

**COMPONENTS OF ARTISTIC STYLE: TURNING PEOPLE INTO
PIGEONS**

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This work is dedicated to Arturo.

Abstract

Family resemblance describes the covarying information across members of a category. In an attempt to demonstrate human categorization based on family resemblance—that is, on the *style* of a category, it seems that categorical definition must be made an incidental part of the task so that participants employ a strategy described by Brooks (1978) as “nonanalytic cognition”. Eigenvectors obtained from the dimension reduction of pixel-maps describe the underlying structural variation across a set of images. Partially reconstructed images made from a subset of their derived eigenvectors were used as stimuli in investigating judgements of style, as they appear to be without human-nameable features. The following exploratory experiments provide evidence for spontaneous judgements based on family resemblance using as little information as is contained in the first 10 eigenvectors of Monet and Picasso paintings.

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Chapter 1

Pigeons' Judgements of Complex Categories

Herrnstein and Loveland (1964) successfully trained pigeons to discriminate between photographs that contained people from those that did not.¹ Many of the people in the photographs were partially obscured by objects, such as vehicles, trees, and window frames. They were located in different areas throughout the photographs: at the centre or off to the side, at the top or the bottom, close up or far off in the distance. Some photographs contained one person, and others contained various sizes of groups. The appearances of the people themselves varied considerably: they were dressed, semi-nude, and nude; male and female; adults and children; standing, sitting up, and lying down; of European, African, or Asian descent. The attributes of the photographs themselves also varied considerably in lighting, colouration, tinting, and season. The photographs of people varied so considerably that there wasn't any apparent consistent characteristic of the images that unified them all, except for the fact that they depicted something about people. These photographs demonstrate a class of visual stimuli so complex that it defies simple description.

The pigeons were able to learn to discriminate photographs containing "people" from those that were "non-people" quite easily, even when the experiment was redone with black and white photos and when the images were out-of-focus. Herrnstein and Loveland (1964) also found the nature of the errors that the pigeons made to be quite interesting. The pigeons sometimes failed at the discrimination task when the people in the photographs were largely obscured, and they occasionally responded to photos that contained objects relating to people, such as vehicles. Although both of these

¹Although the two types of images in Herrnstein and Loveland (1964) are being referred to as "people" and "non-people", these terms refer only to discriminating photographs containing people from those that do not; there was no claim that the pigeons were discriminating people directly.

types of errors decreased as training continued, some errors that the pigeons made were beyond any known explanation.

What is less clear is how the pigeons succeeded. Herrnstein and Loveland (1964) interpreted the pigeons' ability as well as their ease with accomplishing the task as evidence for the pigeons using a pre-existing concept of "people" to discriminate between the photographs. They thought that performing the task allowed the pigeons to make use of an innate concept of "people", and they concluded that these animals have greater powers of conceptualization than what is normally attributed to them. Such an interpretation was particularly compelling, given that the pigeons—once they had been trained—were able to generalize their discriminating ability to never-before-seen photographs. Herrnstein and Loveland (1964) compared the pigeons' learning of the discrimination with their being taught to peck for access to a feeder; the capacity to do so is innate, and training need only be done to teach the animal to map the pre-existing concept in order to receive the rewards of the task.

In a similar vein, Watanabe, Sakamoto, and Wakita (1995) trained pigeons to judge between paintings by Monet and paintings by Picasso. There are many possible cues for such a judgement, but there is unlikely to be a single feature that consistently differentiates one artist's work from the other's. The paintings presented to the pigeons were displayed in grey-scale, left-right reversed, and out of focus, but the pigeons' success at the task persisted. Not only could the pigeons successfully generalise to never-before-seen paintings by Monet and Picasso, but also they were able to judge other Impressionist and Cubist painters, such as Braque and Cezanne. These results have been replicated with paintings by Van Gogh and Chagall (Watanabe, 2001).

These experiments contained such complex categorical structure that there is unlikely to be any simple way to define the photographs containing people (Herrnstein

& Loveland, 1964) or paintings by particular artists (Watanabe et al., 1995). The question, then, is how pigeons are able to perform the task correctly; that is, what is it (if anything) that persisted throughout alterations to the photographs and paintings that made it still possible?

In subsequent research, Herrnstein, Loveland, and Cable (1976) trained pigeons to discriminate images that contained trees, bodies of water, and even specific people from those that did not. The ability to perform such a difficult task appears to pose two problems. First is the analysis of the individual features that enable a participant to determine whether a particular object is a member of a certain class. The other is the analysis of properties of classes that allow them to be discriminable. The traditional explanation describes the common elements that persist across the members of a class. According to such a theory, trees, for example, have something specific that is common to all of them, such as a particular shape or texture (or a combination).

Having carefully looked at the hundreds of images they used for their discrimination tasks, however, Herrnstein et al. (1976) could not even begin a list of common elements. To recognize a tree, for instance, it is not necessary for it to be green. Nor does it have to be leafy, vertical, woody, branching, etc. Further, in order to decide that something is not a tree, that object need not be void of green, leaves, wood, etc. Neither were they able to identify common elements in the experiments involving bodies of water and specific people.

An alternative to common elements is offered: what we see and describe as trees actually make up a complex list of probabilistic co-variations. In a tree, for example, the green should be on the leaves if either one is present. The branching parts should also be woody (rather than anything else), and so forth. The complete listing of all of the probabilistic co-variations that make objects “trees” would then be so long and

complex that the learning of individual items in the list would be an unlikely feat. Rather, categorical inclusion is determined by “family resemblance” (e.g., Wittgenstein, 1953; Ryle, 1951; Brooks, 1978; Brooks, Squire-Graydon, & Wood, 2007; Medin & Schaffer, 1978; Rosch, 1975).

1.1 Family Resemblance

People have no trouble in their everyday lives making categorical judgements. Under most circumstances, one would not confuse, say, a cat and a dog. The task even seems trivially easy; however, the visual information that falls on the retina is remarkably similar for the two animals. Not only that, but we are able to correctly apply the labels of “cat” and “dog” to myriad stimuli without difficulty. Animals as distinct from one another as a husky and a teacup poodle both fall under the same label of “dog”. One might attempt to generate a rule that includes all breeds of dogs and excludes all breeds of cats, but the task is not easy; a typical rule might be something like, “dogs bark and wag their tails, and cats meow”. However, no one would confuse a dog for a cat if it never barked or had its tail fully docked. Furthermore, the category of “dog” is not so strictly defined in itself; a rescued pet with a missing limb would still easily be considered a “dog”. Our explanations for the categorization of stimuli eventually come to an end somewhere.

To be fair, there do exist specific rules in the world of zoology that determine what species a particular organism is a member of. However, we certainly do not run through such a set of rules in our daily lives in order to decide that something is a dog (or, for that matter, a person, a Monet, or a Picasso). Indeed, our decision that something is a dog is instantaneous. We don’t use an explicit rule that defines a dog relative to another animal, such as cat. Rather, membership to these categories

is based on family resemblance. Say, for example, that Picasso's *Ma Jolie* looks like *Guernica*. *Guernica*, in turn, looks like *Old Guitarist*. *Old Guitarist*, then, looks like *Garçon à la pipe*. Although *Ma Jolie* bears no resemblance to *Garçon à la pipe*, the members of the Picasso "family" may be thought of as lying along a continuum according to their degree of similarity to one another. As there are multiple characteristics of each member to be considered, the continuum describing degrees of similarity spans out in multiple directions. Aside from looking for a signature, there seems to be no simple rule that determines the inclusion of these paintings into the one category of "Picasso"; instead, the resemblance of their polymorphous traits creates the basis for indirect categorisation.

1.2 Judgements of Style

Beyond establishing categorical boundaries, the concept of family resemblance suggests that individuals become sensitive to the structural regularities in stimuli through incidental, everyday exposure to examples of categories. People then develop sensitivities to structural regularities such that our judgements of stimuli can be described as the identification of style. That is, for example, we consider a new painting at the gallery to have been painted by an Impressionist because we see a stimulus with an overall style of "Impressionism" (whatever that may be).

It is important to note, however, that Herrnstein et al.'s (1976) example demonstrates the idea of family resemblance using human-nameable features. That is, traits such as verticality or greenness are linguistic labels unique to humans. In doing so, they admit the following:

Having looked at the hundreds of instances used here or even at the two positive instances [shown in a Figure in the original paper] (let alone the

tens of thousands involved in real-life discriminations), we cannot begin to draw up a list of common elements. To recognize a tree, the pigeons did not require that it be green, leafy, vertical, woody, branching, and so on (overlooking the problem of common elements nested within terms like leafy, vertical, woody, and so on). Moreover, to be recognizable as a non-tree, a picture did not have to omit greenness, woodiness, branchiness, verticality, and so on. Neither could we identify common elements in the other two experiments. (pp. 297-298).

Clearly, even those positing family resemblance are uncertain as to its correctness. A slight alternative is proffered here. It may be that family resemblance describes an overall gestalt co-variation rather than a co-variation of nameable features. It seems necessary to generate stimuli that are absent of any human-nameable features in order to test for human participants' judgement ability based on this gestalt covariation. The techniques of dimension reduction described in Chapter 2 will serve to do just that.

Another possibility is that there is some sort of simple consistency across images that has yet to be noticed. It could be, for example, that all images containing trees (or people, or bodies of water, etc.) are also lighter in one particular corner, or are all darker in another. To account for such a possibility, eigen-decomposition is necessary. Our initial inability to detect such a simple regularity does not prove that one does not exist.

The capacity to make indirect categorical judgements based on style would explain the wide assortment of rather sophisticated-looking discrimination tasks that pigeons can perform (Herrnstein & Loveland, 1964; Siegel & Honig, 1970; Poole & Lander, 1971; Malott & Siddall, 1972; Morgan, Fitch, Holman, & Lea, 1976; Herrnstein et al., 1976; Cerella, 1979, 1980; Herrnstein, 1979; Herrnstein & de Villiers, 1980; Blough,

1982, 1985; Bhatt, Wasserman, Reynolds, & Knauss, 1988; Jitsumori & Yoshihara, 1997; Aust & Huber, 2001; Watanabe, 1993). The experiments that follow are exploratory. They are attempts to investigate under what, if any, circumstances human participants may make judgements based on the overall style of paintings as visual stimuli.

Chapter 2

Generating Stimuli with Dimension Reduction for the Investigation of Judgements of Style

Given the human capacity to use language as a tool to describe specific object detail (this point will be discussed more later on), it seems it is imperative to generate stimuli with structure that is not easily articulated (i.e., without human-nameable features), and as well to capture any covariance across the members of a family. Dimension reduction reduces the number of variables in high-dimensional data in order to make the remaining information more tractable. Many common statistical dimension reduction techniques such as principal components analysis (PCA) and singular value decomposition (SVD) use this strategy (Jolliffe, 1986; Stevens, 1996; Tabachnick & Fidell, 2007).

For the purposes of the following experiments, statistical dimension reduction has been used to compile a large set of Monet and Picasso painting images (including the images used by Watanabe et al., 1995) that were constructed with reduced dimensionality. 160 images of Monet paintings and 160 images of Picasso paintings were brought to the standard size of 320 x 240 pixels by expanding or cropping, as needed. The shortest axis for every image was adjusted to either 320 or 240 pixels (depending on which axis), and was then centred and cropped. Thus, each painting was represented as a cropped computer image composed of $240 \times 320 \times 3$ (Red-Green-Blue) = 230,400 pixels. The vectors of the images were assembled into a matrix that was then decomposed into its orthogonal dimensions (i.e., the eigenvectors) that described the underlying structural covariation across the set of images. Each of the images was then partially reconstructed using a weighted, linear combination of some of its eigenvectors (e.g., Devijver & Kittler, 1982; Hancock, Bruce, & Burton, 1998; Valentin,

Abdi, Edelman, & O’Toole, 1997), and coded as to whether it was a Monet or a Picasso image. See Figures 2.1 and 2.2 for examples of full and partially reconstructed images.

2.1 Classifying the Images With a Neural Network

A linear autoassociative neural network is built from simple units that are linked by weighted interconnections. It is a classifier that learns based on prior exposure to stimuli; that is, it adapts. During the process of learning, the weighted interconnections are modified in order to maximise the neural network’s capacity of classification. The network itself, then, may be considered as an artificial memory, as the content gained from exposure to stimuli is stored and disseminated across the interconnections. As a result of exposure to different stimuli, the neural network develops the capacity to recognise stimuli. It can also generalise its knowledge to never-before-seen stimuli (e.g., Abdi, Valentin, & Edelman, 1999; Dayhoff, 1990). Given the distributed nature of its learning capacity, a neural network might serve as an appropriate simulation for learning based on family resemblance.

This memory—the 230,400 pixels \times 230,400 pixels weight matrix, \mathbf{W} , relating the connection value between each pixel and every other pixel over the 320 images—can be computed via the SVD of the 230,400 pixels \times 320 matrix, \mathbf{X} , of the images. The SVD of a rectangular matrix, \mathbf{X} , is expressed as $\mathbf{X} = \mathbf{U}\mathbf{\Delta}\mathbf{V}^T$, for which \mathbf{U} is the matrix of eigenvectors of $\mathbf{X}\mathbf{X}^T$, \mathbf{V} is the matrix of eigenvectors of $\mathbf{X}^T\mathbf{X}$, and $\mathbf{\Delta}$ is the diagonal matrix of singular values—the square-root of the eigenvalues of either $\mathbf{X}\mathbf{X}^T$ or $\mathbf{X}^T\mathbf{X}$ (as they are the same).¹ In statistics, the related eigendecomposition of the data matrix is called principal components analysis (PCA), and so such linear

¹ \mathbf{X}^T denotes the transposition of matrix \mathbf{X} .

autoassociators are often referred to as PCA neural networks (see Abdi et al., 1999). From this perspective, \mathbf{W} can be represented in terms of the eigenvectors, \mathbf{U} , of the pixels \times pixels cross-products matrix (see Abdi et al., 1999):

$$\mathbf{W} = \boldsymbol{\delta}\mathbf{U}\mathbf{U}^T$$

where $\boldsymbol{\delta}$ corresponds to the eigenvalues. The effect of Widrow-Hoff learning is to *spherise* the weight matrix, i.e., render all of the resultant eigenvectors equally important in reconstructing the stimuli (Abdi et al., 1999), yielding:

$$\mathbf{W} = \mathbf{U}\mathbf{U}^T$$

Retrieval of an item from this memory, $\hat{\mathbf{x}}_i$, is computed as

$$\hat{\mathbf{x}}_i = \mathbf{W}\mathbf{x}_i \tag{2.1}$$

$$= \mathbf{U}_{l:m}(\mathbf{U}_{l:m}^T\mathbf{x}_i) \tag{2.2}$$

where the subscript, $l:m$, denotes the range of eigenvectors used to reconstruct the item. For our purposes, the eigenvectors are ordered in terms of the magnitude of the associated eigenvalues (i.e., proportion of variance accounted for), from most to least. As only the eigenvectors with associated eigenvalues greater than zero are retained, there are at most as many eigenvectors as there are items in the training set. The expression in parentheses of Equation 2.2 can be interpreted as the *projection*, $\mathbf{p}_{i|l:m}$, of the item into the space defined by the eigenvectors,

$$\mathbf{p}_{i|l:m} = \mathbf{U}_{l:m}^T\mathbf{x}_i$$

where the values of $\mathbf{p}_{i|l:m}$ are the *weights* on each eigenvector used to reconstruct the item from the linear combination of eigenvectors:

$$\hat{\mathbf{x}}_i = \mathbf{U}_{l:m} \mathbf{p}_{i|l:m}$$

Thus, given the eigenvectors of the set as a whole, each item can be represented in a very reduced form as its projection weights on the eigenvectors. It is in this sense that the eigenvectors can be seen as the “macrofeatures” of the items, as the visual images differ along the dimensions that the eigenvectors encode for (see, e.g., Abdi, Valentin, Edelman, & O’Toole, 1995; Turk & Pentland, 1991, for similar analyses of photographs of faces).²

The learning of the labels (Monet/Picasso) associated with the images was simulated by training a simple classifier, a variant of a *perceptron* known as an “adaline” (see, e.g., Dayhoff, 1990). 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 (see, e.g., Abdi et al., 1995). The inputs to the classifier were the projection weights on the eigenvectors for each 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 Monet images from the Picasso images.

²Using the leave-one-out technique (e.g., Abdi et al., 1995), each image was projected into the space defined by all the remaining 319 images. The cosine similarity of each projected image compared with itself was determined. The cosine similarity is indicative of how representative the image is of that space. In the subsequent experiments to be reported, the cosine similarity was used to select the “best” Monet and Picasso images (i.e., those that are best representatives of their respective spaces).

2.1.1 Results

The classification responses for different ranges of eigenvectors (i.e., representing the use of more and more of the “macrofeatures” of higher dimensionality) of the Monet and Picasso images were scored as hits and false-positives (for the respective positive category it had been trained with), and then converted to a non-parametric, signal-detection measure of discrimination, A' . Values of A' vary between 0.00 and 1.00, and approximate the results of a two-alternative forced-choice (2AFC) task with the same discriminative stimuli; a value of $A' = 0.50$ indicates “chance” discrimination; values of A' greater than 0.50 indicate increasingly successful levels of discrimination (see, e.g., Wickens, 2001). This discrimination index was computed for classification based on just the first “macrofeature” or eigenvector, the first 2, the first 3, . . . , 10, 15, 20, 25, 30, . . . 95, 100, 150, 200, 250, 300, and all 319 eigenvectors.

The results are shown in Figure 2.3. Clearly, substantial levels of discrimination between the Monet and Picasso images is possible with this approach. Discrimination increased as more eigenvectors were used to make the discrimination, although the effect appeared to asymptote once the first 8 or so eigenvectors were included.

2.1.2 The Perceptron Applied Directly to the Pixel

Maps

As mentioned in Chapter 1, it is possible, for example, that the Monet paintings are generally darker than Picasso ones, or contain more blue, etc., and hence, may be discriminated directly in terms of these mean differences rather than the covariant differences in the pixel values themselves. To assess this issue directly, the perceptron classifier was applied directly to the pixel-maps of the images to predict their classi-

fication. Shown as well in Figure 2.3 as a dashed line, mean training discrimination (A') of the Monet from the Picasso images when the perceptron classifier is applied directly to the pixel maps is 0.64—far lower in terms of performance than with items that have undergone eigen-decomposition.

2.2 The Importance of Early Eigenvectors

Every eigenvector has an associated eigenvalue that indicates the degree of variance throughout the whole image set that the corresponding eigenvector accounts for; a larger eigenvalue denotes a larger degree of variance. An image varies along the most salient dimensions that so-called “early” eigenvectors account for. Smaller eigenvalues correspond to “late” eigenvectors, and they represent less salient dimensions of variation.

The early eigenvectors encode for key categorical information; for example, male and female faces have a strong tendency to be oppositely weighted on the second eigenvector (Abdi et al., 1995). The primary dimensions of a stimulus depend on the images that the eigenvectors are extracted from; the first eigenvector is essentially the prototype of all of the images (Devijver & Kittler, 1982). Therefore, the second eigenvector is actually the first one to depict any variation between the images. Eigenvectors only encode for visually-relevant information; semantic labels—like gender or age—have no relevance. Given such information, it is impressive that an explicit semantic category would spontaneously emerge. Another important point is that some eigenvectors—because the model is free to extract whatever information it deems useful for the discrimination of specific images—will encode for visual information that typically possesses no corresponding semantic label (Turk & Pentland, 1991).

2.3 Generality

The concepts of dimension reduction and neural network modeling are not limited to visual stimuli; for example, a linear associator can successfully learn to discriminate music composed by Bach from music composed by Mozart (Crump, 2002). A dimension reduction mechanism can also be successfully applied to language. SVD applied to written text constitutes latent semantic analysis (LSA). Extremely large bodies of text may be reduced into a subset of dimensions of variation. Words are then considered to be nodes in a multidimensional semantic space; words with similar semantic meaning are closer together in the space (Landauer & Dumais, 1997).

LSA offers a possible solution to Plato’s “poverty of the stimulus” problem, as its learning process is extremely inductive, and could provide insight into how children acquire language at a rate that is exponentially greater than what would be expected, given how much could ever be taught directly. The majority of information needed in order for LSA to identify a word on a vocabulary test is based on where the word does not occur. Therefore, it could be that the majority of information contained within language relates to word choice, rather than word order (Landauer, 2002).

It is also possible that dimension reduction may be able to help explain how individuals acquire other forms of knowledge; applying LSA to introductory psychology textbooks and testing it using the same multiple-choice exam administered to undergraduate students yields a grade of 60 percent—only slightly below the class average.

Although not conclusive, it is possible that LSA demonstrates the same mechanism that individuals use when acquiring some types of information. Evidence for such a claim is supported by the fact that the LSA and human participants tend to make the same types of errors; for example, conceptual questions were answered less accurately than factual ones (Landauer, Foltz, & Laham, 1998).

2.4 Physiological and Evolutionary Evidence for Dimension Reduction

The term “natural scene” refers to any image that an individual could possibly encounter as a visual stimulus (so, despite the misleading name, man-made objects such as buildings can occur in natural scenes). Natural scenes merely occupy a small fraction of all possible scenes (Attneave, 1954; Ruderman, 1994). Therefore, all of the images that an individual could encounter in a lifetime are only a minuscule portion of all possible images. When images are considered simply as arrays of pixels, a random image is composed entirely of random pixels; that is, there is no relationship between a pixel and any of the ones adjacent to it. When random images are generated, they appear as white noise (Ruderman, 1994). The pixels in a natural image, however, are correlated with one another, as they typically share a common form; that is, for example, pixels in an image of a sky would have correlated properties, as they are collectively an image of the same object. Such a correlation gives rise to a structure in natural images that does not occur in random images (Atick & Redlich, 1992).

The visual system has had exclusive exposure to natural stimuli throughout history. It would, therefore, be the only environment in which the visual system evolved in. The visual system could possibly have adapted to make use of the structure present in natural visual stimuli (Barlow, 1961, 2001; Marr, 1982). Dimension reduction is based on these structural regularities, and therefore appears to be consistent with the evolutionary history of the visual system (Hancock, Baddeley, & Smith, 1992).

By applying dimension reduction techniques to images of natural scenes, researchers have found remarkable consistencies in the emerging dimensions; the extracted eigenvectors of natural images are very similar, regardless of the size, number, or quality of the images (Baddeley & Hancock, 1991; Hancock et al., 1992; Heide-

mann, 2006). The results provide evidence for a possible innate consistency in the structure of natural images. The visual system might make use of core consistencies, and dimension reduction demonstrates an efficient method for extracting them. Therefore, because natural images vary along the eigenvectors, specifically encoding these dimensions is a logical method for analysing visual stimuli.

There are many characteristics of dimension reduction and of the resulting eigenvectors that seem analogous to physiological structures in the visual system; for example, the first few early eigenvectors are depicted as an oriented bar (Baddeley & Hancock, 1991; Hancock et al., 1992; Heidemann, 2006), and may correspond to “bar” and “edge” detectors in the primary visual cortex (Hubel & Wiesel, 1959). Another parallel occurs when dimension reduction is applied to coloured natural images; early eigenvectors appear that consistently code for red-green, yellow-blue, and black-white dimensions (Buchsbaum & Gottschalk, 1983; Rubner & Schulten, 1990; Usui, Nakauchi, & Miyake, 1994). This specific colour encoding corresponds to the colour-opponent processes (Valois, Abramov, & Jacobs, 1966).

2.5 Non-Human Animals

Given the preceding evolutionary and physiological evidence for dimension reduction, it is possible that non-human animals are capable of using such a mechanism. Herrnstein and Loveland (1964) originally thought they had trained pigeons to use some pre-existing category of “people” in order to discriminate photographs, but Greene (1983) contradicted their claim by training pigeons to discriminate between Herrnstein and Loveland’s stimuli after the people in the photographs had been removed. The pigeons responded to Greene’s photographs just as they had to the originals. Therefore, there may have been a general *style* to the people photographs

that the pigeons could respond to in order to perform the discrimination task; that is, there may be some features in the photographs that occur as a result of the constraints of taking a photograph with people in it.

Although pigeons have a visual acuity comparable to humans, they do not automatically perform the same in certain visual tasks. People can easily understand the concepts of “greater than” and “equal to”, but pigeons do not seem able to do so (Pearce, 1988). However, pigeons can easily discriminate between “small area” and “large area”, although such a task is much more difficult for people to do. Pearce (1988) theorised that the reason for such a discrepancy is that the rules that govern “small area” and “large area” are not easily verbalised. It seems that because the pigeons were not attempting to find any relationships or rules that defined the categories, they were able to do the task.

If pigeons are capable of performing discrimination tasks without regard to possible rules or labels to stimuli, then it is possible that humans can do so as well—under certain conditions. In one sense, the propensity to look for rules and justifications may be deemed a secondary mechanism in that it must serve some sort of advantage (otherwise it would not exist), but it is obviously not necessary. It is not the case that pigeons should be considered less intelligent; as described in Chapter 1, they are quite capable of making rather sophisticated judgements. In order to “turn people into pigeons”, it appears necessary to use stimuli with restrained verbalisable content—and dimension reduction does just that.

2.6 Human Animals and Processing Strategies

Traditionally, implicit learning has been described as an automatic process that is outside of conscious control (e.g., Reber, 1967). Instances of separate automatic and

controlled systems can be seen in ubiquitous descriptions of conscious versus unconscious memory. However, it has been demonstrated through the use of opposition logic that what appears as different memory systems are actually deliberate applications of different strategies (Higham, Vokey, & Pritchard, 2000; Higham & Vokey, 2000).

A human participant, then, is capable of deliberately applying a particular strategy when performing a judgement task. The unintended discriminative effects of a strategy are the sources of different influences. It is these influences on behaviour that can be either controlled or automatic. Control over humans' processing of stimuli is therefore achieved by manipulating what strategy is used.

There is no reason to suspect that the capacity to judge stimuli based on family resemblance has been lost in humans. However it has been notoriously difficult to demonstrate that such a capacity exists, as participants who are brought into the lab for experiments adopt an "analytic" strategy; that is, they actively search for a specific attribute or rule that defines one category relative to another. As analysis depends on verbalisable features upon which to base rules, non-linguistic animals are therefore not capable of it. Some examples of such tasks that require analysis are distinguishing inside vs. outside (Herrnstein, Vaughan, Mumford, & Kosslyn, 1989) and whether two vertical bars stand at equal or unequal heights (Pearce, 1988). By employing an analytic strategy, however, human participants can perform the tasks very easily.

The alternative strategy is what Brooks (1978) has described as nonanalytic cognition, which involves the memory for individual cases. It is nonanalysis that follows the exemplar model of judgements of style by gaining information from individual examples. That is, by processing stimuli nonanalytically, humans might judge stimuli based on family resemblance (e.g., a painting is thought to be by an Impressionist

because it is in the overall style of Impressionism).

Brooks successfully diverted participants' analysis of stimuli by having them focus on the use of the stimuli rather than on the way they are defined. In such a way, classification becomes an incidental part of the task (e.g., Brooks et al., 2007; Whittlesea & Price, 2001). In using human participants, it seems it may be necessary to prevent their approaching the experimental stimuli with an analytic strategy in order to demonstrate stimulus judgements based on exemplars.

2.7 The Current Experiments

Images that have undergone dimension reduction provide for stimuli that are unlikely to possess human-nameable structural regularities or features. By making stimulus definition an incidental part of the task, we hope to elicit a nonanalytic strategy for processing stimuli. By doing so, it may be possible to demonstrate that human participants are able to pick up the information remaining in partially reconstructed images in order to perform an indirect discrimination.

One main goal of the following experiments is to determine whether humans can judge complex categories of images that are only comprised of their primary visual dimensions. Judgements of style above chance should provide evidence that human beings may be “turned into pigeons” in the sense that they would be indirectly discriminating stimuli in the same manner that has been demonstrated in pigeons.

Subsequent experiments also seek to demonstrate not only that humans are capable of making judgements based on family resemblance, but that they can do so undirected. Showing undirected use of a nonanalytic strategy may have implications for humans' ubiquitous use of nonanalysis in everyday matters, and will help to understand the conditions that elicit different processing strategies; as well the relationship

between the visual system of humans and non-human visual systems may be better understood.

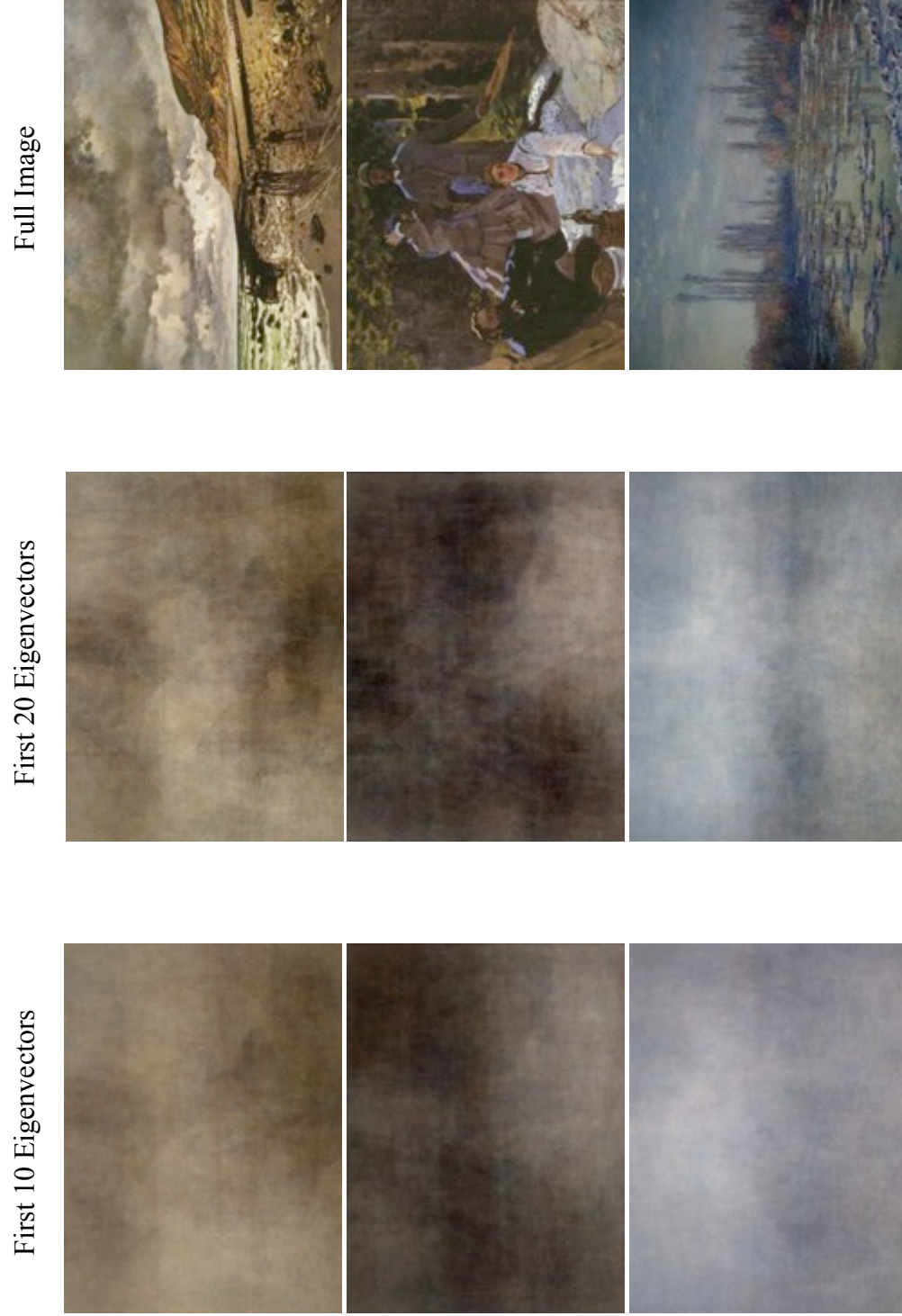


Figure 2.1: Example of some paintings by Monet partially reconstructed using the first 10 eigenvectors and the first 20 eigenvectors. When fewer eigenvectors are used to reconstruct an image, there is less high-level information present and the image is less distinct.

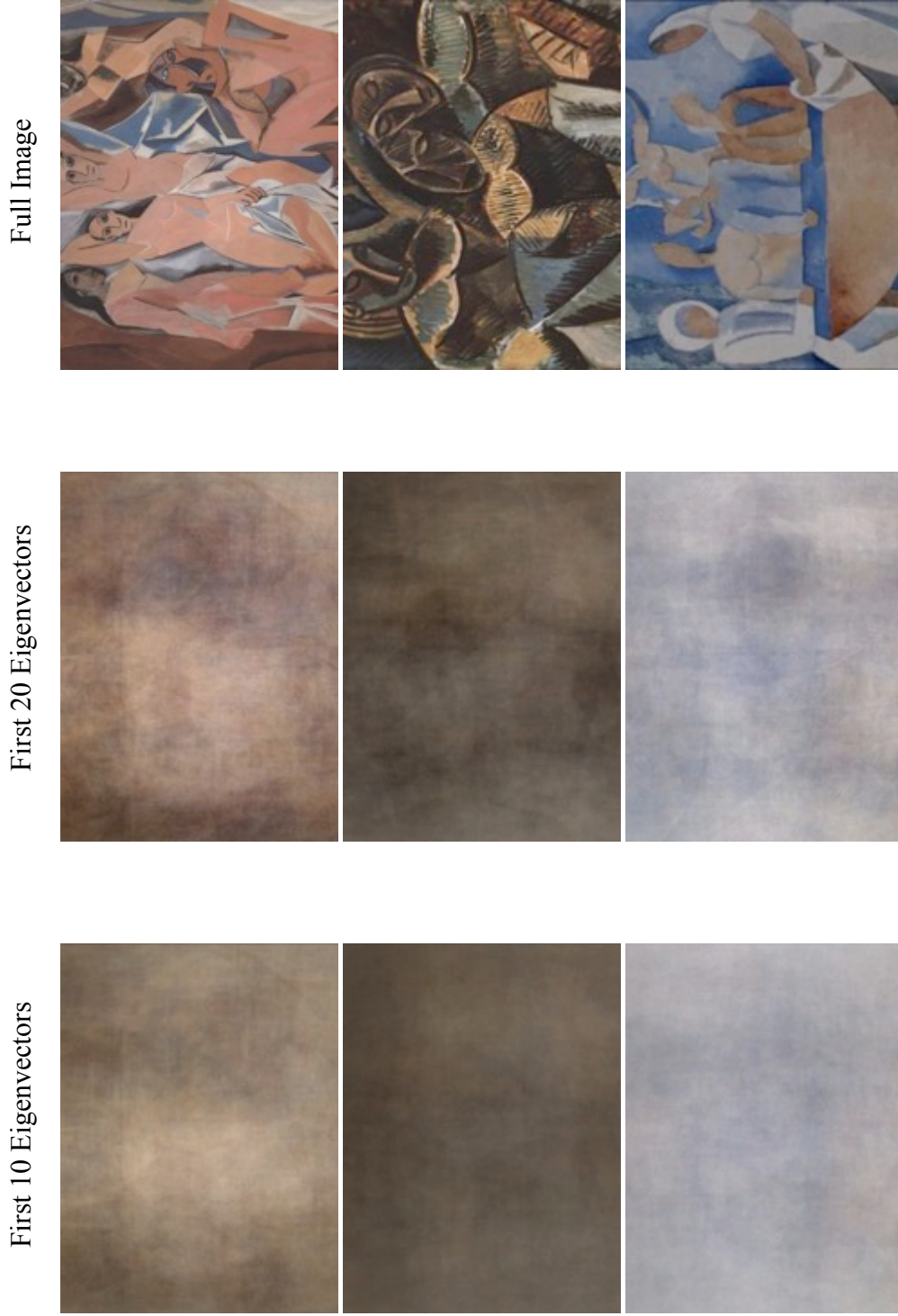


Figure 2.2: Example of some paintings by Picasso partially reconstructed using the first 10 eigenvectors and the first 20 eigenvectors. When compared to partially reconstructed Monet images, the works by the two artists seem indistinct from one another at a glance, especially as fewer eigenvectors are used in their reconstruction.

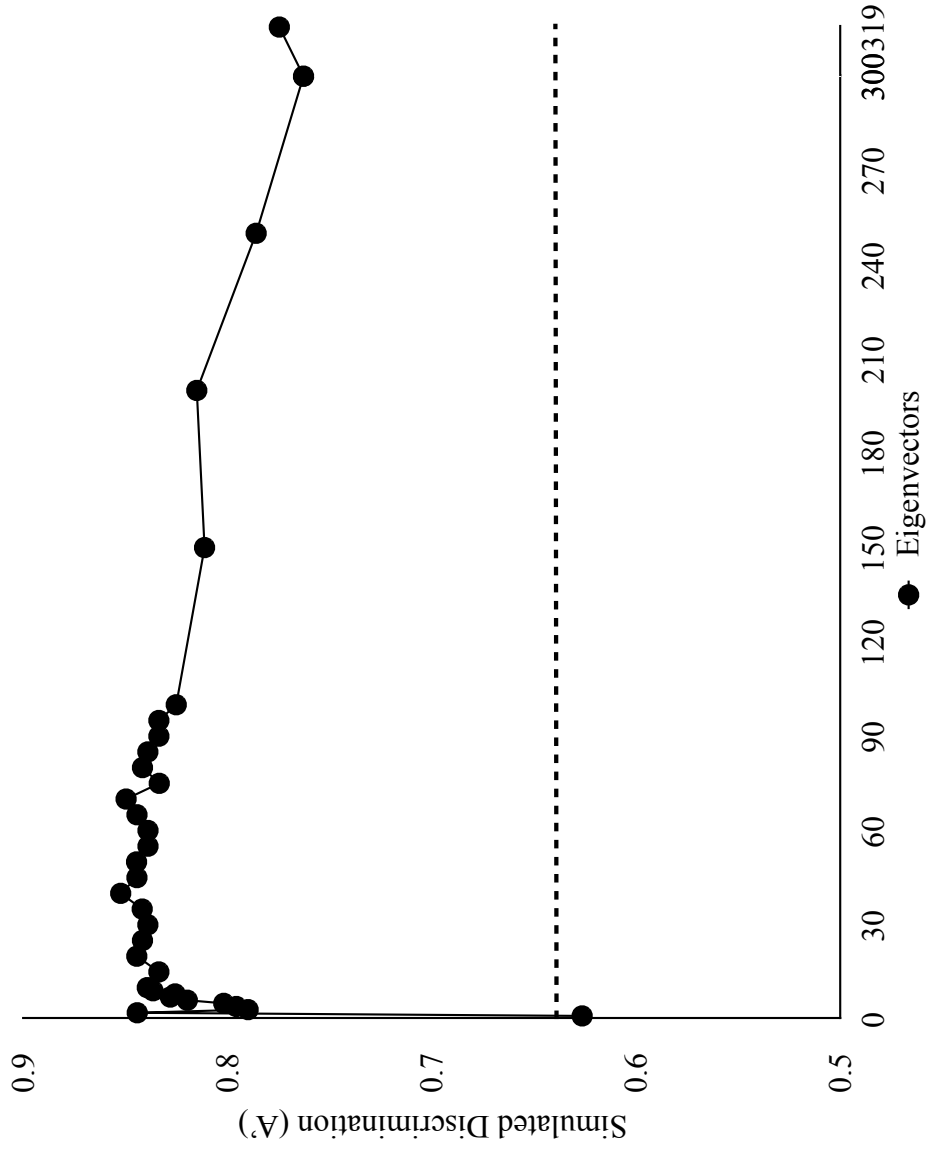


Figure 2.3: Neural network simulation of Monet and Picasso discrimination task with increasing image reconstruction; performance asymptotes around the 8th or so eigenvector. The discriminative ability of the perceptron when applied directly to pixel maps is indicated by the dotted line.

Chapter 3

Experiment 1: Stopping the Analytic Strategy

Given that pigeons are capable of indirectly discriminating between images containing people from those that do not—even when each the information in each image has been rearranged (Aust & Huber, 2001) or flipped (Greene, 1983)—there should be enough redundant visual information across the images within a category to make a categorical judgement. Likewise, pigeons’ sensitivity to the seemingly complex nature of artistic style (e.g., Watanabe et al., 1995) demonstrates that there is enough information within a Monet painting for the pigeon to determine that it is not a Picasso, regardless of the fact that both of the artists painted various scenes, people, and objects.

The learning of complex, polymorphous stimuli exhibited by pigeons may be present as a mechanism within the human capacity for visual processing as well. However, demonstrating such a capacity with human participants in a laboratory setting has been notoriously difficult (Gross & Vokey, 2009). Humans seem unique from other animals in that they possess two different strategies for processing stimuli. An analytic strategy attempts to apply or generate a rule to determine category inclusiveness, whereas a nonanalytic strategy denotes a focus on memory for individual cases (Brooks, 1978). Particularly in an experimental setting, humans have a strong tendency to go analytic in their processing of stimuli (e.g., Gross & Vokey, 2009).

In order to demonstrate the human capacity for non-analysis, it may be an important step to construct experimental conditions that prevent participants from employing an analytic strategy. Brooks et al. (2007) successfully diverted analysis by providing a distractor task that required the use of a rule-finding strategy. To show that judgements of style can be made absent from verbalizable content, stimuli were

used that are likely devoid of any capacity to have semantic, rule-based attributes applied to them.

3.1 Method

3.1.1 *Participants*

Twenty-eight undergraduate students from the University of Lethbridge were recruited from the psychology undergraduate student participant pool, and received course credit in either a first or second year psychology course for their participation. All participants were naïve as to the true intention of the experiment, and instructions were given both verbally and by accompanying text on the computer screen.

3.1.2 *Design*

The 320 standard-sized images of Monet and Picasso paintings were deconstructed and partially reconstructed using a weighted, linear combination of their first 20 eigenvectors. The first 20 were used because, as shown in Figures 2.1 and 2.2, the first 20 eigenvectors should contain the most covariant, category-relevant information before many easily-nameable features of the original image—such as distinct objects and lines—begin to show up.

Using the leave-one-out technique, the 16 “best” Monet and Picasso images (i.e., those that are best representative of their respective spaces) were chosen. The 16 most similar images (i.e., the best matches to the best Monet and Picasso images) and the 16 least similar images (i.e., the worst matches to the best Monet and Picasso images) to the projection of each of the best Monet and Picasso images were selected,

producing conditions of test stimuli conceptually similar to the “near” and “far” stimuli of Vokey and Brooks (1992).

3.1.3 Procedure

The experiment consisted of two conditions (one for being shown Picasso images during training and the other for being shown Monet images), each with a training and test phase. During the training phase, the “best” items of the condition’s category were shown. Each “best” image was paired with the name of a Canadian city, as participants were informed at the start of the experiment that they were to memorize the pairing of each name with each image for a subsequent test of memory. The pairing of images with words served as a diversion to the processing of the style of the images (e.g., Brooks, 1978). Each image and word pair was serially presented 4 times for 3 seconds each for a total of 64 paired stimuli. The reconstructed images did not seem at a glance to actually be pictures in themselves; rather, they were introduced to participants as “image cards”.

During the test phase, the reconstructed “best”, “best match”, and “worst match” images of both categories were shown. Participants were tested for their recognition of the Monet and Picasso 20-eigenvector images using a scale of 1 to 12 (1 being “Sure New” and 12 being “Sure Old”). If the participants retained a memory for the style of the images presented during the training phase, then they should show an effect of recognition for the new test images that are more representative of the space projected for whichever artist’s images were used during training (i.e., their “best matches”).

Following completion of the experiment, the participants were then instructed to fill out a short, hand-written survey. It consisted of two question: “What did you

Table 3.1: Mean Hit and False-positive Rates As a Function of Training Category (Same vs. Different) and Test Item Type in Experiment 1

	Best	Best Match	Worst Match
Same Category	0.74	0.59	0.13
Different Category	0.56	0.48	0.12

use to remember the images?” and “What did you use to reject the images?”. Upon completion of the survey, participants were debriefed and free to leave.

3.2 Results and Discussion

Shown in Table 3.1 and Figure 3.1 are the mean hit and false-positive rates (scale-responses >6) as a function of training category (same vs. different) and test item-type, collapsed over training category (Monet vs. Picasso). Items from the same category as training were identified as “old” ($M = .49$) significantly more frequently than were items from the different category ($M = .38$), $F(1, 27) = 18.14$; $MSE = .023$, $p = .0002$. There was also a significant main effect of test item type: best items ($M = .63$) were labelled as “old” more often than best match items ($M = .54$) and worst match items ($M = .12$), $F(2, 54) = 194.05$; $MSE = .022$; $p < .0001$. Test item type interacted significantly with training category, $F(2, 54) = 9.08$; $MSE = .011$; $p = .0004$. Planned comparisons of the interaction showed that old (same category) best items were labelled as “old” more frequently than new (different category) best items [$t(1, 27) = 4.45$, $p = .0001$], false-positive responses to same category best match items were significantly higher than false-positive responses to different category best match items [$t(1, 27) = 3.0830$, $p = .0047$], but there was no significant difference in false-positive responses between same category and different category worst match items [$t(1, 27) = .5419$, $p = .5924$].

Figure 3.2 depicts the receiver operating characteristic (ROC) curves fitted to the

mean cumulative hit and false-positive rates at each level of confidence to each of the three item type conditions (best, best match, and worst match) for the discrimination of the category of the images. ROC curves plot the unit square of paired hit (same category items) and false-positive (different category items) rates for different criterion settings of the willingness to label an image as one encountered at study. They were derived for each participant (and then averaged) based on the confidence levels assigned to each response (see, e.g., Wickens, 2001). The fitted curves were computed via a web-based program (see Eng, n.d.) assuming equal-variance Gaussian distributions. It is evident from Figure 3.2 that participants in Experiment 1 discriminated best items better than best match items, which, in turn, were better discriminated than worst match items.

This impression was confirmed by an analysis of the area under the ROC curves (AUC) for the three test item types. These AUC statistics were computed for each participant from their 12-point confidence ratings using the equivalent of the trapezoidal rule, the Wilcoxon (or Mann–Whitney) statistic, W , using the Hanley and McNeil (1982) algorithm. Values of AUC typically vary between .50 (chance discrimination) and 1.0 (perfect discrimination) and, accordingly, index discrimination between targets and distractors independent of decision criterion. These AUC values were subjected to a one-way (item type), within-subjects ANOVA, with participants crossing the factor as the random variate. There was a significant difference among the three conditions, $F(2, 81) = 11.2$; $MSE = 0.0123$; $p < 0.0001$.

The mean AUC of the best, [$t(1, 27) = 5.11, p < .0001$], and the best-match, [$t(1, 27) = 3.60, p = .001$] conditions were both significantly greater than chance, but the worst match was not, [$t(1, 27) = 0.1441, p = .8844$]. Best was significantly greater than best match, [$t(1, 27) = 2.78, p = .008$], and best match was significantly greater than worst match, [$t(1, 27) = 3.82, p = 0.001$].

Thus, as with the pigeon studies, participants in Experiment 1 showed some ability to recognize old (i.e., training) items, and some ability to generalise what they had learned of the category to new, highly similar to training, best match items, but not to new, not similar to training, worst match items.

3.2.1 Participants' Spontaneous Utterances and Descriptions

At the onset of the test phase, many participants expressed surprise at being suddenly confronted with the task of deciding whether they had seen the images before. Some of them protested, insisting that there must be more to what they had to do. After all, they had just spent significant effort trying to remember which of the images had been paired with which city name. Similar to Brooks' (1978) participants, they were generally hesitant and not confident that they could correctly perform the task. Many of the participants offered unsolicited guesses as to what the images that they were working with were. Many thought they were looking at streaks or splotches of paint, and several wondered whether they were optical illusions.

Regarding the results of the survey that was completed by each participant at the end of the experiment, the majority of the participants cited general patterns, shapes, and textures as their reasons for remembering and rejecting images. One person specifically stated remembering images based on seeing specific items such as a bottle. Two participants stated that they based their judgements on whether or not the images were familiar to them. The remaining few responses included criteria such as shadows, colour, and brightness.

3.3 Experimental Shortcoming: Too Much Information Remaining in the Images

Given the reports from some participants that they thought they were basing their recognition on objects or features that they thought they could make out, it is possible some high-level information was still present in images constructed from their first 20 eigenvectors. As such, some participants may have been focusing on specific details of images rather than their overall style and inadvertently discriminating the categories on that basis. If we removed this information and participants still selected more same category best match items than different category best match images as old, such results would provide stronger evidence for judgements based on style. The next experiment did just that.

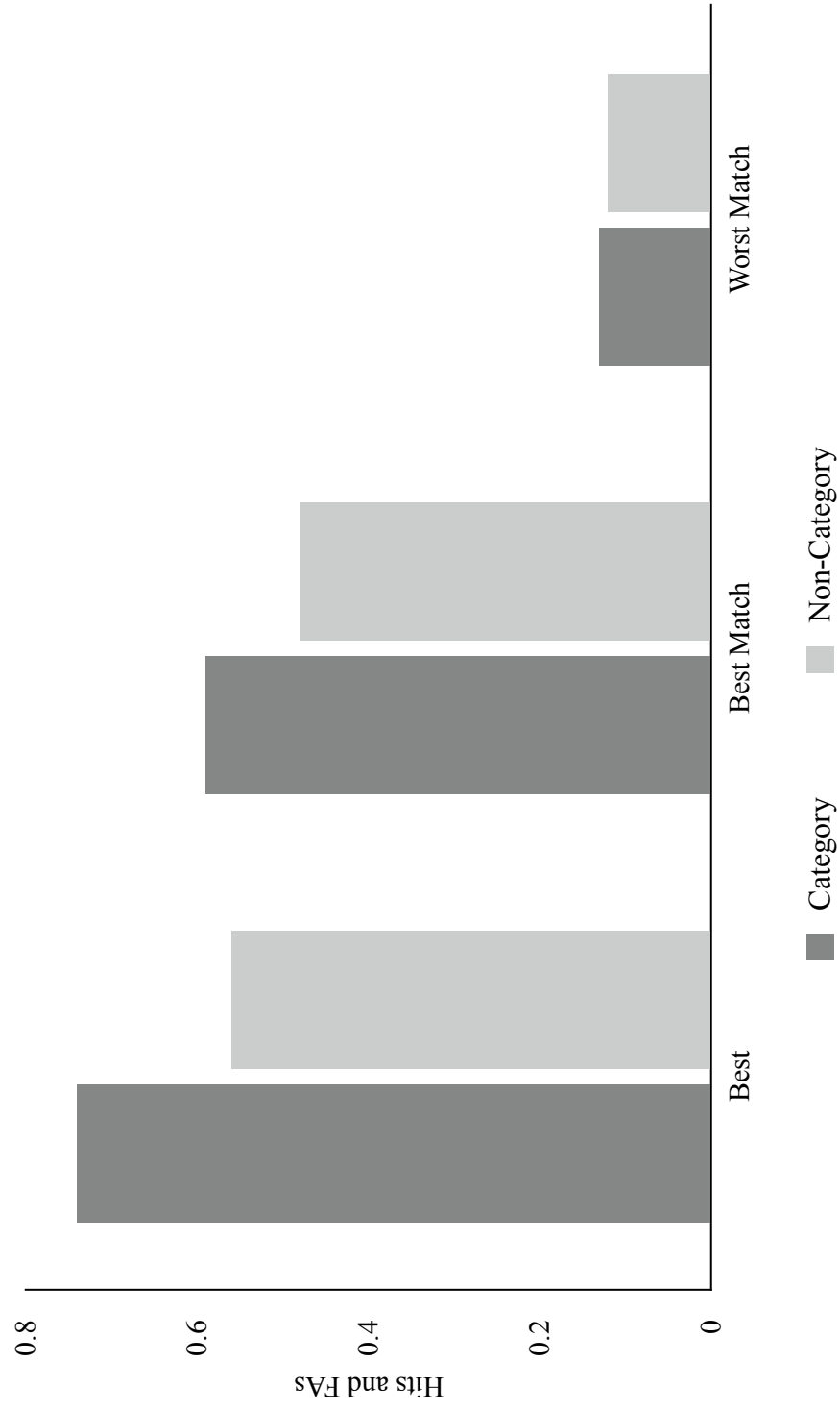


Figure 3.1: Mean hit and false-positive rates as a function of training category (same vs. different) and test item type in Experiment 1.

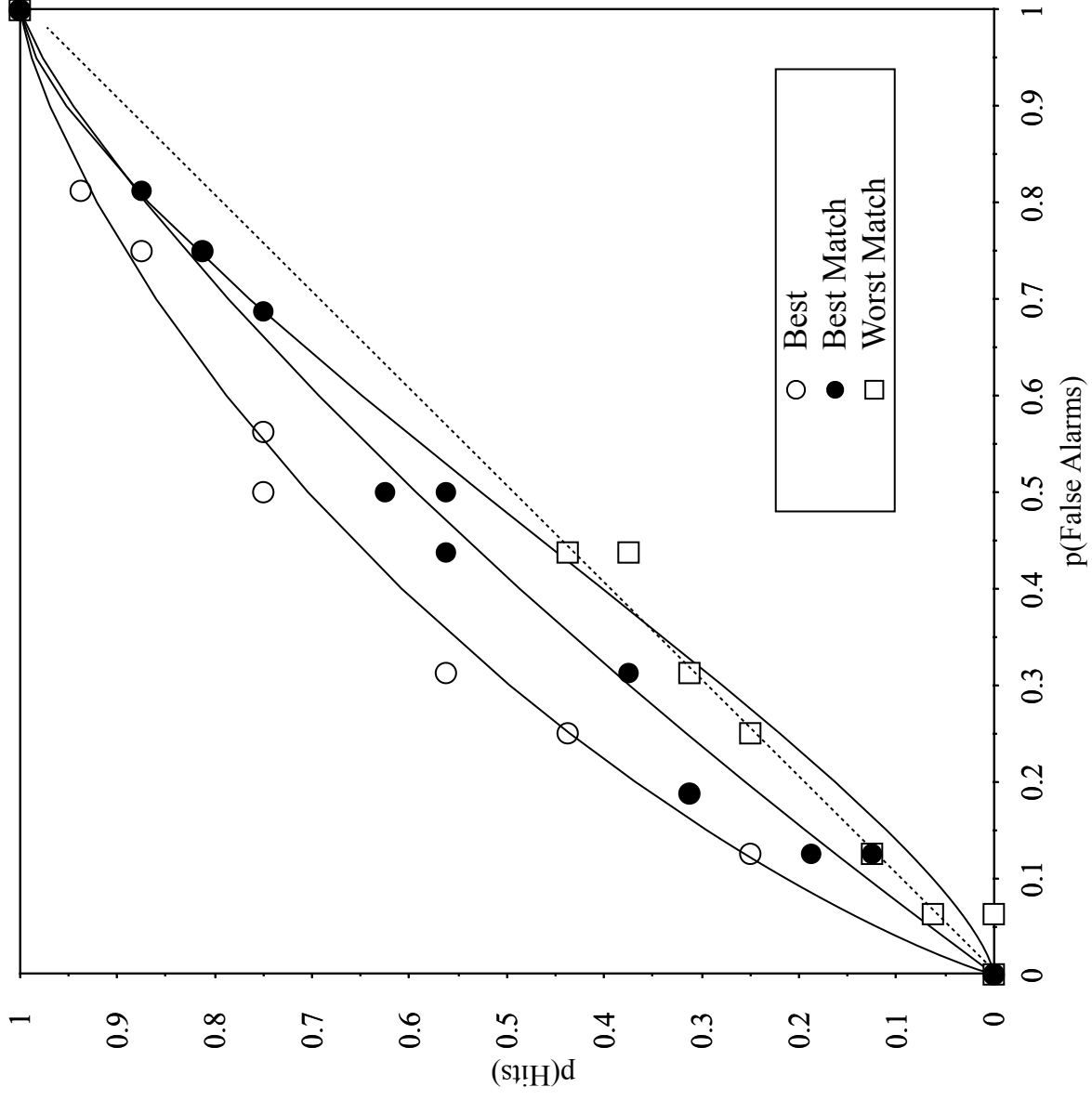


Figure 3.2: Mean receiver operating characteristic (ROC) hit and false-positive values derived from confidence judgements, and the corresponding fitted ROC curves as a function of item type (best, best match, and worst match) in Experiment 1.

Chapter 4

Experiment 2: Reducing the Available Information to Just the First Ten Eigenvectors

The prior experiment provided evidence that human participants are capable of judging stimuli based on the information available across a set of partially reconstructed images. Furthermore, the first 20 eigenvectors contain enough information of the original images to do so. However, many participants reported that they were still able to discern some verbalizable detail from the images, which raises some question as to whether they were basing their judgements on the style of stimuli or on particular human-nameable features. The second experiment attempted to replicate the results of Experiment 1, but with using stimuli containing even less information.

As shown in Figure 2.3, the performance of a neural network in the same sort of discrimination task for reconstructed images tends to asymptote around the 8th to 10th eigenvector (depending on the images). Therefore, the information remaining in images reconstructed with those eigenvectors does contain the information necessary for the neural network to perform the task at above chance levels. If a neural network is a proper model for human judgement of visual stimuli, then those first 10 eigenvectors should hold the information necessary for human participants to perform the task as well.

4.1 Method

4.1.1 *Participants*

Sixteen undergraduate students from the University of Lethbridge were recruited from the psychology undergraduate student participant pool, and received course credit in either a first or second year psychology course for their participation. All participants were naïve as to the true intention of the experiment, and instructions were given both verbally and by accompanying text on the computer screen.

4.1.2 *Design*

Creation of the 320 images was the same as in Experiment 1, except that each of the images was reconstructed using a weighted, linear combination of only the first 10 eigenvectors, rather than the first 20 eigenvectors as in Experiment 1. Using the leave-one-out technique, each image was projected into the space defined by all the remaining 159 images of a given category and the 16 best (i.e., highest reconstruction cosines) were chosen for each category. The 16 best matches and the 16 worst matches to the projection of each the best Monet and Picasso images were then selected.

4.1.3 *Procedure*

As in Experiment 1, this experiment consisted of a training phase and a test phase. Participants were informed at the start of the experiment that they were to memorise the pairing of the name of a Canadian city with each “image card” for a subsequent test of memory, and were evenly divided between the Monet and Picasso conditions. During the training phase, the best images from a condition’s category were shown.

Table 4.1: Mean Hit and False-positive Rates As a Function of Training Category (Same vs. Different) and Test Item Type in Experiment 2.

	Best	Best Match	Worst Match
Same Category	0.72	0.69	0.34
Different Category	0.50	0.55	0.30

Each image and word pair was serially presented 4 times for 3 seconds each for a total of 64 paired stimuli.

Again as in Experiment 1, during the test phase, the best images from training, their best matches, and their worst match were randomly shown. Participants were tested for their recognition of the reconstructed images using a scale of 1 to 12 (1 being “Sure New” and 12 being “Sure Old”). If participants are capable of indirectly discriminating the images of paintings based on information contained within only the first 10 eigenvectors, then they should identify the same category best match items as old more frequently than the different category best match items.

Also as in Experiment 1, following the completion of the test phase, participants were asked to complete a short survey regarding their criteria for remembering and rejecting the images. They were then debriefed and free to leave.

4.2 Results and Discussion

Shown in Table 4.1 and Figure 4.1 are the mean hit and false-positive rates (scale-responses > 6) as a function of training category (same vs. different) and test item-type, collapsed over training category (Monet vs. Picasso). Items from the same category as training were identified as “old” ($M = .57$) significantly more frequently than were items from the different category ($M = .45$), $F(1, 15) = 17.08$; $MSE = .022$, $p = .0009$. There was also a significant main effect of test item type: best items ($M = .61$) were labelled as “old” more often than best match items ($M = .62$)

and worst match items ($M = .30$), $F(2, 30) = 14.98$; $MSE = .069$; $p < .0001$. Test item type interacted significantly with training category, $F(2, 30) = 4.70$; $MSE = .017$; $p = .02$. As in Experiment 1, planned comparisons of the interaction showed that old (same category) best items were labelled as “old” more frequently than new (different category) best items [$t(1, 15) = 4.44$, $p = .0005$], false-positive responses to same category best match items were significantly higher than false-positive responses to different category best match items [$t(1, 15) = 3.25$, $p = .005$], but there was no significant difference in false-positive responses between same category and different category worst match items [$t(1, 15) = .90$, $p = .38$]. Thus, as with the pigeon studies and the results of Experiment 1, participants in Experiment 2 showed some ability to recognize old (i.e., training) items, and some ability to generalise what they had learned of the category to new, highly similar to training, best match items, but not to new, not similar to training, worst match items.

As in Experiment 1, Figure 4.2 depicts the receiver operating characteristic (ROC) curves fitted to the mean cumulative hit and false-positive rates at each level of confidence to each of the three item type conditions (best, best match, and worst match) for the indirect discrimination of the category of the images. Compared with the same curves from Experiment 1, although the category of the best items appears to be relatively well-judged, it is less clear that the same was true for the best match and worst match items. This impression was confirmed by an analysis of the area under the ROC curves (AUC) for the three test item types. These AUC values were subjected to a one-way (item type), within-subjects ANOVA, with participants crossing the factor as the random variate. As in Experiment 1, there was a significant difference among the three conditions, $F(2, 45) = 5.35$; $MSE = 0.0129$; $p = 0.008$, with the mean AUC of the best, [$t(1, 15) = 5.63$, $p < .0001$], and the best-match, [$t(1, 15) = 2.40$, $p = .025$] conditions both significantly greater than chance, but the

worst match was not, [$t(1, 15) = .9440, p = .3450$]. Best was significantly greater than best match, [$t(1, 15) = 3.45, p = 0.001$], but, unlike the results of Experiment 1, best match was not significantly greater than worst match, [$t(1, 15) = 0.8385, p = 0.45$]. Still, for the most part the results of Experiment 2 replicate those of Experiment 1, even though the images were constructed from just the first 10 eigenvectors.

The results of both experiments bode well for neural networks and their attempted modeling of human visual discrimination. Just as the network can learn from images with most of the information removed, so apparently can humans. As well, the results indicate that judgements of style—normally considered to be quite a sophisticated skill—may actually be a lot simpler.

4.2.1 Participants’ Spontaneous Utterances and Descriptions

Unlike the results of Experiment 1, none of the participants in this experiment cited seeing specific shapes as their reason for remembering the images. Instead, virtually all of them gave specific descriptions of colour (such as boldness, variation, and hue) as at least part of their reasons for their judgements. Five of the participants described their judgements as coming from feelings of familiarity or unfamiliarity with the images. Several complained that the task was too difficult, and one specifically claimed to have relied on “gut feelings”. Thus, we appear to have accomplished our goal: successful judgements of style in the absence of nameable features.

4.3 Experimental Shortcoming: May Be Either Exemplars or Prototype

The results of Experiment 2 demonstrate how little visual information is apparently needed in order to make categorically-consistent judgements about Monet and Picasso images. As well, it provides some evidence for the neural network as a plausible model of some visual processing. However, the results do not yet describe whether participants' structural learning is in the form of individual exemplars or prototypes. The prototype view of categorization describes individuals as forming an ideal or average prototype of a category as they come across individual members (e.g., Rosch, 1973, 1975). For the category of "bird", for example, individuals would have formed a prototypical perfect or average bird that is most representative of that category. Judgements about other stimuli would then be based on comparing them to that prototype. Given that the participants in both Experiments 1 and 2 were given the best examples of their training category, it is possible that they simply formed a prototype and made their recognition judgements relative to it, rather than make judgements based on family resemblance and studied instances. The next experiment was an attempt to investigate that issue.

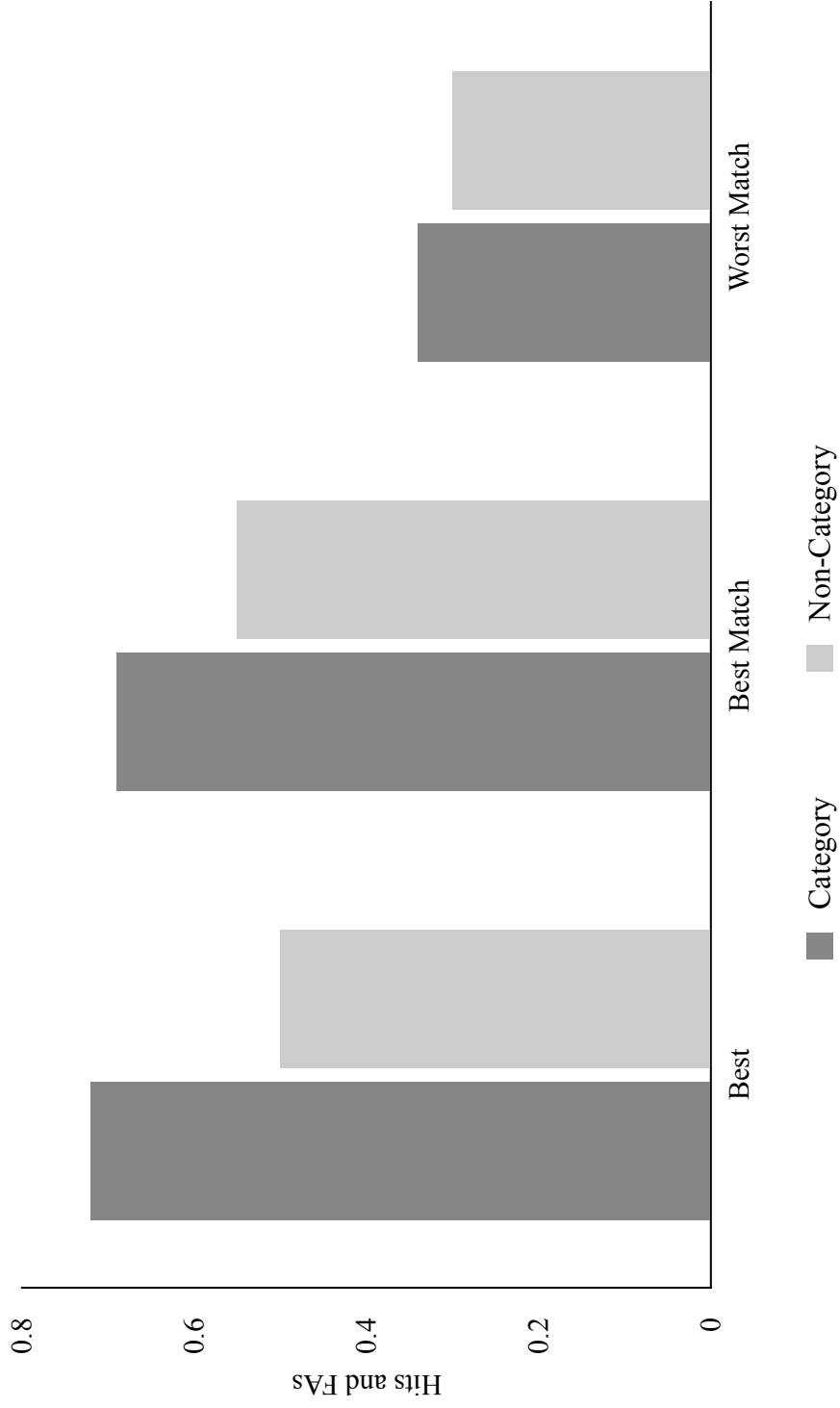


Figure 4.1: Mean hit and false-positive rates as a function of training category (same vs. different) and test item type in Experiment 2.

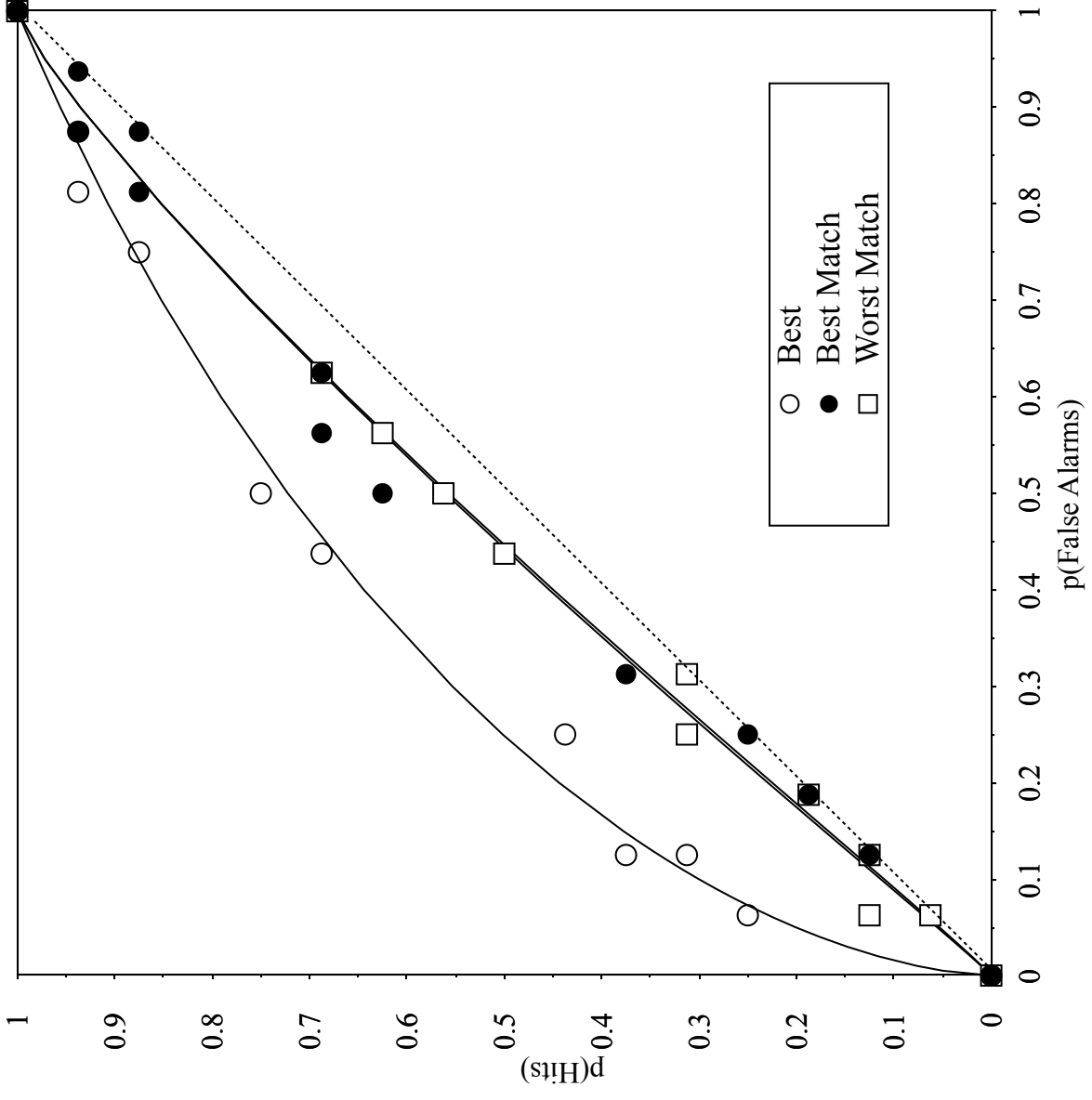


Figure 4.2: Mean receiver operating characteristic (ROC) hit and false-positive values derived from confidence judgements, and the corresponding fitted ROC curves as a function of item type (best, best match, and worst match) in Experiment 2.

Chapter 5

Experiment 3: Disrupting the Formation of a Prototype: Random Selection During Training

The results of Experiments 1 and 2 have successfully demonstrated that human participants are capable of picking up the remaining information in partially reconstructed images. By using a distraction task, such as having to remember which image is paired with which Canadian city name, learning the structure of the images becomes incidental to the main task, and participants' tendency to search for a rule that governs category definition can be diverted. This task can be accomplished when the images have been partially reconstructed using their first 20 eigenvectors—roughly the maximum amount of eigenvectors that can be used for reconstruction before verbalizable aspects of the images (e.g., shapes and lines) seem noticeable—and when the reconstruction uses only the first 10 eigenvectors—around the same number needed for asymptotic performance of a neural network.

However, results so far fail to show whether human participants are making judgments of style based on memory for individual instances or on the formation of a prototype. For each condition, the stimuli selected for the training portion of the experiment were the “best” Monet and Picasso paintings, as these give the participants the best impression of the artists' *styles*. That is, the “best” images are the ones that share the most characteristics with the other images of their category. In terms of the family resemblance continuum, they are the ones with many connections with the other images. In terms of a prototype, they are the ones that are clustered closest around it. In either case, they are, for example, the robins of the “bird” category rather than the ostriches, as robins are closer to an ideal or average bird.

Using the best Monet and Picasso images makes it difficult to determine whether

participants are learning from these excellent examples, or whether they could be abstracting a prototype that the images are gathering around. In the current experiment, it is necessary to introduce particular circumstances where drawing on exemplars would generate better performance in judging stimuli than would drawing on a prototype (e.g., Whittlesea, 1987).

5.1 Method

5.1.1 *Participants*

Sixteen undergraduate students from the University of Lethbridge were recruited from the psychology undergraduate student participant pool, and received course credit in either a first or second year psychology course for their participation. All participants were naïve as to the true intention of the experiment, and instructions were given both verbally and by accompanying text on the computer screen.

5.1.2 *Design*

The images used in this experiment are the same ones that underwent dimension reduction and partial reconstruction. As the prior experiment demonstrated that only the information present within the first 10 eigenvectors is necessary for discrimination, that is the extent to which the current images were reconstructed.

5.1.3 Procedure

Once again, participants were equally divided between Monet and Picasso conditions, each with a training and test phase. During the training phase, *randomly-selected* images from that condition’s category were shown. By using random images from an artist category rather than the “best” images, there should be, at best, loose clustering of the selected images around a possible prototype. The “image cards” were again paired with names of Canadian cities as a diversion to the processing of the style of the images (Brooks, 1978). Each image and word pair was serially presented 4 times for 3 seconds each for a total of 64 paired stimuli.

During the test phase, the randomly-selected training images, the best matches to those images, and another set of randomly-selected images of both categories were shown. Participants were tested for their recognition of the reconstructed images using a scale of 1 to 12 (1 being “Sure New” and 12 being “Sure Old”). If the participants were basing their judgements on memory for instances, then those judgements would be based on the randomly-selected training items rather than a prototype for the category that is formed from them. As such, they should perform better at the best matches to the randomly selected training items than to randomly selected images from that category.

When the experiment was finished, participants were asked to fill out a short survey regarding their reasons for deciding whether images were new or old, and were debriefed about the true intentions of the experiment. They were then free to leave.

5.2 Results and Discussion

Shown in Table 5.1 and Figure 5.1 are the mean hit and false-positive rates (scale-responses > 6) as a function of training category (same vs. different) and test item-

Table 5.1: Mean Hit and False-positive Rates As a Function of Training Category (Same vs. Different) and Test Item Type in Experiment 3

	Random Train	Best Match	Random
Category	0.61	0.59	0.40
Non-Category	0.42	0.39	0.34

type, collapsed over training category (Monet vs. Picasso). Items from the same category as training were identified as “old” ($M = .53$) significantly more frequently than were items from the different category ($M = .38$), $F(1, 15) = 15.19$; $MSE = 0.0354$, $p = 0.001$. There was also a significant main effect of test item type: random training items ($M = .52$) were labelled as “old” more often than best match items ($M = .49$) and random items ($M = .37$), $F(2, 30) = 11.89$; $MSE = 0.0166$; $p = 0.0002$. However, unlike the previous experiments, test item type did not interact significantly with training category, $F(2, 30) = 2.63$; $MSE = .0175$; $p = .09$. Despite that, and similar to the results of the the previous experiments, planned comparisons of the interaction showed that old (same category) random training items were labelled as “old” more frequently than new (different category) random training items [$t(1, 15) = 4.11$, $p = .0009$], false-positive responses to same category best match items were significantly higher than false-positive responses to different category best match items [$t(1, 15) = 3.23$, $p = .006$], but there was no significant difference in false-positive responses between same category and different category random items [$t(1, 15) = 1.16$, $p = .26$]. Thus, as with the pigeon studies and Experiments 1 and 2, participants in Experiment 3 showed some ability to recognize old (i.e., training) items, and some ability to generalise what they had learned of the category to new, highly similar to training, best match items, but not to new, not similar to training, random items.

As with Experiments 1 and 2, Figure 5.2 depicts the receiver operating characteristic (ROC) curves fitted to the mean cumulative hit and false-positive rates at

each level of confidence to each of the three item type conditions (random train, best match, and random) for the judgement of the style of the images. Unlike the previous experiments, there appears to be little to be gained from the ROC analyses, perhaps because the overall levels of indirect categorisation were quite low.

This impression was confirmed by an analysis of the area under the ROC curves (AUC) for the three test item types. As in Experiments 1 and 2, The AUC values were subjected to a one-way (item type), within-subjects ANOVA, with participants crossing the factor as the random variate. Unlike the previous experiments, there was no significant difference among the three conditions, $F(2, 45) = 2.04; MSE = 0.0180; p = 0.142$. However, the mean AUC of the random training, [$t(1, 15) = 3.83, p = .001$], and the best-match, [$t(1, 15) = 3.14, p = 0.0055$] conditions were both significantly greater than chance, but the random test was not, [$t(1, 15) = 1.15, p = .2528$]. Also unlike the previous experiments, random train was not significantly greater than best match, [$t(1, 15) = 0.3936, p = 0.64$], nor was best match significantly greater than random test, [$t(1, 15) = 0.0047, p = 0.15$].

As with the pigeon studies and Experiments 1 and 2, participants in Experiment 3 showed some ability to recognise old (i.e., training) items, and some ability to generalise what they had learned of the category to new, highly similar to training, best match items, but not to new, not similar to training, random items.

Because the training items were selected at random from each category, it is less likely that participants would form a prototype of the training category (or they would form a prototype that was noisier). But even if they had done so, it should apply equally to the best match items as to the random test items. Yet only on the best match items did the participants show significant indirect categorisation. Thus, these results do *not* seem to support what one would expect from the abstraction of category prototypes as much as they are consistent with a simple nonanalytic,

instance-based memory for the source of the effects of category structure.

5.2.1 Participants' Spontaneous Utterances and Descriptions

Five of the participants claimed to be basing their judgements on feelings of familiarity or lack thereof. Several of them described specified strategies that they used to remember the pairings of each image with its city name, such as Nanaimo being blue because it has lots of water and Vancouver being grayish because it is frequently cloudy. One person tried to pair city sport team colours with the colours of the image. Several cited specific aspects of colour, such as “extremeness”, and one person complained of not knowing beforehand how difficult the memory task would be without the city names paired with the images.

5.3 Experimental Shortcoming: Only Inducement Has Been Demonstrated Thus Far

The prior experiments have provided evidence that not only can human participants make categorically-consistent judgements based on what little information remains in images that have been reconstructed with only their first 10 eigenvectors, but also that they seem to do so by learning from individual examples of a category more likely than by forming a prototype. However, the preceding experiments only go so far as to demonstrate evidence under strict laboratory conditions. They cannot speak to whether humans can base their judgements on instances in everyday, undirected life. The following experiments attempted to address that issue, and are intended to

help begin the generalisation of results to circumstances outside the laboratory.

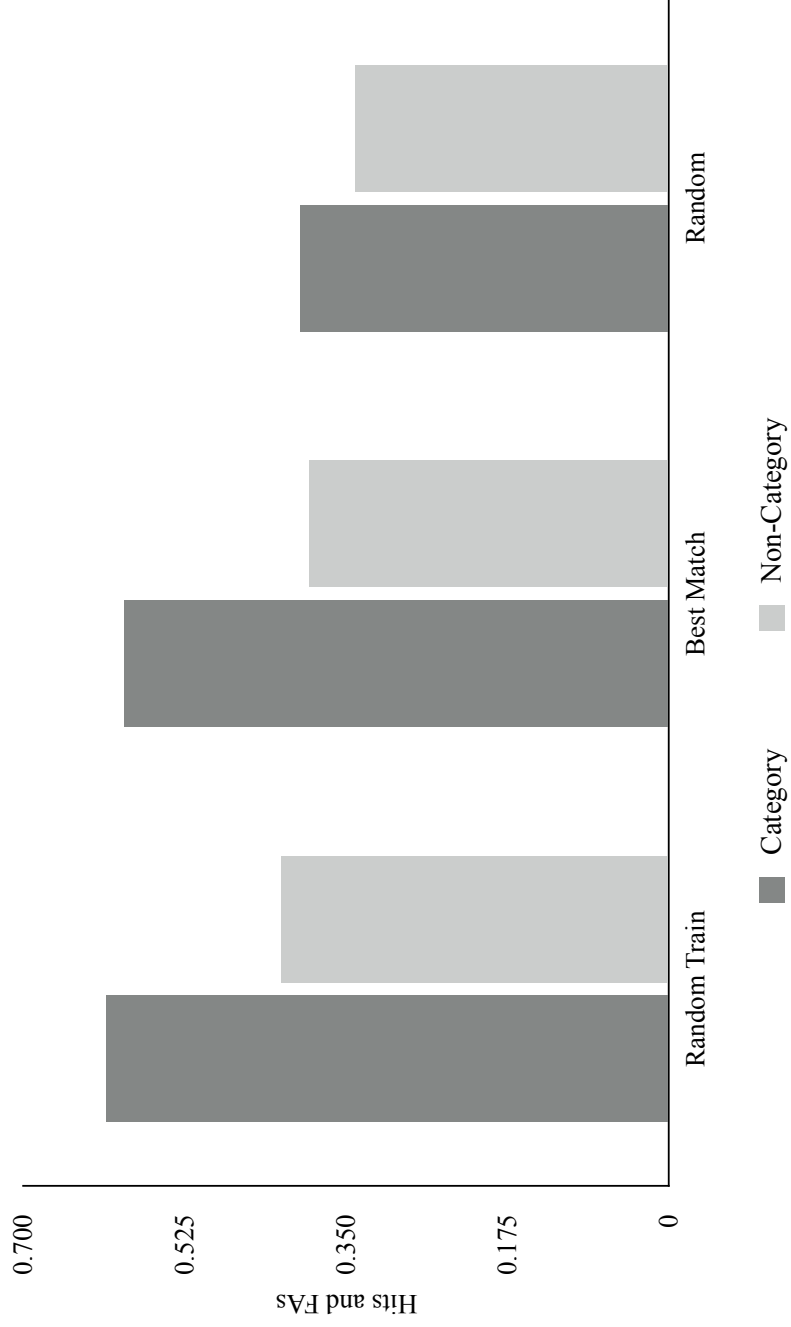


Figure 5.1: Mean hit and false-positive rates as a function of training category (same vs. different) and test item type in Experiment 3.

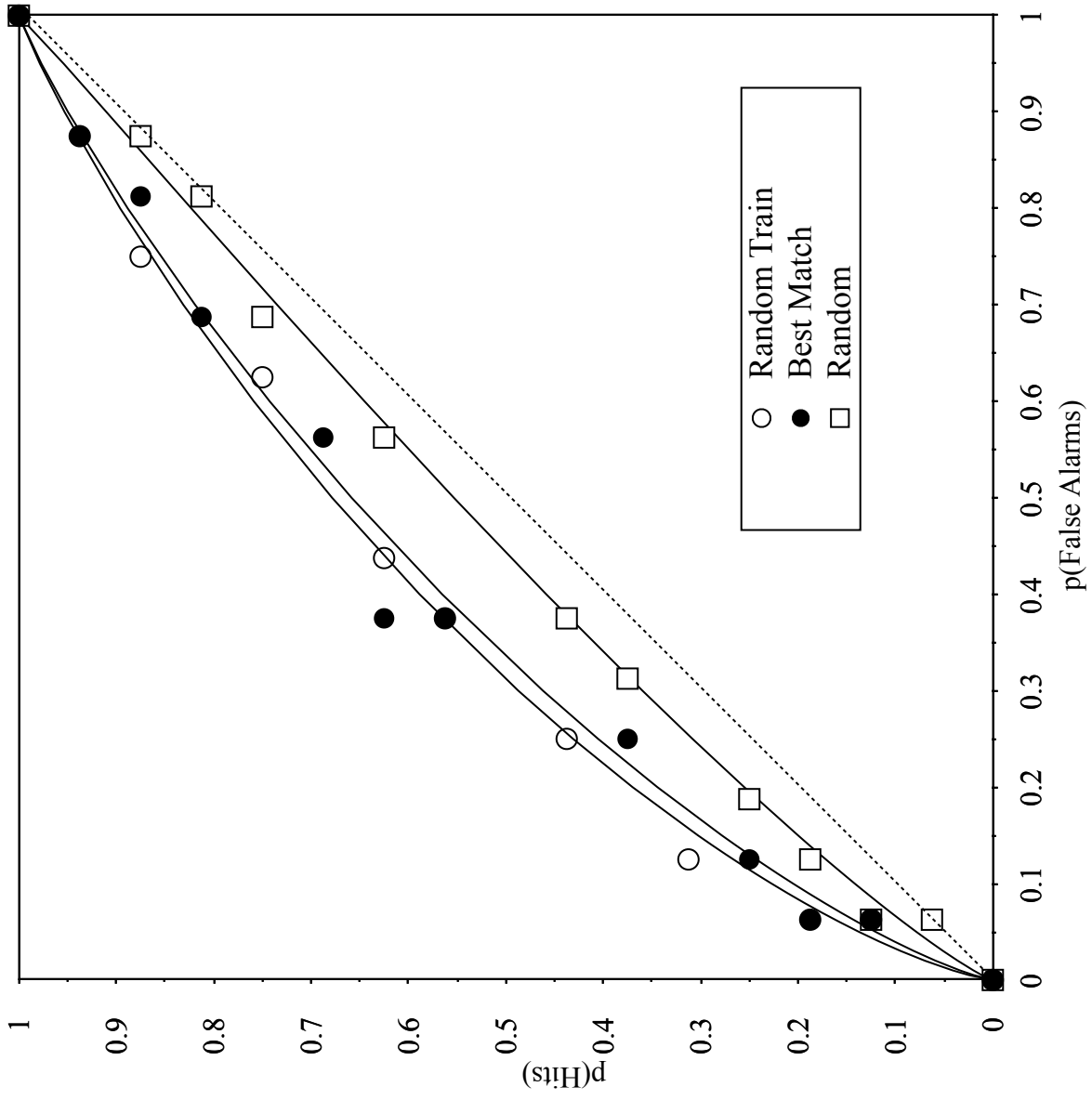


Figure 5.2: Mean receiver operating characteristic (ROC) hit and false-positive values derived from confidence judgments, and the corresponding fitted ROC curves as a function of item type (random train, best match, and random) in Experiment 3.

Chapter 6

Experiment 4: Testing Undirected Sorting Based On Similarity to Instances Using the First Ten Eigenvectors

Prior experiments have provided evidence that humans are capable of making discriminations based on judgements of style when placed under very specific laboratory conditions. The current experiment sought to demonstrate that human participants could still make such judgements when experimental conditions were less restricted. The procedure subsequently described was an attempt to make a small step towards mimicking conditions of the real world. Participants were not specifically directed to use nonanalysis like in the prior experiments, but a sorting task still maintains much of the same properties. Particularly because participants were still able to see images after they had made their judgements on them, it was still very much a matching task.

6.1 Method

6.1.1 Participants

Twenty-four undergraduate students from the University of Lethbridge were recruited from the psychology undergraduate student participant pool, and received course credit in either a first or second year psychology course for their participation. All participants were naïve as to the true intention of the experiment, and instructions were given both verbally and by accompanying text on the computer screen.

6.1.2 Design

The same 160 Picasso and 160 Monet images from Experiments 2 and 3 were used as stimuli for this experiment. The images were partially reconstructed with the first 10 eigenvectors. As demonstrated in prior experiments, the first 10 eigenvectors contain enough information for a judgement above chance. The 320 images were randomly shuffled into a single virtual stack for each participant.

6.1.3 Procedure

Participants were informed that they would be performing a card sorting task, and were seated in front of a vertically bisected computer screen. At the bottom of the centre of the screen sat a randomly shuffled pile of “image cards”. Participants were instructed to sort the pile of images by clicking on and dragging them to either side of the vertical line, forming two separate piles. They were specifically informed that they could use whatever criteria they wanted in order to decide which image belonged in which pile, and could change their minds and rearrange the cards as they wished at any time. At the top centre of the screen was a button labeled “Clean Up” for de-cluttering the two piles that the participants were free to use if they wanted their piles of images to be better organised. Cleaning up the screen only caused the already-sorted images to cluster closer together into their separate piles; it did not change which side of the screen the images had been placed. Once the entire image card pile had been sorted, a “Done” button under the pile could be clicked to end the experiment when the participants were satisfied with how they had sorted the cards. The task was not timed.

Upon confirming that they were finished sorting the cards, each participant was presented with a short survey that inquired about their basis for sorting the cards into

the two piles. When finished, participants were free to leave, and they were debriefed about the true intentions of the experiment if they expressed interest.

6.2 Results and Discussion

As the participants did not label their two piles as “Monet” and “Picasso”, we designated the pile with the largest proportion of Monet images as the “Monet” pile for scoring, and the other pile was designated the “Picasso” pile. Therefore, the hit rate was obtained by dividing the number of Monet images placed in the “Monet” pile by the total number of Monet images (i.e., the proportion of Monet images that were correctly sorted). The false alarm rate was calculated by dividing the number of Picasso images in the same pile by the total number of Picasso images (i.e., the proportion of Picasso images incorrectly labeled as Monet images).

6.2.1 *Estimation of Procedural Response Bias*

Due to the scoring procedure, the hit-rate is necessarily biased to be greater than the false-alarm rate, even if participants were sorting the image cards entirely at random with respect to our Monet and Picasso distinction. To estimate the degree of that bias, and to produce a randomisation distribution with which to compare the results of the experiment, the experiment was simulated 10,000 times. For each of the 10,000 simulated experiments, 24 simulated participants (to match the experimental conditions) were run.

The simulated participants each produced “Pile 1” and “Pile 2” responses drawn from a random uniform distribution containing the equal numbers of the values “1” and “2” for each of the 320 images. The simulated data were then scored in the

same manner as described for the actual participants, creating simulated hit and false-positive rates. The simulated results for each simulated participant were then converted into their associated A' values to provide a measure of the degree to which our procedure for scoring could produce apparent discrimination of the two Monet and Picasso categories in the absence of any real discrimination. For each of the 24 simulated participants, the simulated A' values were averaged and recorded to create a sampling distribution of mean A' values for the 10,000 simulated experiments. The simulated sampling distribution is shown in Figure 6.1.

The 24 real participants who were given the task of sorting a stack of image cards into two separate piles on the computer screen did so with a mean hit rate of 0.53, a mean false-positive rate of 0.39, and A' of 0.62, exceeding even the highest A' of the simulated sampling distribution of such values ($p < 0.0001$), indicating that they were indirectly discriminating the two categories of images at a level well above chance. Thus, even though they could use any criteria at all for sorting the items, the participants still sorted the items along the lines of the Monet and Picasso distinction of the original images.

6.3 Participants' Spontaneous Utterances and Descriptions

It is interesting to note that, upon being given the instructions for the experiment and finally seeing the stack of images to be sorted, many participants responded with unease and uncertainty about the task. Even after being told that they could use whatever criteria they wanted in deciding which of the two piles each card should go, several individuals still asked what criteria the experimenter wanted them to use. Such questions, of course, were met with the assurance that they could use whatever

they wanted. Several of the participants sought to confirm what they were expected to do by asking whether the stack of image cards would flip around so that the image would be visible once they clicked on the card. They were surprised and seemed a bit confused that what they thought was the nondescript backside of a card was actually the image on the card itself.

During the experiment, many participants chose to leave the image cards spread out, and rarely cleaned up their two piles. They spent quite some time in sorting, often mulling over their decisions and hesitating.

Of the 24 participants who were given this sorting task, 18 of them reported in the post-experiment survey that they had based their decisions on colour. Given that the mean performance $A' = 0.62$ is almost identical to that of the perceptron classifier applied directly to the pixel-maps in Chapter 2, this result suggests that sorting by colour might be a the basis for the sorting of the two categories. However, none of the ten eigenvectors used to reconstruct the stimuli is primarily correlated with a simple colour distinction, so despite its popularity as a cited basis, it is unlikely to be a plausible explanation. The remaining responses included such things as whether an image looked “worn like an old couch”, whether the image was more transparent vs. more abstract, and whether the image had texture.

6.4 Experimental Shortcoming: Further Evidence Needed for Generalising Results to the Natural World

Participants given unspecified criteria may make judgements based on style when the stimuli are likely devoid of any human-nameable feature, but, of course, we do not

experience stimuli in the real world that have undergone eigen-decomposition. The next experiment sought to demonstrate whether participants continue to sort on the basis of family resemblance, even when verbalisable image content is present. It was intended as another—albeit small—step toward conditions in the real world.

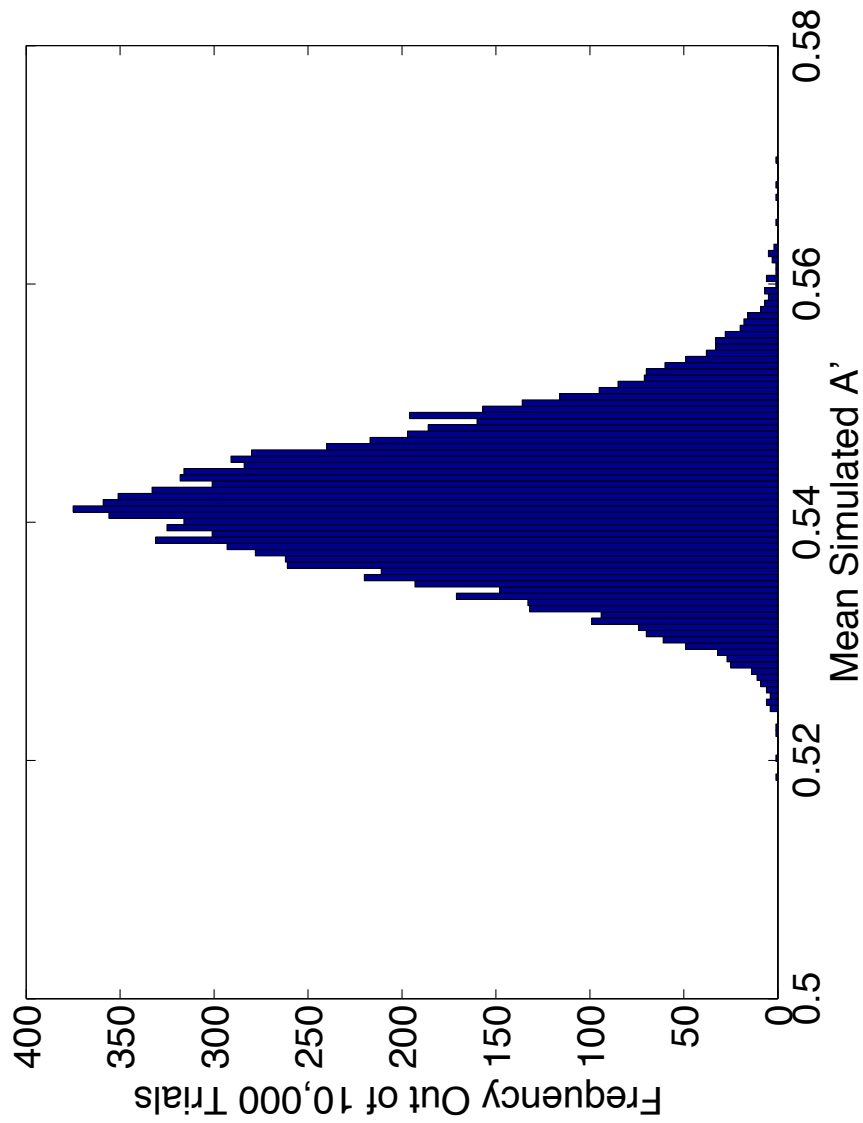


Figure 6.1: Sampling distribution of 10,000 simulated experiments with 24 simulated participants drawing random responses from a random uniform distribution. The .999 distribution cutoff is .5623, and the maximum value is .5707.

Chapter 7

Experiment 5: Testing Undirected Sorting Based On Similarity to Instances Using the Full Images

The results of Experiments 1-4 have successfully provided some evidence that people are capable of sorting Picasso and Monet images based on style both when placed under specific laboratory conditions and also when conditions are less restricted. The remaining question is whether people will continue to do so when the full image (that is, all information—including human-nameable features) is presented.

7.1 Method

7.1.1 *Participants*

Twenty-four undergraduate students from the University of Lethbridge were recruited from the psychology undergraduate student participant pool, and received course credit in either a first or second year psychology course for their participation. All participants were naïve as to the true intention of the experiment, and instructions were given both verbally and by accompanying text on the computer screen.

7.1.2 *Design*

160 Picasso and 160 Monet images were used as stimuli for the experiment. The images used were the original ones of the actual paintings (i.e., fully constructed with all eigenvectors) that had been the source of the eigen-reconstructed images in Experiments 1-4. The 320 images were randomly shuffled into a single virtual stack

for each participant.

7.1.3 Procedure

As in experiment 4, participants were informed that they would be performing a card sorting task, and were seated in front of a vertically bisected computer screen. At the bottom of the centre of the screen sat a randomly shuffled pile of “image cards”. Participants were instructed to sort the pile of images by clicking on and dragging them to either side of the vertical line, forming two separate piles. They could use whatever criteria they wanted to decide which image belonged in which pile, and could change their minds and rearrange the cards as they wished at any time. At the top centre of the screen was the “Clean Up” button for de-cluttering the two piles that the participants were free to use. Once the entire pile of image cards had been moved, a “Done” button under the pile could be clicked to end the experiment if the participants were satisfied with their sorting. The task was not timed.

Participants were required to fill out a short survey regarding their criteria for sorting the images into the two piles at the end of the experiment.

7.2 Results and Discussion

Once again, as the participants did not label their two piles as “Monet” and “Picasso” (or as anything else), we designated the pile with the largest proportion of Monet images as the “Monet” pile for scoring, and the remaining pile as the “Picasso” pile. The hit rate was the proportion of Monet images that were correctly sorted, and the false alarm rate was the proportion of Picasso images incorrectly labeled.

7.2.1 Estimation of Procedural Response Bias

Identically to experiment 4, the scoring procedure results in the hit-rate being biased to exceed the false-alarm rate—even if participants were sorting the image cards entirely at random with respect to our Monet and Picasso distinction. The results of this experiment were compared to the sampling distribution, shown in Figure 6.1. For each of the 24 simulated participants, their simulated A' values were averaged and recorded to create a sampling distribution of mean A' values for the 10,000 simulated experiments.

The 24 real participants who were given the task of sorting a stack of image cards into two separate piles on the computer screen did so with a mean hit rate of 0.86, a mean false-positive rate of 0.19, and $A' = 0.87$, exceeding the the highest value of the simulated sampling distribution ($p < 0.0001$), and indicating sorting of the two categories at a level substantially above chance.

7.2.2 Participants' Descriptions

Unlike the prior experiments, many of the participants seemed at ease with being given this particular task. Several of them confirmed the instructions of using whatever criteria they wished to sort the images into two piles by asking, “Whatever I want, right?”. It is worth noting that, unlike in Experiment 4, participants were very quick to complete the task; they sorted the images with little to no hesitation.

18 of the 24 participants, when asked afterwards for their basis for sorting the images into the two piles, specifically stated that they based their judgements on such criteria as abstract vs. realism/Cubism vs. Impressionism/“artistic style”. Another person specifically claimed, “I saw two different kinds of art”. Given these facts, it appears likely that they generally sorted the image cards on the basis of covariation

information shared across a category; that is, on the basis of *style*. The majority of the remaining participants claimed to be sorting the images on the basis of colour such as “dullness”, which—as already discussed—is unlikely to lead to as good of individual performance as what they actually gave. The rest gave such reasons as some pictures making them happy while others made them sad and whether or not the images contained people.

7.3 Comparing Sorting of Reconstructed and Full Images

Participants who were tasked with sorting partially reconstructed images and participants who sorted full images both indirectly categorised Monet from Picasso images significantly better than their simulated sampling distribution. In addition, a two-sample randomisation test based on 10,000 random permutations using the R statistical computing language (R Core Team, 2013) and the “ez” package (Lawrence, 2013) demonstrates that the mean A' value for participants who sorted full images was significantly greater than the mean A' value for those who sorted the partially reconstructed images ($p < 0.0001$). The mean A' value for the participants who discriminated the full images was near perfect (over half of the participants scored an A' over 0.95).

Given the significant difference between the results of the two experiments, it is obvious that more research is needed in order to determine the full basis for participants’ responses in Experiment 5. It is worth nothing, however, that nonanalysis can work with nameable and non-nameable features. If, for example, participants were placing an image containing a skull on the left because that pile already contained images with skulls, that would still be nonanalysis because the judgement is based

on individual examples.

Chapter 8

General Discussion

The preceding experiments sought to demonstrate whether human participants are capable of judging stimuli based on family resemblance between individual items. Several important insights are provided from the experimental results.

In an attempt to determine the basis for the categorisation of visual stimuli by human beings, images with limited verbalizable content were used in judgement tasks. The first experiment used Monet and Picasso paintings that had been partially reconstructed using only their first 20 eigenvectors. By diverting participants' strong tendency to search for verbalizable rules using a distraction task, it was demonstrated both that there is enough information remaining in the first 20 eigenvectors for human participants to make the discrimination and that humans can be induced to use a non-analytic strategy for processing stimuli. It is in this way that it seems people can be "turned into pigeons".

The second experiment followed the same methodology, but used as stimuli images that had been partially reconstructed with only their first 10 eigenvectors. Despite less information remaining in the images than in the first experiment, participants were still able to indirectly discriminate Monet from Picasso paintings at levels above chance, despite the apparent indistinctness of the images. The results provide evidence as well for the neural network being a plausible model of human learning, as it is at this level of image reconstruction that neural network discrimination asymptotes in performance. Given that neural network asymptotic performance is better than the mean human participant performance, further investigation is necessary in order to determine whether, for example, human performance can be further improved, or whether the neural network possesses a particular advantage over humans in this sort

of task. The neural network was selected as a model to compare human performance against due to the distribution of its nodes resembling the distribution of knowledge believed to relate to family resemblance. It seems preferable for its simultaneity of processing, as compared to a Von Neumann machine that processes information serially. The second experiment also shows that judgements of artistic style—something normally considered to be a rather sophisticated skill—may actually be simpler than originally thought.

The third experiment used randomly-selected members of each category during training, so as to prevent participants from potentially forming a prototype of the category they were trained on. Despite the further restriction in information, participants were still able to indirectly categorise at levels above chance—as long as the items are highly similar to the specific items they were trained with. The results show that participants are possibly learning about and remembering stimuli on the basis of memory of individual examples rather than from an abstracted prototype. Indeed, what appears to be structural learning might actually be a memory for instances.

The fourth experiment provided evidence that, not only are participants capable of making indirect categorical distinctions on the basis of family resemblance, but also they can do so under less restricted conditions. The results have important implications for how people might judge stimuli in a natural setting. That is, when outside of the laboratory people might be using a nonanalytic strategy for much of the time. It would be interesting to determine whether participants are speaking to themselves as they mull over their responses to this sort of task.

The final experiment showed that participants can still use a nonanalytic strategy when verbalizable content is present—attempting to mimic the stimuli in the natural world. The results, however, seem to belie previous research demonstrating the difficulty in depicting a nonanalytic strategy under laboratory conditions (e.g., Gross &

Vokey, 2009). Further investigation is needed in order to determine why the task in the final experiment seemed to work, but other methods, such as incorporating the mere exposure effect, do not seem to demonstrate nonanalytic cognition.

Judgements of stimuli do not seem to be exclusively based on the specific objects or nameable features that differ between them. Rather, the countless attributes of stimuli that together look a certain way may be sufficient. It is this possibility that likely makes the presumed bases of stimulus judgement difficult to articulate.

8.1 Corresponding Research: Wu et al., 2012

Wu, Tangen, Vokey, and Humphreys (2012) investigated whether human participants are sensitive to the stylistic differences constrained by the main target of a photograph—similar to the stylistic constraints between painting styles imposed by artists. They developed two sets of photographs, the first depicting either people or objects that were definable on the basis of their intended targets (people or objects). The second set was identical to the first except for the removal of the category-defining target from each image. That is, that set was intended to be definable on the basis of style.

The first experiment of Wu et al. (2012) was similar to that of Experiment 5 in that participants were asked to sort a stack of complete images. Those who sorted images containing the category-definable target tended to do so analytically; their mean discrimination was near perfect, and the majority of participants explicitly stated the person-target and object-target as their basis for discrimination. Those who sorted the target-absent photographs, however, still showed evidence of sorting on the basis of style. They showed significantly less discrimination (though still above chance), and cited a variety of reasons for their sorting.

Their second experiment was similar to Experiment 4; the target-present and target-absent photographs were reconstructed with their first 10 eigenvectors, and then used again in the same sorting task. Interestingly, reconstructed target-present images look virtually the same as target-absent photographs, suggesting that the covariation shared between individual photographs may not be dependent on the target objects.

The mean A' values for both the target-present and target-absent groups exceeded a simulated sampling distribution similar to the one used in Experiments 4 and 5. Unlike their first experiment, though, there was no significant difference between the two groups. Just as in the current experiments, many of their participants cited colour as the basis for discrimination. Wu et al. (2012), though, also performed a neural network simulation of the categorization task when the linear classifier was applied directly to the pixel maps, and showed that their photographs cannot be distinguished on such bases of colour, brightness, or shading. When eigen-decomposition is included in the simulated task, however, the neural network discriminates both the person-target and object-target photographs well above chance, regardless of whether the target is present. Thus, the results of Wu et al. (2012) provide corroborating evidence that the stylistic information contained across the members of a category may be sufficient for making a distinction, and that an analytic strategy can be diverted by limiting human-nameable features.

8.2 Further Research

The results so far provide some evidence for a human capacity to make judgements based on style. However, no firm conclusions regarding the precise mechanisms may be drawn from them. The significant difference between the results of sorting par-

tially reconstructed images compared to full ones, for example, provides evidence that humans may be using human-nameable features at least some of the time. Sorting full images into two piles—though an attempt to simulate undirected sorting in the real world—is certainly only a small step towards doing so.

Further investigation should explore and seek to discover what circumstances are necessary in order for people to employ a non-analytic strategy. In doing so, it could perhaps be possible to gain some purchase on specifically controlling participants' processing strategies. As well, it is necessary to continue studying the remaining properties of partially reconstructed images. The information remaining within them as well as any corollary to the natural world could provide insight into quotidian visual and cognitive processing.

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