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A multidimensional scaling analysis of own- and cross-race face spaces

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ABSTRACT

We examined predictions derived from Valentine's (1991) Multidimensional Space (MDS) framework for own- and other-race face processing. A set of 20 computerized faces was generated from a single prototype. Each face was saved as Black and White, changing only skin tone, such that structurally identical faces were represented in both race categories. Participants made speeded "same-different" judgments to all possible combinations of faces, from which we generated psychological spaces, with "different" RTs as the measure of similarity. Consistent with the MDS framework, all faces were pseudo-normally distributed around the (unseen) prototype. The distribution of faces was consistent with Valentine's (1991) predictions: despite their physical identity to the White faces, Black faces had lower mean inter-object distances in psychological space. Other-race faces are more densely clustered in psychological space, which could underlie well-known recognition deficits.

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1. Introduction

In general, people are expert face processors, capable of recognizing hundreds of faces, even decades after their last exposure (Bahrack, Bahrack, & Wittlinger, 1975). This expertise, however, does not always extend to faces belonging to members of races other than one's own. Other-race effects¹ (OREs) have been observed in recognition memory (Meissner & Brigham, 2001), speeded classification (Levin, 1996), stereotypical memory distortions (Eberhardt, Dasgupta, & Banaszynski, 2003), and many other measures. To date, theorists have proposed varied explanations for OREs, citing levels of inter-racial contact (Ng & Lindsay, 1994), perceptual expertise (Lindsay, Jack, & Christian, 1991), overlearning (Goldstein & Chance, 1980), and the treatment of race as a basic visual feature (Levin, 2000).

One prominent theory has been Valentine's (1991) Multidimensional Space (MDS) framework, which was proposed to explain effects of distinctiveness, caricaturing, inversion, and race in face perception. According to this framework, faces are represented as points in an n -dimensional Euclidean space, wherein each dimension represents some physiognomic aspect of faces useful for discrimination. The framework assumes that faces are normally distributed in this space around the central tendency, with information derived from a lifetime of experience. Because people have more experience with own-race faces, Valentine predicted that the learned dimensions would mainly reflect the most useful features for differentiating among own-race faces. These dimensions may prove less efficient for other-race faces. Therefore, the MDS model predicts that the dispersion of faces in psychological space will be different for own- and other-race faces. Specifically, own-race faces should disperse relatively sparsely, reflecting precise appreciation of the details used in perception and memory. Other-race faces should cluster more tightly, reflecting their confusability along dimensions better suited for own-race discrimination.

Although the MDS framework is very influential, the idiosyncratic variations in natural faces have made it

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¹ Please note that the term *race*, as typically used, is inconsistent with the literal meaning of the term (i.e., there is one human race). Although the term *ethnicity* would be more accurate, we maintain the more familiar terminology in this article.

difficult to empirically scrutinize. Faces are a class of homogenous stimuli, which vary continuously along many underlying (and unknown) dimensions (Byatt & Rhodes, 1998). Thus, faces may appear clustered in psychological space because of race, but other freely-varying factors can also affect MDS solutions. The functional utility of Valentine's model is that, although dimensions are not specified a priori (but see Catz, Kampf, Nachson, & Babkoff, in press), they are exploited in perceptual decisions. Thus, in a given task, responses can lead to the creation of a visualizable space from which relevant dimensions can be inferred. In the current study, we applied this MDS logic, while controlling the potential confounds that usually arise in cross-race face studies. Specifically, we used established multidimensional scaling techniques (Kruskal & Wish, 1978) with synthesized faces, controlling all structural factors of the faces, and using a speeded "same-different" task that minimizes response strategies.

Valentine's (1991) MDS framework supports two non-mutually exclusive models, a *norm-based coding* (NBC) model, and an exemplar-only, *absolute-coding* (ABC) model. As discussed by Byatt and Rhodes (1998), the primary assumption of NBC is that faces are represented in terms of deviation from a norm (typically the own-race prototype), such that all that is stored per face is a vector distance from the prototype. Conversely, in ABC, each face is encoded according to its absolute value per dimension, and is represented by a single point. The key prediction regarding unequal, race-based dispersion of faces is common to both models, and was the prediction tested here. Note, however, that distinct predictions have been derived and tested for each model (Byatt & Rhodes, 1998).

Prior support for Valentine's (1991) MDS framework has come from both empirical research and computational modeling. Experimental evidence has predominantly come attempts to multidimensionally scale faces, allowing examination of the resultant psychological spaces. Johnston, Milne, Williams, and Hoise (1997) examined the basic that more typical faces should cluster toward the center of psychological space, with more distinctive faces located along the periphery. Using distinctiveness ratings and a similarity judgment task, Johnston et al. (1977) found that the average distance between the origin of the space and the typical faces was smaller than the average distance between the origin and the distinctive faces, supporting the theoretically-predicted architecture of psychological space. Byatt and Rhodes (2004) examined the race-based predictions of the MDS model. They had White participants rate the similarity of pairs of White and Chinese faces (using real photographs), which produced an MDS space with a denser cluster of other-race faces, relative to own-race faces. Furthermore, the spatial locations of faces were valid predictors of future identification performance, such that more proximal faces were more difficult to identify.

Computational analyses have also assessed the spread of faces in psychological space, and have again found differences in face dispersion, based on race. Caldara and Abdi (2006) trained two neural networks as either "pure Caucasians" or "pure Asians" (i.e., each model was trained with only one race, without exposure to the other). After

training, each network was presented with faces from the untrained race. From the models, Caldara and Abdi derived the Euclidean distances and cosine values for each set of faces, both within its own (same-race) network and within the other-race network. In general, the psychological spaces supported Valentine's predictions: faces in the same-race space were represented more diffusely, with greater pairwise distances between the faces, relative to the same faces represented within the other-race space.

Although Byatt and Rhodes (2004) and Caldara and Abdi (2006) demonstrated results consistent with the predictions of Valentine's (1991) MDS framework, their approaches did not allow alternatives to be ruled out. Byatt and Rhodes derived spaces using similarity judgments from only one race of participants; Caldara and Abdi trained neural networks in an extreme and unrealistic manner. In the present study, we evaluated the prediction from Valentine (1991) by deriving psychological spaces from participants' speeded *same-different* ratings to well-specified computer-generated faces. Using these faces, we could test only one race of participants, but still cover the full experimental design. Specifically, we manipulated the perceived race of each face, such that participants rated each face, both when it was an own- and other-race face. Because Valentine's framework is based on the hypothetical "face space" in memory, we used multidimensional scaling procedures. We used the same-different procedure because response times (RTs) in this task provide an indirect measure of psychological similarity (i.e., people are faster to respond "different" when two faces are less similar), while minimizing strategic analysis by participants (Sergent & Takane, 1987). Examining RTs allowed us to generate a psychological space that is intuitive (distance in space is negatively correlated with RT) and free of response bias.

2. Methods

2.1. Participants

Seventy-three Arizona State University undergraduates participated in exchange for partial course credit. Sixty-eight percent of the participants self-reported as White, 3% as Black, and 29% as "other." All participants had normal or corrected vision.

2.2. Stimuli

FaceGen Modeller software (Singular Inversions, 2004) was used to create a racially ambiguous male face,² a prototype from which we created a set of 20 new faces. One of our goals was to examine the psychological space, knowing that the structure can be logically predicted from the design of the materials (i.e., as a validation procedure). Faces were generated by systematically distorting the prototype face with the "genetic randomness" tool available in the

² In a pilot experiment ($N = 83$), we identified two faces, one that was labeled "Black" approximately 75% of the time and one that was labeled "White" approximately 75% of the time. We morphed these faces together to create a racially ambiguous male, shown at the top of Fig. 1.

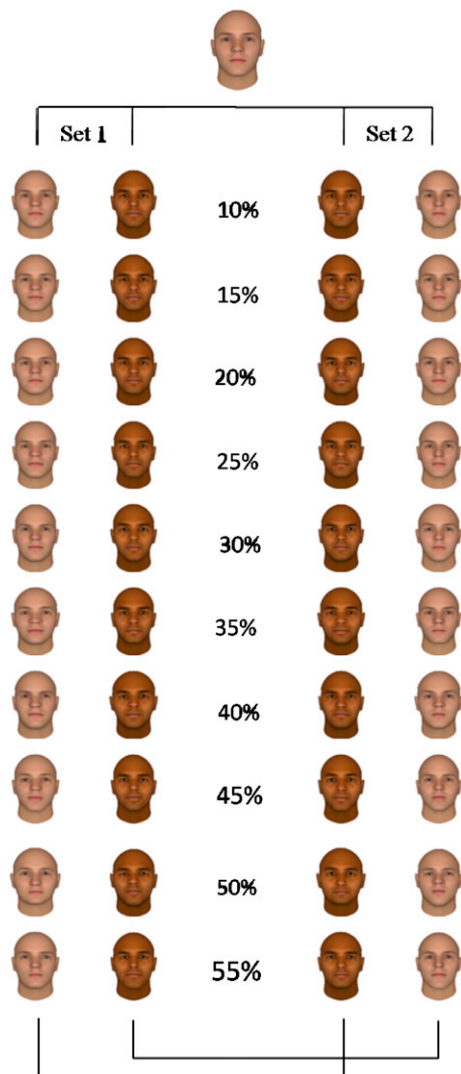


Fig. 1. Two sets of faces generated from a single, racially-ambiguous prototype. The percentages listed down the center represent percentages of distortion from the original image. Faces connected by lines (bottom) are structurally identical and only differ in racial coloring.

185 software. When genetic randomness is set to a low value
186 (e.g., 20%), the new face bears a sibling-like resemblance to
187 the original. As the parameter increases, faces look more like
188 cousins, and eventually unrelated. As shown in Fig. 1, two
189 faces were created at each of the randomness levels in
190 five-step increments from 10% to 55% (the two faces per level
191 were never identical).³ One face per level was set to a
192 Black skin tone; the other was set to a White skin tone. A
193 second set of faces was created by reversing the assignments
194 of skin tone, such that each face represented a Black man
195 and a White man, in counterbalanced fashion across
196 participants. This allowed the same stimuli to served as both

³ Because participants were generally unable to distinguish between faces at the 10% distortion level, these faces were dropped from later analysis.

own- and other-race faces, greatly increasing experimental control. The 61 shape parameters provided by FaceGen were compared for each Black-White pair, confirming that the faces were structurally identical.

2.3. Procedure 201

Participants performed two blocks of speeded same-different judgments, separated by a go/no-go task (Levin, 2000). During each same-different block, participants made judgments to all 192 face pairs in a set (presentation order of the sets was counterbalanced and pair presentation was random), with 40 trials containing identical faces. Each face was 400 × 400 pixels, and pairs were presented side-by-side, approximately 5 cm apart. Participants quickly pressed buttons labeled “same” and “different,” and no feedback was given. Trials were separated by a 1-s ITI. During the go/no-go task, participants completed two blocks, each containing 60 trials. In each block, participants saw individual faces for a maximum of 2000 ms and were asked to push the ‘1’ key, classifying by race. In one block, they responded only to Black faces and, in the other, only to White faces (block order was counterbalanced). Feedback was provided, in the form of a red ‘X’ and a 3000-ms penalty, following incorrect responses. E-Prime software (Psychology Software Tools., 2006) was used to conduct the experiments on 17” CRT monitors (which minimize visual distortion across screen positions).

3. Results 223

We briefly consider the raw same-different RTs, followed by the go/no-go results. We then focus on the critical MDS analyses.

3.1. Go/no-go RTs 227

We replicated the pattern from Levin (2000), finding faster responses to Black faces (232.7 ms) than to White faces (246.4 ms), $t(70) = -2.66, p < .05$. Although these data were not used for MDS analyses, we included this task to verify that our stimuli reproduced a well-documented phenomenon. According to Levin (2000), people are faster to verify Black faces because they impart the basic feature “+Black.” Although our data cannot speak to this interpretation, our results suggest that race differences were perceived as intended.

3.2. Same-different RTs 238

Within-race (White-White and Black-Black) judgment RTs were analyzed in a paired-samples *t*-test. Same-different judgments were significantly slower for pairs of Black faces (1662 ms) than for pairs of White faces (1544 ms), $t(72) = 2.11, p = .03$. This pattern was consistent for all within-race comparisons; RTs were unaffected by the degree of relative distortion between the faces, $F(7, 504) = 1.79, p = .08$.

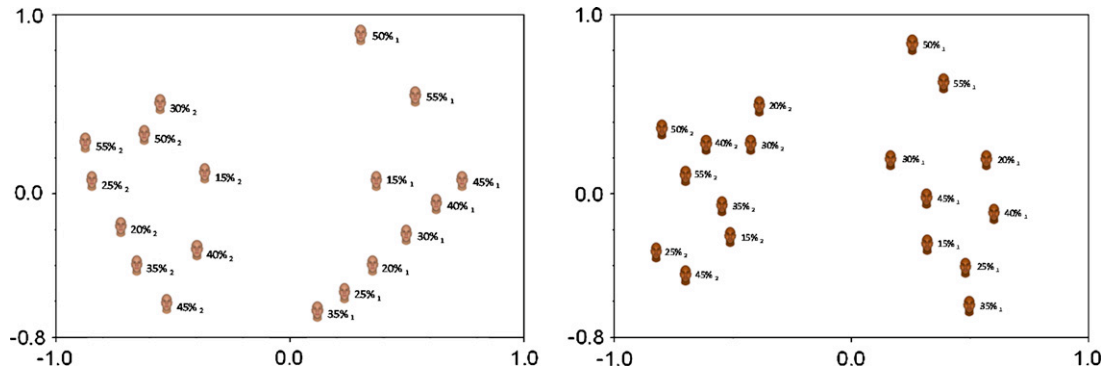


Fig. 2. Separately derived two-dimensional spaces for the White (left panel) and Black (right panel) faces. The axes represent the primary and secondary dimensions, shown in normalized units.

247 3.3. *Scaling solutions*

248 MDS solutions were based on similarity estimates, derived from correct RTs in “different” trials, such that RTs positively correlated with psychological similarity. The scaling analyses were completed in two steps, using functions in SPSS (Giguère, 2006). We conducted our analyses in several stages: we first derived PROXSCAL solutions for each of the matrices derived separately (i.e., the first and second blocks of same-different trials). We derived both two- and three-dimensional solutions for each matrix; these were equivalent in explained variances, with each approximately $R^2 = 75\%$. Given this finding, and their greater visual interpretability, we limited all analyses to two-dimensional solutions.

249 Our next step was to create within-race similarity matrices, for all possible White–White and Black–Black pairs. These matrices were also analyzed using PROXSCAL, leading to the separate two-dimensional solutions shown in Fig. 2. As shown, both solutions were well-formed, with a general trend for smaller distortions to occur toward the center of the spaces. Thus, although the prototype was never presented to participants, the faces appear to organize around it in a distortion-specific manner. This suggests that people appreciated fine differences among the stimuli, whether the faces were Black or White. It is important to note two aspects of the results in Fig. 2: first, although both spaces are well-formed, the space for White faces (left panel) has a more defined shape. Second, although both solutions occupy most of their depicted spaces, MDS solutions do not provide a clear depiction of absolute distance. That is, each solution is illustrated in an optimal manner (the program “zooms in”), which means that one solution is potentially “bigger” in true psychological space than the other. For this reason, our final step was to combine matrices, deriving an overall solution for all possible pairs, including the same faces when perceived as Black and White.

250 To create a combined solution, we used the separate matrices (from blocks 1 to 2), and applied PREFSCAL (multidimensional unfolding) to create a combined common space, using normalized distances (Busing, Groenen, & Heiser, 2005). This analysis seeks the best solution for all

289 stimuli, by adjusting positions of each item in space, in the usual gradient-descent process. We conducted the analysis with 10,000 different starting configurations and random seeds, with highly stable results. The derived common space (Fig. 3) explained 85% of the variance, with normalized stress = .003. The primary (horizontal) dimension was clearly race, as light and dark-skinned faces grouped to separate halves of the space. Despite the physical similarity of certain faces (e.g., light and dark versions of a 40% morph), there were essentially no mixed-race clusters. Within the race groups, faces were again roughly arranged by levels of distortion: similar distortion levels were often close “neighbors.” Of key interest, when all faces are analyzed together, the best-fitting interpretation of the data shows a spread among the White faces, and a general compression among the Black faces, suggesting that absolute psychological distances differed across depicted races.

306 3.4. *Distance analyses*

307 To test Valentine’s (1991) MDS hypothesis, we analyzed the inter-face distances, as estimated by PREFSCAL. Distances were pooled within each set to obtain averages for

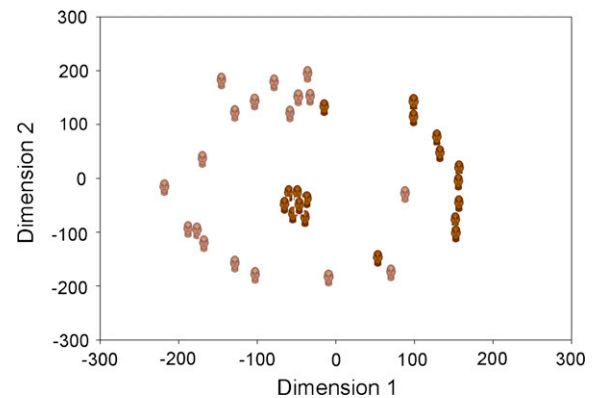


Fig. 3. Combined, two-dimensional solution for all faces. The axes represent the primary and secondary dimensions, shown in arbitrary units.

310 all possible light–light pairs, and all dark–dark pairs; these
 311 averages were tested in a within-subjects, repeated-measures ANOVA. As suggested by Fig. 3, the average distance
 312 among light-skinned faces (210 arbitrary units) was significantly greater than the distance among the dark-skinned
 313 faces (165 units), $F(1, 80) = 186.3$, $p < .0001$, $\eta_p^2 = .85$.

316 4. Discussion

317 In the present study, we empirically constructed a version of Valentine's (1991) theoretical model using physi-
 318 cally identical White and Black faces. The distance estimates obtained from the multidimensional unfolding
 319 analysis provide strong support for the race-based dispersion assumption of Valentine's framework. Valentine
 320 (1991) suggested that other-race faces should be located more distant from the central tendency of their shared psy-
 321 chological space, and that they should be more tightly clustered. Our results corroborated the second prediction, but
 322 not the first (likely owing to the fact that all faces were derived from the same prototype). Although faces from dif-
 323 ferent races possess similar absolute levels of physiognomic variability (Goldstein, 1979), the present approach
 324 ensured that all faces were equivalent. Despite the structural identity among our Black and White sets, inter-face
 325 distances among the Black faces were substantially smaller than distances among the White faces, suggesting that per-
 326 ceived race strongly modulates the dispersion of faces in psychological space.

327 Several previous approaches have been used to investigate the hypothetical, n -dimensional space underlying face
 328 processing. Connectionist models, for instance, have been constructed using principal-components analysis, with
 329 simulations run to test predictions of the MDS framework (Burton, Bruce, & Hancock, 1999; Burton, Miller, Bruce, &
 330 Q4 Hancock, 2001). Other methods involve participants' direct similarity ratings (Lee, Byatt, & Rhodes, 2000) or judgments
 331 about different facial features (Rhodes, 1988). The present study used an indirect, same-different task to
 332 construct a psychological space, ultimately supporting the predictions from Valentine (1991). Our results also
 333 indirectly support predictions from Levin (2000) and Hugenberg and Sacco (2008). These authors suggest that
 334 perceivers first categorize faces by race, seeking individuating information for other-race faces only when moti-
 335 vated. We found evidence for this in our same-different and go/no-go RTs, as participants were fast to classify Black
 336 faces (go/no-go), but slow to individuate them (same-different). Considered together with the finding that
 337 psychological space “shrinks” for other-race faces, these results suggest that other-race faces are encoded or stored
 338 less completely than own-race faces.

339 Because the own- and other-race faces in this study were physically identical, differing only in color, partici-
 340 pants could not use different feature sets for their judgments. As such, our results somewhat contradict Val-
 341 entine's (1991) explanation for differences in the spatial organization of faces. Valentine suggested that the feature
 342 dimensions used to store other-race faces may be inappropriate, reflecting greater experience extracting features

343 from own-race faces. Our results suggest that the same fea- 368
 344 tures were used in processing all faces, but with unequal 369
 345 salience, depending upon perceived race. In fact, we sug- 370
 346 gest that other-race faces are more tightly clustered in psy- 371
 347 chological space because of increased reliance on features. 372
 348 Whereas own-race faces receive enhanced configural pro- 373
 349 cessing (Rhodes, Hayward, & Winkler, 2006), other-race 374
 350 face processing may rely more heavily on featural process- 375
 351 ing, yielding “equivalency clusters” in psychological space. 376
 352 Our future research will focus on identifying the psycho- 377
 353 logical spaces for own- and other-race faces using more 378
 354 naturally-varied stimuli, relating such information to the 379
 355 well-known ORE in recognition memory. 380

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