CMT107 Visual Computing

XI. Object Recognition

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Overview

- Object Recognition
  - Overview
  - History
  - What “Works” Today
- Machine Learning Approach for Recognition
  - The Machine Learning Framework
  - Classifiers
    - Nearest neighbour
    - Linear
  - Recognition Task and Supervision
  - Generalization
  - Datasets
- Face Detection and Recognition
  - The Viola/Jones Face Detector
  - Face Recognition

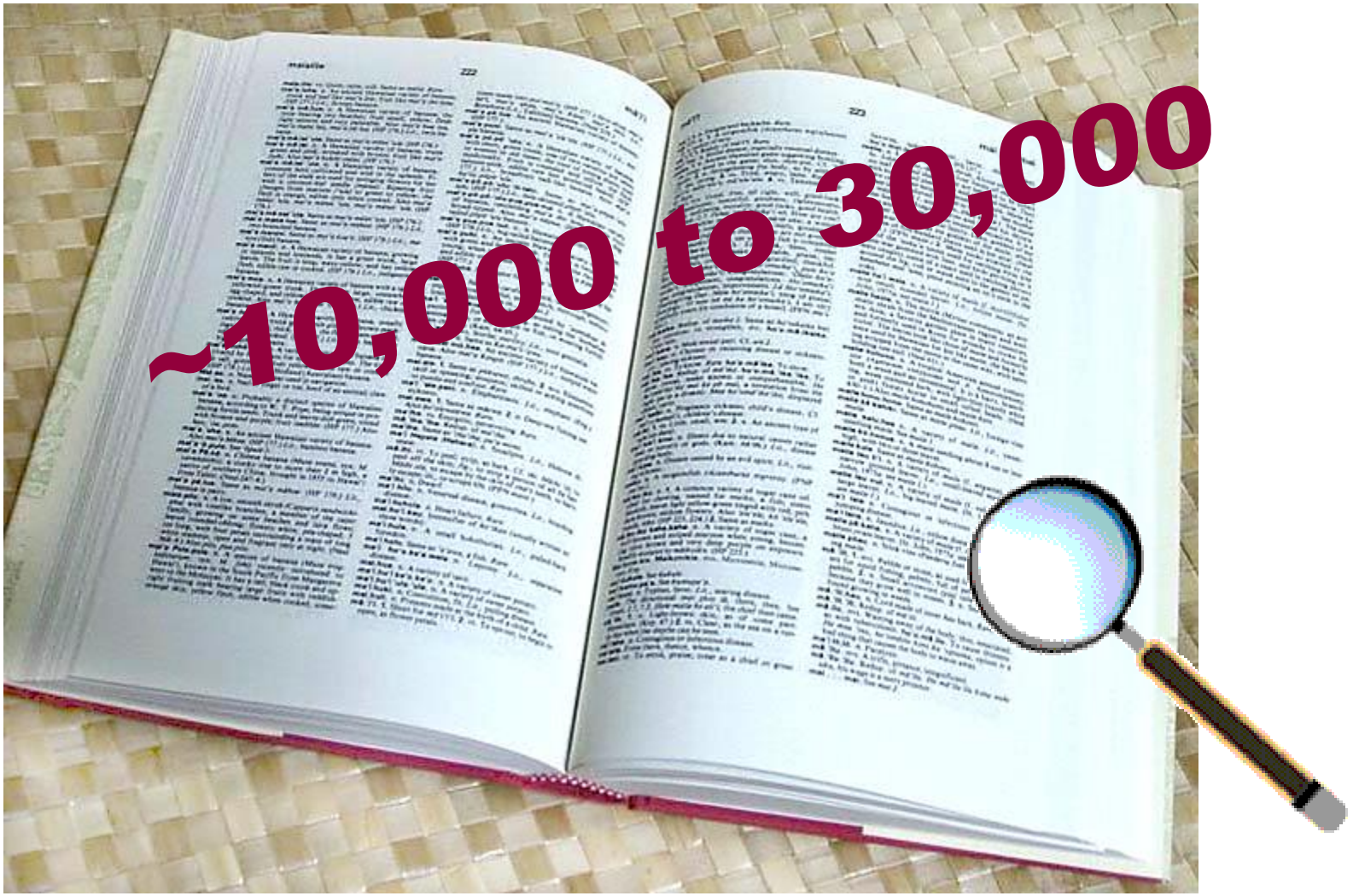
Acknowledgement

The majority of the slides in this section are from Svetlana Lazebnik at University of Illinois at Urbana-Champaign

Object Recognition

- Object recognition is the task of finding a given object in an image or video sequence.
- The object recognition problem can be defined as a labelling problem based on models of known objects.
- Object recognition approaches:
  - Geometric Model-based methods
  - Appearance-based methods
  - Feature-based methods

How Many Visual Object Categories Are There?

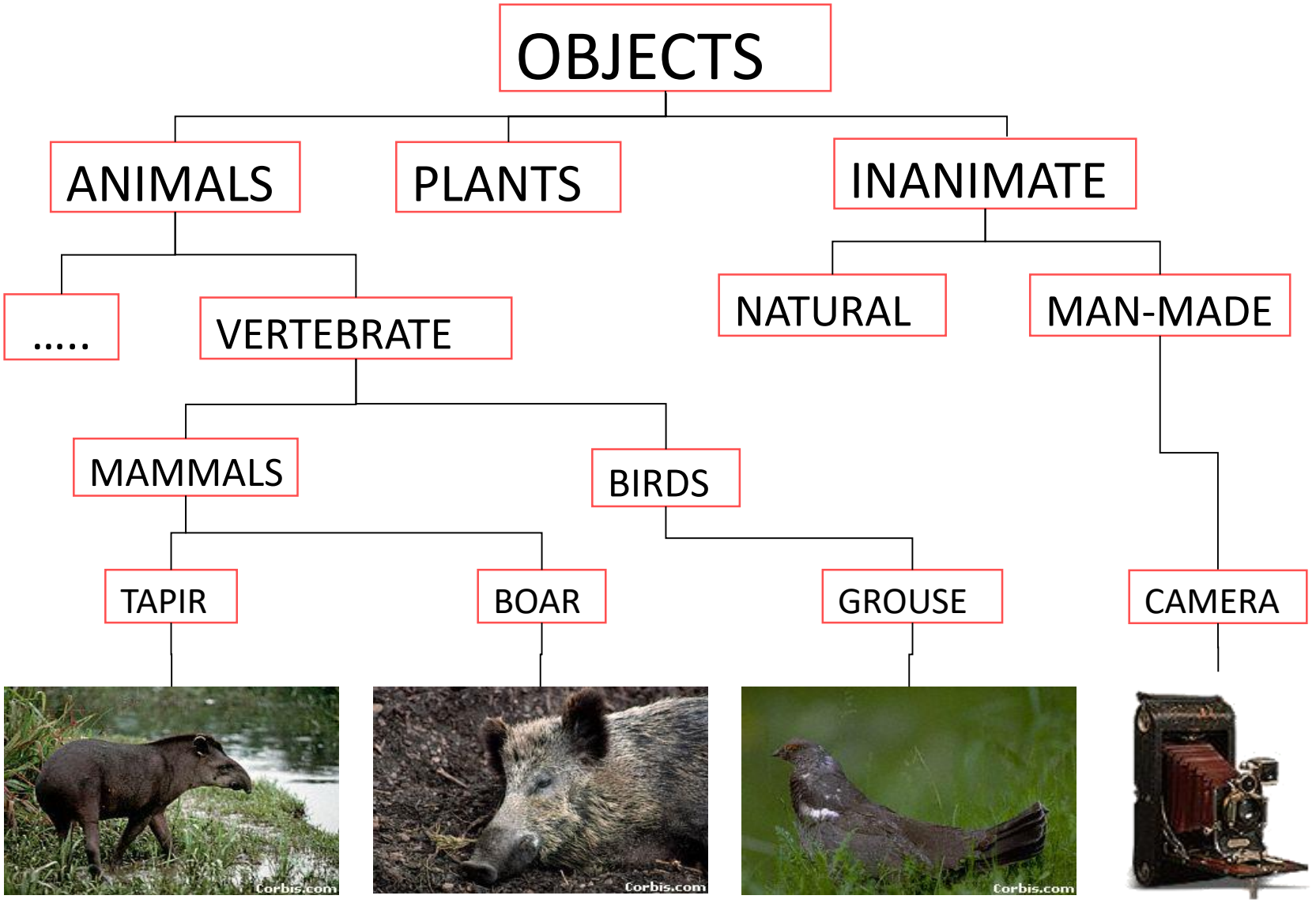


Slides adapted from Fei-Fei Li, Rob Fergus, Antonio Torralba, and Jean Ponce

Biederman 1987

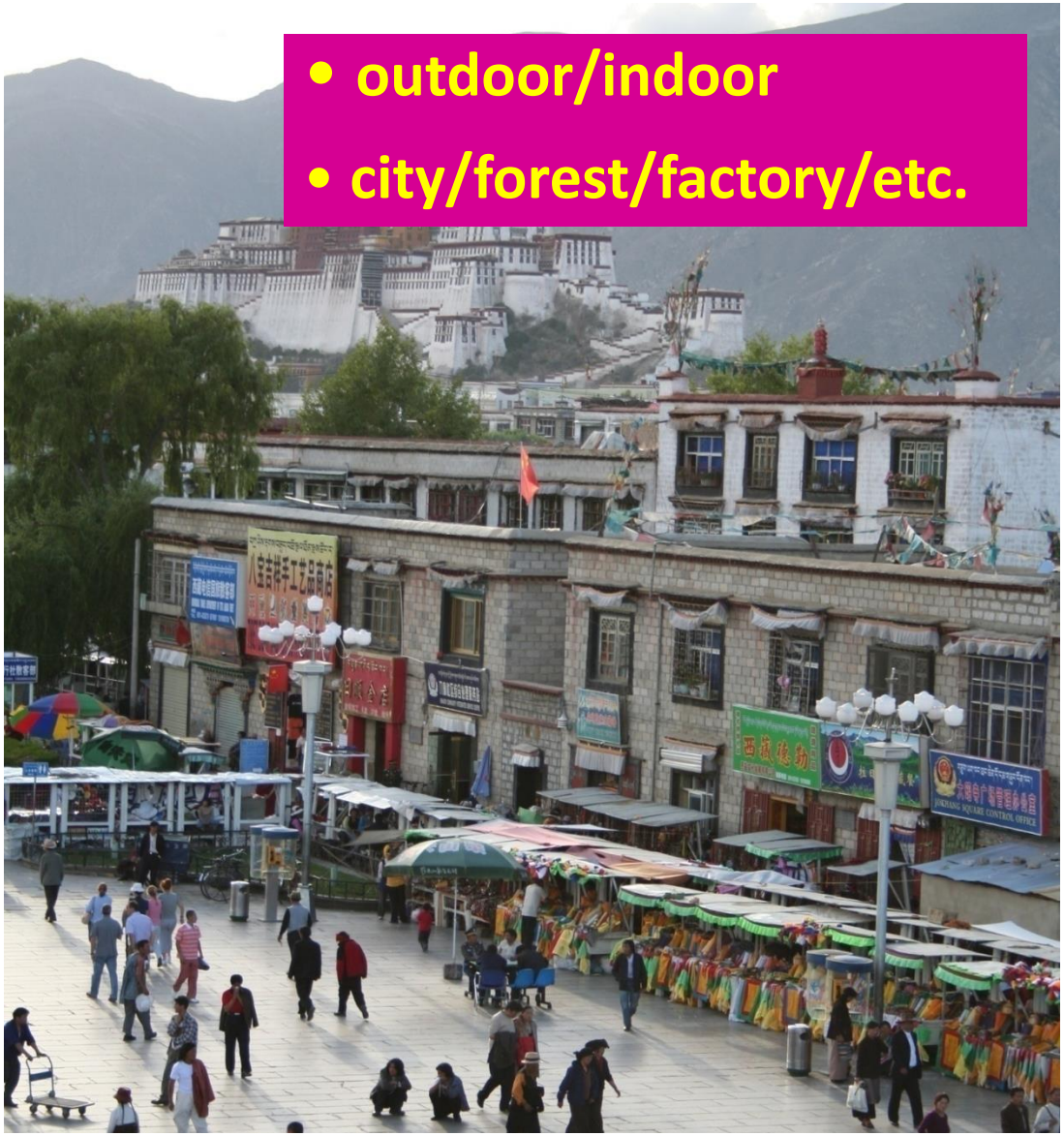
How Many Visual Object Categories Are There?

Object Categories



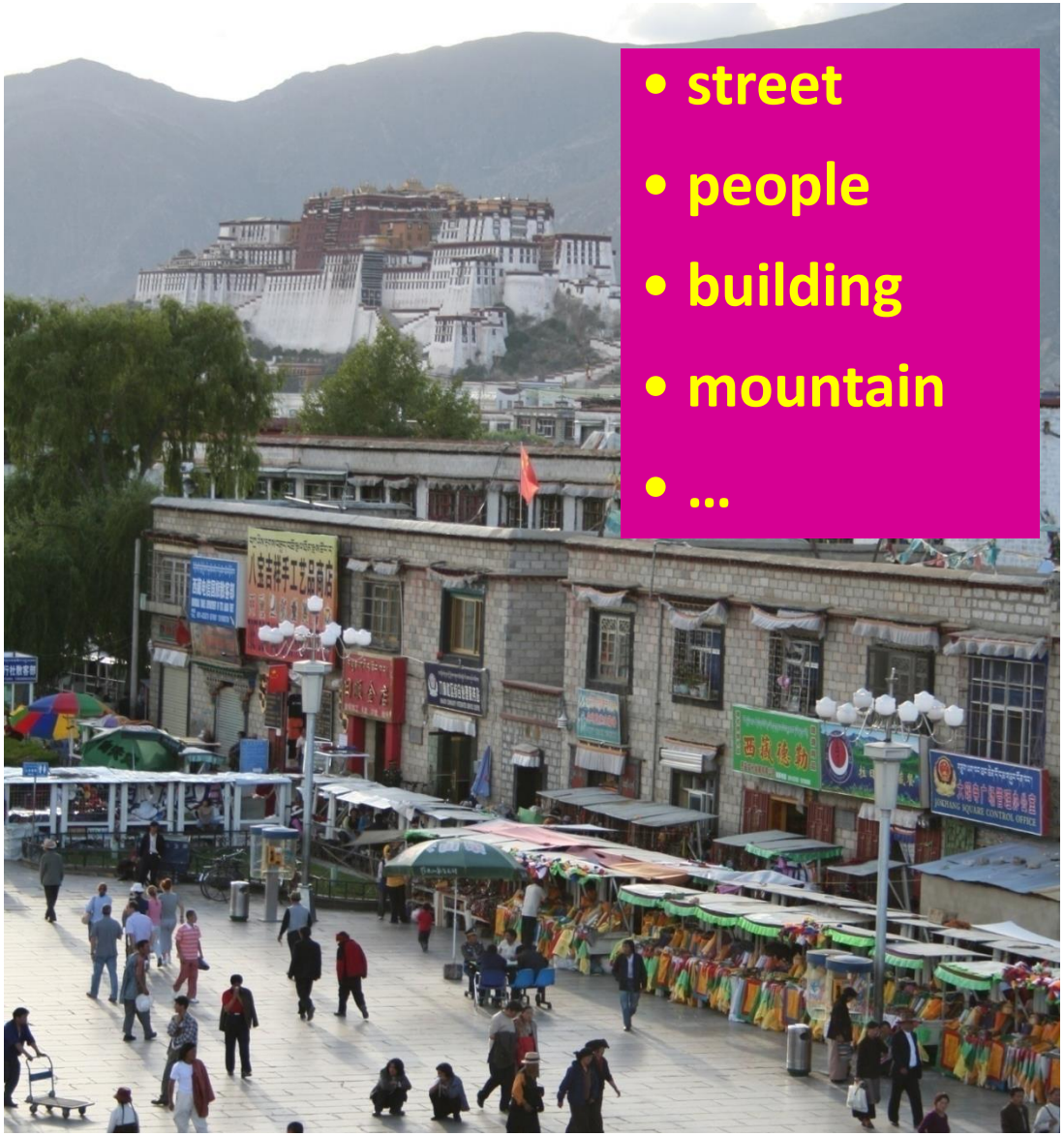
Specific Recognition Tasks

Scene Categorisation



- outdoor/indoor
- city/forest/factory/etc.

Image Annotation/Tagging



Object Detection

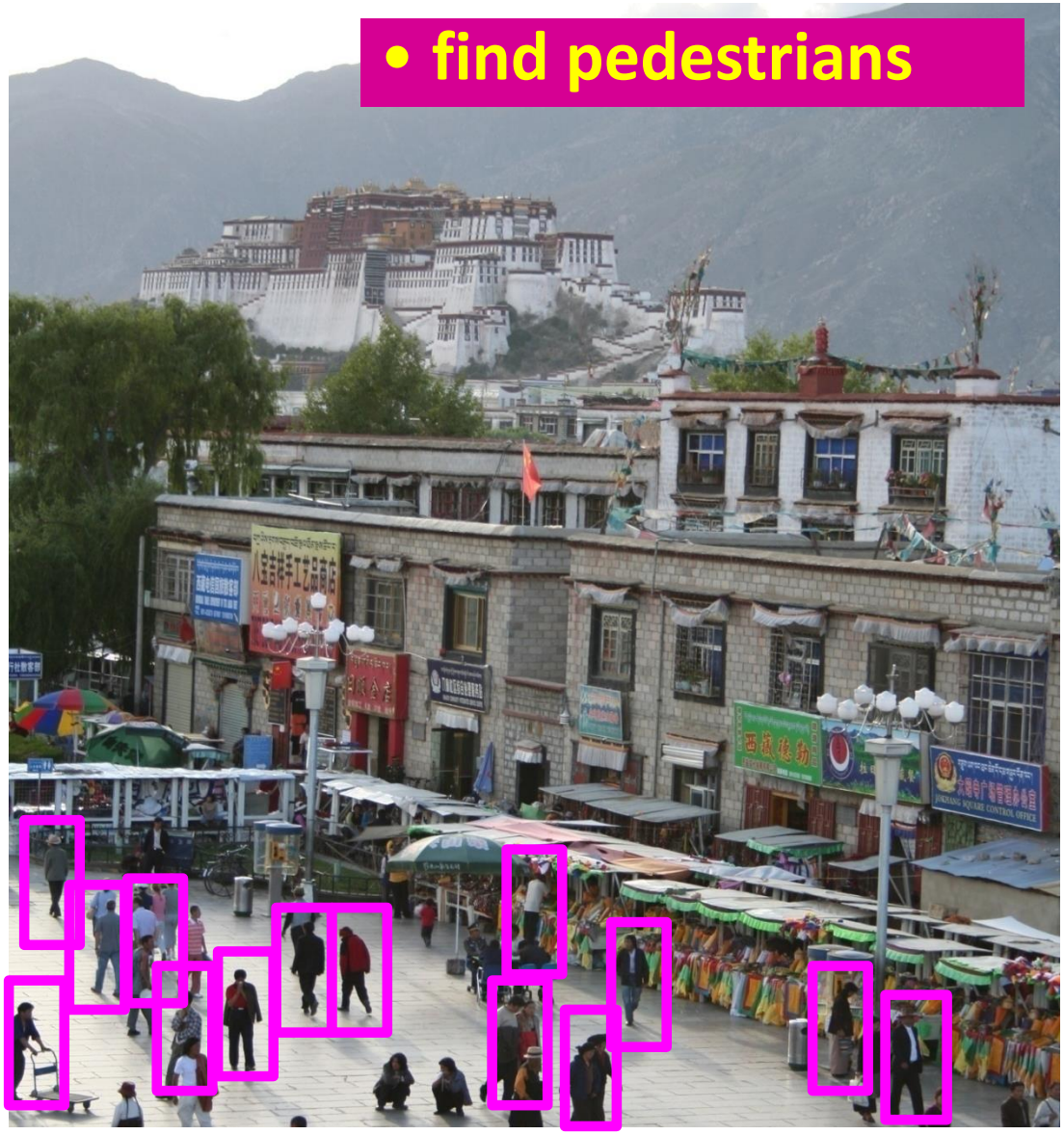
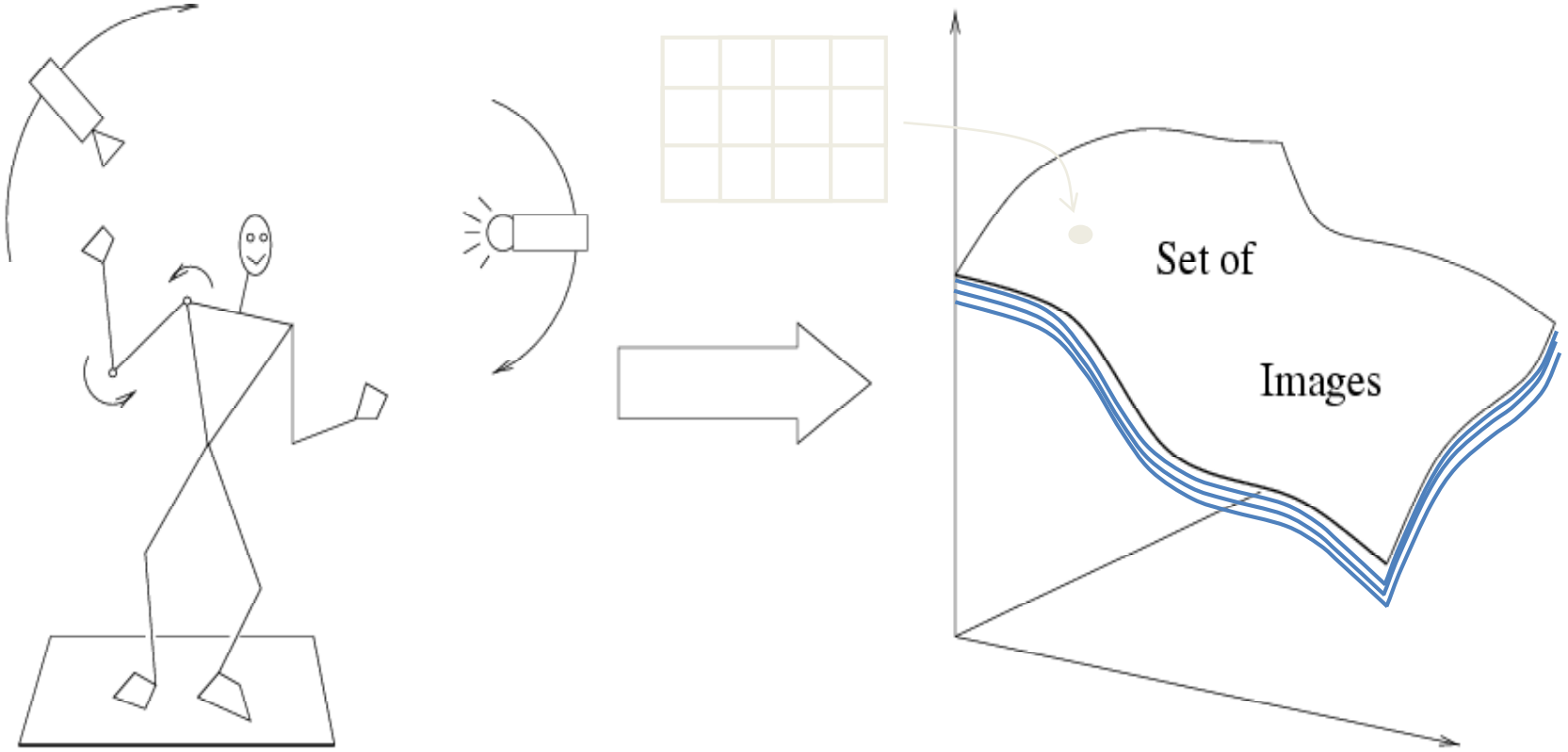


Image Parsing

Image Understanding?

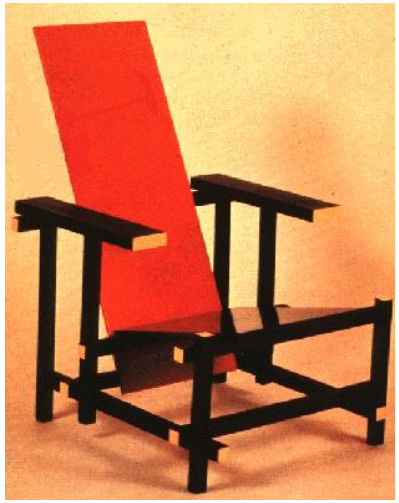
Recognition Is All About Modelling Variability



Variability: Camera position
Illumination
Shape parameters

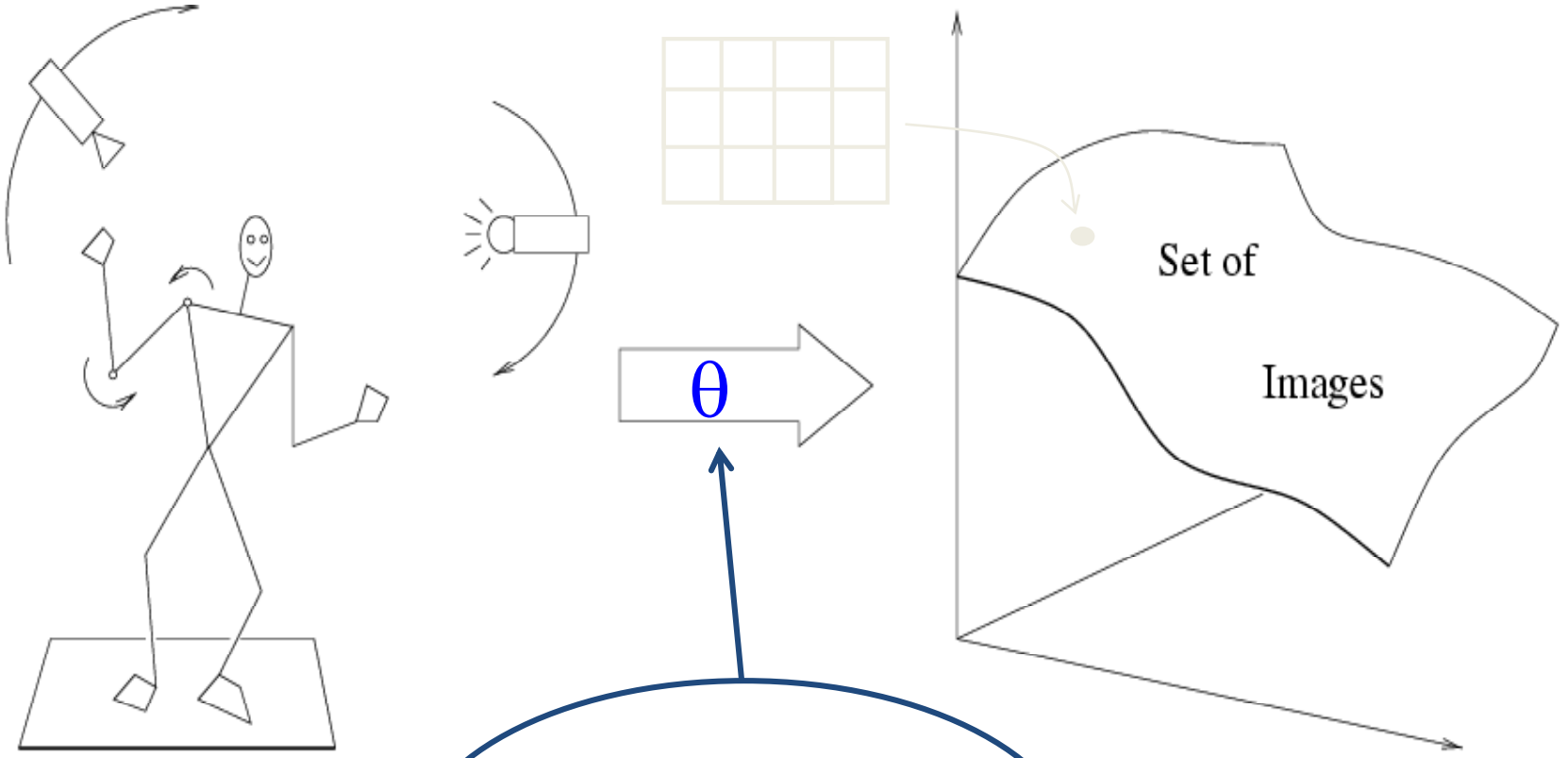
Within-class variations?

Within-class Variations



History of Ideas in Recognition

- 1960s – early 1990s: the geometric era



Variability:

Camera position
Illumination

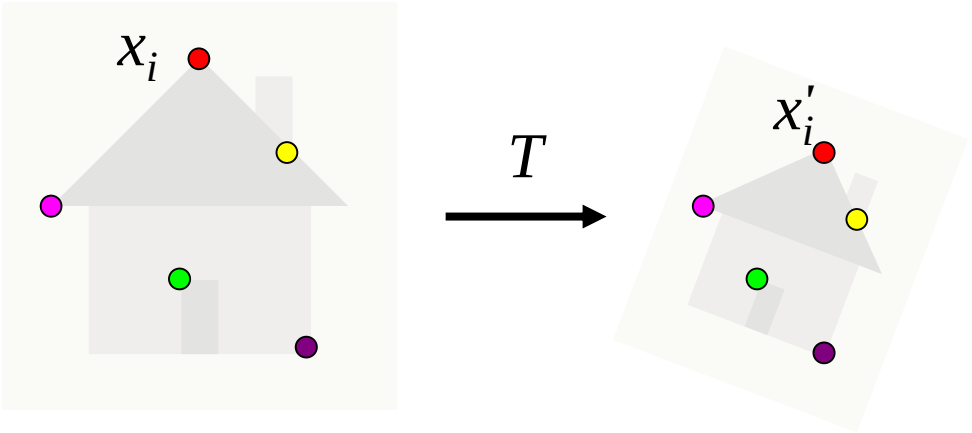
Alignment

Shape: assumed known

Roberts (1965); Lowe (1987); Faugeras & Hebert (1986); Grimson & Lozano-Perez (1986); Huttenlocher & Ullman (1987)

Alignment

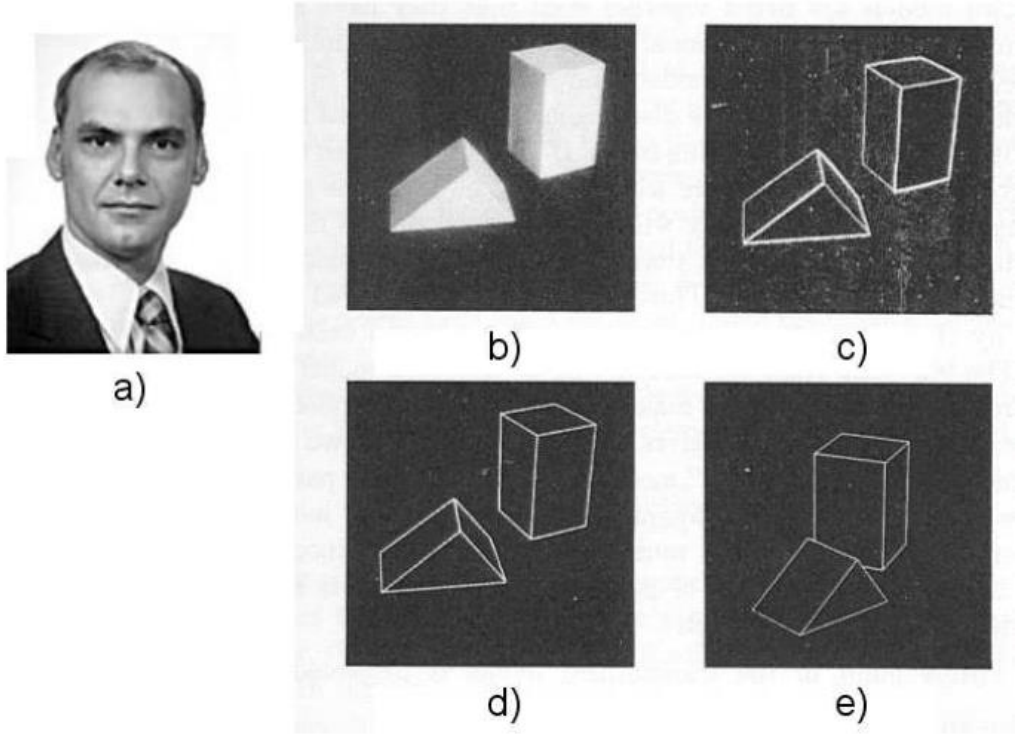
- Alignment: fitting a model to a transformation between pairs of features (*matches*) in two images



Find transformation T that minimizes

$$\sum_i \text{residual}(T(x_i), x_i')$$

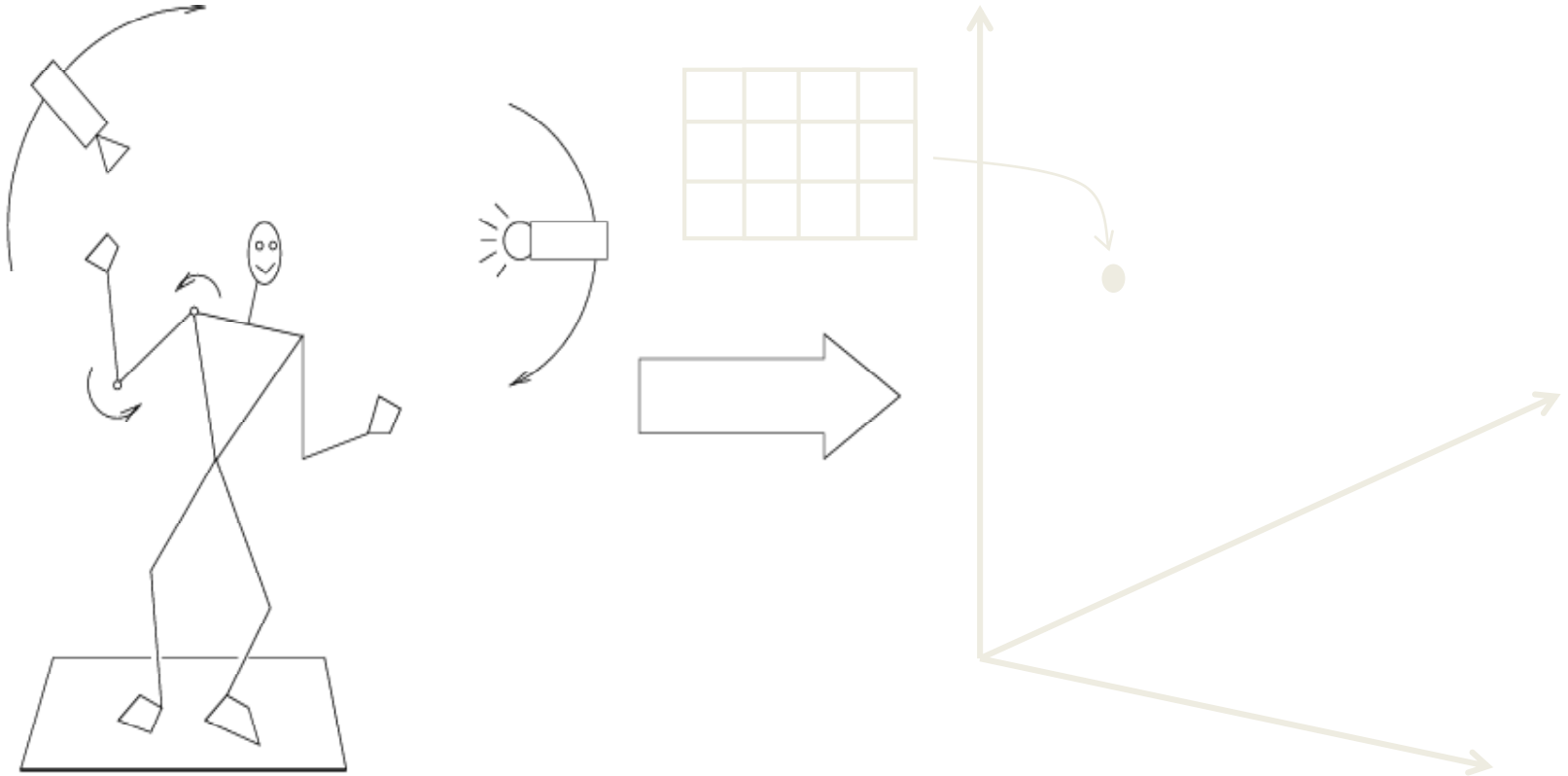
Recognition as an Alignment Problem: Block World



L. G. Roberts, *Machine Perception of Three Dimensional Solids*, Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

Fig. 1. A system for recognizing 3-d polyhedral scenes. a) L.G. Roberts. b)A blocks world scene. c)Detected edges using a 2x2 gradient operator. d) A 3-d polyhedral description of the scene, formed automatically from the single image. e) The 3-d scene displayed with a viewpoint different from the original image to demonstrate its accuracy and completeness. (b) - e) are taken from [64] with permission MIT Press.)

J. Mundy, Object Recognition in the Geometric Era: a Retrospective, 2006



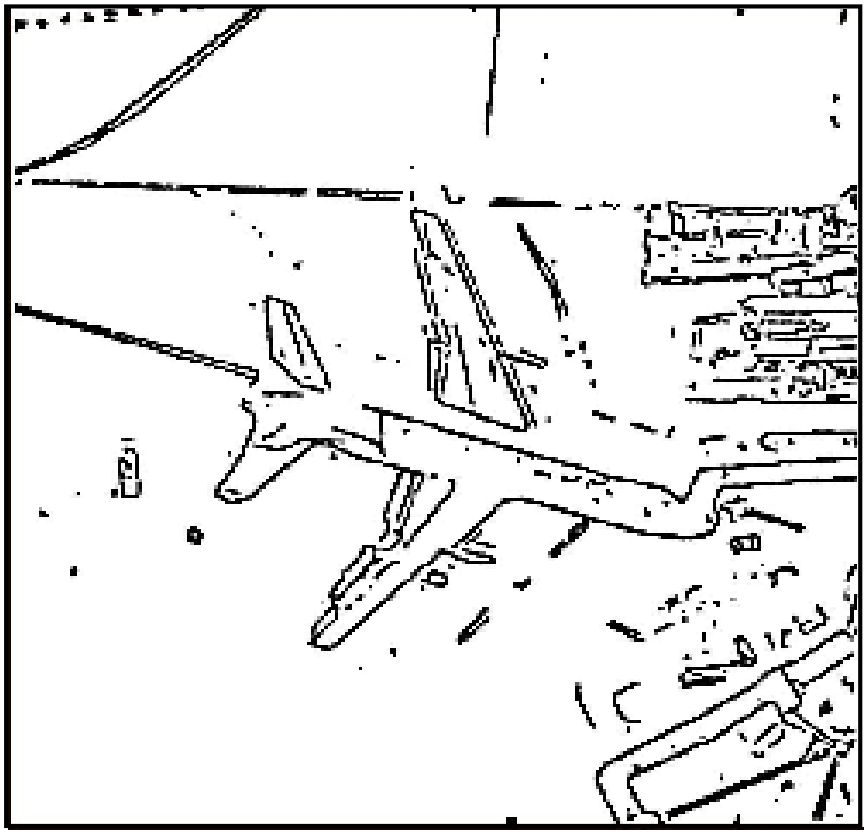
~~Variability~~

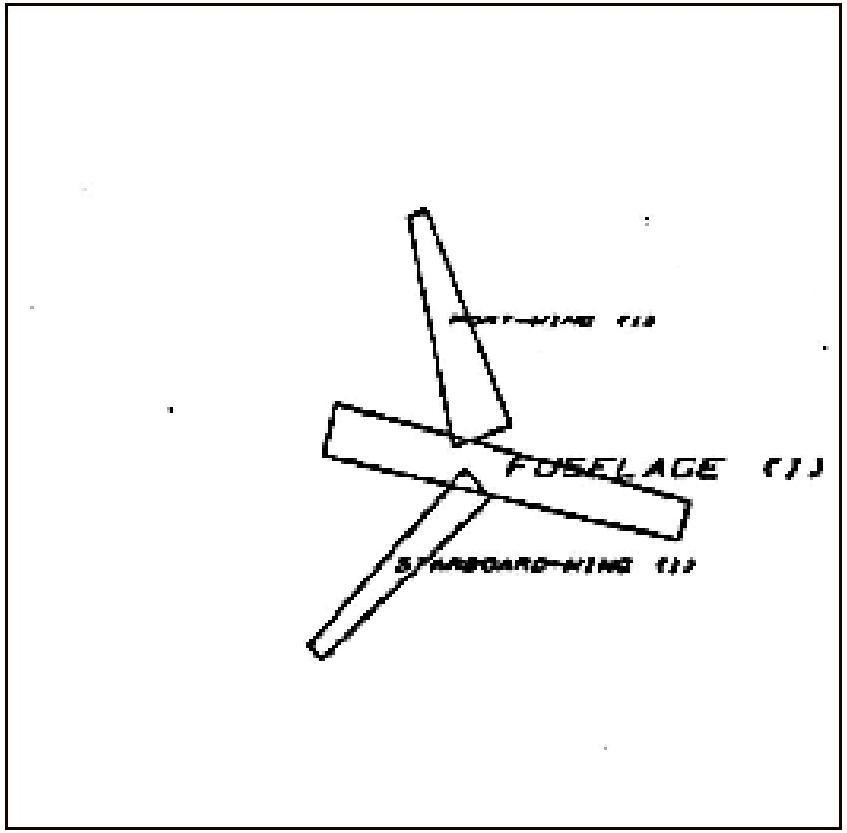
Invariance to:

Camera position
Illumination
Internal parameters

Duda & Hart (1972); Weiss (1987); Mundy et al. (1992-94); Rothwell et al. (1992); Burns et al. (1993)

Representing And Recognising Object Categories Is Harder...





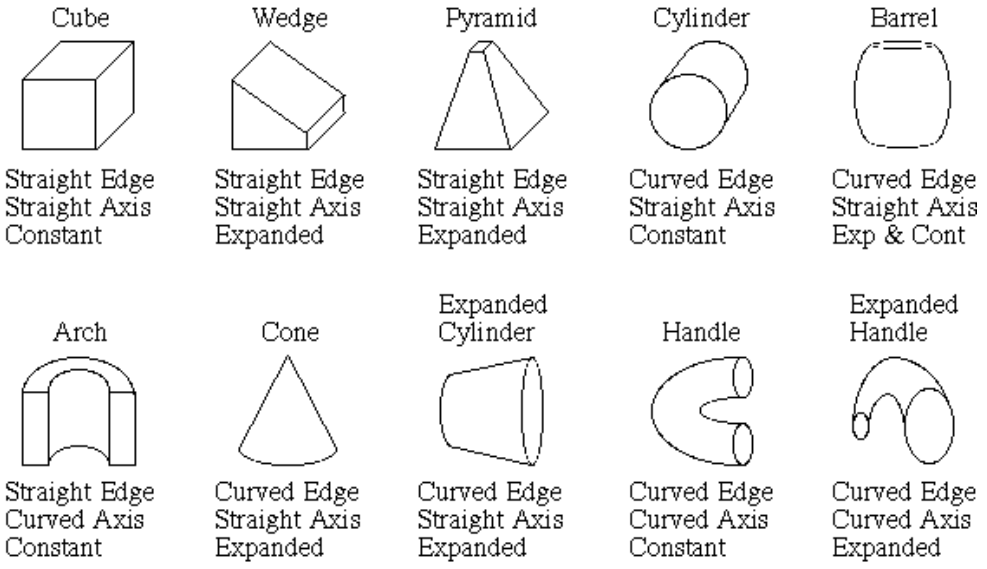
ACRONYM (Brooks and Binford, 1981)

Binford (1971), Nevatia & Binford (1972), Marr & Nishihara (1978)

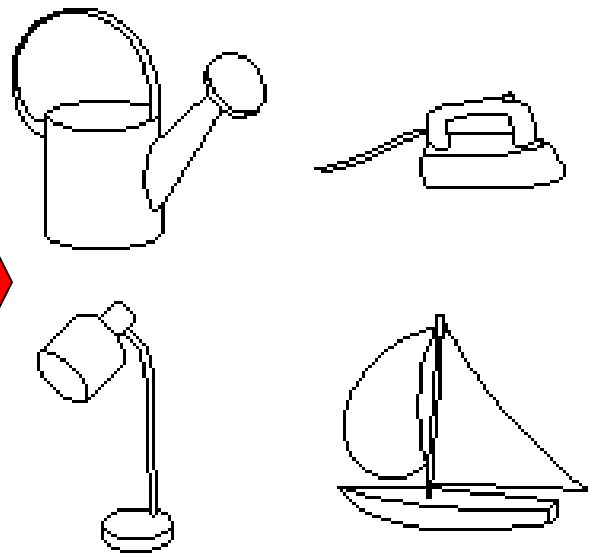
Recognition by Components

Biederman (1987)

Primitives (geons)

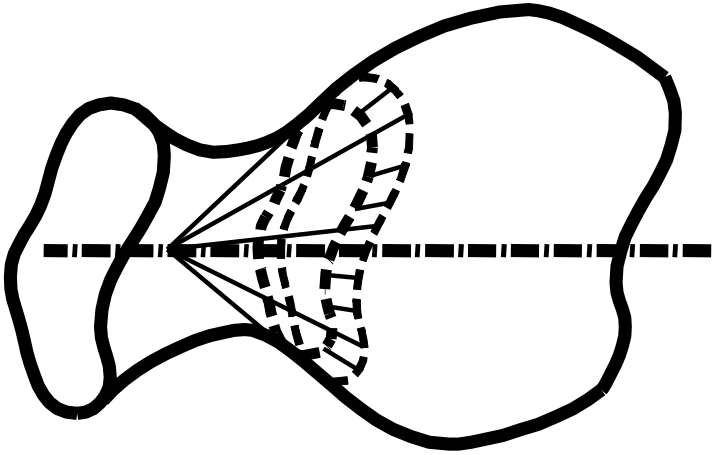


Objects

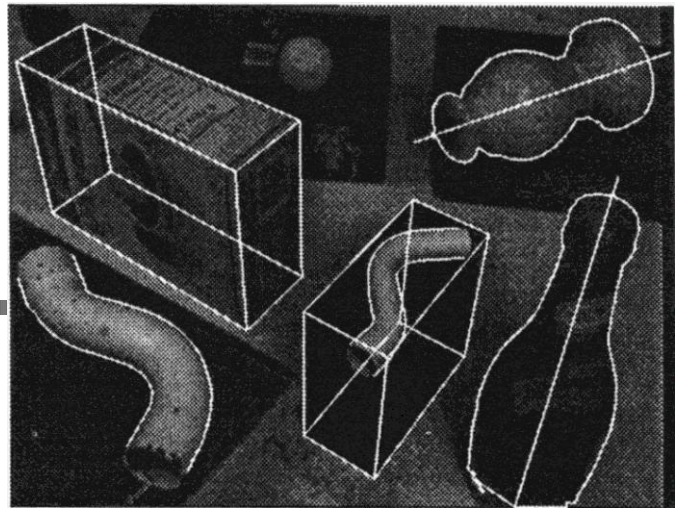


http://en.wikipedia.org/wiki/Recognition_by_Components_Theory

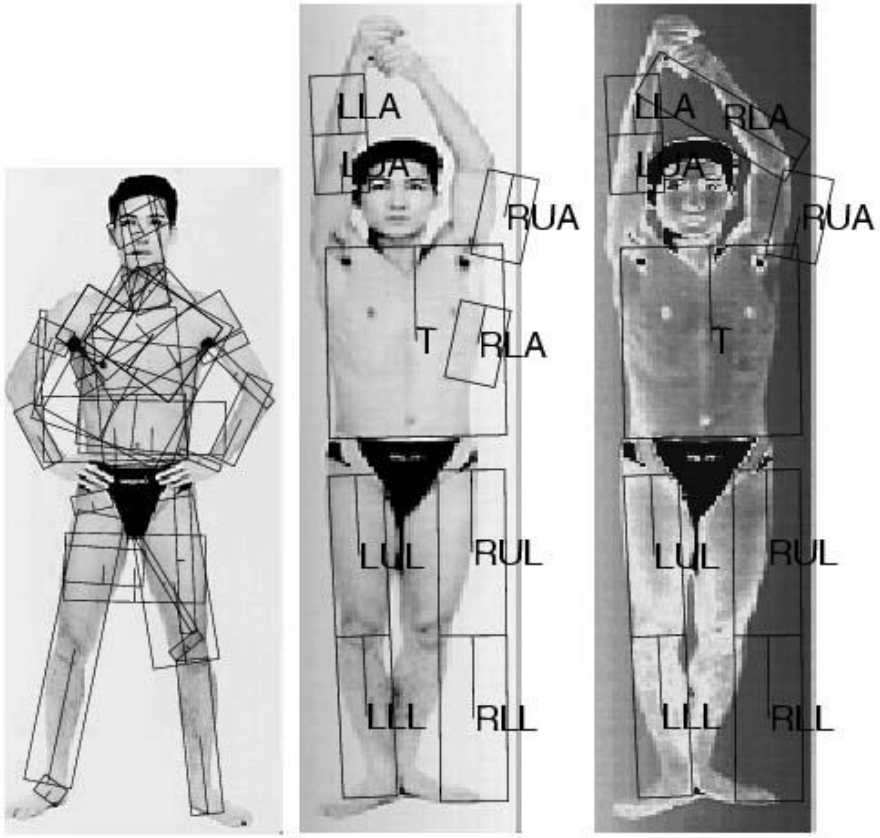
General Shape Primitives?



Generalized cylinders
Ponce et al. (1989)



Zisserman et al. (1995)



Forsyth (2000)

History of Ideas in Recognition

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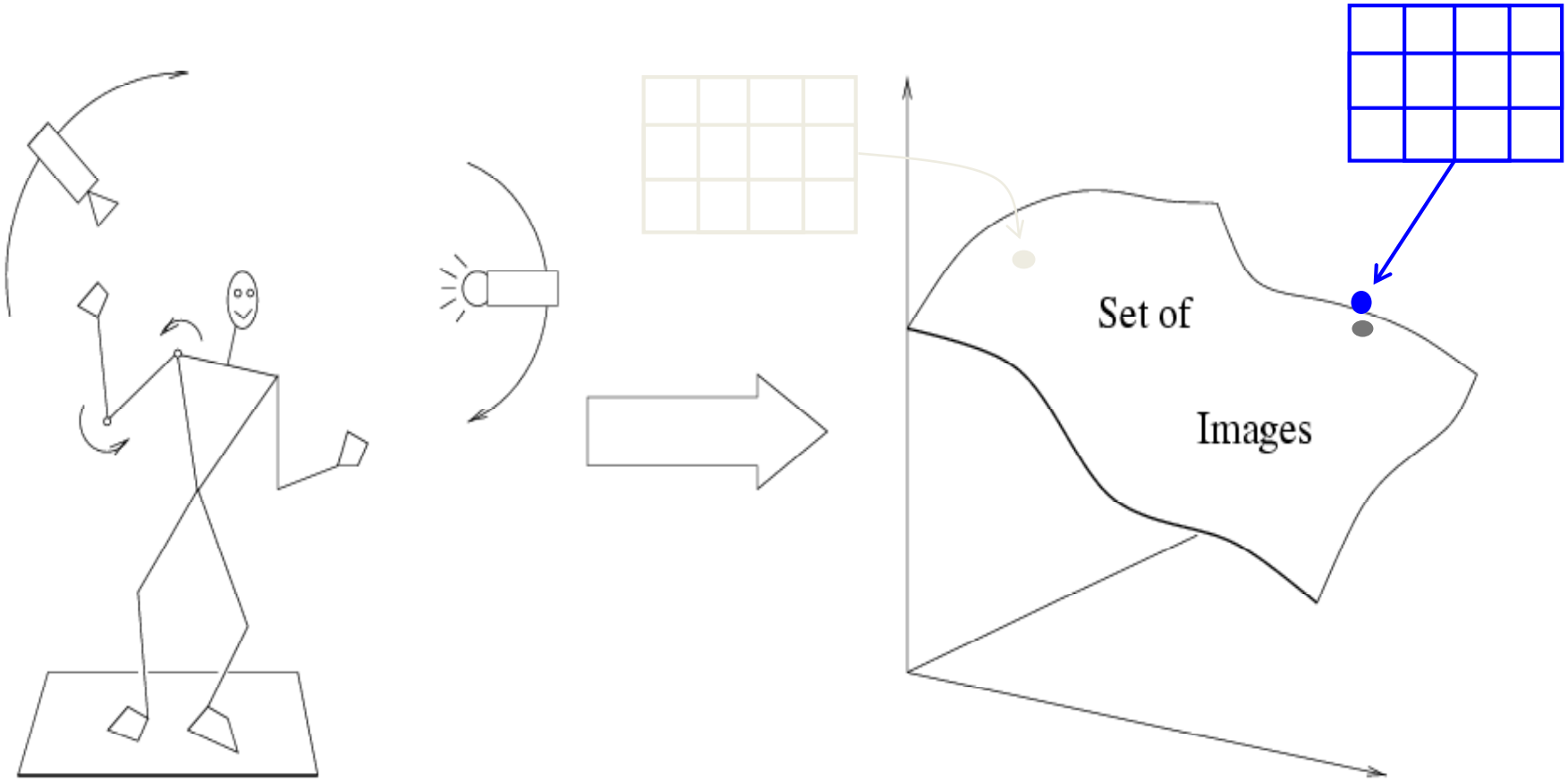
- 1990s: appearance-based models

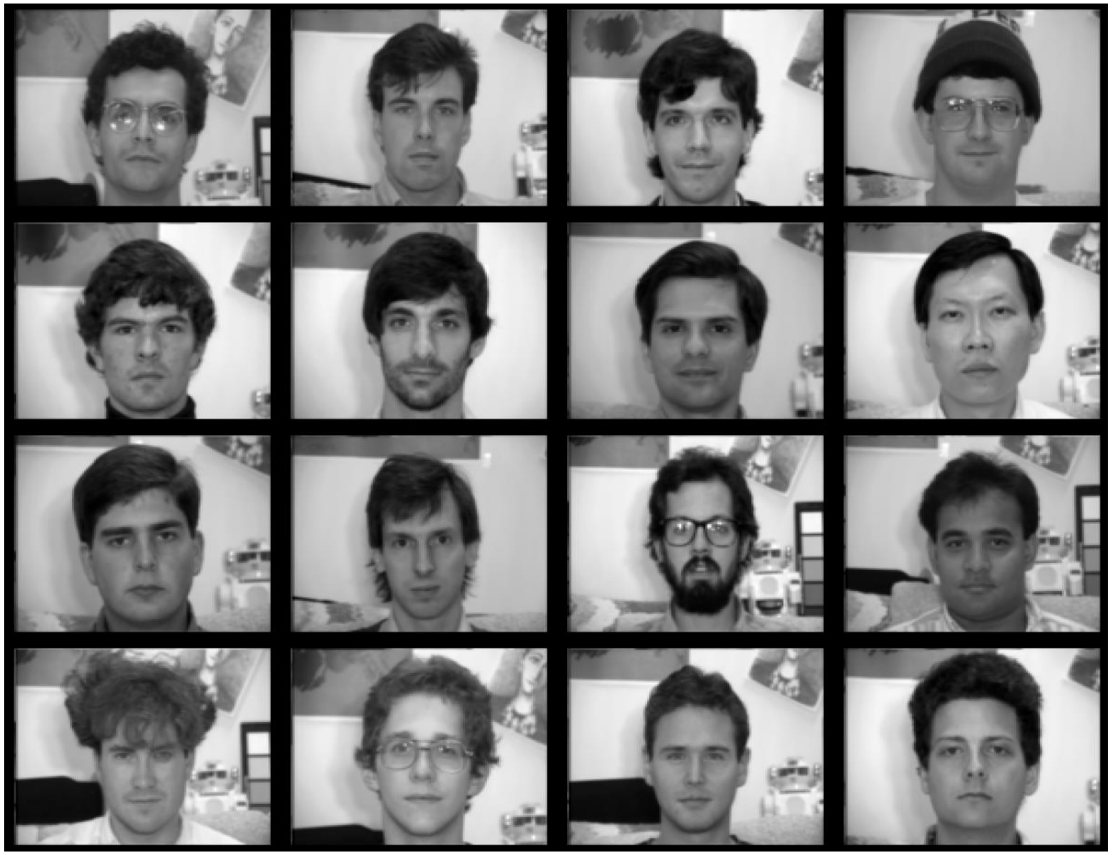


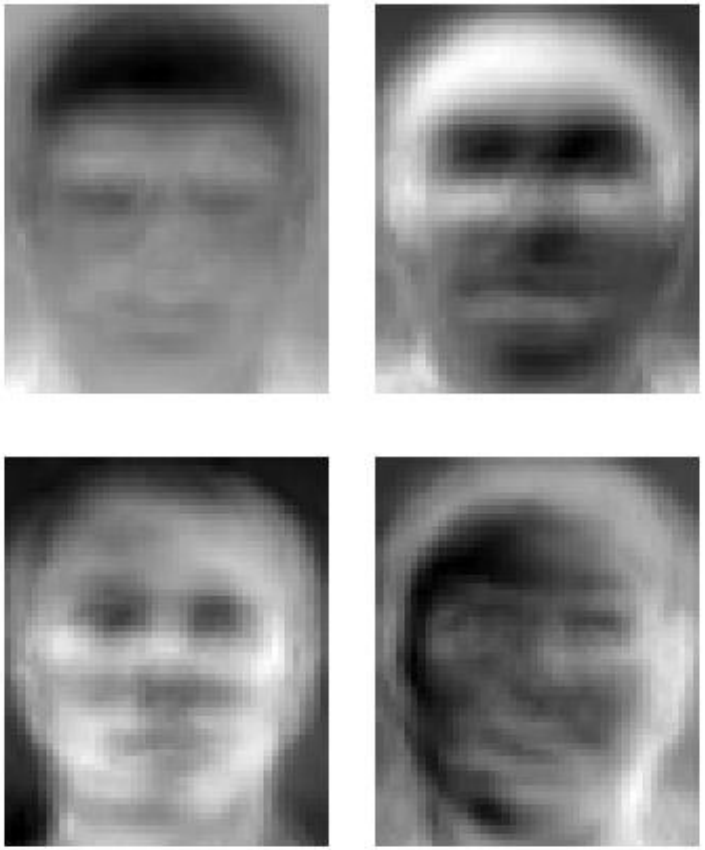
Empirical models of image variability

Appearance-based techniques

Turk & Pentland (1991); Murase & Nayar (1995); etc.

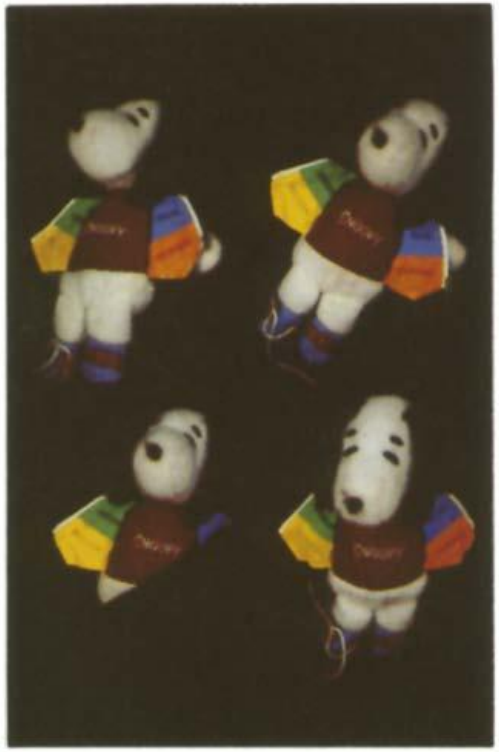
Eigenfaces (Turk & Pentland, 1991)

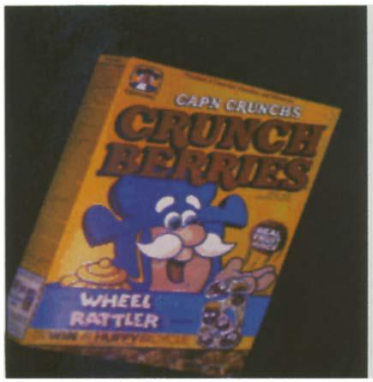


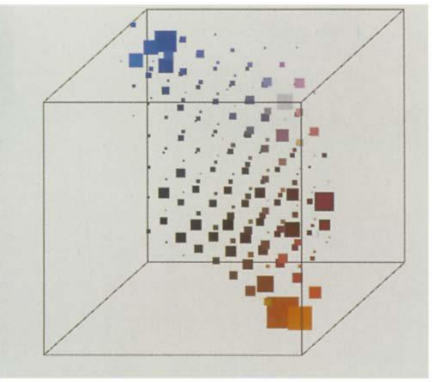


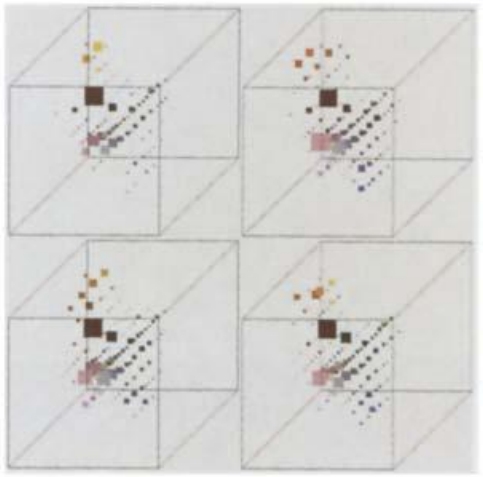
Experimental	Correct/Unknown Recognition Percentage		
Condition	Lighting	Orientation	Scale
Forced classification	96/0	85/0	64/0
Forced 100% accuracy	100/19	100/39	100/60
Forced 20% unknown rate	100/20	94/20	74/20

Colour Histograms



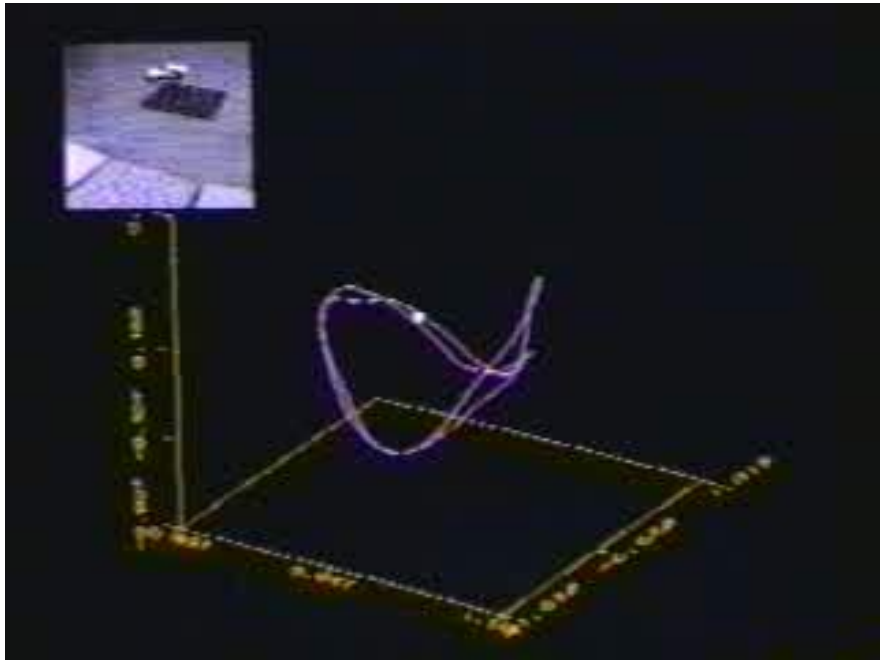






Swain and Ballard, Color Indexing, IJCV 1991.

Appearance Manifolds



H. Murase and S. Nayar, Visual learning and recognition of 3-d objects from appearance, IJCV 1995

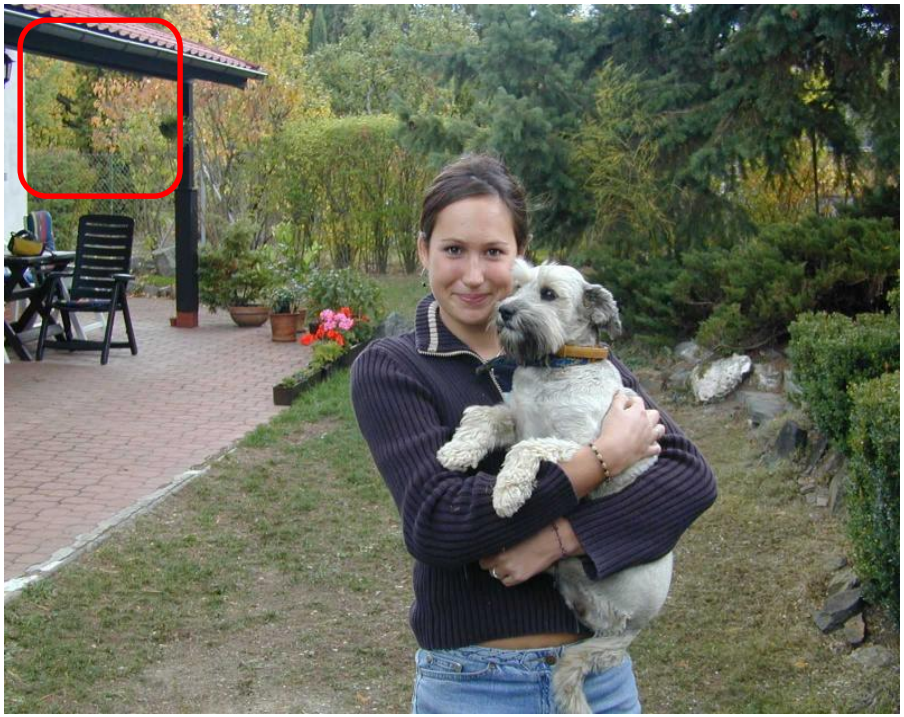
Limitations of Global Appearance Models

- Requires global registration of patterns
- Not robust to clutter, occlusion, geometric transformations

History of Ideas in Recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches

Sliding Window Approaches



Sliding Window Approaches

- Turk and Pentland, 1991
- Belhumeur, Hespanha, & Kriegman, 1997
- Schneiderman & Kanade 2004
- Viola and Jones, 2000

- Schneiderman & Kanade, 2004
- Argawal and Roth, 2002
- Poggio et al. 1993

History of Ideas in Recognition

- 1960s – early 1990s: the geometric era
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- Late 1990s: local features

Local Features for Object Instance Recognition

D. Lowe (1999, 2004)

Large-Scale Image Search

Combining local features, indexing, and spatial constraints

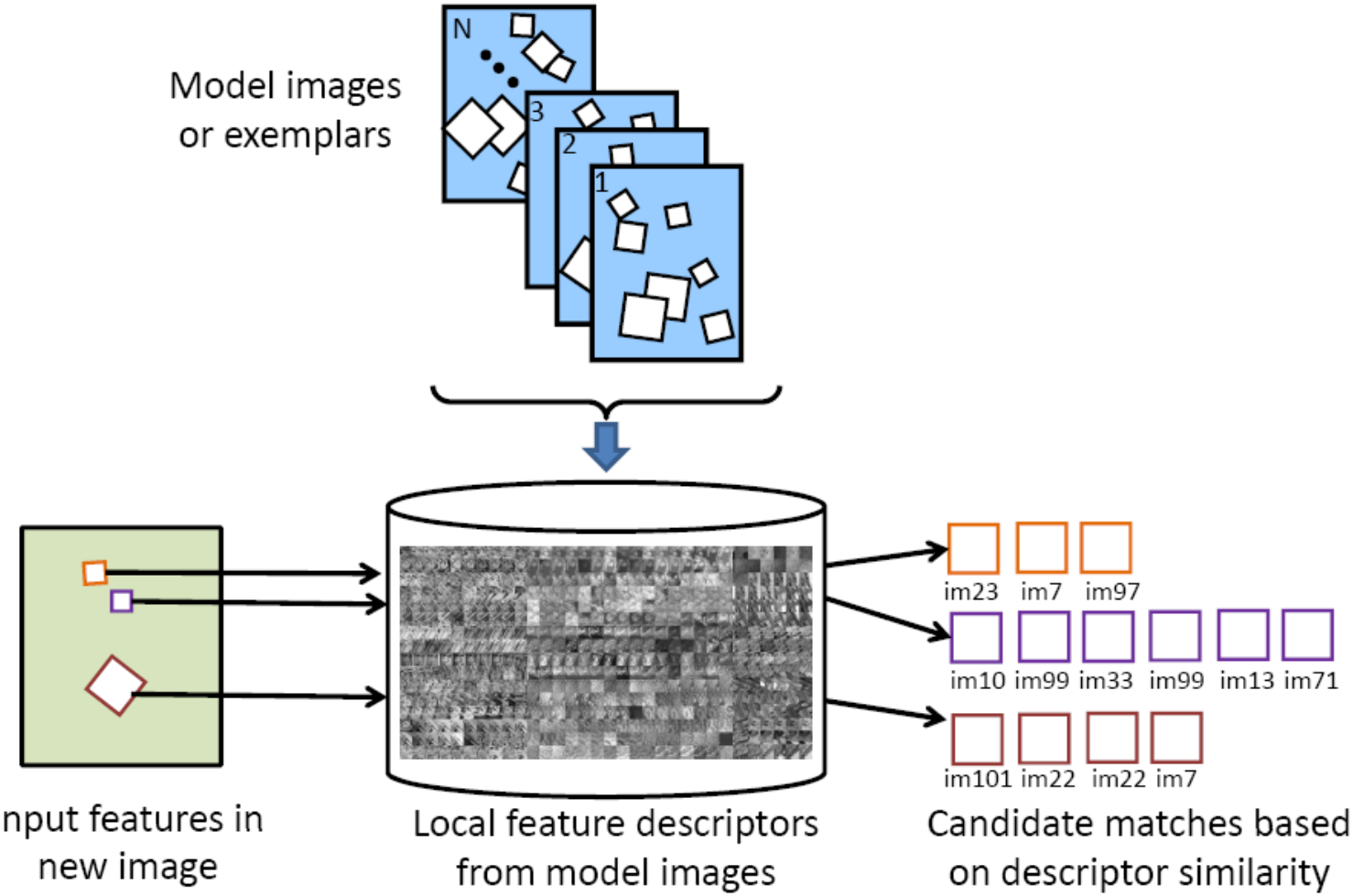

Image credit: K. Grauman and B. Leibe

Large-Scale Image Search

Combining local features, indexing, and spatial constraints

Philbin et al. ‘07

Large-Scale Image Search

Combining local features, indexing, and spatial constraints

Available on phones that run Android 1.6+ (i.e. Donut or Eclair)

History of Ideas in Recognition

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- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models

Parts-and-Shape Models

- Model:
  - Object as a set of parts
  - Relative locations between parts
  - Appearance of part

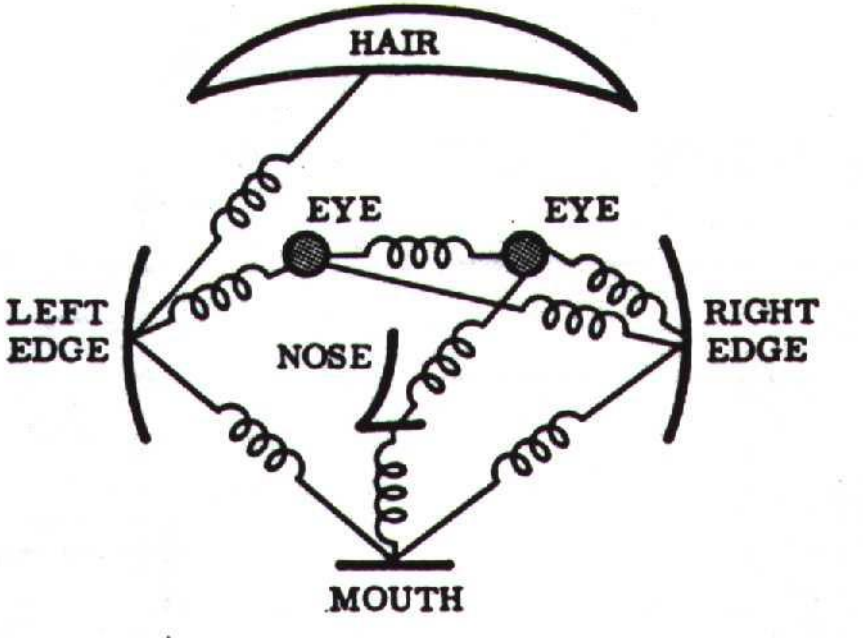


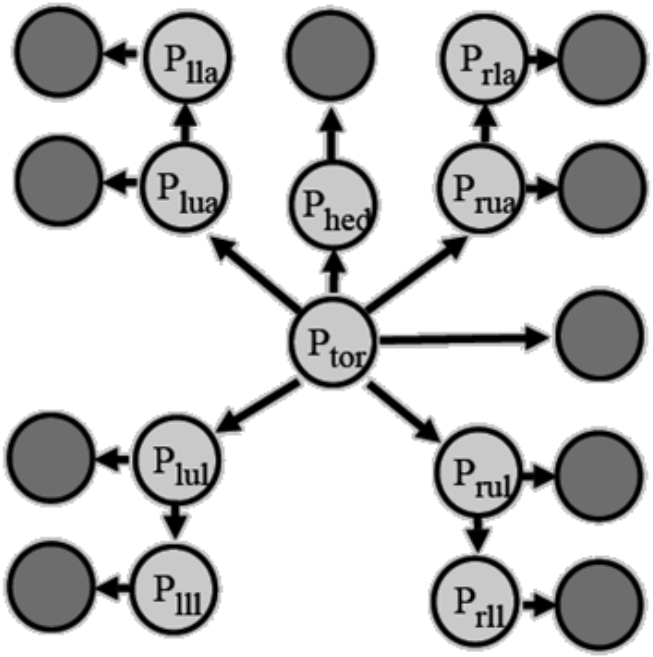
Figure from [Fischler & Elschlager 73]

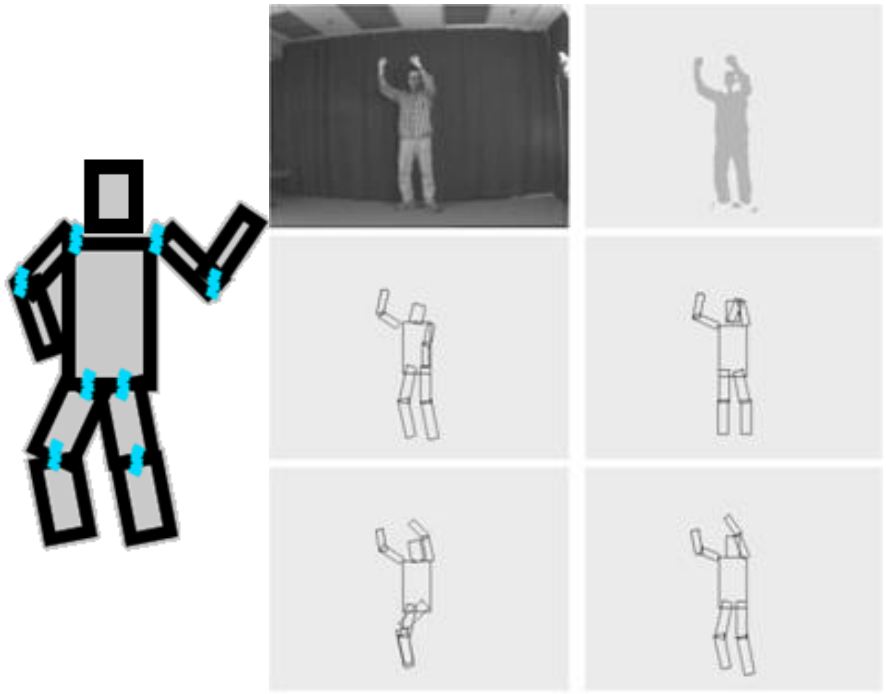
Constellation Models

Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

Pictorial Structure Model

- Representing People





$$\Pr(P_{tor}, P_{arm}, \ldots | \mathrm{Im}) \propto \prod_{i,j} \Pr(P_i | P_j) \prod_i \Pr(\mathrm{Im}(P_i))$$

Part Geometry **Part Appearance**

Fisheler and Elschlager(73), Felzenszwalb and Huttenlocher(00)

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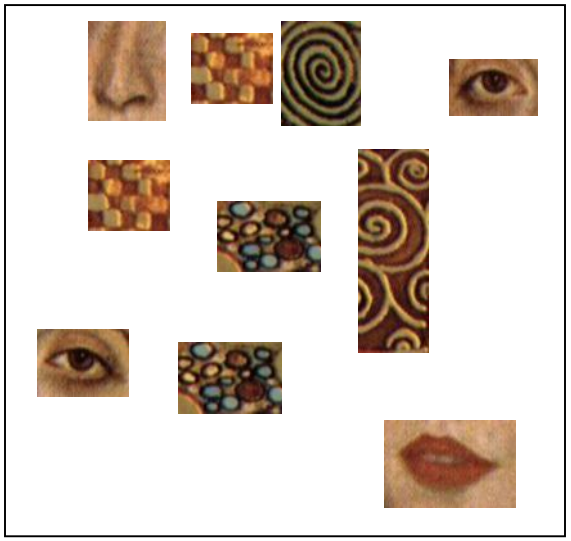
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features

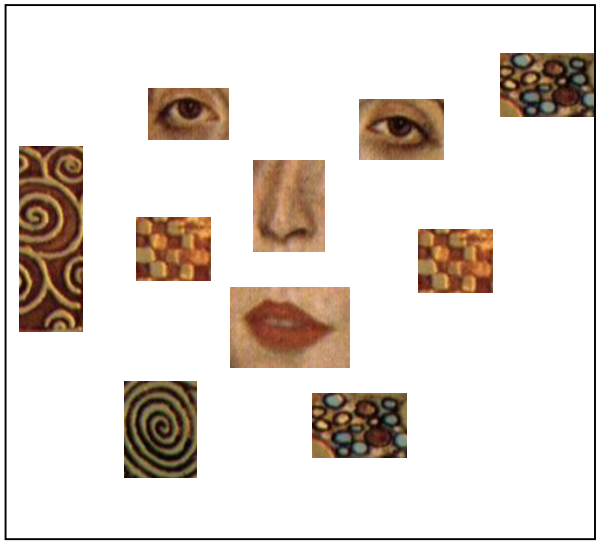
Bag-of-features Models

Object → Bag of 'words'

Objects as Texture

- All of these are treated as being the same





- No distinction between foreground and background: scene recognition?

History of Ideas in Recognition

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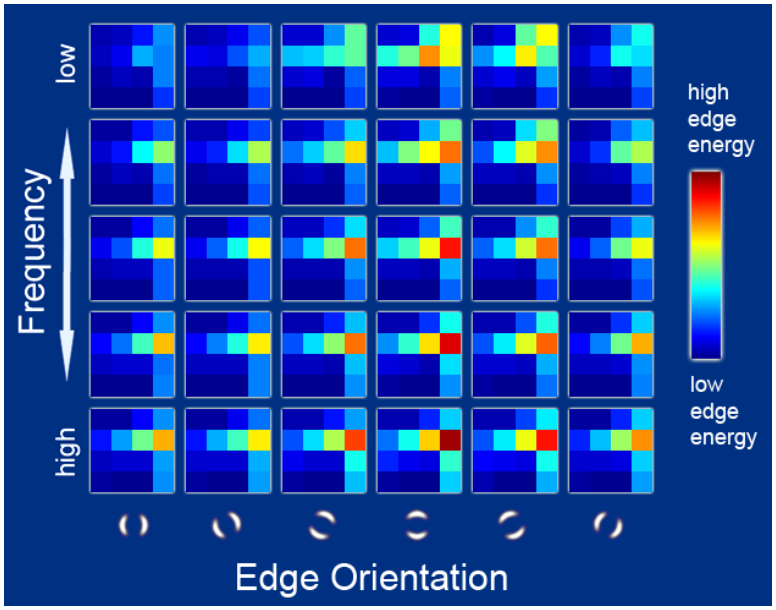
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features
- Present trends: combination of local and global methods, data-driven methods, context

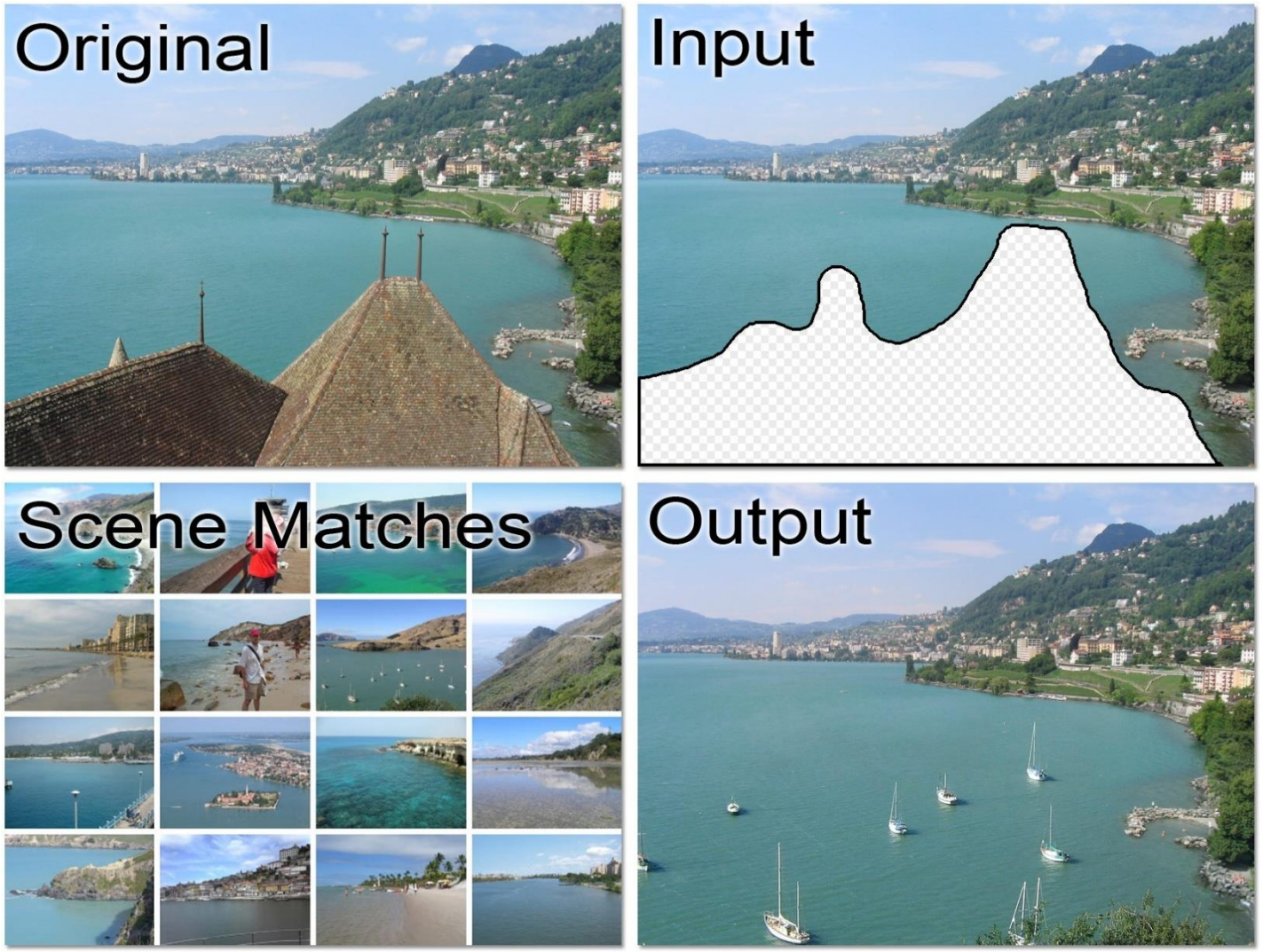
Global Scene Descriptors

- The “gist” of a scene: Oliva & Torralba (2001)



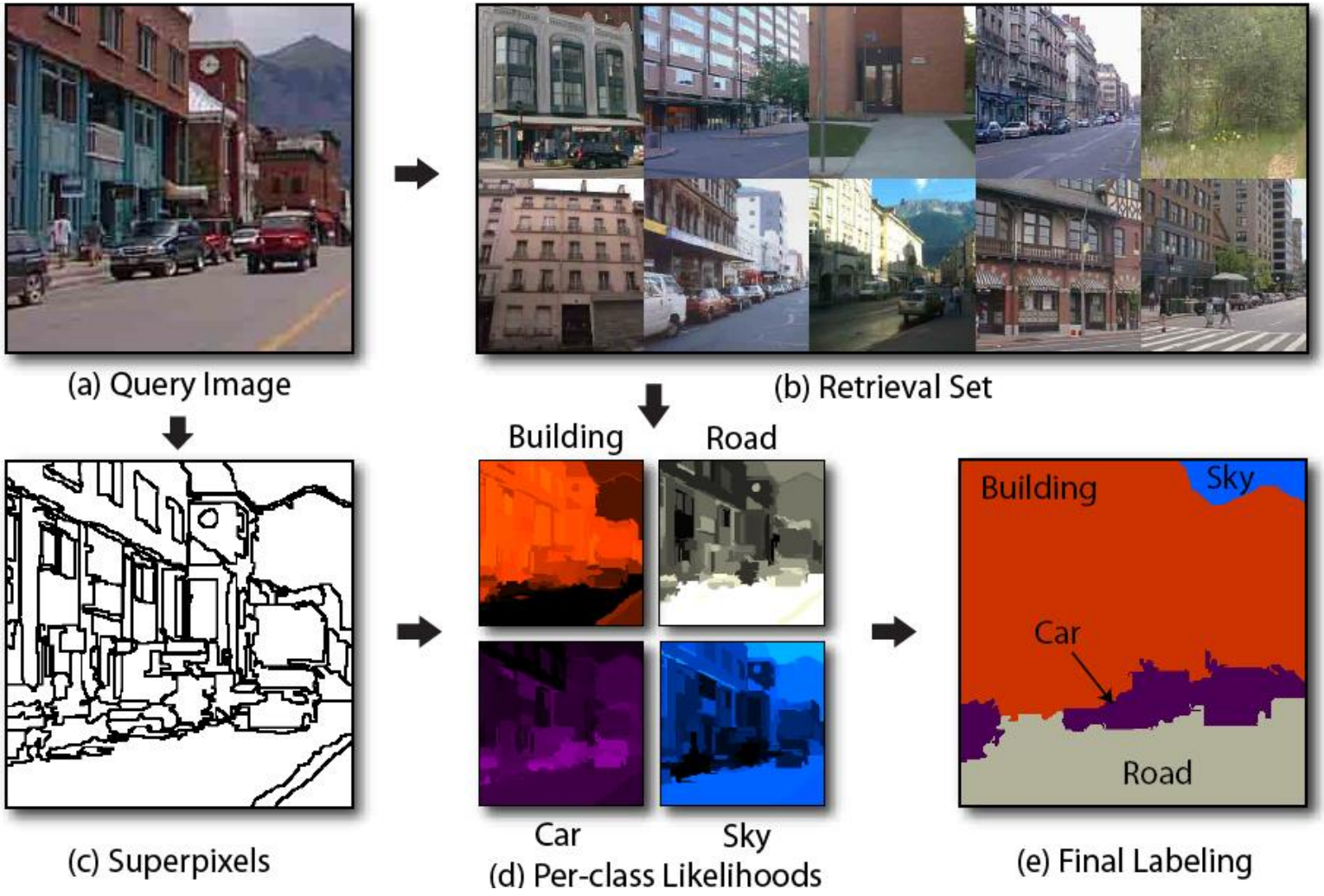
http://people.csail.mit.edu/torralba/code/spatialenvelope/

Data-Driven Methods



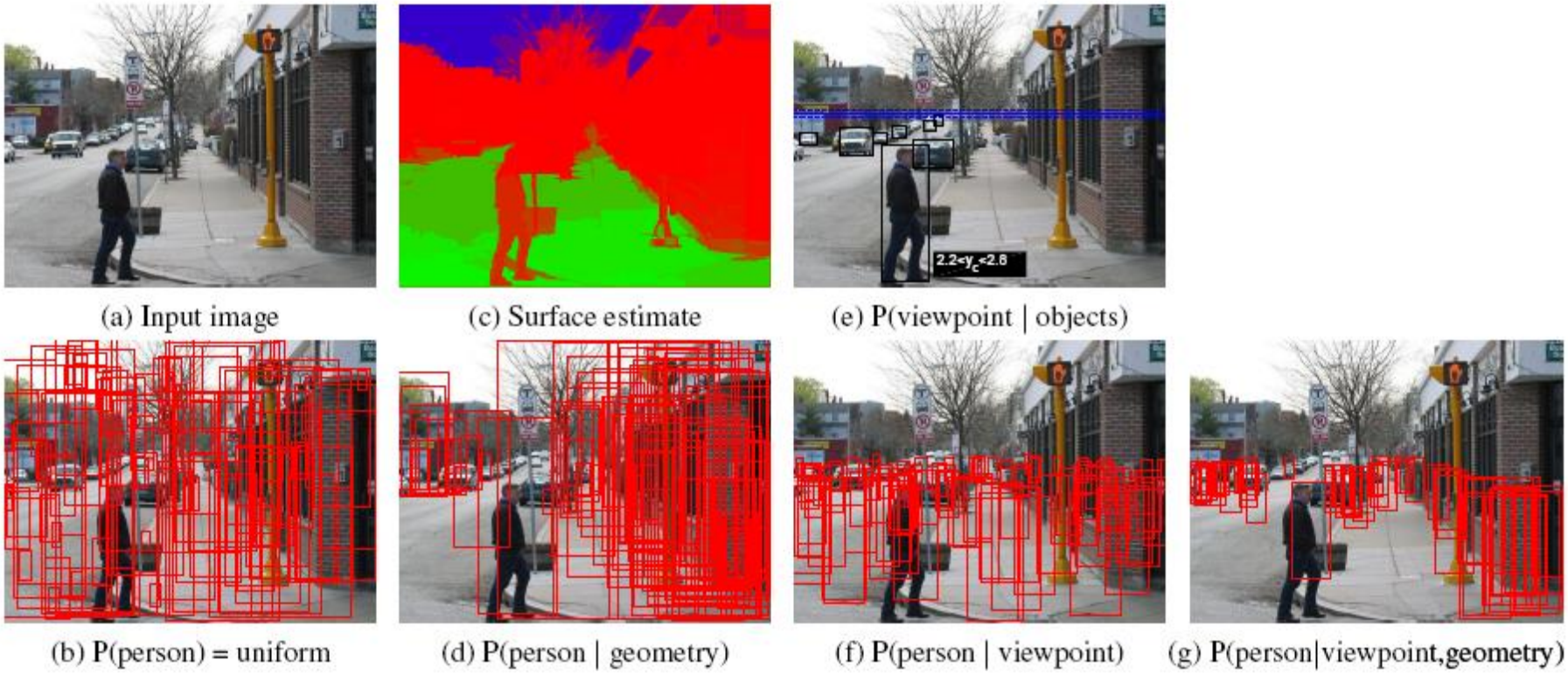
J. Hays and A. Efros, Scene Completion using Millions of Photographs, SIGGRAPH 2007

Data-Driven Methods



J. Tighe and S. Lazebnik, ECCV 2010

Geometric Context

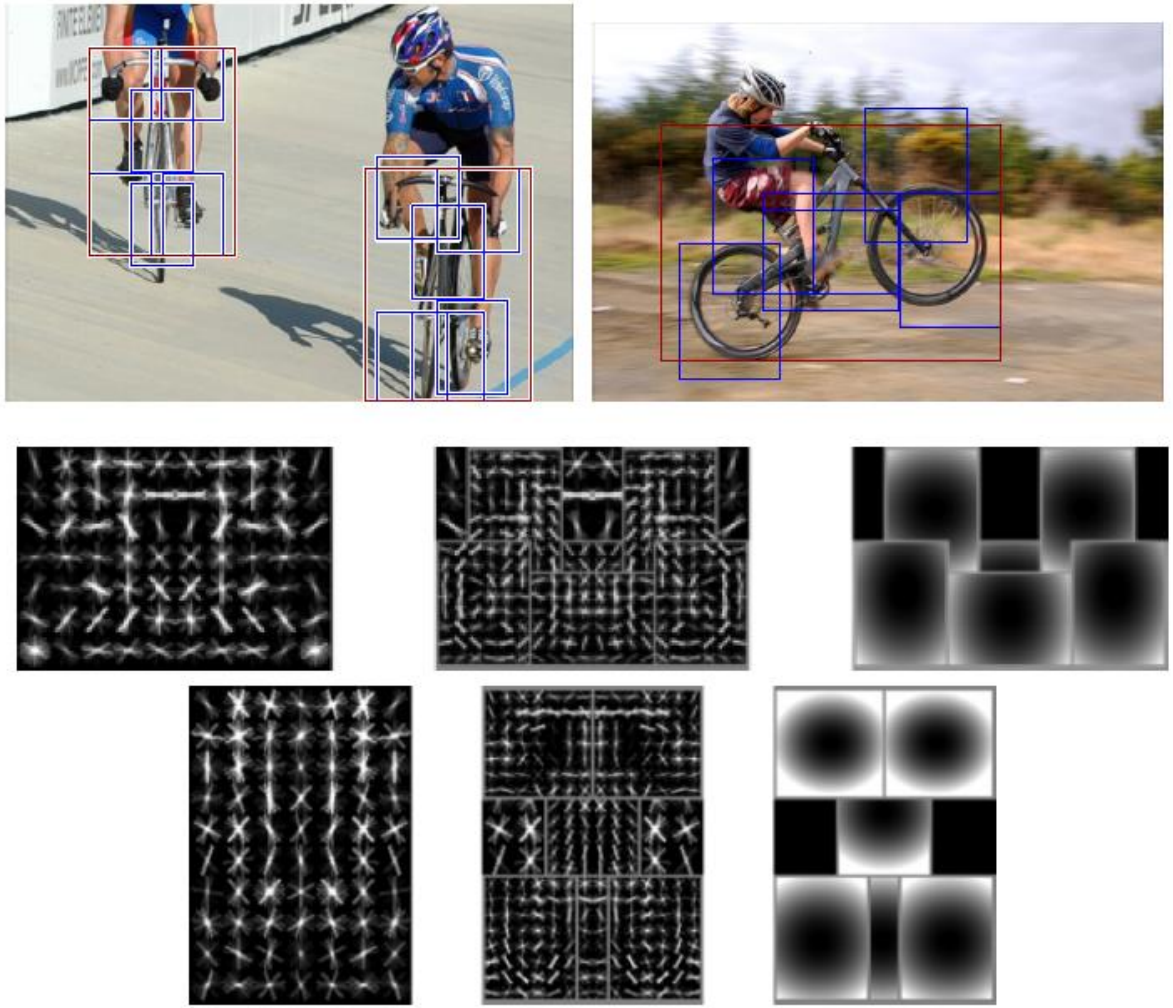


(a) Input image (c) Surface estimate (e) P(viewpoint | objects)

(b) P(person) = uniform (d) P(person | geometry) (f) P(person | viewpoint) (g) P(person|viewpoint,geometry)

D. Hoiem, A. Efros, and M. Herbert. Putting Objects in Perspective. CVPR 2006.

Discriminatively Trained Part-based Models



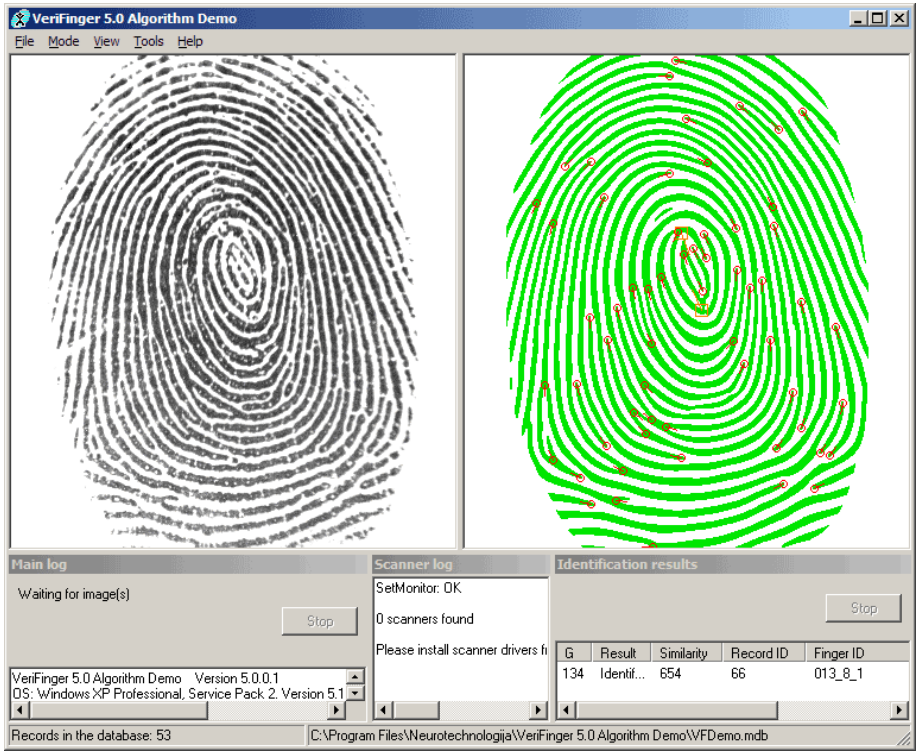
P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, **"Object Detection with Discriminatively Trained Part-Based Models,"** PAMI 2009

What "Works" Today

- Reading licence plates, postcodes, cheques

What “Works” Today

- Reading licence plates, postcodes, cheques
- Fingerprint recognition



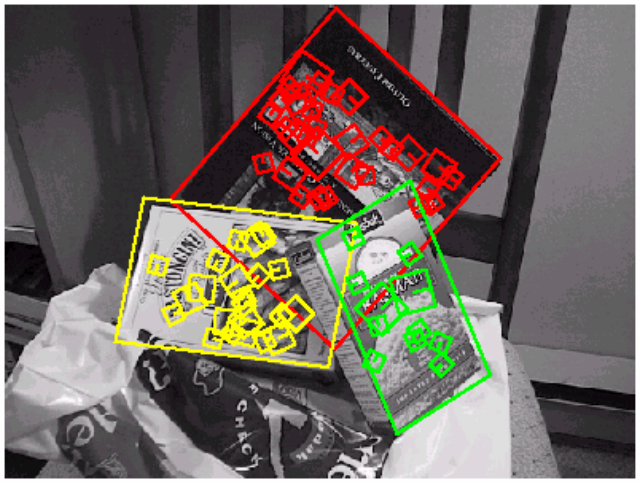
What “Works” Today

- Reading licence plates, postcodes, cheques
- Fingerprint recognition
- Face detection

[Face priority AE] When a bright part of the face is too bright

What “Works” Today

- Reading licence plates, postcodes, cheques
- Fingerprint recognition
- Face detection
- Recognition of flat textured objects (CD covers, book covers, etc.)



Recognition: A Machine Learning Approach

Slides adapted from Fei-Fei Li, Rob Fergus, Antonio Torralba, Kristen Grauman, and Derek Hoiem

The Machine Learning Framework

- Apply a prediction function to a feature representation of the image to get the desired output:

f() = “apple”

f() = “tomato”

f() = “cow”

The Machine Learning Framework

$$y = f(\mathbf{x})$$

output — prediction function — Image feature

- Training: given a *training set* of labelled examples $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- Testing: apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Steps

Training

Training Images

Training Labels

Image Features

Training

Learned model

Testing

Test Image

Image Features

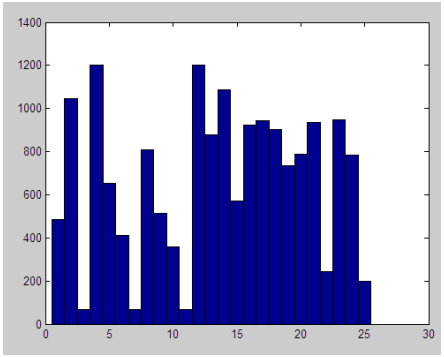
Learned model

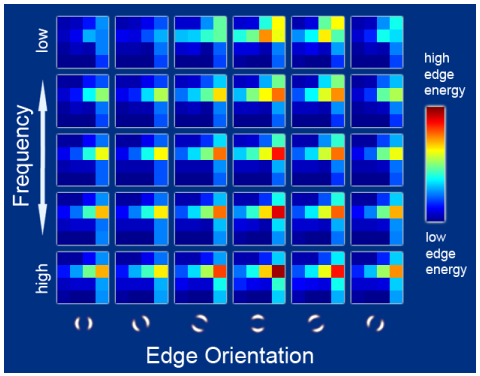
Prediction

Slide credit: D. Hoiem

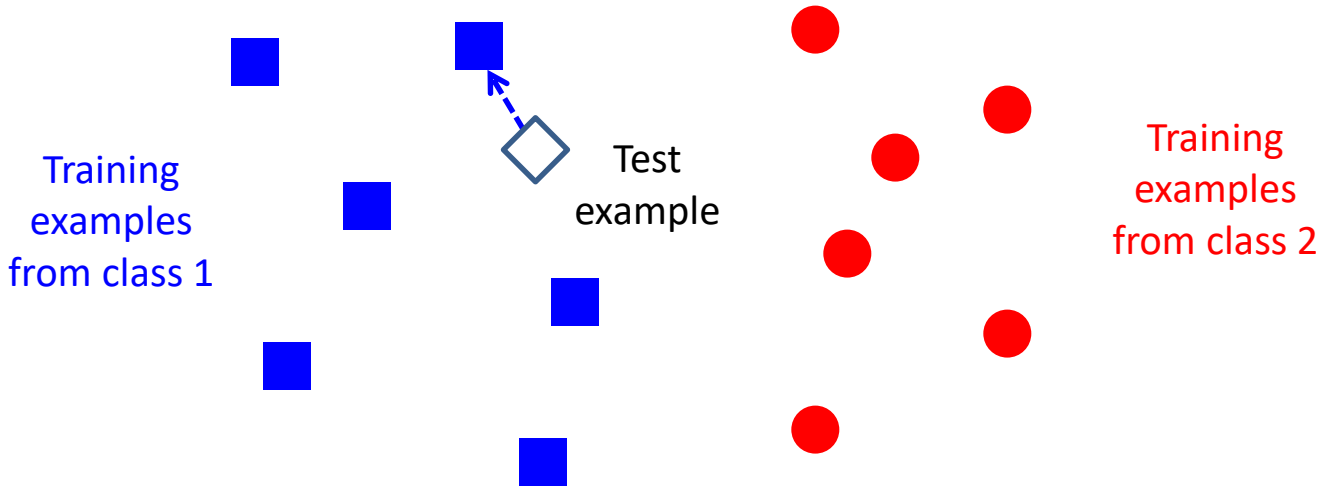
Features

- Raw pixels
- Histograms
- GIST descriptors
- …





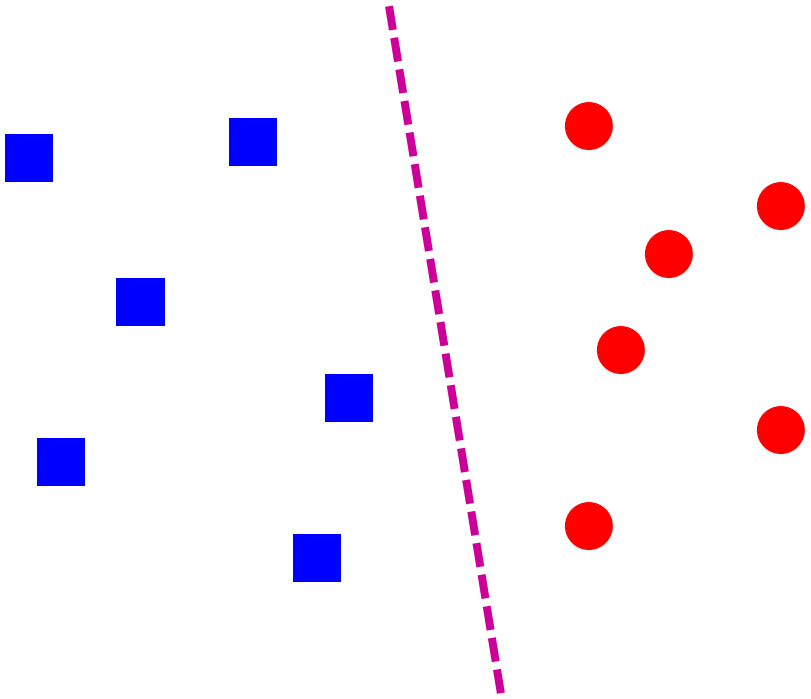
Classifiers: Nearest Neighbour



f(**x**) = label of the training example nearest to **x**

- All we need is a distance function for our inputs
- No training required!

Classifiers: Linear



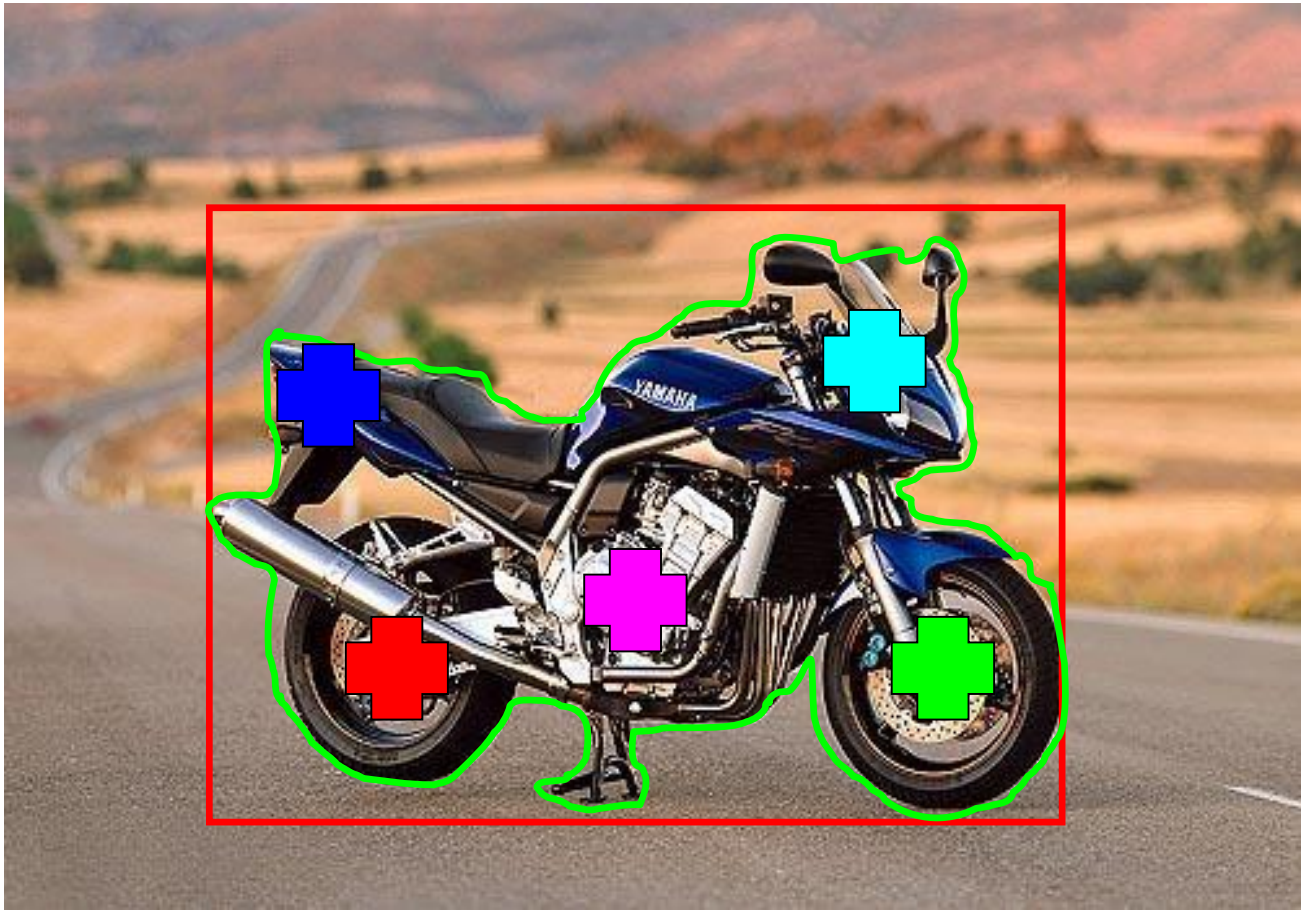
- Find a *linear function* to separate the classes:

$$f(\mathbf{x}) = \text{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$$

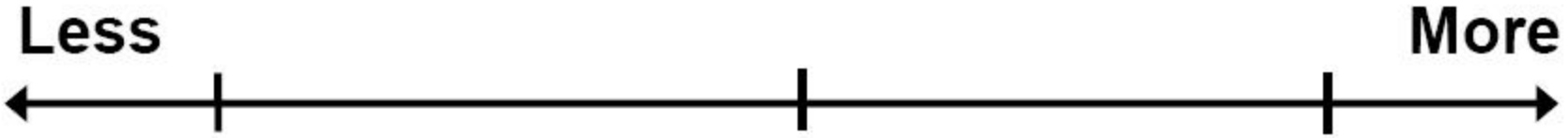
Recognition Task and Supervision

- Images in the training set must be annotated with the “correct answer” that the model is expected to produce

Contains a motorbike



Spectrum of Supervision



Unsupervised

"Weakly" supervised

Fully supervised

Definition depends on task

Generalisation

Training set (labels known)

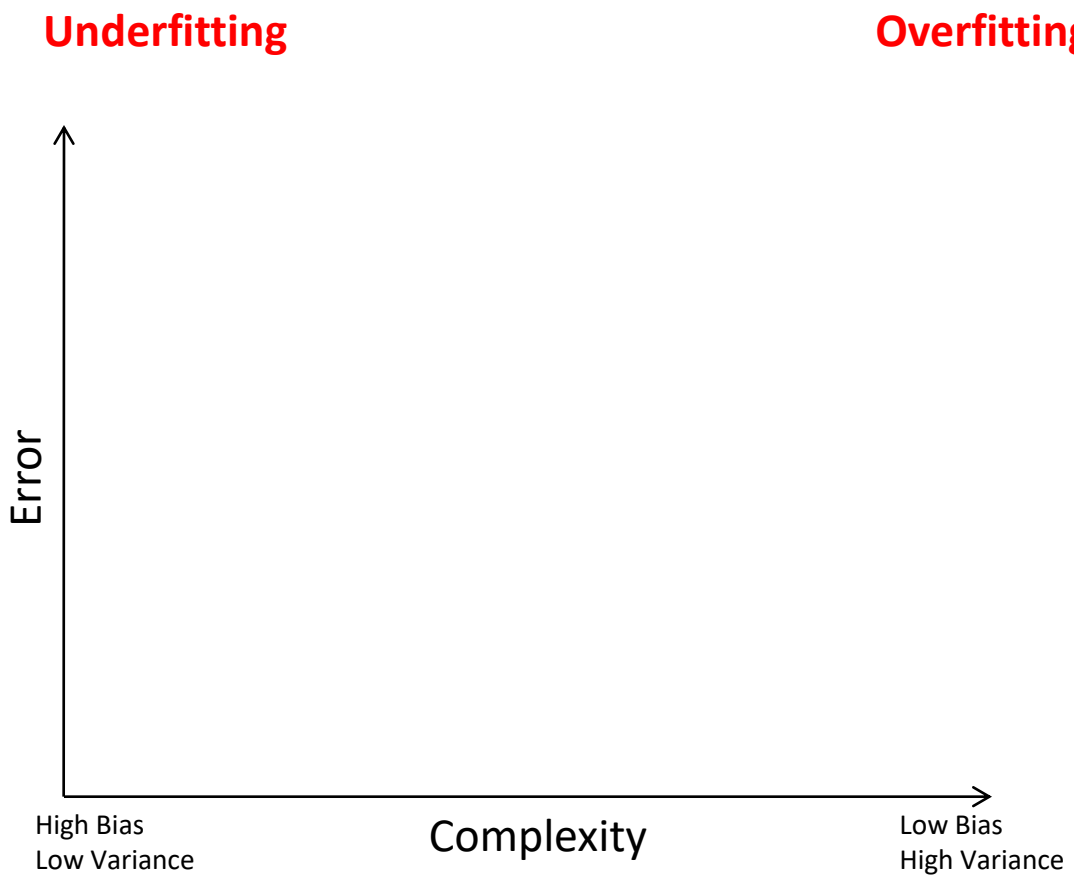
Test set (labels unknown)

- How well does a learned model generalise from the data it was trained on to a new test set?

Generalisation

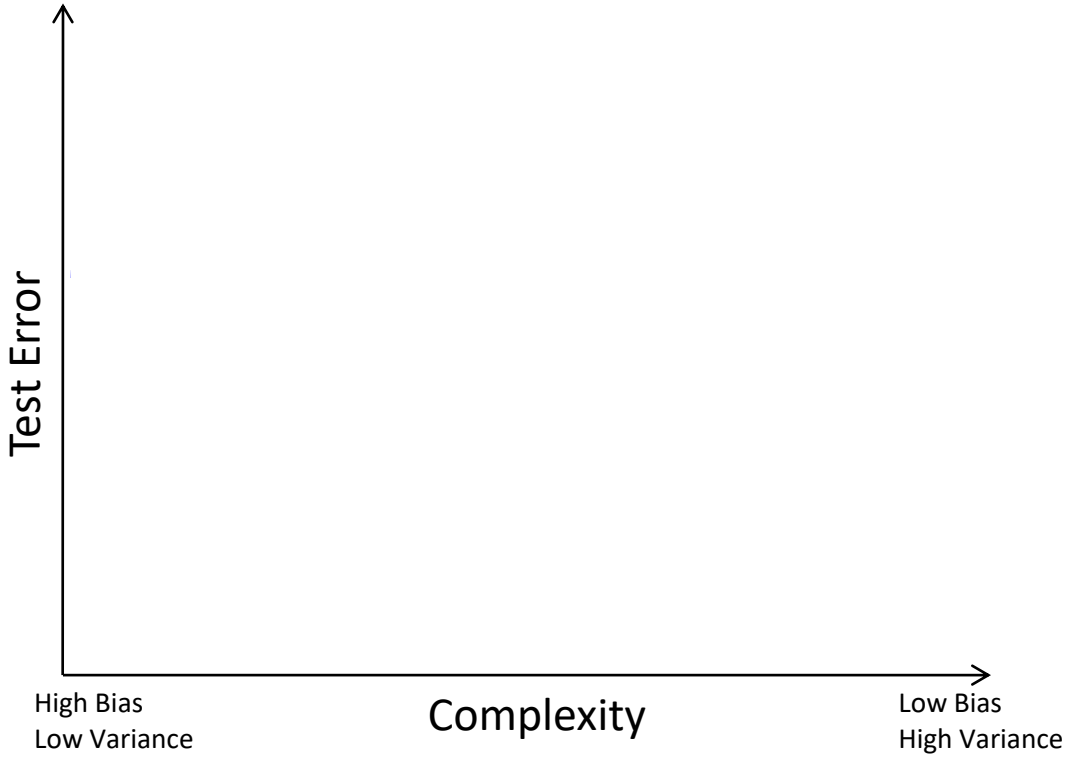
- Components of generalisation error
  - Bias: how much the average model over all training sets differ from the true model?
    - Error due to inaccurate assumptions/simplifications made by the model
  - Variance: how much models estimated from different training sets differ from each other
- Underfitting: model is too "simple" to represent all the relevant class characteristics
  - High bias and low variance
  - High training error and high test error
- Overfitting: model is too "complex" and fits irrelevant characteristics (noise) in the data
  - Low bias and high variance
  - Low training error and high test error

Bias-Variance Tradeoff



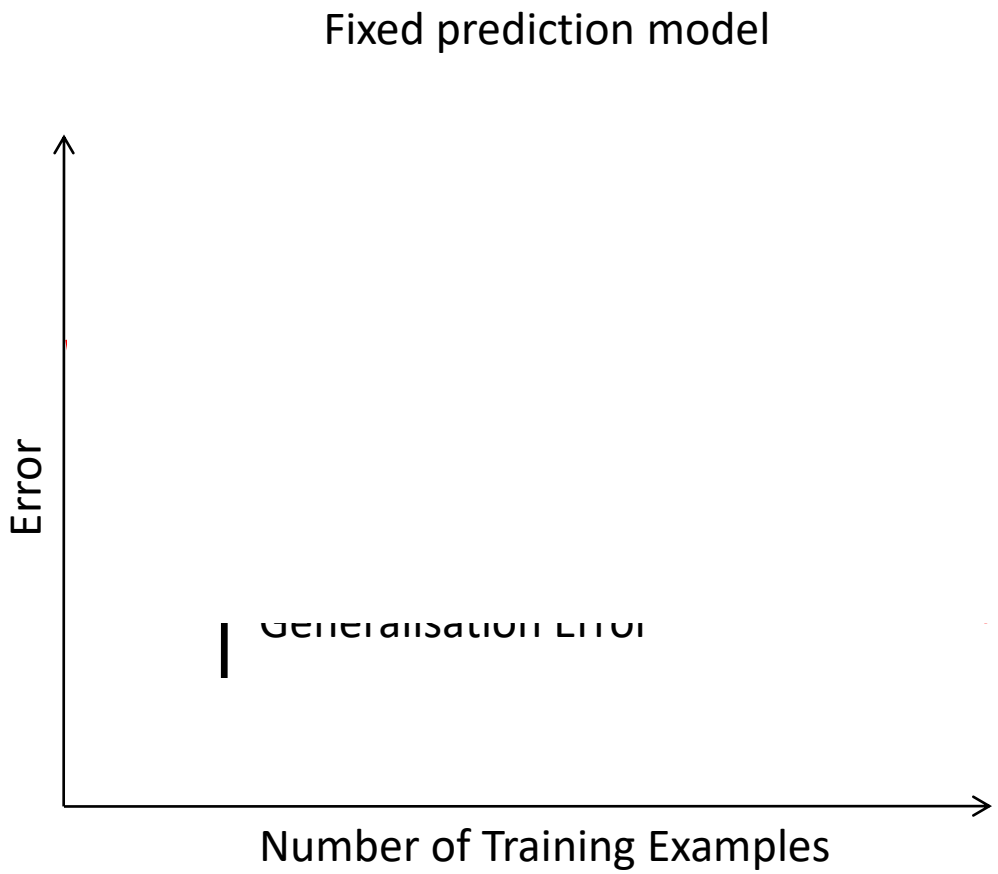
Slide credit: D. Hoiem

Bias-Variance Tradeoff



Slide credit: D. Hoiem

Effect of Training Size



Slide credit: D. Hoiem

Datasets

- Circa 2001: 5 categories, 100s of images per category
- Circa 2004: 101 categories
- Today: up to thousands of categories, millions of images

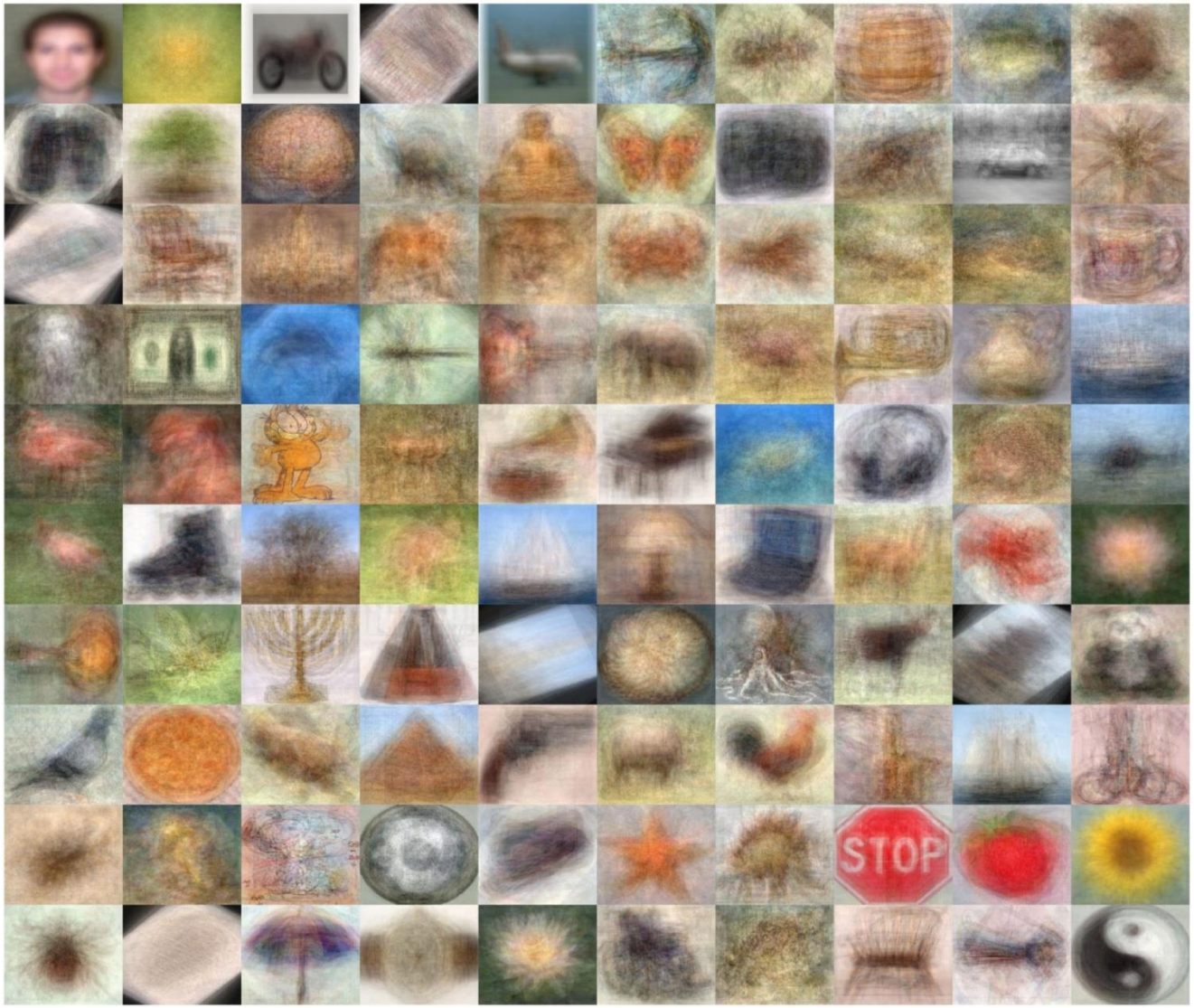
Caltech 101 & 256

http://www.vision.caltech.edu/Image_Datasets/Caltech101/
http://www.vision.caltech.edu/Image_Datasets/Caltech256/

Fei-Fei, Fergus, Perona, 2004

Griffin, Holub, Perona, 2007

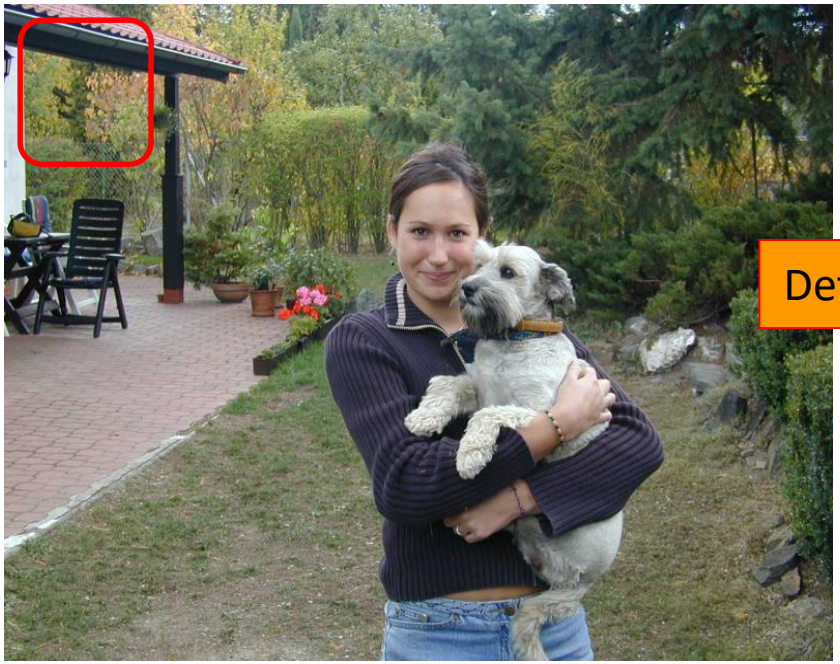
Caltech-101: Intraclass Variability



Face Detection

Behold a state-of-the-art face detector!
(Courtesy Boris Babenko)

Face Detection and Recognition



Detection

Recognition

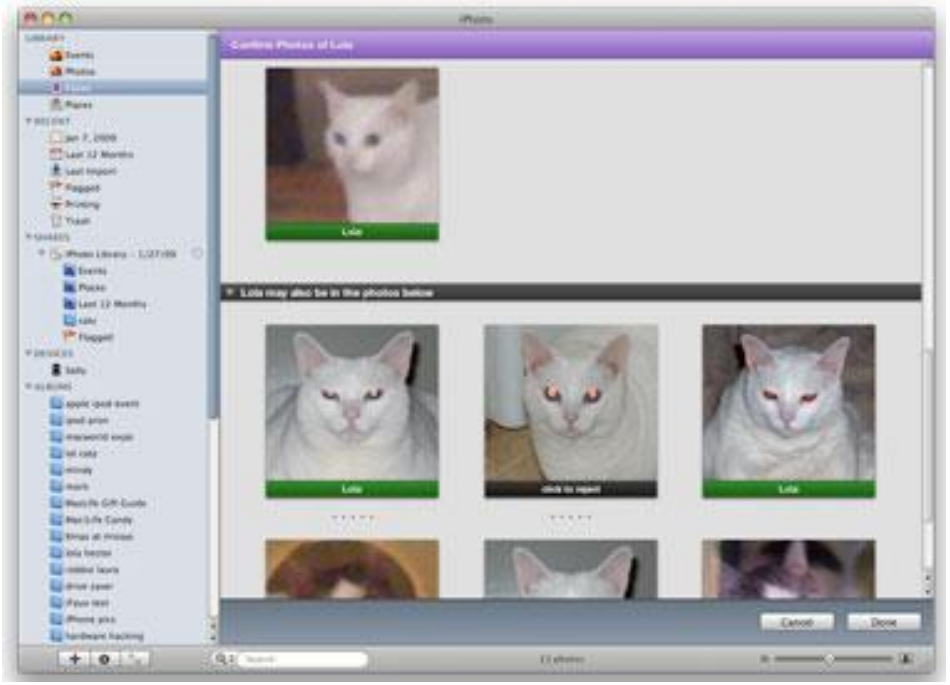
"Sally"

Consumer Application: Apple iPhoto

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

Consumer Application: Apple iPhoto

- Can be trained to recognize pets!



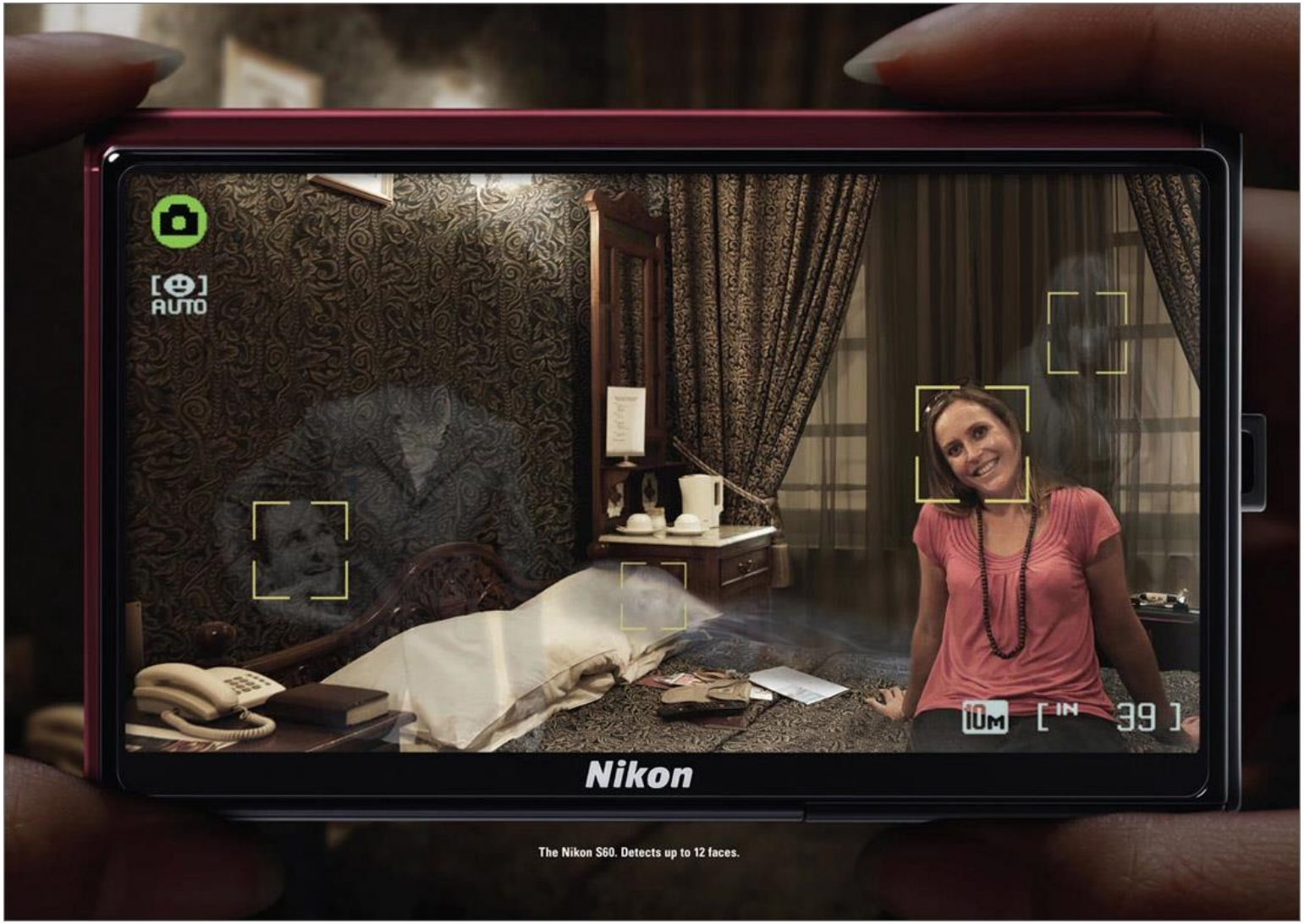
http://www.maclife.com/article/news/iphotos_faces_recognizes_cats

Consumer Application: Apple iPhoto

- Things iPhoto thinks are faces

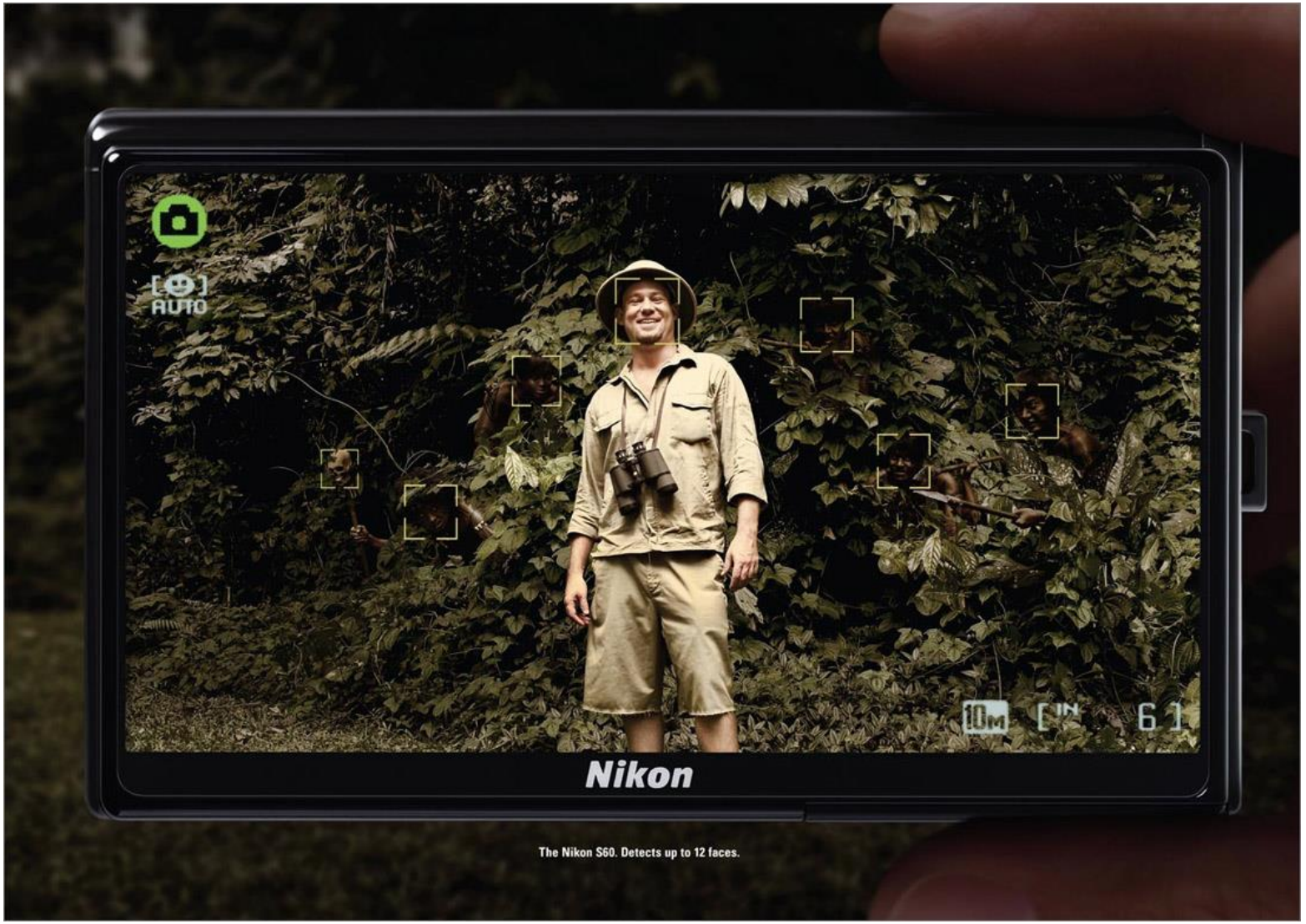
Funny Nikon Ads

"The Nikon S60 detects up to 12 faces."



Funny Nikon Ads

"The Nikon S60 detects up to 12 faces."



Challenges of Face Detection

- Sliding window detector must evaluate tens of thousands of location/scale combinations
- Faces are rare: 0–10 per image
  - For computational efficiency, we should try to spend as little time as possible on the non-face windows
  - A megapixel image has ~10^6 pixels and a comparable number of candidate face locations
  - To avoid having a false positive in every image, our false positive rate has to be less than 10^{-6}

The Viola/Jones Face Detector

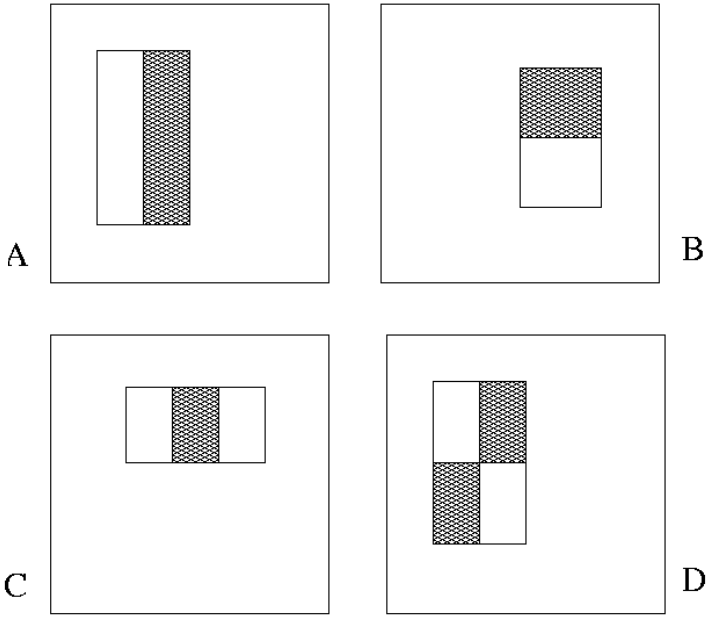
- A seminal approach to real-time object detection
- Training is slow, but detection is very fast
- Key ideas
  - *Integral images* for fast feature evaluation
  - *Boosting* for feature selection
  - *Attentional cascade* for fast rejection of non-face windows

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.

Image Features

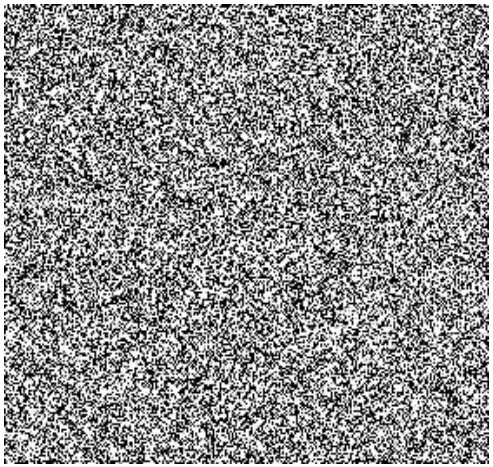
"Rectangle filters"



Value =

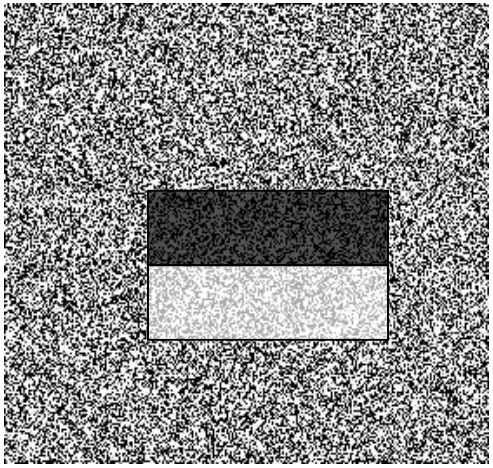
∑ (pixels in white area) –
∑ (pixels in black area)

Example



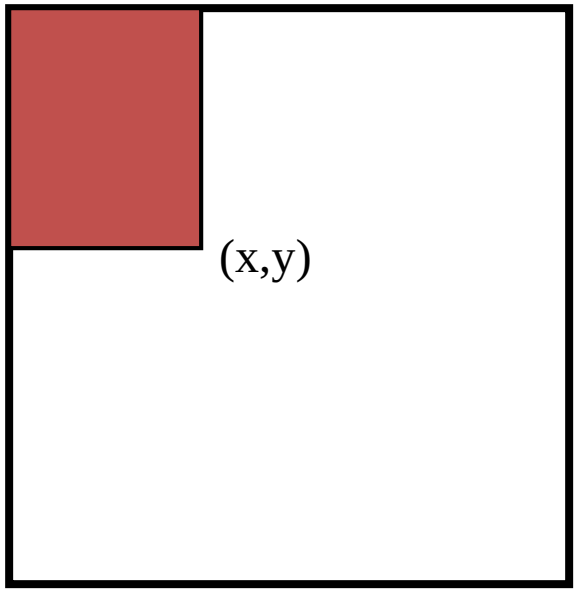
Source

Result

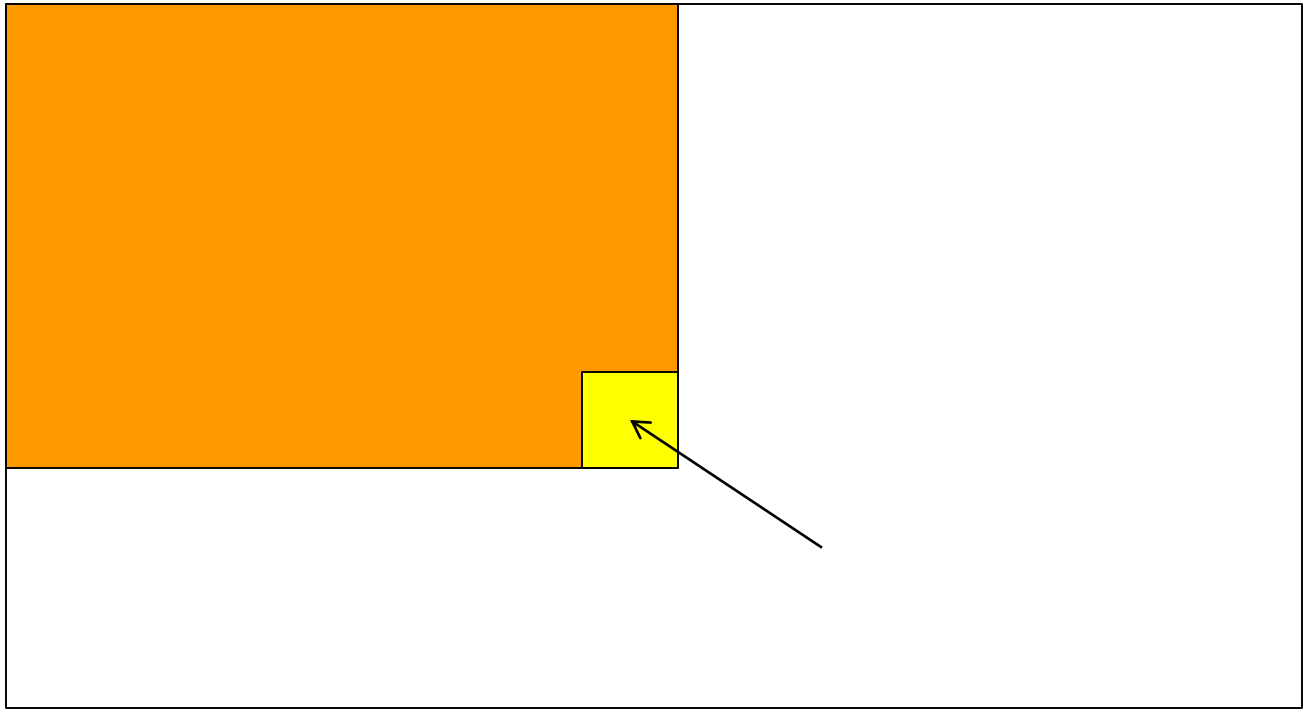


Fast Computation with Integral Images

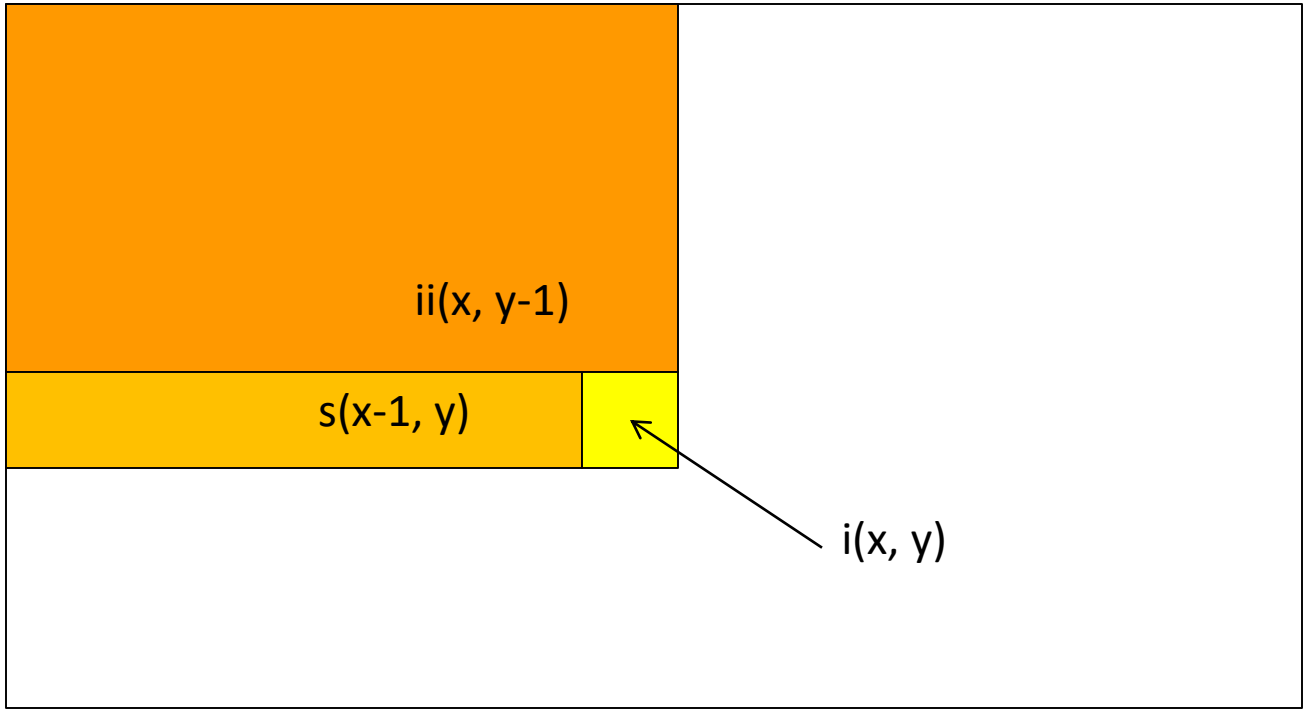
- The *integral image* computes a value at each pixel (*x*,*y*) that is the sum of the pixel values above and to the left of (*x*,*y*), inclusive
- This can quickly be computed in one pass through the image



Computing the Integral Image



Computing the Integral Image



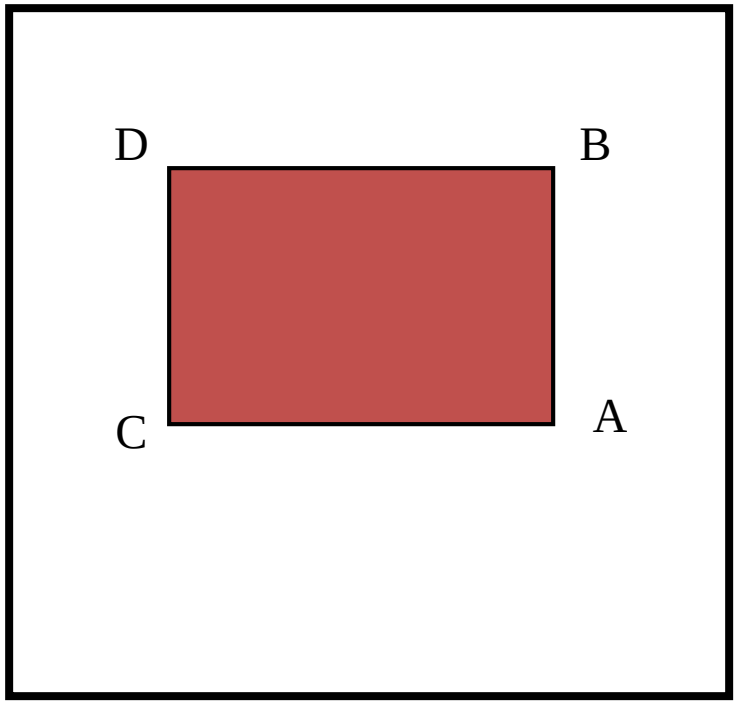
- Cumulative row sum: $s(x, y) = s(x–1, y) + i(x, y)$
- Integral image: $ii(x, y) = ii(x, y–1) + s(x, y)$

Computing Sum within a Rectangle

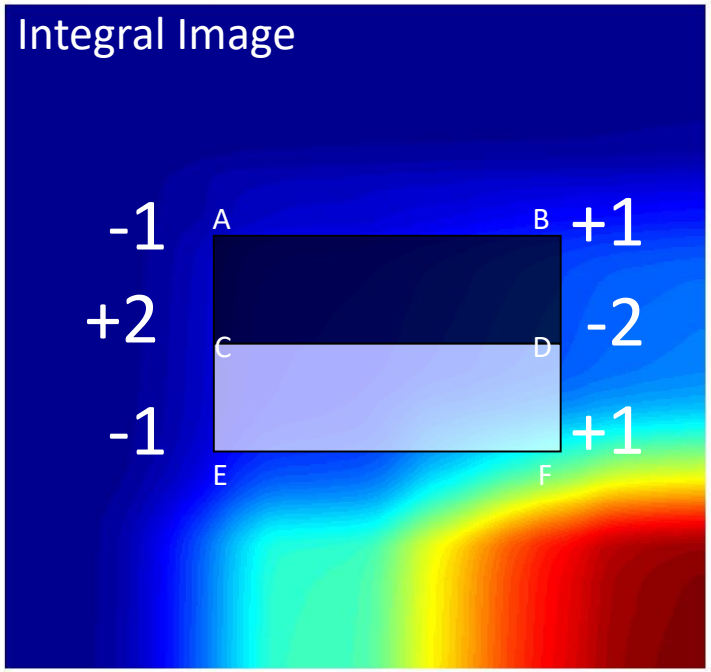
- Let A,B,C,D be the values of the integral image at the corners of a rectangle
- Then the sum of original image values within the rectangle can be computed as:

  sum = A – B – C + D

- Only 3 additions are required for any size of rectangle!



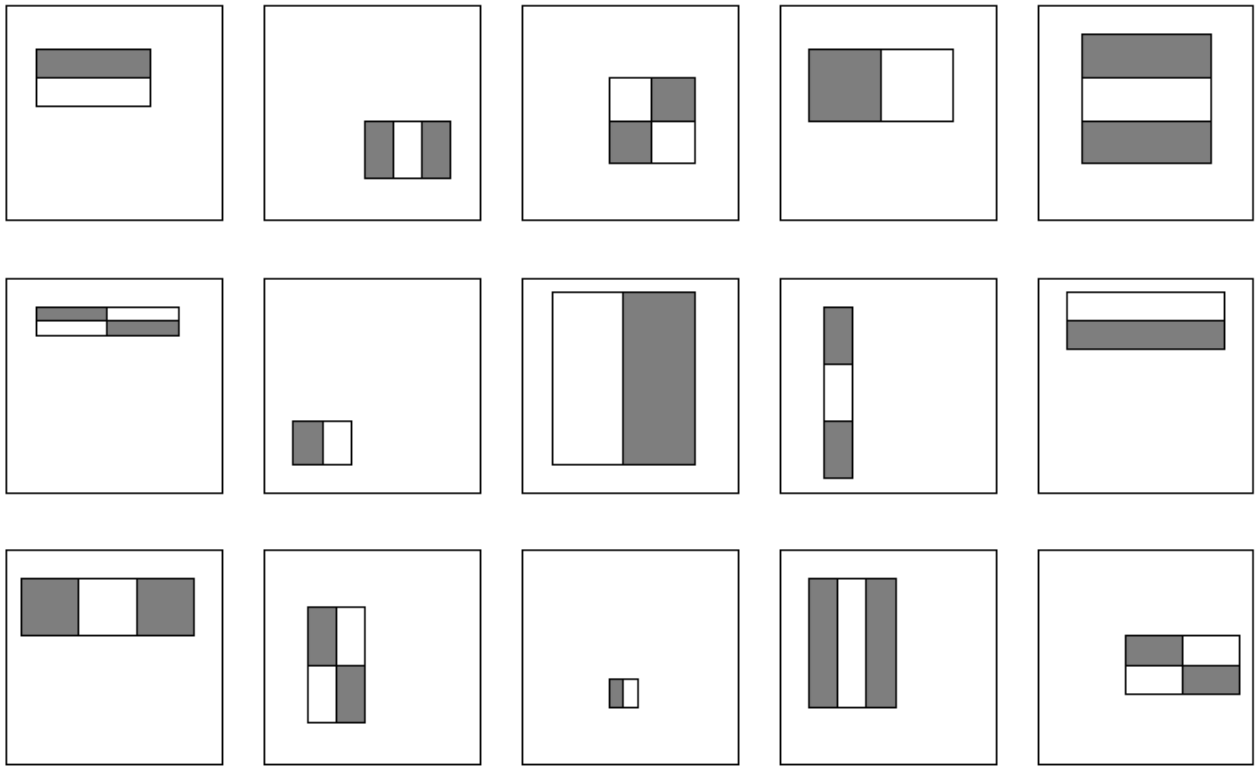
Example



Black = A-B-C+D
White = C-D-E+F
Value = White-Black = -A+B+2C-2D-E+F

Feature Selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!



Feature Selection

- For a 24x24 detection region, the number of possible rectangle features is ~160,000!
- At test time, it is impractical to evaluate the entire feature set
- Can we create a good classifier using just a small subset of all possible features?
- How to select such a subset?

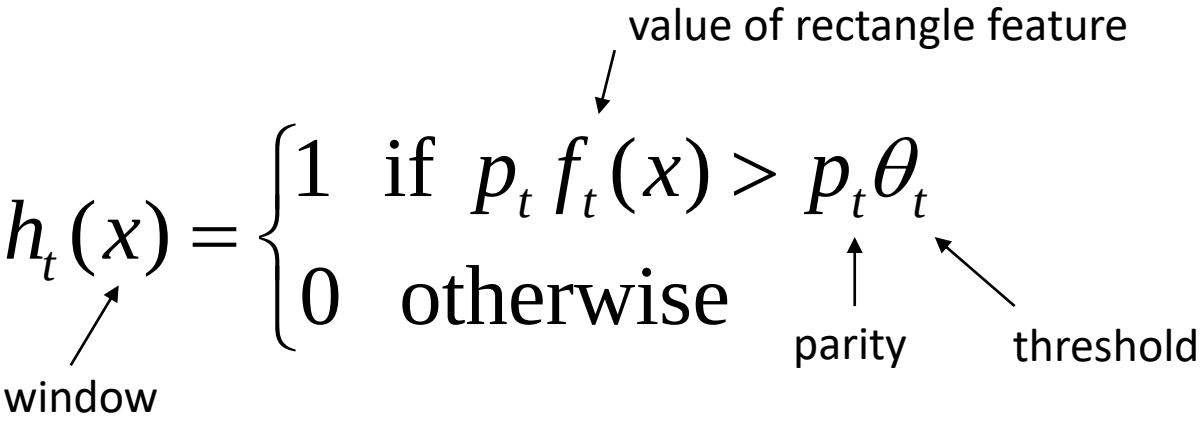
Boosting

- Boosting is a classification scheme that combines *weak learners* into a more accurate *ensemble classifier*
- Training procedure
  - Initially, weight each training example equally
  - In each boosting round:
    - Find the weak learner that achieves the lowest *weighted* training error
    - Raise the 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)

Y. Freund and R. Schapire, A short introduction to boosting, *Journal of Japanese Society for Artificial Intelligence*, 14(5):771-780, September, 1999.

Boosting for Face Detection

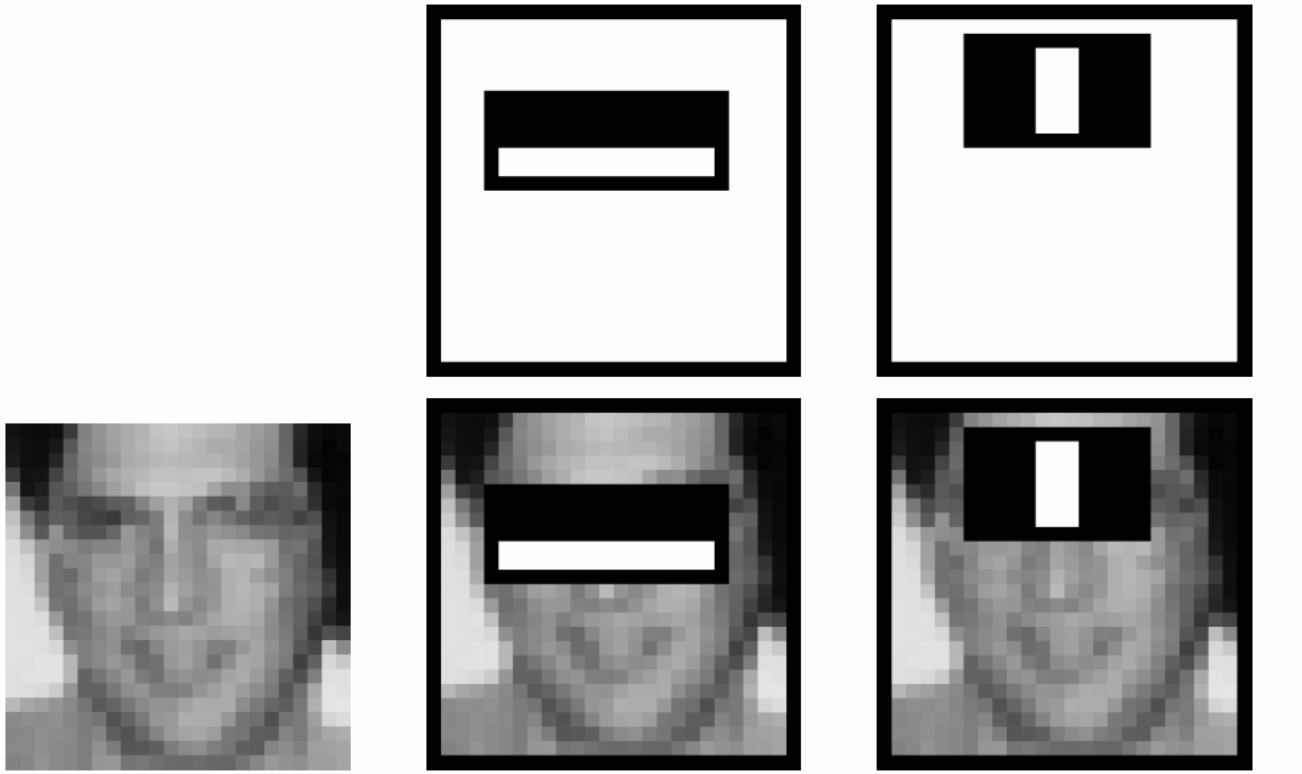
- Define weak learners based on rectangle features



- For each round of boosting:
  - Evaluate each rectangle filter on each example
  - Select best filter/threshold combination based on weighted training error
  - Reweight examples

Boosting for Face Detection

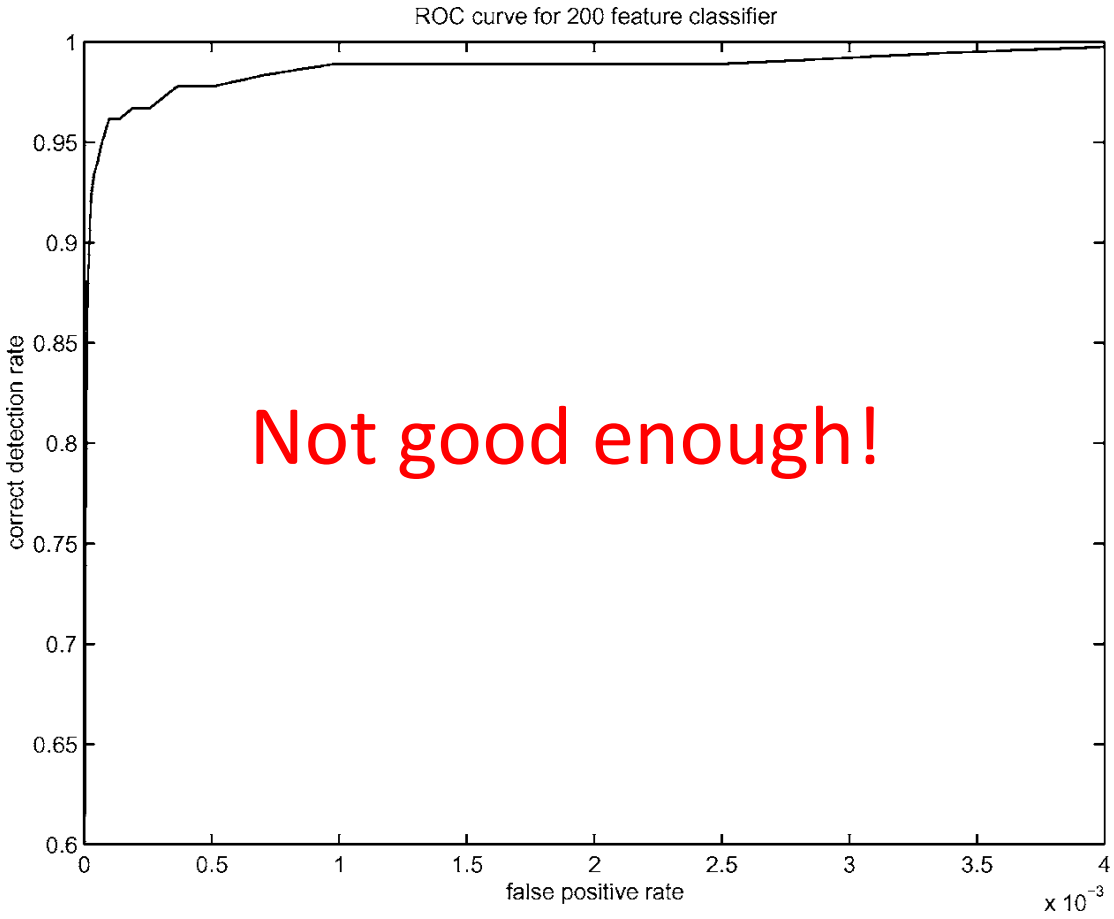
- First two features selected by boosting:



This feature combination can yield 100% detection rate and 50% false positive rate

Boosting for Face Detection

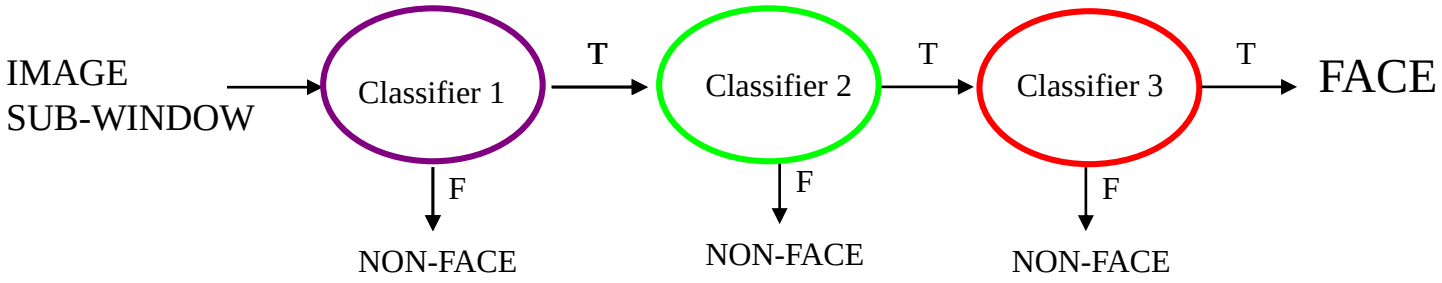
- A 200-feature classifier can yield 95% detection rate and a false positive rate of 1 in 14084



Receiver operating characteristic (ROC) curve

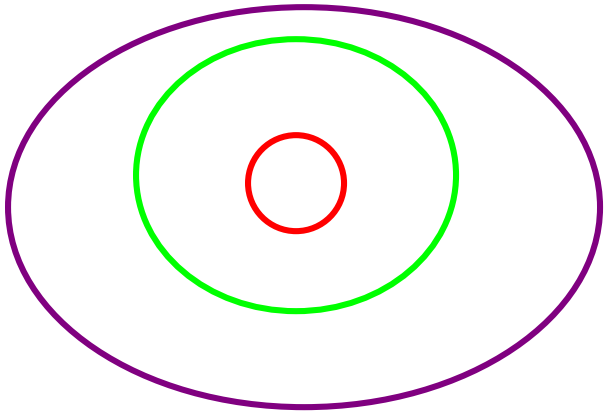
Attentional Cascade

- We start with simple classifiers which reject many of the negative sub-windows while detecting almost all positive sub-windows
- Positive response from the first classifier triggers the evaluation of a second (more complex) classifier, and so on
- A negative outcome at any point leads to the immediate rejection of the sub-window

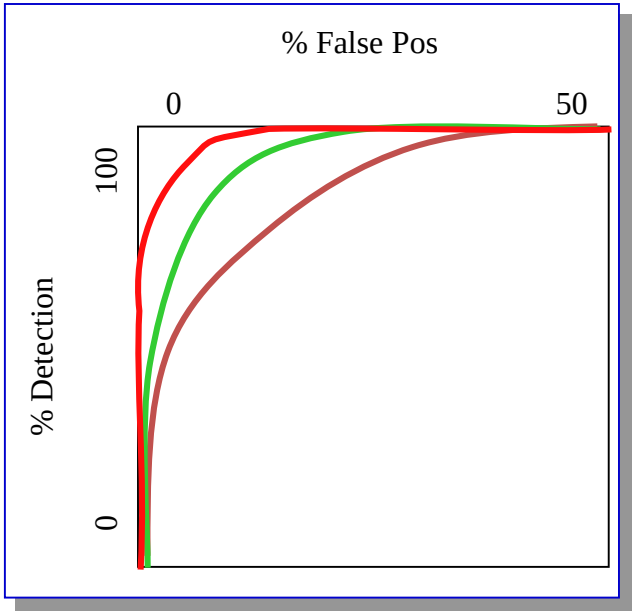


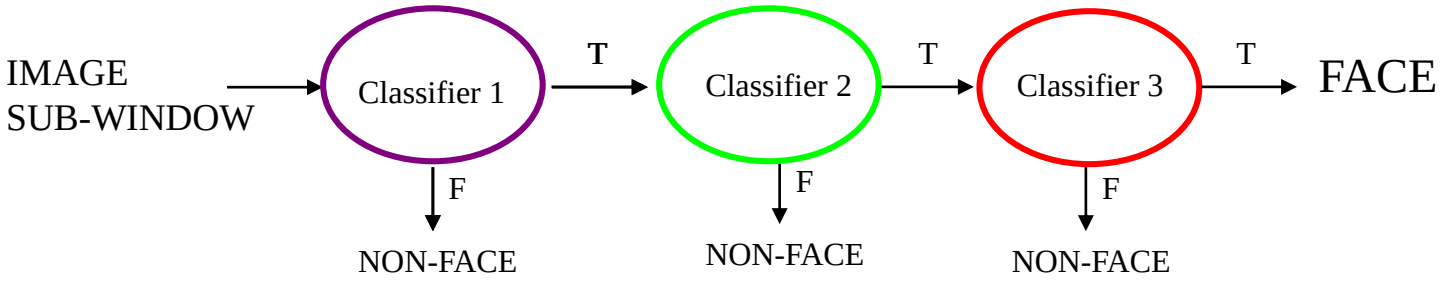
Attentional Cascade

- Chain classifiers that are progressively more complex and have lower false positive rates:



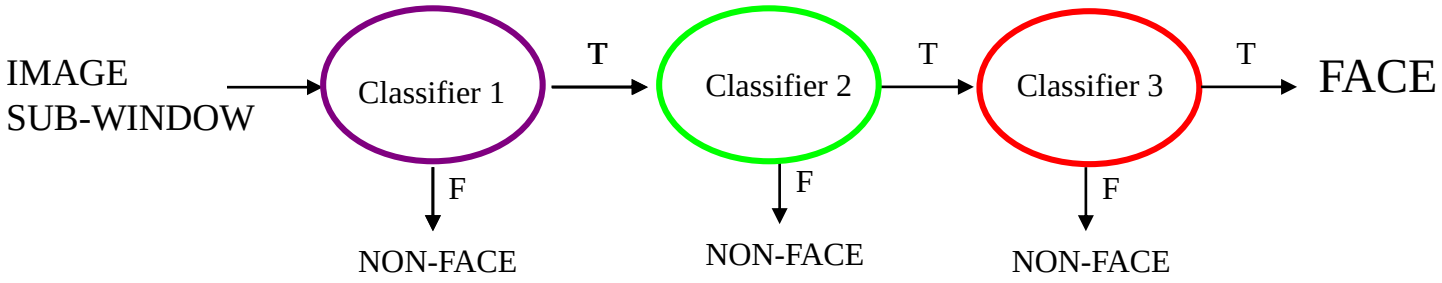
Receiver operating characteristic





Attentional Cascade

- The detection rate and the false positive rate of the cascade are found by multiplying the respective rates of the individual stages
- A detection rate of 0.9 and a false positive rate on the order of 10^{-6} can be achieved by a 10-stage cascade if each stage has a detection rate of 0.99 ($0.99^{10} \approx 0.9$) and a false positive rate of about 0.30 ($0.3^{10} \approx 6 \times 10^{-6}$)



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

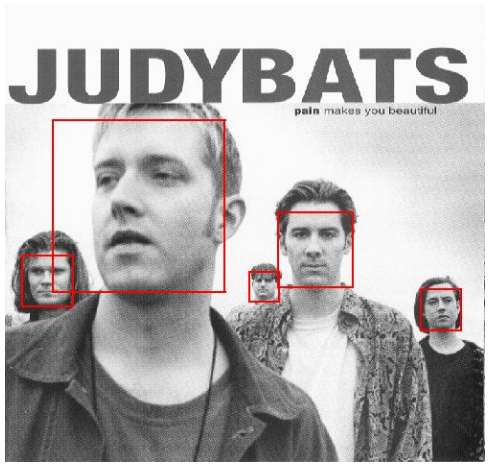
The Implemented System

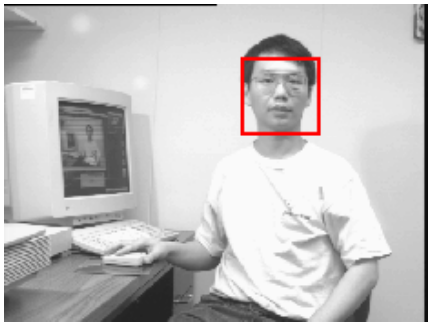
- Training Data
  - 5000 faces
    - All frontal, rescaled to 24x24 pixels
  - 300 million non-faces
    - 9500 non-face images
  - Faces are normalized
    - Scale, translation
- Many variations
  - Across individuals
  - Illumination
  - Pose

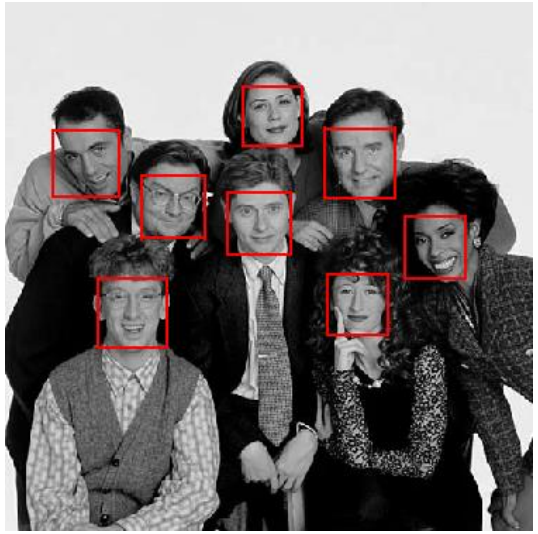
System Performance

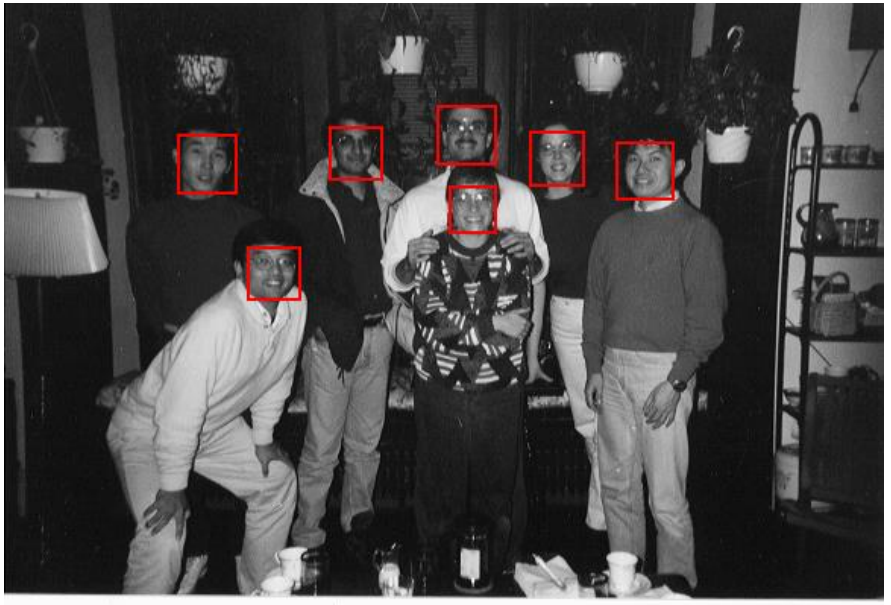
- Training time: “weeks” on 466 MHz Sun workstation
- 38 layers, total of 6061 features
- Average of 10 features evaluated per window on test set
- “On a 700 Mhz Pentium III processor, the face detector can process a 384 by 288 pixel image in about .067 seconds”
  - 15 Hz
  - 15 times faster than previous detector of comparable accuracy (Rowley et al., 1998)

Output of Face Detector on Test Images







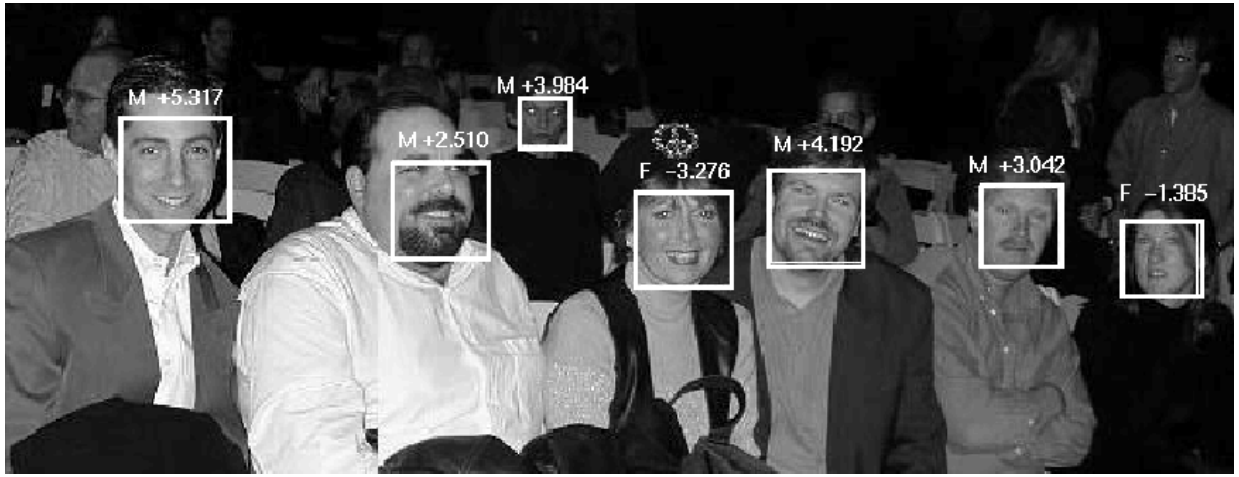


Other Detection Tasks

Facial Feature Localization

Profile Detection

Male vs. female

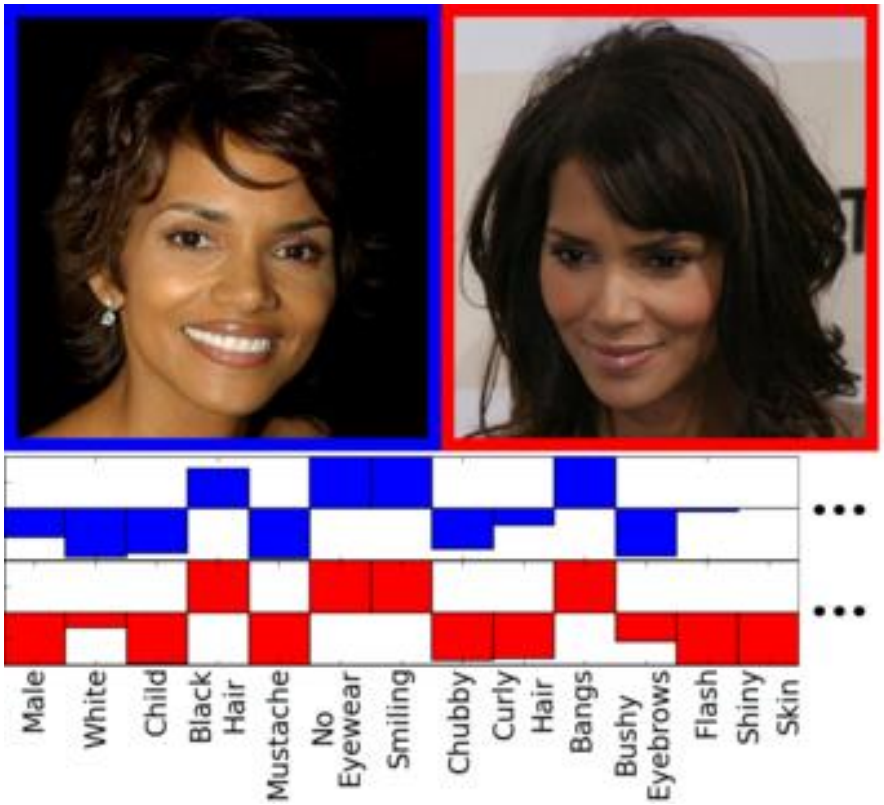


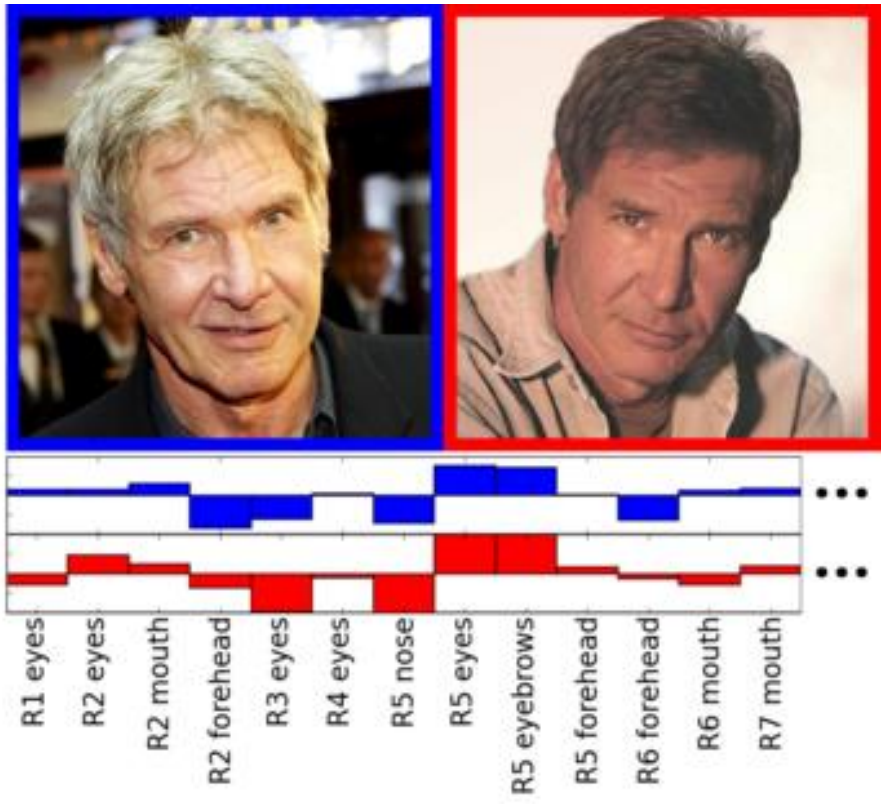
Profile Detection

Viola/Jones Detector Summary

- Rectangle features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows

Face Recognition

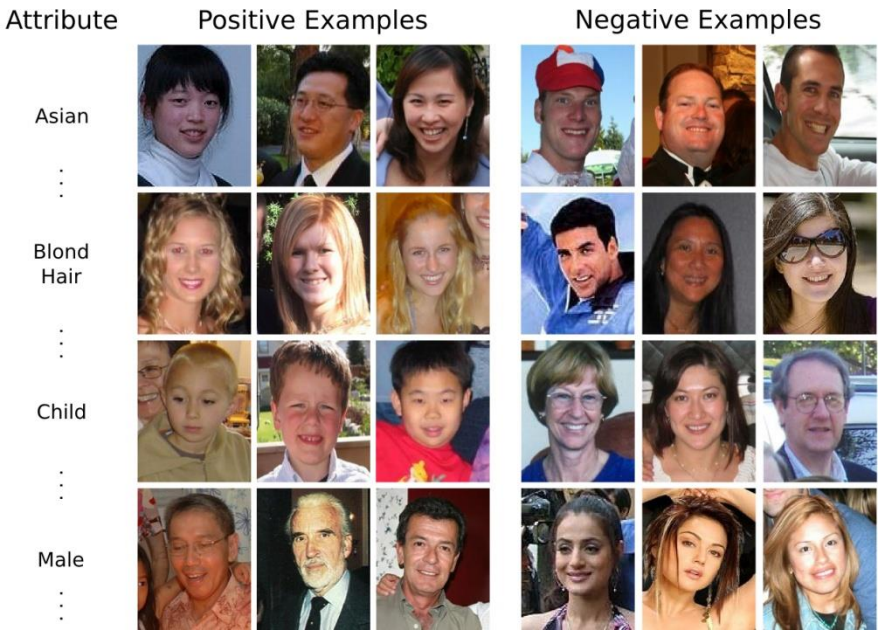




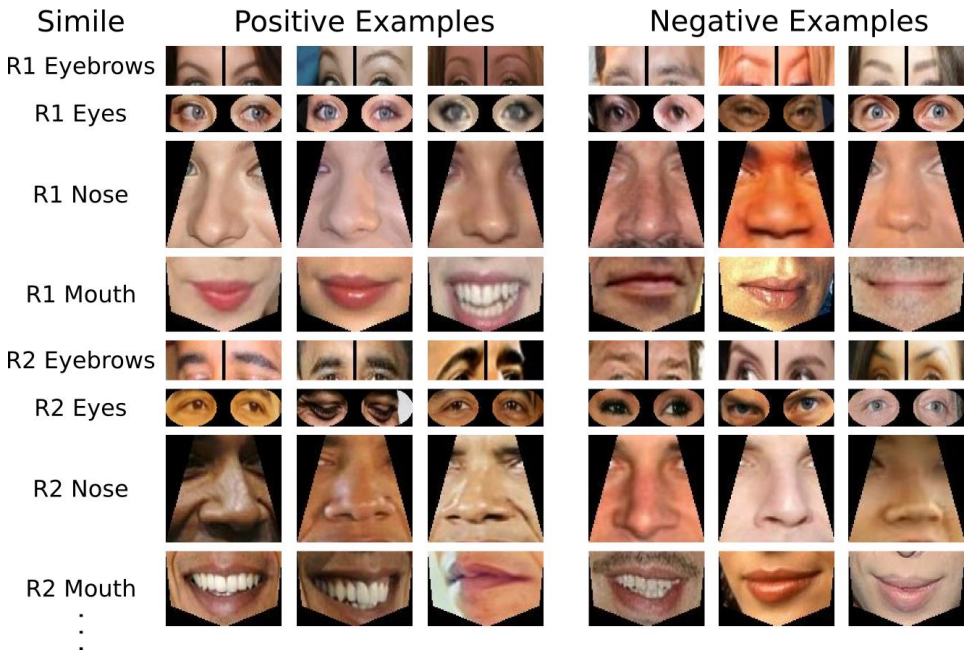
- N. Kumar, A. C. Berg, P. N. Belhumeur, and S. K. Nayar, **"Attribute and Simile Classifiers for Face Verification,"** ICCV 2009.

Face Recognition

Attributes for training



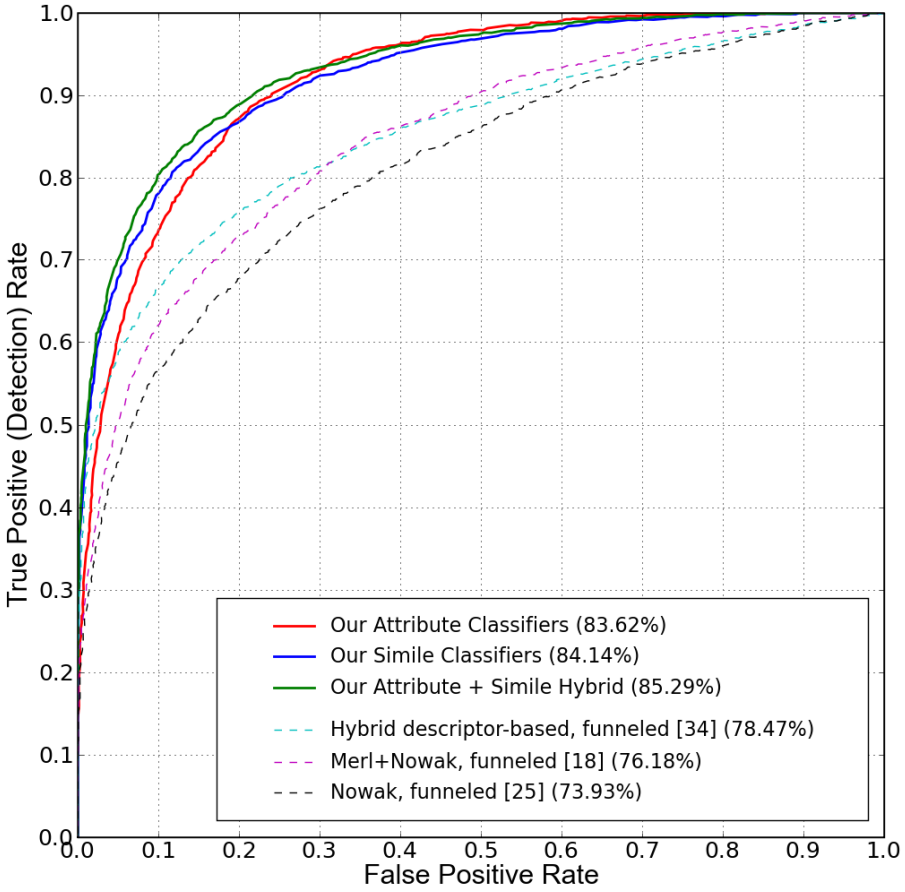
Similes for training



- N. Kumar, A. C. Berg, P. N. Belhumeur, and S. K. Nayar, **"Attribute and Simile Classifiers for Face Verification,"** ICCV 2009.

Face Recognition

Results on Labeled Faces in the Wild Dataset



- N. Kumar, A. C. Berg, P. N. Belhumeur, and S. K. Nayar, **"Attribute and Simile Classifiers for Face Verification,"** ICCV 2009.

Summary

- What is object recognition?
- Briefly describe the history of ideas of object recognition.
- Describe the machine learning framework.
- Describe nearest neighbour and linear classifiers.
- What is the task of face detection and recognition?
- Describe the Viola/Jones Face Detector.