

# ML Week

## Face and Handwriting Recognition

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# PCA

# Principle component analysis

Analyse en composantes principales

## **Remember the Curse of Dimensionality?**

# Principle

- Linear transformations have axes
- Find them (eigenvectors of the covariance matrix)
- Pick the biggest ones

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**Fitting an  $n$ -dimensional ellipsoid to the data**

# Uses

- Exploratory data analysis
- Compression

## Also known as

- Discrete Kosambi-Karhunen–Loève transform (KLT) (signal processing)
- Hotelling transform (multivariate quality control)
- Proper orthogonal decomposition (POD) (ME)
- Singular value decomposition (SVD), Eigenvalue decomposition (EVD) (linear algebra)
- Etc.



# History

- Invented by Karl Pearson in 1901
- Invented (again) and named by Harold Hotelling in 1930's
- Also known as...

## Also known as

- It's a long list, every field uses a different name. . .

# Face Recognition

# Eigenfaces

- Sirovich and Kirby (1987)
- Turk and Pentland (1991)

*Turk, Matthew A and Pentland, Alex P. Face recognition using eigenfaces. Computer Vision and Pattern Recognition, 1991. Proceedings CVPR'91., IEEE Computer Society Conference on 1991.*

# Eigenfaces

Want: a low-dimensional representation of a face

Plan: cluster simplified faces

# Eigenfaces

Viewed as compression:

- Use PCA on face images to form a set of basis features
- Use eigenpictures to reconstruct original faces

# Eigenfaces



# Eigenfaces algorithm

Let  $X = \{x_1, x_2, \dots, x_n\}$  be a random vector with observations  $x_i \in \mathbb{R}^d$ .

Compute

$$\mu = \frac{1}{n} \sum_{i=1}^n x_i$$

*OpenCV*



# Eigenfaces algorithm

Compute the covariance matrix  $S$ :

$$S = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T$$

# Eigenfaces algorithm

Compute the eigenvectors of  $S$ :

$$Sv_i = \lambda_i v_i \quad i = 1, 2, \dots, n$$

Sort the eigenvectors in decreasing order.

We want the  $k$  principal components, so take the first  $k$ .

# Eigenfaces algorithm

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This is PCA.

# Eigenfaces algorithm

The  $k$  principal components of the observed vector  $x$  are then given by

$$y = W^T(x - \mu)$$

where

$$W = \begin{bmatrix} | & | & \cdots & | \\ v_1 & v_2 & \cdots & v_k \\ | & | & \cdots & | \end{bmatrix}$$

# Eigenfaces algorithm

The reconstruction from the PCA basis is then

$$x = Wy + \mu$$

# Eigenfaces algorithm

So the plan is this:

- Project all training samples in the PCA subspace
- Project the query into the PCA subspace
- Find the nearest neighbour to the projected query image among the projected training images

# Eigenfaces algorithm



# Eigenfaces algorithm

Some advantages:

- Easy, relatively inexpensive
- Recognition cheaper than preprocessing
- Reasonably large database possible



# Eigenfaces algorithm

Some problems:

- Need controlled environment
- Needs straight-on view
- Sensitive to expression changes
- If lots of variance is external (e.g., lighting)...

# Handwriting Recognition

# Introduction to Handwriting Recognition

## Choices

- Online
- Offline

# Introduction to Handwriting Recognition

## Choices

- Get path information
- Get time data
- Get pressure information
- Only get image

# Introduction to Handwriting Recognition

## Major techniques

- Clustering (not great performance)
- SVM (until 2006 or so)
- Convolutional neural networks

# Questions?

[ml-week.com/1](http://ml-week.com/1)