Object Detection

Lu Peng
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Machine Vision Technology							
Semantic information				Metric 3D information			
Pixels	Segments	Images	Videos	Camera		Multi-view Geometry	
Convolutions Edges & Fitting Local features Texture	Segmentation Clustering	Recognition Detection	Motion Tracking	Camera Model	Camera Calibration	Epipolar Geometry	SFM
10	4	4	2	2	2	2	2

What we will learn today?

- Introduction of object detection
- Face Detection
- Pedestrian Detection

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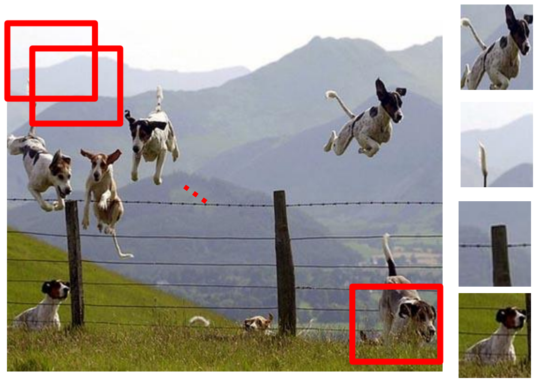
Object Category Detection

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



Object or Non-Object?

Source: James Hays

Challenges in modeling the object class

Illumination

Object pose

‘Clutter’

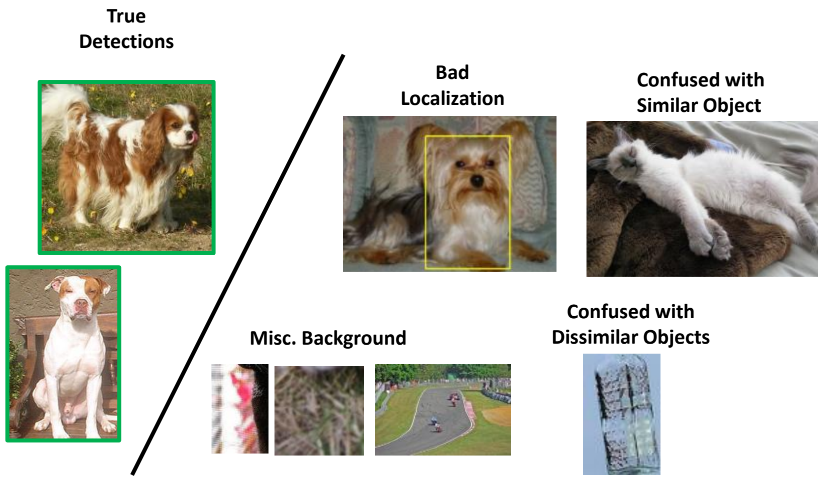
Occlusions

Intra-class appearance

Viewpoint

Source: K. Grauman

Challenges in modeling the non-object class



Source: James Hays

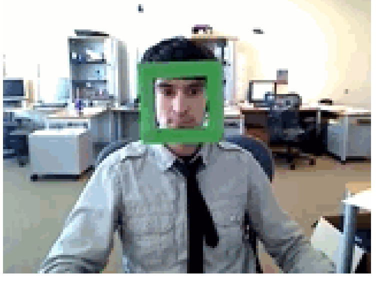
Object Detection Design challenges

- 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

What we will learn today?

- Introduction of object detection
- **Face Detection**
- Pedestrian Detection

Face Detection



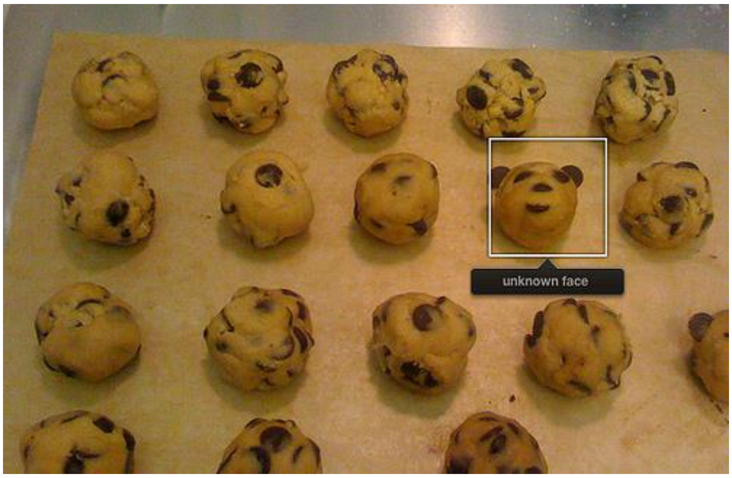
Behold a state-of-the-art face detector!

(Courtesy Boris Babenko)

Source： Svetlana Lazebnik

Consumer application: Apple iPhoto

[Things iPhoto thinks are faces]



Source： Svetlana Lazebnik

"The Nikon S60 detects up to 12 faces."

Source： Svetlana Lazebnik

Face detection and recognition

Source： Svetlana Lazebnik

Challenges of face detection

- **Sliding window = tens of thousands of location/scale evaluations**
  - One megapixel image has ~10^6 pixels, and a comparable number of candidate face locations
- **Faces are rare: 0–10 per image**
  - For computational efficiency, spend as little time as possible on the non-face windows.
  - For 1 Mpix, to avoid having a false positive in every image, our false positive rate has to be less than 10^{-6}

Source:James Hays

Sliding Window Face Detection with Viola-Jones

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.

Source： Svetlana Lazebnik

Rapid object detection using a boosted cascade of simple features
P Viola, M Jones - Proceedings of the 2001 IEEE computer …, 2001 - ieeexplore.ieee.org
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Histograms of oriented gradients for human detection
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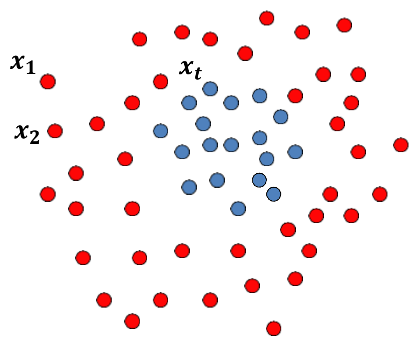
Why boosting?

- A simple algorithm for learning robust classifiers
  - Freund & Shapire, 1995
  - Friedman, Hastie, Tibshhirani, 1998
- Provides efficient algorithm for sparse visual feature selection
  - *Tieu & Viola, 2000*
  - *Viola & Jones, 2003*
- Easy to implement, not requires external optimization tools.

Boosting - mathematics

- **It is a sequential procedure:**



Each data point has a class label:

$$y_t = \begin{cases} +1 & (\bullet) \\ -1 & (\bullet) \end{cases}$$

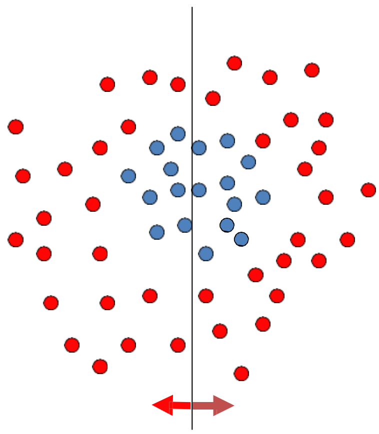
and a weight:

$w_t = 1$

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

Toy example

Weak learners from the family of lines



Each data point has a class label:

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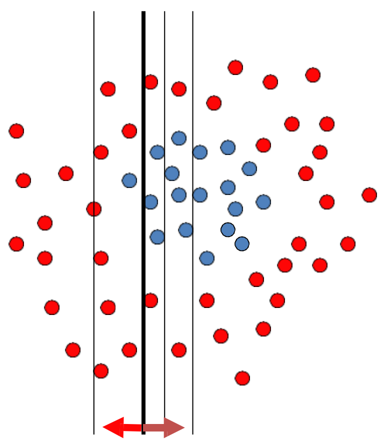
and a weight:

w_t**=1**

h => p(error) = 0.5 it is at chance

Toy example



Each data point has a class label:

$$y_t = \begin{cases} +1 & (\bullet) \\ -1 & (\bullet) \end{cases}$$

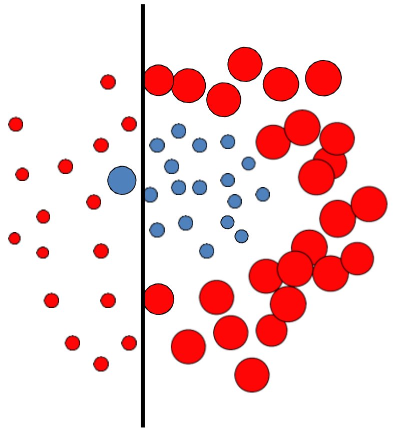
and a weight:

w_t**=1**

This one seems to be the best

This is a 'weak classifier': It performs slightly better than chance.

Toy example



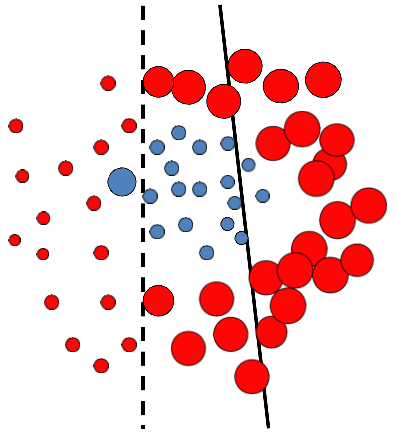
Each data point has a class label:

$$y_t = \begin{cases} +1 & (\text{red}) \\ -1 & (\text{blue}) \end{cases}$$

We update the weights:

$$\boxed{w_{t+1,i} \leftarrow w_{t,i}\beta_t^{1-|h_t(x_i)-y_i|}}$$

Toy example



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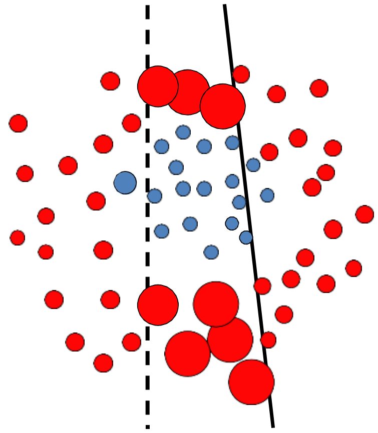

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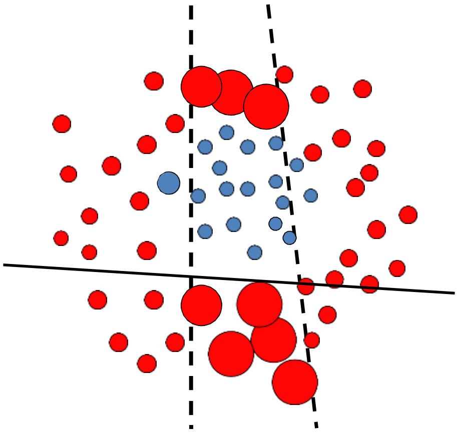

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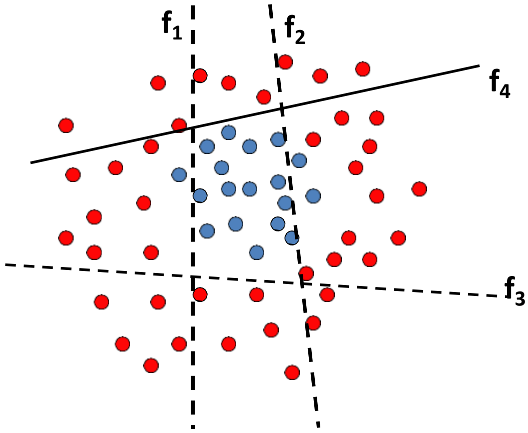

The strong (non- linear) classifier is built as the combination of all the weak (linear) classifiers.

Boosting - mathematics

- Defines a classifier using an additive model:

$$\boldsymbol{h}(\boldsymbol{x}) = \boldsymbol{\alpha}_1\boldsymbol{h}_1(\boldsymbol{x}) + \boldsymbol{\alpha}_1\boldsymbol{h}_1(\boldsymbol{x}) + \boldsymbol{\alpha}_1\boldsymbol{h}_1(\boldsymbol{x}) + \cdots$$

Strong classifier

Features vector

Weight

Weak classifier

- **We need to define a family of weak classifiers**

$\boldsymbol{h}_k(\boldsymbol{x})$ **form a family of weak classifiers**

Boosting - mathematics

- **Weak learners**

value of rectangle feature

$$h_j(x) = \begin{cases} 1 & \text{if } f_j(x) > \theta_j \\ 0 & \text{otherwise} \end{cases}$$

threshold

- **Final strong classifier**

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

Viola & Jones algorithm

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

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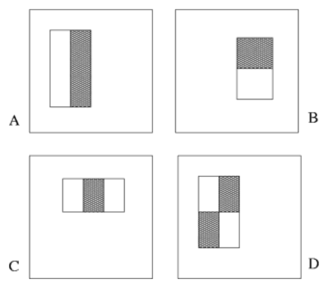
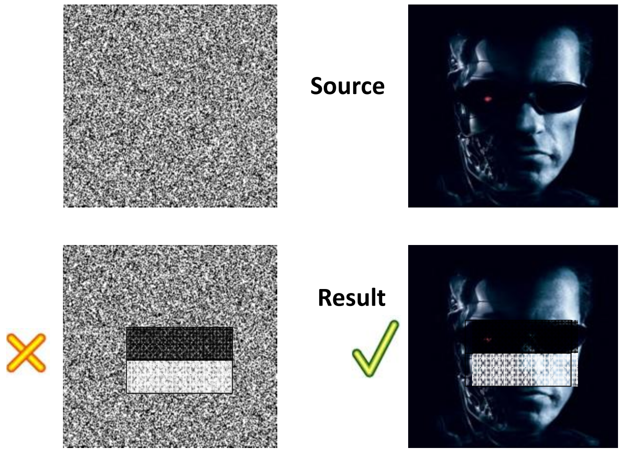
Weak classifier

- 4 kind of Rectangle filters
- Value = ∑ (pixels in white area) – ∑ (pixels in black area)



Source： Svetlana Lazebnik

Weak classifier

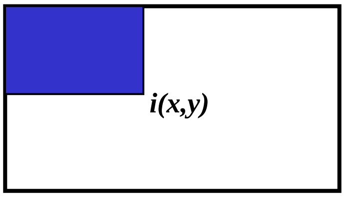


Source： Svetlana Lazebnik

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.
- ‘Summed area table’

$$I_{\Sigma}(x,y) = \sum_{\substack{x' \le x \\ y' \le y}} i(x',y')$$

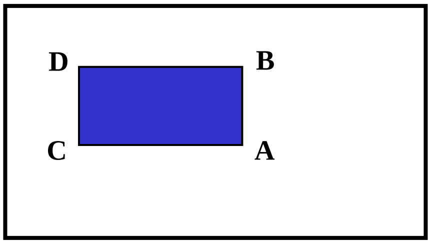


Source： Svetlana Lazebnik

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

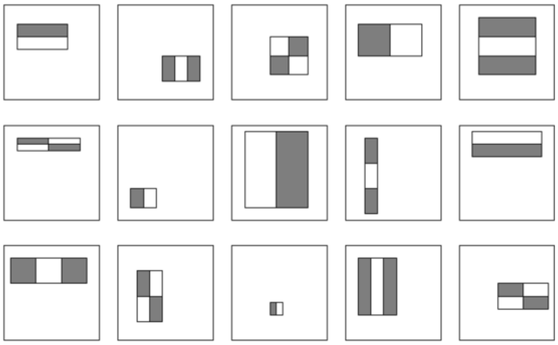


Only 3 additions are required for any size of rectangle!

Source: Svetlana Lazebnik

Viola & Jones algorithm

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



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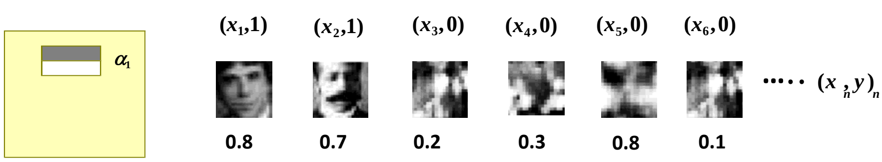
Viola & Jones algorithm

1. Evaluate each rectangle filter on each example



value of rectangle feature

Weak classifier $$h_j(x) = \begin{cases} 1 & \text{if } f_j(x) > \theta_j \\ 0 & \text{otherwise} \end{cases}$$

threshold

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

Viola & Jones algorithm

2. Select best filter/threshold combination

a. Normalize the weights $\boldsymbol{w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_j^n w_{t,j}}}$

$$h_j(x) = \begin{cases} 1 & \text{if } f_j(x) > \theta_j \\ 0 & \text{otherwise} \end{cases}$$

b. For each feature, j $\boldsymbol{\varepsilon_j = \sum_i w_i |h_j(x_i) - y_i|}$

c. Choose the classifier, h_t with the lowest error t

3. Reweight examples

$$\boldsymbol{w_{t+1,i} \leftarrow w_{t,i}\beta_t^{1-|h_t(x_i)-y_i|}} \qquad \boldsymbol{\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}}$$

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

Viola & Jones algorithm

4. The final strong classifier is

$$\boldsymbol{\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}}$$

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

$$\boldsymbol{\alpha_t = \log \frac{1}{\beta_t}}$$

The final hypothesis is a weighted linear combination of the T hypotheses where the weights are inversely proportional to the training errors

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

Viola & Jones algorithm

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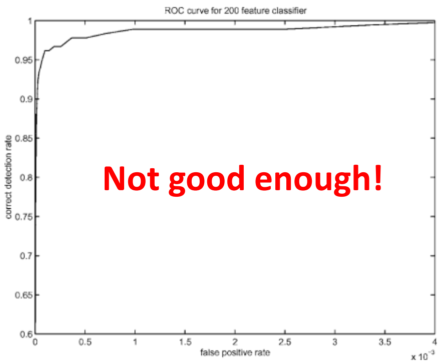
Boosting for face detection

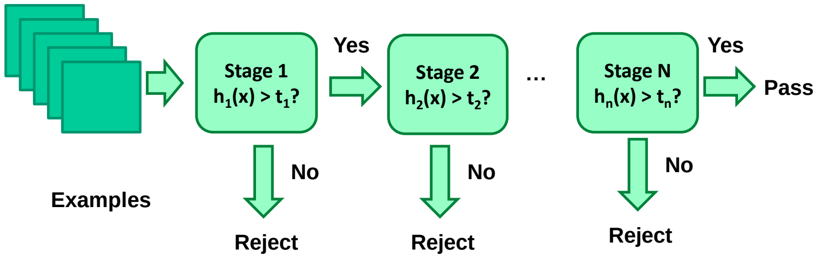
- A 200-feature classifier can yield 95% detection rate and a false positive rate of 1 in 14084



Receiver operating characteristic (ROC) curve

Source： Svetlana Lazebnik

Cascade for Fast Detection

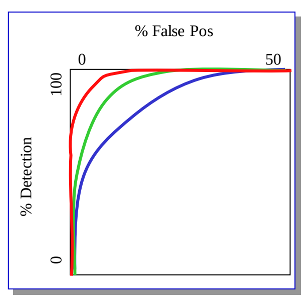


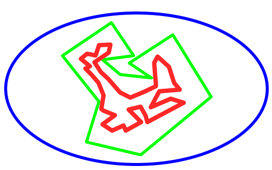
- Fast classifiers early in cascade which reject many negative examples but detect almost all positive examples.
- Slow classifiers later, but most examples don't get there.

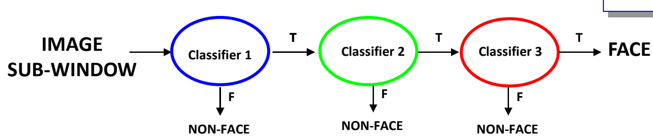
Attentional cascade

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

Receiver operating characteristic



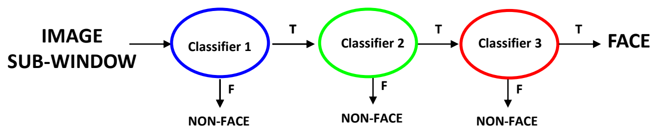




Source： Svetlana Lazebnik

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 ($0.3^{10} \approx 6\times10^{-6}$)



Source：Svetlana Lazebnik

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

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

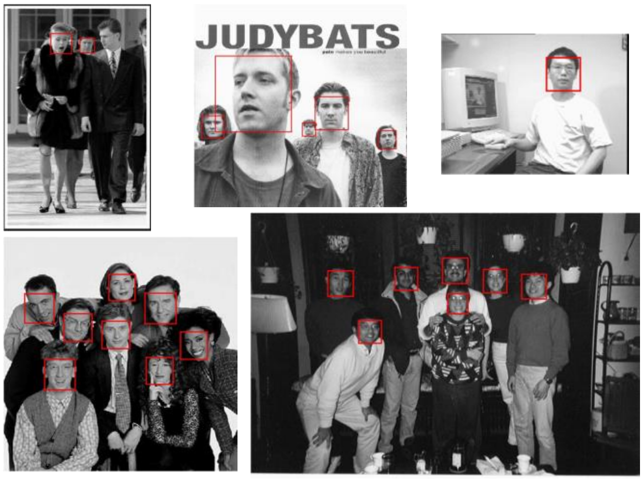
System performance

- 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)

- First two features selected by boosting:
- This feature combination can yield 100% detection rate and 50% false positive rate

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

Output of Face Detector on Test Images



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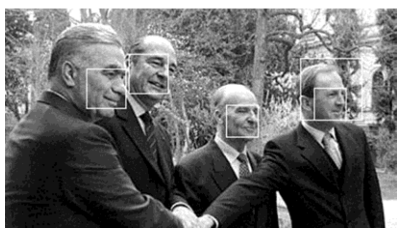
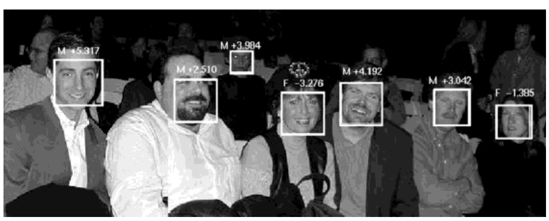
Other detection tasks

Facial Feature Localization



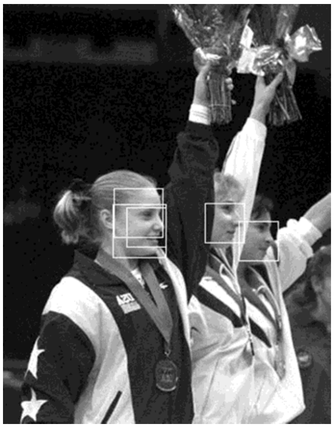
Profile Detection

Male vs. female



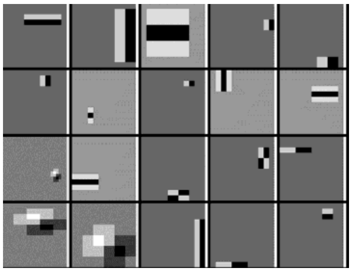
Source： Svetlana Lazebnik

Profile Detection



Source： Svetlana Lazebnik

Profile Features



Source： Svetlana Lazebnik

Face Image Databases

- Databases for face recognition can be best utilized as training sets
  - Each image consists of an individual on a uniform and uncluttered background
- Test Sets for face detection
  - MIT, CMU (frontal, profile), Kodak

What we will learn today?

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- Face Detection
- **Pedestrian Detection**

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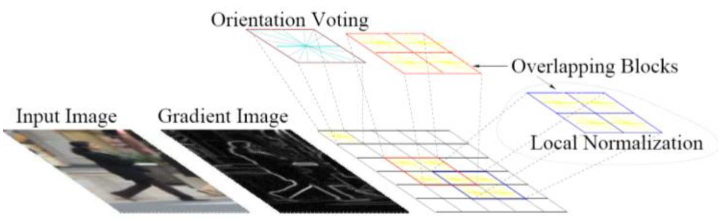
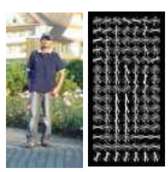
HoG Feature





detection window :64x128

Block size:16x16

Stride:8x8

Cell size:8x8

Bin number: 9

HOG dim： 3780

Code available: http://pascal.inrialpes.fr/soft/olt/

Source： Kristen Grauman

Dalal-Triggs pedestrian detector

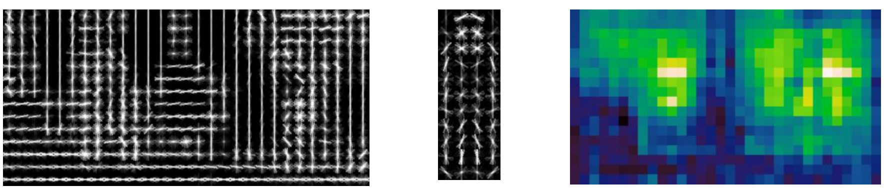
1. Extract fixed-sized (64x128 pixel) window at each position and scale
2. Compute HOG (histogram of gradient) features within each window
3. Score the window with a linear SVM classifier
4. Perform non-maxima suppression to remove overlapping detections with lower scores

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

Pedestrian detection with HOG

- Learn a pedestrian template using a support vector machine
- At test time, compare feature map with template over sliding windows.
- Find local maxima of response
- *Multi-scale*: repeat over multiple levels of a HOG pyramid

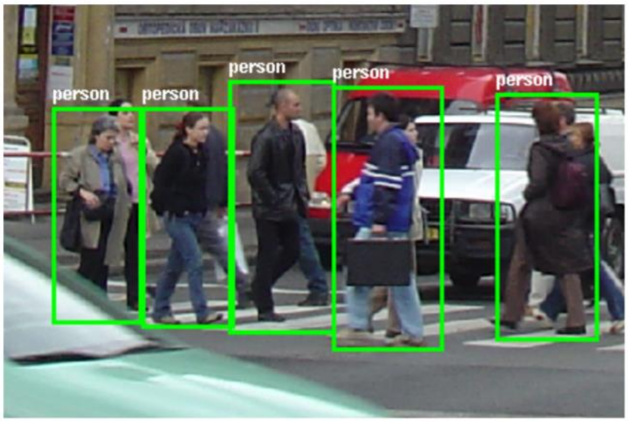
HOG feature map **Template** **Detector response map**



Can be continuous for more sophisticated maxima finding

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

INRIA pedestrian database



Source： Kristen Grauman

Something to think about…

- Sliding window detectors work
  - \- *very well* for faces
  - \- *fairly well* for cars and pedestrians
  - \- *badly* for cats and dogs
- Why are some classes easier than others?

Strengths/Weaknesses of Statistical Template Approach

- **Strengths**
  - Works very well for non-deformable objects with canonical orientations: faces, cars, pedestrians
  - Fast detection
- **Weaknesses**
  - Not so well for highly deformable objects or “stuff”
  - Not robust to occlusion
  - Requires lots of training data