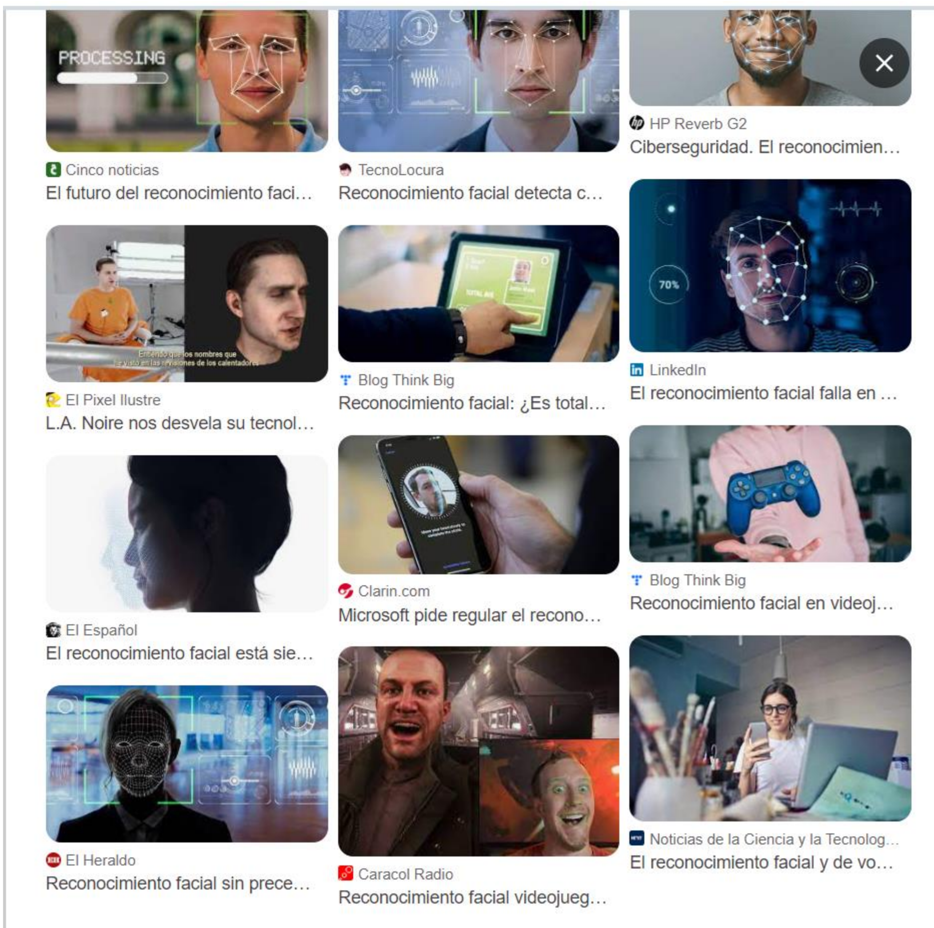
FACE RECOGNITION

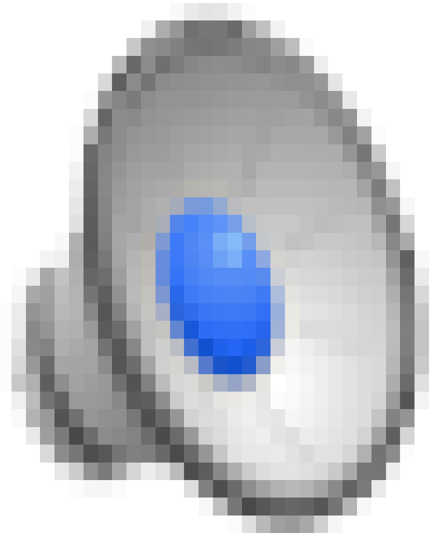
Class 9: Artificial Vision

The “Margaret Thatcher Illusion”, by Peter Thompson

Face recognition: Is it useful?



Why face reconition?



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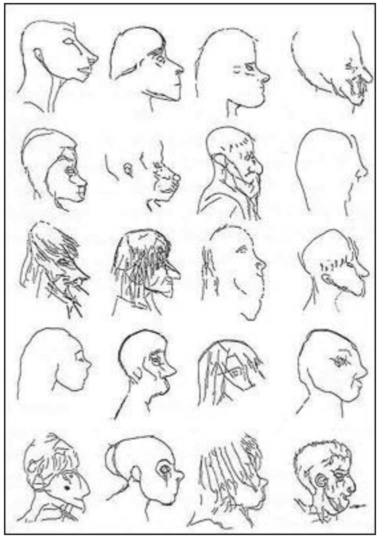
4. Eigenfaces for face detection

Several slides adapted from K. Grauman, S. Lazebnik, J. Vitrià and D. Lowe

Why facial analysis?

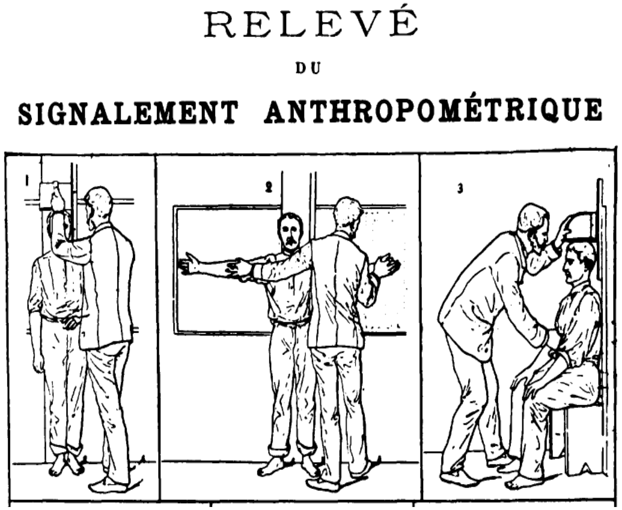
- **The face is essential for human body communication**
  - The primitive people already tried to represent themselves….
- **Evolutionary reasons**: We need to find friends in our group (identification).
- **Socio-cultural reasons**: We predict behavior based on facial expressions (emotion recognition).
- **Other information:**
  - attention focus
  - sexual attraction
  - age
  - gender
  - reading lips
  - personality, etc.



Why facial analysis?

The first predecessors of "biometrics" Alphonse Bertillon go back to the late nineteenth century.

Bertillon designs a registration method for convicts, called the Bertillonage, used in prison in France in 1879.



Biometrics systems

one of the first problems of automated facial analysis

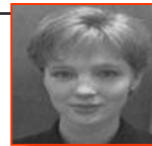



Facial recognition:

- detection
- verification
- identification

- Based on physical or behavioral traits

Biometrics systems

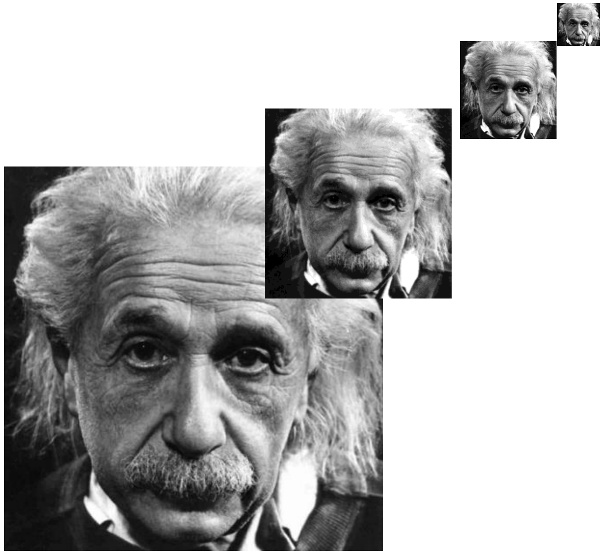
			
Intrusive	No	Yes	Somewhat
Participation	Low	High	High
Maintenance	Minimal	Must clean sensor	Complex camera
Criminal Connotation	No	Yes	No
ID at a Distance	Yes	No	No
Continuous Monitoring	Yes	No	No
Human-Readable Audit	Yes	No	No
Cost	Low	Low	Very high

Problems and difficulties of facial analysis

How complex is the task of automatic recognition ???

From the 70, researchers have asked:

- How much the recognition degrades as a function of the spatial resolution (number of pixels)?!
- What kind of degradation of the image affects the capacity to perceive images of faces?!
- How facial expressions, pose, illumination affect facial recognition?!
- What is the minimum size to detect a face in an image?!



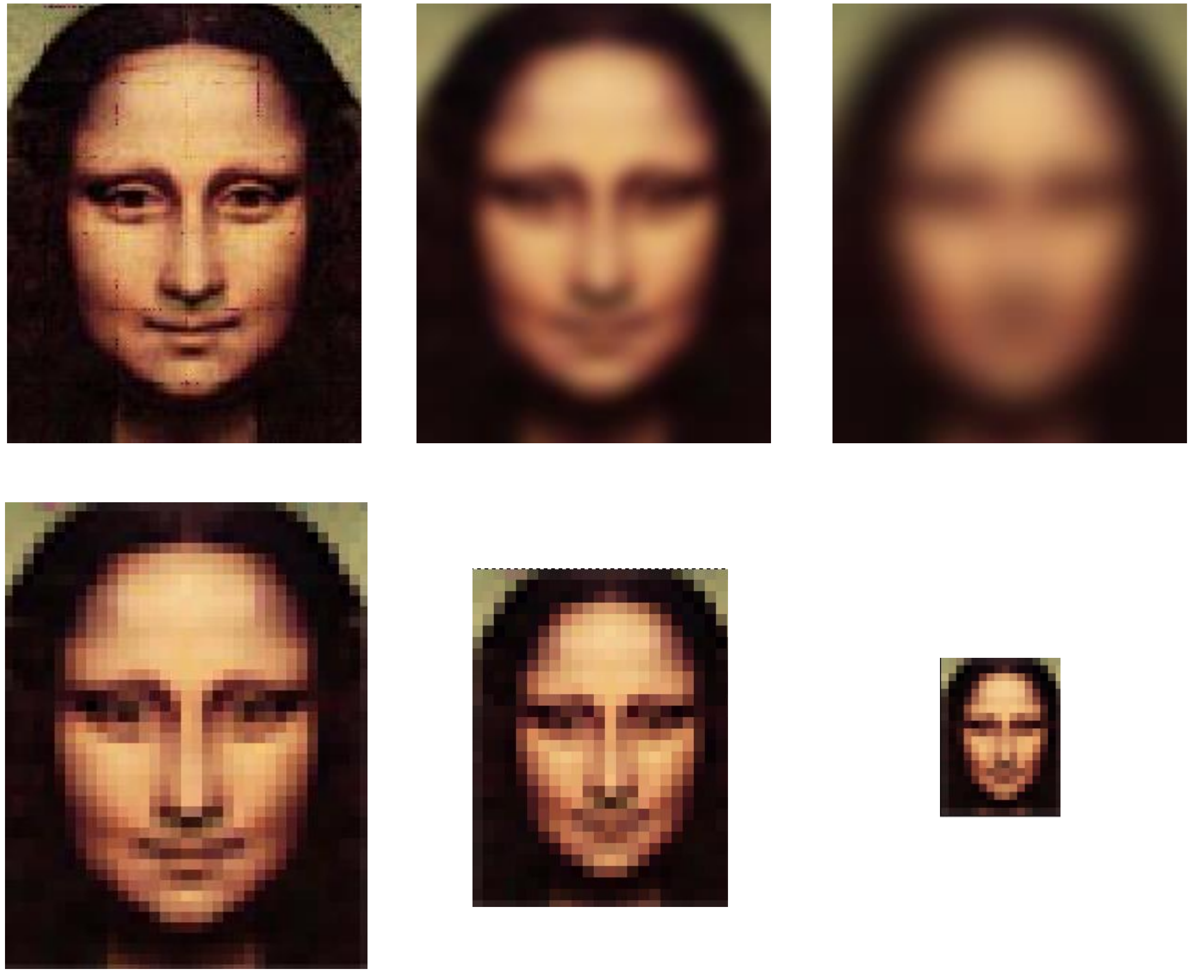
Asperger

Problems and difficulties of facial analysis

Identification

Face

Gender



36x36

24x24

16x16

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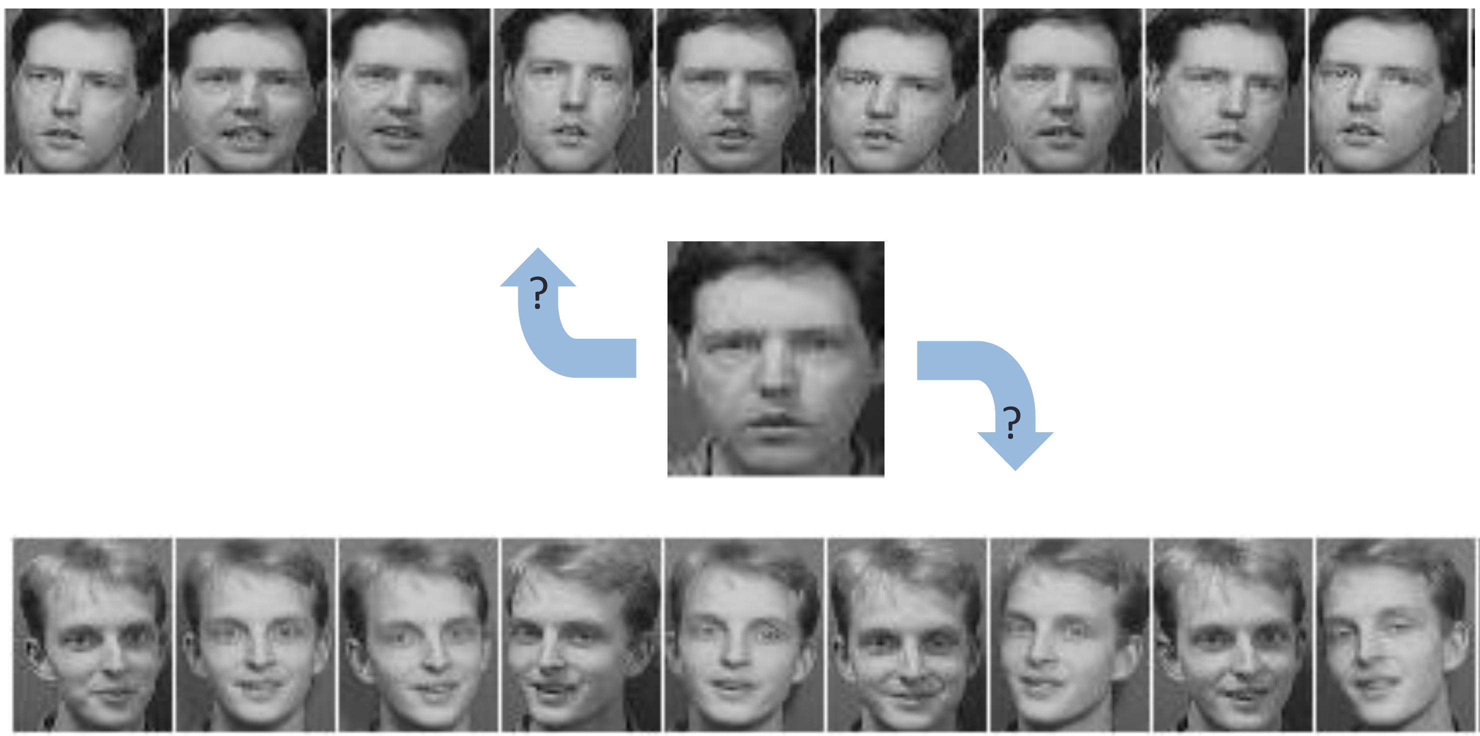
Appearance-based Recognition

Let’s consider the problem of face recognition

The task is to recognize the identity of a person (from a given set of people images - training set).



Goal of the automatic analysis

The problem of face recognition:

Goal: *To define a space of image features that allow to represent objects based on their appearance (or a set of local features) in the image.*

There are several parts to consider:

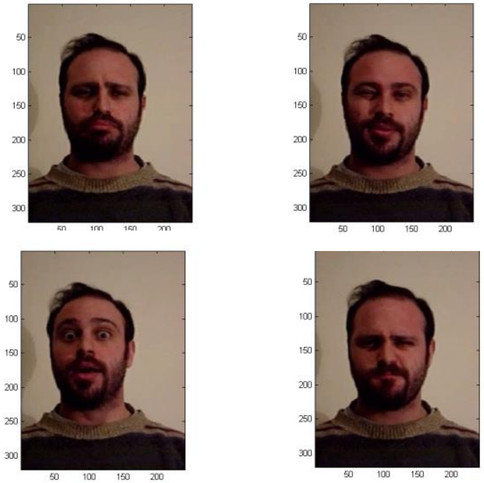
- **Define** an appropriate **representation** (descriptors of objects)
  - Normally, **reduce** the size of the data preserving the invariance and removing redundant dimensions.
- **Train a classifier** from a set of examples with their descriptors.
- **Recognize** a new face example using the learned model.

Problems and difficulties of facial analysis

Problem: Equivalence between stimuli.

In some cases the object recognition can find simple mechanisms of recognition associated with simple characteristics of images that are unambiguous signs of the presence of the object.

But in most cases there is no other way that learning complex descriptions.



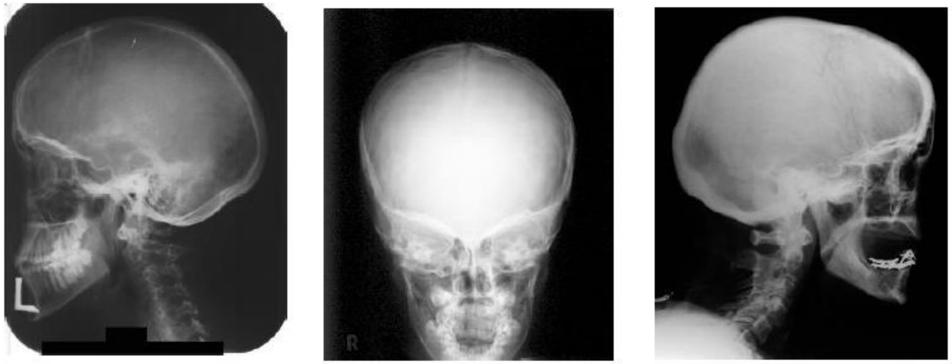
Dimensionality and redundancy

The appearance ...

Instead of storing features or 3D models, directly store a collection of many views of the object.

How can we store this information in a compact and efficient way?

How do we encode this information as interesting visual representation?

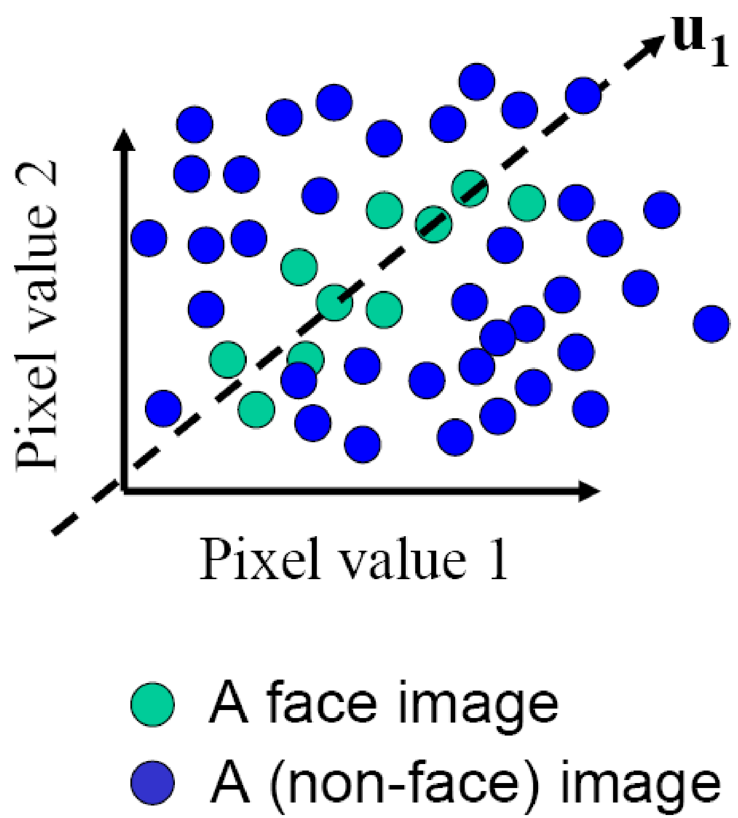


The space of all face images

- When viewed as vectors of pixel values, face images are extremely high-dimensional
  - 100x100 image = 10,000 dimensions
- However, relatively few 10,000-dimensional vectors correspond to valid face images
- We want to effectively model the subspace of face images

The feature space of all face images

- We want to construct a low-dimensional linear subspace that best explains the variation in the set of face images



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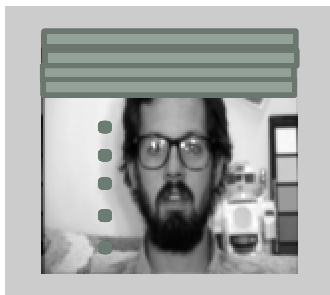
The feature space of faces and eigenfaces recognition

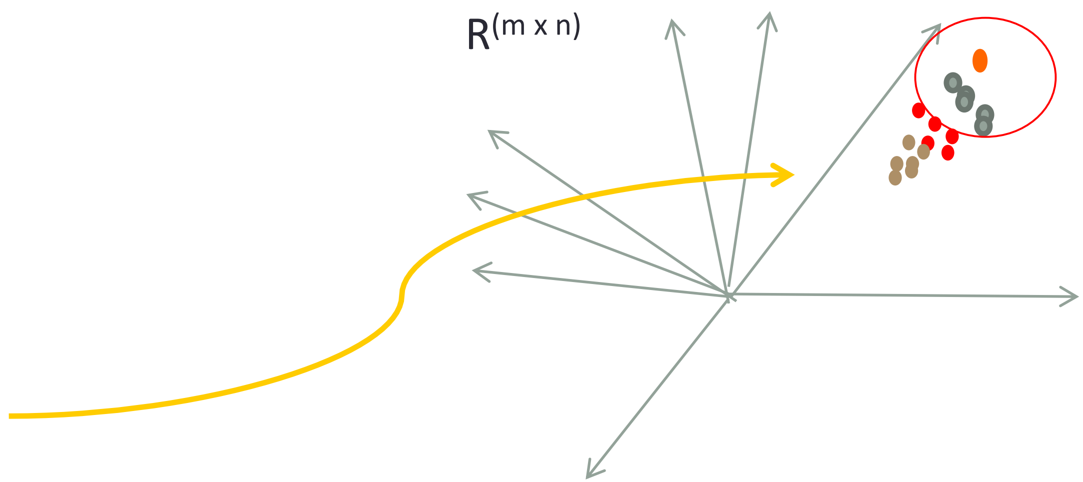
1. Features



$(x_1, x_2, \ldots\ldots\ldots\ldots x_{(m \times n)})$

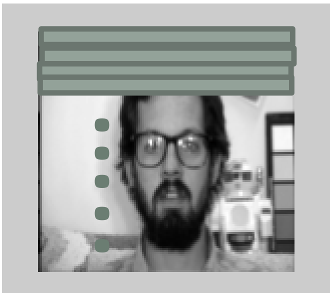
2. Classifier - knn

Training



The feature space of faces and eigenfaces recognition

Representation of faces as points in high dimensional space

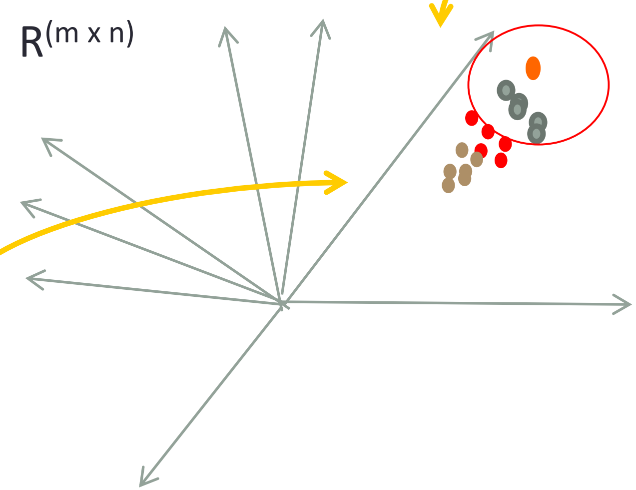


$(x_1, x_2, \ldots\ldots\ldots\ldots x_{(m \times n)})$

Each image has m rows and n columns

-> defines a vector of (mxn) elements.

$R^{(m \times n)}$



Training

Recognition:

Classifier KNN – assigns the majority label of the k closest neighbors of the training set.

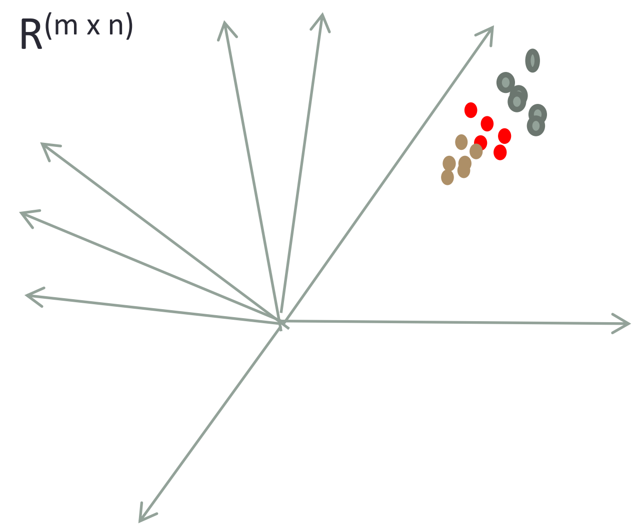
Eigenfaces

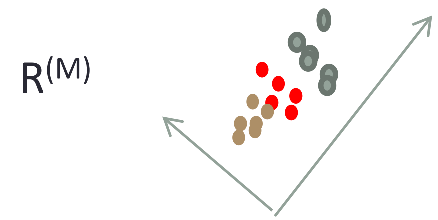
Representation of faces as points in high dimension space

•We use KNN in the R^{mxn} space -> costly and slow (m x n = 256 * 256 = 65536).

•Can we find a more compact representation of images where each face is represented via a small set of parameters?

•We look for a transformation of the original space to a smaller space (M << (m x n)), where faces are represented with their coordinates in this new space R^M?





What is the space of the faces? - Build from the training set of face images!

Eigenfaces method: Dimensionality and redundancy

Tool: dimensional reduction of the original data.

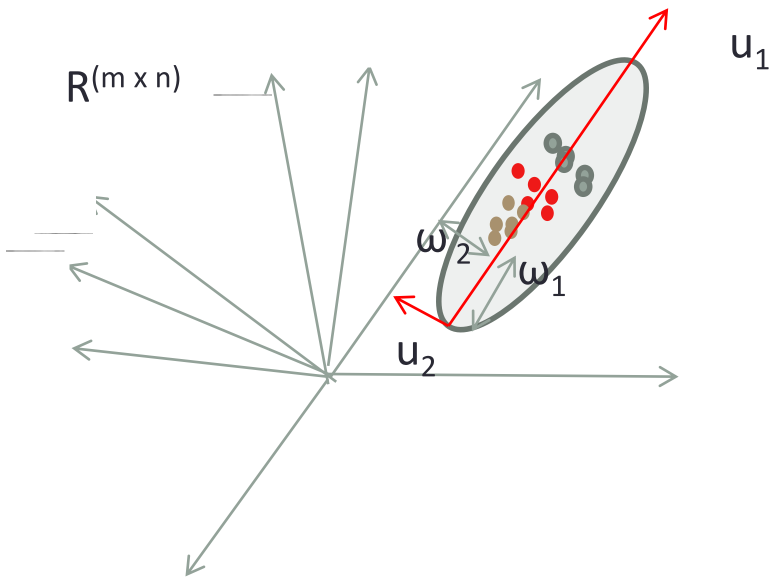
$$T:(x_1, x_2, \ldots, x_n) \rightarrow (y_1, y_2, \ldots, y_m), m << n;$$

... Retaining the information necessary to classify, recognize, etc!

And removing - or minimizing - information that is not relevant (lighting, small variations ..).

Eigenfaces

How to classify the faces?



If you have the reduced space and want to classify a face X_i:
Project it into the new (reduced) space:

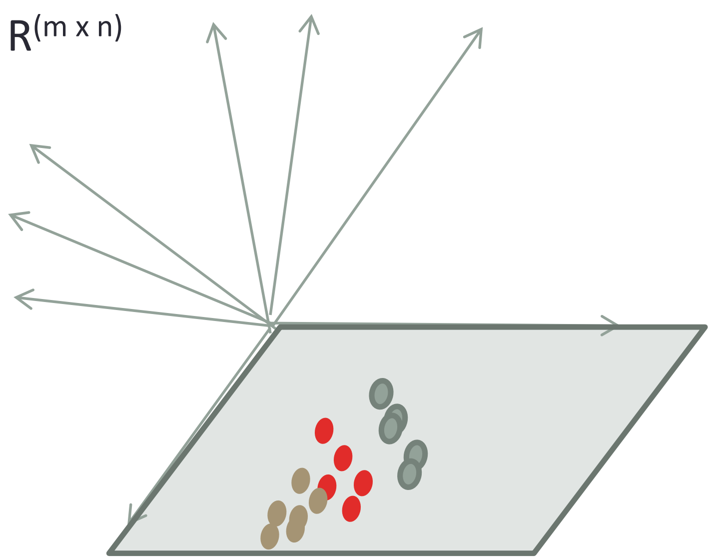
$$Y_i = (X_i - \overline{X})^T * (u_1, u_2, \ldots u_M) \longrightarrow (\omega_1, \omega_2, \ldots \omega_M)$$

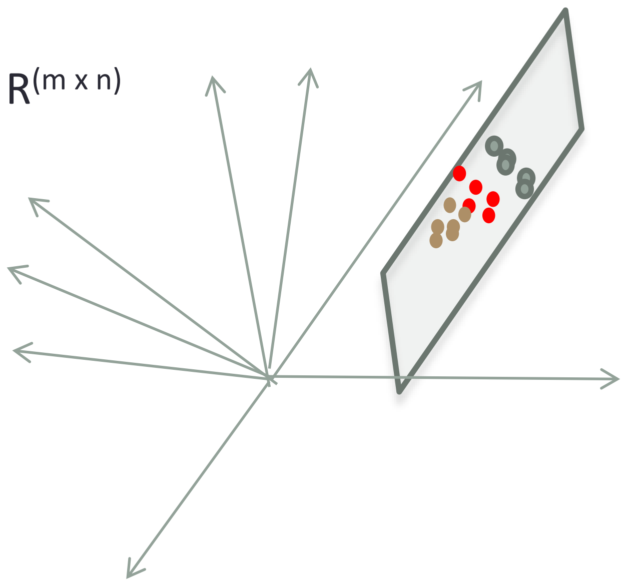
and apply the classifier e.g. knn considering the k projected neighbor faces of the training set.

How to build a reduced space?

Often the data "live" in a smaller space R^M ($M << (m \times n)$).
The data are not always uniformly distributed.

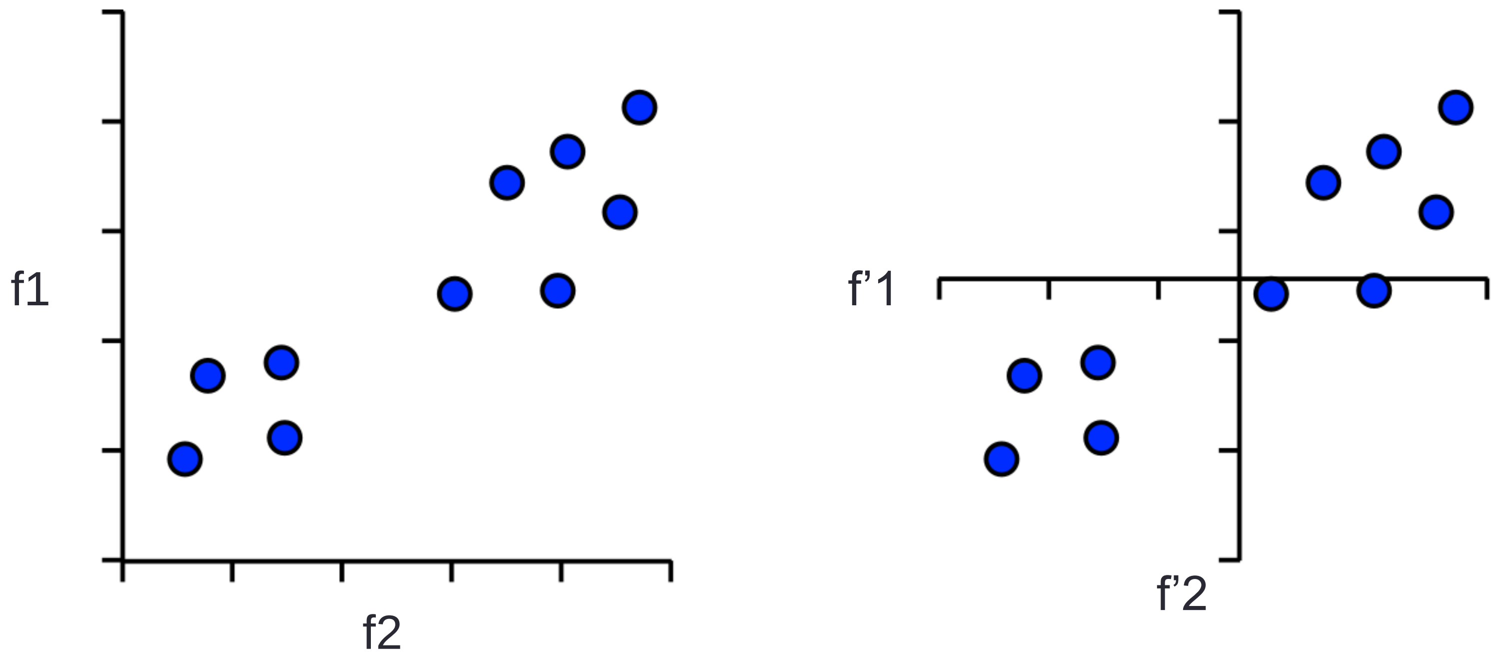
The technique that allows to find the reduced subspace where data live, is called: Principal Component Analysis (PCA).





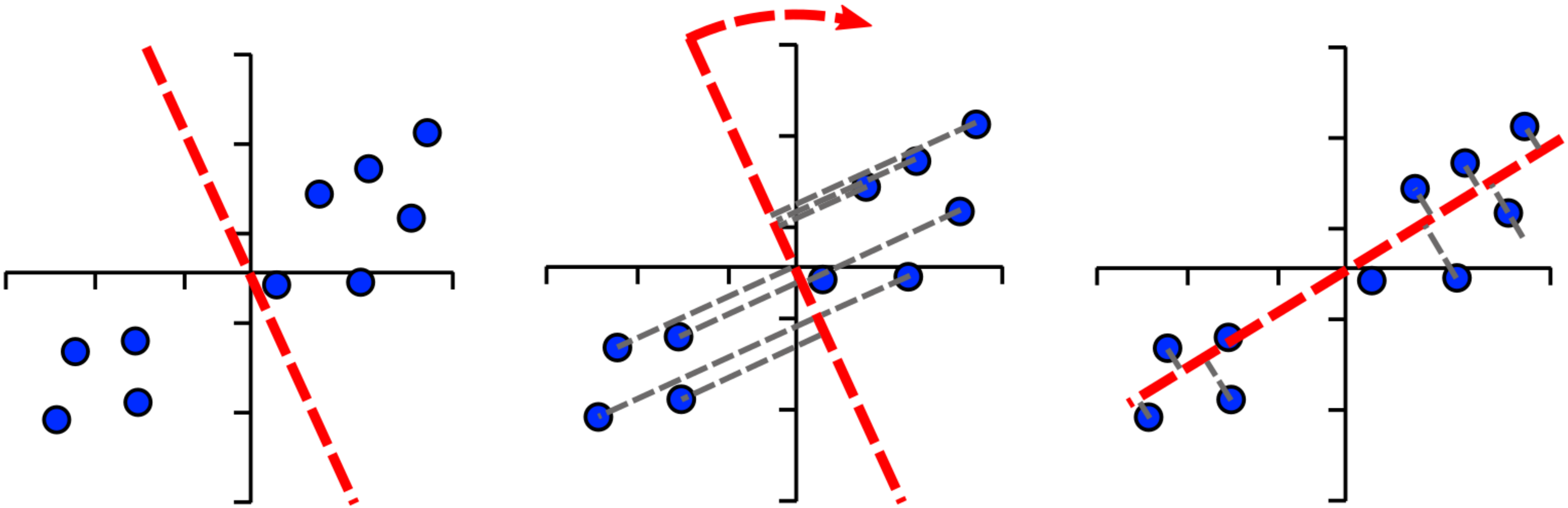
How does PCA work?

- Simple example using 2 features and 10 images



How does PCA work?

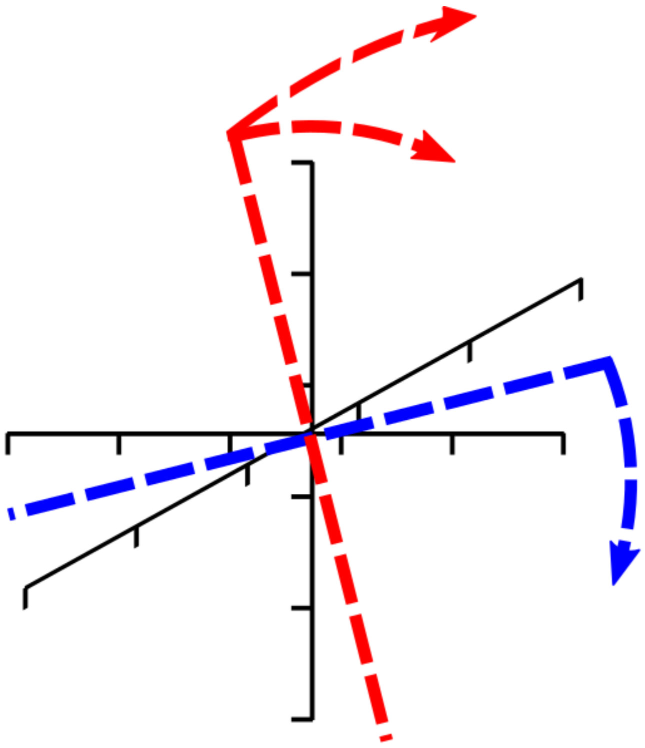
- Find line of best fit, passing through the origin



More dimensions

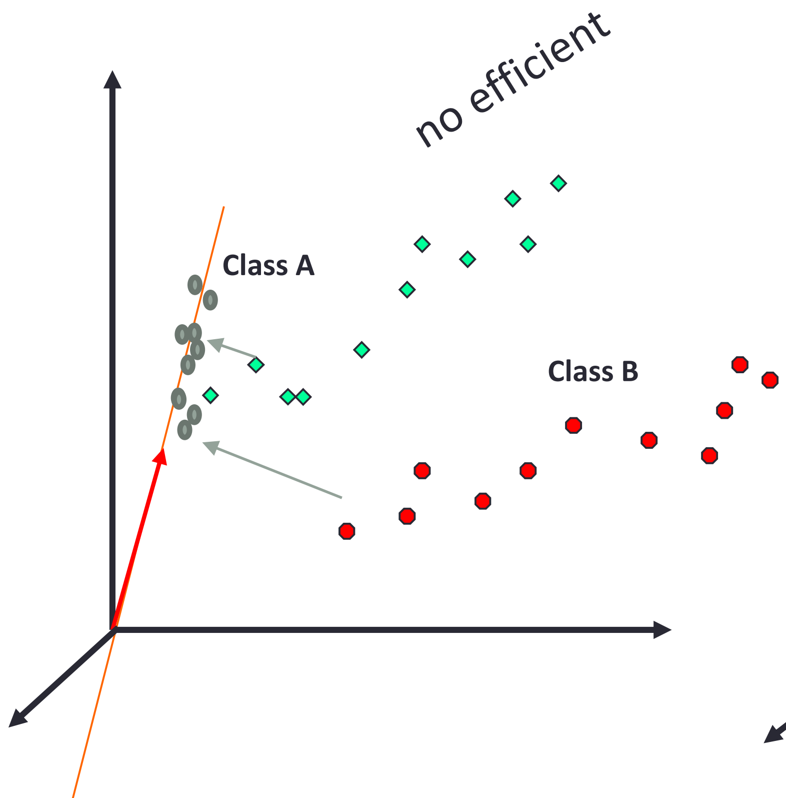
- The same idea extends to larger numbers of dimensions (n)

- Calculation of first PC rotates in (n-1) -dimensions
  - Next PC is perpendicular to PC2, but rotated similarly (n-2)
  - Last PC is remaining perpendicular (no choice)
  - Same number of PCs as features



Properties of Principal Component Analysis

- seeks directions efficient for representing data in all its variance
- reduces the dimensions of data
- accelerates the execution time of the algorithms
- Reduces noise



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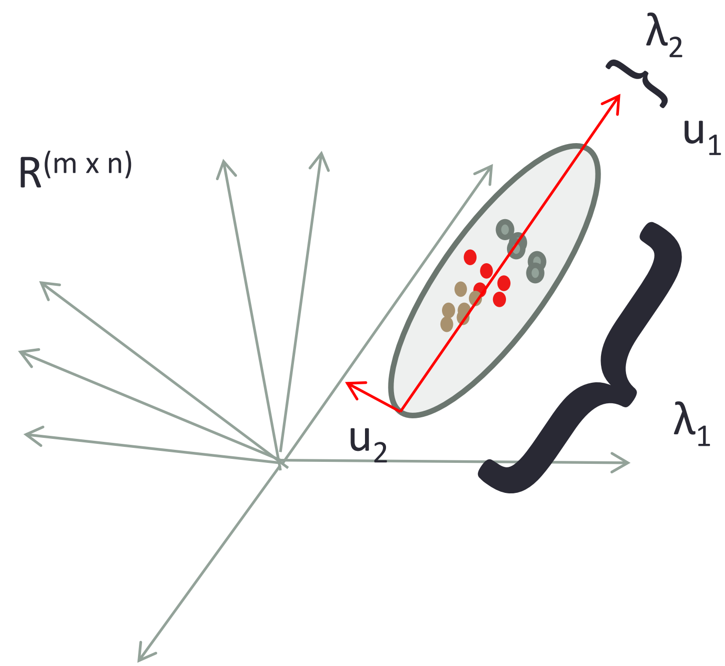
Principal Component Analysis: the algorithm

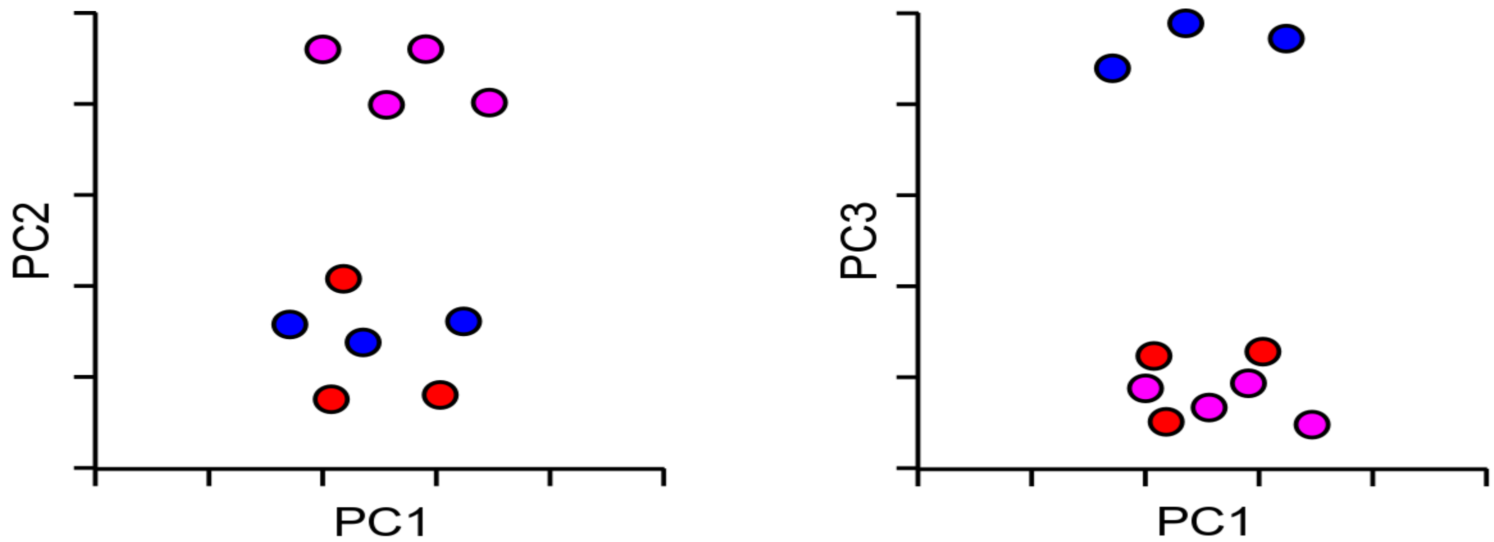
According to the PCA, if we compute:



- the **eigenvectors** (e1, e2, ...) of the **covariance matrix** define the axis of maximum variance,
- and the **eigenvalues** give a measure of the **variance of** the data.

$$\Sigma = \frac{1}{M}\sum_{i=1}^{M}(X_i - \bar{X})(X_i - \bar{X})^T = AA^T;$$

So is PCA great always?



Not optimised for 2-dimensions

Disadvantages of PCA:

a) Linear decomposition
b) Orthogonal axes
c) Represents a transformation consisting of a rotation, affine rescaling and tran
d) Is not discriminative.

Eigenfaces

How to find the best sub-space to represent the face family?

•Given M images of size (mxn) -> let's construct vector X_i, i = 1 ... M in the space $R^{m \times n}$.

•Given the images of training: X_i, i = 1 ... M, let's compute the mean image: $\overline{X} = \frac{1}{M}\sum_{i=1}^{M} X_i$

•Construct the covariance matrix Σ:

$$\Sigma = \frac{1}{M}\sum_{i=1}^{M}(X_i - \overline{X})(X_i - \overline{X})^T = AA^T; \qquad A = [X_1 - \overline{X}, X_2 - \overline{X}, \ldots X_M - \overline{X}]$$

•The eigenvectors of the covariance matrix are called eigenfaces.

•=> A is of size (mxn) x M, A^*A^T is of size (mxn) x (mxn)! En nuestro caso $A_{(65000x200)}$

M. Turk and A. Pentland, Face Recognition using Eigenfaces, CVPR 1991

Eigenfaces

How to find the best sub-space to represent the face family?

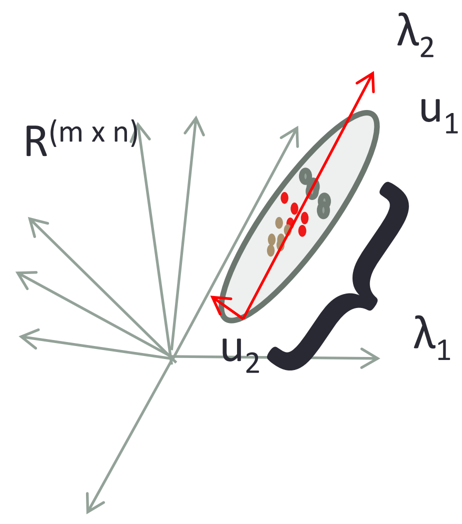
- Eigenvectors (u_1, u_2, ...) of the covariance matrix Σ define the subspace that represents the data (faces) distribution.

- Remember: given any matrix *B*: a vector u is called eigenvector, iff:

$$Bu = \lambda u$$

- λ is the eigenvalue of the matrix.

- Eigenvectors (u_1, u_2, ...) are orthogonal and form a basis.



- The original image once centered is projected into the eigenspace: X-> Y:

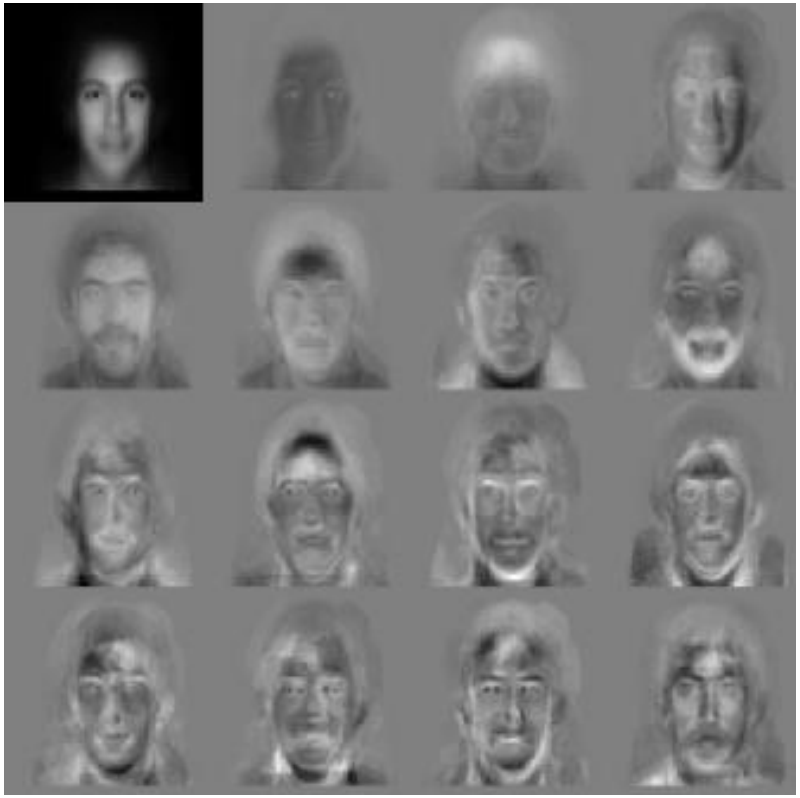
$$Y_i = (X_i - \bar{X})^T * (u_1, u_2, \ldots u_M)$$

Eigenfaces illustration

Example of eigenvectors faces.

The mean face and the eigenfaces of the covariance matrix of the faces (shown as pictures):

Mean face $\overline{X}$

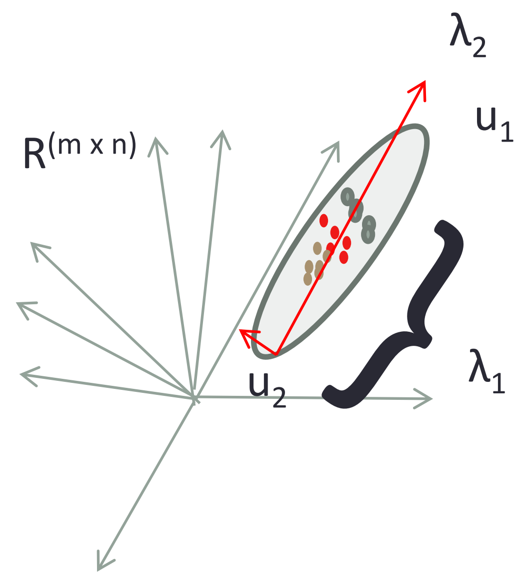


Eigenfaces (U)

Eigenfaces

What is the eigenvalue representing?

•The eigenvalues λ (eigenvalues) measure the variance of the data in the direction of the eigenvector =>



•The larger the λ_i, there is more variance in the data vector in the direction of the eigenvector u_i.

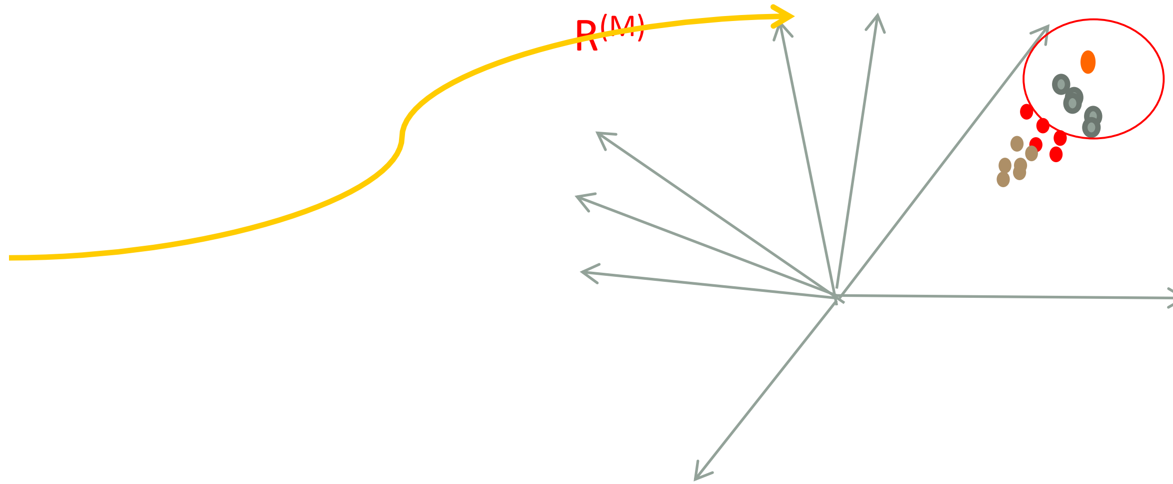
•if $\lambda_i = 0$ => we can avoid eigenvector u_i! Why?

•=> We only are interested in the first k eigenvectors of the largest eigenvalues (k = 1,2, ... M-1).

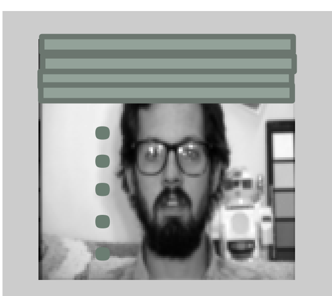
The procedure for recognition with Eigenfaces

1. **Training:** Given the training set, we compute the eigenfaces $U = (u_1, u_2, \ldots u_m)$, U - eigenvectors of $A*A^T$

Training



2. **Recognition:** Given a new face, we center it and project it into the reduced space:



$(x_1, x_2, \ldots\ldots\ldots\ldots x_{(m \times n)}) \rightarrow Y = (\omega_1, \omega_2, \omega_3 \ldots \omega_M)$

Project X:

$$Y = (X - \bar{X})^T * U$$

3. *Classify* – using knn in R^M

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Eigenfaces

How to obtain the eigenface sub-space?

- Objective: To find the eigenvectors and eigenvalues of AA^T.

- **Problem**: The covariance matrix AA^T is size (mxn) x (mxn) -> find the eigenvalues is untreatable!
  - $A_{(65000x200)}$,
  - $AA^T_{(65000x65000)}$
  - $A^T A_{(200x200)}$

- **Tip**: Instead of $AA^T V = \Lambda V$ consider $(A^TA)V = \Lambda V$,
  - V is a matrix with columns - the eigenvectors of A^TA,
  - Λ is a diagonal matrix with elements - the eigenvalues,
  - A^TA is of size MxM (M << mxn)!

- But how to get the eigenvalues and eigenvectors of AA^T?

- **Trick**: Multiplying both sides with A:
  - $A(A^T AV)=A (\Lambda V) \Rightarrow AA^T (AV)= \Lambda (AV) \Rightarrow AA^T U= \Lambda U$ where $U=AV$

- => U is the matrix with columns the eigenvectors of the matrix AA^T, and U = AV.

Eigenfaces

How to obtain the eigenface sub-space?

Advantage: the matrix A^TA is of size M x M, where M is the number of images for training!

Note: If M << (m x n), it can be shown that there will be only M-1 values different from 0!

If the images are of size 256 x 256 = 65536 -> A: 65536xM, AA^T: 65536x65536, A^TA is of MxM.

The eigenvectors of the matrix A^TA V => eigenvectors of the covariance matrix Σ: u_i=A v_i.

A^TA and AA^T have the same eigenvalues Λ!

Eigenfaces

Algorithm to obtain the eigenfaces

1. Construct the matrix A^TA of size M x M where the columns are centered faces:

$$A = [X_1 - \bar{X}, X_2 - \bar{X}, \ldots X_M - \bar{X}]$$

2. Compute the eigenvectors $V = [v_1, v_2, \ldots v_m]$ matrix of A^TA.

3. Sort by magnitude of their corresponding eigenvalues and keep the most important eigenvectors (with higher eigenvalues).

4. The M eigenfaces are obtained by multiplying the matrix A with v_i:

$$u_l = \sum_{k=1}^{M} v_{lk} A_k, \; l = 1, \ldots M$$

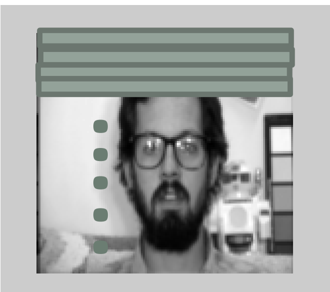
where A_k are the columns of the matrix A.

Notice the large reduction of the problem!

Eigenfaces: the Algorithm for Face Recognition

1. Given the training set, we compute the eigenfaces $U = (u_1, u_2, \dots u_m)$, $U = AV$, V - eigenvectors of A^TA

2. Center and project the new face to recognize it:

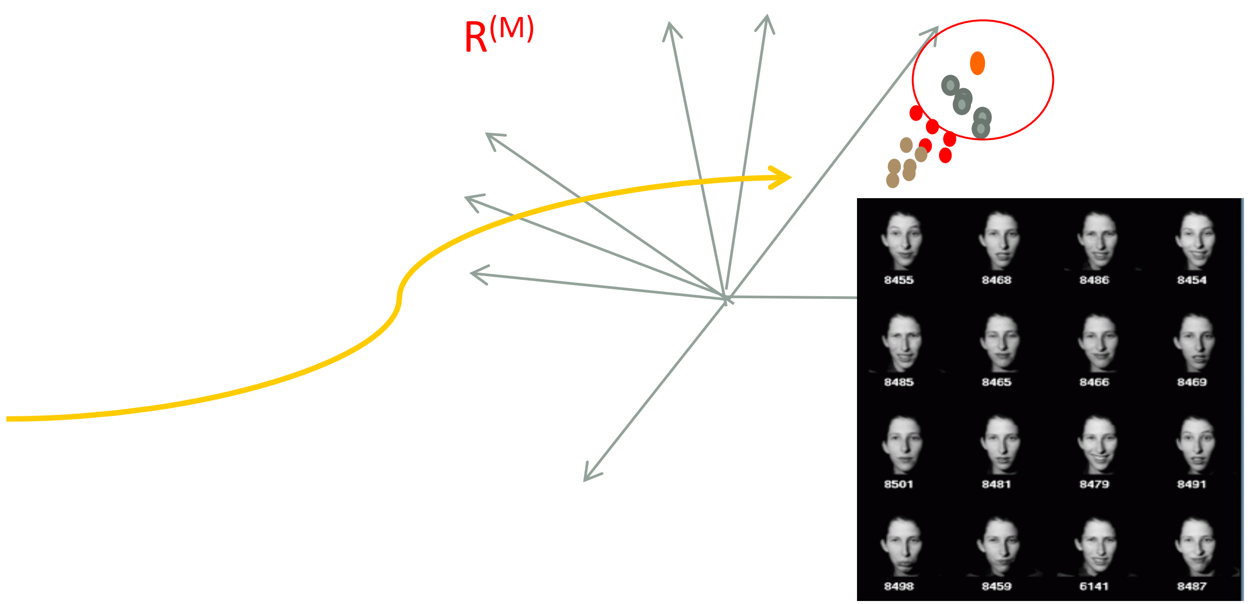


$(x_1, x_2, \dots\dots\dots\dots x_{(m \times n)}) \rightarrow Y = (\omega_1, \omega_2, \omega_3 \dots \omega_M)$

Project X: $$Y = (X - \overline{X})^T * U$$

3. Classify– by knn in R^M

Training set



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   4) Illustration

3) Examples and applications

4) Eigenfaces for face detection

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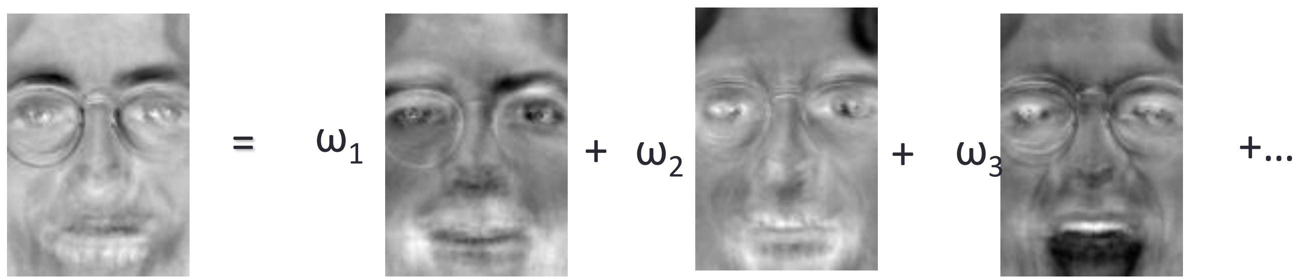
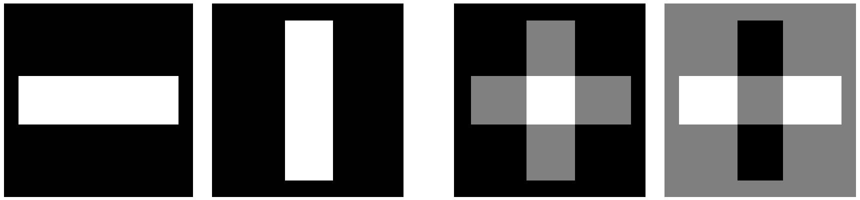
Eigenfaces

Interpretation: Since eigenfaces are forming a base, we can express a face as a linear combination of eigenfaces.





__Exercise__: Given 2 images and 2 eigenfaces, express how each of the right two images is represented by the eigenfaces left images) as base (what would be the weights)?

__Note__: The method of eigenfaces recommends that the faces are aligned (usually, eyes-centered)!

Eigenfaces

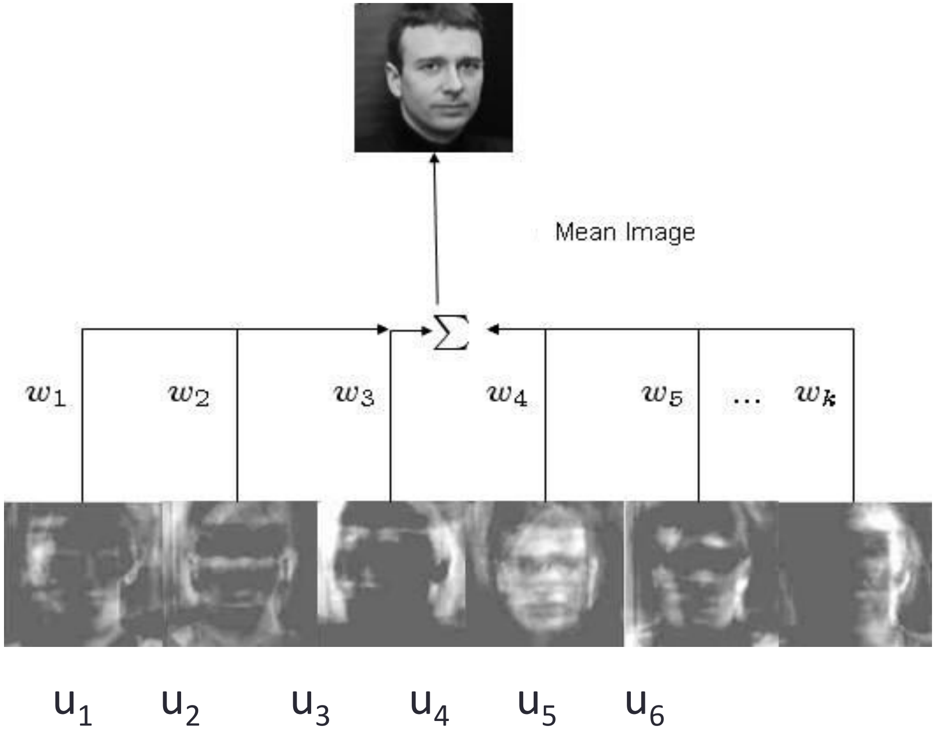
What would be the representation of the original faces in the reduced space?

•The original image X is projected in the reduced space : X->Y:

$$\vec{Y}_i = (X_i - \overline{X})^T * (u_1, u_2, ..u_k)$$

where $Y_i = (\omega_1, \omega_2, \ldots \omega_k)$ is the vector representation in the reduced space (k = 1,2, ... M).

Hence: $$X_i = \overline{X} + \sum_{i=1}^{k} \omega_i u_i$$



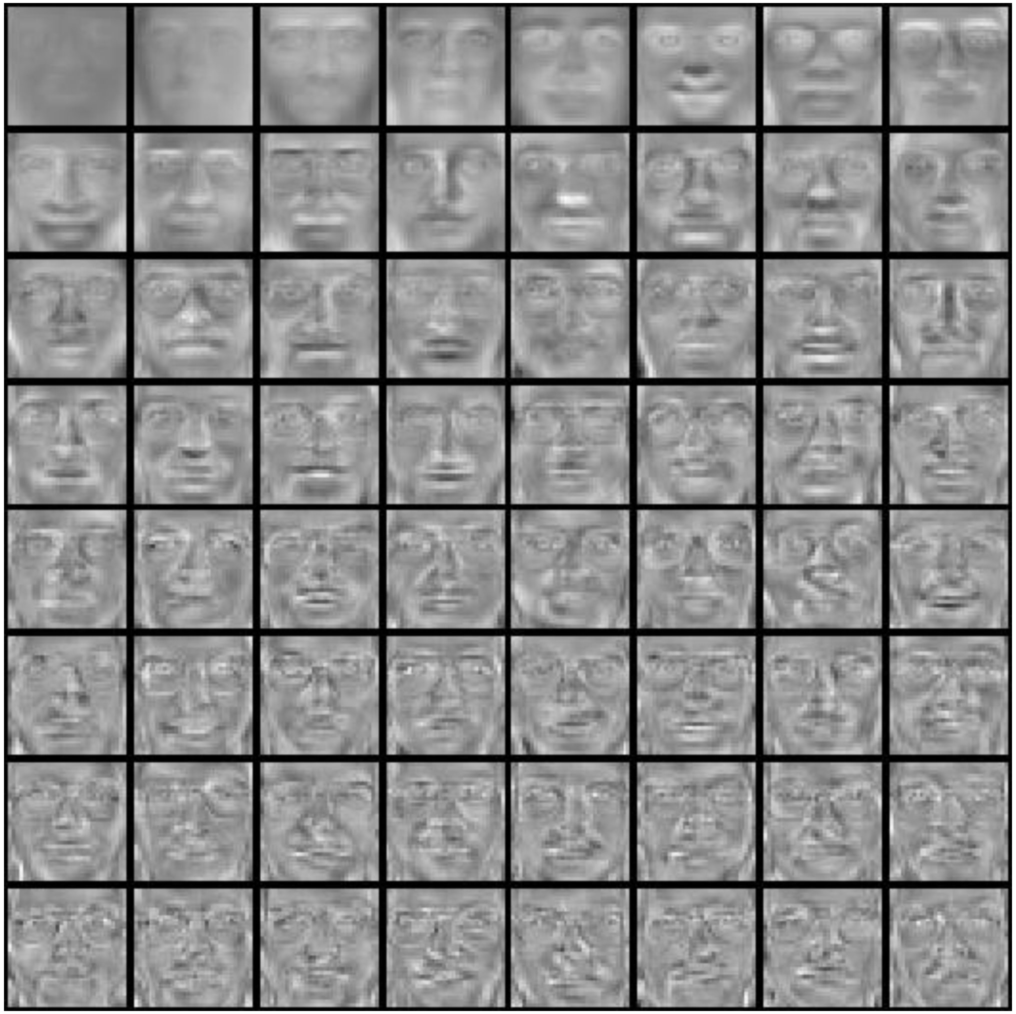
Eigenfaces example

- Training images
  - $\mathbf{x}_1,\ldots,\mathbf{x}_N$

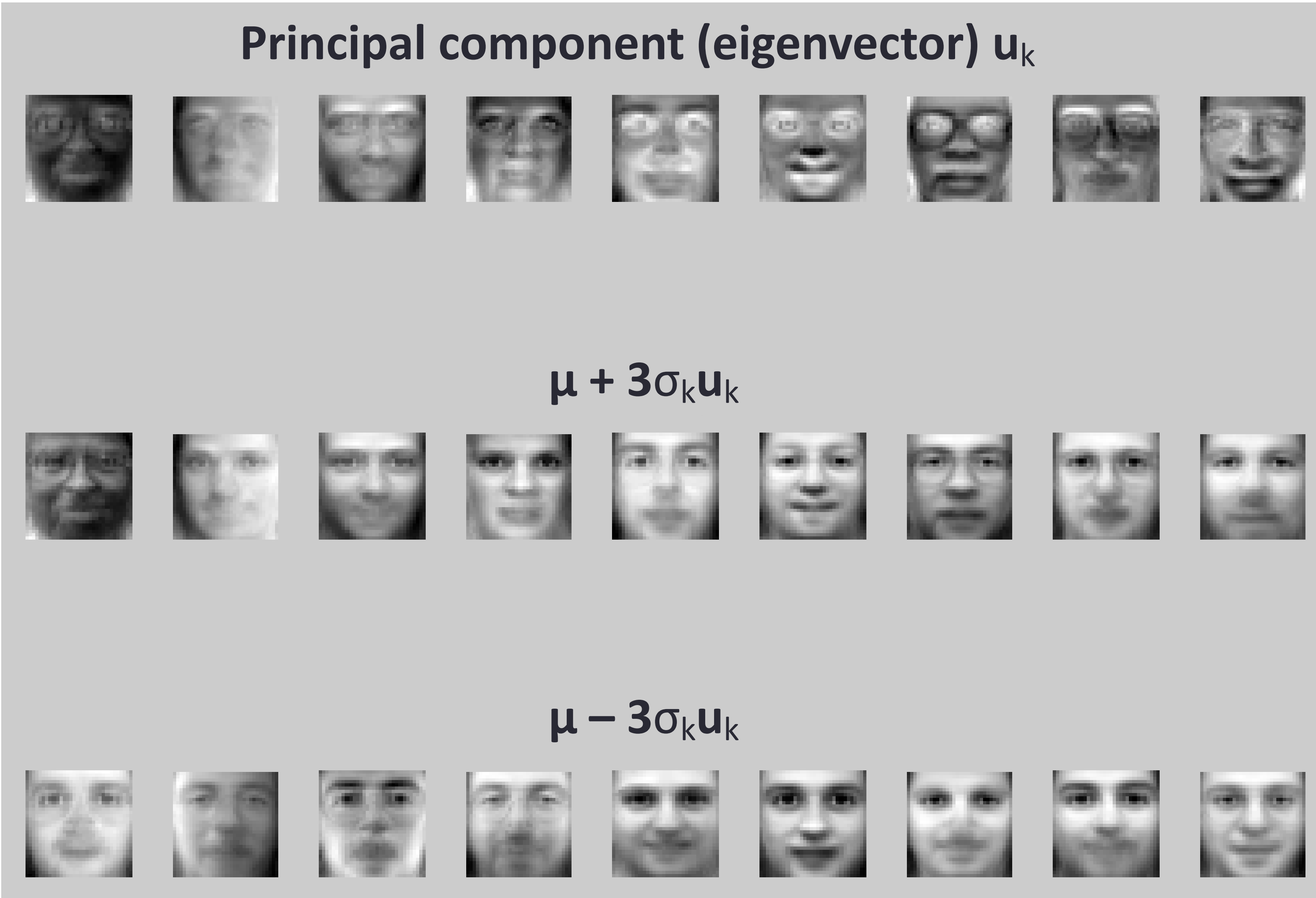
Eigenfaces example

Mean: $\boldsymbol{\mu}$

Top eigenvectors: $\mathbf{u}_1,\ldots\mathbf{u}_k$



Eigenfaces example



Eigenfaces example

- Face **x** in "face space" coordinates:

$$\mathbf{x} \rightarrow [\mathbf{u}_1^{\mathrm{T}}(\mathbf{x} - \mu), \ldots, \mathbf{u}_k^{\mathrm{T}}(\mathbf{x} - \mu)]$$

$$= \quad w_1, \ldots, w_k$$

Eigenfaces example

- Face **x** in "face space" coordinates:

$$\mathbf{x} \rightarrow [\mathbf{u}_1^{\mathrm{T}}(\mathbf{x}-\mu), \ldots, \mathbf{u}_k^{\mathrm{T}}(\mathbf{x}-\mu)]$$

$$= \quad w_1, \ldots, w_k$$

- Reconstruction:

 =  + 

$$\hat{\mathbf{x}} = \boldsymbol{\mu} + w_1\mathbf{u}_1 + w_2\mathbf{u}_2 + w_3\mathbf{u}_3 + w_4\mathbf{u}_4 + \ldots$$

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   - Why to do facial analysis?
   - Biometrics
   - Problems and difficulties
   - Dimensionality of the problem and data redundancy

2) Method of face recognition – eigenfaces
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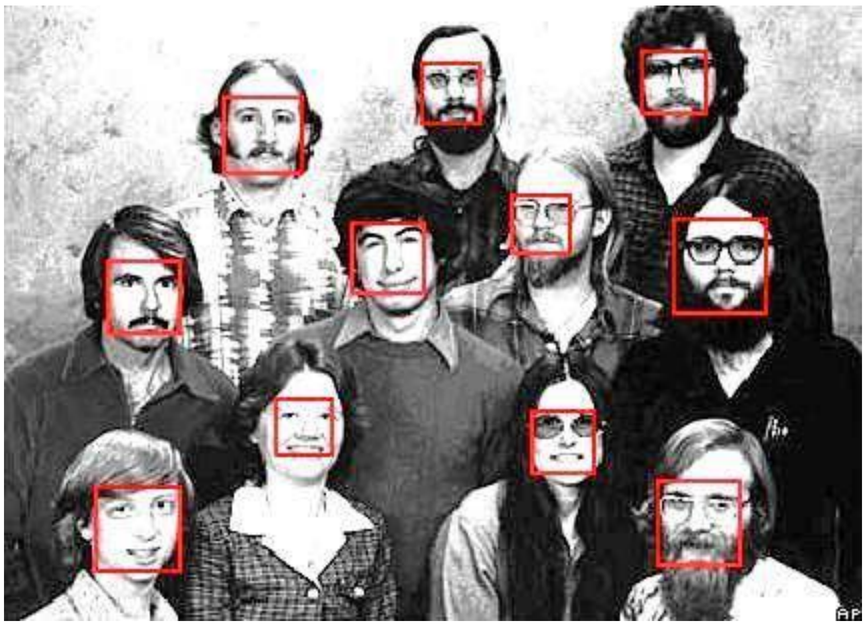
3) Examples and applications

4) Eigenfaces for face detection

Many slides adapted from K. Grauman, S. Lazebnik, J. Vitrià and D. Lowe

Eigenfaces: Example

Face detection and recognition



Limitations

- Global appearance method: not robust to misalignment,

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Eigenfaces

Exemple: Eigenfaces for face detection.

The space defined by the eigenfaces can be viewed as a subspace of the space of images.

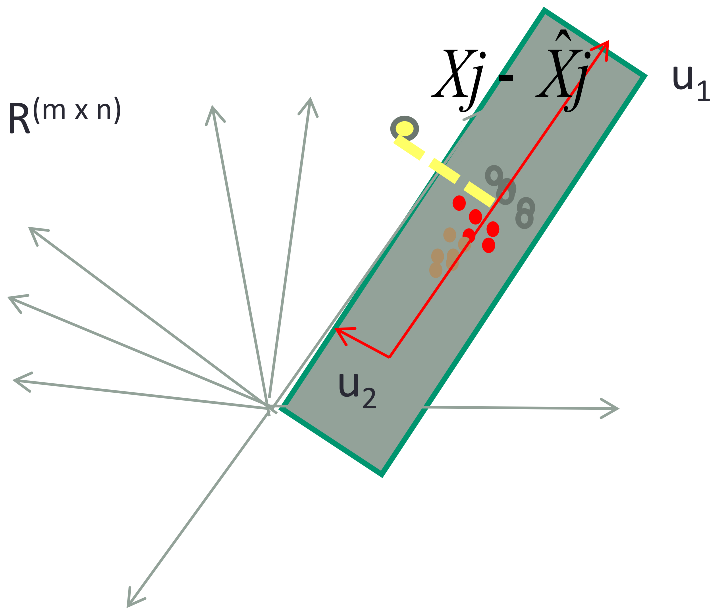
We can always calculate the distance between any image and the face subspace!

And use it as a criterion for deciding whether an image is a face or not.




Eigenfaces

How can we use the eigenfaces space to detect if an imatge is a face?



If you want to know if it is a face or not,
a) Project it
b) Retroproject it in the original space
c) Obtain the difference.

$$Yj = (Xj - \bar{X})^T * (u_1, u_2, \ldots u_l)$$

$$\hat{X}j = \bar{X} + \sum_{i=1}^{k} w_i u_i$$

$$Xj - \hat{X}j$$

Eigenfaces

How do we detect a face?

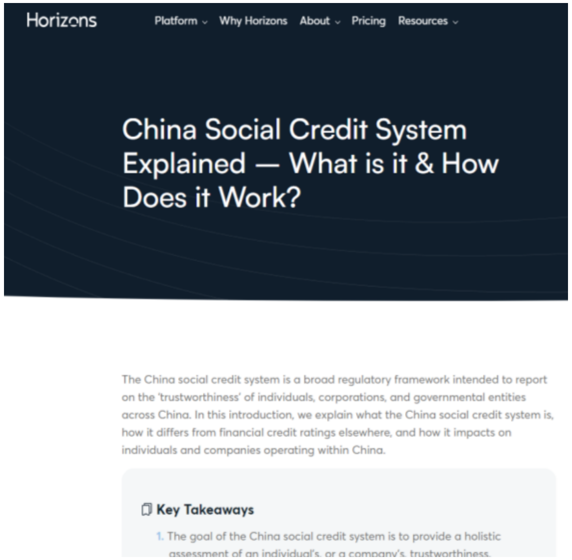
Applications


LOUISE MATSAKIS SECURITY JUL 29, 2019 3:25 PM

How the West Got China's Social Credit System Wrong

It occupies a spot next to 'Black Mirror' and Big Brother in popular imagination, but China's social credit project is far mor powerful numerical score.

It occupies a spot next to Black Mirror and Big Brother in popular imagination, but China's social credit project is far more complicated than a single, all-powerful numerical score. STR/AFP/GETTY IMAGES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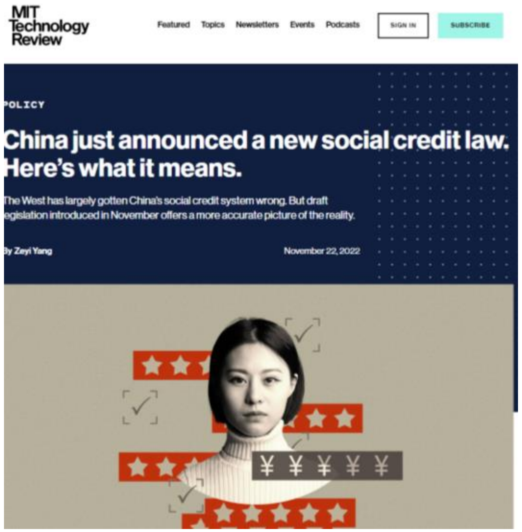
China Social Credit System Explained — What is it & How Does it Work?

The China social credit system is a broad regulatory framework intended to report on the 'trustworthiness' of individuals, corporations, and governmental entities across China. In this introduction, we explain what the China social credit system is, how it differs from financial credit ratings elsewhere, and how it impacts on individuals and companies operating within China.

Key Takeaways

1. The goal of the China social credit system is to provide a holistic assessment of an individual's, or a company's, trustworthiness.

A display for facial recognition and artificial intelligence on monitors at Huawei's Bantian campus in Shenzhen, China.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POLICY

China just announced a new social credit law. Here's what it means.

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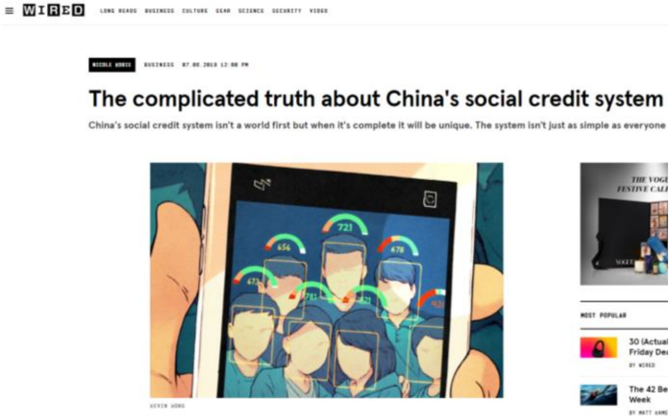
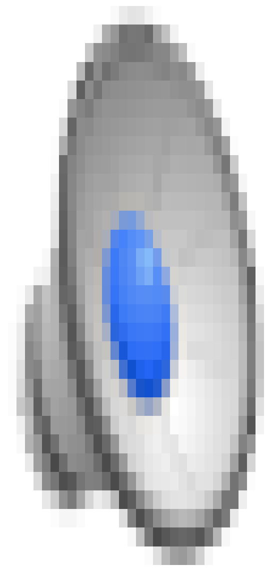
By Zeyi Yang November 22, 2022


WIRED

The complicated truth about China's social credit system

China's social credit system isn't a world first but when it's complete it will be unique. The system isn't just as simple as everyone

Applications



Surveillance cameras: yes or not?

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By Hannah Strange BARCELONA

24 August 2017 • 9:45am

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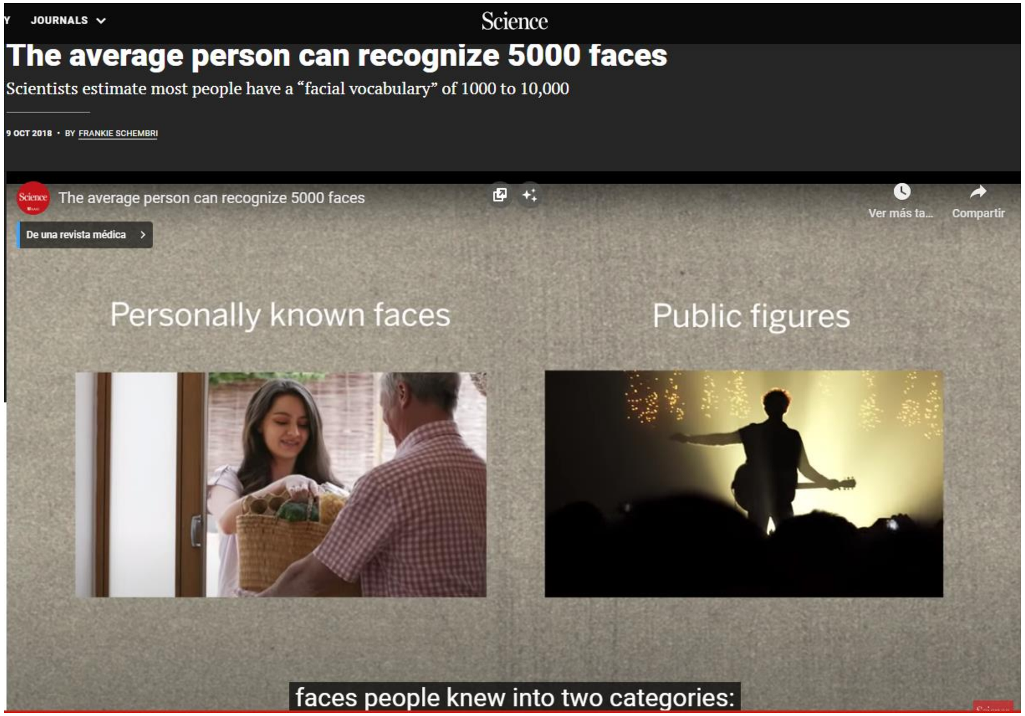
The scalability of the Face recognition problem



How many faces can one person recognize?

You've probably never asked yourself this question, but no matter, science is here to answer it anyway! Indeed, our facial recognition abilities allow us to identify a great number of people. But just how many? Research published in *Acts of the Royal Society B* looked into the question and proposed a method for putting forth the following estimate: 5000. Let's take a closer look.

As a prelude to their study, the authors remind us that for most of history, humans have lived in small, scattered groups. But over the last few centuries, the worldwide population has increased dramatically, and this has consequences on our facial recognition capacities. In addition to all the people we know personally, think about the media figures that we're familiar with through virtual means.

In the research carried out by Rob Jenkins (from the psychology department at the University of York) and his colleagues, it's not a matter of determining how many faces people could recognize, but rather how many faces people *actually recognize*. In addition, facial identification must be dissociated from name recognition. For example, we are most likely incapable of recognizing the authors of many of our favorite books. And conversely, we can recognize a face without knowing the person's name.

Since it's impossible to directly assess the number of faces a person can recognize, the researchers distinguished two categories of faces: faces from the participants' personal lives (family, friends, coworkers, etc.) with whom they had direct social contact; and the faces of famous people (actors, politicians, musicians, etc.). To compile their database, the scientists measured recognition of these two types of faces during different sessions. For this experiment, they recruited 25 undergraduate students from the universities of Glasgow and Aberdeen in Scotland (average age = 24 years; 15 women, 10 men).

First, each participant was asked to write down all the faces they could recognize. They had to be able to form a clear mental image of each face or be able to recognize it on sight. Of course, the researchers had no way of verifying the accuracy of the participants' responses, but these criteria were useful for understanding the task. As mentioned earlier, the participants didn't have to be able to put a name to the face, and semantic descriptions (such as "my mechanic") were accepted. During this first phase, people personally recognized an average of 362 faces (responses varied from 167 to 524). Note that an hour was not enough time to complete the list (participants were still thinking of more faces at the end). From the data collected during these time-limited sessions, and accounting for the decrease in recall rate as the session wore on, the researchers estimated that, without any time constraints, a person could list an average of 549 faces (between 253 and 794).

Second, the students were shown and asked to identify famous people, 3,441 in total, divided into twelve categories (art and media, science, sports, politics, etc.). The rate of identification was lower in this second phase: an average of 290 faces (169 to 407). Given an unlimited amount of time, the researchers calculated that this rate would average 395 (between 230 and 553).

- In the end, considering the huge interindividual variations, people can recognize between 1,000 and 10,000 faces, or about 5,000 on average!

Conclusions

- The problem of detection, localization, identification and recognition of objects / faces is a big challenge with very interesting results.
- Eigenfaces (& eigenspaces) is a robust technique to represent the different appearances of objects in a small and compact way.
- The technique eigenfaces is based on computing the eigenvalues and eigenvectors of the covariance matrix of the training data.
- It has the advantage of being fast and robust.
- It has the limitation that it works only when the faces are aligned and have the same scale, and pose angle.
- Numerous applications to face recognition, gender, facial expressions, monitoring, detection of anatomical organs, etc:
- http://www.youtube.com/watch?v=QZmPEl-YU8g

Facial expression recognition ☺

Iba a cocinar, pero ya no me atrevo... 😂😂
😂😂
... Ver más