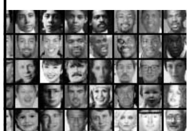
Object detection as supervised classification



Thurs April 13

Kristen Grauman
UT Austin

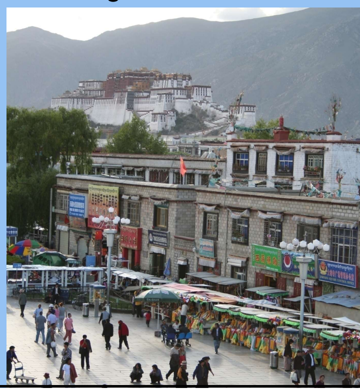
Last time

- Discovering visual patterns
  - Randomized hashing algorithms
  - Mining large-scale image collections

Review questions: on your own

- What kind of input data is searchable with min-hash hashing?
- What kind of input data is searchable with LSH using random projections?
- For Visual “PageRank” what do weights between nodes (images) signify?

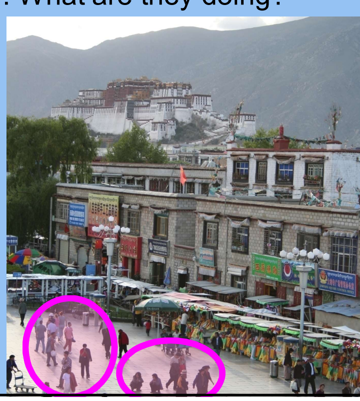
What does recognition involve?



Fei-Fei Li

Detection: are there people?

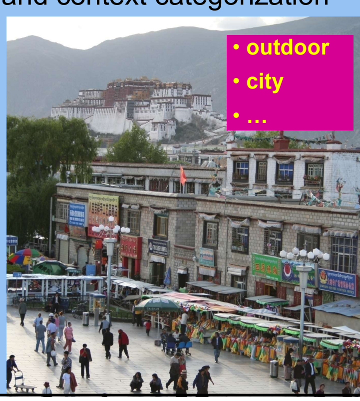
Activity: What are they doing?



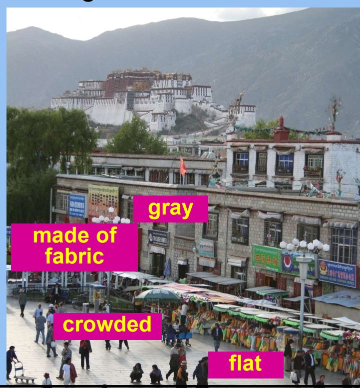
Object categorization

Instance recognition

Scene and context categorization



Attribute recognition



Object Categorization

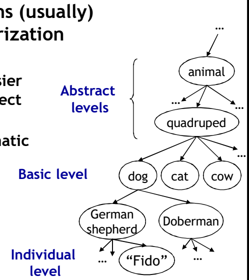
- Task Description
  - "Given a small number of training images of a category, recognize a-priori unknown instances of that category and assign the correct category label."
- Which categories are feasible visually?

Visual Object Categories

- Basic Level Categories in human categorization [Rosch 76, Lakoff 87]
  - The highest level at which category members have similar perceived shape
  - The highest level at which a single mental image reflects the entire category
  - The level at which human subjects are usually fastest at identifying category members
  - The first level named and understood by children
  - The highest level at which a person uses similar motor actions for interaction with category members

Visual Object Categories

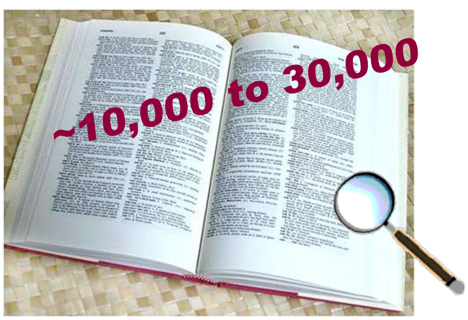
- Basic-level categories in humans seem to be defined predominantly visually.
- There is evidence that humans (usually) start with basic-level categorization *before* doing identification.
  - ⇒ Basic-level categorization is easier and faster for humans than object identification!
  - ⇒ How does this transfer to automatic classification algorithms?



K. Grauman, B. Leibe

Visual Object Recognition Tutorial

How many object categories are there?



Source: Fei-Fei Li, Rob Fergus, Antonio Torralba.

Biederman 1987

Other Types of Categories

- Functional Categories
  - e.g. chairs = *"something you can sit on"*

Visual Object Recognition Tutorial

K. Grauman, B. Leibe

Why recognition?

- Recognition a fundamental part of perception
  - e.g., robots, autonomous agents
- Organize and give access to visual content
  - Connect to information
  - Detect trends and themes

Autonomous agents able to detect objects

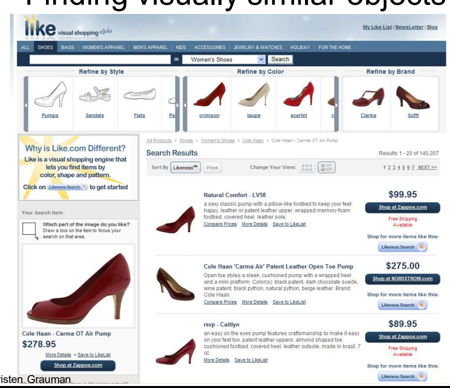
Slide: Kristen Grauman

http://www.darpa.mil/grandchallenge/gallery.asp

Posing visual queries

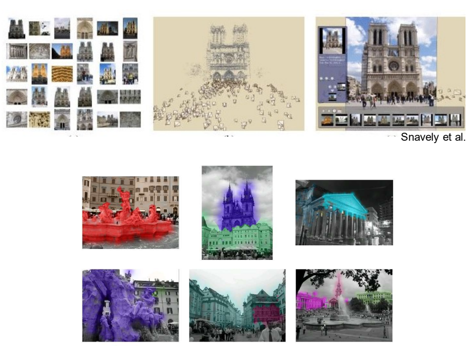
Slide: Kristen Grauman

Finding visually similar objects



Slide: Kristen Grauman

Exploring community photo collections



Slide: Kristen Grauman

Simon & Seitz

Discovering visual patterns

Slide: Kristen Grauman

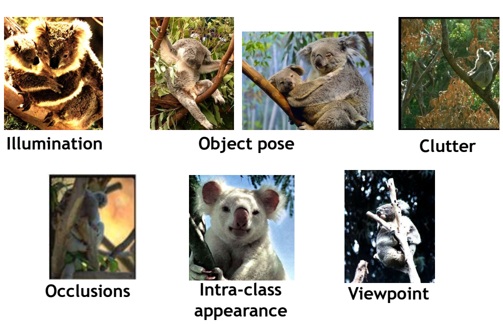
Auto-annotation

Gammeter et al.

T. Berg et al.

Slide: Kristen Grauman

Challenges: robustness



Slide: Kristen Grauman

Challenges: context and human experience

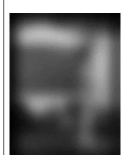
Context cues

Slide: Kristen Grauman

Challenges: context and human experience

Context cues

Function



Dynamics

Slide: Kristen Grauman

Video credit: J. Davis

Challenges: complexity

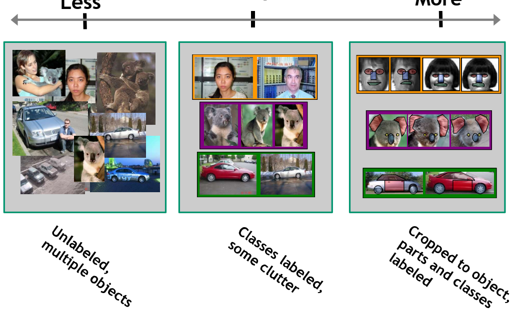
- Millions of pixels in an image
- 30,000 human recognizable object categories
- 30+ degrees of freedom in the pose of articulated objects (humans)
- Billions of images online
- 82 years to watch all videos uploaded to YouTube per day!

…

- About half of the cerebral cortex in primates is devoted to processing visual information [Felleman and van Essen 1991]

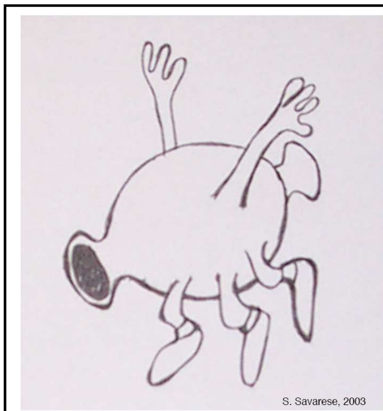
Slide: Kristen Grauman

Challenges: learning with minimal supervision



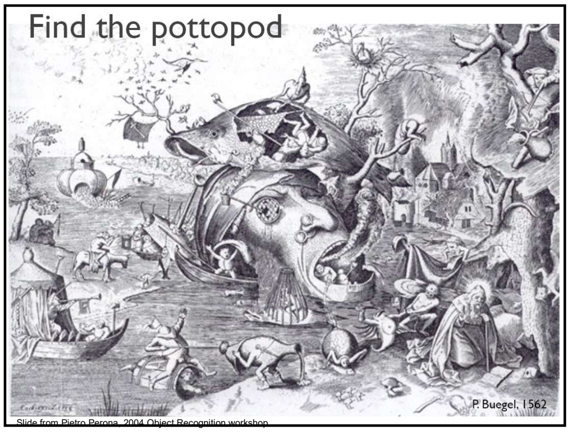
Slide: Kristen Grauman

This is a pottopod



Slide from Pietro Perona, 2004 Object Recognition workshop

Find the pottopod



Slide from Pietro Perona, 2004 Object Recognition workshop

What kinds of things work best today?

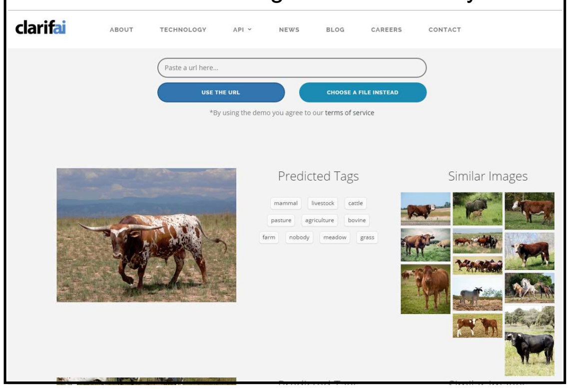
Reading license plates, zip codes, checks

Frontal face detection

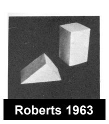
Recognizing flat, textured objects (like books, CD covers, posters)

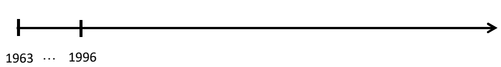
Fingerprint recognition

What kinds of things work best today?



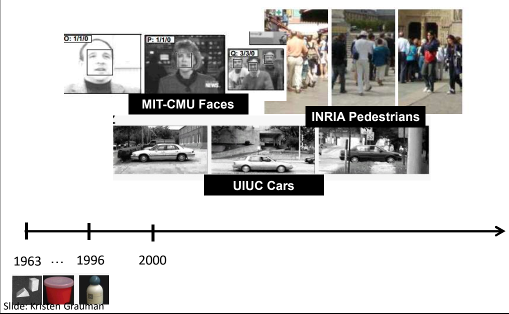
Progress charted by datasets



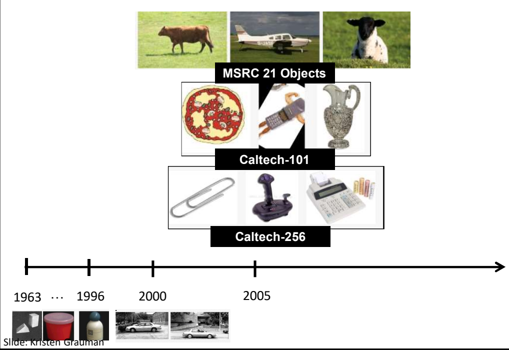


Slide: Kristen Grauman

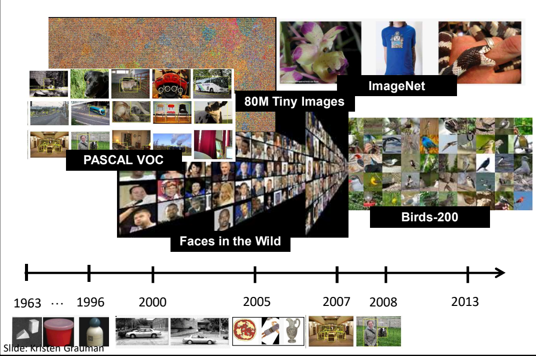
Progress charted by datasets



Progress charted by datasets



Progress charted by datasets



Evolution of methods

- Hand-crafted models
- 3D geometry
- Hypothesize and align

- Hand-crafted features
- Learned models
- Data-driven

- "End-to-end" learning of features and models*,**

Slide: Kristen Grauman

* Labeled data availability
** Architecture design decisions, parameters.

Next

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

Supervised classification

- Given a collection of *labeled* examples, come up with a function that will predict the labels of new examples.

"four"
"nine"

?

Training examples — Novel input

- How good is some function we come up with to do the classification?
- Depends on
  - Mistakes made
  - Cost associated with the mistakes

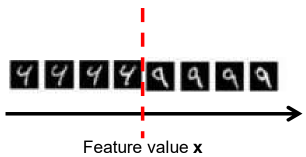
Supervised classification

- Given a collection of *labeled* examples, come up with a function that will predict the labels of new examples.
- Consider the two-class (binary) decision problem
  - L(4→9): Loss of classifying a 4 as a 9
  - L(9→4): Loss of classifying a 9 as a 4
- **Risk** of a classifier *s* is expected loss:

$$R(s) = \Pr(4 \to 9 \mid \text{using } s) L(4 \to 9) + \Pr(9 \to 4 \mid \text{using } s) L(9 \to 4)$$

- We want to choose a classifier so as to minimize this total risk

Supervised classification



Optimal classifier will minimize total risk.

At decision boundary, either choice of label yields same expected loss.

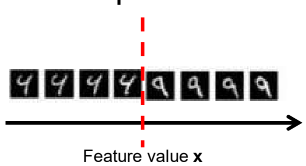
If we choose class "four" at boundary, expected loss is:

$$= P(\text{class is } 9 \mid \mathbf{x})\, L(9 \to 4) + P(\text{class is } 4 \mid \mathbf{x}) L(4 \to 4)$$

If we choose class "nine" at boundary, expected loss is:

$$= P(\text{class is } 4 \mid \mathbf{x})\, L(4 \to 9)$$

Supervised classification



Optimal classifier will minimize total risk.

At decision boundary, either choice of label yields same expected loss.

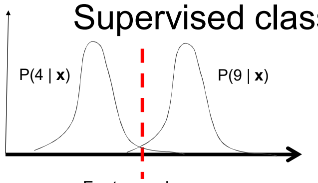
So, best decision boundary is at point **x** where

$$P(\text{class is } 9 \mid \mathbf{x})\, L(9 \to 4) = \mathrm{P}(\text{class is } 4 \mid \mathbf{x}) L(4 \to 9)$$

To classify a new point, choose class with lowest expected loss; i.e., choose "four" if

$$P(4 \mid \mathbf{x}) L(4 \to 9) > P(9 \mid \mathbf{x}) L(9 \to 4)$$

Supervised classification



Optimal classifier will minimize total risk.

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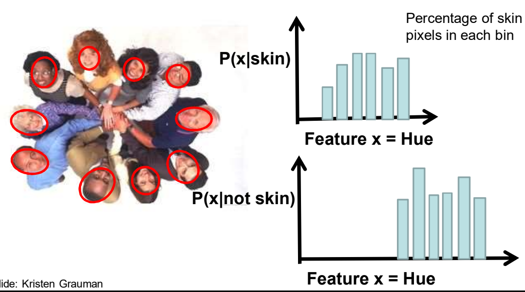
Example: learning skin colors

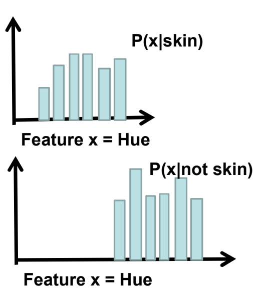
- We can represent a class-conditional density using a histogram (a "non-parametric" distribution)



Slide: Kristen Grauman

Example: learning skin colors

- 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.

What's the probability we care about to do skin detection?

Slide: Kristen Grauman

Bayes rule

posterior, likelihood, prior

$$P(skin \mid x) = \frac{P(x \mid skin) P(skin)}{P(x)}$$

$$P(skin \mid x) \propto P(x \mid skin) P(skin)$$

Where does the prior come from?

Why use a prior?

Example: classifying skin pixels

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

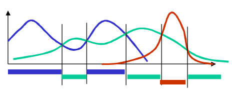
Supervised classification

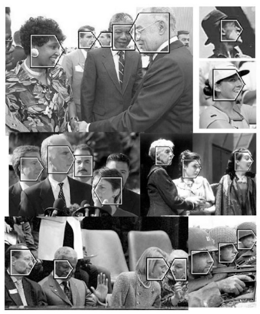
- Want to minimize the expected misclassification
- Two general strategies
  - Use the training data to build representative probability model; separately model class-conditional densities and priors (*generative*)
  - Directly construct a good decision boundary, model the posterior (*discriminative*)

General classification

This same procedure applies in more general circumstances

- More than two classes
- More than one dimension





Example: face detection

- Here, X is an image region
  - dimension = # pixels
  - each face can be thought of as a point in a high dimensional space

H. Schneiderman, T. Kanade. "A Statistical Method for 3D Object Detection Applied to Faces and Cars". IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2000) http://www-2.cs.cmu.edu/afs/cs.cmu.edu/user/hws/www/CVPR00.pdf

H. Schneiderman and T.Kanade

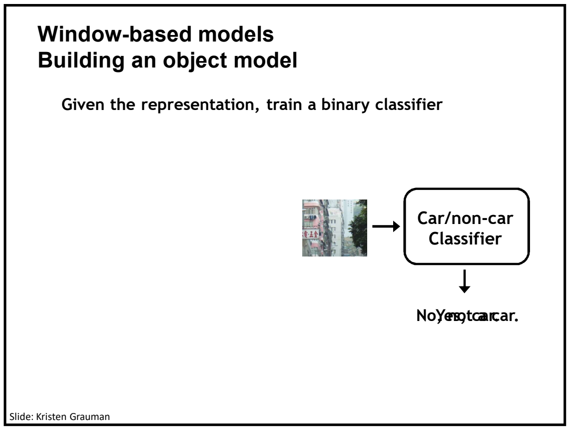
Source: Steve Seitz

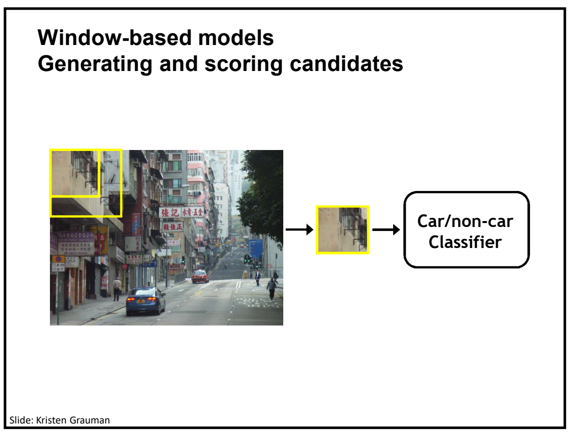
Today

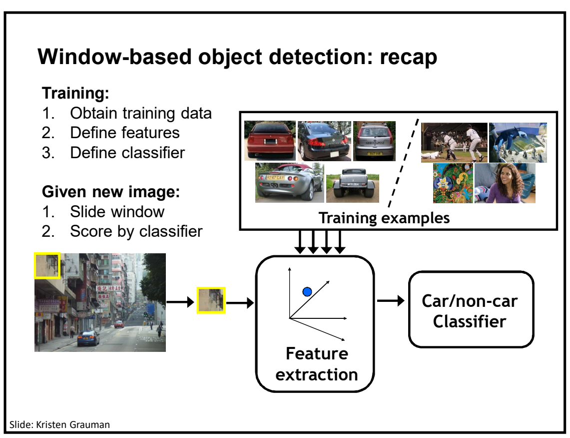
- Supervised classification
- Window-based generic object detection
  - basic pipeline
  - boosting classifiers
  - face detection as case study

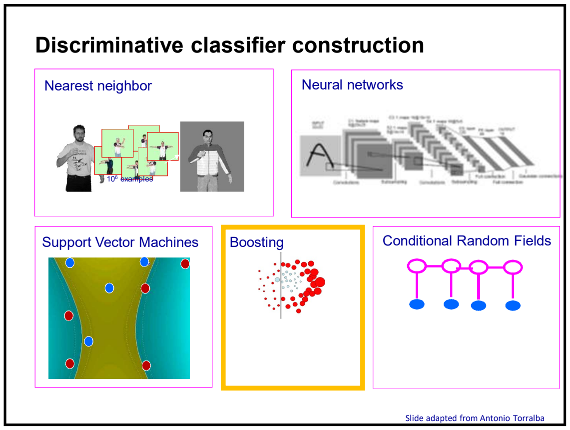
Generic category recognition: basic framework

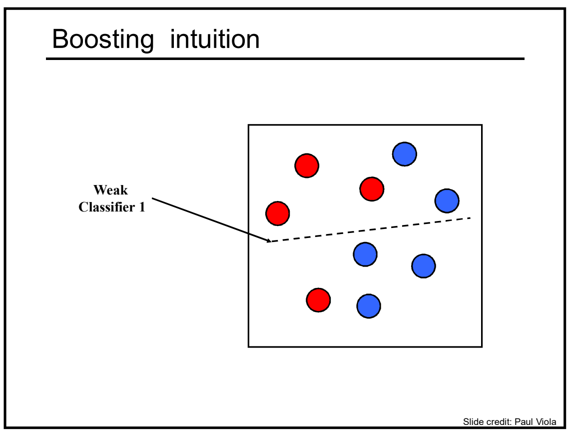
- Build/train object model
  - Choose a representation
  - Learn or fit parameters of model / classifier
- Generate candidates in new image
- Score the candidates

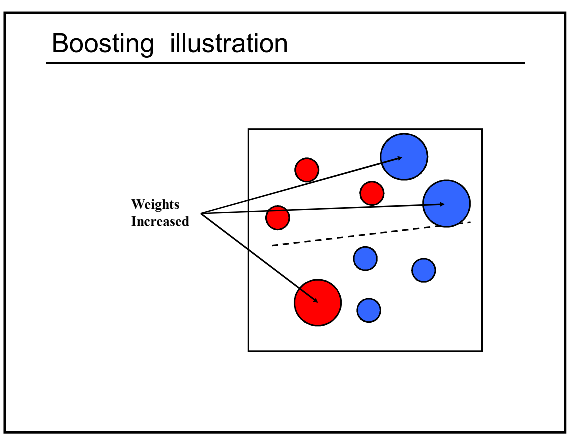

Window-based models
Building an object model
Given the representation, train a binary classifier
Car/non-car Classifier
No, not a car.
Yes, car.
Slide: Kristen Grauman


Window-based models
Generating and scoring candidates
Car/non-car Classifier
Slide: Kristen Grauman

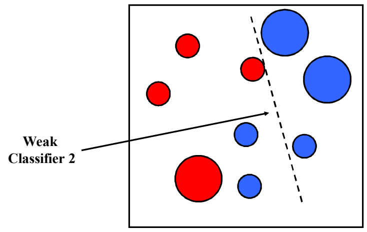

Window-based object detection: recap
Training:
1. Obtain training data
2. Define features
3. Define classifier
Given new image:
1. Slide window
2. Score by classifier
Training examples
Feature extraction
Car/non-car Classifier
Slide: Kristen Grauman


Discriminative classifier construction
Nearest neighbor
Neural networks
Support Vector Machines
Boosting
Conditional Random Fields
Slide adapted from Antonio Torralba

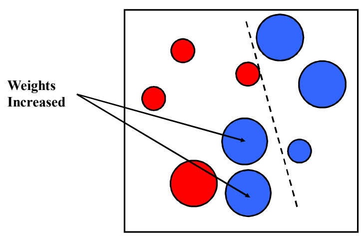

Boosting intuition
Weak
Classifier 1
Slide credit: Paul Viola


Boosting illustration
Weights
Increased

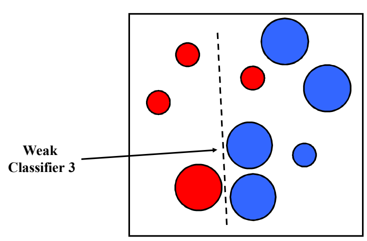
Boosting illustration



Boosting illustration

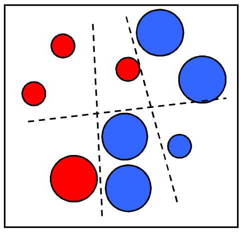


Boosting illustration



Boosting illustration

Final classifier is a combination of weak classifiers



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

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Abstract

This paper describes a machine learning approach for vi-

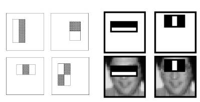
tected at 15 frames per second on a conventional 700 MHz Intel Pentium III. In other face detection systems, auxiliary information, such as image differences in video sequences,

Viola-Jones face detector

Main idea:

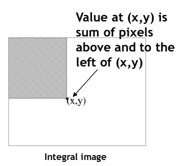
- Represent local texture with efficiently computable "rectangular" features within window of interest
- Select discriminative features to be weak classifiers
- Use boosted combination of them as final classifier
- Form a cascade of such classifiers, rejecting clear negatives quickly

Viola-Jones detector: features



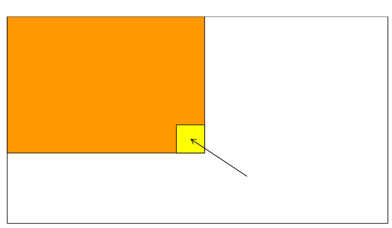
"Rectangular" filters
Feature output is difference between adjacent regions

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



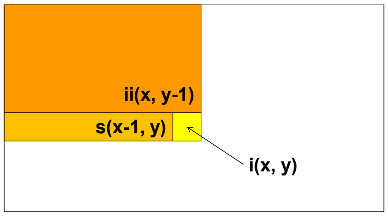
Slide: Kristen Grauman

Computing the integral image



Lana Lazebnik

Computing the integral image

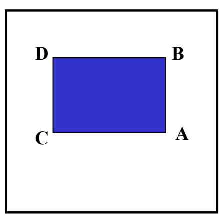


Cumulative row sum: s(x, y) = s(x–1, y) + i(x, y)
Integral image: ii(x, y) = ii(x, y−1) + s(x, y)

Lana Lazebnik

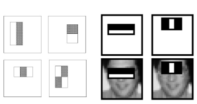
Computing sum within a rectangle

- 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!



Lana Lazebnik

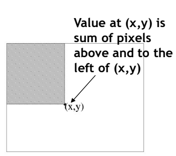
Viola-Jones detector: features



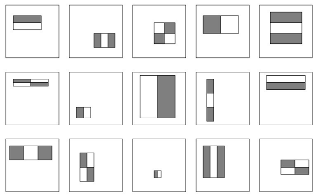
"Rectangular" filters
Feature output is difference between adjacent regions

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

Avoid scaling images → scale features directly for same cost



Viola-Jones detector: features



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

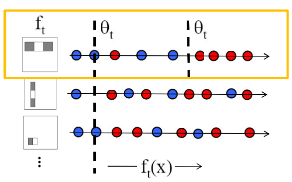
180,000+ possible features associated with each 24 x 24 window

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

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

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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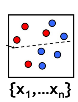
AdaBoost Algorithm

- 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 $\alpha_t = \log \frac{1}{\beta_t}$

Start with uniform weights on training examples



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

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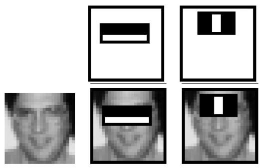
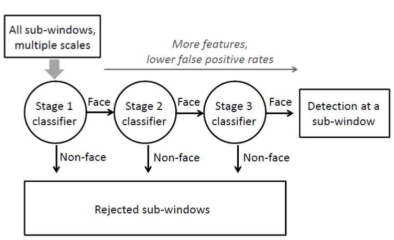


First two features selected

- 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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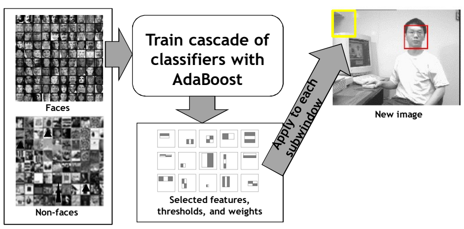
Training the cascade

- Set target detection and false positive rates for each stage
- Keep adding features to the current stage until its target rates have been met
  - Need to lower AdaBoost threshold to maximize detection (as opposed to minimizing total classification error)
  - Test on a *validation set*
- If the overall false positive rate is not low enough, then add another stage
- Use false positives from current stage as the negative training examples for the next stage

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]

Slide: Kristen Grauman

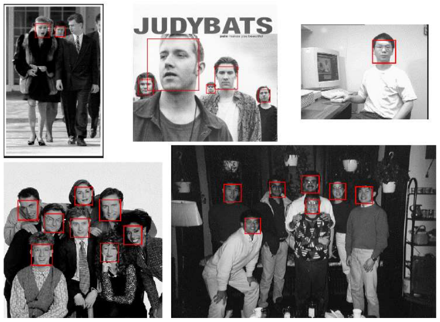
Viola-Jones detector: summary

- A seminal approach to real-time object detection
  - 15,000 citations and counting
- 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.

Viola-Jones Face Detector: Results



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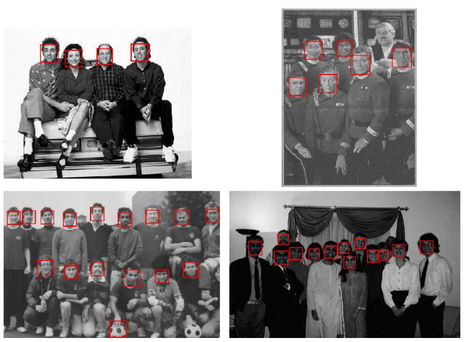
Viola-Jones Face Detector: Results



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Viola-Jones Face Detector: Results

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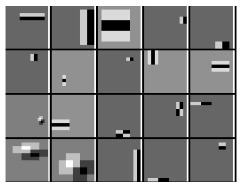
Detecting profile faces?

Can we use the same detector?



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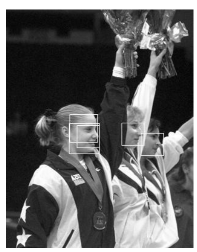
Viola-Jones Face Detector: Results



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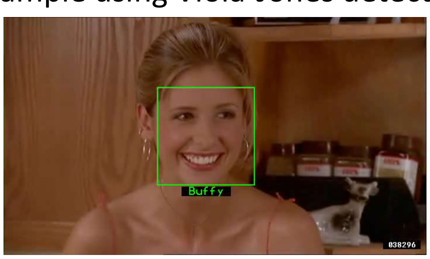
Paul

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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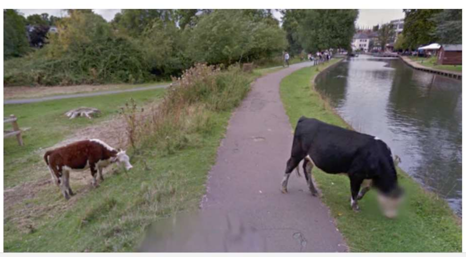
Technology

Google street view blurs face of cow to protect its identity

share



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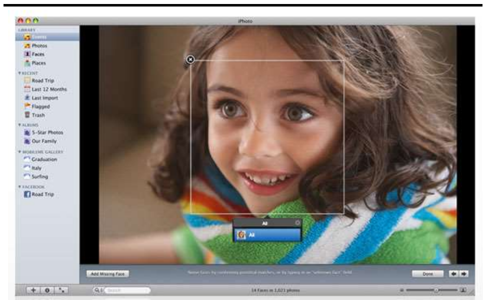
Consumer application: iPhoto



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

Slide credit: Lana Lazebnik

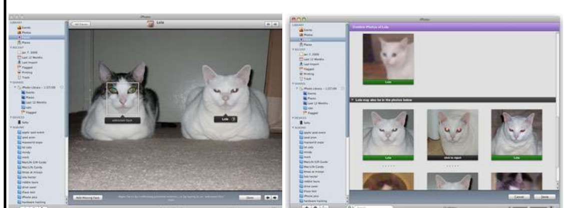
Consumer application: iPhoto

Things iPhoto thinks are faces

Slide credit: Lana Lazebnik

Consumer application: iPhoto

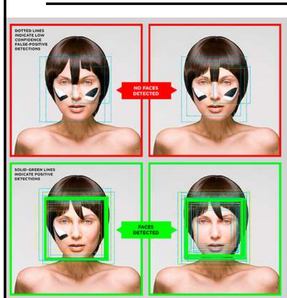
Can be trained to recognize pets!



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

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

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Privacy Visor

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

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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
  - Other discriminative models may outperform in practice (SVMs, CNNs,…)
    - 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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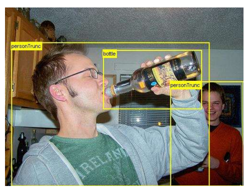
Limitations (continued)

- Not all objects are “box” shaped



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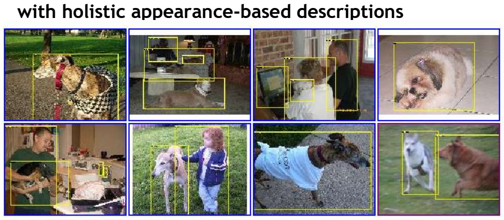
Limitations (continued)

- 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 descriptions



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Limitations (continued)

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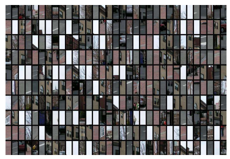
- If considering windows in isolation, context is lost

Sliding window



Detector's view

Figure credit: Derek Hoiem

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Limitations (continued)

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- 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