Object Detection: Sliding Windows

ECS797 Machine Learning for Visual Analysis
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Most slides from Jon Hays (adapted from Kristen Grauman)

Past lectures

- Category recognition
  - Bag of words using *not-so-invariant* local features.
- Instance recognition
  - Manifold learning with dimensionality reduction

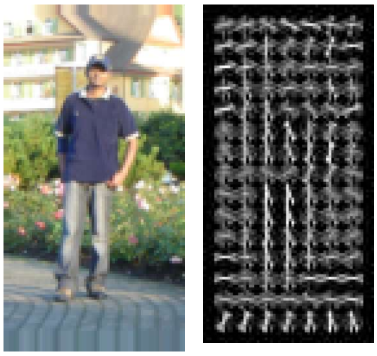
Today

- Window-based generic object detection
  - basic pipeline
  - boosting classifiers
  - face detection as case study

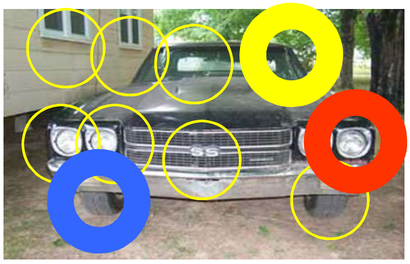
Object category recognition: basic framework

- Build/train object model
  - Choose a representation
  - Learn or fit parameters of model / classifier
- Generate candidates in new image
- Score the candidates

Object category recognition: representation choice



Window-based



Part-based

Window-based models
Building an object model

Given the representation, train a binary classifier

 → Car/non-car Classifier

↓

No, not a car.

Yes, car.

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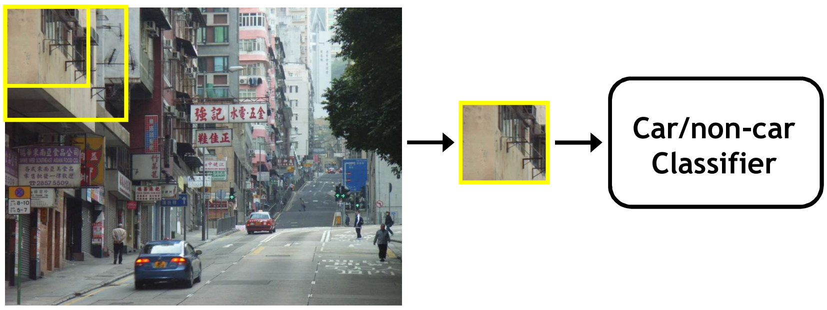
Window-based models – Sliding windows
Generating and scoring candidates



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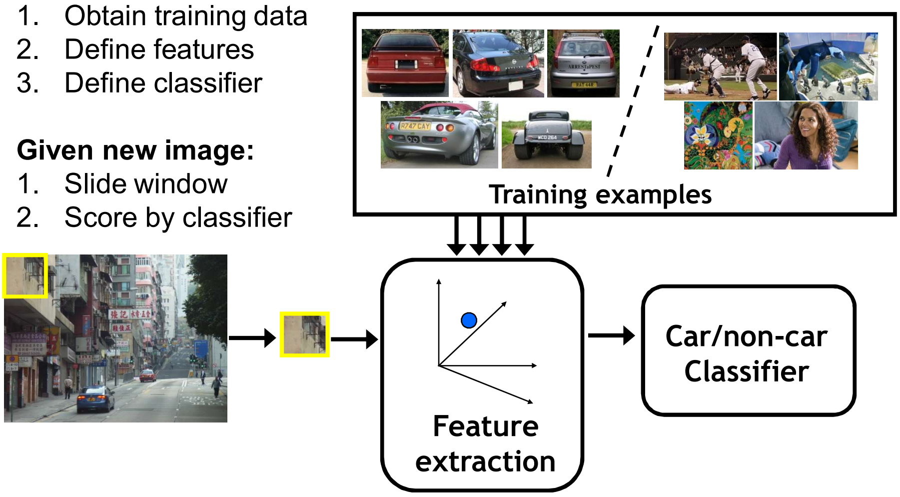
Window-based object detection: recap

Training:
1. Obtain training data
2. Define features
3. Define classifier

Given new image:
1. Slide window
2. Score by classifier



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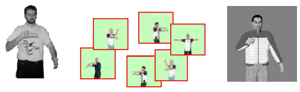
Discriminative classifier construction

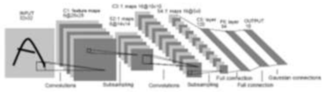
Nearest neighbor



10^6 examples

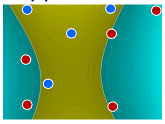
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



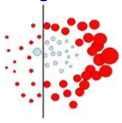
LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
…

Support Vector Machines



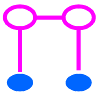
Guyon, Vapnik
Heisele, Serre, Poggio, 2001,…

Boosting



Viola, Jones 2001, Torralba et al. 2004, Opelt et al. 2006,…

Conditional Random Fields



McCallum, Freitag, Pereira 2000; Kumar, Hebert 2003
…

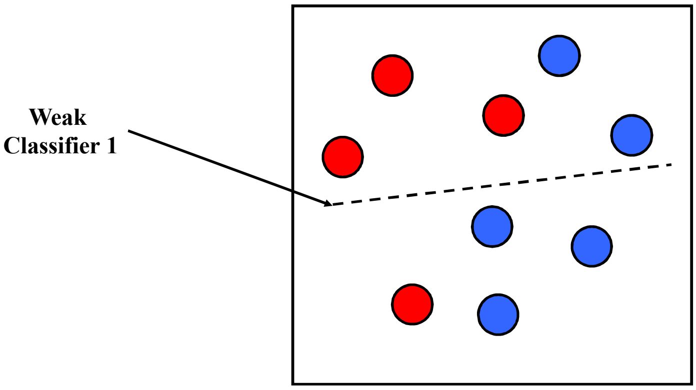
Slide adapted from Antonio Torralba

Influential Works in Detection

- Sung-Poggio (1994, 1998) : ~1800 citations
  - Basic idea of statistical template detection (I think), bootstrapping to get "face-like" negative examples, multiple whole-face prototypes (in 1994)
- Rowley-Baluja-Kanade (1996-1998) : ~3700
  - "Parts" at fixed position, non-maxima suppression, simple cascade, rotation, pretty good accuracy, fast
- Schneiderman-Kanade (1998-2000,2004) : ~1750
  - Careful feature engineering, excellent results, cascade
- Viola-Jones (2001, 2004) : ~8500
  - Haar-like features, Adaboost as feature selection, hyper-cascade, very fast, easy to implement
- Dalal-Triggs (2005) : ~4700
  - Careful feature engineering, excellent results, HOG feature, online code
- Felzenszwalb-Huttenlocher (2000): ~950
  - Efficient way to solve part-based detectors
- Felzenszwalb-McAllester-Ramanan (2008)? ~1300
  - Excellent template/parts-based blend

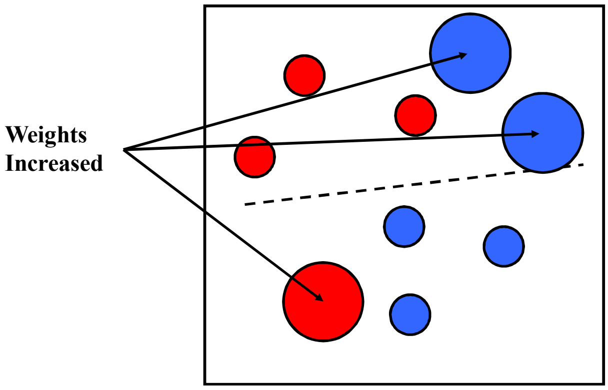
Slide: Derek Hoiem

Boosting intuition

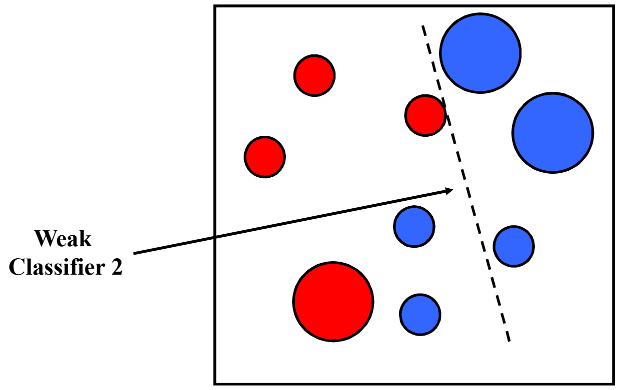


Slide credit: Paul Viola

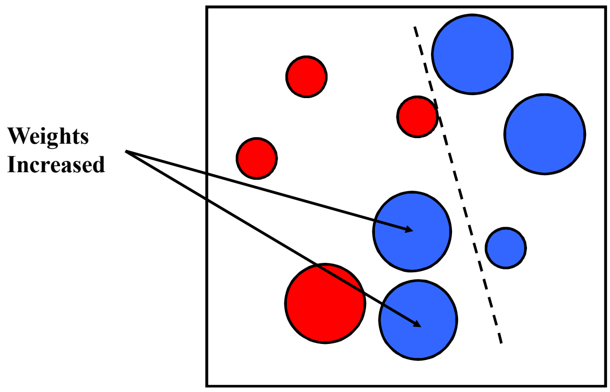
Boosting illustration



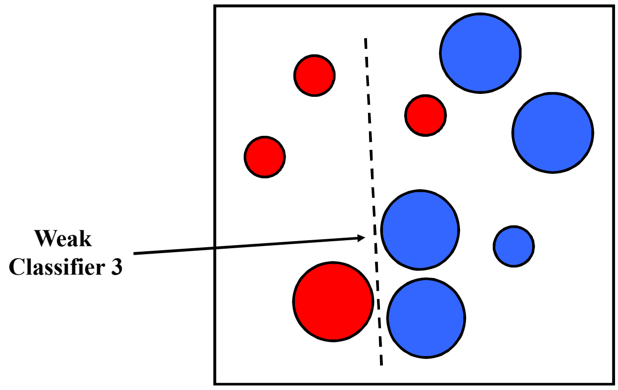
Boosting illustration



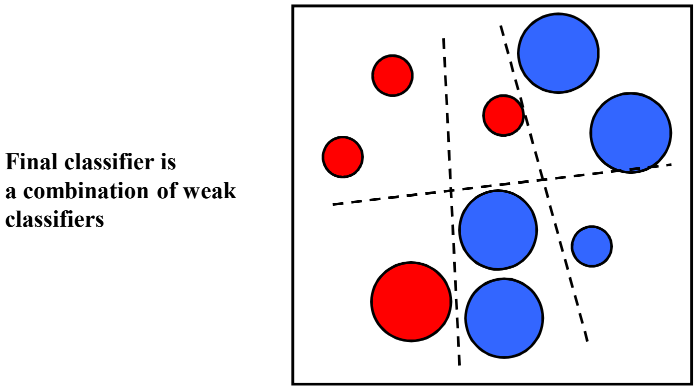
Boosting illustration



Boosting illustration



Boosting illustration



Boosting: training

- 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
- 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

Viola-Jones face detector

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,

Viola-Jones face detector

Main idea:

- Represent local texture with efficiently computable "rectangular" features within window of interest
- Select discriminative features to be weak classifiers
- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

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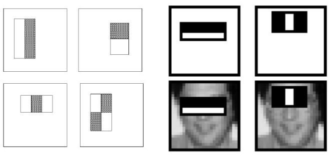
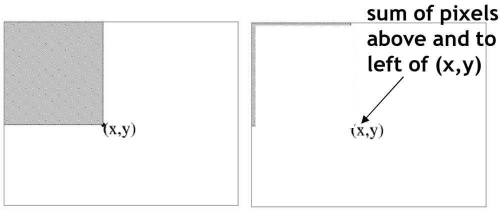
Viola-Jones detector: features



"Rectangular" filters

Feature output is difference between adjacent regions

Efficiently computable with integral image: any sum can be computed in constant time.



Original image

Integral image

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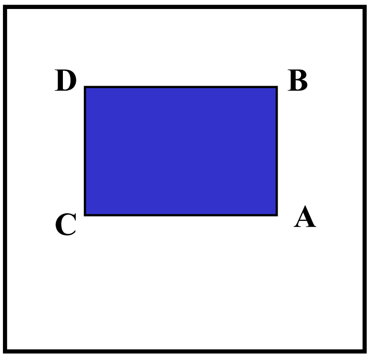
Computing sum within a rectangle

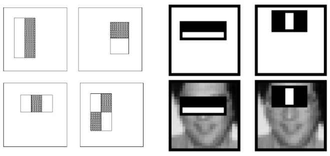
- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- Then the sum of original image values within the rectangle can be computed as:

  sum = A – B – C + D
- Only 3 additions are required for any size of rectangle!



Lana Lazebnik

Viola-Jones detector: features



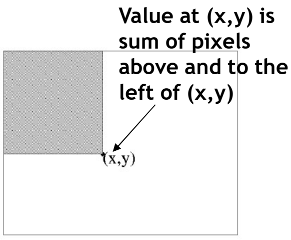
"Rectangular" filters

Feature output is difference between adjacent regions

(Haar features)

Efficiently computable with integral image: any sum can be computed in constant time

Avoid scaling images → scale features directly for same cost



Integral image

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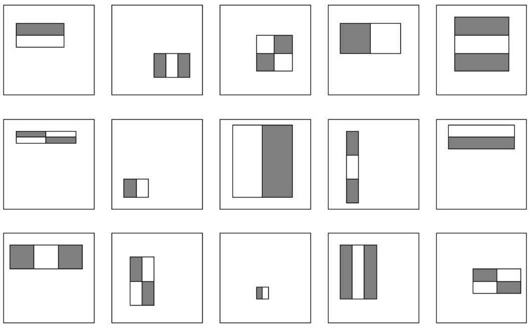
Viola-Jones detector: features



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 determine if a window has a face?

Use AdaBoost both to select the informative features and to form the classifier

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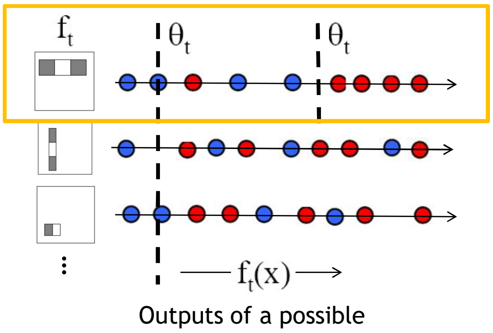
Viola-Jones detector: AdaBoost

- **Want to select the single rectangle feature and threshold that best separates positive (faces) and negative (non-faces) training examples, in terms of *weighted* error.**



Outputs of a possible rectangle feature on faces and non-faces.

Resulting weak classifier:

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

For next round, reweight the examples according to errors, choose another filter/threshold combo.

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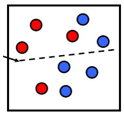
- Given example images $(x_1, y_1), \dots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.
- Initialize weights $w_{1,i} = \frac{1}{2m}, \frac{1}{2l}$ for $y_i = 0, 1$ respectively, where m and l are the number of negatives and positives respectively.
- For $t = 1, \dots, T$:
  1. Normalize the weights,
  $$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}}$$
  so that w_t is a probability distribution.
  2. For each feature, j, train a classifier h_j which is restricted to using a single feature. The error is evaluated with respect to w_t, $\epsilon_j = \sum_i w_i \, |h_j(x_i) - y_i|$.
  3. Choose the classifier, h_t, with the lowest error ϵ_t.
  4. Update the weights:
  $$w_{t+1,i} = w_{t,i} \beta_t^{1-e_i}$$
  where $e_i = 0$ if example x_i is classified correctly, $e_i = 1$ otherwise, and $\beta_t = \frac{\epsilon_t}{1-\epsilon_t}$.
- The final strong classifier is:
$$h(x) = \begin{cases} 1 & \sum_{t=1}^{T} \alpha_t h_t(x) \geq \frac{1}{2} \sum_{t=1}^{T} \alpha_t \\ 0 & \text{otherwise} \end{cases}$$
where $\alpha_t = \log \frac{1}{\beta_t}$

AdaBoost Algorithm

Start with uniform weights on training examples



$\{x_1, \dots x_n\}$

For T rounds

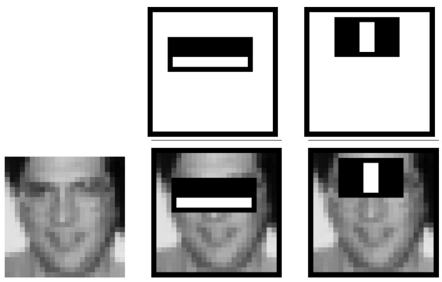
Evaluate *weighted* error for each feature, pick best.

Re-weight the examples:
Incorrectly classified -> more weight
Correctly classified -> less weight

Final classifier is combination of the weak ones, weighted according to error they had.

Freund & Schapire 1995

Viola-Jones Face Detector: Results

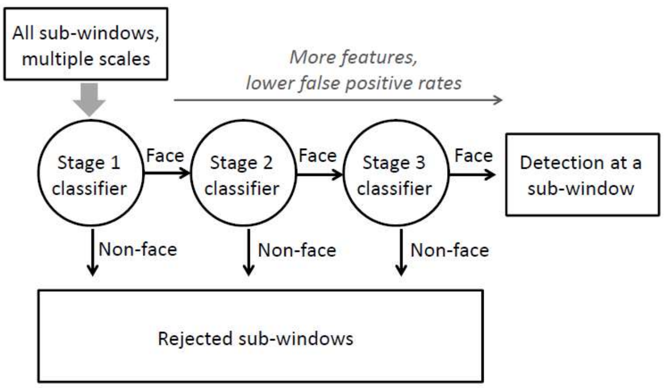


First two features selected

Visual Object Recognition Tutorial

- 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?

Cascading classifiers for detection



- Form a *cascade* with low false negative rates early on
- Apply less accurate but faster classifiers first to immediately discard windows that clearly appear to be negative

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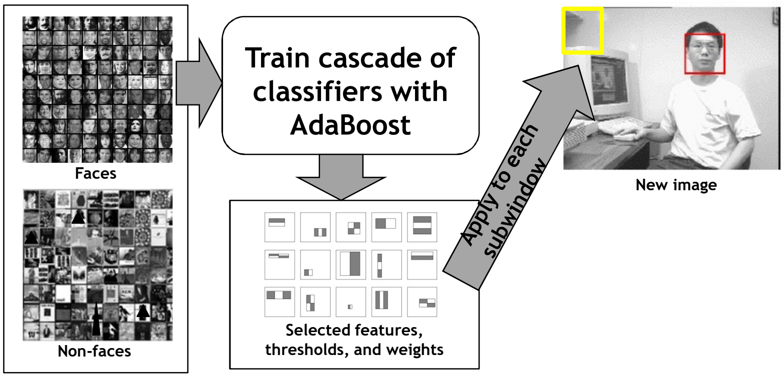
Viola-Jones detector: summary



Train with 5K positives, 350M negatives
Real-time detector using 38 layer cascade
6061 features in all layers

[Implementation available in OpenCV: http://www.intel.com/technology/computing/opencv/]

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Viola-Jones detector: summary

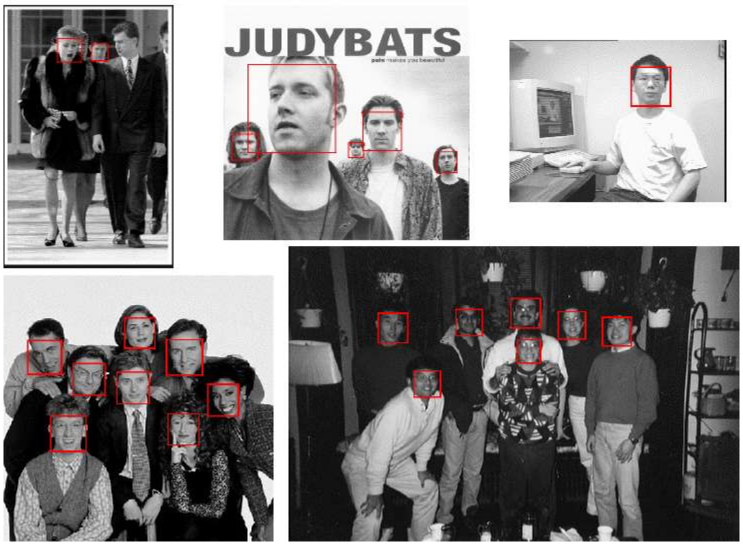
- A seminal approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas
  - Features which can be evaluated very quickly with *Integral Images*
  - Cascade model which rejects unlikely faces quickly
  - Mining hard negatives

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.

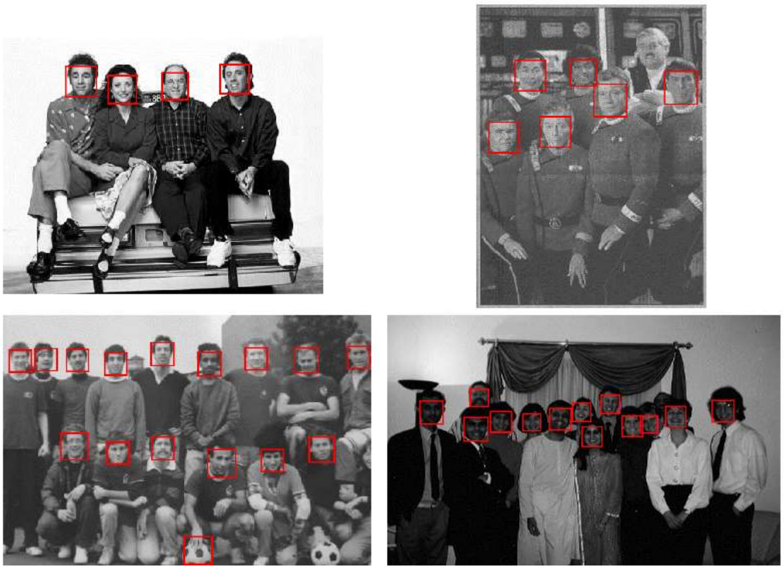
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results



Visual Object Recognition Tutorial

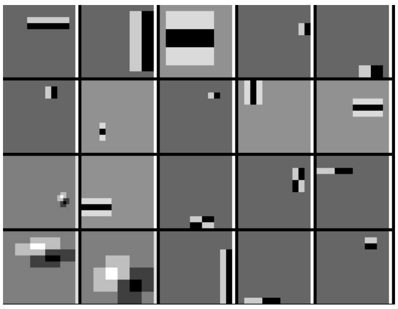
Viola-Jones Face Detector: Results



Viola-Jones Face Detector: Results

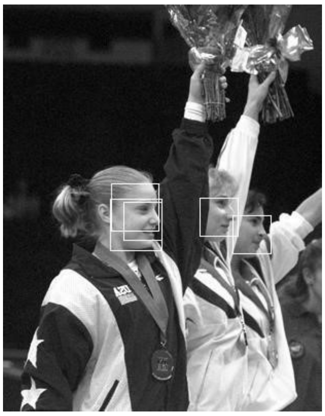
Detecting profile faces?

Can we use the same detector?



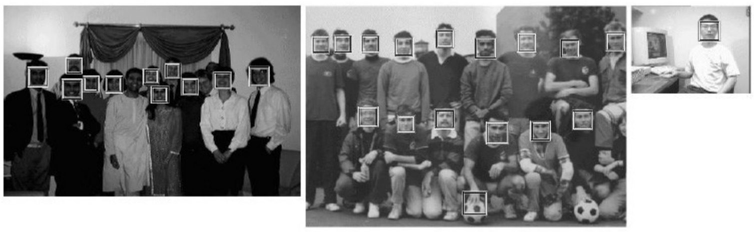
Visual Object Recognition Tutorial

Viola-Jones Face Detector: Results



Paul

Viola Jones Results



False detections / Detector	10	31	50	65	78	95	167
Viola-Jones	76.1%	88.4%	91.4%	92.0%	92.1%	92.9%	93.9%
Viola-Jones (voting)	81.1%	89.7%	92.1%	93.1%	93.1%	93.2 %	93.7%
Rowley-Baluja-Kanade	83.2%	86.0%	-	-	-	89.2%	90.1%
Schneiderman-Kanade	-	-	-	94.4%	-	-	-
Roth-Yang-Ahuja	-	-	-	-	(94.8%)	-	-

MIT + CMU face dataset

Slide: Derek Hoiem

Schneiderman later results

		89.7%	93.1%	94.4%	94.8%	95.7%
Schneiderman 2004	Bayesian Network *	1	8	19	36	56
	Semi-Naïve Bayes*	6	19	29	35	46
Viola-Jones 2001	[6]	31	65	--	--	--
Roth et al. 1999	[7]*	--	--	--	78	--
Schneiderman-Kanade 2000	[16]*	--	--	65	--	--

Table 2. False alarms as a function of recognition rate on the MIT-CMU Test Set for Frontal Face Detection. * indicates exclusion of the 5 images of hand-drawn faces.

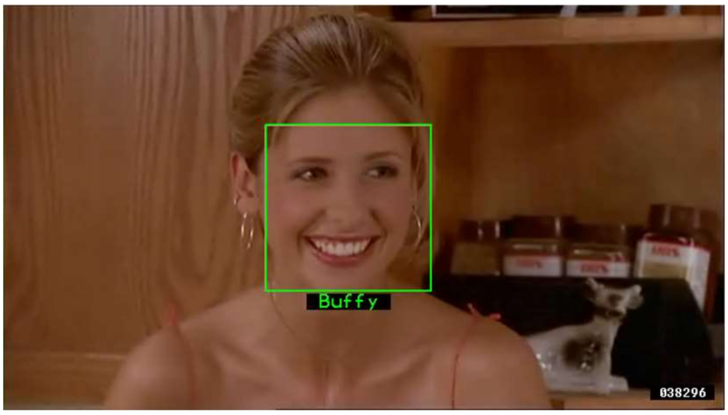
Slide: Derek Hoiem

Speed: frontal face detector

- Schneiderman-Kanade (2000): 5 seconds
- Viola-Jones (2001): 15 fps

Slide: Derek Hoiem

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. http://www.robots.ox.ac.uk/~vgg/research/nface/index.html

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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

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 remove their image.

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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What's Hot | Latest News
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- Report: Amazon may again be mulling Netflix bu
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- Google begins search for Middle East lobbyist
- Google still thinks it can change China

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advertisement
ZDNet Asia TECH SHOWCASE
Brought to
CIS
Cisco Collaboration Solut
rforr

Consumer application: iPhoto 2009

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

Slide credit: Lana Lazebnik

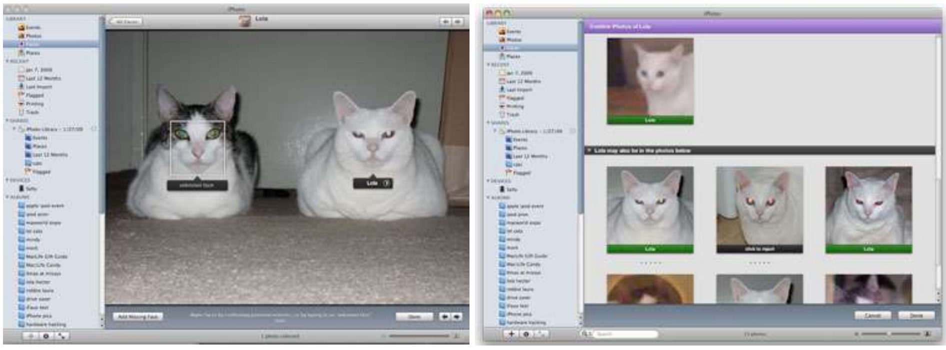
Consumer application: iPhoto 2009

Things iPhoto thinks are faces

Slide credit: Lana Lazebnik

Consumer application: iPhoto 2009

Can be trained to recognize pets!



http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

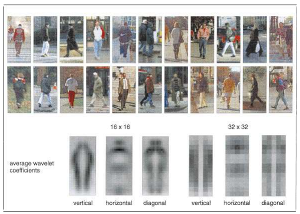
Slide credit: Lana Lazebnik

Discussion

What other categories are amenable to *window-based representation*?

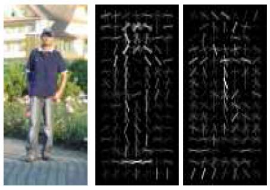
Pedestrian detection

Detecting upright, walking humans also possible using sliding window's appearance/texture; e.g.,



SVM with Haar wavelets [Papageorgiou & Poggio, IJCV 2000]

Space-time rectangle features [Viola, Jones & Snow, ICCV 2003]



SVM with HoGs [Dalal & Triggs, CVPR 2005]

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Boosting: pros and cons

- Advantages of boosting
  - Integrates classification with feature selection
  - Complexity of training is linear 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 found not to work as well as an alternative discriminative classifier, support vector machine (SVM)
    - especially for many-class problems

Slide credit: Lana Lazebnik

Window-based detection: strengths

Sliding window detection and global appearance descriptors:

- Simple detection protocol to implement
- Good feature choices critical
- Past successes for certain classes

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Window-based detection: Limitations

High computational complexity

- For example: 250,000 locations x 30 orientations x 4 scales = 30,000,000 evaluations!
- If training binary detectors independently, means cost increases linearly with number of classes

With so many windows, false positive rate better be low

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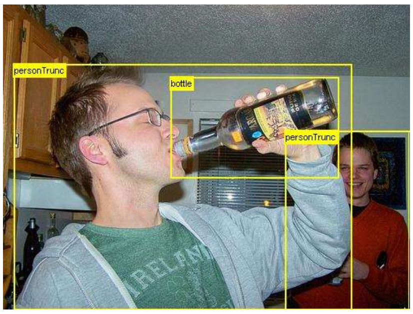
Limitations (continued)

Not all objects are "box" shaped



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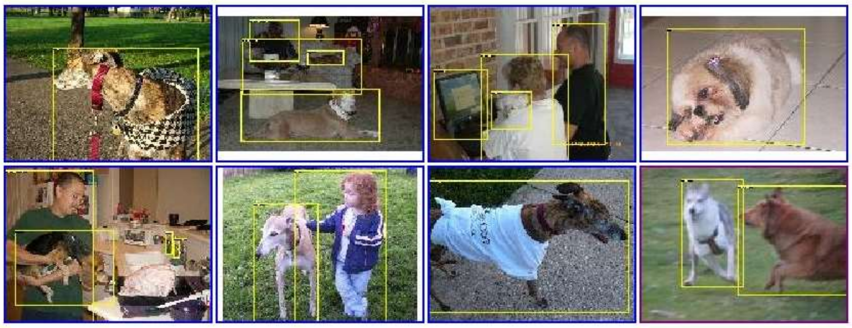
Limitations (continued)

Non-rigid, deformable objects not captured well with representations assuming a fixed 2d structure; or must assume fixed viewpoint

Objects with less-regular textures not captured well with holistic appearance-based



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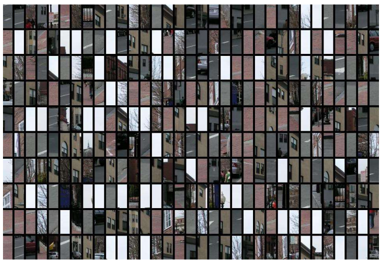
Limitations (continued)

If considering windows in isolation, context is lost

Sliding window



Detector's view

Figure credit: Derek Hoiem

Kristen Grauman

Limitations (continued)

In practice, often entails large, cropped training set (expensive)

Requiring good match to a global appearance description can lead to sensitivity to partial occlusions

Image credit: Adam, Rivlin, & Shimshoni

Kristen Grauman

Summary

Basic pipeline for window-based detection

- Model/representation/classifier choice
- Sliding window and classifier scoring

Viola-Jones face detector

- Exemplar of basic paradigm
- Plus key ideas: rectangular features, Adaboost for feature selection, cascade, hard negatives.

Pros and cons of window-based detection