# Towards a multifaceted understanding of facial attractiveness

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*Abstract*— **Facial attractiveness has been of interest to researchers from multiple disciplines for a long time. The first line of attractiveness research from psychologists have quested for what specific features makes a face attractive. A series of studies following this line have shown various key factors that play a role in attractiveness perception, such as averageness [16], symmetry [7], sexual dimorphism [19], distinctiveness [30], familiarity [20], categorization difficulty [10] and etc. Another line of attractiveness research from social psychology have found that attractive faces are often ascribed more favorable and positive personality traits, known as the "halo effect" of facial attractiveness. They map social dimensions of face spaces into 2 major dimension and found people can make accurate and reliable judgments of social attributes of faces such attractive, trustworthy and etc by within a short time [17], [28], [29]. A third line of attractiveness study aims at building up accurate predictors of attractiveness judgments [1], [5], [8], [11]. The primary goal of this study is to integrate the ideas behind the three lines and to quantitatively and qualitatively understand what makes a face attractive under the context of social perception. Towards this goal, we investigate the relationship between facial attractiveness and social perceptions of faces [3] with supervised learning models. We demonstrate that social features can accurately predict human's attractiveness perception. We demonstrate that social attributes like appearing interesting, sociable, and calm contribute to facial attractiveness whereas appearing boring, and aggressive are negatively correlated with attractiveness. Our secondary goal in the study is to build up a computationally accurate and human interpretable model to predict attractiveness. We revisit the geometric properties of faces in a more interpretable manner and quantitatively measure the contribution of various visual features in attractiveness perception. We also use pretrained neural networks to build up a predictor model and achieve descent prediction performance.**

## I. Introduction

Faces occupy a fundamental status in human psychology. We come across faces everyday on social networks, in the media, and in person. Research have found that people reliably and automatically make personality and social traits evaluations from facial appearance [29] such as how attractive/ trustworthy/ intelligent a person looks from his/ her face. Among the various social attribute judgments people make about faces, facial attractiveness are among the few that receives special attention. People are fond of attractive faces and are curious about what makes a face attractive. Previous research has tackled the mystery of facial attractiveness from multiple perspectives. The major questions raised from different disciplines include:

1) Is attractiveness perception nature or nurture?
2) What features/factors make a face attractive?
3) Why do we evolve to find certain features/ faces attractive? What are the neural mechanisms of beauty perception?
4) Can we predict attractiveness reliably and accurately?
5) How is attractiveness related to social perception/ interactions?

Although people may have different opinions on who are the most attractive actors/ actress in the world, in general the relative preferences are typically built on a universal bedrock of attractiveness. Psychologists have confirmed that not only adults share a high consensus on what attractive faces are [4], even infants as young as 2-8 months old share preferences for attractive faces rated by adults [15], [21]. Furthermore, people from different cultures share a certain degree of consensus on what is attractive faces [4].

The findings suggesting that facial attractiveness may have universal underpinnings drives psychologists to ask what are the specific common features that make a face attractive. Researchers have found that the average [16], [23], and symmetric [25] faces are perceived as more attractive [16], [24]. Later studies also found that although average faces are attractive, the most attractive faces are not average [2].

There are also studies claiming that faces with exaggerated sexusal dimorphic traits are more attractive [19]. There are also other curious factors that affect attractiveness perception, such as the familiarity of the face to the perceiver, [20], and categorization difficulty [10] of the face to the viewer.

To further understand why these features matter, evolutionary psychologists hypothesized that attractiveness judgments may be a behavioral adaptation which helps human beings select strong and healthy mates, so as to maximize their gene propagation probability [27]. Under this view, they suggested that averaged/ symmetric faces may signal greater underlying genetic diversity, exaggerated sexual dimorphism advertises genetic fitness [19]. An alternative hypothesis proposes that certain faces may be perceived as attractive ones due to perceptual processing fluency. Attractive faces might be pleasant to look at since they are closer to the cognitive representation of the face category in the mind. [22]. Halberstadt and Rhodes have found that not only averaged faces are regarded as more attractive, so are averaged birds, fish and automobiles. [9]. Reber, Schwarz & Winkielman have demonstrated that when subjects are asked to do some categorization tasks on the faces, the perceived attractiveness of the face decreased. And the more difficult the categorization task, the less attractive the face is perceived [31], [32]. All these findings led researchers to propose that perceived attractiveness has to do with processing smoothness.

Machine learning researchers have developed various facial features and models to give accurate predictions on facial attractiveness. Yael and Gideon used the geometry ratios and distances of facial features to build an attractiveness predictor

[5]. Researchers also tried to train neural networks to make predictions of attractiveness on a larger scale [8]. They have gained reasonable correlation with human judgment. Amit Kagian and his colleagues have used a combination of landmark-derived features along with global features to gain a correlation with human raters as high as 0.82 [11]. These computational model demonstrate that human preference for attractive faces can be reliably learned and predicted by machines. Yet in most studies, what is learned by the machines are not fully interpretable to human beings. The challenge of building a facial attractiveness predictor with descent performance and human interpretability has remain open.

This challenge is related to the last question. We not only want to predict attractiveness but also desire to understand how attractiveness is related to social perceptions and interactions. Social psychologists already known that beautiful faces sometimes bring up the ”halo effect”, meaning that people tend to associate good attributes to good-looking people [14]. Researchers have demonstrated that people are able to infer personal attributes (attractiveness, trustworthiness, friendliness, etc.) from faces quickly and reliably [17], [28], [29]. But their focus is on the social space of faces, and there is no quantitative study of the contribution of different personal and social features to facial attractiveness and how facial attractiveness is intermingled with other social perception of people’s faces such as friendly, sociable, and aggressive. Faces convey rich social features that are vital for daily interactions.

A primary goal of this study is to predict and understand attractiveness in the spectrum of social perceptions. Having achieved this, our secondary goal is to predict attractiveness automatically. We first choose a set of interpretable geometric features of faces, then evaluate their contributions to attractiveness perception. We also experimented on neural network features and compare the performances of different visual features.

We analyze the social features and geometric ratio-related features, compare the predictive power of interpretable models and non-interpretable ones, and give a qualitative and quantitative analysis of facial attractiveness from multi-faceted views.

## II. Method

In this section, we first describe the dataset chosen in our experiment. Next we describe and analyze the social features of faces collected in the dataset. Finally, we explain how we extract visual features in three different ways: (1) landmark-based geometric features (2) eigenface features from pixels, (3) neural network features extracted from pre-trained networks.

### A. Dataset

To explore the relationship between facial attractiveness and social attributes, we chose the dataset collected by Aude Olivia’s group at MIT [3], [12]. It is composed of 2222 face images all from different identities. All images are close to frontal view. All images are cropped with an oval mask, keeping only the face in the center. These photos contain both male and female, and they include Asian/ Caucasian/ African America/ Hispanic/ Middle Eastern faces. The faces are of different expressions and from different age group. Each face image is rated in 40 social attributes consisting of 20 opposite pairs(such as attractive vs unattractive, introverted vs sociable). Each feature is rated on a scale of 1-9 (1 means not at all, 9 means extremely). The 20 pairs of social features are split into two questionnaires, each containing 20 questions. Each questionnaires select one feature from each pair of features. All ratings were collected from Amazon Mechanical Turk online platform. Each rater gave ratings to around 40 faces. Only one questionnaire will be given to a rater on the same face. In one screen, a face is shown on the left side, questions on 20 social features will be shown on the left. One catchy question is also included to evaluate whether the rater is paying attention or not. Every face’s every social feature is rated by 12-15 subjects. We take the average rating across all raters as a collective estimation of the social feature for every face. A sample questionnaire is shown in Fig. 1 The detailed description of the 40 social features will be elaborated in the social feature section.

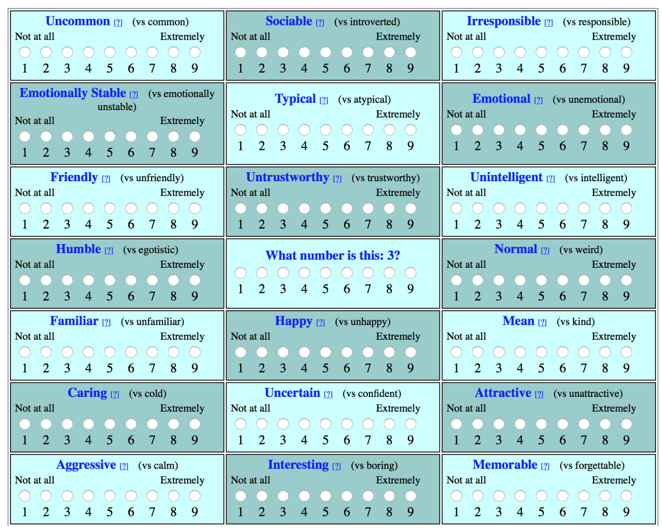


Fig. 1: Questionnaire 1: Social Features

Sample faces from our dataset are shown in Fig. 2.

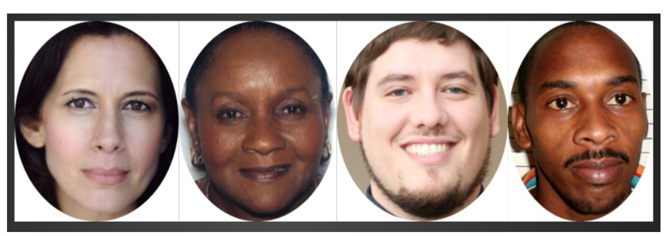

Fig. 2: Sample Faces

In MIT dataset, each rater only view a small subset of faces, therefore it’s not an ideal dataset for us to check the group consistency and the correlation between individuals with the group mean ratings. We refer to another dataset which contains 1500 raters' rating for 200 faces on attractiveness. [6] The 200 face photos are all in frontal view, include both male and female, under different lighting conditions and with neutral expression. Each rater give a rating from 1-7 on the attractiveness level of all the 200 faces. We will report the group consistency and individual consensus with group mean in the Result section.

### *B. Social Features*

We list the 40 social features in pairs shown below. Since these features are all subjective perceptions rated by people, it's informative to evaluate how much people agree with each other about these features. We randomly split the raters into two even groups, then calculate the two group averages' correlation for each social feature, and use this correlation coefficient as an index for reliability and consistency of these social features. (All correlations are statistically significant, $p < 0.05$.) The number after each feature indicates the consistency level for this social feature. Additionally, we also compute the Spearman's rank correlation between every pair of opposite social attributes to illustrate to what extend people perceive them as opposite to each other. All the Spearman's rank correlation are statistically significant. ($p < 0.001$)

The 20 pairs of social features are:

1) attractive(0.72), unattractive(0.62), -0.83
2) happy(0.84), unhappy(0.75), -0.83
3) friendly(0.78), unfriendly(0.72), -0.80
4) sociable(0.74), introverted(0.50), -0.70
5) kind(0.72), mean(0.69), -0.74
6) caring(0.72), cold(0.71), -0.75
7) calm(0.41), aggressive(0.65), -0.49
8) trustworthy(0.62), untrustworthy(0.60), -0.70
9) responsible(0.58), irresponsible(0.55), -0.63
10) confident(0.55), uncertain(0.45), -0.59
11) humble(0.55), egotistic(0.52), -0.66
12) emotional stable(0.53), emotional unstable(0.50), -0.62
13) normal(0.49), weird(0.52), -0.61
14) intelligent(0.49), unintelligent(0.43), -0.52
15) interesting(0.42), boring(0.39), -0.56
16) emotional(0.33), unemotional(0.56), -0.55
17) memorable(0.30), forgettable(0.27), -0.50
18) typical(0.28), atypical(0.24), -0.41
19) familiar(0.24), unfamiliar(0.18), -0.31
20) common(0.25), uncommon(0.27), -0.40

Apart from the attractive/ unattractive pair, there are 19 pairs of social features. We later examine the relationship between these 38 social attributes and attractiveness and build a prediction model based on these social features.

### *C. Visual features*

Although social features can accurately predict attractiveness, these features are expensive to get and therefore cannot be used to predict attractiveness automatically. To directly predict attractiveness from image input, we derived visual features from images in three methods: (1) landmark-based geometric features (2) eigenface features from pixels, (3) neural network features extracted from pre-trained networks.

*1) Geometric features:* Previous studies have found that the geometric ratio and configurations of face is important to facial attractiveness. We list the set of configuration features derived from important face landmarks which make sense to people I.

This set of geometric features is summarized by [reference chicago face dataset]. We further add up skin smoothness and skin color features as a global descriptor of faces since these are also known to play a role in attractiveness perception[refer to human like predictor]. We use a computer vision library (dlib, C++) to automatically label 68 face landmarks (see in figure3) and compute the geometric features accordingly based on definitions described in [chicago paper]. We extract the smoothness feature and skin color features according to the procedure mentioned in [human like predictor paper].

| Facial Feature | Measurement |
|---|---|
| Nose Width | Distance between outside edge of the n |
| Nose Length | Distance between nose tip and upper e |
| Lip Thickness | Distance between top and bottom edge |
| Face Length | Distance between bottom of chin to ed |
| Eye Height | Distance between upper and lower inne (Right and left measured separately and |
| Eye Width | Distance between inner and outer corne (Right and left measured separately and |
| Face Width at Most Prominent Part of the Cheek | Distance between the outer edges of ch |
| Face Width at Mouth | Distance between outer edges of cheek |
| Forehead Length | Distance from center of top of forehea |
| Distance between Pupils | Distance between the center of each pu |
| Distance between Pupil and Top of face | Distance between pupil center to top o (Right and left measured separately and |
| Distance between Pupil and Upper Lip | Distance between pupil center to top e (Right and left measured separately and |
| Chin Length | Distance from the bottom edge of lips |
| Length of Cheek to Chin | Distance between mid-cheek to bottom (Right and left measured separately and |
| Mid-brow to Hairline | Distance between middle eyebrow to to (Right and left measured separately and |
| Facial Width-to-Height Ratio (fWHR) | (Distance between the outer edges of th (Distance between upper lip and brow) |
| Face shape | (Face Width at Most Prominent Part of |
| Heartshapeness | (Face Width at Most Prominent Part of |
| Nose shape | (Nose Width) ÷ (Nose Length) |
| Lip fullness | (Lip Thickness) ÷ (Face Length) |
| Eye shape | (Eye Height) ÷ (Eye Width) |
| Eye size | (Eye Height) ÷ (Face Length) |
| Upper Head Length | (Forehead length) ÷ (Face Length) |
| Midface Length | (Distance between pupil and upper lip |
| Chin size | (Chin Length) ÷ (Face Length) |
| Forehead Height | (Mid-brow to Hairline averaged for rig |
| Cheekbone Height | (Length of cheek to chin averaged for r |
| Cheekbone Prominence | (Face width at most prominent part of |
| Face Roundness | (Face width at mouth) ÷ (Face Length) |

TABLE I: Facial Feature List

Besides these geometric configuration feature, we also select three regions from the face as shown in the figure below to extract skin smoothness and skin color information. We follow the procedure listed on [5], [11].

*2) Pixel features:* Raw pixel features are the most elementary visual features one can directly read out from images and it serves as a basic baseline for the other

Fig. 3: 68 face landmarks labeled by dlib software automatically

visual features. Since the raw pixel features are of high dimensionality(30,000 dimensions) and highly correlated, we first apply PCA on it and reduce the dimension into 100 dimensions.

*3) Neural network extracted Features:* We used pre-trained Convolutional Neural Networks (CNNs) to extract features for attractiveness prediction. Three CNNs were explored, VGG-16 [26], VGG-Face [18] and AlexNet [13]. Among them, only VGG-Face is trained on face images, the other two were trained on object images. In particular, AlexNet was trained on ImageNet, which has over 10 million images and 1,000 classes. We perform PCA on the extracted features to reduce the dimensionality of the feature and then train a supervised model to fit the data.

### D. Feature preprocessing, predictor construction and model validation

*1) Feature preprocessing:* In social feature lists, We first delete attractiveness and unattractiveness from the 40 features, since the former is the target we want to predict and the latter is the directly opposite side of attractiveness. For the remaining 38 social features, there are still a degree of redundancy. To further remove redundancy from them, we apply Principal component analysis on them and fit a model with different number of PCA features. We also conduct the same experiment on geometric features.

For pixel features, we directly reduce the dimensions as so to preserve 95% of the variance and reduced number of dimensions is 100. For neural network features, we first apply k-fold cross validation to select the number of features using a simple linear regression model. We then fix the number of features and experiment with other different models such as SVR(support vector regression), ridge regression, Lasso regression and etc.

*2) Predictor construction:* We experimented with several classical supervised learning algorithm including simple linear regression, ridge regression, Lasso regression, Elastic Net, support vector regression with linear and non-linear kernels, and decision trees. We found that ridge regression shows best performance. Ridge regression also has higher interpretability (the coefficients learned from the model suggest the contribution of each corresponding feature). The hyperparameters in ridge regression, Lasso regression and SVR are found using a leave-one-out cross validation procedure.

*3) Model evaluation:* The prediction performance is evaluated using Spearman's rank correlation. We randomly split the whole dataset into train and test sets on a half-half ratio then repeat the procedure 50 times and take the mean rank correlation as our model's performance. This procedure is the same with [memorability paper] so that we can directly compare our performance with their models' performances on several other image-derived features.

## III. RESULTS

### A. Model comparison

We performed ridge regression on the social features, pixel features, geometric features, and neural network features and compare their performances with the results listed in previous literature.

TABLE II: Comparison of models

| Result Index | Feature/ Model | Rank Correlation |
|---|---|---|
| 1 | Geometric + pixel features [5] | 0.65 |
| 2 | Color [12] | 0.46 |
| 3 | LBP [12] | 0.51 |
| 4 | HOG [12] | 0.72 |
| 5 | SIFT [12] | 0.62 |
| 6 | Shape [12] | 0.54 |
| 7 | Distance + slope + global features | 0.82 |
| 8 | Multi-scale neural netowork [8] | 0.46 |
| 9 | **Social features** | 0.82 |
| 10 | **Pixel features** | 0.48 |
| 11 | **Geometric + skin features** | 0.53 |
| 12 | **Pretrained Neural Network Features** | 0.65 |
| 13 | **Social + geometric features** | 0.84 |
| 14 | Group consistency | 0.99 |
| 15 | Individual vs group correlation | 0.73 |

Result 1 is from paper [5]. It constructed a dataset consisting of 92 young Caucasian female faces in frontal neutral expressions. Compared with the dataset employed in our study, it contains much less variance in gender, race, age and expression and therefore easier to predict. The facial attractiveness rating range is from 1-7 in their dataset, whereas in our chosen dataset the scale is from 1 to 9, which is more difficult to predict then their ratings. The facial features they used is a mixture of geometric configuration and pixel features.

Result 2-6 are from [12]. These results are obtained from the same dataset, so they are most directly comparable with the results from our experiments. [12] extracted low level features from color naming features, local binary pattern, dense HOG2*2, and dense SIFT. Detailed descriptions can be found in [12].

Result 7 is from [11], where they construct a dataset containing 91 facial images. Similar to the setting in study 1, the images were frontal photos of young Caucasian females with a neutral expression and were rated on a 1-7 scale. One difference between their dataset and the dataset from study 1 is that they used color photos. They first obtained 84 landmarks in the face, then compute the distance and the slope between every pair of landmarks. They then applied PCA and feature selection procedure to reduce the dimensionality of these geometric-related features. Lastly, they concatenate skin smoothness, hair color and skin color into the reduced geometric-features to form a feature vector and apply linear regression to build the predictor. Their predictor achieved a correlation with human subjects as high as 0.82. But it may be hard to generalize to a wider range of naturalistic faces that vary in gender, age, expression and etc.

Result 8 comes from a multi-scale neural network trained from scratch [8]. It was trained on a dataset of 2056 young female faces. We can see that its performance is inferior to our pretrained neural network models in result 12. It suggests that training a neural network from scratch with a relatively small dataset size (2000 faces) may not be sufficient to learn a informative representation, but using the pretrained model to learn a weight combination is feasible.

Result 9-13 are our experimental results on MIT dataset [12].

Result 9 comes from our social feature predictor. It achieves the same performance with the best machine predictor in result 7, but on a more challenging dataset. It suggests that human annotated high-level representation of faces' social aspects are informative on facial attractiveness.

Result 10 is the correlation coefficient between a pixel feature predictor's rating with human's ratings. It servers as the baseline model. We can see that even the most rude pixel level description of faces are able to help us predict human attractiveness ratings to a certain degree.

Result 11 is is from the geometric feature predictor. Although it is worse than result 1 and 7 in performance, but it offers more interpretability, which we will discuss more in details in the next sections.

Result 12 comes from our neural network predictor. It extracts high level information implicitly from pre-trained neural network tuned for object classification task. This result suggests that feature representation learned for object classification cannot be directly transferred to face attractiveness judgment.

Result 13 comes from a mixture model that concatenate social and geometric features. We can see that although social features alone can already achieve a high performance, adding extra geometrical information can further boost the performance with 3 percent.

Result 14 and 15 are human-level consistency check. The data we used are from [6].

In result 14, we report the the group consistency on attractiveness ratings. We first randomly split the 1500 raters into 2 even groups, then calculate the mean rating on 200 faces for each group, and then compute the Spearman's rank correlation for two group averages. We then repeat the procedure for 1000 times and report the averaged rank correlation. We can see that the group correlation is as high as 0.99, which confirms previous findings that humans share high consensus on what attractive faces are.

In result 15, we report an average individual's correlation with the group mean ratings. We calculate each individual's 200 ratings' Spearman's rank correlation with the group mean, then take an average across 1500 raters.

Result 14 sets up the upper bound any predictor can achieve whereas result 15 sets up a benchmark level from a normal human individual.

### *B. Social feature analysis*

We first compare the social features with previous studies, then examine the correlation between social features and attractiveness. Next we examine how does the number of social features affects prediction performance and analyze the coefficients learned from the ridge regression models.

*1) The social space of faces: comparison with previous studies:* Although our primary goal is to understand attractiveness's relationship with other social features, we will first make some comparison with existing research results on social feature space. Alexander Todorov's group have done a series of studies on mapping the social space of the face. [17], [28], [29] Their examined social features(dominant, threatening, attractive, frightening, mean, trustworthy, extroverted, competent, likeable) are not identical to the ones we studied here but there are some overlapping(attractive, mean, trustworthy are identical, threatening is similar to aggressive, extroverted is opposite to introverted). To facilitate similar comparison, we put attractiveness and unattractiveness back into the other 38 social features and apply Principal component analysis on all 40 social features and get a 2-dimensional embedding which is maximally comparable to Alexander's study. See fig.7

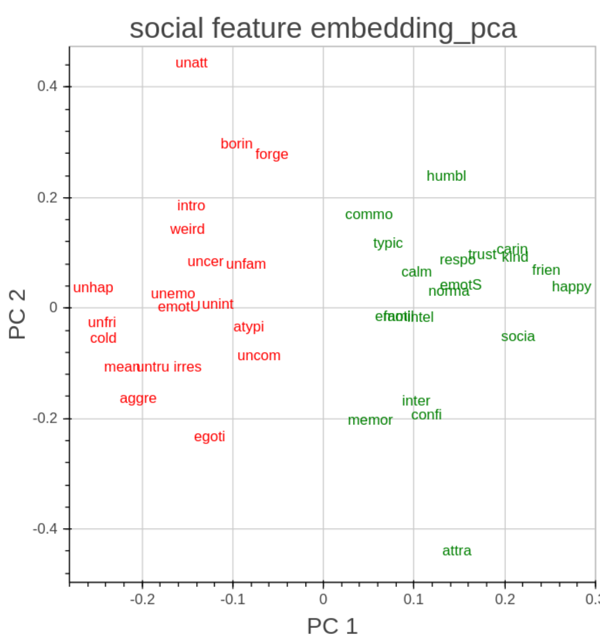


Fig. 4: Social features embedding from PCA

We colored the positive feature in green and negative features in red. It is clear from our figure that the first principal component encodes positive/ negative attributes. This is in accordance with Alexander's conclusion: they found that the first PC can be interpreted as valence of the face given its strong positive relationship with positive trait judgments (e.g., trustworthiness) and strong negative relationship with negative trait judgments (e.g., aggressiveness). They interpreted their second PC component was power/dominance evaluation since it has strong positive correlation with dominance, confidence and aggressiveness. It is also in accordance with their conclusion, since we can see that aggressiveness, confident all have negative values in the second dimension whereas humble, calm, boring, introverted all take positive values in the second dimension.

In our setting, the first two dimensions account for 70% of the variance in the social feature space whereas in their setting the first two PC components account for 80% of the variance. Despite the tiny difference, our result large agree with their studies. One thing worthy noting is that they proposed that trustworthy and dominance can be regarded as the two primary perceptual basis of face evaluation. After comparing trustworthy with attractiveness, we found that attractiveness can serve as a perceptual basis for other social perception, and it is even more reliable than trustworthy. Its consistency index (correlation between two randomly split group) is 0.72 whereas trustworthy is 0.62.

*2) Correlation analysis:* After comparing with the previous studies on social space of faces, we come back to our main focus: how attractiveness is related to other social perceptions.

We further check how these social features are correlated with attractiveness. We found that almost all social features (except "common") are statically significantly correlated with attractiveness either positively or negatively. We list the results in Table III.

TABLE III: Main Social Attributes Predictor

| Positive Correlation with Attractiveness | Negative Correlation with Attractiveness |
|---|---|
| Interesting: 0.66 | Unattractive: -0.83 |
| Sociable: 0.59 | Boring -0.59 |
| Memorable: 0.54 | Weird: -0.56 |
| Confident: 0.53 | Forgettable: -0.51 |
| Normal: 0.53 | Introverted: -0.49 |
| Friendly: 0.50 | Unhappy: -0.47 |
| Happy: 0.50 | Uncertain: -0.47 |
| Emotional Sta: 0.49 | Mean: -0.45 |
| Caring: 0.48 | Unintelligent: -0.45 |
| Familiar:0.45 | Unfriendly: -0.45 |
| Kind: 0.43 | Cold: -0.42 |
| Intelligent: 0.41 | Emo Unsta: -0.40 |
| Trustworthy: 0.40 | Aggressive: -0.40 |
| Emotional: 0.36 | Unemotional: -0.39 |
| Calm: 0.35 | Unfamiliar: -0.39 |
| Responsible: 0.33 | Irresponsible: -0.33 |
| Humble: 0.21 | Atypical: -0.24 |
| Typical: 0.18 | Uncommon: -0.19 |
| | Egotistic: -0.09 |

Our results confirm the halo-effect of attractiveness, i.e. people associate positive descriptions of one's personality with highly attractive faces. The correlations quantitatively demonstrate what aspects of social attributes most closely co-occur with attractiveness. Appearing *interesting* contributes the most to determining facial attractiveness. Next to it, people consider *sociable* people to be highly attractive. Thereafter, we find that appearing *memorable* is also highly correlated with attractiveness. The $4^{th}$ social attribute that correlates highly with attractiveness is *confident*. Familiar is also found to be positively correlated with attractiveness, confirming the previous findings that familiar faces are registered as more attractive.[reference]. Our investigation reveals an interesting link between social attributes of a face and its attractiveness. These findings give us some deeper insights into the higher level attributes that relate to facial attractiveness.

Fig. 9 shows the correlations among the social features. We reordered the features according to hierarchical clustering to show the grouping patterns. Most of the negative social features get clustered together (untrustworthy, atypical etc.), and it is followed by a group of positive social features (friendly, happy, attractive etc.). The third biggest cluster includes boring, unattractive, unfamiliar and common, which agrees with our common sense that if a face is boring, unfamiliar and common, it is more likely to be perceived as unattractive.

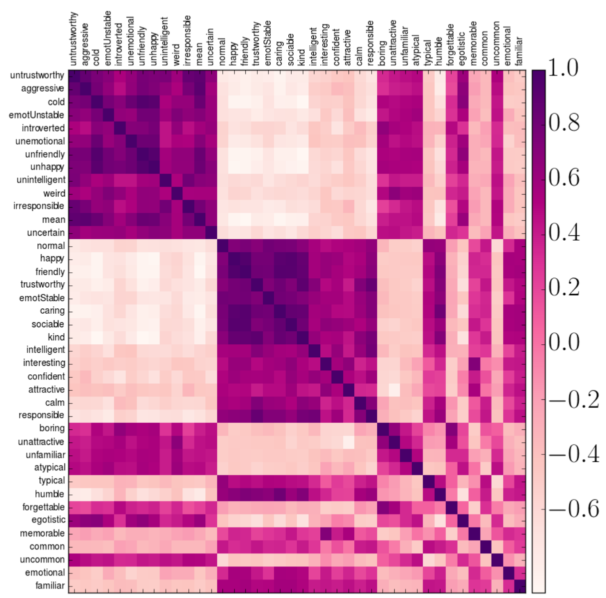


Fig. 5: Correlations between Social Features

*3) Model prediction as a function of the number of features:* Since all 38 social features are highly correlated, we apply principal component analysis on the feature matrix to examine the intrinsic dimensionality of these social features. We also convert the original 38 dimensional feature array into PCA space, and examine how the test correlation changes as a function of the number of features needed. We plot the accumulated explained variance as a function of the number of PC dimensions and put them together with the correlation curve.

*4) Model coefficients analysis:* Next we take a closer look at the coefficients computed from the ridge regression

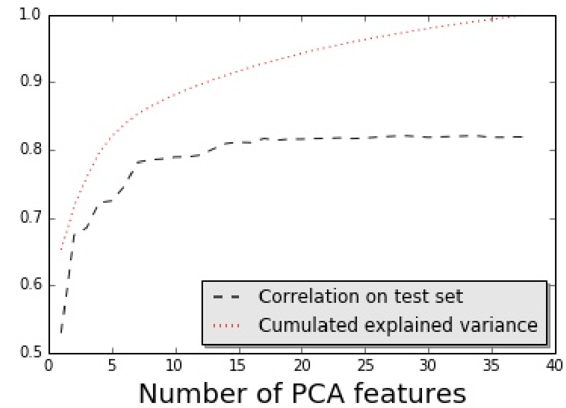


Fig. 6: Correlations and accumulated explained variance as a function of PC number

model, and compare them with each feature's correlation with attractiveness.

The mean weight coefficients of the 38 social features are shown in Fig.7

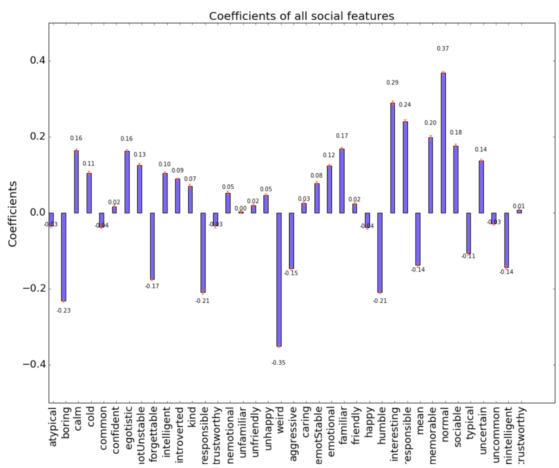


Fig. 7: Social features weights in a ridge regression model

From the figure, we can see that certain positive social features have positive coefficients, which is in accordance with their positive correlation with attractiveness, These features include: normal(0.36), interesting(0.29), memorable(0.20), sociable(0.17), familiar(0.17), calm(0.16), emotional(0.12), intelligent(0.10). Similarly, certain negative social features have negative coefficients, and they are: weird(-0.35), boring(-0.23), forgettable(-0.17), aggressive(-0.14), unintelligent(-0.14), mean(-0.13), atypical(-0.03). However, there also exist features whose weight coefficients flap the sign compared with their correlation coefficient with attractiveness. These features include: irresponsible(0.24), egotistic(0.16), uncertain(0.14), emotional unstable(0.13), cold(0.10), introverted(0.08), unemotional(0.05), trustworthy(-0.03), humble(-0.20), responsible(-0.21). This is partially due to the fact that these features are inter correlated.

### *C. Geometric feature analysis*

We follow the same procedure as we analyze the social perception features, except that we skipped the geometric feature embedding part, since we didn't observe clearly understandable patterns. correlation analysis, model prediction as a function of feature numbers, coefficients analysis.

*1) Geometric feature correlation analysis:* When we calculate the correlation between geometric features and attractiveness, we find that heartshapeness(0.22), cheek prominence(0.19), eye height(0.18), eye size(0.17), forehead length(0.17), eye width(0.16), upper head length(0.14), eye shape(0.13), nose length(0.12), length between cheek to chin(0.12), distance from brow to hair(0.11), distance between pupils to top(0.11), face length(0.11), forehead height(0.10) are positively correlated with facial attractiveness, whereas chin size(-0.32), chin length(-0.31), face roundness(-0.17), middle face length(-0.16), face width to mouth(-0.12), nose shape(-0.12), distance between pupils to lip(-0.10), symmetry(-0.08).

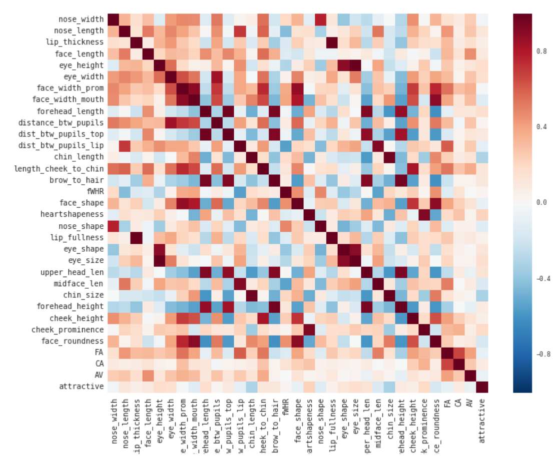

Fig. 8: Correlations between geometric features and attractiveness

*2) Model performance and feature numbers:* Since all 38 social features are highly correlated, we apply principal component analysis on the feature matrix to examine the intrinsic dimensionality of these social features. We also convert the original 38 dimensional feature array into PCA space, and examine how the test correlation changes as a function of the number of features needed. We plot the accumulated explained variance as a function of the number of PC dimensions and put them together with the correlation curve.

From this figure we can see that the performance tend to saturate as the number of features reaches 25.

*3) Ridge regression coefficient analysis:* The geometric features give a descent prediction of attractiveness. It achieves a correlation of 0.53 with average human ratings. The linear coefficients of all social features are shown in Fig.10

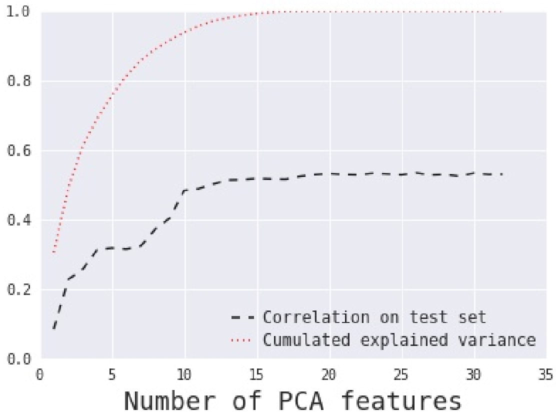


Fig. 9: Correlations and accumulated explained variance as a function of PC number(Geometric features)

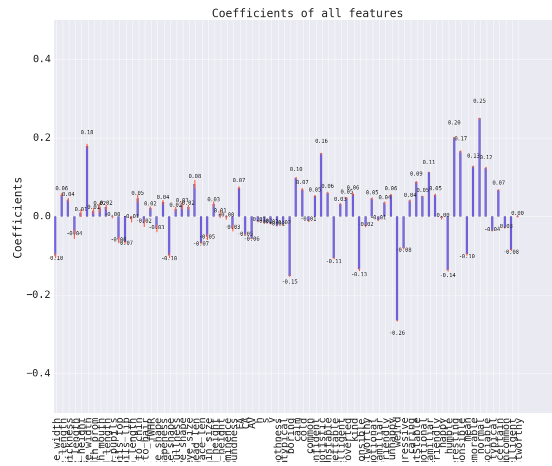


Fig. 11: All features' weights in a ridge regression model

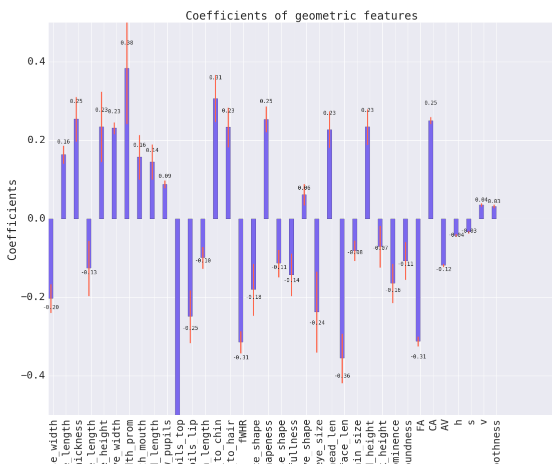


Fig. 10: Geometric features weights in a ridge regression model

From the figure, we can see that geometric features' coefficients have larger error bars, suggesting that they are noisier than social features. The only features that have relatively small std and consistent signs are: nose width(negative), nose length(positive), eye width(positive), forehead length(positive), distance between pupils(positive), distance between pupils to top(negative), distance between brow to hair(negative), fwhr(positive), mid face length(negative), FA(negative), CA(positive), AV(negative).

We also concatenate the social features together with geometric feature and find that the combined features further boost model performance to 0.85%. We plot the coefficient bar graph of all features 11, and compare them with coefficients from social or geometric features only.

## IV. Discussion

We have shown that we can reliably predict human facial attractiveness from other social dimensions of faces. We confirm that human beings share a large degree of consensus regarding what constitutes an attractive face, as well as a large number of social perceptions on faces. Our social feature analysis help us further understand what specific social features are closely related to attractiveness. In particular, we find that attributes such as appearing *interesting*, *sociable*, and *calm* are strong indicators of facial attractiveness.

### A. What remains to be understood?

Even though our social feature model achieves a high correlation with humans, these social features themselves are not easily predicted. Certain social features such as interesting and memorably are reliable predictors of attractiveness, yet human show relatively less consensus on what they really mean. The dataset we used in this study [12] doesn't include much demographic information of the raters. In our future study, we are interested in collecting information on the raters' gender, age, race, sexual orientation, cultural norms, etc. so as to give a more comprehensive investigation on attractiveness.

### B. Future Directions: Is attractiveness a property linked to identity?

We have already known that human show consensus on facial attractiveness. But what remains unknown is whether attractiveness is intrinsic for identity. If person A looks more attractive than person B in neutral expression, does that hold for their smiling faces? What if we change the lighting conditions, the face viewpoint? Previous studies have shown that the memorability of a face is invariant to changes in lights, viewpoint and expression, whether the same property holds for attractiveness remains to be understood.

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