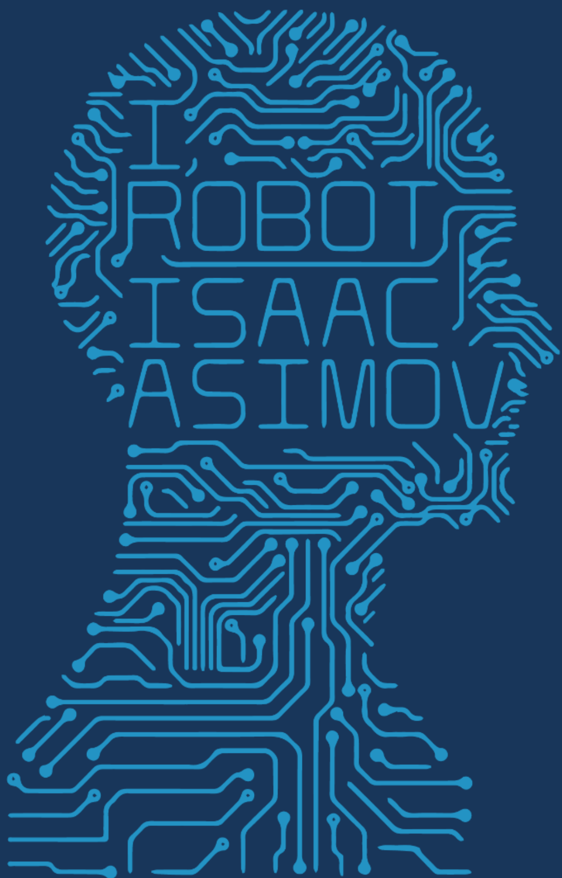
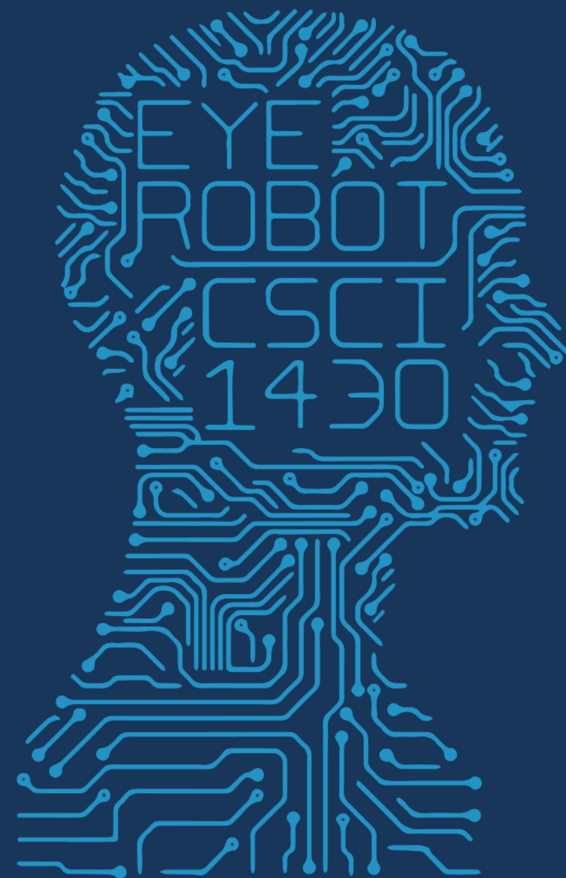


1950

Future Vision



2017 MWF 1pm 368

Computer Vision

Recap – Image Classification with Bags of Local Features

- Bag of Feature models were the state of the art for image classification for a decade.
- Numerous strategies to retain spatial information (spatial pyramid) and lost feature detail due to quantization.

- Doesn’t the spatial pyramid seem kind of recursive / hierarchical?
- Like a SIFT feature on top of SIFT features?

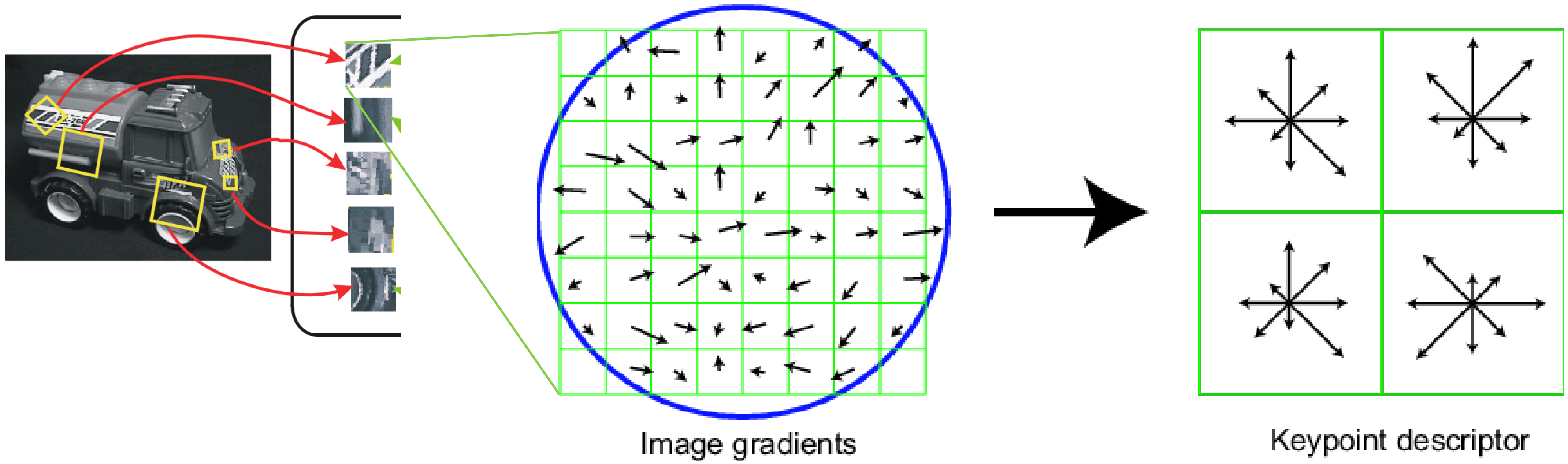
James Hays

SIFT vector formation

4x4 array of gradient orientation histogram weighted by magnitude.

8 orientations x 4x4 array = 128 dimensions.

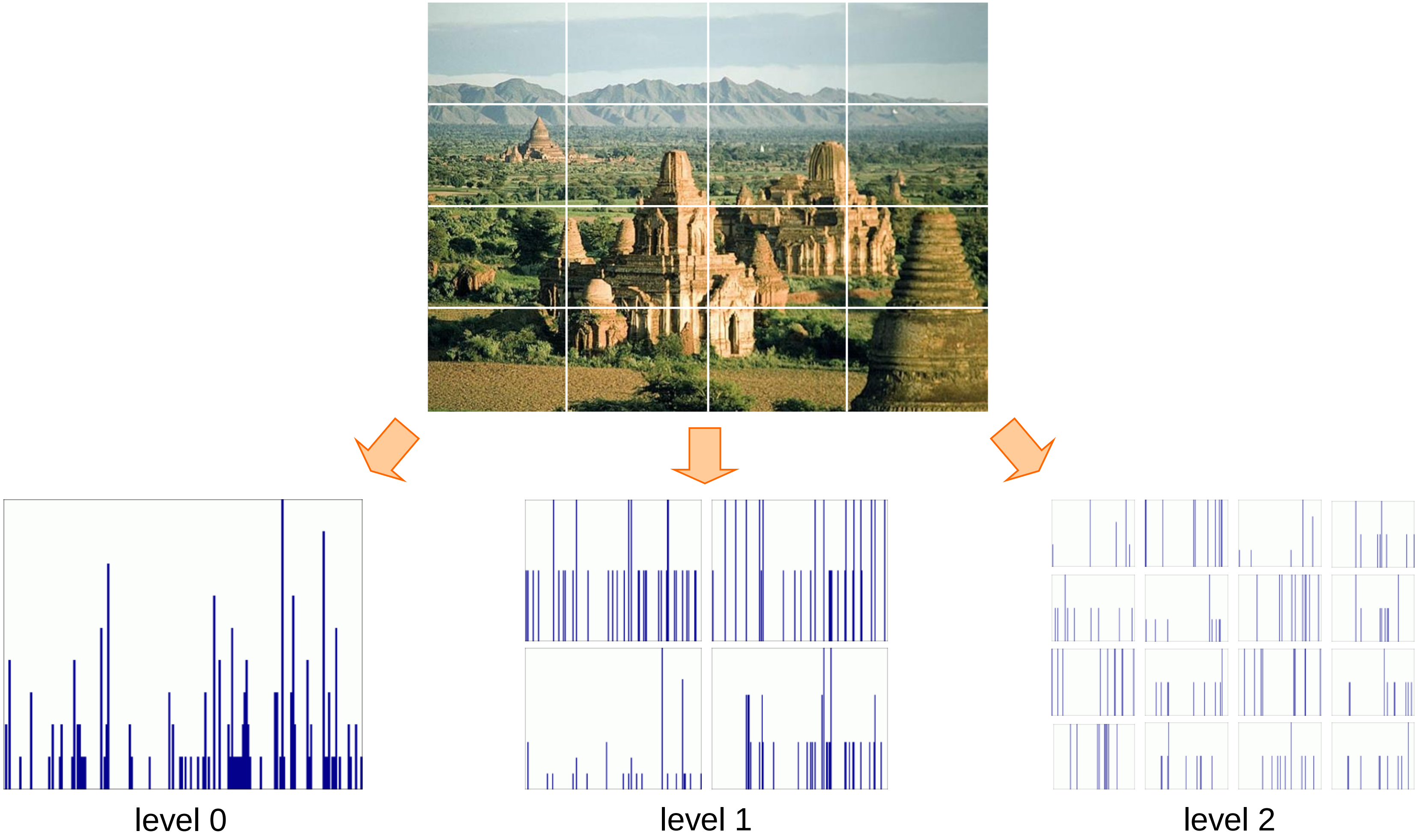
Motivation: some sensitivity to spatial layout, but not too much.



Showing only 2x2 here, but is 4x4

Spatial pyramid representation

- Extension of a bag of features
- Locally order-less representation at several levels of resolution



Lazebnik, Schmid & Ponce (CVPR 2006)

Recap – Image Classification with Bags of Local Features

- Doesn't the spatial pyramid seem kind of recursive / hierarchical?
- Like a SIFT feature on top of SIFT features?

- Seems like there is a tendency for features to involve convolution, spatial pooling, and non-linearities.

Object Detection

- Overview
- Viola-Jones (faces)
- Dalal-Triggs (humans)

- Later classes:
  - Deformable models
  - Deep learning

Person detection with HoG's & linear SVM's

- Histograms of Oriented Gradients for Human Detection, [Navneet Dalal](), [Bill Triggs](), International Conference on Computer Vision & Pattern Recognition - June 2005
- http://lear.inrialpes.fr/pubs/2005/DT05/

Object detection vs. Scene Recognition

- Scenes can be defined by distribution of “stuff” – materials and surfaces with arbitrary shape.

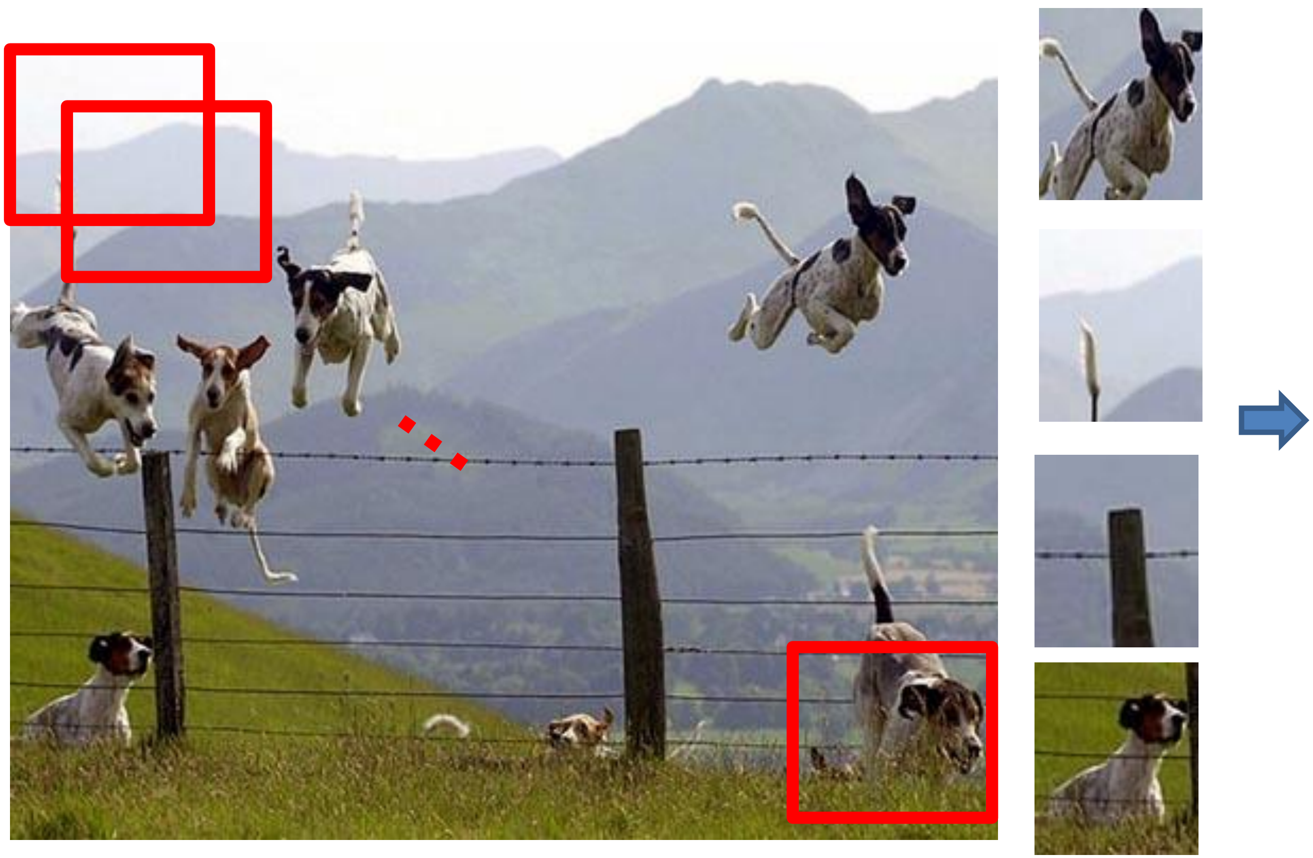
- Objects are “things” that own their boundaries

- Bag of words models are less popular for object detection because they throw away shape info.

James Hays

Object Category Detection

- Focus on object search: “Where is it?”
- Build templates that quickly differentiate object patch from background patch



Object or **Non-Object?**

James Hays

Challenges in modeling the object class

Illumination

Object pose

‘Clutter’

Occlusions

Intra-class appearance

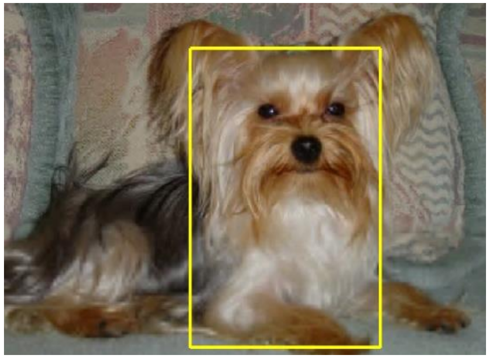
Viewpoint

Slide from K. Grauman, B. Leibe

Challenges in modeling the non-object class

True
Detections

Bad
Localization



Confused with
Similar Object

Misc. Background

Confused with
Dissimilar Objects

James Hays

General Process of Object Recognition

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

Resolve Detections

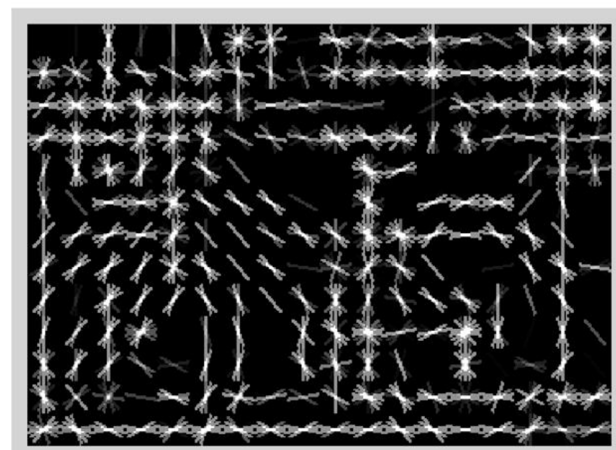
What are the object parameters?

James Hays

Specifying an object model

1. Statistical Template in Bounding Box
   - Object is some (x,y,w,h) in image
   - Features defined wrt bounding box coordinates

Image

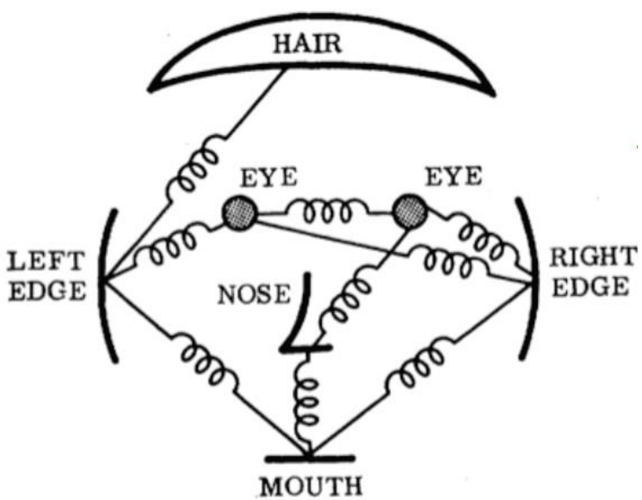


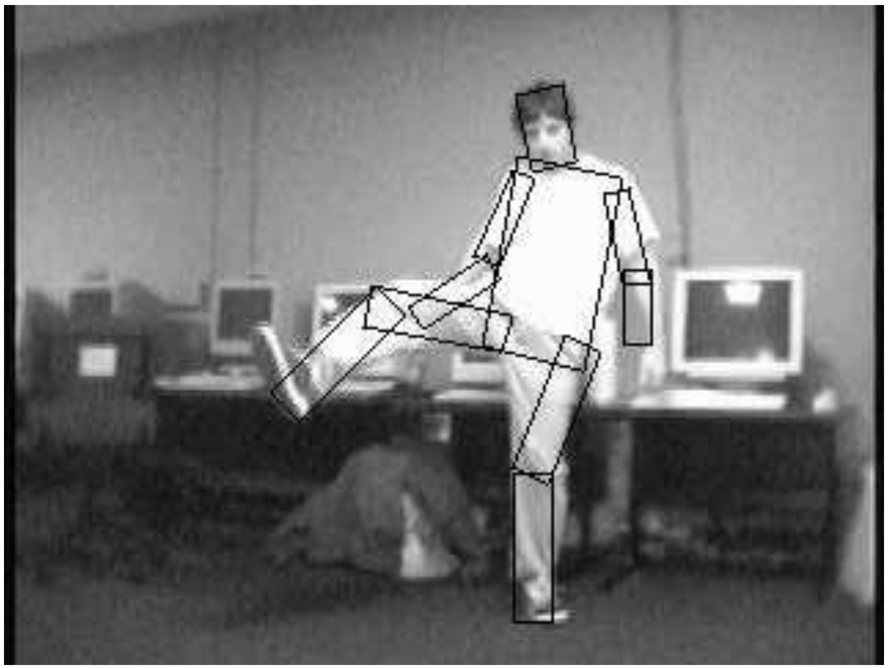
Template Visualization

Images from Felzenszwalb

Specifying an object model

2. Articulated parts model
    - Object is configuration of parts
    - Each part is detectable



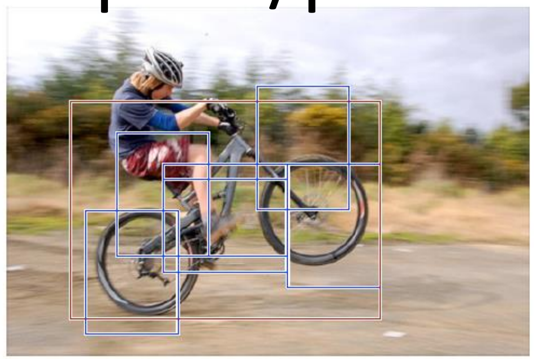


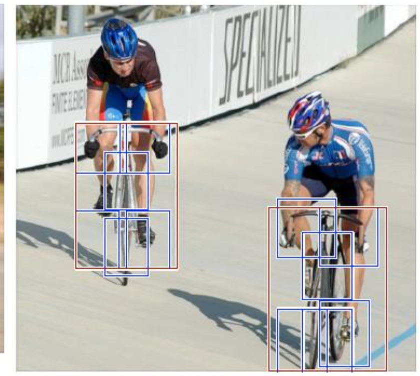
Images from Felzenszwalb

Specifying an object model

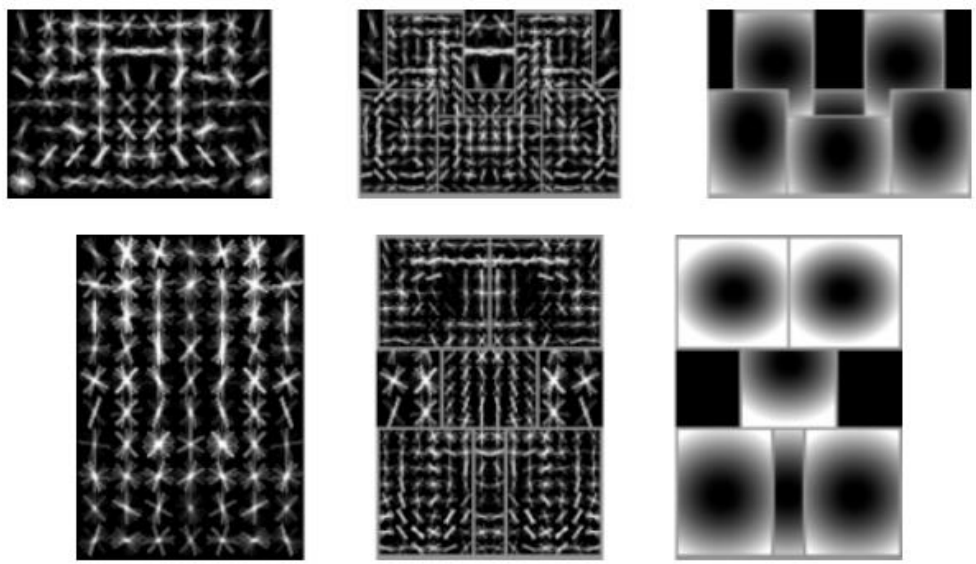
3. Hybrid template/parts model

Detections





Template Visualization



root filters
coarse resolution

part filters
finer resolution

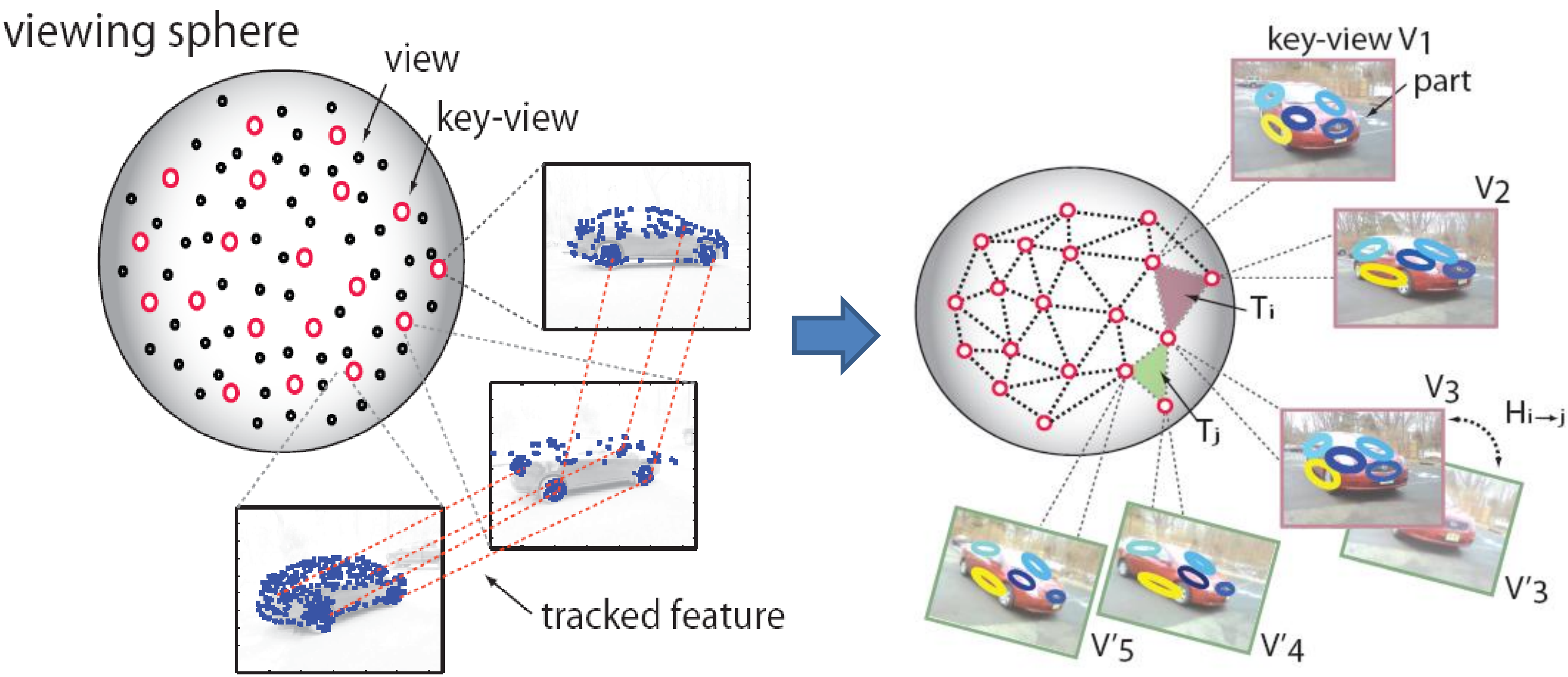
deformation
models

Felzenszwalb et al. 2008

Specifying an object model

4. 3D-ish model

- Object is collection of 3D planar patches under affine transformation



Loper et al. 2015

Specifying an object model

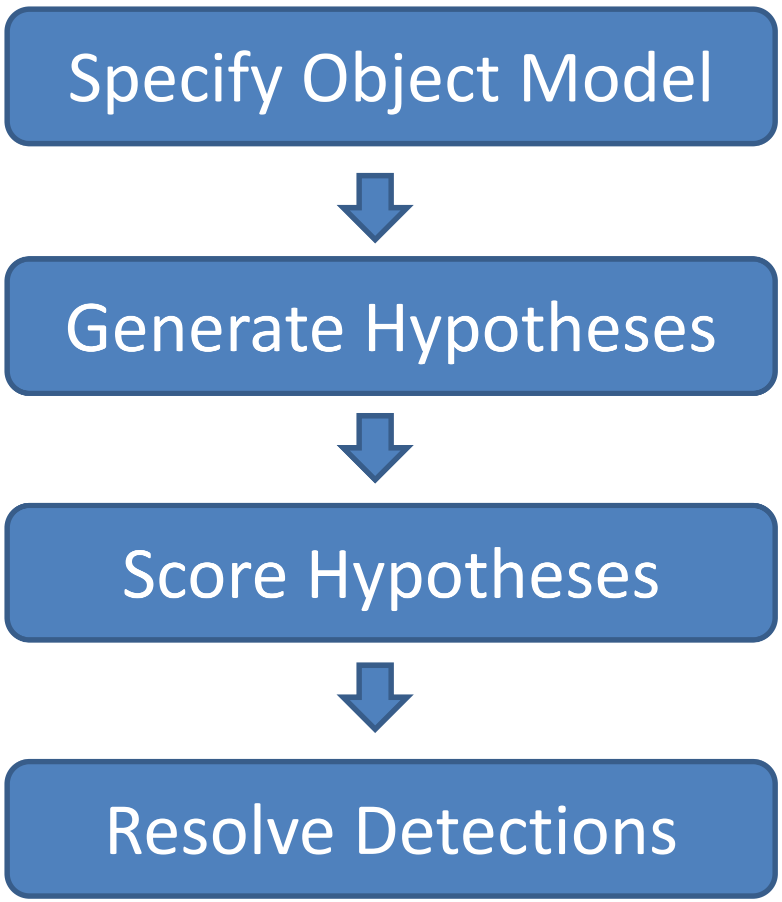
5. Deformable 3D model

- Object is a parameterized space of shape/pose/deformation of class of 3D object

Why not just pick the most complex model?

- Inference is harder
  - More parameters
  - Harder to ‘fit’ (infer / optimize fit)
  - Longer computation

General Process of Object Recognition



Propose an alignment of the model to the image

James Hays

Generating hypotheses

1. Sliding window
   – Test patch at each location and scale

James Hays

Generating hypotheses

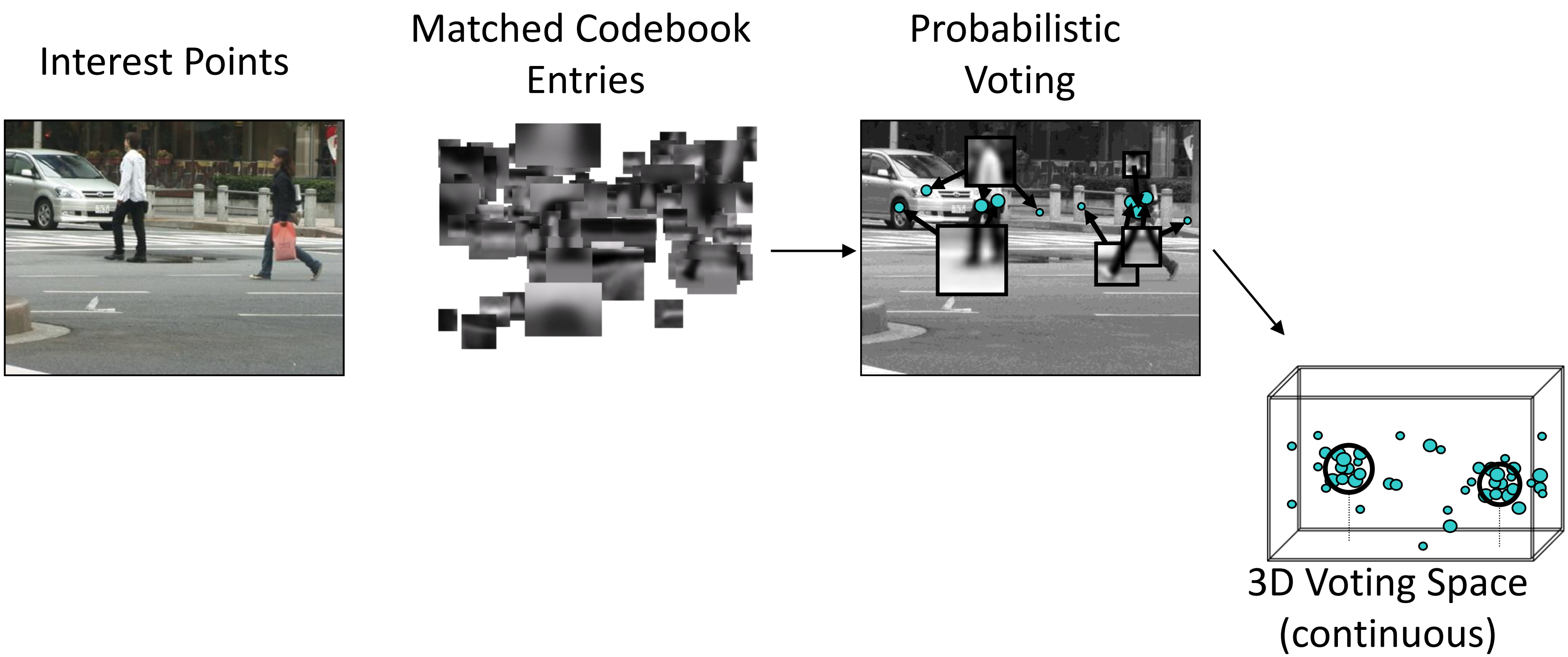
1. Sliding window
   – Test patch at each location and scale

Note – Template did not change size

Each window is separately classified

Generating hypotheses

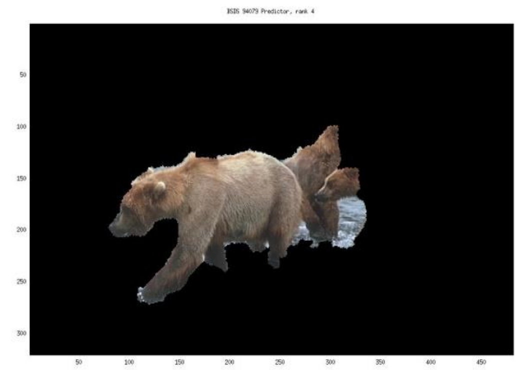
2. Voting from patches/keypoints

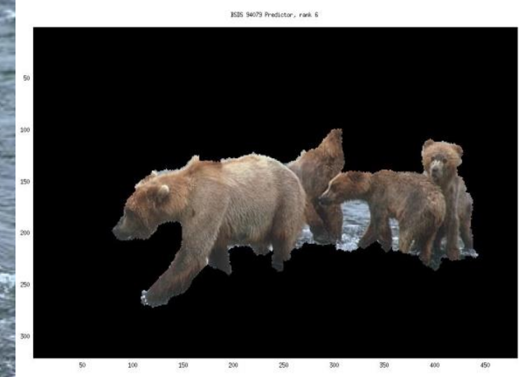


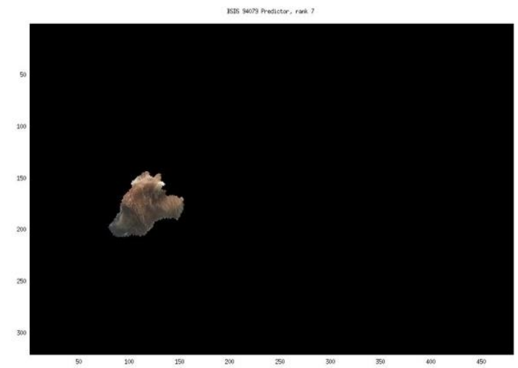
Implicit Shape Model by Leibe et al.

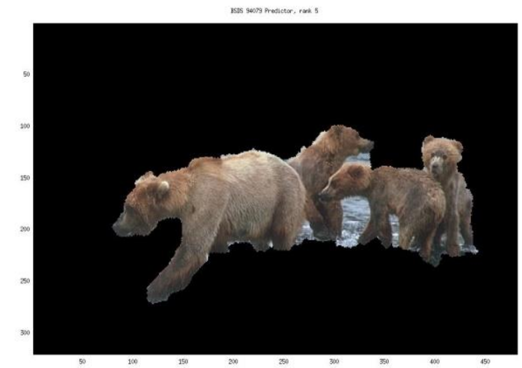
Generating hypotheses

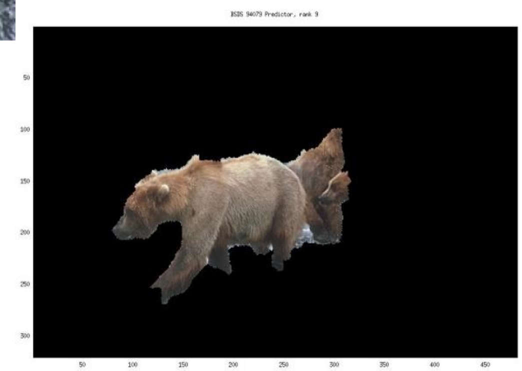
3. Region-based proposal





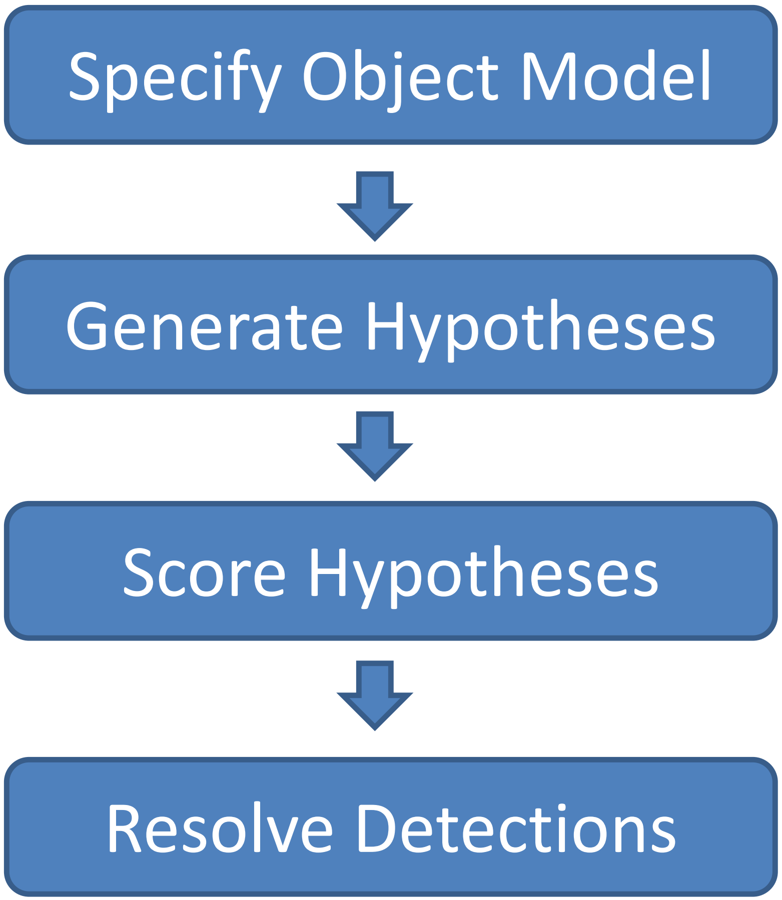






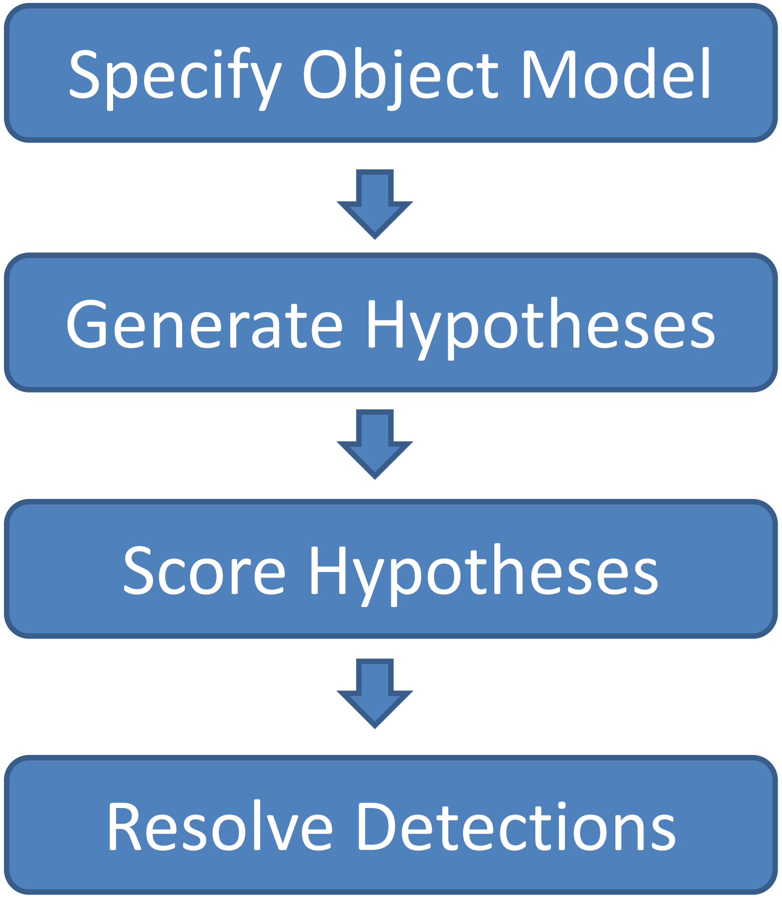
Endres Hoiem 2010

General Process of Object Recognition



Mainly-gradient based features, usually based on summary representation, many classifiers

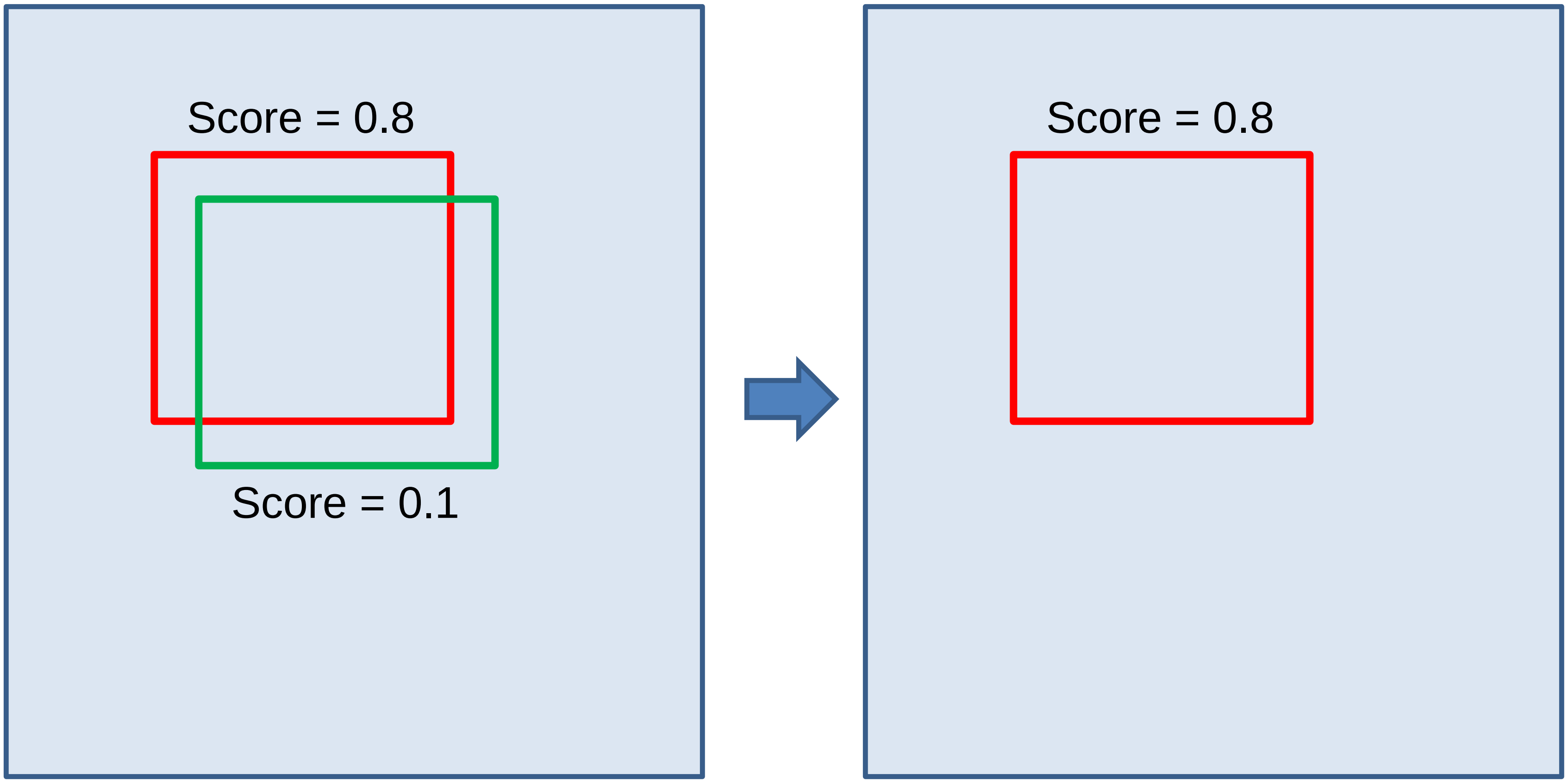
General Process of Object Recognition



Rescore each proposed object based on whole set

Resolving detection scores

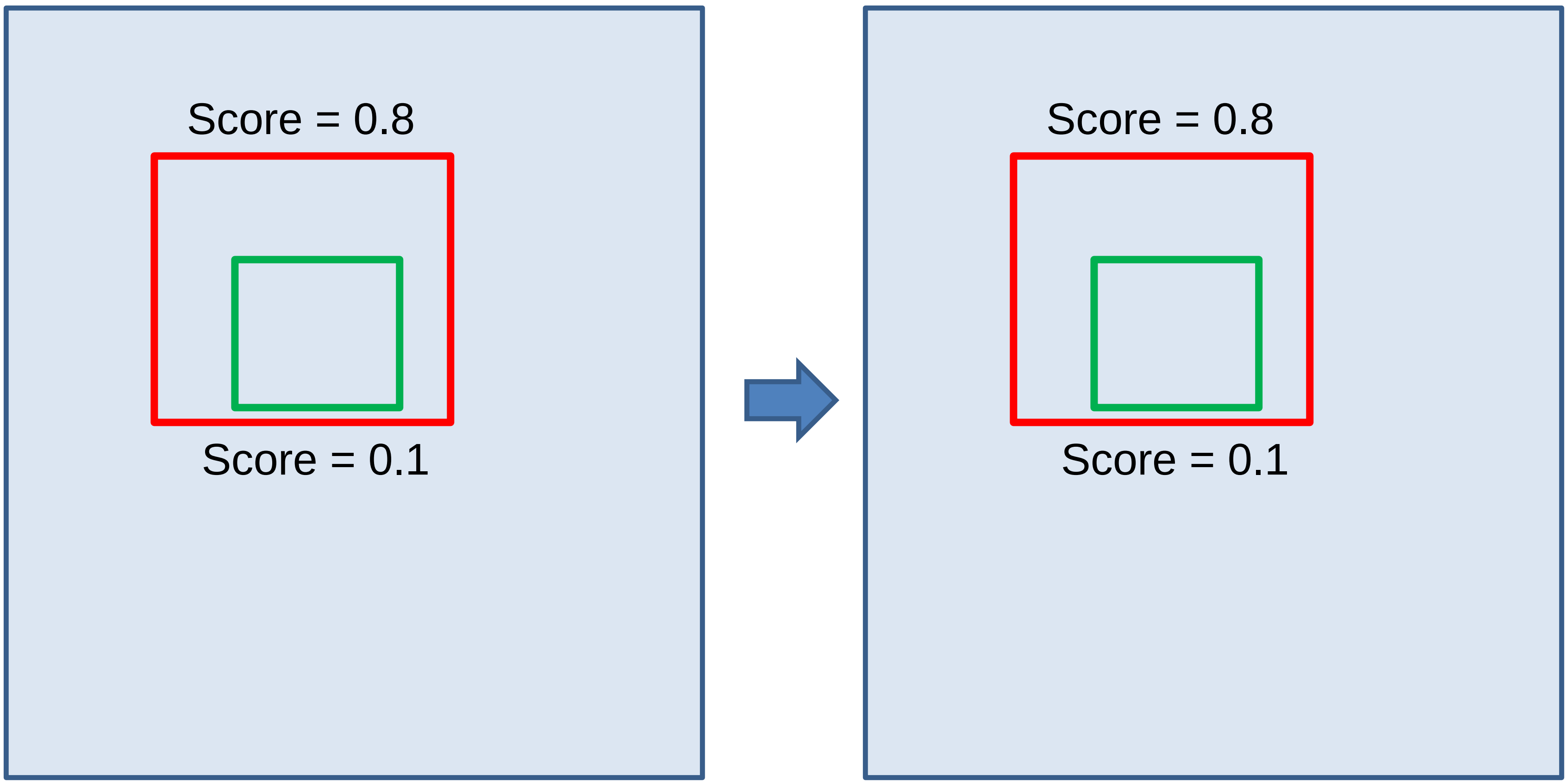
1. Non-max suppression



James Hays

Resolving detection scores

1. Non-max suppression

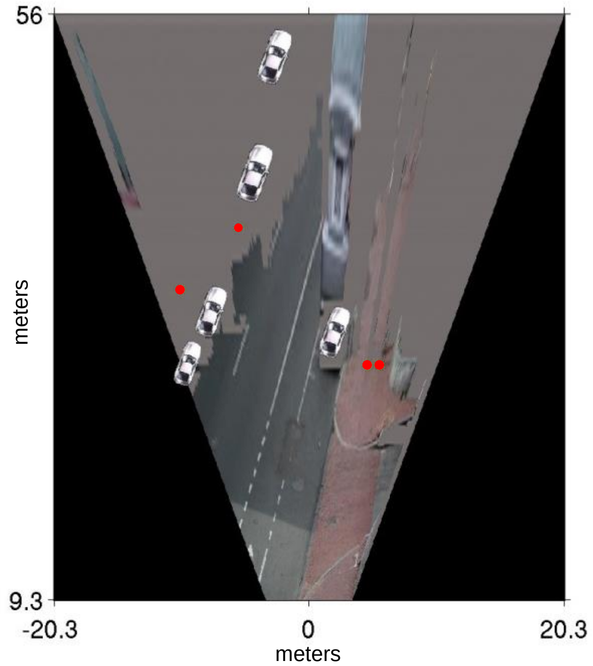


"Overlap" score is below some threshold

Resolving detection scores

2. Context/reasoning

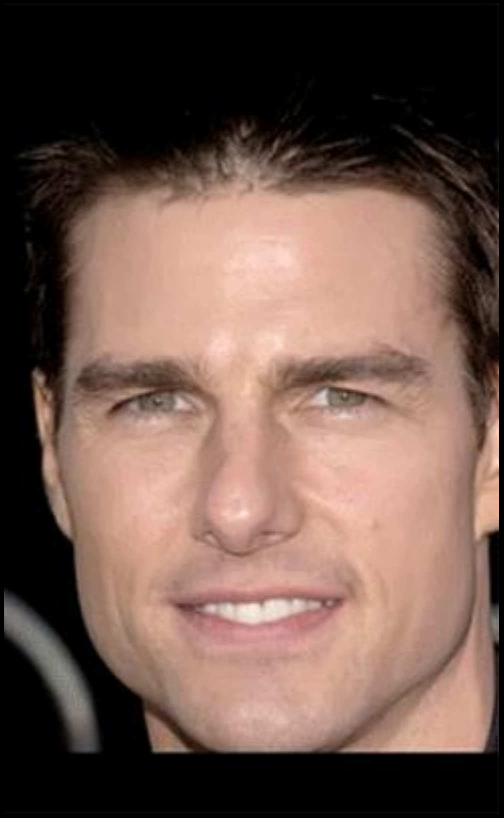
(g) Car Detections: Local (h) Ped Detections: Local



Hoiem et al. 2006

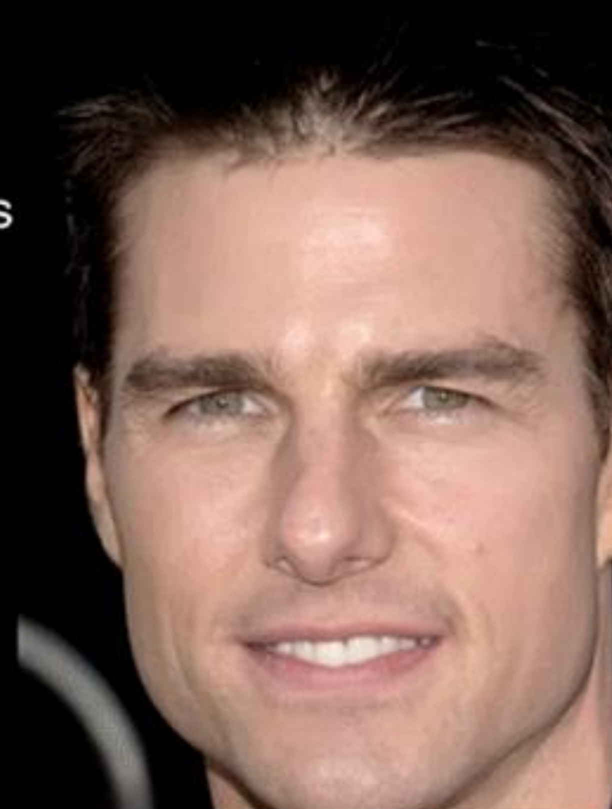
Sliding Window Face Detection with Viola-Jones

Many Slides from Lana Lazebnik

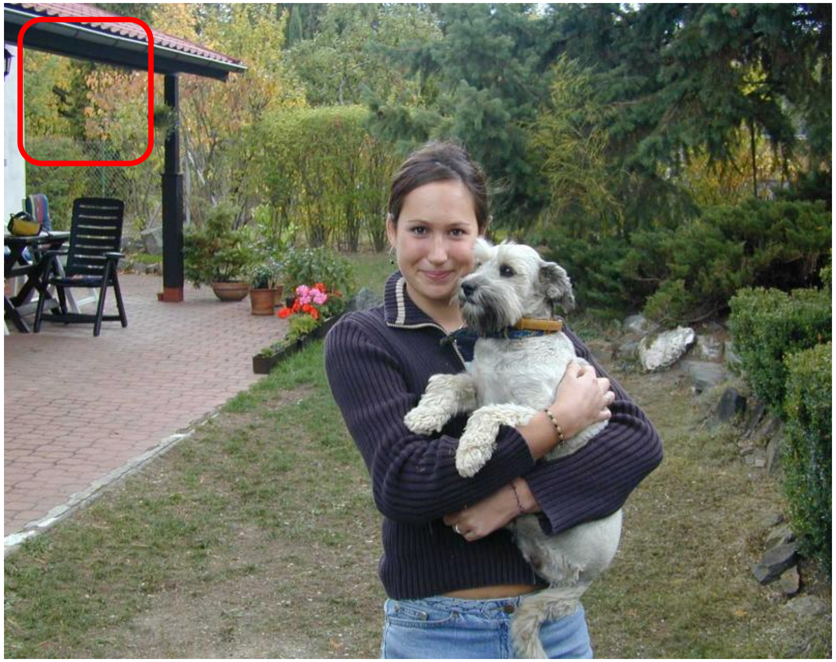


“Flashed Face Distortion”
2nd Place in the 8th Annual
Best Illusion of the Year Contest , VSS 2012

Keep your eyes
on the cross



Face detection and recognition



Detection

Recognition

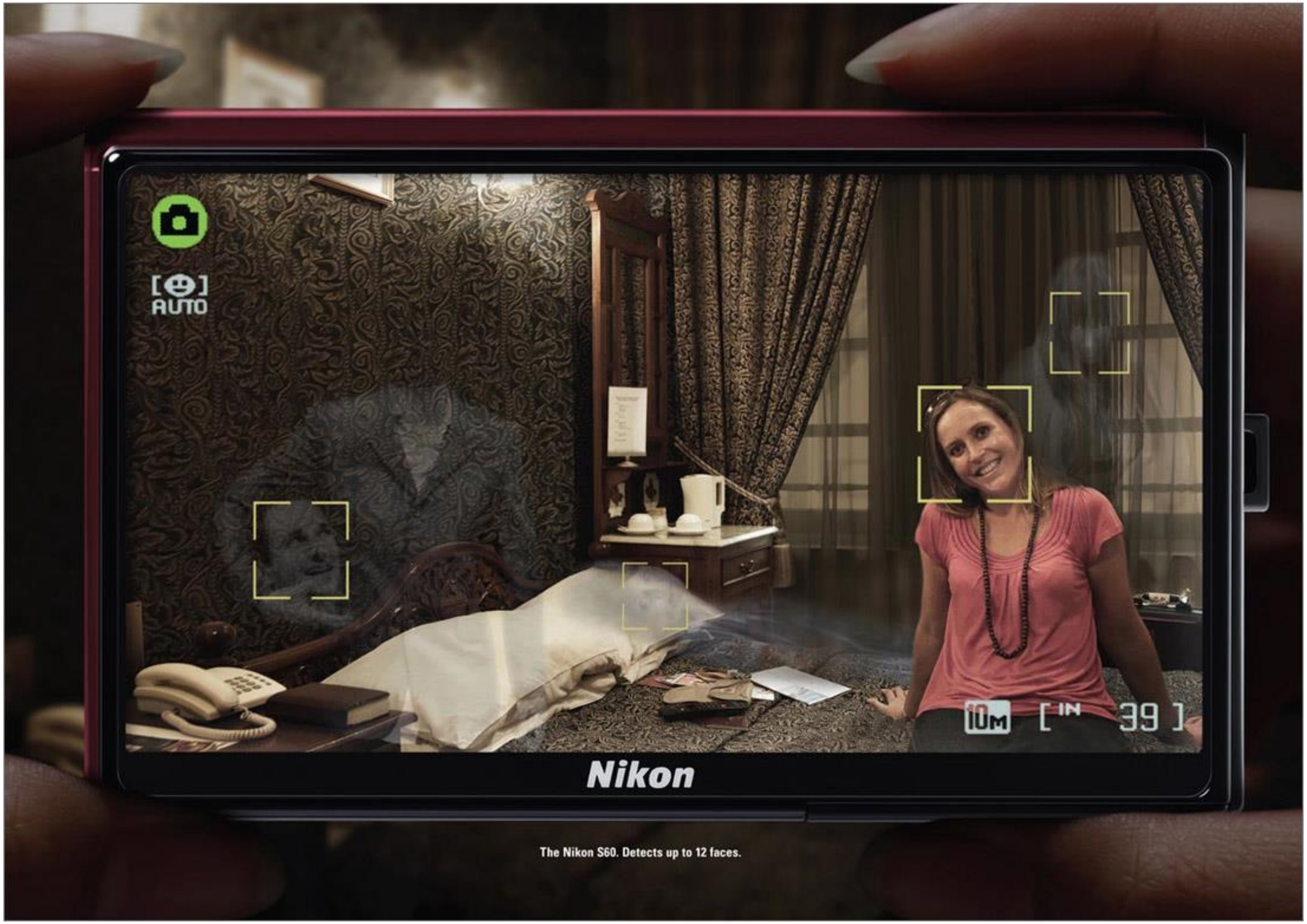
"Sally"

Consumer application: Apple iPhoto

[Things iPhoto thinks are faces]

Funny Nikon ads

"The Nikon S60 detects up to 12 faces."



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, our false positive rate has to be less than 10^{-6}*

James Hays

The Viola/Jones Face Detector

- A seminal approach to real-time object detection
- Training is slow, but detection is very fast

Key ideas:

1. Integral images for fast feature evaluation

2. Boosting for feature selection

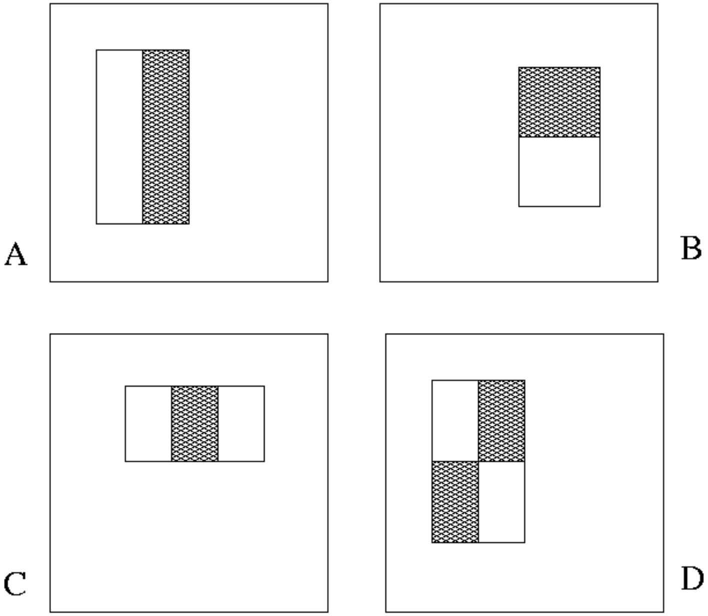
3. Attentional cascade for fast non-face window rejection

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

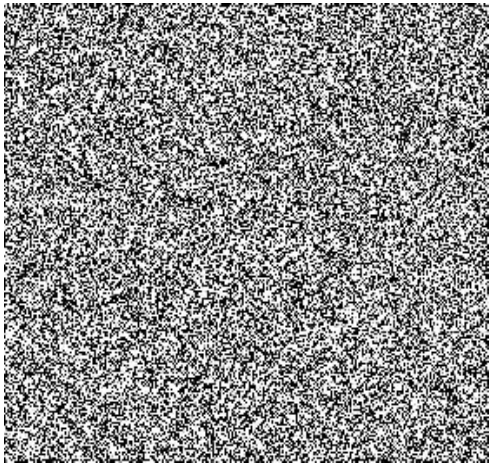
"Rectangle filters"



Value = ∑(pixels in white area)

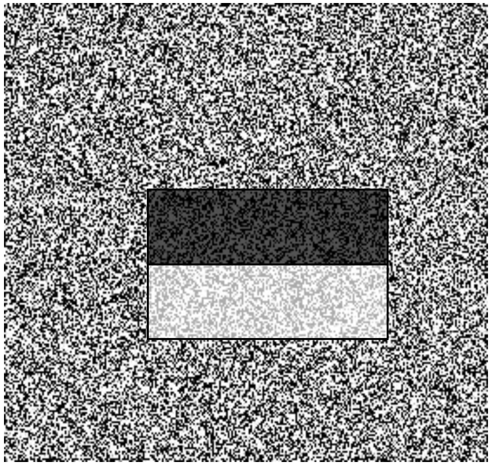
– ∑(pixels in black area)

Example



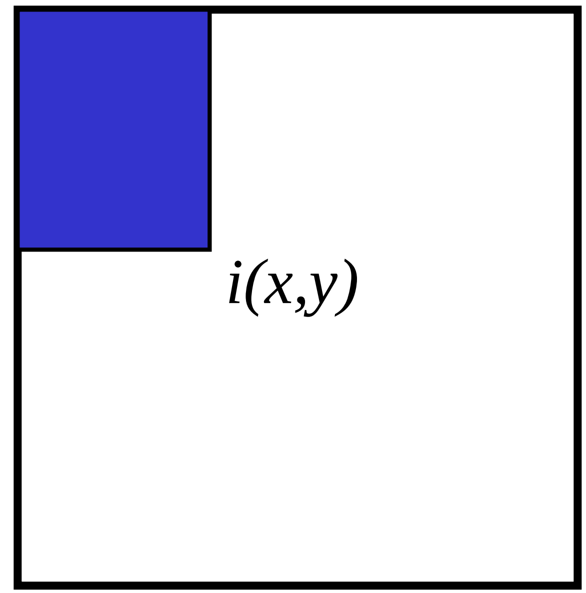
Source

Result



1. Integral images for fast feature evaluation

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

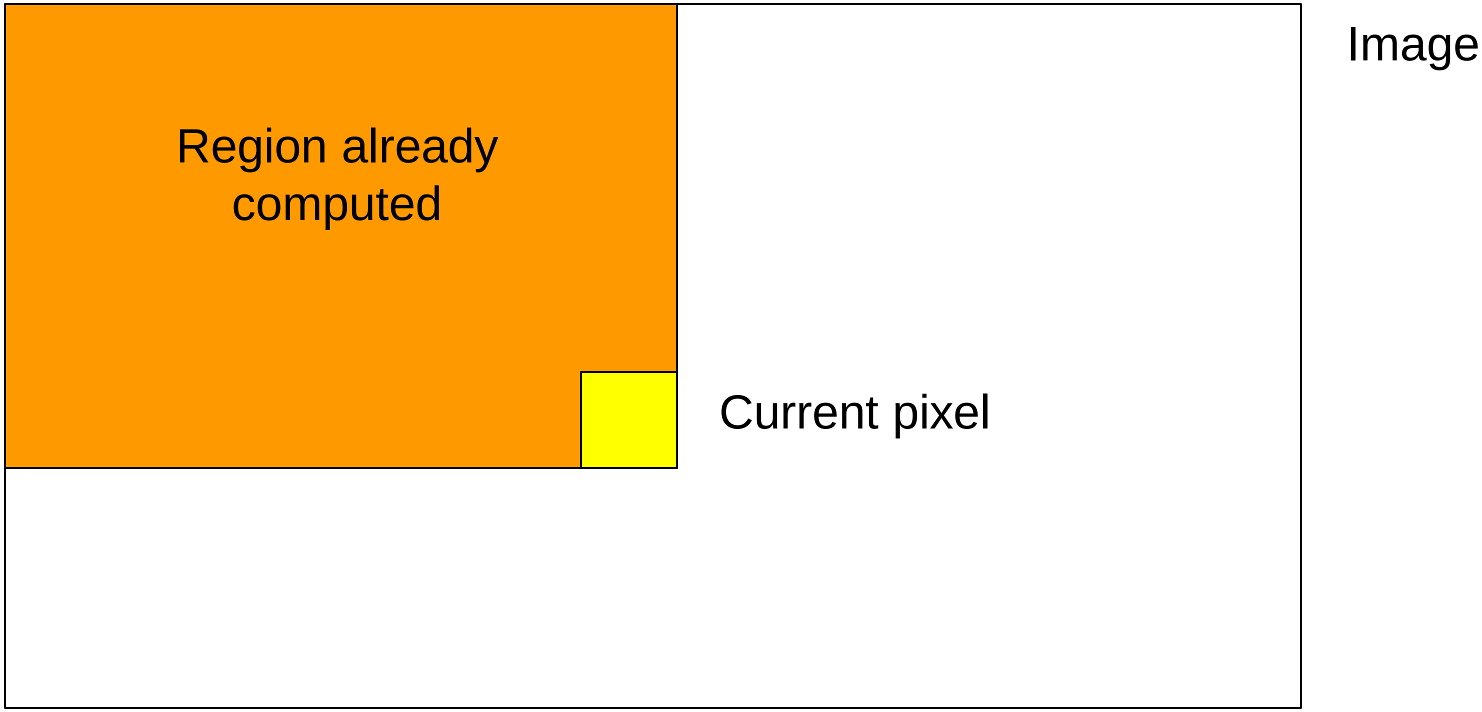


- This can quickly be computed in one pass through the image.

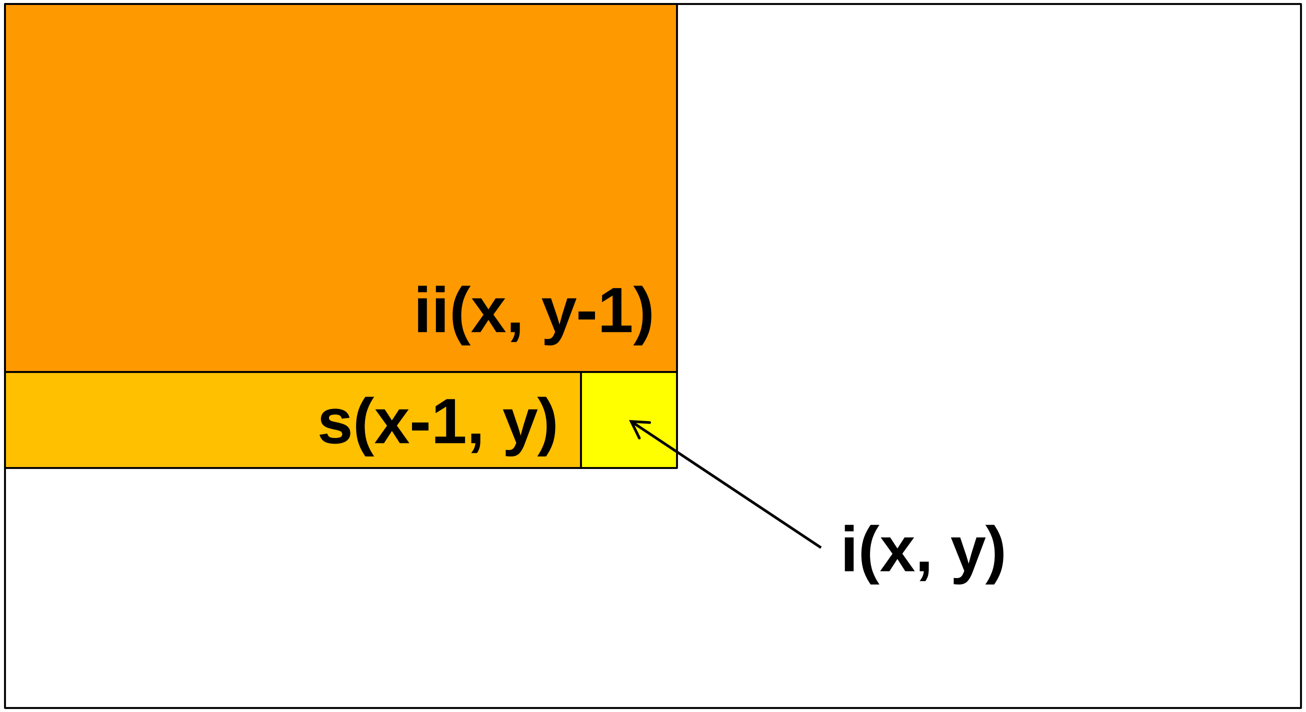
$$I_{\sum}(x,y) = \sum_{\substack{x' \leq x \\ y' \leq y}} i(x', y')$$

- ‘Summed area table’

Computing the integral image



Computing the integral image



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

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

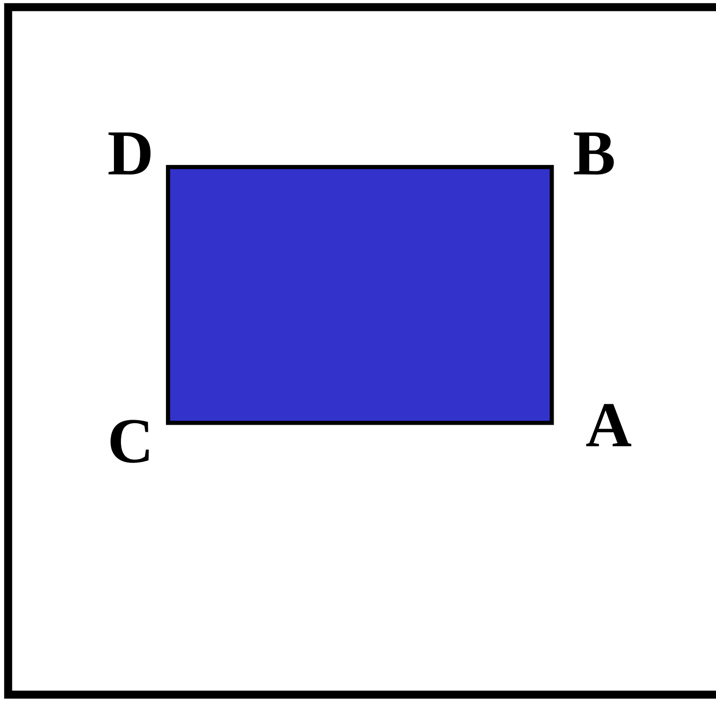
MATLAB: `ii = cumsum(cumsum(double(i)), 2);`

Computing sum within a rectangle

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

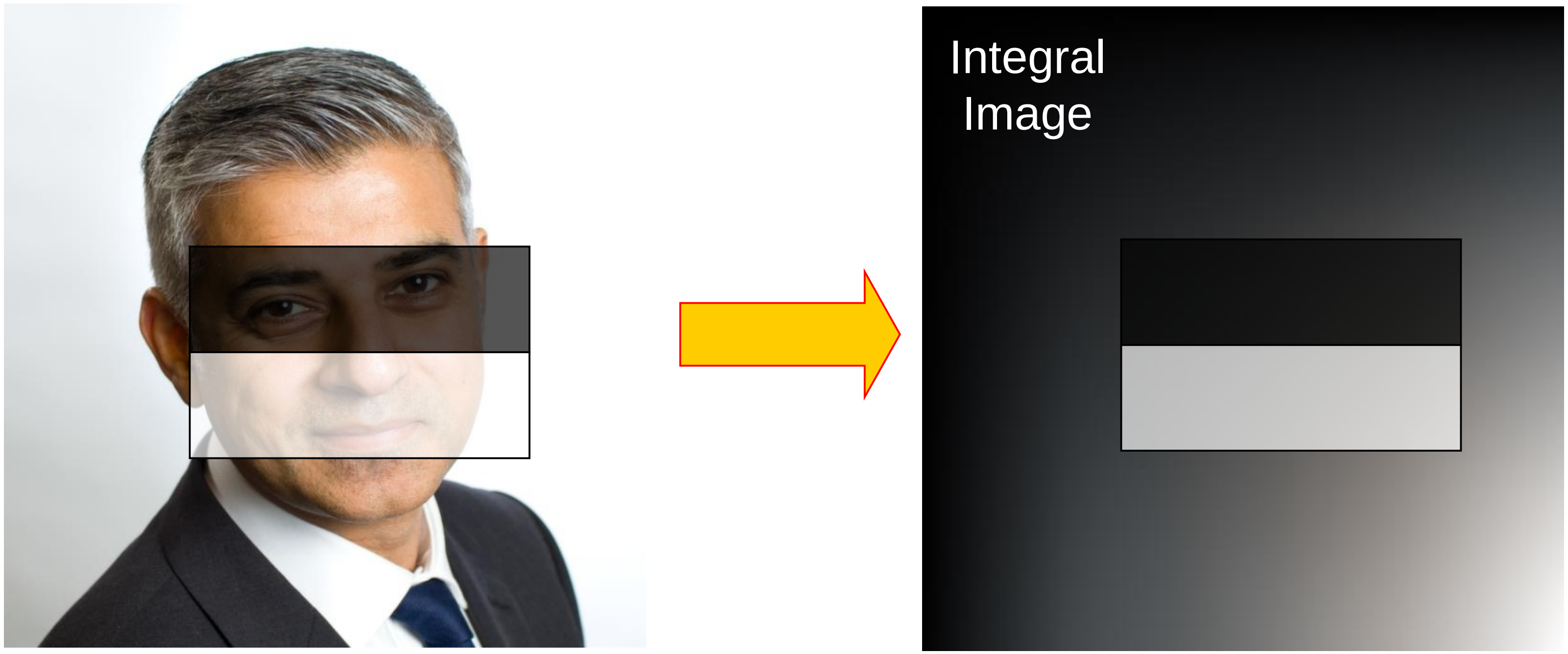
- The sum of original image values within the rectangle can be computed as:

  sum = A – B – C + D



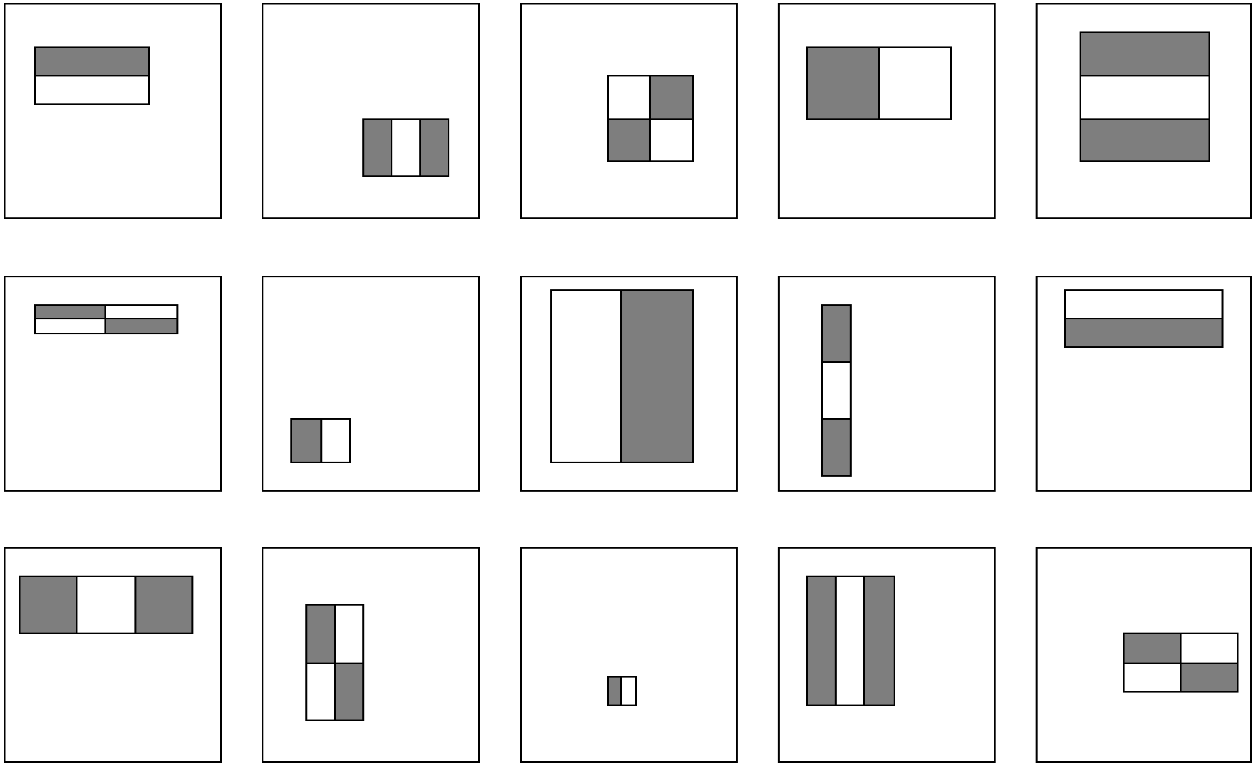
Only 3 additions are required for any size of rectangle!

Computing a rectangle feature



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

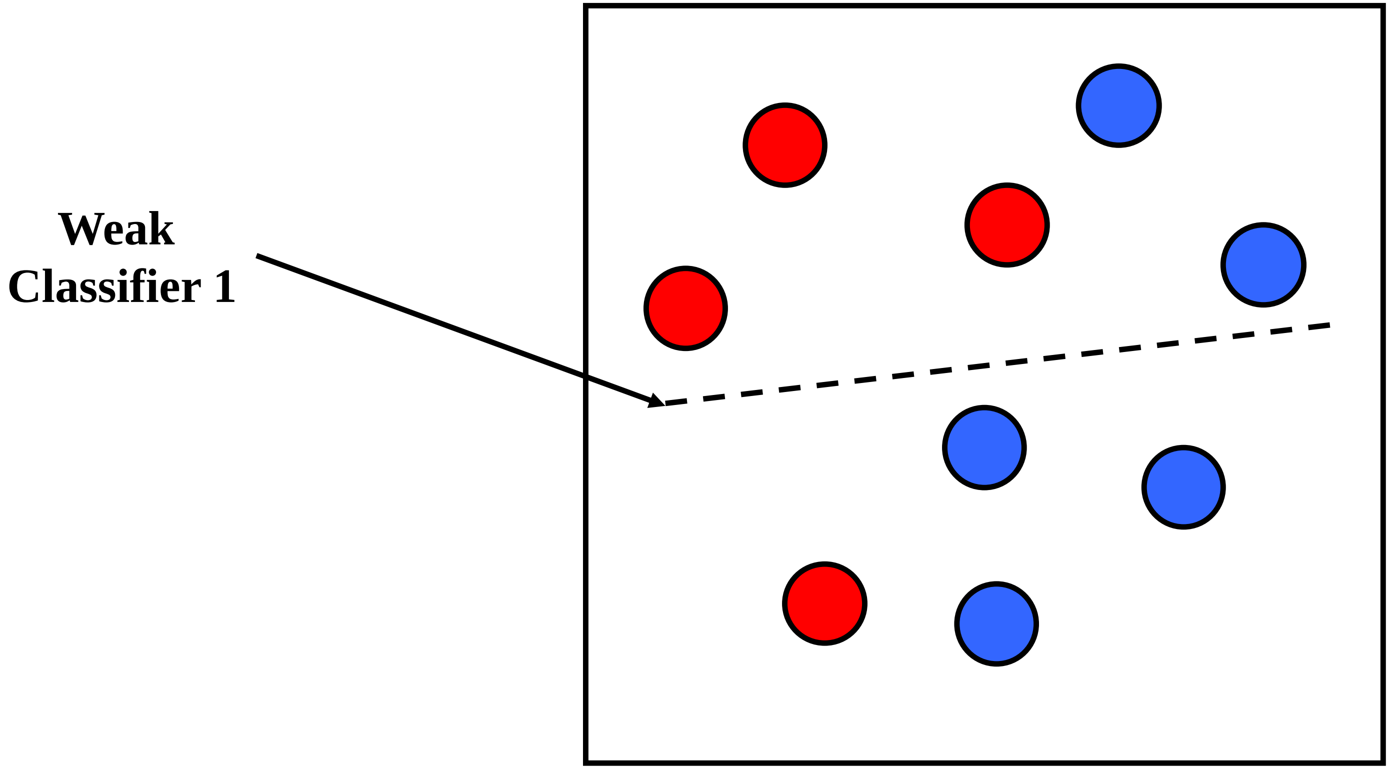
- Can we create a good classifier using just a small subset of all possible features?
- How to select such a subset?

2. *Boosting* for feature selection

- 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)

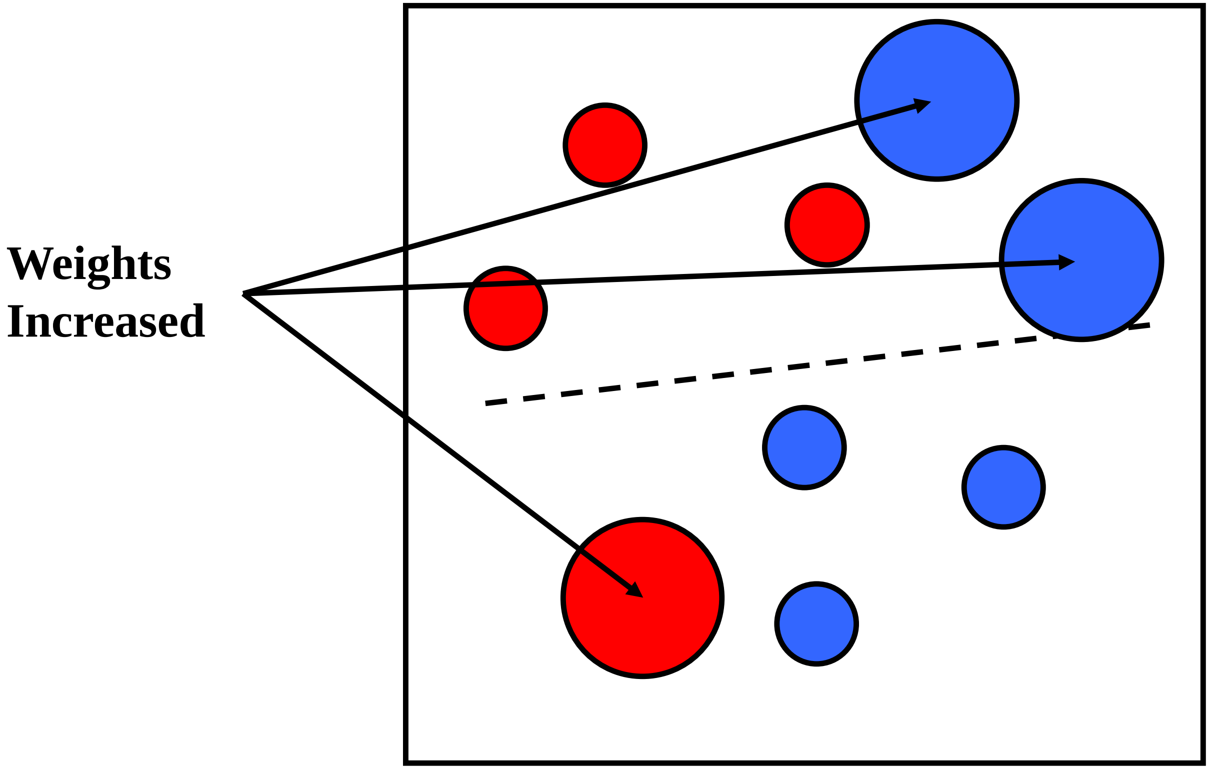
Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, September, 1999.

Boosting intuition

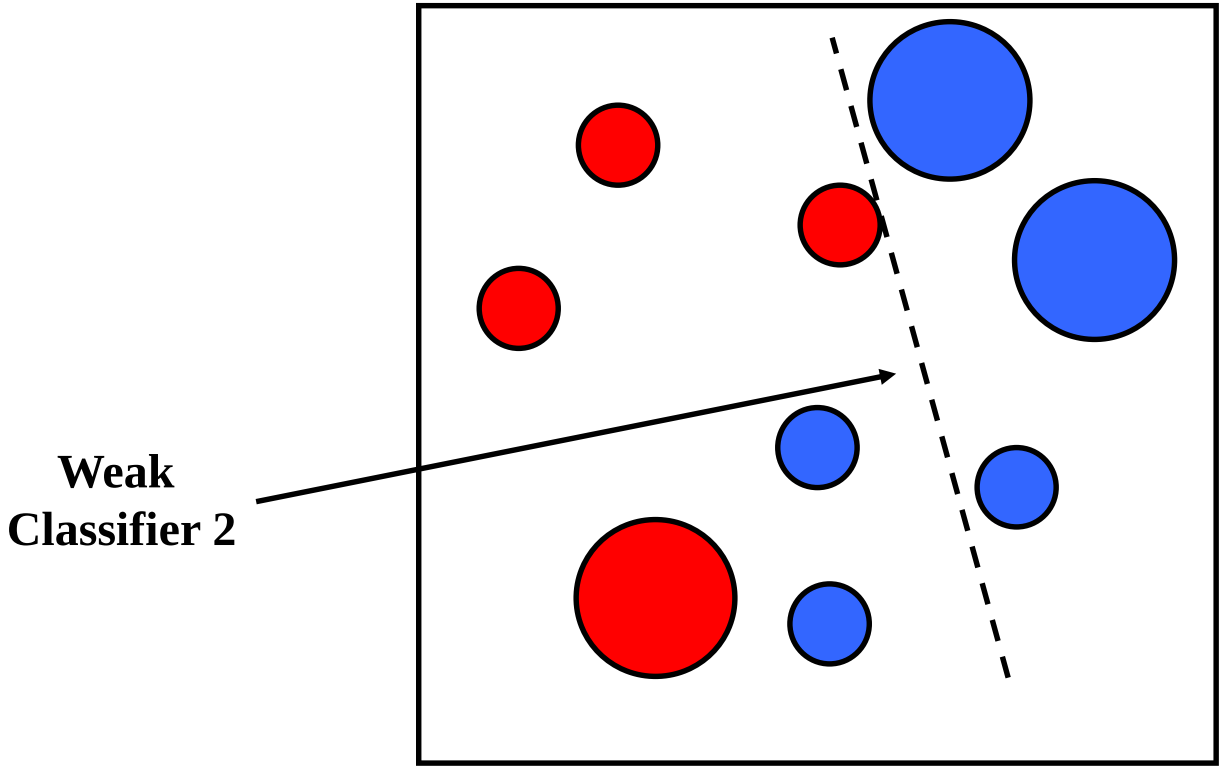


Slide credit: Paul Viola

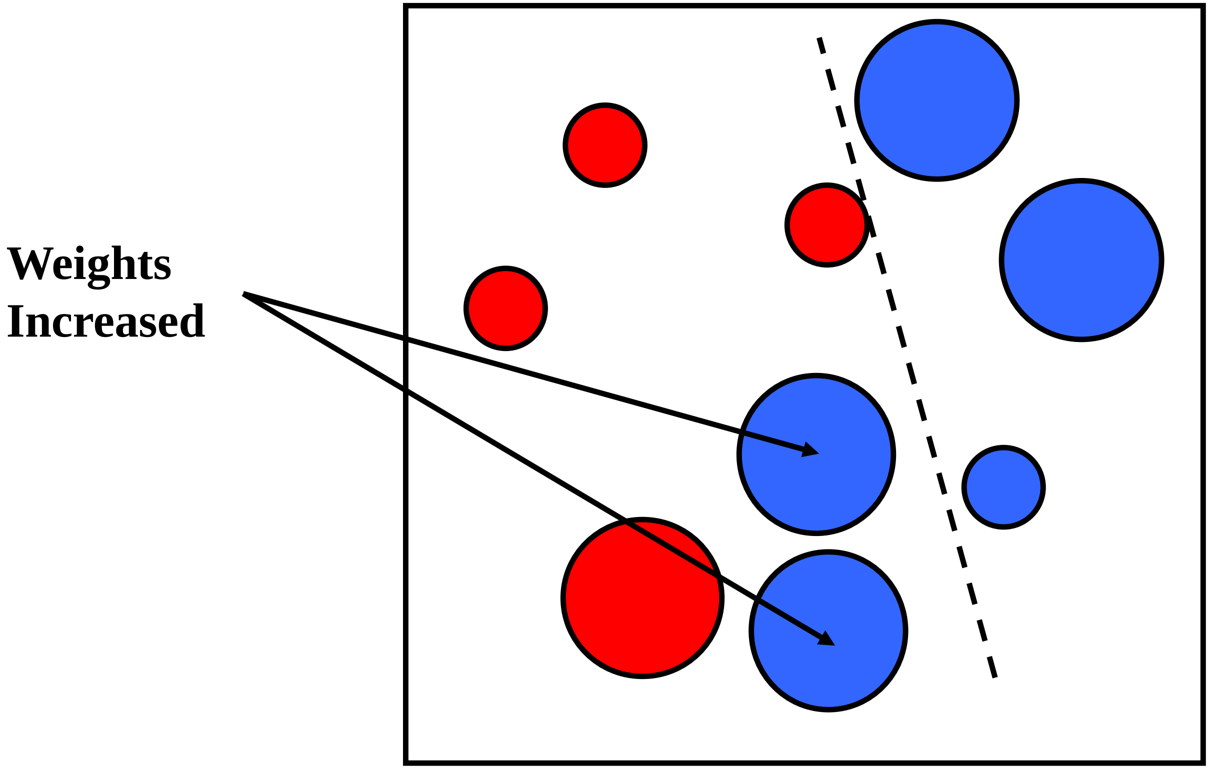
Boosting illustration



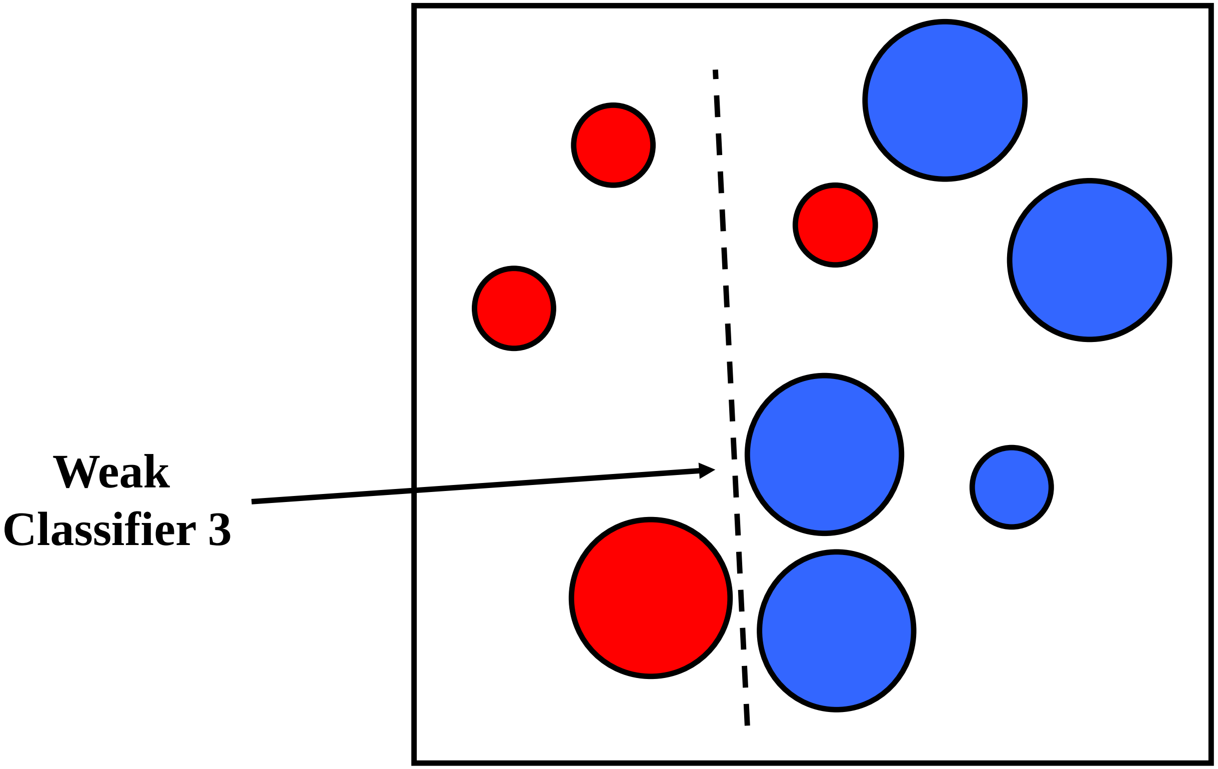
Boosting illustration



Boosting illustration

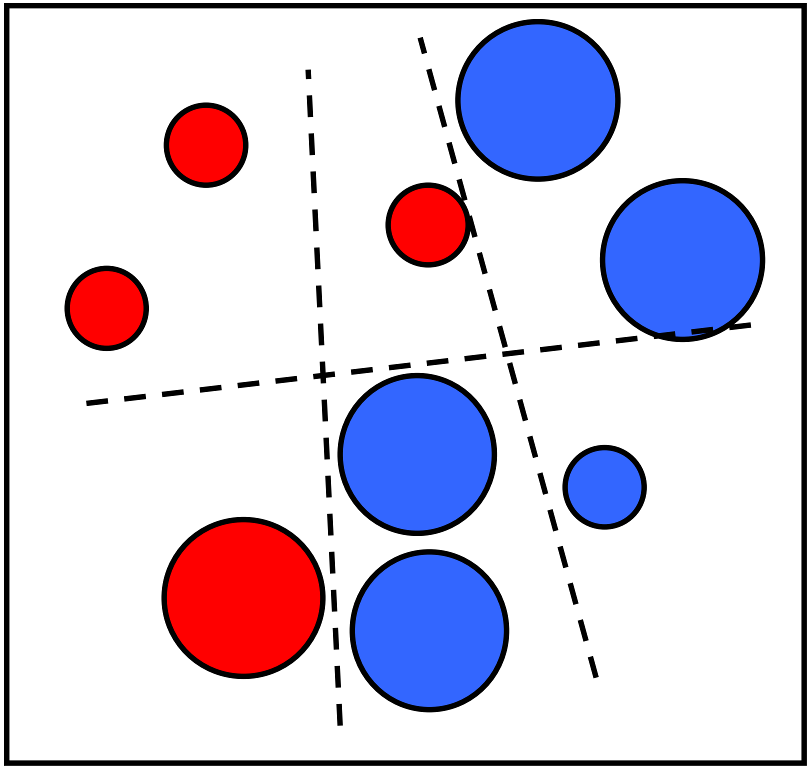


Boosting illustration



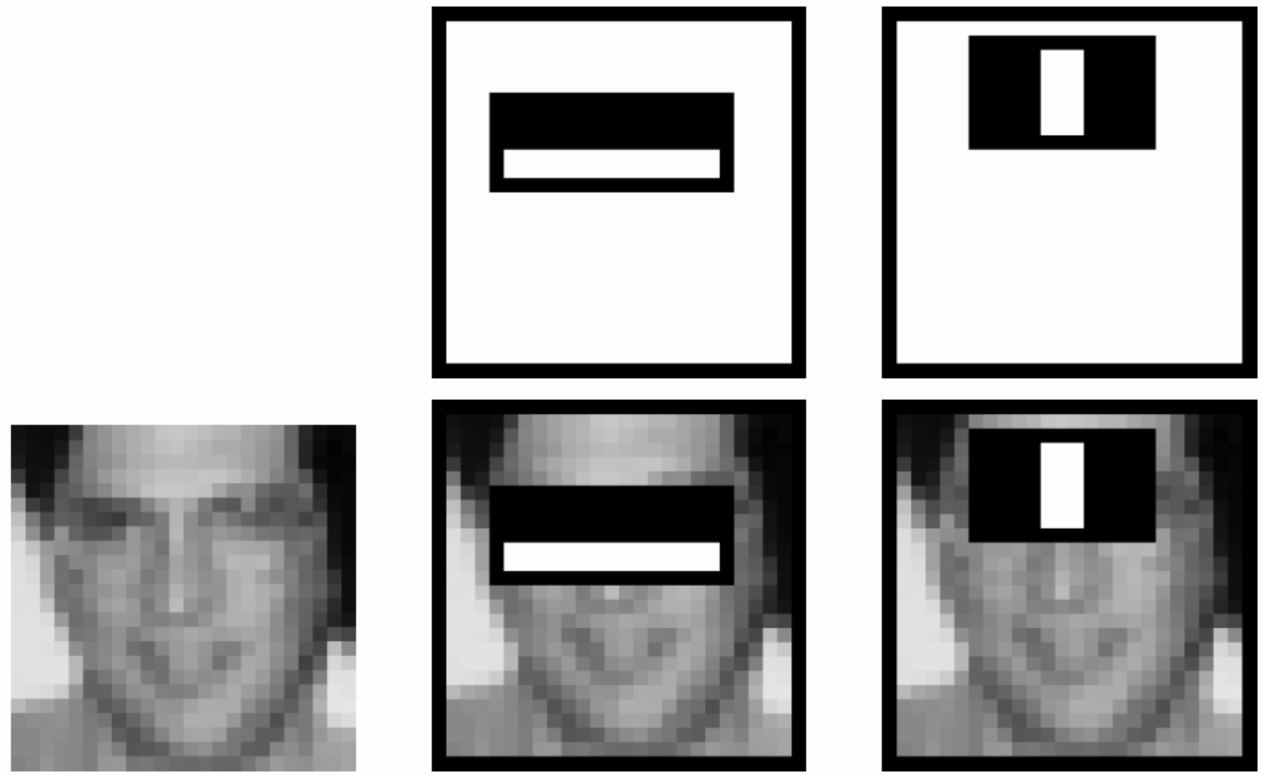
Boosting illustration

Final classifier is
a combination of weak
classifiers



Boosting for face detection

- First two features selected by boosting:



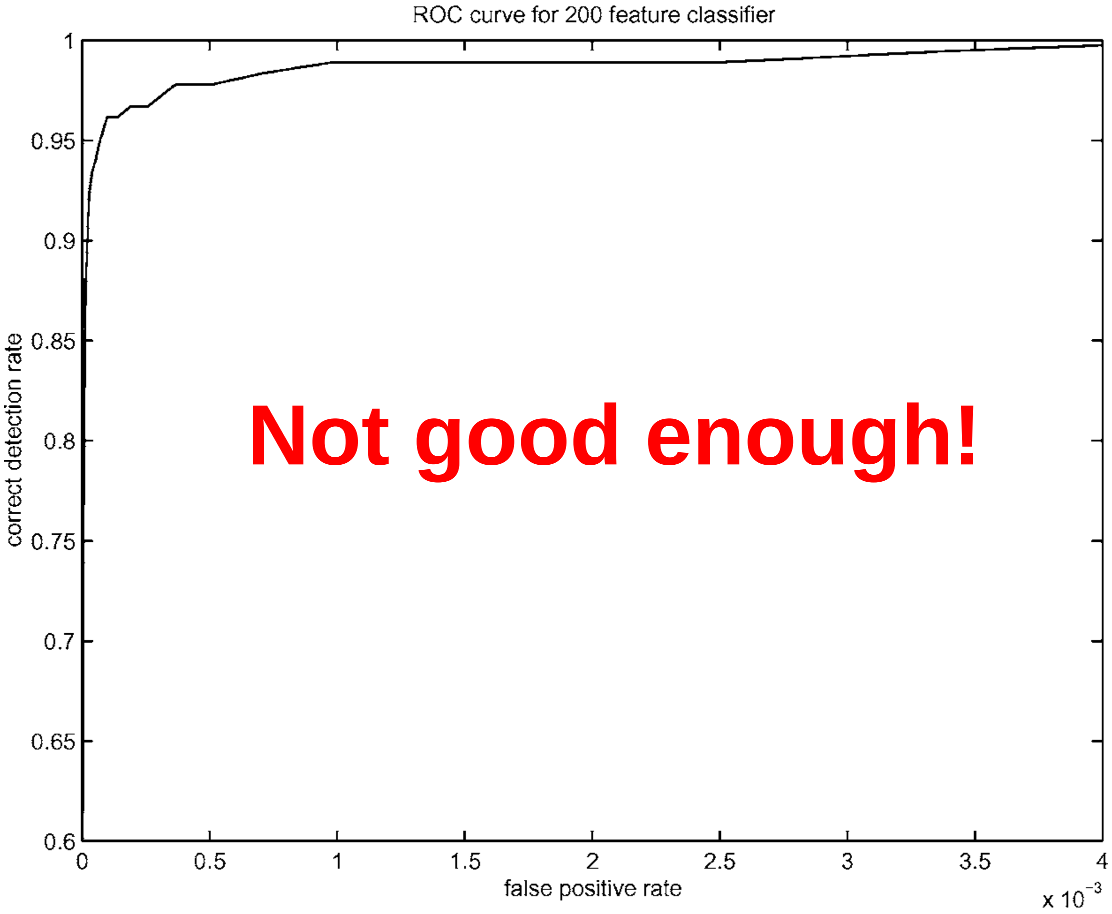
This feature combination can yield 100% recall and 50% false positive rate

Boosting vs. SVM

- Advantages of boosting
  - Integrates classifier training with feature selection
  - Complexity of training is linear instead of quadratic in the number of training examples
  - Flexibility in the choice of weak learners, boosting scheme
  - Testing is 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

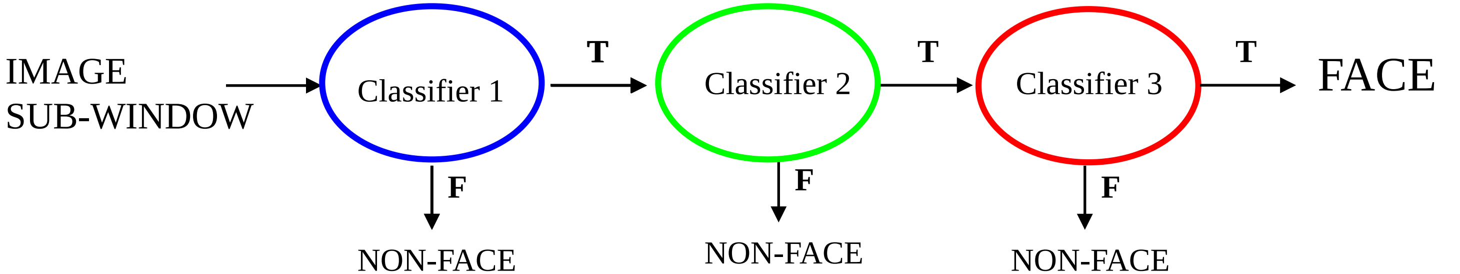
- A 200-feature classifier can yield 95% detection rate and a false positive rate of 1 in 14084



Receiver operating characteristic (ROC) curve

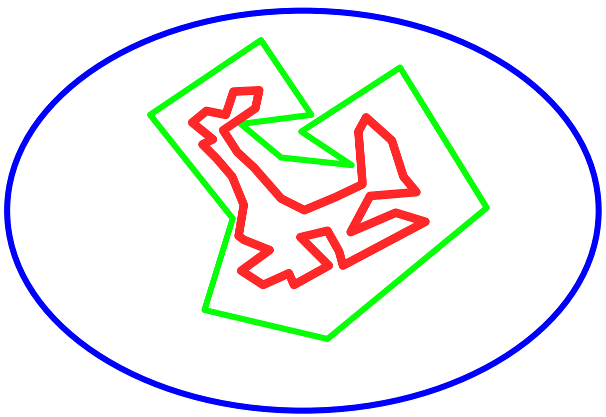
Attentional cascade

- 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

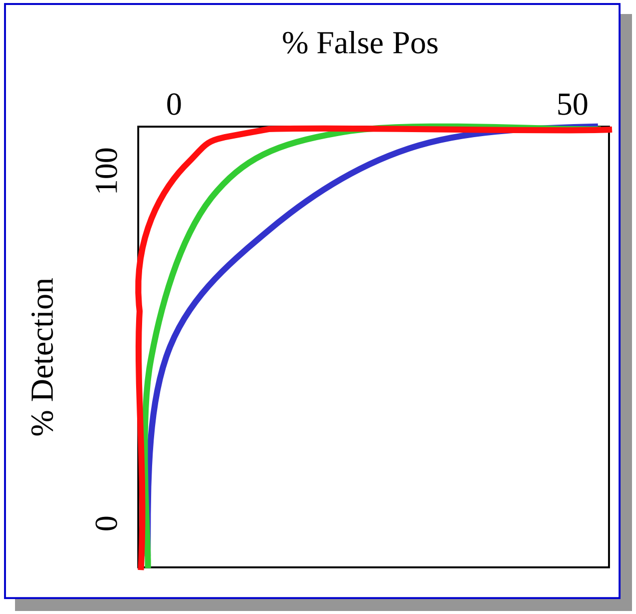


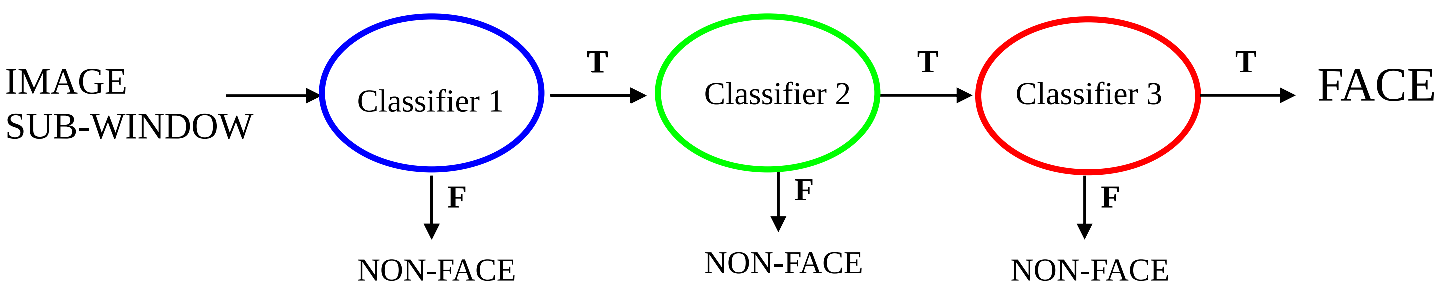
Attentional cascade

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



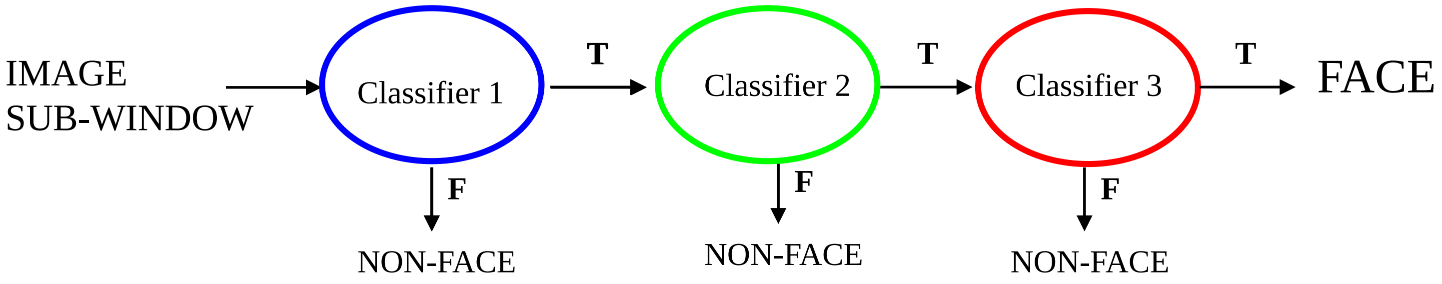
Receiver operating characteristic





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 boosting 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

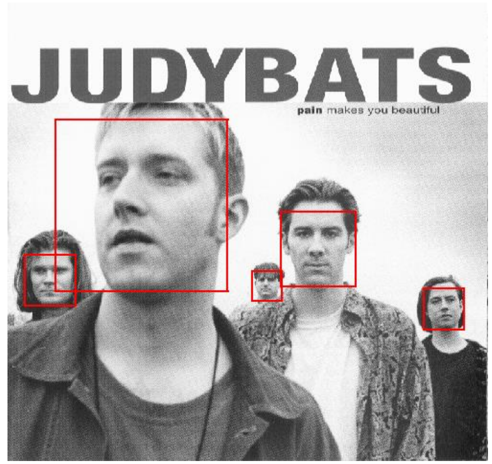
The implemented system

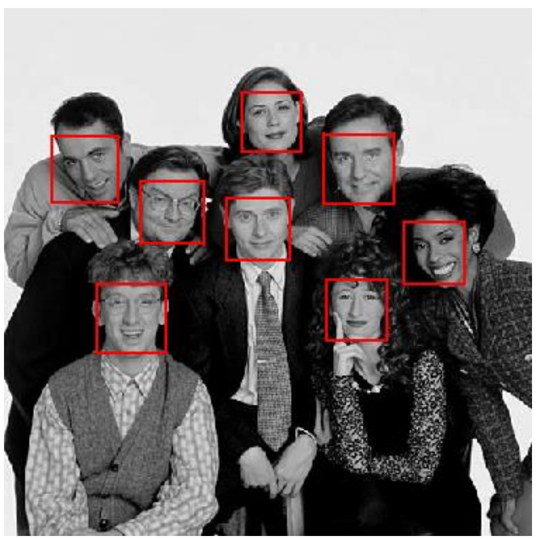
- Training Data
  - 5000 faces
    - All frontal, rescaled to 24x24 pixels
  - 300 million non-faces
    - 9500 non-face images
  - Faces are normalized
    - Scale, translation
- Many variations
  - Across individuals
  - Illumination
  - Pose

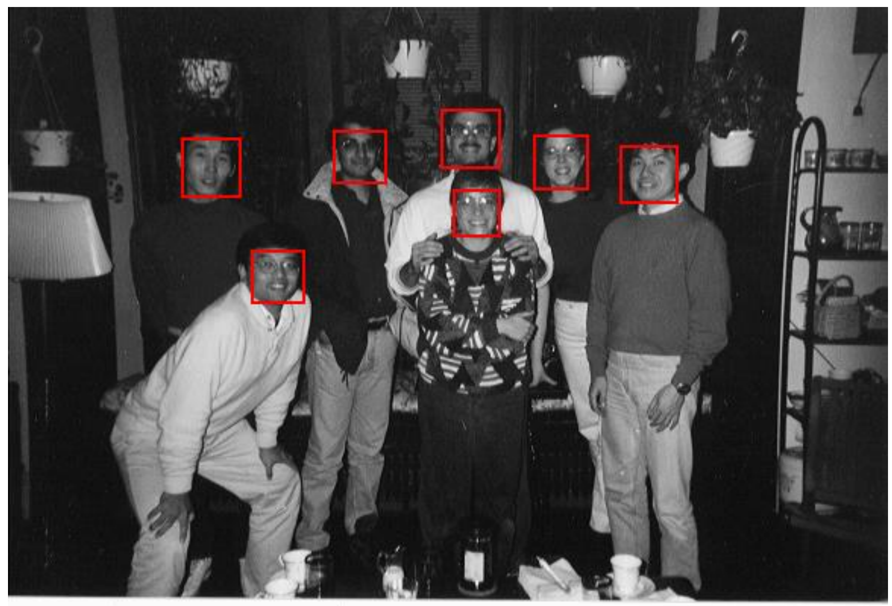
System performance

- 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”
  - 15 Hz
  - 15 times faster than previous detector of comparable accuracy (Rowley et al., 1998)

Output of Face Detector on Test Images

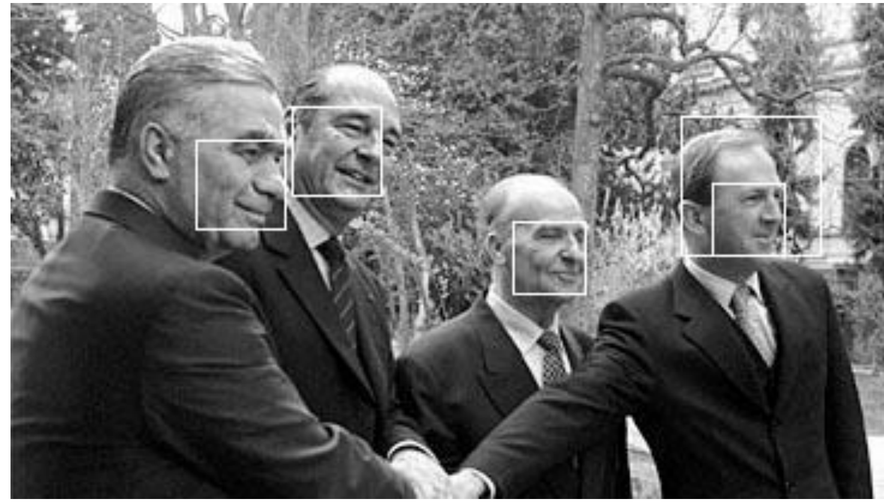






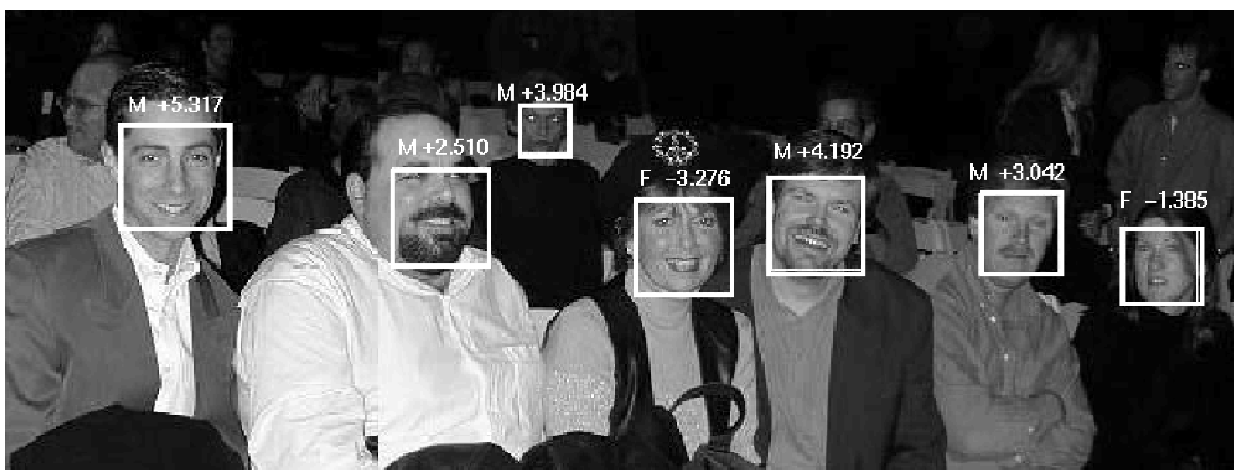
Other detection tasks

Facial Feature Localization

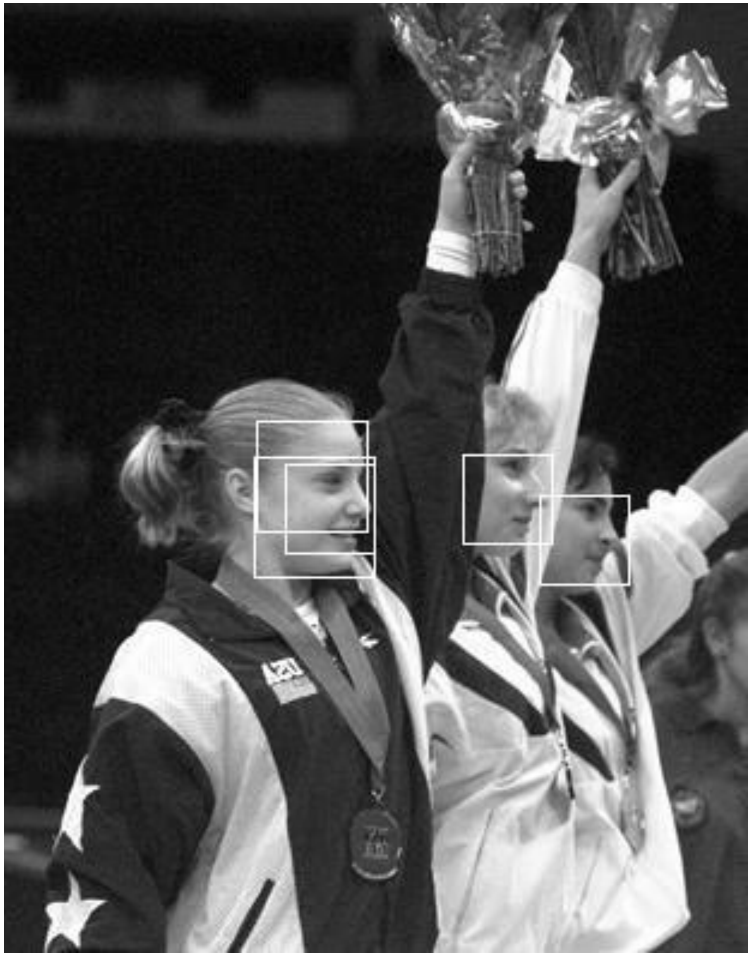


Profile Detection

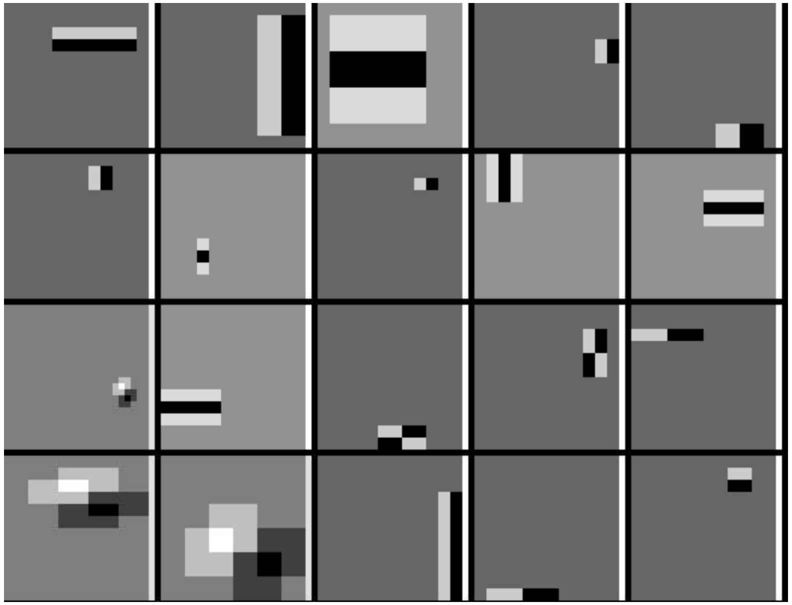
Male vs. female



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