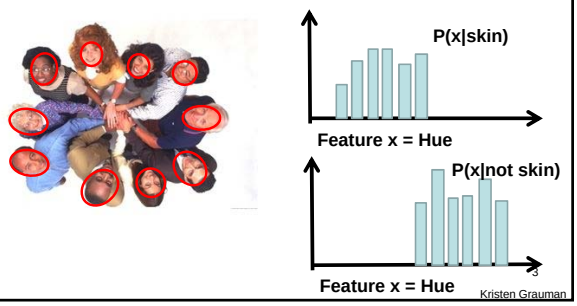
Previously

- 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)



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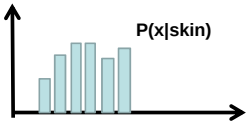
3

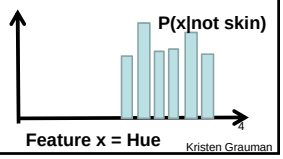
Last time: Example: skin color classification

- 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.

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



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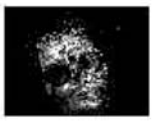
Last time: Example: skin color classification

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

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Today

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

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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

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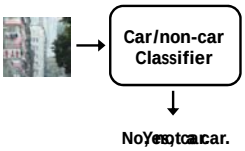
Window-based models Building an object model

Given the representation, train a binary classifier



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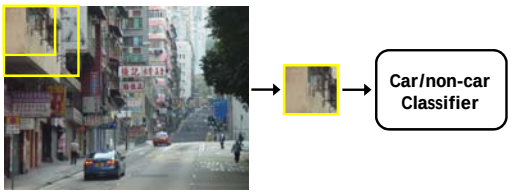
Window-based models Generating and scoring candidates



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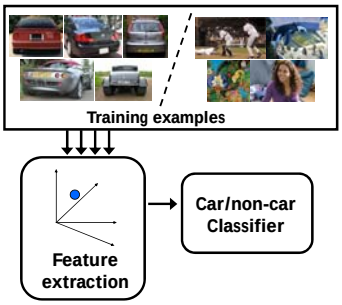
Window-based object detection: recap

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



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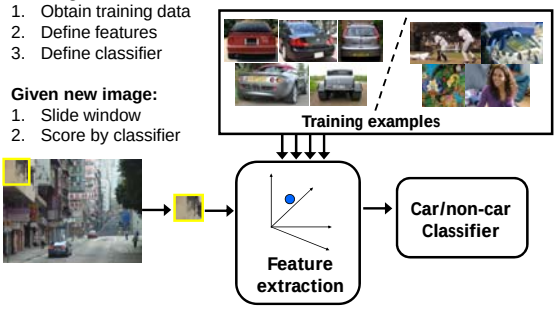
Window-based object detection: recap

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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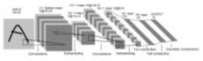
Discriminative classifier construction

Nearest neighbor

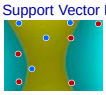
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

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
…

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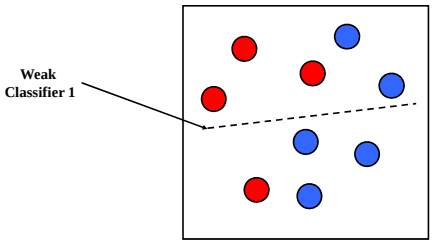
Slide adapted from Antonio Torralba

Boosting intuition



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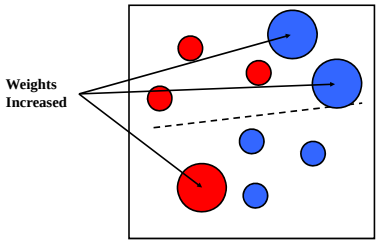
Slide credit: Paul Viola

Boosting illustration



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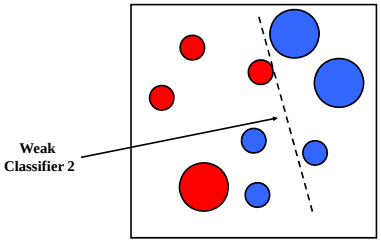
Boosting illustration



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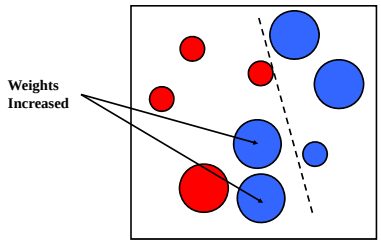
Boosting illustration



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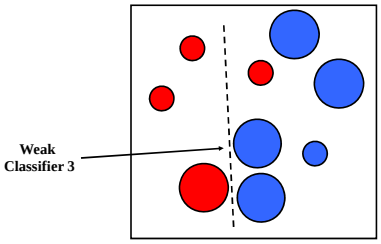
Boosting illustration



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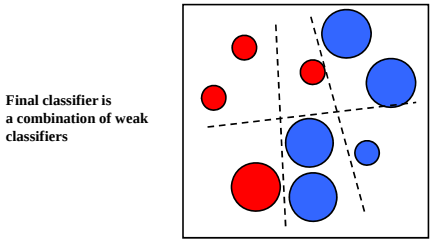
Boosting illustration



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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)

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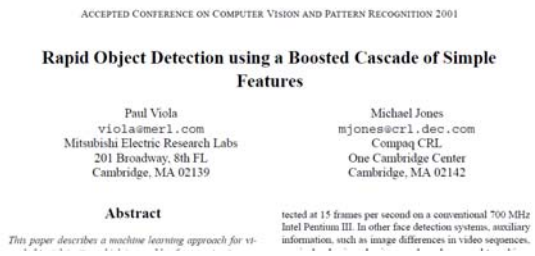
Slide credit: Lana Lazebnik

Viola-Jones face detector



ACCEPTED CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION 2001

Rapid Object Detection using a Boosted Cascade of Simple Features

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Michael Jones
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Compaq CRL
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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,

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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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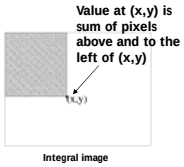
Viola-Jones detector: features

"Rectangular" filters

Feature output is difference between adjacent regions

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



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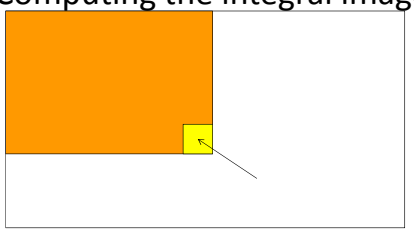
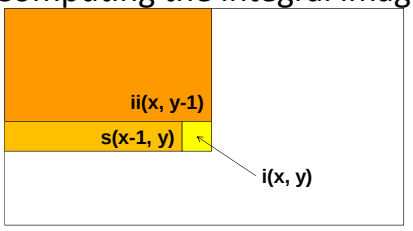
Computing the integral image



Lana Lazebnik

Computing the integral image



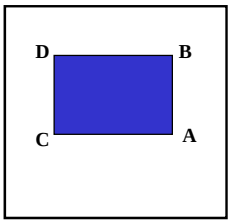
- Cumulative row sum: s(x, y) = s(x–1, y) + i(x, y)
- Integral image: ii(x, y) = ii(x, y−1) + s(x, y)

Lana Lazebnik

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!



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Lana Lazebnik

Viola-Jones detector: features

"Rectangular" filters

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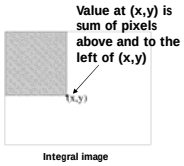

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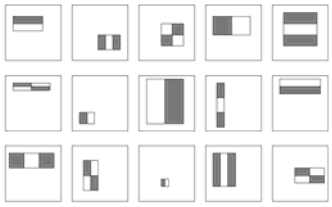
Viola-Jones detector: features



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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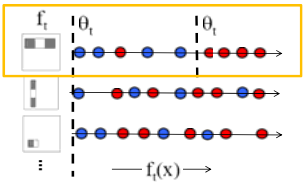
Viola-Jones detector: AdaBoost

- **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 $(x_1, y_1), \ldots, (x_n, y_n)$ 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

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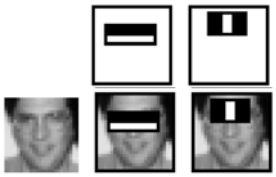
Viola-Jones Face Detector: Results



First two features selected

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- 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?

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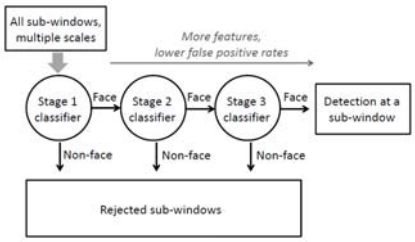
Cascading classifiers for detection



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

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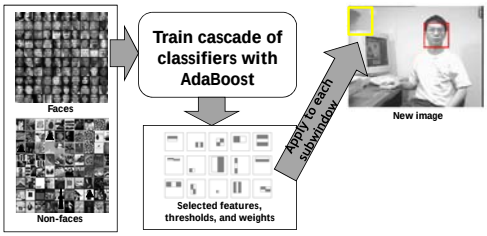
Viola-Jones detector: summary



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
  - *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.

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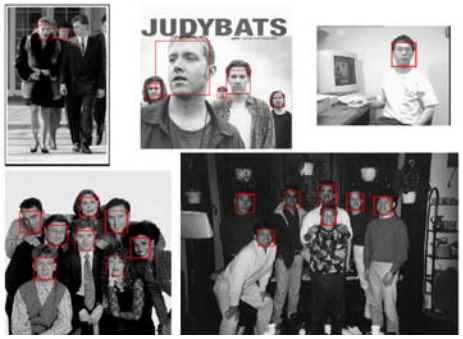
Viola-Jones Face Detector: Results



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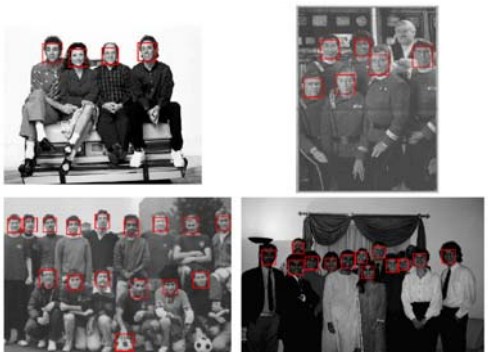
Viola-Jones Face Detector: Results



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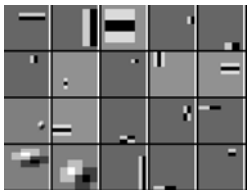
Viola-Jones Face Detector: Results

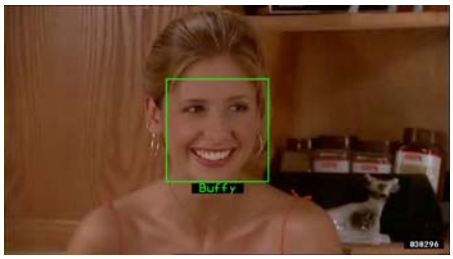
Detecting profile faces?

Can we use the same detector?



Viola-Jones Face Detector: Results

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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Slide: Kristen Grauman

Consumer application: iPhoto 2009

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

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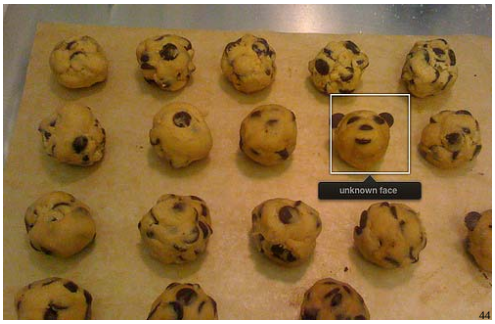
Slide credit: Lana Lazebnik

Consumer application: iPhoto 2009

Things iPhoto thinks are faces



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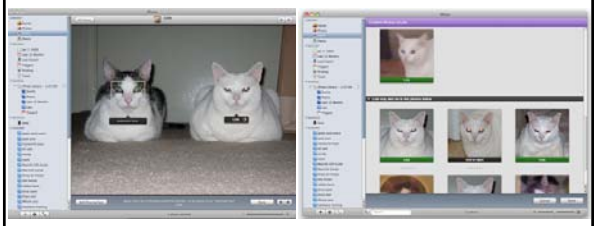
Slide credit: Lana Lazebnik

Consumer application: iPhoto 2009

Can be trained to recognize pets!



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

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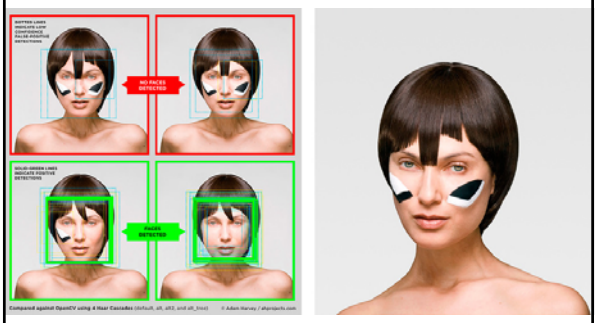
Slide credit: Lana Lazebnik

Privacy Gift Shop – CV Dazzle



http://www.wired.com/2015/06/facebook-can-recognize-even-dont-show-face/
Wired, June 15, 2015

Slide: Kristen Grauman

Privacy Visor

http://www.3ders.org/articles/20150812-japan-3d-printed-privacy-visors-will-block-facial-recognition-software.html

Slide: Kristen Grauman

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

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Slide credit: Lana Lazebnik

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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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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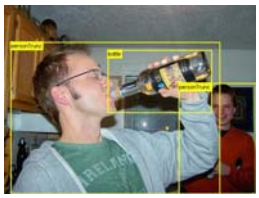
Limitations (continued)

- Not all objects are "box" shaped



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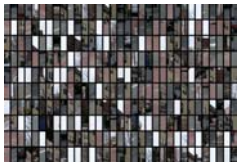
Limitations (continued)

- If considering windows in isolation, context is lost

Sliding window



Detector's view

Figure credit: Derek Hoiem

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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

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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

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Questions?

See you Thursday!

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