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Running head: Face-space models

## **Face-Space Models of Face Recognition**

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## Face-Space Models of Face Recognition

Recent research into face processing has produced considerable technical and theoretical advances. For example, it is possible to generate photographic-quality colour caricatures of faces; principal component analysis can be used to provide efficient storage of facial images; laser scans can produce a 3D model of an individual's head that can be manipulated by use of software; a model head can be animated to appear to speak, and facial images can be 'aged' by application of a mathematical algorithm. Nevertheless, the question 'How do we recognise faces?' remains extremely difficult to answer with any precision. In contrast, formal models have been used successfully to account for human performance in recognising, categorising and identifying artificial concepts. In this chapter the rôle of formal models in providing a basis for understanding our ability to recognise faces in the real world will be critically evaluated.

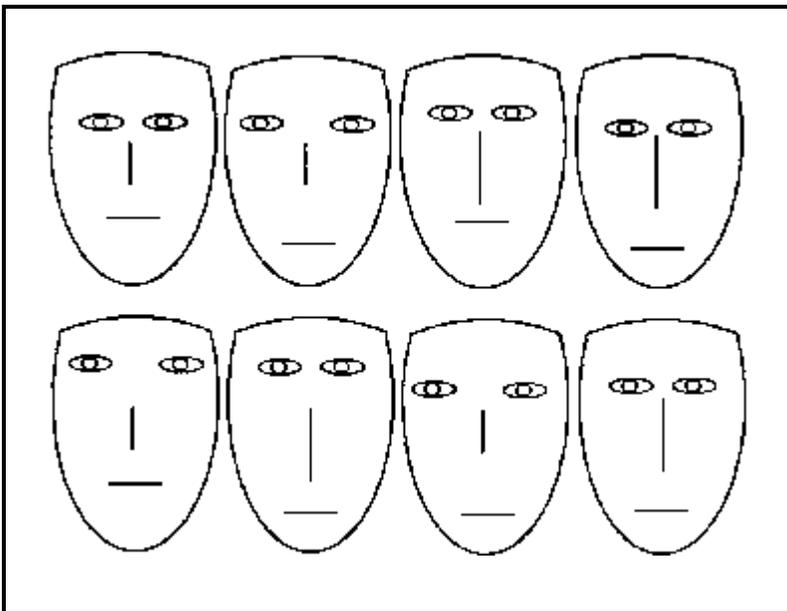


Figure 1: An example of a set of schematic faces. Similar stimulus sets have been used in many categorisation experiments. The faces differ in the distance between the eyes, the position of the eyes, the length of the nose and the position of the mouth.

Can formal models of concept representation tell us anything about face recognition?

Several formal models of the representation, classification and recognition of artificial stimuli have been developed, which assume that the relevant stimuli are represented within a multidimensional space. The central assumptions of many of the models are closely related (see Ashby and Townsend, 1986; Ashby and Perrin, 1985; Nosofsky, 1986; Busey, this volume; Townsend, Soloman & Spencer-Smith, this volume). This formal approach has been highly successful in accounting for human performance in laboratory experiments. In order to develop and test a formal model it is necessary to identify and control the relevant features or dimensions. The approach has, therefore, concerned the processing of sets of highly artificial and relatively simple stimuli. Schematic faces have often been used in these experiments. (For example; Reed, 1972; Goldman and Homa, 1977; Medin and Schaffer, 1978; Neumann, 1977; Nosofsky, 1991;

Solso and McCarthy, 1981). Figure 1 illustrates the type of stimulus set used in these experiments.

As schematic faces have been used to develop formal models of concept representation and recognition, one might imagine that the models would be valuable in understanding the processes involved in recognising familiar faces in everyday life. The question posed is whether a model that can account for recognition of a restricted set of stimuli, similar to those in Figure 1, can also account for recognition of images of natural faces, such as those in Figure 2. The models used to simulate schematic face processing are based on the assumption that a face can be described as a set of values on a fixed number of dimensions. At first sight there are some obvious problems with this approach when it is applied to realistic images of faces. The features that distinguish the faces in Figure 1 are carefully controlled and are easily identifiable (i.e. the position of the eyes, the distance between the eyes, the length of the nose and the position of the mouth). It is not a trivial problem to identify an equivalent set of features that distinguish the faces in Figure 2. In summary, the information available for processing artificial stimuli can be defined and measured, but we do not yet have a suitable means to quantify the information available in natural faces. (See the chapters by O'Toole, Wenger & Townsend; Edelman & O'Toole; Townsend et al. and Campbell, Massaro & Schwartz in this volume for further discussion of this issue.)



Figure 2: A set of photographs of faces. What are the features on which these faces differ?

Following formal treatments of feature salience (e.g. Tversky, 1977), an influential approach to face recognition has been to attempt to define the salience of facial features (e.g. eyes, nose, mouth). However, it was found that the salience of facial features was different for unfamiliar and famous faces (Ellis, Shepherd & Davies, 1979), and that subtle changes in the relative position of facial features can have a dramatic effect on the appearance of a face (Hosie, Ellis & Haig, 1988).

My own approach has been to argue that in order to learn how faces are recognised in the real world, we must base our laboratory experiments on natural faces, or at least photographs of natural faces (e.g. Valentine, 1991a, p.167). Many of the principles of formal models can be used to understand face recognition, but much of the mathematical precision is lost because we do not have precise knowledge of the features or dimensions on which faces vary.

### Distinctiveness

A striking observation is that some faces are much easier to recognise than others. Why should this be so? An intuitive account would be that the faces that are most recognisable are those which are more distinctive in the general population. Of course, the participants in face recognition experiments bring with them a lifetime's experience of looking at faces. This raises the issue of how distinctiveness of faces can be measured. Formal definitions of distinctiveness (e.g. Murdock, 1960, Neath 1993) can provide a measure of the distinctiveness of each stimulus in a set but are restricted to stimuli that vary along a single dimension. The highly multidimensional nature of faces and the lack of definition of 'values' on many dimensions (e.g. hair texture) means that such approaches cannot provide a measure of distinctiveness for faces.

A distinction can be drawn between information and information-processing (e.g. Massaro, 1998). Although we do not know how to measure the information available for face processing, we can measure various outcomes of information-processing and form qualitative predictions of the relationship between these measures. For example, the relative perceived distinctiveness of faces can be assessed by collecting subjective ratings. Respondents are asked to rate, on a scale from 1 to 7, how easy each face in a set would be to spot in a crowd. Subjective ratings might appear to be a rather blunt instrument, but fortunately there is considerable agreement across different respondents in such judgements, so that each face can be assigned a value of distinctiveness based on the mean ratings given by a number of respondents. It is important to note that this approach is entirely different from the concept of 'cue saliency'. Studies of cue salience assume that, for all faces, one feature (e.g. the eyes) is more salient than another (e.g. the mouth). The concept of distinctiveness suggests that the salience of any facial feature will vary from one face to another depending on the distinctiveness of the feature. It is also important to note that distinctiveness can only be judged relative to a population (Murdock, 1960).

In a recognition memory task participants have to identify faces seen previously from a list that includes 'old' faces mixed in a random order with 'new' faces. Participants are more likely to correctly identify an 'old' face if it is distinctive. They are also less likely to make a 'false positive' response to a new distinctive face than to a new typical face (e.g. Light, Kayra-Stuart & Hollander, 1979). Thus, distinctive faces benefit from a double advantage --- more 'hits' and fewer 'false positives' --- making recognition of distinctive faces more accurate than recognition of typical faces. Thus, distinctiveness of faces is one of a class of 'mirror-effect' variables that have opposite effects on hit rate and false alarm rate (Glanzer and Adams, 1985; 1990)

If the effect of distinctiveness reflects a fundamental property of the manner in which faces are represented, an effect of distinctiveness should be observed on recognition of familiar faces (e.g. celebrities' faces). Valentine and Bruce (1986) tested this prediction using a 'face familiarity decision task'. A set of celebrities' faces which were rated as highly distinctive were matched on rated familiarity to a corresponding set of celebrities' faces rated as more 'typical'. These famous faces were presented one at a time in a random order mixed with an equal number of unfamiliar faces. Participants were required to press a button to indicate, as quickly as possible, whether each face was 'familiar' or 'unfamiliar'. Distinctive famous faces were recognised more quickly than typical famous faces

It could be argued that distinctive faces would be processed more quickly or accurately in any task because, being more unusual in appearance than typical faces, people attend more closely to them. This interpretation can be demonstrated to be wrong by consideration of a 'face classification task', in which participants are required to decide whether a stimulus is a face or a jumbled face as quickly as possible. Valentine and Bruce (1986) showed that intact typical faces were judged to be faces more quickly than intact distinctive faces.

The effects of distinctiveness on face processing can be interpreted by thinking of faces as located in 'face-space'. The centre of the space is assumed to represent the average value of the population on each dimension. The dimensions of the space will be those which serve to discriminate between faces. The nature and the number of dimensions required are issues that are addressed by current research (see Townsend et al., this volume). However, face-space is assumed to be multidimensional and may require a high-dimensional space. It is assumed that faces will form a normal distribution on each dimension (i.e. a multivariate normal distribution in face-space). Thus face-space is within the same general class of model as multidimensional generalizations of signal detection theory and multidimensional scaling models (e.g. Ashby & Townsend, 1986; Nosofsky, 1986).

Even for a face-space of high dimensionality, the assumption of a multivariate normal distribution means that two assumptions will be true. First, the centre of the space will be the point of highest exemplar density (for both local and global measures of exemplar density). Second, the exemplar density will decline as a monotonic function of the distance from the centre. There will be many 'typical' faces which will be located relatively close to the centre, and there will be fewer distinctive faces which will be located further from the centre of the space, in less densely 'populated' regions. The similarity between two faces located close to each other is greater than the similarity of two faces that are further apart. Face-space is a psychological space (e.g. Shepherd, 1987) but the similarity metric cannot be determined because the dimensions of the space are not known (see O'Toole et al., this volume; Townsend et al., this volume; Valentin et al., this volume).

It is assumed that the perceptual encoding of a face has some error or 'noise' associated with it (cf. general recognition theory, Ashby and Townsend, 1986). The size of the error would be affected by the encoding conditions, such that difficult encoding (due to a brief exposure or inverted presentation of a face, for example) would increase the error associated with a face. The decision rule that operates in face-space has not been defined, due the lack of definition of parameters of natural faces. However, a minimum distance rule (see for example Ashby & Gott, 1988) is often implicit in the discussion of recognition in face-space (e.g. Valentine, 1991a).

According to the face-space framework, distinctive faces are recognised better because they are further from neighbouring faces in the space and so are less susceptible to confusion between faces located near each other in the space. It is assumed that the exemplar density of faces in the region in which a stimulus is encoded affects the decision latency in a face classification task. Typical faces are classified as faces faster than distinctive faces because typical faces are closer to the centre of the space and so lie in regions of higher exemplar density. Further details of face-space can be found in Valentine (1991a, 1991b, 1995).

The use of multidimensional similarity spaces to represent stimuli is widespread in formal models of cognition and has been a highly influential approach. The need to measure accurately the information available in a stimulus is an important limitation in applying the technique to natural faces. This limitation makes it impossible to develop models that can provide quantitative predictions. It may appear that so much of the essence of a formal approach is lost that the enterprise is inevitably worthless. Notwithstanding the limitations encountered by the formal models, the approach has provided a framework for understanding a wide range of data, including experimental data derived from recognition of faces despite changes in facial expression and orientation. Considerable insight has been gained into understanding the relationship between a number of variables (e.g. the effects of distinctiveness, inversion, caricature, and race) in a range of face processing tasks (e.g. recognition, identification and classification of faces). Examples of the utility of the face-space framework can be found in Valentine (1995).

Before exploring the face-space framework in more detail, it is necessary to distinguish three broad approaches to face-space. They differ in terms of the nature of the dimensions and the metric of the space. First, there is the assumption that the dimensions of the space represent the perceptual dimensions or features of faces. Therefore, if face-space could be fully defined, it would be a psychological similarity space similar to that used in the general Gaussian recognition model (Ashby & Townsend, 1986) or the generalized context model (Nosofsky, 1986).

The second use arises from a computer caricature generator developed by Brennan (1985). Caricatures are generated by manipulating the similarity of an individual face relative to an average face. The process amounts to moving a face in a multidimensional 'face-space' away from the centre. Note however that this space is defined physically by the points on faces measured manually when 'encoding' a face for the caricature generator. Therefore, the space is an image-based space in which the dimensions are physical dimensions of the face. A distinction should be drawn between the image space of a caricature generator and a psychological similarity space.

The third approach to face-space is that provided by principal component analysis and connectionist modelling (e.g. O'Toole, Abdi, Deffenbacher & Valentin, 1995). Usually the pixel values of face images provide the input to an artificial neural network (e.g. an autoassociator). Simulations show some results that are of psychological interest. For example, the networks perform less well recognising faces of a 'minority' race than of a 'majority' race; and can classify the gender of a facial image (O'Toole, Abdi, Deffenbacher & Bartlett, 1991). Analysis of a set of facial images in terms of their principal components has recently been used to code faces for recognition (e.g. Craw, 1995, Hancock, Burton & Bruce, 1996). Use of principal component analysis (PCA) to identify dimensions of a similarity space provides a similar representation to that derived from an autoassociative network. It should be noted that a face-space defined by dimensions derived by PCA or an autoassociator is another example of an image space. Connectionist modelling and PCA have the advantage of specifying the representations and encoding process explicitly, but the disadvantage of a relative lack of psychological plausibility. The representation of faces consists of pixel values of a set of standardised images. The pre-processing required to produce a set of images of standard size and orientation is not accounted for by the models. There is no doubt that considerable processing of visual information takes place in the cortex, even though the exact nature of the processing may still be subject to some debate (e.g. spatial frequency filtering). Therefore, 'pixel' intensity is not a plausible psychological representation (but see O'Toole *et al.*, this volume; Valentin, Abdi, Edelman & Posamentier, this volume).

These three approaches to a face-space framework are based on rather different assumptions but the goal of research on human face processing is that evidence derived from a range of methods will converge on a common understanding. Recent research results justify considerable optimism for this view (e.g. Valentine, 1995).

## The summed-similarity rule and typicality in face recognition

The experimental literature on identification and classification of artificial stimuli provides some evidence of the use of both deterministic decision rules (e.g. Ashby & Gott, 1988) and probabilistic decision rules (e.g. Nosofsky, 1986; Massaro, 1998). Ashby and Gott (1988) point out that sources of internal variability (i.e. perceptual noise) often make deterministic and probabilistic decision rules very difficult to distinguish. The inherent variability of encoding faces, seen under highly variable conditions (e.g. differences in pose, expression, lighting, hairstyle, age), is likely to require the use of a probabilistic decision rule. The generalized context model is one of a number of models that implements the summed-similarity rule. (See Hintzman's (1986) Minerva II model and the Fuzzy Logical Model of Perception (Massaro, 1998, Massaro *et al.*, this volume) for examples of other models that use a similar decision rule.) It is assumed that the similarity between a probe and all exemplars in memory is calculated and summed. Recognition decisions are based on a familiarity signal given by the summed-similarity to the probe

If the similarity between exemplars within a category is much higher than the similarity between exemplars of different categories, application of the summed-similarity rule predicts that typical members of categories will generally be recognised more readily than atypical category members. Recognition judgements of artificial category members support this conclusion (e.g. Nosofsky, 1988). By analogy, typical faces should be recognised better than distinctive faces. However, as we have seen above the opposite is true: distinctive faces are recognised more accurately and more quickly than typical faces.

Nosofsky (1988) proposed that identification performance is specified by a function in which summed-similarity is the denominator. Therefore high summed-similarity implies low identification performance. This rule implies that typical category members will be more difficult to identify than distinctive category members. 'Identification' differs from 'recognition' in that identification requires a judgement of which specific known stimulus has been seen, whereas recognition requires a judgement only that the current stimulus has been seen before.

Valentine and Ferrara (1991) argued that the summed-similarity is consistent with the effect of distinctiveness on face recognition if it is assumed that face recognition judgements are actually based on face identification rather than on familiarity signalled directly by the summed-similarity rule. This argument would apply to 'recognition' of famous faces in a face familiarity decision task in addition to 'recognition' of previously unfamiliar faces in recognition memory experiments. If familiarity, signalled by the sum of similarity to all faces in memory, could form the basis of face recognition, a decision that a face has been seen before would be required in the absence of any attempt to identify who it is or where (s)he was seen before. Use of face recognition in this manner is rather different from the purpose for which our face recognition skills have evolved. Somebody who can reliably tell friend from foe by identifying their face would have an advantage in their chances of surviving long enough to reproduce. In contrast somebody who was able to tell a face was familiar but who could not tell whether they were a friend or foe would not share the same evolutionary advantage. Therefore, the operation of our face recognition system may operate in an automatic and unstoppable manner, in the sense suggested by Fodor (1983) to be associated with a modular input system, to deliver face identification decisions.

Summed-similarity has also been used in a formal account of categorisation (Nosofsky, 1988). In this case, the effects of distinctiveness of faces in a face classification task are similar to those found in tasks which require participants to classify artificial stimuli as members of one category or another. In both cases typical category members are classified faster or more accurately than distinctive category members. The generalized context model predicts this result.

## Direct evidence for face-space

Up to this point, face-space has been discussed as an application of formal models of cognition. Distinctiveness has been shown to have an important influence on face recognition: its effects are consistent with the predictions of the face-space framework. This work has been based on subjective ratings of distinctiveness, however it does not provide any direct evidence that faces are normally distributed in the similarity space. It is extremely difficult to distinguish experimentally between a normal distribution and similar centrally-clustered distributions. Fortunately, this distinction is unnecessary to test the face-space framework. Any centrally-clustered distribution could account for the empirical data on the effects of distinctiveness.

Two studies are reviewed below, both of which provide some evidence of a centrally-clustered distribution of faces in face-space. Bruce, Burton and Dench (1994) make the assumption that faces form a multivariate normal distribution in their analysis of physical measurements of faces, and successfully show a relationship between the physical measurements and subjective ratings of distinctiveness. Johnston, Milne, Williams and Hosie (1997) test the assumption that faces that are rated as distinctive are located further from the centre of face-space than faces rated as typical. This property would be true of any distribution that gives rise to a central cluster.

Bruce *et al.* (1994) took a large number of measurements from a set of 89 male and 86 female faces. They measured distances from a full-face view (e.g. nose length, mouth width) as well as more complicated distances, ratios and angles measured from a full-face and profile photograph taken simultaneously (e.g. beakiness of nose, angle of nose bridge). The faces were rated for distinctiveness by participants to whom they were unfamiliar. The correlation between rated distinctiveness of full-face views and the sum of the absolute values (modulus) of the z-score of each measurement is shown in Table 1. (Note that the calculation of z-scores assumes a normal distribution for each dimension measured.) This modulus of z-scores provides a measure of how much the measurements for each face deviates from the mean for the set of faces. In effect this measure is an estimate of the distance of a face from the centre of face-space. Greater eccentricity should lead to a face being perceived as more distinctive.

When the hair is not visible the correlation between the eccentricity measure and subjective distinctiveness is reasonably strong, especially for male faces. The correlations with 2D and 3D measures are generally no better than the correlations with measurements from the full-face view alone. Including all of the measurements does not increase the correlations over those found with full-face measurements alone (see Table 1). Bruce *et al.* (1994) suggested that this result was due to the redundancy in the measures. In support of this interpretation they report results from stepwise multiple regression analyses, in which up to 6 of the measurements entered the regression equation. Stepwise multiple regressions which included eccentricity measures derived from 2D ratios and 3D distances (measured in full-face and profile views) accounted for more of the variance of rated distinctiveness than did eccentricity derived from the full-face view alone.

The significant correlations between eccentricity and rated distinctiveness confirm the prediction that subjective ratings of distinctiveness reflect eccentricity from a mean value. It is not surprising that including the hair in the image reduced this correlation considerably. None of the measures that Bruce *et al.* took included any measures of the hair. However, the hair is known to be one of the most salient cues used in face recognition especially in recognition of unfamiliar faces. Removing the hair from the image allowed the relationship between the eccentricity of facial measurements and the subjective distinctiveness of the face to emerge. Even with the hair concealed the correlations, especially for female faces, are far from perfect (not more than 0.56

for males and 0.38 for females). The limit on these correlations reflects the effect on perceived distinctiveness of many aspects of faces that are not captured in the measures used. Most notably these aspects include visual texture such as skin texture, hair length and texture, isolated marks or moles etc.

	<b>Distances measured from the full-face view</b>	<b>3D distances, ratios and angles measured from the full-face and profile view.</b>	<b>All measures</b>
<b>Female faces</b>			
Distinctiveness (hair visible)	0.290	0.156	0.245
Distinctiveness (hair concealed)	0.379	0.241	0.345
<b>Male faces</b>			
Distinctiveness (hair visible)	0.176	0.237	0.238
Distinctiveness (hair concealed)	0.533	0.421	0.558

*Note:  $r = 0.28$  is significant at 0.01, two-tailed test.*

Table 1: Correlations between eccentricity measures from faces and rated distinctiveness from Bruce *et al.* (1994).

Johnston *et al.* (1997) tested the assumption that distinctive faces are located further from the centre of the similarity space than are typical faces. Participants provided ratings of the similarity between all pairwise comparisons of 36 faces using a seven point scale (7 = extremely different, 1 = identical). These data provided a set of 630 similarity ratings between the 36 faces. Multidimensional scaling was used to generate solutions in two- to six-dimensional space. The Euclidean distance of each face from the origin of the similarity space was calculated. In all of the solutions the 18 faces which had previously been rated as relatively 'distinctive' (mean 4.5 on a 7 point scale) were located significantly further from the origin than the 18 faces rated as relatively 'typical' (mean 2.6). The solution in two dimensions is illustrated in Figure 3.

In summary, direct measurement of faces shows that faces that have a relatively high degree of eccentricity tend to be rated as highly distinctive. Furthermore, analysis of similarity ratings between pairs of faces shows that distinctive faces are rated as more dissimilar to other faces and are therefore located further from the centre of face-space than faces that are rated as more typical. Both of these lines of evidence suggest that the distribution of faces in face-space is centrally-clustered and are consistent with the assumption of a multivariate normal distribution.

### Emerging Issues and models

Up to this point, I have reviewed the development of the face-space approach and discussed evidence for the basic assumptions. In the remainder of this chapter some current research issues will be evaluated. Two developments of the face-space framework will be discussed: the Voronoi Model (Lewis and Johnston, 1999) and the Manifold Model (Craw, 1995). These models will be introduced as appropriate in the context of discussion of current issues.

The first issue identified is one that has been inherited from the models theoretical roots in concept representation. Does a facial prototype play a role in encoding faces? The effect of caricature on face recognition has become critical in the distinction between a norm-based coding model and a purely exemplar-based model. However, in two recent papers Lewis and Johnston

(1998, 1999) have demonstrated that a new approach, the Voronoi model, provides a different way of thinking about these issues and a neat solution to the some of the difficulties.

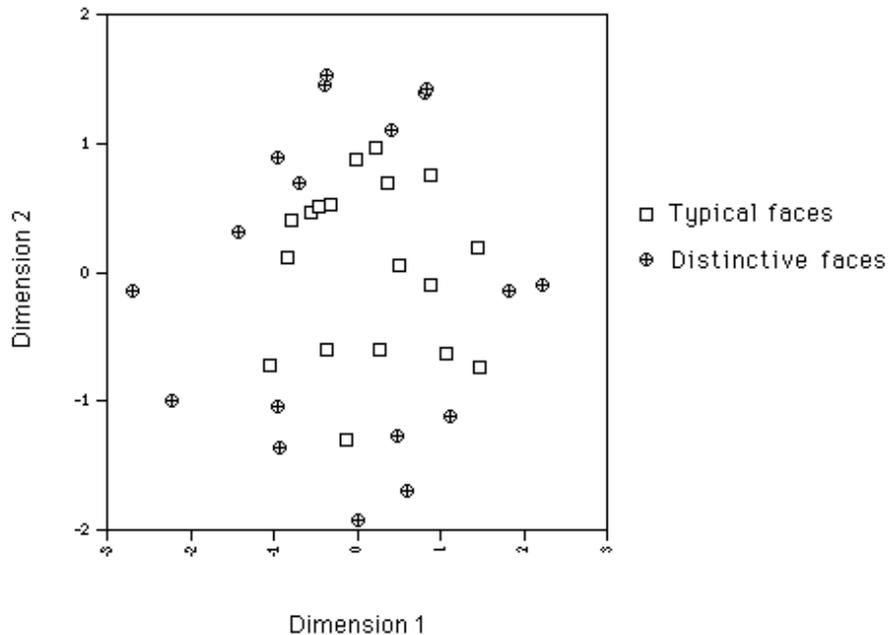


Figure 3: A plot of faces distributed in two-dimensional face-space. Reproduced with permission from Johnston, Milne, Williams and Hosie (1997)

The second 'emerging issue' arises from the observation the faces that are well recognised when they have been seen previously in an experiment are not the same as the faces that are easiest to reject when they have not been seen previously. The face-space model suggests that there should be a close negative relationship between 'hit rate' and 'false positive rate' because both rates should be determined by exemplar density. These data therefore pose a considerable challenge to the face-space framework. Explanations for the lack of a correlation are evaluated.

The development of face-space has been based on empirical work that mostly used only full-face views of faces. However, any credible model of face recognition must account for our ability to recognise faces despite changes in view. Therefore, the third emerging issue discussed concerns the application of face-space models to account for data on the effect of changes in view.

### Norm-based vs. purely exemplar-based models.

It is possible to distinguish two specific models within the face-space framework. They differ only in terms of the rôle played by a facial prototype in encoding faces in memory (Valentine, 1991a). The 'norm-based model' assumes that each face is encoded in terms of its deviations from a face prototype (or average face) located at the centre of face space. In this model each face is described by a vector from the centre to the location in face-space which specifies the value on each dimension of the relevant face. Similarity between faces is given by the similarity between their vector representations. Therefore, in the norm-based model the similarity between two faces is dependent on distance from the centre *per se* in addition to the distance between the two faces. In contrast, the 'purely exemplar-based model' assumes that the centre of the space plays no specific rôle when encoding faces. The similarity between two faces is a function of the distance between them in the space.

The norm-based model and the purely exemplar-based model make very similar predictions because both assume that the density of faces is a function of the distance from the centre. According to both models 'typical' faces are more difficult to distinguish than 'distinctive' faces because they are more similar to each other, all that differs is the method by which similarity is calculated.

It should be noted that both models assume that all different exemplars of faces are stored. Therefore, the distinction between the norm-based coding and purely exemplar-based coding is not the same as that between prototype and exemplar models of concept representation. In the latter, storage of a prototype of a concept is an alternative to storage of specific exemplars (see Smith & Medin, 1981; Medin 1989 for reviews). Neither is norm-based coding equivalent to a minimum distance classifier as identified in the context of the general recognition model (Ashby & Gott, 1988). If the general recognition theory is applied to the task of identifying images of natural faces, all of the decision rules identified by Ashby and Gott (1988) are applied in the context of a purely-exemplar based model. In none of these cases are individual exemplars explicitly coding in terms of deviation from an abstracted prototype. The decision rule used in face-space is as yet unspecified in detail. The lack of specification of the dimensions of face-space and of the exact location of individual faces in face-space makes it extremely difficult to design an empirical test of possible decision rules operating in face-space.

Valentine and Endo (1992) argued that the purely exemplar-based model provided the better account of human data on the effect of race on face processing in several different tasks. However, the effect of caricature on face recognition is problematic for a purely exemplar-based model of face processing to explain.

#### The effect of caricature.

Computer-generated caricatures are created by exaggerating the differences between a face and an average (or composite) face. There is ample evidence that caricatures are easier to recognise than corresponding anti-caricatures, in which differences between the face and the average are reduced, rather than increased, by the same extent. Caricatures of familiar faces can be better recognised than veridical images, especially if the image is impoverished, for example in a line drawing (see Rhodes, 1995 & 1996 for reviews). The process of generating caricatures can be assumed to preserve the direction but increase the magnitude of the vector representation used in the norm-based model. A caricatured face might be more recognisable than a veridical image because its vector has a greater component in the direction of the vector representation of the veridical face than does the veridical stimulus. In a sparsely populated, high dimensional space the direction of a face vector alone may be sufficient to capture the most important aspects of a representation that is unique to a specific face. Alternatively, Rhodes, Brennan and Carey (1987) proposed that face representations may actually be stored as caricatures.

The caricature advantage is more difficult for an exemplar model to explain. It could be argued that although the caricature moves the representation of the stimulus face away from a veridical representation, it may give an advantage because the caricature is also likely to be further from other faces represented in face-space. Rhodes and McLean (1990) make an argument along these lines (their model 2) although it is not made in the context of a distinction between a norm-based and an exemplar-based model. If a veridical image is closer to the stored representation of a familiar face than it is to nearby faces (i.e. it would normally be recognised correctly), it is difficult to imagine how moving the encoding location of the stimulus away from the veridical (by caricaturing) would consistently give a relative advantage to the 'target' face. As the veridical image would be closest to the 'target' representation, any change would tend to generate a greater proportionate increase in the distance (and therefore decreased similarity) to the target face than to nearby faces. As a result caricature is most commonly discussed in terms of norm-based coding.

#### Lateral caricature.

The literature on the effect of caricature is based on processes by which faces are moved either away from the centre of the face-space (caricature) or towards the centre (anti-caricature). Both manipulations preserve the direction of a vector representation of an encoded face but alter its length. Carey, Rhodes, Diamond and Hamilton (1994; cited in Rhodes, 1995) introduced the notion of lateral caricatures. To produce a lateral caricature, a face is caricatured in a direction which is orthogonal to the direction of its vector representation (see Figure 4). According to an exemplar model only two factors should affect the recognition of caricatures:

- The distance between the manipulated image and the veridical image (i.e. the degree of distortion).
- The exemplar density around the location of the stimulus in face-space.

Carey *et al.* (1994) produced caricatures, anti-caricatures and lateral caricatures using an equal percentage of distortion from the veridical, thus holding the first factor constant. The effect of exemplar density in a multivariate normal distribution would predict that caricatures would be easiest to recognise, lateral caricatures would be moderately difficult and anti-caricatures should be the most difficult to recognise. Rhodes (1995; see also Rhodes and Tremewan, 1994) argues that norm-based encoding implies that the direction of the face-vector is more important than the absolute distance of the stimulus from the location of the veridical image. (It should be noted that this is not a necessary prediction of the norm-based model and no rationale for this assumption is given.) If this is the case lateral caricatures would be more difficult to recognise than either anti-caricatures or caricatures. Carey *et al.*'s data support Rhodes' predictions.

It is difficult for an exemplar-based model to explain why lateral caricatures are more difficult to recognise than anti-caricatures. However, it should be noted that a primary account of the study by Carey *et al.* (1994) has never been published. Moreover, the means by which lateral caricatures were produced is not specified in any accounts of the study. There are many directions that are orthogonal to a vector in a high dimensional space. It is not necessarily the case that all directions are equivalent. For example, caricaturing in some directions might make a face more asymmetric. Furthermore, Rhodes (1996, p132) cited a more recent unpublished study in which lateral caricatures were more accurately recognised than anti-caricatures.

Lewis and Johnston (1998) introduced the concept of 'oblique caricatures', which were produced by caricaturing a face in the direction of an arbitrary face (see Figure 4). This process produces 'caricatures' which will move the stimulus face away from the direction of the norm – veridical vector but an oblique caricature is unlikely to be orthogonal to it. It is also unlikely that generating an oblique caricature of a face using the same proportion of caricature, will produce the same degree of distortion as caricaturing relative of the norm. The relative distance of the norm and the reference face from the veridical face will affect the degree of distortion. The

veridical and the reference face will be, on average, further apart than the veridical and the norm. This difference will introduce a systematic bias that would make oblique caricatures look more dissimilar than a caricature or an anti-caricature using the same proportion of caricature. However, this bias acts against the hypothesis tested by Lewis and Johnston. In a carefully controlled study, they showed that anti-caricatures were not judged to be more similar to a

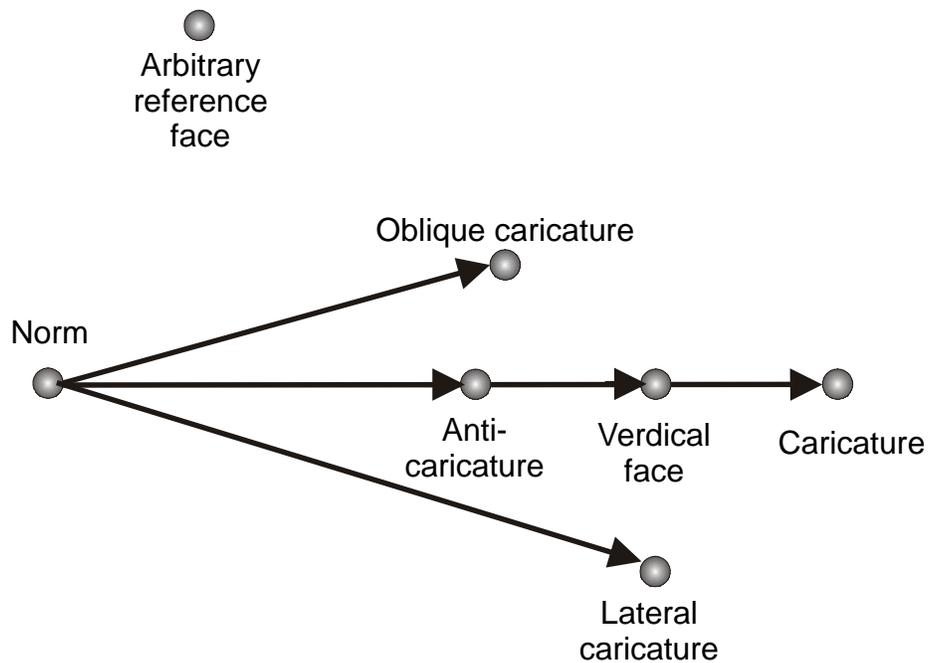


Figure 4: The representation of a caricature, anti-caricature, lateral caricature and oblique caricature in face-space. All are equidistant from the veridical face in this figure. The oblique caricature is produced by caricaturing in the direction of an arbitrary reference face (see Lewis and Johnston, 1998 for further details). The vectors from the norm that represent each face in a norm-based coding model are shown.

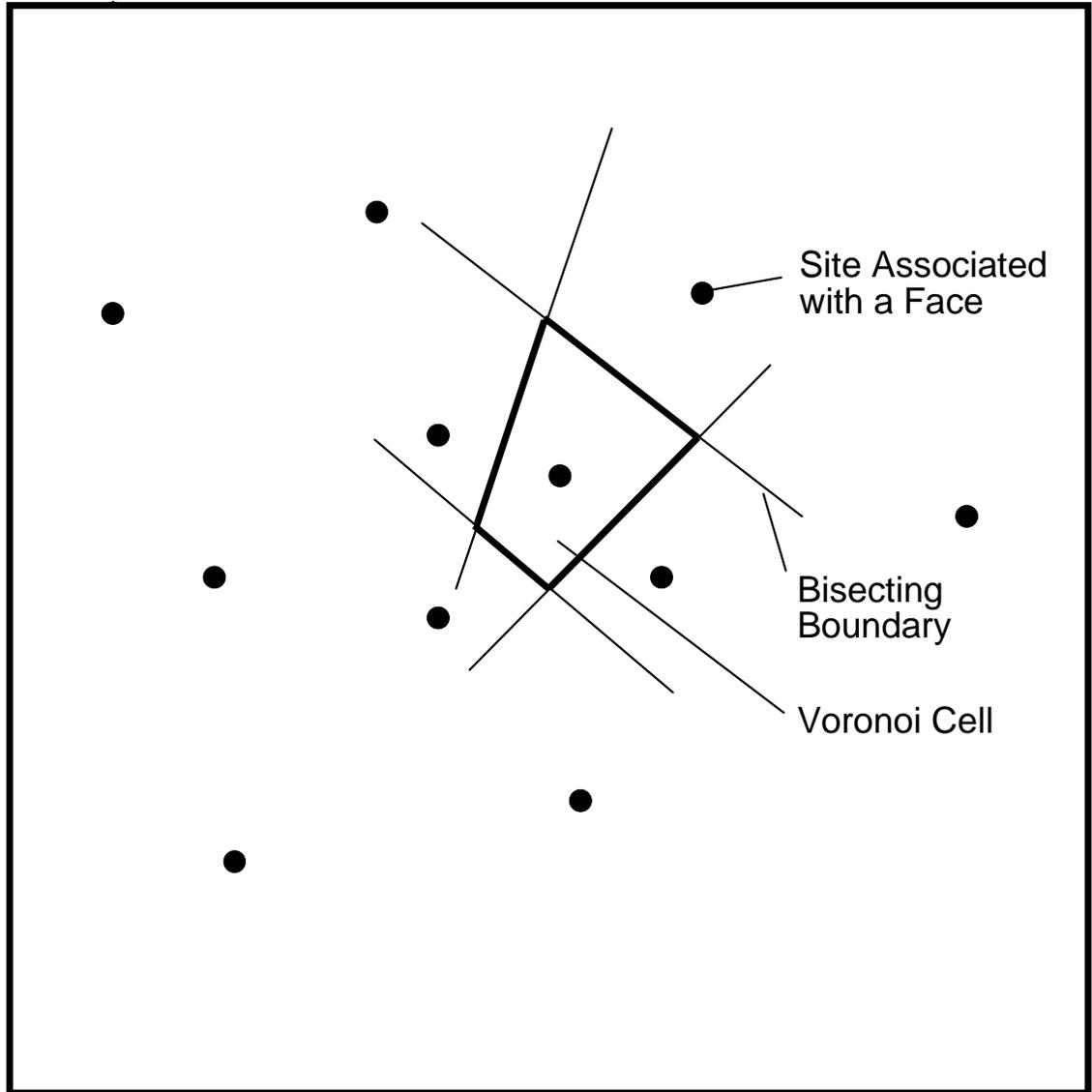


Figure 5

Figure 5: Construction of an identity region (cell) in the Voronoi model. Reproduced with permission from Lewis and Johnston (1999)

veridical image than were oblique caricatures. Furthermore, Lewis and Johnston extrapolated the performance of theoretical lateral caricatures (i.e. faces caricatured in an orthogonal direction to the norm-veridical vector). They concluded that lateral caricatures would be perceived to be more similar to veridical images of faces than anti-caricatures. The order of preferences found by Lewis and Johnston were as follows: Caricatures were judged to be most similar to the veridical face, theoretical lateral caricatures were judged to be less similar and anti-caricatures were judged to be least similar. This pattern of preferences is that which would be predicted on the basis of exemplar density if faces are normally distributed (or centrally-clustered) in face-space. Therefore, Lewis and Johnston concluded that their data support the exemplar-based model and are inconsistent with the prediction derived by Rhodes and Tremewan (1994) from a norm-based coding model.

### Voronoi Model.

Lewis and Johnston (1999) described a development of the purely exemplar-based model that is based on the construction of a Voronoi diagram. For background information on Voronoi diagrams see Fortune (1992) and Bose and Garga (1993). The locations at which faces are encoded in the face-space are used to partition the space into discrete identity regions by bisecting the distance between a face and its nearest neighbour along each dimension of the space (Figure 5). Therefore, all points within an identity region are closer to the face on which the region is based than to any other face. Lewis and Johnston point out that this procedure tessellates face-space into a multidimensional Voronoi diagram with the known faces as sites. The division of the face-space into identity regions is similar to that created by 'multidimensional decision boundaries' described by Thomas (1996) in an application of the multidimensional generalisation of signal detection theory (Ashby and Townsend, 1986). It is assumed that the identity regions are stored in memory but the location of the face used to generate the identity region is discarded. The centre of the identity region would be the optimal point of recognition because this point will be furthest from any other identity regions. Therefore, a face at the centre of a region will induce less activation in neighbouring identity regions and therefore induce less competition in the recognition process.

Rhodes and her colleagues (e.g. Rhodes, Brennan & Carey, 1987; Rhodes & McLean, 1990) have speculated as to whether the recognition advantage for caricatures occurs because the representations are caricatured in memory. Lewis and Johnston (1999) point out that the Voronoi model provides a neat solution to this issue. If faces are represented by identity regions, and the faces that form these regions are normally distributed (or centrally-clustered) on each dimension of face-space, the identity regions will be skewed such that the centre of the region will be slightly further from the centre of the space than the point which formed the identity region (Figure 6). The skew arises because on average the nearest neighbour that is further from the centre than a stimulus face will be further away than the nearest neighbour which is nearer to the centre. The normal distribution will have the effect that the optimum stimulus, which falls at the centre of the region, will be a slight caricature of the veridical image. The answer to the question that Rhodes has posed, according to the Voronoi model, is that an advantage for recognition of caricatures is an emergent property of representing faces by identity regions. Furthermore, Lewis and Johnston demonstrate that the Voronoi model successfully simulates the empirical finding that the advantage for recognition of a caricature over a veridical image is enhanced when the stimuli are degraded (cf. line drawings of faces).

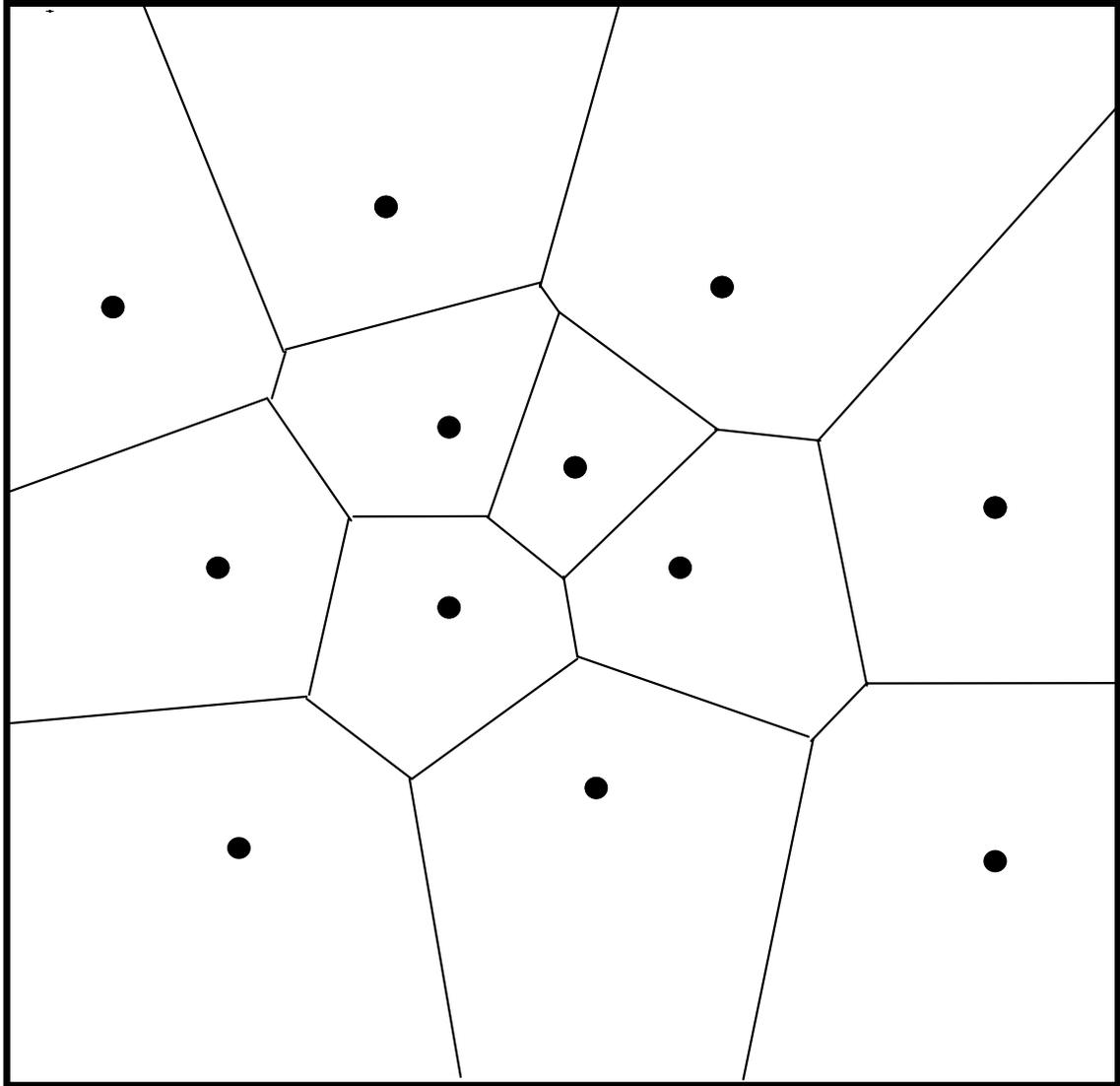


Figure 6

Figure 6: The distribution of identity regions (cells) in the Voronoi model. Reproduced with permission from Lewis and Johnston (1999)

According to the Voronoi model the entire face-space will be partitioned into identity regions. This implies that every point in the space will correspond to a known face. The implication is that participants could never respond that a face has not been seen before. Instead they would always identify the face as the known person who it most resembles. Lewis and Johnston (1999) acknowledge this problem. As a solution they suggest that the activation of an identity region is proportional to the distance to the boundary of the region and that there is an activation threshold that must be achieved for identification to occur. Therefore, face images that lie near a boundary would not be identified because they would not activate the identity region in which they lie above the threshold.

Another mechanism by which the Voronoi model could produce a 'not known' response would be provided by creation of identity regions by, for example, passing somebody on the street. No identity-specific semantic information would be accessible for such a person nor could the episode of encounter be retrieved for many people encountered in this way. If a novel face fell in the identity region of such a face, the response would be 'not known'. These faces might even make up a majority of the space. Valentine (1991a) proposed that these 'seen but unfamiliar' faces would be represented in face-space (pp. 166 and 169). The rôle of a threshold and the representation of 'seen but unfamiliar' faces are not mutually exclusive. Both factors could contribute to the production of 'not known' responses.

Some interesting predictions about the development of face recognition can be derived from the Voronoi model. A child's face-space may be similar to an adult's but less densely populated. Johnston and Ellis (1995) consider this as one possible characterisation of a child's face-space among 4 alternatives. The identity regions will be large in a Voronoi model with a low density of faces encoded. Large identity regions would tend to produce category-inclusion errors. (For example, a tendency for very young children to over-extend the category of 'Daddy' to include men who share a salient feature, such as having a beard, with the child's father.) Category inclusion errors are characteristic of children's face recognition performance. See Johnston and Ellis (1995) for a review of the development of face recognition.

#### The relationship between distinctiveness, hit rate and false positive rate to individual faces.

The probability that a face will be recognised after it has been seen by a participant in an experiment is known to be a function of its rated distinctiveness. The 'hit rate' is greater to distinctive faces than it is to typical faces. The probability of a 'false positive' response to a face that has not been seen before is also known to be a function of facial distinctiveness. The false positive rate is lower to distinctive faces than it is to typical faces. The face-space framework has led researchers to assume that distinctive faces that attracted a high hit rate were the same faces as the distinctive faces that attracted a low false positive rate. In effect, it was assumed that only distinctiveness mediated recognition accuracy of previously unfamiliar faces. Therefore, it came as something of a surprise when Bruce et al. (1994) reported that, despite there being a significant correlation between distinctiveness and hit rate and a significant correlation between distinctiveness and false positive rate, the correlation between hit rate and false positive rate is zero. In short, the faces that are well-remembered are not necessarily those that are easily rejected as not having been seen previously. This result has been replicated by Hancock, Burton and Bruce (1996) and by Lewis and Johnston (1997). Table 2 shows the relevant correlations from these three studies. It should be noted that Lewis and Johnston did not find a significant correlation between distinctiveness and false positive rate. All of these correlations are based on data relating to male faces with the hair visible taking individual faces as the unit of analysis which are averaged across participants.

	Bruce <i>et al.</i> , 1994	Hancock <i>et al.</i> , 1996	Lewis & Johnston, 1997
Distinctiveness	.27*	.49*	.35*
- Hit Rate			
Distinctiveness	-.31*	-.40*	-.13
-False Positive Rate			
Hit Rate	-.02	-.08	-.08
- False Positive Rate			

Note: \* denotes a significant correlation at  $p < .05$ .

Table 2: Correlations between distinctiveness, hit rate and false positive rate from three studies. All of the correlations given are for male faces only rated for distinctiveness with their hair visible.

### Context-free familiarity and memorability.

How can the lack of correlation between hit rate and false positive rate be explained? Clearly there must be some factor other than distinctiveness that is mediating recognition performance. Vokey and Read (1992) demonstrated that rated distinctiveness can be decomposed into two dimensions; one they termed 'memorability', the other they termed 'general familiarity' (also known as 'context-free familiarity'). These two orthogonal dimensions, were derived from a factor analysis of ratings of faces on dimensions of distinctiveness<sup>1</sup>, familiarity, memorability, attractiveness and likability. When rating faces for familiarity, a familiar face was defined to the participants as 'one that they believed they had seen around the university, but particularly in their first-year classes.' In fact none of the pictures shown were of people who had ever attended the university. Vokey and Read found that distinctiveness correlated equally strongly, but with opposite sign, with both derived factors (see Table 3).

Vokey and Read (1995) point to 'an obvious link' between their work and a dissociation between automatic and intentional uses of memory (e.g. Jacoby, 1991). However, their preferred account is that 'general familiarity' reflects the pooled response of all items in memory such as the summed similarity of the generalised context model (Nosofsky, 1986) or the 'echo' of Hintzman's Minerva II model (Hintzman, 1986). Whereas the 'memorability' component reflects the influence of a prior instance stored in memory that is highly similar to the probe item. See Busey (this volume) for further discussion of familiarity and memorability.

Bruce *et al.* (1994) interpreted their own data as support for the rôle of memorability and familiarity in mediating face recognition performance. They suggested that memorability mediates hit rate and context-free familiarity mediates false positive rate. O'Toole, Deffenbacher, Valentin and Abdi (1994) replicated Vokey and Read's (1992) finding that rated distinctiveness can be decomposed into derived factors of familiarity and memorability. In comparison to Vokey and Read's, data, O'Toole *et al.* found that distinctiveness had a rather stronger relationship between memorability than with familiarity (see Table 3). O'Toole *et al.* used an instruction for the familiarity rating that was slightly different to that used by Vokey and Read. O'Toole *et al.* asked participants to rate how confusable the face was with somebody known to the participant.

Hancock *et al.* (1996) derived two factors from rated distinctiveness and measures of hit rate and false positive rate in a face recognition experiment. Although Hancock *et al.* described the factors as 'memorability' and 'familiarity', their relationship with distinctiveness was rather different to that found by Vokey and Read. Hancock *et al.*'s memorability factor is synonymous with distinctiveness ( $r=0.93$ ) and their 'familiarity' factor shows no correlation with distinctiveness.

	<b>Vokey &amp; Read, 1992</b>		<b>O'Toole <i>et al.</i>, 1994</b>		<b>Hancock <i>et al.</i>, 1996</b>	
	<i>Derived factors</i>		<i>Derived factors</i>		<i>Derived factors</i>	
	General	Memorability	General	Memorability	General	Memorability
<i>Rated variables</i>						
	Familiarity		Familiarity		Familiarity	
Familiarity	.65 to .82	.07 to .11	.74	.01	-	-
Memorability	.22 to .26	.93 to .94	.14	.94	-	-
Distinctiveness	-.62 to -.67	.66 to .71	-.34	.88	.08	.93
<i>Performance measures</i>						
Hit rate	see text	see text			.60	.66
False positive rate	see text	see text	-.06	-.09	.75	-.60

Table 3: A comparison of the correlation between rated variables, performance measures and the derived factors of 'memorability' and 'general familiarity' in three studies. Note that Vokey & Read and O'Toole *et al.* collected ratings of 'typicality' rather than of 'distinctiveness'. To assist the comparison between the studies the 'typicality' variable has been relabelled 'distinctiveness' and the sign of the correlation coefficient has been changed. The false positive rate for the O'Toole *et al.* study is from judgements that faces were repeated during the rating task. Data from only the Caucasian faces used in the O'Toole *et al.* study are included to facilitate comparisons between studies.

The factors derived by Hancock *et al.* also show a different relationship with hit rate to that found by Vokey and Read. In Hancock's study both familiarity and memorability correlated strongly and positively with hit rate. Vokey and Read did not report the comparable correlations for familiarity and memorability separately, but they did report the regression equations for hit rate in terms of the two factors for 4 separate experimental conditions. When attempting to predict hit rate, Vokey and Read found that for two conditions neither general familiarity nor memorability entered the regression equation; for one condition only memorability entered the equation with a positive relationship. For the fourth condition both factors entered the equation, but surprisingly general familiarity had a positive relationship with hit rate and memorability had a negative relationship! Thus on no occasion did Vokey and Read find the relationship between hit rate, familiarity and memorability reported by Hancock *et al.* The prediction of false positive rate fared better. In all four of the regression equations reported, Vokey and Read found that general familiarity had a significant, positive relationship with false positive rate and memorability showed a significant, negative relationship. This pattern was also found by Hancock *et al.* The correlation with false positive rate shown in Table 3 from the O'Toole *et al.* (1994) study was derived from a rating in which participants were asked to judge whether a face had been repeated. In fact no faces were repeated in the rating task so all positive responses were 'false positives'. O'Toole *et al.* found that the relationship between ratings of repetition and both memorability and familiarity were close to zero.

It may be unsurprising that the factors derived by Vokey and Read and by Hancock *et al.* behaved so differently given that they were derived from very different data: Hancock *et al.* included performance measures in the data from which their two factors were derived, but Vokey and Read's two dimensions were derived solely from subjective ratings. The possibility that distinctiveness decomposes into two factors is interesting, but the data are contradictory. Hancock *et al.*'s data clearly do not support this conclusion. However, there is good evidence that false positive responses are not determined by distinctiveness alone, context-free familiarity clearly plays an important rôle in determining false positive responses.

Lewis and Johnston (1997) proposed that 'familiarity' predicts false positive responses through resemblance of a novel face to a known face. If this is the case false positive responses should be idiosyncratic to individual participants. One face may seem familiar and therefore induce a false positive response by one participant because it resembles 'Uncle John', however another participant may not know anybody who resembles this face but find another face more familiar due to a resemblance to somebody else. In contrast, Lewis and Johnston suggested that participants used their knowledge of the general population to make distinctiveness ratings and therefore there is a high inter-participant agreement on rated distinctiveness.

To test these ideas Lewis and Johnston collected ratings of 'personal familiarity'. Participants were asked to what extent they thought that each face looked similar to (or reminded them of) somebody they knew prior to the experiment. Participants made their responses on a ten-point scale from "a face almost identical to someone you know" to "like no face you have ever seen before". Personal familiarity contrasts to the measure of general familiarity used by Vokey and Read (1992), which was based on rating the possibility that the person has been encountered before, perhaps around the university. However, Lewis and Johnson's rating task is very similar to that used by O'Toole *et al.* (1994). The correlations reported by Vokey and Read (1992), Hancock *et al.* (1996) and O'Toole *et al.* (1994) were based on data averaged across participants. However, personal familiarity is idiosyncratic and so would not predict false positives averaged across participants. Therefore, Lewis and Johnston reported correlations based on both individual data and averaged data. They found that averaged ratings of distinctiveness predicted hit rate and that individual personal familiarity predicted false positive rate. Participants showed consistency in the faces that elicited false positives only when they saw the same sets of target faces. This effect reflects the influence of resemblance between targets and distractors on false

positive responses. If participants had seen different target faces, the false positive responses showed less consistency across participants than did errors of omission to target faces.

Taken together the available data can be summarised as follows:

- Distinctiveness predicts the probability of recognising a target face and is based on a general distribution of faces in face-space that shows consistency across participants.
- Personal (or context-free) familiarity predicts the probability of making a false positive response to a distractor face. The effect is based on resemblance to a known face and therefore tends to be idiosyncratic to individual participants.
- The evidence that rated distinctive itself comprises components of memorability and context-free familiarity is inconsistent.

### Generalisation across different viewpoints

Almost all of the research discussed in this chapter has been based on recognition of full-face views of faces. The issue of how faces are recognised across changes in viewpoint has tended to be somewhat neglected within the context of face-space models (but see Edelman and O'Toole, this volume). Newell, Chiroro and Valentine (1999) considered how the exemplar-based model of face-space could take the effect of viewpoint into account. Two possible approaches were identified. First, a change of viewpoint could be considered to introduce noise when encoding a face and therefore would be likely to contribute a greater error of encoding than seeing the same view at test (termed the individual-based account). This approach is analogous to the treatment of the effect of inversion by Valentine (1991a). It predicts that the effect of distinctiveness would interact with an effect of view: A change of viewpoint should have less impact on the accuracy of recognising distinctive faces than on recognising typical faces. The higher density of typical faces in face-space would make any increase in the error of encoding more difficult to accommodate. The other possible model considered by Newell *et al.* is that face-space is view-specific and that a separate face-space exists for each view of a face (termed the view-based account). This approach is similar to the manifold model discussed by Craw (1995) in which the identity of a face is represented by a manifold in face-space, which is not necessarily continuous, and that encompasses the appearance of a face of a given identity across all possible transformations (e.g. view, lighting, age). This account would predict that observers would be slower or less accurate to recognise a face from a novel view than from a stored view. The effect of view arises from the need to match images at different points on the manifold. However, the view-based account does not make any a priori prediction that the effect of changing view would be greater for typical faces than for distinctive faces.

Newell *et al.* (1999) investigated the effect of viewpoint on recognition of distinctive and typical faces in two recognition memory tasks. In one task participants saw faces in only one view, in the other the faces were presented in a full-face, a three-quarters and a profile view. In both tasks participants were required to recognise faces from each of these three views. An effect of distinctiveness, and an effect of the view shown at test but no interaction between these factors were found in both of these tasks. Even when all views were presented during the learning phase, profiles were recognised less accurately at test than other views. However, there was no evidence that a change of view or the effect of viewpoint per se caused any greater effect on the recognition of typical faces than on recognition of distinctive faces. This result is consistent with Newell *et al.*'s view-based account and Craw's manifold model. The results cannot be accommodated if a change of view is considered to increase the error of encoding.

The Voronoi model has some difficulty accounting for Newell *et al.*'s results. The most appropriate manner to apply the model is to assume that all views of a face are encoded within a single identity region. The view on which the identity region was based is likely to be closest to the centre of the identity region. If recognition accuracy is dependent upon the distance to neighbouring cells, as Lewis and Johnston (1999) suggest, the Voronoi model predicts that a

change of viewpoint should be more disruptive to recognition of typical faces than to distinctive faces. In effect the difficulty that the Voronoi model encounters is the same as that encountered by the exemplar-based model (Valentine, 1991a) in assuming that a change of view increases the error of encoding.

### Summary and conclusions

In this chapter, I have looked back at the development of the face-space framework from formal models of the representation of artificial concepts and forward to the development of the approach into a more sophisticated model of face processing. The simple idea that a face can be represented in a multidimensional space has brought us a long way. It has provided a unifying framework for a disparate range of empirical effects in face recognition (e.g. the effects of distinctiveness, caricature, inversion and race, see Valentine, 1995 for further discussion of all of these issues).

Although distinctiveness may in the future be shown to be composed of two or more attributes it remains a useful concept in understanding the empirical literature. It has been shown that idiosyncratic resemblance to personally known faces influences face recognition in addition to shared perception of facial distinctiveness. The notion of a specific rôle for an abstracted norm or face prototype in encoding faces has been a powerful idea that has been difficult to shake off. Many face processing researchers (including myself) have found the rôle of a face prototype compelling. However, the unambiguous interpretation of the empirical data has to be that there is no evidence of a rôle for an abstracted prototype.

The limitations of the representation of a face as a point in face-space are becoming clear. Two viable alternatives are now available to us: faces as identity regions and faces as identity manifolds. Regions provide a good account of the effects of caricature; manifolds prove a good account of the effect of view. This contrast may not be the dichotomy it appears. The dimensions of face-space on which different facial identities lie may well form a Voronoi diagram partitioning the space into identity regions on these dimensions. However, other dimensions may represent the changes due to view, lighting, age, expression over which the identity of a face is invariant. Identity manifolds may span these dimensions as proposed in the manifold model. In order to make progress on these issues a clear distinction must be maintained between an image space - often implicit in computational analysis and modelling of facial images - and an identity space that is often implicit in empirical studies of face recognition.

### Footnote

1. Vokey and Read (1992) and O'Toole et al. (1994) use the term typicality rather than distinctiveness. Typicality is the converse of distinctiveness. For clarity, the term 'distinctiveness' is used throughout and the sign of the relevant correlations has been altered as necessary.

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