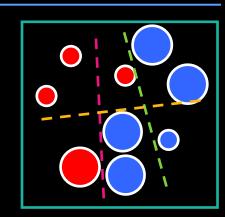
CS4495/6495 Introduction to Computer Vision

8C-L2 Boosting and face detection



Generic category recognition: Basic framework

Train

- Build an object model a representation
 Describe training instances (here images)
- Learn/train a *classifier*

Test

- Generate candidates in new image
- *Score* the candidates

Discriminative classification methods

Discriminative classifiers – find a division (surface) in feature space that separates the classes

Several methods

- Nearest neighbors
- Boosting
- Support Vector Machines

Discriminative classification methods

Discriminative classifiers – find a division (surface) in feature space that separates the classes

Several methods

- Nearest neighbors
- Boosting
- Support Vector Machines

Boosting: Training method

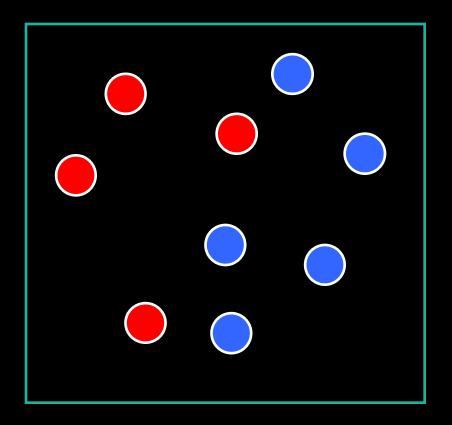
- Initially, weight each training example equally
- In each boosting round:
 - Find the weak learner that achieves the lowest weighted training error
 - Raise weights of training examples misclassified by current weak learner

Boosting: Training method

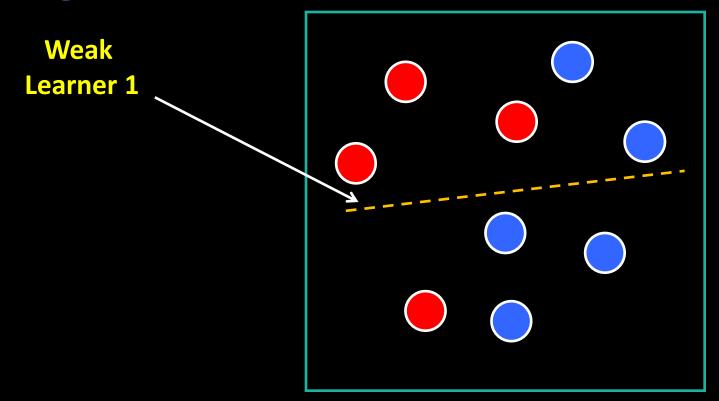
 Compute final classifier as linear combination of all weak learners (weight of each learner is directly proportional to its accuracy)

Weak learners

- What is a weak learner?
- Simply, a function that partitions the space
- Weak in that it doesn't get the answer right but gives some information over the current errors



Slide credit: Paul Viola

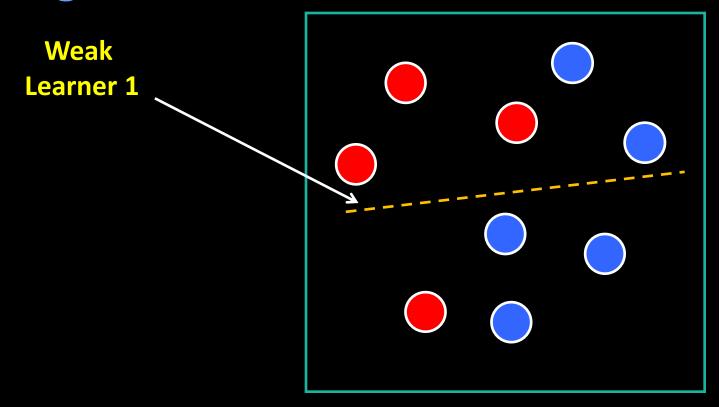


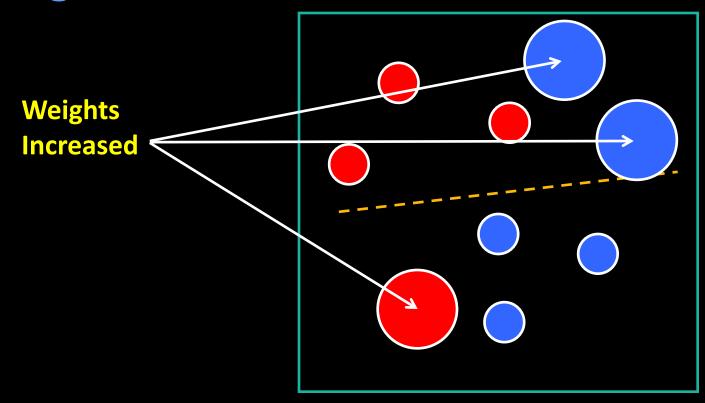
Boosting: Training method

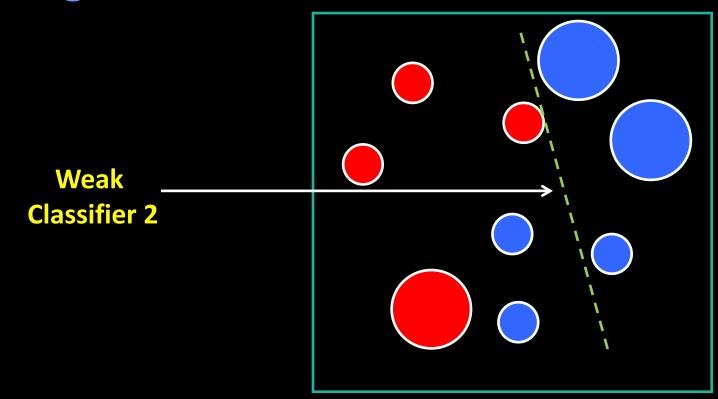
- In each boosting round:
 - Find the *weak learner* that achieves the *lowest* weighted training error
 - Raise weights of training examples misclassified by current weak learner

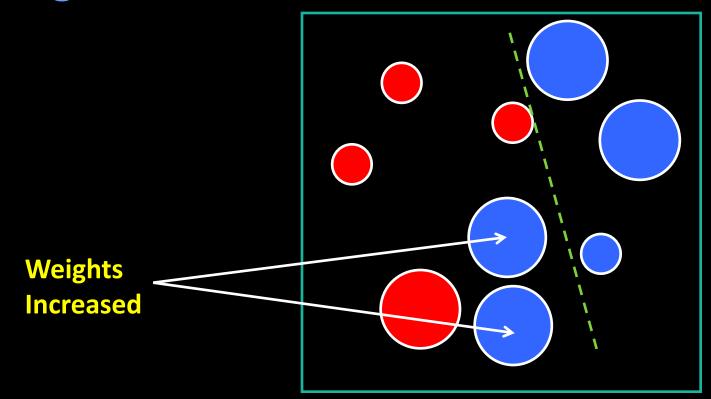
Boosting: Training method

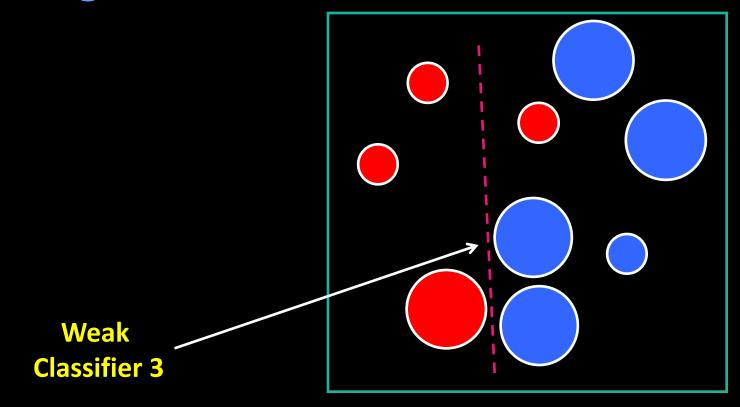
- In each boosting round:
 - Find the weak learner that achieves the lowest weighted training error
 - Raise weights of training examples misclassified by current weak learner



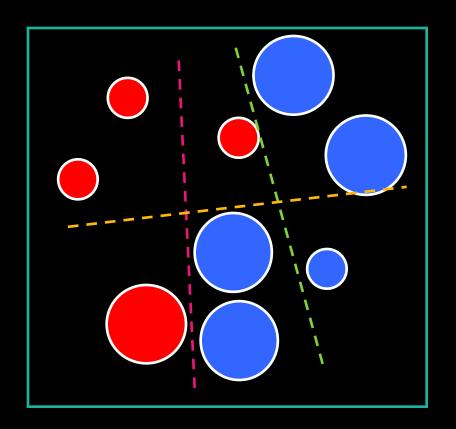








Final classifier is a combination of weak classifiers



Boosting: Training

 General: 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)

Slide credit: Lana Lazebnik

ACCEPTED CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION 2001

Rapid Object Detection using a Boosted Cascade of Simple Features

Paul Viola viola@merl.com Mitsubishi Electric Research Labs 201 Broadway, 8th FL Cambridge, MA 02139 Michael Jones mjones@crl.dec.com Compaq CRL One Cambridge Center Cambridge, MA 02142

Abstract

This paper describes a machine learning approach for vi-

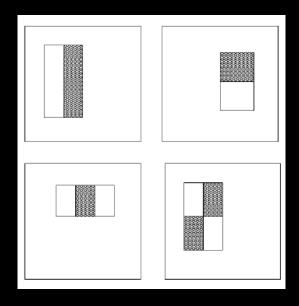
tected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences,

P. Viola & M. Jones. <u>Rapid object detection using a</u> boosted cascade of simple features. CVPR 2001.

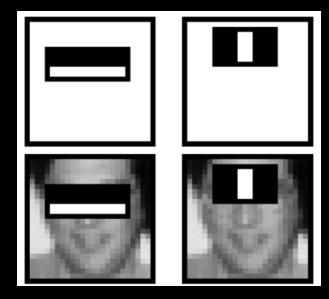
Main ideas:

 Represent brightness patterns with efficiently computable "rectangular" features within window of interest

Viola-Jones detector: Features



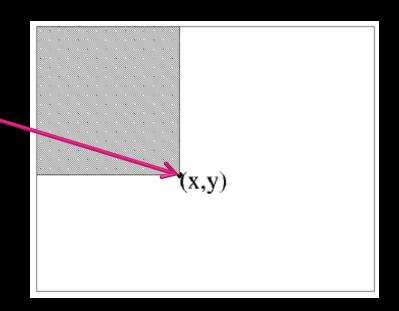
"Rectangular" filters



Feature output is difference between adjacent regions

Viola-Jones detector: Integral image

Integral image: the value at (x,y) is sum of pixels above and to the left of (x,y)

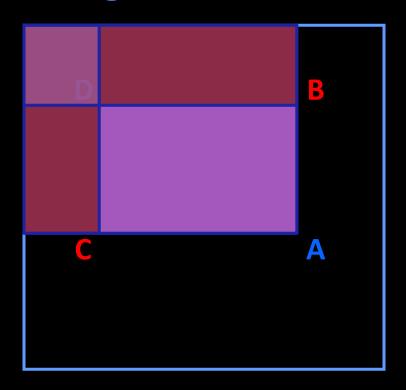


Computing sum within a rectangle

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



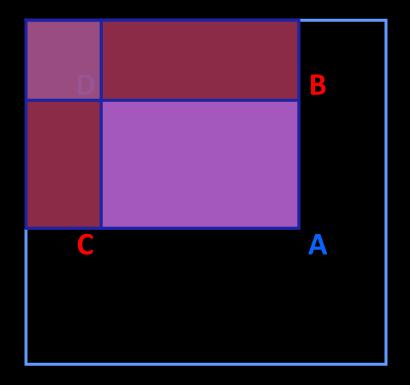
Computing sum within a rectangle

$$sum = A - B - C + D$$

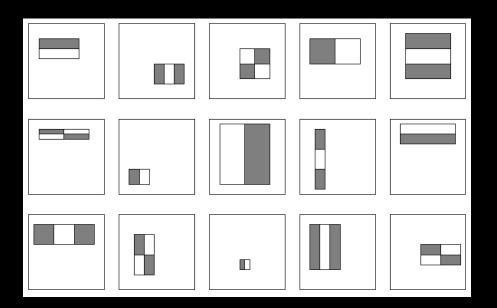
 Only 3 additions are required for any size of rectangle!

Avoid scaling images→ scale features directly for

same cost



Viola-Jones detector: Features



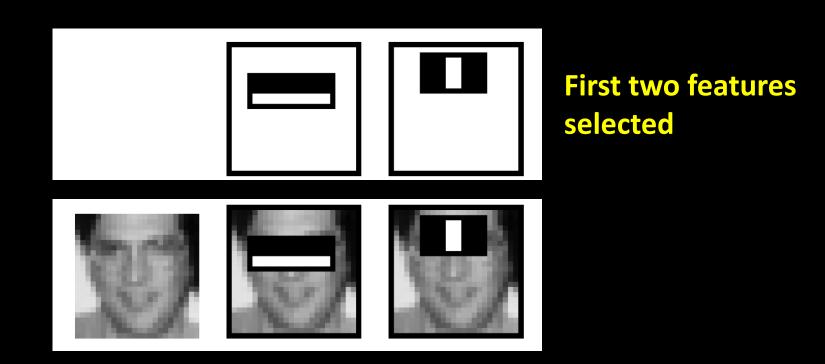
Considering all possible filter parameters – position, scale, and type:

180,000+ possible features associated with each 24 x 24 window

Which subset of these features should we use to find a face?
Use AdaBoost – both to select informative features and to form the classifier

- Represent brightness patterns with efficiently computable "rectangular" features within window of interest
- Choose discriminative features to be weak classifiers/learners.

Viola-Jones Face Detector: Results



- Represent brightness patterns with efficiently computable "rectangular" features within window of interest
- Choose discriminative features to be weak classifiers/learners.

- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

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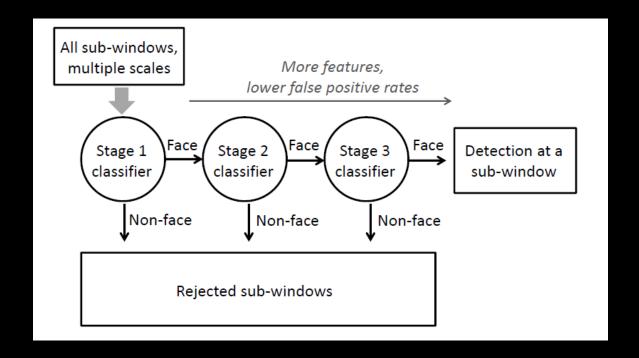
2nd big idea: Cascade...

- Even if the filters are fast to compute, each new image has a lot of possible windows to search
- How to make the detection more efficient?

2nd big idea: Cascade...

Key insight: almost everywhere is a non-face

- So... detect non-faces more quickly than faces
- And if you say it's not a face, be sure and move on

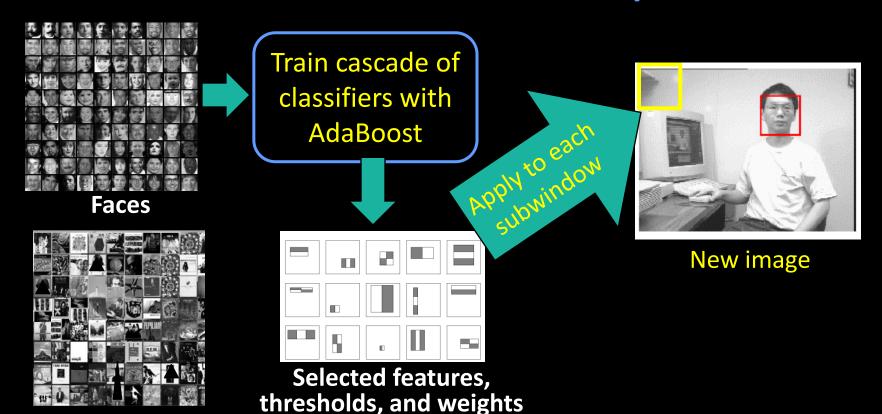


- 1. Form a *cascade* with really low false negative rates early
- At each stage use the false positives from last stage as "difficult negatives"

Kristen Grauman

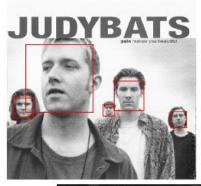
Viola-Jones detector: Summary

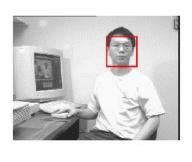
Non-faces

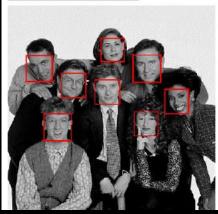


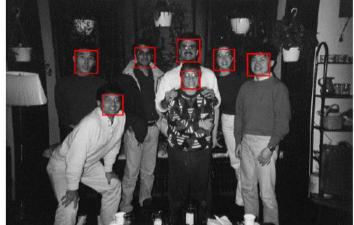
Kristen Grauman

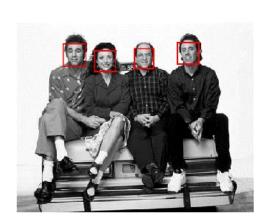


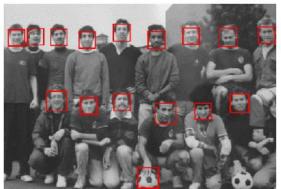


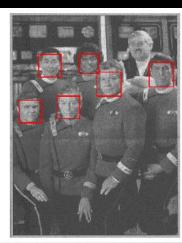














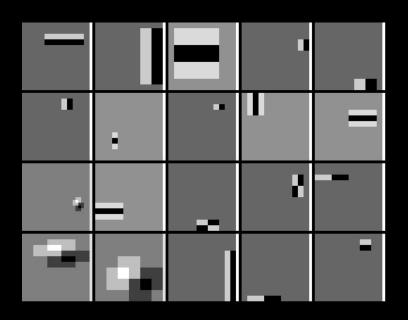




Detecting profile faces?

Can we use the same detector?

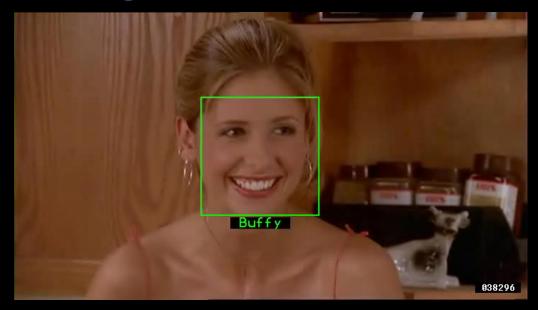








Example using Viola-Jones detector



Frontal faces detected and then tracked, character names inferred with alignment of script and subtitles

Everingham, M., Sivic, J. and Zisserman, A.

"Hello! My name is... Buffy" - Automatic naming of characters in TV video. BMVC 2006.





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Google now erases faces, license plates on Map Street View

By Elinor Mills, CNET News.com Friday, August 24, 2007 01:37 PM

remove their image.

Google has gotten a lot of flack from privacy advocates for photographing faces and license plate numbers and displaying them on the Street View in Google Maps. Originally,

the company said only people who identified themselves could ask the company to

 Google still thinks it can change China But Google has quietly changed that policy, partly in response to criticism, and now anyone can alert the company and have an image of a license plate or a recognizable face removed, not just the owner of the face or car, says Marissa Mayer, vice president of search products and user experience at Google.

"It's a good policy for users and also clarifies the intent of the product." she said in an interview following her keynote at the Search Engine Strategies conference in San Jose, Calif., Wednesday,

The policy change was made about 10 days after the launch of the product in late May, but was not publicly announced, according to Mayer. The company is removing images only when someone notifies them and not proactively, she said. "It was definitely a big policy change inside."

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Cisco Collaboration Solut

Consumer application: iPhoto 2009



http://www.apple.com/ilife/iphoto/

Consumer application: iPhoto 2009



Things iPhoto thinks are faces

Viola-Jones face detector: Summary

Key ideas:

- Rectangular features and integral image
- AdaBoost for feature selection
- Cascade

Training is slow, but detection is very fast Really, really effective....

Boosting (general): Advantages

- Integrates classification with feature selection
- Flexibility in the choice of weak learners, boosting scheme
- Complexity of training is linear in the number of training examples
- Testing is fast
- Easy to implement

Boosting: Disadvantages

- Needs many training examples
- Often found not to work as well as an alternative discriminative classifier, support vector machine (SVM)
 - -Especially for many-class problems