SAIR

Spatial AI & Robotics Lab

CSE 473/573-A

L20: RECOGNITION

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Objects vs Texture vs Scene

The texture

The object

The scene

Scenes vs. objects

A photograph of a firehydrant

A photograph of a street

Scene views vs. objects

- Scene:
  - a place in which a human can act within
  - or a place to which a human being could navigate.

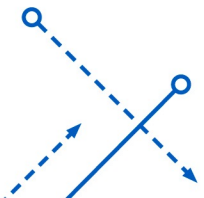




- A lot more than just a combination of objects
  - just as objects are more than the combinations of their parts.
- Associated with specific functions and behaviors (like objects)
  - E.g., eating in a restaurant, reading in a library,
  - Talking in classroom, playing in a park, etc

Why be concerned about the difference?

- Features to be extracted?
- Context for Recognition?
- Various **categories** have features that can be essential for interpretation.



Why do we care about categories?

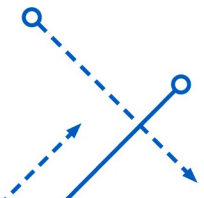
Perception of function:

- We can perceive the 3D shape, texture, material properties, without knowing about objects.
- But, the concept of category encodes 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*.

Why do we care about categories?

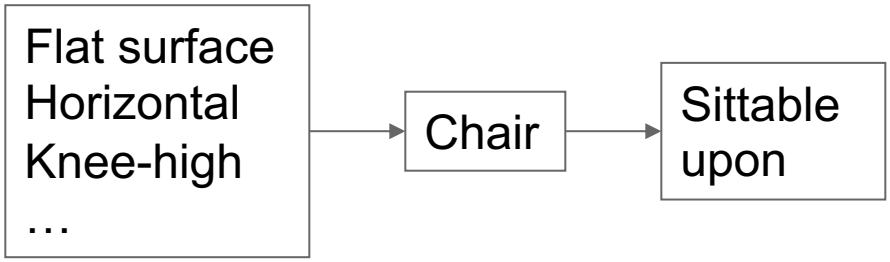
- When we recognize an object, we can make
  - predictions about its behavior in the future
  - beyond of what is immediately perceived.



The perception of function

- Direct perception (affordances): [introduced by Gibson]

- Mediated perception (Categorization)



- One caveat of this comparison:
  - Deciding that something is a chair might require access to more features than deciding that we can sit on something
  - A different level of categorization.

Direct perception

Some aspects of an object function can be perceived directly

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

It does not seem easy to sit-upon this…

Limitations of Direct Perception

- Objects of similar structure might have very different functions

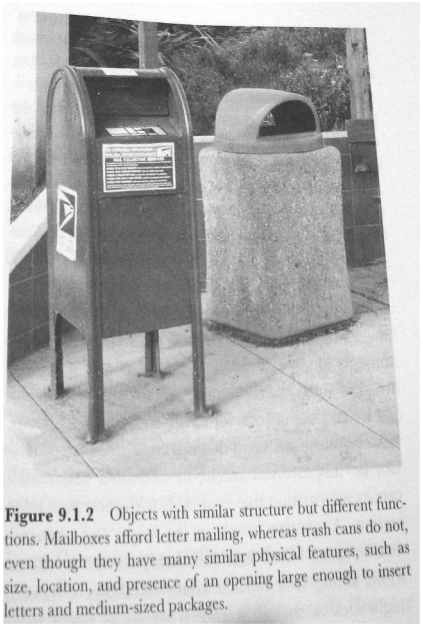


Figure 9.1.2 Objects with similar structure but different functions. Mailboxes afford letter mailing, whereas trash cans do not, even though they have many similar physical features, such as size, location, and presence of an opening large enough to insert letters and medium-sized packages.

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

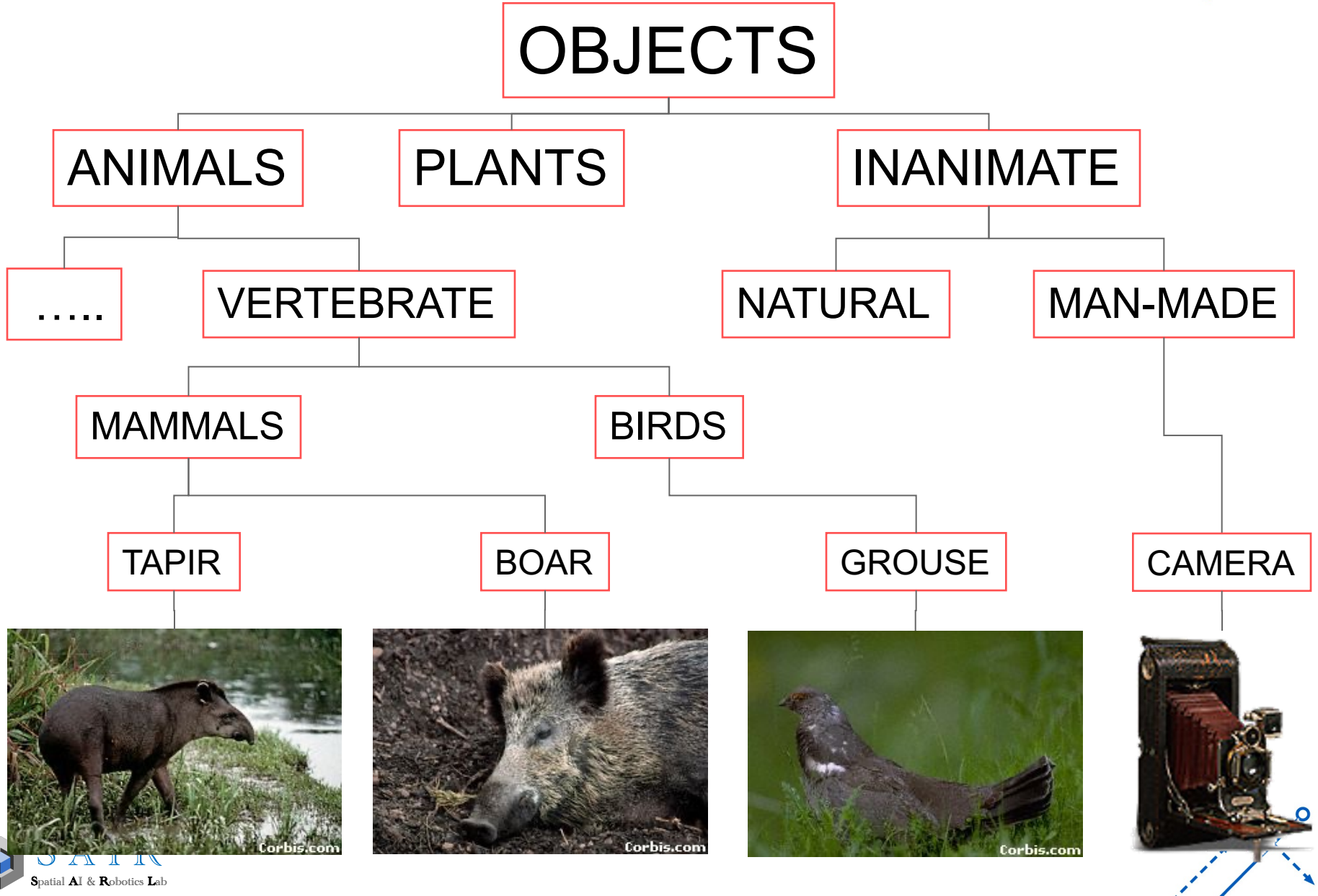
The functions are the same at some level of description: we can put things inside in both and somebody will come later to empty them. However, we are not expected to put inside the same kinds of things…

Which level of categorization is the right one?

- Car is an object composed of:
  - a few doors, four wheels (not always visible), 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.

Object Category



Entry-level categories

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

A bird

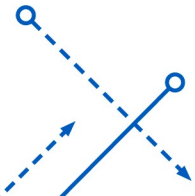
An ostrich

(Jolicoeur, Gluck, Kosslyn 1984)

Demo : Rapid image understanding

Instructions: 9 photographs will be shown for half a second each. Your task is to **memorize these pictures.**

GET READY



Memory Test

Have you seen this picture ?

Memory Test

Memory Test

Have you seen this picture ?

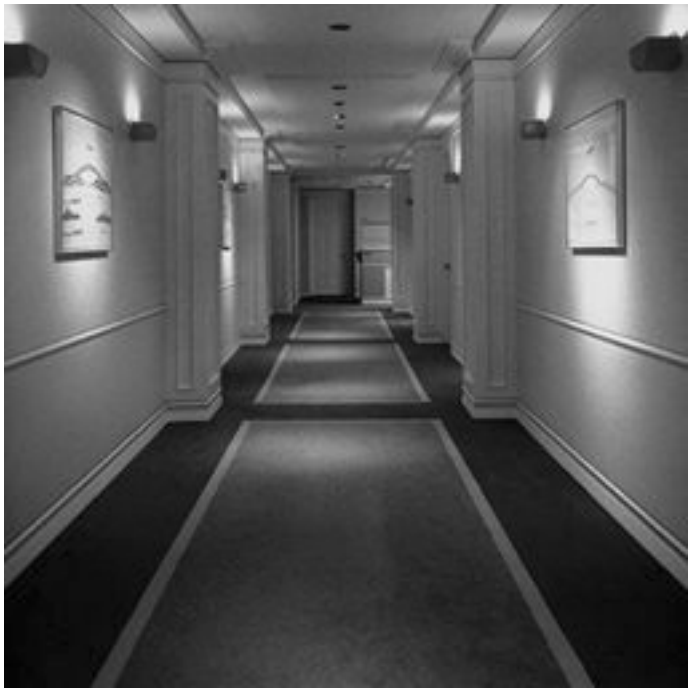
Memory Test

Memory Test

Have you seen this picture ?

Memory Test

Memory Test



Have you seen this picture ?

Memory Test

Memory Test

Have you seen this picture ?

Memory Test

Memory Test

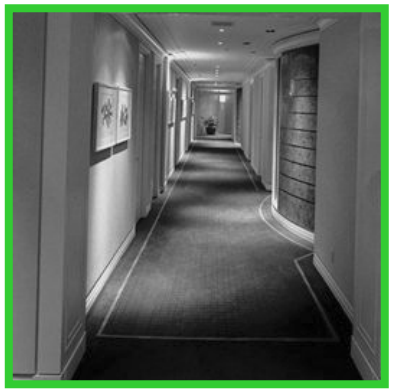
Have you seen this picture ?

Memory Test

Memory Test Overview

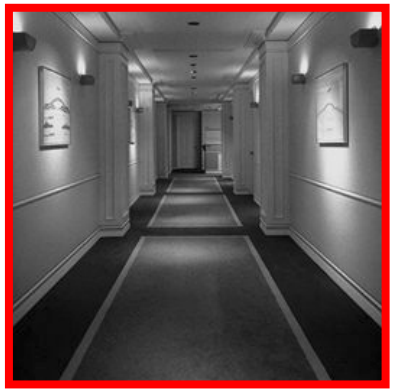
You have seen these pictures






You were tested with these pictures






The gist of the scene

In a glance, we remember the meaning of an image and its global **layout** but some objects and **details** are forgotten

Mary Potter (1976)

Mary Potter (1975, 1976) demonstrated

- during a rapid sequential visual presentation (100 msec per image), a novel picture is instantly **understood** and observers seem to comprehend a lot of visual information

Object Categorization: Easy?

- How to recognize ANY car

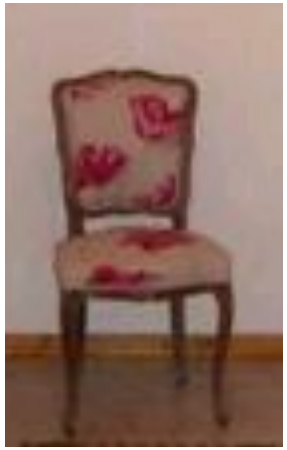




- How to recognize ANY cow

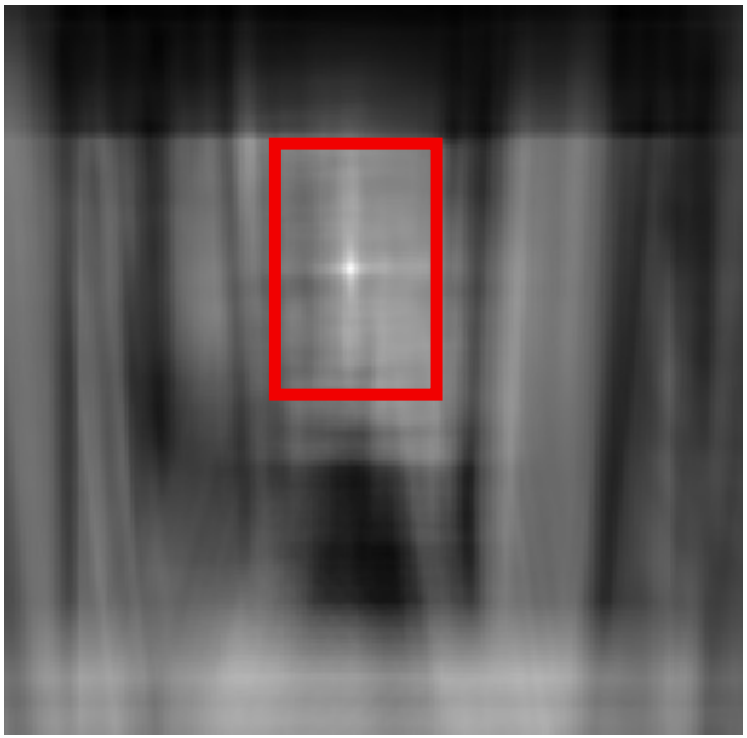

Object recognition: Is it really so hard?

This is a chair



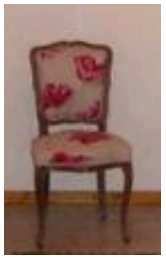
Find the chair in this image

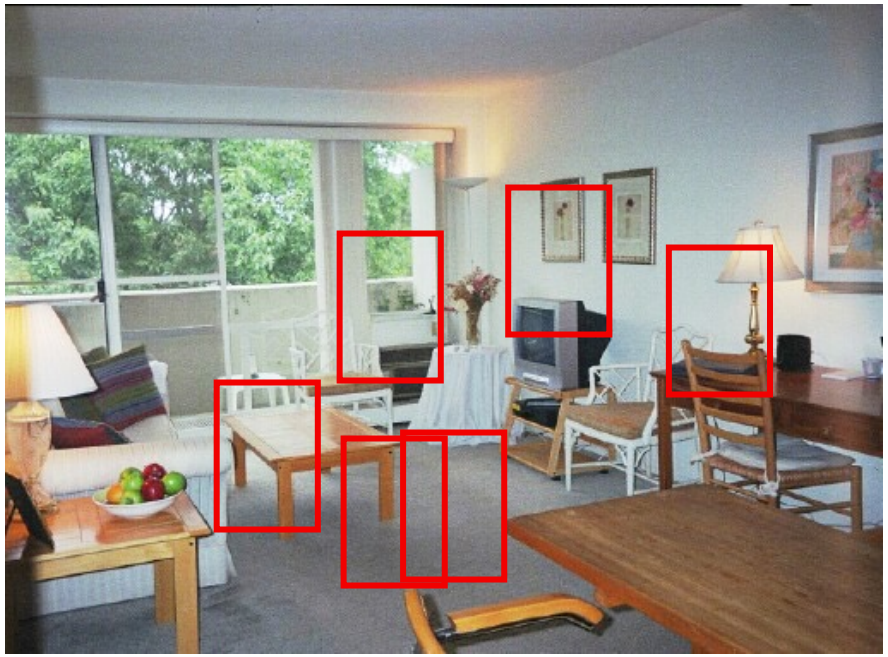
Output of normalized correlation

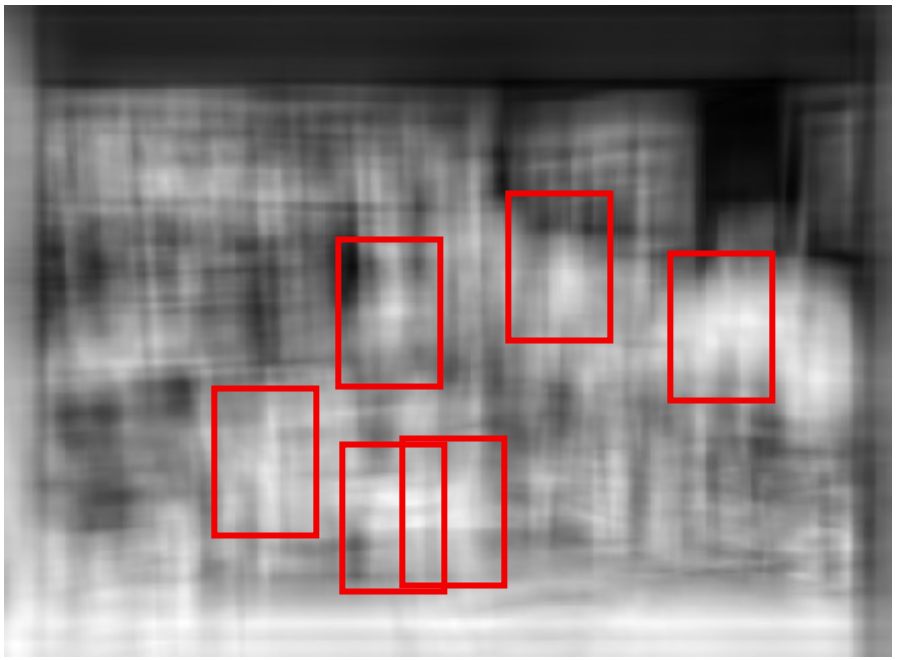


Object recognition: Is it really so hard?

Find the chair in this image







Pretty much garbage
Template matching cannot make it.

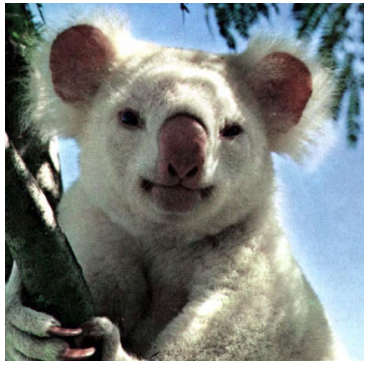
Challenges: robustness

Illumination

Object pose

Clutter

Occlusions

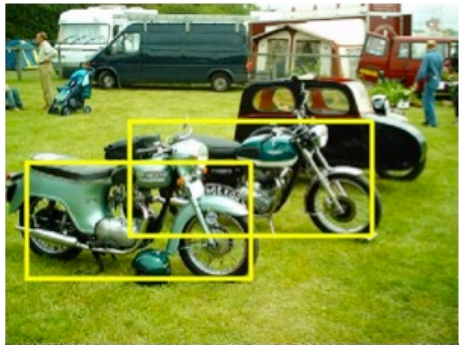


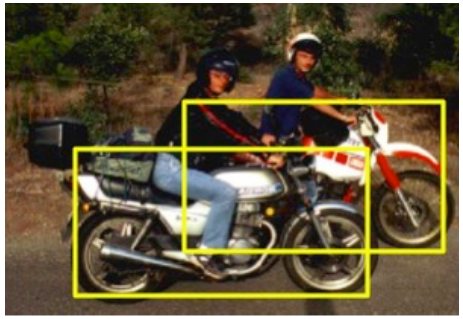
Intra-class appearance

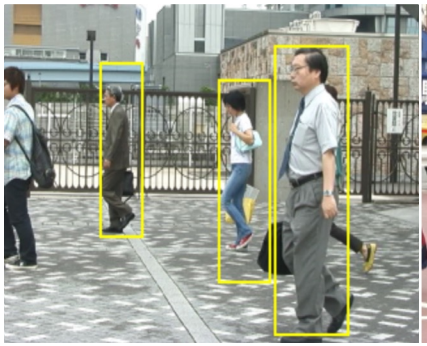
Viewpoint

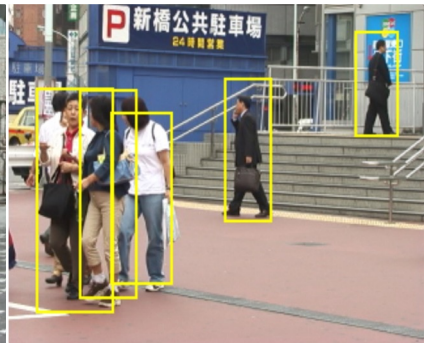
Challenges: robustness/invariance

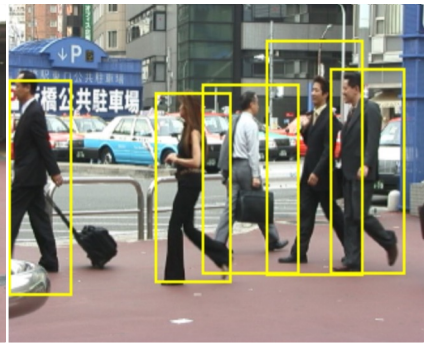
- Detection in Crowded Scenes
  - Learn object variability
    - Changes in appearance, scale, and articulation
  - Compensate for clutter, overlap, and occlusion











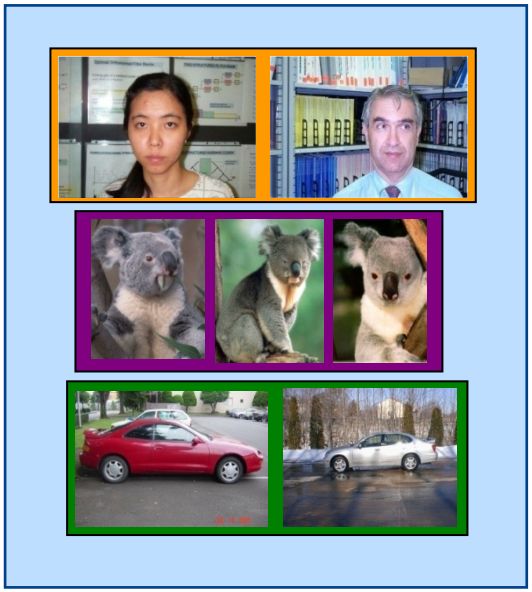
Challenges: context and human experience

Challenges: context and human experience

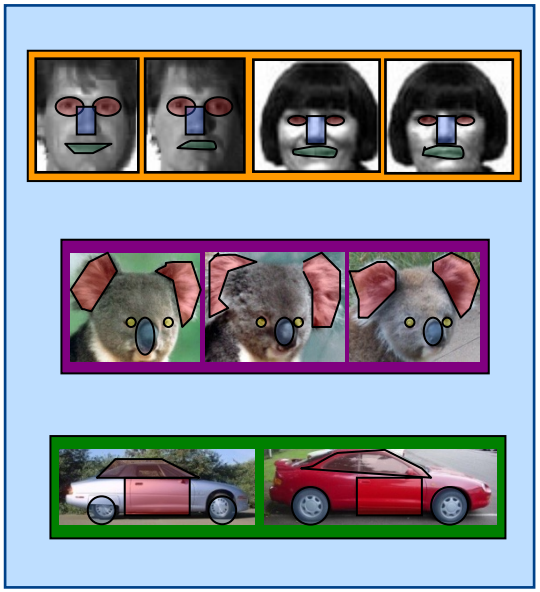
Challenges: learning with minimal supervision

Less ⋮ ⋮ **More**

Unlabeled, multiple objects



Classes labeled, some clutter



Cropped to object, parts and classes labeled

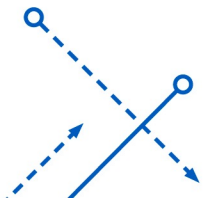
Inputs/outputs/assumptions

What is the **goal**?

- Say yes/no as to whether an object present in image

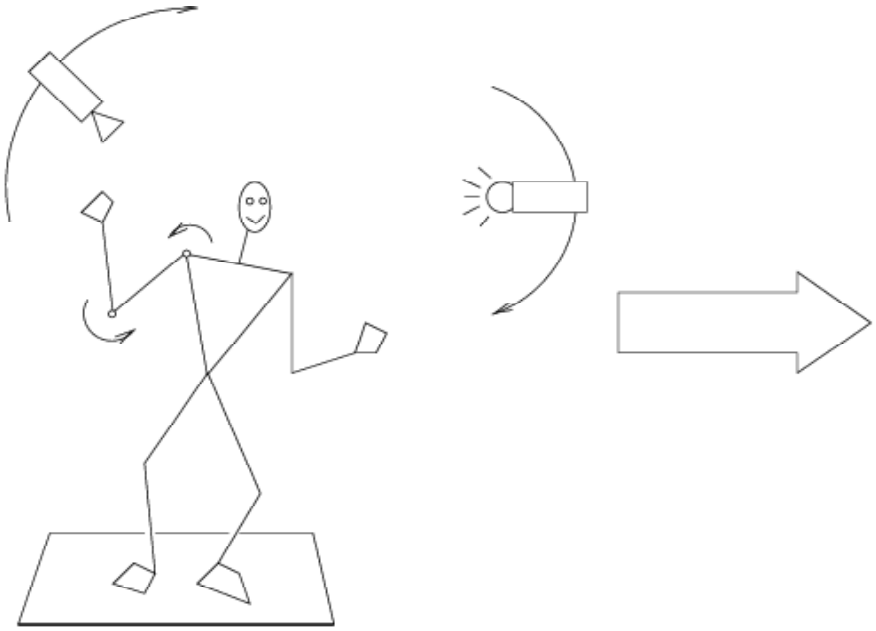
And/or:

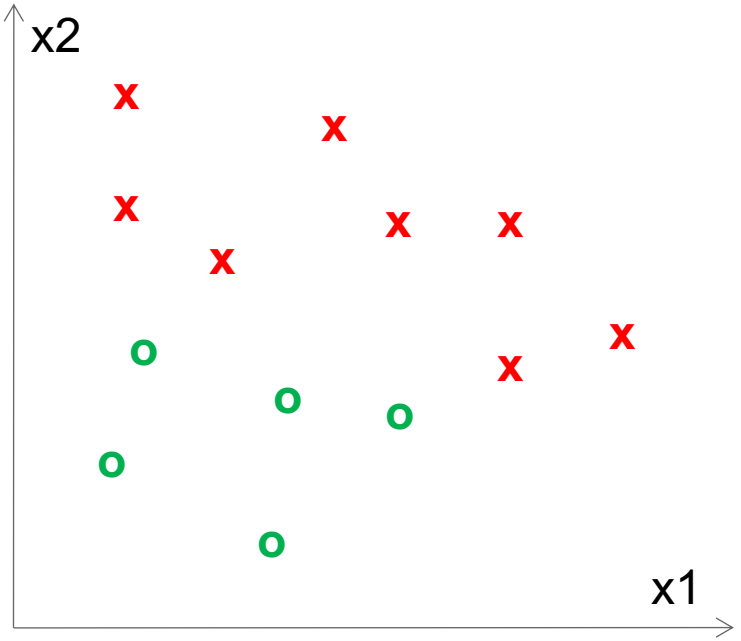
- Categorize all objects
- Forced choice from pool of categories
- Bounding box on object
- Full segmentation
- Build a model of an object category
- Determine pose of an object, e.g., for robot to grasp



Recognition is all about modeling variability

- Invariance is the key challenge to computer vision.





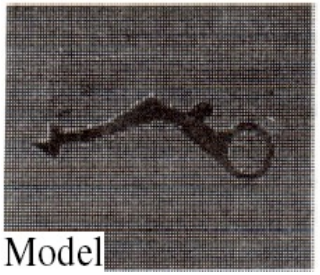
Variability:

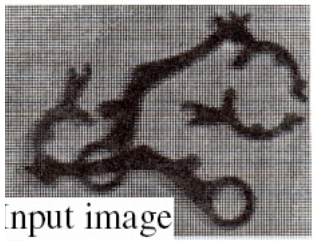
Camera position
Illumination
Shape parameters

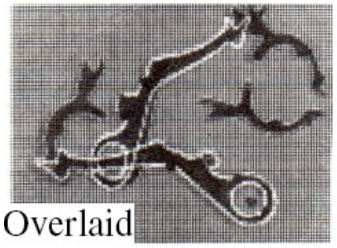
Within-class variations?

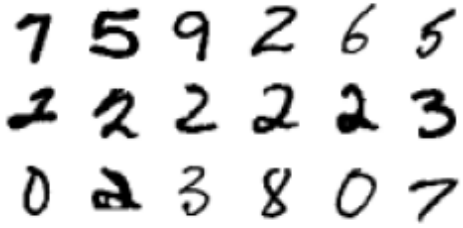
Within-class variations

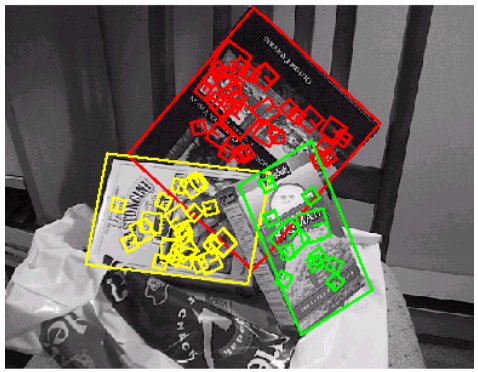
Rough Evolution of Focus in Object Recognition

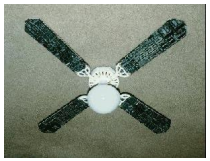


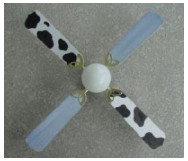


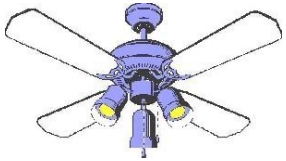






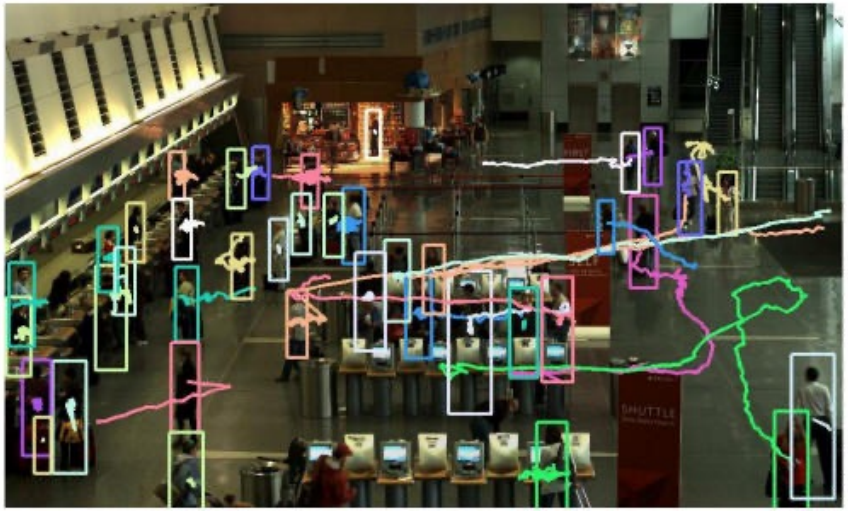


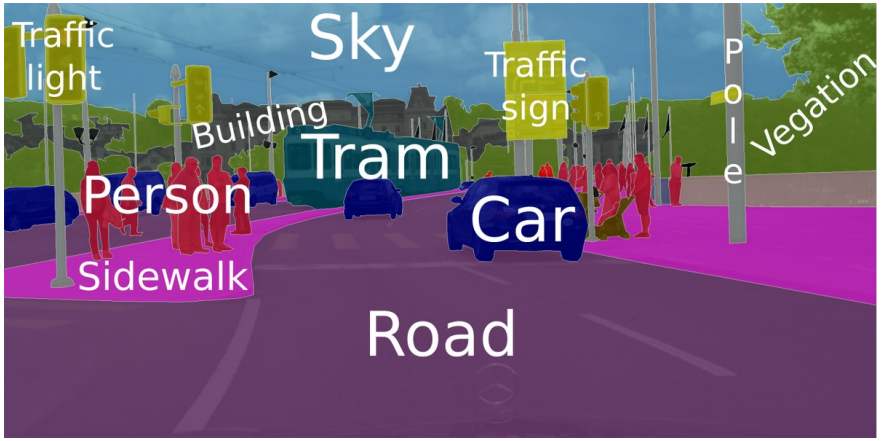


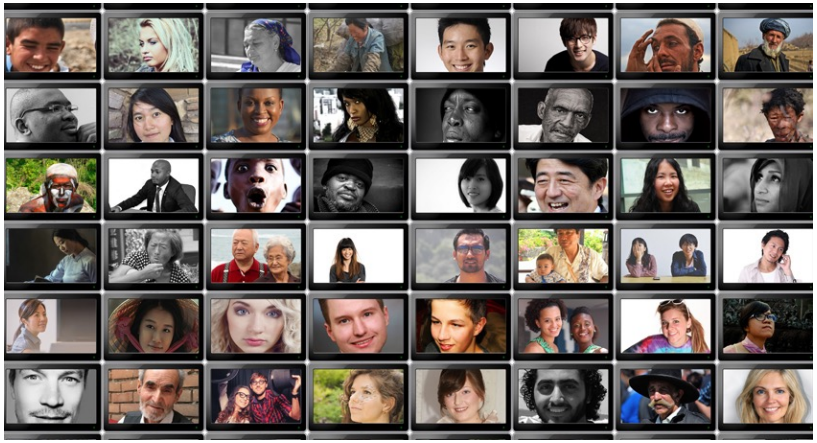


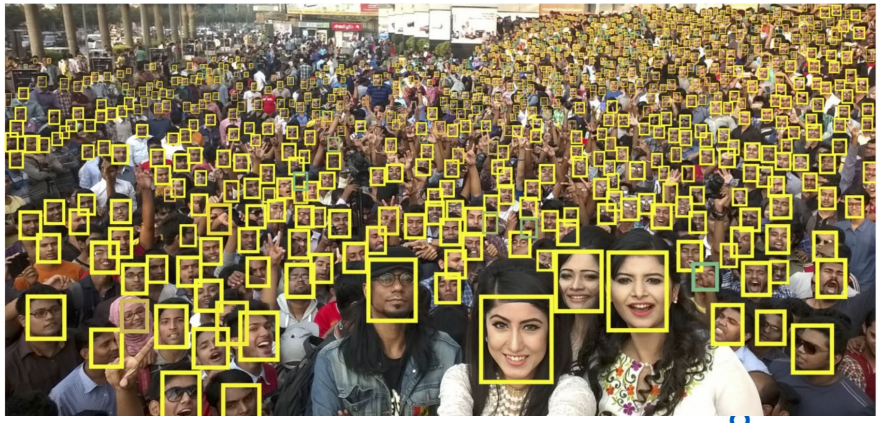
1980s **1990s to early 2000s** **2000-2010…**

Today









In 2014, image recognition by computer outperforms human.

History of ideas in recognition

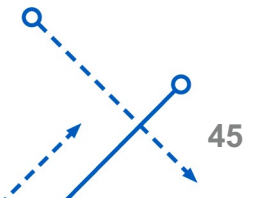
- 1960s – early 1990s: the geometric era

Variability: Camera position
Illumination

Shape: Assumed known

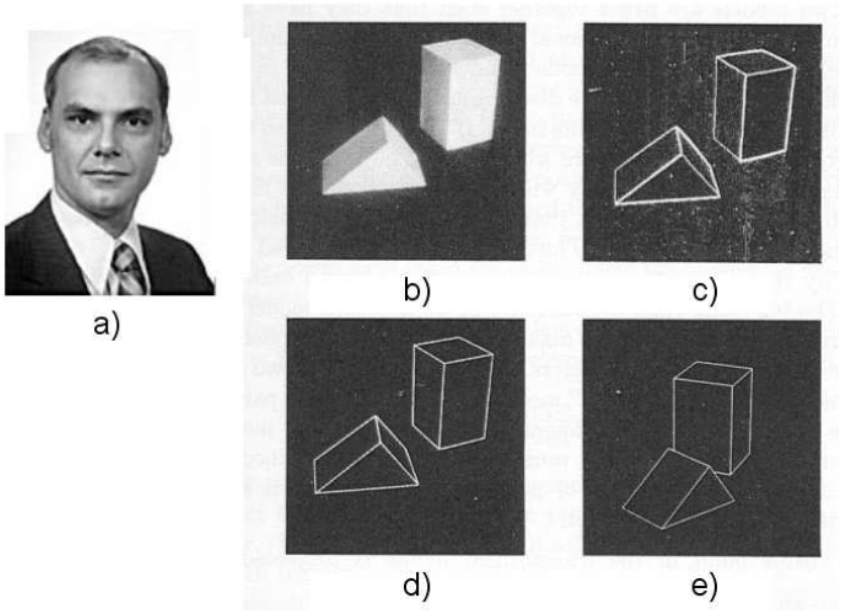
Focus: **Alignment**

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



History of ideas in recognition

- Recognition as an alignment problem: Block world



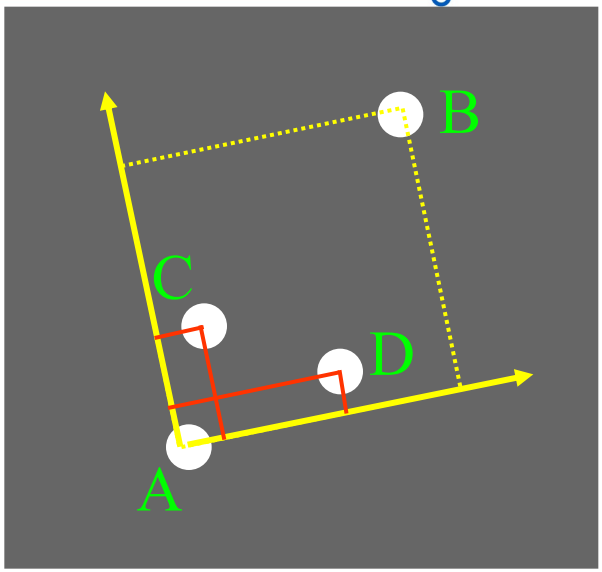
L. G. Roberts, *Machine Perception of Three Dimensional Solids*, Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

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

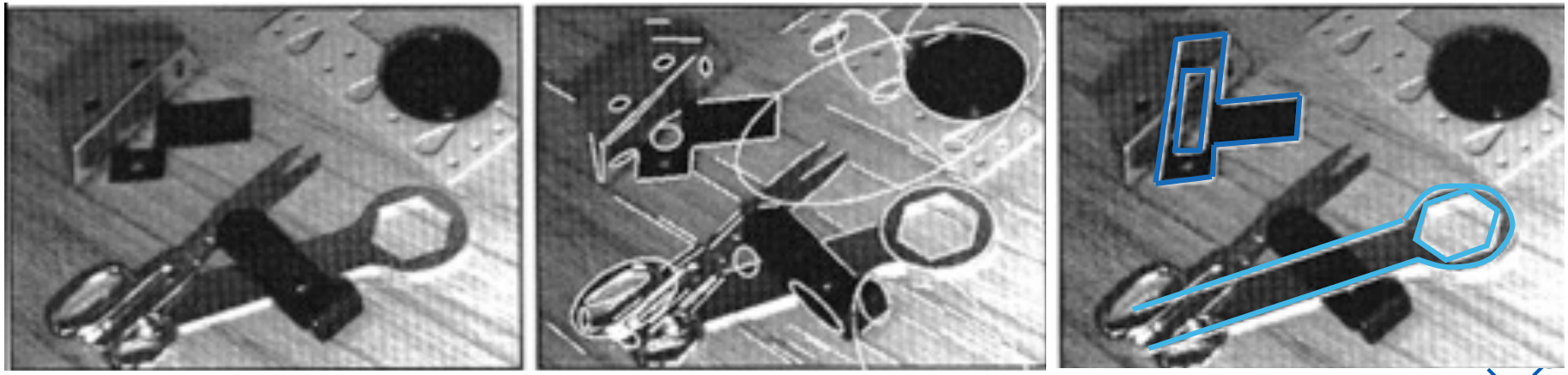
History of ideas in recognition

Example:
invariant to similarity transformations
computed from four points



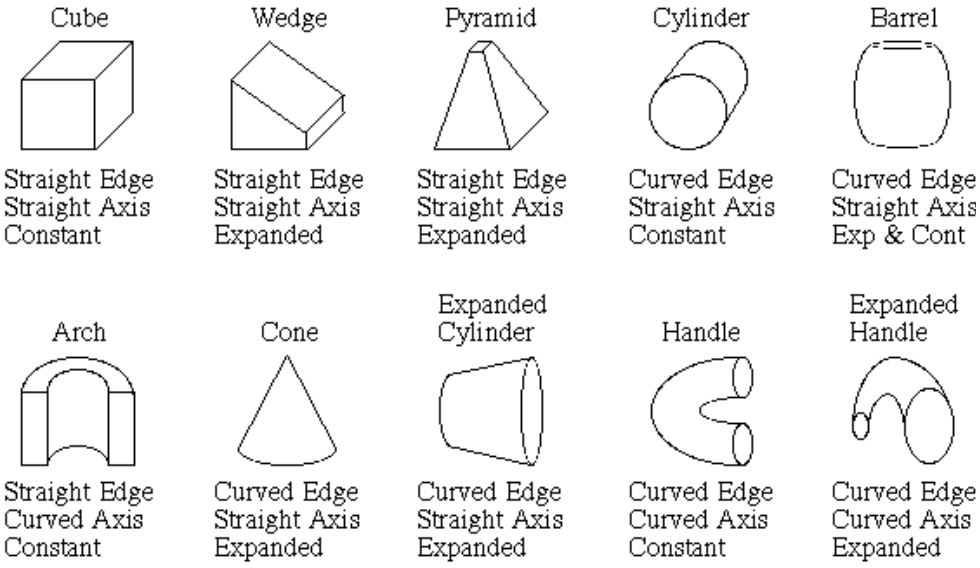
General 3D objects do not admit monocular viewpoint invariants (Burns et al., 1993)

Projective invariants (Rothwell et al., 1992):

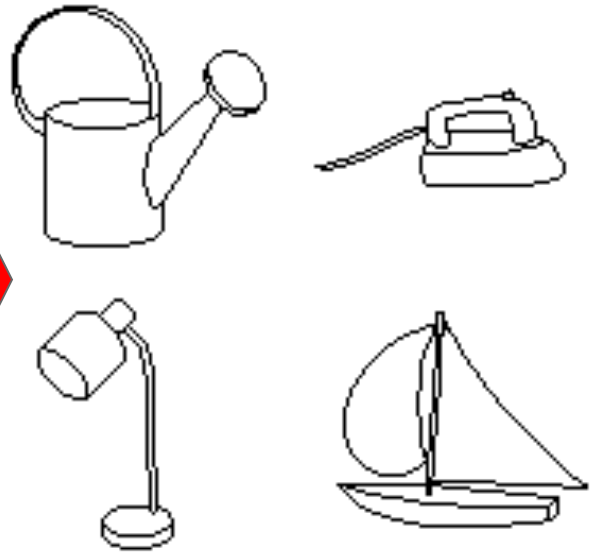


Recognition by components

Primitives (geons) Biederman (1987)

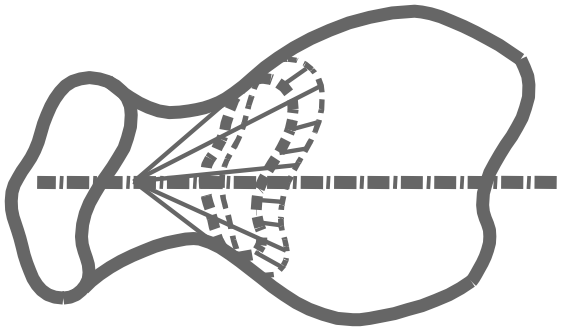


Objects

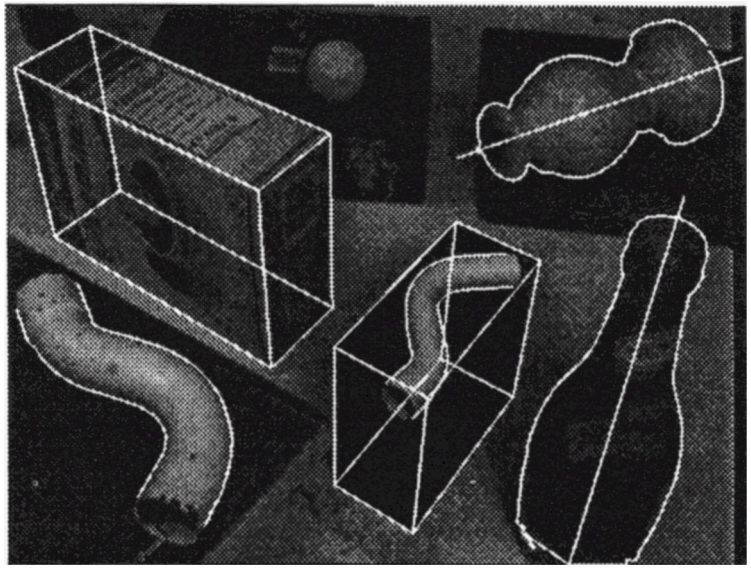


http://en.wikipedia.org/wiki/Recognition_by_Components_Theory

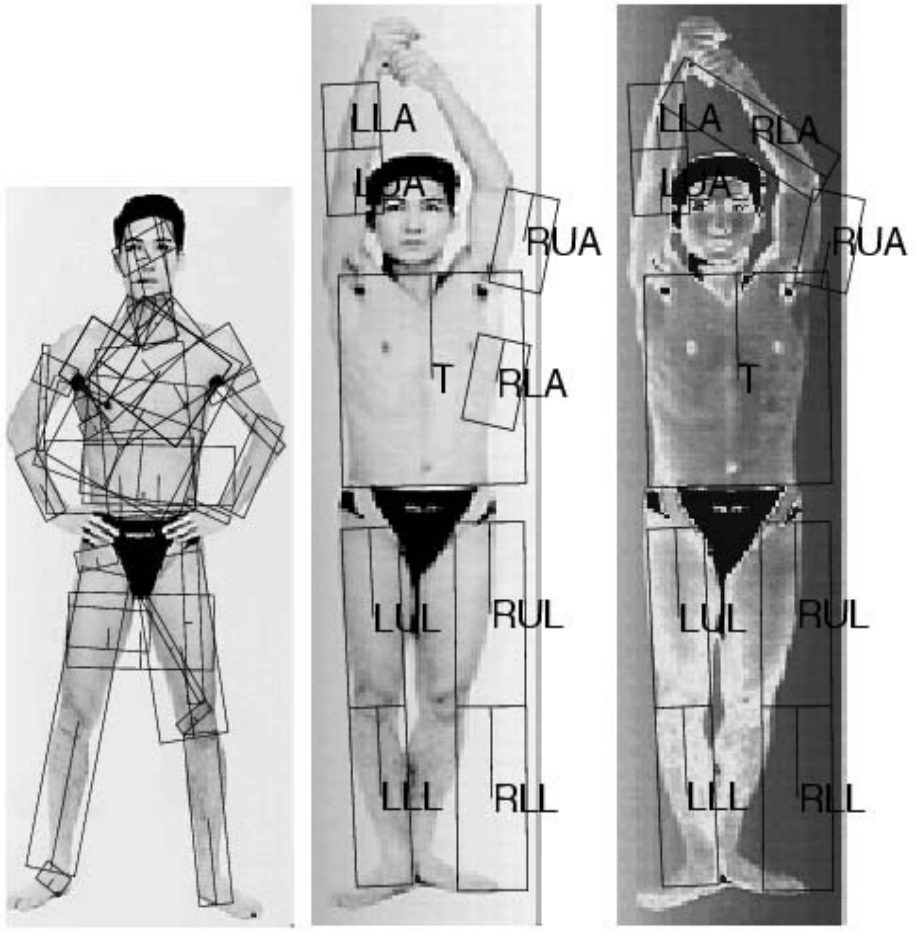
Recognition by components



Generalized cylinders
[Ponce et al. (1989)]



Zisserman et al. (1995)



Forsyth (2000)

History of ideas in recognition

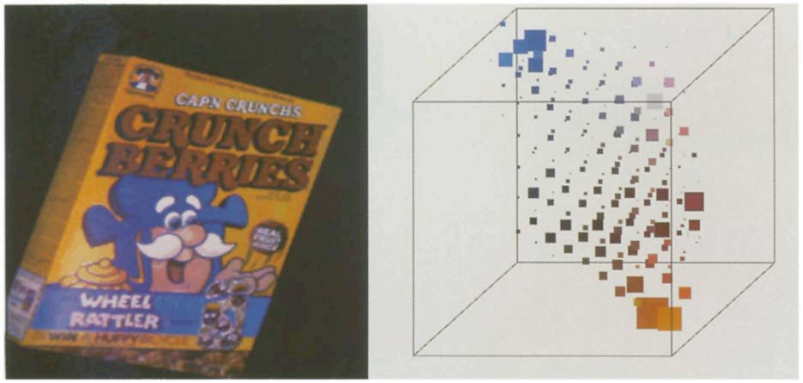
- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models

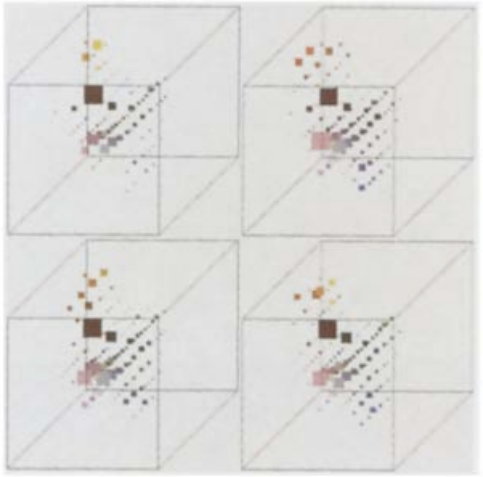
Empirical models of image variability

Appearance-based techniques

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

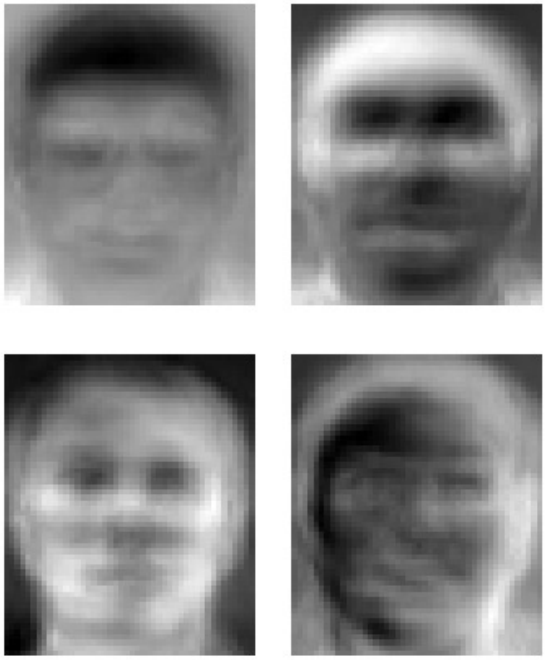
Color Histograms





Swain and Ballard, Color Indexing, IJCV 1991.

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

History of ideas in recognition

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

Sliding window approaches

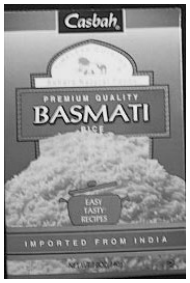
Turk and Pentland, 1991
Belhumeur, Hespanha, & Kriegman, 1997
Schneiderman & Kanade 2004
Viola and Jones, 2000

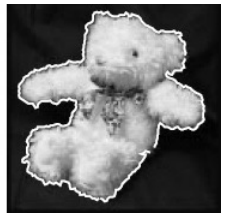
Schneiderman & Kanade, 2004
Argawal and Roth, 2002
Poggio et al. 1993

History of ideas in recognition

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

Local features for instance recognition





D. Lowe (1999, 2004)

Large-scale image search

Combining local features, indexing, and spatial constraints

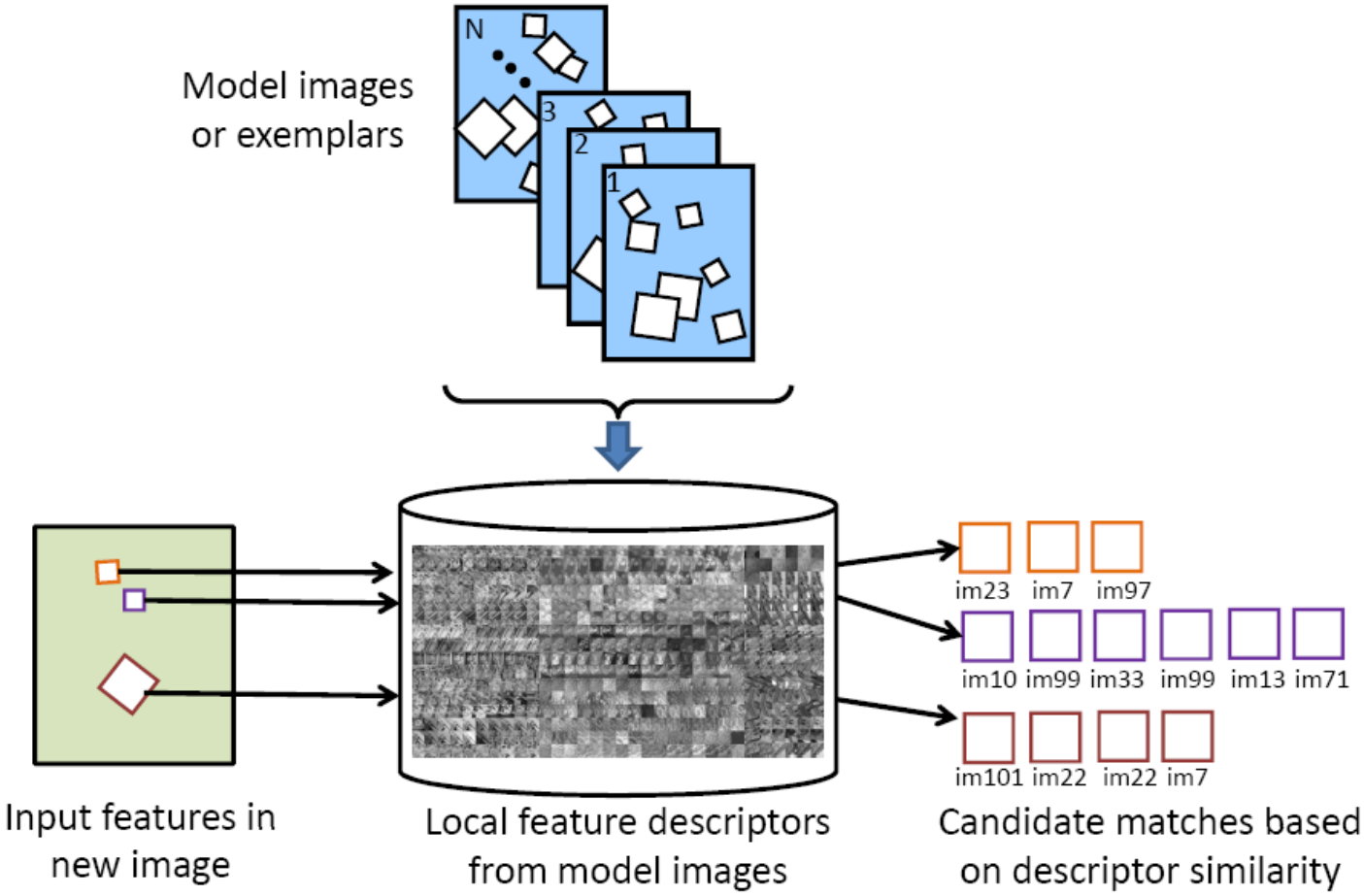


Image credit: K. Grauman and B. Leibe

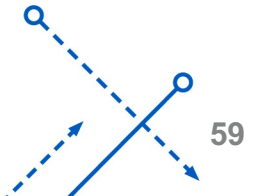
Large-scale image search

Combining local features, indexing, and spatial constraints

Philbin et al. ‘07

History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 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**

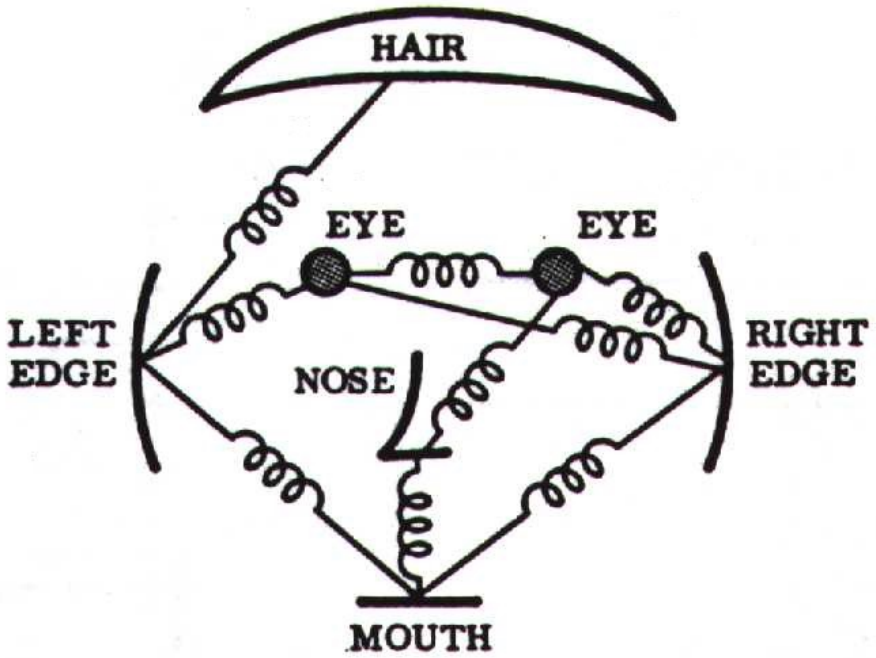
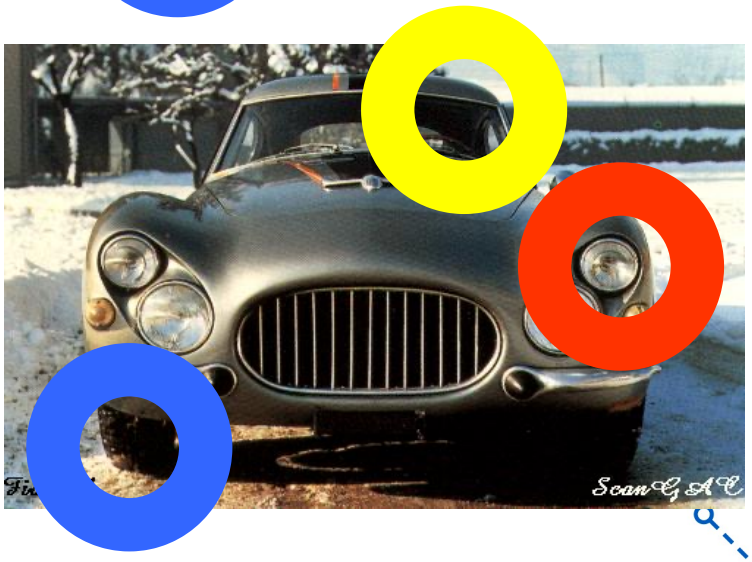


Figure from [Fischler & Elschlager 73]

Constellation models

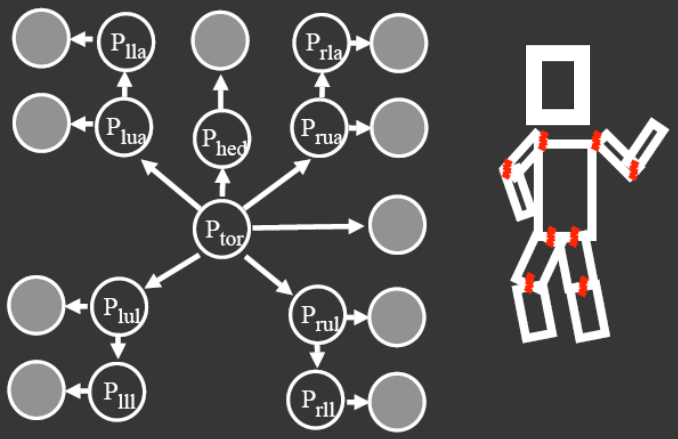


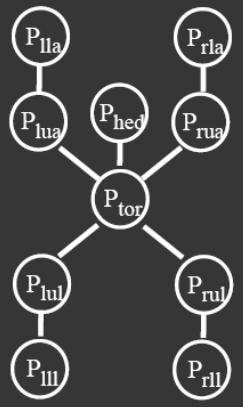
Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

Representing people

Pictorial structure model

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

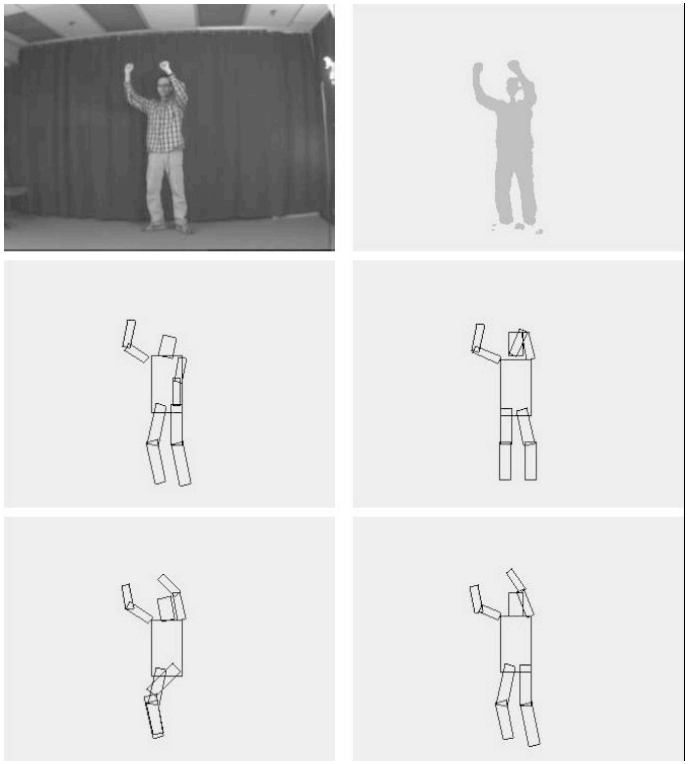




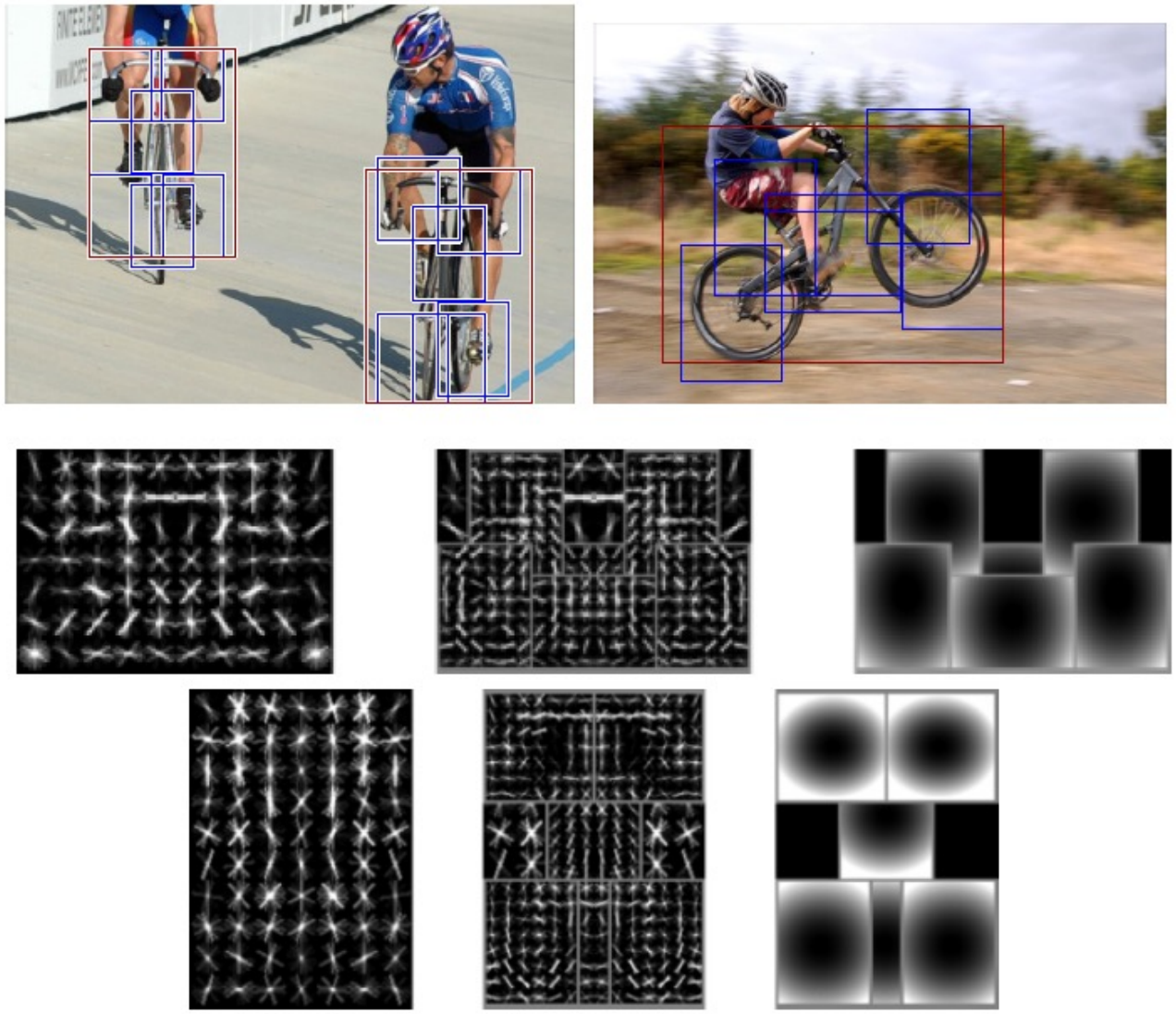
$$\Pr(P_{tor}, P_{arm}, \ldots | \mathrm{Im}) \propto \prod_{i,j} \Pr(P_i \mid P_j) \prod_i \Pr(\mathrm{Im}(P_i))$$

part geometry

part appearance



Discriminatively trained part-based models



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

History of ideas in recognition

- 1960s – early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features

Bag-of-features models

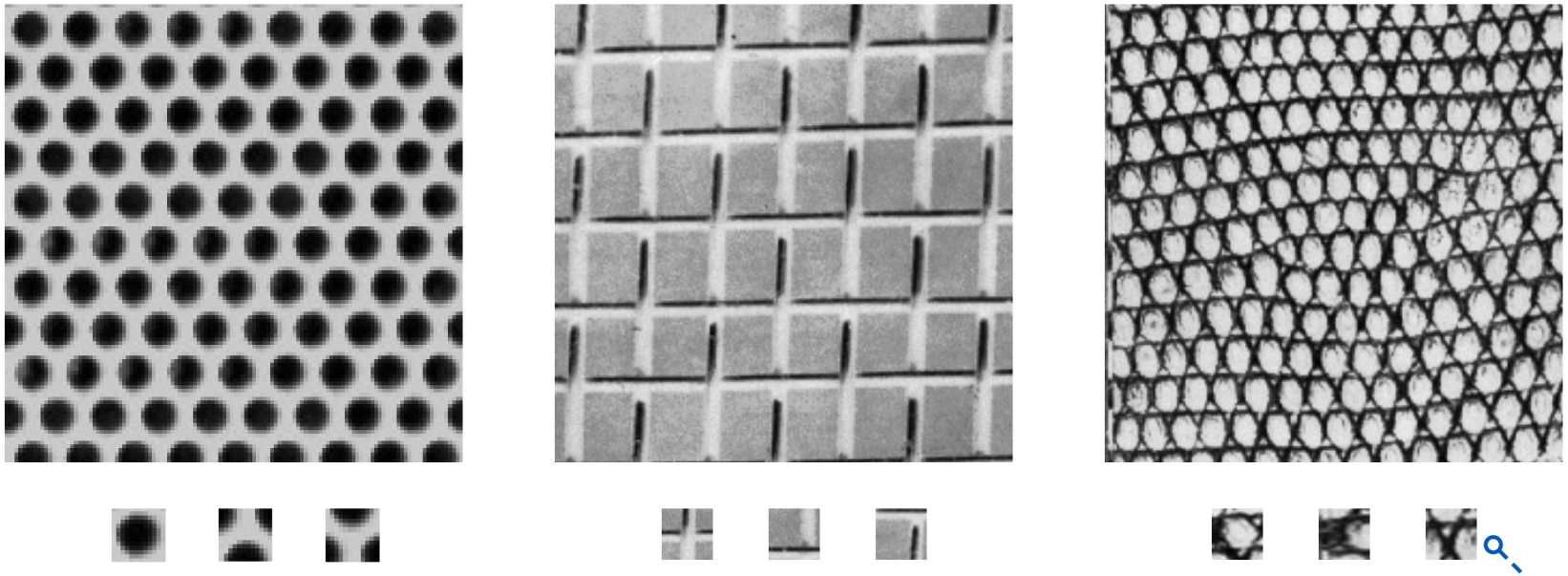
Bag-of-features models

Object

Bag of ‘words’

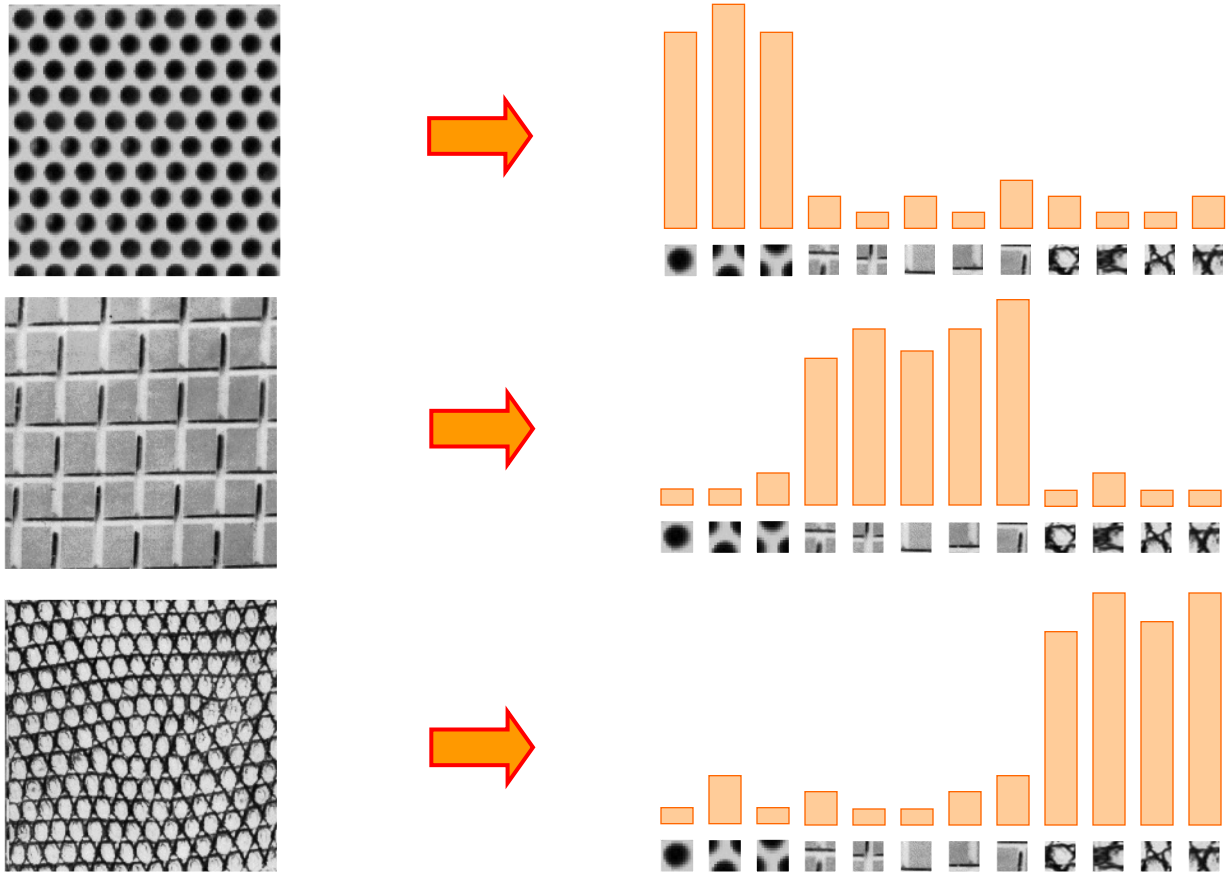
Origin 1: Texture recognition

- Texture is characterized by the **repetition** of **basic elements** or ***textons***
- For stochastic textures, the **identity** of the textons is more important than their **spatial** arrangement



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Origin 1: Texture recognition



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

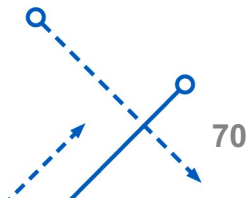
Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

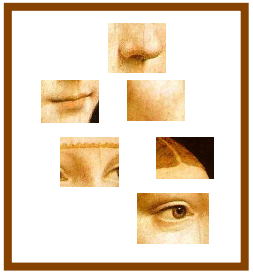
US Presidential Speeches Tag Cloud
http://chir.ag/phernalia/preztags/

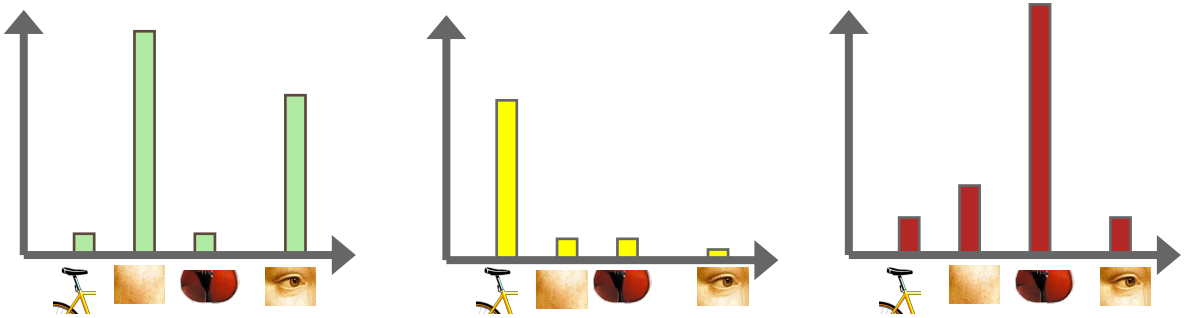
Bag-of-features steps

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



Bag-of-features steps



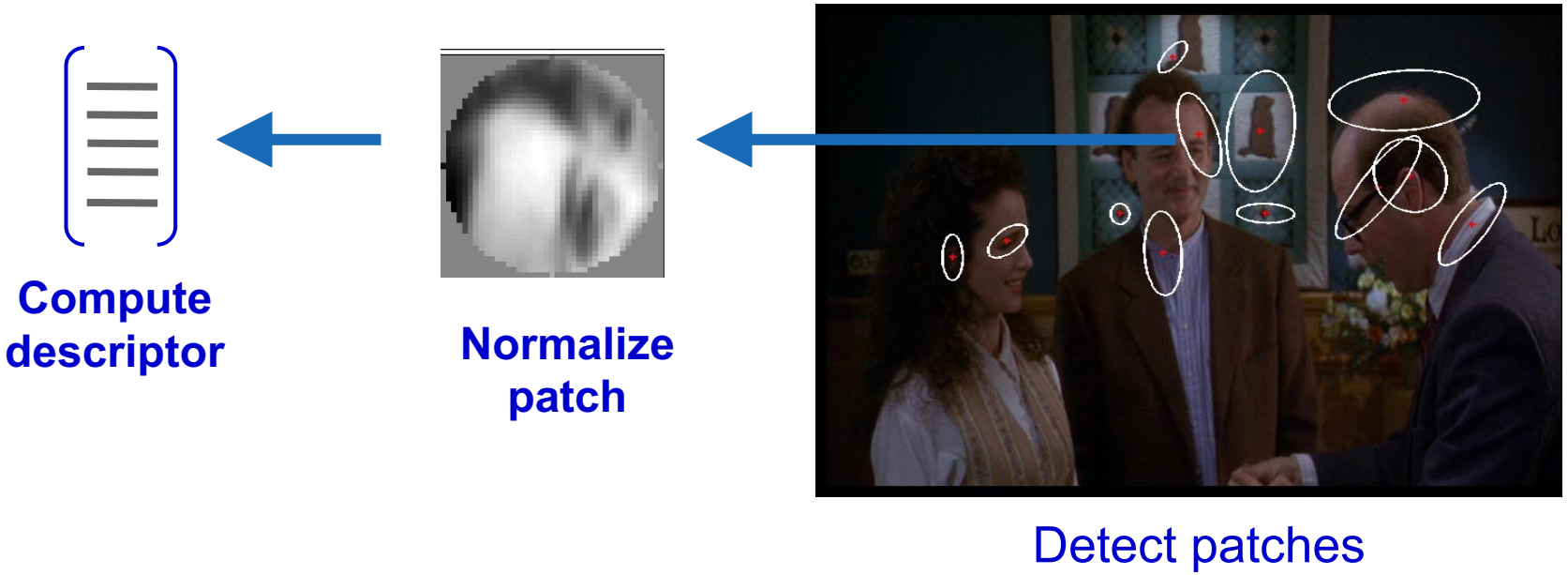


1. Feature extraction

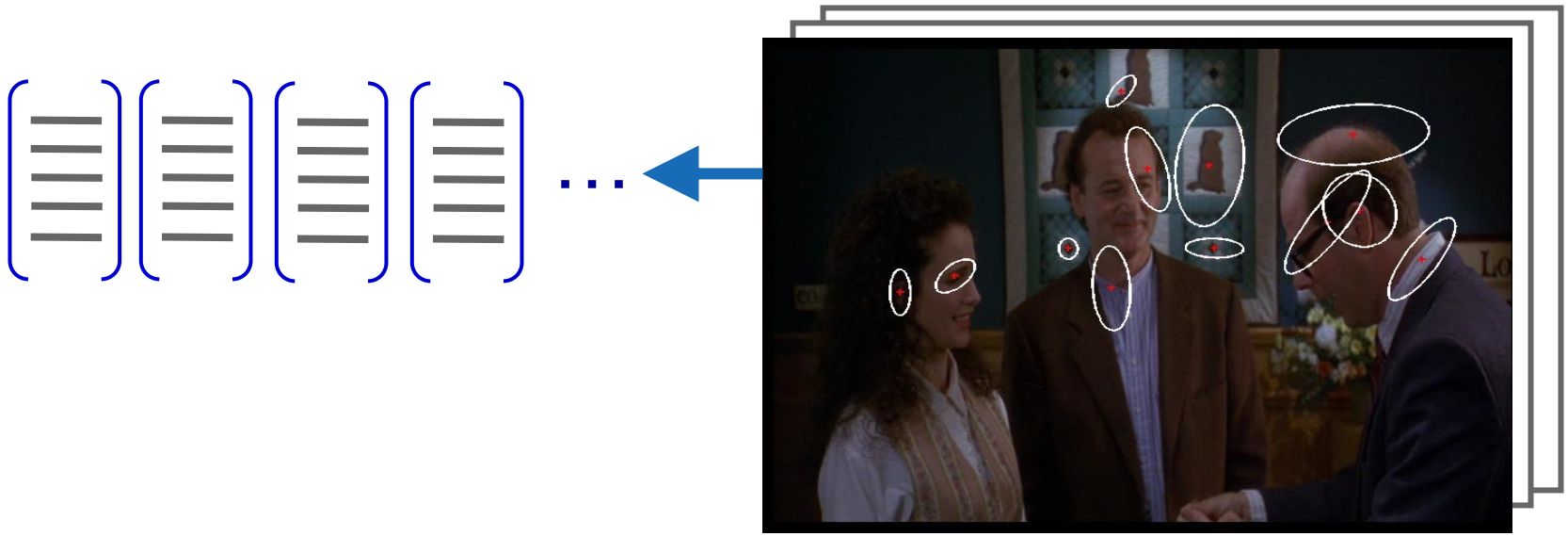
Regular grid

Interest regions

1. Feature extraction

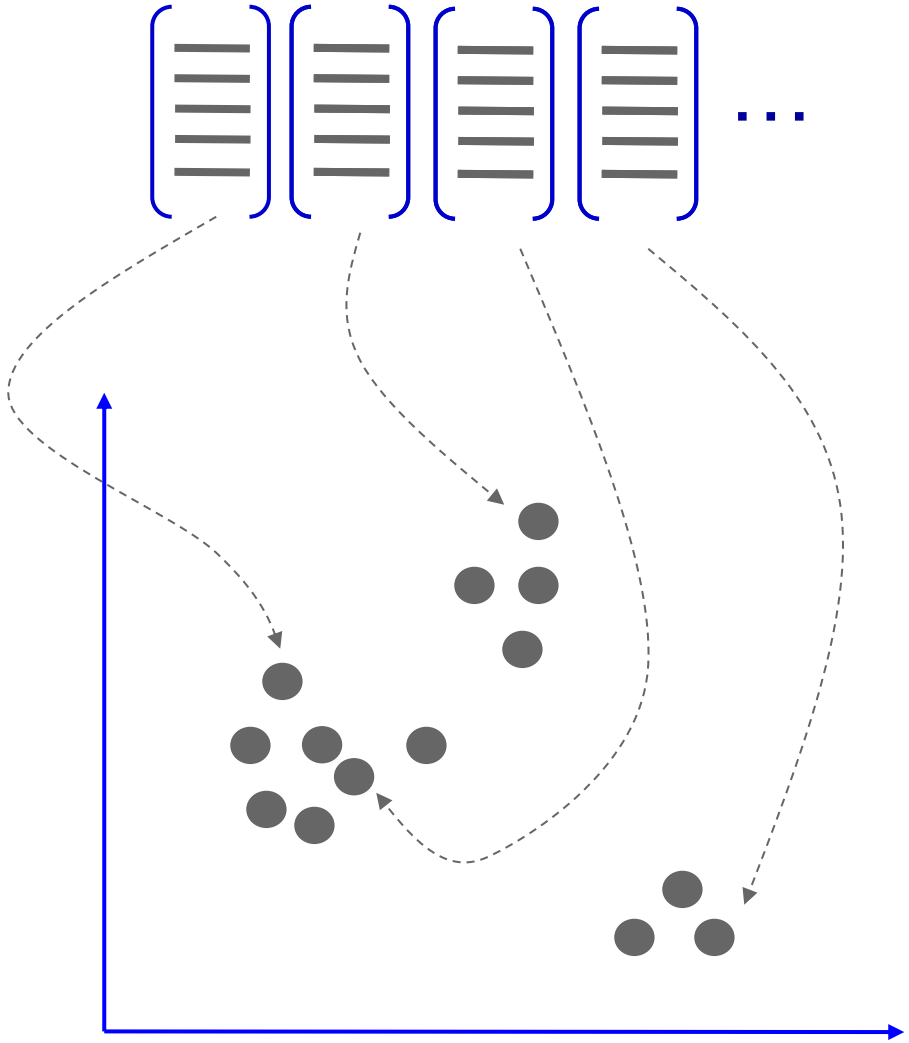


1. Feature extraction



Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

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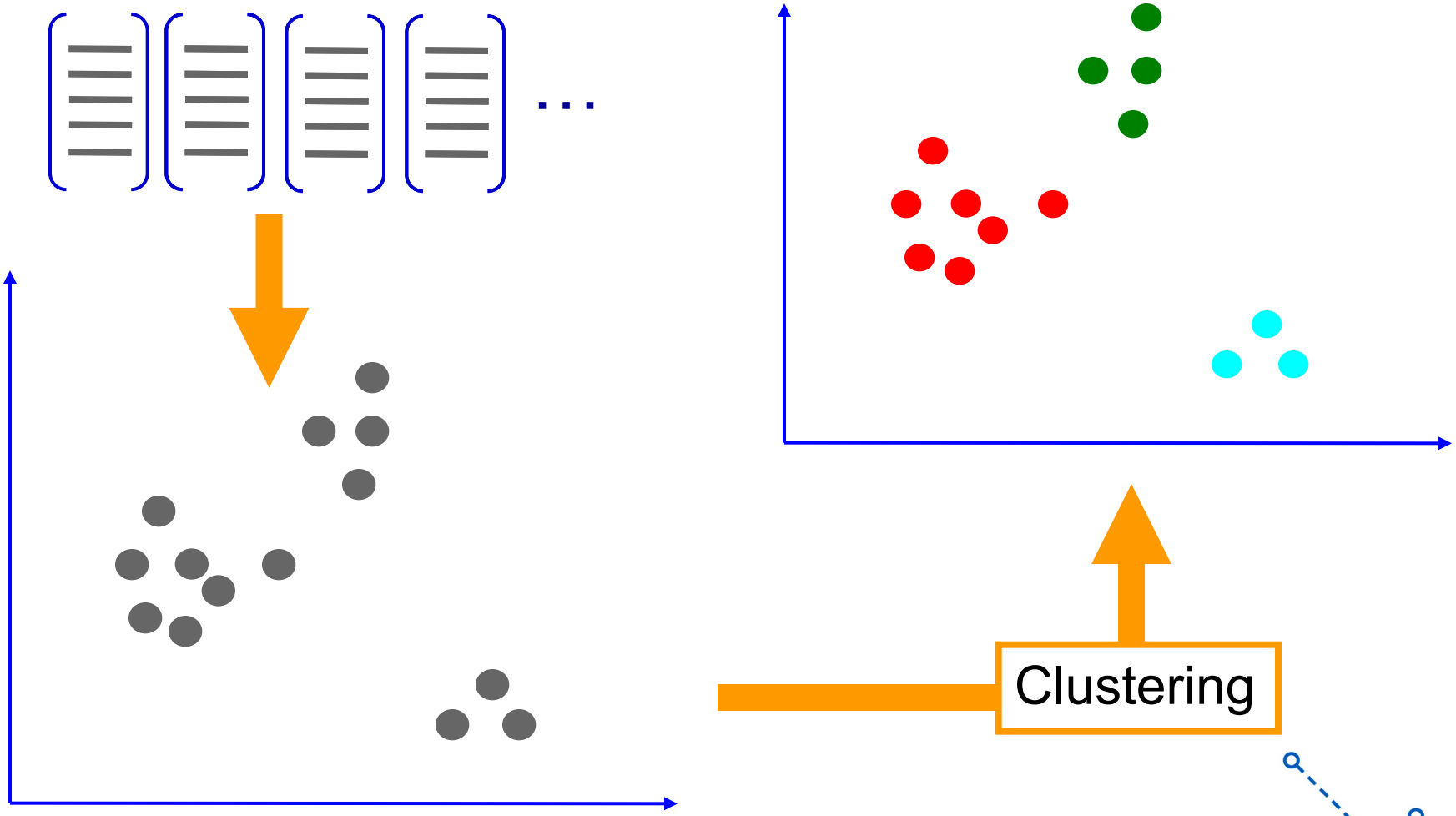

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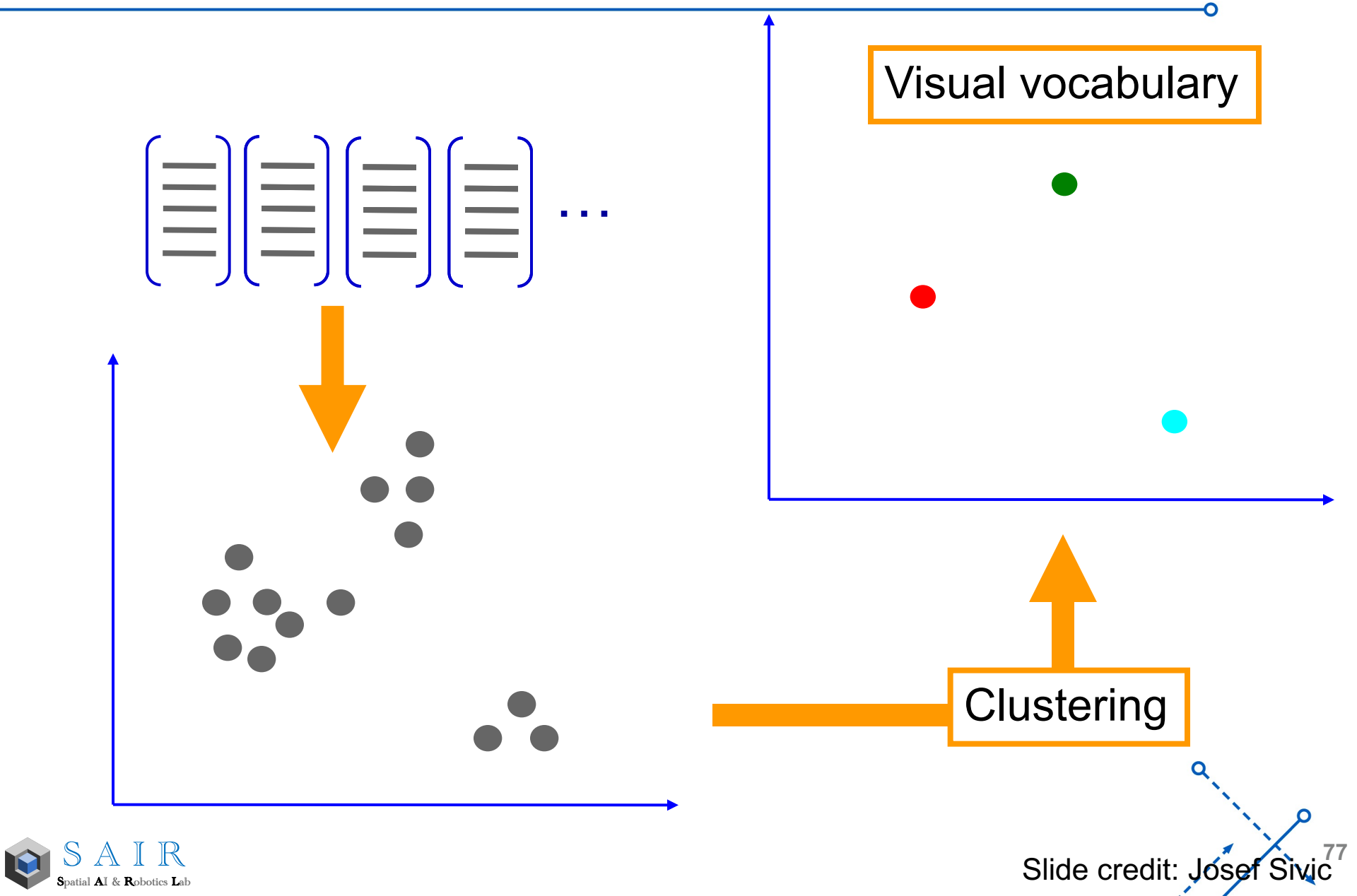
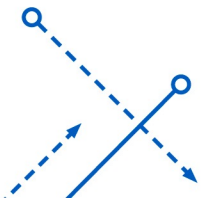


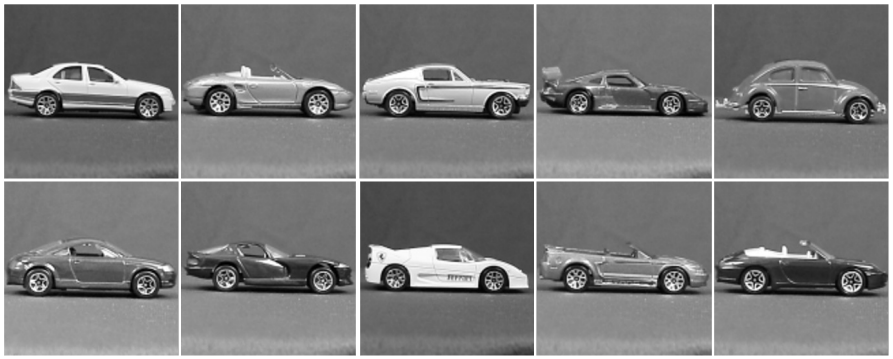
Slide credit: Josef Sivic

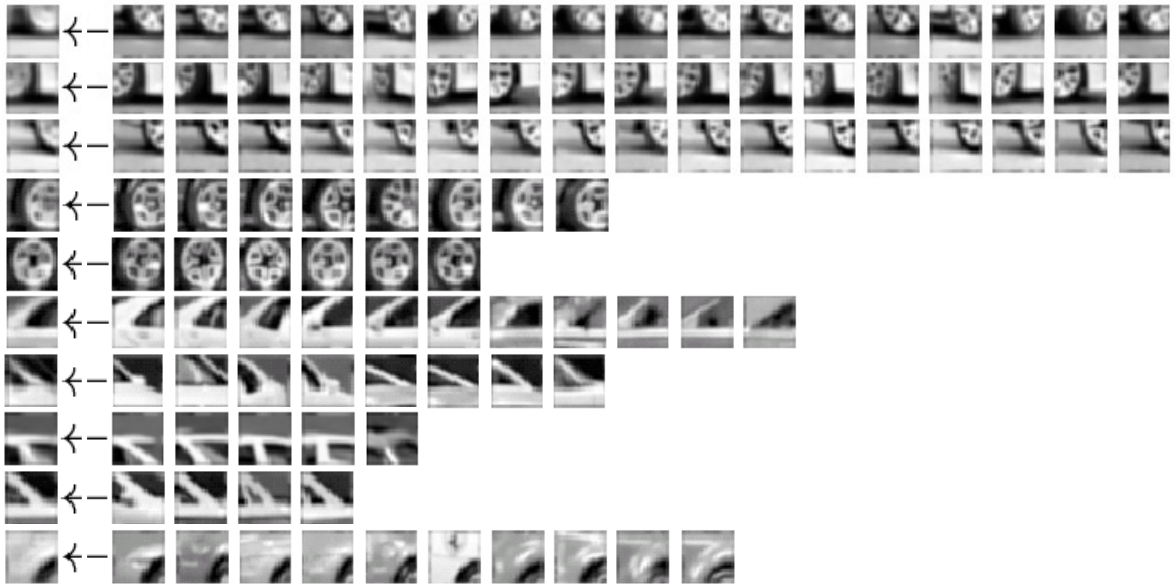
Clustering and vector quantization

- Clustering: learning a visual vocabulary or codebook
  - Unsupervised learning process
  - Each cluster center (e.g., k-means) becomes a codevector
  - Codebook can be learned on a separate training set
  - If the training set is sufficiently representative, the codebook will be “universal”
- The codebook is used for quantizing features
  - A *vector quantizer* takes a feature vector and maps it to the index of the nearest codevector in a codebook
  - Codebook = visual vocabulary
  - Codevector = visual word



Example Codebook

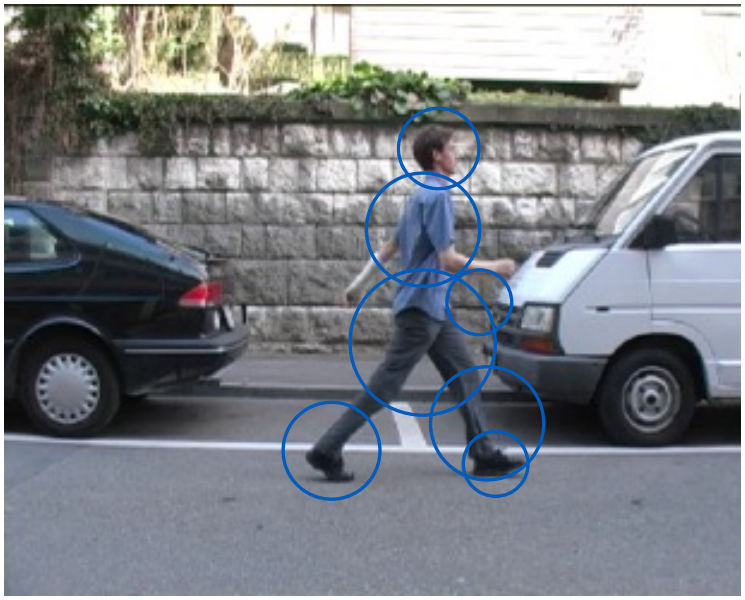


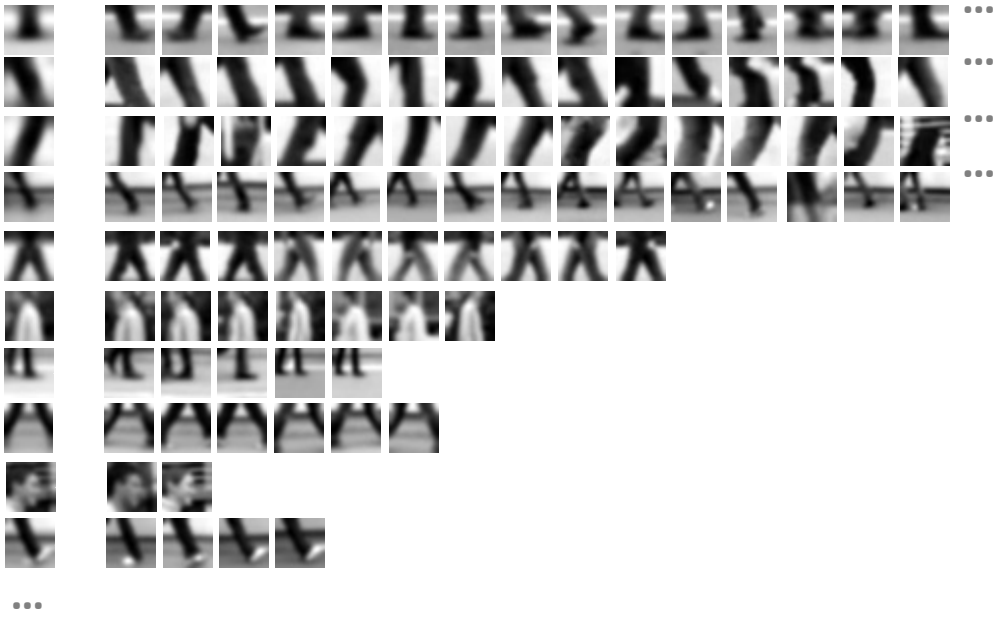


Appearance codebook

Source: B. Leibe

Another codebook





Appearance codebook

Source: B. Leibe