Announcements

- Project 2 due tomorrow night
- Project 3 out Wednesday
  - Jiun-Hung will take photos beginning of class

Recognition

The “Margaret Thatcher Illusion”, by Peter Thompson

Readings

- Szeliski Chapter 14

Recognition

The “Margaret Thatcher Illusion”, by Peter Thompson

Readings

- Szeliski Chapter 14

What do we mean by “object recognition”?

Next 15 slides adapted from Li, Fergus, & Torralba’s excellent short course on category and object recognition

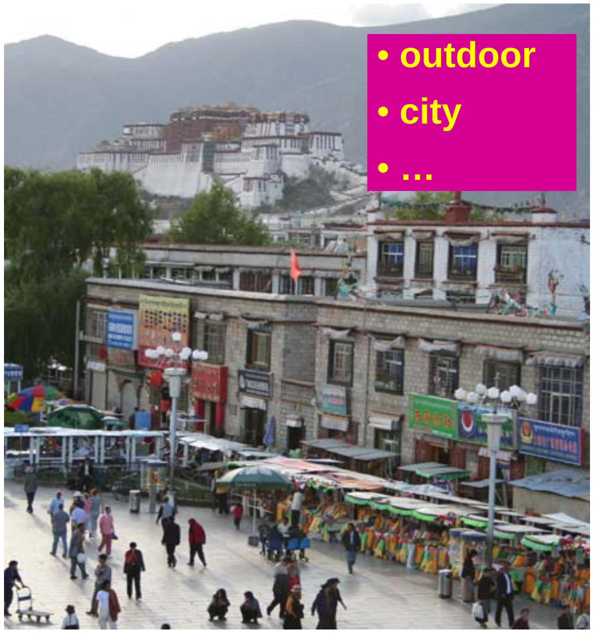
Verification: is that a lamp?

Detection: are there people?

Identification: is that Potala Palace?

Object categorization

Scene and context categorization

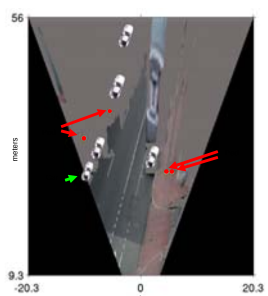


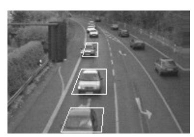
Applications: Computational photography

[Face priority AE] When a bright part of the face is too bright

Applications: Assisted driving

Pedestrian and car detection

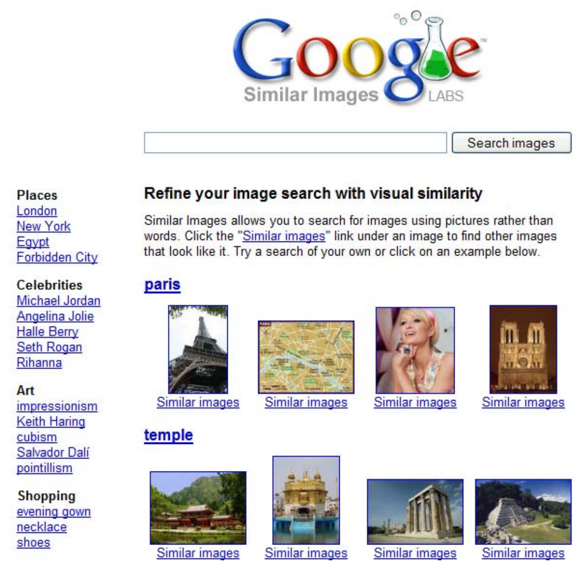




Lane detection

- Collision warning systems with adaptive cruise control,
- Lane departure warning systems,
- Rear object detection systems,

Applications: image search



Challenges: viewpoint variation

Michelangelo 1475-1564

Challenges: illumination variation

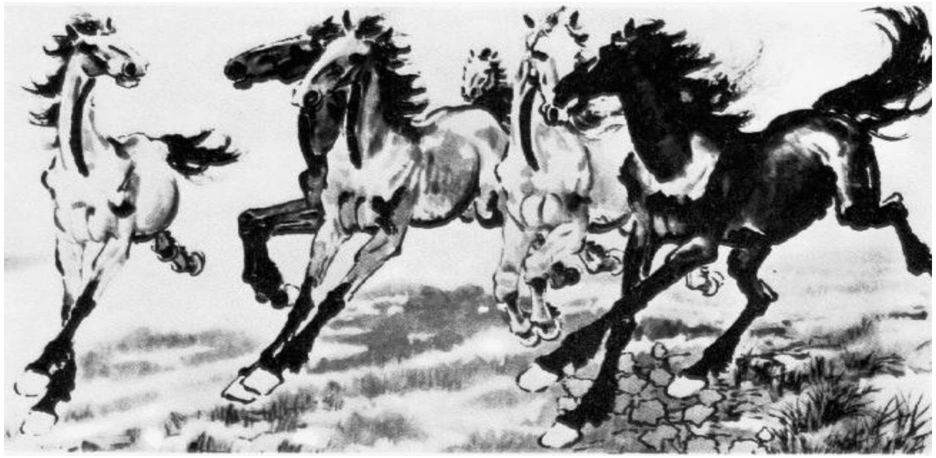
slide credit: S. Ullman

Challenges: occlusion

Magritte, 1957

Challenges: scale

Challenges: deformation



Xu, Beihong 1943

Challenges: background clutter

Klimt, 1913

Challenges: intra-class variation

Let’s start simple

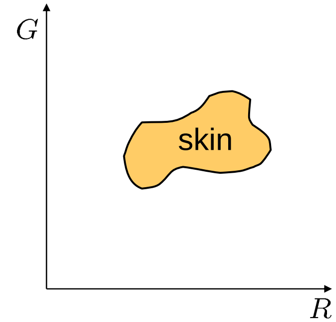
Today

- skin detection
- eigenfaces
- face detection with adaboost

Face detection

How to tell if a face is present?

One simple method: skin detection



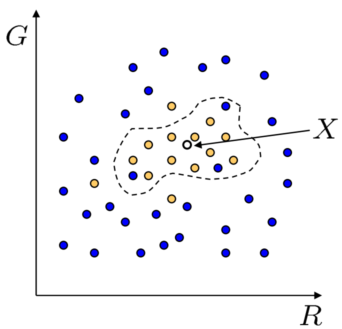
Skin pixels have a distinctive range of colors

- Corresponds to region(s) in RGB color space
  - for visualization, only R and G components are shown above

Skin classifier

- A pixel X = (R,G,B) is skin if it is in the skin region
- But how to find this region?

Skin detection



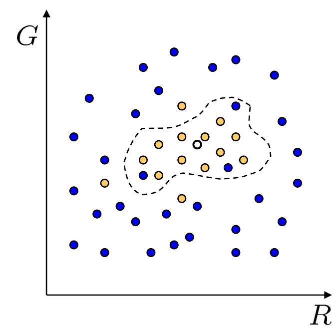
Learn the skin region from examples

- Manually label pixels in one or more "training images" as skin or not skin
- Plot the training data in RGB space
  - skin pixels shown in orange, non-skin pixels shown in blue
  - some skin pixels may be outside the region, non-skin pixels inside. Why?

Skin classifier

- Given X = (R,G,B): how to determine if it is skin or not?

Skin classification techniques



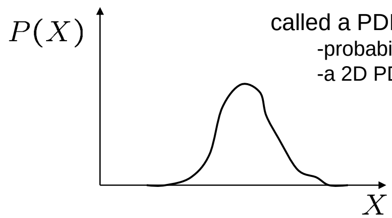
Skin classifier

- Given X = (R,G,B): how to determine if it is skin or not?
- Nearest neighbor
  - find labeled pixel closest to X
  - choose the label for that pixel
- Data modeling
  - fit a model (curve, surface, or volume) to each class
- Probabilistic data modeling
  - fit a probability model to each class

Probability

Basic probability

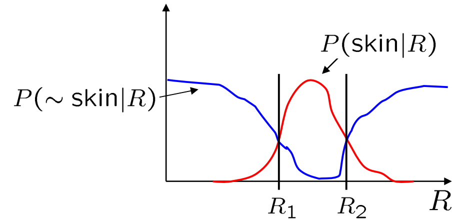
- X is a random variable
- P(X) is the probability that X achieves a certain value



called a PDF
-probability distribution/density function
-a 2D PDF is a surface, 3D PDF is a volume

- $0 \leq P(X) \leq 1$
- $\int_{-\infty}^{\infty} P(X)dX = 1$ or $\sum P(X) = 1$
  continuous X discrete X
- Conditional probability: P(X | Y)
  – probability of X given that we already know Y

Probabilistic skin classification



Now we can model uncertainty

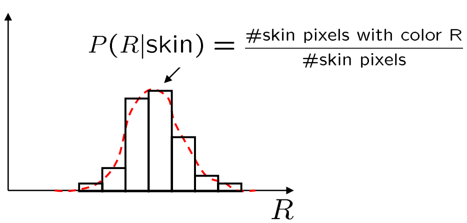
- Each pixel has a probability of being skin or not skin
  – $P(\sim \text{skin}|R) = 1 - P(\text{skin}|R)$

Skin classifier

- Given X = (R,G,B): how to determine if it is skin or not?
- Choose interpretation of highest probability
  – set X to be a skin pixel if and only if $R_1 < X \leq R_2$

Where do we get $P(\text{skin}|R)$ and $P(\sim \text{skin}|R)$?

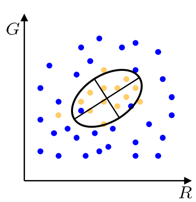
Learning conditional PDF's



We can calculate P(R | skin) from a set of training images

- It is simply a histogram over the pixels in the training images
  – each bin R_i contains the proportion of skin pixels with color R_i

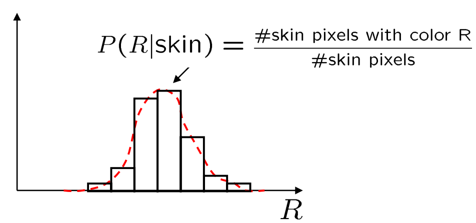
This doesn't work as well in higher-dimensional spaces. Why not?



Approach: fit parametric PDF functions

- common choice is rotated Gaussian
  – center $\mathbf{c} = \overline{X}$
  – covariance $\sum_X (X - \overline{X})(X - \overline{X})^T$
    » orientation, size defined by eigenvecs, eigenvals

Learning conditional PDF's



We can calculate P(R | skin) from a set of training images

- It is simply a histogram over the pixels in the training images
  – each bin R_i contains the proportion of skin pixels with color R_i

But this isn't quite what we want

- Why not? How to determine if a pixel is skin?
- We want P(skin | R) not P(R | skin)
- How can we get it?

Bayes rule

$$P(X|Y) = \frac{P(Y|X)P(X)}{P(Y)}$$

In terms of our problem:

what we measure (**likelihood**)   domain knowledge (**prior**)

$$P(\text{skin}|R) = \frac{P(R|\text{skin})\ P(\text{skin})}{P(R)}$$

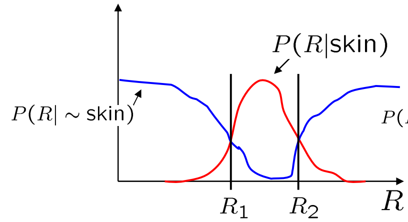
what we want (**posterior**)   **normalization** term

$P(R) = P(R|\text{skin})P(\text{skin}) + P(R|\sim\text{skin})P(\sim\text{skin})$

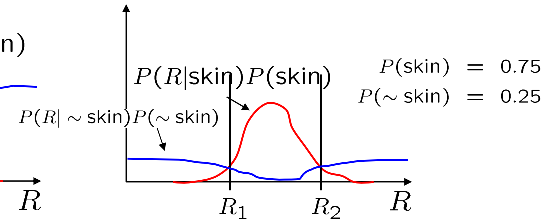
The prior: P(skin)

- Could use domain knowledge
  - P(skin) may be larger if we know the image contains a person
  - for a portrait, P(skin) may be higher for pixels in the center
- Could learn the prior from the training set. How?
  - P(skin) may be proportion of skin pixels in training set

Bayesian estimation



likelihood



posterior (unnormalized)

Bayesian estimation   = minimize probability of misclassification

- Goal is to choose the label (skin or ~skin) that maximizes the posterior
  - this is called **Maximum A Posteriori (MAP) estimation**
- Suppose the prior is uniform: P(skin) = P(~skin) = 0.5
  - in this case $P(\text{skin}|R) = cP(R|\text{skin}),\quad P(\sim\text{skin}|R) = cP(R|\sim\text{skin})$
  - maximizing the posterior is equivalent to maximizing the likelihood
    - » $P(\text{skin}|R) > P(\sim\text{skin}|R)$ if and only if $P(R|\text{skin}) > P(R|\sim\text{skin})$
  - this is called **Maximum Likelihood (ML) estimation**

Skin detection results

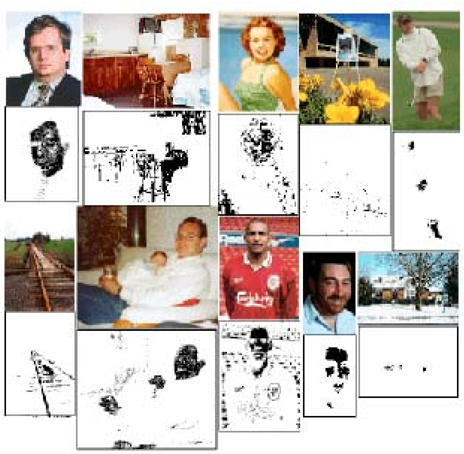
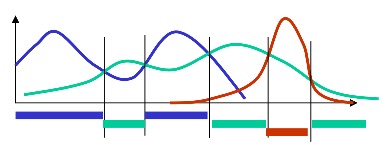


Figure 25.3. The figure shows a variety of images together with the output of the skin detector of Jones and Rehg applied to the image. Pixels marked black are skin pixels, and white are background. Notice that this process is relatively effective, and could certainly be used to focus attention on, say, faces and hands. *Figure from "Statistical color models with application to skin detection," M.J. Jones and J. Rehg, Proc. Computer Vision and Pattern Recognition, 1999 © 1999, IEEE*

General classification

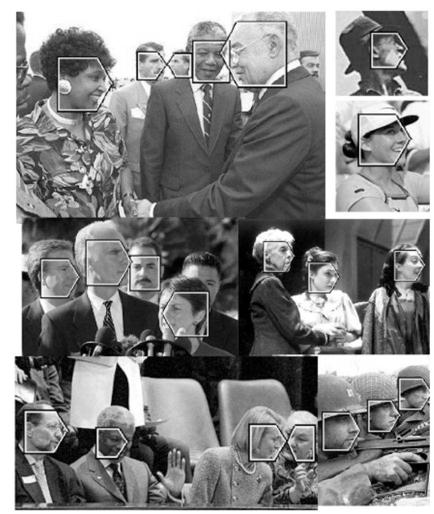
This same procedure applies in more general circumstances

- More than two classes
- More than one dimension



Example: face detection

- Here, X is an image region
  - dimension = # pixels
  - each face can be thought of as a point in a high dimensional space

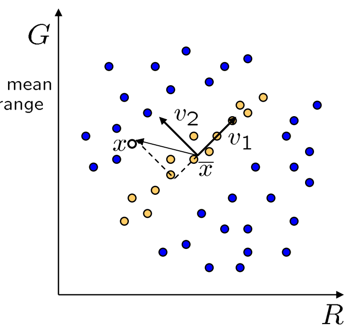


H. Schneiderman and T.Kanade

H. Schneiderman, T. Kanade. "A Statistical Method for 3D Object Detection Applied to Faces and Cars". IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2000)
http://www-2.cs.cmu.edu/afs/cs.cmu.edu/user/hws/www/CVPR00.pdf

Linear subspaces

$\overline{x}$ is the mean of the orange points



convert **x** into $\mathbf{v_1}$, $\mathbf{v_2}$ coordinates

$$\mathbf{x} \to ((\mathbf{x} - \overline{x}) \cdot \mathbf{v_1}, (\mathbf{x} - \overline{x}) \cdot \mathbf{v_2})$$

What does the $\mathbf{v_2}$ coordinate measure?
- distance to line
- use it for classification—near 0 for orange pts

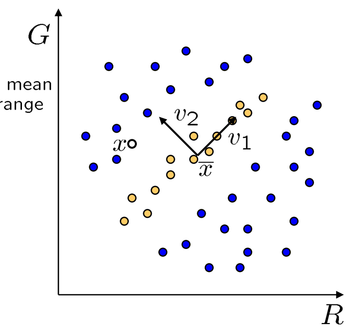
What does the $\mathbf{v_1}$ coordinate measure?
- position along line
- use it to specify which orange point it is

Classification can be expensive
- Must either search (e.g., nearest neighbors) or store large PDF's

Suppose the data points are arranged as above
- Idea—fit a line, classifier measures distance to line

Dimensionality reduction

$\overline{x}$ is the mean of the orange points

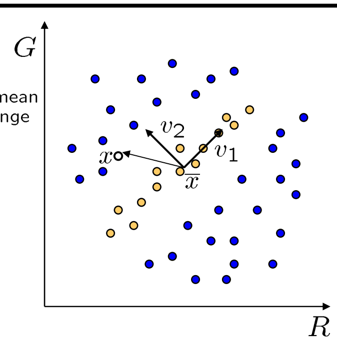


How to find $\mathbf{v_1}$ and $\mathbf{v_2}$?
- work out on board

Dimensionality reduction
- We can represent the orange points with *only* their $\mathbf{v_1}$ coordinates
  - since $\mathbf{v_2}$ coordinates are all essentially 0
- This makes it much cheaper to store and compare points
- A bigger deal for higher dimensional problems

Linear subspaces

$\overline{x}$ is the mean of the orange points



Consider the variation along direction **v** among all of the orange points:

$$var(\mathbf{v}) = \sum_{\text{orange point } \mathbf{x}} \|(\mathbf{x} - \overline{\mathbf{x}})^{\mathbf{T}} \cdot \mathbf{v}\|^2$$

What unit vector **v** minimizes *var*?

$$\mathbf{v}_2 = min_{\mathbf{v}} \; \{var(\mathbf{v})\}$$

What unit vector **v** maximizes *var*?

$$\mathbf{v}_1 = max_{\mathbf{v}} \; \{var(\mathbf{v})\}$$

$$\begin{aligned} var(\mathbf{v}) &= \sum_{\mathbf{x}} \|(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \cdot \mathbf{v}\| \\ &= \sum_{\mathbf{x}} \mathbf{v}^{\mathrm{T}} (\mathbf{x} - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \mathbf{v} \\ &= \mathbf{v}^{\mathrm{T}} \left[\sum_{\mathbf{x}} (\mathbf{x} - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \right] \mathbf{v} \\ &= \mathbf{v}^{\mathrm{T}} \mathbf{A} \mathbf{v} \quad \text{where } \mathbf{A} = \sum_{\mathbf{x}} (\mathbf{x} - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \end{aligned}$$

Solution: $\mathbf{v_1}$ is eigenvector of **A** with *largest* eigenvalue
$\mathbf{v_2}$ is eigenvector of **A** with *smallest* eigenvalue

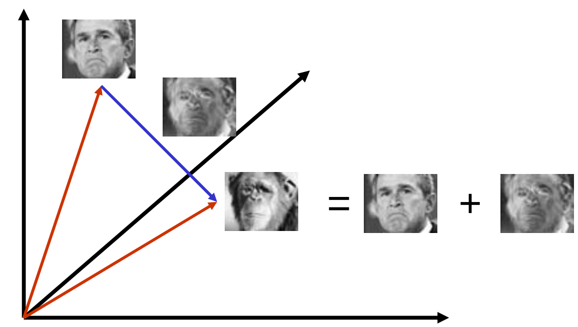
Principal component analysis

Suppose each data point is N-dimensional
- Same procedure applies:

$$\begin{aligned} var(\mathbf{v}) &= \sum_{\mathbf{x}} \|(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \cdot \mathbf{v}\| \\ &= \mathbf{v}^{\mathrm{T}} \mathbf{A} \mathbf{v} \quad \text{where } \mathbf{A} = \sum_{\mathbf{x}} (\mathbf{x} - \overline{\mathbf{x}})(\mathbf{x} - \overline{\mathbf{x}})^{\mathrm{T}} \end{aligned}$$

- The eigenvectors of **A** define a new coordinate system
  - eigenvector with largest eigenvalue captures the most variation among training vectors **x**
  - eigenvector with smallest eigenvalue has least variation
- We can compress the data by only using the top few eigenvectors
  - corresponds to choosing a "linear subspace"
    - » represent points on a line, plane, or "hyper-plane"
  - these eigenvectors are known as the ***principal components***

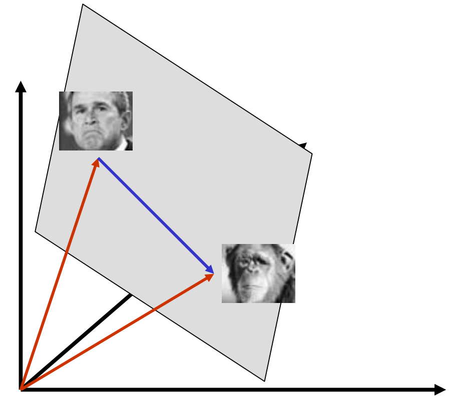
The space of faces



An image is a point in a high dimensional space

- An N x M image is a point in R^{NM}
- We can define vectors in this space as we did in the 2D case

Dimensionality reduction



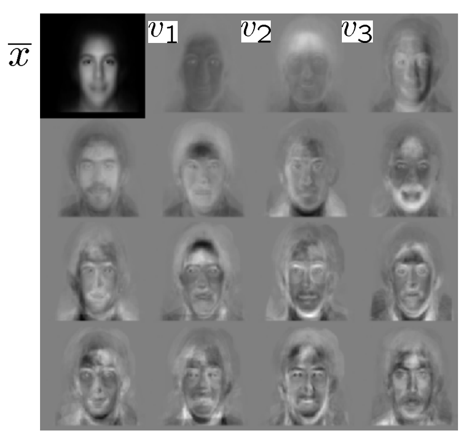
The set of faces is a "subspace" of the set of images

- Suppose it is K dimensional
- We can find the best subspace using PCA
- This is like fitting a "hyper-plane" to the set of faces
  - spanned by vectors $\mathbf{v_1}, \mathbf{v_2}, ..., \mathbf{v_K}$
  - any face $\mathbf{x} \approx \overline{\mathbf{x}} + a_1\mathbf{v_1} + a_2\mathbf{v_2} + \ldots + a_k\mathbf{v_k}$

Eigenfaces

PCA extracts the eigenvectors of **A**

- Gives a set of vectors $\mathbf{v_1}, \mathbf{v_2}, \mathbf{v_3}, ...$
- Each one of these vectors is a direction in face space
  - what do these look like?



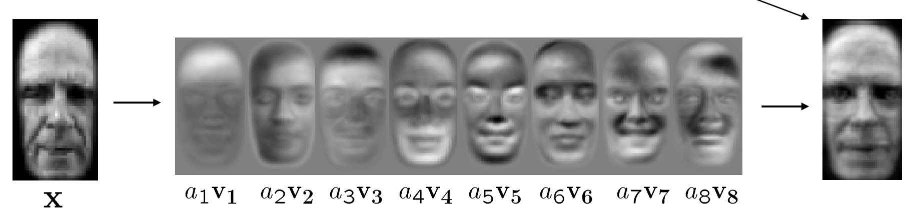
Projecting onto the eigenfaces

The eigenfaces $\mathbf{v_1}, ..., \mathbf{v_K}$ span the space of faces

- A face is converted to eigenface coordinates by

$$\mathbf{x} \rightarrow (\underbrace{(\mathbf{x} - \overline{\mathbf{x}}) \cdot \mathbf{v_1}}_{a_1}, \underbrace{(\mathbf{x} - \overline{\mathbf{x}}) \cdot \mathbf{v_2}}_{a_2}, \ldots, \underbrace{(\mathbf{x} - \overline{\mathbf{x}}) \cdot \mathbf{v_K}}_{a_K})$$

$$\mathbf{x} \approx \overline{\mathbf{x}} + a_1\mathbf{v_1} + a_2\mathbf{v_2} + \ldots + a_K\mathbf{v_K}$$



Recognition with eigenfaces

Algorithm

1. Process the image database (set of images with labels)
   - Run PCA—compute eigenfaces
   - Calculate the K coefficients for each image
2. Given a new image (to be recognized) **x**, calculate K coefficients

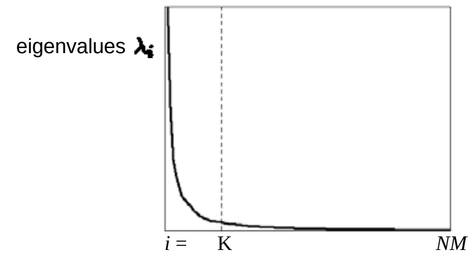
$$\mathbf{x} \to (a_1, a_2, \ldots, a_K)$$

3. Detect if x is a face

$$\|\mathbf{x} - (\overline{\mathbf{x}} + a_1\mathbf{v_1} + a_2\mathbf{v_2} + \ldots + a_K\mathbf{v_K})\| < \text{threshold}$$

4. If it is a face, who is it?
   - Find closest labeled face in database
     - nearest-neighbor in K-dimensional space

Choosing the dimension K



How many eigenfaces to use?

Look at the decay of the eigenvalues

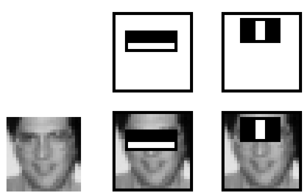
- the eigenvalue tells you the amount of variance "in the direction" of that eigenface
- ignore eigenfaces with low variance

Issues: metrics

What's the best way to compare images?

- need to define appropriate features
- depends on goal of recognition task

exact matching
complex features work well
(SIFT, MOPS, etc.)



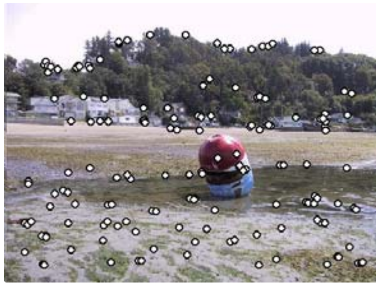
classification/detection
simple features work well
(Viola/Jones, etc.)

Metrics

Lots more feature types that we haven't mentioned

- moments, statistics
  – metrics: Earth mover's distance, ...
- edges, curves
  – metrics: Hausdorff, shape context, ...
- 3D: surfaces, spin images
  – metrics: chamfer (ICP)
- ...

Issues: feature selection



If all you have is one image:
non-maximum suppression, etc.

If you have a training set of images:
AdaBoost, etc.

Issues: data modeling

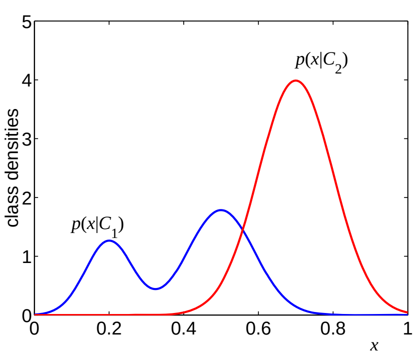
Generative methods

- model the “shape” of each class
  - histograms, PCA, mixtures of Gaussians
  - graphical models (HMM’s, belief networks, etc.)
  - ...

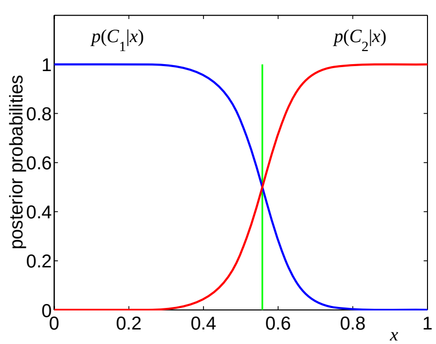
Discriminative methods

- model boundaries between classes
  - perceptrons, neural networks
  - support vector machines (SVM’s)

Generative vs. Discriminative



Generative Approach
model individual classes, priors



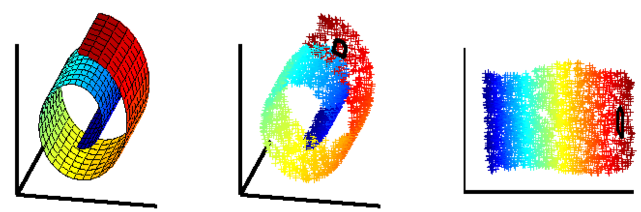
Discriminative Approach
model posterior directly

from Chris Bishop

Issues: dimensionality

What if your space isn’t *flat*?

- PCA may not help



Nonlinear methods
LLE, MDS, etc.

Issues: speed

Case study: Viola Jones face detector

Next few slides adapted Grauman & Liebe's tutorial

- http://www.vision.ee.ethz.ch/~bleibe/teaching/tutorial-aaai08/

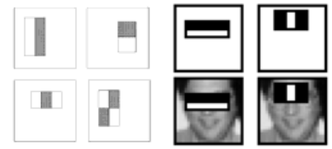
Also see Paul Viola's talk (video)

- http://www.cs.washington.edu/education/courses/577/04sp/contents.html#DM

Visual Object Recognition Tutorial

Feature extraction

"Rectangular" filters

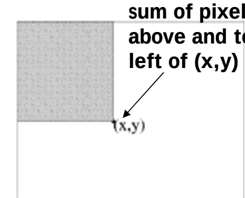


Feature output is difference between adjacent regions

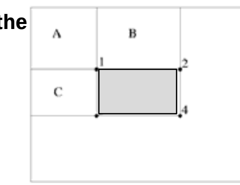
Efficiently computable with integral image: any sum can be computed in constant time

Avoid scaling images → scale features directly for same cost

Value at (x,y) is sum of pixels above and to the left of (x,y)



Integral image

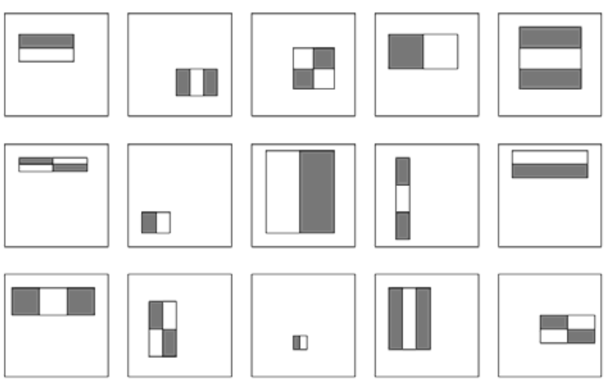


$$D = 1 + 4 - (2 + 3)$$
$$= A + (A + B + C + D) - (A + C + A + B)$$
$$= D$$

Viola & Jones, CVPR 2001

Visual Object Recognition Tutorial

Large library of filters



Considering all possible filter parameters: position, scale, and type:

180,000+ possible features associated with each 24 x 24 window

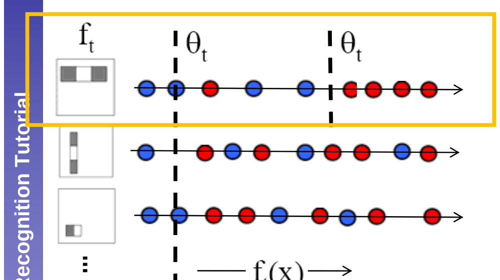
Use AdaBoost both to select the informative features and to form the classifier

Viola & Jones, CVPR 2001

Visual Object Recognition Tutorial

AdaBoost for feature+classifier selection

- **Want to select the single rectangle feature and threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of *weighted* error.**



Outputs of a possible rectangle feature on faces and non-faces.

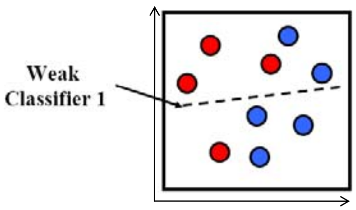
Resulting weak classifier:

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

For next round, reweight the examples according to errors, choose another filter/threshold combo.

Viola & Jones, CVPR 2001

AdaBoost: Intuition



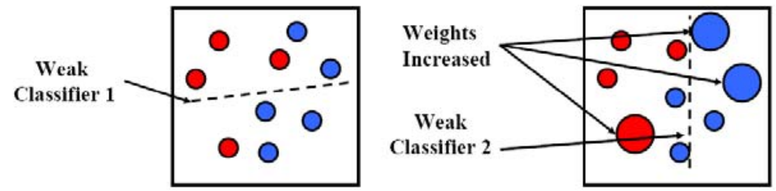
Consider a 2-d feature space with positive and negative examples.

Each weak classifier splits the training examples with at least 50% accuracy.

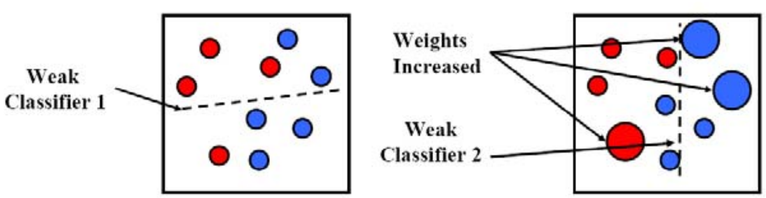
Examples misclassified by a previous weak learner are given more emphasis at future rounds.

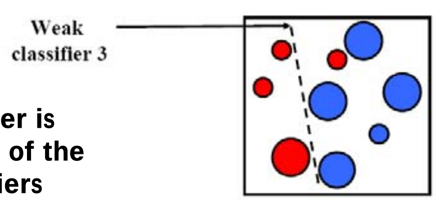
Figure adapted from Freund and Schapire

AdaBoost: Intuition



AdaBoost: Intuition



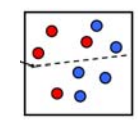


Final classifier is combination of the weak classifiers

AdaBoost Algorithm

- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \ldots, T$:
  1. Normalize the weights,
     $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
     so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \, |h_j(x_i) - y_i|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
     $$w_{t+1,i} = w_{t,i}\beta_t^{1-e_i}$$
     where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
  $$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
  where $\alpha_t = \log \frac{1}{\beta_t}$

Start with uniform weights on training examples



$\{x_1, \ldots x_n\}$

For T rounds

Evaluate *weighted* error for each feature, pick best.

Re-weight the examples:
Incorrectly classified -> more weight
Correctly classified -> less weight

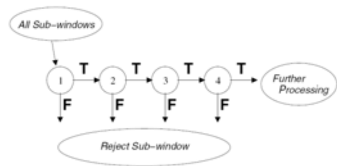
Final classifier is combination of the weak ones, weighted according to error they had.

Freund & Schapire 1995

Cascading classifiers for detection

For efficiency, apply less accurate but faster classifiers first to immediately discard windows that clearly appear to be negative; e.g.,

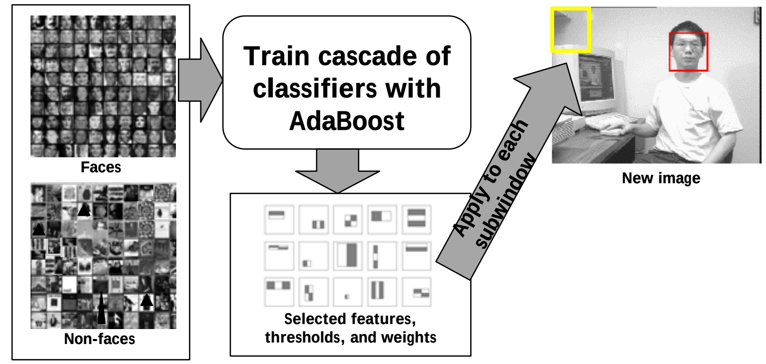
- **Filter for promising regions with an initial inexpensive classifier**
- **Build a chain of classifiers, choosing cheap ones with low false negative rates early in the chain**



Fleuret & Geman, IJCV 2001
Rowley et al., PAMI 1998
Viola & Jones, CVPR 2001

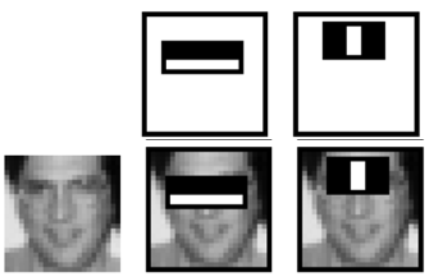
Figure from Viola & Jones CVPR 2001

Viola-Jones Face Detector: Summary



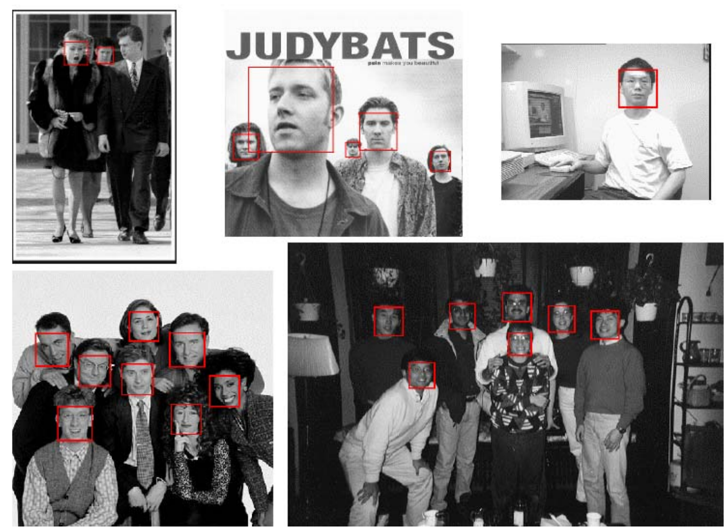
- **Train with 5K positives, 350M negatives**
- **Real-time detector using 38 layer cascade**
- **6061 features in final layer**
- **[Implementation available in OpenCV: http://www.intel.com/technology/computing/opencv/]**

Viola-Jones Face Detector: Results



First two features selected

Viola-Jones Face Detector: Results



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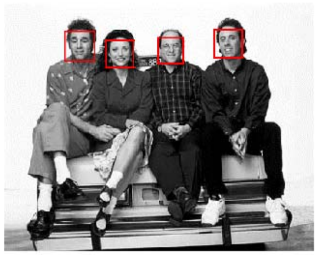
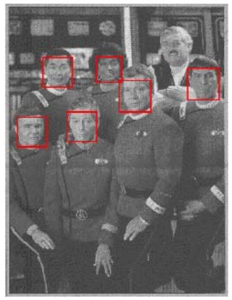
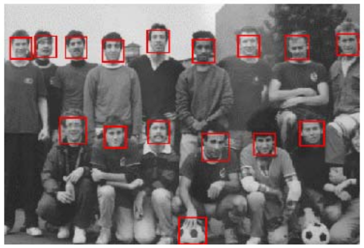
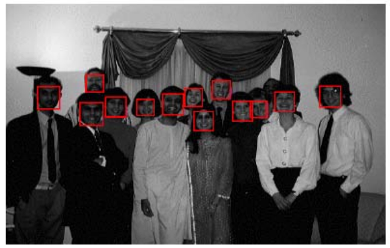
Viola-Jones Face Detector: Results

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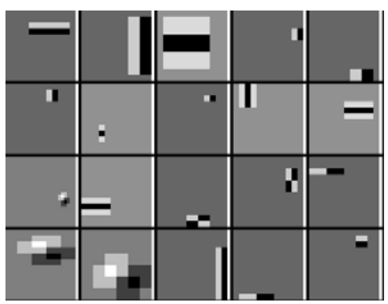
Viola-Jones Face Detector: Results


K. Grauman, B. Leibe

Visual Object Recognition Tutorial

Detecting profile faces?

Detecting profile faces requires training separate detector with profile examples.

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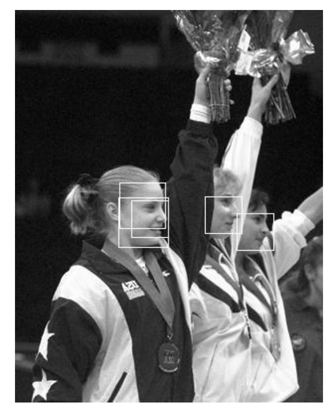
Viola-Jones Face Detector: Results

Paul

K. Grauman, B. Leibe