Judgements of style: People, pigeons, and Picasso

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By Stephanie Goodhew

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I certify that this is my original work and any text that is not my own has been quoted and attributed appropriately in the references. I also declare that I am the student whose name appears above and that this text has not been previously submitted for assessment.

Signature:……………………

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Abstract

Judgements of and sensitivity to style are ubiquitous. People become sensitive to the structural regularities of complex or "polymorphous" categories through exposure to individual examples, which allows them respond to new items that are of the same *style* as those previously experienced. This thesis investigates whether a dimension reduction mechanism could account for how people learn about the structure of complex categories. That is, whether through experience, people extract the primary dimensions of variation in a category and use these to analyse and categorise subsequent instances. We used Singular Value Decomposition (SVD) as the method of dimension reduction, which yields the main dimensions of variation of pixel-based stimuli (eigenvectors). We then tested whether a simple autoassociative network could learn to distinguish paintings by Picasso and Braque which were reconstructed from only these primary dimensions of variation. The network could correctly classify the stimuli, and its performance was optimal with reconstructions based on just the first few eigenvectors. Then we reconstructed the paintings using either just the first 10 (early reconstructions) or all 1,894 eigenvectors (full reconstructions), and asked human participants to categorise the images. We found that people could categorise the images with either the early or full reconstructions. Therefore, people could learn to distinguish category membership based on the reduced set of dimensions obtained from SVD. This suggests that a dimension reduction mechanism analogous to SVD may be operating when people learn about the structure and regularities in complex categories.

Table of Contents

List of Figures

Judgements of style: People, pigeons, and Picasso

What makes a tree, a tree? How is it that a towering gum tree, a weeping willow, and a manicured Bonsai are all exemplars of a single category? Why do people not normally confuse a lamppost for a tree, even though the image falling on the retina would be similar to that of a tall, narrow tree? People's initial reaction to this challenge can be to attempt to generate a rule that defines and differentiates the category "tree". For example, people might claim "a tree is green and leafy, whereas a lamppost is not". Yet they would also recognise a bare deciduous tree (which is neither green nor leafy) as a tree. People might still claim "a tree has branches", and yet they would have no difficulty recognising a tree with its branches sawn off as a tree. It seems, therefore, that no explicit rule can be applied to consistently classify trees, and differentiate them from other, similar-looking objects. This is because "tree" is an example of a complex, "polymorphous", or "family resemblance" category, where category membership is not defined by a simple rule. The individual exemplars that constitute the category tree instead seem to share a common tacit *style* (Ryle, 1951). People can make these sorts of category judgements with ease and accuracy in everyday life. The purpose of this thesis, therefore, is to investigate whether *dimension reduction* can account for how people learn about the structure of complex visual categories. That is, whether through experience with individual exemplars of a category, people become sensitised to the main dimensions of variation that are important for distinguishing those stimuli from one another, and use these dimensions to analyse and classify subsequent stimuli that they encounter.

In this literature review, I will discuss how dimension reduction can account for how we tacitly learn about the structure of a wide variety of complex categories. I will begin by discussing the evidence that this mechanism seems to capture some fundamental principles about the way that people recognise faces. Subsequently, I will consider Latent Semantic Analysis (LSA), which is a form of dimension reduction applied to written text. LSA is currently attracting attention in linguistics for its potential to explain human language acquisition, including the conundrum of how children acquire language at a rate greater than they can possibly be directly taught. I will also examine the evolutionary and physiological evidence, which suggests that it is not only plausible, but likely, that the visual system employs dimension reduction for analysing visual input. Finally, I will consider how this relates to animal learning. The experiment reported in this thesis, furthermore, will demonstrate that a dimension reduction model can successfully categorise Picasso and Braque paintings, and crucially, that dimension reduction may in fact be the basis for people's judgements of style on the same task.

Dimension reduction

Dimension reduction is the notion that through experience with multiple instances of particular categories, people learn to extract the main sources of variation that distinguish one category from another, and use these to analyse and classify subsequent stimuli. This is analogous to many common statistical dimension reduction techniques, such as Singular-Value Decomposition (SVD), nonnegative matrix factorisation, Fourier Transform (FT), Factor Analysis (FA), Independent Components Analysis (ICA), Principal Components Analysis (PCA), and Karhunen-Loeve Transform (KLT) (Dunteman, 1989; Joliffe, 1986; Regment & Joreshog, 1993; Stevens, 1996; Tabachnick & Fidell, 2007). The precise method of dimension reduction, however, is not a pivotal concern here. I wish to show, rather, that the general dimension reduction mechanism is the basis for people's judgements of style. One of the most widely used dimension reduction techniques is PCA, its popularity stemming from the fact that it is (relatively) simple computationally. I will, therefore, focus on PCA. Dimension reduction techniques such as PCA can be characterised equivalently in terms of standard statistical techniques, geometrically in multidimensional space, or as neural network architectures.

Dimension reduction and statistics

Statistical dimension reduction can be used to summarise a large set of visual stimuli into a reduced set of dimensions. The first step is to quantify an image, which means that every pixel in the image is assigned a numerical value representing its intensity or brightness, and the whole image, therefore, can be treated a vector of brightness values. The vectors from any number of images can then be assembled into a covariance matrix, which is subsequently decomposed into the orthogonal dimensions that best distinguish all the images from one another. This is called deriving the *eigenvectors* of the covariance matrix (Calder, Burton, Miller, Young, & Akamatsu, 2001; Devijer & Kittler, 1982; Kirby & Sirovich, 1990). Eigenvectors are the primary dimensions that describe the underlying structure or pattern of variation across a set of images. They have been conceptualised as "macrofeatures", because they encode for the core, salient, dimensions along which the visual images differ (Abdi 1988; Abdi, Valentin, Edelman, & O'Toole, 1995).

Once the eigenvectors have been derived, each image can be represented as its values or projection weights on these dimensions. This means that an image can be reconstructed using a weighted linear combination of the eigenvectors. When an image is reconstructed using all the eigenvectors, it will be a perfect representation of the original image, but an image can often be well (but imperfectly) reconstructed with only a subset of the eigenvectors (Devijer & Kittler; Hancock, Bruce, & Burton, 1998; Valentin, Abdi, Edelman, & O'Toole, 1997).

Each eigenvector also has an associated eigenvalue. The eigenvalue indicates the amount of variance in the whole image set that the eigenvector can account for, where a larger eigenvalue indicates that the eigenvector explains a greater amount of variance. Convention dictates that the eigenvectors are ordered from the greatest to least eigenvalue. The eigenvectors with the larger eigenvalues are often referred to as the “early” eigenvectors, whereas those with the smaller eigenvalues are called “late” eigenvectors. Given that each eigenvector explains progressively smaller amounts of the total variance, the early eigenvectors represent the largest and most obvious dimensions of variation, through to the late eigenvectors which represent the least obvious dimensions of variation (Devijer & Kittler, 1982; Hancock, Burton, & Bruce, 1996; Ripley, 1996).

Dimension reduction and multidimensional space

Dimension reduction can also be understood geometrically in multidimensional space. For example, in human face recognition, the visual information from the faces that a person has encountered would be reduced into a smaller set of dimensions (eigenvectors). These eigenvectors would then be the orthogonal axes that define the multidimensional space, and each face would be represented as a point in this space, where its values on the eigenvectors determine its location. Faces that are perceptually similar to one another will have similar values on the eigenvectors, and therefore will be near one another in the space. The similarity between any two faces can be defined mathematically as the Euclidean distance (cosine) between them. When a new face is encountered, therefore, it is projected into the space, and if the distance between this face and an existing one is below a certain threshold, it is recognised as “familiar”. If not, then it is then judged to be new, and the strength of familiarity will depend on its values on the eigenvectors (Turk & Pentland, 1991; Valentin, Abdi, O'Toole, & Cottrell, 1994; Valentine, 1991).

Dimension reduction and neural networks

Another way of representing dimension reduction is in terms of neural network architectures. Neural networks are statistical models, for example, the commonly used linear autoassociative neural network is equivalent to PCA. A linear autoassociative neural network is a classifier, built from simple units (“neurons”) interlinked by weighted connections. It is adaptive and learns from experience. The process of learning modifies the weighted connections between the neurons to maximise the classification performance. The network, therefore, is characterised as a memory, where the content is stored distributively in the weighted connections. Through experience, the memory will come to “recognise” stimuli, and “generalise” this learning to novel (previously “unseen”) stimuli. The weighted connections that allow for this kind of performance are the dimensions of variation that best distinguish images in the set from one another (Abdi, Valentin, & Edelman, 1999; Abdi et al., 1995; Everson & Sirovich, 1995; Harvey, 1994).

Face recognition and dimension reduction

Recognising faces is a task that people seem to be able to perform reasonably well. The way that this task is accomplished, however, is less obvious. One possibility is that people make use of a perceptual mechanism that extracts the main dimensions of variation from a large set of faces that the person has encountered, and then uses these to analyse and classify newly encountered faces. Face recognition models that make use of dimension reduction are highly accurate at recognising faces. Pentland, Moghaddam and Starner (1994), for example, compiled a set of 7,532 images of approximately 3,000 people, where each person contributed a minimum of two different images. The first 20 eigenvectors were extracted using PCA, and so all the faces could be represented as points in a 20-dimensionsal space. Pentland et al. tested whether the model recognised that multiple images of the same face were different images of the same individual, rather than images from different individuals. To do this, 200 target faces were randomly selected from the image set and projected into the multidimensional space, and whichever face was closest to the target (i.e., smallest Euclidean distance) was selected. If the selected face was a second image of the same individual, then this was counted as a correct response, whereas if it was an image of a different individual, then this was counted as an incorrect response. In this way, the model performed with 95% accuracy.

Clearly, dimension reduction is a highly accurate model of face recognition when there is extensive experience with faces. Extensive experience, however, is not a necessary condition for exceptional performance. Indeed, Kirby and Sirovich (1990) used just 50 faces in the image set and 10 target faces, but were still able to obtain a low error rate of just 3.68% (see Abdi et al., 1995; Vetter & Troje, 1997 for similar results).

Tredoux (2002), furthermore, compared people’s ratings of similarity for a set of faces with the values of similarity derived from a PCA model. People sorted 20 faces into 10 exclusive pairs, starting with the most similar pair, then the next most similar pair, and so on. The PCA-based ratings were defined as the Euclidean distance (cosine) between the faces in multidimensional space. Thus, the most similar pair for PCA would be those closest together in Euclidean space, the next most similar pair would be the second closest, and so on. Tredoux found that the correspondence between PCA-based ratings and people's ratings of similarity was very high (r = .94) (see also Calder et al., 2001; Hancock et al., 1996; Scheuchenpflug, 1999).

The fact that dimension reduction can mimic human performance, however, is still not conclusive evidence that people are using this mechanism when they recognise faces. It would be informative, therefore, to determine whether eigenvectors themselves are perceptually meaningful. Thus, Vetter and Troje (1997) presented participants with a target face on a screen, with two faces beneath it, where one was a duplicate of the target face, and the other was a reconstruction of the target face. The reconstruction was either a pixel-based reconstruction, or an eigenvector-based reconstruction, using 5, 15, or 98 eigenvectors. That is, the images were imperfect reconstructions of the originals, and the basic unit of information used to reconstruct the image was either pixels, or eigenvectors. The participants' task was to distinguish the duplicate from the reconstruction of the target throughout a series of trials (Vetter & Troje).

Vetter and Troje (1997) found that when the pixel-based reconstructions were used, participants made the judgement significantly faster and more accurately than when the eigenvector-based reconstructions were used. This is because the pixel-based reconstructions were perceptually less meaningful, and thus, they were easier to distinguish from the target. Whereas when the eigenvector-based reconstructions were used, people took considerably longer and made more errors in distinguishing them from the target. People also took longer and made more errors as the number of eigenvectors used in the reconstruction increased (i.e., 5, 15 or 98). If dimension reduction was not fundamentally related to how people process faces, then the eigenvector-based reconstructions should have been easy to distinguish from the target faces. Yet they were not. In fact, people found them surprisingly difficult to discriminate. This suggests that eigenvectors are perceptually meaningful and encode for the important visual information in human face recognition.

The "other-race" effect and dimension reduction

Face recognition models based on dimension reduction techniques can account for ubiquitous psychological phenomena, such as how faces from other races are often more difficult to distinguish from one another than faces from one's own race. It has been extensively documented that people demonstrate better recognition accuracy for own-race faces than other-race faces (Bothwell, Brigham, & Malpass, 1989; Brigham & Barkowitz, 1978; Brigham & Malpass, 1985; Brigham & Williamson, 1979; Chance, Goldstein, & McBride, 1975; Chiroro & Valentine, 1995; Cross, Cross, & Daly, 1971; Devine & Malpass, 1985; Lindsay, Jack, & Christian, 1991; Malpass, 1974; Malpass & Kravitz, 1969; Malpass, Lavigueur, & Weldon, 1973; Meissner & Brigham, 2001; O'Toole, Deffenbacher, Valentin, & Abdi, 1994; O'Toole, Peterson, & Deffenbacher, 1996; Shapiro & Penrod, 1986; Shepherd, Deregowski, & Ellis, 1974). This is called the "other-race" or "they all look alike" effect. This effect occurs equally for people from different races, for example, Caucasians have difficulty with Asian faces and Asians have difficulty with Caucasian faces, which discounts the possibility that faces of a particular race are just inherently more physically similar (O'Toole, Deffenbacher, Abdi, & Bartlett, 1991).

O’Toole et al. (1991) proposed a perceptual learning hypothesis to explain the other-race effect. That is, through experience with own-race faces, a person’s visual system attunes itself to the dimensions of variability that best distinguish among own-race faces. Using the face space metaphor, these dimensions are the axes that would make the faces maximally dispersed throughout the space. Any new face encountered (including other-race faces) would be evaluated along these same dimensions and projected into the space. The dimensions that are most important for distinguishing other-race faces, however, would differ from these own-race dimensions. This means that other-race faces would be evaluated along dimensions that are not well-suited to distinguishing them. As a result, the other-race faces would tend to have a restricted range of values on these dimensions, and so be perceived as a homogenous, highly-similar cluster (O’Toole et al.).

To empirically test this perceptual learning account of the other-race effect, O’Toole et al. (1991) trained one PCA neural network with a majority of Caucasian faces and minority of Asian faces, and trained another on a majority of Asian and minority of Caucasian faces. For both networks, the average cosines between the original and reconstructed images were larger for majority than minority race faces. This means that the networks were better able to recognise the faces from the race that they had the most experience with; that is, they showed an other-race effect (O’Toole et al.).

PCA networks are typically trained with the Widrow-Hoff learning rule. This means, essentially, that the network will develop the connection weights between the neurons that optimise the processing of the stimuli that it is exposed to (Abdi et al., 1999). The network, therefore, should learn to focus on the dimensions that are important for distinguishing the majority race faces, and neglect the dimensions that would be important for minority race faces. O'Toole et al. (1991), indeed, found that the average cosine between all possible pairs of reconstructed faces was smaller for minority race faces, which means that the network perceived them as more similar than majority race faces. That is, the network produced the "they all look alike effect" for other-race faces. Other researchers have also found support for this perceptual learning account of the other-race effect (Caldara & Abdi, 2006; Furl, Phillips, & O'Toole, 2002).

Early eigenvectors describe key categorical information

The early eigenvectors have been found to encode for key categorical information, whereas the later eigenvectors seem to contain the information that is important for differentiating individual faces from one another, rather than broad category judgements (Hancock et al., 1996; O'Toole, Abdi, Deffenbacher, & Valentin, 1993; Valentin & Abdi, 1996; Valentin et al., 1994). It has been found, for example, that gender is represented amongst the early eigenvectors (O'Toole et al., 1991, 1994; Valentin et al., 1997). To illustrate, O'Toole et al. (1993) visually displayed the eigenvectors and found that when the second eigenvector was added to the first, the result appeared distinctly masculine, whereas when the second eigenvector was subtracted from the first, it appeared feminine. Similarly, Abdi et al. (1995) found that male and female faces tended to have opposite weights on the second eigenvector. It is important to note, however, that these primary dimensions evolve with the images that the eigenvectors are extracted from. For example, we extracted the eigenvectors depicted in Appendix A from a set of 90 female and 68 male eye-aligned faces across a variety of races (8 African, 33 East Asian, 24 West Asian, and 93 Caucasian). It is clear from these eigenvectors that both ethnicity and gender represent the most obvious dimensions of variation. However, if we limit the face set to, say, only Caucasians, then gender seems to represent the most obvious dimension. On the other hand, if we limit the set to females, then ethnicity alone represents the most obvious dimension.

It is interesting to note that for any image set, the first eigenvector is always the mean or prototype of all the images (Devijer & Kittler, 1982). The second eigenvector, therefore, is essentially the first "real" eigenvector, in that it is the first to depict the variation (as opposed to the similarity) among the images, and it often represents gender information among same-race faces. This is remarkable, given that sex was never explicitly encoded into the model. The model is free to extract whatever eigenvectors are useful for discriminating the images in that particular set – and sex spontaneously emerged. It is important to note, however, that eigenvectors encode for information that is visually, rather than semantically relevant. Some eigenvectors represent dimensions for which there is an explicit semantic label (such as sex), whereas other eigenvectors will encode for the tacit visual information for which such labels do not exist (Turk & Pentland, 1991).

The plausibility of dimension reduction as a model of face recognition

When investigating the nature of the eigenvectors extracted from a set of faces, O'Toole et al. (1993), Abdi et al. (1995), and Valentin et al. (1997) all pre-processed the face images by aligning them at the pupil. This is typically done to ensure that the orientation of the faces, which is not of interest in these studies, is held constant, and is thus not the most obvious dimension of variation. If a dimension reduction model required such artificial standardisation in order to work, then it would not be a realistic model of human face recognition. Valentin and Abdi (1996), however, allowed the orientation of the faces to vary, and still the model performed surprisingly well. In fact, including images of the same face in different orientations enhanced the model's ability to recognise learnt faces.

Dimension reduction contrasted with other models of face recognition

An alternative approach to face recognition is a feature-based model, where particular facial features, such as eyes, eyebrows, nose, or mouth are thought to be the core components of face perception (Haig, 1984, 1986; Roberts & Bruce, 1988; Sadr, Jarudi, & Sinha, 2003). Such feature-based approaches, however, have been found to bear negligible resemblance to the way in which the people recognise faces (Abdi, 1988; Carey & Diamond, 1977; Goldstein, Johnson, & Chance, 1979; Loftus, 1979; Schooler & Engstler-Schooler, 1990; Turk & Pentland, 1991; Woodhead, Baddeley, & Simmonds, 1979). Other researchers have instead emphasised the importance of geometrical features, such as nose width, mouth position or chin shape (Brunelli & Poggio, 1993; Burton, Bruce, & Dench, 1993), or configural information (Diamond & Carey, 1986; Mondloch, Le Grand, & Maurer, 2002; Rhodes, 1988; Young, Hellawell, & Hay, 1987). Face recognition models based on such spatial measurements or configurations, however, are fragile, and falter with superficial changes in the image. Such a model, for example, would have difficulty recognising a previously encountered face, if it was presented with a different orientation, perspective, or luminance. Superficial changes in the face image, furthermore, such as the presence of sunglasses, would also typically thwart such a model's ability to recognise a face (Turk & Pentland, 1991; Valentin et al., 1994). People, however, are still able to recognise familiar faces despite such changes (Abdi et al., 1995; Lowe, 1987; O'Toole et al., 1993; Samal & Iyengar, 1992). PCA, crucially, is also able to recognise previously encountered faces after such changes (Abdi et al.; Everson & Sirovich, 1995; Kirby & Sirovich, 1990; Lowe; Turk & Pentland, 1991). This suggests that PCA is capturing something fundamental about the way that people recognise faces.

The major limitation of these featural or configural models of face recognition is that they rely on the experimenter to arbitrarily choose some dimensions (such as "eyebrows" or "distance between the eyes") to investigate. A model based on such dimensions, therefore, will be incomplete at best. A PCA model of face recognition, in contrast, does not make assumptions about what dimensions of variability are important. The eigenvectors extracted instead depend entirely on the statistical structure of the images, and thus will necessarily capture the important dimensions of variation (Devijer & Kittler, 1982; O'Toole et al., 1993; Valentin et al., 1994). The absence of a priori assumptions in a dimension reduction model, furthermore, means that the eigenvectors are not required to conform to explicit semantic labels (Turk & Pentland, 1991). This is an advantage because it is likely that the dimensions that are important for recognising faces will not always have a corresponding semantic label. This is why, for example, it is difficult to describe a person's face to someone in sufficient detail that they could then walk into a crowded room and pick that person out. This is difficult to do, because the information that is important to the visual information in recognising faces is not easy to summarise in words. The advantage of PCA, therefore, is that it encodes for this salient but tacit visual information.

PCA's sensitivity to subtle visual information has allowed it to detect some unexpected anomalies. Parr and de Waal (1999), for example, tested chimpanzees' ability to match photographs of other unfamiliar chimpanzees and their offspring. The chimps could match the photographs depicting faces of mothers with sons, but not mothers with daughters. The authors then proposed an explanation for this in terms of a specialised mechanism for kin recognition that is independent of previous experience with individuals in question. Vokey, Rendall, Tangen, Parr, and de Waal (2004), however, subsequently applied a linear autoassociator to the images used in the experiment. Several of the resulting early eigenvectors appeared to code for a confound in the way the photographs had been framed. This demonstrates how PCA is sensitive to subtle, perceptually relevant information that is difficult to explicitly detect.

Generality of dimension reduction

Another important advantage is the wide generality of dimension reduction. It is not limited to the visual domain. It has been successfully used for analysing and classifying auditory stimuli. Crump (2002), for example, quantified musical pieces by Bach and Mozart, and simulations revealed that a linear autoassociator could learn to discriminate music composed by Bach from music composed by Mozart. Similarly, Vokey (personal communication) has found that the network can discriminate between gay and straight human voices.

Language and dimension reduction

The dimension reduction mechanism can also be applied to language. Latent Semantic Analysis (LSA) is Singular Value Decomposition (SVD) applied to written text. LSA reduces a very large corpus of text into a smaller subset of dimensions, which represent the most obvious dimensions of variation within the text. Words in the text can then be thought of as points in multidimensional semantic space, where words with similar meaning will cluster closer together than those with dissimilar meaning (Landauer & Dumais, 1997).

LSA treats language like a “bag of words”. That is, it makes use of the words that tend to go together in a particular context (semantics) and ignores word order (syntax). For example, LSA would treat the sentence “the cat sat on the mat” as equivalent to “the mat sat on the cat” (Landauer, 2002). This is a simplification, but a justifiable one. Landauer and Dumais (1997) estimated that over 80% of the information inherent in language is contained in word choice, rather than word order. Furthermore, even though LSA ignores word order, it still performs exceptionally well. Landauer suggests that while syntax is not meaningless, whatever information it provides may well be redundant with the information available from semantics.

Landauer and Dumais (1997) tested whether LSA could account for human language acquisition. They took 4.6 million words from an encyclopaedia intended for young students, to mimic the experience with language a person learning English might have. LSA reduced the text to 300 of the most obvious dimensions of variation. This means, conceptually, that the 4.6 million words can be represented in a 300-dimensional semantic space. Landauer and Dumais then gave LSA a vocabulary test that consisted of 80 items, where each item was a target word followed by four alternatives. LSA was used to choose, from four alternatives, the most appropriate synonym for the target word. This means that the target words and the alternatives were projected into semantic space. The distance between each target word and its corresponding four alternatives was considered, and the alternative that was closest to the target was selected as the response. In this way, LSA scored 64.4% correct on the test. This vocabulary test, interestingly, is used to examine applicants to American colleges who are from non-English speaking backgrounds (i.e., the TOEFL). A large sample of such applicants obtained an average score of 64.5% correct on this test. The fact that LSA's performance was virtually identical to that of people learning English as a foreign language, therefore, indicates that dimension reduction can model the way in which people acquire language (Landauer & Dumais).

A nuance of LSA also offers a solution to the "poverty of stimulus" pondered since Plato: How do children acquire vocabulary at a rate exponentially greater than they could ever be taught directly? Landauer and Dumais (1997) showed that LSA's learning process is highly inductive. In fact, 75% of the information required for LSA to pass a particular item on the vocabulary test was derived from experience with text in which the word did *not* occur. That is, the *absence* of a word in a particular semantic context was more informative than presence of that word in another semantic context. LSA's inductive learning process has been proposed as a way of explaining how children's vocabulary is able to increase disproportionately to direct stimulus input (Landauer, 2002).

There is also evidence, moreover, that dimension reduction can account for how people acquire other types of knowledge. Landauer, Laham, and Foltz (1998) applied

LSA to popular introductory psychology textbooks, and subsequently tested LSA using the same multiple-choice test that psychology students in large classes sit. LSA passed the exam, with 60% of the items correct, which was only slightly below the class average for a sample of students sitting this same test.

While LSA can *mimic* student performance, however, this does not conclusively show that the same underlying mechanism is operating in both cases. It could be informative, therefore, to compare the types of errors that students and LSA made. A single mechanism will likely lead to a distinctive pattern of errors, whereas two different mechanisms, even if their overall accuracy rates are similar, would likely produce different sorts of errors. If both the students and LSA had difficulty with similar sorts of items, then it would more strongly suggest that students and LSA are using the same mechanism to perform the task. Indeed, Landauer et al. (1998) found that both LSA and the students had more difficulty with conceptual items, and they both did much better on factual questions. That is, people and LSA made qualitatively the same sorts of errors. This suggests that LSA could be the means via which people derive knowledge and understanding from lexical input.

Evolutionary evidence for dimension reduction

Dimension reduction is also consistent with an evolutionary perspective. It has been pointed out that natural scenes occupy only a minute part of the multidimensional space of all possible scenes (Attneave, 1954; Field, 1987, 1994, 1999; Ruderman, 1994). In this context *natural* does not necessarily mean images containing, for example, trees and grass, rather, it refers more broadly to any image that a person might encounter in their visual environment. An image containing a building, for example, would be a natural image, as would the words on this page. This means that all the images a person could possibly encounter in their visual environment are only a tiny fraction of all images conceivably possible.

Where does such an idea come from? Think of an image as an array of pixels. A random image is where each pixel has no systematic relationship to the pixels next to it or to any other pixel in the image. Computers can generate random images, and they just look like white noise (Ruderman, 1994). In contrast, the pixels in a natural image are correlated. This is because adjacent pixels typically share a common cause, that is, they depict the same object. For example, in a photograph of a person against a background, the pixels depicting the skin of the person would be correlated with one another, as would the pixels representing the clothes, or the background. The pixels in natural images, therefore, are correlated, giving them a structure that is not apparent in random images (Atick & Redlich, 1992; Bossomaier & Snyder, 1986; Field, 1987, 1994, 1999; Hancock, Baddeley, & Smith, 1992; Ruderman; Srinivasan, Laughlin, & Dubs, 1982).

Natural selection, furthermore, predicts that the visual system would have adapted to the characteristics of the input that it receives. Throughout our evolutionary past, the visual system has been exclusively exposed to natural stimuli. It would have adapted, therefore, to make use of the structure and regularities in this environment (Barlow, 1961, 2001; Laughlin, 1983; Marr, 1982; Shepard, 1992; Srinivasan et al., 1982; van Hateren, 1992). Any model of a perceptual mechanism operating in visual system, therefore, must deal efficiently with this invariance that is ubiquitous in the natural world. Dimension reduction, interestingly, is based on this invariance, and thus is consistent with our evolutionary past (Bossomaier & Snyder, 1986; Hancock et al., 1992).

Physiological evidence for dimension reduction

The evidence presented so far suggests that dimension reduction could be the means via which people learn about the structure of complex categories in the world around them. If dimension reduction is a core perceptual mechanism, however, then there should be physiological evidence for this. To this end, a number of researchers have applied dimension reduction techniques to natural images and examined the resulting eigenvectors. The most remarkable result from this line of research is the consistency of the dimensions that emerge: The eigenvectors extracted from natural images are virtually identical regardless of the content, size, number, or quality of the images (Baddeley & Hancock, 1991; Hancock et al., 1992; Heidemann, 2006). This suggests that there is an inherent consistency in the basis functions or structure of natural images. It seems likely, therefore, that the visual system would have adapted to make use of this inherent consistency, and dimension reduction, which extracts the core, common dimensions along which images vary, is an optimal way of doing this. Given that eigenvectors are the macro dimensions along which natural images vary, furthermore, encoding stimuli along these dimensions would be an efficient means of analysing visual input (Baddeley & Hancock; Hancock et al.).

When the robust dimensions are extracted from natural images, the first few early eigenvectors appear as an oriented bar, and thus seem to encode for the orientation of a stimulus (Baddeley & Hancock, 1991; Hancock et al., 1992; Heidemann, 2006; Olshausen & Field, 1996; Sanger, 1989). This is intriguing, given that there are known to be individual neurons in the primary visual cortex that respond optimally to an oriented edge or bar in their receptive field (De Valois & De Valois, 1988; Heydt, Peterhans, &

Dursteler, 1992; Hubel & Wiesel, 1959, 1962, 1968, 1972, 1974, 1977; Petkov & Kruizinga, 1997). These cells encode for the orientation of a stimulus and are sometimes called "bar detectors" or "edge detectors". The response properties of these cells, however, maps onto the macro dimensions along which natural images have been found to vary. This suggests that these orientation-sensitive cells in the primary visual cortex may in fact be encoding for the primary dimensions of variation inherent in natural images. That is, these cells may not be bar detectors, instead, speculatively, they might be "eigenvector-detectors" (Hancock et al.; Baddeley & Hancock).

When dimension reduction is applied to chromatic natural images, furthermore, there are consistently early eigenvectors that encode for yellow-blue, red-green, and black-white dimensions (Buchsbaum & Gottschalk, 1983; Rubner & Schulten, 1990; Usui, Nakauchi, & Miyake, 1994). This reflects the known physiological set-up of the visual system, in which yellow-blue, red-green, and black-white colour-opponent dimensions process colour (De Valois, 1971; De Valois, Abramov, & Jacobs, 1966; Mitarai, Usui, & Takabayashi, 1982). The striking similarity between the eigenvectors yielded from dimension reduction and the receptive fields of neurons in the visual cortex suggests that such a mechanism is at a minimum neurophysiologically plausible, and may in fact be the very basis for representing visual patterns from the retina.

Dimension reduction and non-human animals

Following from the evolutionary and physiological basis of dimension reduction, it is reasonable to assume that this mechanism is not limited to humans. In the animal learning literature, it has been well-established that pigeons can make some apparently sophisticated discriminations (Aust & Huber, 2001; Bhatt, Wasserman, Reynolds, &

Knauss, 1988; Blough, 1982, 1985; Cerella, 1979; Herrnstein, 1979; Herrnstein & deVilliers, 1980; Herrnstein & Loveland, 1964; Herrnstein, Loveland, & Cable, 1976; Jitsumori & Yoshihara, 1997; Malott & Siddall, 1972; Morgan, Fitch, Holman, & Lea, 1976; Poole & Lander, 1971; Siegal & Honig, 1970; Vaughan & Herrnstein, 1987). Pigeons are capable of making the same judgements of style as people. For example, they can distinguish musical excepts by Bach and Stravinsky (Porter & Neuringer, 1984), male from female human faces (Troje, Huber, Loidolt, Aust, & Fieder, 1999), and Monet from Picasso paintings (Watanabe, Sakamoto, & Wakita, 1995). In all these cases, the pigeons can also successfully generalise to previously unseen stimuli.

The knee-jerk reaction to such findings is often to remark how sophisticated and human-like the pigeons are. It is, of course, possible that pigeons are highly intelligent and have just been hitherto underestimated. It should be remembered, however, that pigeons' entire neural architecture is the size of a pea (hence the term "bird-brain"), and most of that is dedicated to flight (Rendall & Vokey, 2004). Either the psychological processes subserving these abilities in pigeons are more sophisticated than ever before imagined, or the psychological processes subserving the same phenomena in people are somewhat simpler than previously assumed. This latter alternative is rarely considered. It is my aim, therefore, to explore whether people can learn and distinguish artistic style using only basic perceptual information (without reference to any sophisticated "higher order" mental processes), an ability that we may share with creatures such as pigeons.

Summary

The evidence I have reviewed so far suggests that dimension reduction can account for how people learn about complex categories from experience with individual instances. Dimension reduction, furthermore, is at a minimum biologically plausible, and may in fact be the core mechanism that the visual system uses to analyse input. It seems likely, moreover, that this mechanism is not unique to humans.

The current experiment

The current experiment draws on the evidence from the wide range of research reviewed above, and advances an approach that has not been used in prior research. We use a two-pronged approach to testing people's tacit sensitivity to style: (1) we test whether a simple linear autoassociative neural network (which employs dimension reduction) can learn to distinguish between paintings by Braque and Picasso, and (2) we examine whether dimension reduction could be the basis of people's judgement of style on the same task.

We decided to use Cubist paintings by Picasso and Braque in this experiment because they represent a complex category where no single feature or rule defines category membership. It is, therefore, the artistic *style* that defines the category. If we instead used photographs in this experiment, for example, images containing trees constituted one category ("tree present") and photographs not containing trees constituted another ("tree absent"), then it is conceivable that participants may base their assessment of category membership on the presence or absence of an embedded object in the image (i.e., tree). In artwork, conversely, there are no such defining features (see the Picasso and Braque images in Appendices B and C respectively). Categorising these stimuli, therefore, demands a judgement of style, and this will allow us to investigate how people learn about complex or polymorphous categories they encounter in everyday life, where category membership is not defined by a simple rule (Ryle, 1951).

We decided to use Picasso and Braque in particular because they are highly similar visual categories. In prior work, Vokey and Tangen (2006) have shown that a PCA model can discriminate markedly different artistic styles (Impressionism and Cubism). In contrast, paintings by Picasso and Braque are highly similar. Picasso and Braque lived and painted together, producing Cubist art so similar that even art experts have difficulty distinguishing them (Rubin, 1989). One aim of this experiment, therefore, is to determine whether a PCA network can discriminate Cubist paintings by Picasso and Braque.

We also aim to examine whether dimension reduction could be the basis for people's judgements of artistic style. While previous research has shown that dimension reduction can model the way in which people, for example, recognise faces or acquire language, in this experiment we endeavour to bring the learning process under experimental control. To do this, we will ask participants to learn to distinguish visual categories that they presumably do not have extensive experience with (Picasso and Braque artwork). We will, furthermore, extract the eigenvectors from the paintings and use them to reconstruct the original images. These reconstructions will use either the first 10 eigenvectors ("early reconstructions"), or all the eigenvectors ("full reconstructions"). Participants will be tested on their ability to discriminate between Picasso and Braque images using either the early or full reconstructions. If, as argued, dimension reduction is the basis for learning complex categories, then our participants ought to be able to perform this discrimination with the reconstructions using just the first 10 eigenvectors, even though these images do not appear to contain any explicit meaningful information. Therefore, we predict that with the early reconstructions, participants will learn to discriminate between paintings by Picasso and Braque. The full reconstructions, furthermore, using all the eigenvectors, are perfect reconstructions of the originals. Since these are effectively the original images, we predict that people will also learn to discriminate between these paintings by Picasso and Braque.

It is unclear, however, whether to expect higher discrimination accuracy from participants presented with the early versus the full reconstructions. On the one hand, the full reconstructions contain all the information available in the original image, whereas the early reconstructions contain only a fraction of that information, and so the full reconstructions might be expected to yield higher discrimination accuracy. On the other hand, if participants are basing their assessment solely on the most obvious dimensions of variation, then they should perform equally well with both types of reconstructions. We cannot, therefore, make any specific predictions about participants' relative accuracy given the early and full reconstructions.

PCA NEURAL NETWORK SIMULATION

Simulation Method

We scanned 428 images at 1200ppi from Rubin's (1980) *Picasso and Braque: Pioneering Cubism*. Each artwork was represented by its coding on Red, Green, and Blue (RGB) colour channels. This means that each pixel was assigned a value, representing the intensity of the particular colour channel (0-255). Photographs of sculptures or oval-shaped paintings were then eliminated from the set. The remaining 379 paintings were used in both the simulation and the experiment (252 Picasso and 127 Braque) (see Appendices B and C).

Scanning halftone images inevitably results in an artefact referred to as moiré patterns. The recommended technique for dealing with these patterns involves applying a Gaussian mask to the image (Vakulenko, 2002). There is no quantitative test, however, for determining the appropriate amount of blurring to apply. Therefore, we used a random sample of 16 images to make a visual judgement about the best level of blur.

There are two parameters of the Gaussian mask that control the level of blur: its size (hsize) and spread (sigma). We varied these systematically and applied the resulting Gaussian mask to a sample of images, and decided that a Gaussian mask of 12 (hsize) and 12 (sigma) removed the moiré from the sample of images. This Gaussian mask was then applied to the entire image set. The images were subsequently scaled by a factor of .06, and thus ranged in size from 140 x 83 to 573 x 546 pixels.

We used a sub-sampling technique in this experiment, in which random subsamples were extracted from each image in the analysis, rather than using the entire images. This technique has been successfully used in previous research (Vokey & Tangen, 2006). It is designed to capture the notion that no image is encountered in exactly the same way twice, and to simulate the redundancy involved in perceiving a still image. Five 100 x 100 pixel subsamples were randomly extracted from each of the 379 images, resulting in a total of 1,895 subsamples.

The linear autoassociative neural network was then trained and tested using a bootstrap or “leave-one-out” technique. This means that we assembled the covariance matrix of the vectors of pixels for all the subsamples in the set except one (1,894 subsamples) and then performed a Singular-Value Decomposition (SVD) on this matrix. This process yielded the eigenvectors and their corresponding eigenvalues of the covariance matrix. This was repeated 1,895 times so that each subsample was "left out" once. The extracted eigenvectors were ordered from the largest to smallest eigenvalue (see Appendix D for the eigenvectors).

We then computed the projection weights for all 1,895 subsamples cumulatively for each eigenvector. This is equivalent to creating a multidimensional space (where the eigenvectors are the dimensions that define the space) and projecting all the subsamples into that space. The discrimination weights, furthermore, for the 1,894 subsamples were computed. These discrimination weights were then used to classify the "left-out" subsample. In this way, the left-out subsample served as the test item. This is equivalent to projecting the test subsample into the space based on its values on the discrimination weights, and measuring how closely it falls to that subsample projected into multidimensional space based on the discrimination weights. Consequently, the cosine between this test subsample and the original subsample projected into the space provides a measure of the quality of the reconstruction.

The network was also tested directly on the pixel-maps of the images, without first performing PCA. This means that the discrimination weights were computed from the pixel values for the 1,894 and the left-out subsample, and these weights were used to classify the test item.

Simulation Results

We collected 252 paintings by Picasso and 127 by Braque for this simulation and experiment, and took five random subsamples (100 x 100 pixels) from each of these paintings. This means that there were 1,895 (379 x 5) subsamples used in the simulation. The goal was to determine the extent to which a PCA neural network could discriminate between paintings by Picasso and Braque using different ranges of eigenvectors that reflect the most obvious dimensions of variability across the set. The dependent measure is a-prime (A’), which is a non-parametric estimate of discriminability and bias and represents the hit rate over the false alarm rate. An A’ of 1.0 indicates perfect discriminability, while 0.5 indicates chance discriminability. We included another measure of chance performance by applying the perceptron directly to the pixel maps. This essentially represents the network without a memory. The results from this simulation are presented in Figure 1.

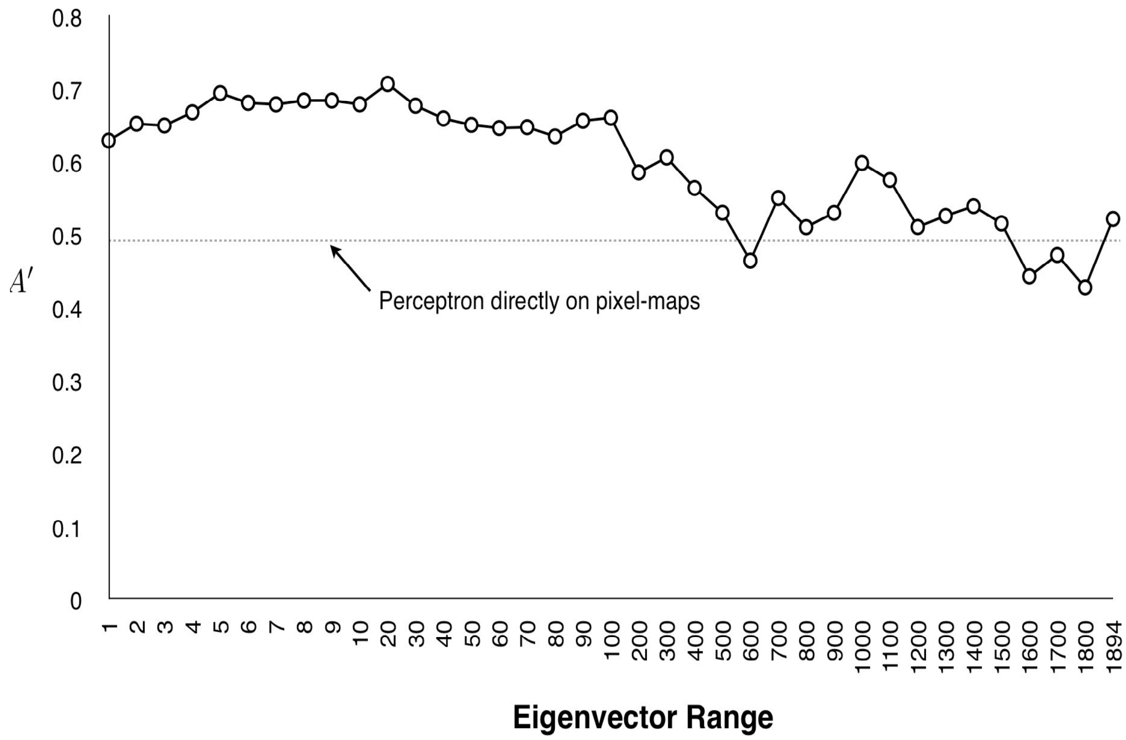

Figure 1. The neural network’s discriminability (A’) plotted as a function of eigenvector range.

The results depicted in Figure 1 indicate that the network could discriminate paintings by Picasso and Braque reasonably well using only the “early” eigenvectors, and that its performance deteriorated as the number of eigenvectors used in the analysis increased. Furthermore, a perceptron applied directly to the pixel maps performed virtually at chance (A' = .49).

HUMAN PARTICIPANT EXPERIMENT

Method

Participants

Sixty introductory Psychology students from the University of Queensland (20 male, 40 female), aged between 17 and 43 (M = 18.92, SD = 3.60) were recruited through the first-year psychology research participation scheme. The only restriction was that they have normal or corrected-to-normal vision. They were given course credit for participation.

Materials

The subsamples from the simulation were used in this experiment. Each subsample was presented on the screen as a 200 x 200 pixel image on a maximally contrasting background. To create this background, the mean values of all the images on the Red-Green-Blue colour channels was calculated, and then the inverse of these values was used to determine the colour of the background. It appeared greyish-blue (R: 120, G: 132, B: 143).

Since there were an unequal number of Picasso and Braque paintings (252 and 127 respectively), Picassos were randomly sampled for each participant. This ensured that an equal number of Picasso and Braque paintings were presented.

Design

In order to examine whether a dimension reduction mechanism is operating when people learn about the structure of complex visual categories, we reconstructed the images in the set using only the most obvious dimensions of variation. This is done by multiplying the projection weights of the image based on the first 10 eigenvectors by the same set of eigenvectors. This means that the images were reconstructed using a weighted linear sum of the first 10 eigenvectors (early reconstructions). These early reconstructions result in images that could be described as nebulous (see Appendix E). In fact, they bear little resemblance to the original images (compare Appendices E and F). In contrast, these paintings were also reconstructed using a weighted linear sum of all 1,895 eigenvectors, resulting in perfect reconstructions of the original images (full reconstructions) (see Appendix F). The main independent variable, therefore, was the type of image reconstruction used (early vs. full) and participants were randomly assigned to conditions.

We decided to use only the first 10 eigenvectors to create the early reconstructions because other researchers have used the first 10 and obtained excellent results (e.g. O'Toole et al., 1991). The exact number of eigenvectors used, however, is not a pivotal concern. Rather, it is important to test whether people can perform the task using the reconstructions that (a) are based on a tiny fraction of the total number of eigenvectors (i.e., 10 out of a possible 1,895), and (b) do not appear to represent anything explicitly meaningful.

The positive stimulus category (i.e., whether the "correct response" for the participant was Picasso or Braque images) was counterbalanced such that for half the participants, Picasso was the positive stimulus category, and for the other half it was Braque. The dependent variable was percentage correct in classifying the images.

To examine whether discrimination accuracy improved over trials, we split the 508 experimental trials into four blocks of 127 trials each, because participants were presented with 127 subsamples from each artist four times. Analysing whether the trials blocks differed from one another in average discrimination accuracy, therefore, allowed us to summarise the effect of learning across trials.

Procedure

Participants read an information sheet outlining the experiment and then gave informed consent to participate. They were asked to enter their age and gender on the computer screen using mouse-activated drop-down menus. The instructions for how to complete the task then appeared on the screen (see Appendix G). Participants were told that they would see two paintings for each trial, and their task was to decide which of the two paintings belonged to "Category A" artist. The experimenter made it clear that while initially they would be guessing, as they proceeded through the experiment, they should learn to recognise the artists' style, and so be able to respond more accurately. After the participant read the instructions, the experimenter checked whether they had any questions and answered them accordingly, and the participant clicked the "Begin" button to start the task.

On each trial, two images were presented on the screen simultaneously (one Picasso and one Braque). The position (left or right) of the Picasso and the Braque was randomised. The images were displayed on the screen until the participant clicked on the image that they thought belonged to Category A artist (see Appendix H).

If the participant made a correct response, then two things happened: a smiley face appeared on the screen in between the two images, and they acquired 100 points. If they made an incorrect response, a frowning face was shown and they lost 100 points. Their cumulative score was displayed on the screen above the two images throughout the 508 trials. Following the experiment, participants were given a verbal debriefing and an educational debriefing sheet and thanked for their participation.

Contributions

The design of this project was collaborative endeavour between my supervisor and I. My supervisor scanned and prepared the Picasso and Braque images. After receiving instruction, I performed the neural network simulation in MATLAB. I was the experimenter for all the human participant data collection, which included counterbalancing and random assignment of participants to conditions. I also compiled and analysed all the data from the experiment.

Since the neural network simulation has not been performed on these stimuli in any previous research, my supervisor has since continued work with the subsamples and simulations in order to assess their stability. The design of the experiment was also completely novel, and so we would like to repeat the experiment using different stimuli. We are currently conducting an experiment with paintings by Picasso and Monet (rather than Picasso and Braque), using the same procedure. I have also taken over 1,000 photographs of natural scenes and developed a searchable database of these images. This will permit future research examining the underlying dimensions of natural scenes.

Results

The broad purpose of this investigation was to determine whether, through experience with stimuli, people use a dimension reduction mechanism to extract the main sources of variation that define a category. More specifically, this experiment tested whether people could accurately discriminate between Picasso and Braque images when they were reconstructed using only the first 10 eigenvectors (early reconstructions), and reconstructed using all 1,895 (full reconstructions).

We predicted that participants would be able to discriminate Picasso from Braque images significantly above chance using the early reconstructions. As illustrated in Figure 2, participants could discriminate 57.3% (SEM = .59%, Range = 45.9-69.3%) of the paintings by Picasso and Braque when they were entirely reconstructed using all 1,895 eigenvectors (full reconstructions), which is reliably above chance performance, $t(29) = 7.75$, $p<.001$. In contrast, participants could discriminate 52.3% (SEM = .94%, Range = 47.2-63.4%) of the paintings when they were reconstructed using only the first 10 eigenvectors (early reconstructions), which is also significantly above chance, $t(29) = 3.97$, $p<.001$.

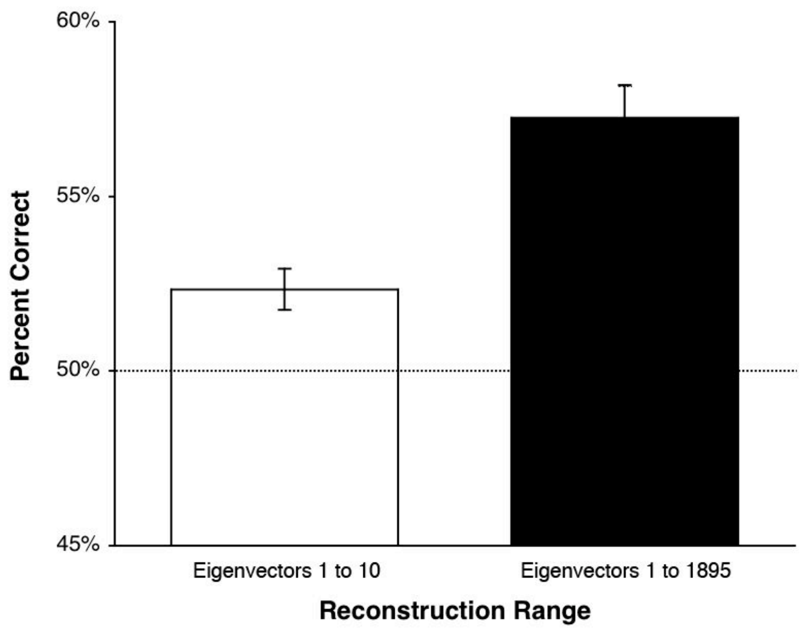

Figure 2. Mean discrimination accuracy for people using the early and full reconstructions. Error bars represent standard errors of the means.

Participants, furthermore, were presented with four subsamples extracted from each of the 127 paintings by the two artists, resulting in four blocks of 127 trials (508 trials in total). For half of the participants, Picasso was the positive stimulus category, that is, the "correct response" was to click on Picasso images, and for the other half, Braque was the positive stimulus category, where the "correct response" was to click on Braque images. In order to examine the effect of learning across the 508 trials, therefore, and to determine whether discrimination was better for Picasso or Braque as the positive stimulus category, we used a mixed ANOVA with reconstruction type (early, full) and positive stimulus category (Picasso, Braque) as between-subject variables and trial block (1-4) as a within-subjects variable. As illustrated in Figure 2, participants who were presented with the full reconstructions were more accurate than those presented with the early reconstructions. This was confirmed with a significant main effect of reconstruction, $F(1, 56) = 19.88$, $p<.001$. From Figure 3 it is evident that participants' discriminative ability improved over trials, as revealed by a significant main effect of trial block, $F(3, 168) = 3.79$, $p<.01$.

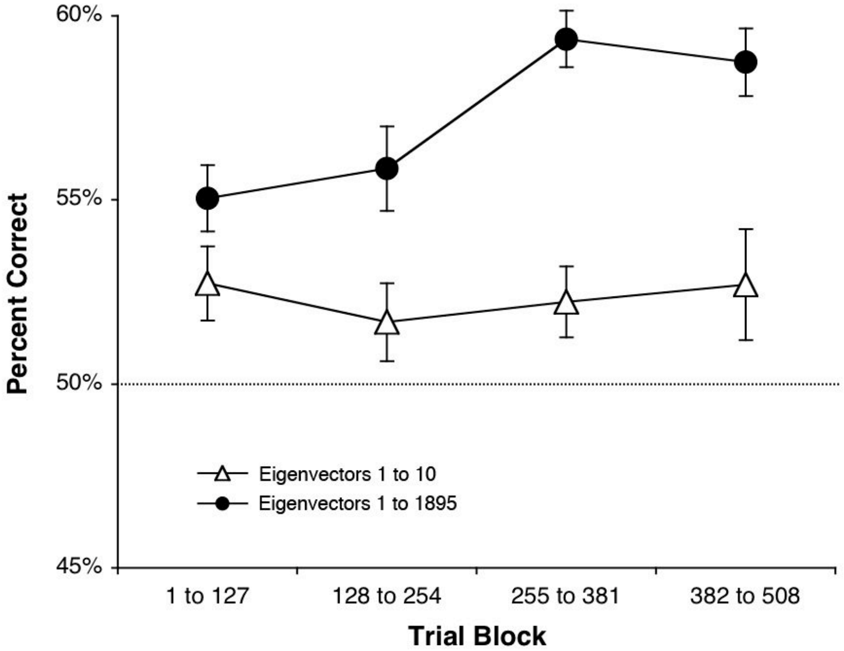

Figure 3. Mean accuracy across the four trial blocks for the early and full reconstructions. Errors bars represent standard errors of the means.

This improvement, however, was greater for participants who were presented with the full reconstructions, as indicated by a significant interaction between reconstruction and trial block, $F(3, 168) = 3.41$, $p = .019$. No other main effects or interactions reached significance.

Discussion

Summary of results

This experiment was designed to test whether dimension reduction could account for how people learn about the structure of a complex or polymorphous category. That is, we tested the notion that through experience with individual exemplars of a category, people will become sensitised to the main dimensions of variation that are important for distinguishing those stimuli from one another, and use these dimensions to analyse and classify subsequent stimuli that they encounter. As predicted, a PCA neural network learnt to discriminate Picasso and Braque images. When the network was applied directly to the pixel maps of the images (i.e., without first performing dimension reduction), it performed virtually at chance. The network, in contrast, performed considerably better with the eigenvector-based reconstructions. It was most accurate at classifying the images reconstructed from the early eigenvectors, and its performance deteriorated as the number eigenvectors included in the analysis increased.

As predicted, furthermore, when our human participants were presented with Picasso and Braque images reconstructed using only the first 10 eigenvectors (early reconstructions), they were able to categorise them significantly above chance. Likewise, when participants were presented with Picasso and Braque images reconstructed using all 1,895 eigenvectors (full reconstructions), they were also able to categorise them significantly above chance. Although no specific predictions were made in this regard, we also found that the participants presented with the full reconstructions performed better at categorising the images than the participants given the early reconstructions. Furthermore, performance increased across trial blocks for participants presented with the full reconstructions, but unexpectedly, it did not increase for those presented with the early reconstructions.

Overview

This discussion will be divided into subsections to guide the reader through the expanse of information and ideas covered. Since I have summarised the results above, I will subsequently interpret these results. This will include offering an explanation for the results in the context of the rationale for the experiment, considering alternative explanations, and relating the findings to prior literature. Following this, I will discuss the methodological considerations of this experiment, including methodological strengths, justifications, and limitations. I will, moreover, explore some potential applications of this research. Finally, I will conclude with a section that summarises the thesis and integrates all the information together. I did not include a separate section for future research, because I found that all my recommendations were intrinsically linked to other sections. Recommendations for future research, therefore, will be interwoven throughout.

Neural network simulation

We found that a PCA network could categorise the Picasso and Braque images, whereas a network applied directly to the pixel-maps of the images (without first performing dimension reduction) could not. This demonstrates how dimension reduction is able to reveal the inherent structure of these highly complex and similar categories. It is important to remember that these categories were not defined by a simple rule or any obvious surface features. Instead, the network accessed information at a more macro level, and in doing so, was able to accomplish a task that the model without this information could not.

We also found that the network performed optimally using only the early eigenvectors, and its accuracy declined as the number of eigenvectors included in the analysis increased. The model, therefore, was more accurate at categorising the images when it was provided with less information. This suggests that the primary dimensions of variation are all that are necessary to categorise these images. The network in this experiment, moreover, performed exclusively a categorisation task (Picasso versus Braque), at no point was it required to differentiate individual exemplars from one another. The fact the early eigenvectors emerged as most important for this task, therefore, is consistent with the notion that the early eigenvectors represent the salient *categorical* information. In the face recognition literature, for example, it has been established that the early eigenvectors encode for key categorical information (e.g., gender, race), whereas the later eigenvectors encapsulate identity-specific information (e.g., this face belongs to Mary not Lisa) (Hancock et al., 1996; O'Toole et al., 1993; Valentin & Abdi, 1996; Valentin et al., 1994). It is likely that if the model in this experiment had been trained to distinguish individual artworks from one another, instead of categorising them, then the later eigenvectors would have been more important. Essentially, the relative importance of the different eigenvectors will depend on task demand.

Human categorisation using the early reconstructions

When presented with the images reconstructed using the first 10 eigenvectors (early reconstructions), participants were able to categorise them significantly above chance. This is interesting because these reconstructions bear minimal resemblance to the original images, and in fact, they do not appear to contain any explicit meaningful information. Yet people were still able to systematically categorise these images. This suggests that the information represented in the eigenvectors is perceptually meaningful. It also supports the notion, moreover, that eigenvectors are a basic unit of information that the visual system extracts when learning to recognise the structure of complex categories.

When I was debriefing the participants who were presented with the early reconstructions, furthermore, many of them were exasperated that there was not an explicit rule that differentiated the categories, and were perplexed about the nature of the experiment. Yet they could perform the task. This suggests that eigenvectors encode for the tacit visual information that distinguishes complex visual categories, which people implicitly become sensitive to through exposure to individual instances of those categories.

Human categorisation using the full reconstructions

When presented with the reconstructions based on all 1,895 eigenvectors (full reconstructions), participants were able to categorise them significantly above chance. Indeed, participants were more accurate at classifying the full reconstructions than the early reconstructions. This contrasts with the results from the PCA network, which performed better when fewer eigenvectors were included in the analysis. There are two explanations that could account for this pattern of results: 10 eigenvectors is not the optimal number for dimension reduction, or participants presented with the full reconstructions adopted a different strategy for categorising them.

The first explanation stems from our somewhat arbitrary decision to use 10 eigenvectors to create the early reconstructions. If people typically base their assessment of stimuli on a greater number of eigenvectors, such as 15 or 20, and we presented people with the reconstructions based on 10 eigenvectors, then they would have missed out on some of the information that the participants presented with the full reconstructions had access to. On the other hand, the PCA model performed optimally with fewer eigenvectors and its performance declined as a greater number of eigenvectors were included, so perhaps 10 eigenvectors was too many, and people would also have performed better with fewer eigenvectors. Either way, there would be an optimal number of eigenvectors to use in the early reconstructions, and given the pioneering nature of this research, it is unlikely that we would have happened to select the optimal number this time. Future research, therefore, could systematically vary the number of eigenvectors used to form the early reconstructions, in order to discover the optimal number for this task.

The second explanation for participants' superior performance using the full relative to the early reconstructions is that they adopted a different strategy for analysing the full reconstructions. It is possible that people used some surface features present in the full reconstructions that were useful (albeit not perfect or definitive) predictors of category membership. For example, Picasso drew a lot of sketches, so if a sketch appeared on the screen, participants may have learnt that there was a good chance that it was a Picasso. This sort of superficial information is not available in the early reconstructions, because for example, a reconstruction of a sketch would not look like a sketch. If participants presented with the full reconstructions strategically searched for predictive surface features, therefore, then this could explain how they were able to categorise the images more accurately than the participants presented with the early reconstructions.

A search for surface features, however, is in stark contrast to how people typically categorise stimuli (Brooks, Squire-Graydon, & Wood, 2007). Brooks et al. argued that in everyday life, the categorisation of an object is usually secondary or incidental to a focus on the *use* of the categorised object. For example, "that is my neighbour's friendly cat so I can pet it" would be a more salient concern than "that creature has four legs, pointy ears, and purrs, so I conclude that it is a cat". The artificial constraints of a traditional categorisation experiment, however, are not conducive to this focus on the *use* of the categorised object, instead, they typically direct participants' focus onto the categorisation task itself. This is because in a traditional categorisation experiment: (a) the categories used will often be those defined by a simple experimenter-defined rule, (b) participants are aware that their categorisation performance is being assessed, and (c) they have nothing else to think about except the categorisation task. This situation compels participants to engage in an effortful and analytic search for category-defining surface features in the stimuli (Brooks et al.).

To overcome the tendency, Brooks et al. (2007) proposed a "diverted analysis" technique. This technique was designed to divert people's attention away from the categorisation itself and onto what the categorised stimulus could be used for. The authors found that under diverted analysis conditions, people could not only categorise stimuli accurately, but they also demonstrated many of the hallmarks of everyday-type categorisation. For example, after completing the experiment under diverted analysis, participants were often convinced that the family resemblance categories that they had been exposed to were defined by a simple rule (even though they were not). This mirrors how people will often claim that the natural categories which they encounter in everyday life are defined by simple rules, when in fact they are not (e.g. "trees are green and leafy"). Whereas when participants were exposed to the same stimuli under traditional categorisation experiment conditions, they typically recognised that the categories were not defined by a simple rule, because they had unsuccessfully searched for one (Brooks et al.). This shows how diverting participants' analysis onto the *use* of categorised objects, rather than focusing on the categorisation task per se, leads people to treat the stimuli in a way that much more closely reflects how they treat stimuli in everyday life.

It would be informative to test whether diverting participants' analysis from the categorisation task in this experiment would eliminate the advantage for the full reconstructions. If so, it would suggest that the analytic search for surface features was a strategy the participants adopted just to perform this experimental task, rather than a strategy that they would usually employ to make categorisation judgements in everyday life. This would suggest, furthermore, that people typically use the broad perceptual information represented in the early eigenvectors, rather than explicit surface features, when they learn about the structure of complex categories in the world around them.

Pattern of performance across trials

The pattern of performance across trials offers further evidence that people were strategically focusing on surface features when categorising the full reconstructions. We found that the accuracy of participants' performance increased across trial blocks when they were categorising the full reconstructions, but not when they were categorising the early reconstructions. This was unexpected. It reveals, however, that the way in which participants were categorising the early reconstructions was stable and consistent. This makes sense if they were relying on a dimension reduction mechanism that is robust and commonly used. When participants were categorising the full reconstructions, dimension reduction could have been operating in conjunction with a search for surface features – a method strategically employed for this experimental task. Assuming that participants had not previously invested time in figuring out what surface features distinguish a Picasso from a Braque, their accuracy in doing so would improve with experience. This could account for why performance increased across trial blocks for participants categorising the full reconstructions, but not for those categorising the early reconstructions.

Dimension reduction and non-human animals

In the Introduction I mentioned that non-human animals such as pigeons can make seemingly sophisticated judgements, such as discriminating Monet and Picasso artwork (e.g. Watanabe et al., 1995). It is likely that pigeons use the macro perceptual information available in the early eigenvectors to do this, and can *only* use this information. Our argument, furthermore, is that people make judgements of style in fundamentally the same way as the pigeon; however, people can also supplement their performance with knowledge of language-based surface features, as they seemed to under the constraints of this experiment. We plan to pursue this idea by having pigeons discriminate Picasso and Braque images using the stimuli from this experiment. If pigeons perform equally well categorising the early and full reconstructions, then it would demonstrate that they use only the perceptual information represented in the early eigenvectors to perform the task. If people also perform equally well with the early and full reconstructions under diverted analysis conditions, then it would suggest that when people make everyday judgements about complex categories, they may base their judgement solely on the most obvious dimensions of variation, just like pigeons.

Methodological considerations

Methodological strengths.

The major methodological strength of this experiment was that we tested both the network model and human participants. This allowed us to examine the similarities and differences between PCA's and people's performance. Crucially, however, we did not merely correlate the two. Rather, we used dimension reduction to obtain the eigenvectors and then experimentally manipulated the range of eigenvectors used to reconstruct the images. This allowed us to definitively establish the effect of dimension reduction on people's categorisation performance.

Furthermore, the Picasso and Braque artistic styles used in this experiment are highly similar, such that even art experts can have difficult distinguishing them (Rubin, 1989). These stimuli, therefore, offered a rigorous challenge for both the PCA network and our human participants. Future research could extend on this by testing how well people generalise their learning. Since we used artwork from Picasso's Cubist era, we could test, for example, whether participants would generalise their learning to Picasso's Blue or Rose period as well.

Finally, this experiment employed a sub-sampling technique, where five subsamples were randomly extracted from each image for analysis. This method seems to capture something fundamental about the way that people process images. Firstly, no stimulus is encountered in the same way twice, and thus why random subsamples were extracted, rather than analysing the entire image. Secondly, there is extensive redundancy in the visual information received as a person shifts their eyes around a still image. This idea was represented by allowing the random subsamples to overlap. Given that this experiment was the first of its kind, however, we did not have prior studies to guide us, and so some of the decisions we made were essentially arbitrary. For example, we arbitrarily chose to extract five subsamples (rather than, say, four or six). Future research, therefore, could systematically vary the number and size of the subsamples, and the number and size of the images, and test how this affects the model's and people's performance.

Methodological justifications.

We used Picasso and Braque images as the stimuli in this experiment because they exemplify the notion of complex categories, where category membership is not defined by a simple rule (Ryle, 1951). The artistic categories are not defined by the presence or absence of embedded objects in the images, because there were no such objects that were unique to one artistic category or the other. If we had used natural images, for example, and had "tree present" as one category and "tree absent" as another, then these categories would be defined by an obvious language-based rule. Artistic categories, in contrast, are defined more subtly in terms of *style*.

Nonetheless, there seems to have been some consistencies in the surface features that our participants learnt about when categorising the full reconstructions. It is likely that these features would be not sufficient to define the category, and so, by themselves, could not be used to make above-chance categorisation, but they were able to enhance performance when used conjunction with more macro perceptual information. To test this possibility, we could reconstruct the images using the later eigenvectors, omitting the early ("late reconstructions"), which would therefore contain exclusively the individuating surface features of the images. If participants could not categorise these reconstructions, then it would demonstrate that while the surface information can enhance categorisation, it is not sufficient for it. This would show, therefore, that surface features in the images do not define artistic categories.

Using artwork was advantageous because of the complex and polymorphous nature of artistic categories. The trade-off for this, however, was that the stimuli were not true images of people or landscapes (the sorts of images that would have more evolutionary significance). This is why I have taken over 1,000 photographs of natural scenes this year, and prepared them in such a way that will allow for a rigorous test of whether people categorise the images based on visual style, or on the basis of the objects depicted in the images. When I took each photograph, I recorded the focus of the image. I have also recorded the presence or absence of particular pre-defined objects. I would take a photograph of a tree, for example, and so record that "tree" was the focus, and I would also record the other objects present in the image (such as human, non-human animal, and water). Or, alternatively, I would take a photograph of a building, and so record "building" as the focus of the photograph, and also record the other objects present in the image (e.g. tree, glass, stone, non-human animal). The photographs *of* a tree should share a common style, regardless of what other objects are also present. Crucially, however, the style of these tree photographs should be distinct from the style of the photographs which contain a tree, but where the focus of the image was some other object.

I want to use these photographs in future research to test whether people will treat the photographs of trees in the same way, and whether this will be qualitatively distinct from how they treat photographs that contain trees, but where some other object was the focus of the image. For example, if these stimuli were presented very briefly to participants in a categorisation task, would they tend to misclassify photographs that were taken of a tree, but with the tree digitally removed, as containing a tree? Would they also tend to misclassify photographs containing a tree, but where the focus of the photograph was some other object, as not containing a tree? If so, then this would strongly suggest that people categorise natural images on the basis of visual *style*, rather than the presence or absence of objects in the image. This would support the idea that people use the broad perceptual information (such as that represented in the early eigenvectors), rather than explicit, language-based features when they analyse natural images.

Another methodological decision we made in this experiment was to use PCA as the method of statistical dimension reduction (SVD is mathematically equivalent to PCA). We chose PCA for two main reasons. Firstly, PCA extracts dimensions of variation that are entirely orthogonal (Tabachnick & Fidell, 2007). Other methods, such as ICA, relax the orthogonality criterion for the dimensions (Brozovic & Andersen, 2006). This would make the interpretation of the dimensions problematic, however, because overlapping information would be represented in separate eigenvectors. Secondly, PCA is relatively simple computationally, compared with some other forms of dimension reduction.

Essentially, however, the exact statistical method used is not a pivotal theoretical concern. Instead, it is just a tool for achieving dimension reduction. The different statistical dimension reduction techniques, furthermore, despite their computational differences, yield similar eigenvectors when applied to natural images (Baddeley & Hancock, 1991; Brozovic & Andersen, 2006; Caywood, Willmore, & Tolhurst, 2004; Hancock et al., 1992; Heidemann, 2006; van Hateren & Ruderman, 1998). The mathematical intricacies of PCA, therefore, are not an important consideration here. What is important, in contrast, is that people could use the limited information from dimension reduction to perform the categorisation task. This suggests that eigenvectors encode for visually important information, and that dimension reduction could be the means via which people learn about the structure of complex categories.

Methodological limitations.

The main methodological limitation was that we did not include an equal number of Picasso and Braque images. There were more Picasso (252) than Braque (127) images, and so we randomly sampled 127 Picassos for each participant. This was done so that each participant would be presented with an equal number of images from each artist. It meant, however, that each participant would be presented with a set of Picasso images, which would most likely differ from the set that the other participants were presented with. This is why we could not statistically compare people's performance with the PCA model's performance.

Future research, therefore, could eliminate the extra Picasso images, and thus use an equal number of images from each artist. This would allow for a statistical comparison between the model and the human data. This is similar to what Landauer et al. (1998) tested with the multiple-choice psychology examinations. They found that both LSA and the students were more likely to make errors on conceptual items than factual items. I expect, therefore, that people and PCA will also make qualitatively similar sorts of errors with the Picasso and Braque categorisation. Specifically, the PCA model should have the highest cosines for those images which people categorise with the highest accuracy, and it should have the lowest cosines for those images which people categorise with the lowest accuracy. This would be strong evidence that people are using a mechanism analogous to PCA when they learn about the structure of complex categories.

Applications

Detecting art fraud.

A potential application of this research is that dimension reduction could be used to detect art fraud. In this experiment we found that the network could use the tacit information in the images to differentiate the highly complex and similar artistic categories. In Vokey et al.'s (2004) research, furthermore, a PCA network revealed a subtle confound in the way the images had been framed. I expect, therefore, that a PCA network could be trained to distinguish a genuine from fake artwork, even if they are highly similar and difficult to differentiate.

Berezhnoy, Postma, and van den Herik (2005) have begun work on designing a computer-based art fraud detection model. However, the unit of information that the model extracts is superficial elements in the paintings, primarily brushstrokes. I suspect, however, that such a feature-based approach will be inadequate. The face recognition literature is informative in this regard. Computerised face recognition models based on facial features such as "distance between the eyes" and "chin shape" are highly fallible, whereas those based on the macro dimensions of variation from PCA, are robust (Abdi et al., 1995; Brunelli & Poggio, 1993; Everson & Sirovich, 1995; Lowe, 1987; Turk & Pentland, 1991). Artwork and faces are alike in the sense that they are both classes of stimuli where a large set of individual instances share the same basic configuration, and are differentiated only by difficult-to-verbalise visual information. This suggests, therefore, that an art fraud detection model that relies on the surface features of the artwork will similarly be fragile, and prone to error under suboptimal test conditions (such as detecting damaged but genuine originals, or fakes that bear the same superficial features as the original). A model based on the dimensions derived from PCA, in contrast, should be robust.

Training novices to be experts.

Another potential application of this research is that the primary dimensions of variability could be used for efficiently training novices to be experts. For example, in training people to distinguish Picasso and Braque artwork, they could be shown the eigenvectors, that is, the main sources of variation in the image set. This would fast track their insight into the dimensions that are most important for distinguishing the categories, an insight which they would normally have to cultivate through extensive experience with individual instances. In the neural network simulation, for example, one of the early eigenvectors appeared to encode for “blue”, that is, the colour blue was an important dimension that distinguished Picasso from Braque images. This was unexpected, as the importance of blue is not something that is obvious from examining the images. Yet when I (repeatedly) completed this experiment myself, I found that this knowledge impressively increased my accuracy. This remains anecdotal, however, and so future research could systematically test whether eigenvectors could be used as a training stimulus to enhance the learning process.

Using eigenvectors as a training stimulus is not necessarily limited to art. Dimension reduction has been found to yield the important dimensions of variation for many diverse tasks (e.g., recognising faces, learning English, and studying introductory psychology). This means that it has the potential to be useful in many different domains. For example, this dimension reduction model could also be used in the medical domain. Specifically, a network could be applied to medical scans (e.g. MRI scans), which would yield the key dimensions of variation for these images. These dimensions could then be used to enhance the training of health professionals to make diagnoses on the basis of these scans. Essentially, dimension reduction could be useful for turning novices into experts in any domain that involves complex visual categories where the key distinguishing information is difficult to summarise in words.

Assisting expert decision-making.

Dimension reduction also has the potential to assist expert decision-making for any task that demands judgements of style about ambiguous visual stimuli. Forensic fingerprint identification, for example, involves making judgements about the “matches” and “non-matches” of complex visual stimuli. Fingerprint professionals currently use a classification system based on simple features such as loops, arches, and whorls in the fingerprints (Vokey, Tangen, & Cole, 2007). This system seems to owe its current usage to precedence, rather than demonstrated validity. Furthermore, given that feature-based approaches to face recognition are incomplete and inadequate, it therefore seems likely that a feature-based approach to fingerprint identification will be similarly limited. Evidence for this is that people do make errors when judging fingerprint matches or non-matches (Vokey et al.). This suggests that fingerprint identification could benefit from an improved classification system.

Dimension reduction is a plausible candidate for a new fingerprint classification system. The advantages of a dimension reduction approach include that: (a) the dimensions do not have to be defined a priori, because the model extracts the important dimensions, and (b) they do not have to be verbally-defined features, but can instead represent the tacit underlying structure of complex visual categories. Future research, therefore, could test whether a network exposed to fingerprint images could learn to accurately make “match” and “non-match” judgements. If so, then dimension reduction could be used to supplement, or even supersede the decision-making processes of fingerprint professionals.

Conclusion

In summary, we found that a PCA network was able to discriminate Picasso and Braque artwork. Its accuracy was optimal using the early eigenvectors, and decreased as more eigenvectors were included. Our human participants, furthermore, could also categorise the Picasso and Braque images reconstructed from the early eigenvectors. They performed better, however, with the images reconstructed using all the eigenvectors. This advantage for the full reconstructions was most likely the result of participants adopting a strategic search for surface features in the images, due to the constraints of the experiment. This explanation is consistent with the pattern of performance across trials, where performance improved for participants presented with the full reconstructions, but not for those presented with the early reconstructions. In future research, we will examine whether under conditions more reflective of everyday life (i.e., diverted analysis), people will perform equally well with the early and full reconstructions. If so, it would suggest that people typically rely on the information encapsulated in the early eigenvectors to make category judgements in everyday life.

The findings from this experiment are consistent with a whole body of other research suggesting that dimension reduction is a psychologically meaningful and biologically plausible model for how people perform a diverse array of tasks, from recognising faces to learning language. In fact, dimension reduction is a comprehensive yet parsimonious explanation of many phenomena that until now have eluded satisfactory scientific explanation. Yet, importantly, this experiment was not just a replication or an extension of prior research with minor modification, instead, it sailed unchartered waters. While other researchers have focused on a single aspect of dimension reduction (such as face recognition, or language acquisition) in isolation, this experiment adopted a broader perspective and investigated whether dimension reduction could be the basis for how people learn about the structure of *any* complex visual category.

Although this study had some minor methodological limitations, it was on the whole a rigorous and meaningful test of the hypothesised dimension reduction mechanism. It has provided direction, furthermore, for future research and potential real-world applications. Ultimately, a deeper understanding of this dimension reduction mechanism has the potential to illuminate many of the mysteries of human cognition.

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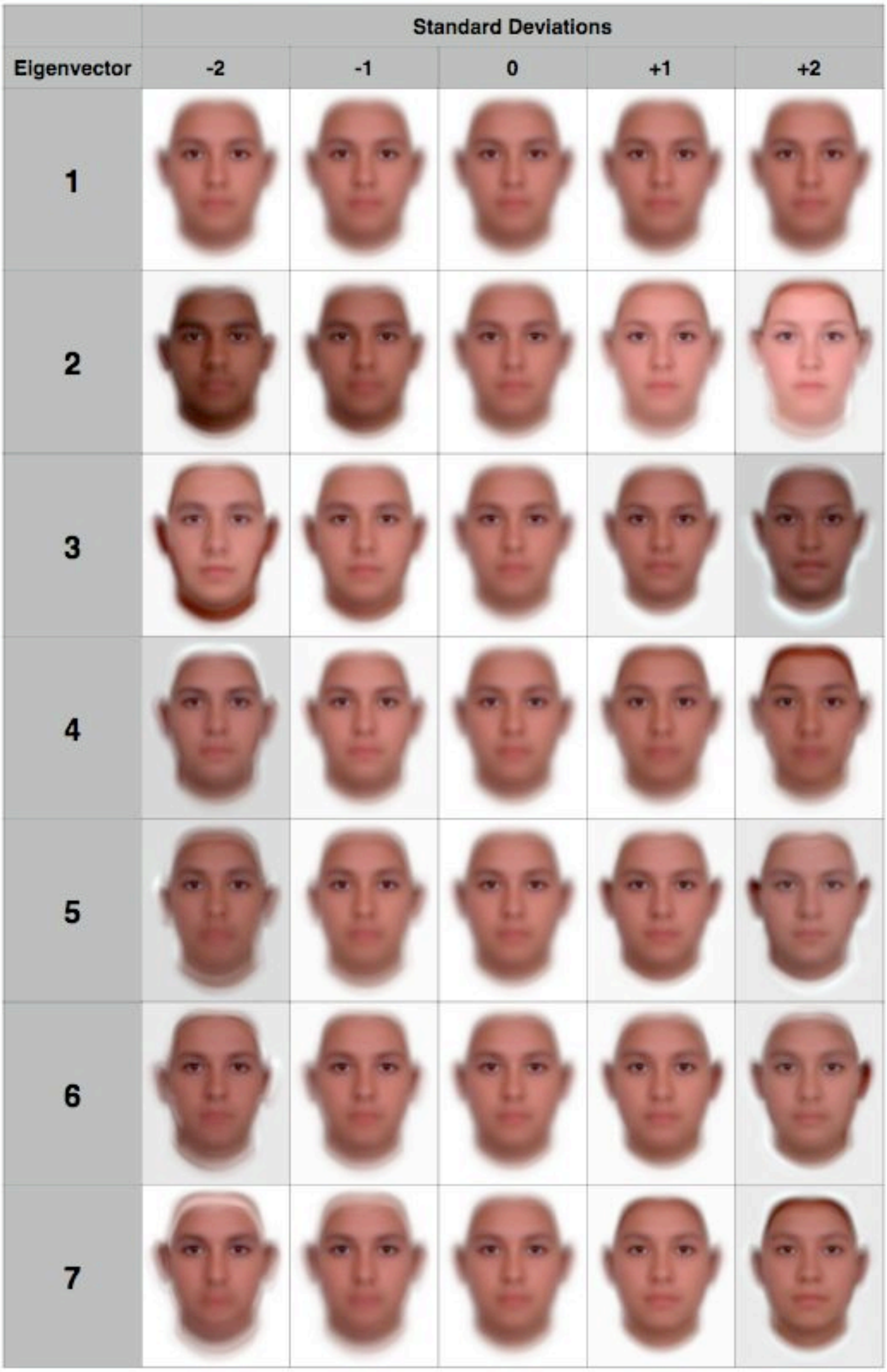
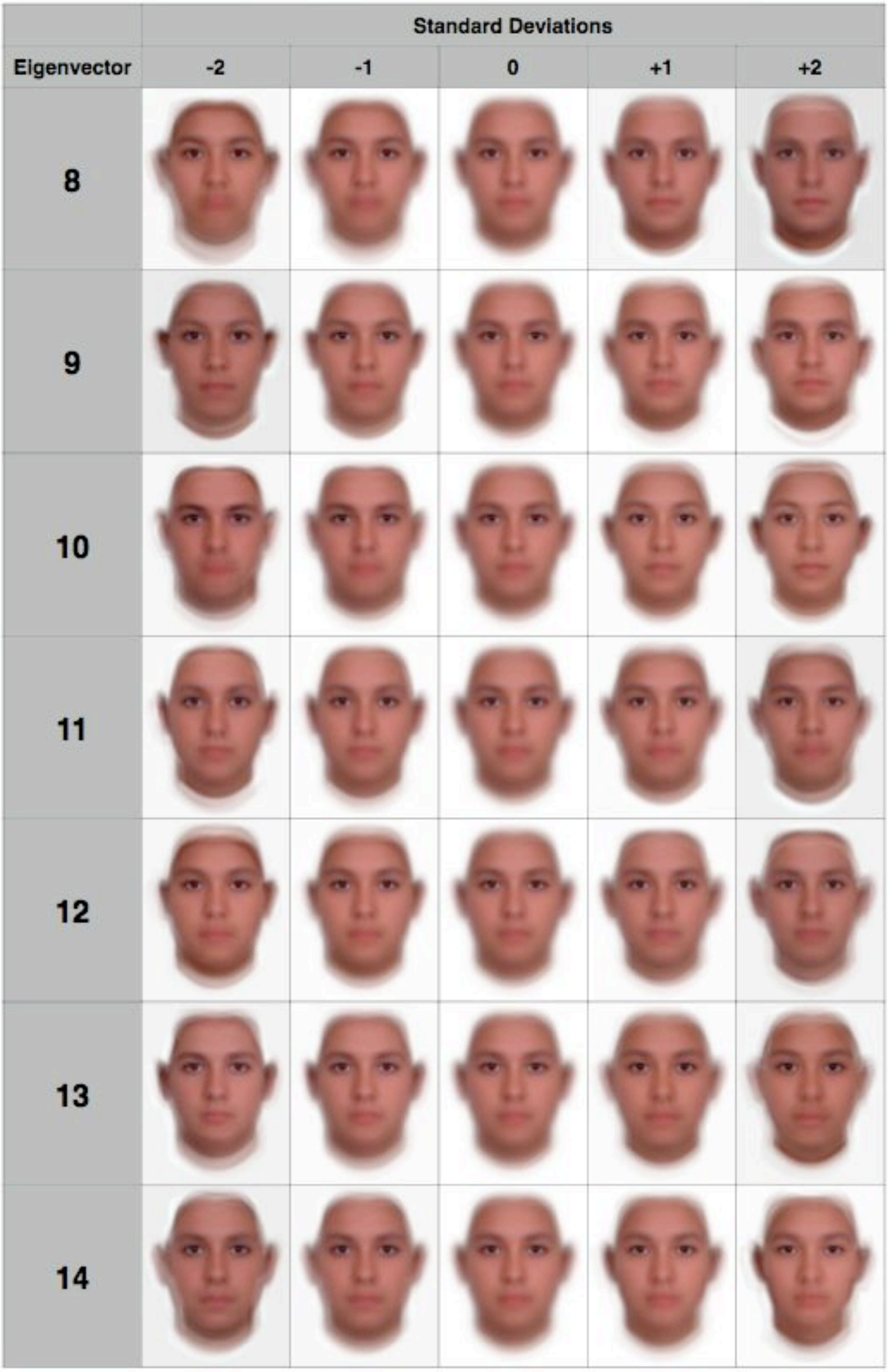
Appendix A



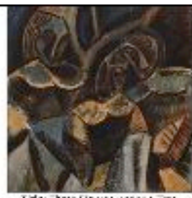

Standard Deviations
Eigenvector
-2
-1
0
+1
+2
8
9
10
11
12
13
14

Appendix B


Title: Jars with Lemon


Title: Les Demoiselles d'Avignon


Title: Pitcher, Bowl, and Lemon


Title: Three Figures under a Tree


Title: Female Nude


Title: Three Women


Title: Bathers in a Forest


Title: Bathers in a Forest


Title: Nude with Raised Arms, in Profile


Title: Standing Nude, Full Front


Title: Friendship


Title: Bathers in a Forest


Title: Kneeling Woman


Title: Composition with Skull

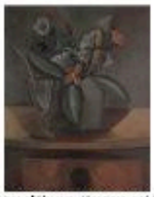

Title: Woman with a Fan


Title: Carafe and Three Bowls


Title: Bowls and Jug


Title: Landscape


Title: Farmer's Wife


Title: Vase of Flowers, Wineglass, and Spoon


Title: House in the Garden

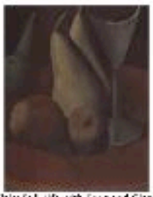

Title: Landscape


Title: Cottage and Trees


Title: The Dryad


Title: Pears and Apples


Title: Fruit Bowl with Pears and Apples


Title: Still Life with Fruit and Glass


Title: Bowl of Fruit


Title: Landscape


Title: Standing Nude Seen from the Back


Title: Landscape with Two Figures


Title: Woman with Raised Arm


Title: Woman with Raised Arm


Title: Three Women


Title: Carnival at the Bistro


Title: Carnival at the Bistro


Title: Still Life with Hat (Cézanne's Hat)


Title: Bread and Fruit Dish on a Table


Title: Fruit Dish


Title: Queen Isabeau


Title: Bather


Title: Woman with Mandolin


Title: St. Anthony and Harlequin


Title: The Chocolate Pot


Title: Landscape with Bridge


Title: Woman with a Book

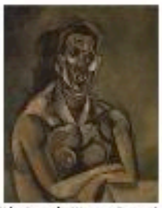

Title: Two Nudes


Title: Woman with a Fan


Title: Woman with a Vase of Flowers

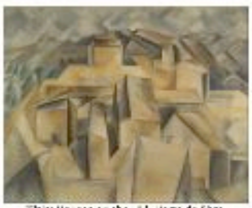

Title: Landscape (Mountain of Santa Barbara)


Title: Portrait of Manuel Pallarès

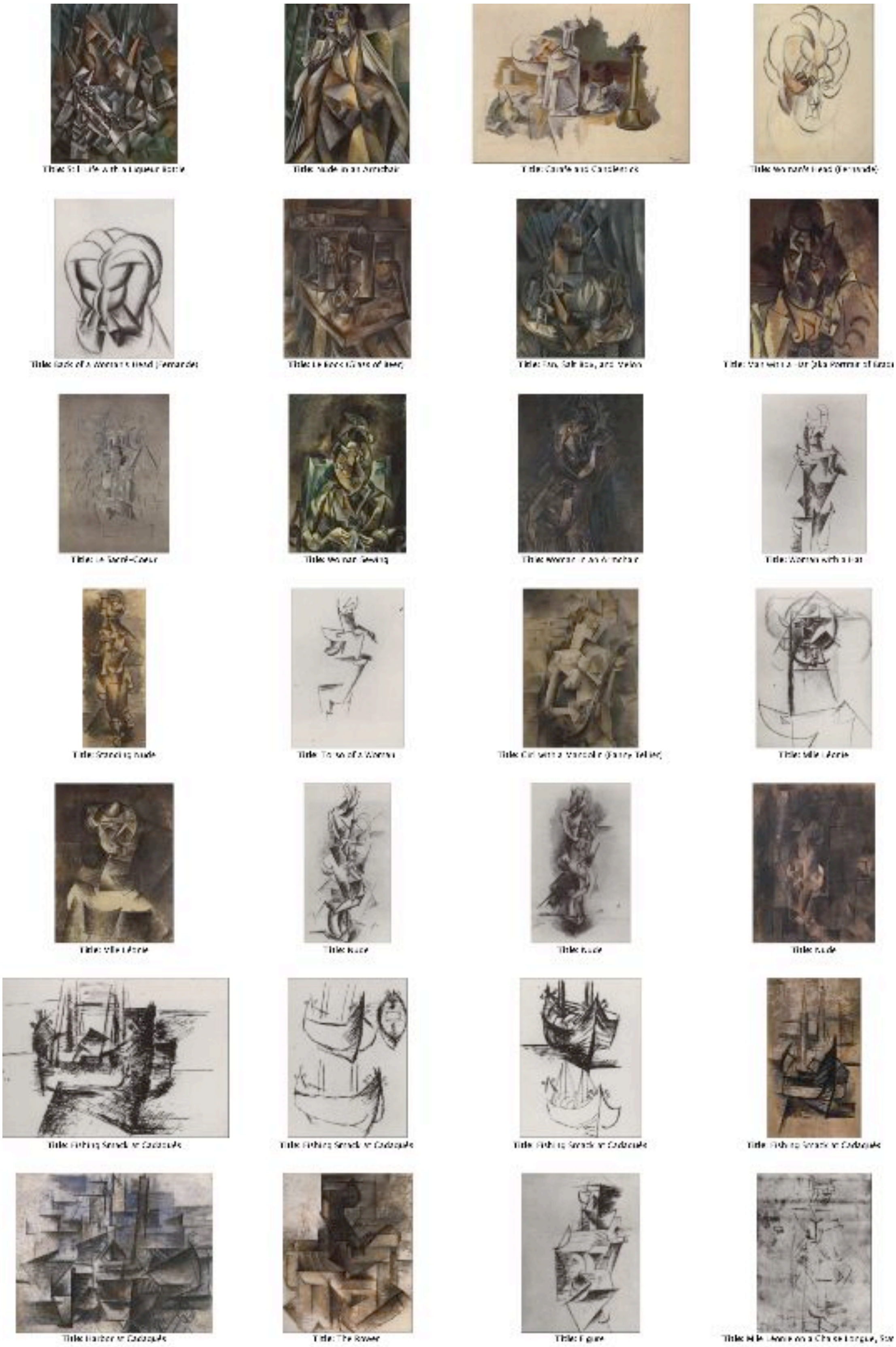

Title: Bust of a Woman (Fernande)


Title: Reservoir at Horta


Title: Mill at Horta


Title: Houses on the Hill, Horta de Ebro


Title: Seated Woman




le: Mlle Léonie (Standing Figure), State II, from Saint Matorel by Max Jacob


Title: Mlle Léonie on a Chaise Longue, State II, from Saint Matorel by Max Jacob


Title: Standing Nude


Title: Woman with a Mandolin


Title: Guitarist


Title: Still Life with Glass and Lemon


Title: The Table, from Saint Matorel by Max Jacob


Title: Standing Nude


Title: Standing Nude


Title: Standing Nude

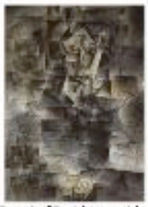

Title: Portrait of Wilhelm Uhde


Title: Portrait of Ambroise Vollard


Title: The Dressing Table


Title: Vase of Flowers


Title: Field Glasses


Title: Portrait of Daniel-Henry Kahnweiler


Title: Buffalo Bill


Title: Woman with a Guitar or Mandolin


Title: Pedestal Table with Wineglasses, Cup, and Mandolin


Title: Woman with a Guitar at a Piano


Title: Accordionist


Title: Glass with Straws


Title: Head of a Man with a Pipe


Title: Head of a Man


Title: Head


Title: Landscape at Céret


Title: Clarinet


Title: Still Life with Fan (L'Indépendant)


Title: Head of a Man with a Moustache


Title: Head of a Man


Title: Head


Title: Man with a Mandolin


Title: Man with a Mandolin


Title: Seated Man


Title: The Aficionado


Title: The Aficionado


Title: Standing Nude


Title: Violin and Grapes


Title: Guitarist


Title: Guitarist


Title: Study for a Construction


Title: Seated Figure with a Guitar


Title: Guitarist


Title: Guitarist


Title: Woman with a Guitar


Title: Guitarist


Title: Table and Dish of Pears


Title: Head of a Man


Title: Head


Title: Seated Woman with Guitar


Title: Head

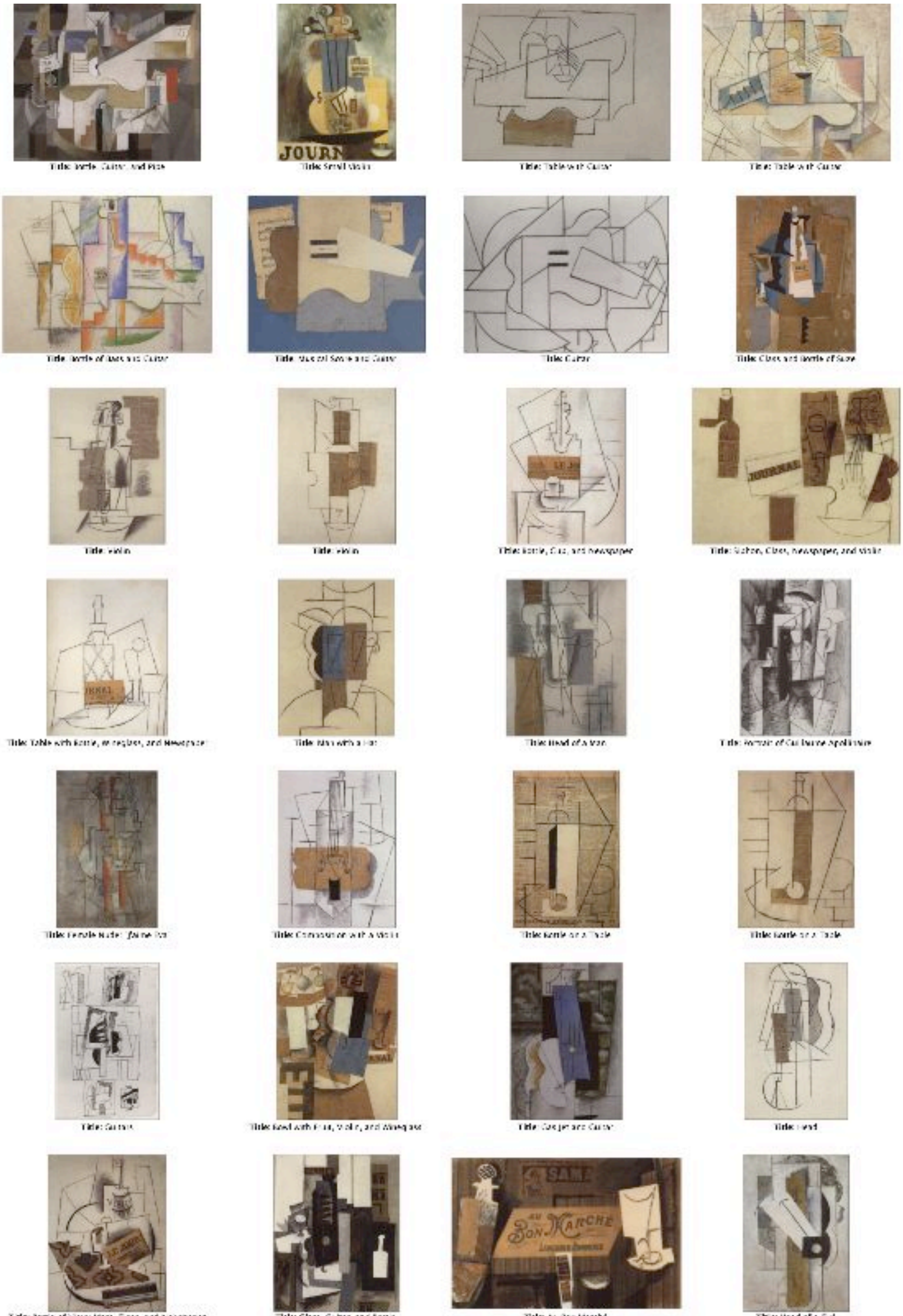

Title: Guitar


Title: L'Arlésienne


Title: Standing Woman


Title: Guitar and Sheet Music

Title: Guitar, Sheet Music, and Glass



Title: Bottle, Guitar, and Pipe
Title: Small Violin
Title: Table with Guitar
Title: Table with Guitar
Title: Bottle of Bass and Guitar
Title: Musical Score and Guitar
Title: Guitar
Title: Glass and Bottle of Suze
Title: Violin
Title: Violin
Title: Bottle, Cup, and Newspaper
Title: Siphon, Glass, Newspaper, and Violin
Title: Table with Bottle, Wineglass, and Newspaper
Title: Man with a Hat
Title: Head of a Man
Title: Portrait of Guillaume Apollinaire
Title: Female Nude: J'aime Eva
Title: Composition with a Violin
Title: Bottle on a Table
Title: Bottle on a Table
Title: Guitars
Title: Bowl with Fruit, Violin, and Wineglass
Title: Gas Jet and Guitar
Title: Head
Title: Bottle of Vieux Marc, Glass, and Newspaper
Title: Glass, Guitar, and Bottle
Title: Au Bon Marché
Title: Head of a Girl


Title: Head of a Man


Title: Head of a Harlequin


Title: Three Heads


Title: Guitarist with a Hat


Title: Guitarist


Title: Man with a Guitar


Title: Guitar


Title: Bar Table with Guitar


Title: Head of a Man with a Moustache


Title: Head

Title: Bottle of Vieux Marc, Glass, Guitar, and Newspaper


Title: Guitar


Title: Standing Woman


Title: Man with a Guitar and Woman


Title: Woman on a Chaise Lounge


Title: Woman in an Armchair


Title: Woman in an Armchair


Title: Woman in an Armchair


Title: Woman in an Armchair


Title: Woman in an Armchair


Title: Woman in an Armchair


Title: Hat Decorated with Grapes


Title: Violin


Title: Woman with a Guitar


Title: Card Player


Title: Student with a Pipe


Title: Student with a Newspaper


Title: Woman with a Mandolin


Title: Still Life with Skull, State 1: from Le Siège de Jérusalem by Max Jacob


Title: Guitar, Skull, and Newspaper


Title: Woman with a Guitar


Title: Wineglass, Bottle of Bass, and Ace of Clubs


Title: Pipe and Wineglass


Title: Pipe and Sheet Music


Title: Bottle of Bass, Wineglass, Packet of Tobacco, and Calling Card


Title: Pipe, Glass, and Bottle of Rum


Title: Pipe, Wineglass, Newspaper, Guitar, and Bottle of Vieux Marc: "Lacerba"


Title: Pipe, Glass, Ace of Clubs, Bottle of Bass, Guitar, and Dice: "Ma Jolie"


Title: Bass, Wineglass, Bottle of Vieux Marc, and Newspaper


Title: Wineglass and Ace of Clubs (homage to Max Jacob)


Title: Pipe, Violin, and Bottle of Bass


Title: Smoker


Title: Green Still Life


Title: Bar Table


Title: Sailor and Figure at a Table


Title: Seated Man at a Table


Title: Sailor and Woman


Title: Seated Man with Cards


Title: Seated Man at a Table


Title: Seated Man at a Table


Title: Seated Man at a Table


Title: Seated Man at a Table


Title: Man with a Mask, Playing a Guitar


Title: Bearded Man Playing a Guitar


Title: Still Life with Cards, Glasses, and Bottle of Rum: "Vive la France"


Title: Portrait of a Girl

Appendix C


Title: Still Life with Jugs and Pipe


Title: Landscape at La Ciotat


Title: Terrace of Hôtel Mistral


Title: Viaduct at L'Estaque


Title: Standing Nude


Title: Landscape at L'Estaque


Title: Standing Nude


Title: Viaduct at L'Estaque


Title: Large Nude


Title: Bay at L'Estaque


Title: Terrace at L'Estaque


Title: Road near L'Estaque


Title: Jug and Coffeepot


Title: Viaduct at L'Estaque


Title: House at L'Estaque


Title: Houses at L'Estaque


Title: Trees at L'Estaque


Title: Musical Instruments


Title: Plate and Fruit Dish


Title: Landscape


Title: Landscape with Houses


Title: Harbor


Title: Fruit Dish


Title: Guitar and Fruit Dish


Title: Harbor in Normandy


Title: Castle at La Roche-Guyon


Title: Castle at La Roche-Guyon


Title: Castle at La Roche-Guyon


Title: Castle at La Roche-Guyon


Title: The Park at Carrières Saint-Denis


Title: Violin and Palette


Title: Still Life with Mandola and Metronome


Title: Lighter and Newspaper: 'Gil Blas'


Title: Glass on a Table


Title: Mandola


Title: Piano and Mandola


Title: Violin and Pitcher


Title: Le Sacré-Coeur


Title: Violin and Candlestick


Title: Figure


Title: Female Figure

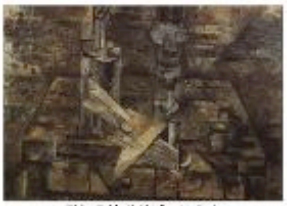

Title: Rio Tinto Factories at L'Estaque


Title: Checkerboard and Playing Cards


Title: Candlestick


Title: Guitar on a Table


Title: Bottle and Fishes


Title: Table (Still Life with Fan)


Title: Harmonica and Flageolet


Title: Still Life on a Table 'Bass'


Title: Still Life with Bottle


Title: Girl with a Cross


Title: Pedestal Table


Title: Job


Title: Man with a Guitar


Title: Rooftops at Céret


Title: Bottle and Glass


Title: Candlestick


Title: Fox


Title: Bar Table


Title: Still Life with Banderillas


Title: Still Life


Title: Bottle of Gentiane


Title: Clarinet and Bottle of Rum on a Mantelpiece


Title: Woman Reading


Title: Still Life with Harp and Violin


Title: Pedestal Table


Title: Still Life with a Glass (Figure with a Guitar)


Title: Pedestal Table

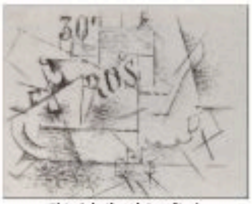

Title: Figure with a Guitar


Title: Figure with a Guitar


Title: Bass


Title: Le Portugais (The Emigrant)


Title: Still Life with a Violin


Title: Still Life with Glass "Ros"


Title: Bottle, Glasses, Fan, and Pipe


Title: Bottle of Bass and Glass on a Table "Bal"


Title: Homage to J.S. Bach


Title: Bottle of Marc


Title: Glass, Sheet Music, and Bottle of Rum


Title: Still Life "Figaro"


Title: Violin and Clarinet


Title: Bottle and Glasses


Title: Violin: "Mozart/Kubelick"


Title: Fruit Dish and Glass


Title: Fruit Dish, Bottle, and Glass: "Sorgues"


Title: Woman in an Armchair: "Sorgues"


Title: Fruit Dish and Glass

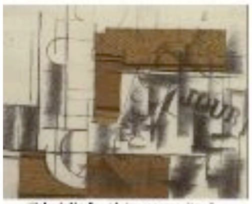

Title: Fruit Dish, "Quotidien du Midi"


Title: Head of a Woman


Title: Man with a Pipe


Title: Violin


Title: Bal


Title: Still Life with Newspaper: "Jour"


Title: Bottle of Marc


Title: Newspaper and Glass: "Jour"


Title: Still Life with a Violin


Title: Glass and Packet of Tobacco: "Bock"


Title: Still Life with Guitar


Title: Violin and Newspaper (Musical Forms)


Title: Pedestal Table


Title: Fruit Dish, Ace of Clubs


Title: Violin and Glass


Title: Violin and Glass


Title: Clarinet


Title: Guitar


Title: Woman with a Guitar


Title: Checkerboard: "Tivoli-Cinéma"


Title: Guitar and Program: "Statue d'Épouvante"


Title: Violin and Pipe: "Le Quotidien"


Title: Glass and Bottle


Title: Bottle of Eau-de-Vie


Title: Still Life with Ace of Hearts

Title: Glass, Bottle, and Newspaper

Title: Pipe, Glass, Die, and Newspaper

Title: Bottle of Rum

Title: Still Life with Bottle

Title: Bottle of Rum

Title: The Violin

Title: Still Life on a Table: "Gillette"

Title: Bottle, Glass, and Pipe

Title: Glass and Cigarette Pack

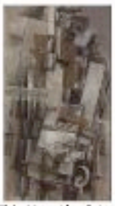
Title: Newspaper, Bottle, Packet of Tobacco

Title: Still Life with Checkerboard and Pack of Cigarettes

Title: Violin: "Mélodie"

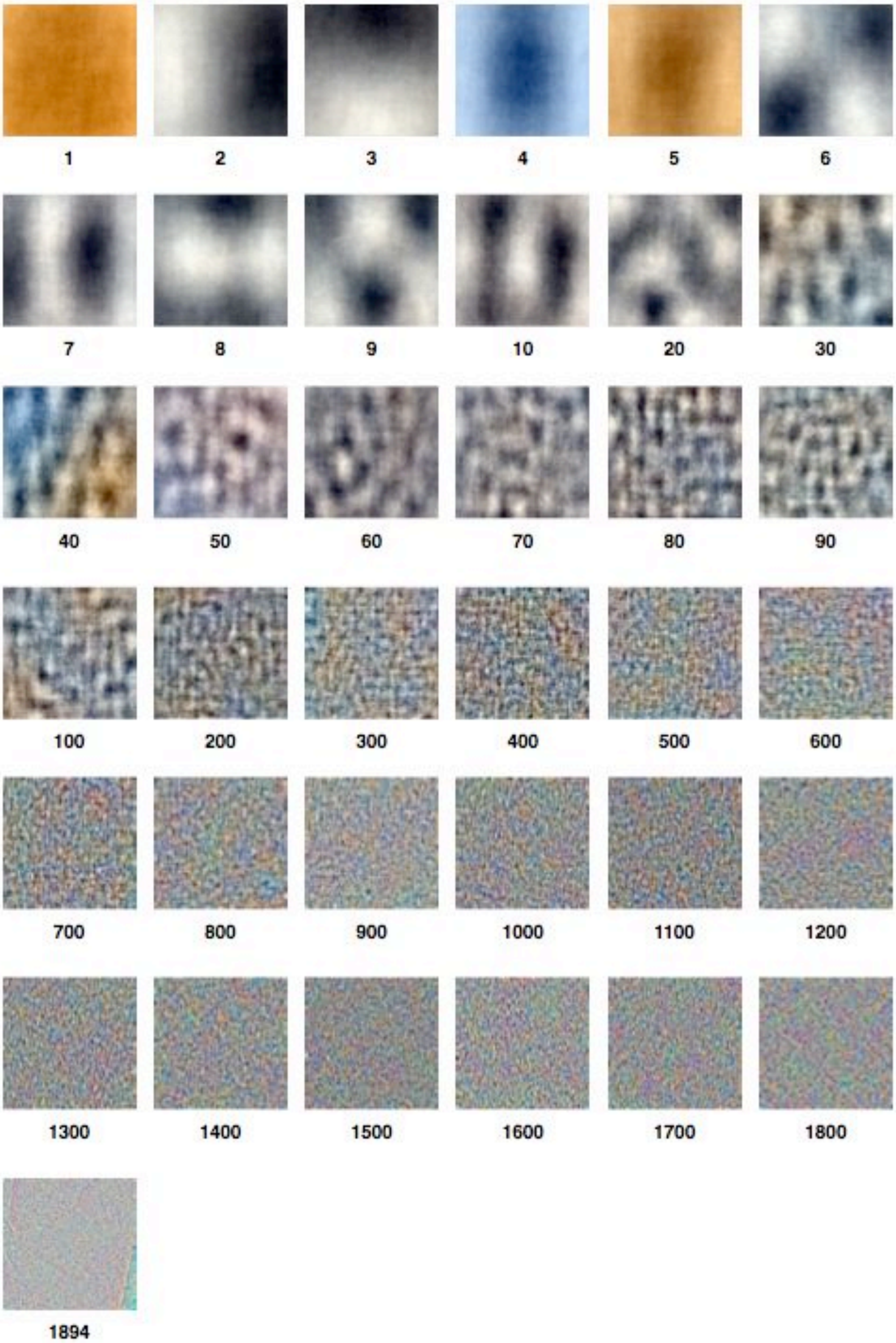
Title: Mandolin

Title: Bottle of Rum



Title: Man with a Guitar

Appendix D


1
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1100
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1400
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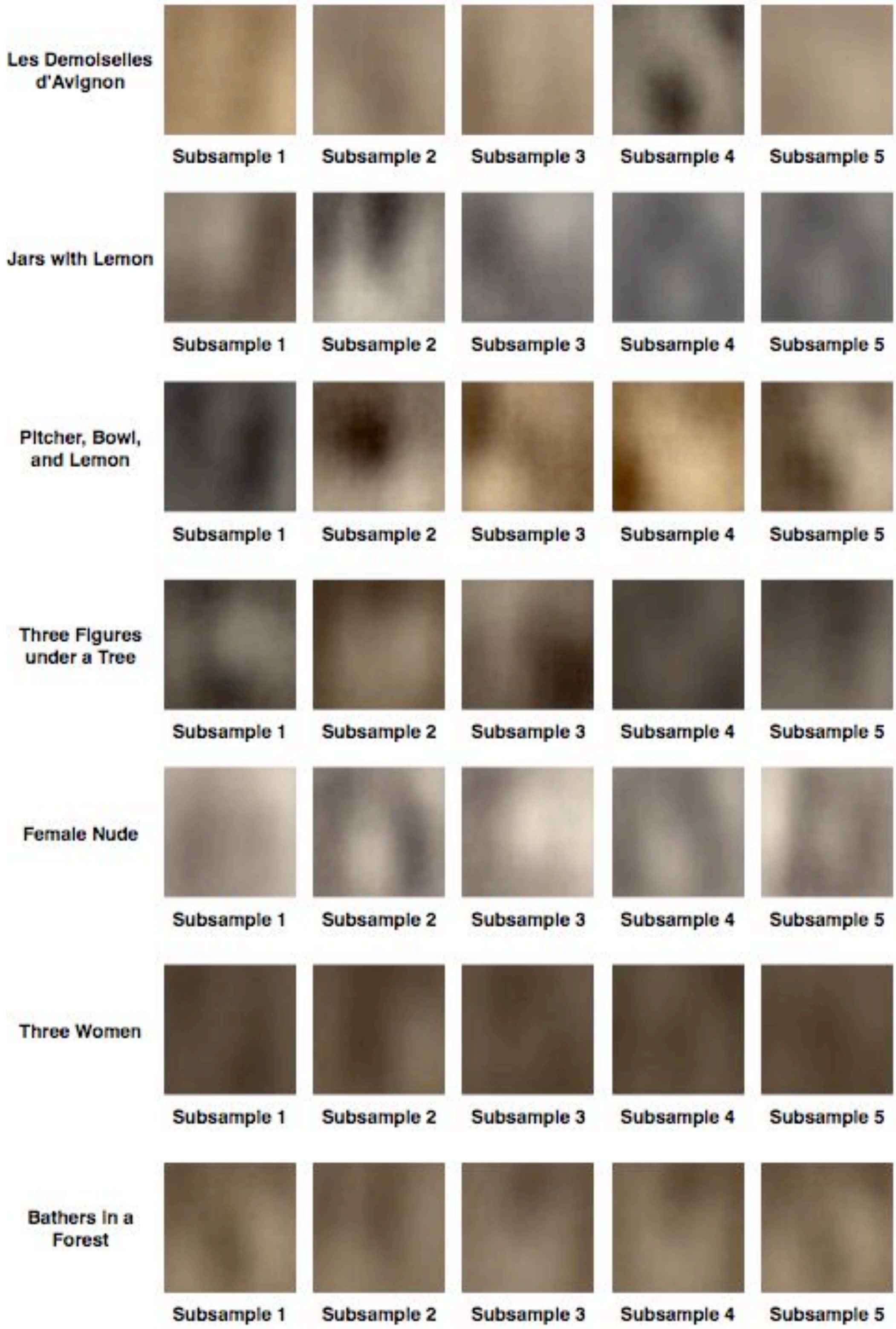
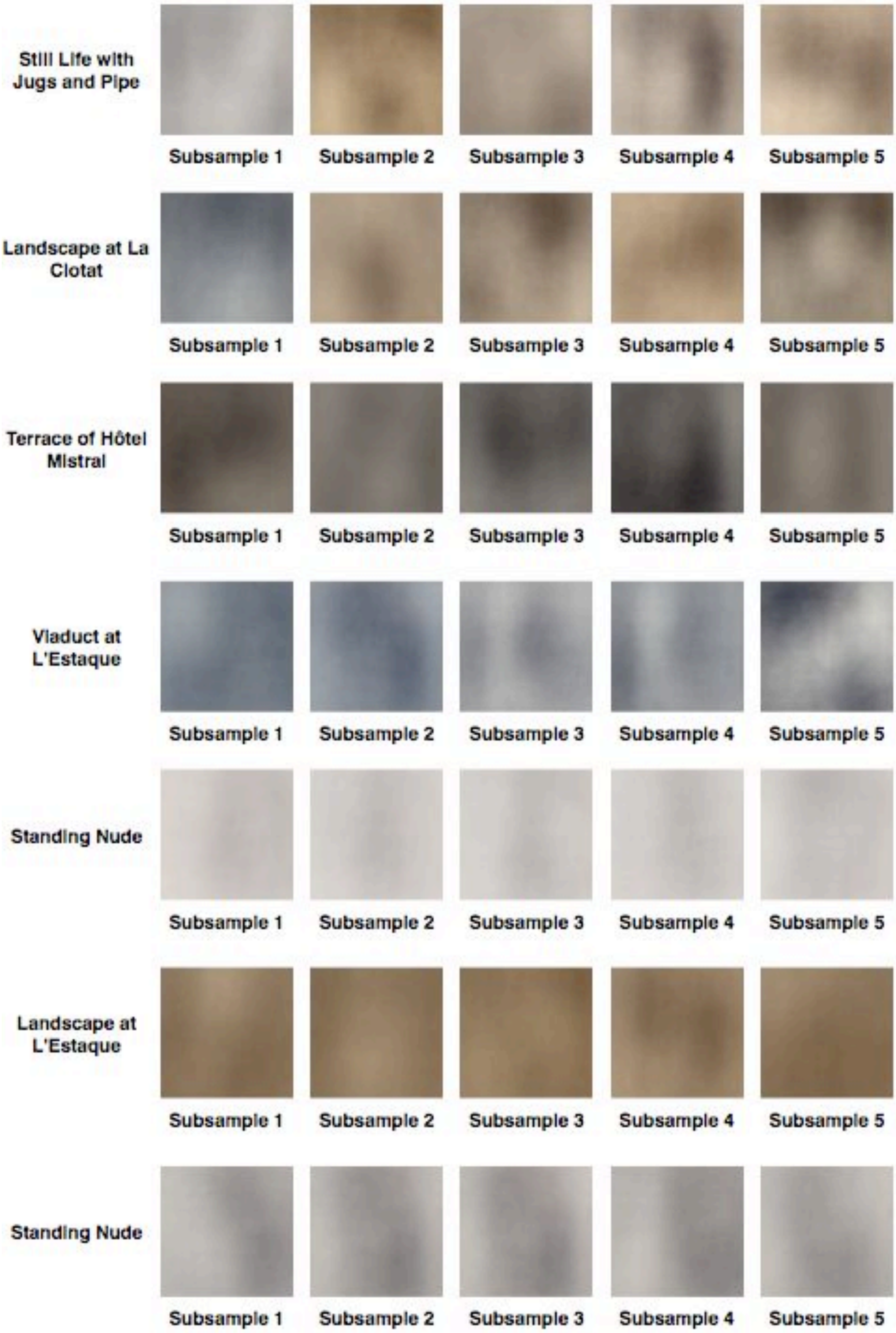
1600
1700
1800
1894

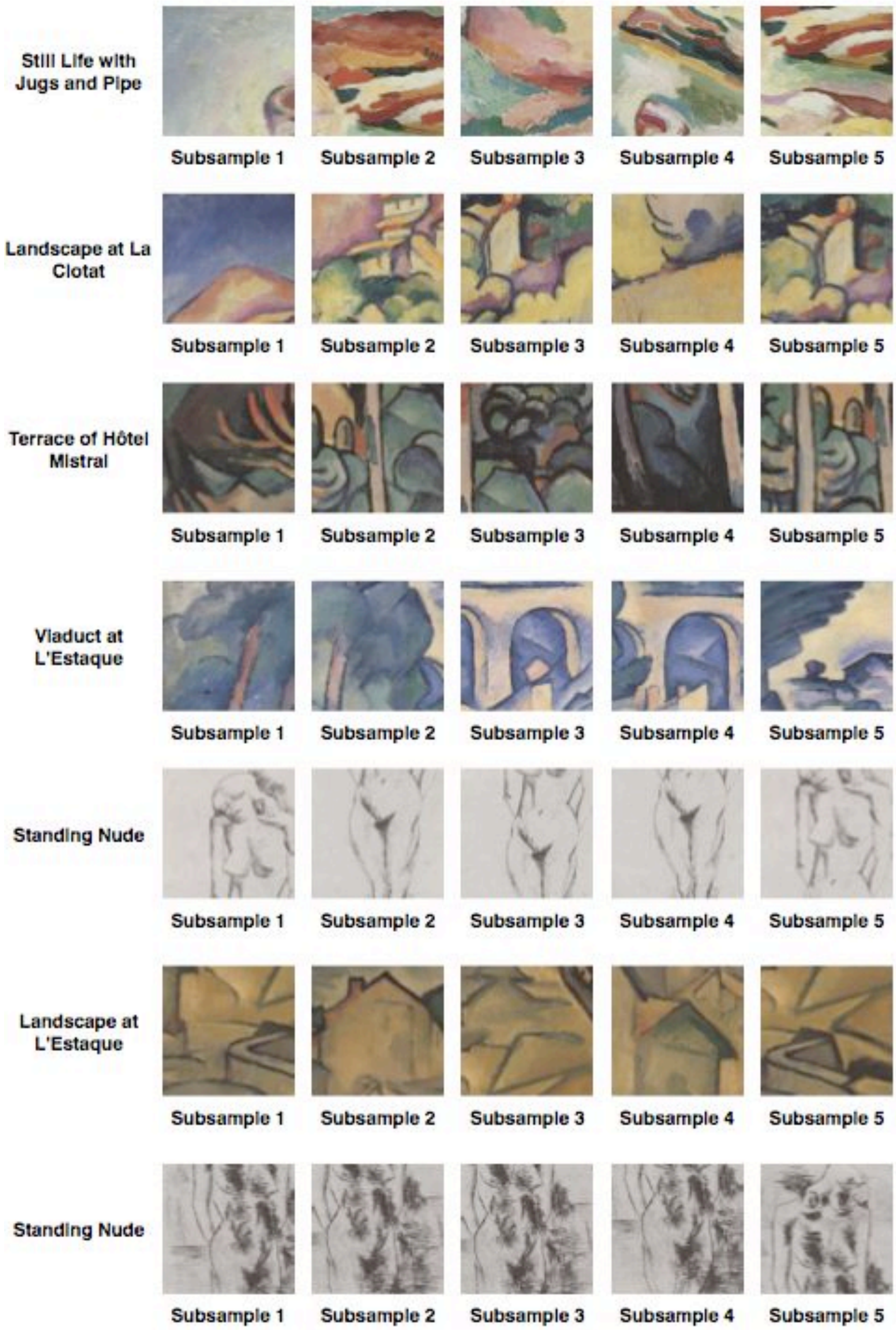
Appendix E


Les Demoiselles d'Avignon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Jars with Lemon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Pitcher, Bowl, and Lemon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Three Figures under a Tree
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Female Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Three Women
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Bathers in a Forest
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5


Still Life with Jugs and Pipe
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Landscape at La Ciotat
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Terrace of Hôtel Mistral
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Viaduct at L'Estaque
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Standing Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Landscape at L'Estaque
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Standing Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5

Appendix F


Les Demoiselles d'Avignon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Jars with Lemon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Pitcher, Bowl, and Lemon
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Three Figures under a Tree
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Female Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Three Women
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Bathers in a Forest
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5


Still Life with Jugs and Pipe
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Landscape at La Clotat
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Terrace of Hôtel Mistral
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Viaduct at L'Estaque
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Standing Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Landscape at L'Estaque
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5
Standing Nude
Subsample 1
Subsample 2
Subsample 3
Subsample 4
Subsample 5

Appendix G

You will be presented with samples of paintings from two different artists (A and B), and it is your job to learn the difference between them. After you click the "Begin" button below, two painting samples will appear side by side on the screen. You will guess which of the two samples belongs to Artist A.

A smiley face will appear on the screen if you are correct, and a frowny face will appear if you're incorrect. In addition, you will be awarded with 100 points for each correct response, and we will take away 100 points for every incorrect response. The goal is to earn as many points as you can during the experiment.

Obviously, you will be guessing initially, but once you begin the learn the particular style of each artist, you will make more correct responses.

Please be sure that you have read the instructions carefully. If you have any questions, please ask the experimenter now. If not, press the "Begin" button below.

Begin

Appendix H