in all three conditions did not use the associated features for source judgments.

Normal-normal receiver operating characteristics (z-ROCs)

The group z-ROCs for the three conditions are shown in the right panels of Figure 9, along with the best-fitting functions generated from the Gaussian SDT model (broken line) and the Threshold model (straight line). As can be seen in all three conditions, the function with a positive quadratic constant fit better than the linear function. For the Perfectly predictive condition, the best fitting function was $Z(\text{Hit}) = 0.849 + 1.176 * Z(\text{false-alarm}) + 0.176 * Z(\text{false-alarm})^2, R^2 = 0.999, \chi^2(1) = 23.563, p < 0.001$. For the IP85 condition, the best fitting function was $Z(\text{Hit}) = 0.819 + 1.206 * Z(\text{false-alarm}) + 0.204 * Z^2(\text{false-alarm}) R^2 = 1.0, \chi^2(1) = 19.416, p < 0.001$. For the IP75, the best fitting

²¹ There was one outlier in the PP condition ($C = -9.980$), and one outlier in the IP85 condition ($C = -5.689$). But excluding the outliers did not change the outcome of the analyses.

function was $Z(\text{Hit}) = 0.750 + 1.240 * Z(\text{false-alarm}) + 0.243 * Z(\text{false-alarm})^2$, $R^2 = 0.999$, $\chi^2(1) = 17.389$, $p < 0.001$.

The group analyses were supported by the individual analyses (see Table 3). For the Perfectly predictive condition, the mean quadratic constant of z-ROC was 0.242, and its different from zero was significant, $t(26) = 4.472$, $p < 0.001$. The mean linear slope, 0.986, was not significantly different from 1.0, $t(26) = -0.381$, $p = 0.706$, indicating that the items from the two sources were equally attended to by the participants. For the IP85 condition, the mean quadratic constant, 0.208, was significantly differently from zero, $t(29) = 4.932$, $p < 0.001$. The mean linear slope, 0.974, was also not significantly different from 1.0, $t(29) = -0.893$, $p = 0.379$. For the IP75 condition, the mean quadratic constant, 0.251, was significantly differently from zero, $t(30) = 6.376$, $p < 0.001$. The mean linear slope, 0.991, was also not significantly different from 1.0, $t(30) = -0.235$, $p = 0.816$.

Consistent with the ROC data analysis, the mean quadratic constant of z-ROC was essentially the same across the three conditions, $F(2, 85) = 0.262$, $p = 0.770$; and the mean linear slope was also the same, $F(2, 85) = 0.070$, $p = 0.932$.

Discussion

The results of Experiment 2 did not support the hypothesis that source recollection would vary to a greater extent in a continuum when the predictive value of the features associated with the source was less than a perfect value. As expected, the source data in the Perfectly-predictive condition replicate that in the Multiple-feature condition of Experiment 1: The curvature of the source ROC was small but significant. However, the same pattern of the results was also observed in both of the Imperfectly-predictive conditions.

Why would the source ROCs in the Imperfectly predictive conditions be the same as those in the Perfectly predictive condition? When the features had some chance of occurring on either side, participants in the Imperfectly-predictive conditions were expected to monitor or evaluate the associated features cautiously before making a source judgment about whether the word was actually studied on the left side of the screen or the right side. Source ROC under such conditions were predicted to exhibit more curvature because recalling two features associated with a source would likely to elicit a stronger confidence than when recalling only one feature. The null effect observed in this experiment could be due to unsuccessful experimental control over what went on during encoding phase and retrieval phase, as discussed in the following.

Firstly, it is possible that the associated features (font type, font color and font size) were not encoded efficiently because they were not very “meaningful”. Recall that the task was to study a series of common nouns (e.g. ocean or window), and then make a left-right source judgment in a memory test. During encoding phase, when the noun *ocean* was presented on either side of the screen, its physical visual attributes or features (e.g., printed in Courier New, in green and a small font size) may not have any meaningful relationship to the noun. Therefore, it would be difficult to integrate the associated features with the noun and form a unified memory representation. Unless participants made great effort to encode those features, their memory would not be very long lasting. Compared to the Perfectly-predictive condition, this scenario was worse in the Imperfectly-predictive conditions, in which all features had a chance of occurring on either side of the screen (many participants reported after the test that the features were confusing). Therefore, participants in the Multiple-feature conditions would likely to

adopt an encoding strategy that would put less weight on those features, perhaps even completely ignoring them. After all, participants knew that they would only be tested on the position of the items. The fact that the memory accuracy in the Imperfectly-predictive conditions was no worse than the Perfectly-predictive condition suggests that a similar encoding strategy was used. A mixture model (Hilford et al. 2002) that captures the effect of unattended source information will be discussed in the General Discussion section. As will be seen, such model may provide a better account of the source data.

Secondly, it is also possible that the features were not carefully monitored or evaluated during source recollection, regardless whether or not the associated features were encoded efficiently into the memory. Since participants were only required to make a left-right source judgment for every item in the test, and the test items were printed in a neutral form in the test phase, it is possible that participants retrieved only that one piece of information –the position of the items–and did not make extra effort to retrieve the other associated features.

CHAPTER 4

GENERAL DISCUSSION

In two experiments, we tried to identify a variety of conditions under which source recollection is best described as continuous or discrete, as reflected by the shape of the source ROC. In Experiment 1, we tested the hypothesis that when the number of features associated with a source increases, source recollection would vary from weak to strong in a continuous manner, reflected by a relatively curvilinear source ROC. In Experiment 2, we tested the hypothesis that when the predictive value of the features associated with a source decreases from perfect level, source recollection should vary continuously to a greater degree (i.e., source ROC should exhibit more curvatures) than when the associated features serve as perfect predictor of the source. The source ROCs observed in all of these conditions were essentially the same; the hypotheses were not supported.

Although we did not observe a significant effect of study condition in either of the two experiments, the source ROCs were similarly shaped across all study conditions: the source ROC was curvilinear with a small but significant curvature, the z -ROC was U-shaped, and the linear slope was close to unity. This critical pattern of findings has also been observed by Hilford et al. (2002) and Slotnick et al. (2000). We believe that this pattern of results is informative about the nature of source recollection in general.

Is source memory continuous or discrete? Despite the two extreme cases observed in the literature (i.e., Yonelinas observed a linear source ROC that is consistent with the threshold model; and Qin et al. observed a curvilinear source ROC that is consistent with the Gaussian SDT), the vast majority of the source data suggest neither extreme model is

correct. A mixture model that can better account for this pattern of result has been introduced by Hilford et al. (2002). Before discussing the mixture model, we will revisit the assumptions of the two extreme models in the next section.

Implications for the Threshold model

According to Yonelinas' dual-process model, if the familiarity of the sources is approximately equal, then source identification will rely primarily on a recollection process resulting a linear source ROC. Yonelinas (1999) reported a linear source ROC in an experiment in which the two sources did not differ in familiarity, and therefore source judgment was assumed to reflect primarily the contribution of recollection. In the same study, he further showed that when a familiarity component was used, the source ROC was relatively curved. In that experiment, source familiarity differences were created by presenting one list of words 5 days after the other, thereby increasing the familiarity of the more recently presented list. However, we failed to replicate his linear source ROCs in our Single-feature condition in Experiment 1. Similarly, Hilford et al. (2000; Experiment 3) also failed to produce linear source ROCs. Furthermore, although familiarity can be assumed to be approximately equal for both sources (i.e., z -slope close to 1.0) in all five conditions from the current two experiments, all source ROCs were found to be nonlinear (i.e., the best-fitting function of the data includes a significant negative quadratic component). In fact, a nonlinear source ROC was consistently observed in the literature (Qin et al., Slotnick et al., Hilford et al., and the current experiments), contradicting with the threshold assumption claimed by the dual-process model.

Malmberg (2002) has recently claimed the discrete-state model can also predict curvilinear ROCs by assuming that participants adopt a strategy that makes use of a different mapping mechanism between the internal states and rating responses. According to this model (see Figure 4), items detected in the two discrete states (e.g., *seen* state and *heard* state) are not necessarily assigned to the highest or lowest confidence response (as should be the case with linear source ROCs). Instead, they can be assigned to any one of the n confidence ratings (c_k). That is, it is assumed that items in the D_{seen} states can be mapped to c_k , with probability w_k (where $0 < w_k < 1$) and items in the D_{heard} can be mapped to c_k , with probability y_k (where $0 < y_k < 1$), with the ratio of w_k/y_k decreasing with the confidence ratings, and with the guessing rate p_k (i.e., $1/n$) held constant. Thus, the hit rate is $P(c_k|\text{seen}) = w_k * q + b$; and the false-alarm rate is $P(c_k|\text{Heard}) = y_k * q + b$, where b is the guessing proportion [i.e., $b = p_k (1-q)$]. Such mapping assumes that items detected as Seen are more likely to be assigned to a relatively high confidence rating, and items detected as Heard are more likely to be assigned a relatively low confidence rating. Therefore, a discrete-state model with this kind of mapping mechanism between the internal states and rating responses can generate a curvilinear source ROC.

This model has a number of limitations. First of all, it is too flexible; it involves a large number of parameters. For example, to fit the source data in the current 2 experiments, the model makes use of 12 parameters to cover 10 data points. Therefore, such model can fit any source memory data because the large number of parameters can compensate each other in the fit.

Secondly, although the model may fit well to the source data in the literature, it involves the assumption of a large q value (the true detection rate). For example, to have

a reasonable fit (keeping $0 < w_k < 1$, $0 < y_k < 1$, and the ratio of w_k/y_k decreasing with k) to the data of Qin et al. (2001), the model requires a *minimum* q of 0.95 in their Experiment 1, and 0.94 in their Experiment 2; for the data of Slotnick et al. (2000), the model assumes a minimum q of 0.92, 0.84 and 0.95 for the 3 experiments. The necessity of such a large value of q is counterintuitive. For example, it does not seem logical to assume that participants in Slotnick et al.'s Experiment 1 had a true detection rate of 0.92, while the overall source memory accuracy (d') was only 0.57. Our demonstrations showed that the model becomes meaningless (obtaining negative values of w_k or y_k) when the guessing proportion b [$b = p_k (1-q)$, where $p_k = 1/n$] is larger than any rating cell. As indicated by the equation for b , in order to keep the guessing proportion small, the model has to assume a relatively large q value.

Thirdly, this kind of mapping mechanism between the discrete states and the rating response seems implausible. The model does not provide clear account as to why participants would adopt such a response strategy. Specifically, why would participants not assign the highest confidence rating when they actually recalled that the item was Seen? Why would they instead claim that they were “unsure” that it was seen? The reason cannot be that the memory strength for the recollection was relatively weak because the very core assumption of the discrete-state model is that source information is either *recalled* or *not recalled*.

Thus, the threshold model did not provide an accurate account of the source performance. Source ROCs are typically nonlinear, contradicting the model's linear prediction.

Implications for the Gaussian SDT model

Signal detection model (either single-dimensional SDT or two-dimensional SDT) assumes the underlying distributions of two sources are Gaussian and overlapping on a continuous dimension (e.g., memory strength). Therefore, source memory can vary continuously from weak to strong, reflected in a curvilinear source ROC. Although a nonlinear source ROC was typically observed (Qin et al., Slotnick et al., Hilford et al., and the current experiments), only one extreme case (Qin et al., 2001) was well described by the model. Furthermore, significantly U-shaped z-ROCs were also typically found for source memory performance (Slotnick et al., Hilford et al., and the current experiments), inconsistent with the linear prediction of the model. All in all, the SDT model with a pure Gaussian assumption does not provide an adequate account for the common findings of source data and needs revision.

Mixture normal SDT model

Hilford et al. has recently revised the two-dimensional signal-detection model (discussed in the Introduction section; or see Figure 3) and proposed a mixture model that can well account for the critical pattern of results observed in the literature. Basically, the model adds one new assumption: *attention* plays a significant role in source memory. According to the model, sometimes the sources of items are attended to during study, whereas other time they are not. Thus, some items are encoded with multiple associated source features, and others are not. To capture this in the model, a distribution of unattended items is added to the representation. When the distributions of the two sources and the distribution of unattended items are projected onto the decision axis, the representation of the model is reduced to a single-dimension, as shown in Figure 10²².

²²The representation of the mixture model depicted in Figure 12 suffices for the source memory task, in which there is no old-new judgment.

The distributions of items from the two sources A and B are normally distributed with means above and below zero on the single-dimension. The distribution of items for which the sources are unattended, N', is also normally distributed with a mean of zero, and is placed midway between A and B. One new parameter is added in the model: the proportion of attended to items, λ . The hit rate and false-alarm rate for the source judgment are characterized by the following equations:

$$P(R_j | A) = \lambda \int_{c_j}^{\infty} G(X | A) dx + (1 - \lambda) \int_{c_j}^{\infty} G(X | N') dx ,$$

$$P(R_j | B) = \lambda \int_{c_j}^{\infty} G(X | B) dx + (1 - \lambda) \int_{c_j}^{\infty} G(X | N') dx ,$$

Where R_j is a rating from confidence level j to the highest rating; c_j is the criterion at rating j ; G is a Gaussian distribution; λ is the proportion of attended to items,

$0 \leq \lambda \leq 1.0$; A is Source A, B is Source B, and N' is a set of items that do not include source information .

As indicated by the two equations above, the proportion of correct “source A” response is obtained by summed across “source A” responses from the attended-to source A distribution and “source A” responses from the unattended-to distribution (represented by N', distribution of items with no source information). Therefore the *hit* rate is contributed by the mixture distributions of A and N'; and the *false-alarm* rate is contributed by the mixture distributions of B and N'. The degree of curvature in the source ROCs is influenced by the value of the *attention* parameter, λ . That is, when participants fully attended to most of the studied items, λ will be close to 1.0, and the source responses will approach the standard Gaussian SDT responses as the N' distribution makes little contribution to the source judgments. In contrast, when

participants do not pay attention to most of the studied items, λ will be low, the source responses will include a large portion of guessing responses contributed heavily by the N' distribution. Because the same proportion of guessing responses is added to both hit and false-alarm rates, the curvature of the source ROC will be flattened. In other word, when λ is low, a linear component is added to the ROC. Such representation allows the mixture model to generate source ROC that is less curved, the z -ROC that is U-shaped, and the z -ROC slope that is close to 1.0, which are consistent with the pattern of source data typically observed in the literature (Slotnick et al., 2000; Hilford et al., 2002; current studies).

Although the mixture model provides a better account for the observed source ROCs, it has limitations. For example, the model cannot account for an above-chance linear source ROC (e.g., Yonelinas, 1999). According to the model, a linear source ROC can occur only when λ is equal to zero, in which case the source judgment are contributed only by N' distribution, resulting the same proportion of hit and false-alarm rates. Therefore, a linear source ROC can only occur at the chance line.

Another limitation of the model is that the new parameter, λ , is a post-hoc variable. That is, the model assumes poor attention was associated with source ROCs that has a small curvature (e.g., Slotnick et al., 2000; Hilford et al., 2003; and the current experiments), and full attention was associated with the source ROCs that has a large curvature (e.g., Qin et al., 2001). However, the role of attention was not directly manipulated in any of the experiment discussed above. Therefore, before the fit of the mixture model can be determined, the role of the attention parameter, λ , must be tested empirically.

Future research directions

Attention is an important assumption in the Mixture normal SDT model. Future studies that examine the role of attention in a source task will be critical in further assessing the mixture model. For example, the attention parameter, λ , should be manipulated in a divided attention versus full-attention experiment. When the learning phase is calling for full attention, λ should be higher and the source ROCs should exhibit a larger curvature. When the learning phase involves multiple tasks, λ should be lower and the curvature of the source ROCs should be smaller.

In the present experiments, we found that the factors such as the number of features associated with the sources, and the predictive value of the features associated with the sources, were not significantly influence the source performance. However, the null result could be due to a weak experimental manipulation as discussed previously. The two factors are still worth being examined further. The current experiments can be modified to ensure that the features are encoded efficiently, and that the features are used during the test.

To increase the likelihood that the features are integrated as a unified whole in the memory, instead of using simple noun, we could use a more complex and information-rich type of study materials. Illustrations, graphs and pictures are good candidates presumably because images are composed of simple features with multiple dimensions. When the study materials are rich and well-integrated, participants should be able to retrieve numerous different types or subsets of information that link the item to a specific source, therefore source memory under such condition should behave in a continuous manner.

To increase the likelihood that features are used during the test, we could include a procedure that involves a memory characteristics questionnaire (MCQ). For each item, before or after giving a source judgment, participants can also be asked to describe the quality of their memory in terms of visual details (e.g., font type, font size and font color) on a 6-point rating scale, ranging from *most information* to *least information*. When participants are instructed to focus on the number of details they can recall for the test item during the test, they would more likely to evaluate other associative features before making a source judgment.

There are other factors that may influence the curvature of the source ROCs. For example, a different encoding strategy may lead to a different source performance. It is very likely that the encoding strategy may be influenced by the study instruction. An explicit study instruction might lead to an encoding strategy that is different from an implicit one. For example, knowing that they would be tested on the left-right source information, participants in the current experiments might emphasize more on encoding that, and only that specific information. In other words, their attention was primarily devoted to the left-right feature during the study phase, while paying less attention to other aspects of the study material. In contrast, not knowing that they would be tested on source, participants may have attended to the study material more generally and ‘naturally’ depending on what the implicit task involves. In Qin et al’s experiments, for example, participants were asked to focus on their own or speakers’ emotions and feelings when watching the videotape (they believed that they were in an experiment other than a memory experiment). Under such condition, participants might devote their attention evenly and naturally to many aspects of the learning episode (i.e., other than

trying to remember only who said what). Therefore during source recollection, participants would more likely to try to retrieve numerous different types of information that would help them to identify the correct source, resulting a curvilinear source ROC.

CHAPTER 5

CONCLUSION

The current two experiments were carried out to examine the retrieval processes underlying source memory in different study conditions. Experiment 1 compared the source ROCs in a condition in which the sources were associated with multiple features, to a condition in which the sources were relatively impoverished. Experiment 2 compared the source ROCs in a condition in which the associated features were less than a perfect predictor of source, to a condition in which the associated features were a perfectly predictor of the source. A null effect was observed in each experiment. However, a consistent pattern of results was observed across all conditions: source ROCs were curvilinear with a small degree of curvature. Thus, the results of the present two experiments join a body of literature showing that neither the Gaussian SDT model nor the Threshold model is accurate. The only model that provided a better account for the source ROC data is the Mixture normal SDT model. The Mixture model introduces the role of attention into the source memory performance and assumes continuous processes underlying source judgments. Future studies that identify the role of attention experimentally are critical in further assessing the Mixture model.

Table 1

Statistics for ROCs and z-ROC for the two conditions in Experiment 1

Condition	ROC		z-ROC		d'
	Quadratic term	Linear term	Quadratic term		
Single-feature	-0.355 (0.371)	0.983 (0.038)	0.297 (0.120)		1.002 (0.117)
Multiple-feature	-0.877 (0.319)	1.016 (0.040)	0.198 (0.074)		0.922 (0.105)

Note. Statistics are means from individual ROCs and z-ROCs.

Standard errors are in parentheses. Terms in bold are significantly different from zero.

ROC = receiver operating characteristic.

Table 2

Statistics for ROCs and z-ROC for the two conditions in Experiment 1 (Excluding one outlier).

Condition	ROC		z-ROC		d'
	Quadratic term	Linear term	Quadratic term		
Single-feature	-0.656 (0.227)	0.983 (0.040)	0.213 (0.090)		1.007 (0.122)
Multiple-feature	-0.877 (0.319)	1.016 (0.040)	0.198 (0.074)		0.922 (0.105)

Note. Statistics are means from individual ROCs and z-ROCs.

Standard errors are in parentheses. Terms in bold are significantly different from zero.

ROC = receiver operating characteristic.

Table 3

Statistics for ROCs and z-ROC for the three conditions in Experiment 2

Condition	ROC		z-ROC		d'
	Quadratic term	Linear term	Quadratic term		
Perfectly-predictive	-0.981 (0.387)	0.986 (0.038)	0.242 (0.054)		0.940 (0.112)
Imperfectly-predictive 85:15	-0.688 (0.238)	0.974 (0.030)	0.208 (0.042)		0.909 (0.109)
Imperfectly-predictive 75:25	-0.562 (0.158)	0.991 (0.037)	0.251 (0.039)		0.875 (0.092)

Note. Statistics are means from individual ROCs and z-ROCs.

Standard errors are in parentheses. Terms in bold are significantly different from zero.

ROC = receiver operating characteristic.

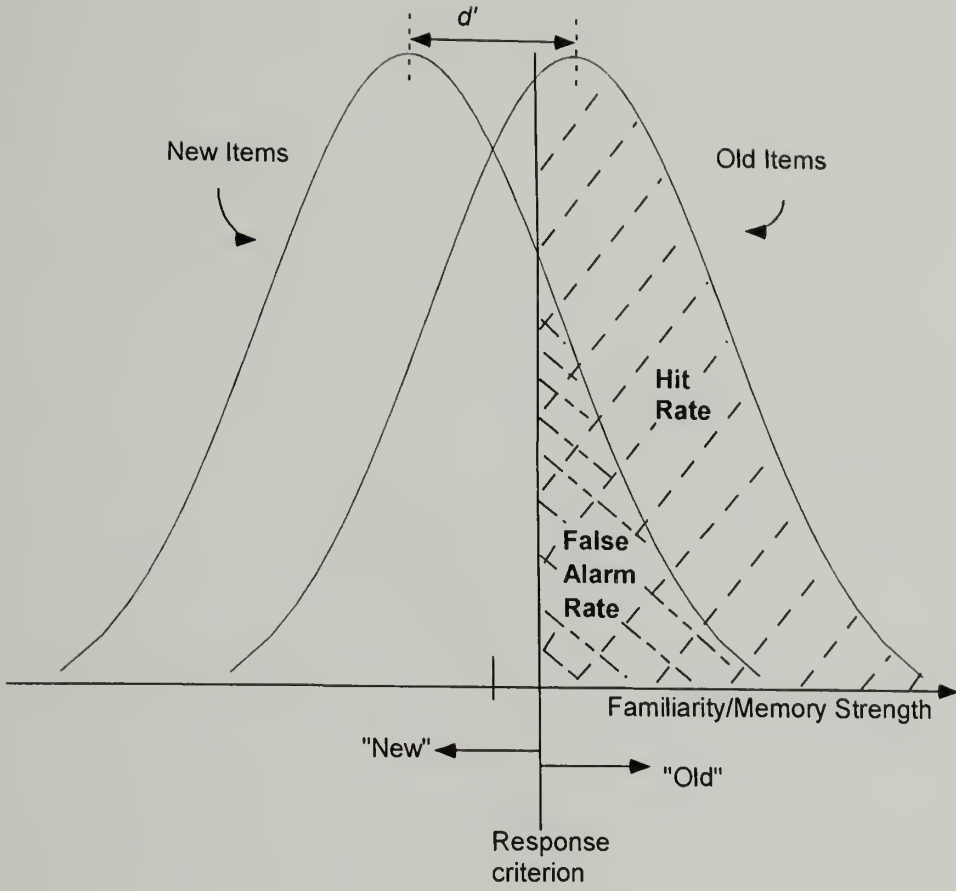


Figure 1. Distribution for Old and New items for equal-variance Gaussian signal-detection model.

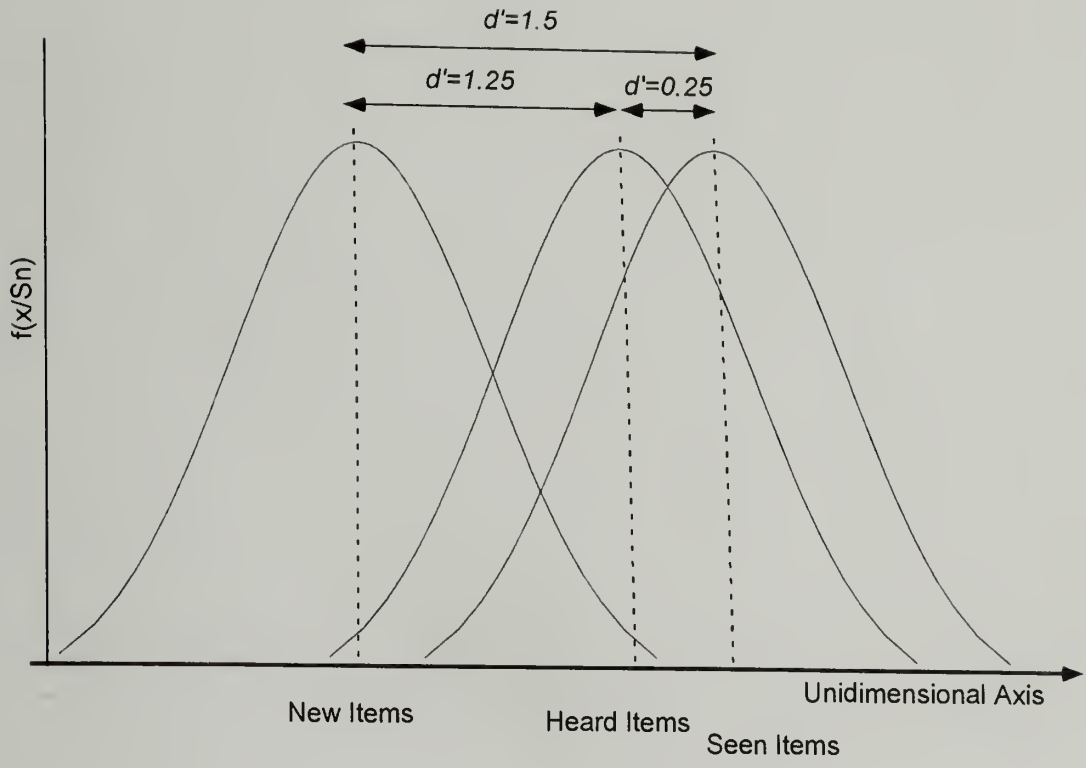
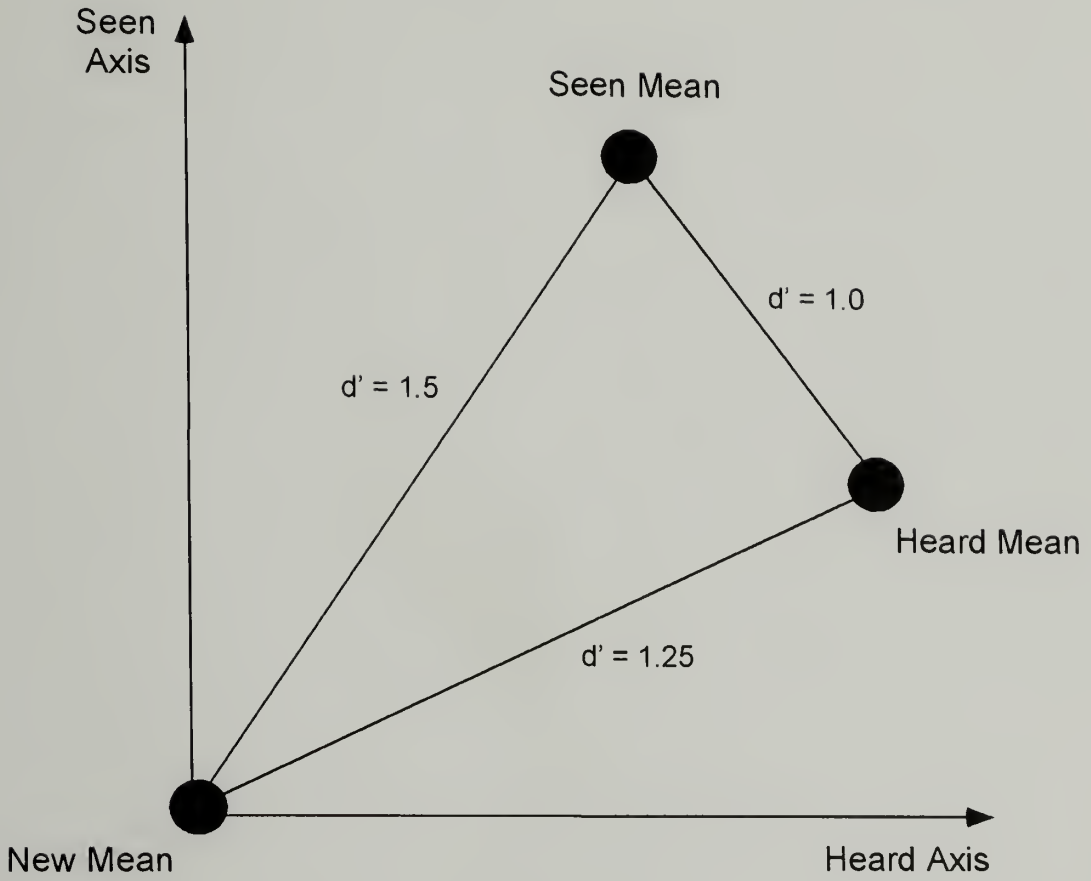


Figure 2. (a) Because the d' for New-Seen discrimination is less than the sum of d' 's for New-Heard discrimination and Heard-Seen discrimination, the mean of the Heard distribution cannot lie on the axis from New-Seen, and a second dimension is needed.

(Cont. next page)



(Figure 2, cont.)

(b) Illustration of how the triangle inequality forces data into a two-dimensional representation. Here it is assumed that the d' for discriminating a Seen item from Heard item is 1.0, and the recognition d' 's are 1.5 for Seen items and 1.25 for Heard items.

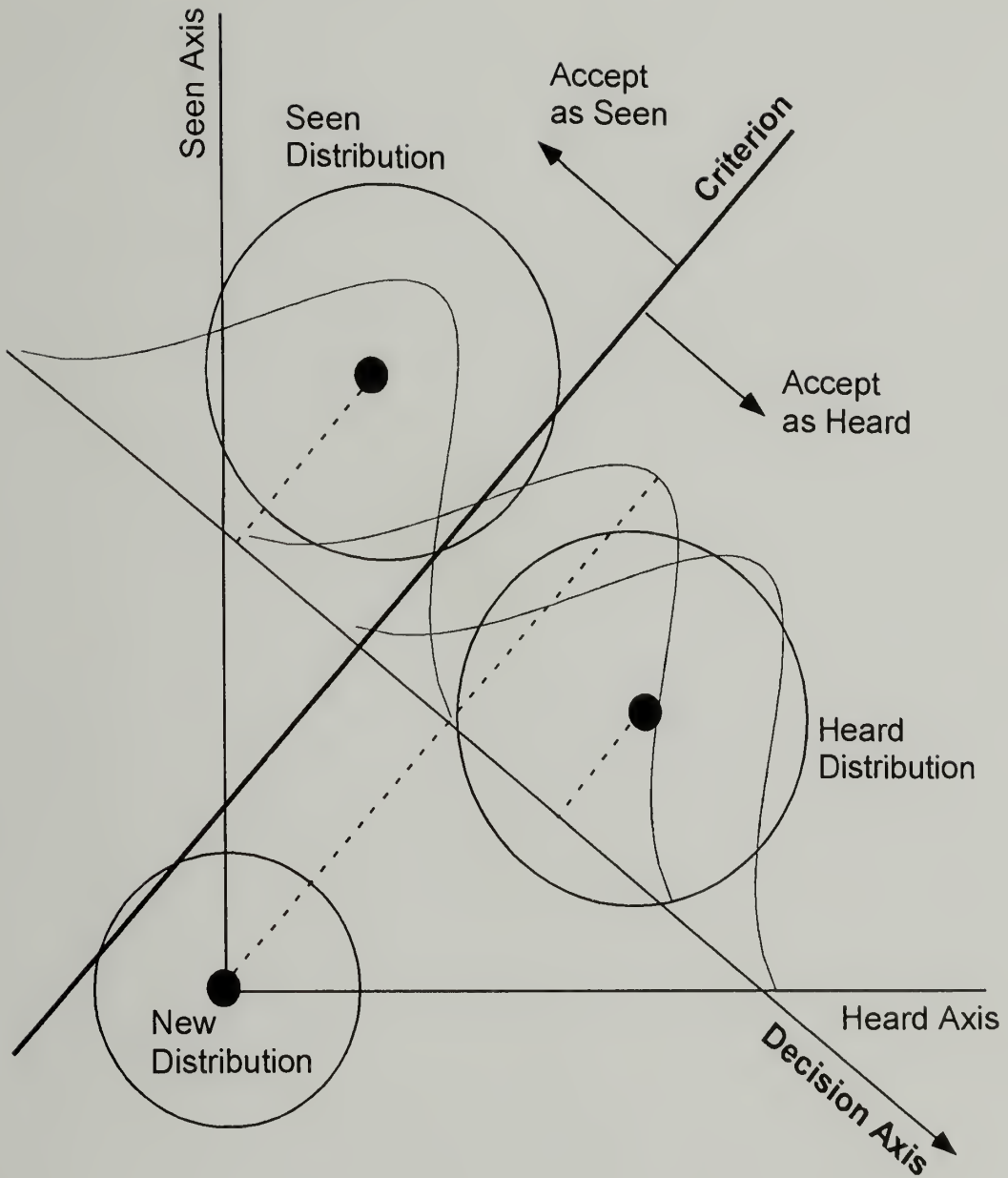


Figure 3. Multi-dimensional representation of source memory derived from the Figure 2 (b). The three distances are arranged in a bivariate normal space. Projections are shown for constructing a decision axis, along which a criterion is placed for discriminating Seen items from Heard items.

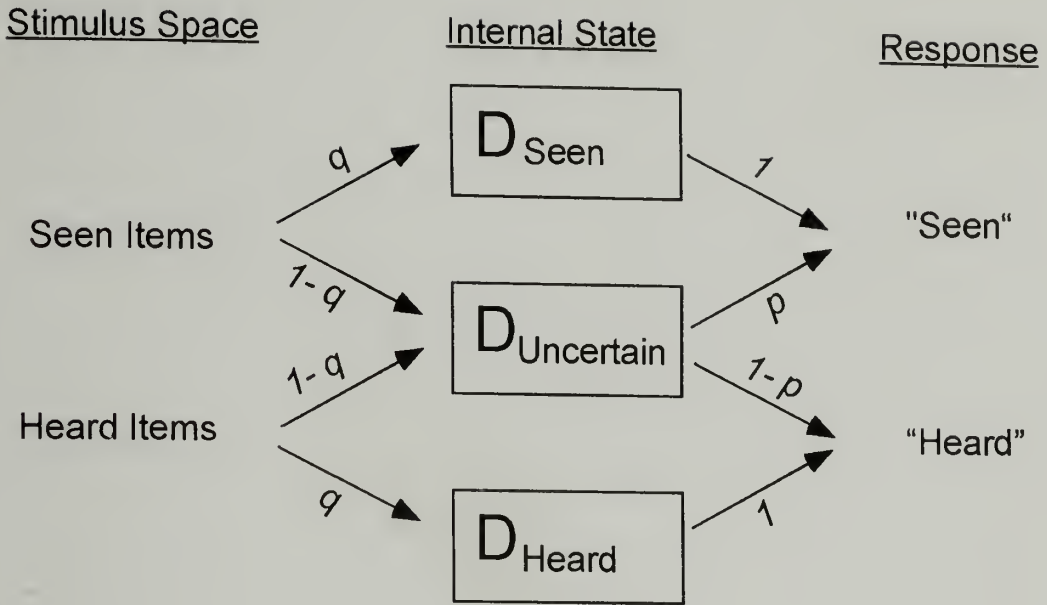


Figure 4. State diagram implied by double-high threshold model. Seen items lead to Seen State with probability q , and to Uncertain State with probability $(1-q)$. The Uncertain State leads to a "seen" response with probability p , to "heard" response with probability $(1-p)$.

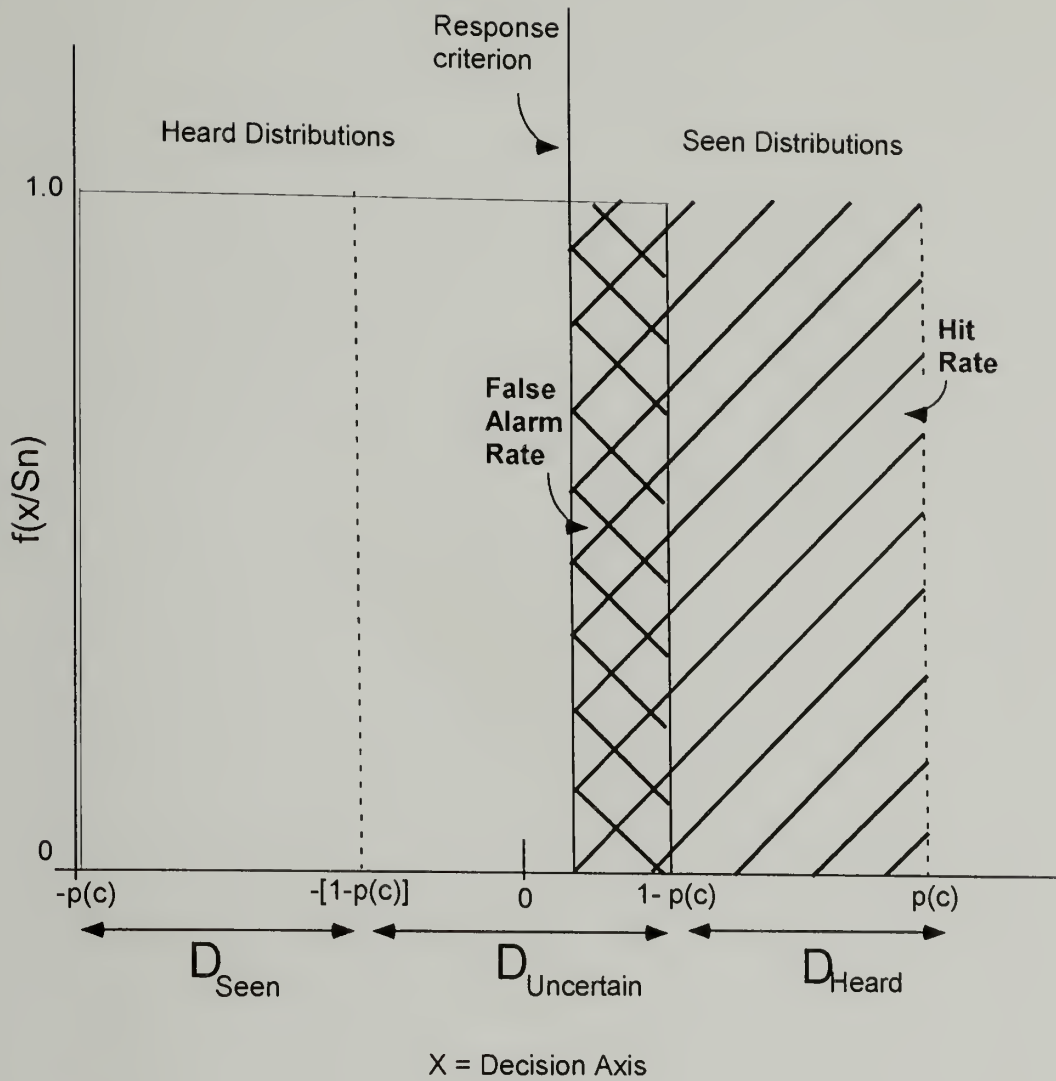


Figure 5. Underlying rectangular distributions consistent with double-high threshold model. Shaded areas are “seen” responses.

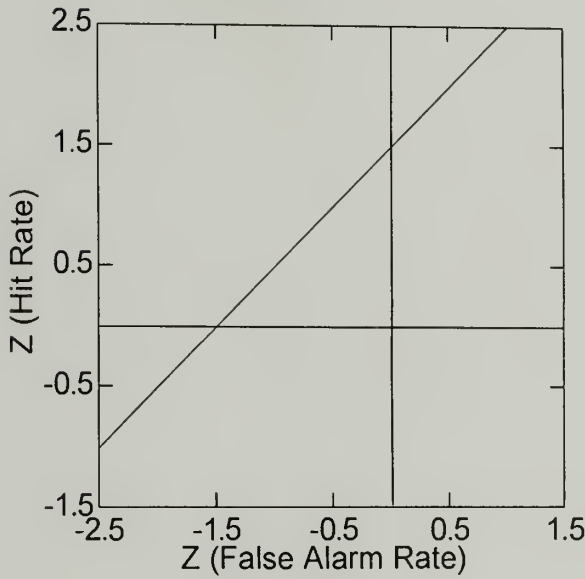
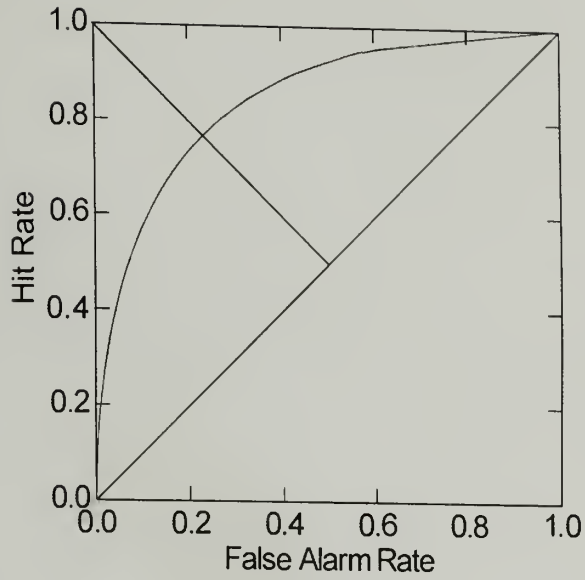
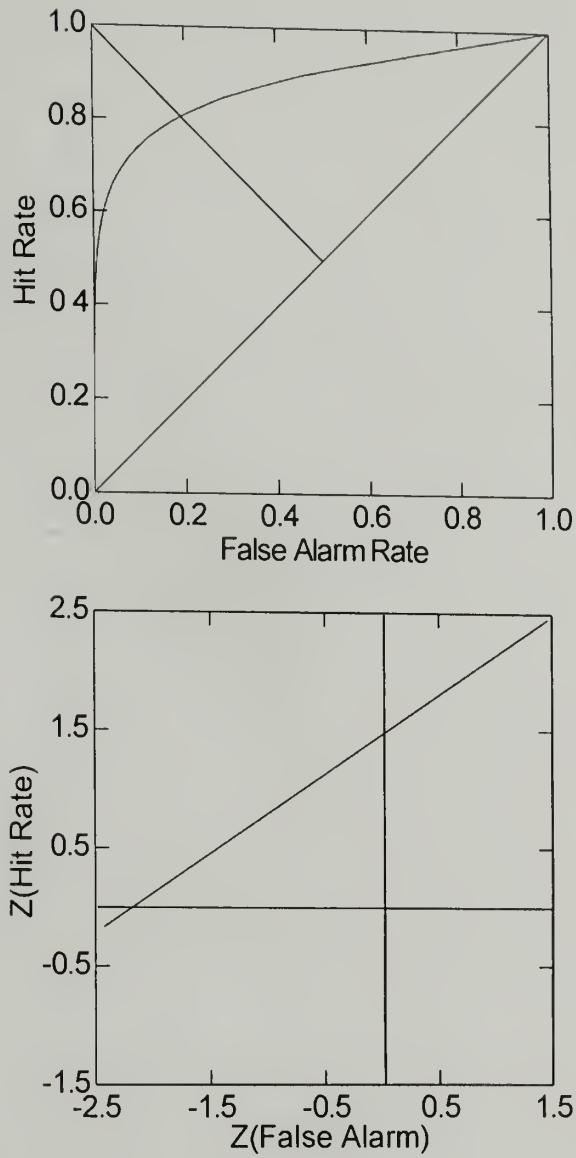


Figure 6. (a) Predicted source receiver operating characteristics (ROCs) for equal variance single-dimensional signal detection model. The ROCs are plotted in probability space and z-space on top and bottom panels, respectively.

(Cont. next page)



(Figure 6, cont.)

(b) Predicted source (ROCs) for unequal variance single-dimensional signal detection model. The ROCs are plotted in probability space and z-space on top and bottom panels, respectively.

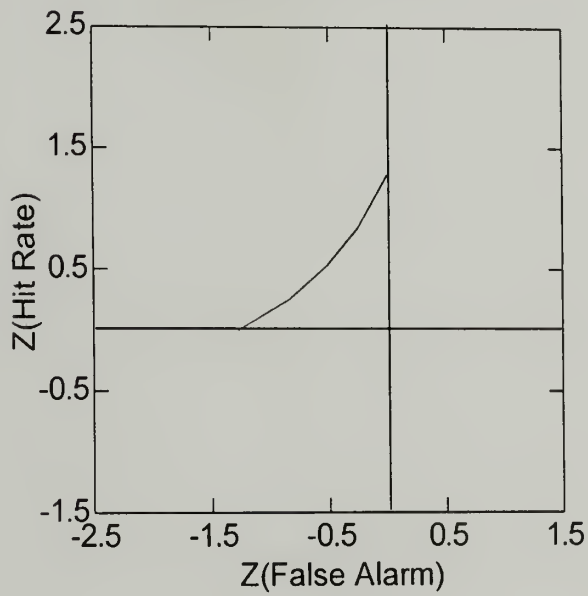
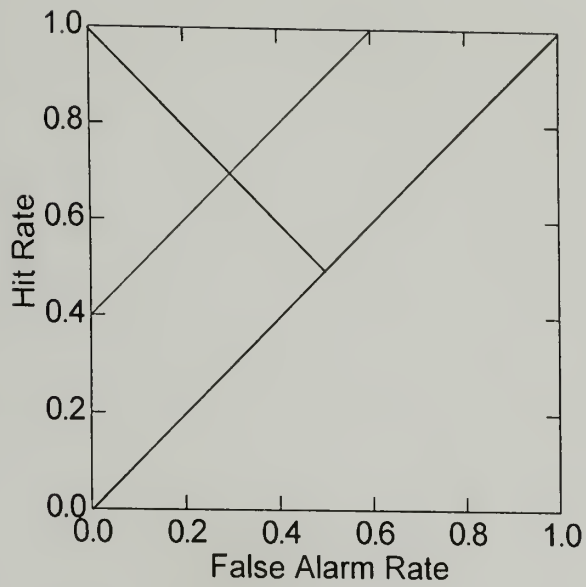


Figure 7. Predicted source receiver operating characteristics (ROCs) for double-high threshold model. The ROCs are plotted in probability space and z-space on top and bottom panels, respectively.

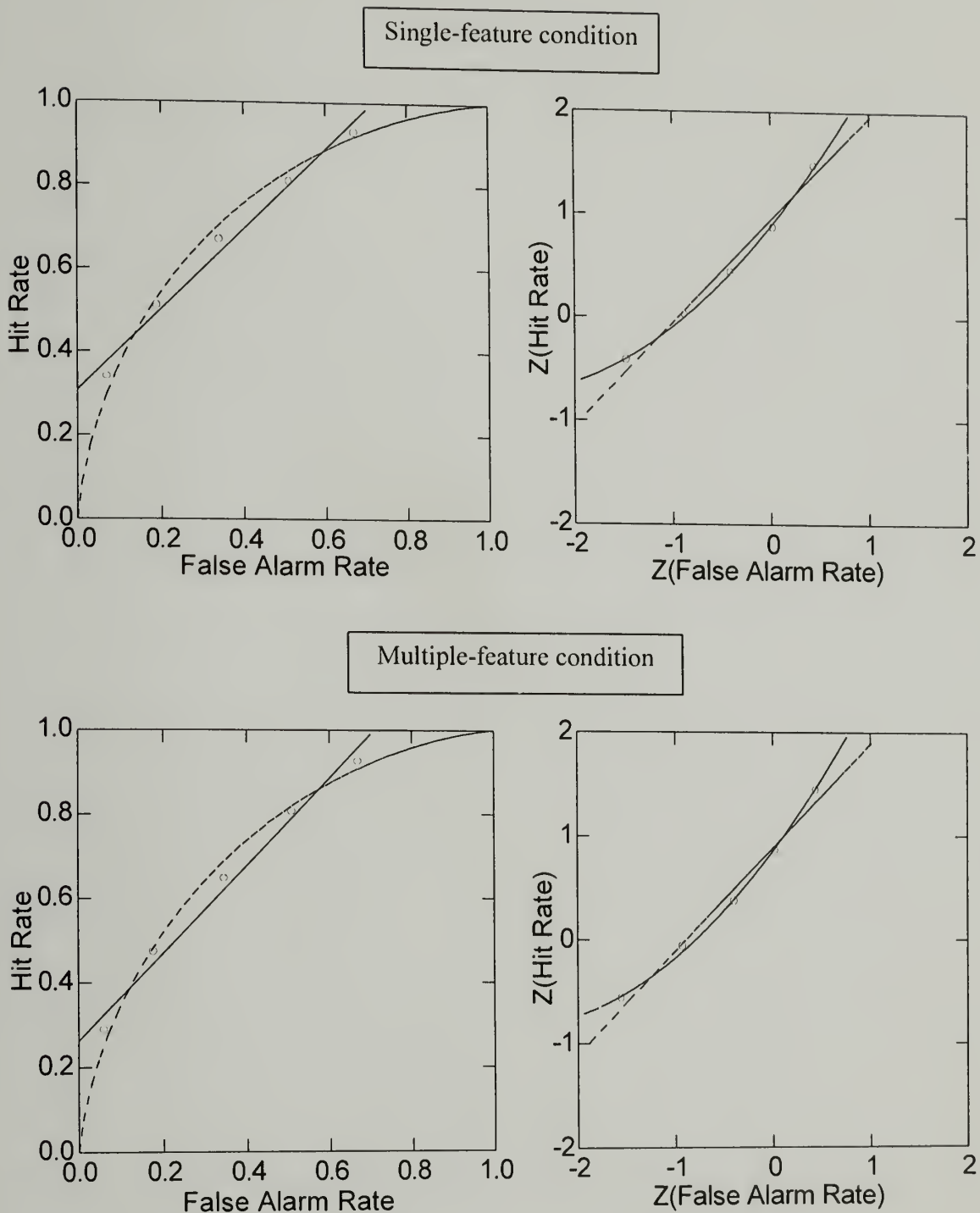


Figure 8. Source receiver operating characteristics (ROC) and source z-ROC for the two conditions in Experiment 1. The solid line is the best fitting ROC curve generated by the Dual-process model; the broken line is the best fitting curve generated by the Gaussian signal-detection model.

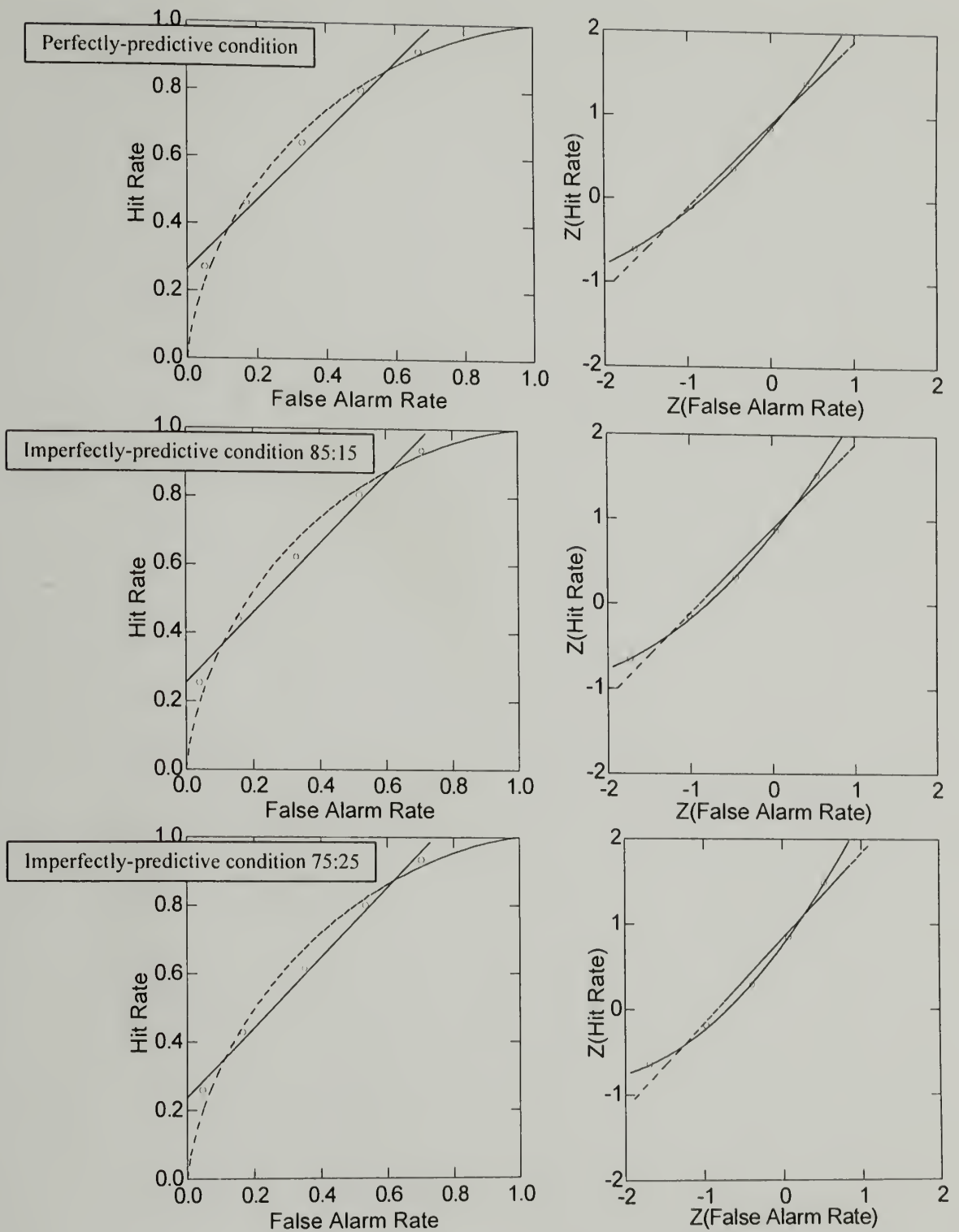


Figure 9. Source receiver operating characteristics (ROC) and source z-ROC for the three conditions in Experiment 2. The solid line is the best fitting ROC curve generated by the Dual-process model; the broken line is the best fitting curve generated by the Gaussian signal-detection model.

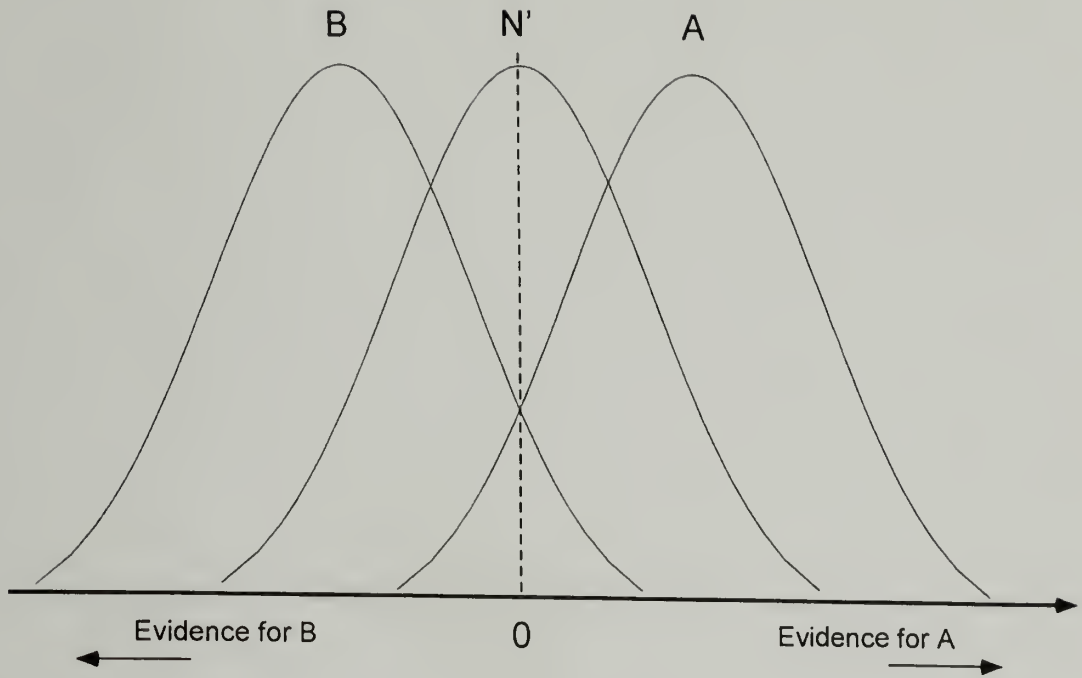


Figure 10. Mixture normal SDT model for source discrimination. A is the distribution of items from Source A, B is the distribution of items from Source B, and N' is the distribution of items for which the sources are unattended to. The three distributions have been projected on a decision axis.

APPENDIX:

COUNTS PER CONFIDENCE CATEGORY

	Confidence Category					
	"sure left"	2	3	4	5	"sure right"
<u>Experiment 1</u>						
Single-feature						
Target (left)	31	155	145	132	111	64
Lure (right)	6	109	141	152	151	302
Multiple-feature						
Target (left)	29	194	180	165	125	77
Lure (right)	6	122	176	169	168	343
<u>Experiment 2</u>						
Perfectly-predictive						
Target (left)	29	207	195	172	127	89
Lure (right)	5	130	173	184	181	356
Imperfectly-predictive (85:15)						
Target (left)	30	223	218	221	157	77
Lure (right)	5	140	207	229	226	348
Imperfectly-predictive (75:15)						
Target (left)	32	209	230	231	165	84
Lure (right)	5	150	230	225	211	367

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