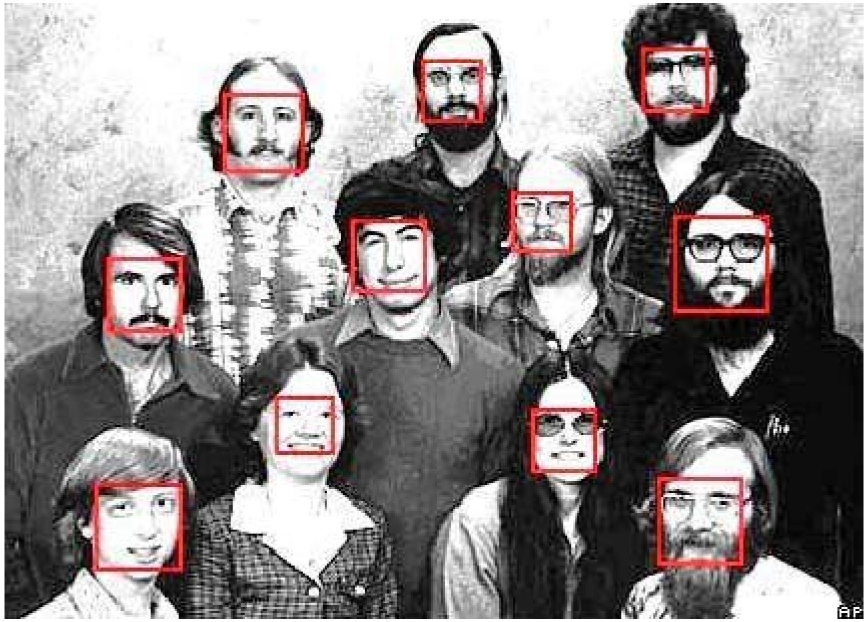
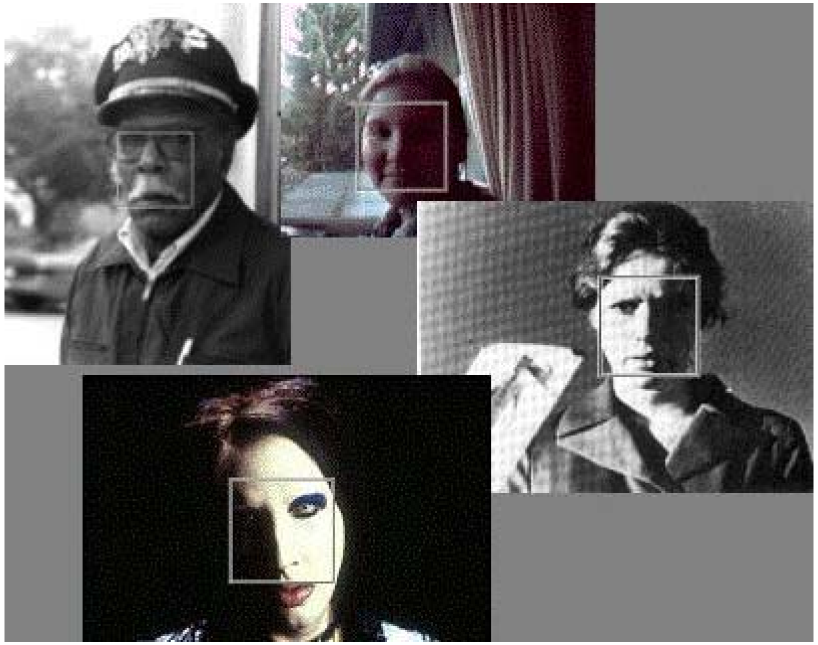
Face detection and recognition

Face detection & recognition

- Viola & Jones detector
  - Available in open CV
- Face recognition
  - Eigenfaces for face recognition
  - Metric learning identification

Face detection





Many slides adapted from P. Viola

Consumer application: iPhoto 2009

http://www.apple.com/ilife/iphoto/

Challenges of face detection

- Sliding window detector must evaluate tens of thousands of location/scale combinations
- Faces are rare: 0–10 per image
  - For computational efficiency, we should try to spend as little time as possible on the non-face windows
  - A megapixel image has ~10^6 pixels and a comparable number of candidate face locations
  - To avoid having a false positive in every image image, our false positive rate has to be less than 10^{-6}

The Viola/Jones Face Detector

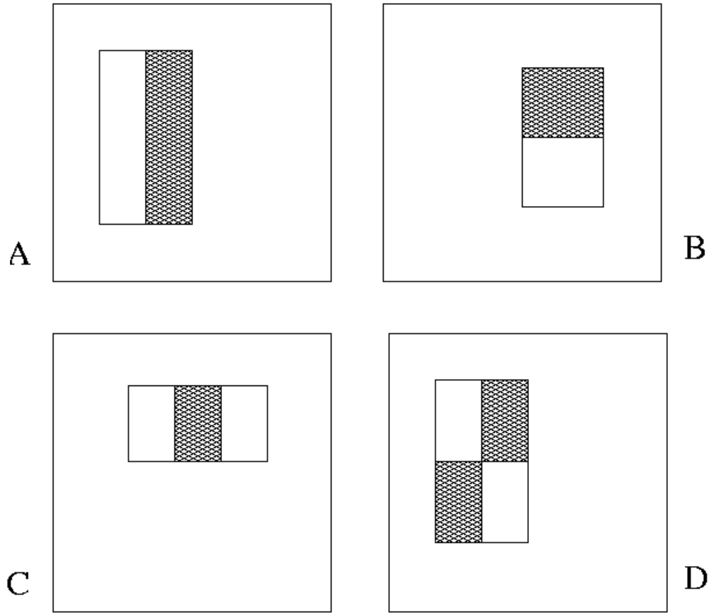
- A seminal approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas
  - *Integral images* for fast feature evaluation
  - *Boosting* for feature selection
  - *Attentional cascade* for fast rejection of non-face windows

P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.

P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

Image Features

"Rectangle filters"

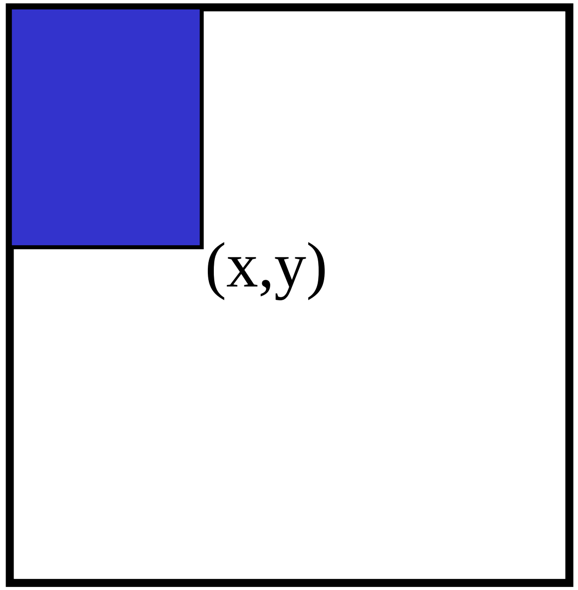


Value =

∑ (pixels in white area) –
∑ (pixels in black area)

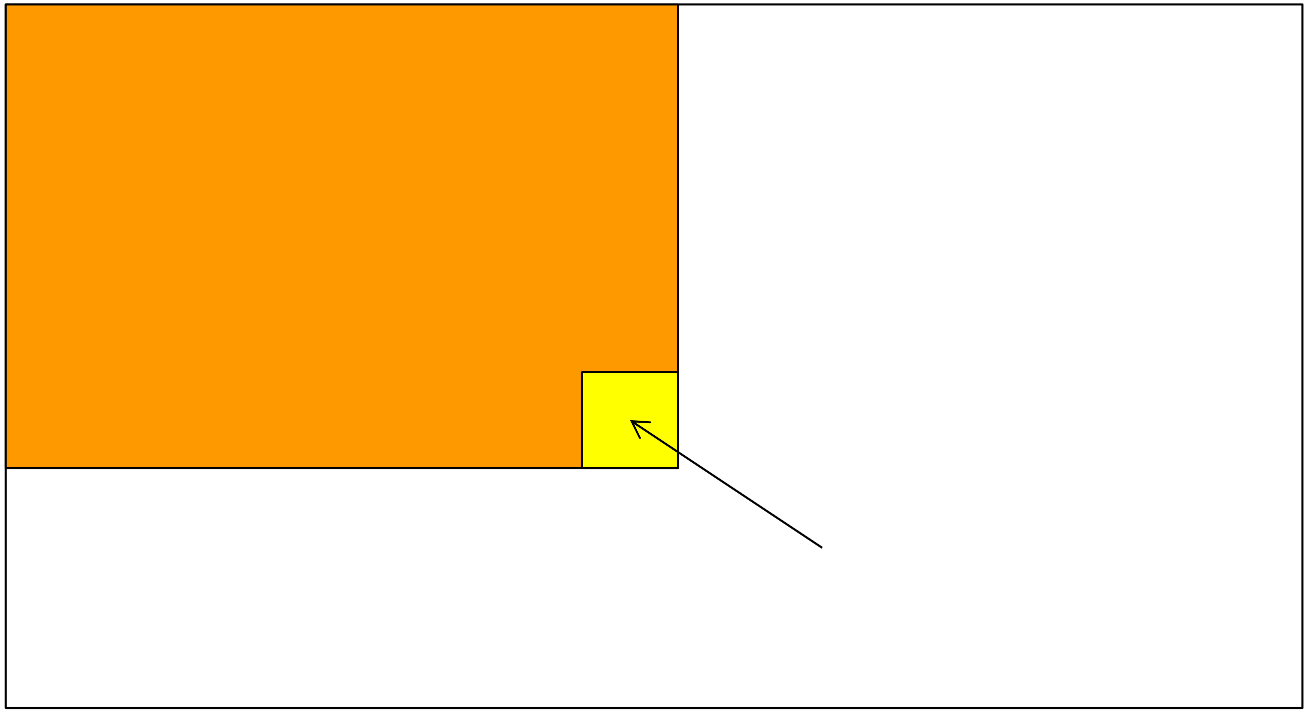
Fast computation with integral images

- The *integral image* computes a value at each pixel (x,y) that is the sum of the pixel values above and to the left of (x,y), inclusive

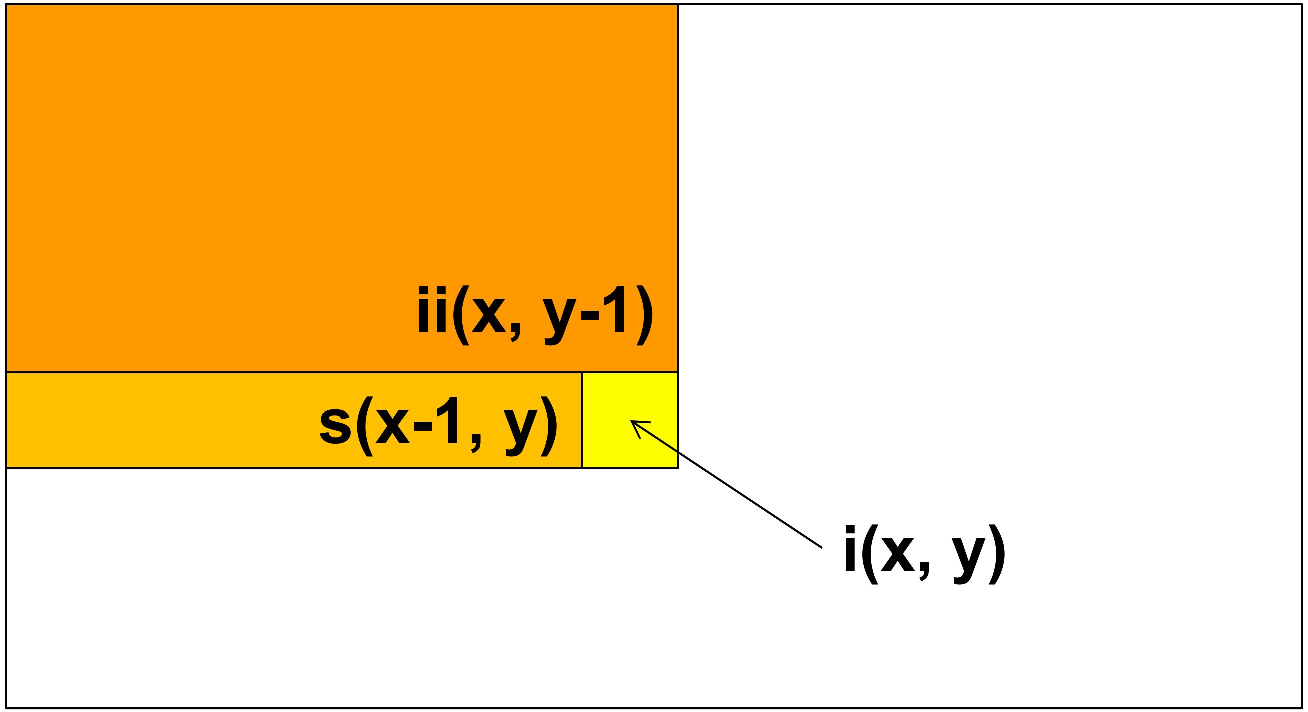


- This can quickly be computed in one pass through the image

Computing the integral image



Computing the integral image



Cumulative row sum: $s(x, y) = s(x–1, y) + i(x, y)$

Integral image: $ii(x, y) = ii(x, y−1) + s(x, y)$

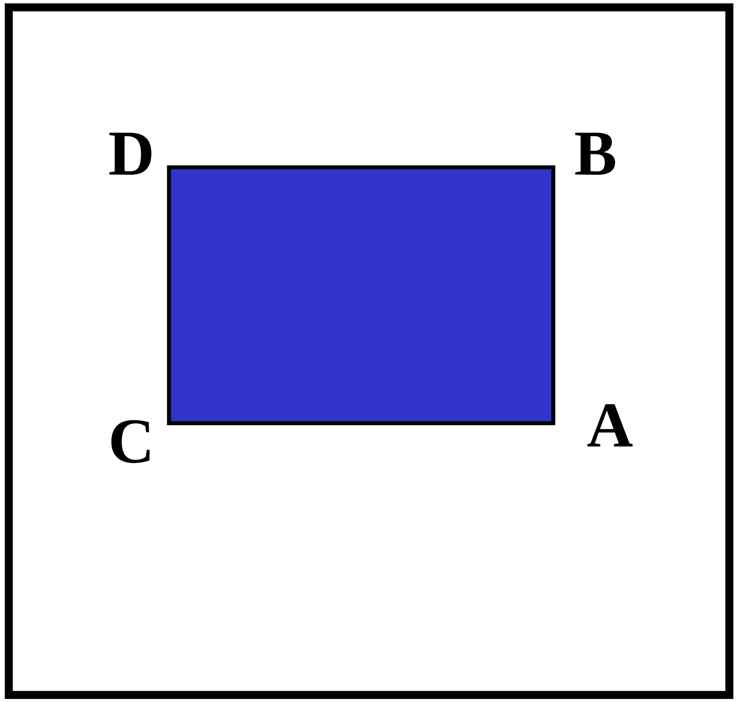
Computing sum within a rectangle

- Let A,B,C,D be the values of the integral image at the corners of a rectangle

- Then the sum of original image values within the rectangle can be computed as:

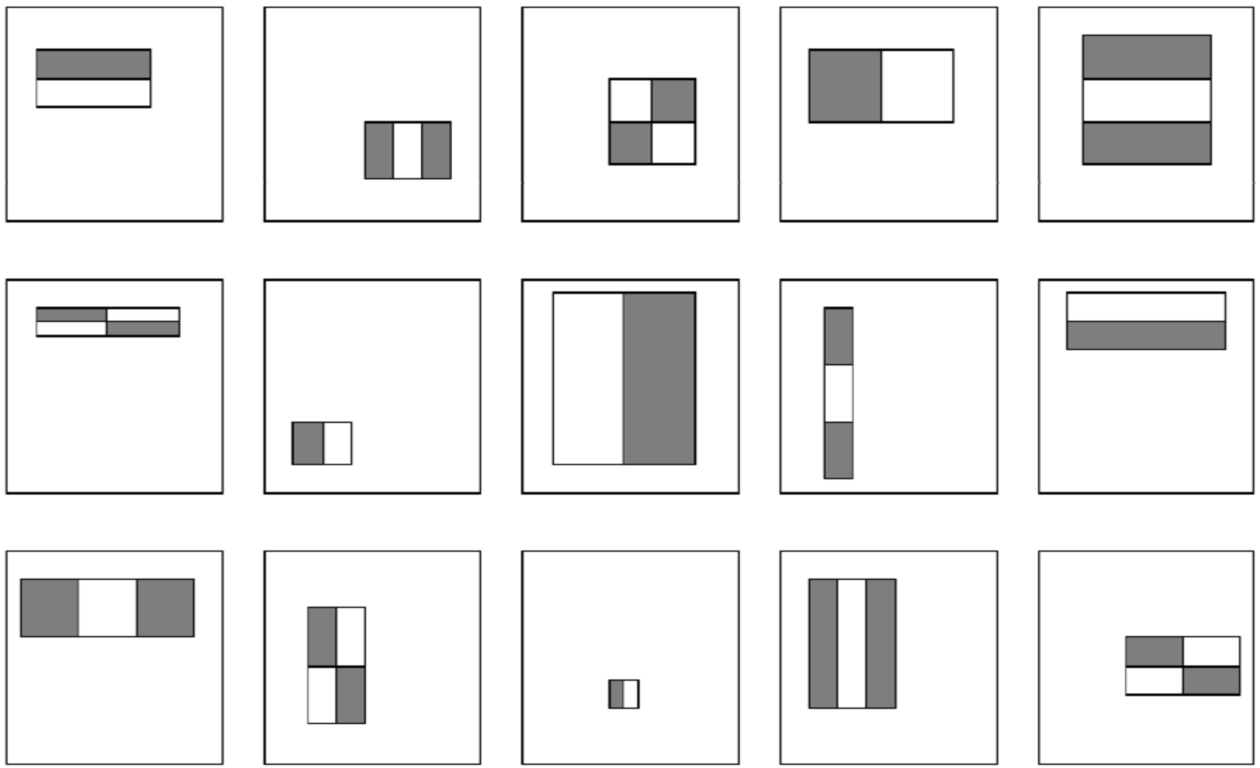
  sum = A – B – C + D

- Only 3 additions are required for any size of rectangle!



Feature selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!



Feature selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- At test time, it is impractical to evaluate the entire feature set
- Can we create a good classifier using just a small subset of all possible features?
- How to select such a subset?

Boosting

- Boosting is a classification scheme that works by combining *weak learners* into a more accurate ensemble classifier

- Training consists of multiple *boosting rounds*
  - During each boosting round, we select a weak learner that does well on examples that were hard for the previous weak learners
  - "Hardness" is captured by weights attached to training examples

Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, September, 1999.

Training procedure

- Initially, weight each training example equally
- In each boosting round:
  - Find the weak learner that achieves the lowest *weighted* training error
  - Raise the weights of training examples misclassified by current weak learner
- Compute final classifier as linear combination of all weak learners (weight of each learner is directly proportional to its accuracy)
  - Exact formulas for re-weighting and combining weak learners depend on the particular boosting scheme (e.g., AdaBoost)

Boosting vs. SVM

- Advantages of boosting
  - Integrates classifier training with feature selection
  - Flexibility in the choice of weak learners, boosting scheme
  - Testing is very fast
- Disadvantages
  - Needs many training examples
  - Training is slow
  - Often doesn't work as well as SVM (especially for many-class problems)

Boosting for face detection

- Define weak learners based on rectangle features

value of rectangle feature

$$h_t(x) = \begin{cases} 1 & \text{if } p_t f_t(x) > p_t \theta_t \\ 0 & \text{otherwise} \end{cases}$$

window

parity

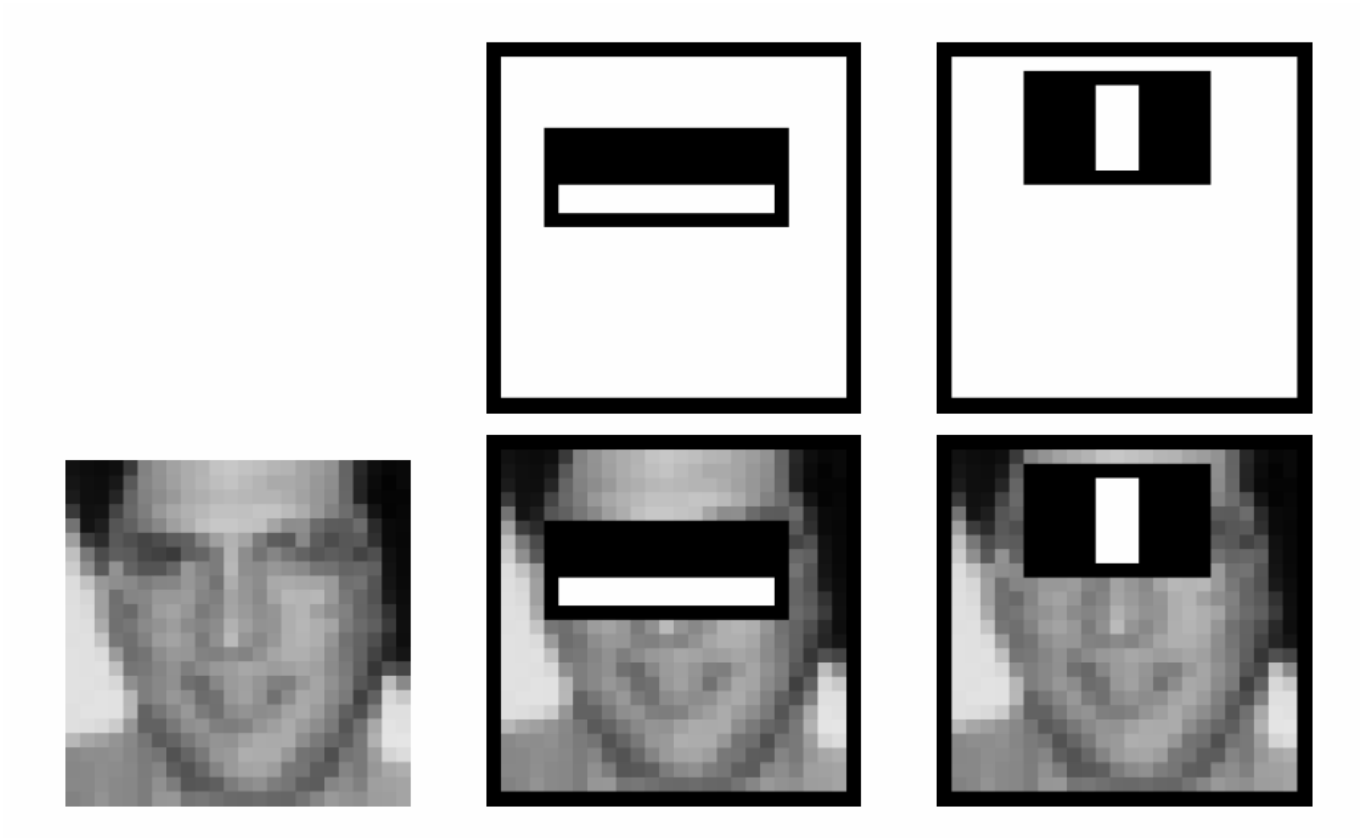
threshold

Boosting for face detection

- Define weak learners based on rectangle features
- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Select best filter/threshold combination based on weighted training error
  - Reweight examples

Boosting for face detection

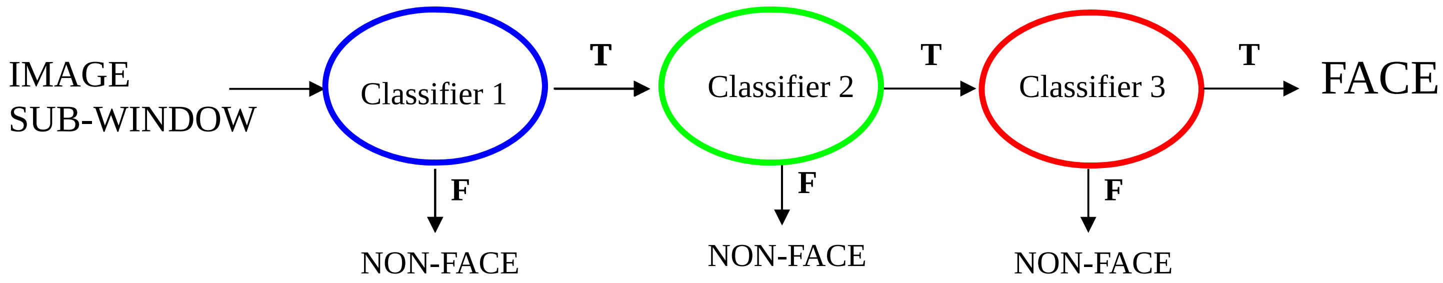
- First two features selected by boosting:



This feature combination can yield 100% detection rate and 50% false positive rate

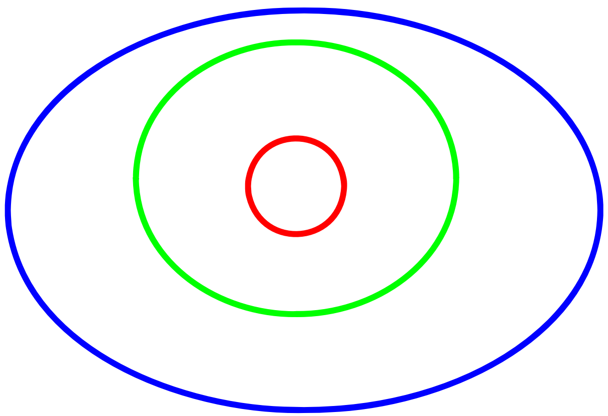
Attentional cascade

- We start with simple classifiers which reject many of the negative sub-windows while detecting almost all positive sub-windows
- Positive response from the first classifier triggers the evaluation of a second (more complex) classifier, and so on
- A negative outcome at any point leads to the immediate rejection of the sub-window

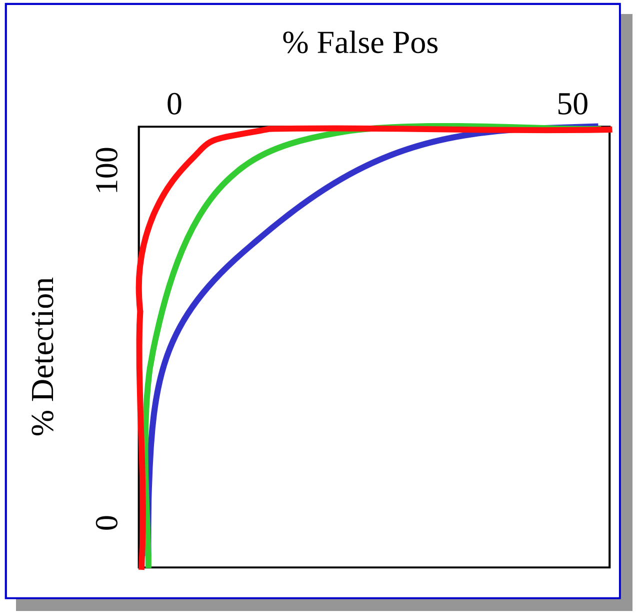


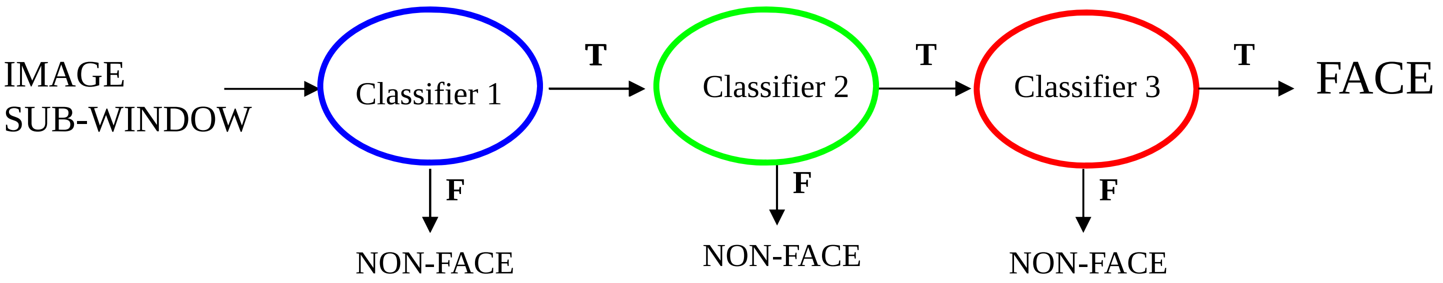
Attentional cascade

- Chain classifiers that are progressively more complex and have lower false positive rates:



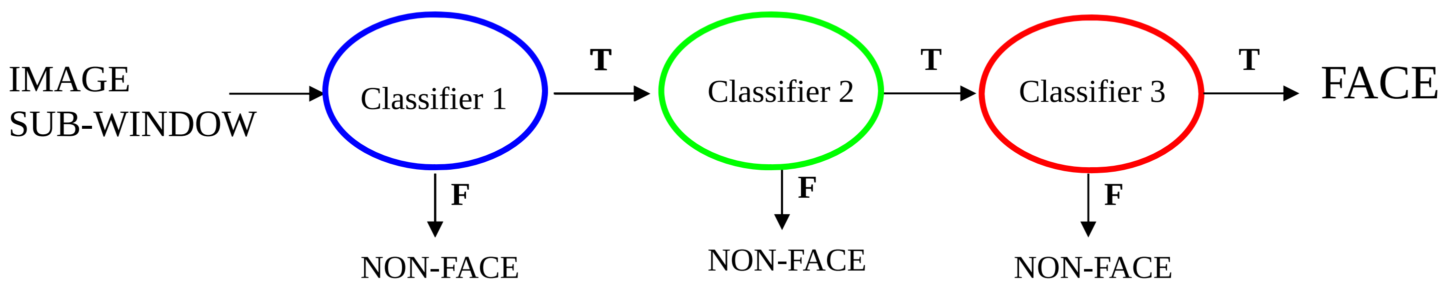
Receiver operating characteristic





Attentional cascade

- The detection rate and the false positive rate of the cascade are found by multiplying the respective rates of the individual stages
- A detection rate of 0.9 and a false positive rate on the order of 10^{-6} can be achieved by a 10-stage cascade if each stage has a detection rate of 0.99 ($0.99^{10} \approx 0.9$) and a false positive rate of about 0.30 ($0.3^{10} \approx 6\times10^{-6}$)



Training the cascade

- Set target detection and false positive rates for each stage
- Keep adding features to the current stage until its target rates have been met
  - Need to lower AdaBoost threshold to maximize detection (as opposed to minimizing total classification error)
  - Test on a *validation set*
- If the overall false positive rate is not low enough, then add another stage
- Use false positives from current stage as the negative training examples for the next stage

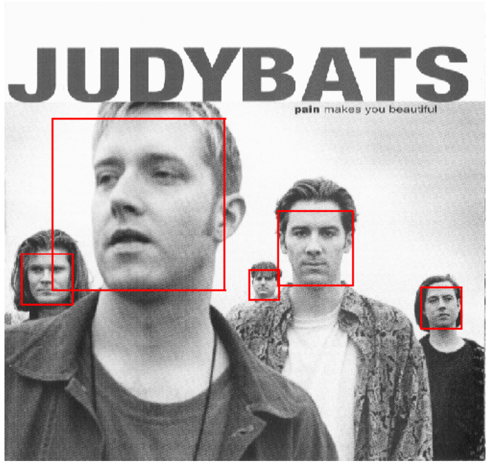
The implemented system

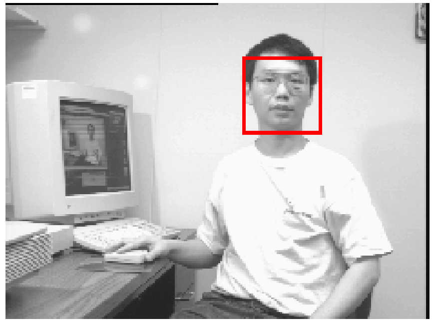
- Training Data
  - 5000 faces
    - All frontal, rescaled to 24x24 pixels
  - 300 million non-faces
    - 9500 non-face images
  - Faces are normalized
    - Scale, translation
- Many variations
  - Across individuals
  - Illumination
  - Pose

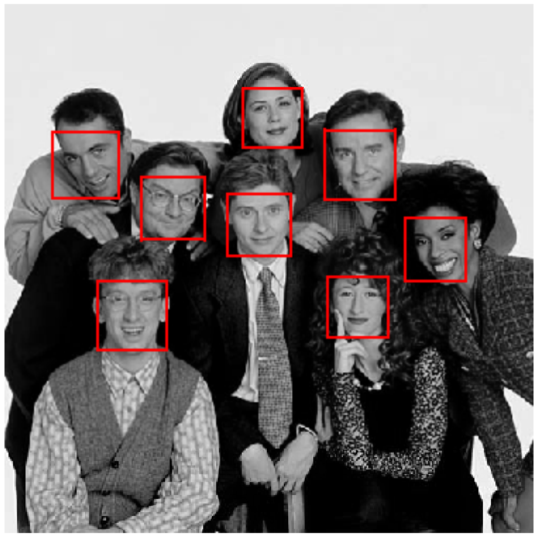
System performance

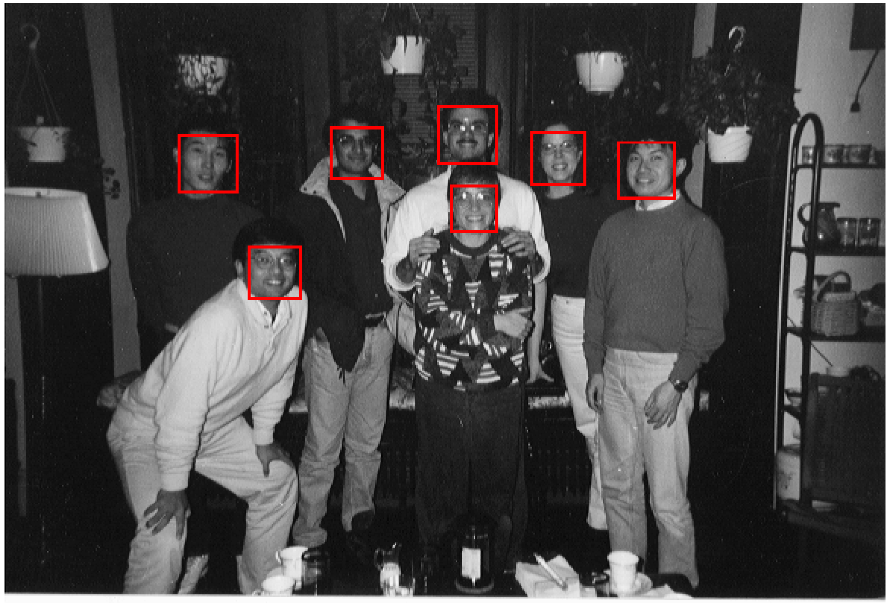
- Training time: “weeks” on 466 MHz Sun workstation
- 38 layers, total of 6061 features
- Average of 10 features evaluated per window on test set
- “On a 700 Mhz Pentium III processor, the face detector can process a 384 by 288 pixel image in about .067 seconds”

Output of Face Detector on Test Images

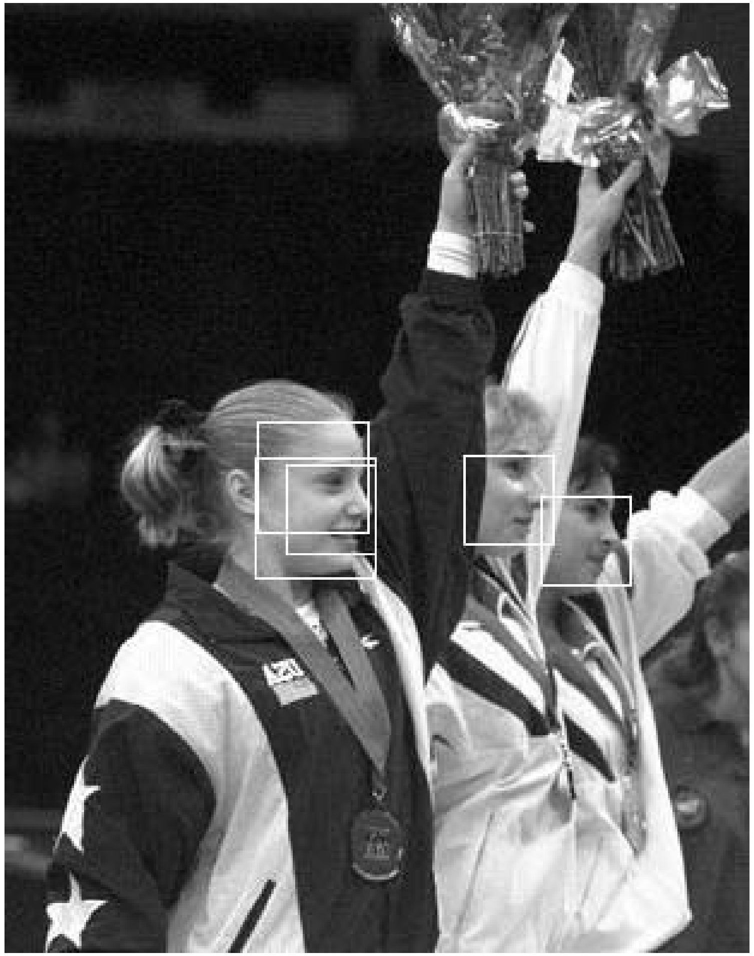




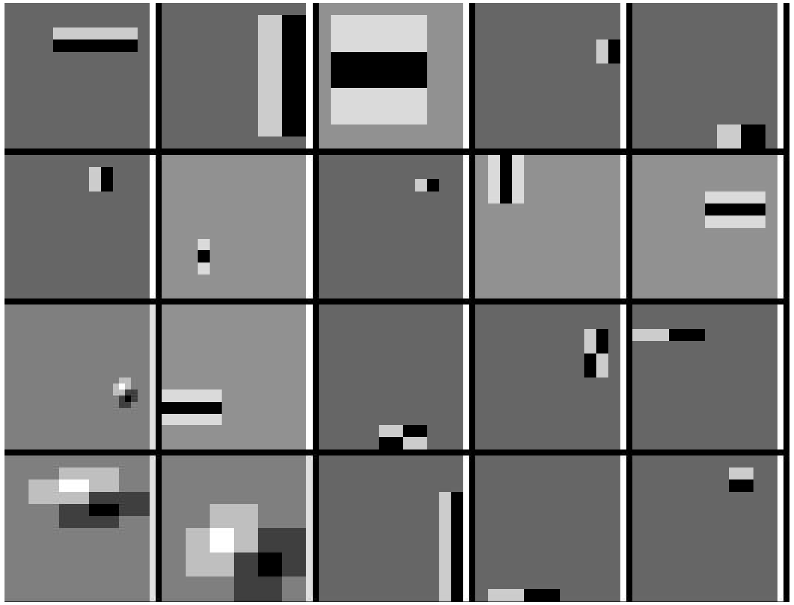




Profile Detection



Profile Features



Summary: Viola/Jones detector

- Rectangle features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows
- Available in open CV

Face detection & recognition

- Viola & Jones detector

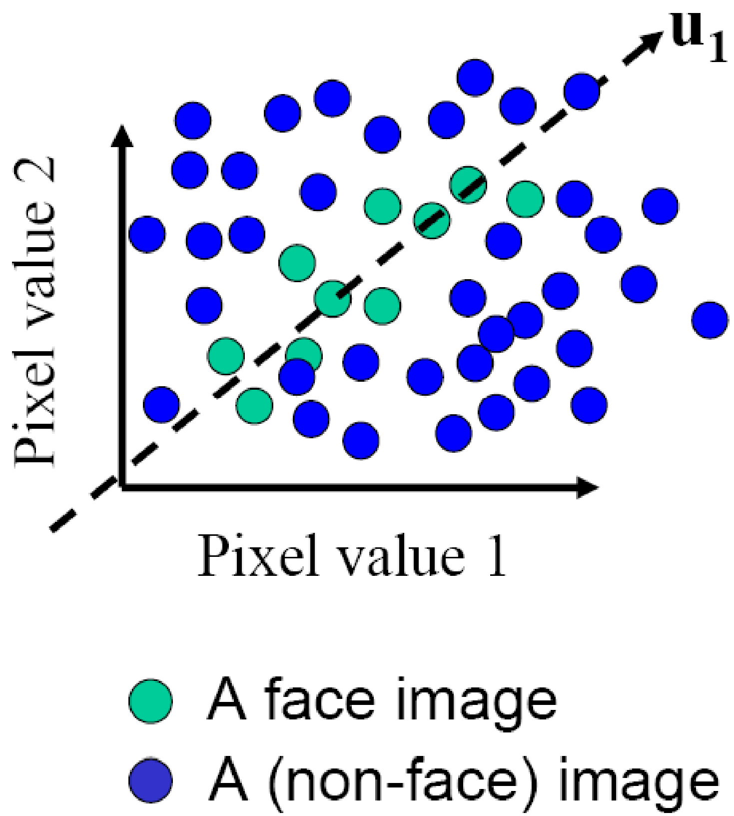
- Face recognition
  - *Eigenfaces for face recognition*
  - Metric learning identification

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 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



Principal Component Analysis

- Given: N data points $\mathbf{x_1}, \ldots, \mathbf{x_N}$ in R^d
- We want to find a new set of features that are linear combinations of original ones:

$$u(\mathbf{x}_i) = \mathbf{u}^T(\mathbf{x}_i - \boldsymbol{\mu})$$

  ($\boldsymbol{\mu}$: mean of data points)

- What unit vector $\mathbf{u}$ in R^d captures the most variance of the data?

Principal component analysis

- The direction that captures the maximum covariance of the data is the eigenvector corresponding to the largest eigenvalue of the data covariance matrix

- Furthermore, the top *k* orthogonal directions that capture the most variance of the data are the *k* eigenvectors corresponding to the *k* largest eigenvalues

Eigenfaces: Key idea

- Assume that most face images lie on a low-dimensional subspace determined by the first *k* (*k*<*d*) directions of maximum variance
- Use PCA to determine the vectors or "eigenfaces" $\mathbf{u}_1, \ldots \mathbf{u}_k$ that span that subspace
- Represent all face images in the dataset as linear combinations of eigenfaces

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

Eigenfaces example

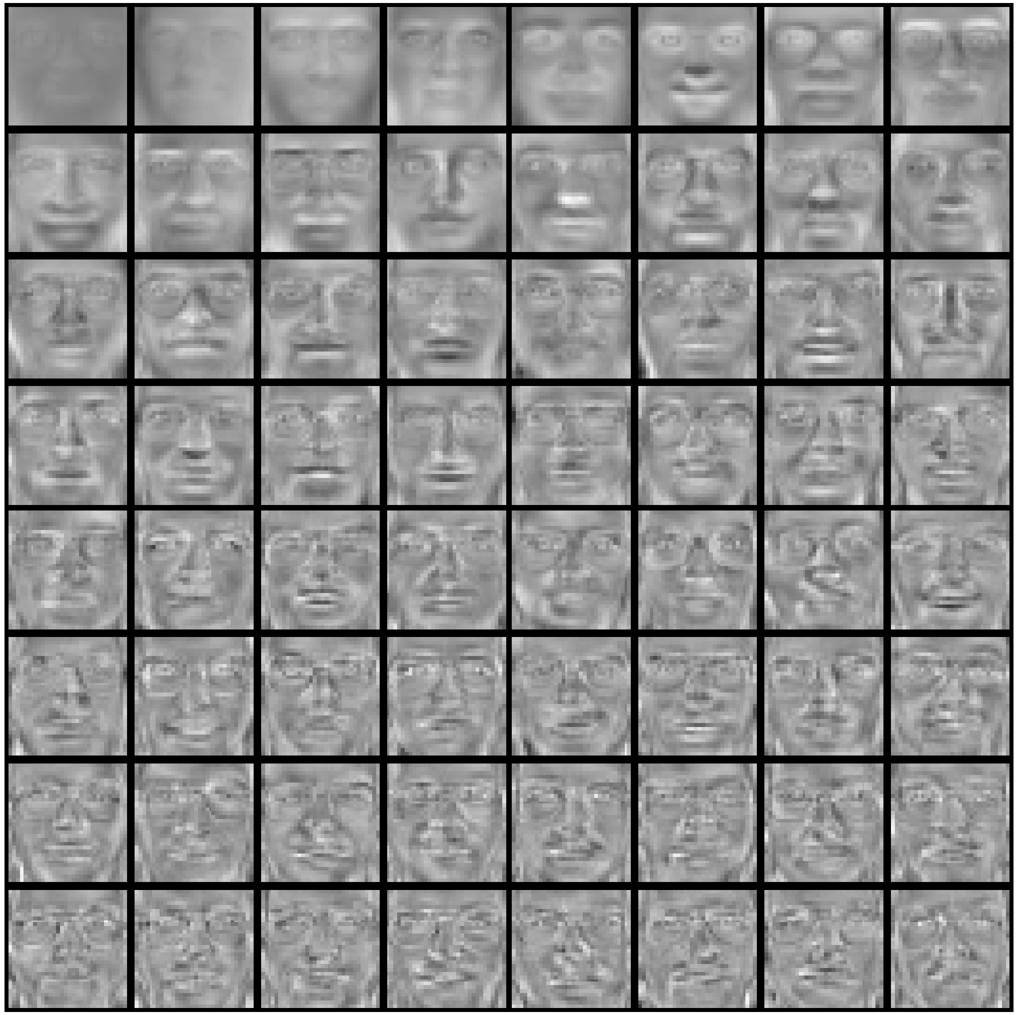
Training images

$\mathbf{x}_1, \ldots, \mathbf{x}_N$

Eigenfaces example

Mean: $\boldsymbol{\mu}$

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

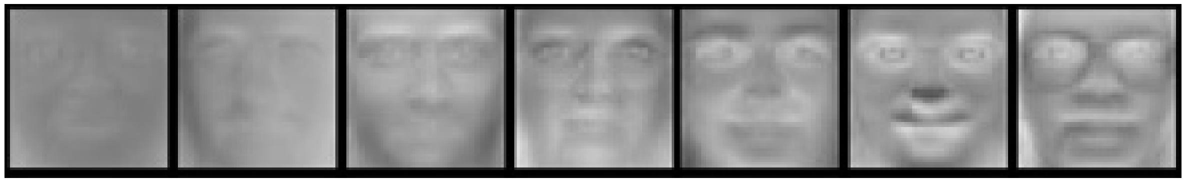


Eigenfaces example

- 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:

 =  + 

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

Recognition with eigenfaces

Process labeled training images:

- Find mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$
- Find k principal components (eigenvectors of $\boldsymbol{\Sigma}$) $\mathbf{u}_1,\ldots\mathbf{u}_k$
- Project each training image $\mathbf{x}_i$ onto subspace spanned by principal components:
  $(w_{i1},\ldots,w_{ik}) = (\mathbf{u}_1^T(\mathbf{x}_i - \boldsymbol{\mu}), \ldots , \mathbf{u}_k^T(\mathbf{x}_i - \boldsymbol{\mu}))$

Given novel image $\mathbf{x}$:

- Project onto subspace:
  $(w_1,\ldots,w_k) = (\mathbf{u}_1^T(\mathbf{x} - \boldsymbol{\mu}), \ldots , \mathbf{u}_k^T(\mathbf{x} - \boldsymbol{\mu}))$
- Classify as closest training face in k-dimensional subspace

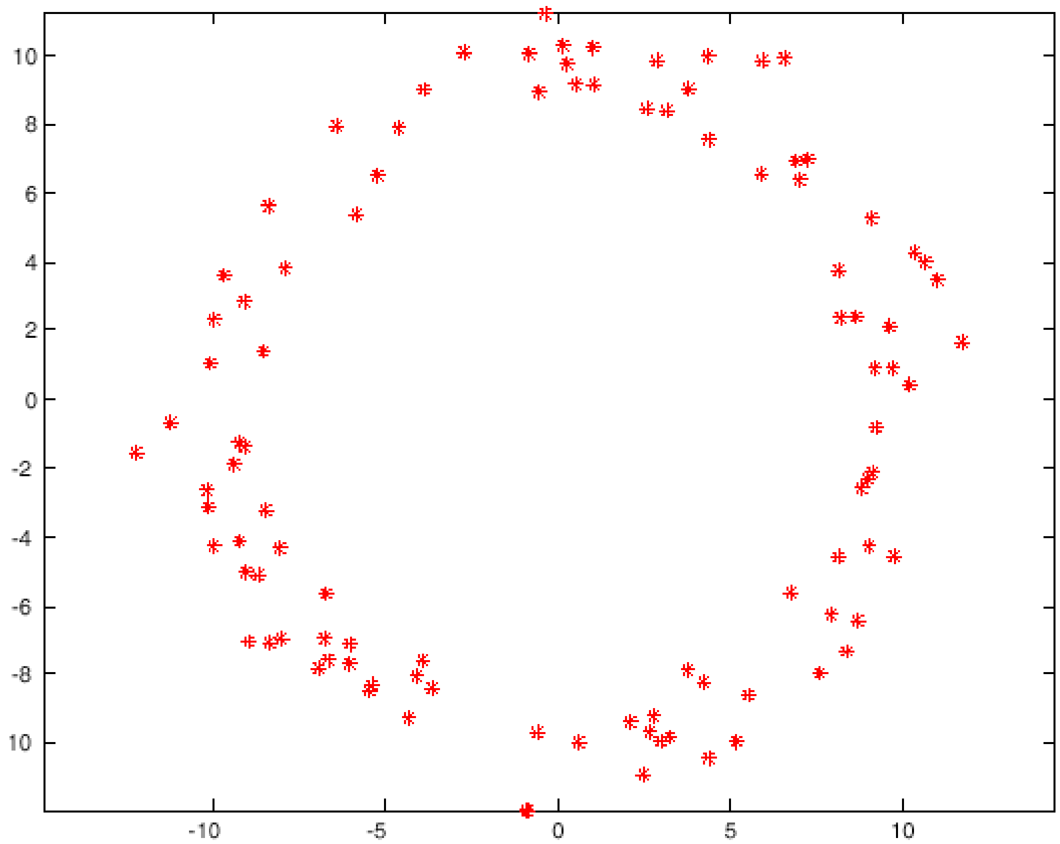
M. Turk and A. Pentland, Face Recognition using Eigenfaces, CVPR 1991

Limitations

- Global appearance method: not robust to misalignment, background variation

Limitations

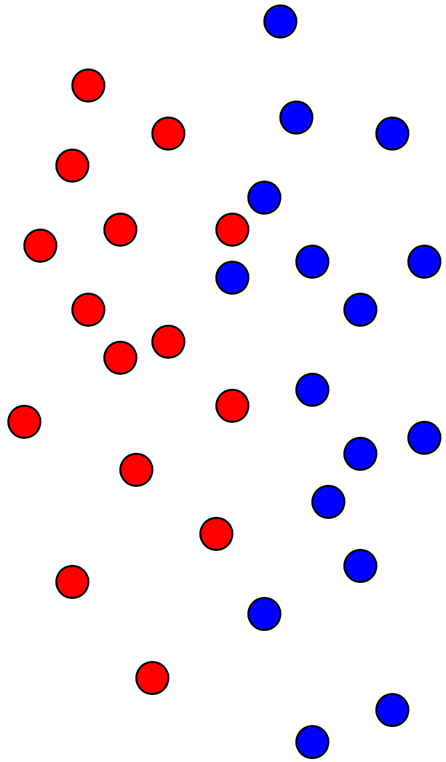
- PCA assumes that the data has a Gaussian distribution (mean μ, covariance matrix Σ)



The shape of this dataset is not well described by its principal components

Limitations

- The direction of maximum variance is not always good for classification



Face detection & recognition

- Viola & Jones detector
  - Available in open CV
- Face recognition
  - Eigenfaces for face recognition
  - *Metric learning for face identification*

Learning metrics for face identification

- Are these two faces of the same person?

- Challenges:
  - pose, scale, lighting, ...
  - expression, occlusion, hairstyle, ...
  - generalization to people not seen during training

M. Guillaumin, J. Verbeek and C. Schmid. Metric learning for face identification. ICCV'09.

Metric Learning

- **Most common form of learned metrics are Mahalanobis**

$$d_M(x,y) = (x-y)^T M(x-y)$$

  - **M is a positive definite matrix**
  - **Generalization of Euclidean metric (setting M=I)**
  - **Corresponds to Euclidean metric after linear transformation of the data**

$$d_M(x,y) = (x-y)^T M(x-y) = (x-y)^T L^T L(x-y) = d_{L2}(Lx,Ly)$$

Logistic Discriminant Metric Learning

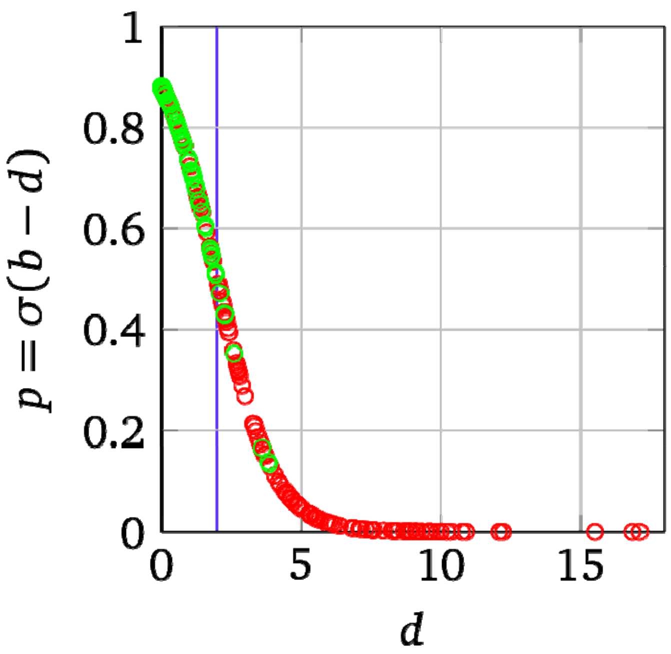
- **Classify pairs of faces based on distance between descriptors**

$$d_M(x,y) = (x-y)^T M(x-y)$$

- **Use sigmoid to map distance to class probability**

$$p(y_{ij} = +1) = \sigma\left(b - d_M(x_i, x_j)\right)$$

$$\sigma(z) = \left(1 + \exp(-z)\right)^{-1}$$



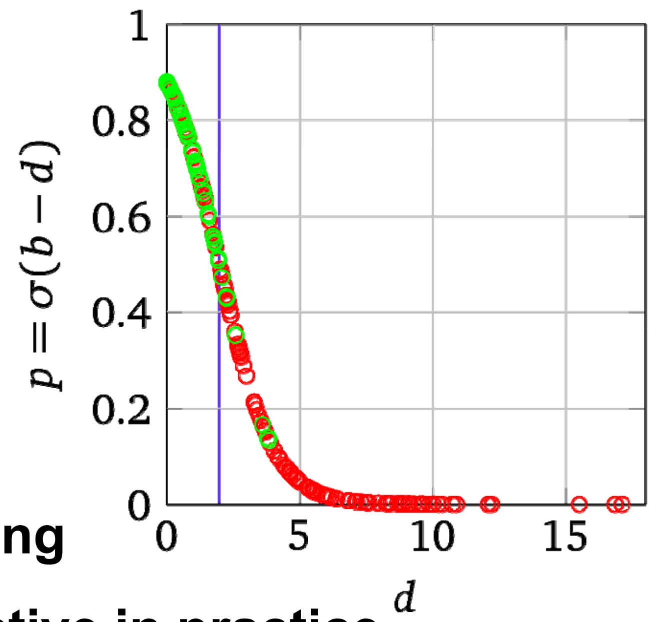
Logistic Discriminant Metric Learning

- **Mahanalobis distance linear in elements of M**

$$d_M(x,y) = (x-y)^T M(x-y)$$
$$= z^T M z = \sum_{i,j} z_i z_j M_{ij}$$

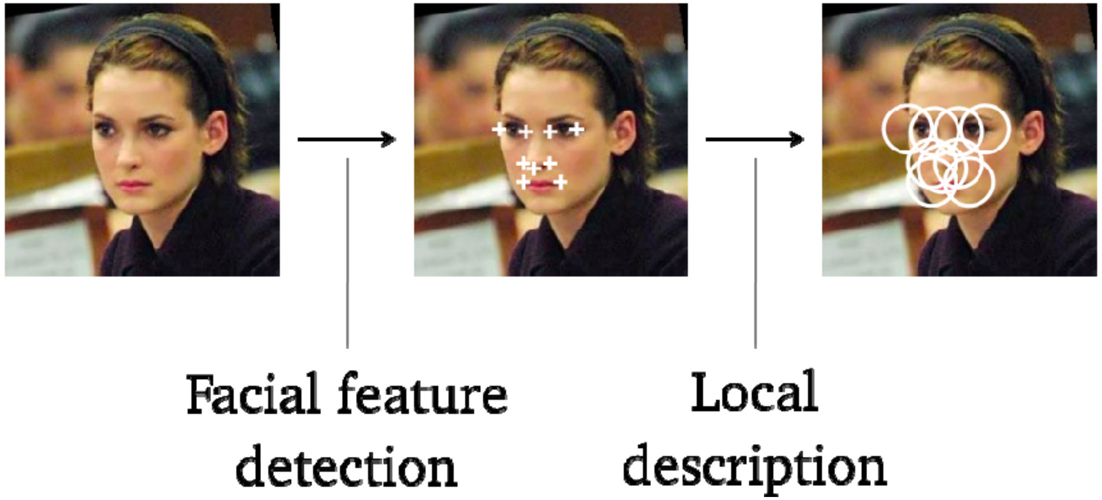
$$p(y_{ij} = +1) = \sigma\left(b - d_M(x_i, x_j)\right)$$

- **Linear logistic discriminant model**
  - **Distance is linear in elements of M**
  - **Learn maximum likelihood M and b**



- **Can use low-rank $M = L^T L$ to avoid overfitting**
  - **Loses convexity of cost function, effective in practice**

Feature extraction process



- Detection of 9 facial features [Everingham et al. 2006]
    - using both appearance and relative position
    - using the constellation mode
    - leads to some pose invariance

- Each facial features described using SIFT descriptors

Feature extraction process

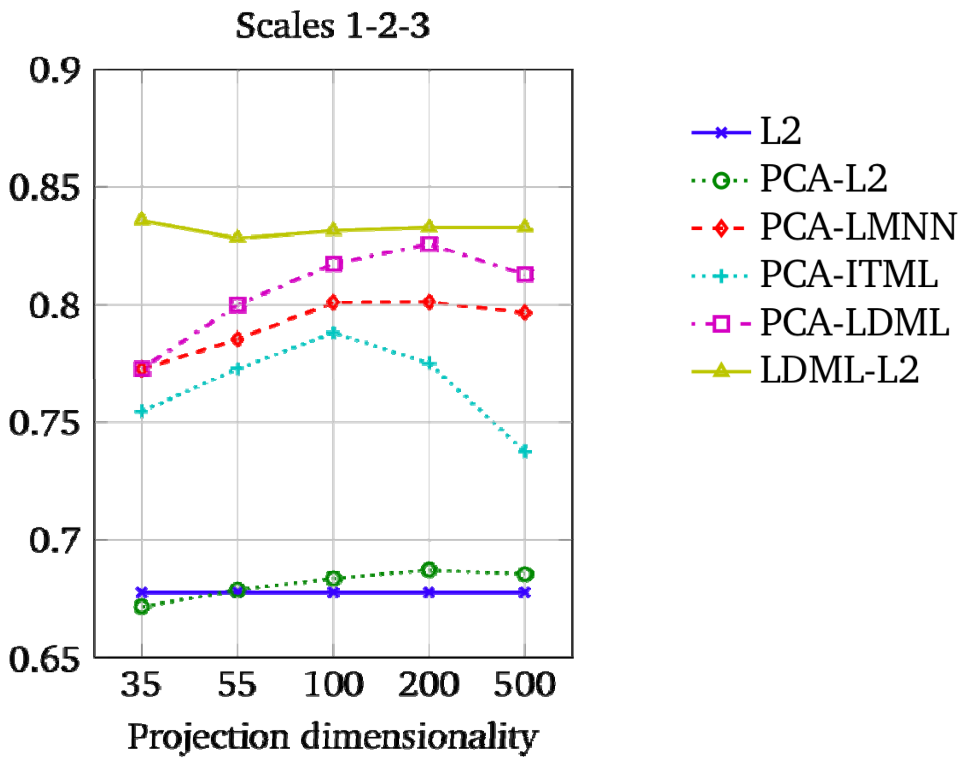
- Detection of 9 facial features
- Each facial features described using SIFT descriptors at 3 scales
- Concatenate 3x9 SIFTs into a vector of dimensionality 3456

Labelled Faces in the Wild data set

- Contains 12.233 faces of 5749 different people (1680 appear twice or more)
- Realistic intra-person variability
- Detections from Viola & Jones detector, false detections removed
- Pairs used in test are of people not in the training set

Experimental Results

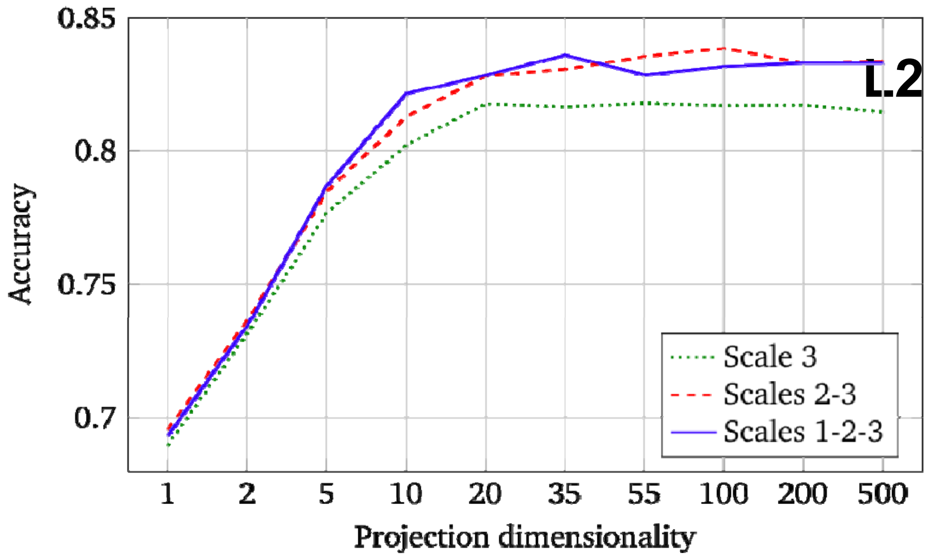
- Various metric learning algorithms on SIFT representation



- Significant increases in performance when learning the metric
- Low-rank metric needs less dimensions than PCA to learn good metric

Experimental Results

- **Low-rank LDML metrics using various scales of SIFT descriptor**



L2: 67.8 %

- **Surprisingly good performance using very few dimensions**
- **20 dimensional descriptor instead of 3456 dim. concatenated SIFT just from linear combinations of the SIFT histogram bins**

Comparing projections of LDML and PCA

• Using PCA and LDML to find two dimensional projection of the faces of Britney Spears and Jennifer Aniston