Face detection

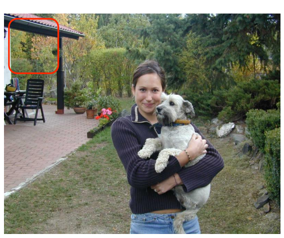
Jana Kosecka

Many slides adapted from P. Viola, S. Lazebnik and many others

Face detection

Face detection

- Basic idea: slide a window across image and evaluate a face model at every location



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

The Viola/Jones Face Detector

- A seminal approach to 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

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

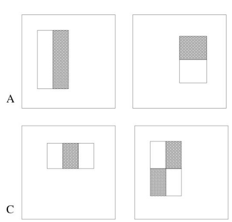
P. Viola and M. Jones. *Robust real-time face detection.* IJCV 57(2), 2004.

A totally different idea

- Use many very simple features
- Learn cascade of tests for target object
- Efficient if:
  - features easy to compute
  - cascade short

Using Many Simple Features

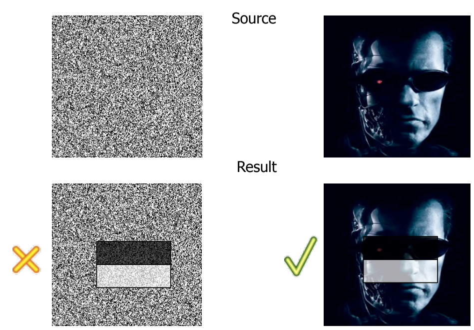
- Viola Jones / Haar Features



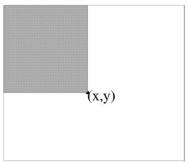
(Generalized) Haar Features:

- rectangular blocks, white or black
- 3 types of features:
  - two rectangles: horizontal/vertical
  - three rectangles
  - four rectangles
- in 24x24 window: 180,000 possible features

Example



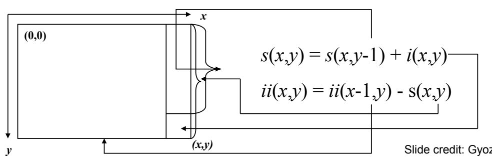
Integral Image



Def: The *integral image* at location (x,y), is the sum of the pixel values above and to the left of (x,y), inclusive. We can calculate the integral image representation of the image in a single pass.

ii(x,y) – value of the integral image – sum of all pixels above and left of (x,y)

s(x,y) – cummulative row sum



$s(x,y) = s(x,y\text{-}1) + i(x,y)$

$ii(x,y) = ii(x\text{-}1,y) - s(x,y)$

Slide credit: Gyozo Gidofalvi

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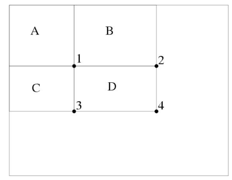
Efficient Computation of Rectangle Value



Using the integral image representation one can compute the value of any rectangular sum in constant time.

Example: Rectangle D

$ii(4) + ii(1) – ii(2) – ii(3)$

As a result two-, three-, and four-rectangular features can be computed with 6, 8 and 9 array references respectively.

Idea: Compute lot of simple features – outputs of convolution with the box like filters

Object detection: classification problem

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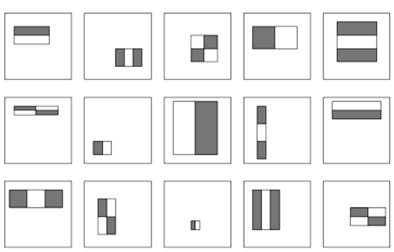
Feature selection

- 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?

Boosting

- Boosting is a classification scheme that works by combining *weak learners* into a more accurate ensemble classifier
  - A weak learner need only do better than chance
- Training consists of multiple *boosting rounds*
  - During each boosting round, we select a weak learner that does well on examples that were hard for the previous weak learners
  - "Hardness" is captured by weights attached to training examples

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

Problem

- How to avoid evaluating (all possible rectangles in 24 x 24 window ?
- 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?

- Answer: Boosting [AdaBoost, Freund/Shapire]
  - Finds small set of features that are "sufficient"
  - Generalizes very well
  - Requires positive and negative examples

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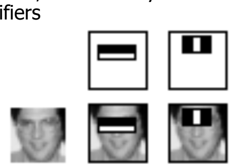
AdaBoost Idea (in Viola/Jones):

- Given set of "weak" classifiers:
  - Pick best one
  - Reweight training examples, so that misclassified images have larger weight
  - Reiterate; then linearly combine resulting classifiers



Weak classifiers: Haar features

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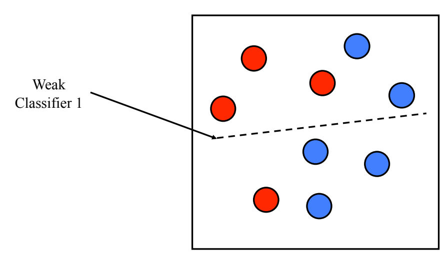
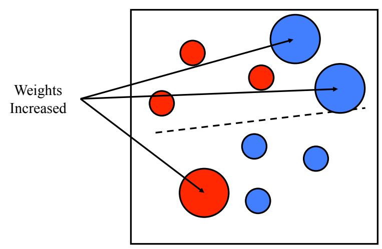
Boosting illustration

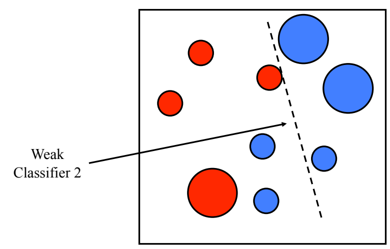
• Weak classifier is a hyperplane



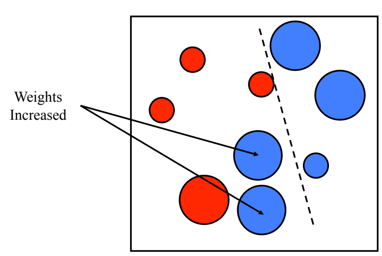
Boosting illustration



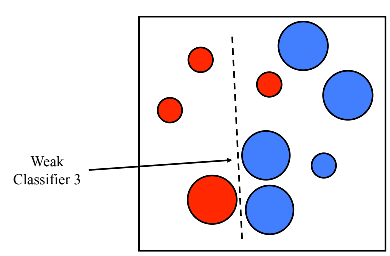
Boosting illustration



Boosting illustration

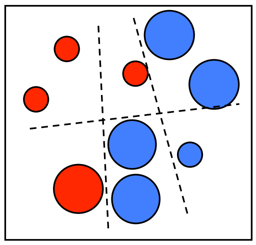


Boosting illustration



Boosting illustration

Final classifier is
a combination of weak
classifiers



Boosting vs. SVM

- Advantages of boosting
  - Integrates classification 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
  - Easy to implement
- Disadvantages
  - Needs many training examples
  - Often doesn’t work as well as SVM (especially for many-class problems)

AdaBoost learning algorithm

Discrete AdaBoost(Freund & Schapire 1996*b*)

1. Start with weights $w_i = 1/N$, $i = 1, \ldots, N$.
2. Repeat for $m = 1, 2, \ldots, M$:
   (a) Fit the classifier $f_m(x) \in \{-1, 1\}$ using weights w_i on the training data.
   (b) Compute $\mathrm{err}_m = E_w[1_{(y \neq f_m(x))}]$, $c_m = \log((1 - \mathrm{err}_m)/\mathrm{err}_m)$.
   (c) Set $w_i \leftarrow w_i \exp[c_m \cdot 1_{(y_i \neq f_m(x_i))}]$, $i = 1, 2, \ldots N$, and renormalize so that $\sum_i w_i = 1$.
3. Output the classifier $\mathrm{sign}[\sum_{m=1}^{M} c_m f_m(x)]$

Boosting for face detection

- Define weak learners based on rectangle features

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

parity

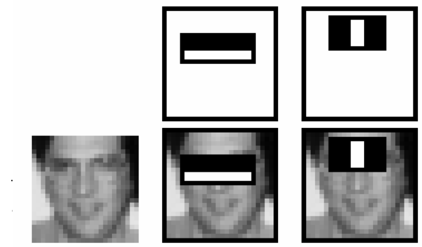
threshold

Boosting for face detection

- Define weak learners based on rectangle features
- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Select best threshold for each filter
  - Select best filter/threshold combination
  - Reweight examples
- Computational complexity of learning: $O(MNK)$
  - M rounds, N examples, K features

Boosting for face detection

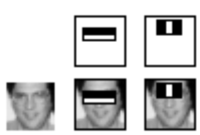
- First two features selected by boosting:

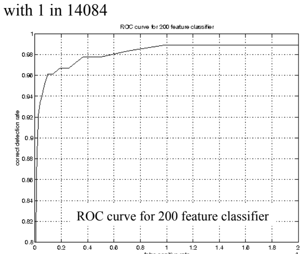


Example Classifier for Face Detection

A classifier with 200 rectangle features was learned using AdaBoost

95% correct detection on test set with 1 in 14084 false positives.





Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce

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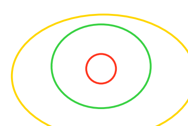
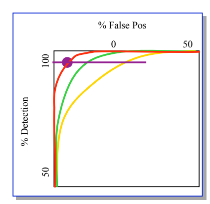
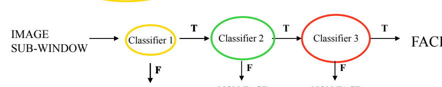
Classifier are Efficient

- Given a nested set of classifier hypothesis classes







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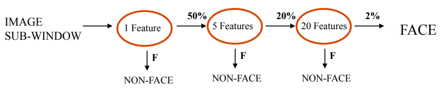
Cascaded Classifier



- A 1 feature classifier achieves 100% detection rate and about 50% false positive rate.
- A 5 feature classifier achieves 100% detection rate and 40% false positive rate (20% cumulative)
  - using data from previous stage.
- A 20 feature classifier achieve 100% detection rate with 10% false positive rate (2% cumulative)

Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce
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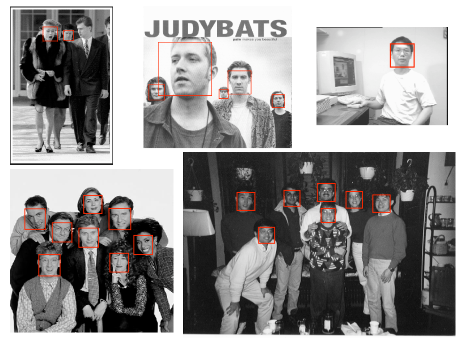
Output of Face Detector on Test Images



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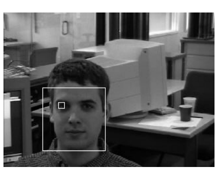
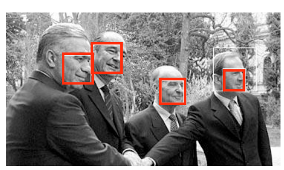
Solving other "Face" Tasks

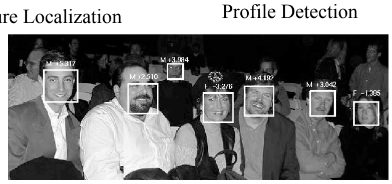


Facial Feature Localization



Profile Detection

Demographic Analysis



Slide credit: Frank Dellaert, Paul Viola, Foryth&Ponce
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Face Localization Features

- Learned features reflect the task

Slide credit: Frank Dellaert, Paul Viola, Forsyth&Ponce
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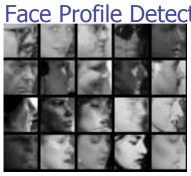
Face Profile Detection



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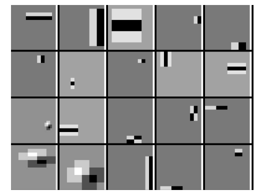
Face Profile Features



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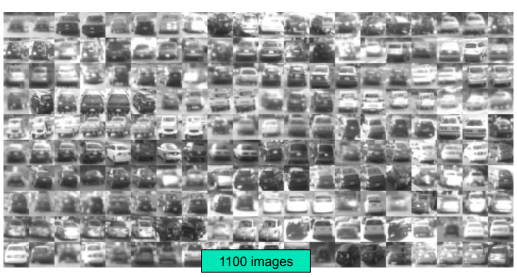
Finding Cars (DARPA Urban Challenge)

- Hand-labeled images of generic car rear-ends
- Training time: ~5 hours, offline



Credit: Hendrik Dahlkamp

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Generating even more examples

- Generic classifier finds all cars in recorded video.
- Compute offline and store in database

Credit: Hendrik Dahlkamp

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Summary Viola-Jones

- Rectangle features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows

- Many simple features
  - Generalized Haar features (multi-rectangles)
  - Easy and efficient to compute
- Discriminative Learning:
  - finds a small subset for object recognition
  - Uses AdaBoost
- Result: Feature Cascade
  - 15fps on 700Mhz Laptop (=fast!)

- Applications, Face detection, Car detection, Many others

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