Detecting Faces in Images

Detecting Faces in Images

- Finding face like patterns
  - How do we find if a picture has faces in it
  - Where are the faces?
- A simple solution:
  - Define a "typical face"
  - Find the "typical face" in the image

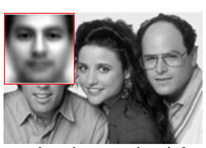
Finding faces in an image

- Picture is larger than the "typical face"
  - E.g. typical face is 100x100, picture is 600x800
- First convert to greyscale
  - R + G + B
  - Not very useful to work in color

Finding faces in an image

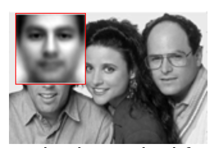
- Goal .. To find out if and where images that look like the "typical" face occur in the picture

Finding faces in an image



- Try to "match" the typical face to each location in the picture

Finding faces in an image



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Finding faces in an image

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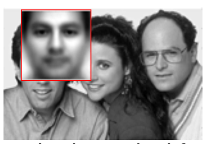

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Finding faces in an image

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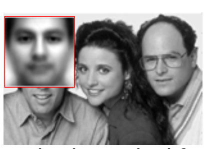
Finding faces in an image



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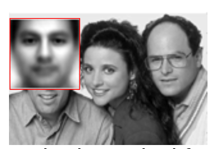
Finding faces in an image



- Try to “match” the typical face to each location in the picture

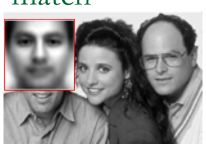
Finding faces in an image

- Try to "match" the typical face to each location in the picture

Finding faces in an image

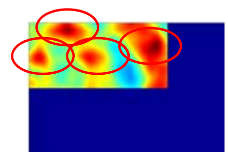
- Try to "match" the typical face to each location in the picture
- The "typical face" will explain some spots on the image much better than others
  - These are the spots at which we probably have a face!

How to "match"



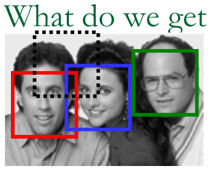
- What exactly is the "match"
  - What is the match "score"
- The DOT Product
  - Express the typical face as a vector
  - Express the region of the image being evaluated as a vector
    - But first histogram equalize the region
      - Just the section being evaluated, without considering the rest of the image
  - Compute the dot product of the typical face vector and the "region" vector

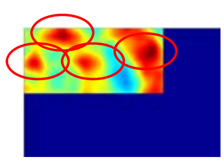
What do we get



- The right panel shows the dot product a various loctions
  - Redder is higher
    - The locations of peaks indicate locations of faces!

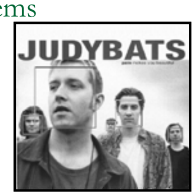
What do we get





- The right panel shows the dot product a various loctions
  - Redder is higher
    - The locations of peaks indicate locations of faces!
- Correctly detects all three faces
  - Likes George's face most
    - He looks most like the typical face
- Also finds a face where there is none!
  - A false alarm

Scaling and Rotation Problems



- Scaling
  - Not all faces are the same size
  - Some people have bigger faces
  - The size of the face on the image changes with perspective
  - Our "typical face" only represents one of these sizes

- Rotation
  - The head need not always be upright!
    - Our typical face image was upright

Solution

- Create many "typical faces"
  - One for each scaling factor
  - One for each rotation
    - How will we do this?
- Match them all
- Does this work
  - Kind of .. Not well enough at all
  - We need more sophisticated models

Face Detection: A Quick Historical Perspective

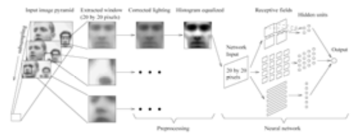


Figure 1: The basic algorithm used for face detection.

- Many more complex methods
  - Use edge detectors and search for face like patterns
  - Find "feature" detectors (noses, ears..) and employ them in complex neural networks..
- The Viola Jones method
  - Boosted cascaded classifiers
- But first, what is boosting

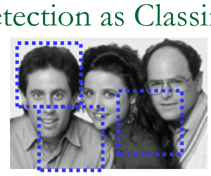
And even before that – what is classification?

- Given "features" describing an entity, determine the category it belongs to
  - Walks on two legs, has no hair. Is this
    - A Chimpanizee
    - A Human
  - Has long hair, is 5'4" tall, is this
    - A man
    - A woman
  - Matches "eye" pattern with score 0.5, "mouth pattern" with score 0.25, "nose" pattern with score 0.1. Are we looking at
    - A face
    - Not a face?

Classification

- Multi-class classification
  - Many possible categories
    - E.g. Sounds "AH, IY, UW, EY.."
    - E.g. Images "Tree, dog, house, person.."
- Binary classification
  - Only two categories
    - Man vs. Woman
    - Face vs. not a face..
- Face detection: Recast as binary face classification
  - For each little square of the image, determine if the square represents a face or not

Face Detection as Classification



For each square, run a classifier to find out if it is a face or not

- Faces can be many sizes
- They can happen anywhere in the image
- For each face size
  - For each location
    - Classify a rectangular region of the face size, at that location, as a face or not a face
- This is a series of ***binary*** classification problems

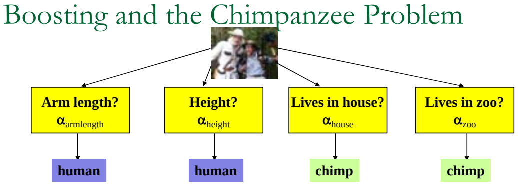
Introduction to Boosting

- An *ensemble* method that sequentially combines many simple ***BINARY*** classifiers to construct a final complex classifier
  - Simple classifiers are often called "weak" learners
  - The complex classifiers are called "strong" learners
- Each weak learner focuses on instances where the previous classifier failed
  - Give greater weight to instances that have been incorrectly classified by previous learners
- Restrictions for weak learners
  - Better than 50% correct
- Final classifier is *weighted* sum of weak classifiers

Boosting: A very simple idea

- One can come up with many rules to classify
  - E.g. Chimpanzee vs. Human classifier:
  - If arms == long, entity is chimpanzee
  - If height > 5'6" entity is human
  - If lives in house == entity is human
  - If lives in zoo == entity is chimpanzee
- Each of them is a reasonable rule, but makes many mistakes
  - Each rule has an intrinsic error rate
- *Combine* the predictions of these rules
  - But not equally
  - Rules that are less accurate should be given lesser weight

Boosting and the Chimpanzee Problem



- The total confidence in all classifiers that classify the entity as a chimpanzee is

$$Score_{chimp} = \sum_{classifier\ favors\ chimpanzee} \alpha_{classifier}$$

- The total confidence in all classifiers that classify it as a human is

$$Score_{human} = \sum_{classifier\ favors\ human} \alpha_{classifier}$$

- If $Score_{chimpanzee} > Score_{human}$ then the our belief that we have a chimpanzee is greater than the belief that we have a human

Boosting as defined by Freund

- A gambler wants to write a program to predict winning horses. His program must encode the expertise of his brilliant winner friend
- The friend has no single, encodable algorithm. Instead he has many rules of thumb
  - He uses a different rule of thumb for each set of races
    - E.g. "in this set, go with races that have black horses with stars on their foreheads"
  - But cannot really enumerate what rules of thumbs go with what sets of races: he simply "knows" when he encounters a set
    - A common problem that faces us in many situations
- Problem:
  - How best to combine all of the friend's rules of thumb
  - What is the best set of races to present to the friend, to extract the various rules of thumb

Boosting

- The basic idea: Can a "weak" learning algorithm that performs just slightly better than random guessing be *boosted* into an arbitrarily accurate "strong" learner
  - Each of the gambler's rules may be just better than random guessing
- This is a "meta" algorithm, that poses no constraints on the form of the weak learners themselves
  - The gambler's rules of thumb can be anything

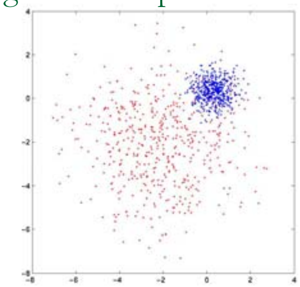
Boosting: A Voting Perspective

- Boosting can be considered a form of voting
  - Let a number of different classifiers classify the data
  - Go with the majority
  - Intuition says that as the number of classifiers increases, the dependability of the majority vote increases
- The corresponding algorithms were called Boosting by majority
  - A (weighted) majority vote taken over all the classifiers
  - How do we compute weights for the classifiers?
  - How do we actually train the classifiers

ADA Boost: Adaptive algorithm for learning the weights

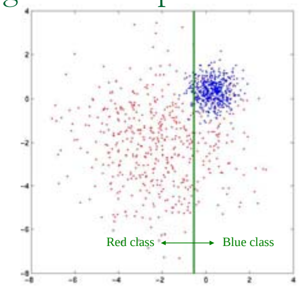
- ADA Boost: Not named of ADA Lovelace
- An *adaptive* algorithm that learns the weights of each classifier sequentially
  - Learning adapts to the current accuracy
- Iteratively:
  - Train a simple classifier from training data
    - It will make errors even on training data
    - Train a new classifier that focuses on the training data points that have been misclassified

Boosting: An Example



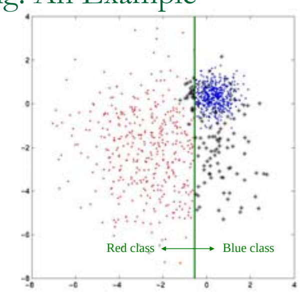
- Red dots represent training data from Red class
- Blue dots represent training data from Blue class

Boosting: An Example



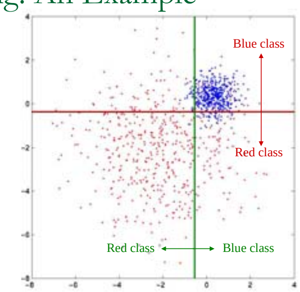
- Very simple weak learner
  - A line that is parallel to one of the two axes

Boosting: An Example



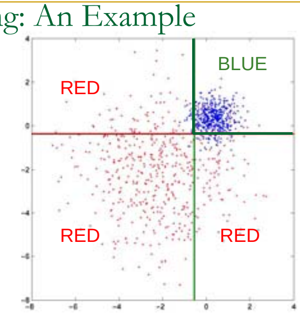
- First weak learner makes many mistakes
  - Errors coloured black

Boosting: An Example



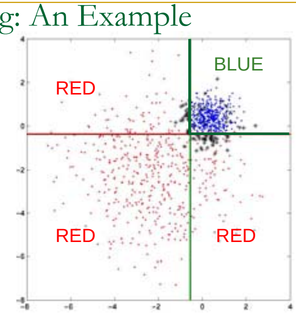
- Second weak learner focuses on errors made by first learner

Boosting: An Example



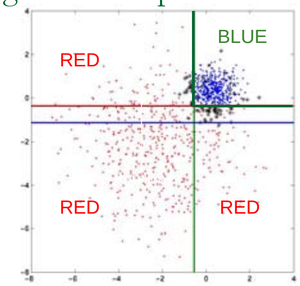
- Second strong learner: weighted combination of first and second weak learners
  - Decision boundary shown by black lines

Boosting: An Example



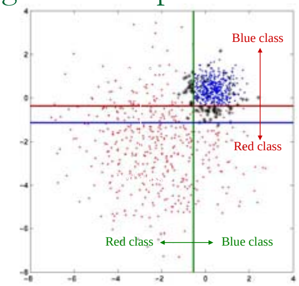
- The second strong learner also makes mistakes
  - Errors colored black

Boosting: An Example



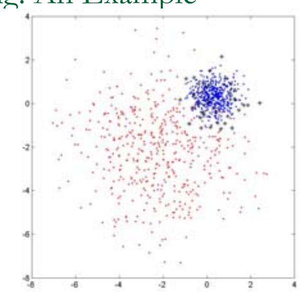
- Third weak learner concentrates on errors made by second strong learner

Boosting: An Example



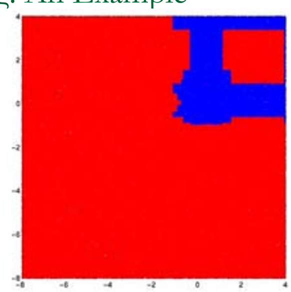
- Third weak learner concentrates on errors made by combination of previous weak learners
- Continue adding weak learners until….

Boosting: An Example



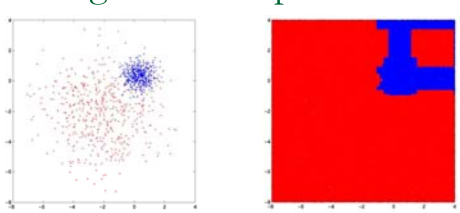
- Voila! Final strong learner: very few errors on the training data

Boosting: An Example



- The final strong learner has learnt a complicated decision boundary

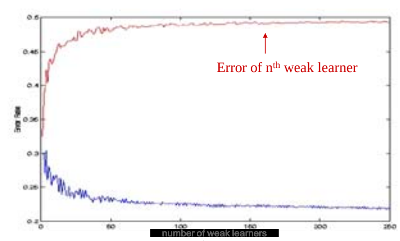
Boosting: An Example



- The final strong learner has learnt a complicated decision boundary
- Decision boundaries in areas with low density of training points assumed inconsequential

Overall Learning Pattern

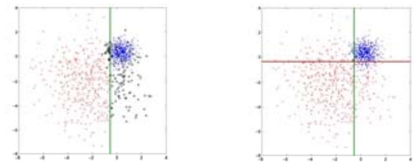
- Strong learner increasingly accurate with increasing number of weak learners
- Residual errors increasingly difficult to correct
  - Additional weak learners less and less effective



ADABoost

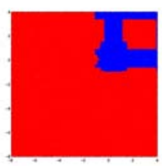
- Cannot just add new classifiers that work well only the the previously misclassified data
- Problem: The new classifier will make errors on the points that the **earlier** classifiers got right
  - Not good
  - On test data we have no way of knowing which points were correctly classified by the first classifier
- Solution: Weight the data when training the second classifier
  - Use all the data but assign them weights
    - Data that are already correctly classified have less weight
    - Data that are currently incorrectly classified have more weight

ADA Boost



- The red and blue points (correctly classified) will have a weight $\alpha < 1$
- Black points (incorrectly classified) will have a weight $\beta\ (= 1/\alpha) > 1$
- To compute the optimal second classifier, we minimize the total weighted error
  - Each data point contributes α or β to the total count of correctly and incorrectly classified points
    - E.g. if one of the red points is misclassified by the new classifier, the total error of the new classifier goes up by α

ADA Boost



- Each new classifier modifies the weights of the data points based on the accuracy of the *current* classifier
- ***The final classifier too is a weighted combination of all component classifiers***

Formalizing the Boosting Concept

- Given a set of instances $(x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)$
  - x_i is the set of attributes of the i^{th} instance
  - y_1 is the class for the i^{th} instance
    - y_1 can be 1 or -1 (binary classification only)
- Given a set of classifiers $h_1, h_2, \ldots, h_T$
  - h_i classifies an instance with attributes x as $h_i(x)$
  - $h_i(x)$ is either -1 or +1 (for a binary classifier)
  - y*h(x) is 1 for all correctly classified points and -1 for incorrectly classified points
- Devise a function $f(h_1(x), h_2(x), \ldots, h_T(x))$ such that classification based on $f()$ is superior to classification by any $h_i(x)$
  - The function is succinctly represented as $f(x)$

The Boosting Concept

- A simple combiner function: Voting
  - $f(x) = \Sigma_i h_i(x)$
  - Classifier $H(x) = \text{sign}(f(x)) = \text{sign}(\Sigma_i h_i(x))$
  - Simple majority classifier
    - A simple voting scheme
- A better combiner function: Boosting
  - $f(x) = \Sigma_i \alpha_i h_i(x)$
    - Can be any real number
  - Classifier $H(x) = \text{sign}(f(x)) = \text{sign}(\Sigma_i \alpha_i h_i(x))$
  - A weighted majority classifier
    - The weight α_i for any $h_i(x)$ is a measure of our trust in $h_i(x)$

Adaptive Boosting

- As before:
  - y is either -1 or +1
  - $H(x)$ is +1 or -1
  - If the instance is correctly classified, both y and $H(x)$ will have the same sign
    - The product y.H(x) is 1
    - For incorrectly classified instances the product is -1
- Define the error for x **:** $\frac{1}{2}(1 - yH(x))$
  - For a correctly classified instance, this is 0
  - For an incorrectly classified instance, this is 1

The ADABoost Algorithm

- Given: a set $(x_1, y_1), \ldots (x_N, y_N)$ of training instances
  - x_i is the set of attributes for the i^{th} instance
  - y_i is the class for the i^{th} instance and can be either +1 or -1

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - $\varepsilon_t = \text{Sum } \{½ (1 – y_i h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln((1 – \varepsilon_t) / \varepsilon_t)$
  - For $i = 1 \ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(- \alpha_t y_i h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t \alpha_t h_t(x))$

First, some example data


= 0.3 E1 - 0.6 E2 | = 0.2 E1 + 0.4 E2
= 0.5 E1 - 0.5 E2 | = -0.8 E1 - 0.1 E2
= 0.7 E1 - 0.1 E2 | = 0.4 E1 - 0.9 E2
= 0.6 E1 - 0.4 E2 | = 0.2 E1 + 0.5 E2


E1


E2

Image = a*E1 + b*E2 → a = Image.E1/|Image|

- Face detection with multiple Eigen faces
- Step 0: Derived top 2 Eigen faces from eigen face training data
- Step 1: On a (different) set of examples, express each image as a linear combination of Eigen faces
  - Examples include both faces and non faces
  - Even the non-face images will are explained in terms of the eigen faces

Training Data


= 0.3 E1 - 0.6 E2 | = 0.2 E1 + 0.4 E2
= 0.5 E1 - 0.5 E2 | = -0.8 E1 - 0.1 E2
= 0.7 E1 - 0.1 E2 | = 0.4 E1 - 0.9 E2
= 0.6 E1 - 0.4 E2 | = 0.2 E1 + 0.5 E2

ID	E1	E2.	Class
A	0.3	-0.6	+1
B	0.5	-0.5	+1
C	0.7	-0.1	+1
D	0.6	-0.4	+1
E	0.2	0.4	-1
F	-0.8	-0.1	-1
G	0.4	-0.9	-1
H	0.2	0.5	-1

Face = +1
Non-face = -1

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Training Data


= 0.3 E1 - 0.6 E2 | = 0.2 E1 + 0.4 E2
= 0.5 E1 - 0.5 E2 | = -0.8 E1 - 0.1 E2
= 0.7 E1 - 0.1 E2 | = 0.4 E1 - 0.9 E2
= 0.6 E1 - 0.4 E2 | = 0.2 E1 + 0.5 E2

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - $\varepsilon_t = \text{Sum } \{D_t(x_i)\ ½(1 - y_i h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln(\varepsilon_t / (1 - \varepsilon_t))$
  - For $i = 1 \ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(-\alpha_t y_i h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t \alpha_t h_t(x))$

The E1"Stump"

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

Sign = +1, error = 3/8
Sign = -1, error = 5/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E1 "Stump"

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

Sign = +1, error = 2/8
Sign = -1, error = 6/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E1 "Stump"

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

Sign = +1, error = 1/8
Sign = -1, error = 7/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E1 "Stump"

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

Sign = +1, error = 2/8
Sign = -1, error = 6/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E1 "Stump"

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

Sign = +1, error = 1/8
Sign = -1, error = 7/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E1 "Stump"

F E H A G B C D

-0.8 0.2 0.2 0.3 0.4 0.5 0.6 0.7

1/8 1/8 1/8 1/8 1/8 1/8 1/8 1/8

threshold

Sign = +1, error = 2/8
Sign = -1, error = 6/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The Best E1 "Stump"

F E H A G B C D

-0.8 0.2 0.2 0.3 0.4 0.5 0.6 0.7

1/8 1/8 1/8 1/8 1/8 1/8 1/8 1/8

threshold

Sign = +1, error = 1/8

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

Sign = +1
Threshold = 0.45

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The E2"Stump"

Note order

G A B D C F E H

-0.9 -0.6 -0.5 -0.4 -0.1 -0.1 0.4 0.5

1/8 1/8 1/8 1/8 1/8 1/8 1/8 1/8

threshold

Sign = +1, error = 3/8
Sign = -1, error = 5/8

Classifier based on E2:
if (sign*wt(E2) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The Best E2"Stump"

G A B D C F E H

-0.9 -0.6 -0.5 -0.4 -0.1 -0.1 0.4 0.5

1/8 1/8 1/8 1/8 1/8 1/8 1/8 1/8

threshold

Sign = -1, error = 2/8

Classifier based on E2:
if (sign*wt(E2) > thresh) > 0)
face = true

sign = -1
Threshold = 0.15

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	-0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The Best "Stump"

F E H A G B C D

-0.8 0.2 0.2 0.3 0.4 0.5 0.6 0.7

1/8 1/8 1/8 1/8 1/8 1/8 1/8 1/8

threshold

Sign = +1, error = 1/8

The Best overall classifier based on a single feature is based on E1

If (wt(E1) > 0.45) → Face

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - $\varepsilon_t = \text{Sum} \{D_t(x_i)\ \tfrac{1}{2}(1 - y_i h_t(x_i))\}$
  - Set $\alpha_t = \tfrac{1}{2} \ln(\varepsilon_t / (1 - \varepsilon_t))$
  - For $i = 1 \ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(-\alpha_t y_i h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t\ \alpha_t h_t(x))$

The Best Error

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

The Error of the classifier is the sum of the weights of the misclassified instances

threshold

Sign = +1, error = 1/8

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	1/8
B	0.5	-0.5	+1	1/8
C	0.7	-0.1	+1	1/8
D	0.6	-0.4	+1	1/8
E	0.2	0.4	-1	1/8
F	-0.8	0.1	-1	1/8
G	0.4	-0.9	-1	1/8
H	0.2	0.5	-1	1/8

NOTE: THE ERROR IS THE SUM OF THE WEIGHTS OF MISCLASSIFIED INSTANCES

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - $\varepsilon_t = \text{Sum}\{D_t(x_i)\ ½(1 - y_i\, h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln((1 - \varepsilon_t) / \varepsilon_t)$
  - For $i = 1 \ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(-\alpha_t\, y_i\, h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t\, \alpha_t\, h_t(x))$

Computing Alpha

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

Alpha = 0.5ln((1-1/8) / (1/8))

= 0.5 ln(7) = 0.97

threshold

Sign = +1, error = 1/8

The Boosted Classifier Thus Far

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

Alpha = 0.5ln((1-1/8) / (1/8))

= 0.5 ln(7) = 0.97

threshold

Sign = +1, error = 1/8

h1(X) = wt(E1) > 0.45 ? +1 : -1

H(X) = sign(0.97 * h1(X))

It's the same as h1(x)

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - $\varepsilon_t = \text{Average}\{½ (1 - y_i\, h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln((1 - \varepsilon_t) / \varepsilon_t)$
  - For $i = 1 \ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(-\alpha_t\, y_i\, h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t\, \alpha_t\, h_t(x))$

The Best Error

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

$D_{t+1}(x_i) = D_t(x_i) \exp(-\alpha_t\, y_i\, h_t(x_i))$

$\exp(\alpha_t) = \exp(0.97) = 2.63$

$\exp(-\alpha_t) = \exp(-0.97) = 0.38$

threshold

ID	E1	E2.	Class	Weight	Weight
A	0.3	-0.6	+1	1/8 * 2.63	0.33
B	0.5	-0.5	+1	1/8 * 0.38	0.05
C	0.7	-0.1	+1	1/8 * 0.38	0.05
D	0.6	-0.4	+1	1/8 * 0.38	0.05
E	0.2	0.4	-1	1/8 * 0.38	0.05
F	-0.8	0.1	-1	1/8 * 0.38	0.05
G	0.4	-0.9	-1	1/8 * 0.38	0.05
H	0.2	0.5	-1	1/8 * 0.38	0.05

Multiply the correctly classified instances by 0.38

Multiply incorrectly classified instances by 2.63

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - ε_t = Average $\{½ (1 – y_i h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln ((1 – \varepsilon_t) / \varepsilon_t)$
  - For $i = 1\ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(- \alpha_t y_i h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t \alpha_t h_t(x))$

The Best Error

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

D' = D / sum(D)

ID	E1	E2.	Class	Weight	Weight	Weight
A	0.3	-0.6	+1	1/8 * 2.63	0.33	0.48
B	0.5	-0.5	+1	1/8 * 0.38	0.05	0.074
C	0.7	-0.1	+1	1/8 * 0.38	0.05	0.074
D	0.6	-0.4	+1	1/8 * 0.38	0.05	0.074
E	0.2	0.4	-1	1/8 * 0.38	0.05	0.074
F	-0.8	0.1	-1	1/8 * 0.38	0.05	0.074
G	0.4	-0.9	-1	1/8 * 0.38	0.05	0.074
H	0.2	0.5	-1	1/8 * 0.38	0.05	0.074

Multiply the correctly classified instances by 0.38
Multiply incorrectly classified instances by 2.63
Normalize to sum to 1.0

The Best Error

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8

threshold

D' = D / sum(D)

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

Multiply the correctly classified instances by 0.38
Multiply incorrectly classified instances by 2.63
Normalize to sum to 1.0

The ADABoost Algorithm

- Initialize $D_1(x_i) = 1/N$
- For $t = 1, \ldots, T$
  - Train a weak classifier h_t using distribution D_t
  - Compute total error on training data
    - ε_t = Average $\{½ (1 – y_i h_t(x_i))\}$
  - Set $\alpha_t = ½ \ln (\varepsilon_t /(1 – \varepsilon_t))$
  - For $i = 1\ldots N$
    - set $D_{t+1}(x_i) = D_t(x_i) \exp(- \alpha_t y_i h_t(x_i))$
  - Normalize D_{t+1} to make it a distribution
- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t \alpha_t h_t(x))$

E1 classifier

```
Classifier based on E1:
if ( sign*wt(E1) > thresh) > 0)
    face = true

sign = +1 or -1
```

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.222
Sign = -1, error = 0.778

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

E1 classifier

```
Classifier based on E1:
if ( sign*wt(E1) > thresh) > 0)
    face = true

sign = +1 or -1
```

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.148
Sign = -1, error = 0.852

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

The Best E1 classifier

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.074

Classifier based on E1:
if (sign*wt(E1) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

The Best E2 classifier

G	A	B	D	C	F	E	H
-0.9	-0.6	-0.5	-0.4	-0.1	0.1	0.4	0.5
.074	.48	.074	.074	.074	.074	.074	.074

threshold

Sign = -1, error = 0.148

Classifier based on E2:
if (sign*wt(E2) > thresh) > 0)
face = true

sign = +1 or -1

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	-0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

The Best Classifier

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.074

Classifier based on E1:
if (wt(E1) > 0.45) face = true

Alpha = 0.5ln((1-0.074) / 0.074)
= 1.26

ID	E1	E2.	Class	Weight
A	0.3	-0.6	+1	0.48
B	0.5	-0.5	+1	0.074
C	0.7	-0.1	+1	0.074
D	0.6	-0.4	+1	0.074
E	0.2	0.4	-1	0.074
F	-0.8	0.1	-1	0.074
G	0.4	-0.9	-1	0.074
H	0.2	0.5	-1	0.074

The Boosted Classifier Thus Far

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold threshold

h1(X) = wt(E1) > 0.45 ? +1 : -1

h2(X) = wt(E1) > 0.25 ? +1 : -1

H(X) = sign(0.97 * h1(X) + 1.26 * h2(X))

Reweighting the Data

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.074

Exp(alpha) = exp(1.26) = 3.5
Exp(-alpha) = exp(-1.26) = 0.28

ID	E1	E2.	Class	Weight	
A	0.3	-0.6	+1	0.48*0.28	0.32
B	0.5	-0.5	+1	0.074*0.28	0.05
C	0.7	-0.1	+1	0.074*0.28	0.05
D	0.6	-0.4	+1	0.074*0.28	0.05
E	0.2	0.4	-1	0.074*0.28	0.05
F	-0.8	0.1	-1	0.074*0.28	0.05
G	0.4	-0.9	-1	0.074*3.5	0.38
H	0.2	0.5	-1	0.074*0.28	0.05

RENORMALIZE

Reweighting the Data

F	E	H	A	G	B	C	D
-0.8	0.2	0.2	0.3	0.4	0.5	0.6	0.7
.074	.074	.074	.48	.074	.074	.074	.074

threshold

Sign = +1, error = 0.074

NOTE: THE WEIGHT OF “G” WHICH WAS MISCLASSIFIED BY THE SECOND CLASSIFIER IS NOW SUDDENLY HIGH

ID	E1	E2.	Class	Weight	
A	0.3	-0.6	+1	0.48*0.28	0.32
B	0.5	-0.5	+1	0.074*0.28	0.05
C	0.7	-0.1	+1	0.074*0.28	0.05
D	0.6	-0.4	+1	0.074*0.28	0.05
E	0.2	0.4	-1	0.074*0.28	0.05
F	-0.8	0.1	-1	0.074*0.28	0.05
G	0.4	-0.9	-1	0.074*3.5	0.38
H	0.2	0.5	-1	0.074*0.28	0.05

RENORMALIZE

AdaBoost

- In this example both of our first two classifiers were based on E1
  - Additional classifiers may switch to E2
- In general, the reweighting of the data will result in a different feature being picked for each classifier
- This also automatically gives us a *feature selection* strategy
  - In this data the wt(E1) is the most important feature

AdaBoost

- NOT required to go with the best classifier so far
- For instance, for our second classifier, we might use the best E2 classifier, even though its worse than the E1 classifier
  - So long as its right more than 50% of the time
- We can *continue* to add classifiers even after we get 100% classification of the training data
  - Because the weights of the data keep changing
  - Adding new classifiers beyond this point is often a good thing to do

ADA Boost

 **= 0.4 E1 - 0.4 E2**

E_1

E_2

- The final classifier is
  - $H(x) = \text{sign}(\Sigma_t\, \alpha_t\, h_t(x))$
- The output is 1 if the total weight of all weak learners that classify *x* as 1 is greater than the total weight of all weak learners that classify it as -1

Boosting and Face Detection

- Boosting forms the basis of the most common technique for face detection today: The Viola-Jones algorithm.

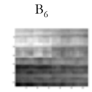
The problem of face detection

- 1. Defining Features
  - Should we be searching for noses, eyes, eyebrows etc.?
    - Nice, but expensive
  - Or something simpler
- 2. Selecting Features
  - Of all the possible features we can think of, which ones make sense
- 3. Classification: Combining evidence
  - How does one combine the evidence from the different features?

Features: The Viola Jones Method

B_1 B_2 B_3 B_4 B_5 B_6

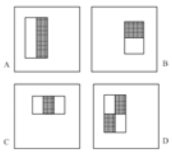
$$Image \approx w_1 B_1 + w_2 B_2 + w_3 B_3 + \ldots$$

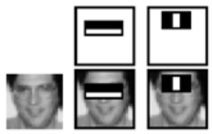


- Integral Features!!
  - Like the Checkerboard
- The same principle as we used to decompose images in terms of checkerboards:
  - The image of any object has changes at various scales
  - These can be represented coarsely by a checkerboard pattern
- The checkerboard patterns must however now be *localized*
  - Stay within the region of the face

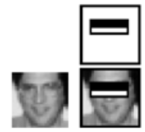
Features

- Checkerboard Patterns to represent facial features
  - The white areas are subtracted from the black ones.
  - Each checkerboard explains a *localized* portion of the image
- Four types of checkerboard patterns (only)



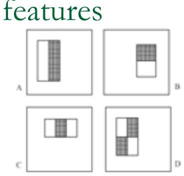


Explaining a portion of the face with a checker..



- How much is the difference in average intensity of the image in the black and white regions
  - Sum(pixel values in white region) – Sum(pixel values in black region)
- This is actually the dot product of the region of the face covered by the rectangle and the checkered pattern itself
  - White = 1, Black = -1

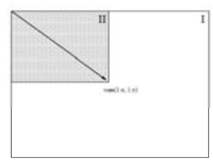
"Integral" features



- Each checkerboard has the following characteristics
  - Length
  - Width
  - Type
    - Specifies the number and arrangement of bands
- The four checkerboards above are the four used by Viola and Jones

Integral images

- Summed area tables



- For each pixel store the sum of ALL pixels to the left of and above it.

Fast Computation of Pixel Sums

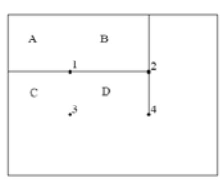
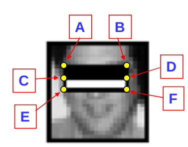


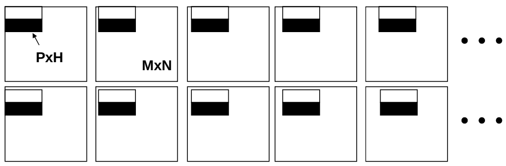
Figure 3: The sum of the pixels within rectangle D can be computed with four array references. The value of the integral image at location 1 is the sum of the pixels in rectangle A. The value at location 2 is $A + B$, at location 3 is $A + C$, and at location 4 is $A + B + C + D$. The sum within D can be computed as $4 + 1 - (2 + 3)$.

A Fast Way to Compute the Feature



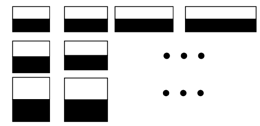
- Store pixel table for every pixel in the image
  - The sum of all pixel values to the left of and above the pixel
- Let A, B, C, D, E, F be the pixel table values at the locations shown
  - Total pixel value of black area = D + A – B – C
  - Total pixel value of white area = F + C – D – E
  - Feature value = (F + C – D – E) – (D + A – B – C)

How many features?



- Each checker board of width P and height H can start at
  - (0,0), (0,1),(0,2), … (0, N-P)
  - (1,0), (1,1),(1,2), … (1, N-P)
  - ..
  - (M-H,0), (M-H,1), (M-H,2), … (M-H, N-P)
- (M-H)*(N-P) possible starting locations
  - Each is a unique checker feature
    - E.g. at one location it may measure the forehead, at another the chin

How many features



- Each feature can have many sizes
  - Width from (min) to (max) pixels
  - Height from (min ht) to (max ht) pixels
- At each size, there can be many starting locations
  - Total number of possible checkerboards of one type: No. of possible sizes x No. of possible locations
- There are four types of checkerboards
  - Total no. of possible checkerboards: VERY VERY LARGE!

Learning: No. of features

- Analysis performed on images of 24x24 pixels only
  - Reduces the no. of possible features to about 180000
- Restrict checkerboard size
  - Minimum of 8 pixels wide
  - Minimum of 8 pixels high
    - Other limits, e.g. 4 pixels may be used too
  - Reduces no. of checkerboards to about 50000

No. of features

	F1	F2	F3	F4	…..	F180000
	7	9	2	-1	…..	12
	-11	3	19	17	…..	2

- Each possible checkerboard gives us one feature
- A total of up to 180000 features derived from a 24x24 image!
- Every 24x24 image is now represented by a set of 180000 numbers
  - This is the set of features we will use for classifying if it is a face or not!

The Classifier

- The Viola-Jones algorithm uses a simple Boosting based classifier
- Each "weak learner" is a simple threshold
- At each stage find the best feature to classify the data with
  - I.e the feature that gives us the best classification of all the training data
    - Training data includes many examples of faces and non-face images
  - The classification rule is of the kind
    - If feature > threshold, face (or if feature < threshold, face)
    - The optimal value of "threshold" must also be determined.

The Weak Learner

- Training (for each weak learner):
  - For each feature f (of all 180000 features)
    - Find a threshold $\theta(f)$ and polarity $p(f)$ ($p(f) = -1$ or $p(f) = 1$) such that ($f > p(f)*\theta(f)$) performs the best classification of faces
      - Lowest overall error in classifying all training data
        - Error counted over *weighted* samples
    - Let the optimal overall error for f be error(f)
  - Find the feature f' such that error(f') is lowest
  - The weak learner is the test ($f' > p(f')*\theta(f')$) => face
- Note that the procedure for learning weak learners also identifies the most useful features for face recognition

The Viola Jones Classifier

- A boosted threshold-based classifier
- First weak learner: Find the best feature, and its optimal threshold
  - Second weak learner: Find the best feature, for the weighted training data, and its threshold (weighting from one weak learner)
    - Third weak learner: Find the best feature for the weighted data and its optimal threshold (weighting from two weak learners)
      - Fourth weak learner: Find the best feature for the weighted data and its optimal threhsold (weighting from three weak learners)
        - ..

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To Train

- Collect a large number of histogram equalized facial images
  - Resize all of them to 24x24
  - These are our “face” training set
- Collect a much much much larger set of 24x24 non-face images of all kinds
  - Each of them is histogram equalized
  - These are our “non-face” training set
- Train a boosted classifier

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The Viola Jones Classifier

- During tests:
  - Given any new 24x24 image
    - $R = \Sigma_f \alpha_f (f > p_f \theta(f))$
    - Only a small number of features (f < 100) typically used
- Problems:
  - Only classifies 24 x 24 images entirely as faces or non-faces
    - Typical pictures are much larger
    - They may contain many faces
    - Faces in pictures can be much larger or smaller
  - Not accurate enough

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Multiple faces in the picture

- Scan the image
  - Classify each 24x24 rectangle from the photo
  - All rectangles that get classified as having a face indicate the location of a face
- For an NxM picture, we will perform (N-24)*(M-24) classifications
- If overlapping 24x24 rectangles are found to have faces, merge them

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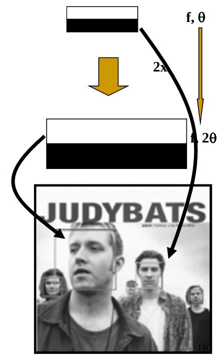
Picture size solution

- We already have a classifier
  - That uses weak learners
- *Scale each classifier*
  - Every weak learner
  - Scale its size up by factor α. Scale the threshold up to $\alpha\theta$.
  - Do this for many scaling factors



Overall solution

- Scan the picture with classifiers of size 24x24
- Scale the classifier to 26x26 and scan
- Scale to 28x28 and scan etc.

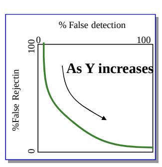
- Faces of different sizes will be found at different scales

False Rejection vs. False detection

- False Rejection: There's a face in the image, but the classifier misses it
  - Rejects the hypothesis that there's a face
- False detection: Recognizes a face when there is none.

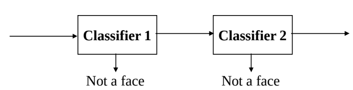
- Classifier:
  - Standard boosted classifier: $H(x) = \mathrm{sign}(\Sigma_t\, \alpha_t\, h_t(x))$
  - Modified classifier $H(x) = \mathrm{sign}(\Sigma_t\, \alpha_t\, h_t(x) + Y)$
    - $\Sigma_t\, \alpha_t\, h_t(x)$ is a measure of certainty
      - The higher it is, the more certain we are that we found a face
    - If Y is large, then we assume the presence of a face even when we are not sure
  - By increasing Y, we can reduce false rejection, while increasing false detection

ROC



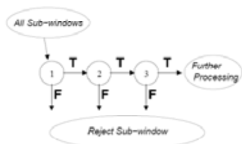
- Ideally false rejection will be 0%, false detection will also be 0%
- As Y increaases, we reject faces less and less
  - But accept increasing amounts of garbage as faces
- Can set Y so that we rarely miss a face

Problem: Not accurate enough, too slow



- If we set Y high enough, we will never miss a face
  - But will classify a lot of junk as faces
- Solution: Classify the output of the first classifier with a second classifier
  - And so on.

Problem: Not accurate enough, too slow



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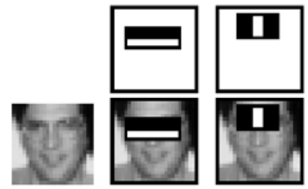
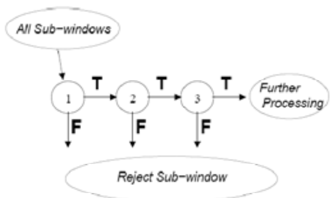
Useful Features Learned by Boosting



A Cascade of Classifiers



Detection in Real Images

- Basic classifier operates on 24 x 24 subwindows
- Scaling:
  - Scale the detector (rather than the images)
  - Features can easily be evaluated at any scale
  - Scale by factors of 1.25
- Location:
  - Move detector around the image (e.g., 1 pixel increments)
- Final Detections
  - A real face may result in multiple nearby detections
  - Postprocess detected subwindows to combine overlapping detections into a single detection

Training

- In paper, 24x24 images of faces and non faces (positive and negative examples).

Sample results using the Viola-Jones Detector

- Notice detection at multiple scales

More Detection Examples

Practical implementation

- Details discussed in Viola-Jones paper
- Training time = weeks (with 5k faces and 9.5k non-faces)
- Final detector has 38 layers in the cascade, 6060 features
- 700 Mhz processor:
  - Can process a 384 x 288 image in 0.067 seconds (in 2003 when paper was written)