State-Trace Analysis of Associative Recognition:

Comparing Single-Process and Dual-Process Models

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February 2014
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Abstract

The aim of this thesis is to investigate competing explanations of the processes underlying associative recognition. Like recognition memory for individual items, associative recognition is currently understood through two different classes of model. The first is the single-process model class which holds that associative recognition decisions are based on a continuum of associative memory strength. The second is the dual-process model class, which holds that associative recognition decisions are based on two sources of information, called familiarity and recollection. Familiarity is conceptualised as a fast-acting, context-free ‘feeling of knowing’, while recollection is said to be a slower, more conscious process allowing for the recall of detail and context. Familiarity may play a role in associative recognition through a mechanism called unitisation, whereby two distinct stimuli are bound into a single individual memory trace.

State-trace analysis is a method to determine the number of latent variables or processes that contribute to performance on a set of tasks, under mild assumptions. A critical diagnostic feature is the dimensionality of the state-trace plot – a plot of performance on one dependent variable against the other. If associative recognition depends on a single latent variable then manipulation of experimental factors affecting memory should result in a unidimensional state-trace plot. If associative recognition depends on two or more latent variables which are differentially affected by the experimental factors then a bidimensional state-trace will result. State-trace analysis therefore provides a method of discriminating a class of single-process models from a class of dual-process models.
State-trace analysis was applied to associative recognition in four experiments. Each experiment utilised two independent variables that previous research had suggested could differentially affect familiarity and recollection. Experiment 1 investigated associative recognition of word pairs by manipulating attention and study presentation frequency. Experiments 2 investigated associative recognition of word pairs under conditions designed to encourage unitisation by pairing an encoding-based unitisation manipulation with a working memory load manipulation. Experiment 3 manipulated the same unitisation instructions as well as varying study time. Experiment 4 examined the effect of unitisation using pairs of faces and manipulated visual similarity and study time.

State-trace analysis of the four experiments consistently revealed unidimensional state-trace plots. Using a recently developed monotonic regression statistical test, unidimensionality could not be rejected at either aggregate or individual participant level. Therefore, no evidence was found for the differential activation of familiarity and recollection in associative recognition. The results of this thesis are therefore consistent with a single-process account of associative recognition. These results also pose a challenge to dual-process models to identify alternate experimental manipulations that reveal the involvement of different component processes such as recollection and unitized familiarity.
Declaration

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for joint-award of this degree. I give consent to this copy of my thesis, when deposited in the University Library, being made available for loan and photocopying, subject to the provisions of the Copyright Act 1968. I also give permission for the digital version of my thesis to be made available on the web, via the University's digital research repository, the Library catalogue and also through web search engines, unless permission has been granted by the University to restrict access for a period of time.

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February 2014
Acknowledgements

Many people have provided support throughout my candidature, and I hope that this section may provide some measure of gratitude for the help that has been so graciously provided to me these past few years.

First, I would like to extend thanks to The University of Adelaide for providing the necessary resources, funding and structured development that led to me to and through my candidature. Many thanks especially to the teaching staff of Psychology and Philosophy who provided so much insight, guidance and inspiration.

I would like to thank my supervisors, Dr Anna Ma-Wyatt and especially Professor John Dunn. Without John, my candidature would have been far less rewarding and I owe a great deal of professional and personal development to his sustained efforts. I have learned a great deal from John and I am greatly appreciative of being able to serve under his supervision.

To Fernando, Victoria, Angela, Rachel, Dragana, Annemarie, my friends from the lab, with whom were had many enjoyable meetings, lunches and various other social events I will always remember. A special mention to my friend Matt, whose contact helped preserve my sanity.

And finally to my mother, who suffered through conversation after conversation about monotonicity and parameter estimation and various other topics, ever the patient sounding board. Of her continued support, both emotionally and financially, I am deeply grateful.
Associative Recognition Memory

Associative recognition memory is recognition memory for the co-occurrence of two items. Studies investigating associative recognition are frequently conducted by asking experiment participants to study pairs of pictures, faces or words such as PENDULUM-WINDOW, REMOTE-COMPUTER and ISLAND-SCISSOR. Following a variable retention interval, participants are then shown a list of items in which some pairs have remained unchanged from the study phase (e.g. PENDULUM-WINDOW), and others have been rearranged (e.g. REMOTE-SCISSOR). Participants are asked to discriminate which pairs are intact from those that are rearranged, and associative recognition memory can be conceptualised as the ability of people to accurately perform this discrimination. To assess associative recognition performance, researchers will frequently analyse hits (correct discrimination of intact pairs or targets) and false alarms (incorrect discrimination of rearranged pairs or lures). Associative recognition memory is distinct in the wider context of memory research because unlike item recognition, in which individual studied items are discriminated from individual new items, participants discriminate rearrangements of previously seen items and no new items are introduced at test. Since the participant can seemingly not rely on their memory of each individual item (since all individual constituents of test pairs have been previously studied), participants must instead use an association between the two items to successfully discriminate intact from rearranged pairs.
1.1 Associations, Associative Memory & Associative Information

The roots of recent investigation into associative recognition memory stretch back to when the behaviourist paradigm was still at the fore of psychological research. At this time, associative memory was understood as an application of stimulus-response learning (e.g. Martin, 1967). The principal experimental task was paired-associate learning. In this procedure, a participant studies a list of stimulus pairs, then after a short break the participant is shown the first item of the pair, and is asked to generate the missing item to complete the pair. This procedure would today not be considered the study of associative recognition; the generative nature of the test phase would mark it as recall instead of recognition, and the two are usually considered distinct constructs (e.g. Haist, Shimamura & Squire, 1992). At this time, recognition was considered the domain of item recognition (Murdock, 1974), and the kinds of processes involved in item recognition were thought distinct to those involved in associative memory.

The behaviourist empirical tradition was succeeded by the cognitivist framework, and with it came renewed investigation into associative recognition memory. However, the development of a cognitivist framework for investigating associative memory did not mean the abandonment of the kind of experimental design seen in Martin (1967). Paired-associate learning continued to be a widespread method of inquiry into associative memory and was utilised throughout the 1970s and 1980s, although for a different and more cognition-focused purpose (Murdock, 1974). Rather than serving as an application of the stimulus-response framework, the concept of associative memory was incorporated into computational models of memory. Computational models are mathematical descriptions of how the processes of cognition are functionally realised; in the case of memory, how items are represented, stored and accessed. Ideas from associative memory research helped to
inform the design of computational models such as Murdock’s (1982) theory of distributed associative memory (TODAM).

Out of the paired-associate tradition grew an experimental design that was used to investigate associative memory in a recognition rather than recall context, and which can be viewed as the link between the paired-associate task and the more recent design. This particular task was fairly straightforward: as with the paired-associate task, study lists were again composed of stimulus pairs, and again participants were only shown one item of the pair at test. However, the nature of the test phase decision was distinct. Participants made Old/New discriminations on that single item, but on some trials the other item from the pair was shown alongside the item to be discriminated (Humphreys & Bain, 1983). Experimentation using this design resulted in recognition performance that was better when the original study context was repeated and both items were shown at test (e.g. Tulving & Thomson, 1971). This finding has been taken as evidence that there exist two different sources of information on which recognition decisions can be based: item information and associative information (Humphreys & Bain, 1983).

The possibility of there being two sources of information or processes underlying recognition was an idea under consideration in both item and associative recognition research throughout the 1970s and 1980s (e.g. Mandler, 1980), and here associative recognition research has been useful in driving current conceptions of recognition memory. The distinction between item and associative information materialised in various theoretical guises as, for example, item versus relationship information (Humphreys, 1976) or integrative versus elaborative information (Mandler, 1980), but the general form of the argument remained the same: one source of information/process was recognition-like, the other recall-like, and it was possible that both could contribute to Old/New discrimination. This distinction led to a series of verbal decision models that incorporated
these two sources of information (e.g., Atkinson & Juola, 1973; e.g. Jacoby & Dallas, 1981; Mandler, 1979). These models were an early form of what would now be classed as dual-process models of recognition memory.

1.2 Recent Associative Recognition Research: The Single-Process versus Dual-Process Debate

More recently, Yonelinas (1997) reported the results of three experiments comparing the difference in shape of receiver operating characteristic (ROC) curves produced by versions of the item and associative recognition tasks. An ROC curve is a popular method for summarising and displaying the output of recognition memory experimentation. The curve is constructed by plotting a hit rate (proportion of correctly discriminated targets) against a false alarm rate (proportion of incorrectly discriminated lures) across varying levels of decision confidence (Macmillan & Creelman, 2005). Yonelinas (1997) reported the results of three experiments in which participants studied random pairings of English words then, at test, were shown either a single word or a pair of words. Participants were instructed to discriminate between old and new words when a single word was shown (which is item recognition), and between intact and rearranged pairs when two words were displayed (the standard associative recognition design described above).

The importance of the results of Yonelinas (1997) led to widespread usage of the intact-from-rearranged discrimination task in associative recognition research. This occurred for two reasons: First, the associative recognition ROC curves reported were interpreted by Yonelinas (1997) as linear rather than the curvilinear form usually reported. These were the first reported linear ROC
curves in recognition memory research (Mickes, Johnson & Wixted, 2010). Second, the linearity of these ROCs was predicted by Yonelinas’ (1994) version of the dual-process model, thereby offering major support for the dual-process model class as a viable explanation for associative recognition.

The Yonelinas (1994) dual-process model is situated within a recent debate over the correct description of the structure underlying associative recognition. The associative recognition memory research landscape is currently dominated by competition between two primary contrasting explanations: model classes referred to as single-process and dual-process, with the Yonelinas (1994) dual-process model an example of the latter. These models are instances of formal mathematical decision models that attempt to describe, explain and predict experimental and theoretical data by utilising particular quantitative structures to represent psychological phenomena (Lewandowsky & Farrell, 2011). Within each class are differently structured models that rest on differing assumptions about what characterises associative recognition decisions. Importantly, however, models within each class share one key trait with others from the same class: associative recognition memory is due to the activation of either one or two processes, hence ‘single-process’ or ‘dual-process’. Examples of single-process models include the high-threshold model, the equal-variance signal detection model and the unequal-variance signal detection model. Examples of dual-process models are the high-threshold signal-detection dual-process model and the Xu and Malmberg (2007) dual-process model.

The two leading candidate models of associative recognition are the unequal-variance single-process (UVSD) model (Egan, 1958) and the Yonelinas (1994) high-threshold signal-detection dual-process (HTSD) model. The UVSD single-process model proposes that associative recognition decisions are based on a single, continuous strength-of-evidence axis, while HTSD dual-process model explains associative recognition through two sources of memory information named familiarity and recollection. The historical development and structure of these models is detailed in
the section below. Each model grew out of previous single-process or dual-process models, and they were first designed to account for item recognition before later being extended to associative recognition memory. The account of the UVSD and HTSD models detailed below, therefore, is one of their development in item recognition research followed by a description of their application to associative recognition. The research later presented within this thesis is an attempt to resolve evidence for either the UVSD or HTSD model as the more suitable model of associative recognition.

1.2.1 The Unequal-Variance Signal-Detection Model: Development in Item Recognition

The lineage of the UVSD model can be traced through two earlier single-process models: high-threshold theory and the equal-variance signal-detection (EVSD) model. High-threshold theory (Green & Swets, 1966), which was popular in the mid-20\textsuperscript{th} century (Wixted 2007a), held that old items presented at test either did or did not produce a memory signal according to some probability. Recognition memory therefore could exist in one of two distinct states (on or off), with no continuum existing between them. This is as a discrete-state model. New items produced no memory signal at all and participants either correctly declared new items as “New”, or guessed according to some liberal or conservative criterion, with false alarms attributed to these guesses. The popularity of high-threshold theory diminished because it predicted a linear item recognition ROC curve and empirical item recognition ROC curves have consistently shown evidence of curvilinearity (Wixted 2007a).
Figure 1.1. The equal-variance signal-detection (EVSD) model of item recognition memory. The left distribution represents the strength-of-evidence of new items and is arbitrarily set to a mean of 0 and standard deviation of 1. The right distribution represents the strength-of-evidence of old items and possesses a mean of $d'$ and a standard deviation equal to that of the distribution of new items. The second model parameter $c$ represents the boundary between decisions of “New” and “Old”.
High-threshold theory was succeeded by the EVSD model, which unlike high-threshold theory correctly predicts a curvilinear ROC curve. The EVSD model is an application of Signal Detection Theory (SDT), which models the ability of an operator to differentiate signal from noise. SDT was developed in relation to military radar operator research, and later applied within recognition memory by Egan (1958) and to psychophysics research by Green and Swets (1966). Recent single-process models of recognition memory are an attempt to map the pre-existing parameters of SDT onto the study of recognition memory (Lockhart & Murdock, 1970).

Figure 1.1 above is a graphical representation of the logic underpinning the EVSD model. In SDT terms, the signal to be detected is that produced by an old item at test. Old items are collectively represented by the normal distribution to the right. The noise inherent in this decision is represented by the normal distribution to the left, which is the distribution of strength-of-evidence produced by new items. The lure distribution is arbitrarily centred at 0, with a standard deviation set to 1. This implies that the difference between the means of the distributions, $d'$, doubles as a measure of the mean of the target distribution. A conceptually crucial component of the EVSD and all single-process models is the axis which represents a continuous strength-of-evidence signal. This is in contrast to the high-threshold theory, where memory strength was discrete rather than being a continuous or graded phenomenon.

Participants make Old/New decisions by setting a criterion at a particular location on the memory strength axis. The confidence criterion is represented by the vertical line in Figure 1.1. Items that produce memory strength higher than this criterion are judged “Old” and lower values produce “New” responses. As can be seen in Figure 1.1, false alarms are produced by lure distribution items occurring above the criterion, and misses are those items within the Old
distribution located below the criterion. Multiple confidence ratings for Old/New decisions such as “Sure”, “Probably” and “Possibly” are a simple extension of this conceptualization. Rather than there being one confidence criterion, \( c \), a ratings task would involve the separation of the strength continuum by \( c_1 \) through \( c_{k-1} \), where \( k \) is the total number of confidence categories. Participants are assumed to vary the placement of criterions according to factors such as reward payoff and list composition.

The EVSD model for item recognition is formally defined below in equations (1) and (2). \( f(c) \) and \( h(c) \) are the false alarm and hit rates for a given decision criterion, \( c \). \( \Phi \) is the normal cumulative distribution function, corresponding to the area of the normal distribution to the left of a particular value (Macmillan & Creelman, 2005). In this context, \( d' \) represents the distance between the old and new distributions. A higher value of \( d' \) indicates a greater distance between distributions and therefore better recognition memory performance.

\[
f(c) = \Phi(-c) \quad (1)
\]

\[
h(c) = \Phi(d' - c) \quad (2)
\]

A key component of the EVSD model is the setting of the variance/standard deviation of the old distribution to be equal to that of the new distribution. The validity of this, however, has been challenged on empirical grounds in a review conducted by Ratcliff, Sheu and Gronlund (1992). According to the principles of SDT, an equal ratio of new distribution standard deviation to old distribution standard deviation implies a zROC (a plot the z-transformed hit rate against the z-transformed false-alarm rate (Macmillan & Creelman, 2005)), with a unit slope and a symmetrical
Figure 1.2. The unequal-variance signal-detection (UVSD) model of item recognition memory. The left distribution represents the strength-of-evidence of lure items and is arbitrarily set to a mean of 0 and standard deviation of 1. The right distribution represents the strength-of-evidence of target items and possesses a standard deviation equal to $s$ and a mean of $d'$. The final model parameter $c$ represents the boundary between decisions of “New” and “Old”.
ROC curve. A meta-analysis of empirical ROC curves demonstrated that ROC curves tend toward asymmetry and zROCs generally do not possess a unit slope. Rather, the slope of zROCs was shown to be approximately .8 (Ratcliff, Sheu & Gronlund, 1992). This implies an old distribution standard deviation of approximately 1.25 times that of the new distribution (Wixted, 2007a), a direct rebuke of a fundamental component of the EVSD model.

The response to Ratcliff, Sheu and Gronlund’s (1992) evidence that empirical ROC curves are asymmetrical and zROCs do not possess a unit slope is shown above in Figure 1.2. This is the unequal-variance signal-detection (UVSD) model. Conceptually, this model is equivalent to the that ROC curves tend toward asymmetry and zROCs generally do not possess a unit slope. Rather, the slope of zROCs was shown to be approximately .8 (Ratcliff, Sheu & Gronlund, 1992). This implies an old distribution standard deviation of approximately 1.25 times that of the new distribution (Wixted, 2007a), a direct rebuke of a fundamental component of the EVSD model. EVSD model in all respects save the variance of the old distribution, which is greater than the variance of the new distribution.

\[
f(c) = \Phi(-c) \quad (3)
\]

\[
h(c) = \Phi\left(\frac{d' - c}{s}\right) \quad (4)
\]
Conceptual explanation for the old distribution’s increase in variance is as follows: when participants study a list of items, the memory strength added to each item is itself a random variable, with randomness attributed to factors such as participant attention variability and individual item memorability difference (Wixted, 2007a). The UVSD model is formally defined above in equations (3) and (4). Equation (4) extends equation (2) by including an $\sigma$ parameter when defining hit rates for $c$. This parameter represents the standard deviation of the old distribution.

1.2.2 The Unequal-Variance Signal-Detection Model: Application to Associative Recognition

The UVSD single-process model of associative recognition is a direct application of the UVSD model of item recognition described above (Wixted 2007a). The mechanics of this application can be seen below in Figure 1.3. This extension of model to an associative recognition context is relatively simple: the lure/new distribution is replaced with a distribution of rearranged pairs, and the target/old distribution is now the intact distribution. As with item recognition, associative recognition decisions are made through placement of a criterion on a continuum of memory strength. If the memory signal exceeds the criterion, participants respond “Intact”, and otherwise “Rearranged”. Both distributions are still normal in shape and it is assumed that the intact distribution has a higher variance that the rearranged distribution (Wixted, 2007a). Furthermore, the false-alarm and hit rate model equations shown above in (3) and (4) also apply to associative recognition decisions.
Figure 1.3. The unequal-variance single-process (UVSD) model applied to associative recognition judgements. The left distribution represents the strength-of-evidence of rearranged pair associative information and is again arbitrarily set to a mean of 0 and standard deviation of 1. The right distribution represents the strength-of-evidence of intact pair associative information and possesses a standard deviation equal to $s$ and a mean of $d'$. The final model parameter $c$ represents a decision criteria that forms the boundary between decisions of “Rearranged” and “Intact”.

"Rearranged"  \hspace{1cm}  $c$  \hspace{1cm}  "Intact"

$0$  \hspace{1cm}  "Rearranged"  \hspace{1cm}  $c$  \hspace{1cm}  "Intact"  \hspace{1cm}  $0$

$0$  \hspace{1cm}  $s$  \hspace{1cm}  $d'$  \hspace{1cm}  $0$  \hspace{1cm}  $0$
A primary feature of the UVSD model of associative recognition is that it assumes one key point about recognition memory decisions: discrimination judgements are based on only one source of memory information. While the UVSD model allow more than one model parameter to vary (i.e., \( c \) and \( s \) are either free parameters or constrained to vary in relation to memory strength), recognition memory is conceptualised as one distinct construct: a continuous memory strength signal.

1.2.3 The High-Threshold Signal-Detection Model: Development in Item Recognition

The results of recognition memory experimentation are often interpreted within a framework which is in direct competition with the single-process model. This fundamentally different way of understanding and explaining recognition memory performance is the dual-process class of models. These models conceptualise recognition memory as being composed of not one underlying process but by two processes - two distinct sources of information which people use to make recognition memory judgements.

The Butcher on the Bus (Mandler, 1980) is a thought experiment often used to illustrate the concepts underlying dual-process models of recognition memory (e.g. Curran, 2000), and to offer a sense of the intuitive nature of the constructs involved. The thought experiment is as follows: imagine you are on a bus and you see a fellow passenger. This person provokes a sense of familiarity in you; you seem to know this person, but you cannot quite remember who they are. Later that day, you attend your local butcher’s shop and are struck by the sight of your local butcher – you realise now that this was the familiar person on the bus. Why did you seem to know the butcher on the bus,
but failed to *recognise* him? Why did a change of location help you to reach full recall? Dual-process theorists explain this phenomenon with appeal to context (Mandler, 1980). The original memory or representation of the butcher was formed in a specific context – the butcher’s shop – a context that was lacking while you were on the bus. Experiencing the butcher in an unusual context only provided a sense that this person had been known previously but, lacking correct context, this was insufficient for full recollection. The take home message, however, is simply the notion that an individual is capable of *knowing without recollection*, and, conversely, *recollecting with full detail*.

The Butcher on the Bus narrative illustrates the basic, most general properties of the two components of a dual-process theory of recognition memory: *Familiarity*, the ‘feeling of knowing’ and *recollection*, the conscious, context-dependent access of detail. Familiarity is conceptualised as a fast process in which an object or event’s status as previously encountered can be inferred without access to retrieval of details associated with the study episode. The dual-process conception of familiarity is often conceptualised as similar in nature to the single-process model of recognition memory; that is, a continuum of memory strength (e.g. Yonelinas, 1994). In contrast, recollection is conceptualised as a slower process in which specific details such as context are made consciously available for decision-making (Yonelinas, 2002). Recollection and familiarity are generally proposed to provide different sources of information for recognition memory decisions and influence decision outcomes independently (Curran, 2000).

Dual-process models have existed in various verbal forms since the period in which the EVSD model was dominant; iterations of the dual-process model have been described since the late 1960’s, when the possibility of two processes explaining a data set was hinted at in a discussion of categories and recall performance by Mandler, Pearlstone and Koopmans (1969). Mandler later produced a more concrete conceptualisation (e.g., Mandler, 1979, 1980), while other important and
influential dual-process models were produced by Atkinson (e.g., Atkinson & Juola, 1973), and Jacoby (e.g. Jacoby & Dallas, 1981).

The dual-process models listed above share certain similarities in their conceptualisations of familiarity and recollection. For example, in the models proposed separately by Mandler, Jacoby and Tulving, familiarity is faster than recollection and each process is activated concurrently. Similarly, they conceptualised familiarity and recollection as existing and operating independently of one another. Atkinson, however, proposed that while familiarity is indeed faster than recollection, recollection is only activated once familiarity has failed; consequently recollection is tied to familiarity and therefore not entirely independent. Additionally, each model describes familiarity as a continuous rather than discrete process. This continuous nature of familiarity was defined by Jacoby as a signal-detection-like process, mirroring single-process models. Jacoby also explicitly stated that familiarity is an automatic process, while recollection is consciously controlled, a feature largely ignored by the other theorists but which is nonetheless compatible with their models (Yonelinas, 2002).

Certain key differences between these models also exist. For example, theorists disagree on how best to characterise the forgetting rates of each process. Each model is in agreement that information contained within familiarity is assumed to degrade more quickly than recollected details, but there is disagreement regarding when this difference becomes apparent (Yonelinas, 2002). The most relevant point of disagreement between these models, however, is whether each process can learn novel information and form associations between concepts; that is, can each process support the kind of learning one finds in an associative recognition task. Both Atkinson and Mandler treat familiarity as the activation of previously learned concepts and recollection as the only process in
which new concepts can be formed. Tulving and Jacoby, however, argue that both familiarity and recollection can support the learning of novel information (Yonelinas, 2002).

The models described above were influential in their time and continue to have an impact to this day, particularly because of the way they have been used to interpret neuroimaging data (Yonelinas, 2002). However, the nature of recent competition between single and dual-process models, and the progress made because of it, is largely because of the work done by Yonelinas (1994) to provide a mathematical description of a dual-process model. In reaction to the characterisation of ROC curves as asymmetric by Ratcliff, Sheu and Gronlund’s (1992), Yonelinas (1994) provided the first formally described dual-process model which, like the UVSD model, also predicted an asymmetric ROC curve. The introduction of the Yonelinas (1994) model meant that, for the first time, both single and dual-process models were capable of providing specific predictions about ROC curve recognition memory data (Wixted, 2007a).

Yonelinas’ (1994) dual-process model is the high-threshold signal-detection (HTSD) model. Like Jacoby before him, Yonelinas (1994) conceptualised familiarity within a signal-detection framework, characterised by the EVSD model discussed above. In this model, familiarity is still a feeling-of-knowing, detail-bereft notion of prior experience, but one that is conceptually captured by a continuum of memory strength, equal-variance lure/target distributions and confidence criterion, in (exactly) the same way that all recognition memory decisions are understood in the EVSD model. However, in contrast to the EVSD model, participants may also make recognition memory judgements based on a second process: recollection. Yonelinas’ (1994) model conception of recollection assumes it to be an all-or-none retrieval process, by which it either completely succeeds or completely fails, with no gradient between the two states. The recollection component of the HTSD model is essentially high-threshold theory discussed in the single-process section above. Both
processes can contribute to recognition decisions, with successful recollection leading to high confidence decisions.

The equations for the HTSD model are given below in equations (5) and (6):

\[
f(c) = \Phi(-c) \tag{5}
\]
\[
h(c) = r + (1 - r) \Phi(d' - c) \tag{6}
\]

The false alarm rate for a given decision criterion, \( f(c) \), reduces to the same mathematical structure as the EVSD model because it is assumed that recollection has failed (otherwise it would be a hit). For the hit rate given a particular criterion value, \( h(c) \), \( r \) represents the probability of recollection occurring. If recollection fails – the probability of which is \( 1 - r \) – hits are expressed as \( \Phi(d' - c) \), i.e., familiarity or, again, the EVSD model’s equation for an item recognition hit rate.

The HTSD model accounts for asymmetry in ROC curves with the variable presence of recollection. Recognition memory decisions based on recollection are accompanied by conscious awareness of detail, which in turn leads to high confidence in these decisions as participants have access to specific information about the study episode. Therefore, recollection increases the proportion of old items declared old with high confidence (Yonelinas, 1994). Concurrently, recollection has no effect on the false alarm rate. As can be seen above in this model’s equations, the false alarm rate is conceptualized as a signal-detection like process, which excludes any probability of recollection activation. This higher rate of participant confidence for old items compared to a null effect on new items, means that when recollection and familiarity are both active in discrimination, the HTSD model predicts an asymmetric ROC curve largely consistent with that seen in Ratcliff,
Sheu and Gronlund’s (1992). When discrimination is based solely on familiarity, the HTSD model predicts a curvilinear but symmetrical ROC curve because it reduces to the EVSD model. When discrimination is based solely on recollection, the HTSD model predicts a linear ROC, as the model is reduced to only the high-threshold component.

1.2.4 The High-Threshold Signal-Detection Model: Application to Associative Recognition

The historical utility and impact of associative recognition research is largely tied to the dual-process theory of recognition memory. This is because the single-process versus dual-process debate has long been at the fore of recognition memory research, and associative recognition task can be used to test specific predictions related to the dual-process conceptualisations of familiarity and recollection. In the standard associative recognition task, because each individual item that composes a pair has been seen by a participant in the same study list, and excepting any strength manipulations, the same number of times, under dual-process theory, this implies that individual items each have the same level of familiarity and that familiarity can therefore not be used to discriminate intact pairs from rearranged pairs. Furthermore, the HTSD interpretation of familiarity is a process unable to support the binding together of novel concepts necessary for associative recognition encoding (Yonelinas 1997). Consequently, associative recognition decisions should be based solely on recollection. The original application of the HTSD model to associative recognition was therefore the discrete-state recollection-only model.
Like the high-threshold theory before it, a recollection-only discrete-state model predicts a linear ROC curve; therefore a recollection-only task like associative recognition should be described by a linear ROC. Yonelinas (1997) tested this prediction by asking participants to perform Old/New discrimination and intact-from-rearranged discrimination. The ROC curves produced from this experiment were curvilinear for item recognition but the associative recognition ROC curves were reported as linear – providing support for the HTSD model prediction that associative recognition is accurately described by a discrete-state recollection-only model.

The linearity of Yonelinas’ (1997) associative recognition ROC curves is now considered an unsupported anomaly. The evidence that has accumulated in the time since has shown that associative recognition ROC curves are not linear (e.g., Healy, Light & Chung, 2005; Mickes, Johnson & Wixted, 2010; Qin, Raye, Johnson & Mitchell, 2001; Verde & Rotello, 2004). It should also be noted that the original interpretation of linearity made by Yonelinas (1997) could have potentially been different; the ROC curves reported in Yonelinas (1997) may instead resemble a flattened asymmetric curve. Since a curvilinear ROC implies the activation of either familiarity and recollection or just familiarity, the continued finding of curvilinear associative ROC curves has been taken as a disconfirmation of the recollection-only account of associative recognition. However, as has been noted by Mickes, Johnson and Wixted (2010), associative recognition ROC curves have been shown to tend towards curvilinearity as recognition performance increases and towards linearity as performance decreases. While still not actually linear, empirical associative ROC curves are not as curvilinear as item recognition curves, and this is more apparent when sample memory performance is near-chance. Yonelinas’ (1997) sample performance was particularly poor and consequently his results serve as evidence of the midpoint between linearity and curvilinearity found in poor performance associative ROC curves.
1.2.5 The Single Process versus Dual-Process Debate: Summary

The structure underlying judgements of associative recognition is currently understood in two different ways: the single-process model class and the dual-process model class. The two leading candidate models from within these classes are the UVSD model and the HTSD model. The UVSD model conceptualises associative recognition decisions as due to a single source of information, and while the HTSD model utilises familiarity and recollection as two sources of information, it originally explained associative recognition as due to only the activation of recollection. However, while the UVSD correctly predicted a curvilinear asymmetric ROC curve, the recollection-only component of the HTSD model incorrectly predicted a linear ROC curve. To accommodate the empirical curvilinearity and asymmetry of associative recognition ROC curves, more recent investigation using the HTSD model has argued that both recollection and familiarity may play a role due to an encoding process named *unitisation*.

1.3 Unitisation

Yonelinas (1997) noted that experiment 2 of his study produced an unexpected deviation from linearity, and that one subject in particular exhibited performance which could be described as curvilinear. Yonelinas hypothesised that these may have been instances in which familiarity did in fact play a role in performance due to unitisation, a hypothetical encoding process in which the two
individual items are bound into a single memory trace. As an example of unitisation, Yonelinas considered the English compound word GRAPE-FRUIT. Although presented as a pairing of two words, this is easily thought of as one concept, in contrast to random pairings of more disparate concepts like CAR-MONKEY or SPANNER-CRUMPET. Yonelinas argued that since familiarity can only be used to encode individual items, familiarity may have been activated by the random occurrence of related word pairs like GRAPE-FRUIT, or the isolated ability of a participant to very easily compound random pairings into individual concepts. Thus although recollection was still conceptualised as the only process capable of forming associative links between concepts, familiarity could theoretically support the encoding of a random word pairing under circumstances which facilitated the encoding of that pairing as a unitary concept. As associative recognition ROC curves are empirically curvilinear, and curvilinear ROC curves must be due to the activation of familiarity, the legitimacy of unitisation is central to the viability of the dual-process model as an explanation of associative recognition. Therefore recent associative recognition dual-process research has sought to examine the circumstances under which unitisation may be activated.

Unitisation as a method for controlling the activation of familiarity was first directly explored by Yonelinas, Kroll, Dobbins, and Soltani (1999) in an item recognition task. In this experiment participants studied schematic faces that were constructed to include a full, detailed face together with hair and visible clothing shown to the chest. In the study phase, participants studied each face individually and were instructed to note the relevant characteristics of each person. At test, participants were asked to discriminate faces they had viewed in the study phase from distractor faces formed by swapping the external features (ears, hair, head outline and clothing) of one face, with the internal features of another face (eyes, eyebrows, nose and mouth). This discrimination occurred under one of two conditions: faces were either presented upright or inverted, and this was preserved from study to test. Yonelinas et al. (1999) hypothesised that the upright presentation of
faces allowed them to be coalesced into an individual memory trace during, as might be expected when people normally encode human faces. Inverted faces, however, would remain a series of distinct features and so would not be unitised.

ROC analysis undertaken by Yonelinas et al. (1999) indicated that model estimates of familiarity were significantly higher for the upright condition compared to the inverted condition. Additionally, the ROC curve in the upright condition was interpreted as curvilinear whereas the ROC curve in the inverted condition was interpreted as linear. However, as with the ‘linear’ ROC curves reported by Yonelinas (1997), these ROC curves could feasibly be interpreted as flattened asymmetric curves. Regardless, the study conducted by Yonelinas et al. (1999) has been taken as initial evidence of the direct manipulation of unitisation (e.g. Giovanello, Keane, & Verfaellie, 2006; Jäger & Mecklinger, 2009).

Two recent studies investigated unitised familiarity as conceptualised by Yonelinas (1997), in which word pairs may be encoded as a single concept due to their resemblance to pre-existing English compound words. Quamme et al. (2004) and Giovanello, Keane, and Verfaellie (2006) both conducted associative recognition experiments using study lists composed of randomly paired words such as NIGHT-FENCE, together with compound words such as BASE-BALL. Quamme (2004), like Yonelinas et al. (1999) assessed this through ROC analysis while Giovanello, Keane, and Verfaellie (2006) assessed the input of familiarity through a procedure named Remember/Know, where it is assumed that if a participant responds “Remember”, this represents recollection while responding “Know” represents familiarity in the absence of recollection. In both studies, estimates of familiarity contribution were higher for the compound word condition as expected if these compound words had been unitised. However, as noted by Jäger and Mecklinger (2009), the difference in form of ROC curves (and therefore difference in familiarity contribution) across
conditions in Quamme et al. (2004) may have been a function of the substantial differences in sample memory performance rather than the activation of unitisation.

Quamme, Yonelinas and Norman (2007) investigated the effect of unitisation on the associative recognition of participants with hippocampal damage (amnesic patients). The aim of the study was to determine whether unitised encoding could result in better associative recognition performance in amnesic patients and to determine whether this difference was manifested as an increase in familiarity. Previous research has suggested that familiarity is associated with activation of the perirhinal cortex activity while recollection is associated with activation of the hippocampus (Quamme, Yonelinas and Norman, 2007). By extension, patients with sufficient hippocampal damage should be unable to use recollection for associative recognition and must rely on familiarity. Therefore, if a patient with hippocampal damage is capable of associative recognition under unitised encoding conditions, this suggests that unitisation reflects the activation of familiarity.

The study conducted by Quamme, Yonelinas and Norman (2007) also aimed to extend the methods through which unitisation can be manipulated. In line with the original speculation by Yonelinas (1997), previous research by Quamme et al. (2004) and Giovanello, Keane, and Verfaellie (2006) manipulated unitisation through use of pre-existing compound words such as BLACK-BIRD. However, associative recognition is more often investigated using random, arbitrary pairings of words. Consequently, Quamme, Yonelinas and Norman (2007) investigated whether unitisation could also be manipulated using the random word pairings that are usually the focus of associative recognition research. Unitisation for word pairs was manipulated through an encoding frame shown with each study pair. In the unitised condition, the study pair was presented with a sentence that linked the words in some way. For example, the word pair CLOUD-LAWN may have been accompanied by the definition "A yard used for sky-gazing." Sentences accompanying word pairs
from the unitised condition were constructed such that the second word was the main noun and the leading word was used to modify that noun (Quamme, Yonelinas & Norman, 2007). In the non-unitised condition, the word pair was accompanied by a sentence that included the items comprising a pair. For example, CLOUD-LAWN may have instead been shown alongside “The _____ could be seen from the ______.” Testing was performed on amnesic patients together with age-matched controls, young controls and left temporal lobotomy patients.

ROC analysis performed by Quamme, Yonelinas and Norman (2007) indicated that for word pairs presented in the non-unitised condition, amnesic patient associative recognition performance was close to chance, as well as being worse than left temporal lobotomy patients and substantially worse than both control groups. However, for word pairs presented in the unitised condition, performance was better than left temporal lobotomy patients and though again worse than both control groups, showed moderate associative recognition performance. The amnesic patient ROC curve for words presented in the unitised condition was also more asymmetric and curvilinear. This increase in associative recognition performance quality was only demonstrated by the amnesic patients, suggesting that amnesic patients cannot perform the encoding necessary for associative recognition except under unitised encoding conditions. This also indicated that for amnesic patients, the use of sentence frame as a unitisation manipulation was successful. However, the ROC curves obtained for controls displayed similar curvilinearity and asymmetry across conditions, perhaps because performance was at ceiling. Unfortunately, Quamme, Yonelinas and Norman’s (2007) did not provide HTSD model estimates or use a procedure such as Remember/Know when investigating amnesic patients, so whether unitisation increases familiarity estimates in amnesic patients remains an open question.
Like Quamme, Yonelinas and Norman (2007), Haskins, Yonelinas, Quamme & Ranganath (2008) investigated unitisation as it related to activation of the perirhinal cortex and hippocampus. Haskins et al. (2008) proposed that if encoding with unitisation is successful and activated familiarity, this would be due to increased activation of the perirhinal cortex. However, rather than using amnesic patients, (non-amnesic) participants in Haskins et al., (2008) performed associative recognition judgements while scanned with functional magnetic resonance imaging (fMRI). Haskins et al., (2008) built on the research conducted by Quamme, Yonelinas and Norman (2007) by manipulating the unitisation of random word pairings with the same encoding frames used previously, and provided HTSD model estimates across different unitisation conditions.

The results of fMRI analysis provided support for the main prediction made by Haskins et al., (2008): word pairs in the unitised condition showed an increase in perirhinal cortex activity compared to word pairs in the non-unitised condition. The results of HTSD model-fitting also provided support for the dual-process account of unitisation, as estimates of familiarity were higher for ROC curves obtained in the unitised condition. However, the curvilinearity and asymmetry of ROC curves obtained in the unitised and non-unitised conditions were similar. Since the ROC curves obtained in the non-unitised condition were also curvilinear and asymmetric, this suggests that unitisation contributed to encoding in both the unitised and non-unitised conditions.

Recently, Jäger and Mecklinger (2009) have offered evidence for a different direct manipulation of unitisation. In this study, unitisation was manipulated through the nature of the stimuli itself (in this case, pairs of faces). According to Jäger, Mecklinger and Kipp (2006), which Jäger and Mecklinger (2009) sought to build on, the ease with which individual items can be unitised into a single memory trace is a function of their perceptual ‘overlap’: items which share high perceptual similarity may likely be coalesced into a single trace (although not explicitly mentioned in
either publication, this is essentially the similarity principle from Gestalt Psychology (Wertheimer, 1923)).

Jäger and Mecklinger (2009) manipulated unitisation by varying the similarity of studied face pairs. Participants studied either morphed face pairs or random pairings of human faces, which were taken from a face database their lab had developed earlier (see Jäger, Seiler & Mecklinger, 2005). Morphed pairs represented the unitised condition and random pairings the non-unitised condition. Morphed pairs were constructed by creating multiple groups of four faces from a starting point of two unique faces. For the sake of explication name these two of these unique faces Simon and Mark. At study, Simon was paired with a face that was 35% of Mark and 65% Simon, while Mark was paired with a face that was 70% Mark and 30% Simon. At test, intact pairs were constructed by discarding the original unique faces and pairing the morphed images. In this example, the test pair would be the 35% of Mark and 65% Simon face paired with the 70% Mark and 30% Simon face. Test pairs were constructed this way to control for the similarity between items. Jäger and Mecklinger (2009) hypothesised that the perceptual similarity between each face of the originally studied intact morphed pair meant that at study they could be unitised into a single memory trace, and therefore that the contribution of familiarity would be higher in the unitised condition.

The results obtained by Jäger and Mecklinger (2009) provided some evidence in favour of their hypothesis. HTSD model parameter estimates indicated that the contribution of familiarity was higher for unitised faces compared to non-unitised faces. The results of ROC analysis were also typical of prior findings: ROC curves obtained in the unitised condition showed superior performance compared to ROC curves obtained in the non-unitised condition. Additionally, the ROC curve obtained in the unitised condition showed greater asymmetry and curvature. However, it should be noted that the difference between condition ROC curves was slight, and as with the
results of Quamme, Yonelinas and Norman (2007), the non-unitised ROC curve displayed near-chance performance.

### 1.3.1 Unitisation Summary

To account for the asymmetry and curvilinearity of associative recognition ROC curves, dual-process researchers proposed that familiarity was activated through unitisation, whereby two distinct items could be bound together into a single trace (Yonelinas, 1997). Much research since (Giovanello, Keane, & Verfaellie, 2006; Haskins et al., 2008; Jäger & Mecklinger, 2009; Quamme et al., 2004; Quamme, Yonelinas & Norman, 2007; Yonelinas et al., 1999) has been dedicated to directly manipulating unitisation. Originally, research investigated the proposal by Yonelinas (1997) that unitisation was activated through pre-existing compound words. Recently, however, dual-process researchers have attempted to manipulate the unitisation of random word pairings through encoding sentence frames and the perceptual similarity of faces. Research using these manipulations has been used as evidence that familiarity can in fact be activated through unitisation, and that these factors therefore successfully activate unitisation.

Research into unitisation has generated two consistencies. First, some studies (e.g. Jäger & Mecklinger, 2009; Quamme, Yonelinas & Norman, 2007) produce results in which the unitised condition ROC curve indicates better recognition performance than the ROC curve produced in the non-unitised condition, which is often close to chance performance and has a shape resembling linearity. The unitised condition ROC curve is also markedly more asymmetric and curvilinear. Second, other studies (e.g. Haskins et al., 2008; resulted obtained for controls in Quamme,
Yonelinas & Norman, 2007) produce results in which ROC curves are similar in curvilinearity and asymmetry across unitisation conditions. Both of these consistencies weaken the possibility that unitisation is a conduit to familiarity. First, a study conducted by Mickes, Johnson and Wixted (2010) suggested that empirical associative recognition ROC curves naturally tend towards asymmetry as recognition performance increases and towards linearity as it decreases. Since these previous studies did not attempt direct manipulation of unitisation, these prior results suggest either that unitisation is not necessary to explain this shift in ROC curve shape or that unitisation consistently occurred in these previous studies incidentally. This shift in ROC shape is also parsimoniously accounted for by the UVSD model without the involvement of unitisation as an additional concept: previous research has suggested that as the distance between target and lure distributions increases (that is, performance gets better), the variance of the target distribution increases (Glanzer et al., 1999), resulting in greater asymmetry. Second, if the curvature and asymmetry of ROC curves obtained for word pairs in both a unitised and non-unitised condition is similar (as in Haskins et al., 2008 and resulted obtained for controls in Quamme, Yonelinas & Norman, 2007), it implies that both recollection and familiarity were activated in both conditions. That is, in the condition in which unitisation and therefore familiarity is not supposed to occur, the ROC curve displayed a shape which indicated both recollection and familiarity were activated.

Despite the possibility that unitisation may not be necessary to explain the curvilinearity of associative recognition ROC curves, the results of neuroimaging (e.g. Haskins et al., 2008), together with increases in HTSD model parameter estimates of familiarity for unitised word pairs (e.g. Jäger & Mecklinger, 2009) has lent some support to the explanatory utility of unitisation and therefore the HTSD model as a viable explanation of associative recognition. Because of this, the HTSD model remains a leading candidate model in associative recognition research, and unitisation remains a prominent component of recent dual-process research.
1.4 Other Recent Models of Associative Recognition

While the single-process versus dual-process debate is primarily dominated by competition between the UVSD and HTSD models, other recent attempts have been made to formally characterise the structure underlying associative recognition judgements. Three notable examples of these are the *some-or-none* (SON) model proposed by Kelley and Wixted (2001), the *mixture signal-detection* (MSD) model originally developed by DeCarlo (2002) for item recognition and later applied to associative recognition by Mickes, Johnson and Wixted (2010), and the dual-process model put forth by Xu and Malmberg (2007; see also Malmberg & Xu, 2007).

The SON model (Kelley & Wixted, 2001), has much in common with the UVSD model of associative recognition. Like the UVSD model, the SON model conceptualises associative recognition decisions as due to the placement of a criterion on a single, continuous source of memory strength. Also like the UVSD model, intact and rearranged items convey a measure of this continuous strength, and these items taken together are characterised by two normal distributions. However, the SON model adds to the UVSD model by including a third normal distribution representing the memory strength of the individual items that form each pair. The final source of information that serves as the basis for intact-from-rearranged discrimination is a mix of the information offered by these three distributions. For judgements made on intact pairs, evidence from each individual item is added to the associative evidence produced by the pair. For judgements made on rearranged pairs, item information is subtracted from associative information.
The MSD model (DeCarlo, 2002; Mickes, Johnson & Wixted, 2010) structures the process underlying associative recognition in a similar way to the SON model. Associative recognition decisions are again due to the placement of a decision criterion along a continuous strength-of-evidence axis, and information is provided by normal distributions representing intact and rearranged pairs, along with a distribution representing item information. The primary difference between the SON model and the MSD model is the nature of the information provided by encoding based on the individual items of a pair. In the SON model, the probability of responding “Intact” to an intact pair is increased if individual item information is added to the information provided by the intact pair itself. In contrast, Mickes, Johnson and Wixted (2010) proposed that item information was irrelevant, and item information decreases the probability of correct discrimination for both intact and rearranged pairs. The probability of the involvement of irrelevant item information is due to a parameter representing attention, $\lambda$. When $\lambda$ is at a ceiling of 1, the model reduces to the intact and rearranged distributions, as in the EVSD and UVSD models.

A competing dual-process model of associative recognition has been developed by Xu and Malmberg (2007; see also Malmberg & Xu, 2007). Like the HTSD model, this model characterises associative recognition as due to familiarity and recollection in recognition memory, and conceptualises these two processes in line with other dual-process models. However, in contrast to recent HTSD model investigation, the Xu and Malmberg (2007) dual-process model does not predicate the activation of familiarity in associative recognition on unitised encoding. Rather, the tendency for a participant to rely on either familiarity or recollection (a recall-to-reject strategy in their parlance) is under conscious control by the participant and is a function of the demands of the experimental context. This model conceptualises associative recognition judgements as three steps: first, participants compare the familiarity signal of a test pair with a criterion. If it is lower, they respond “New”, if it is higher, they attempt activation of recollection. If recollection fails, the
participant guesses. If recollection is successful, the participant gains access to details associated with
the test pair and compares these details against those of their encoded items. Participants respond
“Old” to a match and “New” to a mismatch. The participant subjectively controls the activation of
recollection by modifying the placement of the criterion in step one; a lower criterion represents the
deferral of more decisions to step two. In a similar vein to the early work of Yonelinas (1997), Xu
and Malmberg (2007) hypothesise that associative recognition tasks result in more activation of
recollection because activation of familiarity is an inefficient strategy given the similar memory
strength of items in intact and rearranged pairs.

1.5 Model Fitting

The viability of specific associative recognition models is frequently judged with respect to
testable predictions regarding some particular element of experimental output – what can be thought
of as a model’s “signature prediction” (Cohen, Rotello & Macillan, 2008). Due to the particular
mathematical properties of different models, the existence of distinctive experimental output
characteristics or specific patterns of data can be used to support or disconfirm a particular model.
An example of this methodology can be seen in the work of Yonelinas (1997), whose HTSD model
predicted a linear associative recognition ROC curve. Evaluating models through identification of
signature predictions is frequently diagnostic. This has been demonstrated in the time following
Yonelinas’ (1997) initial publication, as the curvilinearity of associative ROC curves has driven a re-
think of the dual-process explanation of associative recognition (that is, unitisation). However,
danger lies in the fragmenting of experimental output space into subdivisions, then emphasising the
value of one subdivision over another purely because it lends support to a particular model; for example, more can be said of an ROC curve than whether it is straight or curved. A method of examining the overall correspondence of model to data goes some way toward avoiding the issues associated with selective attention to particular data patterns, while simultaneously taking into consideration all characteristics of a data set (Cohen, Rotello & Macillan, 2008).

Given the above, the primary method for establishing the viability of a model is to determine the overall numerical proximity of its predictions to empirical data; that is, the fit of a model to data. Assessing model fit is integral to the value of formalizing models in general. In associative recognition, formal models allow for precise mathematical estimates of obtained empirical ROC curves, and consequently, model fit provides an exact quantitative measure of how well a model corresponds to actual associative recognition performance in a given sample. However, as is detailed below, this method has not provided conclusive support for either a single-process or dual-process model as the best candidate model in associative recognition research.

Model fitting in psychological research is akin to tuning the dials on a radio to find the best available signal for a particular station. The variables utilised within a model (its parameters) are given particular values iteratively, such that the resulting outcome of the model is as close as possible to the observed data (Dunn, 2010). This process is known as parameter estimation. Two common methods of parameter estimation used in psychological research are least-squares estimation and maximum likelihood estimation (Myung, 2003). While these methods are underwritten by different mathematical assumptions and techniques, their overall goal is the same: they are used by researchers to provide estimates of model parameters (often for conceptual reasons, as when estimating the contribution of familiarity in unitisation research), minimize the difference between a model’s prediction and a data set, and generate a summary measure of how close the model is to the
observed data. This measure of overall model fit is known as *goodness-of-fit* (GOF). Common GOF measures include chi-square, \(G^2\), and mean squared difference.

### 1.5.1 Single and Dual-Process Model-Fitting in Associative Recognition

Kelley and Wixted (2001) directly examined the HTSD-predicted linearity of associative recognition ROC curves by fitting a variant of the EVSD model that allowed differing contributions of item and associative information and the high-threshold component of the HTSD model. Utilising a standard associative recognition task, Kelley and Wixted (2001) manipulated pair strength within lists by varying study pair presentation frequency, resulting in a weak study condition in which items were studied once and a strong condition in which items were studied six times. The linear recollection component of the HTSD model and the full UVSD model were compared by parameter estimation with Pearson’s chi-square as a GOF measure. For the weak condition, the predictions of both models were significantly different from the data, with the signal-detection model performing slightly better. The strong condition, however, provided strong evidence in favour of the signal detection model. The HTSD model was substantially worse than the signal detection model in this condition. This pattern of model fit was also present for experiments two, three and four, all of which slightly modified the standard associative design present in experiment one but maintained pair strengthening as the core manipulation. Interestingly, the results of model fitting performed on data obtained by Kelley and Wixted (2001) indicate that both the single-process signal detection model and recall-only component of the HTSD model do not correspond well to
standard one-presentation associative ROC data. However, when pairs are strengthened, the signal detection model described the data well.

Healy, Light and Chung (2005) conducted three experiments comparing associative and item recognition performance for young and older participants. The goal of Healy, Light and Chung’s (2005) research was to assess the possible decline of recollection in older participants as a possible explanation for diminished overall performance. Their first experiment used a modified associative recognition task featuring new word pairs as well as intact and rearranged pairs shown at test. Experiments two and three modified this design further by instructing participants to form associations between words, with experiment three intermittently including an item recognition test in place of an associative test phase. Recollection was operationalized and measured in a manner consistent with other research: for each sample, estimates of recollection were obtained through parameter estimation from fitting a dual-process model to the data. Healy, Light and Chung (2005) also fit the unequal-variance signal detection model and Kelley and Wixted (2001) SON model for comparative purposes. Healy, Light and Chung (2005) used maximum-likelihood estimation to minimise the Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Schwarz, 1978). These measures are more commonly used as a means of balancing GOF with model complexity, given that the AIC and BIC penalise models with more free parameters.

Healy, Light and Chung’s (2005) model selection produced a fairly even split between the UVSD model and the Kelley and Wixted (2001) model. The unequal-variance signal-detection model was superior when the BIC was used to assess the superior model, whereas the signal-detection model was superior for the AIC, perhaps suggesting it was penalised for model complexity (single-process models generally score well on measures of relative model complexity (Cohen,
The results of Healy, Light and Chung (2005) have been interpreted as a victory for the curvilinear class of models over models that, at that time, predicted linear associative ROC curves (Wixted, 2007a). This interpretation is supported by a review undertaken by Healy, Light and Chung (2005) in tandem with their experimentation, in which the results of 13 published studies were modelled against linear and curvilinear models, showing support for a curvilinear account. However, the story is more complex than this. Healy, Light and Chung (2005) a priori rejected the notion that familiarity does not play a role in associative recollection, and the dual-process models which they modelled were not constrained to their linear form; the parameters representing both recollection and familiarity were free to vary. Consequently, the results of Healy, Light and Chung (2005) are evidence for the superiority of models that predict curvilinearity in associative recognition data, and the superiority of single-process models over fully-realised dual-process models that predict curvilinearity; that is, the results of Healy, Light and Chung (2005) suggest that even if familiarity may play a role in associative recognition due perhaps to unitisation, the predictions of the UVSD model still fit associative recognition data better.

The fit of the MSD model was examined across two experiments by Mickes, Johnson and Wixted (2010). Experiment one mirrored the strength manipulation used by Kelley and Wixted (2001), with pairs studied either once or five times. Mickes, Johnson and Wixted extended this framework by asking participants to perform a remember/know discrimination on test pairs after assigning a confidence rating to a test pair’s intact/rearranged discrimination. Participants were asked to decide whether they could consciously recollect details of the study event associated with a test pair (remember) or whether the test pair invoked a detail-bereft sense of familiarity (know). The addition of a remember/know discrimination was a direct test of the unitisation hypothesis (e.g. Giovanello, Keane, & Verfaellie, 2006): if, according to this interpretation, curvilinearity in ROCs increases with familiarity activation, a condition resulting in a more curvilinear ROC should result in
comparatively more ‘know’ responses, since ‘know’ is taken to represent familiarity. This manipulation was cross-referenced with the extra addition of a surprise cued-recall task on test pairs, in which one item of a pair was shown and the participant was instructed to provide the remaining item. According to dual-process models cued-recall should correlate with recollection. This HTSD prediction was not matched by data obtained for either Remember/Know or cued-recalled testing, in contrast to the results obtained by Giovanello, Keane, and Verfaellie (2006). The results of Experiment one did not lend support to the dual-process model.

Experiment two of Mickes, Johnson and Wixted (2010) examined the noise distribution assumption of the MSD. Before making intact/rearranged discriminations, participants first completed old/new discriminations on test pairs, regardless of their view regarding subsequent intact/rearranged discriminations. If the MSD model’s assumptions are accurate, pairs judged ‘new’ are pairs for which no associative information is available, and are therefore pairs that possess memory strength values drawn from the noise rather than intact or rearranged distribution. Removing these pairs from ROC analysis should result in a model captured by two strength distributions, rather than three; that is, the MSD model without a noise distribution reduces to the standard signal-detection account.

The MSD and HTSD models were fit with chi-square again used as a GOF measure. Mickes, Johnson and Wixted (2010) fit models to both group and individual data, however, fits to individual data were consistently extremely poor across all models and conditions, ultimately providing no means for model comparison. Interestingly, the UVSD model was not considered a candidate model for assessment because initial fits were so poor. The MSD and HTSD model fits were extremely similar, either fitting extremely well or poorly in a consistent pattern across conditions.
Model fitting by Mickes, Johnson and Wixted (2010) was not useful in discriminating candidate models since fit was consistently poor across all models. However, Mickes, Johnson and Wixted (2010) also asked participants to first provide old/new responses for each test pair, before making an associative recognition judgement. When the ROC curves produced from experiment two were separated according to their old/new rating into groups of either “New”, medium confidence “Old” or high confidence “Old”, the results of model-fitting were more diagnostic. Removing pairs which participants rated as “New” resulted in ROCs well described by the EVSD model. Therefore, although the MSD and UVSD models fit the obtained ROC curves equally well, further analysis lent support to a core prediction of the MSD, that the removal of items forming a noise distribution reduced the extant model to a standard signal-detection account on par with the EVSD model.

It is rare for HTSD GOF measurement to be reported in unitisation research (e.g., Haskins et al. 2008; Jäger & Mecklinger, 2009; Quamme, Yonelinas & Norman, 2007). The approach to modelling used by these researchers is similar in to parts of the work done by Healy, Light and Chung (2005), where the model is fit to the data to estimate parameters for conceptual reasons rather than to generate a GOF measure. This makes some sense in the context of unitisation research, given that estimates of familiarity should be higher in the unitised condition, and detecting this is largely the point of the research. Haskins et al. (2008) did, however, use parameter estimation to estimate unequal-variance signal-detection model parameters, but again, did not provide a GOF measure, making model comparison impossible even though both models were fit to the data.

Model fitting as model specific parameter estimation rather than for purposes of model comparison is also present in the work of Malmberg and Xu (2007). In their analysis, model fitting was performed through minimisation of the mean square difference between the model and the data.
- a fairly simple and broad measure of the proximity of the model to the data. However, this was very specific and highly constrained model fitting. Only the parameter representing the contribution of recollection was allowed to vary, therefore handicapping the explanatory power of the model. Again, this does make some sense in the context of the research; Malmberg & Xu (2007) were addressing the possibility of recollection varying in contribution across tasks, and their modelling reflecting that. However, this usage of modelling as parameter estimation without model comparison leaves little in the way of overall evidence to decide whether this particular model is a more viable option than another. As with parameter estimation of familiarity in unitisation experimentation, the authors simply assume the veracity of the model then use model fitting to make claims about a parameter within that model. This is a problematic considering the existence of viable contemporary models which could easily be extended to the data obtained by Malmberg and Xu (2007).

1.5.2 Model Fitting Summary

The evidence reviewed about does not provide a strong basis for model selection. The UVSD model fits some associative recognition data well (e.g. Healy, Light & Chung, 2005 and the strong condition ROCs in Kelley & Wixted) and other data poorly (e.g. Mickes, Johnson & Wixted, 2010). The HTSD model fits some data well (e.g. the non-conditionised ROC data in both experiments of Mickes, Johnson & Wixted, 2010) and other data poorly (e.g. Healy, Light & Chung, 2005). A constrained form of the MSD model appears to fit data well, but only after reconceptualising associative recognition ROC curves in a novel way by conditionalising them on old/new ratings. To compound the issues surrounding the obtained fit of current models,
Researchers use different measures of GOF (e.g. chi-square versus mean square difference), which are capable of selecting disparate candidate models within the same data set (e.g. the AIC versus the BIC). Still other researchers will fit their models to obtain parameter estimates and not report a GOF measure at all (e.g. Jäger & Mecklinger, 2009).

From the evidence reviewed thus far, comparing individual model fits has not allowed for definitive conclusions to be drawn while model signature predictions have allowed for some progress to be made. For example, the linearity prediction of Yonelinas’ (1994) model has had a substantial impact on subsequent research and model development (Wixted, 2007a). However, signature predictions capable of producing results that clearly decide between models are rare. This is compounded by the introduction of unitisation, which means that both the HTSD and UVSD model currently predict the curvilinearity and asymmetry of empirical associative recognition ROC curves.

A more general method for assessing and differentiating the behaviour of different model classes would offer a means of progress not currently offered by fitting individual models to ROC curves. When using factors that predict the activation of unitisation, the single-process UVSD model predicts that associative recognition is due to one source of information, whereas the dual-process HTSD model predicts that familiarity and recollection will be activated. While model-fitting has been non-diagnostic since both models now predict curvilinear asymmetric ROC curves, the two models make differing claims about the number of sources of information that contribute to performance. Ideally, a method for detecting whether associative recognition performance shows the activation of either one process or two would provide strong evidence for either the HTSD model or UVSD model as the best explanation of associative recognition. A method for detecting the activation of either one or two process is state-trace analysis.
Chapter 2

State-Trace Analysis

2.1 State-Trace Analysis: General Introduction

Introduced by Bamber (1979), and subsequently developed and applied by Loftus (e.g. Busey, Tunnicliff, Loftus, & Loftus, 2000; Loftus, Oberg, & Dillon, 2004) and Dunn (Dunn, 2004; Dunn 2008; Newell & Dunn, 2008; Newell, Dunn & Kalish, 2010), state-trace analysis is a general method for examining the number of mediating psychological variables that govern performance on an experimental task. Given experimental manipulations performed on one or more relevant independent variables or factors, state-trace analysis allows for the quantification of the intervening processes that affect two or more outcome variables. In simple terms state-trace analysis has one goal and one outcome: determination of the number of cognitive “processes,” “systems,” “mental states,” or “sources of information” that underpin the results of an experimental task (Dunn, 2008). This method is used to adjudicate between competing model classes which singularly represent the purported existence of either individual or multiple independent model parameters. This is a debate which frequently occurs throughout cognitive science (e.g. judgments of learning (Jang & Nelson, 2005), contrast and visual memory (Harley, Dillon & Loftus, 2004) and the face-inversion effect (Loftus, Oberg & Dillon, 2004; examples taken from Newell & Dunn, 2008).

Figure 2.1 below is a schematic of the general logic of state-trace analysis. In a standard state-trace analysis experimental design, levels of \( m \) experimental factors are mapped onto \( k \)
Figure 2.1. Schematic outline of state-trace analysis experimentation, showing the mediation of an intervening parameter structure on the relationship between independent and dependent variables. The top section represents the schematic outline of the single-process model class and the bottom section shows the dual-process model class.
independent parameters of a hypothetical intermediary model, values of which map onto \( n \) outcome variables. The most common method for determining the value of \( k \) in state-trace analysis is a state-trace plot: a scatter-plot of one dependent variable as a function of another, plotted across different experimental conditions (Newell, Dunn & Kalish, 2010). The result is a representation of the relationship between the dependent variables – a representation of the activation of the underlying psychological structure, manifested as changes in the structure of the relationship between outcomes variables (Bamber, 1979). State-trace analysis can be thought of as a reverse-prism. Where a prism converts the collapsed spectrum of white light into individual wave forms, state-trace analysis takes the individual contribution of experimental manipulations and collapses them into a general representation of the underlying parameter structure, realised as structured relationships among dependent variables.

2.2 State-Trace Analysis of Unidimensional and Bidimensional Models

In the context of state-trace analysis, single-process models may also be named \textit{unidimensional models}, and are simply the case where one underlying parameter (or set of correlated parameters) mediates the effects of independent variables on an experiment’s outcome variables. This may be contrasted with dual-process models, also named \textit{bidimensional models} wherein patterns in experimental outcomes are due to the activation of two functionally independent underlying parameters (Dunn, 2004). State-trace analysis is theoretically amenable to contexts involving more than two underlying processes, provided the quantity of manipulated factors and outcome variables is increased as necessary. However, the present research is focused on single and dual-process
models of recognition memory and as such this introduction to state-trace analysis co-occurs as an introduction to the application of state-trace analysis to the previously discussed models of associative recognition memory.

State-trace analysis characterises the mapping of factor through latent variables to outcome state-trace through description of the dimensionality of each space. Two of these spaces represented schematically in Figure 2.1 are factor space and outcome space. The factor space and outcome spaces are the full range of possible combinations of values given to the independent and dependent variables. The dimensionality of each space is dependent on the number of variables used in each. Two independent variables define a two-dimensional factor space while three dependent variables define a three-dimensional outcome space and so on (Dunn, 2008).

The diagnostic space in state-trace analysis is the state-trace of a proposed underlying model. This space allows for the number of underlying processes to be determined by examining whether the obtained state-trace plot agrees with what would be expected given the makeup of this hypothetical model state-trace (Dunn, 2008). The expected form of a state-trace model is a function of the number of processes in that model mapped onto the outcome variables of an experiment. For a unidimensional model, given $x, y$ and $a$ as values of outcome variables $X, Y$ and a single underlying process $A$, the state trace for each outcome variable is defined thusly:

\[
\begin{align*}
x &= f(a) \\
y &= g(a)
\end{align*}
\]
Where \( f \) and \( g \) are unknown monotonic parameter activation functions (Newell & Dunn, 2008), and where a monotonic function is one that is either never decreasing or never increasing. For the equations above, \( f \) and \( g \) could be exponential functions, power functions, or functions as yet undiscovered. Characterisation of the exact functions that map the activation of underlying processes onto levels of a dependent variable is not relevant to the dimensionality of a model state-trace. Rather, state-trace analysis is predicated upon the assumption that the function mapping latent variable to dependent variable is one where an ordinal scale has been preserved; that is, the size of differences between levels of latent and dependent variable could be anything, but rank ordering of levels is the same for each variable type. This is a relatively uncontroversial and plausible assumption that has survived from the work of Loftus (1978) through to recent work done by Wagenmakers, Krypotos, Criss and Iverson (2012). Because of this preservation of rank ordering, the equations above represent a monotonic curve in outcome space. Consequently, for a state-trace plot to show evidence of one underlying process monotonicity must be evident. A monotonic function indicates the mapping of each independent variable to different levels of a sole process; in effect, performance would be due to more or less of that process being activated across different conditions and the activation of this process can be represented along a continuous single dimension (Dunn, 2008).

Effects on dependent variables which are due to the existence of numerous sources of activation, and therefore numerous continuous underlying dimensions, result in a deviation from monotonicity. This is the case for a bidimensional parameter structure. In this case, again given \( x \) and \( y \) but also \( a \) and \( b \) as values of underlying processes \( A \) and \( B \), the state-trace is defined as:
Equations (11) and (12) represent a two-dimensional state-trace surface in outcome space, rather than a monotonic curve (Dunn, 2008). Therefore, for present purposes, the issue to be resolved is whether an empirical associative recognition state-trace plot is best described by either a one-dimensional monotonic curve or a two-dimensional surface.

The preceding is recapitulated graphically in Figures 2.2 and 2.3 below. Each figure represents an example state-trace experiment in which a two-by-three factorial design is mapped onto a theoretical intermediary model, which in turns maps the resulting model’s state-trace onto a two-dimensional outcome space. In a recognition memory experiment, these factors could be something like study time per item or divided versus intact attention, provided those particular factors were relevant to the underlying processes and predicted differential activation of the bidimensional model’s latent variables. For the purposes of illustration, one can imagine that factor one is study item presentation frequency (items shown once, twice or three times) and factor two is stimulus type (words versus pictures). Figure 2.2 represents the mapping of a unidimensional model, while Figure 2.3 represents a bidimensional model mediating the path from factor space to outcome space.

Figure 2.2 and 2.3 demonstrate the full mapping of factor space to model state-trace in three stages. First, Figures 2.2a and 2.3a show the dimensional structure of each factor, parameter and outcome space. The difference between Figure 2.2a and 2.3a is the dimensionality of the intervening parameter space. In Figure 2.2a, the parameter space is a continuous one-dimensional number line, representing different levels of activation of a single process, source of information or other
(a) 2D factor space, 1D parameter space and unresolved outcome space.

(b) Mapping of the first level of factor two onto 1D parameter then outcome space

(c) Mapping of the second level of factor two onto 1D parameter then fully resolved outcome space

*Figure 2.2.* Unidimensional mapping from factor space to outcome space.
(a) 2D factor space, 2D parameter space and unresolved outcome space.

(b) Mapping of the first level of factor two onto 2D parameter then outcome space

(c) Mapping of the second level of factor two onto 1D parameter then fully resolved outcome space

*Figure 2.3.* Bidimensional mapping from factor space to outcome space.
continuous resource function. In Figure 2.3a, however, the parameter space consists of two continuous number lines, representing the variable activation of two distinct processes and resulting in a two-dimensional co-ordinate space.

Figures 2.2b and 2.3b show a hypothetical mapping of the first level of the first factor onto each parameter space; continuing with our example, this would be the activation that occurs when participants study words once, twice or three times. As one might expect, some noise in mapping is evident: the different levels of the factor do not produce equidistant activation in the intervening parameter. The key, however, is the structure of parameter activation in each model. At this stage, each model produces mathematically equivalent one-dimensional state-trace spaces in outcome space. Figures 2.2c and 2.3c show the difference made by the introduction of the second level of factor two. After the second level of factor two has been mapped (e.g. pictures shown once, twice or three times) each model’s full state-trace is plotted within the outcome space. Figure 2.2c clearly shows a monotonic curve, while Figure 2.3c shows a two-dimensional space.

2.3 Application to Models of Associative Recognition

State-trace analysis offers a comparatively broad method for evaluating the number of underlying processes activated within an experiment and therefore evaluating which model class best describes a data set. State-trace analysis can be used to cut through broad swathes of model predictions by making a very general demarcation between model classes: either one or two processes are in operation, and one can determine from state-trace analysis which of the unidimensional or bidimensional model class is supported (Dunn, 2008).
The intention of this thesis is to apply state-trace analysis to associative recognition, ultimately to determine evidence in favour of either the HTSD or UVSD model as the more viable explanation of associative recognition. However, given the number of free parameters in each associative recognition model, can the UVSD and HTSD models be constrained to function according to unidimensionality or bidimensionality? A conceptually ideal usage of state-trace analysis would be a discrimination of a single continuous memory signal from the activation of both familiarity and recollection. Therefore the goal is to determine whether this difference in model class can be isolated experimentally by experimentally constraining other model parameters (as was done in Dunn, 2008).

Reproduced below are the hit-rate equations for the leading candidate single-process and dual-process models. The UVSD is shown first (13) followed by the HTSD model (14):

\[
\begin{align*}
    h(c) &= \Phi \left( \frac{d' - c}{s} \right) \\
    h(c) &= r + (1 - r) \Phi(d' - c)
\end{align*}
\]

The UVSD model in (13) uses three free parameters: \(d'\), representing the distance between rearranged and intact distributions, \(c\), marking the location of a criterion demarcating intact from rearranged judgements, and finally \(s\), representing the standard deviation of the intact distribution. The HTSD model shown in (14) utilises three free parameters: the probability of recollection occurring, \(r\), and the EVSD model operating on familiarity judgements, represented by \(d'\) and \(c\).
The parameter corresponding to placement of a decision criterion along a continuous axis, $c$, is present in both models. This parameter also corresponds to the false alarm rate across different levels of the independent variable, since for all models the placement of $c$ is a measure of the proportion of the rearranged distribution corresponding to ‘intact’ judgements. Manipulating variables within-list constrains the false alarm rate (and by implication placement of the decision criterion) to be consistent across varying levels of the independent variable (Dunn, 2008). Utilising a within-list independent variable manipulation such as this constrains $c$ in all models under consideration, leaving the UVSD and HTSD models to have two free parameters remaining.

The UVSD model may be further constrained when consideration is placed upon the relationship between $d'$ and $s$. If it were feasible to constrain the $s$ parameter across different levels of independent variables, the UVSD would reduce to a sole memory parameter, $d'$. A review conducted by Glanzer et al. (1999) into the behaviour of $s$ has suggested that the parameter is variable across some experimental manipulations (concreteness, word frequency, encoding task, and list length) and invariant across others (presentation frequency, study time). However, when a manipulation has produced changes in $s$, this change has been reflected in changes in $d'$; variance was greater in conditions which were more accurate. Consequently, the relationship between $s$ and $d'$ may be modelled one of two ways: either $s$ is static across levels of an experimental variable, in which case the UVSD model possesses only $d'$ as a free parameter, or $s$ is a function of $d'$, in which case, again, the UVSD model only allows $d'$ to vary (Dunn, 2008). Therefore while the evidence available presents a somewhat inconsistent account of the behaviour of $s$ in relation to experimental manipulations, it suggests that in the context of state-trace experimentation, the UVSD can be reasonably constrained to a single free parameter representing the activation of a continuous memory signal.
Therefore, the HTSD model can be expressed with reference to two free parameters (\(r\) and \(d'\)) that represent the activation of distinct sources of memory information. The UVSD model is represented by one free parameter (\(d'\)) which represents the activation a single continuous memory signal. A series of state-trace analysis experiments, operationalized with the above in mind, can therefore be used to discriminate the predictions of single versus dual-process accounts of associative recognition, by detecting either a unidimensional or bidimensional model state-trace. This research will therefore address whether associative recognition can be explained by the activation of one or two memory components.

2.3.1 Differential Activation and State-Trace Interpretation

The choice of manipulated factors used to activate a bidimensional parameter structure should be based on previous research indicating that a relationship exists between those factors and the underlying processes of a bidimensional model. Specifically, for a bidimensional state-trace to result from an underlying two process structure, one independent variable should predict changes in one latent variable and the other independent variable should predict changes in the other latent variable (Dunn, 2008). However, it is not the case that activation of each latent variable has to be completely selective, whereby an independent variable activates a latent variable and does not affect the other latent variable at all. Rather, one independent variable should (at least) activate one latent variable more than the other independent variable activates it, and vice-versa (Pratte & Rouder, 2012). Again taking presentation frequency and stimulus type as hypothetical manipulated factors, if the purpose of a state-trace experiment using these manipulations was to detect the activation of
Figure 2.4. Differential activation of HTSD model parameters and resulting bidimensional state-trace plot.
familiarity and recollection, bidimensionality would result if presentation frequency affected familiarity more than stimulus type affected familiarity, and stimulus type affected recollection more than presentation frequency affected recollection, or the other way around (Pratte & Rouder, 2012). In the bidimensional example given above in Figure 2.3, different levels of the independent variables resulted in sufficiently independent changes in the underlying processes akin to this, and the result was a bidimensional state-trace. This is the concept of differential activation: levels of an independent variable manifesting as differentiable effects on each underlying latent variable.

An example of how differential activation can result in a bidimensional state-trace is illustrated above in Figure 2.4. Using the formal model presented above in equation (6), HTSD model parameter values were translated into high confidence and low confidence hit rates. Figure 2.4 illustrates that presentation frequency affected model estimates of familiarity more than stimulus type, and stimulus type affected model estimates of recollection more than presentation frequency. This differential activation resulted in a clear deviation from monotonicity, shown within the state-trace plot of high confidence versus low confidence hit rates.

The necessity of differential activation implies that a unidimensional state-trace does not necessarily reflect the falsity of a bidimensional model class. A unidimensional state-trace can result from one of three mechanisms:

1) The single-process model class is correct and the unidimensional state-trace resulted from the independent variables of an experiment mapping onto different levels of that one underlying process.

2) Only one process of the dual-process model class was activated by the factors used in an experiment and therefore the resultant state-trace resembles what it would if the single-process model class were correct.
Figure 2.5. Non-differential activation of HTSD model parameters and resulting unidimensional state-trace plot.
3) The two underlying processes were activated by the independent variables but not differentially.

Non-differential activation and the unidimensional state-trace that can result from this is shown above in Figure 2.5. As with Figure 2.4, the model defined above in (6) has been used to translate HTSD parameter values into high confidence and low confidence hit rates. However, in contrast to the parameter values shown in Figure 2.4, the parameter values shown in Figure 2.5 illustrate that presentation frequency and stimulus type affected familiarity and recollection in similar ways, rather than one serving as a familiarity-enhancing manipulation and the other serving as a recollection-enhancing manipulation, as would be the case had differential activation occurred (Pratte & Rouder, 2012). The result is that even though the state-trace plot is the output of two underlying process, the function that results from plotting high confidence hit rates again low confidence hit rates is monotonic and so is indistinguishable from a state-trace plot produced from the activation of one underlying process.

It is not currently possible to distinguish between a unidimensional state-trace that results from the activation of a single process and that which results from non-differential activation of two underlying processes. However, if numerous state-trace experiments failed to detect the activation of two processes despite utilising various theoretically relevant factors, the strength of the dual-process model class as an explanation of that field would at the very least be weakened; while an alternate explanation might be logically possible, the accumulation of consistently unidimensional state-trace plots would still be an accumulation of evidence for the single-process model class as the correct explanation of that particular field.
2.4 Implementation

The work presented hereafter utilises a novel implementation of state-trace analysis. What follows is an overview of this framework: a Null-Hypothesis Significance Testing (NHST) procedure that uses bootstrap monotonic regression to attach a probability value to the unidimensional model’s goodness-of-fit (see Newell & Dunn, 2008 for an introduction to this framework).

2.4.1 Outcome Space

State-trace analysis has been previously applied to a similar debate in recognition memory by Dunn (2008). This research used state-trace analysis to investigate the Remember/Know paradigm. As discussed previously, Remember/Know is held by some researchers (e.g., Yonelinas, 2002) to correspond to a demarcation of responses representing recollection (Remember responses) from those representing familiarity (Know responses), while other researchers have interpreted this in single-process terms as demarcating high and low confidence responses (e.g., Donaldson, 1996; Dunn, 2004). Dunn (2008) used the logic of state-trace analysis to investigate whether the Remember/Know paradigm showed evidence of one or two underlying processes, and therefore resolve evidence for either the single or dual-process class of recognition memory models.

The meta-analysis conducted by Dunn (2008) operationalized state-trace analysis by defining a two-dimensional outcome space. Using studies with manipulations equivalent to a two-dimensional factor space (that is, studies that purported to produce differential effects on
recollection and familiarity), Dunn plotted the proportion of Remember responses to old items ($R_o$) against the sum of the proportion of Remember and Know responses to old items ($RK_o$), and visually assessed whether the resulting plot best resembled a monotonic curve or a two-dimensional plane. The results of this meta-analysis showed very clear evidence of a monotonic curve and therefore support for the single-process class of models.

The two-dimensional outcome space defined by Dunn (2008) was determined by the makeup of the Remember/Know paradigm; all else being equal, the outcome of Remember/Know experiments are Remember responses and Know responses. Associative recognition experimentation, however, is usually not constrained to only two dependent variables. Rather, associative recognition output will often take the form of a confidence scale, resulting in around four-to-six output measures, depending on the number of confidence options available to participants. While it would be valid to compare high confidence Old responses and low confidence Old responses (that is, plotting ‘Sure Old’ against ‘Possibly Old’), and this would form an analogue for the analysis used in Dunn (2008), a more complete representation of associative recognition is one that takes into account the full confidence spectrum. Therefore, the state-trace analysis outcome space used in the research presented below is a five-dimensional space, representing the cumulative proportion of responses made with Sure Old, Probably Old, Possibly Old, Possibly New and Probably New (cumulating leaves Sure New responses with a fixed value of one and is therefore not diagnostic of anything).

Unidimensional and bidimensional model classes predict the same model state-trace in both two- and five-dimensional outcome spaces. When a five-dimensional outcome space is formed by using five confidence measures as dependent variables, a unidimensional parameter structure still predicts a monotonic curve and a bidimensional model still predicts a two-dimensional plane, even
though each will be realised within a higher-than-two-dimensional structure. The difference made by higher dimensionality in this context is an increase in descriptive work. In terms of the descriptive accuracy of a model, rather than needing to approximate two dependent variables while maintaining a particular structure, a model state-trace must capture the major features of a data set while minimizing deviations from five dependent variables.

2.4.2 Monotonic Regression

The monotonic regression implementation of state-trace analysis does not rely on restriction of both the unidimensional and bidimensional models to a particular form. Instead, only evidence for the unidimensional model’s predicted monotonic curve is assessed. In NHST terms, a probability value is attached to the fit of the monotonic curve predicted by the unidimensional model and it is either rejected or not rejected (cf. the null-hypothesis).

The unidimensional monotonic curve is realised in outcome space through monotonic constraints. The curve is constrained to meet the following conditions:

\[ x_i > x_j \implies y_i \geq y_j, \forall 1 \leq i, j \leq n, \]  
\[ y_i > y_j \implies x_i \geq x_j, \forall 1 \leq i, j \leq n. \]

In the above, \( x \) and \( y \) represent dependent variables, and \( i \) and \( j \) represent experimental conditions. (15) and (16) can be read as the following: an ordering of conditions for one level of a dependent
Figure 2.6. An isotonic function fit to example data using monotonic regression.
variable implies the same ordering for a corresponding level of a dependent variable, and the reverse
also follows, as per (16). Identical ordering of conditions across levels of confidence reflects the
underlying unidimensional parameter structure. Given the logic that conditions can only map onto a
sole latent variable in one order (see Figures 9 and 10), this single ordering must be reflected as that
parameter structure is mapped onto each dependent variable (cf. the rank-ordering assumption
discussed above in section 2.3.2). These constraints form the unidimensional model to be examined,
the fit of which is assessed through monotonic regression. This is a form of constrained
optimisation whereby a never-decreasing (isotone) or never-increasing (antitone) function is fit to a
series of data points in some coordinate space (Leeuw, Hornik & Mair, 2009). An example of
monotonic regression can be seen in Figure 2.6 below, where an isotonic function has been fit to
example data.

Monotonic regression is distinct in that it does not make use of a model function relating
parameters to predicted data, as the model is manifested through constraints instead of a function.
Rather than iteratively optimising model parameters, monotonic regression iteratively fits the
predicted data itself; in the case of associative recognition research, this would be the cumulative
counts of confidence levels per condition. These values are approximated according to the
monotonicity constraints in (15) and (16) by minimizing the sum of squared errors of prediction
($SSE$).
2.4.3 Bootstrapping

$SSE$ is approximately distributed as chi-square with $n$ degrees of freedom and this relationship can be used to attach a probability to an obtained $SSE$ value. This process, however, cannot be replicated in monotonic regression. The sampling distribution of $SSE$ under monotonic regression is unknown, as there is no practical way of determining the degrees of freedom.

Fortunately, many sampling distributions can be estimated through bootstrapping (Efron & Tibshirani, 1993). Bootstrapping is a process whereby the data is re-sampled numerous times, and a given test statistic (e.g. $SSE$) is calculated for that sample per iteration. With enough samples, the distribution of an obtained test statistic approximates the correct form of the statistic’s true sampling distribution.

The monotonic regression state-trace analysis framework builds on previous work done by Wagenmakers, Ratcliff, Gomez and Iverson (2004) by using bootstrapping in the following way: First, the original data is fit under monotonic regression to obtain a $SSE$ goodness-of-fit measure. Then the data is resampled, and every sample is fit using monotonic regression to obtain a distribution of $SSE$ values. The original $SSE$ value can then be compared against that distribution to determine the probability that the monotonic model represents the empirical data. This probability value can be used to reject or fail to reject the unidimensional model, overall resulting in a framework wherein a researcher can use an obtained numeric value to judge whether a data set supports or does not support a unidimensional model.
2.5 Summary

The literature review in Chapter 1 illustrated that a core debate in associative recognition memory research is a disagreement over the explanatory viability of single versus dual-process models. While several forms of these models exist, two leading candidate models are the UVSD single-process model and the HTSD dual-process model. The UVSD model conceptualises associative recognition judgement as being based on a single continuous memory signal. In contrast, the HTSD model explains associative recognition judgements as being due to the activation of two distinct sources of memory information: familiarity and recollection. The literature review presented in Chapter 2 highlighted the practicality of state-trace analysis as a method for distinguishing evidence for unidimensional models or bidimensional models, and this is a method that can be easily extended to associative recognition memory research. Since the UVSD and HTSD models can be experimentally constrained to represent only their memory information components, state-trace analysis can therefore be used to assess which of the UVSD or HTSD model is the better explanation of associative recognition by adjudicating evidence for either a unidimensional or bidimensional model class.

2.6 Thesis Overview

The following four chapters present research examining the dimensionality of associative recognition memory. Each chapter presents the results of an individual associative recognition experiment that was designed to elicit differential activation of familiarity and recollection by
manipulating relevant factors, with an emphasis on the unitisation manipulations discussed above. ROC analysis and state-trace analysis was applied to the results of each experiment to examine evidence for the activation of either one or two latent variables.

Chapter 3 presents the results of an intact-from-rearranged discrimination experiment designed to invoke differential activation of familiarity and recollection by manipulating study presentation frequency and attention. These manipulations were chosen due a review conducted by Yonelinas (2002) that suggested familiarity and recollection are directly manipulable through these variables. Chapters 4 and 5 present the result of experimentation where familiarity is manipulated through an encoding frame unitisation manipulation used by Quamme, Yonelinas and Norman (2007) and Haskins et al. (2008), and recollection is manipulated through a memory load manipulation and a study time manipulation respectively. Chapter 6 extends this investigation through an examination of a perceptual unitisation manipulation used by Jäger and Mecklinger (2009) paired with a study time manipulation. Chapter 6 also presents the results of a direct examination of the MSD model whereby ROC curves were conditionalised on Old/New ratings. In each of these chapters, the monotonic regression framework was applied to hit-rates to derive evidence for either the unidimensional or bidimensional model class as an explanation for associative recognition memory.
Chapter 3

Experiment 1 – State-Trace Analysis of Non-Unitised Associative Recognition

The aim of Experiment 1 was to investigate whether associative recognition is best explained by one or two underlying processes, which was achieved by applying the logic of state-trace analysis to an intact-from-rearranged discrimination experiment. Experiment 1 utilised independent variables that predicted differential activation of familiarity and recollection, but activation of familiarity was not attempted through the direct manipulation of unitisation. Although Yonelinas (1997) argued that both familiarity and recollection could only be activated in associative recognition when encoding was performed through unitisation, it is common for associative recognition ROC curves to be asymmetric and curvilinear in experiments that have not attempted any direct manipulation of unitisation (e.g. Mickes, Johnson & Wixted, 2010), thereby displaying evidence that both familiarity and recollection were activated. Therefore Experiment 1 was used to examine evidence for the existence of these two processes in a standard associative recognition experiment. Subsequent experimentation will cover the dimensionality of associative recognition under unitisation manipulations, and cumulatively these results will serve as coverage of a wide range of experimental contexts in which evidence for either the UVSD or HTSD model was resolved.

Experiment 1 was designed such that two factors influenced the encoding of pairs at study: divided attention and number of study presentations. According to previous research (Yonelinas, 2002) divided attention and number of study presentations affect estimates of recollection and familiarity. Importantly for state-trace analysis, divided attention and number of study presentations,
used together, predict differential activation of recollection and familiarity, and therefore predict a
bidimensional state-trace.

Dividing attention during encoding reduces estimates of recollection more that it reduces
estimates of familiarity. For example, Craik, Govoni, Naveh-Benjamin and Anderson (1996)
investigated the effect of divided attention on recall versus item recognition, finding evidence that
recall is more impaired by divided attention than item recognition. Since recall is thought to be
dependent on recollection while item recognition is thought to be based more on the activation of
familiarity, these results have been construed as evidence that recollection is affected more by
divided attention than familiarity (Yonelinas, 2002). Similarly, Troyer, Winocur, Craik, and
Moscovitch (1999) investigated the effect of divided attention on source memory performance
compared to item recognition performance. Source memory involves the recognition of how an
item was presented at study, such as being on one of two lists or spoken by a female or male voice.
The encoding that supports source memory is also thought to be based primarily on recollection.
Troyer, Winocur, Craik, and Moscovitch (1999) found that source memory was affected more than
item recognition by divided attention. Furthermore, research using the Remember/Know procedure
in item recognition has also produced evidence that divided attention reduces recollection more than
familiarity. A study conducted by Mangels, Picton, and Craik (2001) found that “Remember”
responses, thought to reflect the contribution of recollection, were diminished more than “Know”
responses, which are thought to reflect the contribution of familiarity in the absence of recollection.

In contrast to divided attention, increasing the number of study presentations increases
estimates of both recollection and familiarity (Yonelinas, 2002). Evidence from investigations using
the Remember/Know procedure (Parkin & Russo, 1993) and source memory (Benjamin & Craik,
2001) indicate that increasing the number of study presentations increases estimates of recollection
and familiarity by a similar amount. Remember/Know research conducted by Dewhurst and 
Anderson (1999) conflicts with this somewhat, producing results where repetition resulted in an 
effect primarily realised on estimates of recollection. However, the research by Dewhurst and 
Anderson (1999) used a very high study presentation number of eight presentations compared to 
only two by Benjamin and Craik (2001), which suggests that using a lower number of total study 
presentations produces comparable changes in familiarity and recollection.

In summary, divided attention should result in a larger effect on recollection than familiarity, 
and a moderate increase in number of study presentations should result in comparable changes to 
both familiarity and recollection. Number of study presentations and divided attention together 
therefore predict differential activation of recollection and familiarity, and this differential activation 
predicts a bidimensional state-trace. Detection of this bidimensional state-trace will be evidence that 
associative recognition can be explained due to the activation of recollection and familiarity, rather 
than just a continuous memory signal.

3.1 Method

3.1.1 Participants

63 undergraduate Psychology students from the University of Adelaide participated in this 
experiment. Participants were mainly female (49 females and 14 males participated) with a mean age 
of 23.0 years ($SD = 7.61$). Each student received course credit for their participation. Participants
provided informed consent before taking part in the study and were instructed that they could withdraw at any stage. 13 participants were excluded from the final analyses due to poor accuracy on either the associative memory test or the divided-attention task (a 55% cut-off was used to judge performance on each test). Two more participants were excluded from modelling and state-trace analysis for failing to respond appropriately to the experiment by providing the same response to every test stimulus, both intact and rearranged.

3.1.2 Design

A 2 x 3 factorial design was used to investigate the dimensionality of associative recognition. The factors were attention (focused or divided) and number of study presentations (1, 2 or 4 study presentations). Both factors were manipulated within the study phase of the experiment; attention was manipulated through a divided-attention task on half of all study trials and study presentation was manipulated by displaying study items once, twice or four times. Factors were varied within participants and within lists in order to prevent variance in participant decision criteria between conditions.

3.1.3 Materials

Stimuli were random pairings of 240 high frequency words (100-200 occurrences per million) taken from the MRC Psycholinguistic Database. Words were monosyllabic and
homophones were excluded from selection. Words were randomly paired at the beginning of each experimental session to minimise the likelihood that two participants would receive the same list of word pairs to study. All words were randomly assigned to conditions and each had an equal probability of being presented in each block and condition.

The stimuli for the change detection task (described below) were 16 full-colour photographs depicting visual scenes such as a sailboat, statue or canal. Photographs were of varying width and height, ranging in size from to 415 x 533 to 867 x 650 pixels. All materials were presented on a standard 17 inch computer screen.

### 3.1.4 Procedure

Participants were first provided with detailed instructions on how to complete the tasks within the experiment. Participants were made aware of the nature of all tasks to be performed, including that they were to be studying items for a later memory test. Participants were also encouraged to remember each word pair as a whole by forming an association between the two words.

Experimentation was divided into five discrete study-test blocks. Each block contained a study phase, followed by a brief distractor task then a test phase. Each block and block phase occurred sequentially, with no forced rest in between phases. The experiment began with instructions again presented to the participant on a computer screen and a series of practice trials explaining the particulars of each experimental task. Before continuing, participants were required to
demonstrate understanding through accurate performance on two consecutive trials per experiment task.

Each study phase trial began with a small black fixation cross displayed for 200 milliseconds. The fixation cross was centred within a white box the size of half of the computer screen, also centred. The remaining background space was black. The fixation cross was replaced with the study word pair, appearing as all upper case in black, with one word above the other. Words were displayed as size 48 using the Arial font.

Each study phase involved the presentation of 24 word pairs. Word pairs were shown for three seconds and presented either once, twice or three times non-consecutively. Each word pair was presented either in isolation or concurrently with a divided-attention task. In this task, two numbers were displayed on either side of the study word pair for one second then briefly covered on-screen by small square white boxes for two seconds (the duration of word pair presentation). Numbers were randomly chosen but constrained to be between 1 and 9 inclusive and non-repeating in a single trial. One number was presented in a font size larger than the other (size 80 versus 40). Allocation of size was random for each trial. After the three second period had passed, the word pair and two numbers/white boxes were replaced by a screen displaying either ‘size?’ or ‘value?’ The participant was instructed to indicate either the location of the visually largest (size) or the numerically largest (value) number by pressing z for left or / for right. The divided attention task occurred on half of all trials and was ordered randomly. Average percentage correct was provided after each study phase to encourage participants to pay attention.

To negate variation in participant rehearsal strategy between study and test, participants took part in a brief Change-Blindness task immediately following each study phase. This task involved the presentation of a series of full-colour photographs depicting a particular visual scene, which
participants were instructed to memorize. Then after viewing a quick visual mask, participants were shown the same scene again but with one detail changed (e.g., a sculpture within a church façade had been reversed). Participants were instructed to use a mouse to click the area which had been altered. Each photograph was set against a black background and the size of each photograph varied between trials. The task duration was 25 seconds and occurred within every block. Although 16 trials were possible, given the difficulty of this task no participant exceeded the 8th trial.

During the test phase of the block, participants were shown a list of 12 rearranged word pairs and 12 intact pairs per block randomly intermixed. Memory was tested by asking participants to pick which word pairs were intact and which had been rearranged. Participants indicated their answer and level of confidence simultaneously by clicking one of six grey square boxes located below the test item. From left to right, boxes were labelled ‘Sure Intact’, ‘Probably Intact’, ‘Possibly Intact’, ‘Possibly Rearranged’, ‘Probably Rearranged’ and ‘Sure Rearranged’. Participants were encouraged to use the full range of the confidence scale before experimentation began, and this encouragement was reinforced by providing participants with a histogram displaying the frequency of each box’s selection for that block’s test phase. Participants were encouraged to even out this histogram if it appeared skewed or biased towards a particular confidence level. This feedback also served as a break between experiment blocks, as participants were asked to press a key to continue once they were ready to begin the next block. Word pairs were swapped randomly but constrained to be swapped within condition and study trial visual location (top or bottom) was preserved. Test item presentation order was also randomised.
3.2 Results

3.2.1 Attention Study Task Performance

Mean percentage correct for the divided-attention study task was assessed to ensure that participants followed instructions and were engaged with the experiment. Overall sample mean accuracy was 92.0% correct, with a standard deviation of 9.70% correct, indicating that participants did indeed pay attention. Divided-attention task performance was similar across levels of the study presentation manipulation, with the sample displaying a mean performance of 91.03 (9.68), 90.83 (11.28) and 91.33 (10.77) for items presented once, twice and four times respectively. One-way analysis of variance did not detect a significant difference between levels of study presentation.

3.2.2 Associative Recognition Performance

Table 3.1 below lists associative recognition hit rates, false-alarm rates and $d$'s per condition of Experiment 1. Measures were computed by collapsing “Sure Intact”, “Possibly Intact” and “Probably Intact” into “Intact” and likewise for rearranged confidence levels. Hit rates and $d$'s were better in the focused-attention condition, and increased across increasing levels of presentation frequency for both the divided and focused-attention conditions. False-alarm rates were not consistent with this pattern, showing relative consistency across conditions.
Table 3.1

Experiment 1 mean hit rates, false-alarm rates and d’s per condition (standard deviations in parentheses)

<table>
<thead>
<tr>
<th>Presentations</th>
<th>Hit Rate</th>
<th>False-Alarm Rate</th>
<th>d’</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Divided</td>
<td>Focused</td>
<td>Divided</td>
</tr>
<tr>
<td>1</td>
<td>.53 (.21)</td>
<td>.79 (.20)</td>
<td>.16 (.15)</td>
</tr>
<tr>
<td>2</td>
<td>.70 (.20)</td>
<td>.90 (.11)</td>
<td>.20 (.19)</td>
</tr>
<tr>
<td>4</td>
<td>.81 (.18)</td>
<td>.96 (.07)</td>
<td>.16 (.15)</td>
</tr>
</tbody>
</table>

A 2 x 3 (attention by study presentation number) within-subjects analysis of variance of hit-rates yielded a significant effect of attention, $F(1, 47) = 143.70, p < .001$, partial $\eta^2 = 0.75$ and study presentation number, $F(2, 94) = 80.61, p < .001$, partial $\eta^2 = 0.63$, and a small significant interaction effect, $F(2, 94) = 4.20, p < .05$, partial $\eta^2 = 0.08$.

Analysis of variance testing performed on false-alarm rates yielded no significant effect for attention or study presentation number, but did detect a small interaction effect, $F(2, 94) = 4.07, p < .05$, partial $\eta^2 = 0.08$. A within-subjects analysis of variance was also performed on $d$’s, which showed significant main effects of attention, $F(1, 47) = 73.34, p < .001$, partial $\eta^2 = 0.61$, and study presentation number, $F(2, 94) = 37.56, p < .001$, partial $\eta^2 = 0.44$, but no significant interaction effect.

The ordering and clear differences between experimental conditions can be seen in the ROC curves presented below in Figure 3.1. Performance was generally good, with focused-attention
Figure 3.1. ROC curves per condition of Experiment 1.
pairs producing better associative recognition performance for all study presentation frequencies except divided-attention pairs shown four times, where performance was similar. ROC curve ordering among presentation frequencies is consistent with what would be expected, for both levels of attention. Also of note in Figure 3.1 is that the ROC curves are clearly asymmetric and curvilinear (confirmed by model-fitting, see Appendix A), and a systematic flattening as performance decreases is not as apparent as previous research might suggest it should be. This lack of flattening may reflect the generally high level of performance exhibited by the sample.

3.2.3 State-Trace Analysis

The state-trace plot of high confidence versus low confidence old responses for Experiment 1 is shown below in Figure 3.2. As is often the case in associative recognition research, the false-alarm rate remained largely unaffected by the experimental manipulations. The result of this is a non-diagnostic clump of data in the lower left hand corner representing low and high confidence “Old” responses made to rearranged items. However, as analysis of variance also indicated, Figure 3.2 demonstrates that hit-rates were successfully influenced by the manipulations used. The experimental manipulations produced clear effects and there is some overlap between focused and divided conditions. Figure 3.2 is strong evidence for unidimensionality as it shows clear monotonicity.

That the dataset is unidimensional is further supported by the data presented in Figure 3.3, which shows all levels of confidence plotted against all other levels. The first row of Figure 3.3 shows “Probably Intact” plotted against “Sure Intact”, followed by “Possibly Intact” plotted against
Figure 3.2. State-trace plot of high versus low confidence hit rates.
Figure 3.3. State-trace plots of all possible response comparisons for Experiment 1
“Sure Intact” et cetera, until all possible combination of confidence levels for responses made to both intact and rearranged pairs are pictured. While some comparisons in Figure 3.3 show a small deviation from monotonicity where the lower focused-attention hit rate data point meets the higher divided-attention hit rate data point, this is very slight and is not consistent throughout the comparisons.

State-Trace Analysis using the monotonic regression framework confirmed that monotonicity was consistent across hit-rates. Analysis was performed on responses made to intact items, as the false alarm rate was unaffected by the experiment’s manipulations and therefore did not represent the hypothetical activation of an underlying bidimensional parameter structure. The results of monotonic regression used to minimise \( \text{SSE} \) produced an extremely small and not significant value of 0, \( p = .99 \), meaning the fit of the unidimensional model could not be rejected. Analysis was also performed at the individual level and no individual participant produced hit-rates that resulted in the rejection of the unidimensional model (see Appendix B for a full listing).

3.3 Discussion

The primary goal of Experiment 1 was to manipulate independent variables that according to previous research (Benjamin & Craik, 2001; Craik, Govoni, Naveh-Benjamin & Anderson, 1996; Mangels, Picton, & Craik, 2001; Parkin & Russo, 1993; Troyer, Winocur, Craik, & Moscovitch, 1999) predict differential activation of recollection and familiarity, and to conduct a full state-trace analysis on the experiment’s outcome variables to detect the predicted bidimensional state-trace. Analysis of variance testing indicated that the choice of factors was successful as significant main
effects of both manipulations on the experiment’s hit rates were detected. ROC analysis also indicated that a state-trace analysis should show the activation of two underlying processes, had the two processes been sufficiently differentially activated. The ROC curves obtained in Experiment 1 showed clear curvilinearity and asymmetry, which according to the dual-process interpretation of associative recognition indicate that familiarity was activated as well as recollection. This activation of familiarity must have occurred because of unitisation, even though the experiment did not directly manipulate it. However, despite the significant main effects of both manipulated factors and the form of the obtained ROC curves, the results of state-trace analysis did not show evidence of bidimensionality. Experiment 1 state-trace plots, combined with the monotonic regression framework analysis at both the group and individual level are consistent in adherence to unidimensionality. No evidence for the activation of two processes was detected in any aspect of state-trace analysis.

Explanation for the unidimensionality of this data may lie in the HTSD dual-process model being incorrect. If familiarity and recollection do not exist, state-trace analysis will not detect a bidimensional state-trace. However, it may be that the HTSD dual-process model is correct, but the two processes were not detected because the manipulated factors did not differentially activate recollection and familiarity. It was noted in the results summarised above that the Experiment 1 ROC curves did not display the pronounced flattening of curves across conditions sometimes seen in other research (e.g. Mickes, Johnson & Wixted, 2010). If the Experiment 1 ROC curves were curvilinear and asymmetric because of unitisation incidentally activating familiarity, and that the lack of ROC curve flattening suggests that familiarity contribution was consistent across conditions, this consistency of familiarity contribution may have led to a failure of differential activation. Differential activation may potentially be achieved through direct manipulation of unitisation, such that
familiarity contributes less to one group than another, rather than incidentally contributing to all conditions by a similar amount as it may have done here.

Interpretation of the results of Experiment 1 (and the experiments following) should be tempered somewhat by the spacing of effects shown within this chapter’s state-trace plots. While the results of Experiment 1 show clear spacing between conditions, indicating that the experimental factors were moderately successful, the hit-rate data points do not overlap in an ideal fashion. In Figure 2.4 above, the overlap of conditions demonstrate the results of an experiment in which the power to reject the unidimensional model is near-ideal. While some overlap is present in the Experiment 1 state-trace plots, a more successful experiment would be one in which more overlap was present. However, while these results are not ideal, they are not invalid. Since the Experiment 1 hit-rates fall on a straight line, they do not represent the especially problematic case in which conditions are located in parallel to one another and also do not overlap. In such a case, results of monotonic regression testing may indicate that the unidimensional model could not be rejected but visual inspection would also indicate that a bidimensional model may instead represent the true nature of the data. Consequently, while the conclusions of this experiment should be drawn in light of potential issues with statistical power, the pattern of condition spacing is such that they are not potentially masking a lack of power to reject the unidimensional model, and the conclusions of this chapter are the same regardless.

In summary, the results of Experiment 1 do not lend support to the HTSD model of associative recognition. State-trace analysis performed on hit-rates produced no evidence in favour of two latent variables. Since it is possible that the manipulated factors did not differentially activate recollection and familiarity, further experimentation will follow in which different manipulations will be used to attempt differential activate recollection and familiarity.
Chapter 4

Experiment 2 – State-Trace Analysis of Unitised Associative Recognition

Experiment 1 applied state-trace analysis to an experimental design involving intact-from-rearranged discrimination. The purpose of this experiment was to determine whether associative recognition memory is more likely explained by a single-process model such as the UVSD model or by the activation of two underlying processes. While ROC analysis indicated that familiarity and recollection both contributed to performance, state-trace analysis produced no evidence of two processes and application of our monotonic regression framework did not allow the unidimensional model to be rejected. This was despite using independent variables that predicted differential activation of recollection and familiarity and therefore predicted a bidimensional state-trace. However, it is still possible for the HTSD dual-process model to be correct, familiarity and recollection to have both contributed to performance and to have produced a unidimensional state-trace. This could have been due to a failure of the chosen factors to sufficiently differentially activate familiarity and recollection. The purpose of Experiment 2, therefore, was to apply state-trace analysis to a different associative recognition design to allow the usage of alternate independent variables and to potentially procure the differential activation of recollection and familiarity. The focus of Experiment 2 was to achieve this differential activation in part through the direct manipulation of unitisation.

The viability of the dual-process model as an explanation of associative recognition is largely dependent on the legitimacy of unitisation. However, incidental unitisation shown by ROC analysis in Experiment 1 did not result in a bidimensional state-trace. If recollection and familiarity do in fact
contribute to associative recognition performance, encoding under explicit unitisation conditions which can be experimentally controlled may provide the best means for detecting the activation of these two processes.

Much recent dual-process research has attempted to directly manipulate unitisation. Initially, this was achieved by examining pre-existing compound words (e.g. Yonelinas et al., 1999) but the focus has shifted towards attempts to activate unitisation for the kinds of random word pairings usually seen in associative recognition research (Haskins et al., 2008; Quamme, Yonelinas & Norman, 2007). These studies have used encoding frames formed by presenting relevant sentences together with word pairs at study. These sentences are designed to bias participants to either bind the two words of a part into a new singular concept, or to think of them as disparate concepts; one condition aims to activate unitised encoding and with it familiarity, while the other aims to impair unitised encoding and activate only recollection. According to parameter estimation undertaken by Haskins et al. (2008), use of this factor results in familiarity contribution that is significantly higher for unitised word pairs, and that the contribution of recollection across unitisation conditions is not significantly different.

Experiment 2 was designed to differentially activate familiarity and recollection by pairing the Haskins et al. (2008) unitisation manipulation with a study phase memory load manipulation. Unitisation was used to activate familiarity while the memory load manipulation was used to attempt activation of recollection. This latter manipulation was an alternate method for operationalizing the attention manipulation used in Experiment 1. In this previous experiment, the divided-attention condition involved asking participants to make judgements about digits at the same time as they were studying word pairs. This was not practical to use concurrently with the Haskins et al. (2008) unitisation manipulation, as participants were asked to read sentences that were presented with study
word pairs. The Experiment 2 memory load manipulation instead involved the presentation of numbers to remember before they were shown study pairs. Participants were asked to remember these numbers while learning the word pairs and reading the sentences.

According to Yonelinas (2002) memory load during encoding behaves in a similar way to the divided-attention manipulation used in Experiment 1, which means that recollection should be moderately diminished with a low-to-negligible effect on familiarity. These two manipulations used together predicted differential activation of familiarity and recollection, and therefore predicted a bidimensional state-trace.

4.1 Method

4.1.1 Participants

54 undergraduate Psychology students from the University of Adelaide participated in Experiment 2 in exchange for course credit. Participants were again predominately female, with 40 females and 14 males completing the experiment. The mean age of the participants was 20.6 years ($SD = 5.93$). All participants provided informed consent before taking part in the study. A total of 11 participants were not included in final analyses due to sub 55% accuracy on the working memory task used within Experiment 2. In Experiment 1, participants were excluded from analysis of the associative recognition task due to sub-55% accuracy. However, given the difficulty of experiments 2, 3 and 4 compared to Experiment 1, subsequent experimentation instead excluded participants
who failed to achieve a $d'$ measure of .3 across 5 of 6 conditions. Of the 43 participants who performed above chance on the working memory task, all achieved this level of performance and were included in final statistical analyses.

4.1.2 Design

A 2 x 3 factorial design was used for the experiment. The unitisation manipulation had two levels: the presence of a study phase encoding environment purported to activate unitisation, and the absence of such an environment representing normal, non-unitised encoding. Participants also took part in a working memory task during the study phase of the experiment. This task had three levels as participants were required to remember 0, 3 or 6 numbers during stimuli encoding. Factors were varied within participants and within study lists.

In contrast to the design of Experiment 1, only one test-study cycle was used in Experiment 2. This change was made as Experiment 2 was designed as an incidental memory task. This was necessary to counter potential ceiling effects, given that the factors used in Experiment 2 encouraged deep encoding.

4.1.3 Materials
Figure 4.1. A graphical representation of the Experiment 2 procedure using example stimuli. The blue column represents the presence of a memory load manipulation, while the purple column represents a trial on which no working memory task was present.
The stimuli used in this experiment were taken from Haskins et al. (2008). This study used 384 four to six letter English nouns with moderate to high word frequency (10-1000 occurrences per million) which were combined to form 192 word pairs. Due to the particulars of the experiment design outlined below, words were assigned as pairs only once and remained with their partner; that is, in contrast to experiment one, every participant studied the same list of word pairs.

For each word pair, two corresponding condition frames were constructed, such that pairs possessed both a unitised and a non-unitised frame. Frames constructed to facilitate unitisation consisted of a sentence outlining a definition of that word pair as if it were a new concept. For example, the word pair CARE JUDGE had the unitising frame “One who makes decisions about child custody disputes”. Frames constructed to facilitate non-unitised encoding consisted of sentences in which each word of a pair could be mentally inserted into a sentence gap by using one’s normal understanding of the individual word’s meaning. For CARE JUDGE, the non-unitising frame was “He was placed in her ______ by the _____.” Per participant only one frame was utilised for each word pair and the allocation of word pair to frame was randomised. Additionally, the working memory load task utilised the digits 1 through 9. All stimuli were presented on a standard 17 inch computer screen and responses were collected through mouse and keyboard.

4.1.4 Procedure

Participants were first provided with an information sheet and asked to supply written consent indicating that they understood the general outline of the experiment and wished to continue. Following this, participants were given detailed instructions outlining the particulars of the
first phase of the study. Unlike the previous experiment, participants were not informed that they were to be participating in a later memory test on the studied word pairs. Rather, this information was explained to each participant at the conclusion of the study phase.

The experimental session involved only one study-test block. This block contained a study phase followed by a test phase, with no task performed in between. Due to the length of each experiment phase, three minute-long breaks were granted after trials 48, 96 and 144 within both the study and test phase. During these rest periods, the words “Enjoy a short break” were displayed on screen above a count-down timer showing the seconds remaining until recommencement of participation. Each phase of the experiment began with a brief text-based introductory screen informing the participant to press a key to begin.

Study trials began with the presentation of a small black fixation cross on a white background. This cross was centred on screen and displayed for 200 milliseconds. Depending on the study item’s condition, this screen then automatically changed to either the beginning of the memory load task detailed below or the presentation of a study item. The display of each study item involved the simultaneous presentation of a word pair and a frame. Each was shown in black text on a white background, with the frame shown in the top half of the screen and the word pair the lower half. Each was displayed in black and with a text size of 100 and 50 for the word pair and frame respectively. After three seconds, this screen changed to one showing the word ‘Fit?’, again in black on a white background and using text size 100. Below this, were four clickable grey boxes, labelled (from left to right) ‘Very Poor’, ‘Poor’, ‘Good’, and ‘Very Good’. Participants were instructed that ‘Fit’ was a measurement of how well they thought the frame captured the meaning of the word pair. This referred to either the conveyance of a novel meaning for unitised frames or the capture of participant’s preconceived notion of each individual word for non-unitised word pairs. Participants
rated the fit of the frame to the word pair by using their mouse to click one of the boxes. If this trial did not involve a memory load question, clicking a box ended the trial and took the participant to the next fixation cross and the next trial.

The memory load task took place on two-thirds of all study trials, given that one condition of the task was a memory load of zero. The ordering of study trials for these conditions was random. This task consisted of three screens in total, flanking the other screens used for an individual study trial. The first screen was displayed immediately after a fixation cross. This screen presented a sequence of digits in black on a white background and in Arial font of size 100. Each digit could take a value between 1 and 9 inclusive and digits did not repeat in a single trial. Depending on the trial condition, either 3 or 6 digits were displayed. This screen was shown for 3500 milliseconds. The participant’s instructions were to consciously remember these numbers such that they could later recall the number to the left of a prompt number. For example, if a participant was shown 4 5 6, and was later shown a prompt of 6, the correct response would be 5. Note that the prompt number was never the furthest left in the sequence.

The memory load task’s second screen was displayed after the participant had clicked an appropriate box on the previously detailed ‘Fit?’ screen and viewed the fixation cross. This screen showed a single number, again black on a white background using the same font and text size as the number sequence. The participant indicated their choice for the number to the left position of the prompt by entering the appropriate number on the keyboard in front of them. To encourage participants to pay attention, their response was followed by a feedback display. If the participant’s answer was correct, the feedback screen showed the message “Correct!” on a green background. This screen disappeared after 500 milliseconds. If the participant’s answer was incorrect, the
participant received the message “Your answer was incorrect” on a red background. This particular screen was displayed for 2500 milliseconds, a time penalty of 2000 milliseconds.

As with Experiment 1, memory was tested using a standard associative recognition memory test phase. Test trials presented either intact or rearranged word pairs and participants were instructed to use a six point scale to rate their level of confidence that a word pair was either intact or rearranged. Participants were again asked to use the full range of the confidence scale. However, given that feedback in the form of a frequency histogram may too acutely bias a response that may not occur otherwise, the form of feedback present in experiment one was not present in this study or subsequent studies. The test phase consisted of 192 trials and all study words were used to compose intact and rearranged test items.

4.2 Results

4.2.1 Working Memory Study Task Performance

Total sample mean accuracy for the working memory task was 77.01% correct, with a standard deviation of 13.76% correct. Accuracy across conditions was as follows: For the non-unitising sentence frame, accuracy for sequence lengths of three and six numbers was 81.50% (11.65%) and 70.61% (15.12%). For the unitising compound frame, accuracy for three and six numbers was 83.53% (9.62%) and 72.38% (13.67%). A repeated measures analysis of variance
Table 4.1

Experiment 2 mean hit rates, false-alarm rates and d’s per condition (standard deviations in parentheses)

<table>
<thead>
<tr>
<th>Memory Load</th>
<th>Hit Rate</th>
<th>False-Alarm Rate</th>
<th>d’</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Compound</td>
<td>Sentence</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>.68 (.13)</td>
<td>.60 (.18)</td>
<td>.31 (.19)</td>
</tr>
<tr>
<td>3</td>
<td>.61 (.16)</td>
<td>.60 (.14)</td>
<td>.34 (.18)</td>
</tr>
<tr>
<td>6</td>
<td>.61 (.16)</td>
<td>.55 (.16)</td>
<td>.32 (.17)</td>
</tr>
</tbody>
</table>

detected a significant effect of sequence length, $F(1,36) = 37.88, p < .001$, partial $\eta^2 = 0.51$, but no significant main effect of frame or interaction.

4.2.2 Associative Recognition Performance

Table 4.1 shows associative recognition hit rates, false-alarm rates and d’s per condition of Experiment 2. The compound encoding condition engendered higher hit rates than the sentence condition, and both compound and sentence hit rates decreased or steadied as memory load increased. False-alarm rates were slightly higher overall for compound frame pairs, but lacked a consistent pattern of increase or decrease across levels of memory load, and this was also the case for d’ measures.
Figure 4.2. ROC curves per condition of Experiment 2
Hit rates, false-alarms and $d'$s were analysed with a $2 \times 3$ (frame by memory load) within-subjects test of analysis of variance. For hit rates, testing detected a significant effect of frame, $F(1,42) = 10.52, p < .05$, partial $\eta^2 = 0.20$, and memory load, $F(2,84) = 4.83, p < .05$, partial $\eta^2 = 0.10$, and no significant interaction effect. Analysis of false-alarm rates yielded a significant effect of frame, $F(1,42) = 7.35, p < .05$, partial $\eta^2 = 0.15$, but no significant effect of memory load or interaction. $d'$s showed no significant effect of frame or memory load, but a slight significant interaction effect was detected, $F(2,84) = 3.55, p < .05$, partial $\eta^2 = 0.08$.

The ROC curves for Experiment 2 are produced above in Figure 4.2. Overall, the ROC curves show intermediate associative recognition performance, a lack of clear spacing between conditions. As with other associative recognition memory ROC curves, these curves show a flattening as performance decreases, which was a pattern not seen in the results of Experiment 1. The results of model-fitting indicate that the ROCs were asymmetric (see Appendix A).

4.2.3 Unitisation
The full HTSD model was fit to the data obtained in Experiment 2 in to obtain parameter estimates of recollection and familiarity. Since state-trace analysis was later performed on hit-rates, reported parameter estimates apply to responses made to intact pairs. Figure 4.3 shows the best fitting parameter estimates obtained for both group and individual data. Estimates of both familiarity and recollection were higher for the compound condition. Within-subjects analysis of variance performed on individual fits detected a main effect of encoding frame on familiarity estimates $F(1,42) = 4.74, p < .05$, partial $\eta^2 = 0.10$, and a main effect of memory load on recollection, $F(2,84) = 9.22, p < .001$, partial $\eta^2 = 0.10$.

4.2.4 State-Trace Analysis

The high confidence responses produced from Experiment 2 are plotted against low confidence responses below in Figure 4.4. False alarms were again nonresponsive to experimental manipulations do not show the characteristic spacing necessary for drawing conclusions. Hit rates in Figure 4.5 suggest monotonicity; however the lack of clear spacing between conditions and a lack of overlap between compound and sentence hit rates makes definitive conclusions difficult to draw. However, the more thorough analysis offered by the monotonic regression framework indicated clear monotonicity. As responses made to rearranged items were typically impervious to the experiment, analysis was performed on responses made to intact items. The monotonic regression framework yielded a not significant value of 1.37, $p = .83$, meaning the fit of the unidimensional
Figure 4.4. State-trace plot of high versus low confidence hit rates.
Figure 4.5. State-trace plots of all possible response comparisons for Experiment 2.
model could not be rejected. In line with this, monotonic regression analysis performed at the individual level did not detect any individual with a bidimensional state-trace (see Appendix B for a full listing).

4.3 Discussion

The goal of Experiment 2 was to examine the underlying dimensionality of associative recognition under study conditions designed to support unitised encoding. Recent research has suggested that unitisation is a viable method for manipulating the activation of familiarity and therefore unitisation was incorporated into the design of Experiment 2 in an effort to activate both familiarity and recollection. The design of Experiment 2 was such that the unitisation manipulation (taken from Haskins et al. (2008)) was utilised alongside a memory load manipulation because these manipulations together predicted differential activation of familiarity and recollection. Consequently, if this differential activation occurred, a bidimensional state-trace was also predicted. However, no evidence for bidimensionality was detected.

A key issue to address is whether unitised encoding did in fact occur since this is a central issue to the current dual-process interpretation of associative recognition. Within the framework of Haskins et al. (2008), there are two proxies for occurrence of unitisation. The first of these is an increase in model estimates of familiarity. The second proxy is simply that performance was better in the unitised condition. Our results reflected those of Haskins et al. (2008) in both cases: familiarity model estimates were higher for word pairs presented with compound sentences and overall performance was also better for that condition.
The unitisation manipulation produced results in line with those of Haskins et al. (2008) and the memory load produced significant main effects on the Experiment 2 hit-rates. However, no evidence for the activation of two processes was detected. As with Experiment 1, it may simply be that the dual-process model is incorrect and that recollection and familiarity do not exist as meaningful, independent processes. However, it may also be the case that both manipulations affected recollection and familiarity in a similar way and differential activation did not occur.

Experiment 1 and Experiment 2 both used forms of a divided-attention manipulation to activate recollection. Since pairing these with different familiarity-enhancing manipulations has not produced evidence for two processes, further research applying state-trace analysis to associative recognition may benefit from an alternate mechanism for manipulating recollection. This is something that will be explored in Experiment 3. Regardless, Experiment 2 represents further evidence for the single-process interpretation of associative recognition.
Chapter 5

Experiment 3 – Reinvestigating Unitisation

Experiment 1 applied the logic of state-trace analysis to a standard intact-from-rearranged discrimination experiment, and this resulted in evidence for unidimensionality. Experiment 2 built on these findings by applying state-trace analysis to unitised associative recognition, which has been used by some researchers (e.g. Haskins et al., 2008; Quamme, Yonelinas & Norman, 2007) as an explanation for the activation of familiarity in associative recognition. The result of applying state-trace analysis to an experiment that paired unitised associative recognition with a recollection-enhancing manipulation was also evidence for unidimensionality. Since the curvilinearity and asymmetry of the Experiment 1 and Experiment 2 ROC curves precludes the possibility that only recollection or only familiarity was activated, unidimensionality means that either the HTSD dual-process model is false or that differential activation did not occur.

Comparison of the results of Experiment 2 to the behavioural data obtained by Haskins et al. (2008) suggested that the unitisation manipulation used in Experiment 2 produced appropriate results: model estimates of familiarity were significantly higher for pairs presented with the compound frame and performance was also generally superior for unitised word pairs. Therefore, assuming the logic of Haskins et al. (2008) is valid, Experiment 2 presumably activated unitisation and familiarity. It is possible, then, that state-trace analysis did not detect two processes because the memory load manipulation used in Experiment 2 failed as an appropriate recollection-enhancing manipulation. Memory load may have not substantially affected recollection at all or it may have affected it in the same way that familiarity was affected by the unitisation manipulation, causing the
behaviour of the two processes to mimic a single-process structure. Experiment 3 was therefore
designed using an alternate recollection-enhancing manipulation: different levels of study time across
pairs.

Previous research has shown that increasing study time produces an increase in estimates of
both recollection and familiarity (Yonelinas, 2002). Evidence for this comes from studies of recall
and item recognition (e.g., Murdock, 1974; Paivio & Csapo, 1969), where increasing study time
improved performance on both tasks. This has been corroborated by studies investigating the effect
of study time on estimates of recollection and familiarity through Remember/Know (e.g. Dewhurst
& Anderson, 1999) and ROC analysis (Yonelinas et al., 1996). This effect is moderate but may be
less than that produced by increasing study presentation number, which was used as a factor in
Experiment 1.

Experiment 3 was designed with study time as one factor, and the unitisation manipulation
from Experiment 2 as the other. Unitisation predicts a moderate increase in familiarity and a
negligible effect on recollection. Study time predicts a moderate increase in the activation of both
familiarity and recollection. As with Experiments 1 and 2, these factors together predict differential
activation of familiarity and recollection. If this differential activation occurs, state-trace analysis
should detect bidimensionality.

5.1 Method

5.1.1 Participants
51 undergraduate Psychology students from the University of Adelaide took part in Experiment 3. Participants were 31 females and 20 males, with a mean age of 20.9 years (SD = 3.05). Students received course credit for their participation. Participants provided informed consent before taking part in the study and were instructed that they could withdraw at any stage. Two participants were excluded from final analyses due to below chance performance across 5 of 6 conditions (operationalized as a $d'$ of .3), and one other participant’s data was excluded due to their failure to adhere to instructions.

### 5.1.2 Design

A 2 x 3 factorial design was utilised for Experiment 3: two levels of unitisation and three levels of study time. The levels of unitisation were again defined through the presence and absence of particular encoding conditions during study. Study time was varied across three levels: 1000, 2000 or 3000 msec. Therefore there were six experimental conditions: word pairs studied for either 1000, 2000 or 3000 milliseconds under unitised conditions (referred to throughout as a ‘Compound’ encoding frame) and word pairs studied for either 1000, 2000 or 3000 under non-unitising conditions (referred henceforth as a ‘Sentence’ Frame). Factors were varied within participants and within lists.

### 5.1.3 Materials
The stimuli used for Experiment 3 were the same word pairs and frames used in Experiment 2. Please see the method section of Experiment 2 for a detailed description.

5.1.4 Procedure

The block structure used within Experiment 3 was the same as that used in Experiment 2. Experimentation involved only one study-test block, with no filler task occurring between study and test. Participants were provided with three short minute-long breaks in each study and test phase. As with Experiment 2, the associative recognition test used in Experiment 3 was incidental; participants were not initially informed that they would be completing a later memory test. The instructions for completing the study and test phases were presented to participants separately before the commencement of each phase.

The study phase used in Experiment 3 was an alteration of the presentation of frame and study pair from the format used in Experiment 2. This was achieved through separation of their presentation into individual screens, where frame and word pair had been presented together within Experiment 2. Study trials began with a small black fixation cross centred on screen against a white background for one second. This automatically changed to a sentence/frame shown centred on screen for three seconds, in black Ariel text against a white background in font-size 50. Participants were instructed that they would need to read this frame and keep it in memory while viewing the next screens. Shown next was a fixation cross, again for one second. Then a word pair was shown, again in black Ariel text against a white background in font-size 50. Participants were instructed to
use their memory of the frame to relate that word pair back. Following this, participants were shown a screen asking them to rate the fit of the frame and word pair. Participants clicked one of four boxes labelled very poor, poor, good and very good, which were presented below the word ‘Fit?’ on this screen. As an example, participants may have first viewed the sentence ‘A vendor of caffeinated beverages’ for three seconds. This may have then been replaced by the word pair ‘COFFEE PERSON’. The participant may have thought this definition of coffee person as a new concept was bad, since ‘A vendor of caffeinated beverages’ is already called a barista, and may have then indicated this opinion by clicking the ‘poor’ box when the screen showed ‘Fit?’ and the four rating boxes. In total, 192 trials were used in the study phase.

The Experiment 3 associative recognition test phase followed the same standard procedure outlined previously. Word pairs were shown on screen either in intact or rearranged form. Participants rated their confidence and choice of intact or rearranged by clicking one of six boxes labelled from sure rearranged to sure intact.

### 5.2 Results

#### 5.2.1 Associative Recognition Performance

Experiment 3 hit rates, false-alarm rates and $d$’s are summarized in Table 5.1. Hit rates increased as study time increased and were generally better in the compound condition. False-alarm rates also rose as study time increased in the compound condition but this ordering was not present
for sentence frame pairs and the overall pattern was a null-effect on false-alarms. $d'$ values were higher overall in the compound condition, but were not ordered according to study time as was seen in sample hit rates. In general, encoding conditions which encouraged unitisation produced better associative memory performance.

A $2 \times 3$ within-subjects analysis of variance (frame by study time) was performed on the measures summarized in Table 5.1. Hit rates showed a substantial main effect of frame, $F(1,47) = 33.66, p < .001$, partial $\eta^2 = 0.42$, and a weaker main effect of study time, $F(2,94) = 6.49, p < .05$, partial $\eta^2 = 0.12$; no interaction effect was detected. False-alarms showed no significant effects, and $d'$ measures showed only a main effect of frame, $F(1,47) = 11.36, p < .001$, partial $\eta^2 = 0.20$.

The ROC curves produced from Experiment 3 are shown below in Figure 5.1. ROC curves for Experiment 3 are clearly spaced and reflect the proficient sample memory performance summarised in Table 5.1. These curves are also asymmetric (see Appendix A), indicating either the activation of a secondary process (familiarity or attention) or higher variance for the underlying

<p>| Table 5.1 |</p>
<table>
<thead>
<tr>
<th>Experiment 3 mean hit rates, false-alarm rates and $d'$s per condition (standard deviations in parentheses)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hit Rate</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td><strong>1s</strong></td>
</tr>
<tr>
<td><strong>2s</strong></td>
</tr>
<tr>
<td><strong>3s</strong></td>
</tr>
</tbody>
</table>
Figure 5.1. ROC curves per condition of Experiment 3.
intact distribution compared to the rearranged distribution, depending on model interpretation. Figure 5.1 also shows that these ROC curves flatten in curvature across conditions as performance moves toward the major diagonal. The ROC curves produced from Experiment 1 were similar in their spacing and demonstration of good performance. However, those ROC curves did not flatten across conditions where these do, making these ROC curves more similar to ROC curves shown in past associative recognition research.

5.2.2 Unitisation

As with Experiment 2, familiarity and recollection parameter estimates per condition of Experiment 3 HTSD model estimates for data fit at both the group and individual level.

*Figure 5.2.* Experiment 3 HTSD model estimates for data fit at both the group and individual level.
Experiment 3 were obtained by minimizing the fit of the HTSD model. Again, estimates of both parameters were higher in the compound condition across both group and individual participant fitting and this is summarised in Figure 5.2 below. Within-subjects analysis of variance testing on individual parameter values detected a significant effect of encoding frame on familiarity, $F(1,47) = 6.38, p < .05$, partial $\eta^2 = 0.12$. Both encoding frame, $F(1,47) = 26.80, p < .001$, partial $\eta^2 = 0.36$, and study time, $F(2,94) = 5.10, p < .05$, partial $\eta^2 = 0.10$, produced significant main effects on individual fits of the HTSD recollection parameter.

5.2.3 State-Trace Analysis

Figure 5.3 below shows high confidence “Old” responses plotted against low confidence “Old” responses for Experiment 3, and the data are clearly unidimensional. As indicated by Table 5.1 and the results of analysis of variance testing, false-alarms were largely unaffected by the manipulations used in Experiment 3 and this is evident in the state-trace plot shown above. The hit rates produced by Experiment 3, however, show clear spacing between conditions and also strongly indicate monotonicity. This pattern is repeated throughout Figure 5.4, where all levels of confidence are plotted against one other. While Figure 5.4 shows that in some conditions the second most top condition deviates from the near-perfect hit-rate linearity present in Figure 5.3, this is still not a departure from unidimensionality since visual inspection indicates that a monotonic plot could still easily fit this data. This is confirmed statistically by the results of the monotonic regression framework, which yielded a minimized $SSE$ value approximately equal to 0, with a $p$-value = .99,
Figure 5.3. State-trace plot of high versus low confidence hit rates.
Figure 5.4. State-trace plots of all possible response comparisons for Experiment 3
meaning, as Figure 33 would indicate, the fit of the unidimensional model could not be rejected. This finding is supported by the results of monotonic regression individual subjects fitting, where no individual participant produced data that could permit the unidimensional model to be rejected (see Appendix D for a full listing).

5.3 Discussion

The purpose of Experiment 3 was to re-investigate the dimensionality of unitised associative recognition memory. Given that the unitisation manipulation used in Experiment 2 produced expected patterns of sample accuracy and model estimates, but this manipulation together with a recollection-enhancing manipulation did not result in differential activation of familiarity and recollection, Experiment 3 was designed to reassess unitised associative recognition with a replicated unitisation manipulation and a different recollection-enhancing manipulation. This new combination of independent variables predicted differential activation of the underlying components of the dual-model class and therefore predicted a bidimensional state-trace.

The results obtained from Experiment 3 indicated that the manipulated factors successfully demarcated performance conditions. Both the unitisation manipulation and study time manipulation produced substantial and significant main effects on hit-rates, though again a null-effect on false-alarms was observed. The ROC curves obtained in Experiment 3 showed clear differences within and between levels of each manipulation. As with Experiment 1 and Experiment 2, the ROC curves obtained in Experiment 3 were asymmetrical and curvilinear. The unitisation manipulation also produced expected performance: memory accuracy and familiarity model estimates were higher...
overall for the compound conditions, and analysis of variance testing detected a significant main
effect of encoding frame on the HTSD familiarity parameter. However, despite the success of the
experimental manipulations, state-trace analysis again did not show evidence of two underlying
processes. Monotonic regression framework analysis at the group level clearly indicated a
unidimensional state-trace, and analysis at the individual level indicated that no individual participant
produced bidimensional data.

Three disparate modifications of intact-from-rearranged discrimination have thus far failed
to show evidence of two processes. While the three experiments may have simply failed to properly
activate recollection and familiarity, the experimentation covered above represents an accumulation
of evidence for the single-process model class; as the number of experiments that fail to show
evidence of their activation increases, the possibility of their existence becomes increasingly unlikely.

In the discussion of Experiment 2 it was noted that the pattern of results produced for the
unitisation manipulation was similar to that of Haskins et al. (2008), suggesting that this
manipulation was sufficiently activating familiarity. However, two unitisation experiments have now
failed to show differential activation despite pairing this manipulation with different recollection-
enhancement manipulations. While it may be the case that both recollection-enhancements failed to
work in tandem with the Haskins et al. (2008) manipulation to produce differential activation, it may
also be possible that sentence/compound encoding failed to adequately produce sufficiently
different contributions of familiarity across conditions. While model estimates do show an increase
in the HTSD familiarity component across each condition of this manipulation, ROC curves
obtained in Experiments 2 and 3, as well as those in Haskins et al. (2008) (see Figure 5.5 below)
show a high level of consistency in shape across both conditions of the manipulation. Since the
dual-process theory holds that an increase in the curvilinearity of an associative recognition ROC
curve is due to the added activation of familiarity, the same shape for ROCs obtained from both the
sentence and compound condition may suggest that the contribution of familiarity to each condition
is similar. Furthermore, while model estimates of familiarity are significantly higher for word pairs
encoded under compound conditions, model estimates of familiarity in the sentence condition of
Haskins et al. (2008) are still substantial, as they were for the results of Experiment 2 and
Experiment 3. Consequently, the failure of differential activation to occur may be due to the failure
of the unitisation manipulation to produce sufficiently different activation of familiarity across
conditions. Fortunately, Jäger and Mecklinger (2009) have proposed an alternative method for
manipulating unitisation, which may offer a superior way of manipulating familiarity and therefore
of producing differential activation. This will be explored in Experiment 4.
Experiment 4 – The Dimensionality of Unitised Morphed Face Stimuli

The experimentation detailed above has examined the dimensionality of associative recognition memory across two distinct domains. Experiment 1 was used to assess the dimensionality of a standard intact-from-rearranged design, a design that has been at the fore of associative recognition research since the foundational work of Yonelinas (1997). Experiment 2 and Experiment 3 were used to examine the dimensionality of a more recent modification of this design, where the familiarity-enhancing factor was controlled through a unitisation manipulation replicated from the research conducted by Quamme, Yonelinas and Norman (2007) and Haskins et al. (2008). State-trace analysis applied to these domains did not yield evidence for the activation of two underlying processes in either case. Two possible explanations are that either the dual-process model class is incorrect or that the dual-process model class is correct but the manipulated factors used in Experiments 1, 2 and 3 did not differentially activate recollection and familiarity. Both the single-process model class and dual-process model class with insufficiently distinct activation of its two underlying parameters each predict a unidimensional state-trace, which experimentation has thus far consistently detected.

Experiments 2 and 3 each paired a recollection-enhancing manipulation (memory load and study time, respectively) with the unitisation familiarity-enhancing manipulation replicated from by Quamme, Yonelinas and Norman (2007) and Haskins et al. (2008). This manipulation had two levels: sentence frame encoding and compound frame encoding. Haskins et al. (2008) found that intact-from-rearranged discrimination was superior for words encoded in the compound condition.
and that model estimates of familiarity were also higher. This pattern of results was replicated in Experiments 2 and 3. Haskins et al. (2008) argued that these two findings indicate that unitised encoding activated familiarity. However, despite this, state-trace analysis detected unidimensionality when unitisation was paired with recollection-enhancing manipulations in Experiment 2 (memory load) and Experiment 3 (study time). The failure of recollection and familiarity to differentially activate may be due to the failure of the recollection-enhancements to properly activate recollection. Alternatively, it may be that compound/sentence encoding did not produce substantial differences in familiarity activation. The similarity in shape of ROC curves Haskins et al. (2008) (and Experiments 2 and 3) may suggest that this method for directly manipulating unitisation does not produce substantial differences in familiarity contribution across conditions. This would mean a failure of the familiarity-enhancement manipulation to appropriately contribute to differential activation in Experiments 2 and 3, and a resulting unidimensional state-trace – as was detected.

Jäger and Mecklinger (2009) recently extended the manipulation of unitisation beyond pre-existing compound words (e.g. Yonelinas et al., 1999) or encoding frames (Haskins et al., 2008; Quamme, Yonelinas & Norman, 2007). This research instead investigated unitisation through the perceptual similarity of faces at study. Jäger and Mecklinger (2009) argued that the perceptual overlap of stimuli such as faces meant that they could be bound into a single memory trace during encoding. Jäger and Mecklinger (2009) examined the contribution of familiarity due to unitisation using a similar method to that used by Haskins et al. (2008): familiarity contribution was assessed through ROC analysis and by fitting HTSD model parameters. In line with the results obtained by Haskins et al. (2008), parameter estimates of familiarity were higher for pairs encoded under unitisation conditions. However, in contrast to the results of Haskins et al. (2008), ROC curves obtained for unitised word pairs displayed a greater degree of asymmetry and curvature. This may indicate that the Jäger and Mecklinger (2009) method for manipulating unitisation allows for a
greater difference in familiarity contribution across conditions, and may therefore offer a superior method for obtaining differential activation using state-trace analysis.

The manipulation of unitisation through the perceptual similarity of stimuli is a distinct context in which to apply the logic of state-trace analysis and offered a new method for producing differential activation through more substantial activation of familiarity. Therefore, Experiment 4 utilised a design that incorporated the stimuli and morphed versus random pairing design used within Jäger and Mecklinger (2009). This was paired with a study time manipulation similar to that used in Experiment 3. Although modifying memory performance through study time in Experiment 3 did not lead to differential activation when paired with sentence/compound encoding, it did show promise as a solid experimental manipulation in producing significant and moderate main effects and so was re-used. As previously indicated, study time produces moderate effects on both recollection and familiarity (Yonelinas, 2002) and unitisation through perceptual similarity produces a moderate effect on familiarity and a low-to-null effect on unitisation (Jäger & Mecklinger, 2009), and this again is differential activation that predicts the activation of two underlying processes that should be detected by state-trace analysis. In the interests of accurately replicating the major features of Jäger and Mecklinger’s study, the unitisation manipulation used in Experiment 4 was not randomized within blocks. Rather, individual study-test blocks were designed to either elicit unitisation or encourage non-unitised encoding.

An additional goal of Experiment 4 was to extend the current state-trace analysis of unitisation by utilising a component of the research undertaken by Mickes, Johnson and Wixted (2010). In this study, participants made Old/New judgements on each test pair before deciding if it was intact or rearranged, and associative recognition ROC curves were later group according to these Old/New ratings. Mickes, Johnson and Wixted (2010) produced associative recognition ROC
curves based on item recognition ratings of either “New”, medium confidence “Old” or high confidence “Old”. This conditionalisation was designed to test whether a lack of Old/New information represents a form of noise that impairs associative recognition discrimination.

Experiment 4 incorporated this design by performing a state-trace analysis on associative recognition for pairs that had been rated high confidence “Old”. Since these pairs represent items for which full item information should be available, associative recognition decisions made on these pairs should be of high quality, as they were in Mickes, Johnson and Wixted (2010). Application of state-trace analysis to these pairs was a promising means for detecting the activation of two processes, for two reasons. First, previous unitisation experimentation has consistently shown that unitised encoding results in superior associative recognition performance compared to non-unitised encoding (e.g. Haskins et al., 2008). Therefore, unitised familiarity activation may be larger when item recognition and associative recognition are strongest. Second, recollection activation in item recognition is thought to be largest when confidence is high and more Old/New information is available (Yonelinas, 1994), and this may also be the case in associative recognition. Consequently, if associative recognition ROC curves for pairs rated high confidence “Old” showed asymmetry and therefore the activation of familiarity and recollection, the large nature of their contribution may have increased the chance of detecting bidimensionality.

Experiment 4 explored the above through a modification of the design used by Mickes, Johnson and Wixted (2010), in which participants responded with some level of confidence “Old” or “New” to each pair. It is possible that within this study participants were producing pair ratings by combining Old/New ratings for each individual item. Depending on the strategy used to combine these individual ratings into a pair rating, this could allow for a high confidence “Old” rating to be weakened by the inclusion of a lower confidence item rating or a rating of “New”. Therefore, participants in Experiment 4 instead provided two Old/New ratings for each pair: one
for each individual item. This allowed three methods of conditionalisation, which included possible strategies participants may have used to provide pair ratings. These were pair ratings composed of items that were given the same Old/New rating, pair ratings constructed by anchoring on the lowest rated item and finally pair ratings constructed by anchoring on the highest rated item. For low anchor conditionalised pairs, if for example one item of a pair was rated “New” and the other high confidence “Old”, the associative recognition ROC curve was conditionalised as “New”. For high anchor pairs, if one item of a pair was rated “New” and the other high confidence “Old”, the associative recognition ROC curve was conditionalised as high confidence “Old”. As a consequence of this, a conditionalised state-trace analysis could be run on pairs where both items had been rated high confidence “Old”, thereby helping to maximise the amount of item and associative information available, and by implication maximise the activation of recollection and familiarity. Additionally, comparison of the conditionalised Experiment 4 ROC curves to those produced within Mickes, Johnson and Wixted (2010) allowed for investigation into whether participants in their study were anchoring their pair ratings on one item of a pair.

6.1 Method

6.1.1 Participants

42 participants were recruited from The University of Adelaide’s first-year Psychology courses. Of those, 29 were female and 13 male. The mean age of the sample was 18.9 years with a
Figure 6.1. Morph percentage examples for an example set of morphed condition stimuli.

standard deviation of 1.28 years. Participants provided written consent before commencing experimentation. One participant provided incomplete data and was subsequently excluded from later analyses. All other participants provided suitable recognition memory performance and were included in final analyses.

6.1.2 Design

A 2 x 3 factorial design was used to investigate the dimensionality of associative recognition. The factors were unitisation and study time. The two levels of the unitisation manipulation were formed by the presence and absence of perceptual encoding conditions purported to engender unitised encoding (c.f. Jäger & Mecklinger, 2009). These conditions were morphed face pairs (unitised stimuli) and unmorphed faces pairs (non-unitised stimuli), each used as study items. Three levels of study time formed the second factor. Participants were exposed to each study item for
either 3, 4.5 or 6 seconds. Factors were varied within participants but only study time was varied within each list; study-test blocks used either unitised or non-unitised stimuli. The ordering of blocks was randomised per participant.

### 6.1.3 Materials

The stimuli used in Experiment 4 were taken from a head shot database developed by Saarland University’s Experimental Neuropsychology Unit (see Jäger, Seiler & Mecklinger, 2005 for a detailed report on the database’s creation and composition). Images were 384 emotionally neutral unfamiliar adult faces. The study used an equal number of male and female faces, and gender was varied within study and test lists. All stimulus images were grey-scale and 257 x 379 pixels in size. Of the 384 total faces used in the experiment, half were utilised in each unitisation/morph condition. Placement of faces into each category was non-random and consistent across participants. For reasons outlined below, the Saarland University database is composed of faces which are a priori considered either morphed or unmorphed.

Each unmorphed face was randomly paired in the study phase with a gender matched counterpart to form 96 total unmorphed pairs. Only 96 of the 192 faces used in the morphed condition were pictures of unique individual faces. The remaining 96 faces were morphed variations of pairs of unique faces. As illustrated in Figure 6.1, all faces in the morphed condition could be one of a 0% morph, 35% morph, 70% morph, or 100% morph. 0% and 100% morphs were unique individuals. A 35% morphed face was a 35% morph of a 0% unique face to a 100% unique face. A 70% face was a 30% morph of a 100% unique face to a 0% unique face. Morphed faces were
Figure 6.2. Test pair construction. Note that pairs B and Y are discarded if assigned to the intact condition and items 0%, 100%, X2 and Y2 are discarded if assigned to the rearranged condition.

NOTE:
These figures/tables/images have been removed to comply with copyright regulations. They are included in the print copy of the thesis held by the University of Adelaide Library.
constructed once only; i.e., a particular 0% face would always form a morph continuum with a particular 100% face. Study pairs were formed by pairing 0% with 35%, and 70% with 100%. This experiment featured the same intra-block change detection colour photographs as used previously in experiment one. Please see the Experiment 1 materials section for more details.

6.1.4 Procedure

For the purposes of later comparison, Experiment 4 was designed to replicate some aspects of Jäger and Mecklinger (2009). As will be detailed below, study and test pair composition followed the same form. However, timing, intra-block task structure and block structure were novel. Participants began the session by viewing relevant introductory materials then providing written consent. Due to the complex nature of the experiment’s tasks, great care was then taken to explain the particulars of the experiment and participant feedback was requested to ensure that the task was understood. Participants were made aware that they would be taking a later memory test on the study items. Participants were instructed to form associations between pairs of faces by focusing on distinct facial features and any other information that could be personally related to each pair.

The experiment was divided into eight study-test blocks. Blocks utilised either morphed or unmorphed stimuli and block order was randomised. Four blocks examined morphed stimuli and four examined unmorphed stimuli. Between study and test phases, participants took part in a change detection task for 30 seconds. Each block was discrete in that test items were comprised only of items shown in the study phase of that particular block. Block phases began with a text display asking participants to press the spacebar to continue.
Each study phase involved the presentation of 24 pairs of faces. Study trials began with a small black fixation cross on a white background. The cross remained on screen for one second before changing automatically to the study item face pair. Pairs were displayed in grey-scale against a white background and in their original 257 x 379 size. Faces were positioned alongside one another in the centre of screen, separated by a small amount of whitespace. Each pair was shown for either 3, 4.5 or 6 seconds. Allocation of study pair to study time condition was randomised along with condition ordering within study and test list. Unmorphed faces were randomly allocated to left or right position. For the purposes of later test pair construction and presentation, morphed faces were shown in set screen locations: 35% and 100% morphs were shown left of screen while 0% and 70% morphs were displayed on the right.

Each test phase consisted of 12 test items. Per block, six test items were intact study pairs and six had been rearranged. Test pair construction is summarised in Figure 6.2. For the morphed condition, intact pairs consisted of the 35% and 0% morphs from a morph set. The 70% and 100% pair of that set was discarded. Rearranged morphed pairs were composed of 35% and 70% faces while the 0% and 100% faces were discarded. The morph degrees of intact and rearranged pairs were chosen to control for the degree of similarity between faces: both intact and rearranged faces differed in morph value by 35% (Jäger & Mecklinger, 2009). The unmorphed condition utilised the same pattern of test list creation. Depending on their position within the study list and their screen position during study, faces were assigned to either an intact or rearranged pair, or discarded. However, because the specifics of test list creation were instantiated to control for stimulus features of morphed items, unmorphed item designation to intact, rearranged or discarded was largely arbitrary. Unmorphed faces were randomly assigned to sets prior to study (e.g. set XY from the top of Figure 6.2) and test lists were created according to their status within these sets (e.g. X1 or Y2).
After participating in a change detection task for 30 seconds, participants completed a three-stage test phase. For each test pair, participants were first tested on their recognition of each individual face. Participants were shown the left face first, with the words “Do you remember seeing this face?” printed above it. Before experimentation began, participants were made aware that due to the nature of the experiment, every individual face had been seen previously – a fact one assumes would have become obvious to most participants eventually. However, participants were instructed that the experiment was examining their personal feeling of familiarity toward an item, not a judgement of the likelihood of an item being old. Participants rated their familiarity on a six point confidence scale by clicking one of six boxes labelled from ‘Sure No’ through to ‘Sure Yes’. The other points on the scale were ‘probably’ and ‘possibly’. Following this, participants made the same judgement on the right face of a test pair. Faces shown individually were centred rather than appearing in their original position. Finally, participants were shown the test pair proper and asked to rate their confidence that the pair was either intact or rearranged by clicking one of six boxes labelled from ‘Sure Rearranged’ to ‘Sure Intact’. The test phase followed the same procedure for both morphed and unmorphed items.

6.2 Results

6.2.1 Associative Recognition Performance

Experiment 4 associative recognition hit rates, false-alarm rates and $d'$s per morph and study
Table 6.1

Experiment 4 mean hit rates, false-alarm rates and d’s per condition (standard deviations in parentheses)

<table>
<thead>
<tr>
<th>Study Time</th>
<th>Hit Rate</th>
<th>False-Alarm Rate</th>
<th>d’</th>
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<tbody>
<tr>
<td></td>
<td>Morphed</td>
<td>Unmorphed</td>
<td>Morphed</td>
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<tr>
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<td>.38 (.21)</td>
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<td>.47 (.22)</td>
<td>.43 (.23)</td>
</tr>
<tr>
<td>Long</td>
<td>.66 (.22)</td>
<td>.46 (.22)</td>
<td>.38 (.24)</td>
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</tbody>
</table>

Differences between conditions were reasonably moderate but were ordered unexpectedly, with the medium study time condition producing a better hit-rate for both stimulus types and the unmorphed pairs producing a better medium study time d’ than that produced by the sample for longer study time. To quantify these condition differences, hit rates, false alarms and d’ values were analysed with a 2 x 3 (morph by study time) within-subjects test of analysis of variance. As with Experiments 1 and 2, hit-rates produced significant main effects across both manipulations. Both morph, $F(1,40) = 32.21, p < .001$, partial $\eta^2 = 0.45$, and study time, $F(1,40) = 13.56, p < .001$, partial $\eta^2 = 0.25$, produced strong main effects, and no interaction effect was detected. Interestingly, a substantial main effect of morph, $F(1,40) = 21.67, p < .001$, partial $\eta^2 = 0.35$, was detected for false-alarms. Analysis of variance testing performed on $d’$ did not yield any significant main effects or a significant interaction effect. ROC curves produced from Experiment 4 (Figure 6.3 below) demonstrate the poor level of memory performance obtained by this sample; curves for all conditions are located
Figure 6.3. ROC curves per condition of Experiment 4.
very close to the major diagonal, indicating near-chance performance across conditions. This set of ROC curves also shows a characteristic flattening. However curvature is not at all pronounced in the better conditions and the poorer performance conditions are basically straight.

While this sample’s performance was poor, the ROC curves in Figure 6.3 show that the data set is well-structured enough to undertake further analysis: condition curves are reasonably well spaced (if somewhat out of order) indicating that the experimental conditions produced moderately differential effects, a position supported by the results of analysis of variance testing reported above. Evidence for the possible activation of two factors is demonstrated by the results of model-fitting, which indicated asymmetry (see Appendix A).

### 6.2.2 Unitisation

Experiment 4 HTSD model parameter estimates are summarised below in Figure 6.4. Again, model estimates of both recollection and familiarity were higher in the unitisation condition for both group and individual data. However, in contrast to the results of Experiment 2 and Experiment 3, differences between conditions were larger for group data compared to averaged individual fits. In line with this finding, within-subjects analysis of variance testing on parameter values fit to individual participants did not detect any significant effects on the familiarity component. However, both stimulus morph ($F(1,40) = 22.02, p < .001$, partial $\eta^2 = 0.36$) and study time ($F(2,80) = 3.87, p < .05$, partial $\eta^2 = 0.09$) produced significant main effects on individual fits of the HTSD recollection parameter.
6.2.3 Conditionalised ROC curves and State-Trace Analysis

The results of conditionalising associative recognition ROC curves based on Old/New ratings are shown below in Figure 6.5. The six-point rating scale was collapsed to form ratings of “New” (“Sure New”, “Probably New” and “Possibly New”), medium confidence “Old” (“Possibly Old” and “Probably Old”) and high confidence “Old” (“Sure Old”). Of all rated pairs, 66% received the same collapsed category of Old/New rating. The results of constructing these ROC curves are shown together with the curves produced by Mickes, Johnson and Wixted (2010). Visual inspection of Figure 6.5 suggests that the “Low Anchor” curves maintain a higher amount of asymmetry than the “High Anchor” pairs, and the high anchor pairs more closely resemble those found by Mickes, Johnson and Wixted (2010). This was confirmed by the results of model-fitting (see Appendix A): testing indicated that the medium and high confidence high anchor pairs were both symmetric, and the medium and high confidence low anchor pairs were asymmetric. Note that due to the anchoring
Figure 6.5. Experiment 4 conditionalised ROC curves (left) and conditionalised ROC curves reproduced from Mickes, Johnson and Wixted (2010) (right). Top left ROC curves represent curves constructed by anchoring the pair rating on the lowest confidence response made to an item, middle left ROC curves show curves constructed based on anchoring the highest rated item, and bottom left show only those where Old/New ratings were the same across both items of a pair. Curves reproduced from Mickes et al. (2010) represent associative recognition judgements made on items not recognised as Old (A), recognised with low or medium confidence (B), and recognised with high confidence (C).
Figure 6.6. State-trace plot of high versus low confidence hit rates for associative recognition memory decisions made on pairs first rated high confidence “Old”.
process, the low anchor curve for high confidence “Old” is the same curve as that produced by conditionalisation for when ratings agree. This is also the case for the high anchor “New” curve.

6.2.4 State-Trace Analysis

Given the asymmetry of the high confidence “Old” curve for ratings that agree, a state-trace analysis was run on those pairs. Figure 6.6 above displays the results of plotting high confidence versus low confidence responses for associative discrimination on high confidence “Old” pairs. Visual inspection of this plot indicates that drawing strong conclusions is difficult. While the plot could potentially be well-described by a monotonic function, it could alternatively indicate two processes, and the lack of overlap between conditions makes rejection of the latter possibility difficult. However, application of the monotonic regression framework did not allow the unidimensional model to be rejected ($\text{SSE} = 1.21, p = .93$). For exploratory purposes the monotonic regression framework was also applied to the remaining conditionalised data and the unidimensional model could not be rejected in any case.

Experiment 4 produced hit rate main effects on both face morph and time, meaning that a state-trace analysis could proceed in the same way as Experiments 1, 2 and 3. Figure 6.7 below shows high confidence responses plotted against low confidence responses. As has been seen previously, the high confidence versus low confidence state-trace plot shows some slight scattering of data points but is indicative of a monotonic function. However, the data produced from Experiment 4 are unique: where previous experimentation described above has produced a nonresponsive clump of false-alarms, state-trace plots from this experiment show spacing among
Figure 6.7. State-trace plot of high versus low confidence hit rates.
Figure 6.8. State-trace plots of all possible response comparisons for Experiment 4
the false-alarm data points. This pattern is repeated in the full comparison plot shown below in
Figure 6.8. Most plots are similar in nature to Figure 6.7. Hit-rates generally show monotonicity with
an occasional slight deviation. The false-alarms, however, are not as characteristically monotonic.
The overall picture that emerges from Figure 6.8 is one of general monotonicity with some
comparisons showing slight non-monotonic deviations in the false-alarms. The hit-rate visual
indication of monotonicity in Figure 6.8 is strongly supported by the results of monotonic
regression testing, where least-squares minimization produced a figure of 0 and a $p$-value of
approximately .98. Additionally, application of the monotonic regression framework to the hit rates
of individual participants indicated that one participant produced data where the unidimensional
model could be rejected, producing an $SSE$ value of 0.7 and a $p$-value of 0.05 (see Appendix E for a
full listing). While this is evidence that in general the data produced shows monotonicity, this
indicates that the monotonic regression framework is at least capable of allowing unidimensionality
to be rejected.

Although the results of analysis of variance testing did not show two main effects on false-
alarm rates (meaning there would be no prediction of dual-process activation), given the
uncharacteristic spacing of false-alarms seen in Figure 6.8, and for the sake of exploration, the
monotonic regression was run on both the full model (both hit rates and false-alarms) and just the
false-alarms, producing non-significant $SSE$ values of 5.15 ($p = 0.56$) and 1.84 ($p = 0.41$)
respectively.

6.3 Discussion
The primary objective that motivated Experiment 4 was the application of state-trace analysis to an alternate method for operationalizing unitisation, previously seen in research undertaken by Jäger and Mecklinger (2009). Where Experiment 2 and Experiment 3 operationalized unitisation through word pairs shown together with a unitising frame, Experiment 4 involved asking participants to study pairs of faces, and unitisation was manipulated through the perceptual similarity of those stimuli. This familiarity-enhancing manipulation combined with a manipulation designed to activate both recollection and familiarity (study time) predicted differential activation of the two underlying processes, which in turn predicted a bidimensional state-trace.

The perceptual similarity manipulation used in Experiment 4 replicated the major performance markers of a familiarity-enhancing manipulation, as seen previously in Jäger and Mecklinger (2009). While overall associative recognition memory performance was poor, performance was better for unitised pairs as it was in Jäger and Mecklinger (2009). Model estimates of familiarity were also higher in the unitisation condition (although in contrast to Experiment 2 and Experiment 3, analysis of variance did not detect a significant main effect of the familiarity-enhancing manipulation on HTSD model estimates of familiarity). Despite this, and the detection of main effects on hit-rates for both independent variables, application of the monotonic regression framework to hit-rates did not allow for rejection of the unidimensional model. At the individual level, only one participant demonstrated bidimensionality in responding.

Conditionalising associative recognition discrimination based on Old/New information also did not result in the detection of bidimensionality. ROC analysis of responses conditionalised on joint high confidence “Old” ratings indicated that the curve was asymmetric, and therefore suggested evidence of dual-process activation. However, while application of the monotonic regression framework did not allow for the unidimensional model to be formally rejected,
generalisation from these results should proceed with caution. The conditionalised state-trace plot indicated monotonicity but also indicated that two processes may have been activated. The lack of overlap between conditions means that clear evidence for either unidimensionality or bidimensionality could not be properly resolved. This ambiguity was compounded by the potential influence of noise in the data, since conditionalising responses based solely on two high confidence “Old” responses meant that few data points were included in final analyses. However, while only guarded conclusions can be drawn, these results are nonetheless interesting and further research may perhaps be conducted to shed light on the issue. Aside from the dimensionality of the data, comparison of the asymmetry of Experiment 4 conditionalised ROC curves to the results of Mickes, Johnson and Wixted (2010) suggests that when participants are asked to make pair ratings of the Old/New status of stimulus pairs, their strategy may be to construct their rating based on the highest felt confidence toward each pair (if the two items do not already have equal ratings).

In more general terms, the results of Experiment 4 possess some interesting characteristics that mark them as somewhat distinct when compared to the results of Experiments 1, 2 and 3. As descriptive statistics and the ROC curves demonstrated, sample memory performance was poor. This was not altogether unexpected given the obvious difficulty of the task and that sample memory accuracy in Jäger and Mecklinger (2009) was also poor. Note that the poor sample performance may explain the lessened asymmetry of the ROC curves, as has been demonstrated in prior research (e.g. Kelley & Wixted, 2001). Additionally, while the false-alarm rate has previously remained largely unaffected by any manipulation in Experiments 1, 2, or 3, the results of Experiment 4 showed a main effect of stimulus condition on the false-alarm rate. While this is interesting in the context of this thesis (since this has not previously occurred), this is not entirely uncommon in associative recognition research (Xu & Malmberg, 2007) and both the existence of the main effect and the direction of the effect (a higher false-alarm rate in the morphed face condition compared to
discrimination of unmorphed trials) replicated that found by Jäger and Mecklinger (2009). However, the combined direction of effects of stimulus similarity on hit rates and false-alarm rates in the results of Experiment 4 and Jäger and Mecklinger (2009) is somewhat rare: an increase in stimulus perceptual similarity significantly increased both hit rates and false-alarm rates. Historically, in both item and associative recognition, a manipulation that increases the hit rate will usually decrease the false alarm rate and vice-versa, a phenomenon named the *mirror effect* (Hockley, 1994). While the mirror effect occurs less frequently in associative recognition than item recognition (Kelley & Wixted, 2001), a wide range of independent variables have produced mirror effects in associative recognition (e.g. Hockley, 1994; Xu & Malmberg, 2007) and have been found for both within-lists and between-lists designs (e.g. Clarke & Shiffrin, 1992). The reverse-mirror effect obtained in Experiment 4 is decidedly less common in associative recognition research, but not unique, having been previously found by Nairne (1983) when manipulating rehearsal rate and Hockley (1991) when using a retention interval manipulation. Generalizing conclusions from the designs of Nairne (1983) and Hockley (1991) is problematic, however, since their stimuli were word pairs and manipulations were based on time and seemingly had little to do with perceptual similarity.

The increase in both hits and false-alarms for associative recognition judgements on morphed stimuli may have been due to the nature of the experimental manipulations used in Experiment 4. Where Experiments 1, 2 and 3 utilised within-list manipulations, the morphed versus non-morphed manipulation used in Experiment 4 was between-list. Consequently, participants may have used a different criterion for judgements within each block of the experiment. The pattern of results produced from Experiment 4 may indicate that participants used a more liberal strategy for morphed stimuli compared to unmorphed stimuli, leading to both more false-alarms and hits for these stimuli. However, the size of this effect was negligible. Usually, the UVSD model would only be constrained to one free parameter in a within-list design (see discussion above) while a between-
list design would predict that both memory strength and the criterion parameter would be free to vary. Since state-trace analysis of this experiment led to the detection of only one parameter, the shift is criterion was not substantial enough to play a major role in the predicted structure of each model.

The results of state-trace analysis performed on hit-rates obtained from Experiment 4 show the activation of one process, and this is support for the single process model, in line with the results of Experiments 1, 2 and 3. Experiment 4 therefore extends the list of associative recognition experiments that have failed to detect the activation of two processes.
Chapter 7

Discussion

The aim of this thesis has been to address whether associative recognition memory is explained by a single-process model such as the UVSD model, or a dual-process model such as the HTSD model. The single-process class of models propose that associative recognition judgements are based on a single continuum of memory strength. This is in contrast to the explanation proposed by the dual-process model class, where associative recognition judgements are based on the activation of two distinct sources of memory information. These two processes are generally referred to as familiarity and recollection, and they are conceptualised as providing distinct contributions to associative recognition decisions.

Evidence for the single-process or dual-process model class was investigated through application of state-trace analysis. State-trace analysis is a general method for determining the number of latent variables or processes that govern performance on a task; whether an area of research such as associative recognition is best explained by a single or dual-process model class. A secondary goal of this thesis was to extend the state-trace analysis framework previously seen in other research (e.g. Dunn, 2008) to include a statistical test allowing the unidimensional model to be formally rejected as a null-hypothesis. This extended framework was used to provide an overall assessment of the dimensionality of associative recognition memory and therefore ascertain evidence for either the single-process or dual-process model class as the leading candidate for explanation.

The dimensionality of associative recognition was examined across four experiments. The purpose of each experiment was to manipulate factors that previous research indicated may produce
changes in the activation of familiarity and recollection. The aim of utilising these manipulated factors was to obtain differential activation of familiarity and recollection, whereby factors were affected sufficiently differently by the independent variables used in an experiment (see Figure 2.4 for an example). The potential success of differential activation predicted that state-trace analysis would detect bidimensionality, and this would form evidence for the dual-process HTSD model as a viable explanation of associative recognition.

Experiment 1 assessed the dimensionality of intact-from-rearranged discrimination of word pairs. The factors manipulated were number of study presentations and divided attention. Divided attention was predicted to activate recollection more than familiarity (e.g. Craik, Govoni, Naveh-Benjamin & Anderson, 1996), while increasing number of study presentations was predicted to produce comparable changes in both processes (e.g. Parkin & Russo, 1993). Experiments 2 and 3 also assessed intact-from-rearranged discrimination of word pairs, but both experiments were designed to manipulate familiarity through a unitising sentence presented together with each study item (see Quamme, Yonelinas & Norman, 2007). Previous research has indicated that this unitisation manipulation produces an increase in familiarity contribution while having a negligible effect on recollection (Haskins et al., 2008). In Experiment 2, this manipulation was paired with a memory load manipulation that predicted similar changes to recollection as the divided attention manipulation in Experiment 1 (Yonelinas, 2002). In Experiment 3, the unitisation manipulation was paired with a study time manipulation that previous research suggested may activate both recollection and familiarity (Yonelinas, 2002). Finally, Experiment 4 extended this research by investigating intact-from-rearranged discrimination of face stimuli, where unitisation was controlled through perceptual similarity (see Jäger & Mecklinger, 2009) and differential activation was attempted by pairing this manipulation with the study time manipulation from Experiment 3.
Across the four experiments, factors were chosen because their combination of process activation predicted differential activation, and because they cumulatively represented a broad account of the dimensionality of associative recognition. For example, Experiment 1 represented encoding where unitisation may have only contributed in an incidental manner, whereas in Experiments 2, 3 and 4, two different types of unitisation factor were used to assess the dimensionality of associative recognition under unitised encoding conditions. Furthermore, differential activation was attempted through study time manipulations, increasing number of study presentations and divided attention, meaning that manipulation of both familiarity and recollection was attempted across a wide range of factors.

Despite the broad range of independent variables with which state-trace analysis was applied, no combination of factors resulted in evidence for the activation of familiarity and recollection. Across each experiment, neither state-trace plots nor application of the monotonic regression framework at the group or individual level resulted in evidence for the activation of two processes. All four experiments resulted in state-trace plots that indicated they could be fit by a monotonic function, and only one participant produced data that allowed for the rejection of the unidimensional model (out of one-hundred and eighty total). No analysis of data at the group level allowed for the unidimensional model to be rejected.

### 7.1 Single-Process and Dual-Process Interpretation of Empirical Unidimensionality

The four experiments discussed above indicate that when people perform intact-from-rearranged discrimination of stimulus pairs, the form of their performance may be due to only one
process or one source of information. Although recent research has suggested that associative recognition decisions can be characterised according to the joint and distinct activation of familiarity and recollection (e.g. Haskins, Yonelinas, Quamme & Ranganath, 2008; Jäger & Mecklinger, 2009; Quamme, Yonelinas & Norman, 2007), no evidence of this was found.

One interpretation of the detected unidimensionality of associative recognition is that the single-process model class is a viable explanation of associative recognition. The leading candidate single-process model is the UVSD model, primarily because it can account for the empirical asymmetry of ROC curves (Wixted, 2007a). The UVSD model has $\epsilon$, $d'$ and $s$ as free parameters. As discussed in Chapter 2, $\epsilon$ can be constrained using within-lists manipulations and $s$ can be reasonably conceptualised (theoretically and empirically) as dependent on $d'$, leaving $d'$ as the sole free parameter (Dunn, 2008). The UVSD therefore predicts that when using a within-list design as was done, associative recognition decisions reduce to the strength of associative information available for an intact or rearranged pair, that is, $d'$. This in turn predicts a unidimensional state-trace, as was found. The UVSD model offers a parsimonious account of the results presented above, and this thesis is a catalogue of empirical results that lends support to the core prediction of the UVSD model: associative recognition decisions are based on one source of information.

Although the unidimensionality of associative recognition agrees with the central prediction of the single-process model class and the UVSD model, the dual-process model class may still be considered a possible alternate candidate for explanation of associative recognition. When familiarity and recollection are differentially activated, the dual-process model-class predicts a bidimensional state-trace. However, if only one of recollection or familiarity is activated by the intact-from-rearranged discrimination task, a unidimensional state-trace would result. Similarly, if both
recollection and familiarity were activated by an experiment’s factors but not differentially, a unidimensional state-trace is also predicted.

That only one of familiarity or recollection was activated is not a viable explanation for the results of this thesis. ROC analysis performed on the results of these experiments indicated that the curves obtained were asymmetric and curvilinear. According to the dual-process interpretation of ROC curves, both processes were activated. Since a recollection-only HTSD model predicts a linear ROC curve, a familiarity-only HSTD model predicts a symmetrical curve, and the full model predicts a curvilinear, asymmetric curve (Yonelinas, 1994), this implies that the ROC curves obtained in the four experiments were indicative of both recollection and familiarity activation.

The strongest dual-process interpretation of the unidimensionality of the results of this thesis is that differential activation of familiarity and recollection did not occur. While these experiments incorporated independent variables that according to prior research predicted differential activation of recollection and familiarity, it is still possible that their activation was insufficiently distinct, and therefore a unidimensional state-trace resulted from an underlying dual-process structure where the two processes were activated in the same way (as per Figure 2.5). The current state-trace analysis framework does not allow differentiation between a unidimensional state-trace resulting from the single-process model class being correct, and a unidimensional state-trace resulting from the dual-process model class being correct but differential activation failing. Consequently, the dual-process model may be correct but bidimensionality may only result from a different choice of manipulated factors, or through more substantial effects. Further to this, as noted in the discussion section of Chapter 1, a more powerful design is one which maximises the overlap of conditions in a relevant state-trace plot – a situation which did not occur, perhaps due in part to this thesis attempting to incorporate factors used in major unitisation studies. Regardless, while it
might be possible for the dual-process model class to be a valid explanation of associative recognition, and further experimentation may be aided by increasing the power of the study to successfully reject the unidimensional account through more overlap, state-trace analysis across four disparate experimental designs has failed to detect any evidence of the existence of familiarity and recollection.

### 7.2 The Implications of Unidimensional Associative Recognition

This thesis has offered evidence that associative recognition judgements may be based on one source of information. However, a great deal of recent associative recognition research has been interpreted under the assumption that the dual-process model is correct, and that associative recognition judgements are based on familiarity and recollection. An implication of the research presented above is that if no evidence for the dual-process model has been detected, the UVSD model may be the correct explanation of associative recognition. Therefore, associative recognition research can be extended through a single-process reinterpretation of major findings that have previously been interpreted in terms of familiarity and recollection.

#### 7.2.1 Unitisation

A major component of the recent dual-process interpretation of associative recognition is unitisation. The concept allows for familiarity to contribute to the encoding of pairs at study, where
previously encoding was supported solely by recollection. This joint contribution of recollection and familiarity allows the HTSD model to accurately account for the curvilinear, asymmetric ROC curves typically seen in associative recognition research. However, if the unidimensionality of associative recognition means that recollection and familiarity do not exist, unitisation is therefore not an encoding manipulation that increases the contribution of familiarity to associative recognition. As the research presented above indicates support for the single-process model class, the results of unitisation research should be re-interpreted as activation of UVSD model components.

Experimentation directly manipulating unitisation has thus far explored the concept using four different experimental designs. Initial work investigated unitisation by comparing upright and inverted faces (Yonelinas et al., 1999). This was followed by research comparing arbitrary random word pairings against associative recognition for pre-existing compound words (Giovanelli, Keane, & Verfaellie, 2006; Quamme et al., 2004). More recent research has extended this approach to include unitisation through sentences shown concurrently with word pairs (Quamme, Yonelinas & Norman, 2007; Haskins et al., 2008) and a perceptual, similarity-based manipulation (Jäger & Mecklinger, 2009). Across these manipulations, unitised encoding has consistently resulted in better associative recognition performance (except where performance is very similar across conditions for controls in Quamme, Yonelinas & Norman, 2007). These unitisation manipulations may perhaps be classed as manipulations that simply improve associative recognition performance in some way, without necessarily binding two items into a single memory trace. Furthermore, the increase in asymmetry and curvature that occurs concurrently with this increase in performance has been shown empirically to be a component of the UVSD model. As discussed above, across many manipulations (see Glanzer et al., 1999) $s$ is a positive function of $d'$, meaning that as recognition performance increases so does the asymmetry of ROC curves.
The increase in performance that occurs under unitisation conditions is manifested differently across different studies. In some unitisation studies, the conditions representing unitisation are encoding conditions that represent prima facie easier discrimination. This can be seen in the initial exploration of unitisation conducted by Yonelinas et al. (1999), where associative recognition for inverted faces was compared against faces shown normally. Similarly, later research by Quamme et al. (2004) and Giovanello, Keane, & Verfaellie (2006) investigated unitisation by comparing associative recognition for pre-existing compound words such as BASE-BALL against arbitrary random pairings that people must learn anew. Discrimination made on inverted faces and arbitrary random pairings could be considered more difficult than discrimination made on regular faces and pre-existing compound words, regardless of whether or not they may activate unitisation.

In Quamme, Yonelinas and Norman (2007), Haskins et al. (2008) and Experiments 2 and 3, unitisation was encouraged through an encoding frame shown alongside study pairs. In this case, unitisation may be akin to a levels-of-processing manipulation. Previous research has shown that deep processing results in consistently superior performance compared to shallow processing across both recognition and recall (Yonelinas, 2002). For example, asking participants to think about a word’s semantic content at study (‘what does this word mean?’) yields consistently better performance than asking participants to think about perceptual qualities (‘what case is this word in?’); the former is deep processing while the latter is shallow processing. These two conditions are similar to the compound and sentence frames used in Experiments 2 and 3, Haskins et al. (2008) and Quamme, Yonelinas and Norman (2007). While Haskins et al. (2008) may have attempted to prevent this interpretation (since participants were asked in both conditions to think about semantic meaning), the compound condition may still ask for a greater level of overall semantic processing since ‘think about these concepts as something new’ adds an extra processing layer which is not asked of ‘think about these concepts as something you’re already used to’. The compound condition allows
participants to consider not only the individual words, but the semantic implication of joining those words together. In contrast, the sentence condition biases participants to only consider the words individually. As with the levels-of-processing manipulation, the results of Experiments 2 and 3 showed that performance was superior in the compound condition – what could be considered the unitisation version of the ‘deep’ condition. This pattern of performance is what would be expected if compound/sentence was actually deep/shallow encoding (Yonelinas, 2002).

However, if unitisation were reducible to just easier discrimination or (as in Experiment 4) a levels-of-processing manipulation, the issue remains whether a unitisation-like process is capable of binding two distinct memory traces into a single trace in associative recognition. This issue is most applicable to the results of Experiment 4, where the wholly perceptual nature of the unitisation manipulation means that it was most likely not reducible to the kind of levels-of-processing manipulation discussed above or easier performance, as in the case of pre-existing compound words or inverted versus upright faces. This issue requires further associative recognition experimentation because it is not properly addressed by the current research conducted into unitisation. Evidence for the existence of unitisation generally takes the form of HTSD model estimates of familiarity. The logic used in these studies is that if familiarity can only be utilised on individual memory traces it follows that a condition that has higher estimates of familiarity represents stimuli that have been joined into individual memory traces. However, if the dual-process model is false, familiarity estimates are meaningless. Whether unitisation is capable of binding distinct memory traces into individual traces in an associative recognition task cannot be accurately assessed using the current evidence because there is no evidence for unitisation that is not predicated on the validity of the dual-process model.
7.2.2 Neuroimaging Data and Lesion Studies

A substantial amount of recent research has explored the brain’s functional specialisation. Within this framework, different cognitive systems or processes are thought to be served by different areas of the brain (Wixted & Squire, 2011). In studies of recognition memory, this approach has manifested as attempts to localise familiarity and recollection within the medial temporal lobe. Studies involving patients with hippocampal lesions, together with studies that have mapped brain activation with event-related potentials (ERP) and functional magnetic resonance imaging (fMRI), have been interpreted by dual-process researchers as indicating that familiarity is supported by the perirhinal cortex and recollection by the hippocampus (e.g. Yonelinas, 2002).

The functional localisation of recollection and familiarity is of particular importance to dual-process associative recognition research. Neuroimaging studies have been used by some researchers (e.g. Giovanello, Keane, & Verfaellie, 2006; Haskins et al., 2008) to argue that unitised encoding can selectively increase the activation of familiarity. According to this neuroimaging research, since the perirhinal cortex can only support familiarity, perirhinal cortex activation correlated with associative recognition discrimination implies that performance was therefore due to the activation of familiarity. Since participants studied under unitised encoding conditions, this is also taken to mean that unitisation allowed for this familiarity activation.

Some researchers (e.g. Squire, Wixted & Clark, 2007; Wixted & Squire, 2011), however, have contested the dual-process interpretation of lesion studies and neuroimaging research. According to this perspective, if the dual-process model is correct, past research has demonstrated that the perirhinal cortex can support both recollection and familiarity. If, however, the single-process model
is correct, previous research has instead detailed the neurological correlates of weak versus strong memories (Wixted & Squire, 2011). For example, under certain conditions, patients with hippocampal lesions have been shown to produce symmetrical and curvilinear item recognition ROC curves (Yonelinas et al. 1998). Since according to the prevailing dual-process interpretation, hippocampal deficit precludes patients from performing discrimination based on recollection, recognition performance must instead be due to activation of the perirhinal cortex and therefore familiarity. The symmetrical ROC curve produced by patients in this study was therefore in agreement with the Yonelinas (1994) HTSD model prediction. However, Wais, Wixted, Hopkins and Squire (2006) investigated whether it was possible for patients with hippocampal lesions to produce asymmetrical item recognition ROC curves if an experiment compensated for their overall memory decrement. In this study, patients were first compared with controls on a 50-item list. In line with previous research, controls produced an asymmetric ROC while patients produced a symmetrical ROC curve. However, when patients performed recognition discrimination on a 10-item list to compensate for their lessened memory capacity, they produced an asymmetric ROC curve. Under the dual-process interpretation, these patients therefore exhibited a performance pattern associated with both recollection and familiarity activation. Under the single-process interpretation, these patients exhibited weak memory in the 50-item condition, and strong memory in the 10-item condition, and the asymmetry of the latter condition’s ROC curve is evidence of this (Wixted & Squire, 2011).

If the perirhinal cortex is capable of supporting both recollection and familiarity irrespective of unitisation (as Wais et al., 2006 may indicate), the fMRI results of Haskins et al. (2008), for example, are therefore not evidence for unitisation as a means for activating familiarity. The logic of Haskins et al. (2008) relies on increased activation of the perirhinal cortex as a selective indicator of familiarity activation: according to this perspective, increased activation of the perirhinal cortex
means selective familiarity activation, and since familiarity can only be activated through unitisation, this implies that unitised encoding occurred. However, if increased perirhinal cortex activation can instead mean an increase in familiarity and recollection activation, or some other combination thereof, perirhinal cortex activation cannot be used to determine if one of either familiarity or recollection were increased, and can therefore not be used to determine the success of unitisation. Rather, since the results of Haskins et al. (2008) primarily demonstrate that better associative recognition discrimination co-occurs with increased perirhinal cortex activation (due perhaps to some combination of increased familiarity and recollection activation), these results may instead simply be further evidence that encoding conditions that promote strong memory (as in the 10-item patient condition in Wais et al., 2006) can lead to discrimination that correlates with increased perirhinal cortex activation.

7.2.3 Other Models of Associative Recognition

The empirical unidimensionality of associative recognition is evidence for a single-process model class as the better explanation of associative recognition. It is also evidence against the dual-process model class. However, how that evidence is manifested as a test of specific models within those classes requires further analysis.

This thesis has primarily focused on comparison between the UVSD model and the HTSD model, as they are historically the leading candidate single-process and dual-process models. Because of this, the chosen factors in each experiment were designed to elicit differential activation of the HTSD model conceptualisations of recollection and familiarity. The logic of state-trace analysis is
dependent on the relevance of manipulated factors and if those factors are irrelevant, bidimensionality would be not be predicted or subsequently detected. Therefore, since the factors used in these experiments were designed to elicit only recollection and familiarity, these experiments are primarily a test of the HTSD model. Whether, for example, this thesis counts as evidence against the dual-process model put forth by Xu and Malmberg (2007) depends on whether their conception of the two processes is similar to that put forth by Yonelinas (1994). If, for example, Xu and Malmberg (2007) regard unitisation as irrelevant to their model’s idea of familiarity, this thesis does not form evidence against their model despite it being a dual-process model. This also applies to the SON (Kelley & Wixted, 2001) and MSD models (Mickes, Johnson & Wixted, 2010). Both of these models could be described as dual-process models, providing the item information parameter is distinct to the associative information parameter (as has been suggested by Mickes, Johnson & Wixted, 2010). These experiments could only be considered evidence against the SON and MSD models if the manipulated factors concurrently predicted differential activation of item information and associative information as well as familiarity and recollection, which is unlikely. However, state-trace analysis could easily be extended to models such as SON and MSD and the processes governing associative recognition would be better understood if future research sought to investigate this.

7.3 Concluding Remarks

The research presented in this thesis demonstrated that associative recognition is perhaps best explained by the single-process model class and therefore the leading candidate UVSD model.
Application of state-trace analysis to a broad catalogue of associative recognition experimentation resulted in consistent evidence for underlying unidimensionality. Despite previous research indicating that unitisation allows for familiarity-based encoding alongside recollection, experimentation designed to differentially activate these two processes did not result in any evidence of their existence.

The debate over associative recognition is an important aspect of a wider controversy regarding which model-class accurately describes recognition memory in general. This debate has implications extending into behavioural research covering item recognition, but is also important for cognitive neuroscience where model components are driving investigation of brain localization and understanding of brain lesions. Following the work of Yonelinas (1994; 1997), associative recognition has served as a crucial testing ground for core predictions of the dual-process model and as such the findings presented in this thesis that state-trace analysis did not uncover evidence for familiarity and recollection is a significant one, with implications for other subfields within recognition memory and cognition research in general.

This thesis has also highlighted the ease and utility of applying state-trace analysis to a field in which there is debate over the number of processes that govern performance on a task. State-trace plots allow for visual determination of the monotonicity of an output variable comparison, and this approach is formalised through the monotonic regression framework extended within this thesis.
References


Appendix A

The asymmetry of ROC curves shown in Figure 3.1, Figure 4.2, Figure 5.1 and Figure 6.3 was examined by computing the difference between minimized $G^2$ fit of two versions of the UVSD model across averaged data. The first version of the UVSD model was fit as normal (that is, the variance parameter was free to vary) while the second version was constrained with a variance parameter set equal to one. In each experiment, the difference between the constrained and unconstrained model was significant at $p < 0.01$, indicating that the ROC curves were well described by the asymmetric version of the UVSD.

The same analysis was undertaken for conditionalised ROC curves. For medium and high confidence pairs low anchor pairs, the difference between unconstrained and constrained UVSD model fit was significant at $p < 0.05$. The difference was not significant when the models were fit for high anchor pairs.
Appendix B

Least-squares fit of individual subjects for Experiment 1

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Appendix C

Least-squares fit of individual subjects for Experiment 2

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Note. *p < .05, **p < .001
## Appendix D

*Least-squares fit of individual subjects for Experiment 3*

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*Note.* $^*p < .05$, $^{**}p < .001$
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