Window-based models for generic object detection

May 21st, 2015

Yong Jae Lee
UC Davis

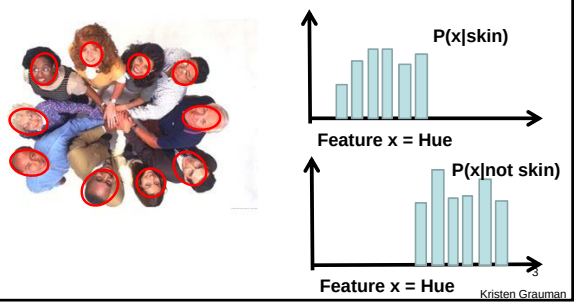
Previously

- Intro to generic object recognition
- Supervised classification
  - Main idea
  - Skin color detection example

2

Last time: Example: skin color classification

- We can represent a class-conditional density using a histogram (a "non-parametric" distribution)

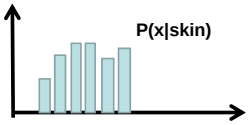


Kristen Grauman

3

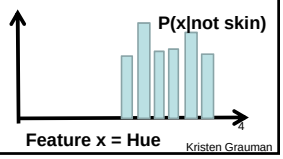
Last time: Example: skin color classification

- We can represent a class-conditional density using a histogram (a "non-parametric" distribution)



Now we get a new image, and want to label each pixel as skin or non-skin.

$$P(skin \mid x) \; \alpha \; P(x \mid skin) P(skin)$$

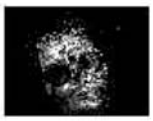


4

Kristen Grauman

Last time: Example: skin color classification

Now for every pixel in a new image, we can estimate probability that it is generated by skin.



Brighter pixels → higher probability of being skin

Classify pixels based on these probabilities

- if $p(\text{skin}|\boldsymbol{x}) > \theta$, classify as skin
- if $p(\text{skin}|\boldsymbol{x}) < \theta$, classify as not skin

5

Kristen Grauman

Today

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

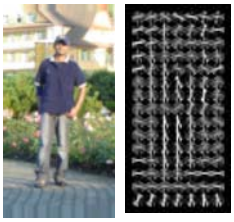
6

Generic category recognition: basic framework

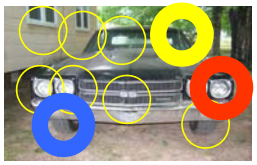
- Build/train object model
  - Choose a representation
  - Learn or fit parameters of model / classifier
- Generate candidates in new image
- Score the candidates

7

Generic category recognition: representation choice



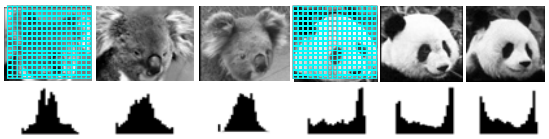
Window-based



Part-based

8

Window-based models
Building an object model



Simple holistic descriptions of image content

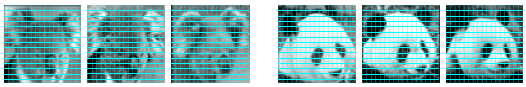
- **grayscale / color histogram**
- **vector of pixel intensities**

9

Kristen Grauman

Window-based models
Building an object model

- Pixel-based representations sensitive to small shifts

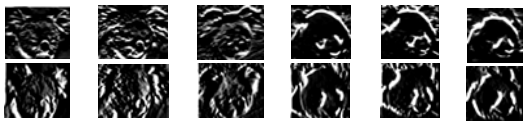


- Color or grayscale-based appearance description can be sensitive to illumination and intra-class appearance variation

10
Kristen Grauman

Window-based models
Building an object model

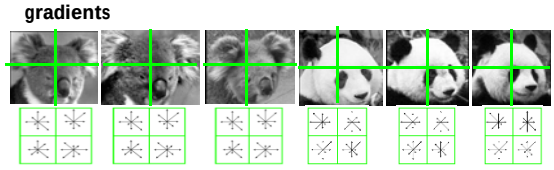
- Consider edges, contours, and (oriented) intensity gradients



11
Kristen Grauman

Window-based models
Building an object model

- Consider edges, contours, and (oriented) intensity gradients



- Summarize local distribution of gradients with histogram
  - Locally orderless: offers invariance to small shifts and rotations
  - Contrast-normalization: try to correct for variable illumination

12
Kristen Grauman

Window-based models
Building an object model

Given the representation, train a binary classifier

→ **Car/non-car Classifier**

↓

Yes, it's a car. **No, not a car.**

13

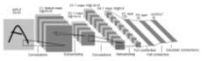
Kristen Grauman

Discriminative classifier construction

Nearest neighbor

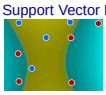
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

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
…

14

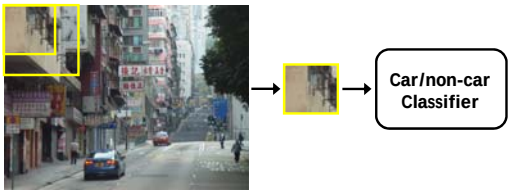
Slide adapted from Antonio Torralba

Generic 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**

15

Window-based models
Generating and scoring candidates

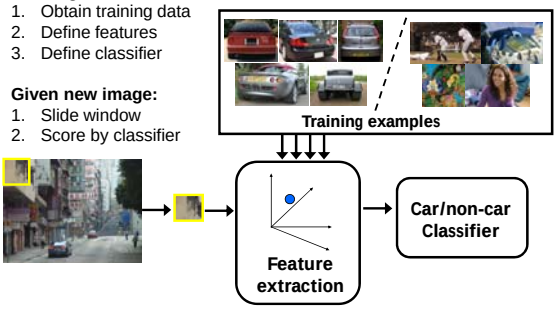


16
Kristen Grauman

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



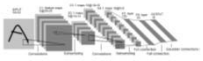
17
Kristen Grauman

Discriminative classifier construction

Nearest neighbor

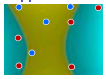
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



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

Support Vector Machines



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

Boosting

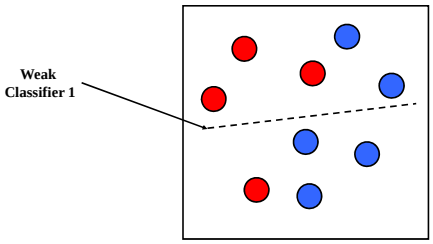
Viola, Jones 2001, Torralba et al. 2004, Opelt et al. 2006,…

Conditional Random Fields

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

18
Slide adapted from Antonio Torralba

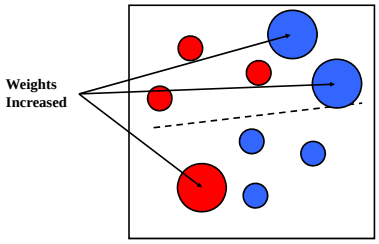
Boosting intuition



19

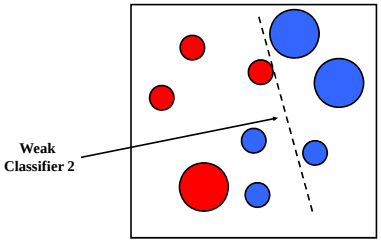
Slide credit: Paul Viola

Boosting illustration



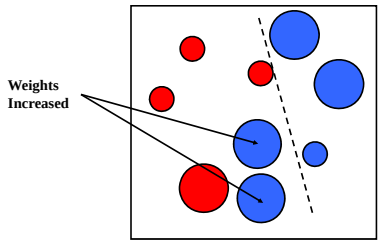
20

Boosting illustration



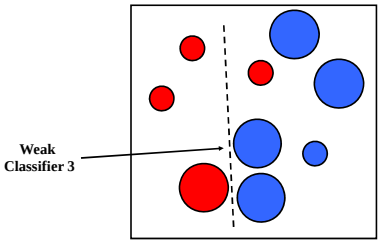
21

Boosting illustration



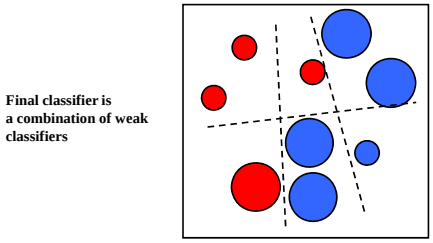
22

Boosting illustration



23

Boosting illustration



24

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)

25

Slide credit: Lana Lazebnik

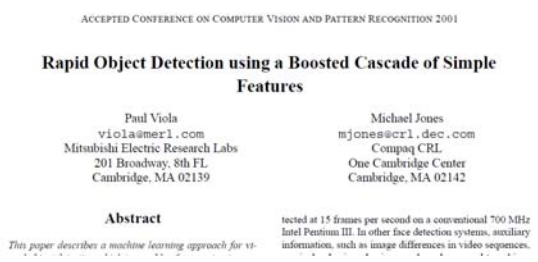
Boosting: pros and cons

- Advantages of boosting
  - Integrates classification with feature selection
  - 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

26

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,

27

Viola-Jones face detector

Main idea:

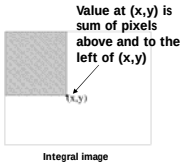
- Represent local texture with efficiently computable "rectangular" features within window of interest
- Select discriminative features to be weak classifiers
- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

28
Kristen Grauman

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.

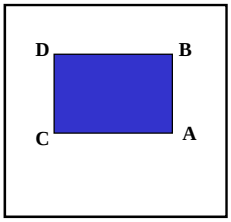


29
Kristen Grauman

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!



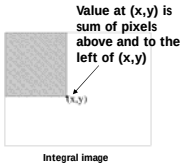
30
Lana Lazebnik

Viola-Jones detector: features

"Rectangular" filters

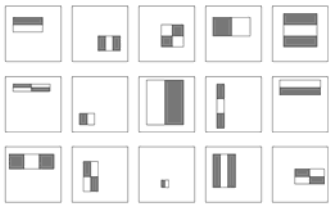
Feature output is difference between adjacent regions

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



31
Kristen Grauman

Viola-Jones detector: features



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

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

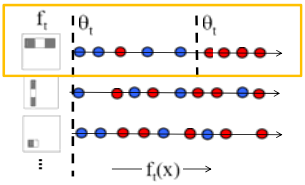
Which subset of these features should we use to determine if a window has a face?

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

32
Kristen Grauman

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.

33
Kristen Grauman

- Given example images $(x_1, y_1), \ldots, (x_n, y_n)$ where $y_i = 0, 1$ for negative and positive examples respectively.

AdaBoost Algorithm

Start with uniform weights on training examples

$\{x_1, \ldots x_n\}$

For T rounds

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

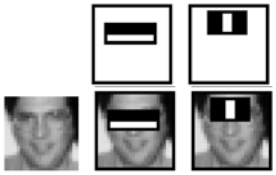
Re-weight the examples:
Incorrectly classified -> more weight
Correctly classified -> less weight

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

Freund & Schapire 1995

34

Viola-Jones Face Detector: Results



First two features selected

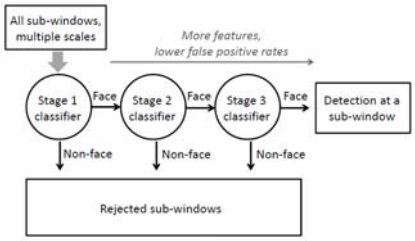
Visual Object Recognition Tutorial

35

- 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?

36

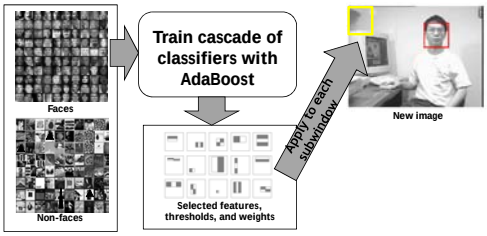
Cascading classifiers for detection



- 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

37
Kristen Grauman

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/]

38
Kristen Grauman

Viola-Jones detector: summary

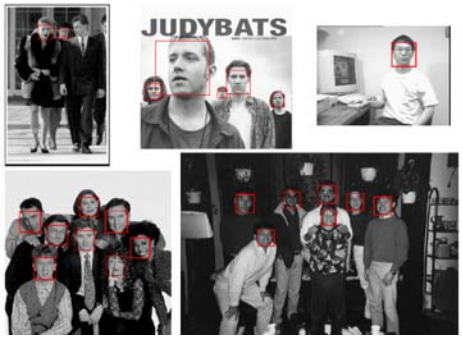
- A seminal approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas
  - *Integral images* for fast feature evaluation
  - *Boosting* for feature selection
  - *Attentional cascade* of classifiers for fast rejection of non-face windows

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.

39

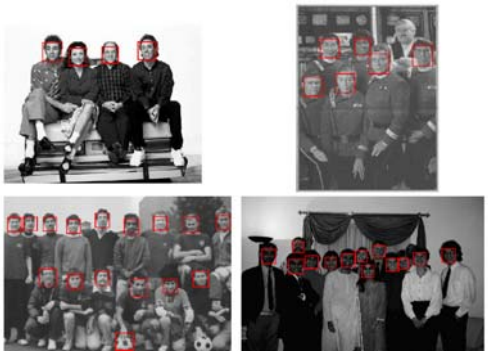
Viola-Jones Face Detector: Results



Visual Object Recognition Tutorial

40

Viola-Jones Face Detector: Results



Visual Object Recognition Tutorial

41

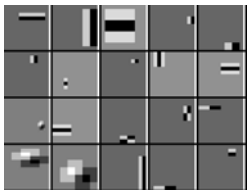
Viola-Jones Face Detector: Results

Visual Object Recognition Tutorial

42

Detecting profile faces?

Can we use the same detector?



Visual Object Recognition Tutorial

43

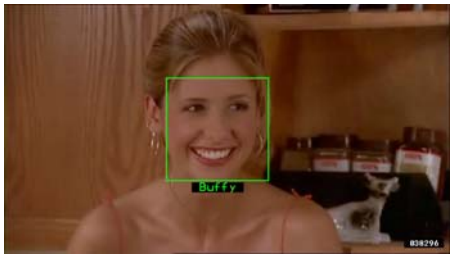
Viola-Jones Face Detector: Results

Visual Object Recognition Tutorial

Paul

44

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

45

46

Consumer application: iPhoto 2009

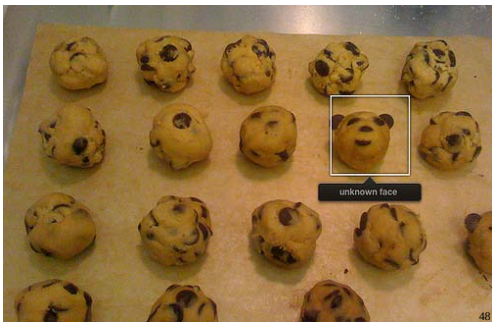
http://www.apple.com/ilife/iphoto/

47

Slide credit: Lana Lazebnik

Consumer application: iPhoto 2009

Things iPhoto thinks are faces

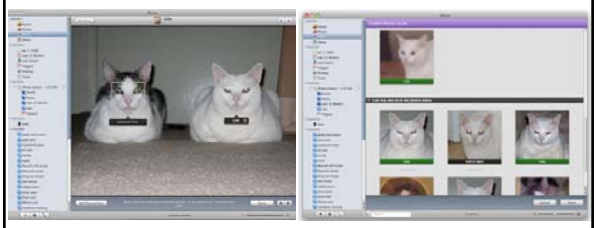


48

Slide credit: Lana Lazebnik

Consumer application: iPhoto 2009

Can be trained to recognize pets!



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

49

Slide credit: Lana Lazebnik

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

50

Visual Object Recognition Tutorial

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]

51

Kristen Grauman

Window-based detection: strengths

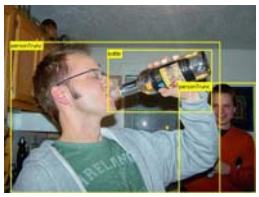
- Sliding window detection and global appearance descriptors:
  - Simple detection protocol to implement
  - Good feature choices critical
  - Past successes for certain classes

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

Limitations (continued)

- Not all objects are "box" shaped



Limitations (continued)

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

Visual Object Recognition Tutorial

55
Kristen Grauman

Limitations (continued)

- If considering windows in isolation, context is lost

Sliding window

Detector's view

Figure credit: Derek Hoiem

Visual Object Recognition Tutorial

56

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

Visual Object Recognition Tutorial

57
Kristen Grauman

Summary

- Basic pipeline for window-based detection
  - Model/representation/classifier choice
  - Sliding window and classifier scoring
- Boosting classifiers: general idea
- Viola-Jones face detector
  - Exemplar of basic paradigm
  - Plus key ideas: rectangular features, Adaboost for feature selection, cascade
- Pros and cons of window-based detection

58

Questions?

See you Tuesday!

59