Nonanalytic Cognition: Generalizing Without Thinking

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Abstract

Humans are constantly extracting and storing information for future use. How do we process and use information in selecting a wine, making a medical diagnosis, or appreciating art? In distinguishing Picasso’s from Monet’s painting style, it seems obvious that we would consciously consider the requisite features that describe each artist’s work. To test our thinking in this context, we stripped the nameable features, such as mandolins and waterlilies, from their paintings and showed that enough information remained to distinguish them. However, participants were only able to perform this task if their analysis was diverted away from the ways that the paintings differed. We then showed that those who learned the reduced images could transfer this learning to new instances of full paintings and vice versa, even though this transfer cannot be attributed to nameable features. Our conclusion is that people routinely rely on presymbolic information in episodic memory and other higher cognitive tasks, even when dealing with materials that are rich in specific meaning and nameable features.
Nonanalytic Cognition: Generalizing Without Thinking

A host of human behaviors are influenced by perceptual information that may be hard to verbalize or even hard to distinguish. From the ways that medical doctors make diagnoses to how consumers choose wine, there is much to be explained about how people learn about complex stimuli. For example, in consumer behavior, many choices have been described as “introspectively blank” (Dijksterhuis, Smith, van Baaren, & Wigboldus, 2005). There is a great deal of interest in habitual consumer behavior (Wood and Neal, 2009), but the myriad ways that an individual comes to form habits is open for investigation. The central thesis of this paper is that people routinely rely on presymbolic information in episodic memory and other higher cognitive tasks, even when dealing with materials that are rich in specific meaning and nameable features. Perhaps we buy the detergent in the green box due to regularly perceived covariation of green claims with green expressions in advertising without the product actually being environmentally friendly or even a conscious belief that it is environmentally friendly.

Following Bruner, Goodnow, and Austin (1956), most research on categorization and concept formation has used stimuli that consist of nameable features. This has been true even for the advocates of nonanalytic processes such as comparing instances with a prototype or other instances (Brooks, 1978; Kruschke, 1992; Medin & Schwanenflugel, 1981; Nosofsky, Palmeri, & McKinley, 1994; Rosch & Mervis, 1975). There has of course been some work with stimuli that are difficult to describe verbally. For example, in presenting a theory of category learning, Ashby, Alfonso-Reese, Turken, and Waldron (1998) mention learning to respond to a tennis serve and wine tasting as situations where experiential or procedural learning would apply. Nevertheless, in testing their theory, they used stimuli in which the rule was difficult to verbalize,
but the relevant features were easy to verbalize (e.g., lines that differed in length and orientation). Similarly, Nosofsky (1988) used color patches varying in hue and saturation. With these stimuli it is difficult to verbalize the underlying dimensions (hue and saturation), although it is easy to arrive at a stable perceptual concept (e.g., the difference between pink and red). As another example, Posner and Keele (1968; also see Fried & Holyoak, 1984; Seger, et al., 2000) started with a dot pattern as a prototype and had participants learn instances that were random perturbations of the original pattern. They would then classify unlearned patterns as belonging to the concept insofar as they were similar to the prototype. With these stimuli, the complexity of the arrangements make an overall verbal description difficult, even though the location of individual dots is verbalizable and possibly even the configurations involving small numbers of dots.

There is considerable evidence that people can use information that is extracted from a scene in a very brief glance, well before explicit representations of the features contained in that scene are available (Alvarez & Oliva, 2008; Schyns & Oliva, 1994; Oliva & Schyns, 1997; Greene & Oliva, 2009a; Greene & Oliva, 2009b; Mack & Palmeri, 2010; Loschky, Hansen, Tethi, & Pydimarri, 2010). This information can be used to categorize the scene as a lake, forest, beach, desert, etc. It can also be used to make global judgments about the depth of the scene, whether it permits someone to easily move through it, even its temperature. Sekular and Kahana (2007) have also shown that stimuli that they characterize as “resistant to symbolization” are used in short term memory. Others characterize this information as “low level perceptual information” (Loschky, Hansen, Sethi, & Pydimarri, 2010), which may indicate a belief that the information is extracted in the early stages of visual processing. Still others talk about statistics
that represent global spatial structure without explicitly representing objects (Mack & Palmeri, 2010). We will refer to such information as *presymbolic*, though we acknowledge that while some contrast is needed with information that is clearly symbolic (words, concepts, objects, nameable features, stable patterns composed of lower level features such as dots), the exact basis of this contrast is uncertain.

In addition to questions of information extraction, use and characterization in short term memory, it is important to understand the way it is used in episodic memory or higher cognition. That is, information that is used in short term memory may not be used in long term memory. Alternatively, it may be that the presence of easy to symbolize information in a stimulus reduces or eliminates the use of hard to symbolize information. Similar considerations apply to the information that is extracted in a very brief glance at a scene. That is, this information may not be used when there is ample opportunity to view a scene that is rich in meaning and nameable features. In this respect, Oliva and Schyns (1997) trained participants on stimuli where low spatial frequency information was diagnostic and high spatial frequency information was not, or vice versa. After training, participants classified ambiguous scenes where the low spatial frequency information came from one scene and the high spatial frequency information came from another in accordance with their training. Thus, there is some selectivity in the information that is used.

While there is only limited evidence for the involvement of presymbolic information in episodic memory and higher cognition, a good argument for its use by pigeons can be made. That is, over the last 50 years, pigeons have been shown to make relatively—and sometimes, remarkably—*sophisticated* judgments. For example, Herrnstein and Loveland (1964) found that
laboratory pigeons could be trained to discriminate slides depicting humans (or parts thereof) from otherwise similar slides not depicting humans (see Herrnstein, Loveland, & Cable, 1976, for a replication with pigeons’ discrimination of slides depicting a particular human). More important, they could generalize this ability to previously unseen slides. They initially concluded that pigeons were relying on preexisting concepts to make these discriminations (Herrnstein & Loveland, 1964). However, this hypothesis became increasingly less likely with each new demonstration, especially with no basis in evolution or the individual learning history of the pigeons that would support the existence of the relevant concept. For example, other researchers have shown that pigeons can discriminate slides of different breeds of pigeons from those of other bird species, animals, or objects (Poole & Lander, 1971); silhouettes of oak leaves from those of other deciduous trees (Ceralla, 1979); underwater scenes containing fish from those without fish (Herrnstein and de Villiers, 1980) and photographs of aerial views of artifacts from photos with no artifacts (Lubow, 1974). Perhaps most surprisingly (thereby winning the Ig Nobel prize), Watanabe, Sakamoto, and Wakita (1995) showed that pigeons could discriminate slides of paintings by Picasso from his Cubist period from Impressionist paintings by Monet, and then generalize this discrimination to paintings by other Cubist (e.g., Braque) and Impressionist (e.g., Cezanne) artists.

Although pigeons do remarkably well with such real-world categories, they often fail with even the simplest linguistic rules: they cannot, for example, differentiate between a dot inside or outside a set of curves (Herrnstein, Vaughan, Mumford, Kosslyn, 1989), or ‘equal to’ versus ‘different’ in the heights of two colored bars – something most people find trivially easy. In contrast, people find it considerably difficult to learn to distinguish between colored histograms
that are large (i.e., greater than 50% of the background) or small (i.e., less than 50% of the background), but pigeons learn the discrimination very quickly (Pearce, 1988).

Our surprise at the sophistication required for pigeons’ successful judgments suggests that we have the descriptions wrong. Herrnstein’s slides were of a wide variety of indoor and outdoor scenes, and differed widely in the people shown and their depictions. Indeed, there is really no evidence that pigeons can directly discriminate \textit{per se} people, fish or objects in photographs. Instead, we propose that the pigeons are responding to a certain “look” of the photographs or paintings imposed by the presence of the embedded object or style of painting. If this is true for pigeons, then it might be that under certain conditions, people learn a concept in the same way that pigeons do.

There have been at least two proposals about how concepts are acquired that may be applicable to understanding whether people learn like pigeons. Ashby et al. (1998; also see Ashby, Maddox, & Bohil, 2002) proposed an explicit rule based system and a procedural learning system where the procedural system was more likely to be engaged with a feedback learning procedure than with an observational learning procedure. They also proposed that these two forms of learning were mediated by different neural structures. In particular, they suggested that a reward-mediated feedback signal is provided by the release of dopamine following reward (success feedback). This proposal is certainly limited and possibly wrong. Izawa (1985) reviews a very large amount of work and provides compelling new evidence about the relationship between the anticipation procedure (feedback learning) and the study-test procedure (observational learning) in the paired associate literature. The study-test procedure is generally better due to the shorter retention intervals involved when study and test lists are randomly
ordered. However, when the retention interval is controlled, the two procedures produce very similar results across a wide variety of experimental manipulations. Without any differential response to independent variables, there is no basis to assume that different learning mechanisms are involved in the study-test and anticipation procedures in paired associate learning. It is also hard to see how a dopamine-based reward system would produce different results in classification and paired associate learning.

The alternative approach to understanding pigeon-like learning comes from Brooks, Squire-Graydon, and Wood (2007) and Brooks (1978). They argued that it was difficult to make people give up on explicit rule based learning if they thought that rules were involved. However, if their attention was diverted from the possible involvement of rules, and they focused instead on the learning of specific pairings, then concept-like performance could emerge.

Our approach to demonstrating that low-level sensory or perceptual information that is hard-to-verbalize (i.e., presymbolic information) is involved in episodic memory—and by extension concept formation—starts with 160 Cubist paintings by Picasso and 160 Impressionist paintings by Monet. We used these stimuli precisely because of the previously mentioned work with pigeons by Watanabe, et al. (1995). We applied a standard dimension reduction technique to pixel-maps of the paintings to strip them of nameable features while leaving enough information behind so that the style of the paintings could be discriminated statistically (we refer to these as reduced paintings). We then devised a task where a participant’s analysis was diverted away from explicit concept learning toward learning specific painting-name pairs (Humphreys, Tangen, Cornwell, Quinn, & Murray, 2010). We refer to this task as a nonanalytic task, though the task itself is not nonanalytic, it is simply designed to facilitate nonanalytic processing. We then
created a control task that we refer to as an *analytic* task. This task was used to determine the likelihood that explicit concept formation processes (analytic processes) would be successful if they occurred during the nonanalytic task. More details about the analytic and nonanalytic tasks are provided below.

In Experiment 1, we used the nonanalytic task with reduced paintings. Our objective was to show that the reduced paintings paired with names could be learned and that this learning would enhance the learning of pairs of new, unstudied paintings and names. In Experiment 2, we used both full and reduced paintings and compared the analytic and nonanalytic learning tasks. We expected to see that explicit concept formation was easy with the full paintings but difficult, if not impossible, with the reduced paintings. Such a finding would help to rule out the possibility that explicit concept formation is involved in the nonanalytic task using reduced paintings. Finally, in Experiment 3, we used the nonanalytic task and had participants learn the full paintings and transfer to the reduced paintings or vice versa. These transfer results were designed to show that presymbolic information is routinely used in the nonanalytic task, even when the stimuli are rich in meaning and nameable features.

**Stimuli**

We scanned 160 paintings by Picasso during his Cubist period and 160 Impressionist paintings by Monet and assigned a numerical value to every Red/Green/Blue pixel in each of the paintings and strung them together to form a pixels by paintings matrix (see Appendix for a detailed description of the stimuli). A simple linear classifier could not discriminate between the artists based on these raw pixel values, which rules out the possibility that, for example, Picasso’s paintings are generally darker than Monet’s or contain more blue, and hence may be
discriminated directly in terms of these mean differences. Singular value decomposition of the pixels by paintings matrix was used to reveal the primary dimensions that describe the underlying structure or pattern of variation across the entire set. Each painting was projected into the space defined by the dimensions of all the paintings in the set and then reconstructed using various subsets of the dimensions. For example, Picasso’s “Les Demoiselles d’Avignon” and Monet’s “Japanese Bridge” depicted in Figure 1 were reconstructed using subsets of these dimensions, such as the first ten.

Figure 1. Picasso’s “Les Demoiselles d’Avignon” and Monet’s “Japanese Bridge” reconstructed using various dimensions of variation.
We applied the linear classifier to the weights that encode for these dimensions to predict the artist of each painting, and relying only on the first ten dimensions was sufficient to produce a substantial level of discrimination. This result establishes that there is sufficient information in the paintings to discriminate statistically between the artists after the symbolic information has been removed. Sample paintings by Picasso and Monet have been reconstructed from the first ten dimensions and presented in Figure 1 alongside the same paintings fully reconstructed from all 320 dimensions (a perfect reconstruction of the original). The issue now is whether people are capable of using this presymbolic information.

**Experiment 1**

We devised a “diverted analysis” task (Brooks, Squire-Graydon, & Wood, 2007) shown in Figure 2 that required participants to study small sets of reduced Picasso and Monet paintings, each paired with a unique name (e.g., Picasso’s “Woman with a Fan” may have been paired with “Marilyn”). From the participants’ perspective, the aim of the task was to remember what name was paired with what painting. This explicit memory task was used to divert attention from our goal: to determine whether they would learn the tacit association between an artist and the gender of the names. This tacit association was designed to be imperfect, so some painting-name pairs were incongruent with the overall association. For example, on training trials, Picassos were paired with female names and Monets with male names (congruent pairings), but on the critical trials, half of the Picassos were paired with male names and and half of the Monets with female names (incongruent pairings).
Figure 2. Illustrations of the study and test lists used in the miniature associative recognition task on the training trials. In this example, Picasso paintings are paired with female names and Monet paintings with male names. Half of the pairs retained their arrangement between study and test (Intact) and half did not (Rearranged). Both the full and reduced paintings are illustrated here.

As illustrated in Figures 2 and 3, learning was tested by presenting the study pairs either as studied (intact test pairs) or by swapping the name from another painting (rearranged test pairs). Participants had to identify whether each pair was intact or rearranged. Intact pairs identified as “intact” are scored as hits and rearranged pairs identified as “intact” are scored as false alarms. If
people learned this tacit artist-gender association, then a learning system that automatically generalizes the difference between the rates of hits and false-alarms should be greater for new congruent pairs than new incongruent pairs (Dosher & Rosedale, 1991; Naveh-Benjamin, Hussain, Guez, & Bar-On, 2003). This prediction will be examined in more detail in the final discussion. We refer to the difference between the congruent hit rate minus the congruent false alarm rate and the incongruent hit rate minus the incongruent false alarm rate, simply as the “difference score,” which is a rough index of participants’ sensitivity to this tacit artist-gender association. The more sensitive the participants are to this association, the more the congruent and incongruent scores will differ, and the larger this difference score will be. Note, however, that in general, an explicit concept formation process should have no impact on the difference score. That is, knowing that Picasso paintings are generally paired with female names and that Monet paintings are generally paired with male names is of no help in deciding whether a test pair is intact or rearranged. There is an exception to this generalization, which will be discussed when we present multinomial models of explicit processes after Experiment 2.
**Figure 3.** Illustrations of the study and test lists used in the miniature associative recognition task on the critical trials. Two Picasso paintings are paired with female names (a pairing congruent with the pairings on the training trials) and two are paired with male names (a pairing incongruent with the pairings on the training trials), while two Monet paintings are paired with male names (a pairing congruent with the pairings on the training trials) and two are paired with female names (a pairing incongruent with the pairings on the training trials). On the test, which immediately follows the study trial, half of the pairs retain their arrangement between study and test (Intact) and half do not (Rearranged). As a result, at test, there are two intact congruent pairings (one Picasso and one Monet), two intact incongruent pairings (one Picasso and one Monet), two rearranged congruent pairings (one Picasso and one Monet), and two rearranged incongruent pairings (one Picasso and one Monet). Both the full and reduced paintings are illustrated here.
Method

Participants.

Forty students from the University of Lethbridge participated in this experiment for course credit.

Design and Procedure.

There were 40 trials with each trial consisting of the presentation of a study list and a test list. The trials were divided into 8 blocks. Within each block, the first four trials were training trials where all the painting-name pairs on the study list were presented in the congruent arrangement. On the test list, half of the pairs were intact and half were rearranged. All the rearranged pairs preserved the artist-gender relationship of the study pairs. The study list for the fifth or critical trial in each block contained four congruent and four incongruent study pairs. Half of the congruent study pairs were then tested as intact pairs and half were tested as rearranged pairs. Likewise, half of the incongruent study pairs were tested as intact pairs and half were tested as rearranged pairs.

The participants alternated between one of two counterbalancing conditions: (1) paintings by Picasso were paired with female names and paintings by Monet were paired with male names during the training trials and critical congruent pairs, and this artist-gender association was reversed for the critical incongruent pairs; or (2) paintings by Picasso were paired with male names and paintings by Monet were paired with female names during the training trials and critical congruent pairs, and this artist-gender association was reversed for the critical incongruent pairs.
During the training trials, a series of eight painting and name pairs (four congruent Picasso pairings and four congruent Monet paintings) were presented on a computer screen and participants were instructed to remember what name was paired with what painting. Each pair was presented on the screen for three seconds with a 250 millisecond inter-pair interval. We then tested their memory by presenting them with eight pairs (two intact Picasso and two intact Monet pairings plus two rearranged Picasso and two rearranged Monet pairings) and asked them to indicate whether each pair was intact or rearranged. All the rearranged pairs preserved the artist-gender relationship of the study pairs from which they had been created. The test pairs were presented sequentially and were self paced.

During each of the critical trials, participants studied two congruent Picasso pairings, two congruent Monet pairings, two incongruent Picasso pairings, and two incongruent Monet pairings. Presentation times were the same as on the training trials. We then tested participants’ sensitivity to the artist-gender association by comparing their memory for the painting-name arrangement on the congruent pairs (one Picasso and one Monet intact pairing and one Picasso and one Monet rearranged pairing) to their memory for the painting-name arrangement on the incongruent pairs (one Picasso and one Monet intact pairing and one Picasso and one Monet rearranged pairing). These test trials were self paced, as were the test trials on the training trials. Across all 32 training and 8 critical trials, each painting and each name were only presented twice (once on a study list and then again on the corresponding test list).

The object was to see whether the consistent pairing of reduced Picasso paintings with female names and Monet paintings with male names that occurred on the training trials would enhance performance on pairings of new reduced Picassos with new female names and new
reduced Monets with new male names and/or reduce performance on pairings of new reduced Picassos with new male names and new reduced Monets with new female names. That is, whether performance after a single study opportunity is better on new congruent pairings than it is on new incongruent pairings.

Following the completion of the 8 trial blocks, the participants were asked a series of questions to gauge their sensitivity to the tacit artist-gender association in the nonanalytic condition and their strategies for classifying the full and reduced paintings in the analytic condition.

**Results**

The mean hit and false alarm rates for the congruent and incongruent pairings on the critical trials as a function of the eight blocks are illustrated in Figure 4 and collapsed across the eight blocks and depicted in Table 1. A 2 (congruent, incongruent) × 2 (hits, false alarms) × 8 (blocks 1-8) within-subjects ANOVA revealed significant main effects of congruency, $F(1, 39) = 22.05, MSE = .08, p < .001$, and hits and false alarms, $F(1, 39) = 59.38, MSE = .35, p < .001$, as well as a significant interaction between them, $F(1, 39) = 24.38, MSE = .08, p < .001$. No other main effects or interactions reached significance. A simple effects analysis revealed that the congruent hit rate was significantly greater than the incongruent hit rate, $F(1, 39) = 46.82, MSE = .08, p < .001$, but the congruent false alarm rate was not significantly greater than the incongruent false alarm rate $F(1, 39) = .02, MSE = .08, p = .89$. In addition, the difference between the difference scores, or simply the “difference score” (collapsed across the eight blocks) was significantly greater than zero, $t(39) = 4.91, p < .001$. 


Figure 4. Mean hit and false alarm rates for Experiment 1 as a function of Blocks 1-8. Error bars represent standard errors of the means.

<table>
<thead>
<tr>
<th>Study Task</th>
<th>Materials</th>
<th>Congruent</th>
<th>Incongruent</th>
<th>Difference</th>
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<td></td>
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<td>FAs</td>
<td>Hits</td>
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<td>Reduced</td>
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<td>Reduced</td>
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<tr>
<td></td>
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<td></td>
<td></td>
<td>Full to Reduced</td>
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<td>.33</td>
</tr>
</tbody>
</table>

Table 1. Mean hit and false-alarm rates and corresponding difference between the difference scores [(congruent hit rate – congruent false alarm rate) – (incongruent hit rate – incongruent false alarm rate)] or simply the “difference scores” for Experiments 1-3.
Discussion

Participants were clearly sensitive to the tacit artist-gender association as indicated by a significant difference between the hit and false alarm rates in Figure 4 and corresponding difference score depicted in Figure 5. To rule out the possibility that participants in Experiment 1 were relying on an explicit concept formation process to learn the distinction, we performed a second experiment to determine whether they could learn to classify the hard-to-verbalize reduced paintings.

*Figure 5. Mean difference scores [(congruent hit rate – congruent false alarm rate) – (incongruent hit rate – incongruent false alarm rate)] for the reduced and full paintings in Experiments 1-3. The greater the difference score, the more sensitive participants were to the tacit artist-gender association. Error bars represent the standard error.*

**Experiment 2**

Experiment 2 used both the full and reduced paintings, and compared the diverted analysis (or “nonanalytic”) task as termed by Brooks (1978) from Experiment 1 to an explicit concept
learning (or “analytic”) task, where the aim was to explicitly sort the paintings into two categories.

In the analytic task, Picasso paintings were assigned to one category (in this instance, B) and Monet paintings to another (A). Participants studied small sets of paintings labelled “A” or “B” and were then asked to assign each painting in the set to the appropriate category to demonstrate that they had learned the association. As in the nonanalytic task, there was an imperfect association between an artist (Picasso or Monet) and category (A or B), and we measured sensitivity to the artist-category association with the difference score.

Method

Participants.

Ninety-six students from the University of Queensland participated for course credit split equally across the four conditions: the nonanalytic task with reduced paintings (a direct replication of Experiment 1), the nonanalytic task with full paintings, the analytic task with reduced paintings, and the analytic task with full paintings.

Design and Procedure.

On the training trials for the analytic task, Picasso paintings were assigned to category B and Monet paintings to category A, or vice versa. The aim was to learn the category to which each painting had been assigned. As in the nonanalytic task, in each block, participants were trained on four, eight-pair lists of paintings. In the training lists, all pairings were congruent (e.g., Picassos were assigned to category B and Monets to category A). Following each study list, there was a test list. On the test, the paintings were presented by themselves and the participants clicked on a button indicating whether they thought it belonged to category A or B. After four
training trials, there was a critical trial. On this trial, two of the Picassos were in the congruent arrangement (assigned to category B) and two were in the incongruent arrangement (assigned to category A). Likewise, two of the Monets were in the congruent arrangement (assigned to category A) and two were in an incongruent arrangement (assigned to category B). As in the nonanalytic task, there were eight blocks, each consisting of four learning trials and a fifth critical trial resulting in 40 trials total. The object was to see whether learning produced differential transfer to the paintings that had congruent assignments and those that had incongruent assignments on the critical (i.e., fifth) trials. The study lists were paced at the same rate as the study lists in the nonanalytic procedure used in Experiment 1 and in this experiment. The test lists were self paced as were the test lists in the nonanalytic procedure.

If a participant studied a typical Picasso-B pairing and then labelled the painting a “B,” we counted it as a “congruent hit”, studying a typical Monet-A pairing and then labeling the painting a “B” was counted as a “congruent false alarm,” studying an atypical Monet-B pairing and then labeling the painting a “B” was counted as an “incongruent hit,” and studying an atypical Picasso-A pairing and then labeling the painting a “B” was counted as an “incongruent false alarm.” The typical and atypical pairings alternated between participants in two counterbalancing conditions as in Experiment 1. That is, Picasso-female names and Monet-male names in the nonanalytic conditions (or vice versa) and Picasso-“A” and Monet-“B” in the analytic conditions (or vice versa).

Results
The mean hit and false alarm rates for the congruent and incongruent pairings on the
critical trials collapsed across the eight blocks are depicted in Table 1 for Experiment 2 and the
resulting difference scores are depicted in Figure 5.

**Nonanalytic Reduced.**

A 2 (congruent, incongruent) \( \times \) 2 (hits, false alarms) \( \times \) 8 (blocks 1-8) within-subjects
ANOVA revealed a significant difference between hits and false alarms, \( F(1, 23) = 58.42, \ MSE = .31, p < .001 \), which interacted with congruency, \( F(1, 23) = 9.11, \ MSE = .17, p = .006 \). No
other main effects or interactions reached significance. A simple effects analysis revealed that the
congruent hit rate was significantly greater than the incongruent hit rate, \( F(1, 23) = 10.35, \ MSE = .17, p = .004 \), but the congruent false alarm rate was not significantly greater than the
incongruent false alarm rate, \( F(1, 23) = 1.11, \ MSE = .17, p = .30 \). In addition, the difference
score (collapsed across the eight blocks) was significantly greater than zero, \( t(23) = 3.02, p = .006 \). The results from this nonanalytic reduced condition provide a direct replication of
Experiment 1.

**Nonanalytic Full.**

A 2 (congruent, incongruent) \( \times \) 2 (hits, false alarms) \( \times \) 8 (blocks 1-8) within-subjects
ANOVA revealed a significant main effect of congruency, \( F(1, 23) = 40.84, \ MSE = .08, p < .001 \),
hits and false alarms, \( F(1, 23) = 127.23, \ MSE = .37, p < .001 \), as well as a significant interaction
between them, \( F(1, 23) = 17.63, \ MSE = .08, p < .001 \). No other main effect or interaction reached
significance. A simple effects analysis revealed that the congruent hit rate was significantly
greater than the incongruent hit rate, \( F(1, 23) = 56.76, \ MSE = .08, p < .001 \). The congruent false
alarm rate was slightly, but not significantly greater than the incongruent false alarm rate, \( F(1, \)
23) = 2.55, \(MSE = .08, p = .12\). In addition, the difference score (collapsed across the eight blocks) was significantly greater than zero, \(t(23) = 3.91, p < .001\). As we will discuss below, most of the results from this condition are inconsistent with an explicit concept formation process. However, one result (the slightly but not significantly larger false alarm rate for the congruent rearranged pairs than for the incongruent rearranged pairs) may indicate the presence of such a process.

**Analytic Reduced.**

A 2 (congruent, incongruent) \(\times\) 2 (hits, false alarms) \(\times\) 8 (blocks 1-8) within-subjects ANOVA revealed a significant difference between hits and false alarms, \(F(1, 23) = 58.81, MSE = .21, p < .001\). No other main effects or interactions reached significance. A simple effects analysis revealed that the congruent hit rate was not significantly greater than the incongruent hit rate, \(F(1, 23) = 1.48, MSE = .14, p = .24\), and the congruent false alarm rate was not significantly less than the incongruent false alarm rate, \(F(1, 23) = .11, MSE = .14, p = .74\). In addition, the difference score (collapsed across the eight blocks) was not significantly greater than zero, \(t(23) = .57, p = .58\). Because participants were randomly assigned to the four conditions of Experiment 2, we can directly compare the results from each. Clearly, participants learned the tacit artist-gender association in the nonanalytic reduced condition, but they did not learn to classify explicitly the same paintings in the analytic version of the task.

**Analytic Full.**

A 2 (congruent, incongruent) \(\times\) 2 (hits, false alarms) \(\times\) 8 (blocks 1-8) within-subjects ANOVA revealed a significant difference between hits and false alarms, \(F(1, 23) = 185.85, MSE = .42, p < .001\), which interacted with congruency, \(F(1, 23) = 11.96, MSE = .22, p = .002\). No
other main effects or interactions reached significance. A simple effects analysis revealed that the congruent hit rate was not significantly greater than the incongruent hit rate, $F(1, 23) = 3.09$, $MSE = .22$, $p = .09$, but the congruent false alarm rate was significantly less than the incongruent false alarm rate, $F(1, 23) = 9.81$, $MSE = .22$, $p = .005$. In addition, the difference score (collapsed across the eight blocks) was significantly greater than zero, $t(23) = 3.49$, $p = .002$. The results from this condition are consistent with an explicit concept formation process.

**Multinomial Models.**

A pair of multinomial models illustrated in Figures 6 and 7 is used to distinguish between concept-like behavior that results from explicit concept learning and that which results from an automatic generalization across specific instances. These models assume that an explicit concept formation process occurs in both the analytic and nonanalytic conditions, along with the learning of individual instances, and a guessing process. If participants are using an explicit concept formation process (as opposed to the automatic generalization across specific instances), then these two models make very specific predictions about our results. To anticipate, a consideration of the predictions of the multinomial models helps to show that the process in the nonanalytic condition with reduced paintings is not explicit concept formation whereas the process in the analytic condition with full paintings is.
Figure 6. Multinomial model of explicit concept formation for the analytic conditions. The model makes specific predictions about the hit, false alarm rates and corresponding difference score for each trial type, assuming that participants are explicitly forming concepts.
Figure 6 depicts a simple multinomial model for propositional learning with the analytic procedure. In this model, participants can correctly classify a painting because they have a specific memory for the painting-letter pair (this painting was paired with B) or because they have the correct concept (this painting is of the type that is generally a B), or because they guess correctly. According to the model, the concept formation process increases the congruent hit rate, which is defined as the probability of saying “B” to a Picasso painting that had been paired with B (the typical pairing). It also increases the incongruent false alarm rate defined as the probability of saying “B” to a Picasso painting that had been paired with A (the atypical pairing). The concept formation process has no effect on the congruent false alarm rate defined as the probability of saying “B” to a Monet that had been studied with A (the typical pairing) or on the incongruent hit rate defined as the probability of saying “B” to a Monet that had been paired with B (the atypical pairing). The multinomial model, therefore, predicts that the congruent hit rate should be larger than the incongruent hit rate and the congruent false alarm rate should be smaller than the incongruent false alarm rate (i.e., because the congruent hit rate and the incongruent false alarm rate both contain the \( (1-a) \) concept component, whereas the congruent false alarm rate and incongruent hit rate do not).

The results from the analytic full condition in Experiment 2 indicate that the congruent hit rate was not significantly greater than the incongruent hit rate (note that there may be a ceiling effect that prevented this difference from being significant), but the congruent false alarm rate was significantly less than the incongruent false alarm rate, and the difference score was significantly greater than zero as the multinomial model predicted. In addition, the model predicts that the largest concept effect \( 2(1-a)t \) will occur when the congruent false alarm rate is
subtracted from the congruent hit rate, the incongruent false alarm rate is subtracted from the incongruent hit rate and then the difference between these difference scores is computed:

$$\text{Congruent Hit: } P(B) = a + (1-a)t + (1-a)(1-t)g$$

$$- \text{ Congruent FA: } P(B) = a + (1-a)t$$

$$\text{Incongruent Hit: } P(B) = a + (1-a)(1-t)g$$

$$- \text{ Incongruent FA: } P(B) = a - (1-a)t$$

$$= [a+(1-a)t] - [a-(1-a)t] = 2(1-a)t$$

Again, the data from the analytic full condition in Experiment 2 confirm this prediction with a mean difference score of .23, which is significantly greater than zero. The data from the analytic condition in Experiment 2, in which participants explicitly classify full paintings, therefore, track the predictions of a multinomial model of what an explicit concept learning process should look like.

Participants in the analytic condition who were presented with the reduced paintings, on the other hand, did not show the same pattern of results. The analytic model predicts that the congruent hit rate (.66) should be significantly larger than the incongruent hit rate (.61), which it is not. The model also predicts that the congruent false alarm rate should be smaller than the incongruent false alarm rate. The mean congruent false alarm rate (.39), however, was not significantly different from the mean incongruent false alarm rate (.38). Finally, the difference scores should also be large in the analytic condition, but a mean difference score of .03, was not
significantly different from zero. Our conclusion is that there is learning of individual painting-letter pairings in this condition, but no learning of a concept.

As we previously noted, knowing that Picasso paintings are generally paired with female names and Monet paintings are generally paired with male names is of no help in deciding whether any particular test pair is intact or rearranged. Thus, there should be no impact on the difference scores. However, in Figure 7, we present a multinomial model of how an explicit concept learning process could have an impact on the difference scores in the nonanalytic condition. Again, we assume that a correct response can occur because the participant has a specific memory. In this case, they could have a specific memory about the pair being intact or a memory about the pair being rearranged. Probabilities may not be the same, so we have provided different parameters for them. In addition, participants might have gender-based illusory correlations. There is no real correlation in the experiment, but an illusory correlation is possible. That is, participants may think that because paintings of a certain type are generally paired with female names, that a painting of that type paired with a female name is more likely to be intact than rearranged. It is through such a belief that an explicit concept learning process could impact the results for the nonanalytic condition. Finally, participants can be correct through guessing.
Figure 7. Multinomial model of explicit concept formation for the nonanalytic conditions. The model makes specific predictions about the hit, false alarm rates and corresponding difference score for each trial type, assuming that participants are explicitly forming concepts.
In this model, the concept formation process increases the congruent hit rate (saying “Intact” to an intact Picasso-female pair or to an intact Monet-male pair) and the congruent false alarm rate (saying “Intact” to a rearranged Picasso-female pair or to a rearranged Monet-male pair). The concept formation process plays no role in the incongruent hit rate (saying “Intact” to an intact Picasso-male pairing or an intact Monet-female pairing) or in the incongruent false alarm rate (saying “Intact” to a rearranged Picasso-male pairing or to a rearranged Monet-male pairing). Note that congruence and incongruence are defined by whether the test pair is a typical or atypical pairing and that this is independent of whether the test pair is intact or rearranged.

In the nonanalytic task, concept formation simply serves as a bias. This would be the same if we modeled the task as a signal detection task. The result is that the congruent hit rate should be larger than the incongruent hit rate and the congruent false alarm rate should be larger than the incongruent false alarm rate. In addition, if the congruent false alarm rate is subtracted from the congruent hit rate and the incongruent false alarm rate is subtracted from the incongruent hit rate, then the difference between these difference scores should tend towards zero. However, a zero effect will occur only if the probability of having a specific memory for an intact pair equals the probability of having a specific memory for a rearranged pair. More generally, we do not know how to infallibly remove a bias process from the results of a recognition experiment. Nevertheless, it should be possible to distinguish between the general pattern produced by a bias process and the transfer of prior learning which, as we have noted, should increase the congruent hit rate while having little or no impact on the congruent false alarm rate.

The results from the nonanalytic reduced condition in Experiment 1, however, do not conform to the predictions of the multinomial model. Even though the nonanalytic model
predicts that the congruent hit rate (.76) should be larger than the incongruent hit rate (.61), which it is, the congruent false alarm rate (.43) was the same as the incongruent false alarm rate (.43), though it should be larger. The model also predicts that the difference score should be small (possibly zero) in the nonanalytic condition. The data from Experiment 1 suggest otherwise, however, with a mean difference score of .16, which is significantly greater than zero.

The same pattern of results for the replication of Experiment 1 was obtained in the nonanalytic reduced condition of Experiment 2: a larger congruent (.71) than incongruent hit rate (.58), a nonsignificant trend for the congruent false alarm rate to be smaller (.32), not larger, than the incongruent false alarm rate (.36), and a difference score of .18, which is significantly greater than zero. The latter two findings are incompatible with the assumption that an explicit concept formation process is involved. Thus, the concept-like performance found in the nonanalytic conditions with reduced paintings appears to result from automatic generalization, not an explicit concept formation process.

The results from the nonanalytic full condition of Experiment 2 also do not track the predictions of the multinomial model. Even though the congruent hit rate (.84) was in fact larger than the incongruent hit rate (.62), the congruent false alarm rate (.26) was not significantly larger than the incongruent false alarm rate (.21), as the model would predict. And, even though the difference score should be small in the nonanalytic condition, a score of .17 is significantly greater than zero. Note, however, that the small and non-significant increase in the false alarm rate from the incongruent to the congruent condition might indicate that some explicit concept formation is taking place.

**Verbal Reports.**
Following completion of the 8 trial blocks in Experiment 2, the participants were asked a series of questions to measure the extent to which they could describe the tacit artist-gender association in the nonanalytic condition and their strategies for classifying the full and reduced paintings in the analytic condition. We included these questions to collect a list of attributes that participants claimed to rely on in the various conditions of the experiment and to provide some indication of whether our memory task was effective in diverting participants’ analysis away from the tacit artist-gender association. As we have discussed elsewhere, evidence of awareness using post-experimental questionnaires is weak at best (Humphreys, et al., 2010; Higham & Vokey, 2004).

The five nonanalytic questions were increasingly targeted at the artist-gender association:

1. What do you think the study was about?
2. Describe how the style of the images that we showed you differed?
3. Did you notice anything about the names we showed you? If so, what did you notice?
4. Did you notice anything about the male and female names? If so, what did you notice?
5. Did you notice any difference between the images that were paired with male and female names? If so what did you notice?

As expected, the vast majority of participants in the nonanalytic reduced and full groups thought the purpose of the experiment was to measure their memory in the miniature associative recognition task. The transfer of old learning to new learning was not noted. Participants in the full painting condition described the stylistic difference between the paintings (e.g., abstract, realism, Impressionism), differences in the features (e.g., humans, waterlillies, bridges), and colors. Participants who were presented with the reduced paintings described their differences in
terms of color, brightness, contrast, and texture. Neither group mentioned anything about the names with which the paintings were paired. When we asked them specifically about the names, some thought that a few names repeated throughout the experiment (they did not), some commented on their commonality (e.g., modern or old fashioned), similarity (e.g., same first letter or similar spelling), or simply the wide range of names in the experiment. Again, there was no mention of the paintings with which they were paired. When we mentioned the gender of the names specifically and asked them whether they noticed anything about the male and female names, 38% in the full condition and 58% in the reduced condition said no. Some commented on the ratio of male to female names (male names outnumbering females and vice versa), and others commented on the similarity of the names, or their sequence (e.g., blocks of male or female names or groups of two). In the full condition, nine of 24 participants (38%) commented on features in the paintings that the names were paired with (e.g., male or female names were paired with paintings of females, male or female names were paired with houses and landscapes, male or female names were paired with masculine or feminine pictures). Of the 24 participants presented with the reduced paintings, two (8%) commented on the paintings when asked about the gender of the names (i.e., male or female names were matched with lighter colors or brighter patterns). Finally, when we asked them directly about the differences between the paintings that were paired with male and female names, nine (38%) in the full group and 18 (75%) in the reduced group said they did not notice any differences. Those who did note differences, commented on the style, features, colors or brightness of the paintings that were paired with the male or female names.

Discussion
In the nonanalytic task in Experiment 2, we observed the same sensitivity to the tacit artist-gender association for both the reduced and the full paintings. Participants in the analytic condition who were presented with the full paintings were also clearly sensitive to the artist-category association as revealed by a large difference score. The results from the analytic full condition are consistent with the assumption that the participants are capable of explicitly learning the concept. However, those given the analytic task and asked explicitly to sort the reduced paintings failed to learn the artist-gender association, as revealed by a negligible difference score. It is possible that there would have been evidence of learning with more training trials or if we had used a feedback learning procedure (Ashby et al., 1998). However, these possibilities do not detract from our intended use of the analytic condition with the reduced paintings. That is, our intention was to use it as a control for the possibility that an explicit concept formation process could explain the results from the nonanalytic condition with the reduced paintings. The nonanalytic condition is an observational learning task (as is the analytic condition). In addition, the same number of learning trials is used in both tasks. The response requirements differ between the two tasks (i.e., a yes-no recognition decision in the nonanalytic condition and the production of a response in the analytic condition). However, in deciding whether the analytic condition serves as an adequate control for the possibility that explicit concept formation processes are involved in the nonanalytic condition with reduced paintings requires more than a consideration of structural similarities between the two tasks. In our multinomial models, we have presented a theory about how an explicit concept formation process could affect performance on the nonanalytic task. Briefly, the participant has to form the belief that paintings of a certain type are generally paired with female names while paintings of
another type are generally paired with male names. The learning involved should be very similar to that involved in the analytic task where participants must learn that paintings of a certain type are generally paired with the letter B while paintings of another type are generally paired with the letter A. Because of the additional processes involved with the nonanalytic task (deciding that gender is relevant and deciding that if a painting of a certain type is generally paired with a particular gender, then test pairs of that type are more likely to be intact than rearranged), it would appear that the analytic task is a very conservative control for the possibility that a specific concept formation process is involved in the nonanalytic task with reduced paintings.

**Experiment 3**

Clearly, there is usable information in the reduced paintings and this information can assist learning about new, reduced paintings by the same artist. This information is not acquired through an explicit concept formation process, but we have not established whether this information is routinely extracted and used. To do so, in Experiment 3, we tested whether the presymbolic information in the reduced paintings assists participants in learning about the full paintings by the same artist, or vice versa.

In Experiment 3, one group of participants was presented with the nonanalytic task and reduced paintings during training, and we measured the extent to which they would transfer their learning about the structure of these reduced paintings to new full paintings presented during the critical trials (see Figure 3). Another group was presented with the full paintings during training and we measured the extent to which they would transfer their learning about the structure of new full paintings to the reduced paintings presented during the critical trials. *Because there is no contingency between artist and gender on the critical trials in Experiment 3, it is impossible*
to learn a concept on the critical trials, and any evidence of concept-like behavior must be due to
the transfer in learning about one set of materials to performance on the other set of materials.

Method

Participants and Design.

Forty-eight students from the University of Queensland participated for course credit. All participants received eight blocks where each block consisted of four training trials and one critical trial. In each block, one group of 24 participants received four training trials where each trial consisted of eight-pair lists of reduced paintings and male and female names in which all pairs were presented in the congruent arrangement (i.e., Picasso paintings paired with female names and Monet paintings with male names or vice versa for half the participants). The fifth list then contained four congruent and four incongruent pairs as before, but instead of using reduced paintings as on the study trials, full paintings were used. The object was to see whether learning the reduced paintings produced differential transfer on the congruent and incongruent full paintings in the critical trials. We also included a “full to reduced” group of 24 participants. This group was trained on the full paintings and transferred their learning to the reduced paintings during the critical trials.

Procedure.

The procedure for these transfer tasks was the same as the previous nonanalytic conditions. Participants were simply asked to remember what painting went with what name without elaborating on the difference between the paintings during the training and critical trials.

Results
It is clear from the hit and false alarm rates in Table 1 and resulting difference scores in Figure 5 that learning about the artist-gender association during training had transferred to the critical trials, even though the depictions of the paintings had changed from full to reduced or from reduced to full.

**Nonanalytic Reduced to Full.**

A 2 (congruent, incongruent) × 2 (hits, false alarms) × 8 (blocks 1-8) within-subjects ANOVA revealed a significant main effect of congruency, $F(1, 23) = 4.7, MSE = .09, p = .04$, hits and false alarms, $F(1, 23) = 304.66, MSE = .21, p < .001$, block, $F(1, 23) = 2.2, MSE = .07, p = .04$, and a significant interaction between hits/false alarms and congruency, $F(1, 23) = 36.33, MSE = .05, p < .001$. No other main effects or interactions reached significance. A simple effects analysis revealed that the congruent hit rate was significantly greater than the incongruent hit rate, $F(1, 23) = 38.8, MSE = .05, p < .001$, and the congruent false alarm rate was significantly less than the incongruent false alarm rate $F(1, 23) = 5.27, MSE = .05, p = .03$. In addition, the difference score (collapsed across the eight blocks) was significantly greater than zero, $t(23) = 4.99, p < .001$.

**Nonanalytic Full to Reduced.**

A 2 (congruent, incongruent) × 2 (hits, false alarms) × 8 (blocks 1-8) within-subjects ANOVA revealed a significant difference between hits and false alarms, $F(1, 23) = 33.34, MSE = .41, p < .001$, which interacted with congruency, $F(1, 23) = 10.91, MSE = .13, p = .003$, and block, $F(7, 161) = 2.52, MSE = .11, p = .02$. No other main effects or interactions reached significance. A simple effects analysis revealed that the congruent hit rate was significantly greater than the incongruent hit rate, $F(1, 23) = 12.03, MSE = .13, p = .002$, but the congruent
false alarm rate was not significantly different from the incongruent false alarm rate, $F(1, 23) = 1.45, MSE = .13, p = .24$. In addition, the difference score (collapsed across the eight blocks) was significantly greater than zero, $t(23) = 3.3, p = .003$.

**Multinomial Model.**

The nonanalytic multinomial model for propositional learning does not fare any better in predicting the results from Experiment 3 than it did in Experiment 2. Participants who were trained on the reduced paintings and presented with the full paintings during the critical block provided a significantly greater congruent hit rate (.87) than incongruent hit rate (.72). Even though the nonanalytic model predicts that the congruent false alarm rate should be larger than the incongruent false alarm rate, the congruent false alarm rate (.19), was significantly less than the mean incongruent false alarm rate (.24). Contrary to the model’s prediction, the difference score (.20) is also significantly greater than zero. Training participants on the full paintings and testing them on the reconstructed paintings in Experiment 3 resulted in the same pattern of results: a greater congruent hit (.69) than incongruent hit rate (.58), and a lower (though not significant) congruent false alarm rate (.33) than incongruent false alarm rate (.38). The difference score (.17) is also significantly greater than zero.

**Discussion**

Participants in Experiment 3 demonstrated that they could transfer their learning about the structure of the reduced paintings to the full paintings and vice versa. This finding establishes that the information contained in the reduced paintings is also used when learning about full paintings. It is unlikely that this transfer is mediated by language because the language that one uses to describe the full paintings, which are rich in specific meaning and nameable features, is
very different from the language used to describe the reduced paintings that were devoid of such information. This difference in language was confirmed by verbal reports provided during a post-experimental questionnaire. Indeed, the same pattern of results was obtained for the full to reconstructed and reconstructed to full conditions in Experiment 3 as described in the results of Experiment 2.

**General Discussion**

We stripped the nameable features from paintings by Picasso and Monet by reducing them to only the first ten dimensions (i.e., those associated with the most variance across the pixel-maps of the paintings). We then paired the reduced Picasso paintings with female names and reduced Monet paintings with male names, or vice versa. Each painting was paired with a unique name and there was only a single learning opportunity to learn the name that was paired with a specific painting. This learning of many different painting-name pairs, where the paintings by an artist were generally (but not exclusively) paired with names from one gender, generalized across both paintings and names. That is, new painting-name pairs that were congruent with the original learning (e.g., Picasso with female and Monet with male) were easier to learn than new pairings that were incongruent with the original learning.

We replicated this finding in a second experiment, and at the same time showed that our participants did not learn an explicit concept formation task (our analytic task) using the reduced paintings, but could easily do so using full paintings. Thus, performance in the nonanalytic task with reduced paintings is being mediated by learning/memorial processes and not explicit concept formation processes. This conclusion receives further support from the analysis of the verbal reports provided during a post-experimental questionnaire. Here, the participants in the
nonanalytic condition using the reduced paintings did not spontaneously report knowing about a relationship between the gender of the names and the characteristics of the reduced paintings. These findings establish that presymbolic information can be used when nameable features are stripped from paintings. In Experiment 3, we established that this presymbolic information is also used when namable features are present. That is, in Experiment 3, we observed transfer between old learning conducted on full paintings to new learning about reduced paintings, and vice versa.

Our conclusion is that people routinely use presymbolic information in episodic memory tasks, and possibly higher cognition, even when dealing with materials that are rich in meaning and nameable features. Furthermore, this usage is through nonanalytic, memory based processes that are not rule based and not readily verbalizable. These conclusions, however, raise a variety of issues about the nature of the memory processes involved. For example, why does transfer occur between old learning and new learning? Do our results invalidate the distinction between procedural and declarative memory? A further major issue involves the distinction between nonanalytic processes and analytic processes and/or explicit concept learning processes. Another concerns the information that is left behind in the paintings, which have been reduced to the first ten dimensions. Finally, why does concept learning not always occur? The answers we propose for these issues about memory, for the analytic versus nonanalytic distinction, and for the information left behind also have implications for the role of unaware cognition.

**Memory Issues**

In our experiments, old learning is transferring to new learning, improving hit rates when the new pair being learned was typical (e.g., a Picasso painting with a female name or a Monet
painting with a male name) without increasing false alarm rates when a rearranged pair was
typical. Such transfer is consistent with three previous findings. First, transfer is observed
between preexisting associations and new learning in an associative recognition task. That is,
preexisting learning as indexed by free association responses increases the hit rate without
having much effect on the false alarm rate (Dosher & Rosedale, 1991; Naveh-Benjamin,
transfer between recent learning and new learning in a cued recall version of the current task.
More generally, Humphreys, et al. (2010) argued that there were many situations in which old
learning transfers to new learning in an unbidden manner. That is, they did not believe that
people were intentionally trying to retrieve the old learning. Instead, they referred to the intrusion
of old learning in new learning as a breakdown in access control. In the current situation, we
would assume that participants are trying to retrieve memories about the last list. However, the
human memory system is not so finely tuned that it can focus just on the last list, especially
when the retention interval is longer than a few seconds (Tehan & Humphreys, 1995, 1996).

As implied by the Ashby et al. (1998) theory, it is possible that procedural memory is
responsible for the learning of the information that is left behind in the reduced paintings. If this
is the case, then there is a close link between procedural memory and episodic memory, which
may undercut this distinction. However, the procedural-declarative distinction is somewhat
vague and it does not lend itself to asking testable questions. Thus, at this time, we think that it is
more reasonable to ask questions about how peripheral or central the memory is (Rubin, 2006)
and questions about its computational characteristics (McClelland, McNaughton, & O’Reilly,
1995). In English, male and female names can, on average, be distinguished by their phonology
and to some extent by their orthography (Cassidy, Kelly, & Sharoni, 1999). Thus, it is possible that the learning that is producing the transfer is entirely within a visual learning system (i.e., visual information extracted from the paintings being associated with visual information about the names). However, according to Cassidy et al. (1999), there is a stronger relationship between phonology and gender than between orthography and gender. If the associations producing transfer are between visual information from paintings and phonological information about the names (or semantic information about gender), then something more central is indicated, such as the McClelland et al. (1995) neocortical system or episodic memory. Our transfer effects appear to emerge on the first critical trial (see Figure 4), and in McClelland et al.’s analysis, this kind of rapid learning is more characteristic of the episodic system than of the neocortical system. A key issue here is whether we are dealing with a largely linear system (e.g., the pixel-based linear autoassociator that we showed could learn to classify the paintings using the first ten dimensions) or with a nonlinear process that can learn to achieve a greater separation of inputs. Our procedure, in which participants only study each pair once, is not suited to discriminating between these alternatives. However, if we mapped each of several sets of stimuli onto a unique verbal response, then we might be able to show that after enough training, perception of the stimuli within each set becomes more categorical. Such a result would be consistent with McClelland et al.’s characterization of the neocortical system. In addition, such a result would be highly relevant to a large number of situations involving experts who have to map complex sensory inputs that have a family resemblance onto a verbal response. For example, dermatologists, radiologists, and other medical professionals become highly skilled in discriminating between complex and highly variable visual patterns to diagnose various diseases.
or conditions (Brooks, Norman, & Allen, 1991). In this task, the input is a complex visual pattern and the output is a verbal label. Wine expertise manifests itself, at least in part, as a more consistent mapping between the sensory input and the vocabulary used to describe that input (Hughson & Boakes, 2001). Absolute pitch is almost always acquired in conjunction with formal musical training, which provides the vocabulary on to which the tones are mapped (McLachlan & Wilson, 2010).

The Analytic-Nonanalytic Distinction

Traditionally, nonanalytic or memory based processes were contrasted with analytic or rule based processes (Brooks, 1978). Rule based processes essentially involve the identification of the necessary and sufficient conditions for an instance to belong to a category. The nonanalytic processes include instance based theories where the similarity between the test item and the entire set of items belonging to a category is computed (Nosofsky, 1986). They also include prototype theories (Posner & Keele, 1968) where the test item is compared to a prototype that has been extracted from the studied category instances.

What has generally been overlooked in the literature on nonanalytic theories is that they require some realization that a concept formation/identification process is operating. That is, the memory access process needs to be controlled and this can occur either through post-access processes or through pre-access processes (Humphreys, et al., 2009; Jacoby, Shimizu, Daniels, & Rhodes, 2005). For example, in the Nosofsky (1986) GCM model, the similarity between the test item and the entire set of items belonging to a category is calculated. In order for this to occur, the items belonging to a particular category must be separated from all the items belonging to other categories. There are mechanisms within memory models that would serve to isolate one
set of items from the other items that have been studied (Humphreys, Bain, & Pike, 1989; Humphreys, Pike, Bain, & Tehan, 1989). Basically, they involve incorporating context, or in the concept formation case, incorporating the category label into the cue that is used to access memory. However, this use of a concept label in the memory access process implies at least some understanding that the task involves concept learning/identification.

Our task is also nonanalytic in the sense that the concept-like behavior emerges from a memory process. In addition, it appears that no understanding of the fact that concepts are present and/or that they need to be identified is involved. That is, the miniature associative recognition task provides a good means of diverting participants analysis away from concept learning. This diversion is helped by the fact that each study pair contains a unique painting and a unique name and that each pair is studied only once. In addition, although gender is an obvious characteristic of names, it is not an attention grabbing characteristic. That is, male and female names occur together in a very large number of situations so their occurrence together in an experiment is unlikely to attract attention. This observation is supported by the results of our post experimental questionnaire. Finally, the use of reduced paintings, which seem to contain few if any stable features or patterns, is likely to inhibit most efforts to identify similarities across paintings. Therefore, we think that we have isolated a learning mechanism that is producing generalization across both reduced paintings and names without any input from a rule based process or even from the control mechanisms that existing nonanalytic theories of concept formation need to assume in order to isolate appropriate memories.

**Why does Concept Learning Sometimes Fail?**
Our participants in Experiment 2 did not learn to classify the reduced paintings in the analytic condition. This, however, may indicate a difficulty in forming an association between the information extracted from the reduced painting and the name rather than a failure to encode the relevant information from the reduced painting. That is, the cognitive demands of forming hypotheses and trying to verbally encode aspects of the reduced painting may have interfered with learning (van Merriënboer & Sweller, 2005). A similar explanation may apply to Kornell and Bjork’s (2008) examination of massed and distributed presentations on the ability of people to learn artistic style. They selected six paintings from each of 12 different artists, and presented them one at a time along with the name of the artist of each painting. They were either massed as a block by artist, or spaced in a distributed fashion. Participants incorrectly believed that massing the paintings by artist was better for discrimination. However, they found that performance was significantly better when the paintings were interleaved with other artists’ paintings than when they were massed together. Kornell, Castel, Eich, and Bjork (2010) replicated these results and showed the same effect for older adults.

These findings were initially surprising. The authors believed that massing the paintings would allow participants to treat them analytically, comparing and contrasting the high level features that define the artists’ style and store the verbal description of those features. Instead, it seems that analysis may be the enemy of induction. Interleaving the paintings may have focused participants to learn the specific painting-artist instances, and this produced better generalization than an attempt to explicitly identify and learn diagnostic features. Our results exploit the same counterintuitive notion. Participants who focused their analysis on the defining features of the
reduced paintings in Experiment 2 performed worse than those in the nonanalytic condition without focused analysis (see also Brooks, 1978; Reber & Allen, 1978).

**What Kind of Information Remains?**

The common dimension reduction technique (i.e., singular value decomposition) that we employed on the brightness values of all the pixels in all the paintings allowed us to re-express and reduce the information in a painting into a smaller number of dimensions that accounts for as much of the variance among the pixels as possible. This allows for an enormous reduction in the amount of information that needs to be stored. Rather than storing the entire 230,400 pixels × 230,400 pixels weight matrix, we reduced the space to 230,400 × 10 simply by selecting only the ten dimensions with the highest variance. The precise method of decomposition and number of dimension retained, however, is not a pivotal concern here. The point is, that the knowledge that remains latent among the reduced set of dimensions along with the information stored about a particular painting, is sufficient to capture important aspects about the artists’ style. Regardless of whether a discrimination is based on a reduced or a full painting, much of the critical information remains intact, so the classification responses are largely indistinguishable. That is, each item is projected into the space (for the reduced images, a subset of the space, consisting of the first ten dimensions) and reconstructed, and the cosine of the angle between the reconstruction and the original item is computed. The higher the cosine, the better the reconstruction, and the more the memory can be said to be “familiar” with the item. The projections of the training items are used to train a simple heteroassociative classifier, a variant of a perceptron known as an “adaline”; the projections of the test items are then classified by the adaline. In other cases, these cosine familiarities can then be compared to a response criterion (or multiple criteria for confidence
responses), and a “yes” or “no” response given to that item in a standard signal detection manner (see Vokey & Higham, 2004, for an example of the application of both response models). The classification performance of this model applied to the Picasso and Monet paintings in our experiment performed nearly as well for the paintings reconstructed from the first 10 dimensions as for the paintings reconstructed from all 320 dimensions. Our human participants performed similarly in the nonanalytic conditions.

Our participants are obviously not entirely naive about the nature of the stimuli in our experiments. Even if they do not have any experience with Cubist or Impressionist paintings specifically, they most certainly have some knowledge about scenery, people or still life that they might use to help them to distinguish the paintings. For example, they could easily use verbal rules such as Marilyn = woman, Daniel = waterlily, or Christine = fruit bowl, to remember the particular painting-name pairs. But if they are relying on these verbal rules to perform the task, then it would be difficult to explain their excellent transfer performance in Experiment 3. That is, one group of participants transferred their learning about the full paintings to the reduced paintings, and another group transferred their learning about the reduced paintings to the full paintings. If those who were trained on the full paintings relied on features such as people, scenery, and Cubism to perform the memory task (as they claimed in their verbal reports), then why are we getting as much transfer as we are to the reduced paintings? It’s not just that the language is different. We are still getting a lot of transfer from the reduced paintings, where the available rules seem much harder to come by. These participants do not get features like people, waterlilies, and fruit bowls. If there was a reduced or partial language that was rich with labels regarding colors, contrast, and texture, then why don’t we see this in the analytic task? That is, if
this low level verbalization was all that was driving performance in the nonanalytic task, then it should have driven performance in the analytic task. And vice versa: the rules that could easily drive performance in our analytic task with full paintings, just do not exist for the reduced paintings.

One possible solution is to turn our data reduction and reconstruction processes into a theory of the information that is stored and used. This information in turn should be compatible with many different process models. Such a process should produce information that is largely invariant between the full and reduced paintings. For example, this invariant information could take the form of a reduced set of dimensions or vectors in a multidimensional space (e.g., Abdi, Valentin, Edelman, & O’Toole, 1995) that would be well established at the beginning of the experiment through experience or evolution (e.g., Hancock, Baddeley, & Smith, 1992; Shepard, 1992). These weights are then stored in memory and adjusted with the presentation of each new painting. Although, it is unclear how gradual this updating must be in order to exploit the structure in the inputs (McClelland, et al., 1995) and whether the updating would be fast enough to support episodic memory performance. During the test trials, participants are presented with congruent or incongruent painting-name pairs where each painting-name pair is projected into space defined by the previous trials and prior experience. It is conceivable that the visual names and paintings that we presented in our experiments could be reduced in the same memory (e.g., the pixels in the name “Marilyn” and the pixels in the painting of the fruit bowl). But, names might not just be visual, they may have orthographic and semantic information as well as sequential dependencies. At the very least, we would have to assume that a reduced description of a visual name would activate a reduced description of the faces/people that the name had been
paired with. However, if we used the auditory presentation of “Marilyn” or novel sentences instead, which have very different temporal characteristics than paintings, then it appears that the paintings and words/sentences would have to be reduced to different sets of weights. An example of what data reduction would look like with a sentence would be Elman’s simple recurrent network (Elman, 1990), where each word of a sentence is input one at a time to the network, but after the last word has been entered, the pattern of activity in the hidden units could be used to reconstruct its temporal order. This would require a module that reduces a painting to a series of weights that can be applied to the eigenvectors and another module that is based on somewhat different principles, which reduces a sentence to a set of weights, which can be used to reconstruct the sentence, and an association between those two reduced representations is stored in memory through conjunctive encoding or context. The degree of similarity between the current stimulus and the stimuli stored in memory drives one’s feeling of familiarity. This feeling of familiarity “flows like water” for the congruent items and results in a “retrieval clang” for the incongruent items producing an intact or rearranged response, respectively. This resulting “fit” between the incoming and stored information (i.e., the similarity score) should be identical for both the reduced and full images. Any global matching model would suffice for recognition memory of this sort.

If participants were presented with a painting and asked to recall the name or sentence that it was originally paired with (instead of simply recognizing the painting-name arrangement as our participants were asked to do), then rather than simply computing the similarity between the word(s) and the stored weights of the paintings and word(s), participants would need to retrieve a reduced representation from memory and then use the reduced set of dimensions or vectors to
reconstruct the word(s) in order to produce them. Similarly, if they were presented with a name or sentence, and asked to recall the painting that it was originally paired with, they would need to retrieve the reduced representation from memory and then reconstruct it in order to form an image or to draw or describe it. Just as we reconstructed each of the paintings in our experiment using a small set of weights that is unique to each painting and the first ten dimensions that we extracted from all the others, we could project the current word(s) or painting into the space or spaces defined by the first ten dimensions in order to reconstruct the word(s) or painting from memory.

As we indicated above, however, our participants have some direct or incidental experience with the stimuli in our experiments. And this prior experience with scenery, people or still life would certainly influence the structure of these latent dimensions and thereby influence the information that is encoded about a particular painting. It is a relative encoding, where each item is stored relative to all the other items in experience. It therefore provides a nice account of the other-race effect (i.e., where faces from other races are often more difficult to distinguish than faces from one’s own race; O’Toole, Deffenbacher, Abdi, & Bartlett, 1991). If encoding is relative to what is already in one’s experience, then storing new information ought to be much more efficient for experts who have accumulated several experiences already. It seems likely that an art historian would be better able to reconstruct a painting from memory than most of us. Experts do not simply rely on an elaborate set of rules, but they also have very efficient coding mechanisms, which make them right most of the time. This solution also provides generality of mechanism by encoding stimuli of all sorts, from images (Vokey, Rendall, Tangen, Parr, and de Waal, 2004) to taste (Ballester, Abdi, Langlois, Peyron, & Valentin, 2009) and words (Landauer
& Dumais, 1997). This invariant solution can also provide an account for how we might associate stimuli such as images with sentences, that differ fundamentally in their spatial and sequential properties. Both remain latent in, and distributed over, a memory for the specific episodes until they are retrieved collectively in response to a similar current event. This information may also serve as the basis of our participants’ descriptions and could be retrieved very rapidly. It may be also be correlated with the global properties defined by Oliva and Torralba (2001), which capture the linear combinations of a scene’s spatial frequency content.

We refer to the information that is left behind after we reduce the paintings to the first ten dimensions as presymbolic, as it does not seem to be closely aligned with any preexisting concepts or verbal expressions. However, there have been many experiments that have used stimuli with classification rules that are difficult to articulate. For example, the dot patterns used by Posner and Keele (1968), Nosofsky’s (1988) color patches that varied along continuous dimensions of brightness and saturation, and Schyns and Rodet (1997) synthesized “Martian cell” categories to better approximate the complexity of the stimuli commonly found in medical diagnosis. It still seems possible that with these materials, there are still low level verbal descriptions and stable percepts that allow concept formation to take place. Our transfer results from Experiment 3 demonstrate, however, that we need a very different kind of information that was never apparent with the stimuli listed above. Information that remains largely intact in both the full and reduced paintings that is not intrinsic to the features that are embedded in any single image. Instead, the information reflects the underlying structural variation across the entire set of images, and as such, has been described in terms of “macro-features” (Anderson & Mozer, 1981). The “semantic global properties” defined by Greene and Oliva (2009a): openness,
expansion, mean depth, temperature, etc., are likely to be correlated with this presymbolic information. Our findings, however, do not allow us to directly contrast these approaches.

**Unaware Cognition**

Our methodology and findings are relevant to the role of unconscious processes in tasks that are considered cognitive: subliminal advertising and purchase decisions (Bermeitinger, et al., 2009), attitude change without effortful attention (Olson & Fazio, 2001; Staats & Staats, 1958; Zanna, Kiesler & Pilkonis, 1970), or whether people can report the biases that influence their choices (Nisbett & Wilson, 1977). Our findings—but not the specifics of the methodology—are also relevant to similar tasks that do not involve complex visual stimuli such as unconscious rule learning of artificial grammars (Reber & Allen, 1978; Reber, 1989; Vokey & Brooks, 1992).

It seems probable that many marketing communications are learned nonanalytically. That is, individuals experience marketing communications under conditions of time pressure, low motivation, low attention and distraction. This is especially true for the information or image that is to-be-communicated by sponsorships or product placements. These have been referred to as “advertising fragments” (Pham & Vanhuele, 1997) or “impoverished” messages (Cornwell, Weeks, & Roy, 2005). These communications receive low-level processing partly because they are simple and do not need elaborate processing for understanding; and partly because they are typically received when exposure to them is incidental – where the focus of attention is elsewhere. In these situations, it is likely that very little will be learned after a single exposure. However, learning can be quite good after multiple distributed exposures even when those exposures occur under very low levels of attention (Humphreys, et al., 2010; Batra & Ray, 1986; Weijo & Lawton, 1986). Because they are not subject to close scrutiny (Hawkins & Hoch, 1992),
it is less likely that your existing knowledge base will be invoked, which would accompany an analytic learning process. That is, the knowledge that the advertiser is trying to persuade you and the knowledge needed to critically examine the persuasion attempt may not be invoked. How might this work? For example, repeated exposures to a fast food brand depicting active and healthy individuals may allow the non-deliberate extraction of body size and shape as related to the brand. This learning may in turn result in buying foods that are not actually consistent with maintenance of a healthy body size and shape.

This work on unconscious processes has focused on the question of whether participants are aware of the learning contingencies (Dulaney, Carlson, & Dewey, 1984; Mitchell, De Houwer, & Lovibond, 2009). In our case, the association between painting style and gender. Attempts to prevent people from becoming aware of these contingencies can involve extremely complicated learning situations (Olsen & Fazio, 2006) that can seriously reduce learning. In contrast, we used a very good learning task but concealed the fact that there was a contingency between the paintings and the names. Humphreys, et al. (2010) have also argued that prior learning can intrude in an unbidden manner and that appears to be happening with the current task. In addition, the current results show that people are largely unaware that they are using presymbolic information especially when they are working with stimuli that are rich in meaning and nameable features. None of these observations means that people will be entirely unaware of the learning contingencies if they are asked to reflect on and think back to their learning experience. However, because different cues may be involved on a post experimental questionnaire than are involved in the original decision, one cannot infer from the answers to such a questionnaire that people were aware when they made their original decision. This would
be especially true if the original decision was made under time pressure or under distracting conditions, as would be the case for many consumer decisions. In addition, participant selection artifacts may well mean that the data from participants that display some level of awareness may differ from the data from those who do not display any level of awareness. Furthermore, just as training can improve the consistency with which people describe wines, it is possible that with training, people could become more aware of the information that is left behind in the reduced paintings.

It should also be possible to alter our procedures to make a stronger case for relevancy to advertising and other attempts to influence decisions through image development. We chose to examine transfer between old learning and new learning in a single task because this arrangement would provide the greatest concealment for the true aims of the experiment. That is, if we stopped participants after the old learning was complete and asked them to perform a new task, we thought it could invoke a problem solving set that might induce some participants to consider possible relationships between the two tasks. In addition, we mapped sets of stimuli (Picasso and Monet paintings) onto sets of responses (male and female names) and presented each painting and each name only once at study and again once at test. However, now that we have shown that we can obtain transfer in an arrangement that provides a very high level of concealment, it should be possible to show continuity between conditions in which the concealment level is very high and conditions with a lower level of concealment.
References


Appendix

Stimuli

Paintings.

We scanned 160 paintings by Picasso during his Cubist period and 160 Impressionist paintings by Monet from various art catalogues (Gordon & Forge, 1983; Poggi, 1992; Rubin, 1989; Stuckey, 1995) at a resolution of 1200dpi. A 12 pixel Gaussian blur was applied to each painting and scaled to 6% of the original size to remove the moiré patterns inherent in scanning bitmapped images. Each painting was then re-scaled so that the smaller of its height or width just filled the corresponding slide dimension and then cropped and centered to 640×480 pixels.

The color of the paintings was represented by coding each image as three separate Red, Green, and Blue (RGB), 8-bit sub-images—the intensity of the pixel in each sub-image corresponding to the intensity (on a scale of 0-255) of the corresponding color. Each painting was represented as a cropped computer graphic image consisting of $320 \times 240 \times 3 = 230,400$ pixels. The 320 paintings were learned as the equivalent of a linear autoassociative memory using the Widrow-Hoff learning algorithm. This memory—the $230,400 \times 230,400$ pixels weight matrix, $W$, relating the connection value between each pixel and every other pixel over the 320 paintings—can be computed via the singular value decomposition (SVD) of the pixels by paintings matrix ($230,400 \times 320$ pixels), $X$ (see, e.g., Abdi, Valentin, & Edelman, 1999, for details).

The learning of the labels (Picasso/Monet) associated with the stimuli was simulated by training a simple classifier, a variant of a perceptron known as an “adaline” (Anderson, 1995). The adaline is a simple linear heteroassociator with Widrow-Hoff error-correction, composed of
a multiple-unit input layer and one binary output unit. In statistical terms, it is a simple linear
discriminant function analysis of the inputs to predict the binary classification of the items. The
inputs to the classifier were the projection weights on the eigenvectors for each trial item to
produce a final set of discriminative weights to predict the artist category, in the form of a simple
linear equation, from the projection weights for any given input item. This approach is equivalent
to fitting a hyper-plane to the projections of the items that best (in the sense of the least-squares
criterion) separates the Picasso training inputs from the Monet training inputs – perfectly, if all
eigenvectors are used (a consequence of the Widrow-Hoff error-correction), or maximally if
some subset of eigenvectors is used. These prediction weights were then frozen for test, and used
to predict the artist category from the projection weights of the test stimuli. For example,
Picasso’s “Les Demoiselles d’Avignon” and Monet’s “Japanese Bridge” depicted in Figure 1
were reconstructed using subsets of these dimensions, such as, just the first, the first ten, and so
on. When a painting is reconstructed using all 320 dimensions, it is a perfect representation of
the originally submitted image.

The classification responses for different ranges of eigenvectors of the 160 Picasso and 160
Monet paintings were scored as hits and false-alarms. The perceptron applied to the projection
weights resulted in 79% hits and 27% false alarms using only the first ten dimensions. In order to
determine whether the paintings can be discriminated directly in terms of these mean—rather
than covariant—differences in the pixel values themselves, the perceptron was applied directly to
the pixel-maps of the other 319 paintings and then the obtained weights applied directly to the
pixels of the remaining painting to predict its classification. We repeated this process for each of
the 320 paintings in the set. The perceptron applied directly to the pixel-maps resulted in 45%
hits and 44% false alarms, ruling out the possibility that the paintings can be discriminated directly in terms of the mean—rather than covariant—differences in the pixel values themselves. This rules out the possibility that, for example, Picasso’s paintings are generally darker than Monet’s or contain more blue, and hence may be discriminated directly in terms of these mean differences. We reduced each of the 320 paintings to only these primary dimensions of variation, which are sufficient for substantial levels of discrimination, but lack high level features such as mandolins or waterlillies. Consequently, we had two sets of materials: 320 full paintings by Picasso and Monet and a second set of 320 images that have been reduced to only the first ten dimensions of covariation.

Sample paintings by Picasso and Monet that have been reduced to the first ten dimensions are presented in Figure 1 alongside the same paintings fully reconstructed from all 320 dimensions. This result establishes that there is sufficient information in the paintings to discriminate statistically between the artists after the symbolic information has been removed.

Names.

In order to develop a learning task, we paired names with faces. We selected 160 male names and 160 female names from lists of common Australian names. In English, the phonology and to some extent the orthography of a name is correlated with its gender (Cassidy, Kelly, & Sharoni, 1999). Thus, the two sets of names differed in phonology and orthography as well as in gender per se.
Author Note

This research was supported by an Australian Research Council grant DP0985830, and a Natural Sciences and Engineering Research Council of Canada Discovery grant to JRV. We thank Hervé Abdi, Bart Anderson, and Samuel Hannah for comments on earlier drafts of this article. Correspondence should be addressed to jtanen@psy.uq.edu.au.