Classifying Eigenfaces by Gender

Jonathan Boiser

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When you a see a person’s face, you can usually determine their gender immediately. Although you take this for granted, have you ever wondered why?

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In this project, we explore the possibility of automatically classifying faces by gender using so-called *eigenfaces* (where the prefix *eigen-* is intended to invoke the concept of *eigenvector*), which are low-dimensional representations of faces, in combination with some of the classification techniques learned in this course.

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In particular, we use k-nearest neighbors (KNN) and Gaussian mixture models (GMM's) to model and perform gender classification on the basis of facial appearance.

Mathematical Background

Definition (Singular Value Decomposition)

If $\mathbf{A}$ is an $m \times n$ matrix of rank k, $\mathbf{A}$ can be decomposed as

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}$$

where $\mathbf{U}$ is an $m \times k$ matrix whose columns form an orthonormal basis for the column space of $\mathbf{A}$, $\mathbf{V}$ is $k \times n$ matrix whose rows for an orthonormal basis for the row space of $\mathbf{A}$, and $\mathbf{\Sigma}$ is a $k \times k$ diagonal matrix whose entries are the singular values of $\mathbf{A}$ (which are analogous to eigenvalues for symmetric matrices).

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To tie things back to the project, the *eigenfaces* are the *principal components* themselves.

Creating the Eigenfaces

We begin with N grayscale images of size $h \times w$, where h is the height in pixels and w is the width in pixels. Each image is converted to a vector in $\mathbb{R}^{wh}$. So a 250×250 image would correspond to a vector in $\mathbb{R}^{62500}$.

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Step 1: Each of the N vectorized images x_i are placed into a matrix:

$$\mathbf{X} = [x_1 \; \ldots \; x_N]$$

Creating the Eigenfaces

Step 2: The mean face $\overline{x}$ is calculated and subtracted from the columns of $\mathbf{X}$. This centers the data at the origin.

$$\mathbf{Y} = [x_1 - \overline{x} \; \ldots \; x_N - \overline{x}]$$

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Step 3: The non-zero eigenvalues and eigenvectors of the covariance matrix $\mathbf{C} = N^{-1}\mathbf{Y}\mathbf{Y}^T$ are computed. This, however is equivalent to doing the SVD on $N^{-1/2}\mathbf{Y}$:

$$N^{-1/2}\mathbf{Y} = \mathbf{U\Sigma V}$$

The columns of $\mathbf{U}$ form an orthonormal basis for the eigenspace of $\mathbf{C}$ (i.e. the eigenfaces or principal components) and the diagonal elements of $\mathbf{\Sigma}$ are the associated eigenvalues.

Creating the Eigenfaces

If the rank of $\mathbf{C}$ is too high, we can take a subset of the columns of $\mathbf{U}$ to create a basis for a ν-dimensional subspace. That is, we retain the first ν columns of $\mathbf{U}$ to create $\mathbf{U}_\nu$.

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Step 4: To project a (training or testing) face f onto our ν-dimensional space, we seek to solve

$$\mathbf{U}_\nu y = f$$

for y, so

$$y = {\mathbf{U}_\nu}^T f$$

since the columns of $\mathbf{U}_\nu$ form an orthonormal basis.

How Eigenfaces are Normally Used

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Several commercial systems use this technique, and there is even some evidence that this is how our brains recognize familiar faces.

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As a result, our approach is different from the facial recognition task, which relies on many pictures of the same small group of people. Here, we take many pictures of *different* people, label them as male or female and see if the classifier can correctly determine a new face's gender.

Experiment 1

The first experiment uses a small set of faces, which I call the "nice" data set since each photo is more or less alike—i.e. of the same resolution and having the same background (blackness). The dataset was too small to satisfy the requirements of the project, but we use it here to illustrate the technique.

Nice Eigenfaces

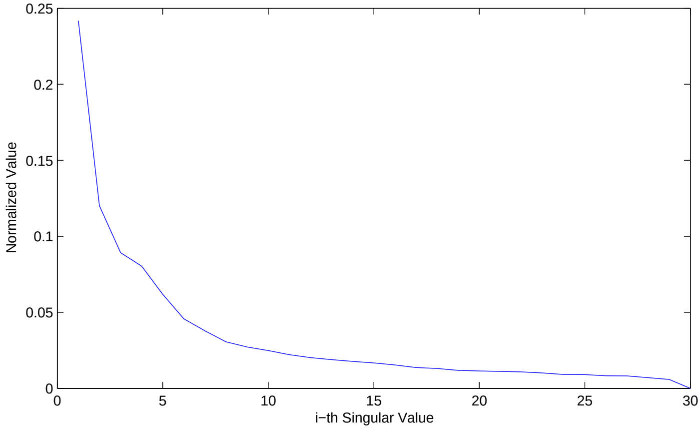
Eigenface Reconstruction

If y is the projected face, then we can recover the original face f by

$$f = \mathbf{U}y + \overline{x}$$

For this example, we only used 10 eigenfaces. Using all thirty would have returned a perfect reproduction.

Graph of Singular Values



Classifying by Gender via KNN

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	Predicted	Gender
Actual Gender	Male	Female
Male	11	3
Female	2	14

Overall Misclassification: $5/30 \approx 0.1667$.

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The individuals pictured also differed tremendously in race and age.

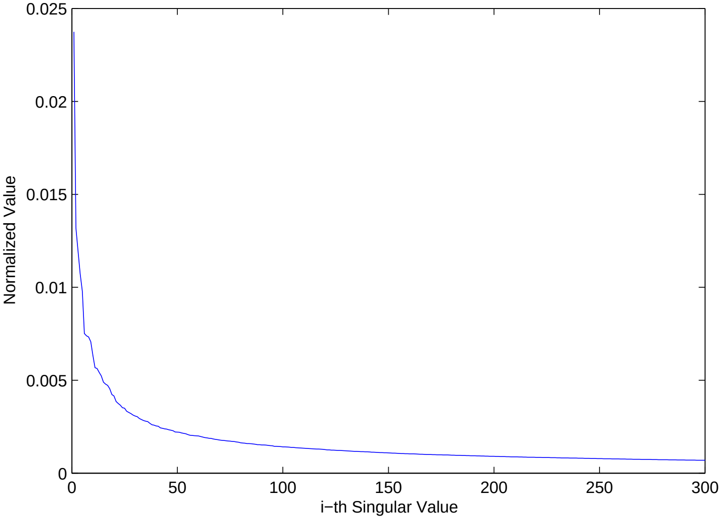
Experiment 2

Due to memory constraints, we only used 1000 male and 1000 female photographs to create the eigenfaces. The remaining images were then used for testing.

Not-So-Nice Faces

Not-So-Nice Eigenfaces

Not-So-Nice Singular Values



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For the first treatment, we tried KNN again with $k = 7$. That is, we compared each (mean-subtracted) test face to the 2000 projected training faces and classified genders by majority vote.

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Two pairs of GMM's, Φ_{male} and Φ_{female}, consisting of 8 and 16 components were created for both genders. Classification for a given picture was then based on the maximum a posteriori rule:

$$\delta(\text{face}) = \underset{g \in \{\text{male}, \text{female}\}}{\arg\max} \; P(\text{face} \mid \Phi_g)$$

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To make the computation tractable for EM algorithm the data was truncated to 10 dimensions and halted after 5 iterations.

KNN Results

Actual Gender	Predicted Male	Predicted Female	Total
Male	2218	1056	3274
Female	180	295	475

% Males classified as Female = 32.25%

% Females classified as Males = 37.89%

Overall Misclassification Rate = 32.97%

GMM Results (8 components)

Actual Gender	Predicted Male	Predicted Female	Total
Male	1846	1428	3274
Female	166	309	475

% Males classified as Female = 43.62%

% Females classified as Males = 34.95%

Overall Misclassification Rate = 42.51%

GMM Results (16 components)

Actual Gender	Predicted Male	Predicted Female	Total
Male	1877	1397	3274
Female	183	292	475

% Males classified as Female = 42.67%

% Females classified as Males = 38.52%

Overall Misclassification Rate = 42.14%

Not-So-Nice Summary of Results

Error/Method	KNN7	GMM8	GMM16
$M \rightarrow F$	32.25%	43.62%	42.67%
$F \rightarrow M$	37.89%	34.95%	38.52%
Total	32.97%	42.51%	42.14%

Conclusion and Further Studies

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Might be interesting to study relationship between PCA of images and biometric measurements.

About the Data

Nice Faces: From Douglas Huntley, Whitman College. (Files no longer available online)

Not-So-Nice Faces: From the “Labeled Faces in the Wild Project”, University of Massachusetts, Amherst. URL: `http://vis-www.cs.umass.edu/lfw/`.

Thanks for Listening.

Congratulations Class of 2009!