The University of Texas at Austin
Electrical and Computer Engineering
Cockrell School of Engineering

Spring 2022

INTRODUCTION TO COMPUTER VISION

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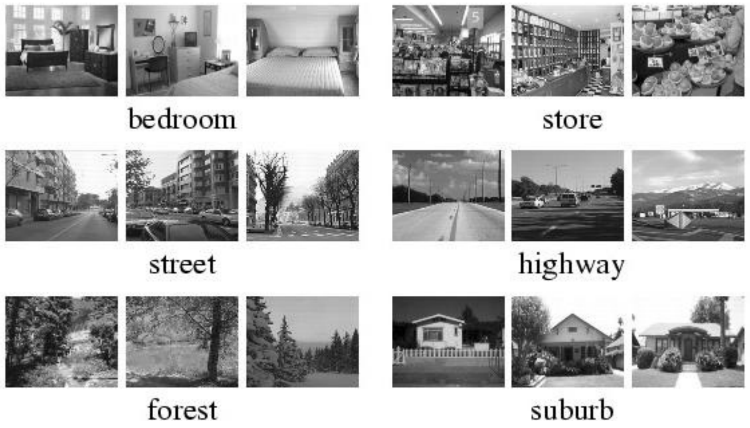
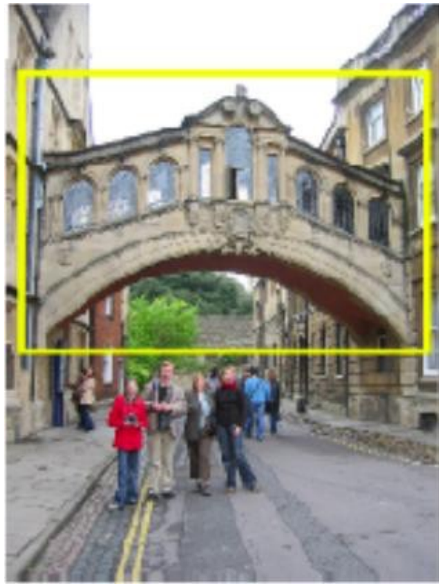
Many slides here were adapted from Brown CSCI 1430

Recognition so far

Category:
- Is this a bedroom?
- What class of scene is this?
- Holistic features/quantization



Instance:
- Find this specific famous building.
- Find this person.
- Local features/precise correspondence
- Often within a database of images



"Image classification is not real computer vision… so don't be too obsessed with that"

Recognition so far

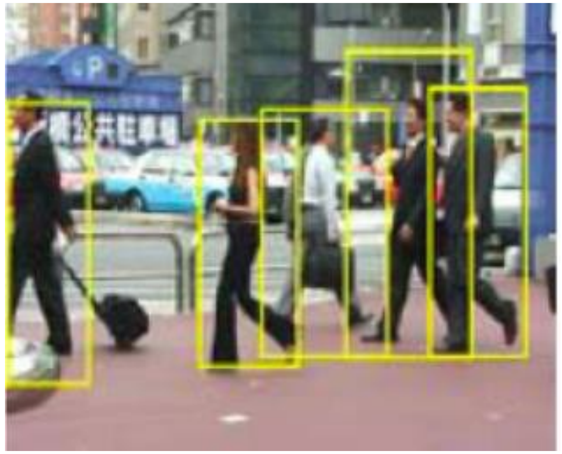
Object (category) detection:

– Find all the people

– Find all the faces

– Often within a single image

– Often ‘sliding window’



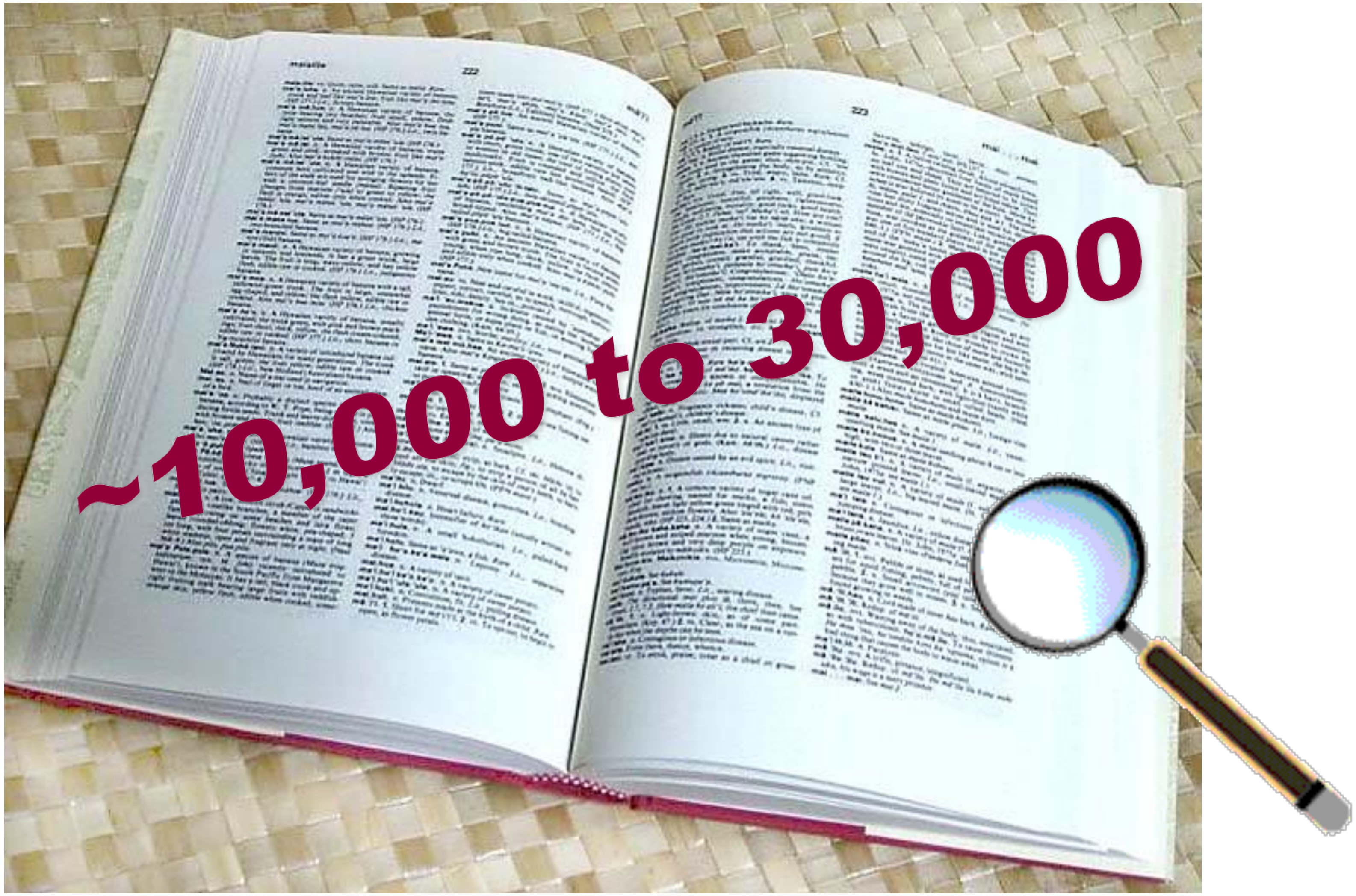
Scenes have “stuff” – distribution of materials and surfaces with arbitrary shape.

- Bag of Words ok!

Objects are “things” with shape, boundaries.

- **Bag of Words less ok as spatial layout is lost!**

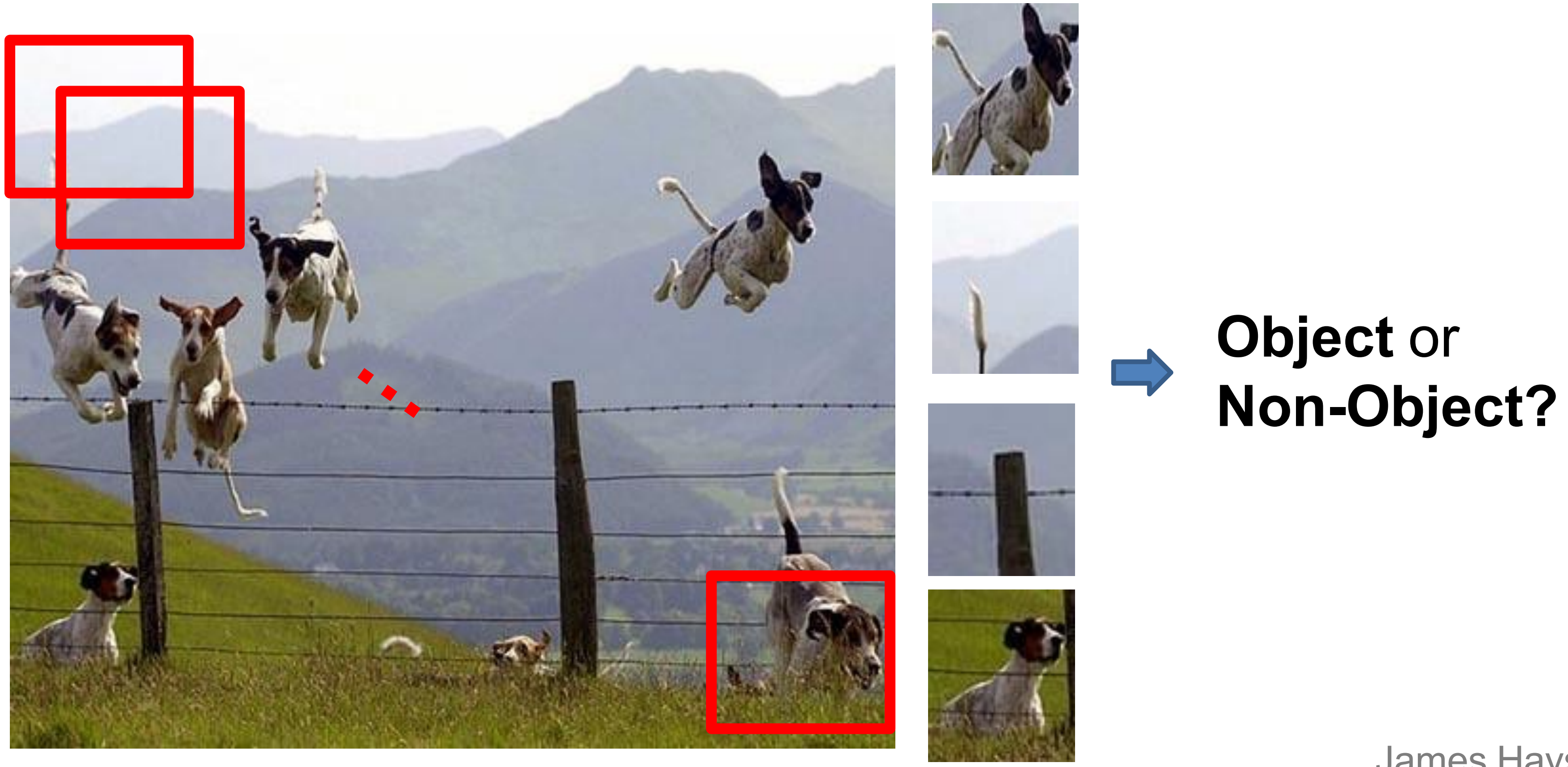
How many object categories are there?



Biederman 1987

Object Category Detection

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



James Hays

Challenges in modeling the object class

Illumination

Object pose

‘Clutter’

Occlusions

Intra-class appearance

Viewpoint

[K. Grauman, B. Leibe]

Object Detection Design challenges

- How to efficiently search for likely objects
  - Even simple models require searching hundreds of thousands of positions and scales.

- Feature design and scoring
  - How should appearance be modeled?
  - What features correspond to the object?

- How to deal with different viewpoints?
  - Often train different models for a few different viewpoints

General Process of Object Detection

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

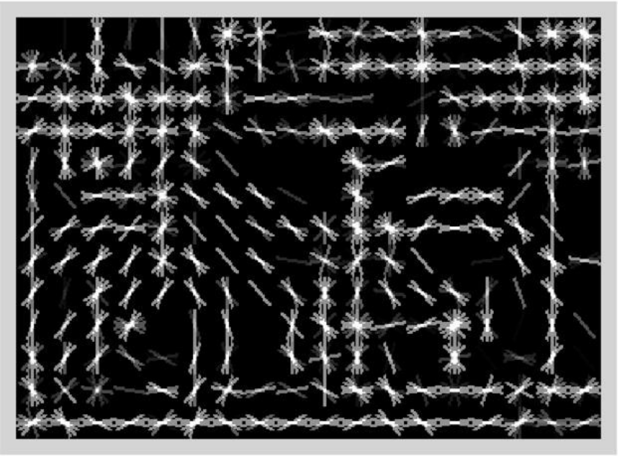
Resolve Detections

What are the object parameters?

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

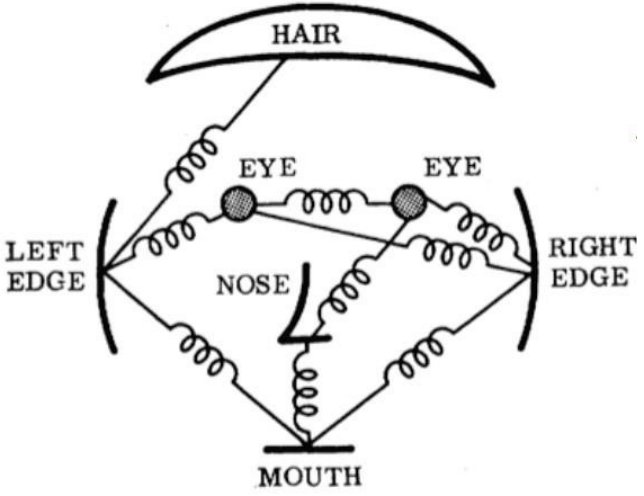


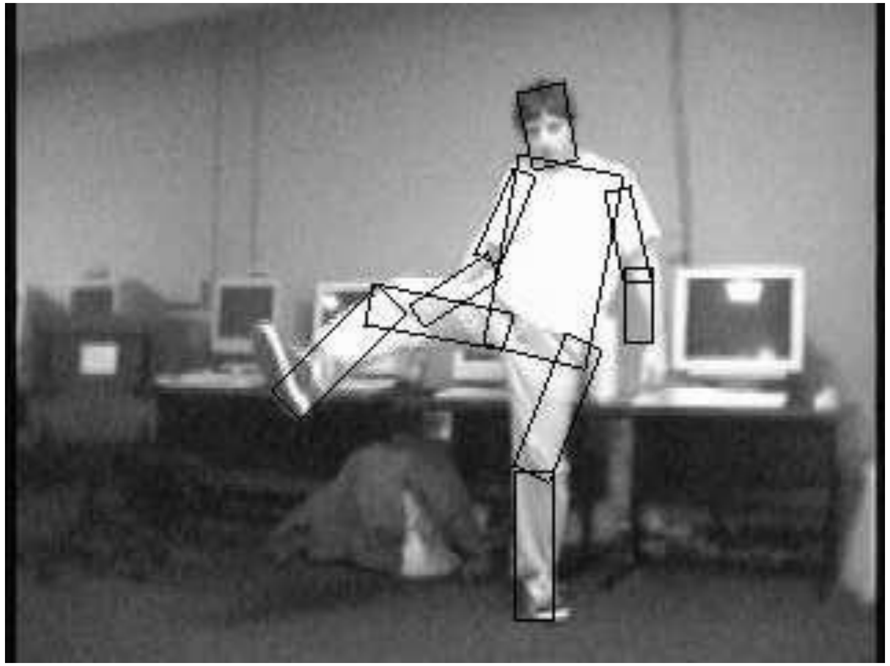
Template Visualization

Images from Felzenszwalb

Specifying an object model

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





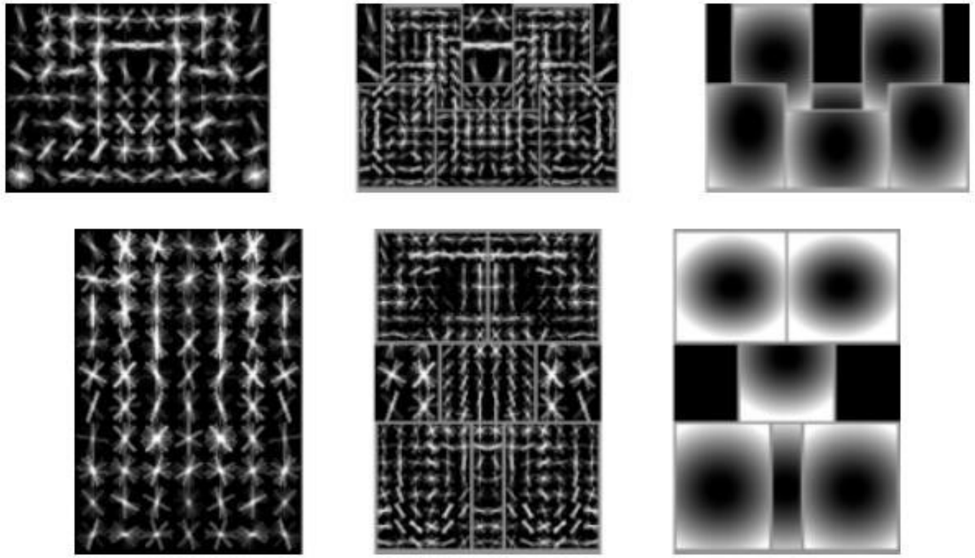
Images from Felzenszwalb

Specifying an object model

3. Hybrid template/parts model

Detections

Template Visualization



root filters
coarse resolution

part filters
finer resolution

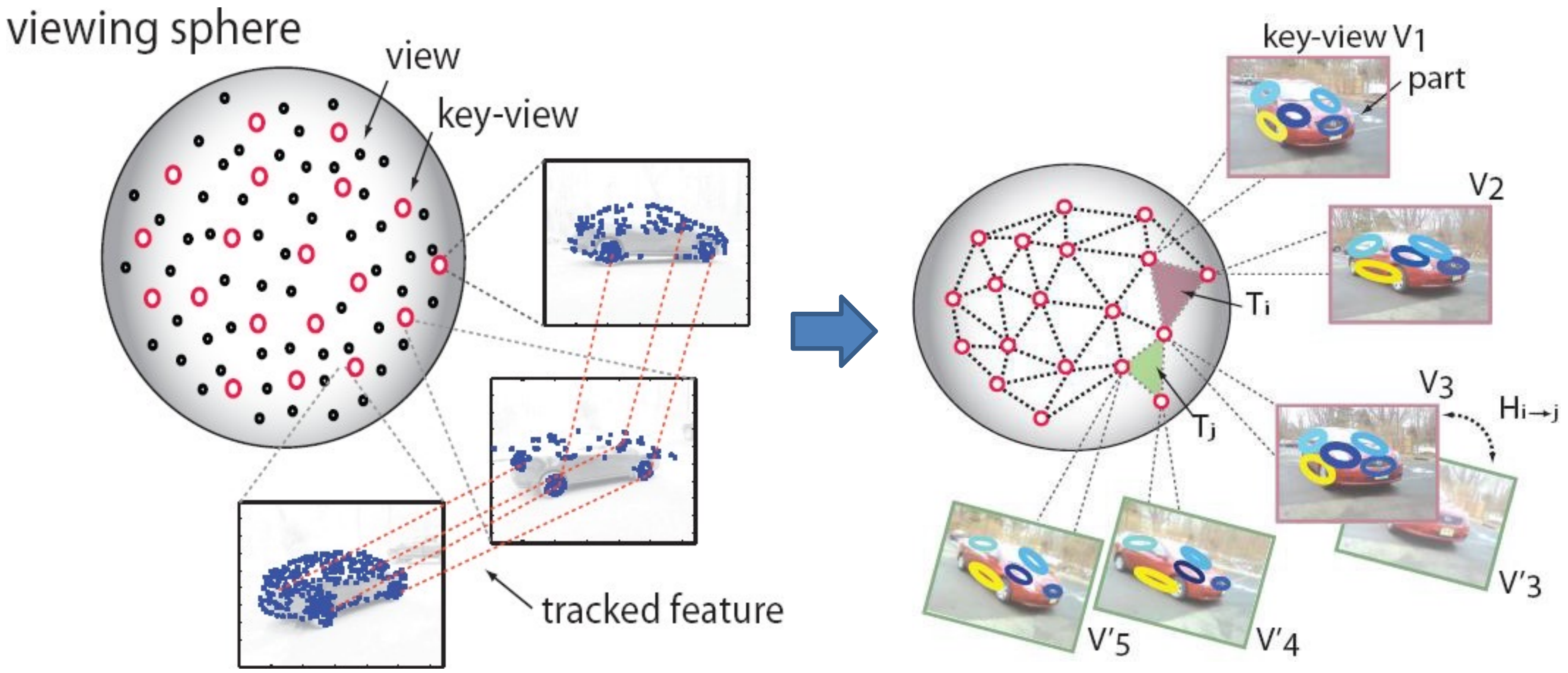
deformation
models

Felzenszwalb et al. 2008

Specifying an object model

4. 3D-ish model

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

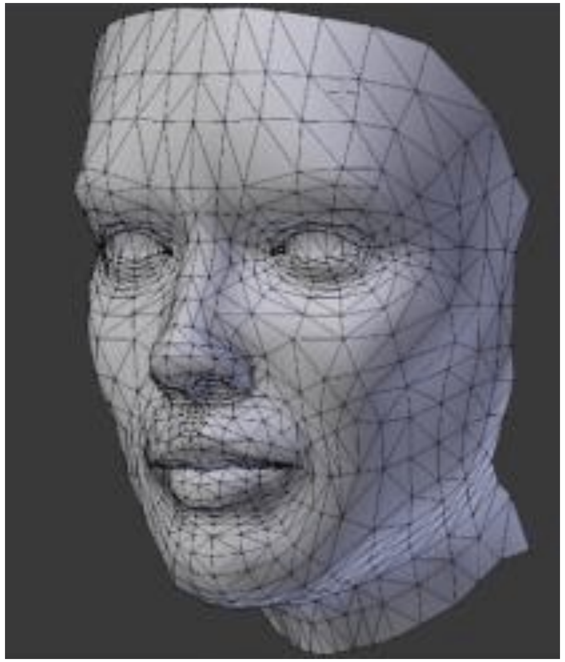


Loper et al. 2015

Specifying an object model

5. Deformable 3D model

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

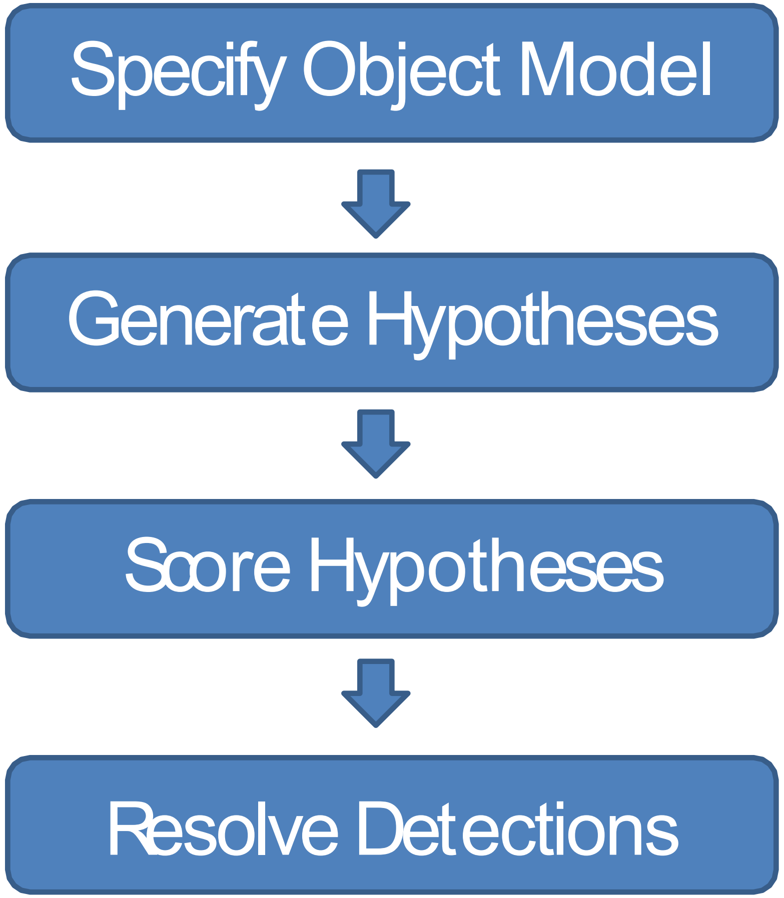


Why not just pick the most complex model?

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

- “Bounding Box” is still practically the most popular

General Process of Object Detection



Propose an alignment of the model to the image

Generating hypotheses

1. 2D template model / sliding window

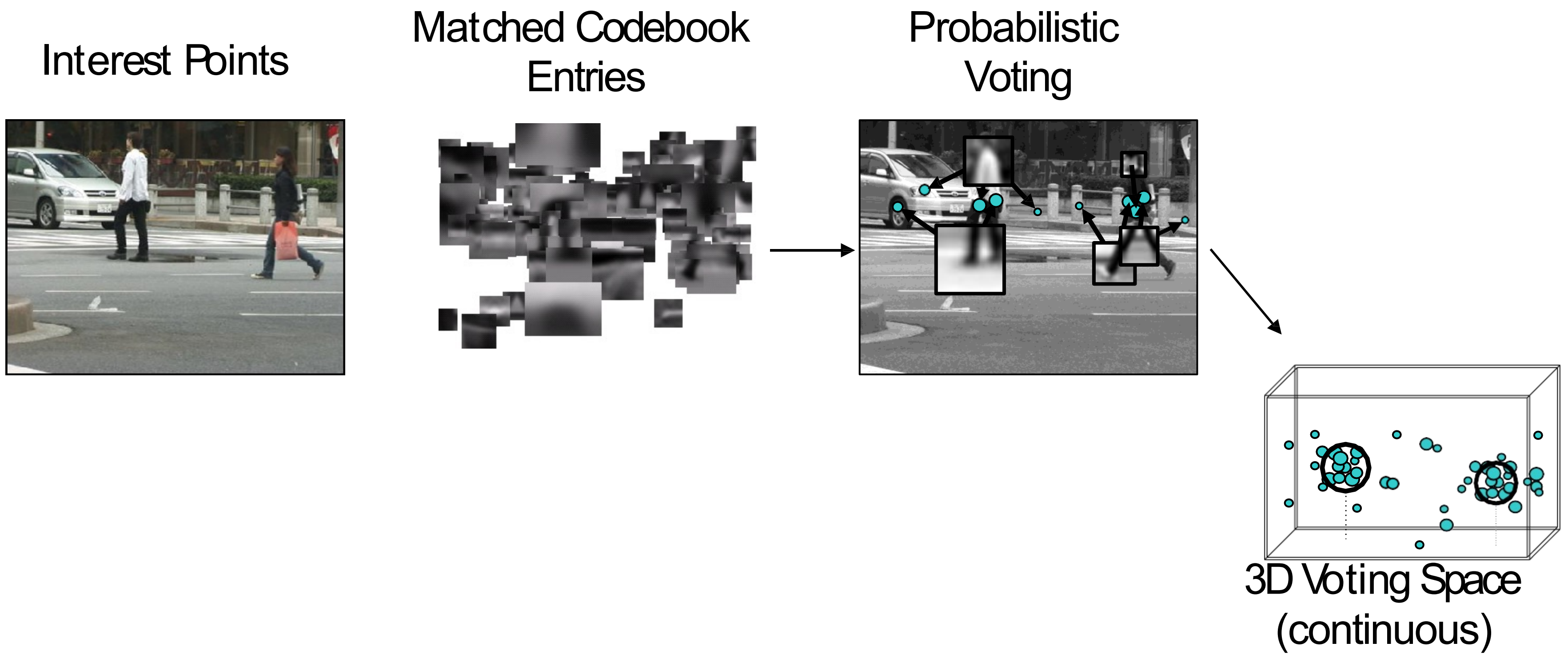
– Test patch at each location and scale

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.

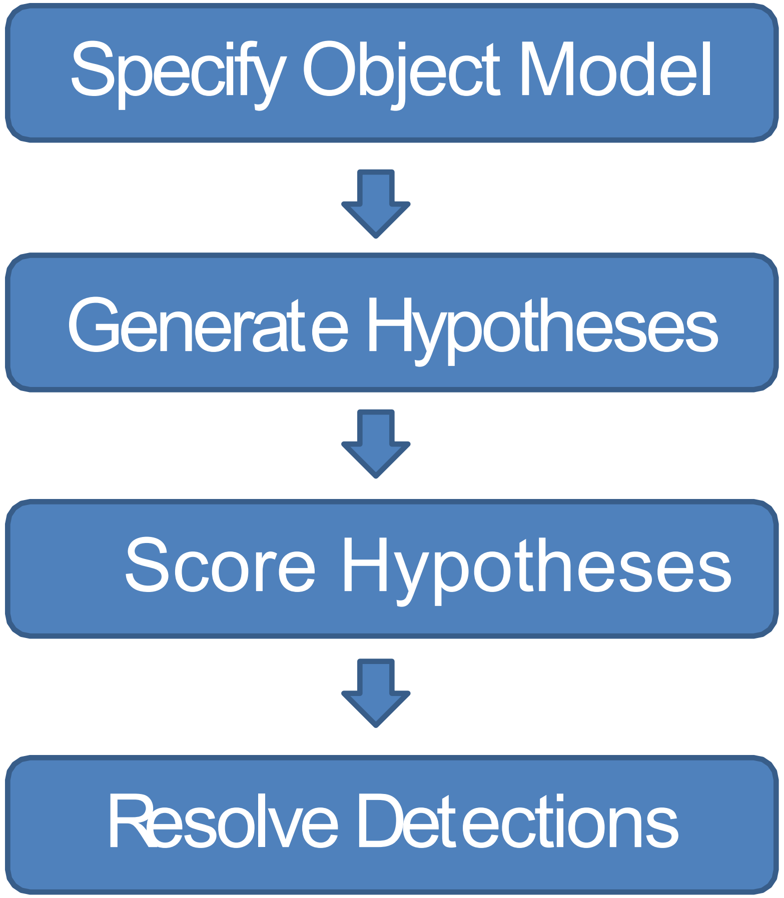
Generating hypotheses

3. Region-based proposal

- Arbitrary bounding box + image ‘cut’ segmentation

Endres Hoiem 2010

General Process of Object Detection



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

General Process of Object Detection

Specify Object Model

↓

Generate Hypotheses

↓

Score Hypotheses

↓

Resolve Detections

“Globally ”rescore each proposed object based on whole set, to resolve conflicts (non-max suppression, context-reasoning…)

Influential Works in Object Detection

- Sung-Poggio (1994, 1998) : ~2000 citations
  – Basic idea of statistical template detection, bootstrapping to get “face-like” negative examples, multiple whole-face prototypes (in 1994)
- Rowley-Baluja-Kanade (1996-1998) : ~3600
  – “Parts” at fixed position, non-maxima suppression, simple cascade, rotation, pretty good accuracy, fast
- Schneiderman-Kanade (1998-2000,2004) : ~1700
  – Careful feature engineering, excellent results, cascade
- Viola-Jones (2001, 2004) : ~13,000
  – Haar-like features, Adaboost as feature selection, hyper-cascade, very fast
- Dalal-Triggs (2005) : ~16,000 citations
  – Careful feature engineering, excellent results, HOG feature, online code
- Felzenszwalb-McAllester-Ramanan (2008): ~4,600 citations
  – Template/parts-based blend
- Girshick et al. (2013): ~2000 citations
  – R-CNN / Fast R-CNN / Faster R-CNN. Deep learned models on object proposals.

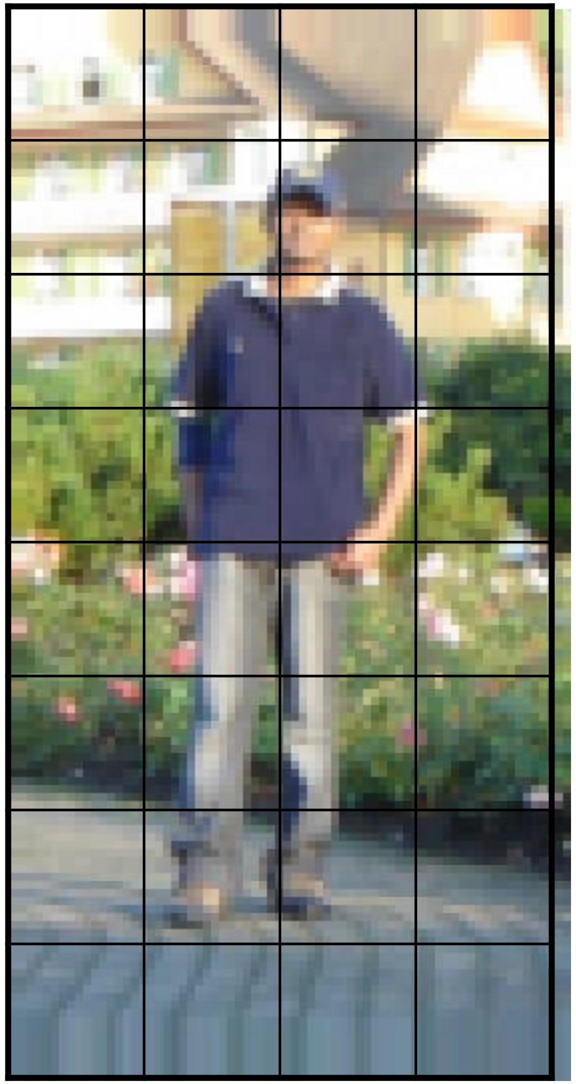
Dalal-Triggs Object Detector

- 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/

Example: Dalal-Triggs pedestrian detection

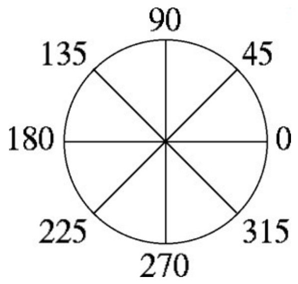
1. Extract fixed-sized (64x128 pixel) **window** at each position and scale
2. Compute **HOG** (histogram of oriented gradient) features within each window
3. Score the window with **a linear SVM classifier**
4. Perform **non-maxima suppression** to remove overlapping detections with lower scores

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

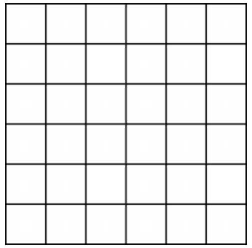


Histogram of Oriented Gradients

Orientation by bins



Histograms over
k x k pixel cells



– Votes weighted by magnitude

– Bilinear interpolation between cells

Navneet Dalal and Bill Triggs, Histograms of Oriented Gradients for Human Detection, CVPR05

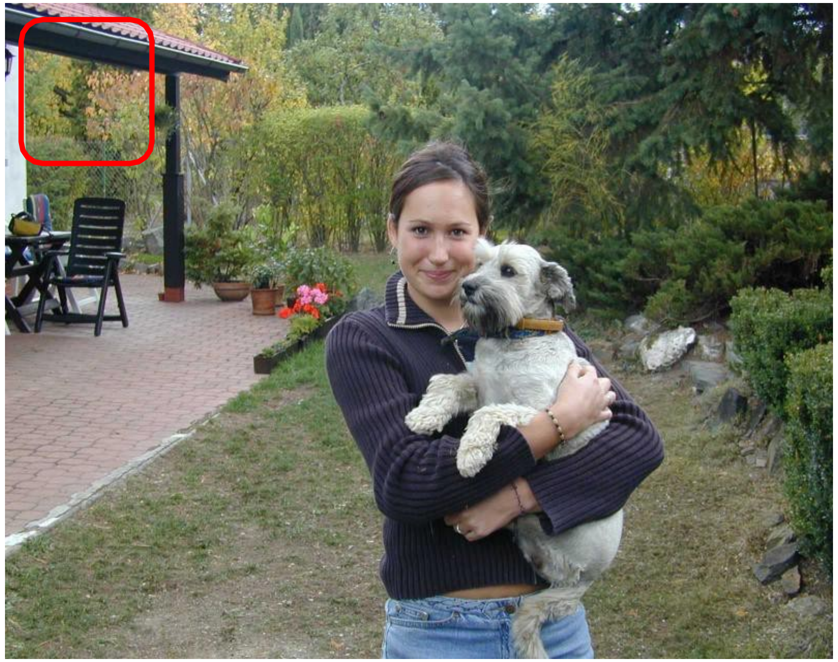
Dalal-Triggs uses a template with a **rigid form**

- Human bodies are boxed shaped
- That’s why Dalal-Triggs is best known for pedestrian detection

But…is there a way to learn the spatial layout more **fluidly**?

- Might help us capture more appearance variation…
- What about faster, too? Since many positions might be “filtered”

Face detection and recognition



Detection

Recognition

"Sally"

Challenges of Face Detection

Sliding window = tens of thousands of location/scale evaluations, especially since faces are small

- One megapixel image has ~10^6 pixels
- …and a comparable number of candidate face locations

Faces are also rare: 0–10 per image

- For computational efficiency, spend as little time as possible on non-face windows.
- For 1M pix, to avoid having a false positive in every image, our false positive rate must 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:

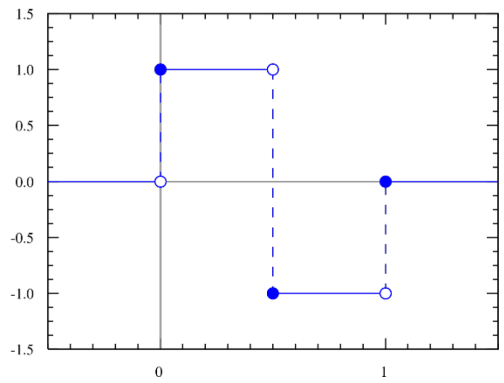
1. *Integral images* for fast feature evaluation
2. *Boosting* for feature selection
3. *Attentional cascade* for fast non-face window rejection

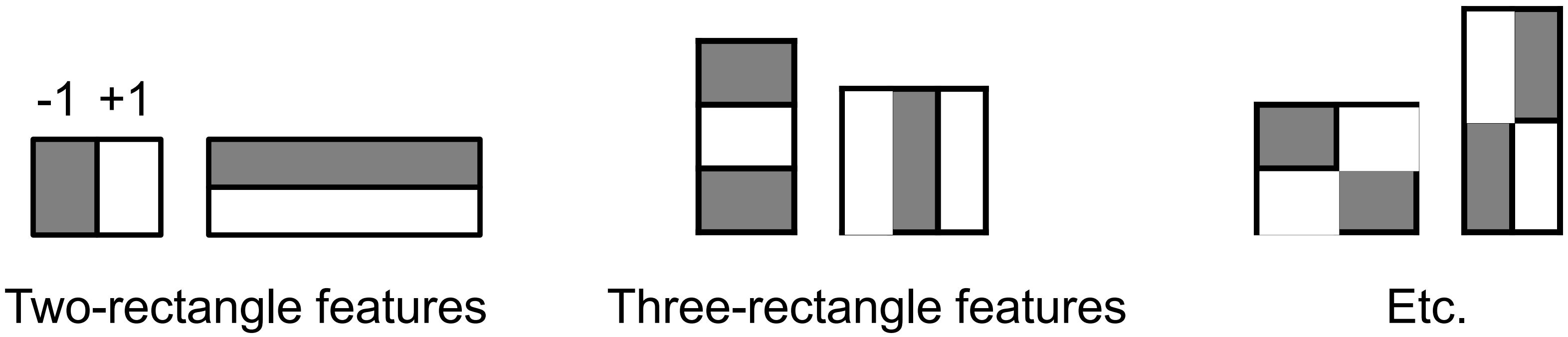
P. Viola and M. Jones. *Rapid object detection using a boosted cascade of simple features.* CVPR 2001.
P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

"Haar-like features"

- Differences of sums of intensity
- Computed at different positions and scales within sliding window
- Very fast to compute (thanks to "integral image")

Haar wavelet



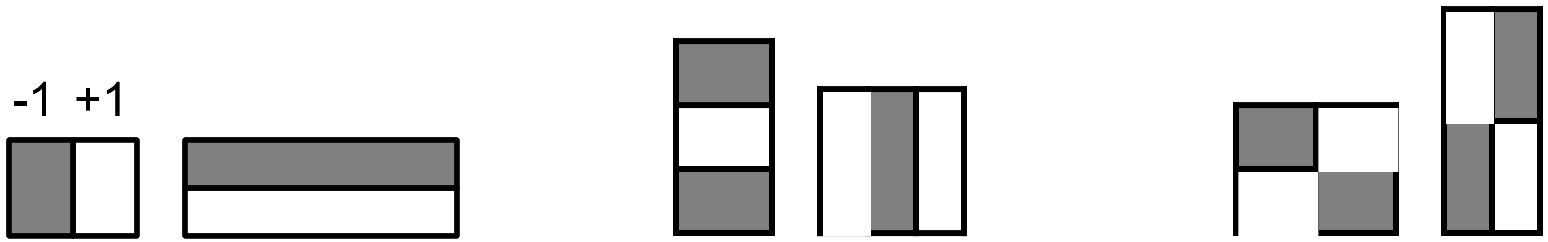


But these features are rubbish…!

Yes, individually they are ‘weak classifiers’

Jargon: ‘feature’ and ‘classifier’ are used interchangeably here.
Also with ‘learner’, ‘filter’.

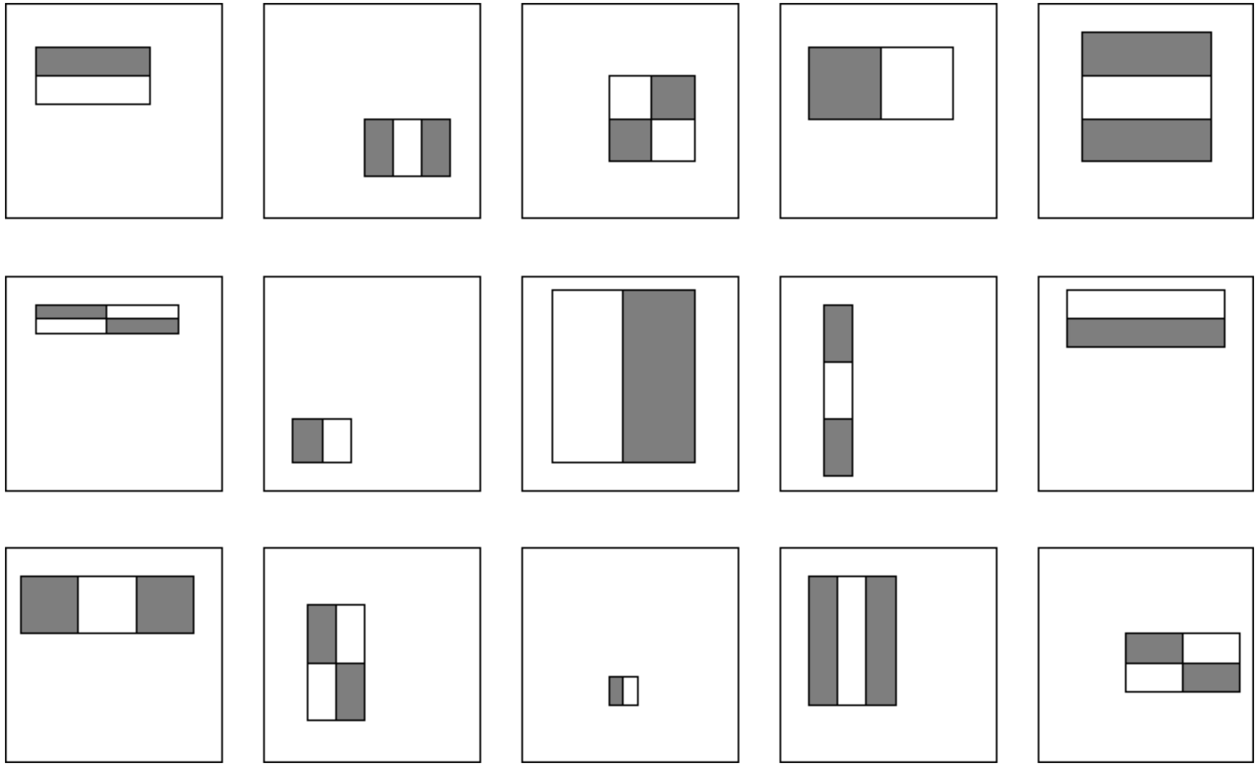
But, what if we combine *thousands* of them…



Two-rectangle features   Three-rectangle features   Etc.

How many features are there?

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



How many features are there?

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

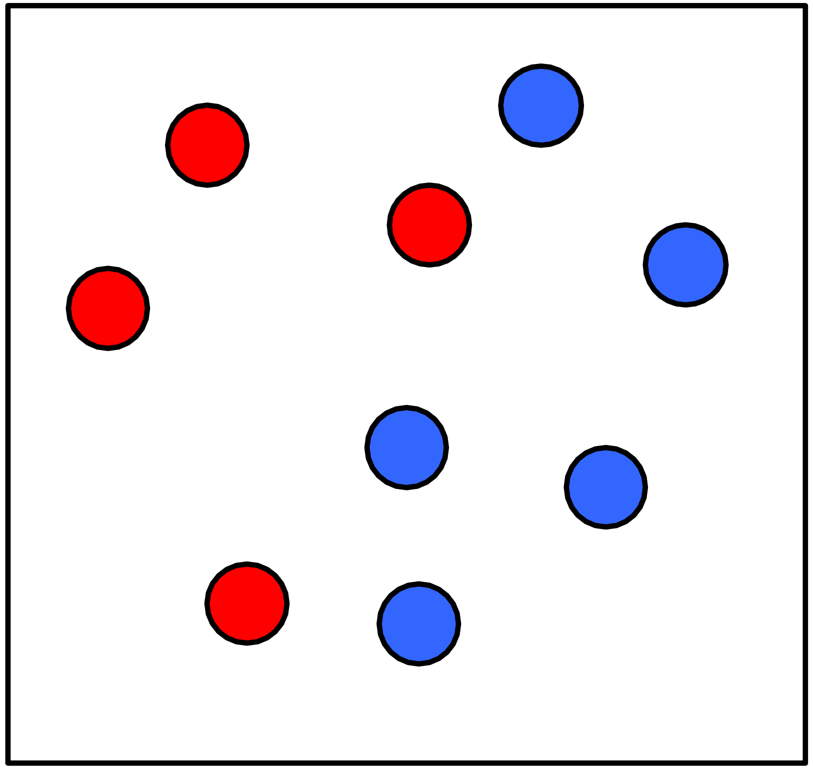
- At test time, it is impractical to evaluate the entire feature set.

- Can we learn a ‘strong classifier’ using just a small subset of all possible features?

Boosting for feature selection

Initially, weight each training example equally.

Weight = size of point



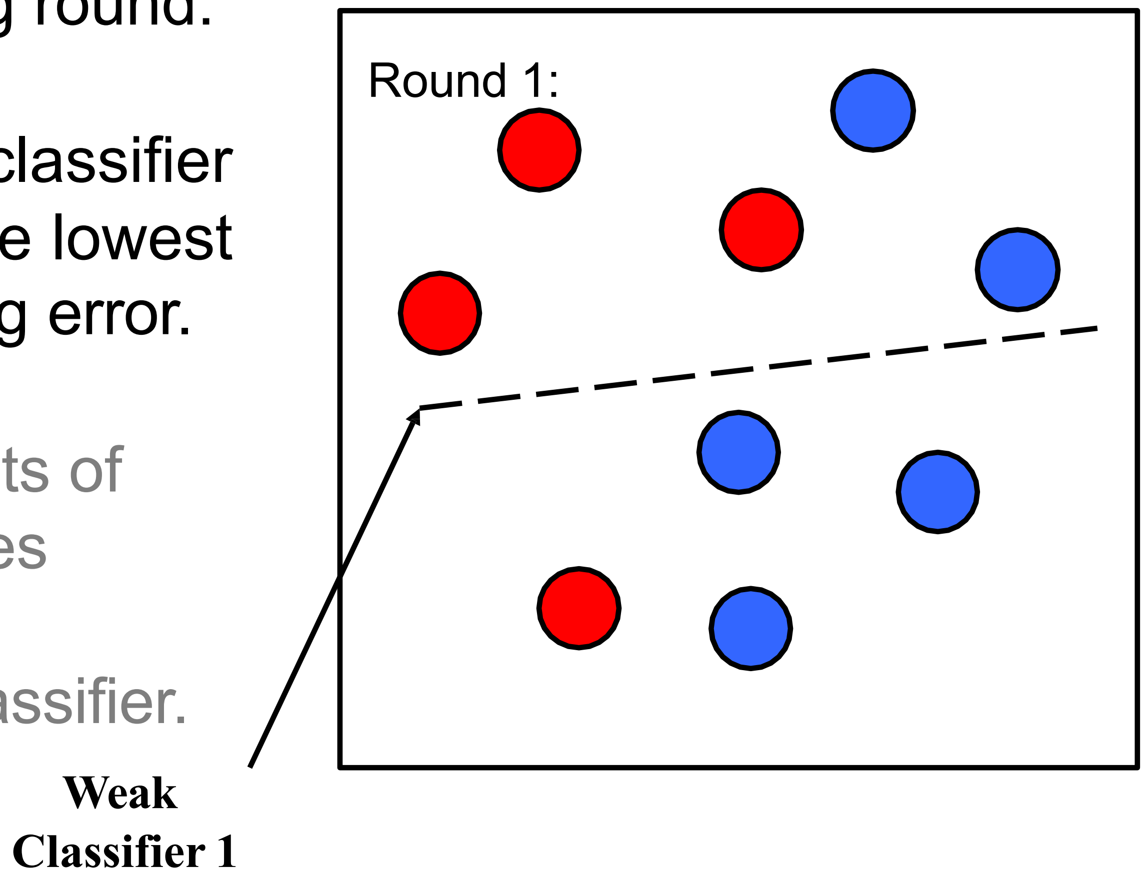
Slide credit: Paul Viola

Boosting for feature selection

In each boosting round:

Find the weak classifier that achieves the lowest *weighted* training error.

Raise the weights of training examples misclassified by current weak classifier.



Slide credit: Paul Viola

Boosting illustration

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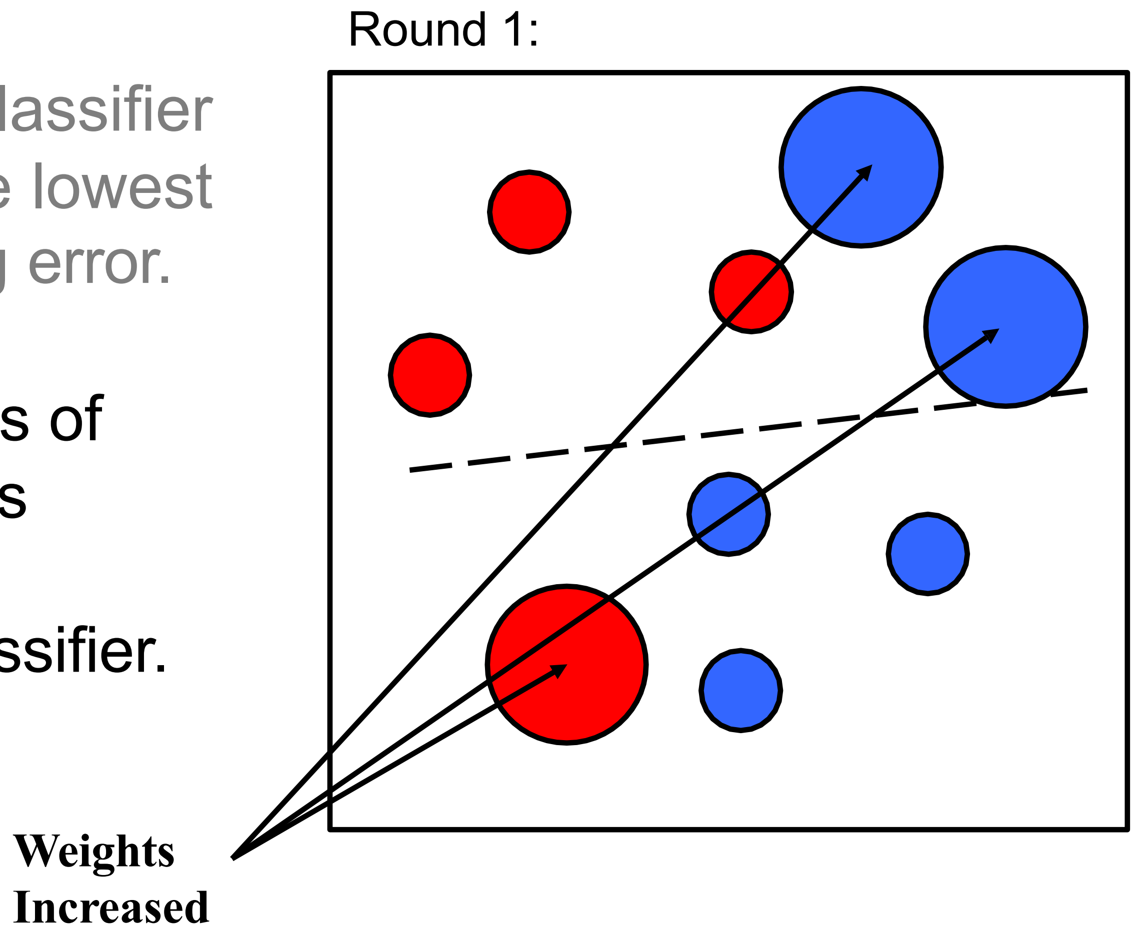

Boosting illustration

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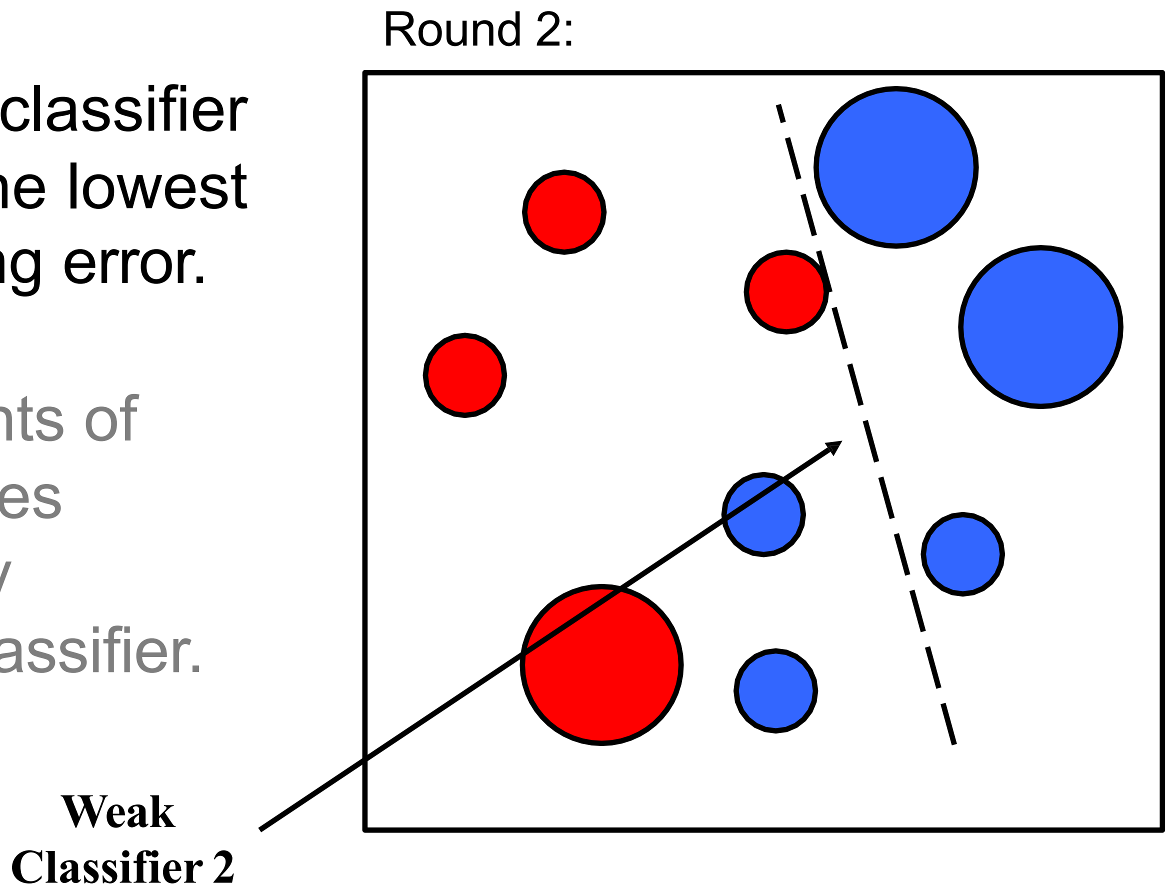

Boosting illustration

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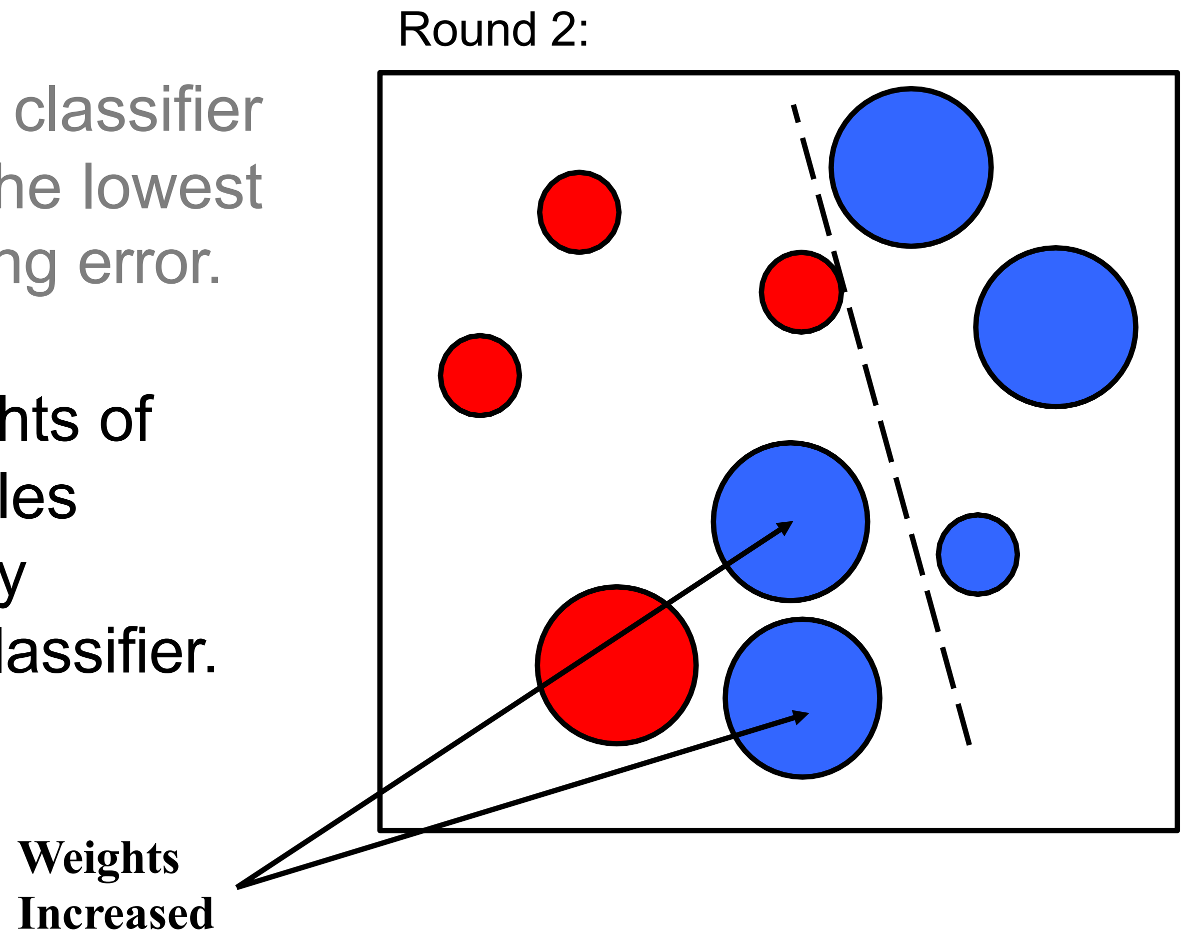

Boosting illustration

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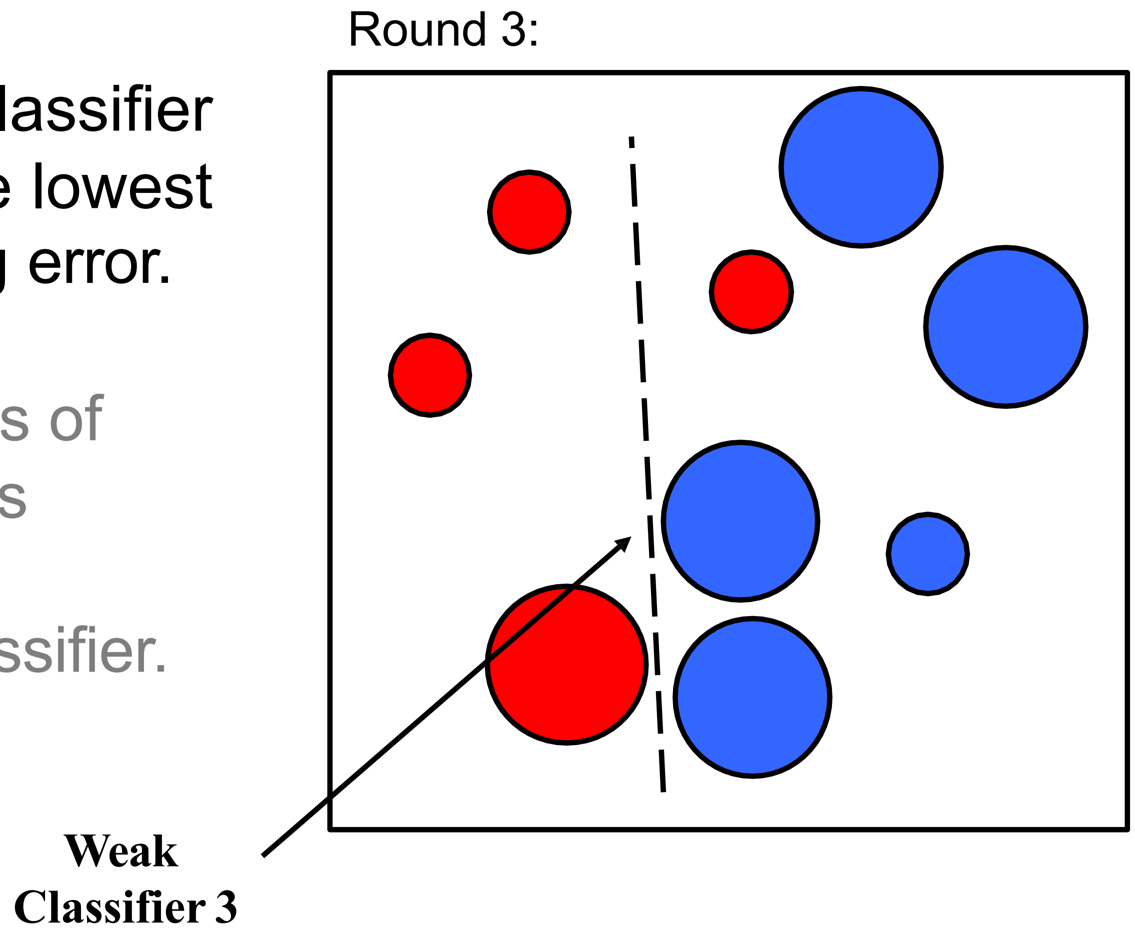
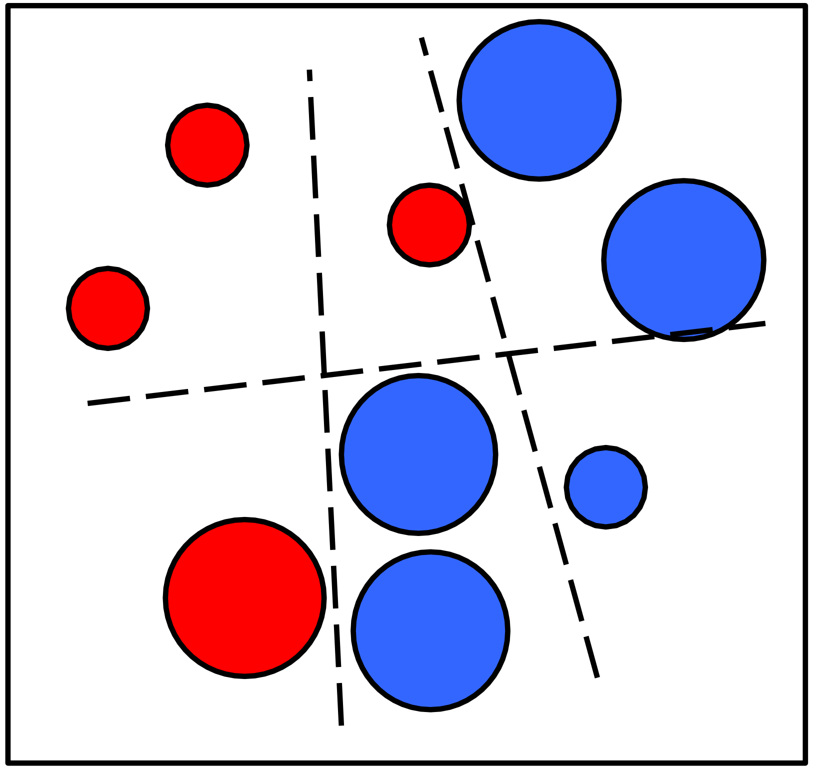


Boosting illustration

Round 3:



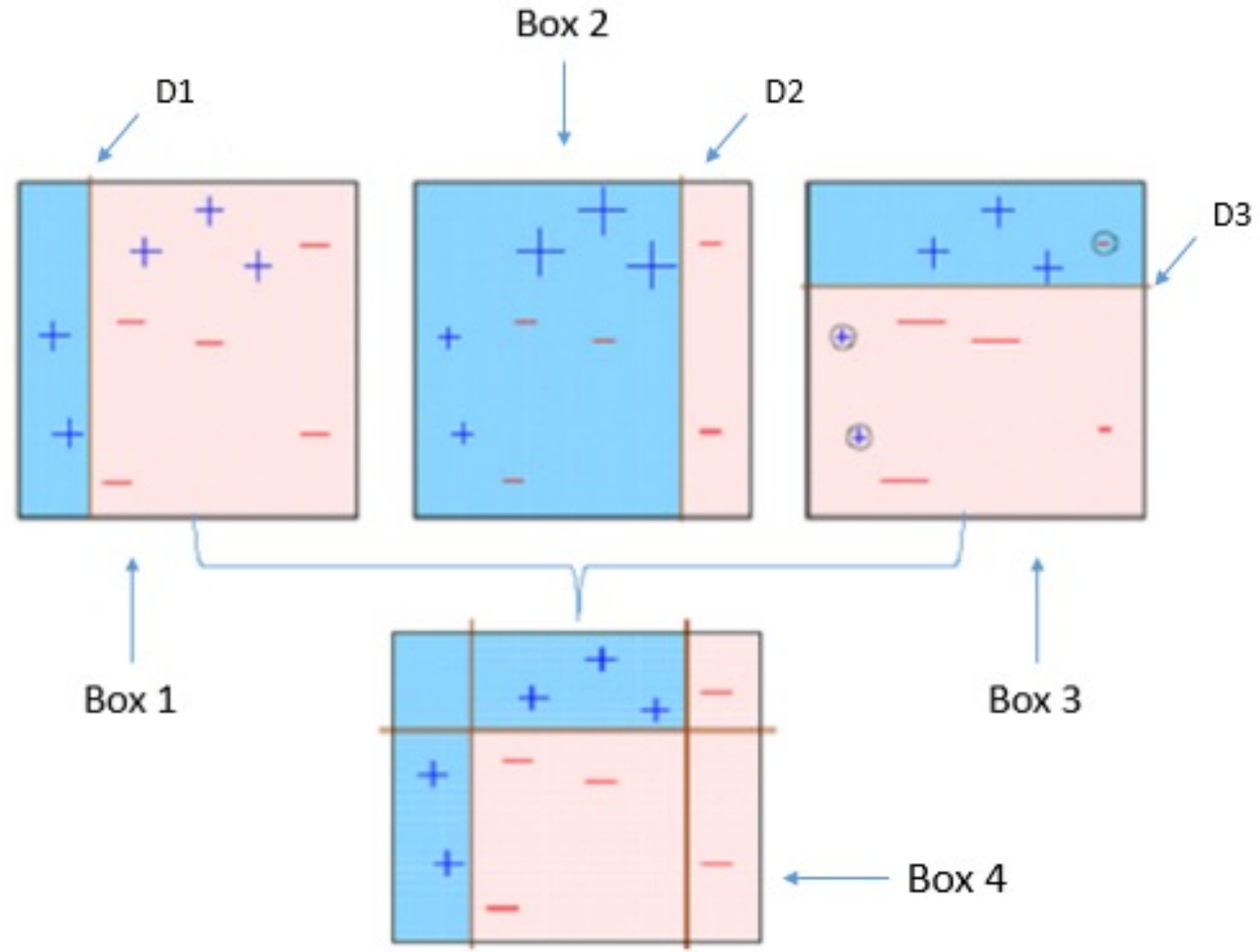
Compute final classifier as linear combination of all weak classifier.

Weight of each classifier is directly proportional to its accuracy.

Exact formulas for re-weighting and combining weak learners depend on the 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 illustration



Feature selection with boosting

- Create a large pool of features (160K)
- Select discriminative features that work well together

Final strong learner

window

$$h(\mathbf{x}) = \text{sign}\left(\sum_{j=1}^{M} \alpha_j h_j(\mathbf{x})\right)$$

Weak learner

Learner weight

  - "Weak learner" = feature + threshold + 'polarity'

value of rectangle feature

$$h_j(\mathbf{x}) = \begin{cases} -s_j & \text{if } f_j < \theta_j \\ s_j & \text{otherwise} \end{cases}$$

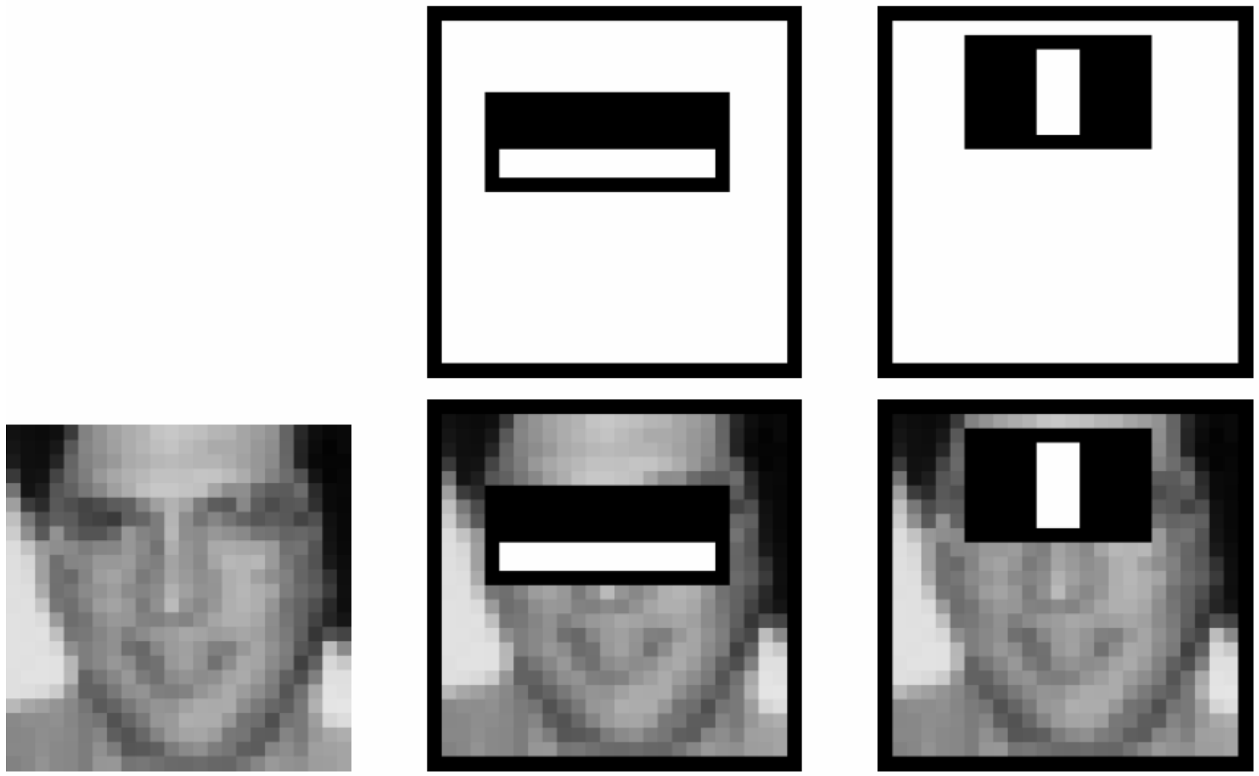
threshold

'polarity' = black or white region flip → $s_j \in \pm 1$

  - Train & choose weak learner that minimizes error on the weighted training set, then reweight

Boosting for face detection

- First two features selected by boosting:



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

Boosting for feature selection

Boosting combines *weak learners* into a more accurate *ensemble classifier.*

- Weak learners based on rectangle filters:

value of rectangle feature

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

window

polarity

threshold

- Ensemble classification function:

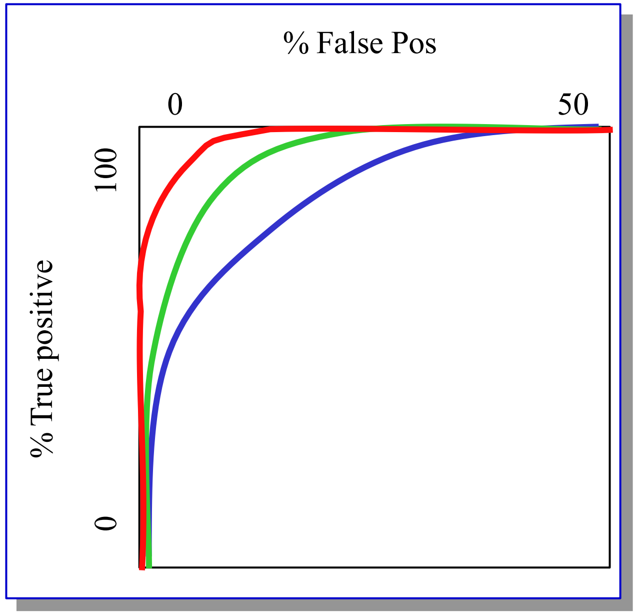
$$C(x) = \begin{cases} 1 & \text{if } \sum_{t=1}^{T} \alpha_t h_t(x) > \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$

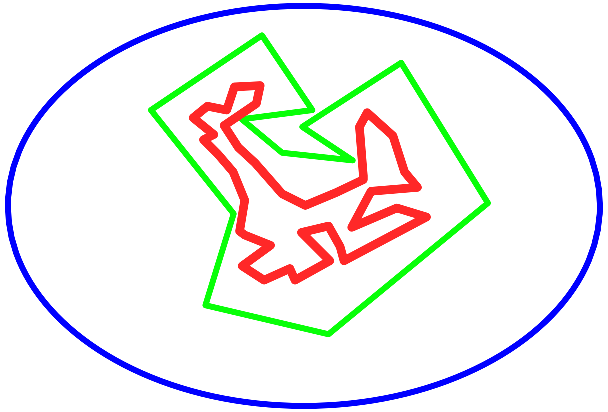
learned weights

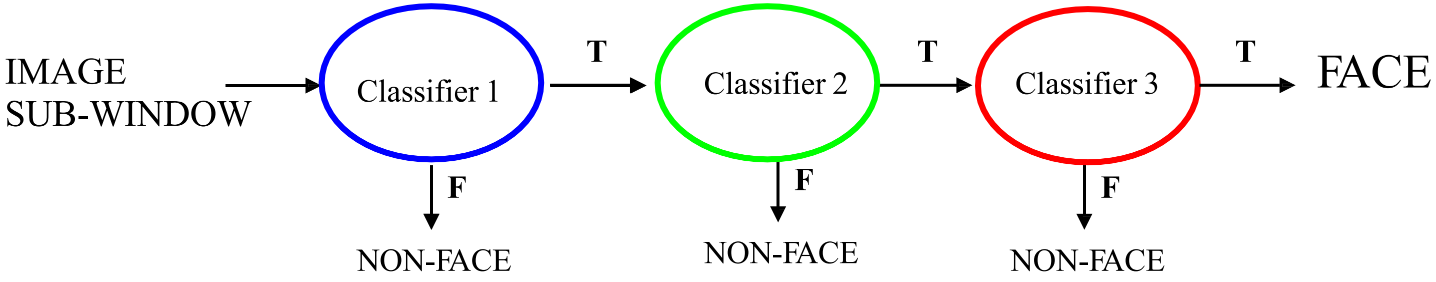
3. Attentional cascade

- Chain classifiers that are progressively more complex
- Minimize *false positive rates* at each stage, not absolute error

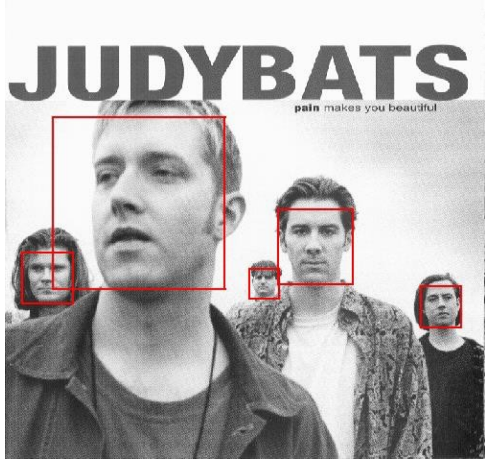
Receiver operating characteristic

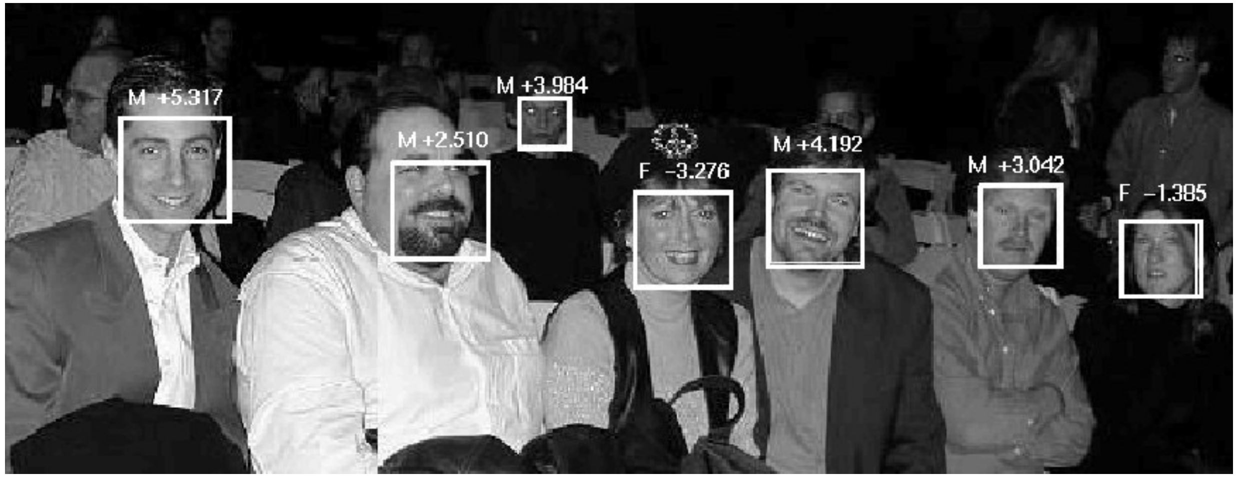


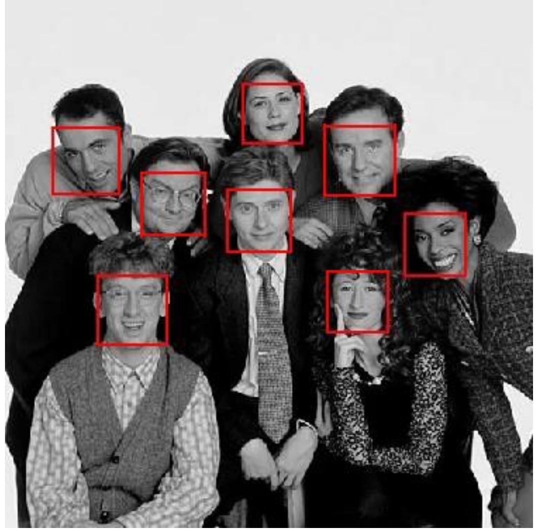


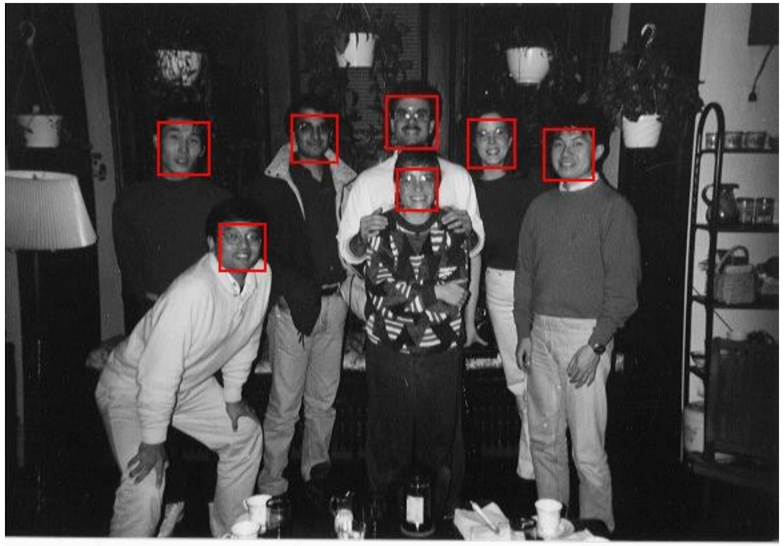


Viola/Jones detector is very powerful









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