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A Statistical Model of Facial Attractiveness

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Abstract

Previous research has identified facial averageness and sexual dimorphism as important factors in facial attractiveness. The averageness and sexual dimorphism accounts provide important first steps in understanding what makes faces attractive, and should be valued for their parsimony. However, we show that they explain relatively little of the variance in facial attractiveness, particularly for male faces. As an alternative to these accounts, we built a regression model that defines attractiveness as a function of a face's position in a multidimensional face space. The model provides much more predictive power than the averageness and sexual dimorphism accounts and reveals previously unreported components of attractiveness. The model shows that averageness is attractive in some dimensions but not in others and resolves previous contradictory reports about the effects of sexual dimorphism on the attractiveness of male faces.

Keywords

face, attractiveness

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Attractiveness is one of the most important social characteristics of the human face. Facial attractiveness predicts mate choices (Rhodes, 2006) and income (Frieze, Olson, & Russell, 1991) and is used as a basis for a number of social attributions, including attributions of social and intellectual competence, concern for other people, integrity, and adjustment (Eagly, Makhijani, Ashmore, & Longo, 1991). In light of such findings, it is not surprising that scientists have long been interested in identifying the facial properties that define attractiveness (Galton, 1878; Rhodes, 2006; Symons, 1979). Identifying these properties is critical for both evolutionary and nonevolutionary hypotheses about the origins and functional significance of attractiveness (Buss, 1989; Thornhill & Gangestad, 1999).

Here we introduce a regression model of attractiveness that relates the attractiveness of faces to their position in face space. Face space is a high-dimensional space in which every face can be approximated as a point defined by its coordinates on the face dimensions (Valentine, 1991). These dimensions define abstract, global properties of faces and can be extracted empirically from statistical analysis of three-dimensional laser scans of real faces (Blanz & Vetter, 2003). Face-space models have been successfully used to account for a number of face-perception findings (Valentine, 1991) and to model social perception of faces (Oosterhof & Todorov, 2008; Walker & Vetter, 2009).

Our model of facial attractiveness can (a) accurately predict the attractiveness of faces chosen arbitrarily from the face space, (b) help resolve previous inconsistencies in the literature about the effects of face averageness and masculinity/femininity, and (c) reveal a new, previously unreported component of attractiveness. The face-space approach also allowed us to implement two of the previous accounts of attractiveness—averageness and sexual dimorphism—as explicit alternative models that we quantitatively compared with each another and with our own model. Although we implemented all accounts of facial attractiveness using standard multiple regression, we refer to them all as models in order to highlight the fact that we implemented them explicitly and used them to make predictions.

To build our model, we used a 50-dimensional face space with 25 shape dimensions and 25 reflectance dimensions. Based on previous research demonstrating the importance of shape and reflectance information in face perception (Hill, Bruce, & Akamatsu, 1995; Walker & Vetter, 2009) and attractiveness (O'Toole, Price, Vetter, Bartlett, & Blanz, 1999), the model incorporates both types of information. As noted previously, the empirically derived face dimensions reflect global face properties. For example, the first shape dimension is face width, and the first reflectance dimension is darkness/lightness. The same face space was used for male and female faces, so that the average female face and the average male face were both points in the space. We randomly sampled a large number of faces (i.e., faces corresponding to randomly sampled coordinates) from this space and collected ratings on

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their attractiveness. Using these attractiveness ratings, we built a simple model for each gender that takes a face's position in face space as input and provides predicted attractiveness as output.

Specifically, the model was built with a second-order polynomial regression analysis on the attractiveness ratings of 2,000 male and 2,000 female symmetric faces. In contrast with previous models of social perception that assumed linearity between facial dimensions and attractiveness (Oosterhof & Todorov, 2008; Walker & Vetter, 2009), our model included a second-order, quadratic term for each face dimension. This nonlinear approach allowed us to capture the intuitive idea—also predicted by the averageness account of attractiveness—that faces on either extreme of a dimension (e.g., extremely wide or extremely thin) are unattractive.

Once built, the model was able to address a number of topics that have been central to attractiveness research. For example, previous research has found that the mathematical average of faces in a population is attractive. This simple and elegant effect has been demonstrated by averaging a large number of face images (Langlois & Roggman, 1990) and by a variety of other experimental techniques (Bronstad, Langlois, & Russell, 2008; O'Toole et al., 1999), although there is debate about the importance of the effect (Langlois, Roggman, & Musselman, 1994; Perrett, May, & Yoshikawa, 1994; Rhodes, 2006), and little has been done to specify the features in which averageness is and is not attractive. Many researchers have also found that sexual dimorphism (femininity vs. masculinity) is related to attractiveness. For female faces, there is widespread agreement that femininity is attractive (Cunningham, 1986; Koehler, Simmons, Rhodes, & Peters, 2004; Rhodes, Chan, Zebrowitz, & Simmons, 2003). For male faces, some studies have found that masculinity is attractive (Cunningham, Barbee, & Pike, 1990; DeBruine et al., 2006; Johnston, Hagel, Franklin, Fink, & Grammer, 2001; Russell, 2003), others have found that femininity is attractive (DeBruine, Jones, Smith, & Little, 2010; Penton-Voak, Jacobson, & Trivers, 2004; Perrett et al., 1998; Rhodes, Hickford, & Jeffery, 2000; Welling et al., 2007), and others have found small or mixed effects (Rennels, Bronstad, & Langlois, 2008; Rhodes, 2006; Swaddle & Reierson, 2002). Our model shows that the mixed results regarding masculinity and male attractiveness may have been due to differences in the effects of the shape and reflectance dimensions on attractiveness.

The averageness and the sexual dimorphism accounts are parsimonious and explain much of what researchers know about facial attractiveness. We developed our model in an attempt to reveal aspects of facial attractiveness that are not explained by these other models and, in doing so, to resolve some of the inconsistencies in the literature.

Method

The study consisted of two experiments. In the first experiment (model training), we collected attractiveness ratings for 2,000 male and 2,000 female symmetric faces in order to create the model. In the second experiment (model testing), we collected attractiveness ratings for 100 male and 100 female symmetric faces used to test the model after it had been created.

Participants

In both experiments, subjects rated faces of the opposite gender only. Twenty male and 20 female subjects (mean age = 19.9 years, *SD* = 1.4) participated in model training. Twenty-four male and 23 female subjects (mean age = 19.8 years, *SD* = 1.3) participated in model testing. More details about the participants are provided in the Participants section in the Supplemental Material available online.

Stimuli

In both experiments, each subject viewed a series of faces drawn from a 50-dimensional uniform distribution (width = 2.5 *SD*) centered around the mean face of the gender opposite to that subject's gender. Faces were generated with FaceGen software (Singular Inversions, www.facegen.com). The 25 shape dimensions corresponded to the first 25 components of a principal component analysis of the changes in vertex positions from an average face (Blanz & Vetter, 2003). Reflectance was represented as a color texture map, which, like face shape, was separated into 25 principal components. More details about the stimuli are provided in the Facegen Stimuli section of the Supplemental Material; Fig. S1 in the Supplemental Material provides examples of two of the reflectance dimensions.

We used the default normalized (or Mahalanobis) space, in which 1 unit for each dimension corresponds to 1 standard deviation in the population. It is also possible to use an unnormalized space, in which each dimension is scaled by its raw magnitude. In the unnormalized space, the results of this study were numerically different, but the pattern of significant results and the signs of the relationships between all reported vectors were the same. The performance of our model compared with alternative models was similar for normalized and unnormalized spaces. We used one space for both male and female faces so that the average female face and the average male face were both points in the space.

Analysis

Subjects rated the faces on a 9-point Likert scale, ranging from 1 (*extremely unattractive*) to 9 (*extremely attractive*). Ratings were then standardized for each subject. For each gender, the mean ratings across subjects in the first experiment were submitted to a multiple regression with 101 predictor variables: 50 for each of the dimensions, 50 for the squares of the dimension values, and a constant. The coefficients from this regression were then used to define the attractiveness function for each gender. The direction of maximal change in attractiveness is the gradient of the attractiveness function:

$$\nabla f(\mathbf{x}) = \sum_{i=1}^{50} \frac{\partial f}{\partial x_i} \mathbf{e}_i ,$$

where f is the attractiveness function, or model, that relates each position in face space to attractiveness. Each x_i represents one of the 50 dimensions, and each $\mathbf{e}_i$ is a basis vector of the face space. In conceptual terms, the attractiveness function $f(x)$ takes any face as input and provides a predicted attractiveness score as output. The attractiveness gradient $\nabla f(x)$ also accepts any face as input but provides the direction in face space that—for a small fixed distance—the face should move to maximally increase its attractiveness.

We tested a number of hypotheses about attractiveness by inspecting the attractiveness gradient at the position of the average female face and of the average male face. In particular, for each gender, we defined the vector of maximal change in attractiveness, $\mathbf{v}$, as the vector pointing in the direction of maximal change in attractiveness at the average face for that gender. This vector can be compared with a normalized vector $\hat{\mathbf{u}}$ pointing in the direction of femininity, which is defined as the difference between the average female face and the average male face. In other words, $\hat{\mathbf{u}}$ is the face-space representation of sexual dimorphism. For each gender, a new component of facial attractiveness that is not explained by sexual dimorphism can then be defined as $\mathbf{v} - (\mathbf{v} \cdot \hat{\mathbf{u}})\hat{\mathbf{u}}$. This component is conceptually similar to the residual of facial attractiveness after regressing out the sexual dimorphism component.

In general, vectors pointing in the direction of maximal change in attractiveness will be long where each unit change in the dimension results in a large change in attractiveness, and short where each unit change in the facial dimension results in a small change in attractiveness. At the position of the average face, short vectors are more consistent with the averageness account than are long vectors. To test the hypothesis that averageness is more attractive for the face shape dimensions than for the face reflectance dimensions, we separately computed the vector of maximal attractiveness for the shape dimensions and the reflectance dimensions. The effect of averageness for each of these classes of dimensions was measured as the inverse norm of these vectors (1 divided by the vector's length).

For each gender, we used bootstrapping to test whether the direction of the maximal change in attractiveness pointed in the direction of femininity or masculinity (see the Statistics section in the Supplemental Material).

Alternative models

For comparison purposes, we tested three alternative models. The first implemented the averageness account, the second implemented the sexual dimorphism account, and the third implemented both accounts. The averageness model used linear regression to predict attractiveness from the euclidean distance between each face's position and the mean position for its gender. The sexual dimorphism model used the projection of each face's position on the sexual dimorphism vector to predict attractiveness. The combined model used both euclidean distance from the mean and the projection on the sexual dimorphism vector as predictors. All alternative models included intercepts. An R^2 value was calculated for each model. Confidence intervals around each R^2 value were computed by bootstrapping.

Although our model included more parameters than the alternative models, we emphasize that we compared the models' performance on a novel set of faces not previously seen by any of the models. Had we compared the models using the training data, our complicated model would have been unfairly advantaged. Because complicated models such as ours can overfit noise in data, statistics such as ΔR^2, Akaike's information criterion (AIC), or the Bayesian information criterion (BIC) are sometimes used to correct for the high number of parameters. However, these corrections were not necessary in this case because we compared the models using novel testing data. Any overfitting by our high-parameter model would have helped fit only the training set, and not the testing set (Bishop, 2006).

Results

Model validation and model comparison

To validate our model, we collected attractiveness ratings for a new set of 100 randomly sampled male and 100 randomly sampled female faces not previously seen by the model. We were able to accurately predict the attractiveness of the female faces ($r = .79$, $p < .05$) and the male faces ($r = .84$, $p < .05$; see Fig. 1). Our model substantially outperformed the three alternative models (Fig. 2): a regression model based on only distance from the mean face for each gender (i.e., averageness; female faces: $r = .27$, $p < .05$; male faces: $r = .20$, $p < .05$), a regression model based on only the sexual dimorphism of the face (female faces: $r = .57$, $p < .05$; male faces: $r = .10$, $p > .05$), and a regression model based on both the distance from the mean face and sexual dimorphism (female faces: $r = .61$, $p < .05$; male faces: $r = .21$, $p < .05$). Although averageness and sexual dimorphism were significant predictors of attractiveness, they explained only a small proportion of the variance.

Averageness and attractiveness

To test the strong version of the averageness account—that the average face is maximally attractive—we included the average male face and average female face in our validation sample. FaceGen previously defined the average faces as the average of 162 real male and 109 real female faces represented in the face space (see the Facegen Stimuli section in the Supplemental Material). For both male and female faces, faces that were predicted to be more attractive than the average face

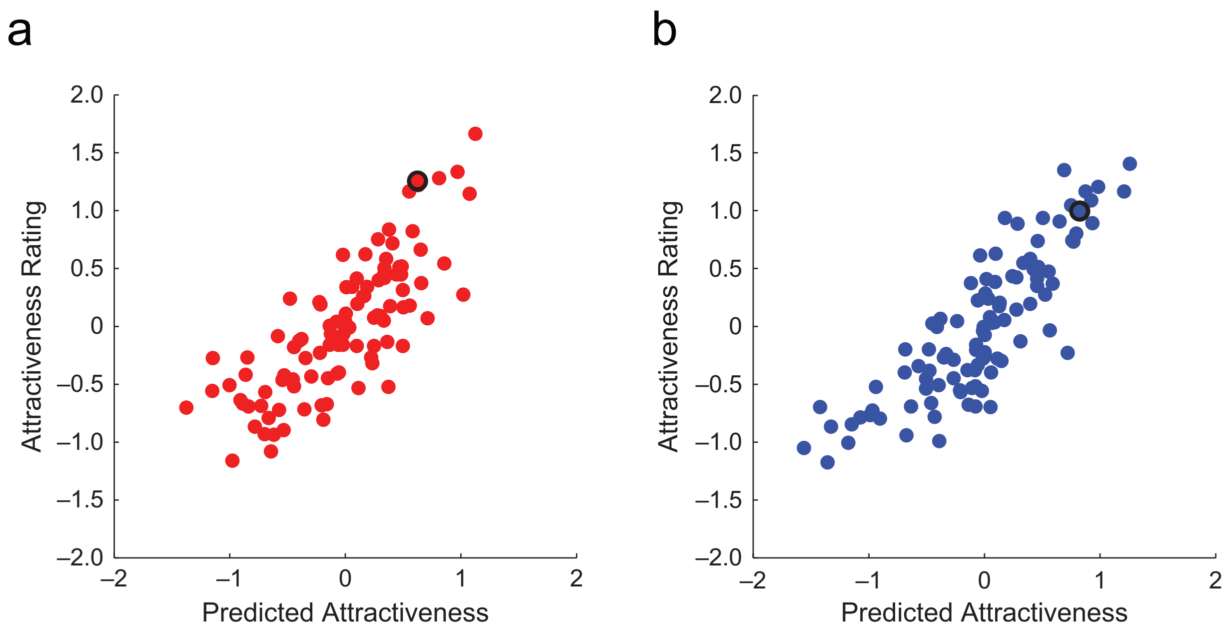

Fig. 1. Relation between predicted attractiveness and actual attractiveness ratings in the model-testing experiment. Ratings were obtained for (a) a set of 100 female faces and (b) a set of 100 male faces not previously seen by our model. The data points for the average female face and the average male face are outlined in black.

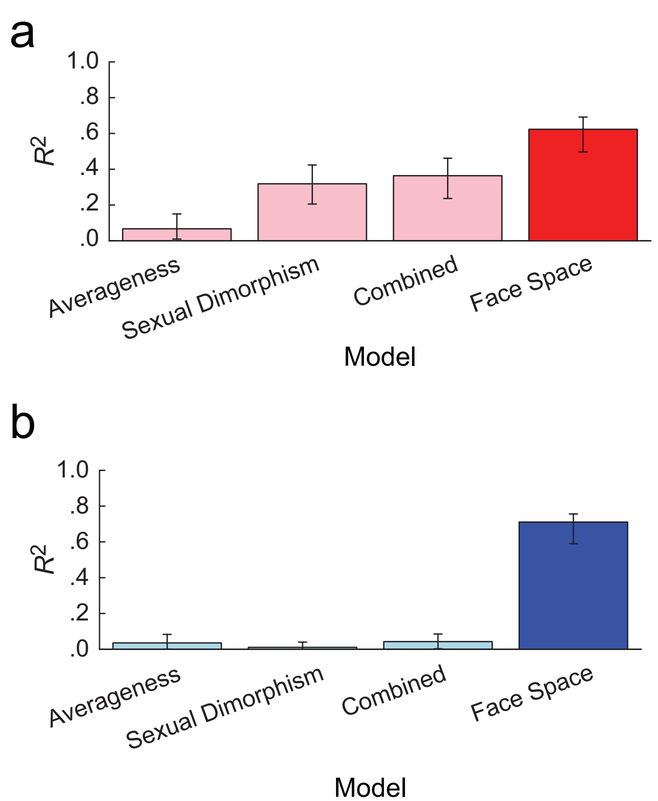

Fig. 2. Performance of the face-space model and three alternative models (averageness, sexual dimorphism, and averageness and sexual dimorphism combined) in the model-testing experiment. The graphs show the variance in attractiveness explained separately for (a) female faces and (b) male faces. Error bars represent 90% confidence intervals based on bootstrapping.

were indeed rated as more attractive than the average face by our test subjects (Fig. 1).

To further illustrate the relationship between our model and the averageness model, we examined the shape of the attractiveness function in our model separately along each dimension in face space. We found that for many dimensions, the most attractive faces were near the average face. However, for many other dimensions, the most attractive faces were far from the average face (Fig. 3), and in many cases, the most attractive faces fell outside the range of faces used in the training set. For the 20 dimensions that explained most of the variance of female attractiveness, 5 contained their maximally attractive point within the 2.5–standard deviation sampling range. For the 20 dimensions that explained most of the variance of male attractiveness, 10 contained their maximally attractive point within this sampling range. The full model specification is publicly available in MATLAB (The MathWorks, Inc., Natick, MA) code on our Web sites (http://www.cns.nyu.edu/~csaid/ and http://webscript.princeton.edu/~tlab/databases/). In general, averageness was more attractive for the shape dimensions than for the reflectance dimensions for both male and female faces, although this was not the case for all these dimensions.

Compared with the average male face, attractive male faces have darker skin, more beard, darker brows and eye lines, and less bulk around the cheeks and upper neck. Compared with the average female face, attractive female faces have lighter skin, redder lips, darker eye lines, and less fat around the cheeks and upper neck. The reflectance dimensions with the strongest effects on female attractiveness involved the contrast

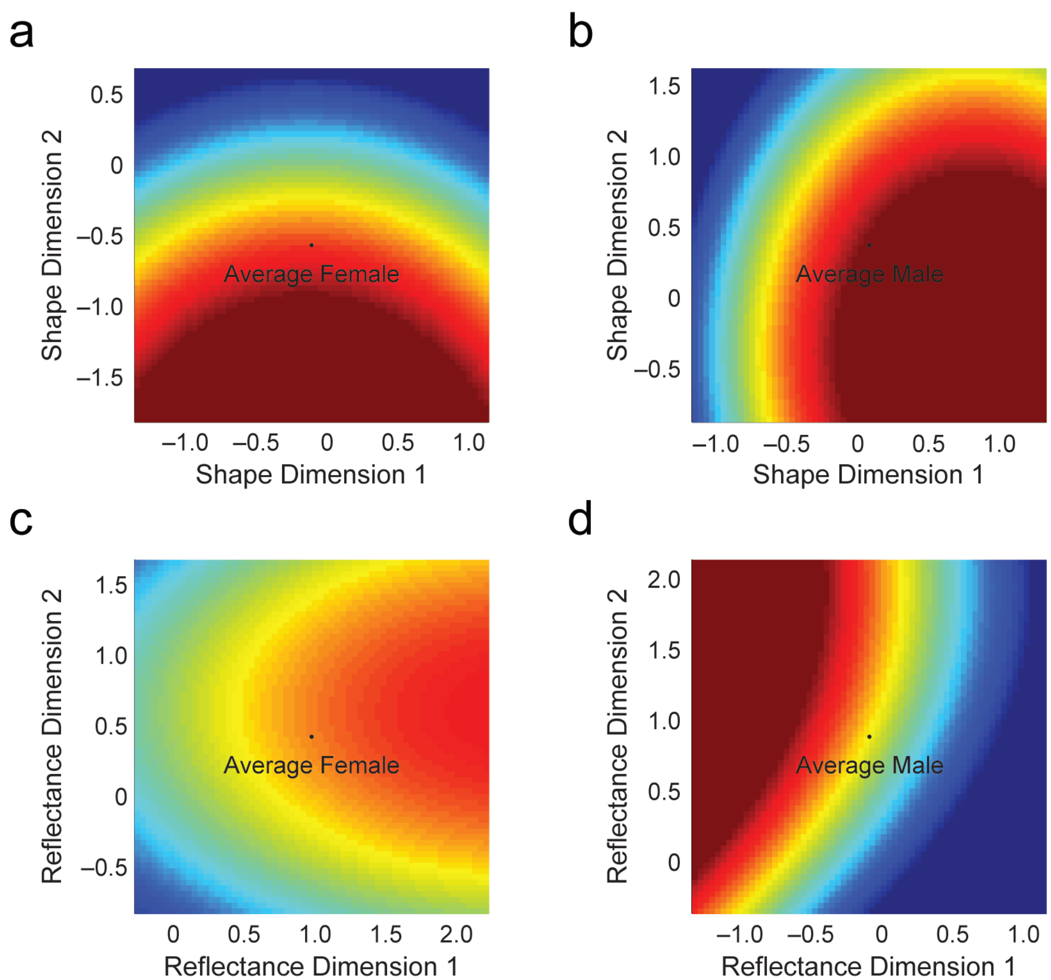

Fig. 3. Cross-sections of attractiveness in face space. Each plot shows the attractiveness predicted by the function for faces varying along two dimensions, with all other dimensions fixed at the mean for that gender. Colors closer to red represent attractive faces, and colors closer to blue represent unattractive faces. In the top row, attractiveness as a function of the first two shape dimensions is shown for (a) female and (b) male faces. In the bottom row, attractiveness as a function of the first two reflectance dimensions is shown for (c) female and (d) male faces.

around the eye lines and the redness of the lips. This finding confirms recent research on the relationship between cosmetics and female attractiveness (Russell, 2003, 2009).

Sexual dimorphism and attractiveness

Because the model can predict the attractiveness of any face, it can also specify the direction in face space in which any arbitrary face should be moved to produce maximal change in its attractiveness. Many questions about facial attractiveness can be answered by examining the direction of maximal change in attractiveness at both the positions of the average male face and of the average female face. In particular, we compared the direction of maximal change in attractiveness with the direction of sexual dimorphism.

We found that for the average female face, the direction of maximal change in attractiveness is relatively similar, but not identical, to the direction of femininity (cosine similarity = .72, $p < .01$; see Fig. 4a). The residual component of female attractiveness, orthogonal to the sexual dimorphism line, can also be specified. By exaggerating this component, we show in Figure 4a how a female face can become more attractive without moving along the sexual dimorphism line: The face becomes darker, especially around the eyes, and the cheeks become thinner. Attractiveness for average females is thus a linear combination of the femininity direction and this new component.

For the average male face, we found that the direction of maximal change in attractiveness was nearly orthogonal to the masculinity direction (Fig. 4b; cosine similarity = .06, $p < .01$). The residual component, which contributed heavily to attractiveness, can be described as a darkening of the face, especially around the eyes, eyebrows, and beard, as well as an overall thinning of the face, particularly around the cheeks. This component, which is orthogonal to the sexual dimorphism line, contains a balance of positive and negative weights on dimensions that are positively weighted in masculinity. Our results

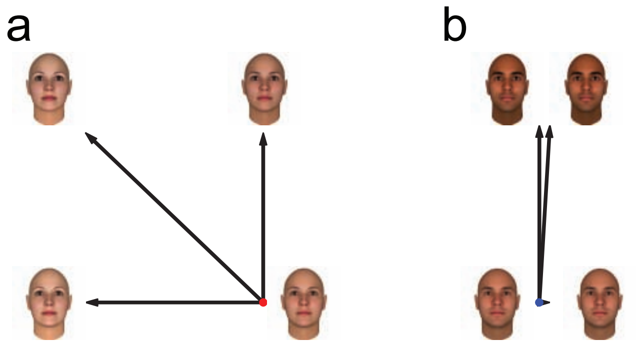

Fig. 4. The direction of maximal change in attractiveness for the average (a) female and (b) male face. The average female face is represented by the red point and shown in the adjacent image. The direction of maximal change is represented by the diagonal vector. This vector can be expressed as the sum of a change in femininity (horizontal vector) and an orthogonal component (vertical vector). The average male face is represented by the blue point and shown in the adjacent image. The diagonal vector represents the direction of maximal change in attractiveness for males, the horizontal vector represents masculinity, and the vertical vector represents the residual component. For visualization in two dimensions, the maximal-change vectors and the orthogonal-component vectors have been each rotated by the same amount around the *x*-axis so that the plane spanned by all three vectors is flat on the page. The face images used to illustrate these vectors have been exaggerated so that their properties are easily visible.

showing a weak relationship between male attractiveness and masculinity are consistent with many previous reports (Rennels et al., 2008; Rhodes, 2006; Swaddle & Reierson, 2002), but are seemingly inconsistent with reports showing either positive or negative effects of masculinity on facial attractiveness (Cunningham et al., 1990; DeBruine et al., 2006, 2010; Johnston et al., 2001; Penton-Voak et al., 2004; Perrett et al., 1998; Rhodes et al., 2000; Russell, 2003; Welling et al., 2007).

To examine this issue further, we performed the same sexual dimorphism analysis separately for the shape dimensions alone and for the reflectance dimensions alone. For the average female face, the direction of maximal change in attractiveness is similar to the direction of femininity for both the shape and the reflectance dimensions (shape: cosine similarity = .68, $p < .01$; reflectance: cosine similarity = .75, $p < .01$; bootstrap test; see the Statistics section and Fig. S2 in the Supplemental Material). For the average male face, the direction of maximal change depends on whether only shape or only reflectance is allowed to vary. For reflectance, the direction of maximal change in attractiveness is similar to the direction of masculinity (cosine similarity = .36, p < .01). For shape, the direction is similar to the direction of femininity (cosine similarity = .35, $p < .01$). Thus, the weak effect of masculinity when both shape and reflectance dimensions were allowed to vary (Fig. 4b) can be explained by differences between the effects of masculine shape and the effects of masculine reflectance (see Fig. S2 in the Supplemental Material).

Discussion

We built a regression model that defines the attractiveness of a face as a function of its position in a multidimensional face space. When tested in predicting the attractiveness of novel faces in the face space, the model substantially outperformed alternative regression models based on averageness and sexual dimorphism. We do not believe that any researchers adhere to the strict versions of the averageness and sexual dimorphism accounts that we implemented in this study, and we suspect that modified versions of these accounts could perform better. However, we think it is illuminating to make direct comparisons of explicitly defined models, as we have done here.

Testing our model revealed several findings that should be of interest to researchers investigating the evolutionary origins and functional significance of facial attractiveness. We found that facial averageness is attractive for many dimensions, especially the shape dimensions, but that it is not highly attractive for many other dimensions, especially the reflectance dimensions. This finding is consistent with earlier work showing that averageness for shape dimensions has a greater effect on attractiveness than does averageness for reflectance dimensions (O'Toole et al., 1999). In general, although the average male face and the average female face were perceived to be attractive, they were not the maximally attractive faces (Figs. 1 and 3). An analysis of the direction of maximal change in attractiveness for the average faces showed that attractiveness can be broken up into a sexual dimorphism component and a new, previously unreported component. For both males and females, this component involved a darkening of the skin, especially around the eyes, and thinner cheeks.

We also found that the overall weak effect of masculinity on the attractiveness of male faces (Rennels et al., 2008; Rhodes, 2006; Swaddle & Reierson, 2002) can be explained by a dissociation between the effects of the shape and reflectance properties of male faces. In general, we found that masculinity in male faces is attractive in the reflectance properties, but that femininity is attractive in the shape properties. This dissociation may also explain the many previously observed contradictory effects of masculinity, given that previous experiments typically defined masculinity with an unspecified combination of shape and reflectance cues. In fact, the one experiment in which manipulations were clearly restricted to reflectance cues showed that masculinity is attractive in males (Russell, 2003). Studies in which sexual dimorphism appeared to be most restricted to shape cues typically showed that femininity is attractive in males (Perrett et al., 1998; Rhodes et al., 2000). These results are consistent with the findings reported here.

Some of the inconsistencies in the literature may be due in part to individual differences. Females' preferences for male faces have been shown to depend on the menstrual cycle (Penton-Voak et al., 1999), the personality of the rater (Johnston et al., 2001), the attractiveness of the rater (Little, Burt, Penton-Voak, & Perrett, 2001), and the age of the rater's parents (Perrett et al., 2002). The effects of these individual differences should mostly cancel out in a large set of raters, but it is important to emphasize that different observers have different attractiveness functions.

Our stimuli were artificial faces drawn from a well-defined face space. This approach has some clear advantages. The stimuli were well controlled, and the face-space approach greatly increases the number of analytic techniques that can be used. For example, whereas simple averaging techniques can reveal that averageness is attractive, the face-space approach can directly specify the dimensions in which averageness is and is not attractive. Similarly, whereas single-dimensional approaches to studying sexual dimorphism may reveal that sexual dimorphism is correlated with attractiveness (DeBruine et al., 2010; Johnston et al., 2001; Penton-Voak et al., 1999; Perrett et al., 1998; Rennels et al., 2008), the multidimensional face-space approach can directly compare directions of attractiveness and directions of sexual dimorphism. The face-space approach can help resolve previous contradictions in the literature, and, as we described here, it can identify new directions of facial attractiveness that could not be identified with a single-dimensional approach. Furthermore, our approach makes it possible to generate and exaggerate new faces to illustrate properties of the model, as in Figure 4.

At the same time, there are some limitations to the face-space approach. Even though our face space itself was defined by a statistical analysis of a large number of real faces, the stimuli themselves were artificial. It is possible that artificial faces are rated for attractiveness in a different way than real faces are. Moreover, it is not easy to reliably bring high-dimensional real faces into a lower-dimensional face space, and our specific model parameters might not predict the attractiveness of real faces. We view our model not as a prediction machine for real faces, but rather as a way of understanding attractiveness within a simplified, yet statistically valid, face space. A further limitation of the face-space approach is that the effects of sexual dimorphism may also depend on whether sexual dimorphism is measured by subjective ratings or manipulated with computer graphics techniques (Rhodes, 2006), although this issue is debated (DeBruine et al., 2006, 2010; Rennels et al., 2008).

Despite these limitations, there is good reason to believe that our conclusions will generalize to real faces. For instance, the finding that averageness contributes relatively little to the variance in facial attractiveness has already been reported in three recent studies using real faces (Chen & Zhang, 2010; Komori, Kawamura, & Ishihara, 2009; Scott, Pound, Stephen, Clark, & Penton-Voak, 2010).

To trigger further research on facial attractiveness, we are making our model, data, and faces publicly available on our Web sites (http://www.cns.nyu.edu/~csaid/ and http://webscript.princeton.edu/~tlab/databases/). Researchers might use the faces and model to examine the effects of averageness, sexual dimorphism, and the components orthogonal to sexual dimorphism on brain and behavior. For instance, researchers could investigate how differences between shape cues and reflectance cues relate to adaptive qualities. It is known that facial reflectance cues provide more information than facial shape cues about gender (Hill et al., 1995). This might help explain why masculine reflectance is attractive in males and feminine reflectance is attractive in females, but it leaves unanswered why feminine shape is attractive in males.

Researchers might also use the data to improve our model. Regardless of how it is used, we hope that the model, by virtue of being explicit, will clarify the nature of facial attractiveness.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information may be found at http://pss.sagepub.com/content/by/supplemental-data

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