MIT CSAIL

6.869: Advances in Computer Vision

MIT
COMPUTER
VISION

Lecture 20

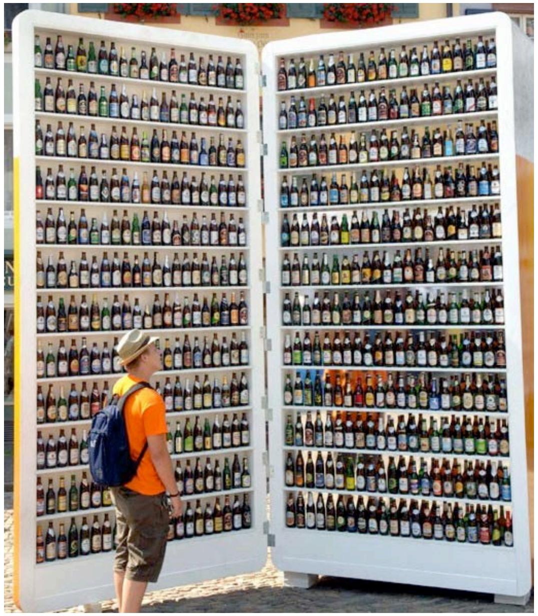
Object recognition 1

The object

The texture

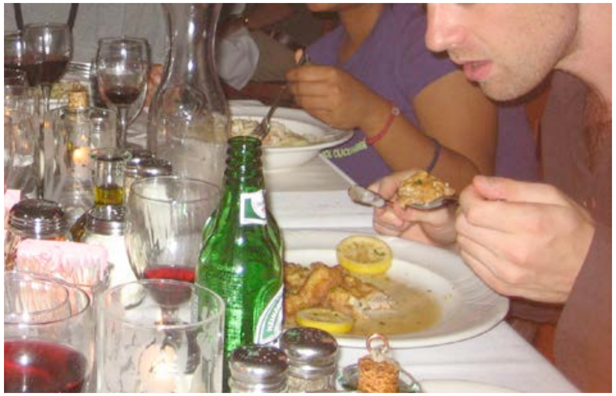
The object

The texture



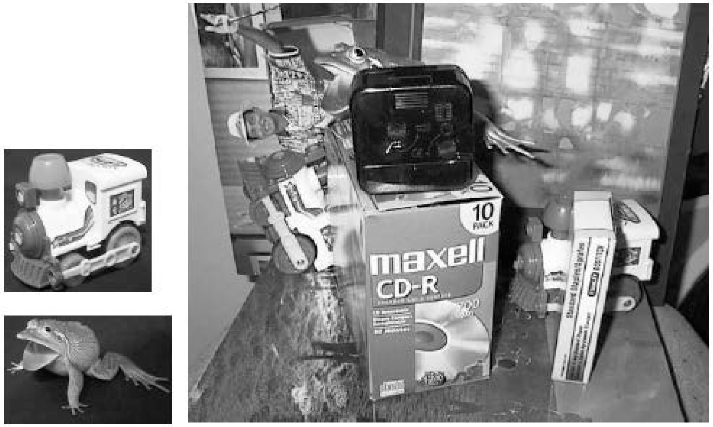
The object

The scene



Instances vs. categories

Instances Find these two toys



Can nail it

Categories Find a bottle:

Can’t do
unless you do not
care about few errors…

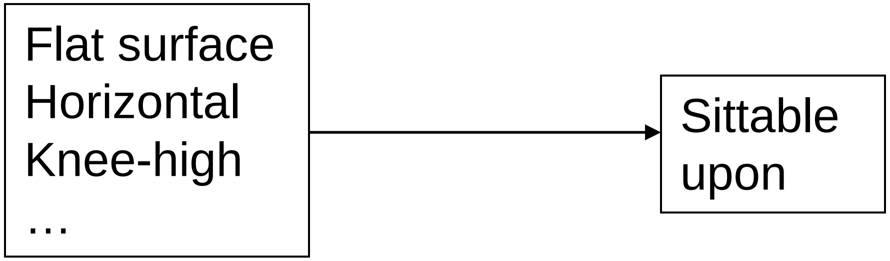
Why do we care about recognition?

Perception of function: We can perceive the 3D shape, texture, material properties, without knowing about objects. But, the concept of category encapsulates also information about what can we do with those objects.

"We therefore include the perception of function as a proper –indeed, crucial- subject for vision science", *from Vision Science, chapter 9, Palmer*.

The perception of function

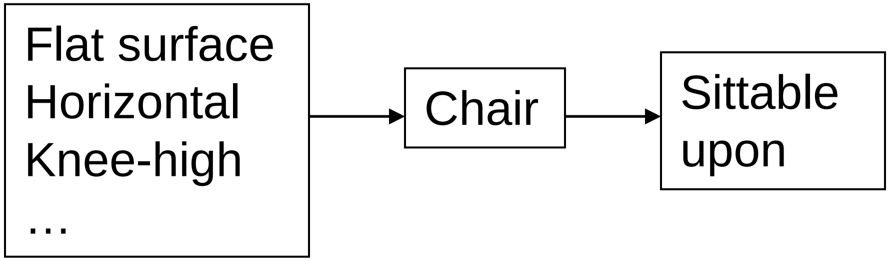
- Direct perception (affordances): Gibson



Flat surface
Horizontal
Knee-high
…

Sittable upon

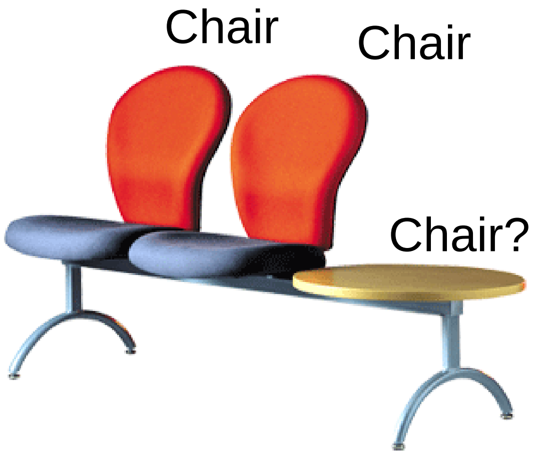
- Mediated perception (Categorization)



Flat surface
Horizontal
Knee-high
…

Chair

Sittable upon



Direct perception

Some aspects of an object function can be perceived directly

- Functional form: Some forms clearly indicate to a function (“sittable-upon”, container, cutting device, …)

Sittable-upon

Sittable-upon

Sittable-upon

It does not seem easy to sit-upon this…

Direct perception

Some aspects of an object function can be perceived directly

- Observer relativity: Function is observer dependent

From http://lastchancerescueflint.org

Limitations of Direct Perception

Objects of similar structure might have very different functions

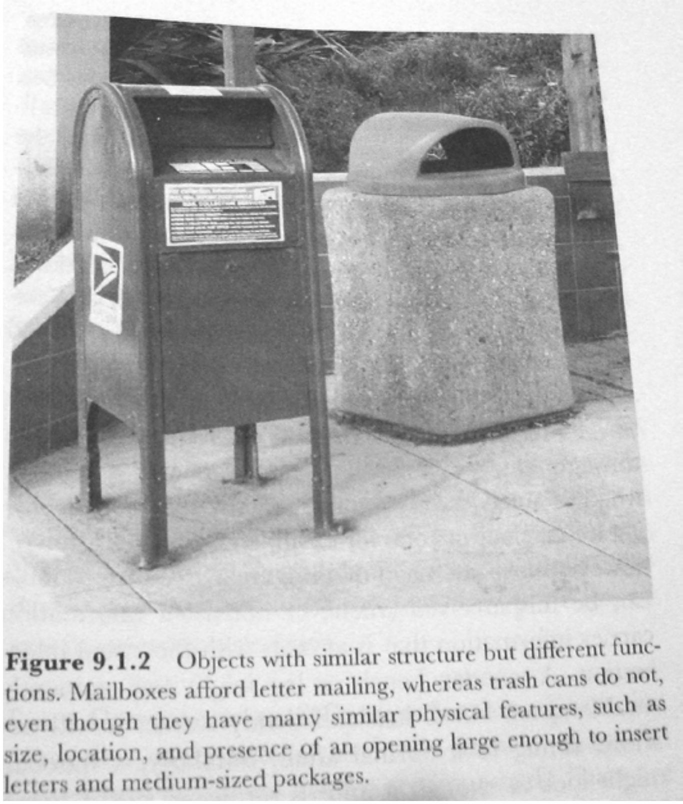
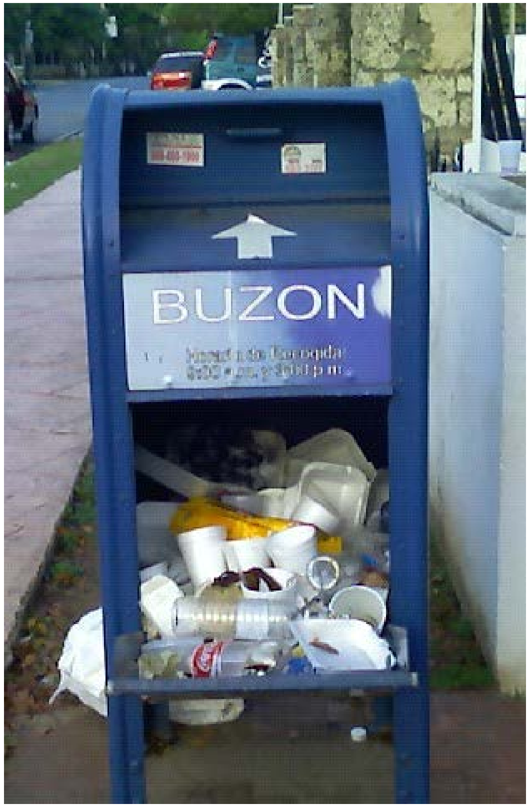


Figure 9.1.2 Objects with similar structure but different functions. Mailboxes afford letter mailing, whereas trash cans do not, even though they have many similar physical features, such as size, location, and presence of an opening large enough to insert letters and medium-sized packages.

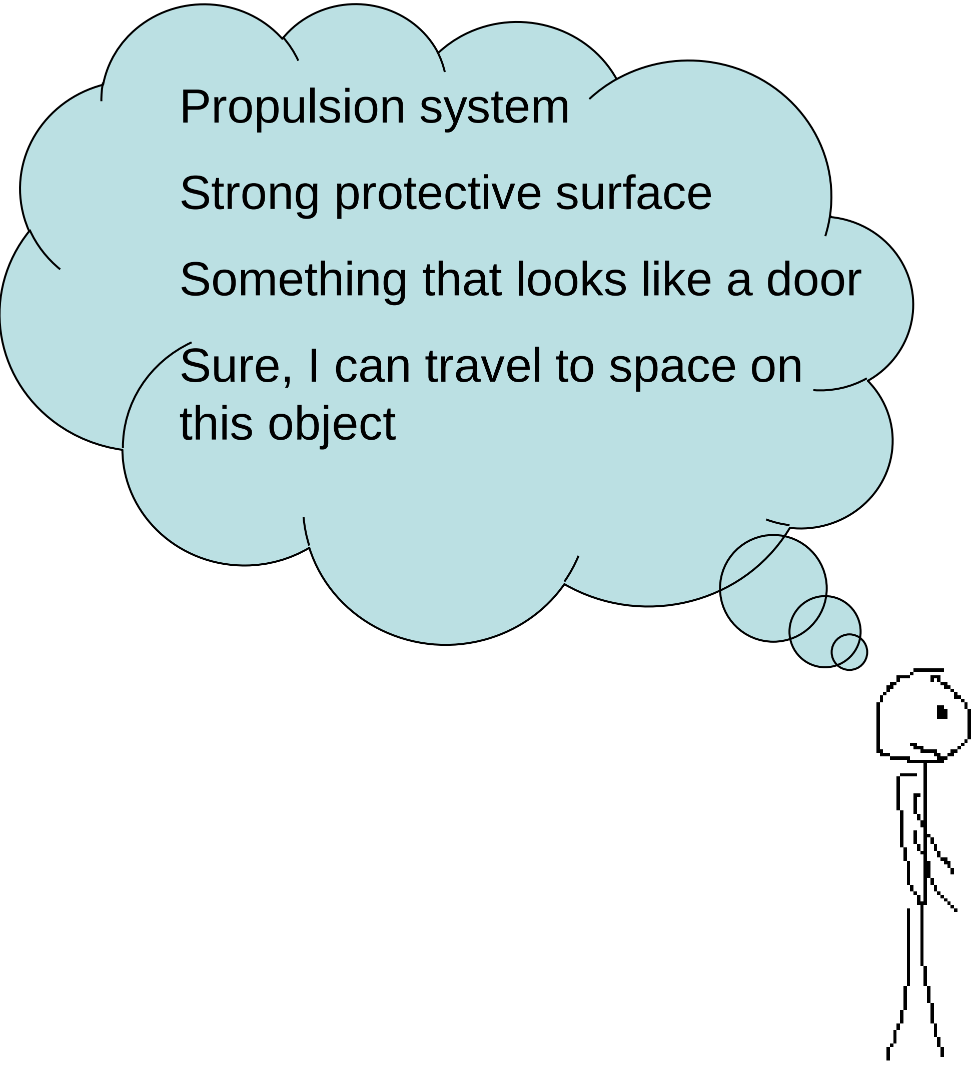


Not all functions seem to be available from direct visual information only.

The functions are the same at some level of description: we can put things inside in both and somebody will come later to empty them. However, we are not expected to put inside the same kinds of things…

Limitations of Direct Perception

Visual appearance might be a very weak cue to function



Propulsion system

Strong protective surface

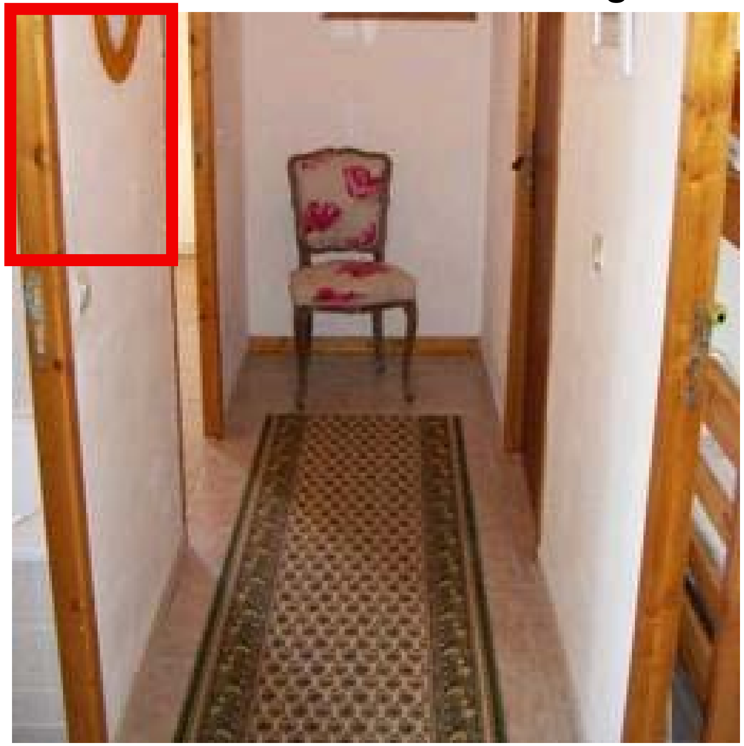
Something that looks like a door

Sure, I can travel to space on this object

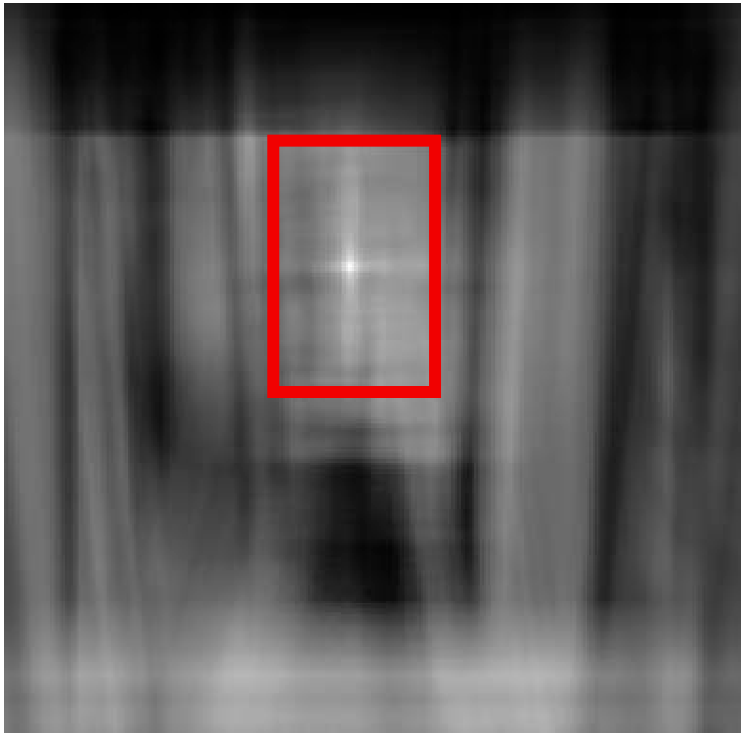
Object recognition
Is it really so hard?

This is a chair

Find the chair in this image

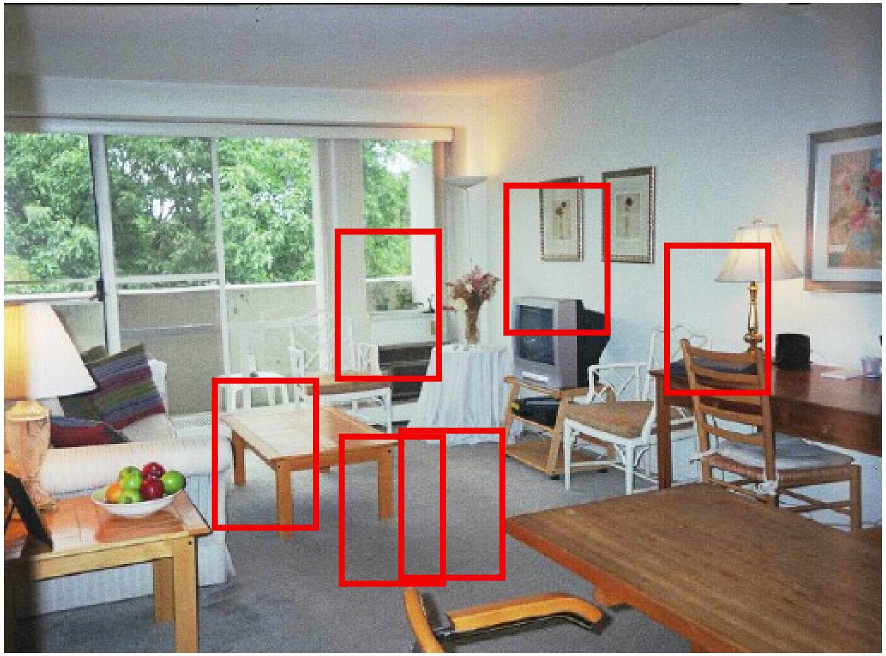


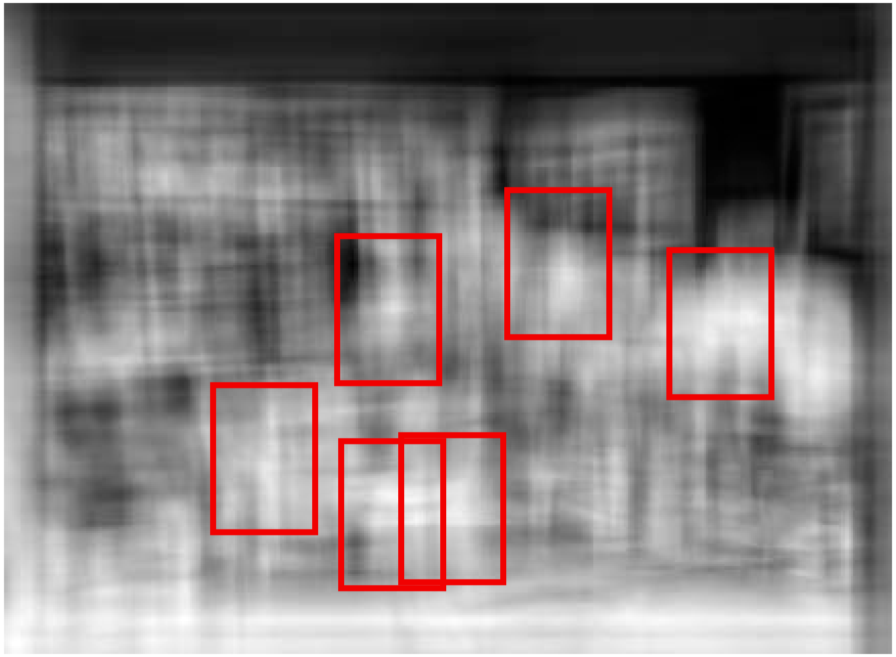
Output of normalized correlation



Object recognition
Is it really so hard?

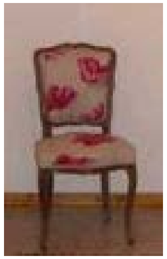
Find the chair in this image





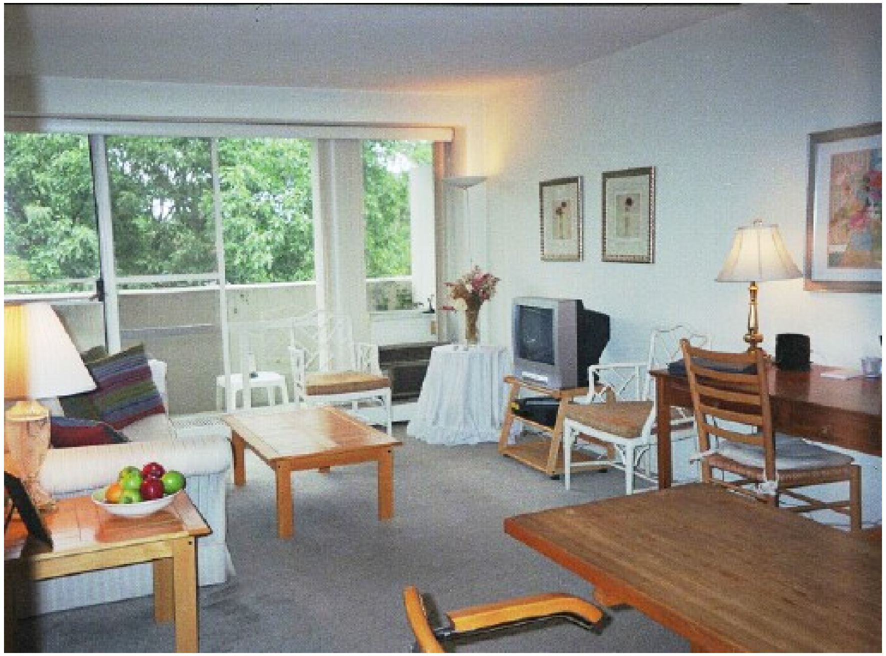
Pretty much garbage
Simple template matching is not going to make it

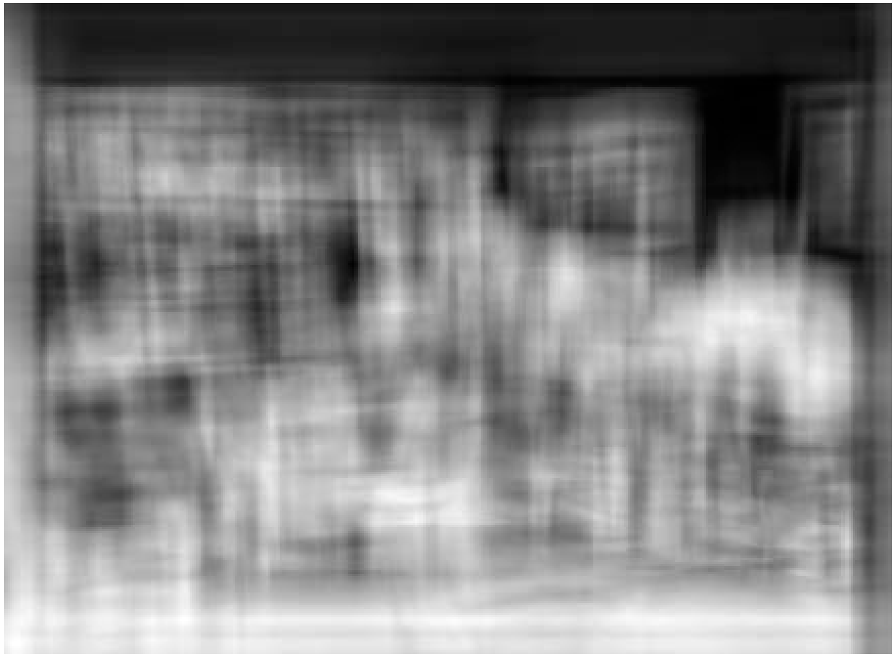
My biggest concern while making this slide was:
how do I justify 50 years of research, and this course, if this experiment did work?



Object recognition
Is it really so hard?

Find the chair in this image

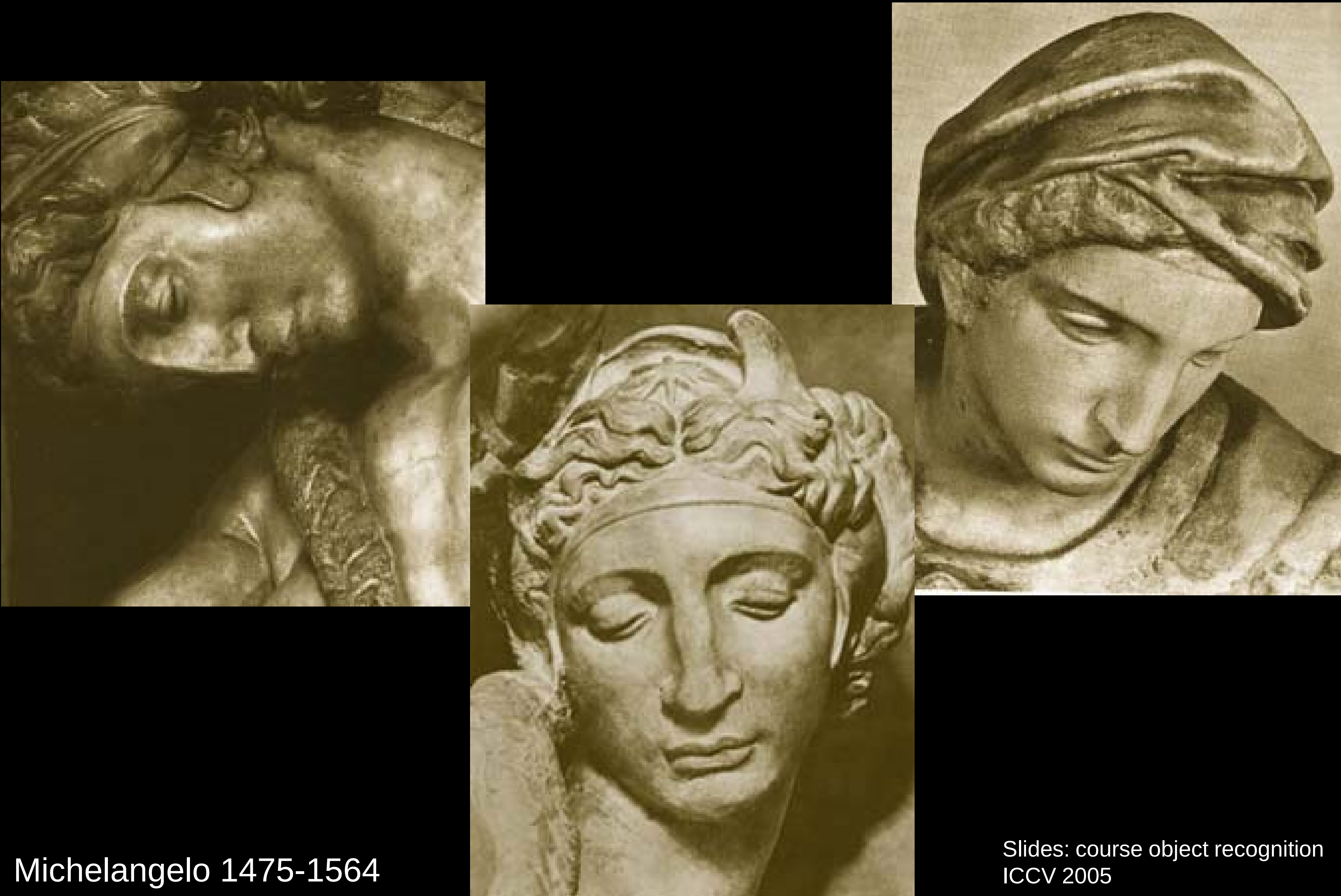




A “popular method is that of template matching, by point to point correlation of a model pattern with the image pattern. These techniques are inadequate for three-dimensional scene analysis for many reasons, such as occlusion, changes in viewing angle, and articulation of parts.” Nivatia & Binford, 1977.

Why is object recognition a hard task?

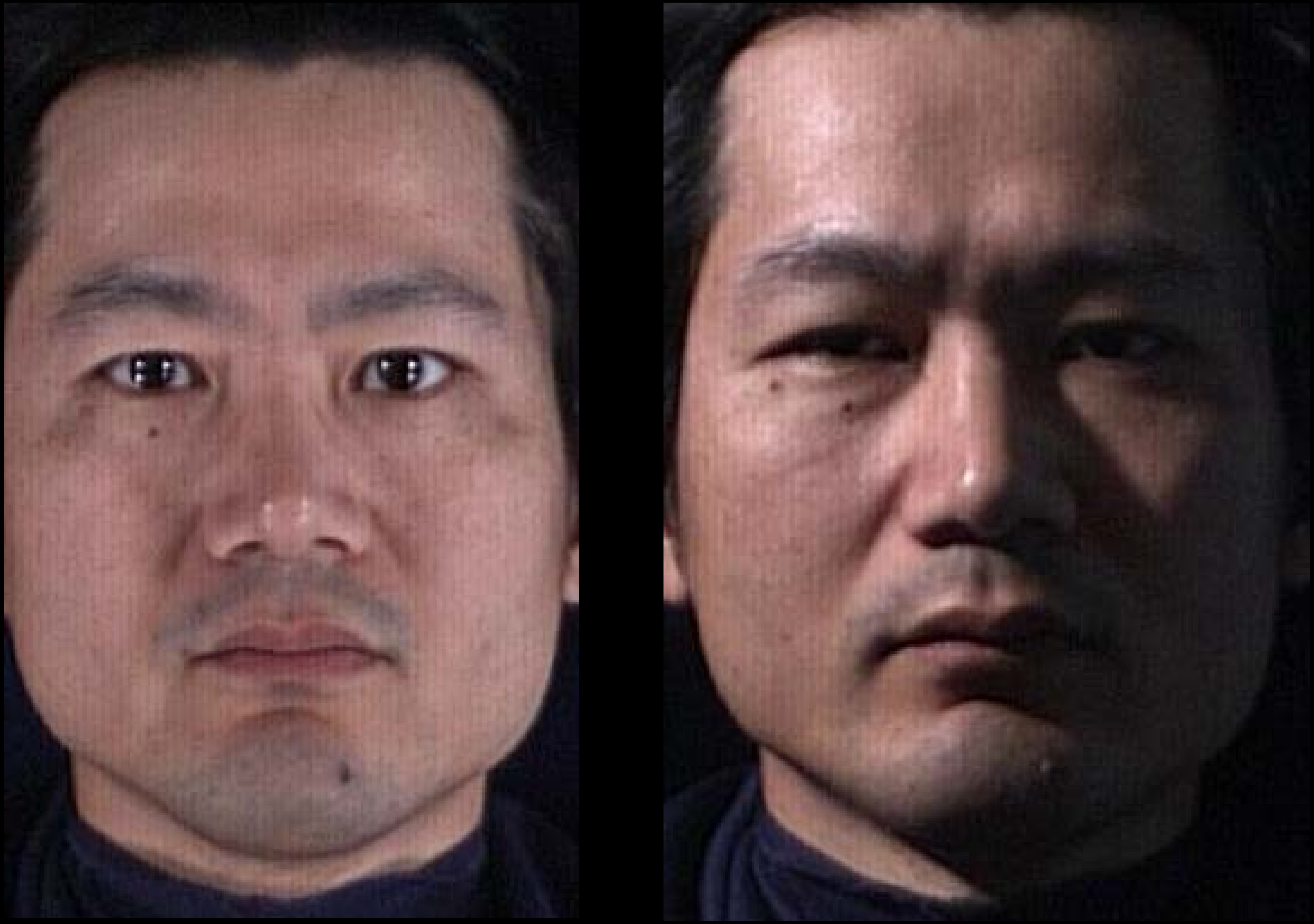
Challenges 1: view point variation



Michelangelo 1475-1564

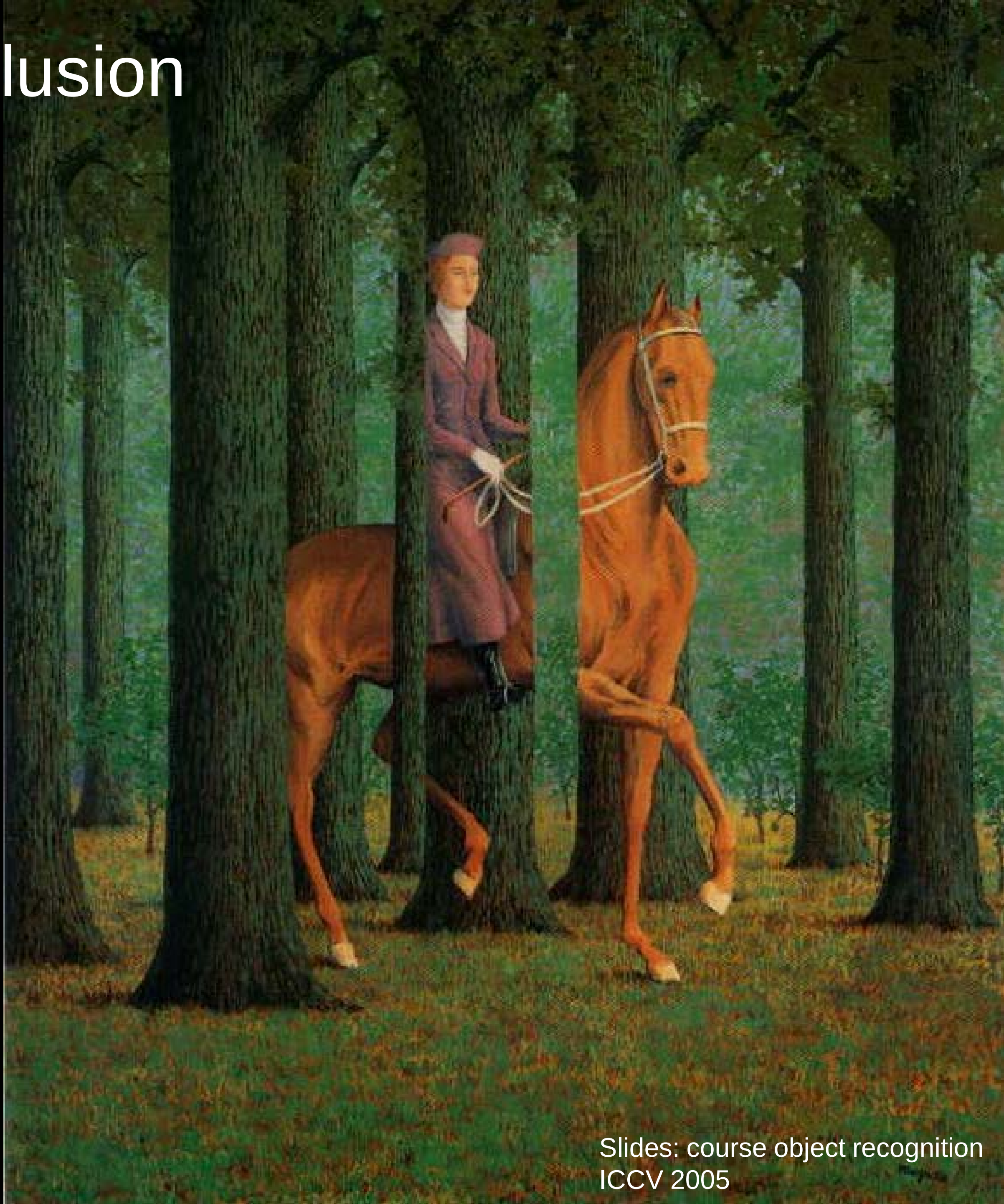
Slides: course object recognition
ICCV 2005

Challenges 2: illumination



slide credit: S. Ullman

Challenges 3: occlusion



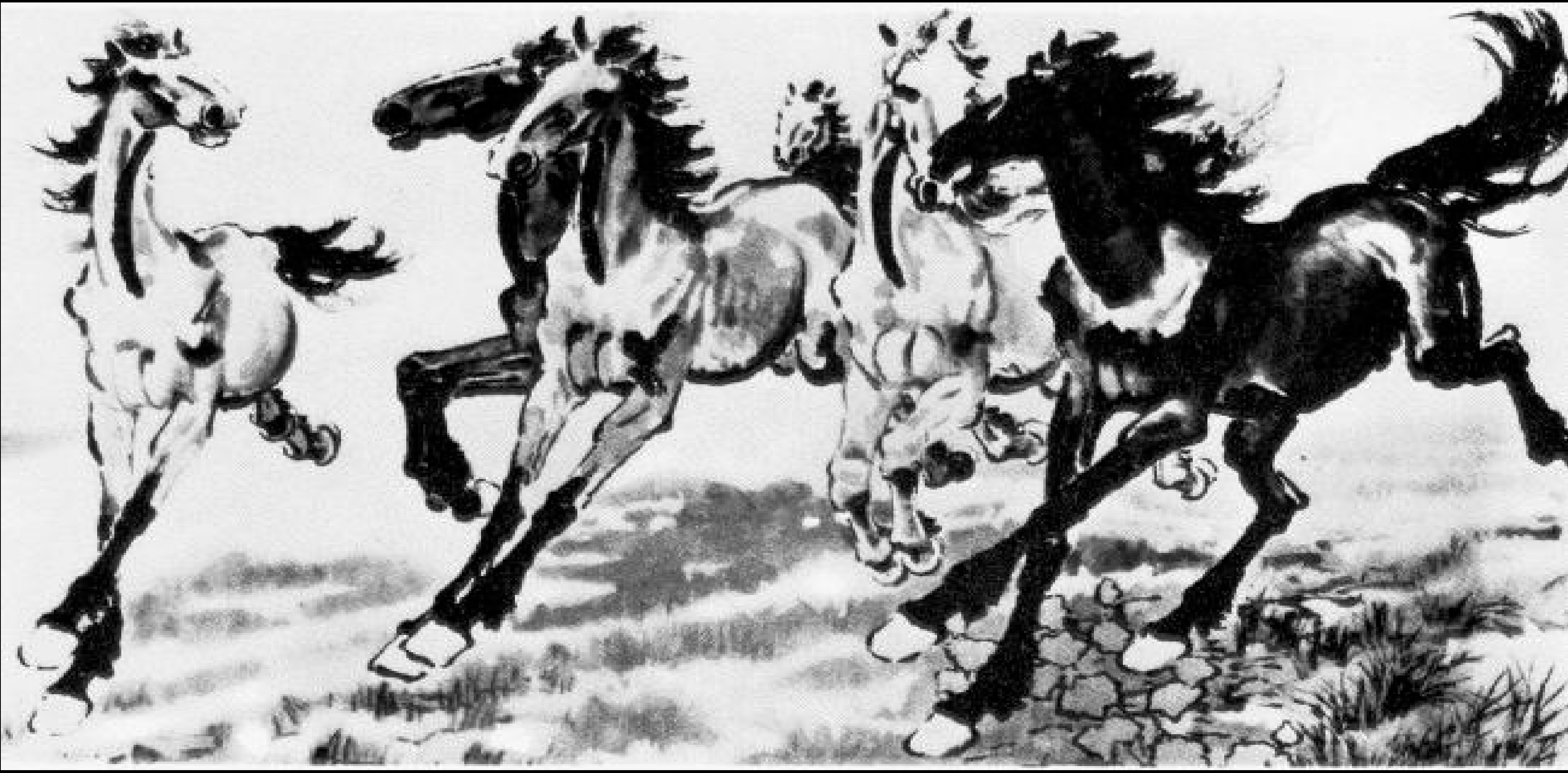
Magritte, 1957

Slides: course object recognition
ICCV 2005

Challenges 4: scale

Slides: course object recognition ICCV 2005

Challenges 5: deformation



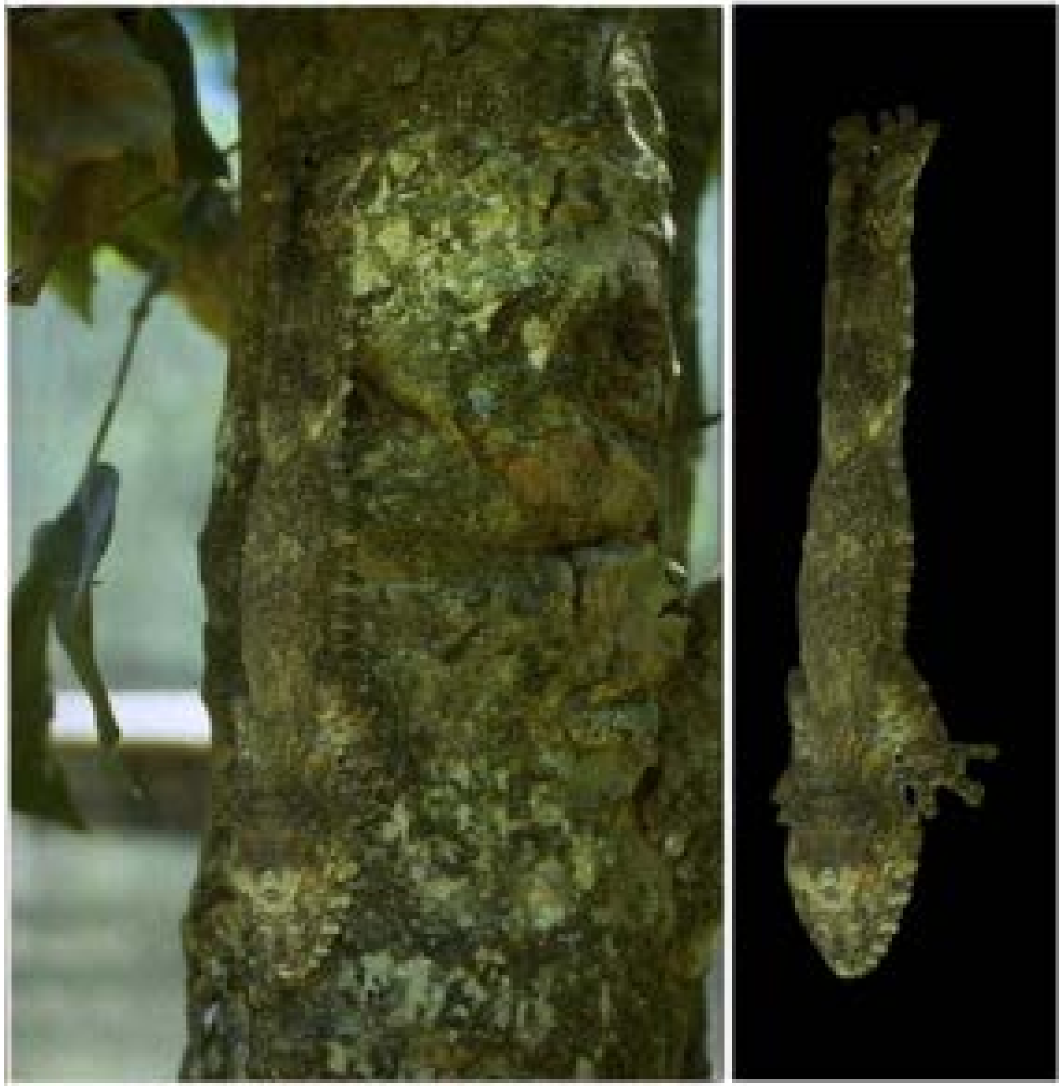
Slides: course object recognition
ICCV 2005

Xu, Beihong 1943

Challenges 6: intra-class variation

Slides: course object recognition
ICCV 2005

Challenges 7: background clutter

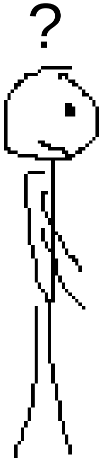


Brady, M. J., & Kersten, D. (2003). Bootstrapped learning of novel objects. J Vis, 3(6), 413-422

Which level of categorization is the right one?

Car is an object composed of:

a few doors, four wheels (not all visible at all times), a roof, front lights, windshield



If you are thinking in buying a car, you might want to be a bit more specific about your categorization.

Entry-level categories
(Jolicoeur, Gluck, Kosslyn 1984)

- Typical member of a basic-level category are categorized at the expected level
- Atypical members tend to be classified at a subordinate level.

American Robin

Photo from Coffee Creek Watershed Preserve

A bird

An ostrich

Creation of new categories

A new class can borrow information from similar categories

Object recognition
Is it really so hard?

Yes, object recognition is hard…

(or at least it seems so for now…)

So, let’s make the problem simpler: Block world

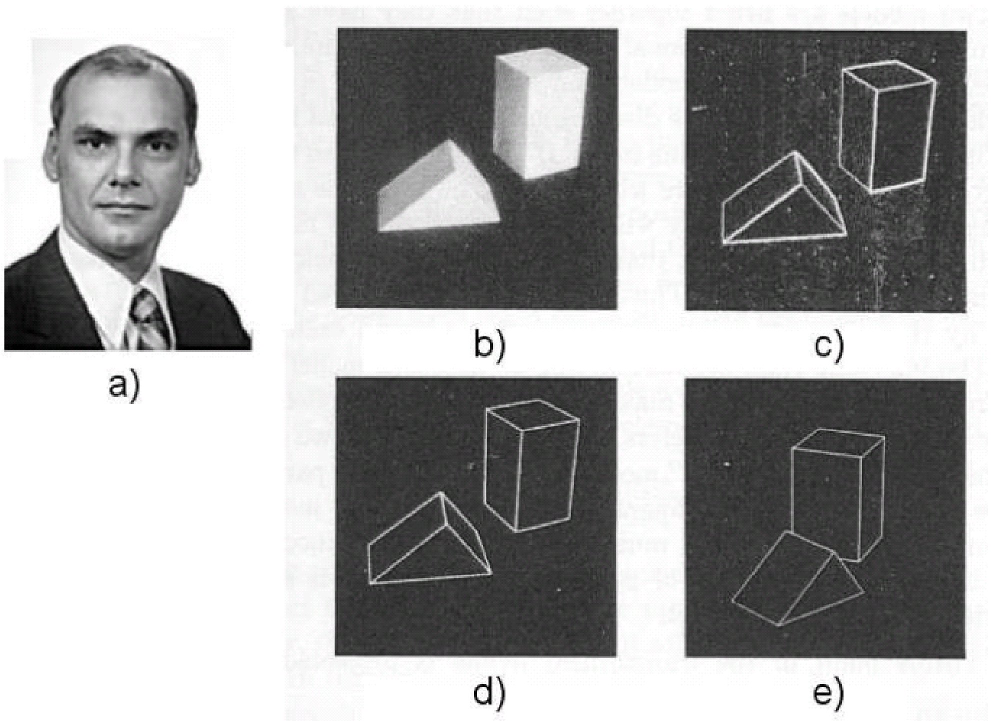


Fig. 1. A system for recognizing 3-d polyhedral scenes. a) L.G. Roberts. b)A blocks world scene. c)Detected edges using a 2x2 gradient operator. d) A 3-d polyhedral description of the scene, formed automatically from the single image. e) The 3-d scene displayed with a viewpoint different from the original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

Nice framework to develop fancy math, but too far from reality…

Object Recognition in the Geometric Era: a Retrospective. Joseph L. Mundy. 2006

Binford and generalized cylinders

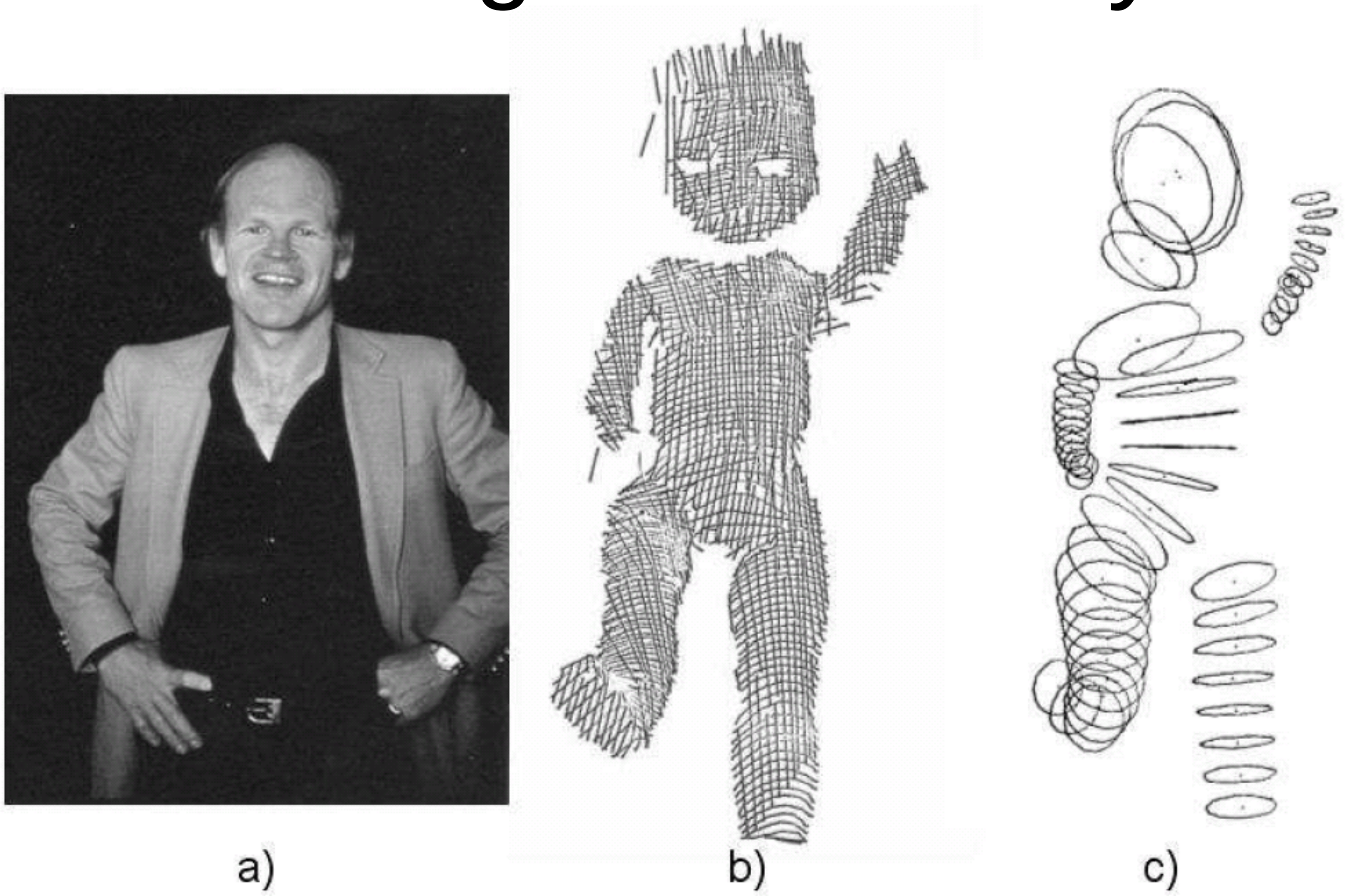
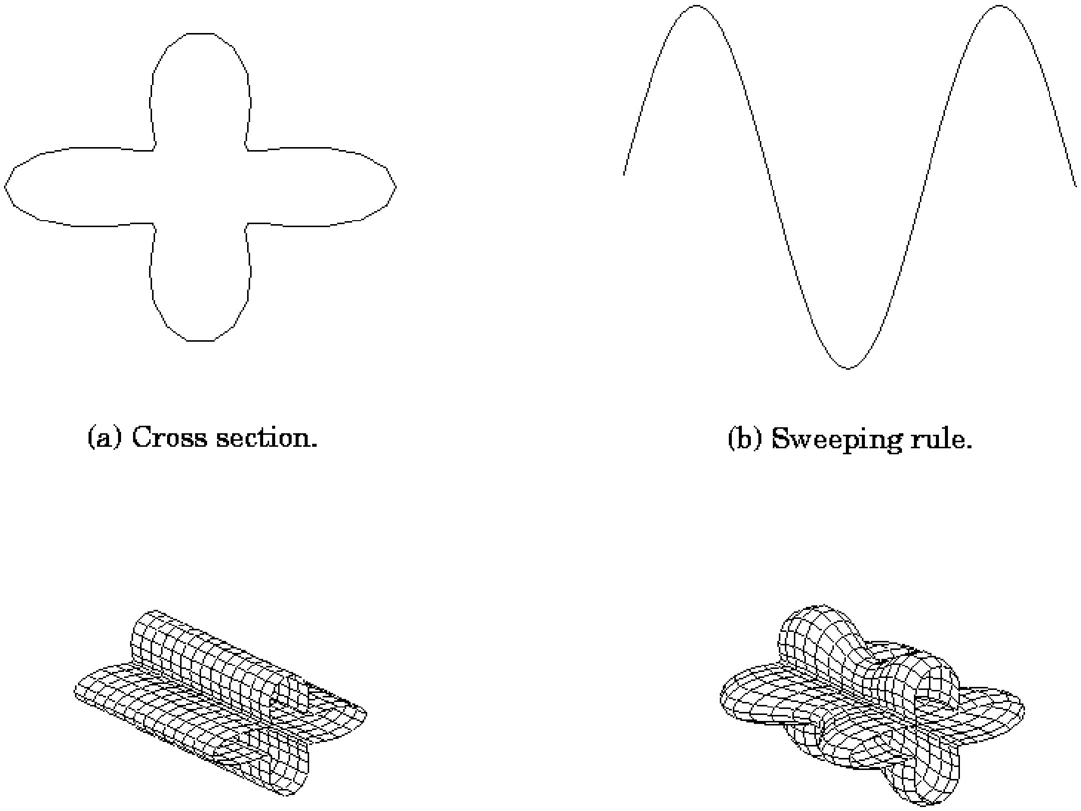


Fig. 3. The representation of objects by assemblies of generalized cylinders. a) Thomas Binford. b) A range image of a doll. c) The resulting set of generalized cylinders. (b) and c) are taken from Agin [1] with permission.)

Object Recognition in the Geometric Era:
a Retrospective. Joseph L. Mundy. 2006

Binford and generalized cylinders



(a) Cross section.

(b) Sweeping rule.

(c) True cylinder

(d) Generalized cylinder

Recognition by components

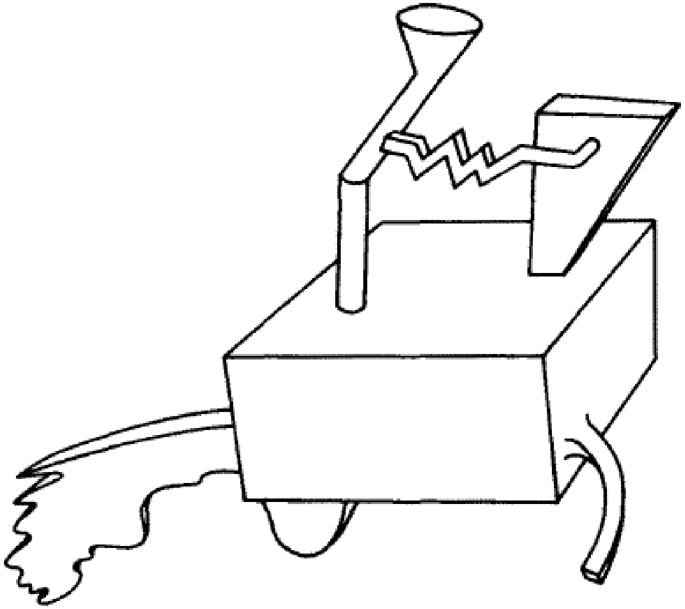
Irving Biederman
Recognition-by-Components: A Theory of Human Image Understanding.
Psychological Review, 1987.

Recognition by components

The fundamental assumption of the proposed theory, recognition-by-components (RBC), is that a modest set of generalized-cone components, called geons (*N* = 36), can be derived from contrasts of five readily detectable properties of edges in a two-dimensional image: curvature, collinearity, symmetry, parallelism, and cotermination.

The “contribution lies in its proposal for a particular vocabulary of components derived from perceptual mechanisms and its account of how an arrangement of these components can access a representation of an object in memory.”

A do-it-yourself example



1) We know that this object is nothing we know
2) We can split this objects into parts that everybody will agree
3) We can see how it resembles something familiar: “a hot dog cart”

“The naive realism that emerges in descriptions of nonsense objects may be reflecting the workings of a representational system by which objects are identified.”

Hypothesis

- Hypothesis: there is a small number of geometric components that constitute the primitive elements of the object recognition system (like letters to form words).

- “The particular properties of edges that are postulated to be relevant to the generation of the volumetric primitives have the desirable properties that they are invariant over changes in orientation and can be determined from just a few points on each edge.”

- Limitation: “The modeling has been limited to concrete entities with specified boundaries.” (count nouns) – this limitation is shared by many modern object detection algorithms.

Constraints on possible models of recognition

1) Access to the mental representation of an object should not be dependent on absolute judgments of quantitative detail

2) The information that is the basis of recognition should be relatively invariant with respect to orientation and modest degradation.

3) Partial matches should be computable. A theory of object interpretation should have some principled means for computing a match for occluded, partial, or new exemplars of a given category.

Stages of processing

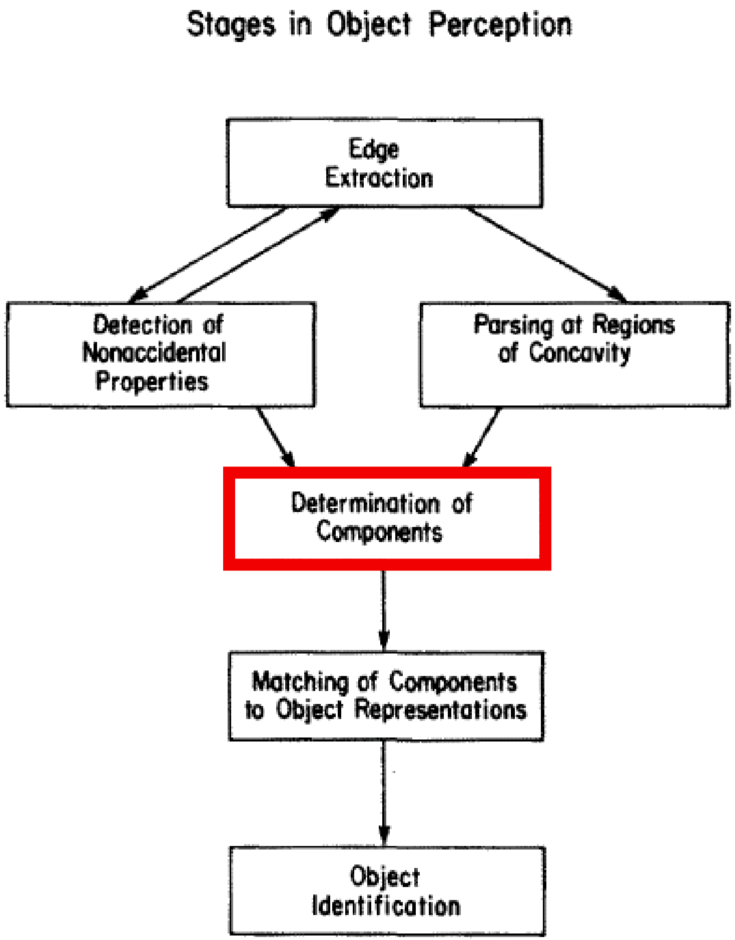

Stages in Object Perception
Edge Extraction
Detection of Nonaccidental Properties
Parsing at Regions of Concavity
Determination of Components
Matching of Components to Object Representations
Object Identification

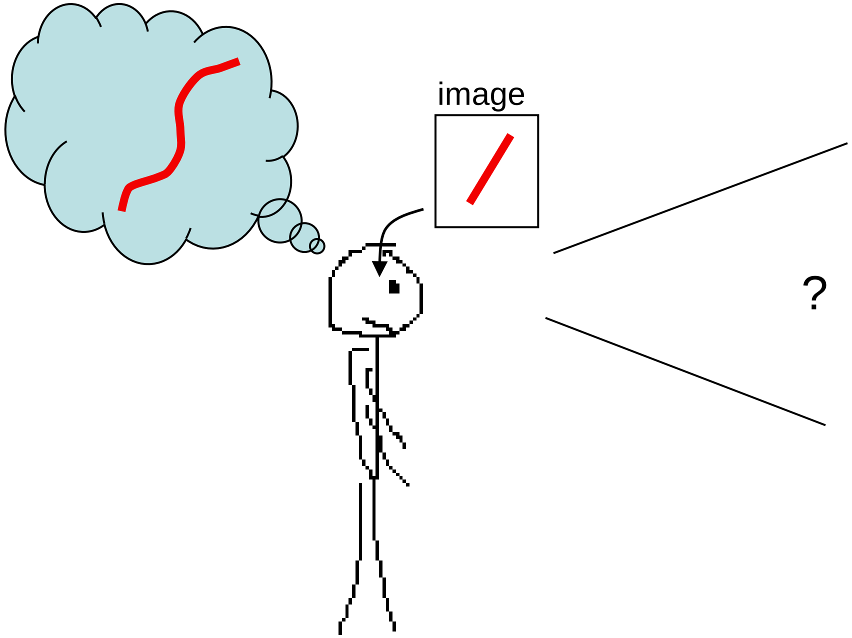
Figure 2. Presumed processing stages in object recognition.

“Parsing is performed, primarily at concave regions, simultaneously with a detection of nonaccidental properties.”

Non accidental properties

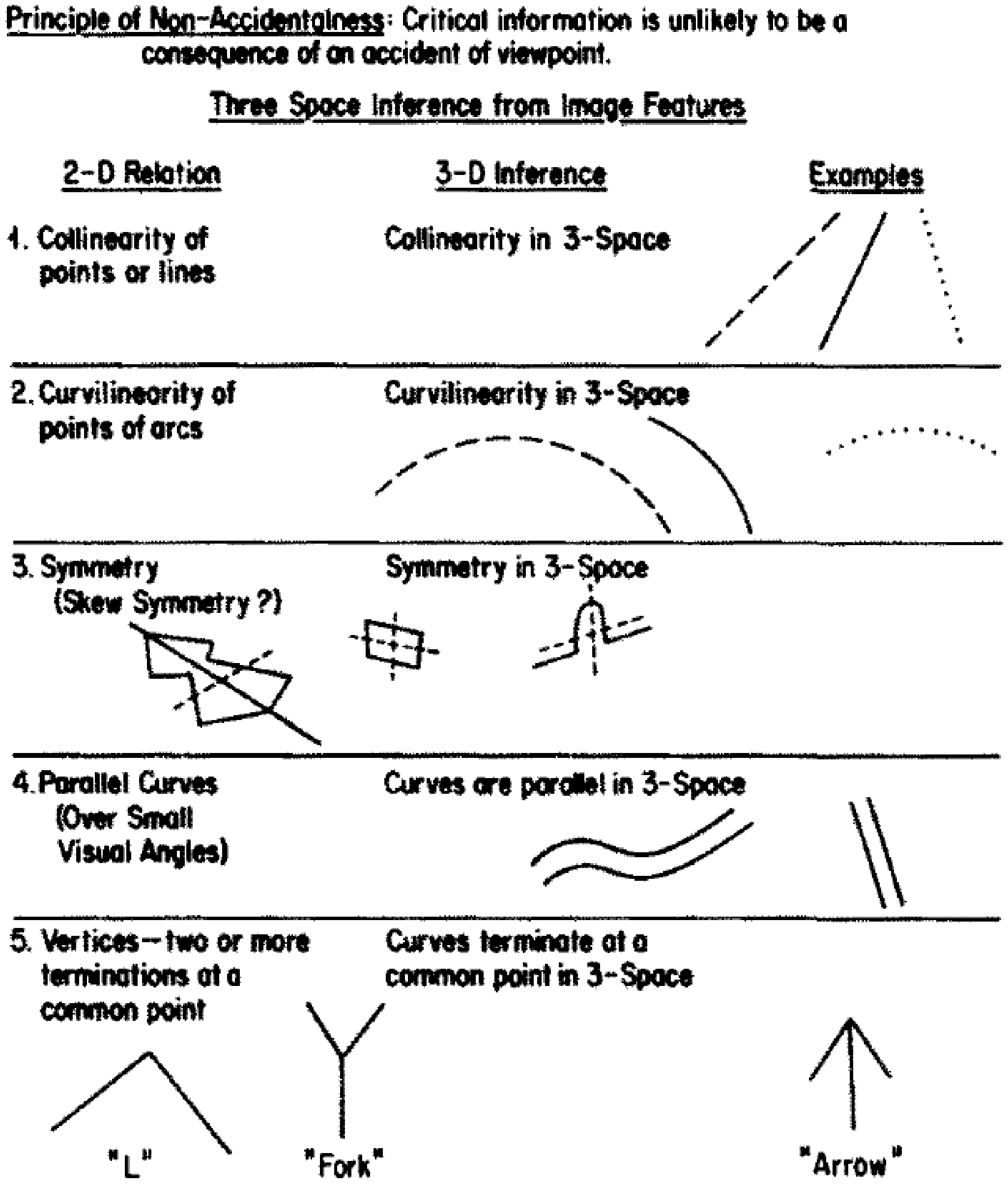
Certain properties of edges in a two-dimensional image are taken by the visual system as strong evidence that the edges in the three-dimensional world contain those same properties.

Non accidental properties, (Witkin & Tenenbaum,1983): Rarely be produced by accidental alignments of viewpoint and object features and consequently are generally unaffected by slight variations in viewpoint.



Examples:

- Colinearity
- Smoothness
- Symmetry
- Parallelism
- Cotermination



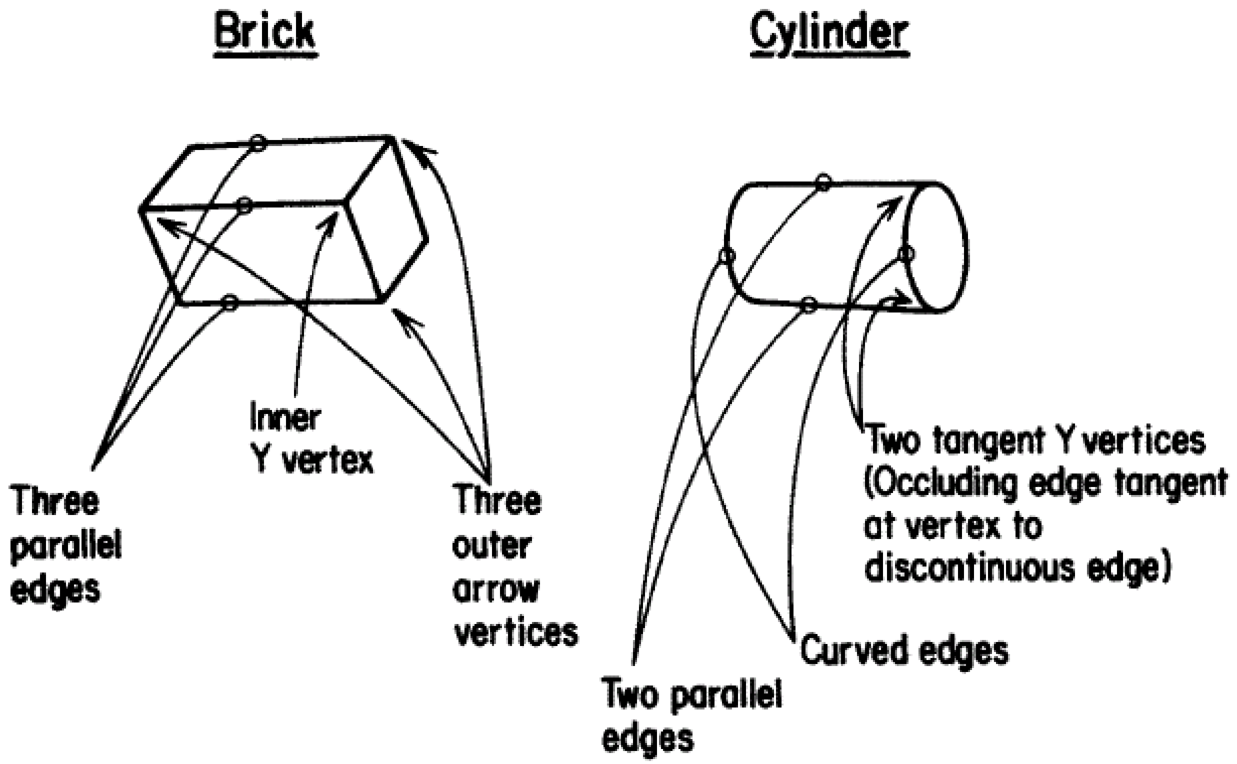
Principle of Non-Accidentalness: Critical information is unlikely to be a consequence of an accident of viewpoint.

Three Space Inference from Image Features

2-D Relation	3-D Inference	Examples
1. Collinearity of points or lines	Collinearity in 3-Space	
2. Curvilinearity of points of arcs	Curvilinearity in 3-Space	
3. Symmetry (Skew Symmetry ?)	Symmetry in 3-Space	
4. Parallel Curves (Over Small Visual Angles)	Curves are parallel in 3-Space	
5. Vertices—two or more terminations at a common point "L" "Fork"	Curves terminate at a common point in 3-Space	"Arrow"

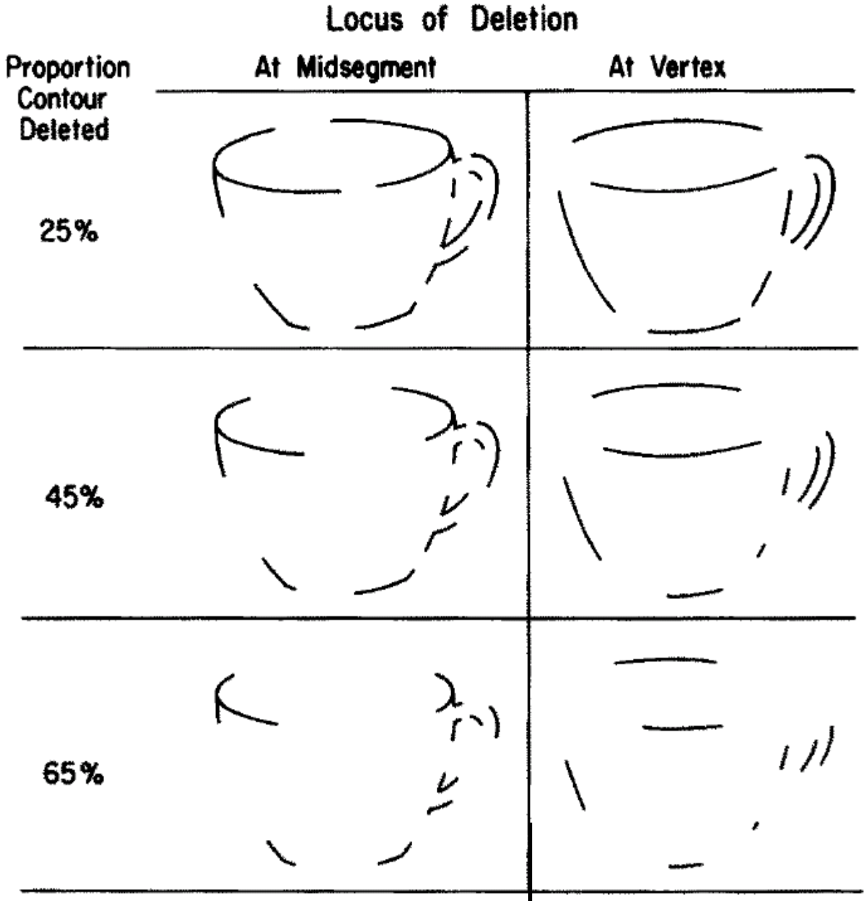
Figure 4. Five nonaccidental relations. (From Figure 5.2, *Perceptual organization and visual recognition* [p. 77] by David Lowe. Unpublished doctorial dissertation, Stanford University. Adapted by permission.)

Some Nonaccidental Differences Between a Brick and a Cylinder


Brick
Cylinder
Inner Y vertex
Three parallel edges
Three outer arrow vertices
Two tangent Y vertices (Occluding edge tangent at vertex to discontinuous edge)
Curved edges
Two parallel edges

The high speed and accuracy of determining a given nonaccidental relation {e.g., whether some pattern is symmetrical) should be contrasted with performance in making absolute quantitative judgments of variations in a single physical attribute, such as length of a segment or degree of tilt or curvature.

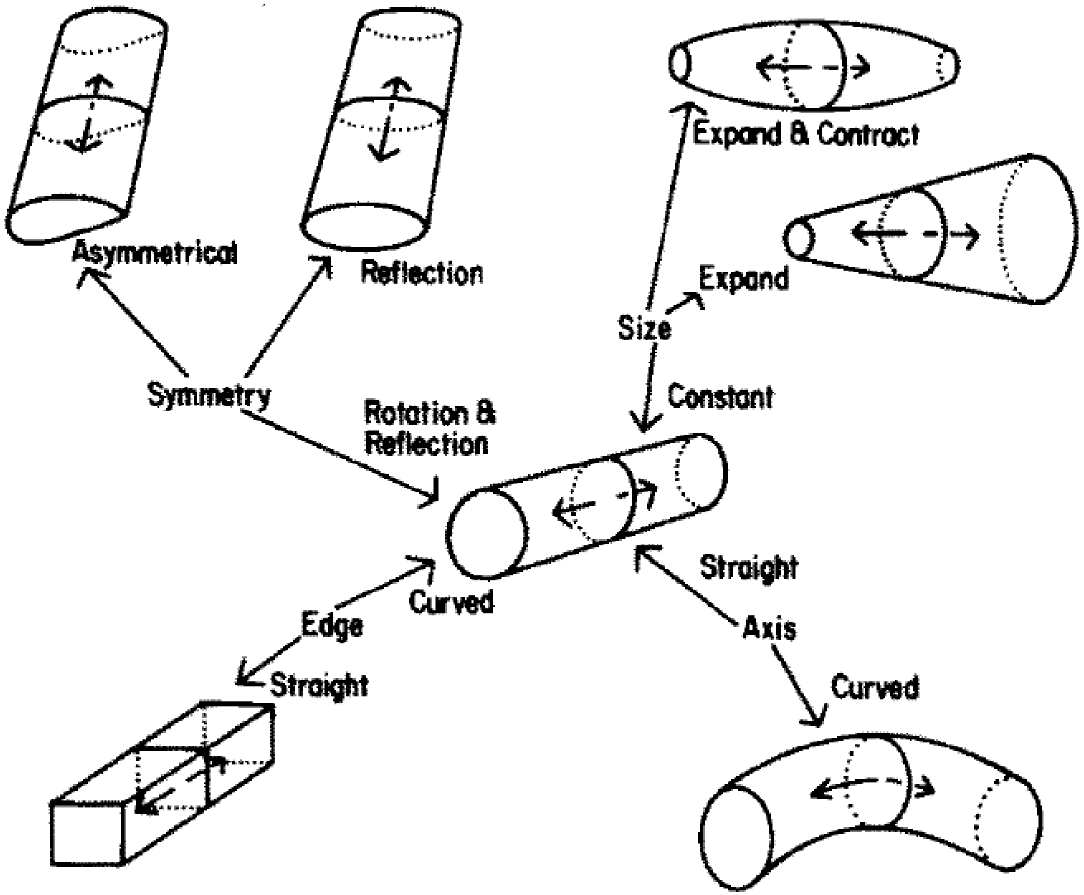
Object recognition is performed by humans in around 100ms.



Recoverable | Unrecoverable

“If contours are deleted at a vertex they can be restored, as long as there is no accidental filling-in. The greater disruption from vertex deletion is expected on the basis of their importance as diagnostic image features for the components.”

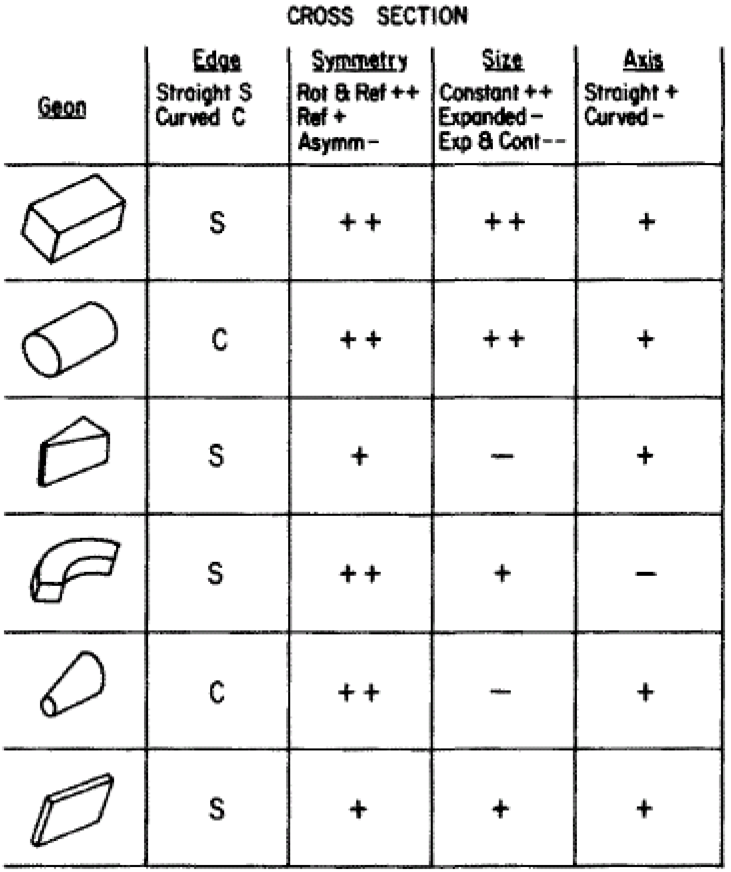
From generalized cylinders to GEONS



“From variation over only two or three levels in the nonaccidental relations of four attributes of generalized cylinders, a set of 36 GEONS can be generated.”

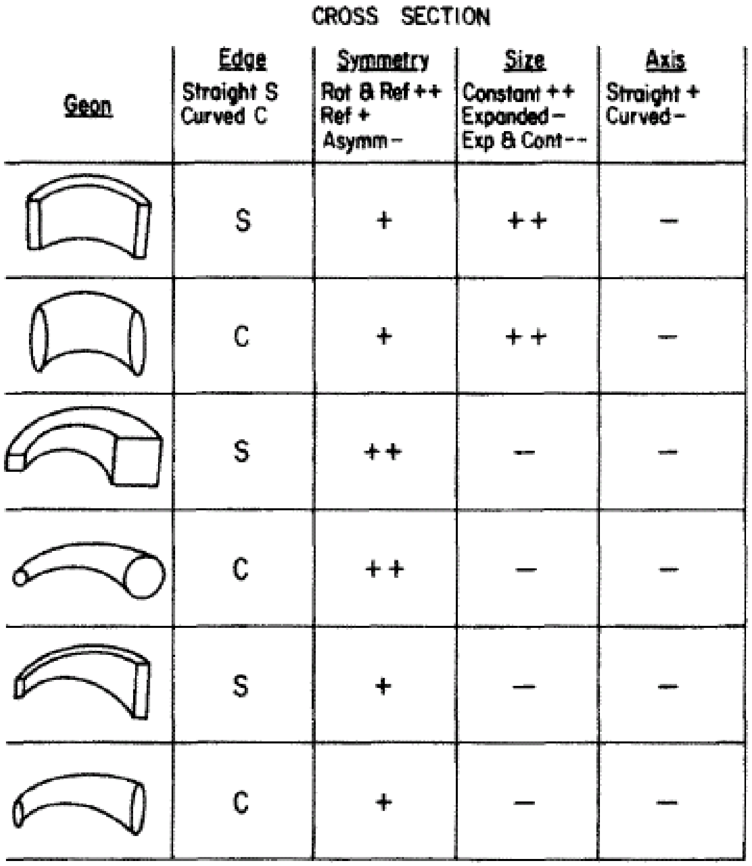
Geons represent a restricted form of generalized cylinders.

More GEONS



	CROSS SECTION			
Geon	Edge Straight S Curved C	Symmetry Rot & Ref ++ Ref + Asymm −	Size Constant ++ Expanded − Exp & Cont −−	Axis Straight + Curved −
	S	++	++	+
	C	++	++	+
	S	+	−	+
	S	++	+	−
	C	++	−	+
	S	+	+	+

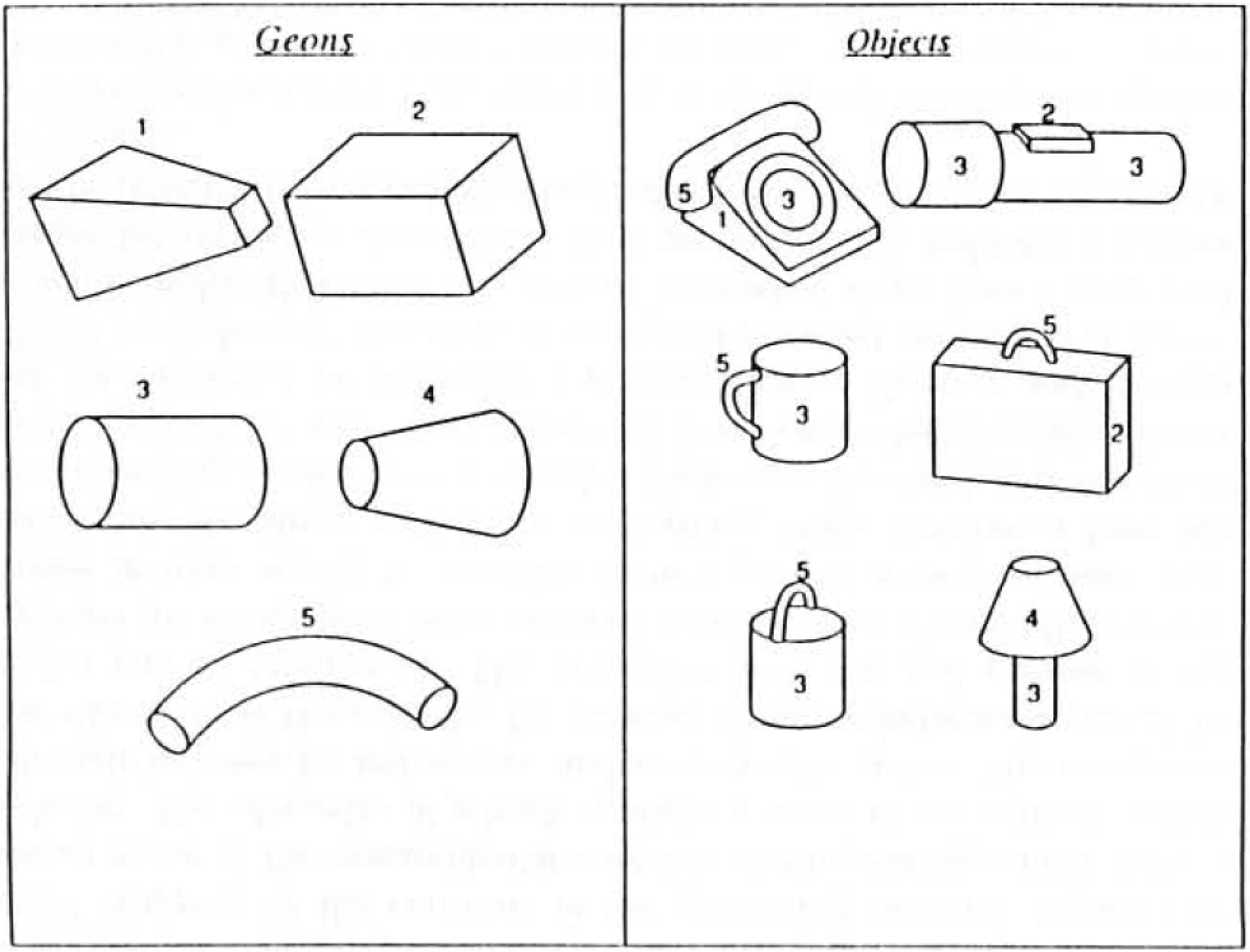
Figure 7. Proposed partial set of volumetric primitives (geons) derived from differences in nonaccidental properties.



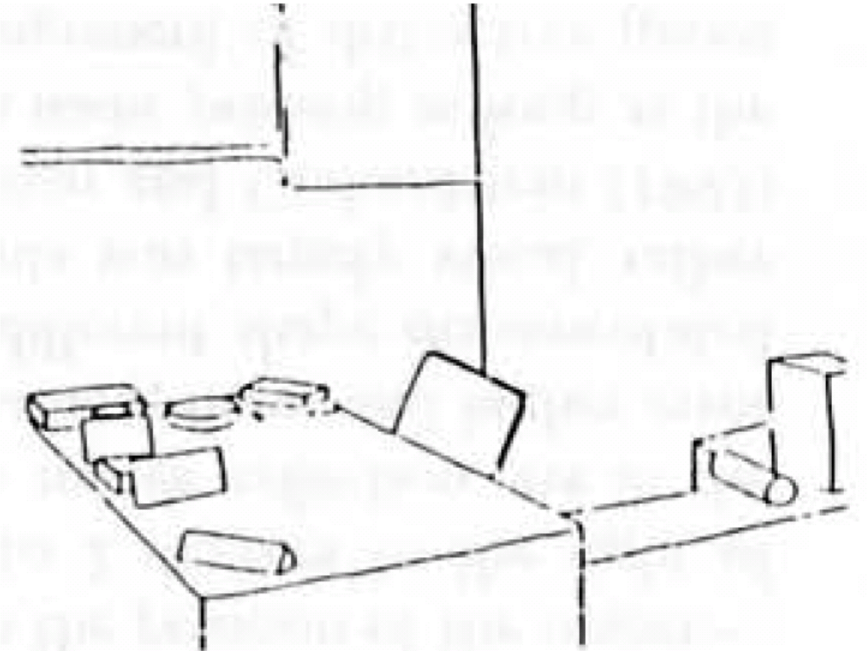
	CROSS SECTION			
Geon	Edge Straight S Curved C	Symmetry Rot & Ref ++ Ref + Asymm −	Size Constant ++ Expanded − Exp & Cont −−	Axis Straight + Curved −
	S	+	++	−
	C	+	++	−
	S	++	−	−
	C	++	−	−
	S	+	−	−
	C	+	−	−

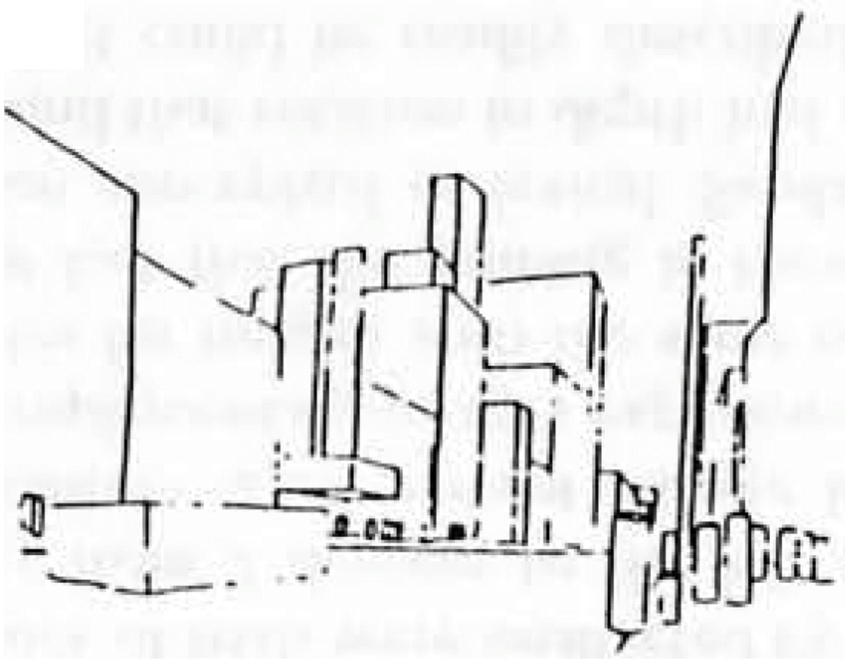
Figure 9. Geons with curved axis and straight or curved cross sections. (Determining the shape of the cross section, particularly if straight, might require attention.)

Objects and their geons



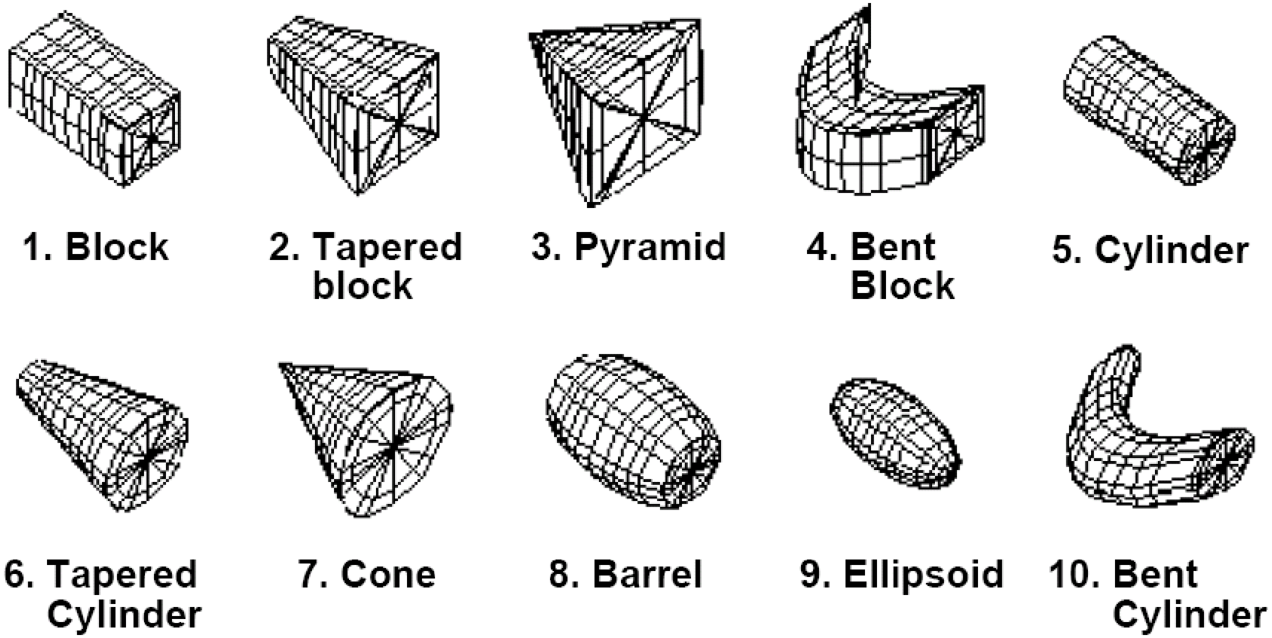
Scenes and geons





Mezzanotte & Biederman

Supercuadrics



Introduced in computer vision by A. Pentland, 1986.

What is missing?

The notion of geometric structure.

Although they were aware of it, the previous works put more emphasis on defining the primitive elements than modeling their geometric relationships.

The importance of spatial arrangement

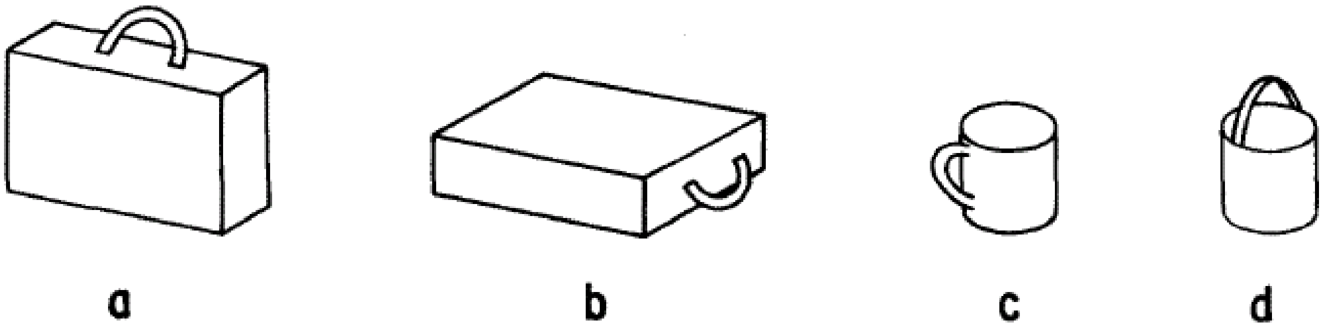


Figure 3. Different arrangements of the same components can produce different objects.

Parts and Structure approaches

With a different perspective, these models focused more on the geometry than on defining the constituent elements:

- Fischler & Elschlager 1973
- Yuille ‘91
- Brunelli & Poggio ‘93
- Lades, v.d. Malsburg et al. ‘93
- Cootes, Lanitis, Taylor et al. ‘95
- Amit & Geman ‘95, ‘99
- Perona et al. ‘95, ‘96, ’98, ’00, ’03, ‘04
- Felzenszwalb & Huttenlocher ’00, ’04
- Crandall & Huttenlocher ’05, ’06
- Leibe & Schiele ’03, ’04
- Many papers since 2000

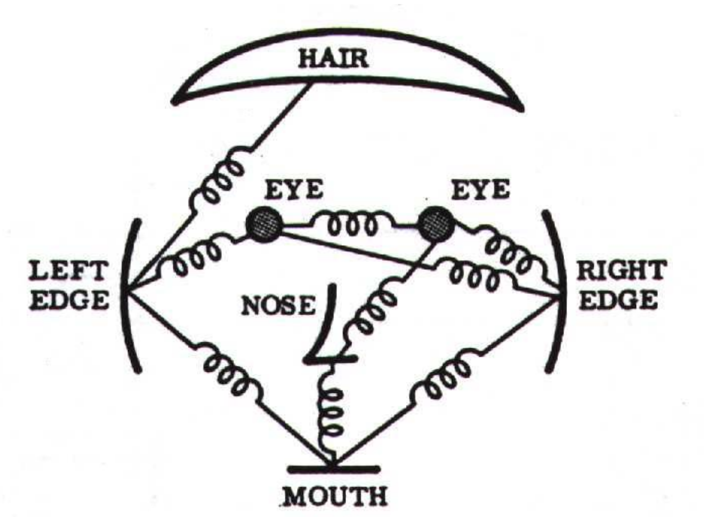


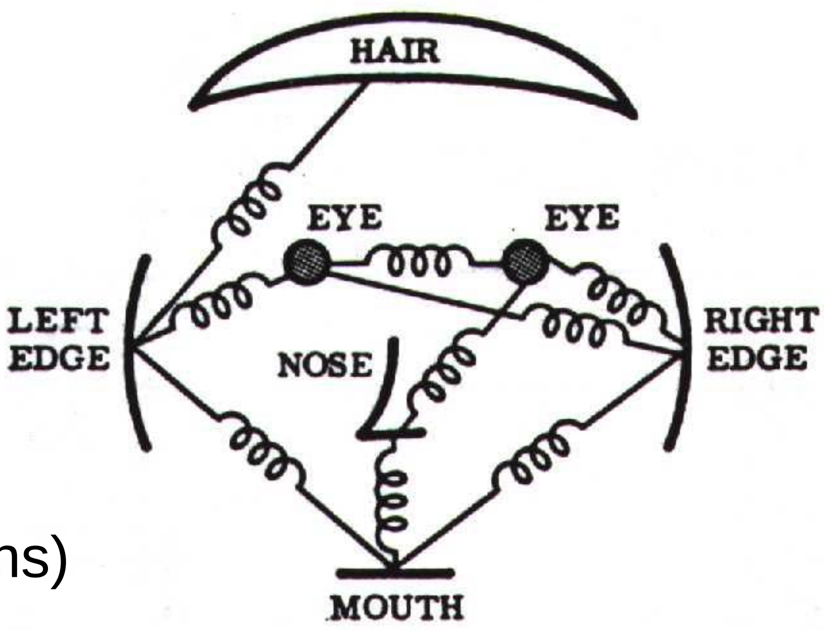
Figure from [Fischler & Elschlager 73]

Representation

- Object as set of parts
  - Generative representation

- Model:
  - Relative locations between parts
  - Appearance of part

- Issues:
  - How to model location
  - How to represent appearance
  - Sparse or dense (pixels or regions)
  - How to handle occlusion/clutter



We will discuss these models more in depth later

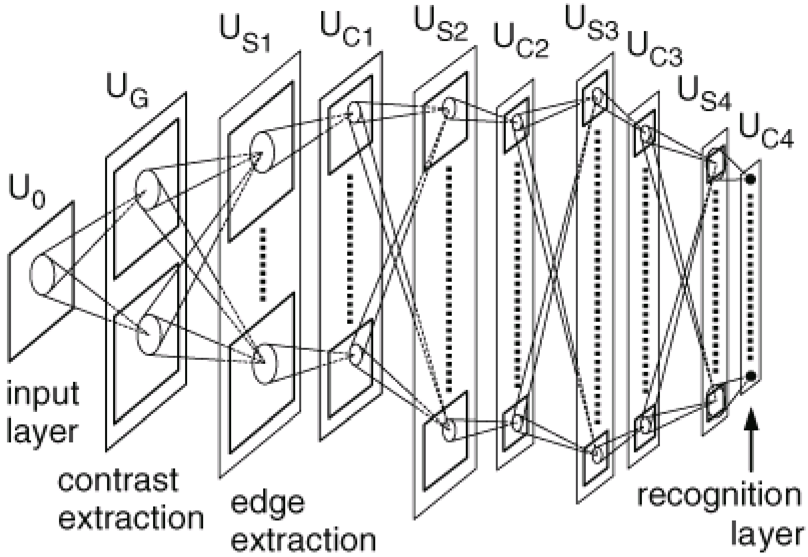
But, despite promising initial results…things did not work out so well (lack of data, processing power, lack of reliable methods for low-level and mid-level vision)

Instead, a different way of thinking about object detection started making some progress: learning based approaches and classifiers, which ignored low and mid-level vision.

Maybe the time is here to come back to some of the earlier models, more grounded in intuitions about visual perception.

Neocognitron

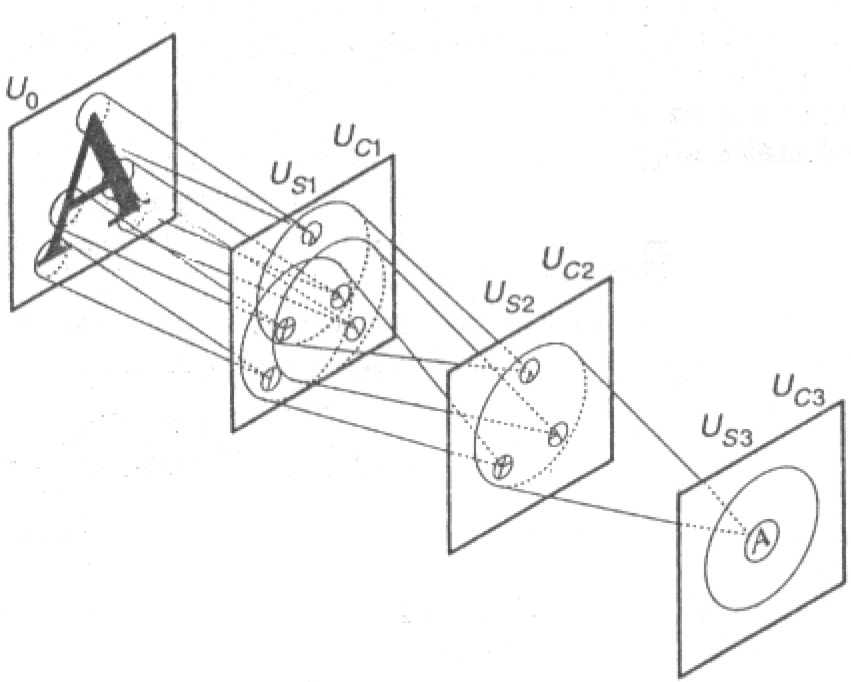
Fukushima (1980). Hierarchical multilayered neural network

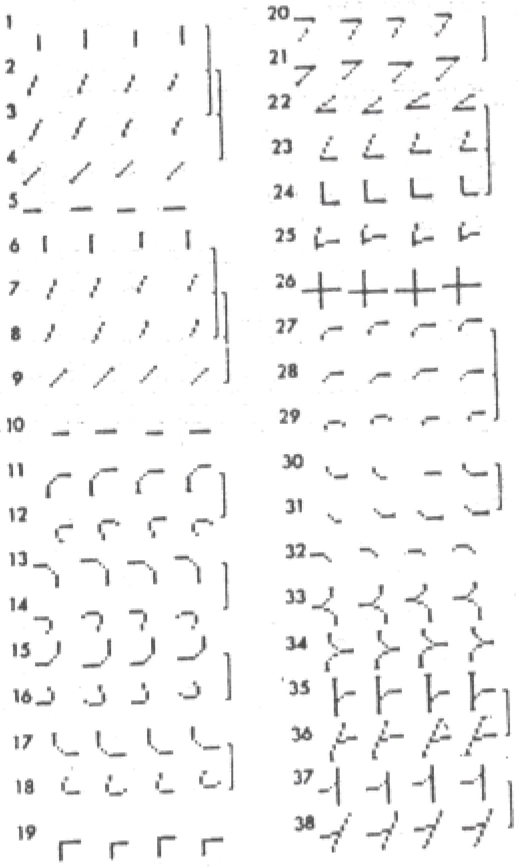


S-cells work as feature-extracting cells. They resemble simple cells of the primary visual cortex in their response.

C-cells, which resembles complex cells in the visual cortex, are inserted in the network to allow for positional errors in the features of the stimulus. The input connections of C-cells, which come from S-cells of the preceding layer, are fixed and invariable. Each C-cell receives excitatory input connections from a group of S-cells that extract the same feature, but from slightly different positions. The C-cell responds if at least one of these S-cells yield an output.

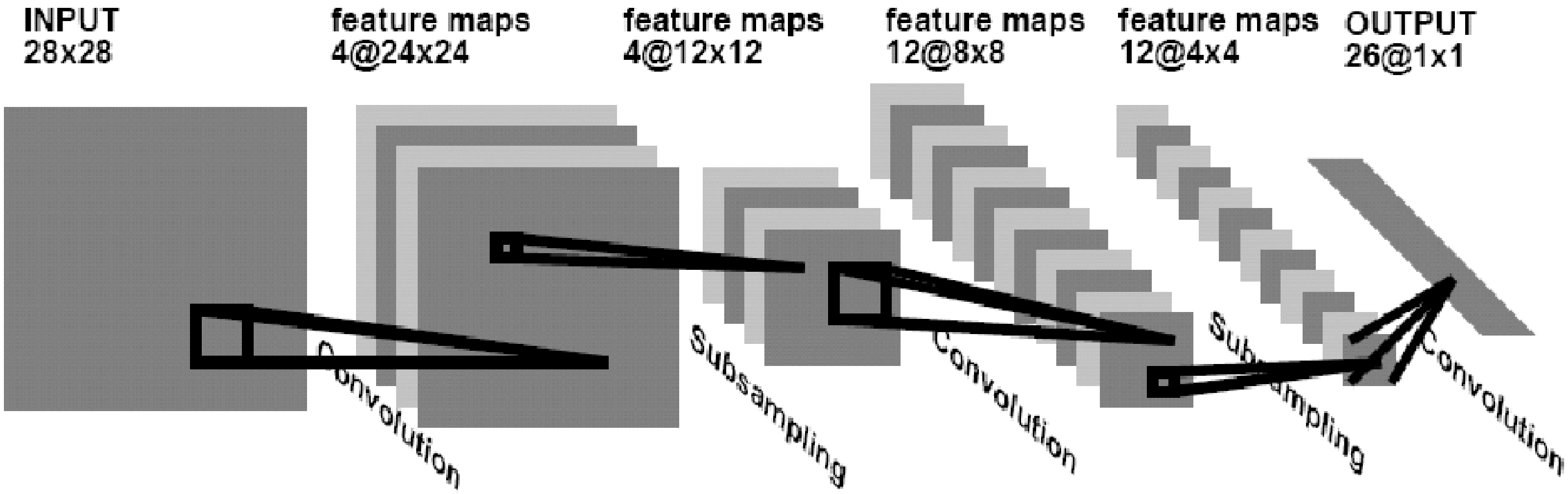
Neocognitron





Learning is done greedily for each layer

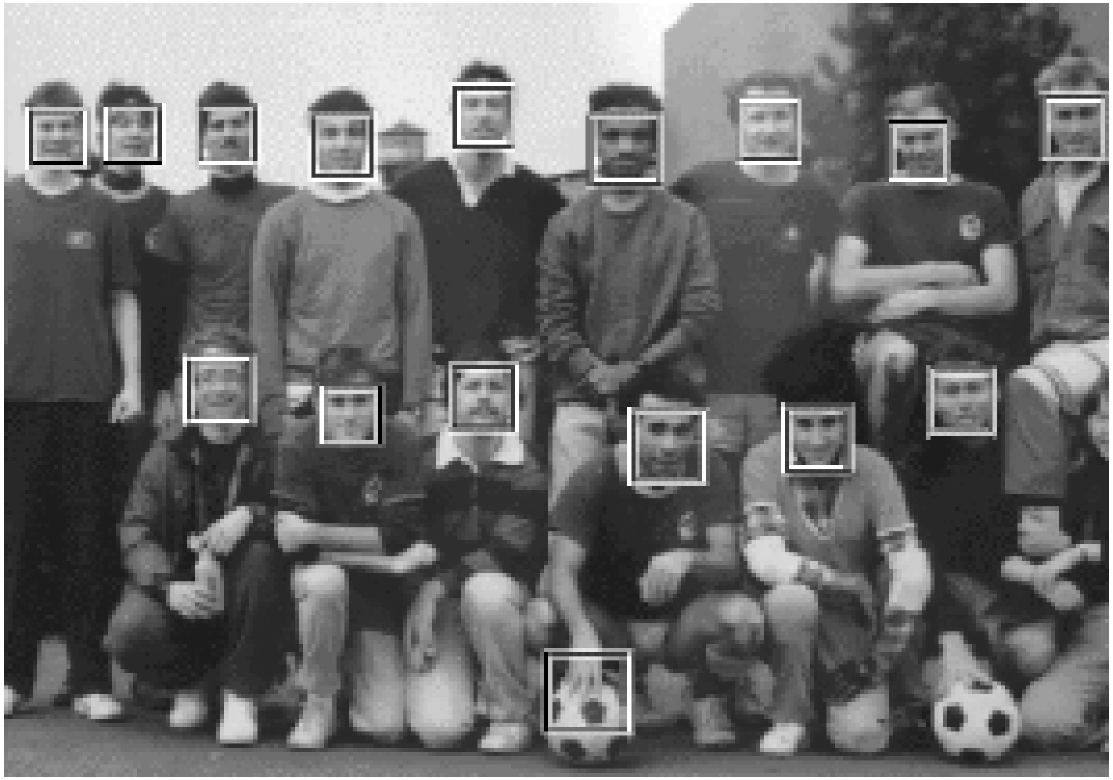
Convolutional Neural Network



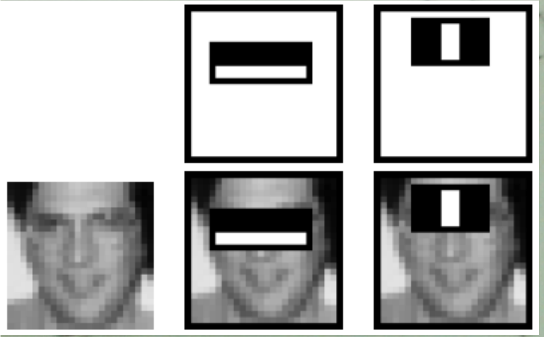
Le Cun et al, 98

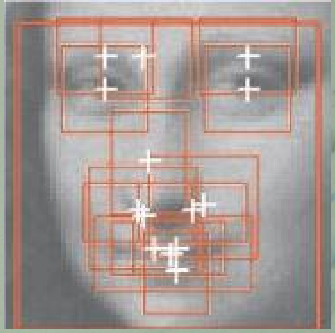
The output neurons share all the intermediate levels

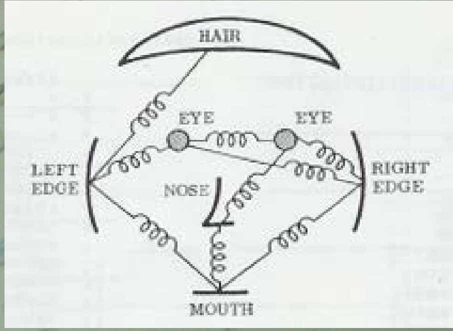
Face detection and the success of learning based approaches



- The representation and matching of pictorial structures Fischler, Elschlager (1973).
- Face recognition using eigenfaces M. Turk and A. Pentland (1991).
- Human Face Detection in Visual Scenes - Rowley, Baluja, Kanade (1995)
- Graded Learning for Object Detection - Fleuret, Geman (1999)
- Robust Real-time Object Detection - Viola, Jones (2001)
- Feature Reduction and Hierarchy of Classifiers for Fast Object Detection in Video Images - Heisele, Serre, Mukherjee, Poggio (2001)
- ….







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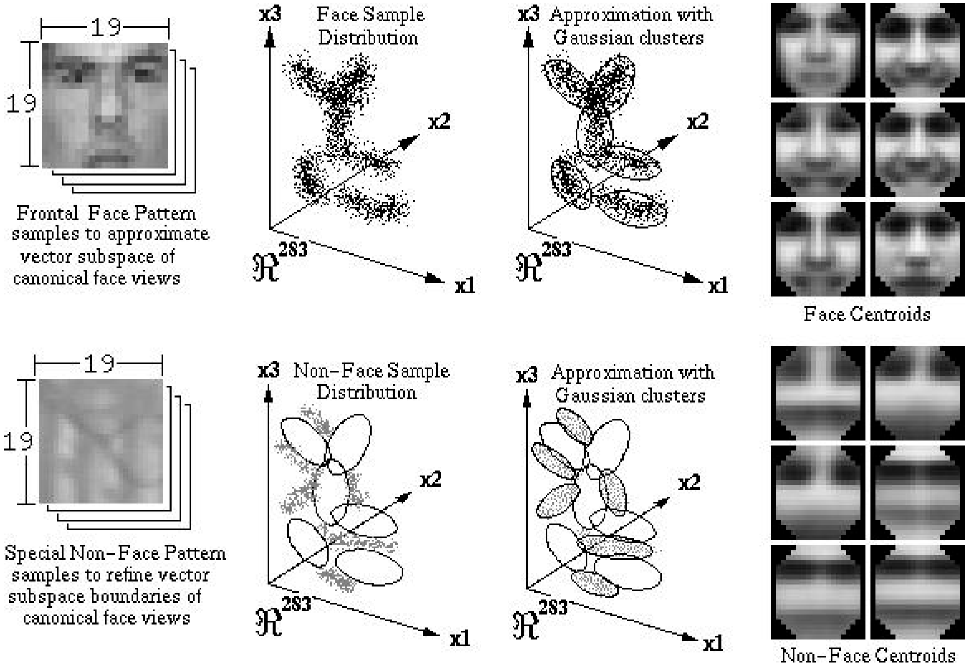
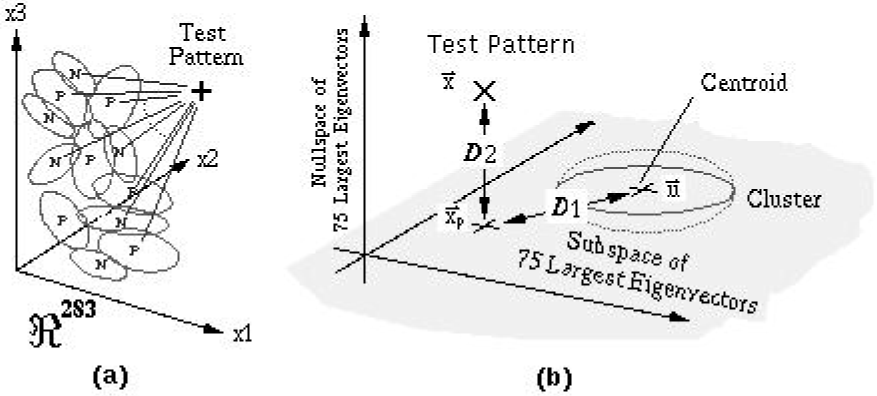
- Feature Reduction and Hierarchy of Classifiers for Fast Object Detection in Video Images - Heisele, Serre, Mukherjee, Poggio (2001)
- ….

Distribution-Based Face Detector

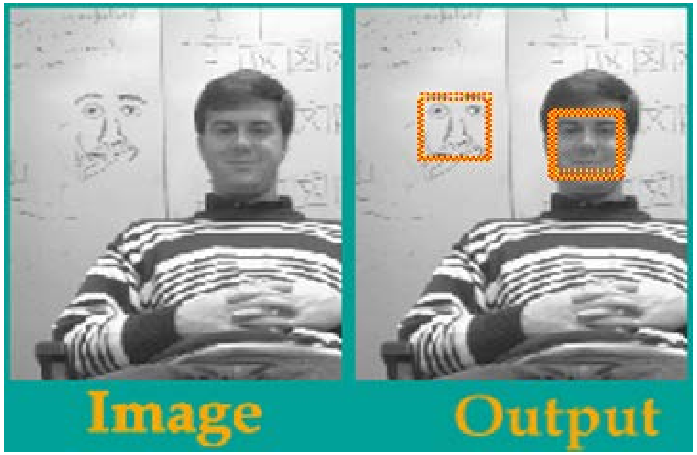
- Learn face and nonface models from examples [Sung and Poggio 95]
- Cluster and project the examples to a lower dimensional space using Gaussian distributions and PCA
- Detect faces using distance metric to face and nonface clusters


19
19
Frontal Face Pattern samples to approximate vector subspace of canonical face views
x3
Face Sample Distribution
x2
x1
ℜ283
x3
Approximation with Gaussian clusters
x2
x1
ℜ283
Face Centroids
19
19
Special Non-Face Pattern samples to refine vector subspace boundaries of canonical face views
x3
Non-Face Sample Distribution
x2
x1
ℜ283
x3
Approximation with Gaussian clusters
x2
x1
ℜ283
Non-Face Centroids



Distribution-Based Face Detector

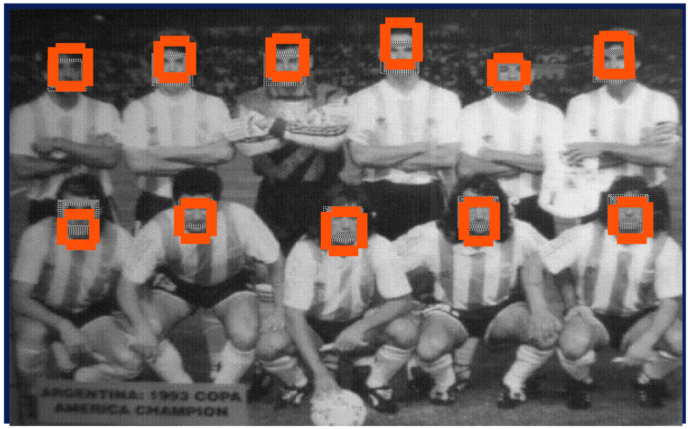
- Learn face and nonface models from examples [Sung and Poggio 95]



Training Database

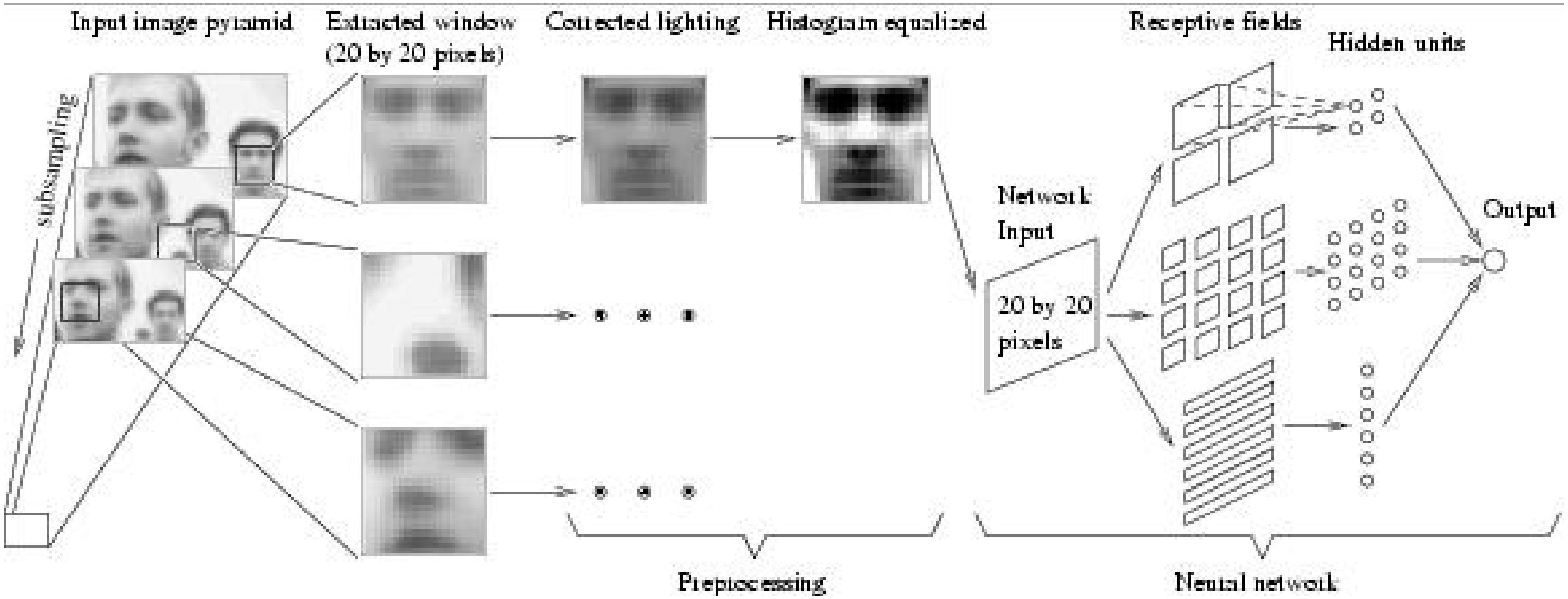
1000+ Real, 3000+ *VIRTUAL*

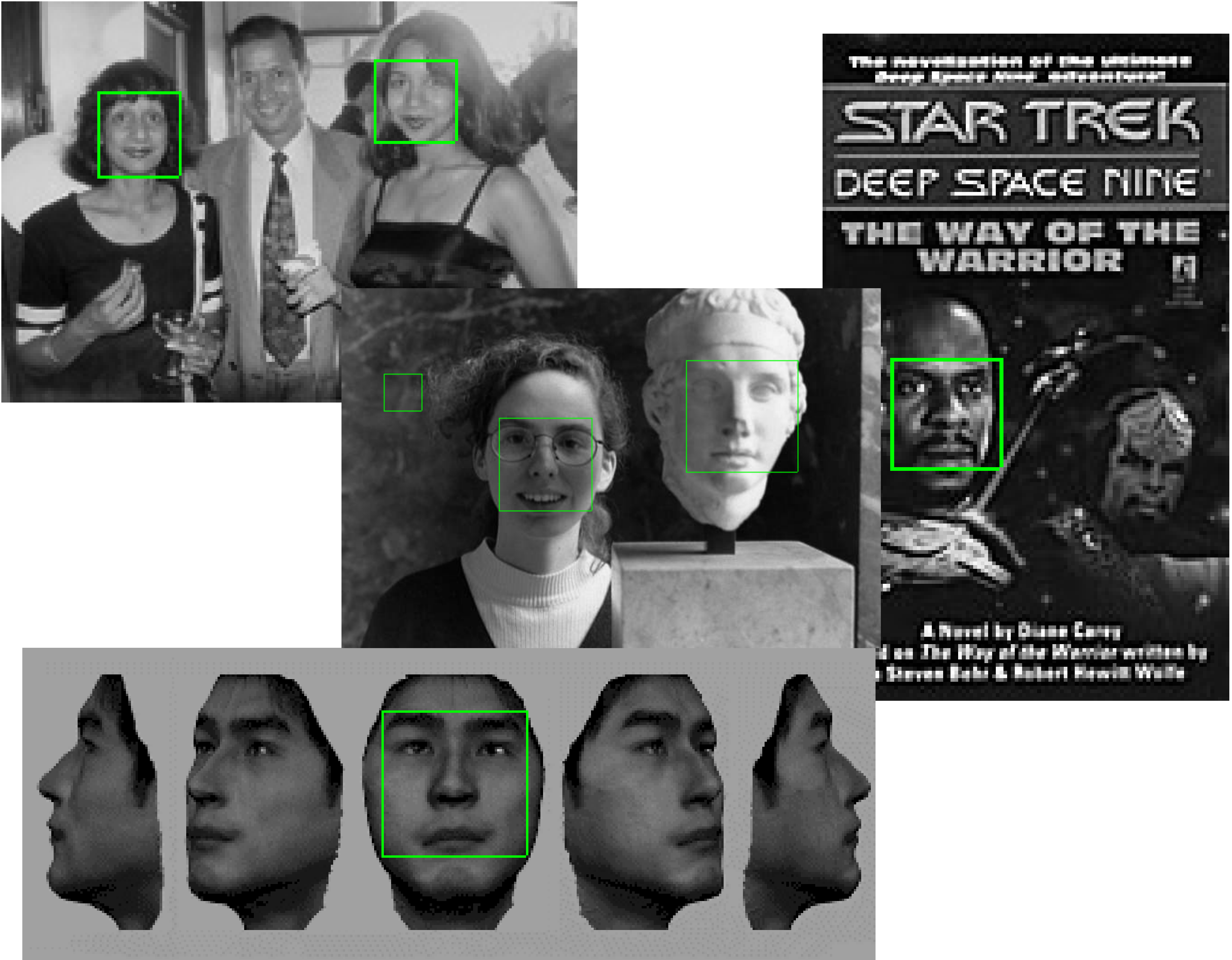
50,0000+ Non-Face Pattern



Neural Network-Based Face Detector

- Train a set of multilayer perceptrons and arbitrate a decision among all outputs [Rowley et al. 98]

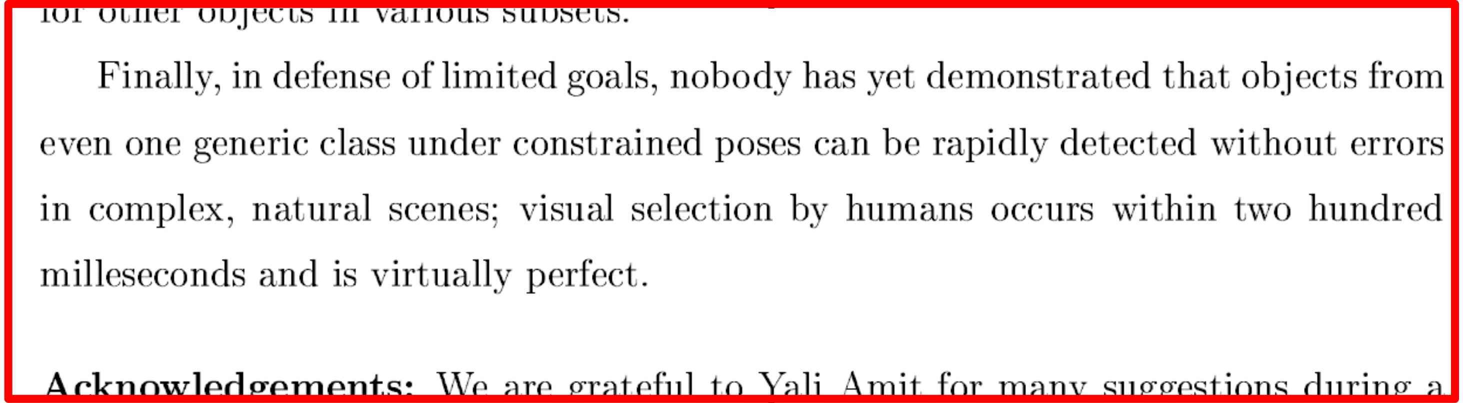



The novelization of the ultimate
Deep Space Nine adventure!
STAR TREK
DEEP SPACE NINE
THE WAY OF THE
WARRIOR
A Novel by Diane Carey
d on The Way of the Warrior written by
Steven Behr & Robert Hewitt Wolfe

Coarse-to-Fine Face Detection

François Fleuret [*] Donald Geman [†]

June 2000



for other objects in various subsets.

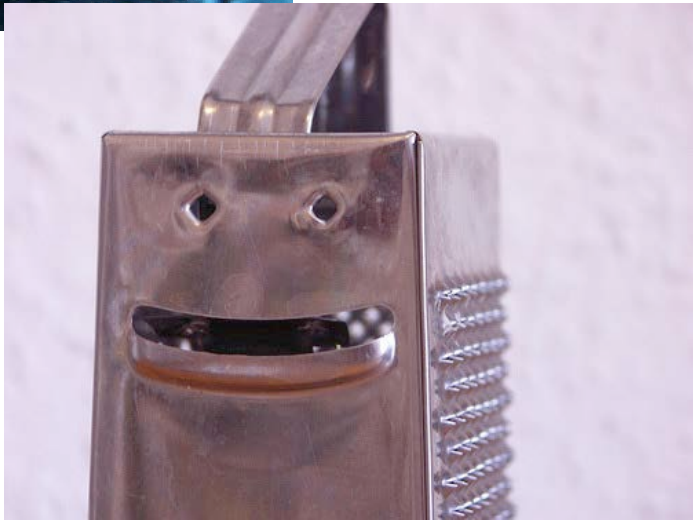
Finally, in defense of limited goals, nobody has yet demonstrated that objects from even one generic class under constrained poses can be rapidly detected without errors in complex, natural scenes; visual selection by humans occurs within two hundred milleseconds and is virtually perfect.

Acknowledgements: We are grateful to Yali Amit for many suggestions during a

[*] Avant-Projet IMEDIA, INRIA-Rocquencourt, Domaine de Voluceau, B.P.105, 78153 Le Chesnay. Email:Francois.Fleuret@inria.fr. Supported in part by the CNET.

[†] Department of Mathematics and Statistics, University of Massachusetts, Amherst, MA 01003. Email:geman@math.umass.edu. Supported in part by ONR under contract N00014-97-1-0249 and ARO under MURI grant DAAH04-96-1-0445.

Faces everywhere



http://www.marcofolio.net/imagedump/faces_everywhere_15_images_8_illusions.html

Rapid Object Detection Using a Boosted Cascade of Simple Features

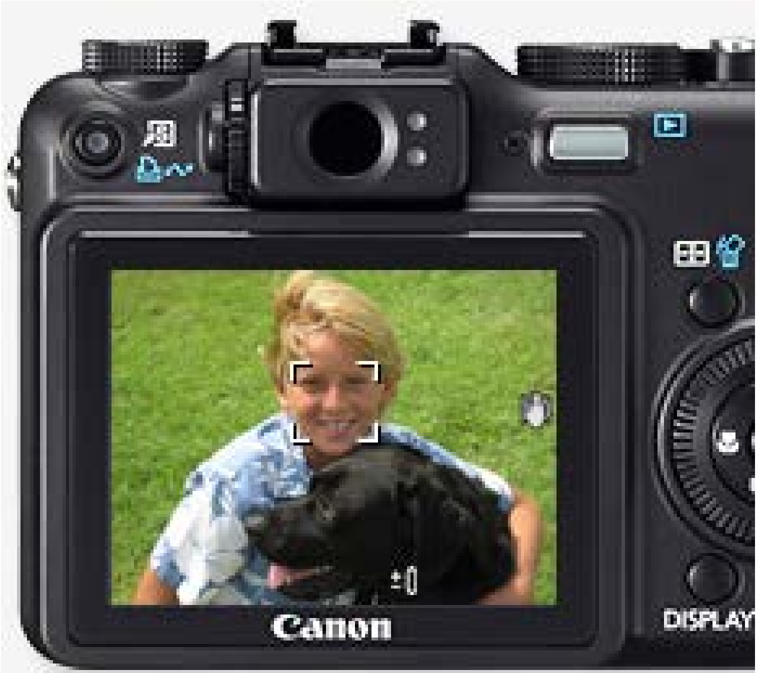
Paul Viola Michael J. Jones
Mitsubishi Electric Research Laboratories (MERL)
Cambridge, MA

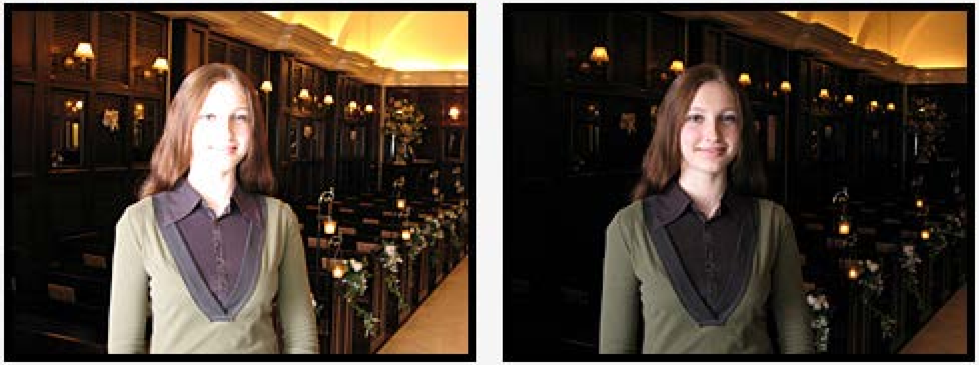
Most of this work was done at Compaq CRL before the authors moved to MERL

Manuscript available on web:

http://citeseer.ist.psu.edu/cache/papers/cs/23183/http:zSzzSzwww.ai.mit.eduzSzpeoplezSzviolazSzresearchzSzpublicationszSzICCV01-Viola-Jones.pdf/viola01robust.pdf

Face detection





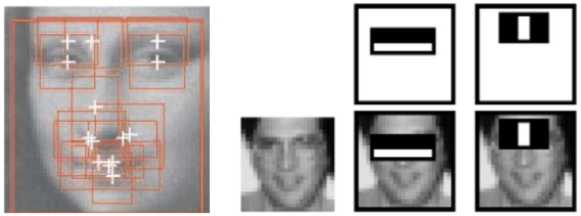
[Face priority AE] When a bright part of the face is too bright

Families of recognition algorithms

Bag of words models

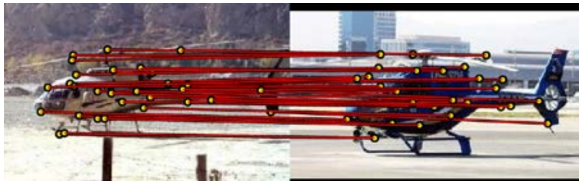
Csurka, Dance, Fan, Willamowski, and Bray 2004
Sivic, Russell, Freeman, Zisserman, ICCV 2005

Voting models



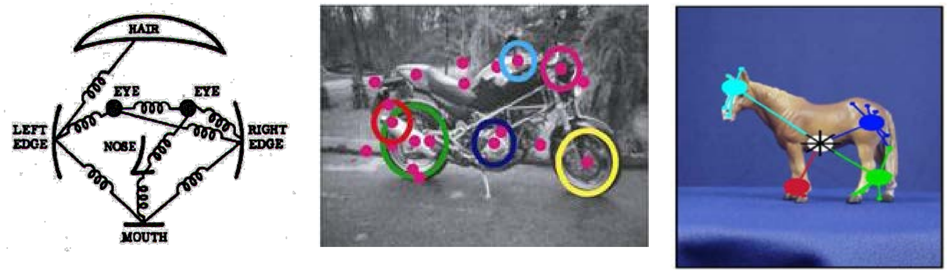
Viola and Jones, ICCV 2001
Heisele, Poggio, et. al., NIPS 01
Schneiderman, Kanade 2004
Vidal-Naquet, Ullman 2003

Shape matching
Deformable models



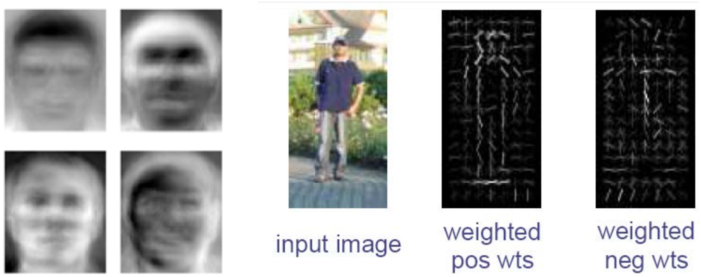
Berg, Berg, Malik, 2005
Cootes, Edwards, Taylor, 2001

Constellation models



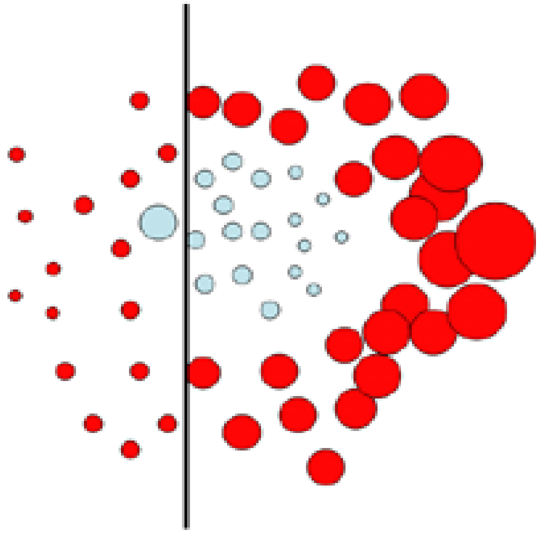
Fischler and Elschlager, 1973
Burl, Leung, and Perona, 1995
Weber, Welling, and Perona, 2000
Fergus, Perona, & Zisserman, CVPR 2003

Rigid template models



Sirovich and Kirby 1987
Turk, Pentland, 1991
Dalal & Triggs, 2006

A simple object detector



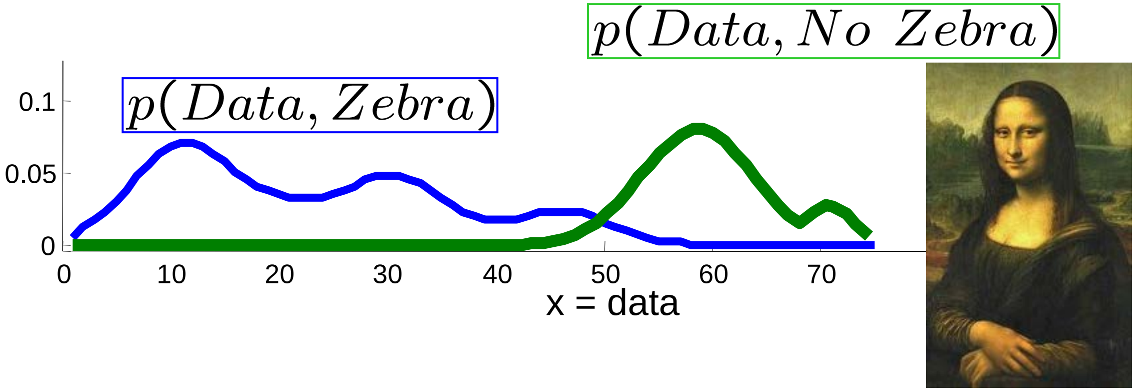
- Simple but contains some of same basic elements of many state of the art detectors.
- Based on boosting which makes all the stages of the training and testing easy to understand.

Most of the slides are from the ICCV 05 short course
http://people.csail.mit.edu/torralba/shortCourseRLOC/

Discriminative vs. generative

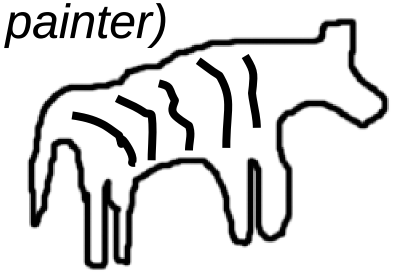
- Generative model

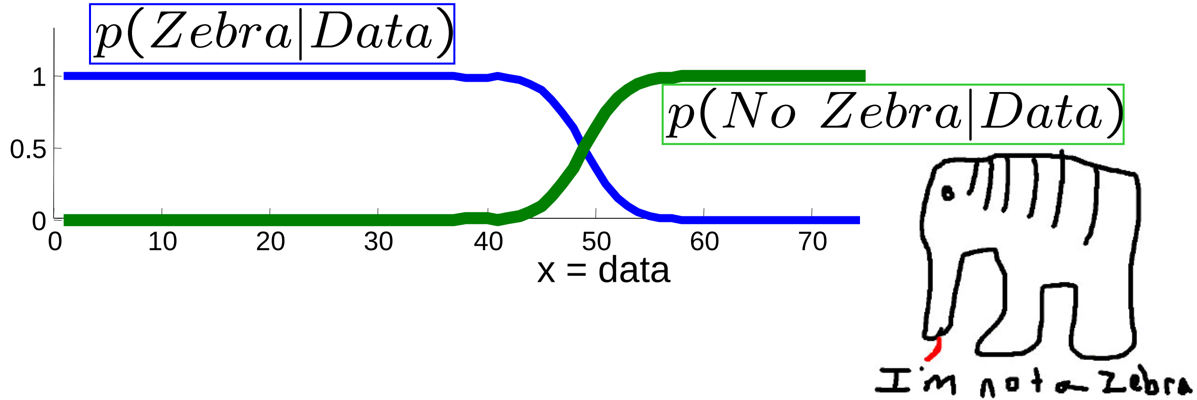
  (*The artist*)



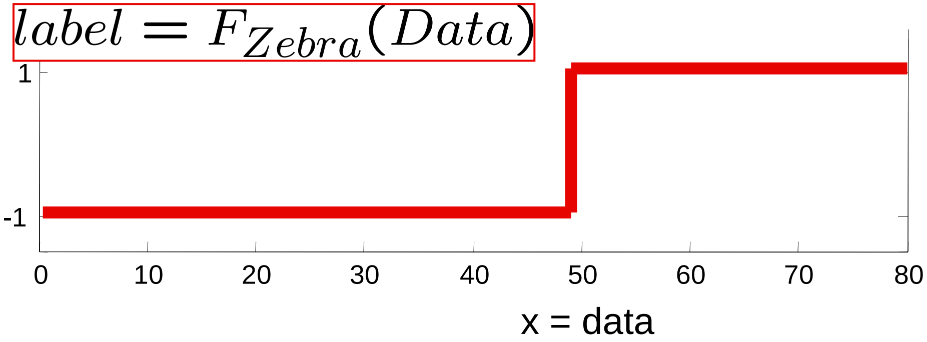
- Discriminative model

  (The lousy painter)





- Classification function

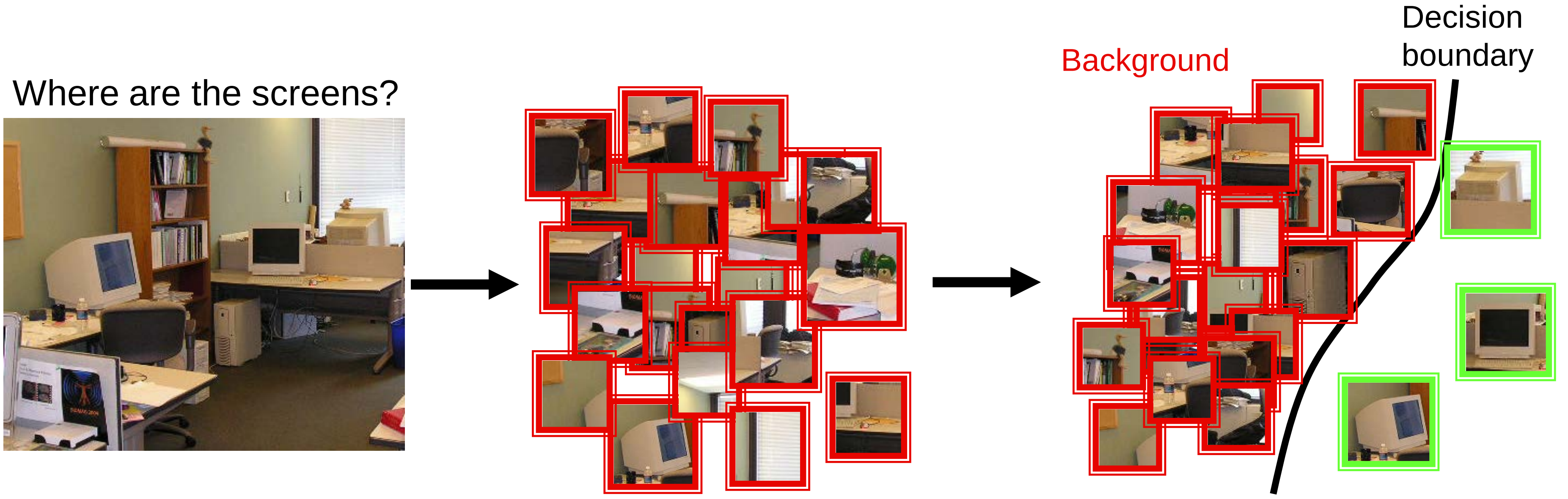


Discriminative methods

Object detection and recognition is formulated as a classification problem.

The image is partitioned into a set of overlapping windows

… and a decision is taken at each window about if it contains a target object or not.



Where are the screens?

Bag of image patches

Background

Decision boundary

Computer screen

In some feature space

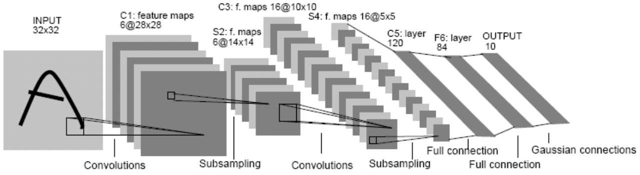
Discriminative methods

Nearest neighbor

10^6 examples

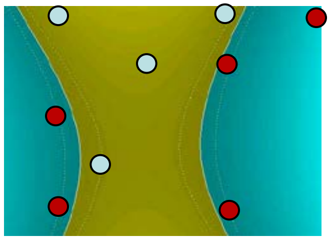
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005
…

Neural networks



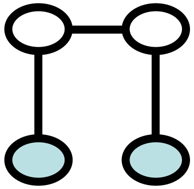
LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
…

Support Vector Machines and Kernels



Guyon, Vapnik
Heisele, Serre, Poggio, 2001
…

Conditional Random Fields



McCallum, Freitag, Pereira 2000
Kumar, Hebert 2003
…

Formulation

- Formulation: binary classification

Features	x =	x_1	x_2	x_3	⋯	x_N	x_{N+1}	x_{N+2}	⋯	x_{N+M}
Labels	y =	-1	+1	-1		-1	?	?		?

Training data: each image patch is labeled as containing the object or background

Test data

- Classification function

$\hat{y} = F(x)$ Where $F(x)$ belongs to some family of functions

- Minimize misclassification error

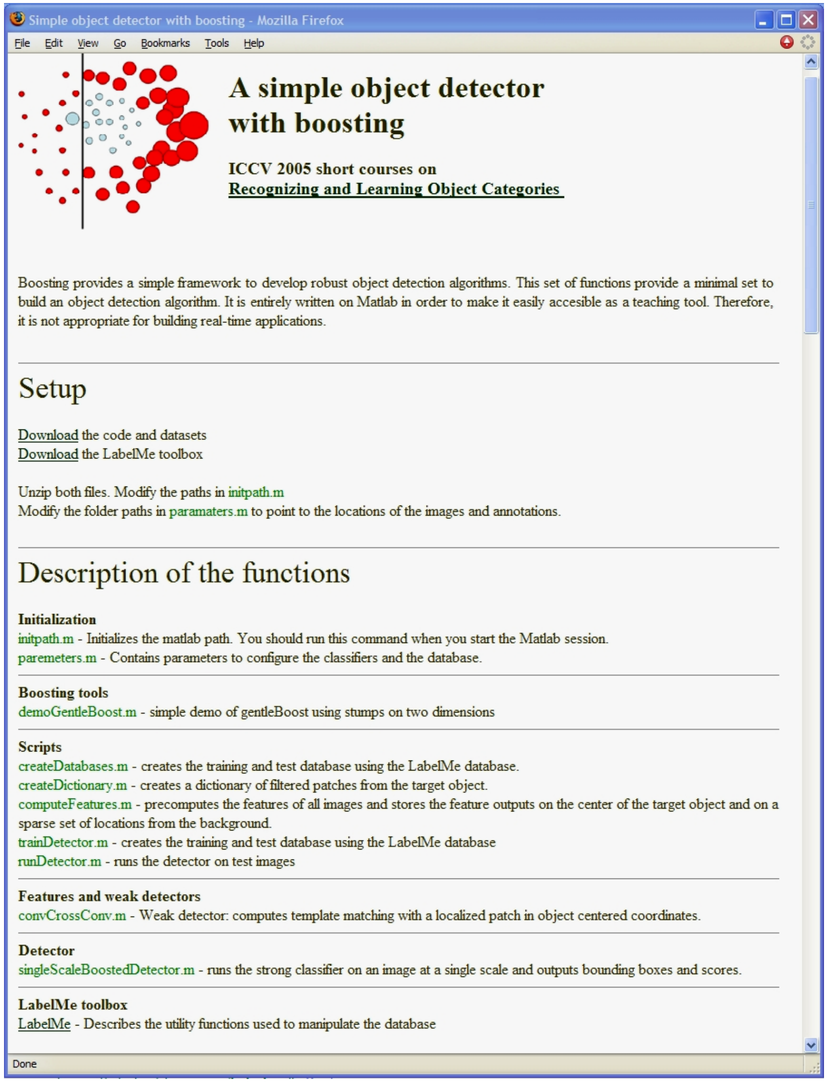
(Not that simple: we need some guarantees that there will be generalization)

Overview of section

- Object detection with classifiers

- **Boosting**
  - Gentle boosting
  - Weak detectors
  - Object model
  - Object detection

A simple object detector with Boosting


Simple object detector with boosting - Mozilla Firefox
File Edit View Go Bookmarks Tools Help
Done

A simple object detector with boosting

ICCV 2005 short courses on
Recognizing and Learning Object Categories

Boosting provides a simple framework to develop robust object detection algorithms. This set of functions provide a minimal set to build an object detection algorithm. It is entirely written on Matlab in order to make it easily accesible as a teaching tool. Therefore, it is not appropriate for building real-time applications.

Setup

Download the code and datasets
Download the LabelMe toolbox

Unzip both files. Modify the paths in initpath.m
Modify the folder paths in paramaters.m to point to the locations of the images and annotations.

Description of the functions

Initialization
initpath.m - Initializes the matlab path. You should run this command when you start the Matlab session.
paremeters.m - Contains parameters to configure the classifiers and the database.

Boosting tools
demoGentleBoost.m - simple demo of gentleBoost using stumps on two dimensions

Scripts
createDatabases.m - creates the training and test database using the LabelMe database.
createDictionary.m - creates a dictionary of filtered patches from the target object.
computeFeatures.m - precomputes the features of all images and stores the feature outputs on the center of the target object and on a sparse set of locations from the background.
trainDetector.m - creates the training and test database using the LabelMe database
runDetector.m - runs the detector on test images

Features and weak detectors
convCrossConv.m - Weak detector: computes template matching with a localized patch in object centered coordinates.

Detector
singleScaleBoostedDetector.m - runs the strong classifier on an image at a single scale and outputs bounding boxes and scores.

LabelMe toolbox
LabelMe - Describes the utility functions used to manipulate the database

http://people.csail.mit.edu/torralba/iccv2005/

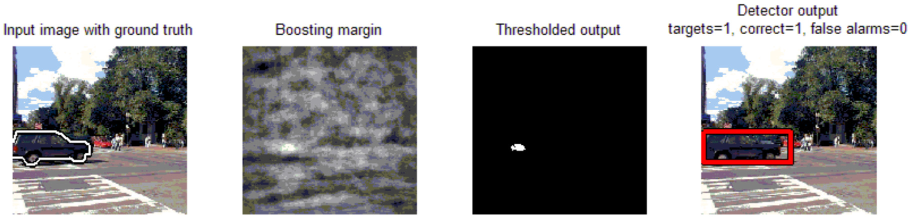
Download

- Toolbox for manipulating dataset
- Code and dataset

Matlab code

- Gentle boosting
- Object detector using a part based model

Dataset with cars and computer monitors


Input image with ground truth
Boosting margin
Thresholded output
Detector output
targets=1, correct=1, false alarms=0

Why boosting?

- A simple algorithm for learning robust classifiers
  - Freund & Shapire, 1995
  - Friedman, Hastie, Tibshhirani, 1998
- Provides efficient algorithm for sparse visual feature selection
  - *Tieu & Viola, 2000*
  - *Viola & Jones, 2003*
- Easy to implement, not requires external optimization tools.

For a description of several methods:
Friedman, J. H., Hastie, T. and Tibshirani, R.
Additive Logistic Regression: a Statistical View of Boosting. 1998

Boosting

- Defines a classifier using an additive model:

$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) + \dots$$

Strong classifier

Weak classifier

Weight

Features vector

Boosting

- Defines a classifier using an additive model:

$$F(x) = \alpha_1 f_1(x) + \alpha_2 f_2(x) + \alpha_3 f_3(x) + \dots$$

Strong classifier

Weak classifier

Weight

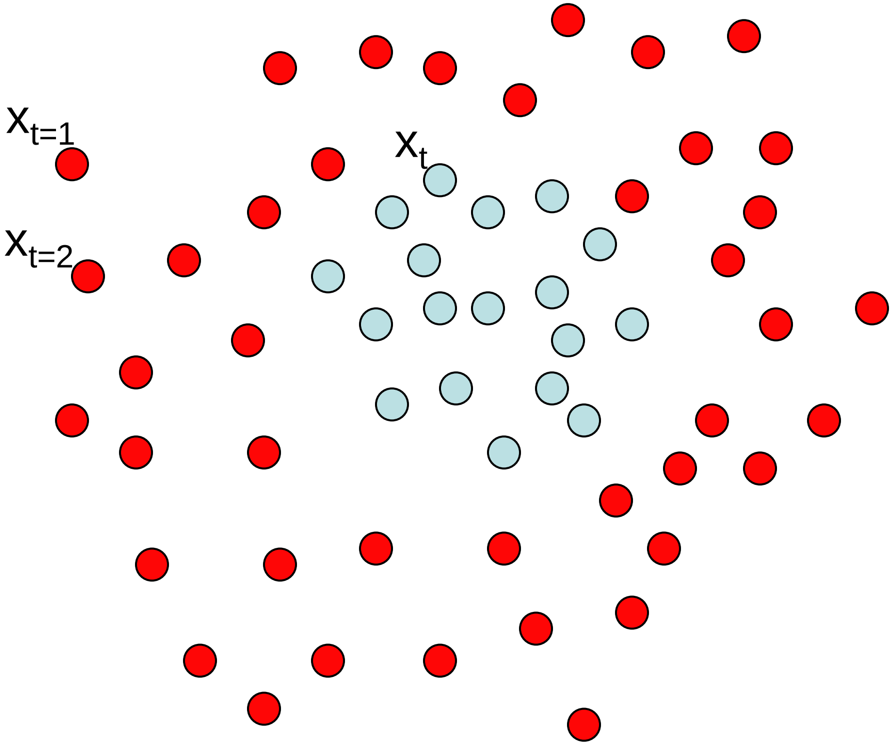
Features vector

- We need to define a family of weak classifiers

$f_k(x)$ from a family of weak classifiers

Boosting

- It is a sequential procedure:



Each data point has

a class label:

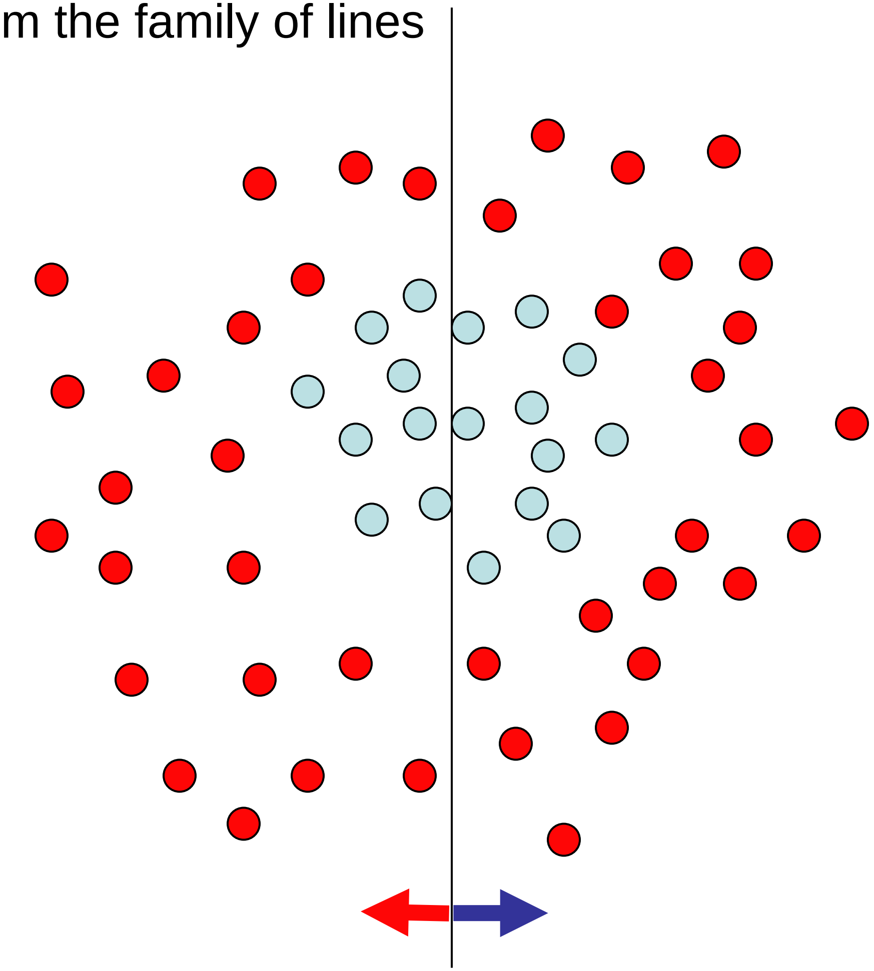
$$y_t = \begin{cases} +1 & (\bullet) \\ -1 & (\circ) \end{cases}$$

and a weight:

$w_t = 1$

Toy example

Weak learners from the family of lines



Each data point has

a class label:

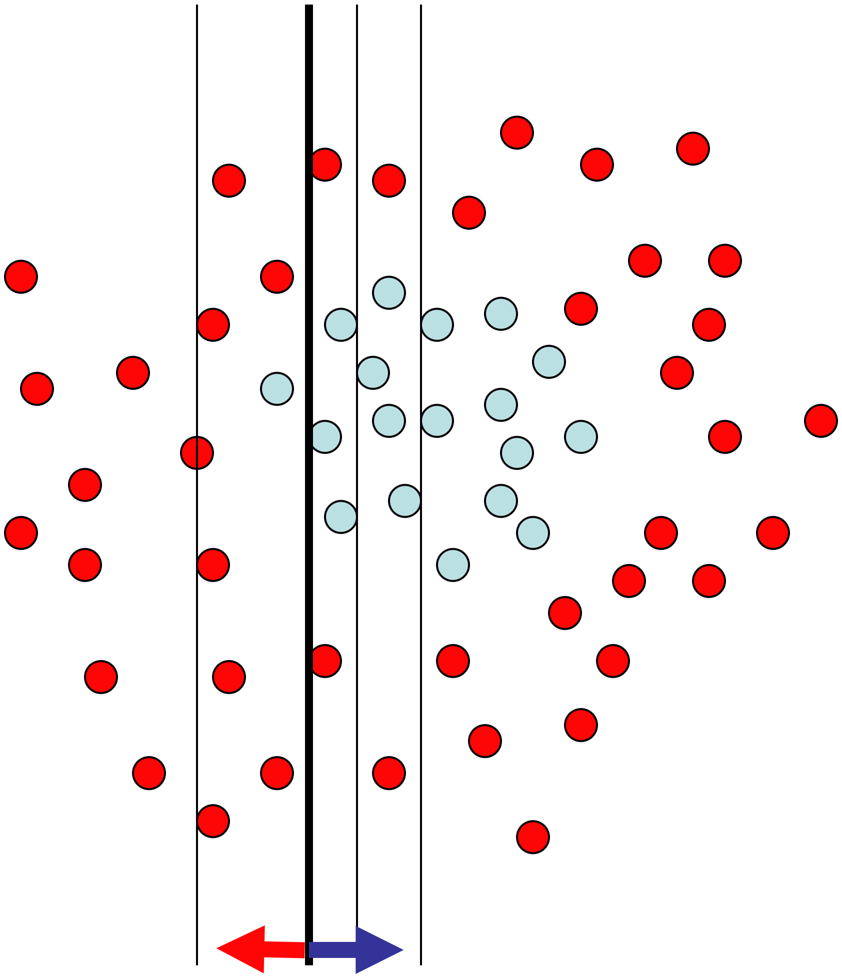
$$y_t = \begin{cases} +1 & (\bullet) \\ -1 & (\circ) \end{cases}$$

and a weight:

$w_t = 1$

h => p(error) = 0.5 it is at chance

Toy example



Each data point has

a class label:

$$y_t = \begin{cases} +1 \ (●) \\ -1 \ (○) \end{cases}$$

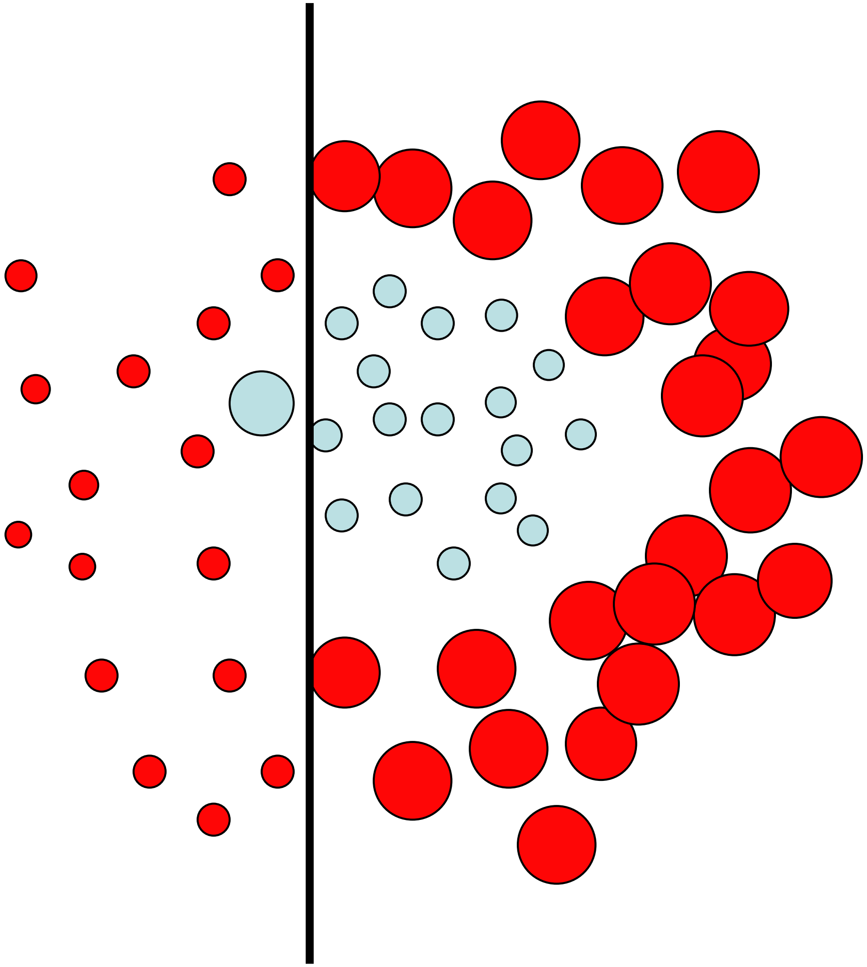
and a weight:

$w_t = 1$

This one seems to be the best

This is a ‘**weak classifier**’: It performs slightly better than chance.

Toy example



Each data point has

a class label:

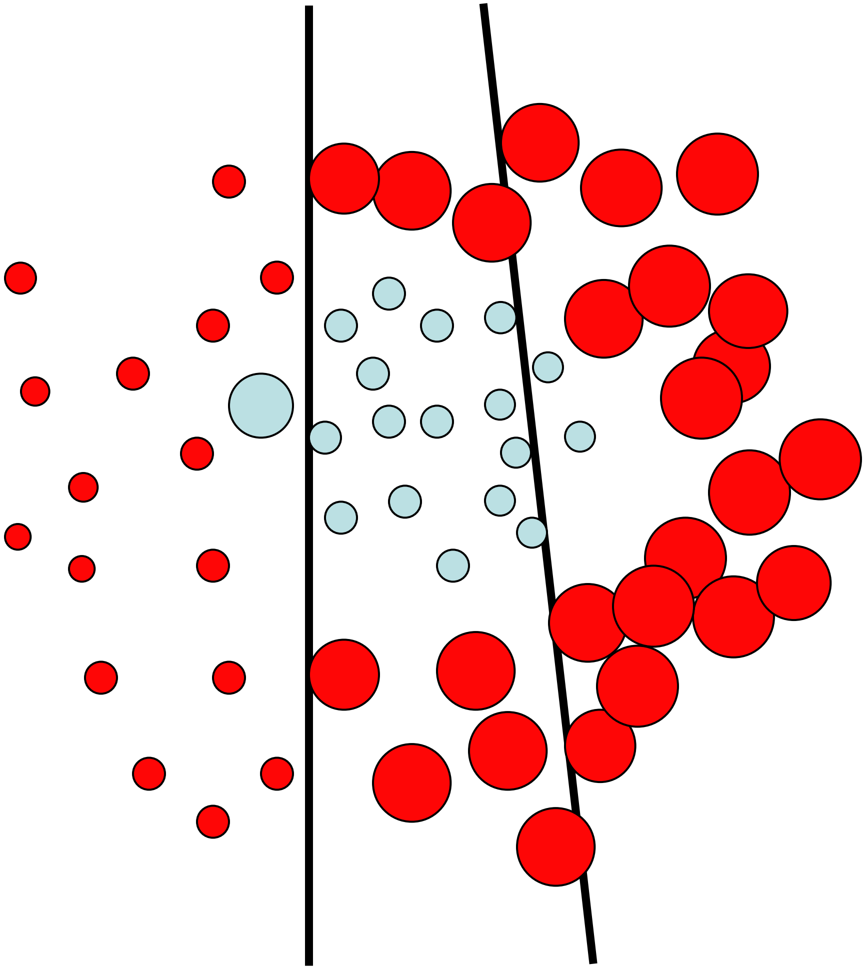
$$y_t = \begin{cases} +1 \text{ (●)} \\ -1 \text{ (○)} \end{cases}$$

We update the weights:

$$w_t \leftarrow w_t \exp\{-y_t H_t\}$$

We set a new problem for which the previous weak classifier performs at chance again

Toy example



Each data point has a class label:

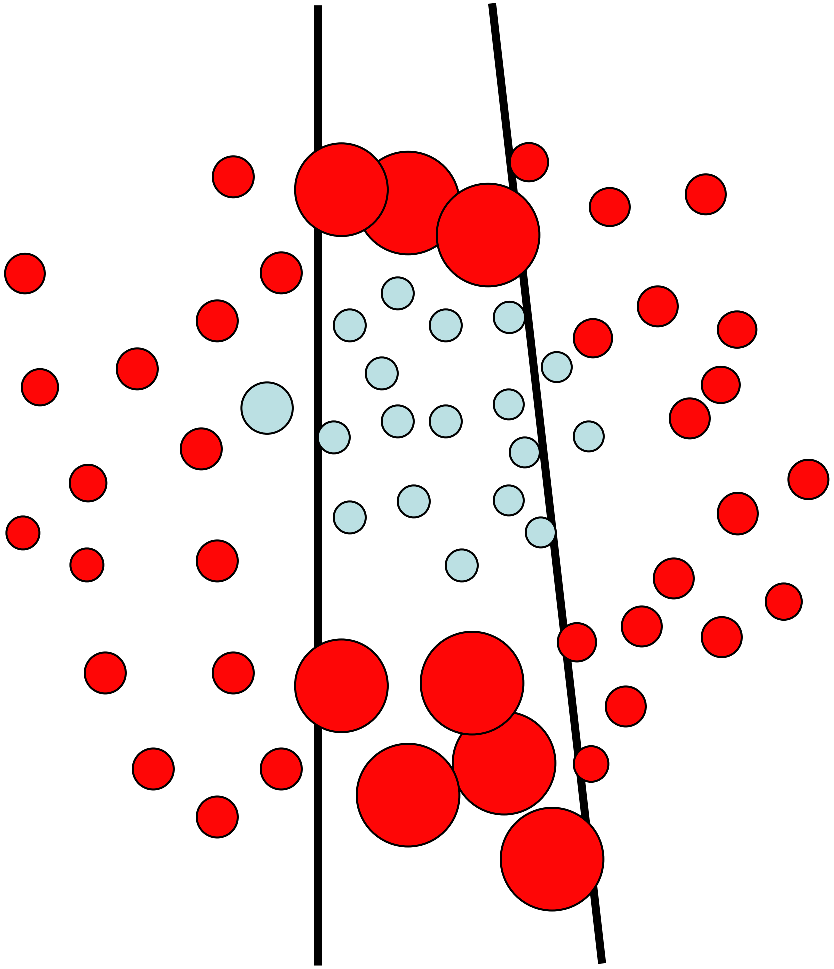
$$y_t = \begin{cases} +1 \ (●) \\ -1 \ (○) \end{cases}$$

We update the weights:

$$w_t \leftarrow w_t \exp\{-y_t \, H_t\}$$

We set a new problem for which the previous weak classifier performs at chance again

Toy example



Each data point has

a class label:

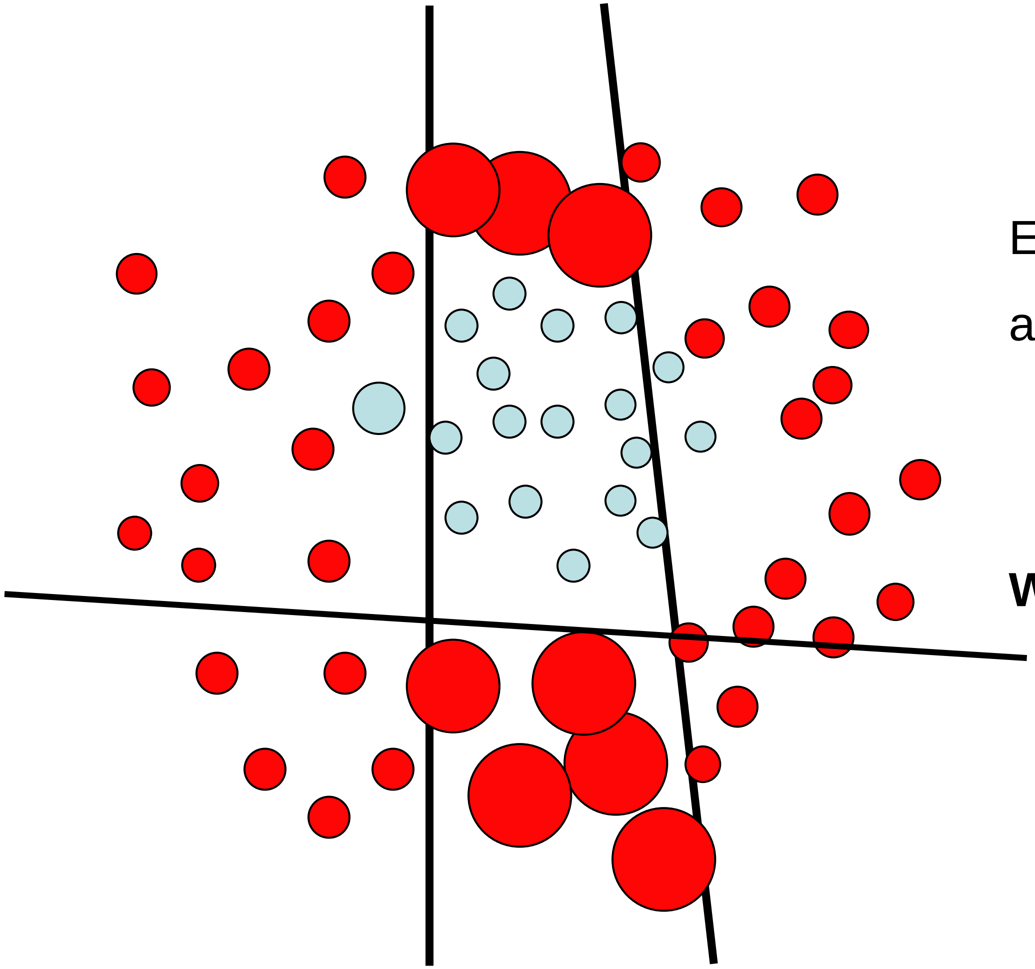
$$y_t = \begin{cases} +1 \; (●) \\ -1 \; (○) \end{cases}$$

We update the weights:

$$w_t \leftarrow w_t \exp\{-y_t H_t\}$$

We set a new problem for which the previous weak classifier performs at chance again

Toy example



Each data point has

a class label:

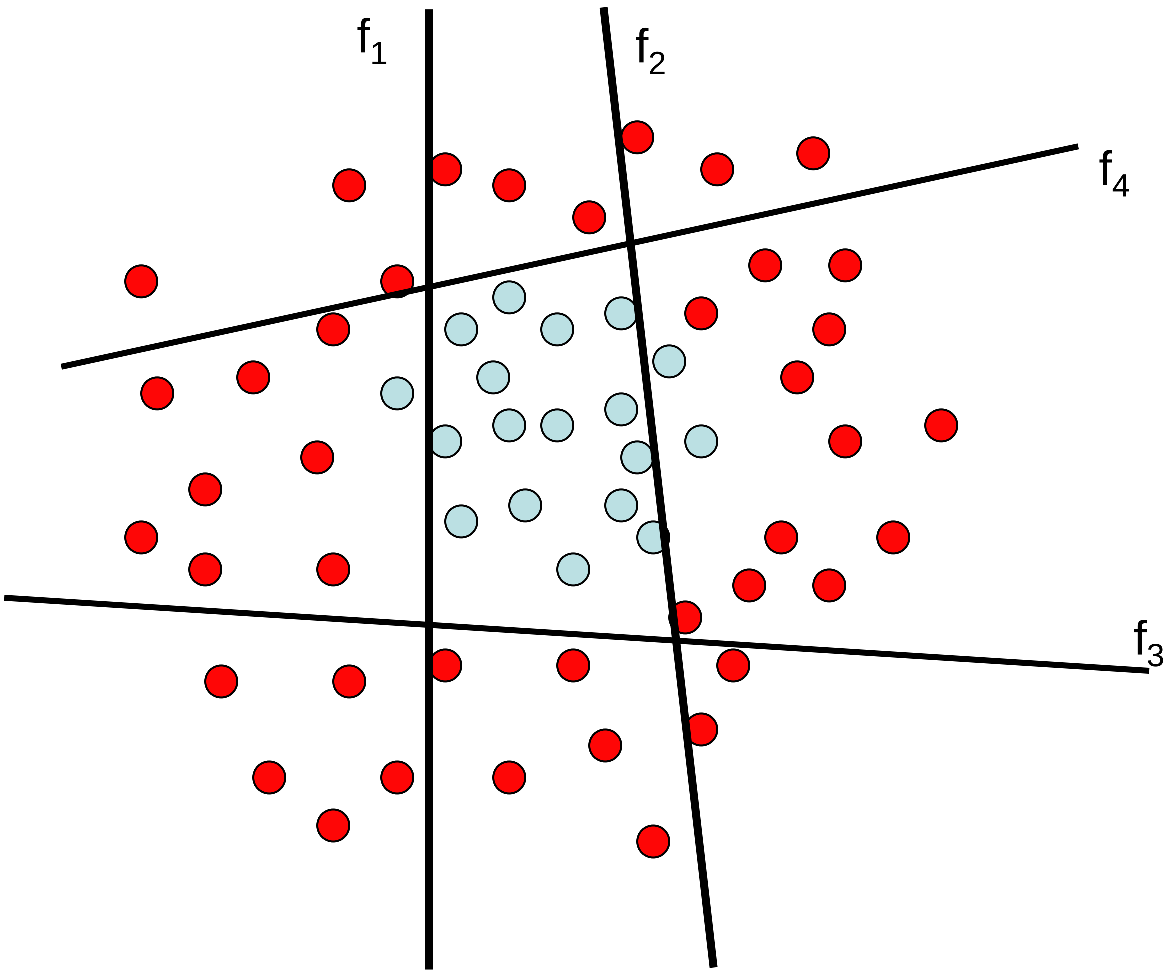
$$y_t = \begin{cases} +1 & (\text{●}) \\ -1 & (\text{○}) \end{cases}$$

We update the weights:

$$w_t \leftarrow w_t \exp\{-y_t H_t\}$$

We set a new problem for which the previous weak classifier performs at chance again

Toy example



The strong (non- linear) classifier is built as the combination of all the weak (linear) classifiers.

Boosting

- Different cost functions and minimization algorithms result is various flavors of Boosting
- In this demo, I will use gentleBoosting: it is simple to implement and numerically stable.

Overview of section

- Object detection with classifiers

- Boosting
  - **Gentle boosting**
  - Weak detectors
  - Object model
  - Object detection

Boosting

Boosting fits the additive model

$$F(x) = f_1(x) + f_2(x) + f_3(x) + \ldots$$

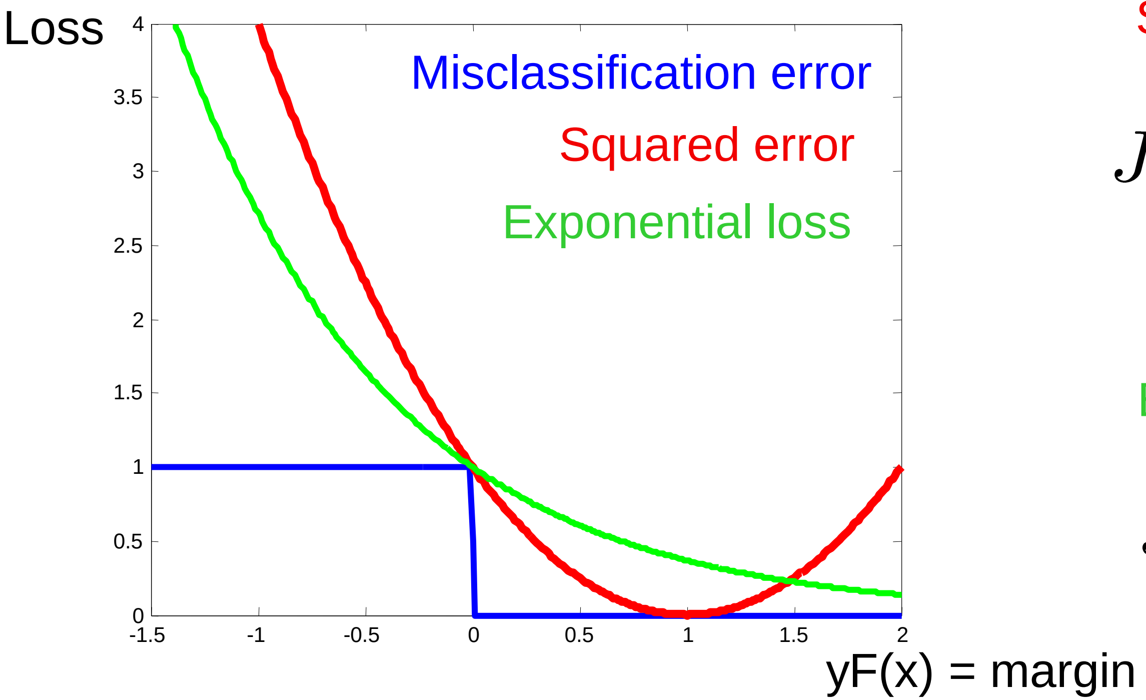
by minimizing the exponential loss

$$J(F) = \sum_{t=1}^{N} e^{-\underset{\uparrow}{y_t} F(\underset{\uparrow}{x_t})}$$

Training samples

The exponential loss is a differentiable upper bound to the misclassification error.

Exponential loss



Squared error

$$J = \sum_{t=1}^{N} [y_t - F(x_t)]^2$$

Exponential loss

$$J = \sum_{t=1}^{N} e^{-y_t F(x_t)}$$

Boosting

Sequential procedure. At each step we add

$$F(x) \leftarrow F(x) + f_m(x)$$

to minimize the residual loss

$$(\phi_m) = \operatorname{arg\,min}_{\phi} \sum_{t=1}^{N} J\left(y_i, F(x_t) + f(x_t; \phi)\right)$$

Parameters
weak classifier

Desired output

input

For more details: Friedman, Hastie, Tibshirani. “Additive Logistic Regression: a Statistical View of Boosting” (1998)

gentleBoosting

- At each iteration:

We chose $f_m(x)$ that minimizes the cost:

$$J(F + f_m) = \sum_{t=1}^{N} e^{-y_t(F(x_t)+f_m(x_t))}$$

Instead of doing exact optimization, gentle Boosting minimizes a Taylor approximation of the error:

$$J(F) \propto \sum_{t=1}^{N} \boxed{e^{-y_t F(x_t)}} (y_t - f_m(x_t))^2$$

Weights at this iteration

→ At each iterations we just need to solve a weighted least squares problem

For more details: Friedman, Hastie, Tibshirani. “Additive Logistic Regression: a Statistical View of Boosting” (1998)

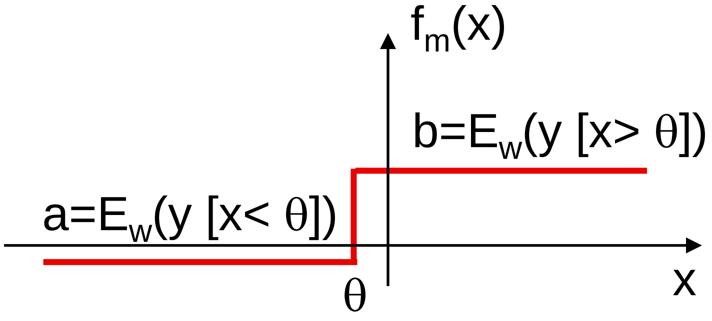
Weak classifiers

- The input is a set of weighted training samples (x,y,w)

- Regression stumps: simple but commonly used in object detection.

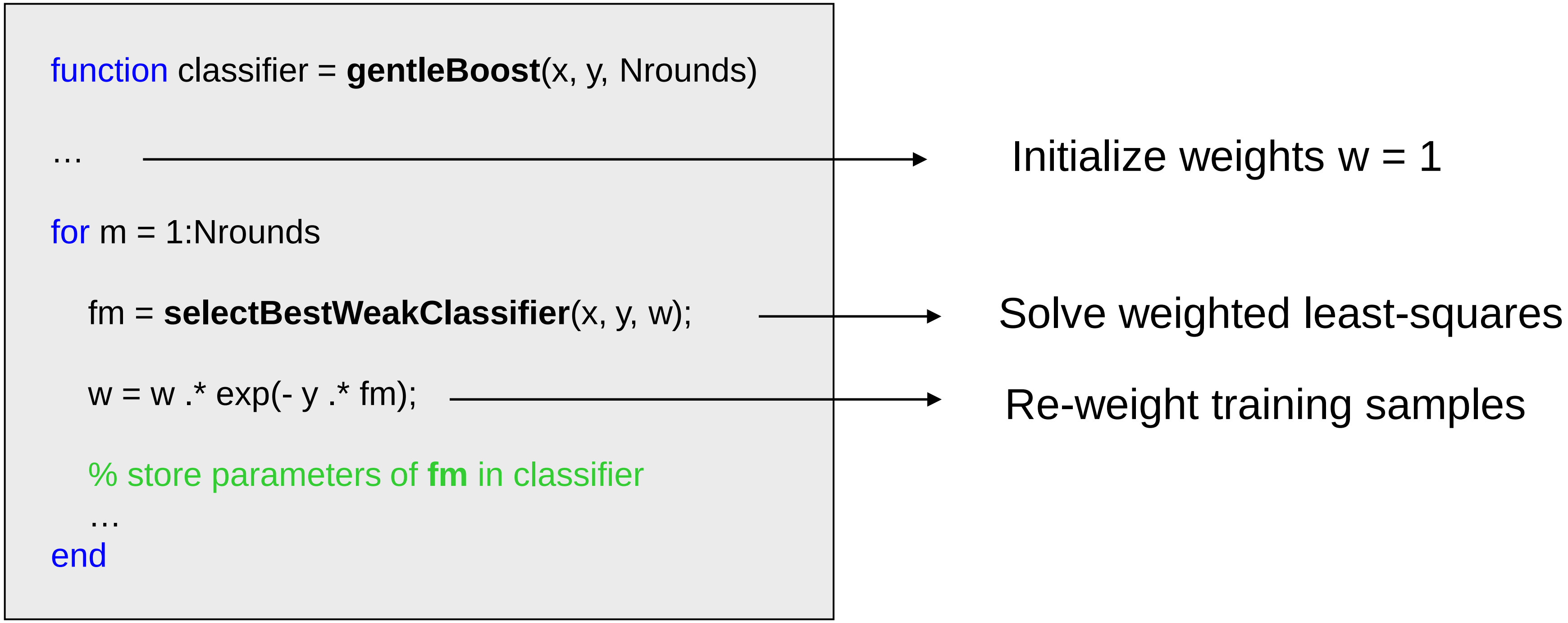
$$f_m(x) = a[x_k < \theta] + b[x_k \geq \theta]$$

Four parameters: $[a, b, \theta, k]$



fitRegressionStump.m

gentleBoosting.m



```
function classifier = gentleBoost(x, y, Nrounds)

…

for m = 1:Nrounds

   fm = selectBestWeakClassifier(x, y, w);

   w = w .* exp(- y .* fm);

   % store parameters of fm in classifier
   …
end
```

Initialize weights w = 1

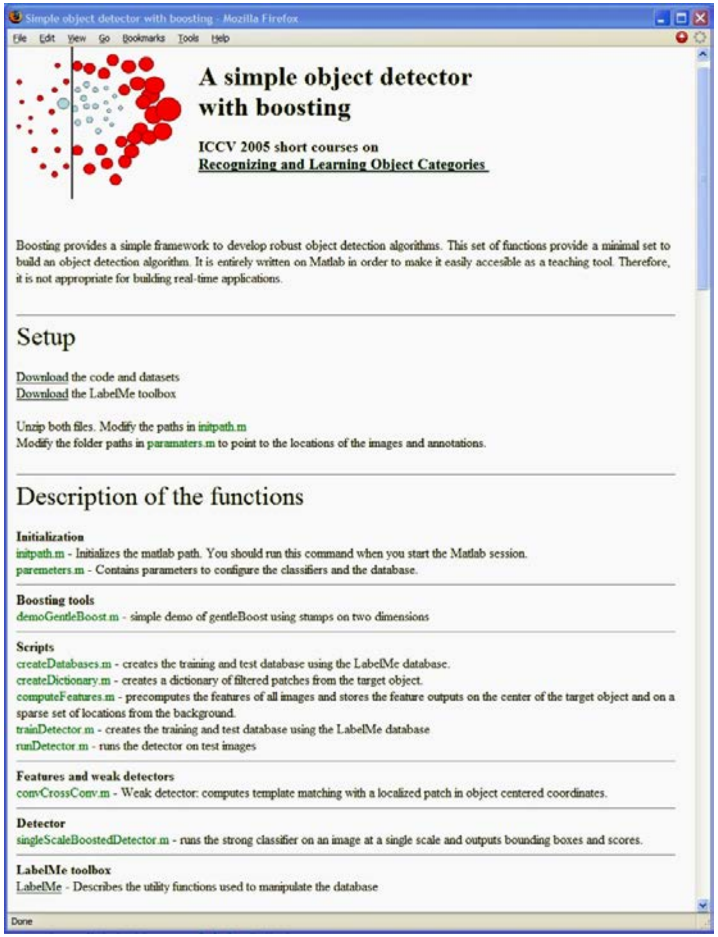
Solve weighted least-squares

Re-weight training samples

Demo gentleBoosting

Demo using Gentle boost and stumps with hand selected 2D data:

> demoGentleBoost.m


Simple object detector with boosting - Mozilla Firefox
File Edit View Go Bookmarks Tools Help
Done

A simple object detector with boosting

ICCV 2005 short courses on
Recognizing and Learning Object Categories

Boosting provides a simple framework to develop robust object detection algorithms. This set of functions provide a minimal set to build an object detection algorithm. It is entirely written on Matlab in order to make it easily accesible as a teaching tool. Therefore, it is not appropriate for building real-time applications.

Setup

Download the code and datasets
Download the LabelMe toolbox

Unzip both files. Modify the paths in initpath.m
Modify the folder paths in paramaters.m to point to the locations of the images and annotations.

Description of the functions

Initialization
initpath.m - Initializes the matlab path. You should run this command when you start the Matlab session.
paremeters.m - Contains parameters to configure the classifiers and the database.

Boosting tools
demoGentleBoost.m - simple demo of gentleBoost using stumps on two dimensions

Scripts
createDatabases.m - creates the training and test database using the LabelMe database.
createDictionary.m - creates a dictionary of filtered patches from the target object.
computeFeatures.m - precomputes the features of all images and stores the feature outputs on the center of the target object and on a sparse set of locations from the background.
trainDetector.m - creates the training and test database using the LabelMe database
runDetector.m - runs the detector on test images

Features and weak detectors
convCrossConv.m - Weak detector: computes template matching with a localized patch in object centered coordinates.

Detector
singleScaleBoostedDetector.m - runs the strong classifier on an image at a single scale and outputs bounding boxes and scores.

LabelMe toolbox
LabelMe - Describes the utility functions used to manipulate the database

Flavors of boosting

- AdaBoost (Freund and Shapire, 1995)
- Real AdaBoost (Friedman et al, 1998)
- LogitBoost (Friedman et al, 1998)
- Gentle AdaBoost (Friedman et al, 1998)
- BrownBoosting (Freund, 2000)
- FloatBoost (Li et al, 2002)
- …

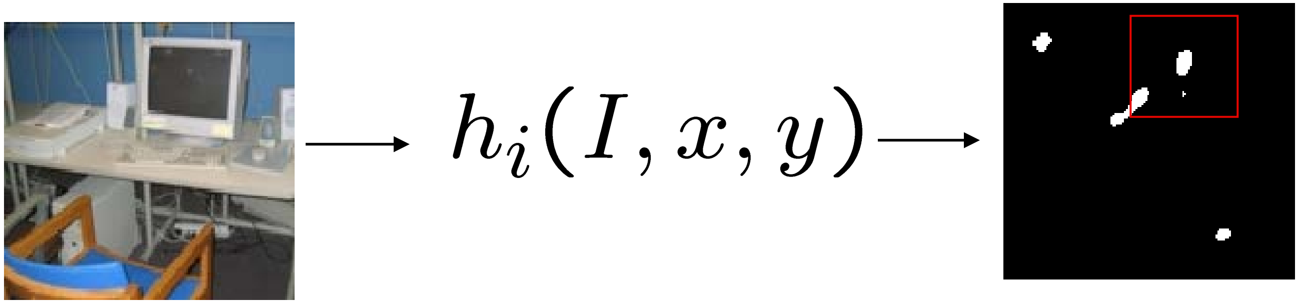
Overview of section

- Object detection with classifiers

- Boosting
  - Gentle boosting
  - **Weak detectors**
  - Object model
  - Object detection

From images to features:
Weak detectors

We will now define a family of visual features that can be used as weak classifiers (“weak detectors”)

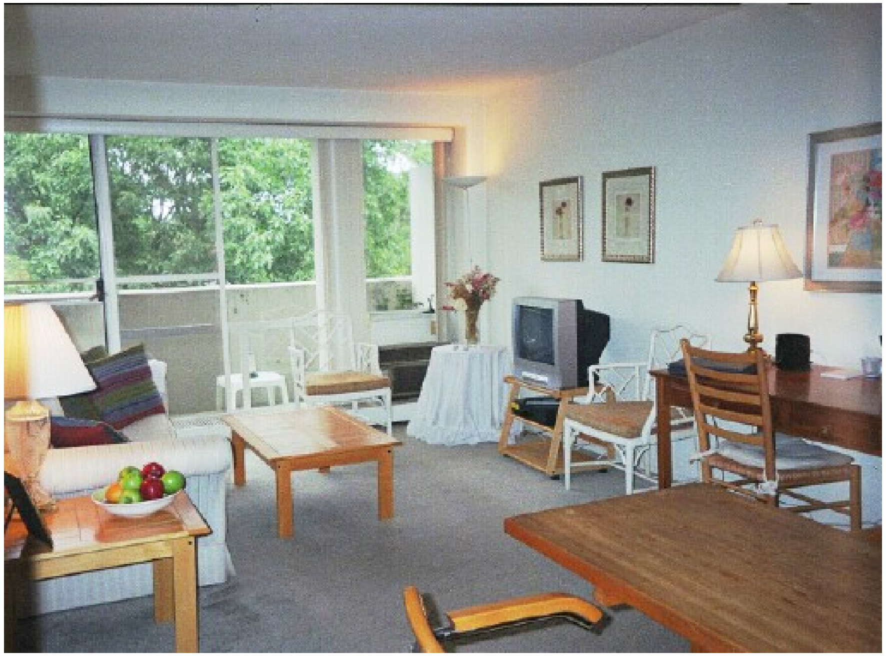


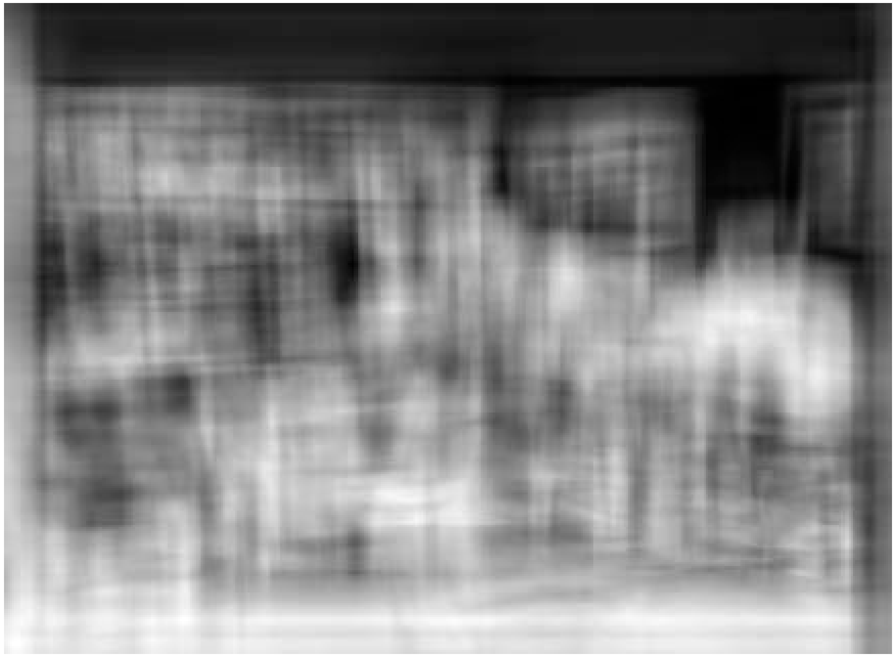
$$\longrightarrow h_i(I, x, y) \longrightarrow$$

Takes image as input and the output is binary response.
The output is a weak detector.

Object recognition
Is it really so hard?

Find the chair in this image

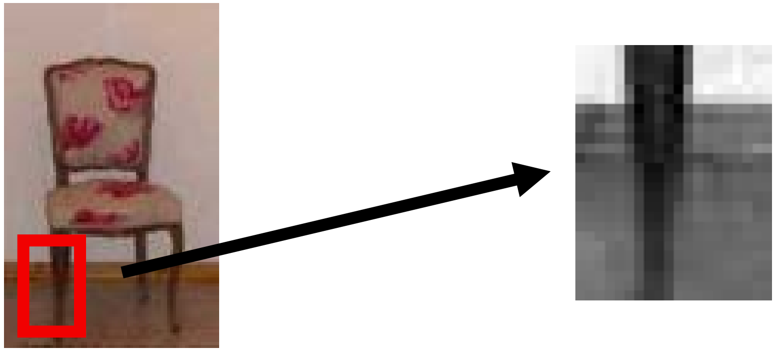




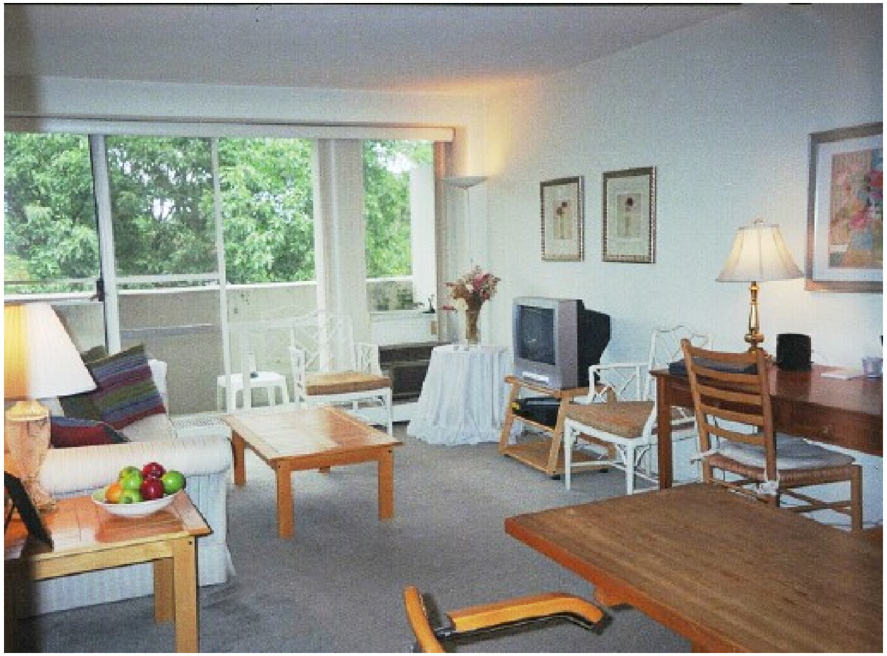
But what if we use smaller patches? Just a part of the chair?

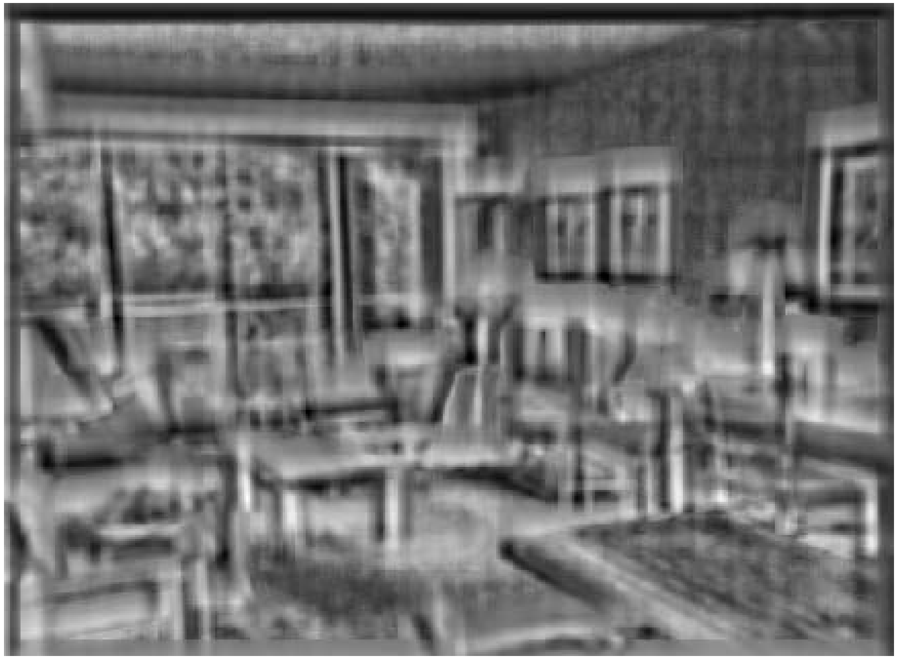
Parts

But what if we use smaller patches? Just a part of the chair?



Find a chair in this image





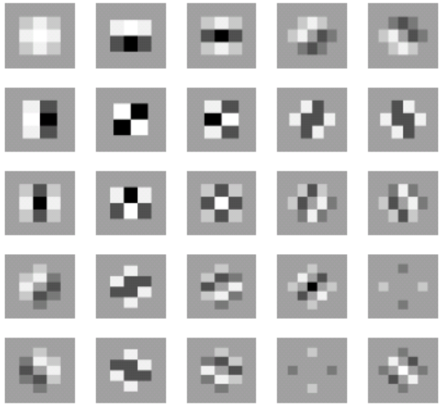
Seems to fire on legs… not so bad

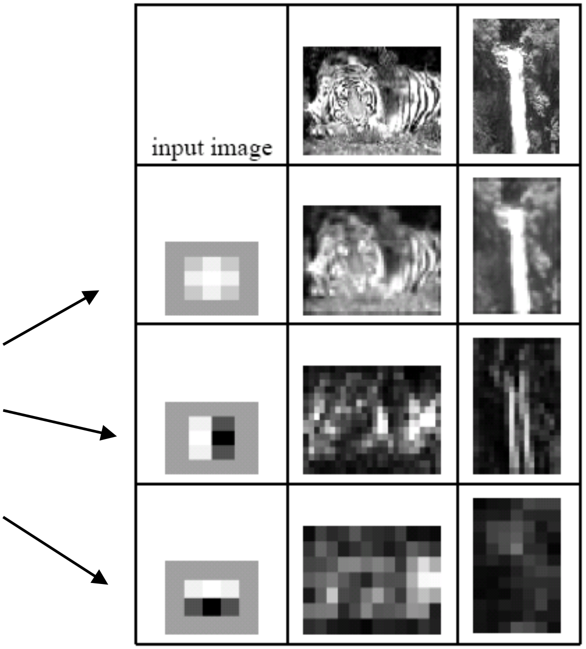
Weak detectors

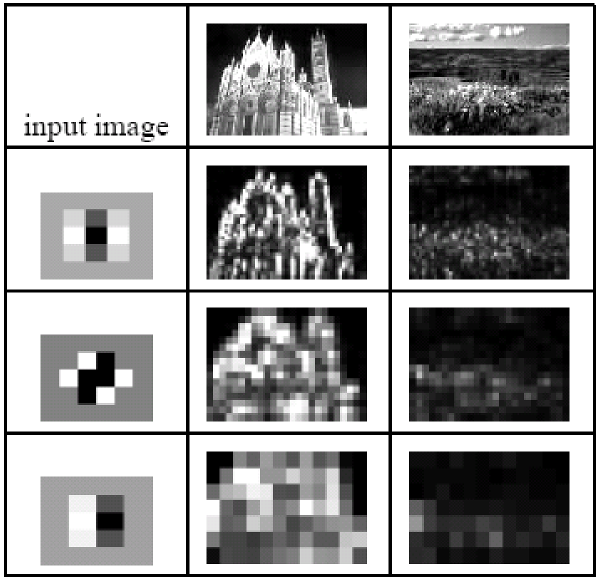
Textures of textures

Tieu and Viola, CVPR 2000. One of the first papers to use boosting for vision.

$$g_{i,j,k} = \sum_{pixels} ||I * f_i| \downarrow_2 * f_j| \downarrow_2 * f_k$$







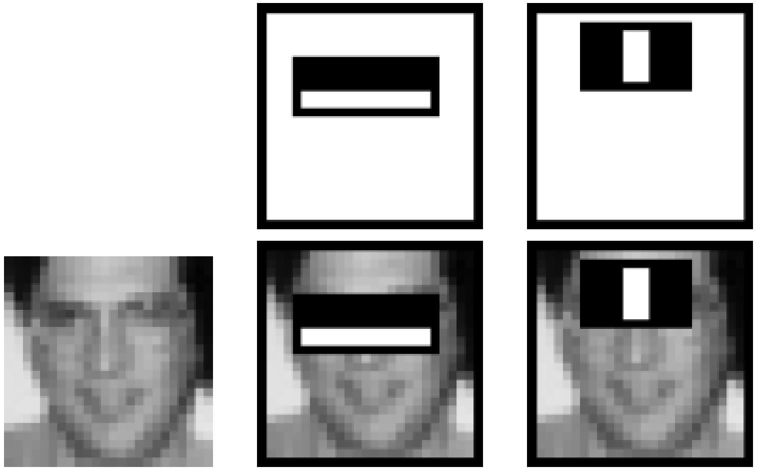
Every combination of three filters generates a different feature

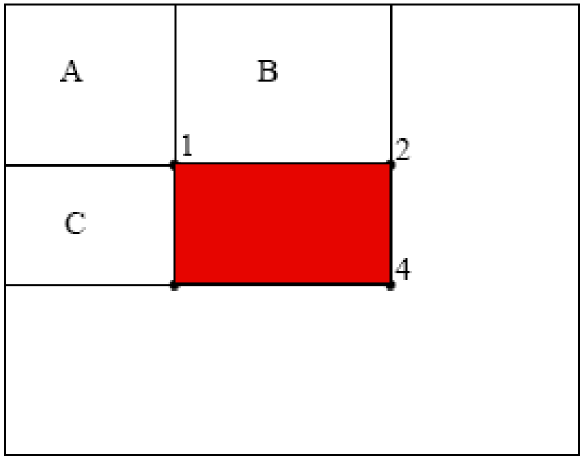
This gives thousands of features. Boosting selects a sparse subset, so computations on test time are very efficient. Boosting also avoids overfitting to some extend.

Weak detectors

Haar filters and integral image

Viola and Jones, ICCV 2001





The average intensity in the block is computed with four sums independently of the block size.

Edge fragments

J. Shotton, A. Blake, R. Cipolla.
Multi-Scale Categorical Object Recognition
Using Contour Fragments. In *IEEE Trans. on PAMI*, 30(7):1270-1281, July 2008.

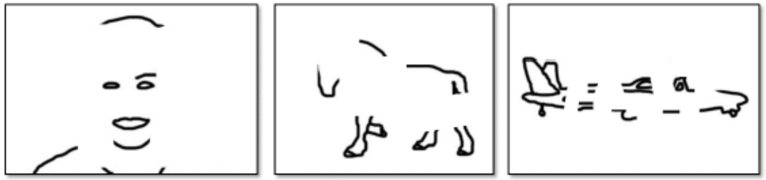
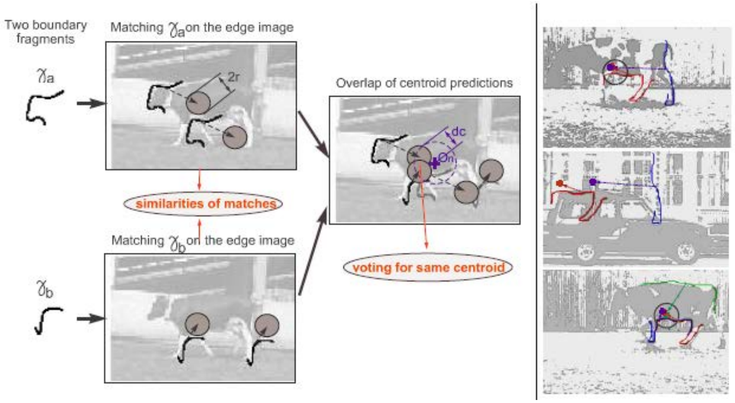
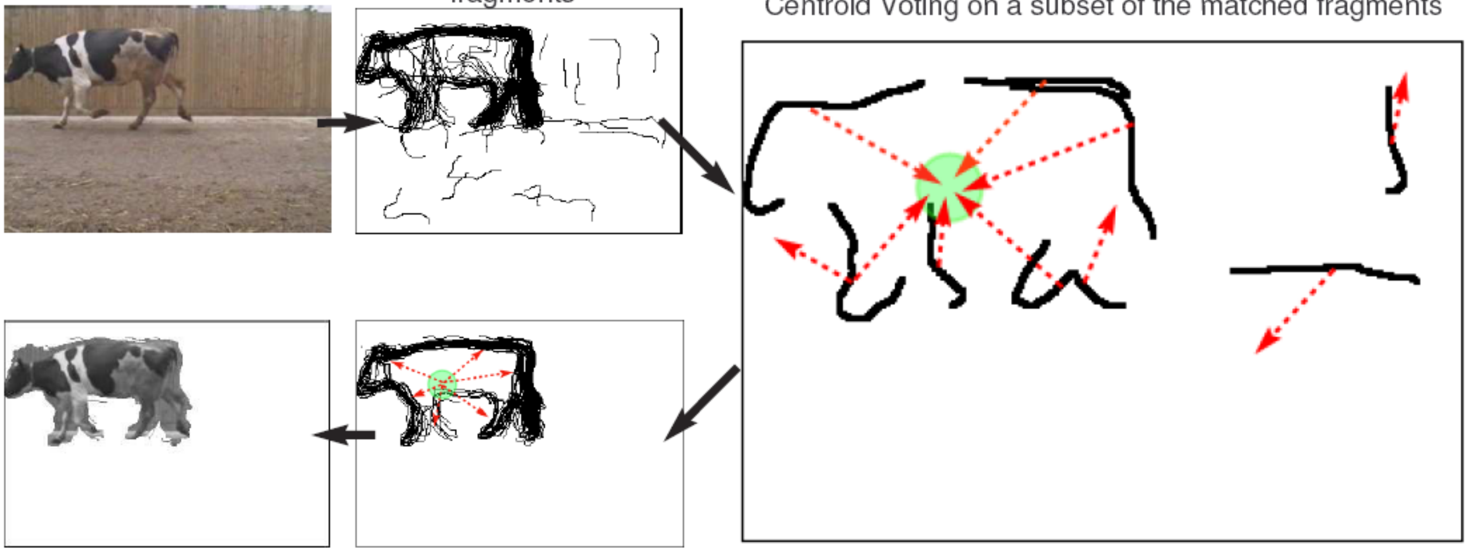


Fig. 1. **Object recognition using contour fragments.** Our innate biological vision system is able to interpret spatially arranged local fragments of contour to recognize the objects present. In this work we show that an automatic computer vision system can also successfully exploit the cue of contour for object recognition.

Opelt, Pinz, Zisserman, ECCV 2006


Two boundary fragments
γ_a
Matching γ_a on the edge image
2r
similarities of matches
Matching γ_b on the edge image
γ_b
Overlap of centroid predictions
dc
On
voting for same centroid



Original Image

All matched boundary fragments

Centroid Voting on a subset of the matched fragments

Segmentation / Detection

Backprojected Maximum

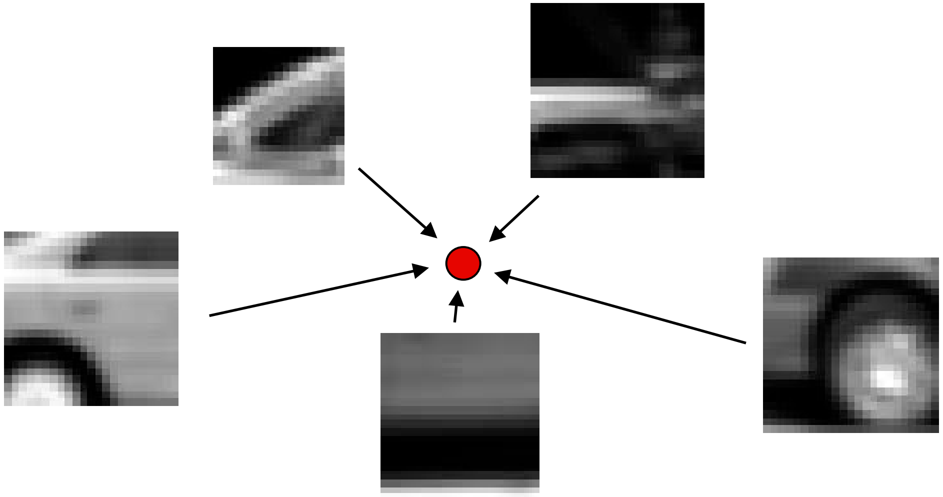
Weak detectors

Other weak detectors:

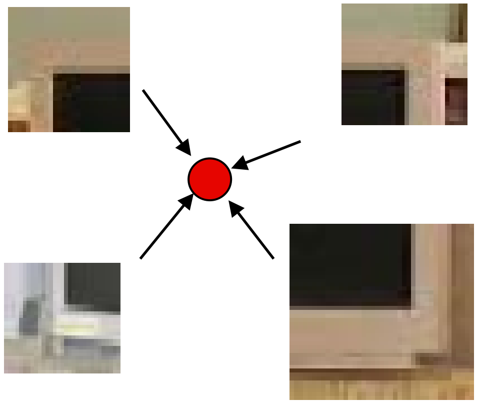
- Carmichael, Hebert 2004
- Yuille, Snow, Nitzbert, 1998
- Amit, Geman 1998
- Papageorgiou, Poggio, 2000
- Heisele, Serre, Poggio, 2001
- Agarwal, Awan, Roth, 2004
- Schneiderman, Kanade 2004
- …

Weak detectors

Part based: similar to part-based generative models. We create weak detectors by using parts and voting for the object center location



Car model



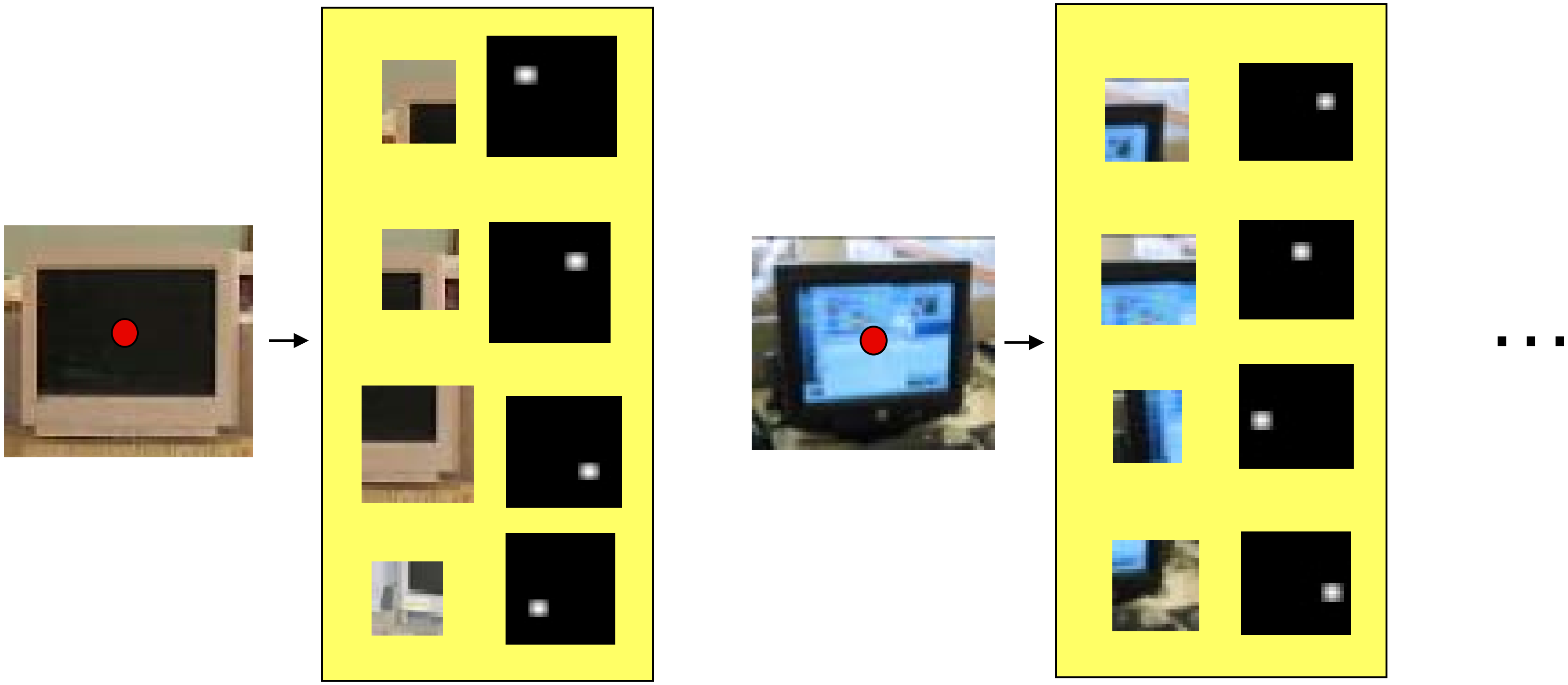
Screen model

These features are used for the detector on the course web site.

Weak detectors

First we collect a set of part templates from a set of training objects.

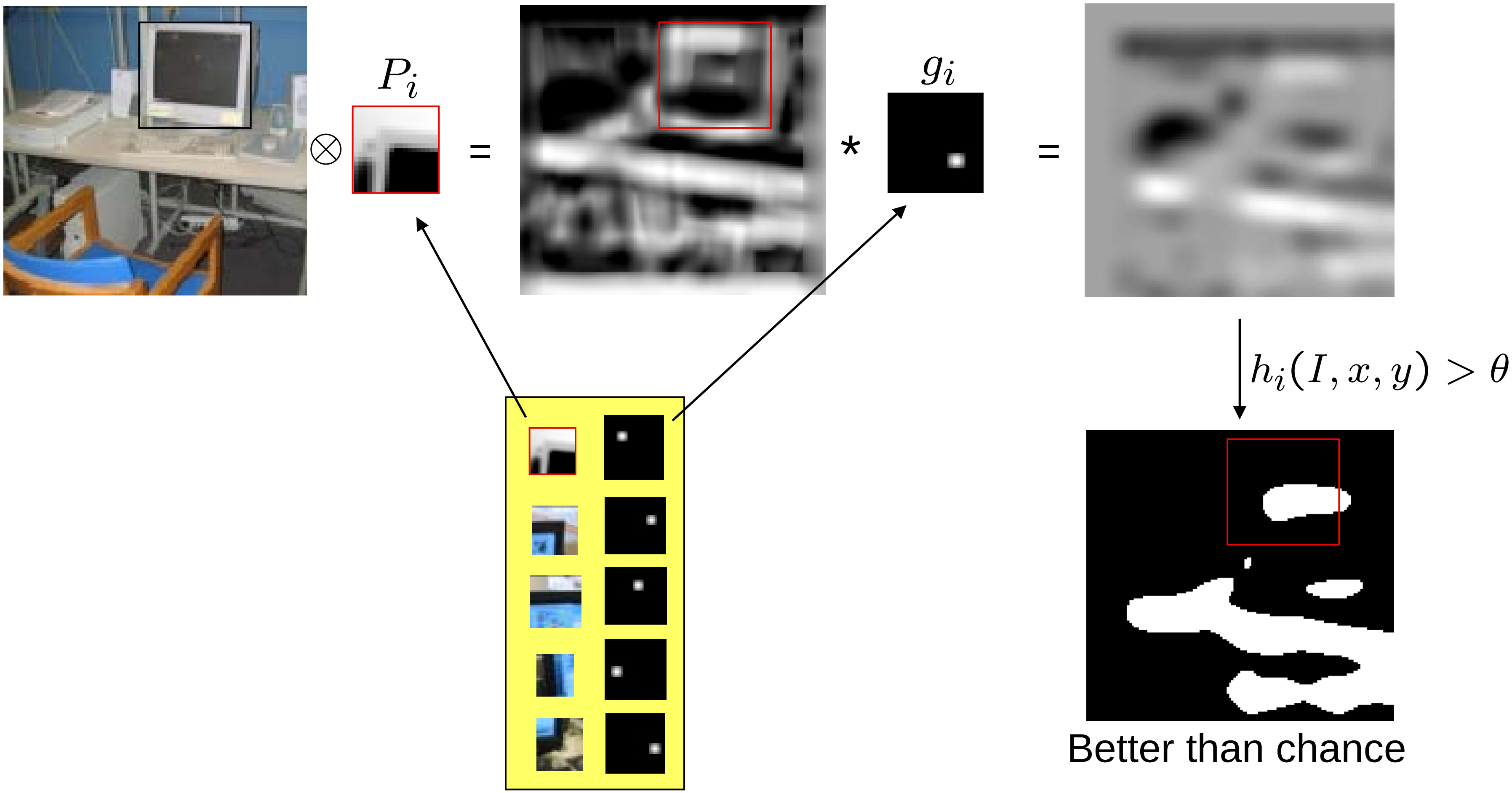
Vidal-Naquet, Ullman (2003)



Weak detectors

We now define a family of “weak detectors” as:

$$h_i(I, x, y) = [I \otimes P_i] * g_i$$

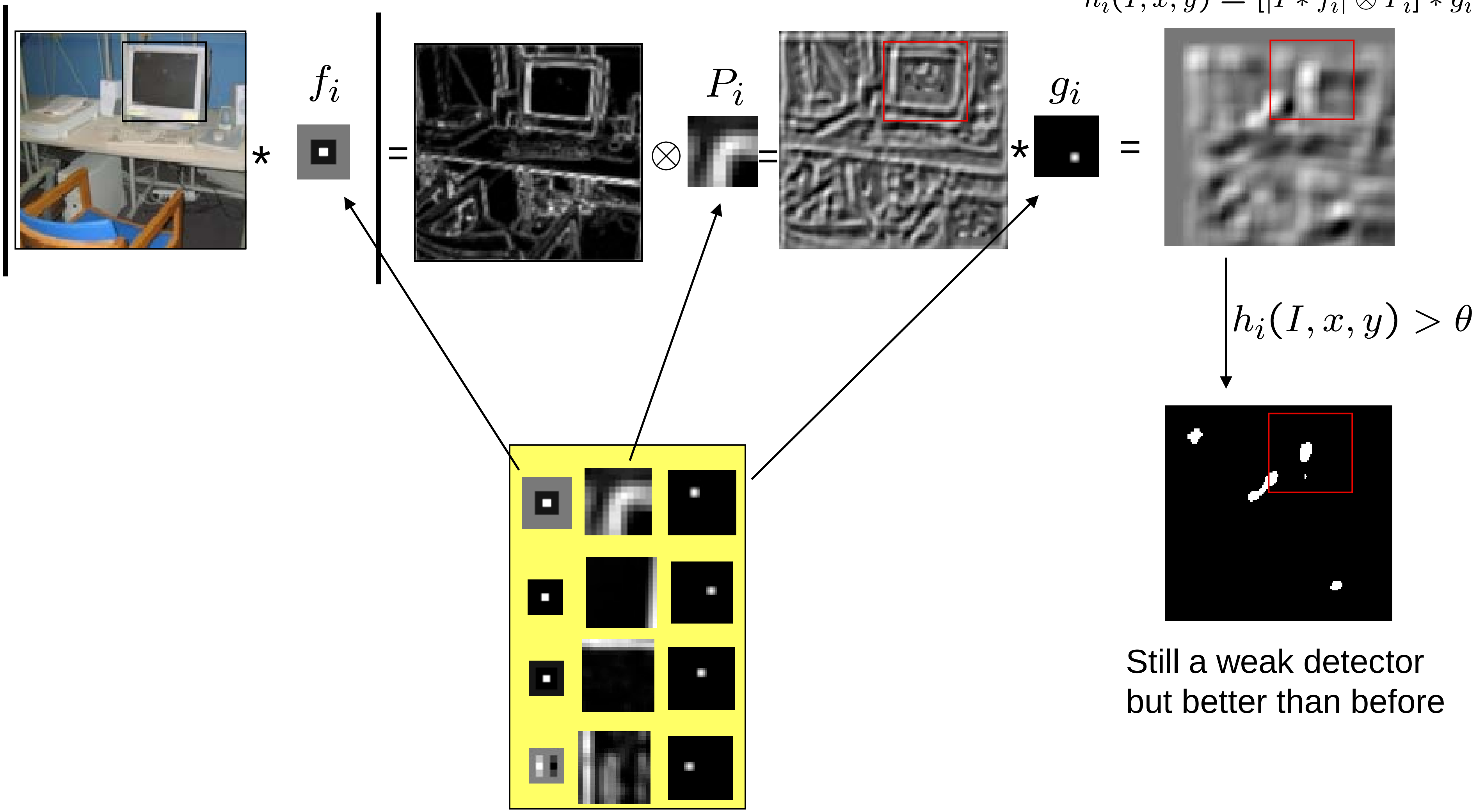


Better than chance

Weak detectors

We can do a better job using filtered images

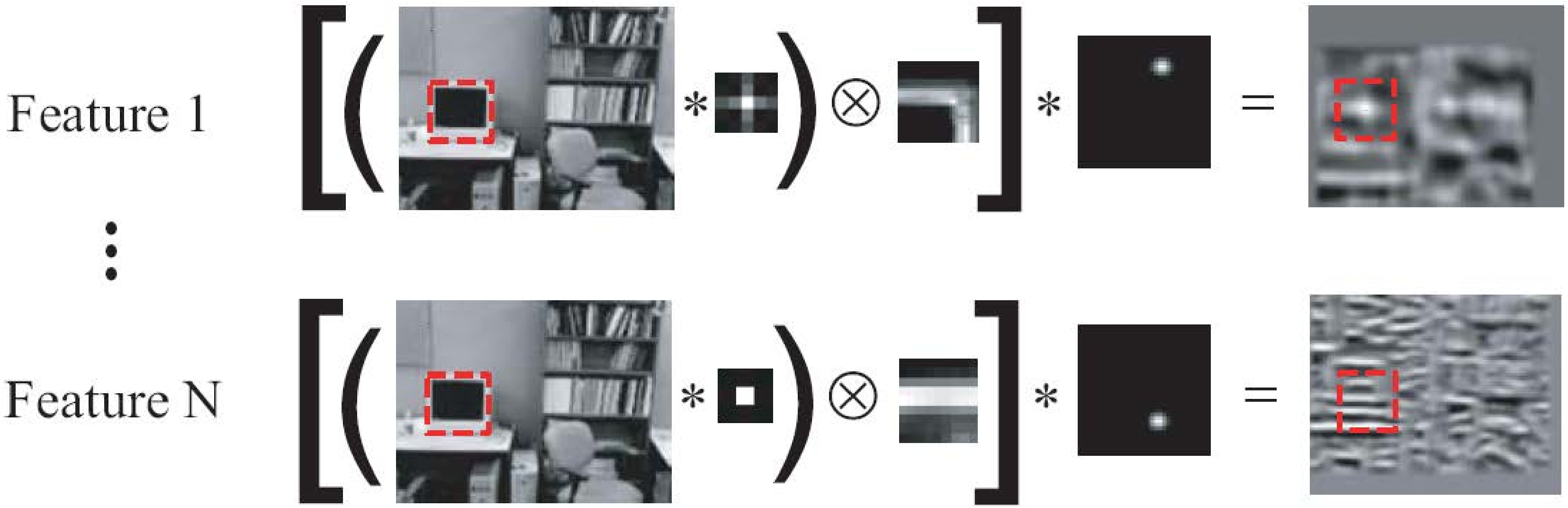
$$h_i(I,x,y) = [|I * f_i| \otimes P_i] * g_i$$



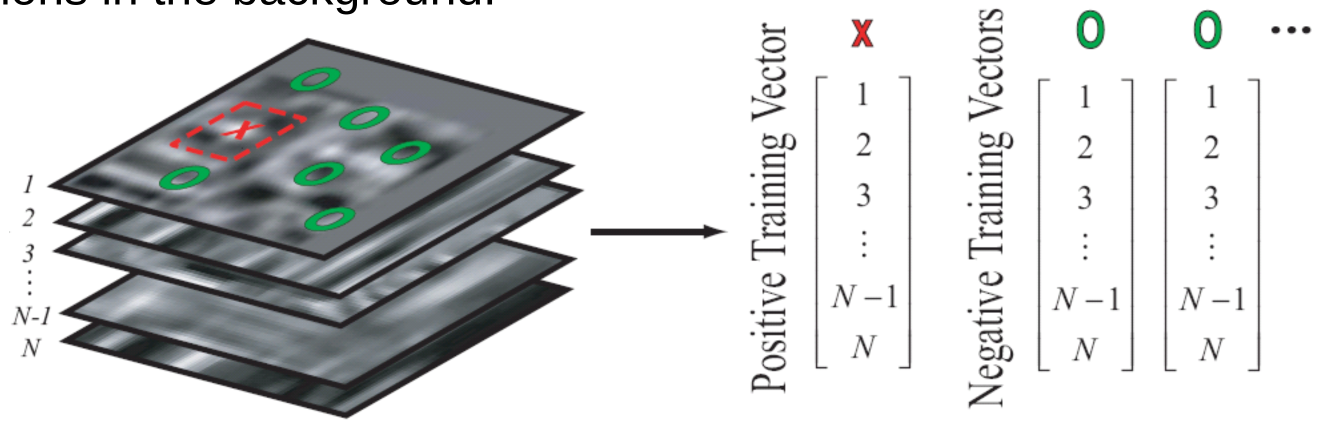
Still a weak detector
but better than before

Training

First we evaluate all the N features on all the training images.

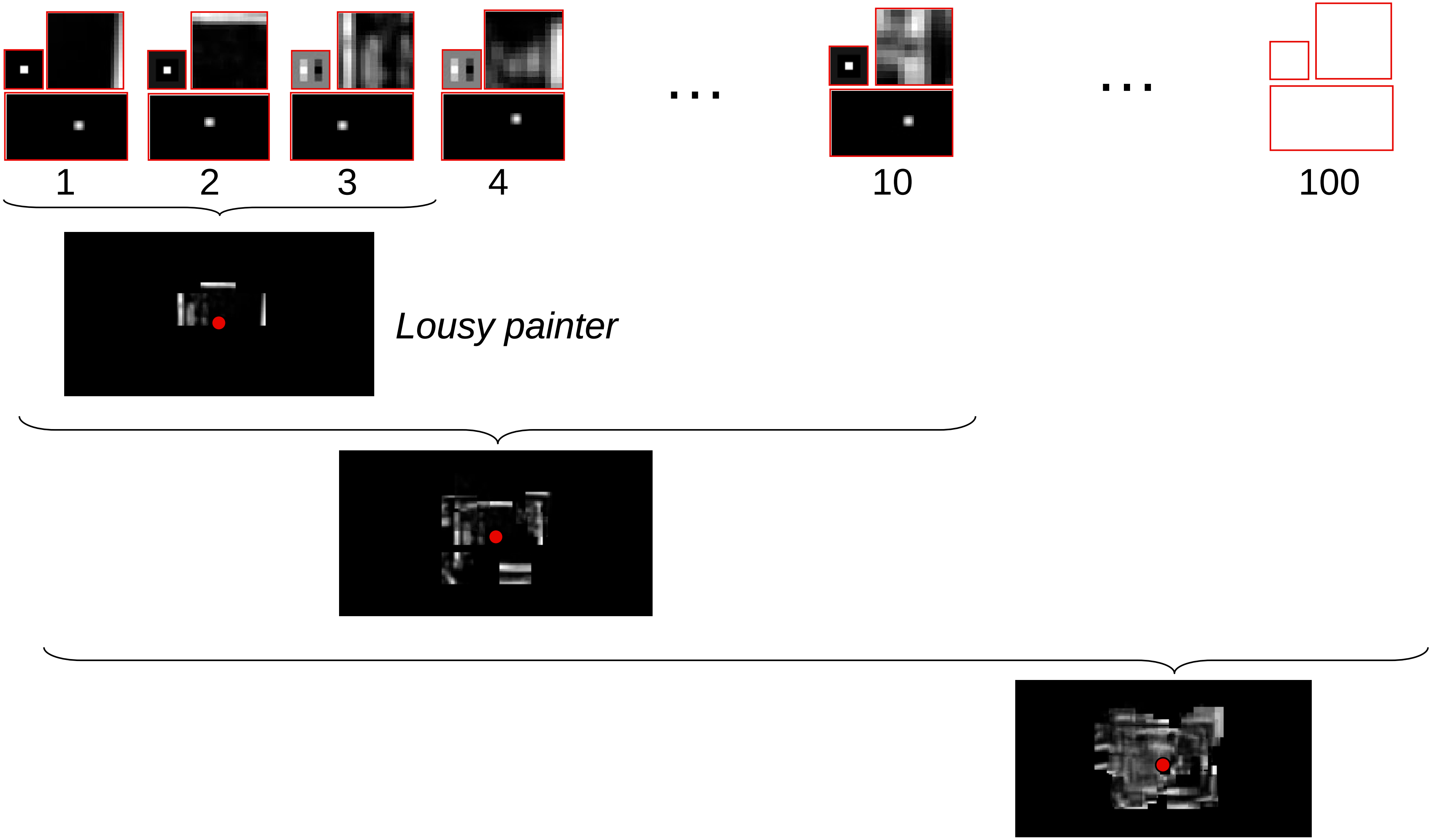


Then, we sample the feature outputs on the object center and at random locations in the background:



Representation and object model

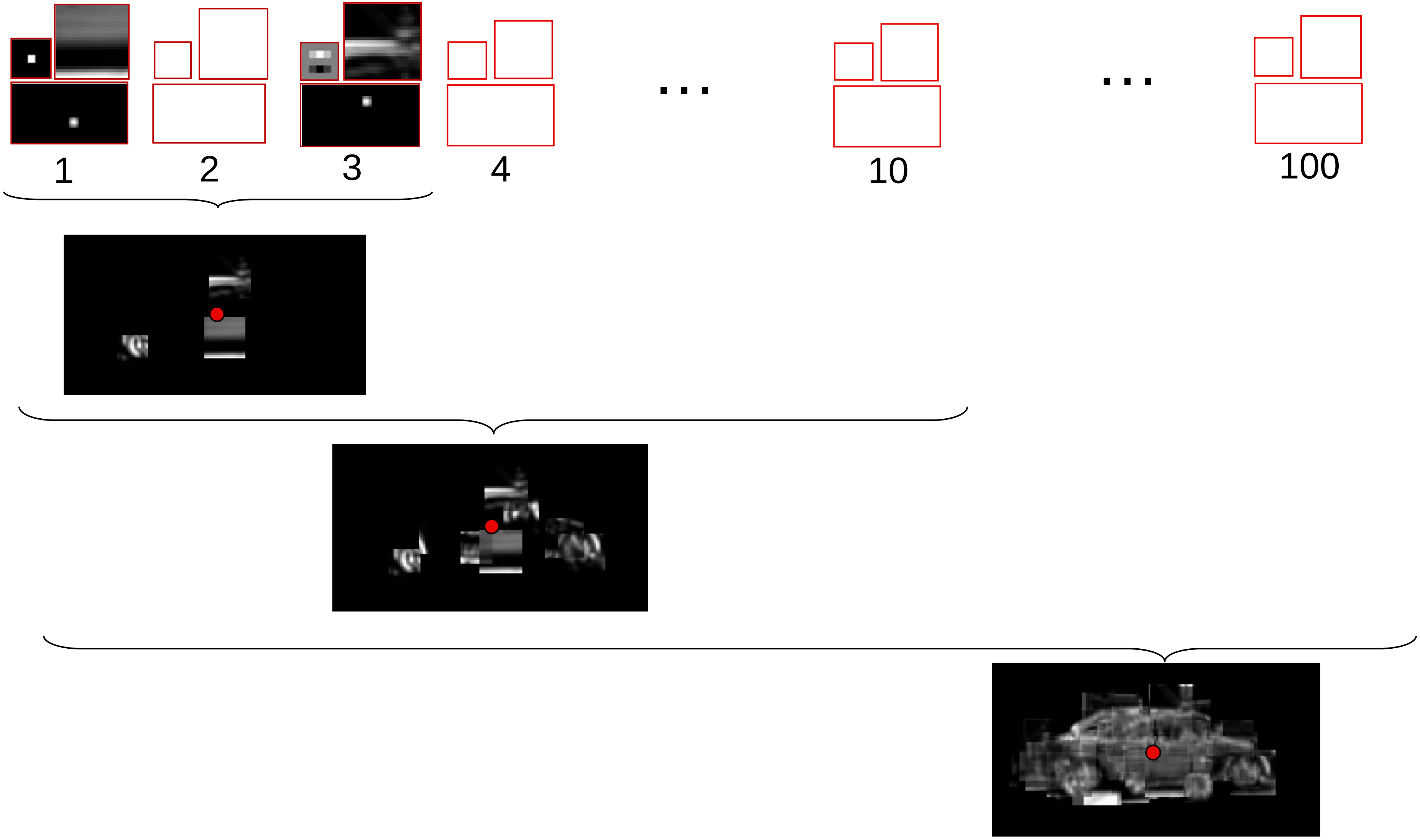
Selected features for the screen detector



Lousy painter

Representation and object model

Selected features for the car detector



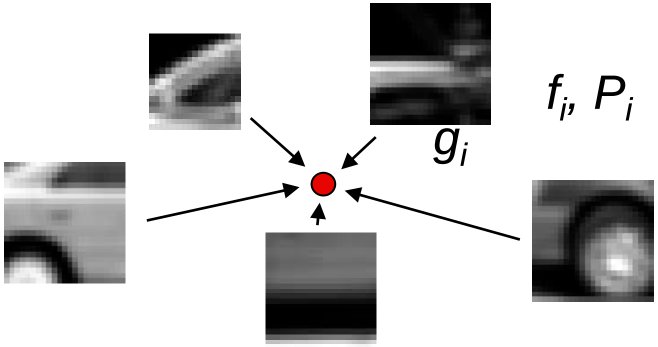
Overview of section

- Object detection with classifiers

- Boosting
  - Gentle boosting
  - Weak detectors
  - Object model
  - **Object detection**

Object model

- Voting

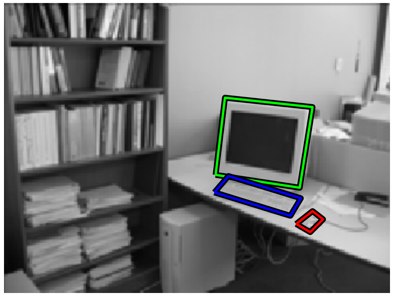


- Invariance: search strategy

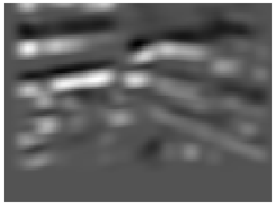
Here, invariance in translation and scale is achieved by the search strategy: the classifier is evaluated at all locations (by translating the image) and at all scales (by scaling the image in small steps).

The search cost can be reduced using a cascade.

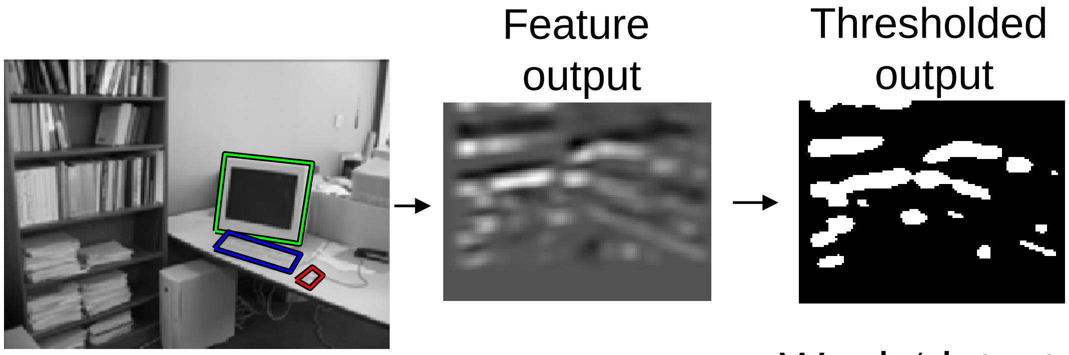
Example: screen detection



Feature
output



Example: screen detection



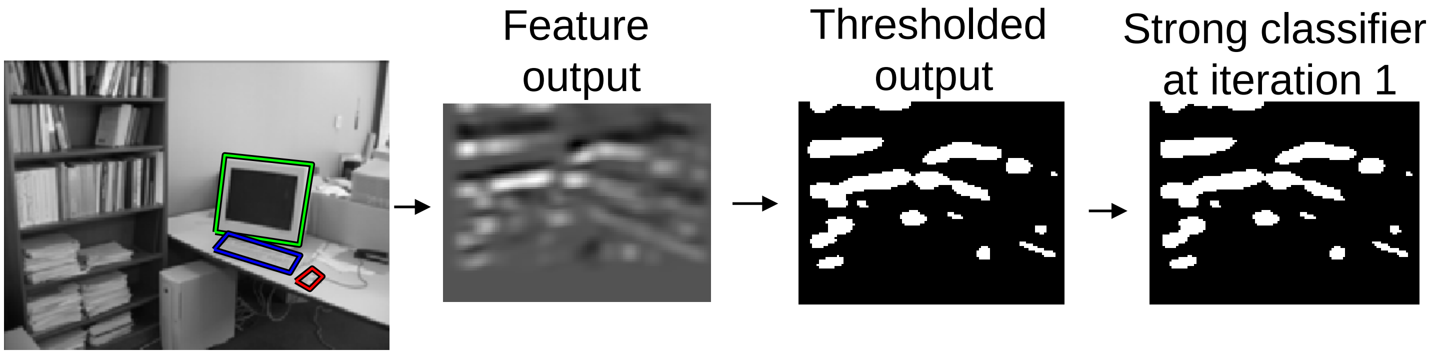
Feature output

Thresholded output

Weak ‘detector’

Produces many false alarms.

Example: screen detection

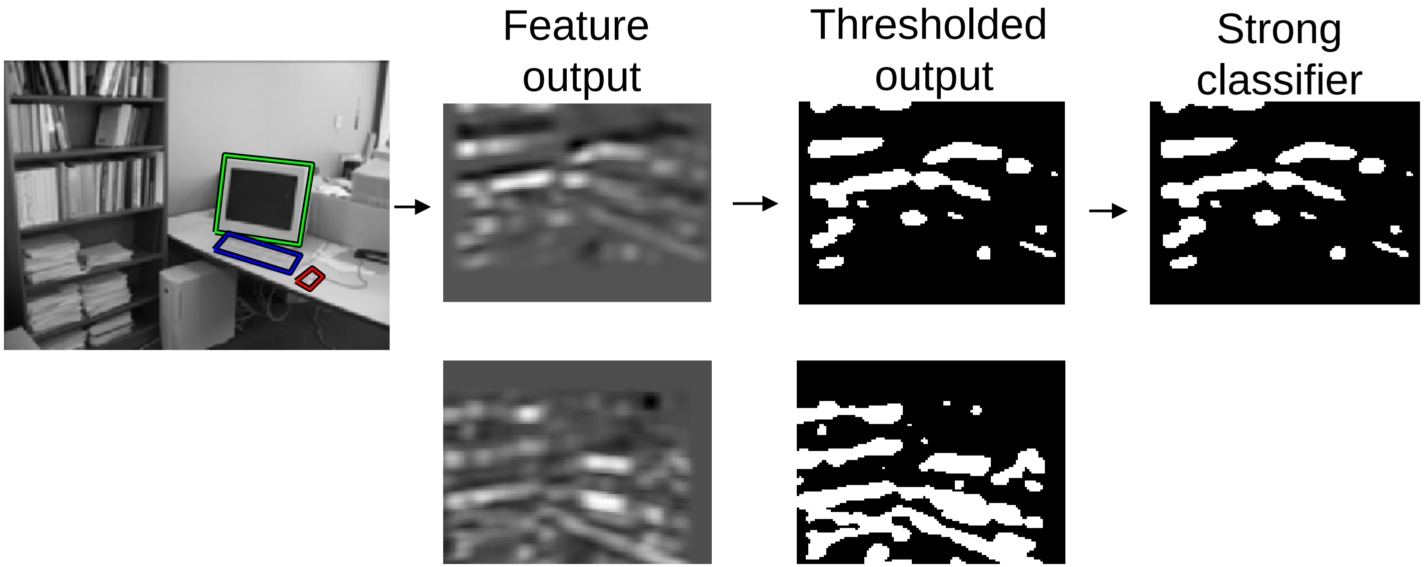


Feature output

Thresholded output

Strong classifier at iteration 1

Example: screen detection



Feature output

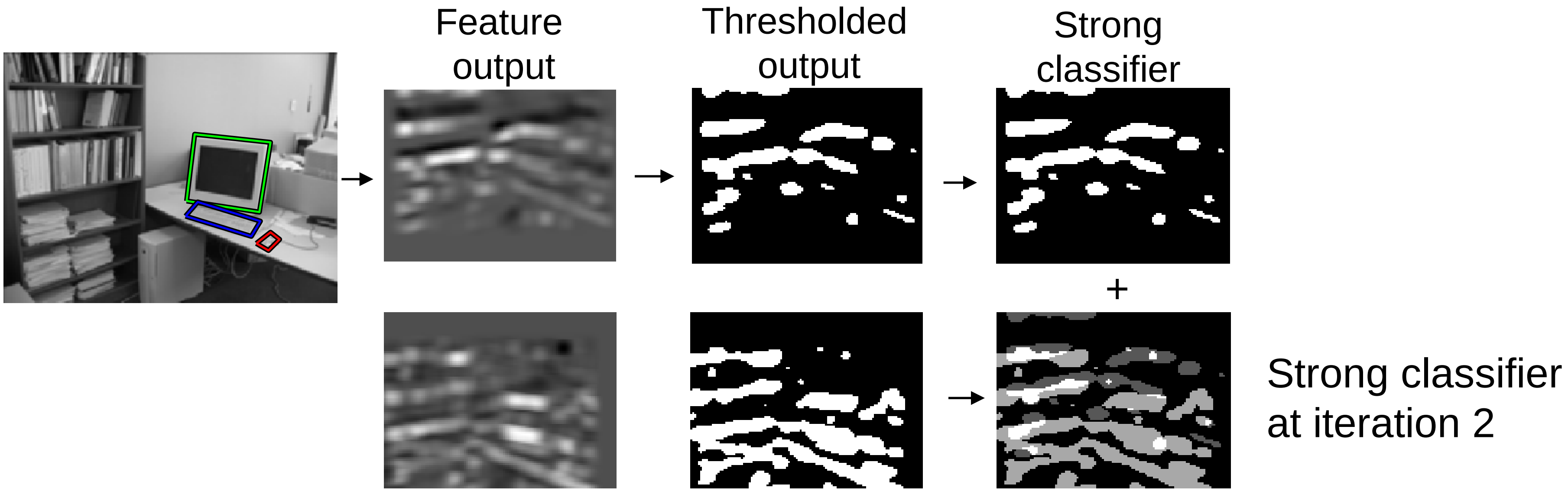
Thresholded output

Strong classifier

Second weak ‘detector’

Produces a different set of false alarms.

Example: screen detection



Feature output

Thresholded output

Strong classifier

+

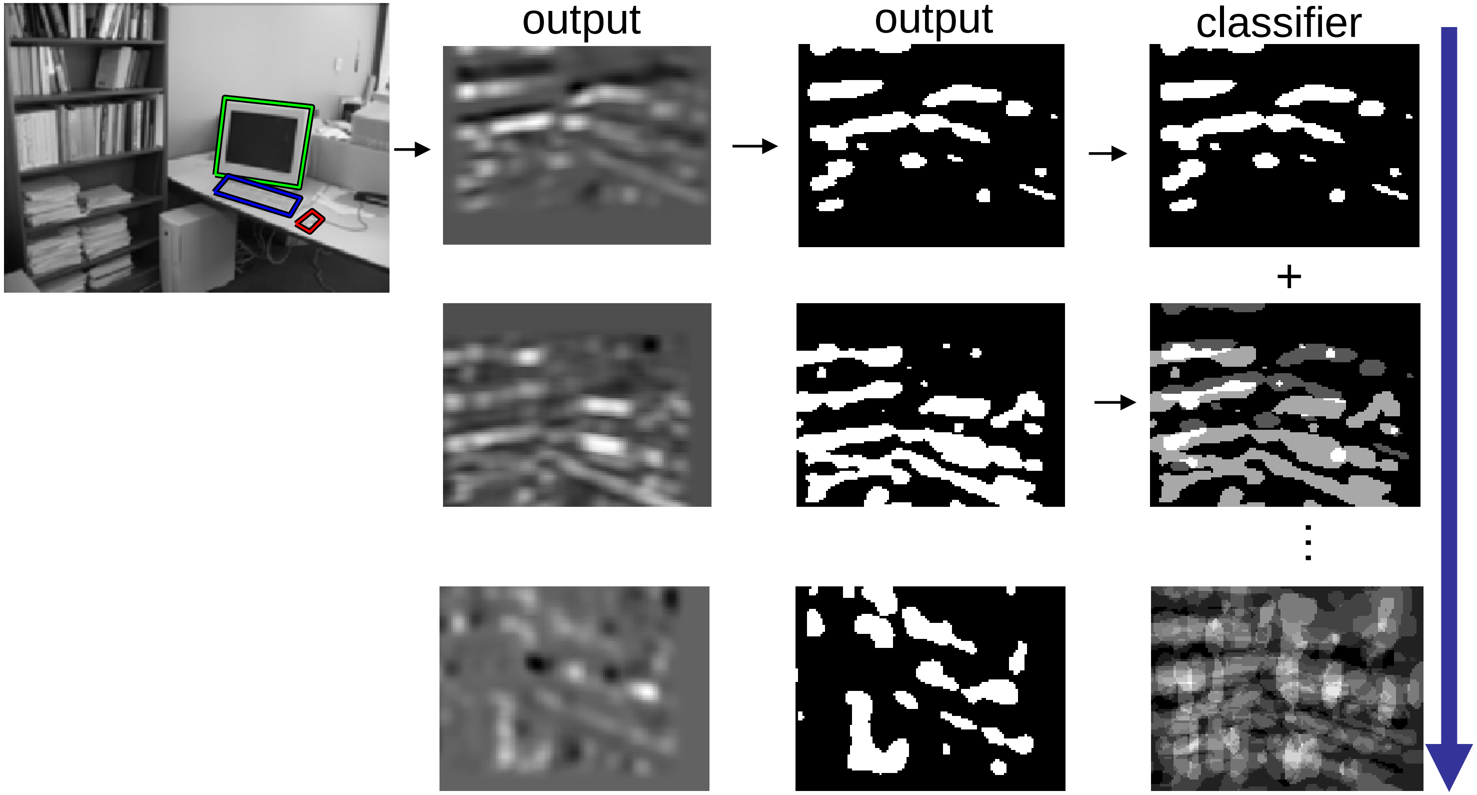
Strong classifier at iteration 2

Example: screen detection

Feature output

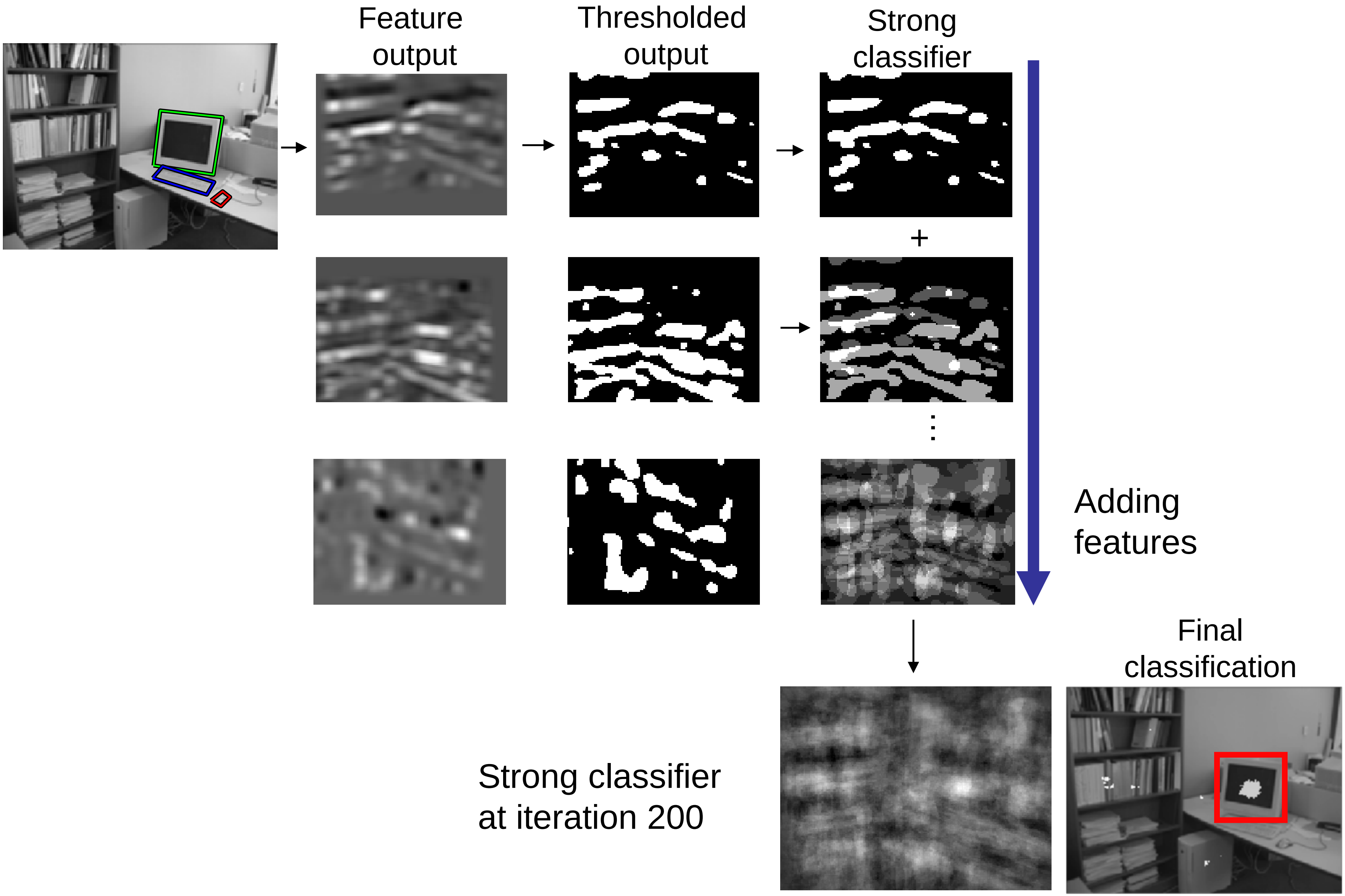
Thresholded output

Strong classifier



Strong classifier at iteration 10

Example: screen detection



Feature output

Thresholded output

Strong classifier

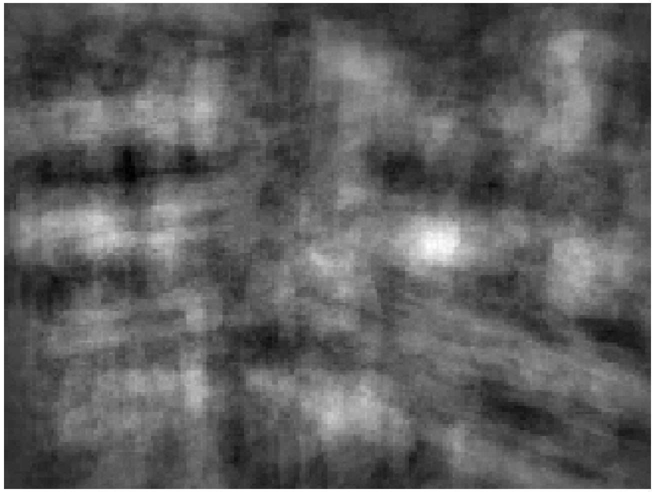
+

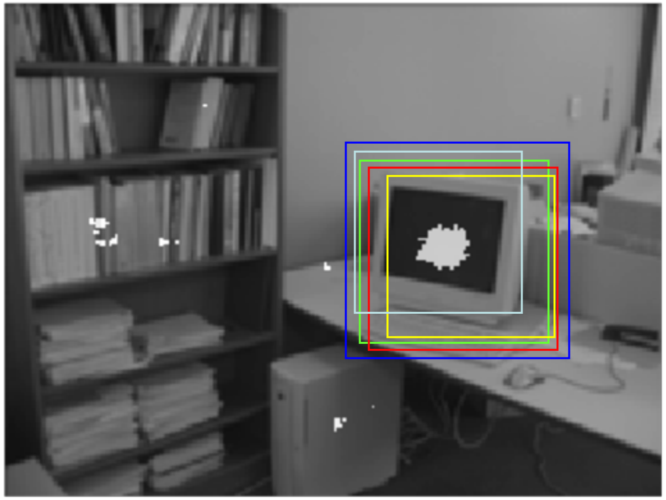
Adding features

Strong classifier at iteration 200

Final classification

Maximal suppression





Detect local maximum of the response. We are only allowed detecting each object once. The rest will be considered false alarms.

This post-processing stage can have a very strong impact in the final performance.