Whats Your Type? Personalized Prediction of Facial Attractiveness

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I. INTRODUCTION

Attempts to obtain a universal model of facial beauty by the way of symmetry, golden ratios, and measured placement of various facial features fall short in explaining the varied attraction that is actually witnessed in the world. In this investigation, we devise an application to give a user some insight about their 'type' as users swipe yes or no on a large dataset of images

There is a wealth of interesting literature attempting to map the psychophysics of attraction. For example, Johnston and Franklin (1993) use a genetic algorithm which evolves a "most beautiful" female face according to interactive user selections. They sought to mimic the way humans filter for features they find the most attractive.

Our approach builds on Kagian et. al (2007), where it was shown that feature selection and training procedure with the original geometric features instead of the eigenfeatures fails to produce good predictors due to the strong correlations between the original geometric features.

The input to our algorithm is a dataset of face images. Each image in the dataset is labelled with a positive or a negative rating from a given user — positive rating implies that the user finds the face attractive. Features are extracted from these images using NMF (Non Negative Matrix Factorization) and then a Naive Bayes classifier is employed to predict whether this particular user will rate an unseen image as attractive or not.

II. DATASET AND FEATURES

We obtained access to the 10K Adult Faces Dataset [3]— a large and comprehensive image dataset of 10, 168 face photographs representative of the adult U.S population. The dataset was created using a random name generator on 1990 U.S. Census name distribution, for each name several

publicly available colored photos were scraped from Google Image search.

A. Labelling

In order to figure out a user's type, we require the user to go through a large number of face images, labelling each image as it attracts them subjectively. We created a web interface with Flask that serves images from the database and records the user's associated {yes}/{no} preference. At most we could get the users to label up to 2000 - 3000 images in this way.
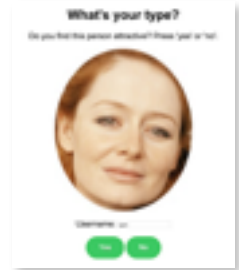
B. Preprocessing

We obtained a training set of images from the 10K dataset by cropping or padding the images as required so that they are uniformly sized. Once grayscaled, each image is normalized by subtracting from the mean.

III. METHODS

A. Eigenfaces

It is possible find an information rich encoding of a face image that best captures the significant local / global "features" of the face, albeit these features do not necessarily correspond to usual facial features like the eyes, nose, lips, hair and so on. Such encoding can be found by capturing the variation in a collection of face images which is then using it to find a low dimensional representation of each face. Mathematically this translates to finding the principle components of a distribution of faces in the dataset which is achieved by

finding eigenvectors of the covariance matrix of the set of face images where each image is treated as a point in a high dimensional space.

These eigenvectors characterize the variation between faces the faces in the 10K dataset. It follows that each individual face in the 10K dataset can be reconstructed as a linear combination of these eigenfaces.

B. Non-Negative Matrix Factorization (NMF)

NMF takes a matrix X, where $x_{i,j}$ is the i-th element of the j-th image in the dataset. NMF decomposes X = ZH. The lines of matrix can be considered as a basis images and the vector h_j as the corresponding weight vector. The NMF imposes non-negative constraints in both the elements of Z and of H. Thus only non-subtractive combinations are allowed, this corresponds with better features as images don't cancel each other out.

$$\arg \min_{W,H} \frac{1}{2}\|X - WH\|_{Fro}^2 = \frac{1}{2}\sum_{i,j}(X_{ij} - WH_{ij})^2$$

The NMF implementation in scikit-learn finds a decomposition of X into W and H, by optimizing for the squared Frobenius norm.

First 50 sparse components found with NMFactorization of images in the 10K Adult Faces Dataset:
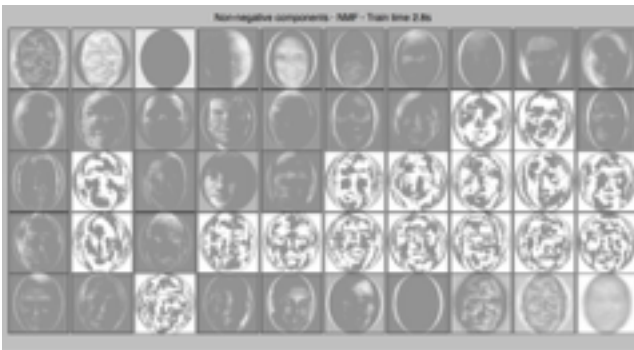
C. Prediction

1. k-nn

To predict whether a given user will like a previously unseen face, we find a labelled face image with the encoding closest to the face in question. It is then possible to predict whether the user will like this face given how they rated its nearest neighbors. These K-nearest neighbors are found using euclidean and mahalanobis distance.

2. Gaussian Naive Bayes

In this approach, the continuous values associated with each feature are modeled as a Gaussian distribution and a (naive) independence is assumed between the features.

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

IV. RESULTS

A. k-NN with Eigenfaces

This method succeeds 96% of the time in identifying unattractive faces but only shows 3% accuracy on recommending faces that a user may find attractive. This result makes sense given the structure of this data, where the average user in our study only rated 3.4% of the images as attractive, so most of the image points are negatively rated.

B. Gaussian Naive Bayes with NMF

Features were generated using 1000 faces from the data base, The classifier was trained on 2000 ratings and tested on 1000 ratings. We found that using top 25 non-negative eigenvectors yields 77% accuracy on predicting unattractive faces and 37% accuracy on attractive faces. The table below shows how the classifier performance shifts with the number of eigenfaces used.

# Eigenfaces	0 Accuracy	1 Accuracy	Overall Accuracy
5	0.9917780062	0	0.965
10	0.6988694758	0.4814814815	0.693
25	0.8612538541	0.1851851852	0.843
50	0.5971223022	0.3703703704	0.591
100	0.4224049332	0.7037037037	0.43

0/1 correspond with negative and positive ratings respectively.

V. CONCLUSIONS AND FUTURE WORK

Reconstructed images that represents the ideal 'type' for our users given how they labelled the many varied faces on our data set. The image is generated by taking a mean of all the weights associated with faces that the user rated positively.

Samantha's type   Nate's type   Dan's type   Kate's type   Ben's type
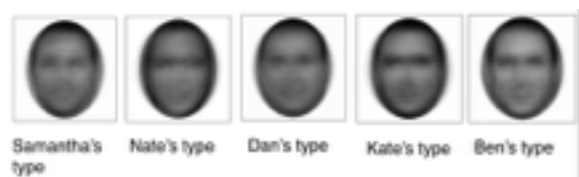
Attraction is subtle and difficult to verbalize, yet patterns in attraction can be found as users swipe through tens of images every day on the dating apps that have cropped up. These dating services could improve the user experience considerably by making use of this information. Our investigation shows that it is feasible to recognize such patterns particularly in that we mimic the constrained binary input a user might offer to an app like Tinder.
There are many directions this work can take in the future, more obviously we would like to leverage demographic labels in a dataset so that users can choose a target age range and gender when labelling images. This way we can hope to have more positively rated image points that the algorithm can learn from. Having a prior distribution on features that demonstrably indicate health could improve the prediction step.

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