
Suren Manvelyan

By Suren Manvelyan, http://www.surenmanvelyan.com/gallery/7116


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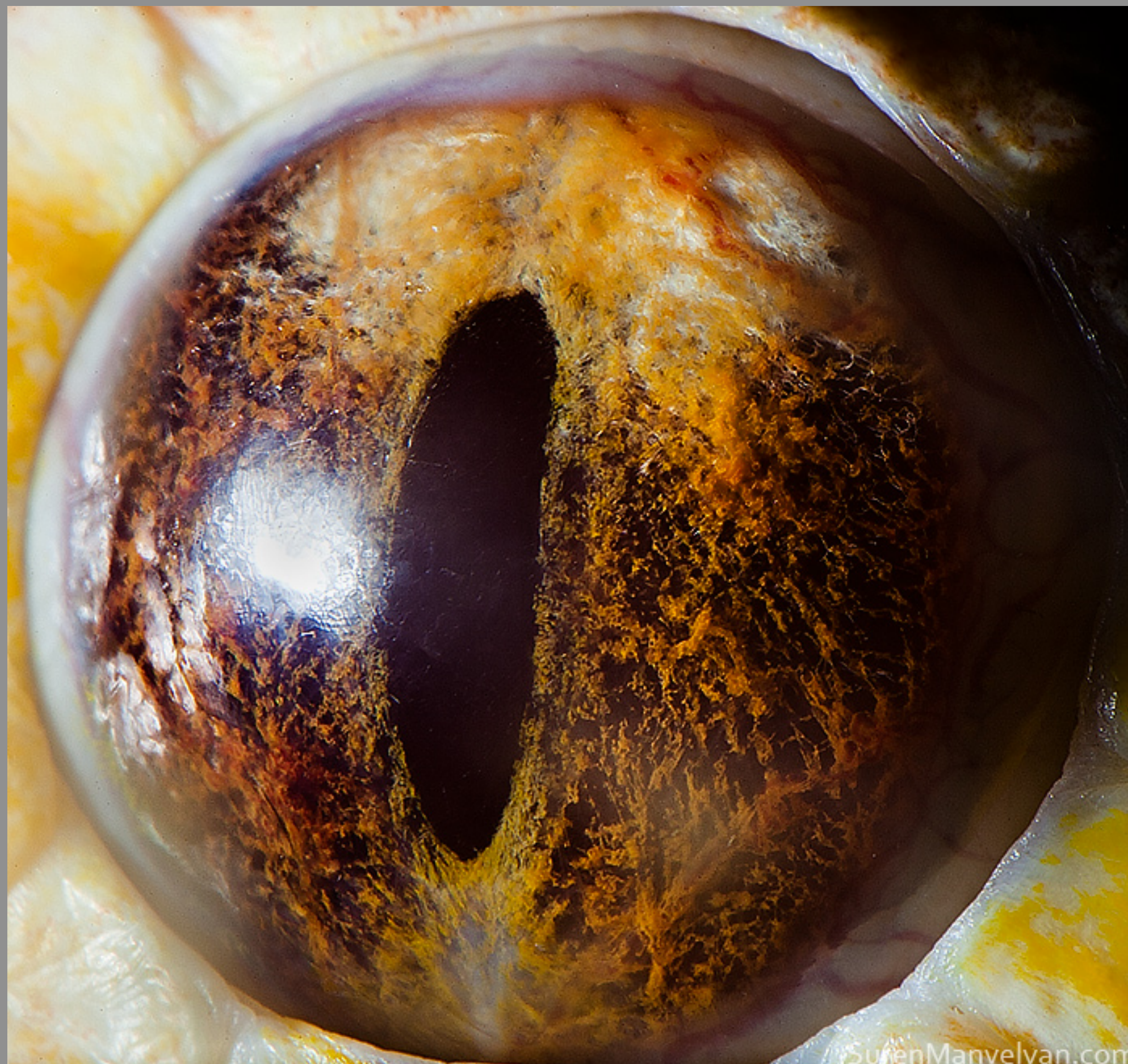

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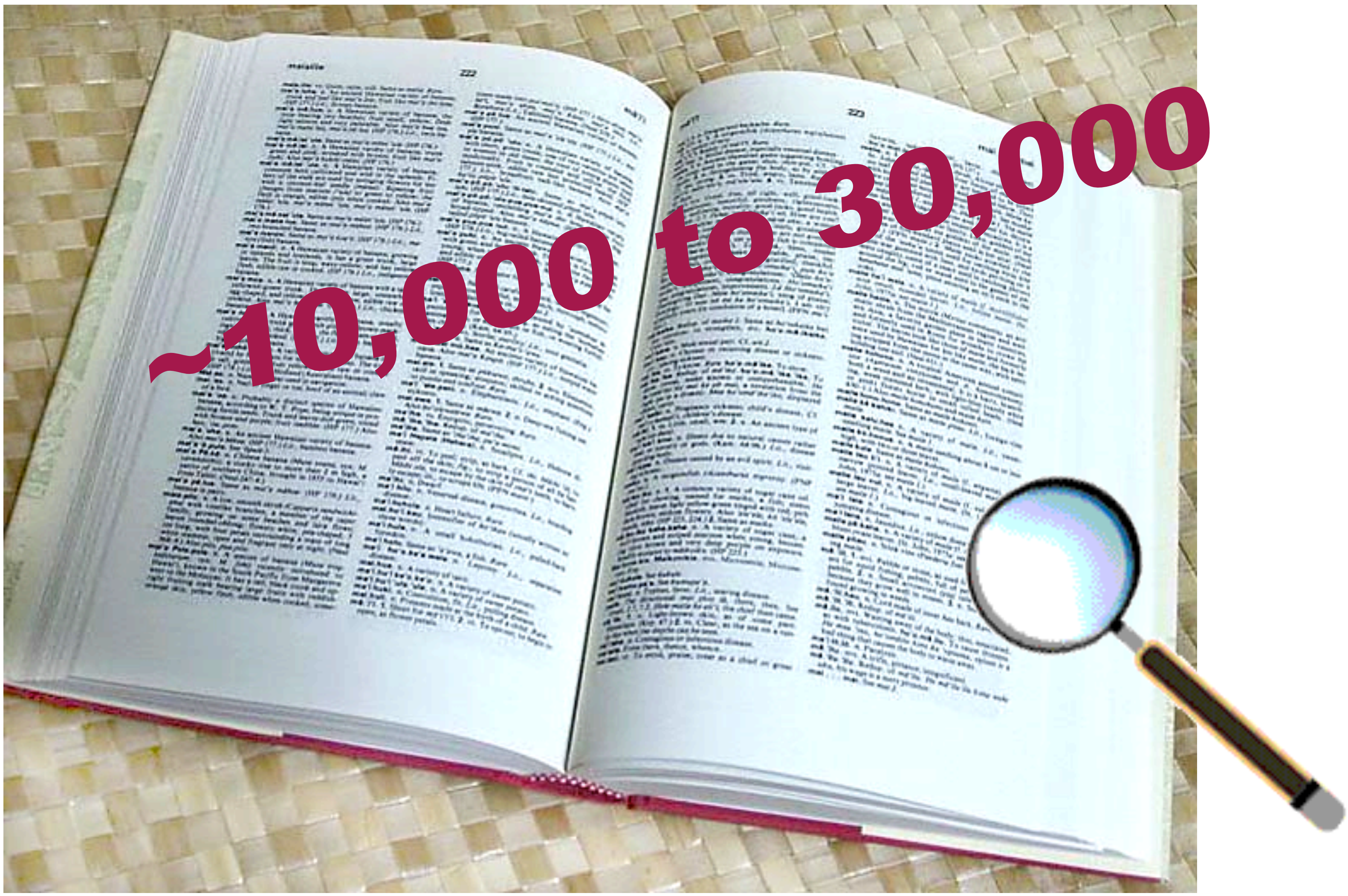
Recognition: Overview and History

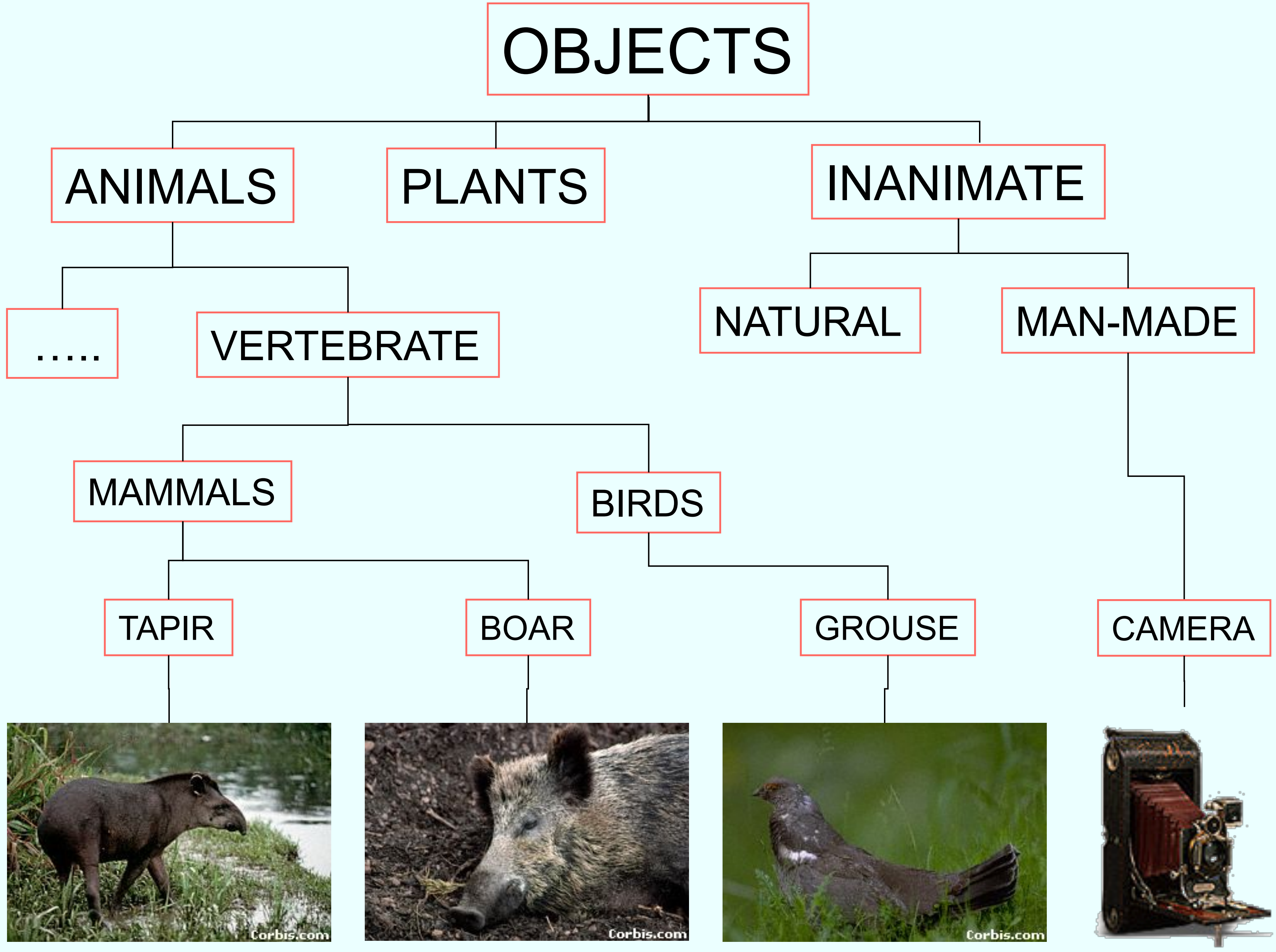
Slides from James Hays, Lana Lazebnik, Fei-Fei Li, Rob Fergus, Antonio Torralba, and Jean Ponce

How many visual object categories are there?



Biederman 1987


~10,000 to 30,000


OBJECTS
ANIMALS
PLANTS
INANIMATE
.....
VERTEBRATE
NATURAL
MAN-MADE
MAMMALS
BIRDS
TAPIR
BOAR
GROUSE
CAMERA
Corbis.com
Corbis.com
Corbis.com

Specific recognition tasks

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Scene categorization or classification

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

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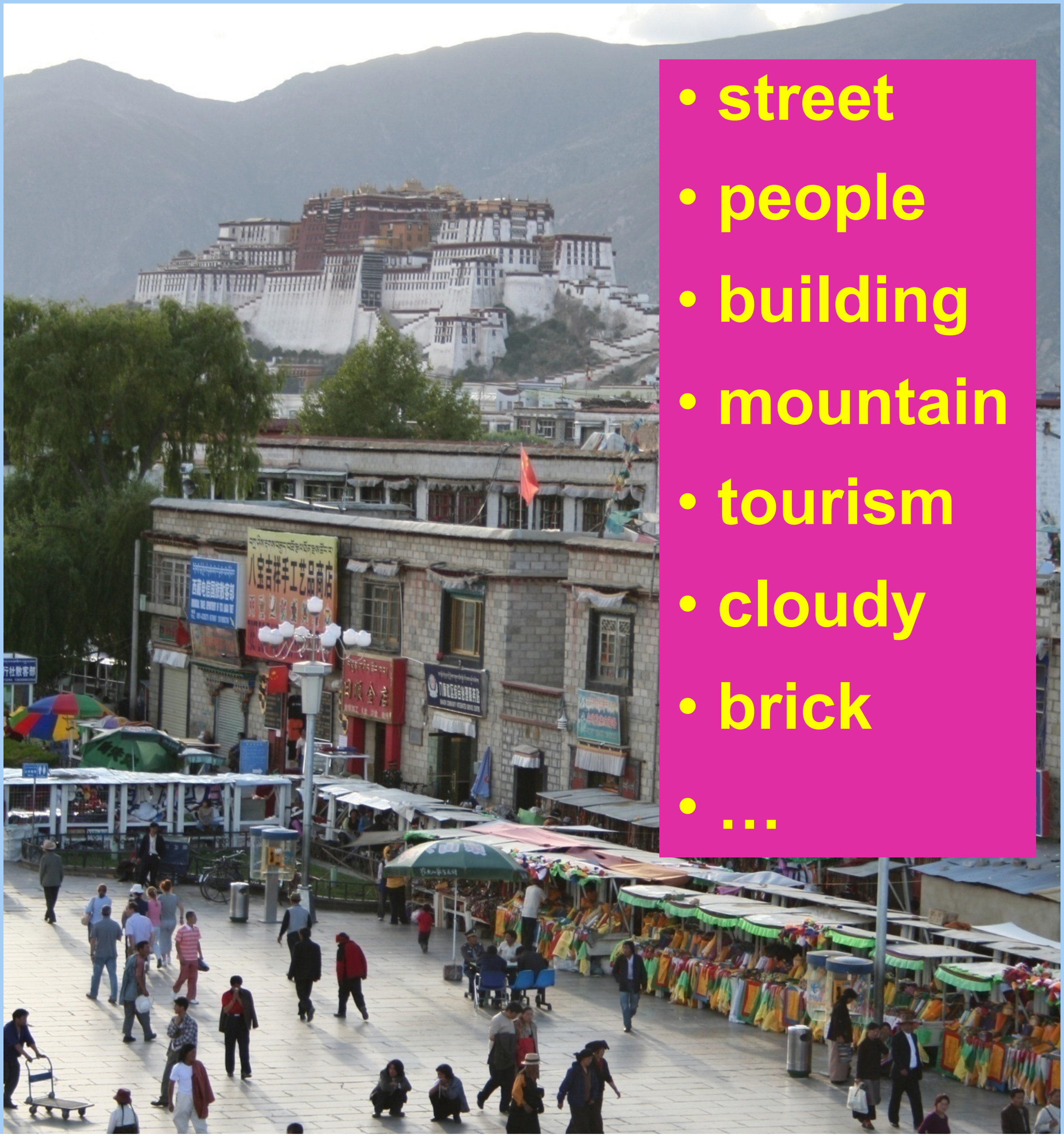
Image annotation / tagging / attributes



- **street**
- **people**
- **building**
- **mountain**
- **tourism**
- **cloudy**
- **brick**
- **…**

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Object detection

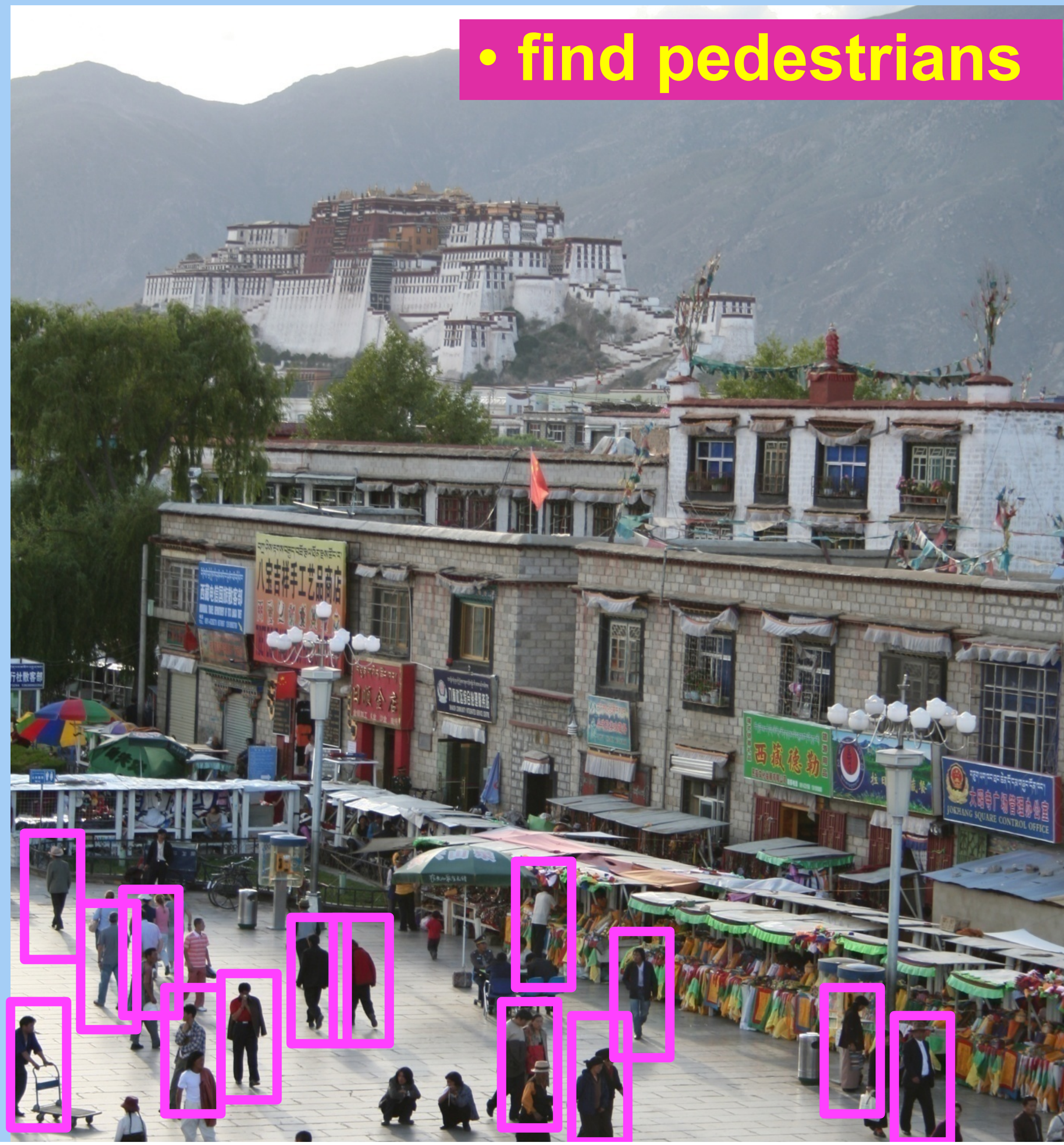

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Image parsing / semantic segmentation

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Scene understanding?

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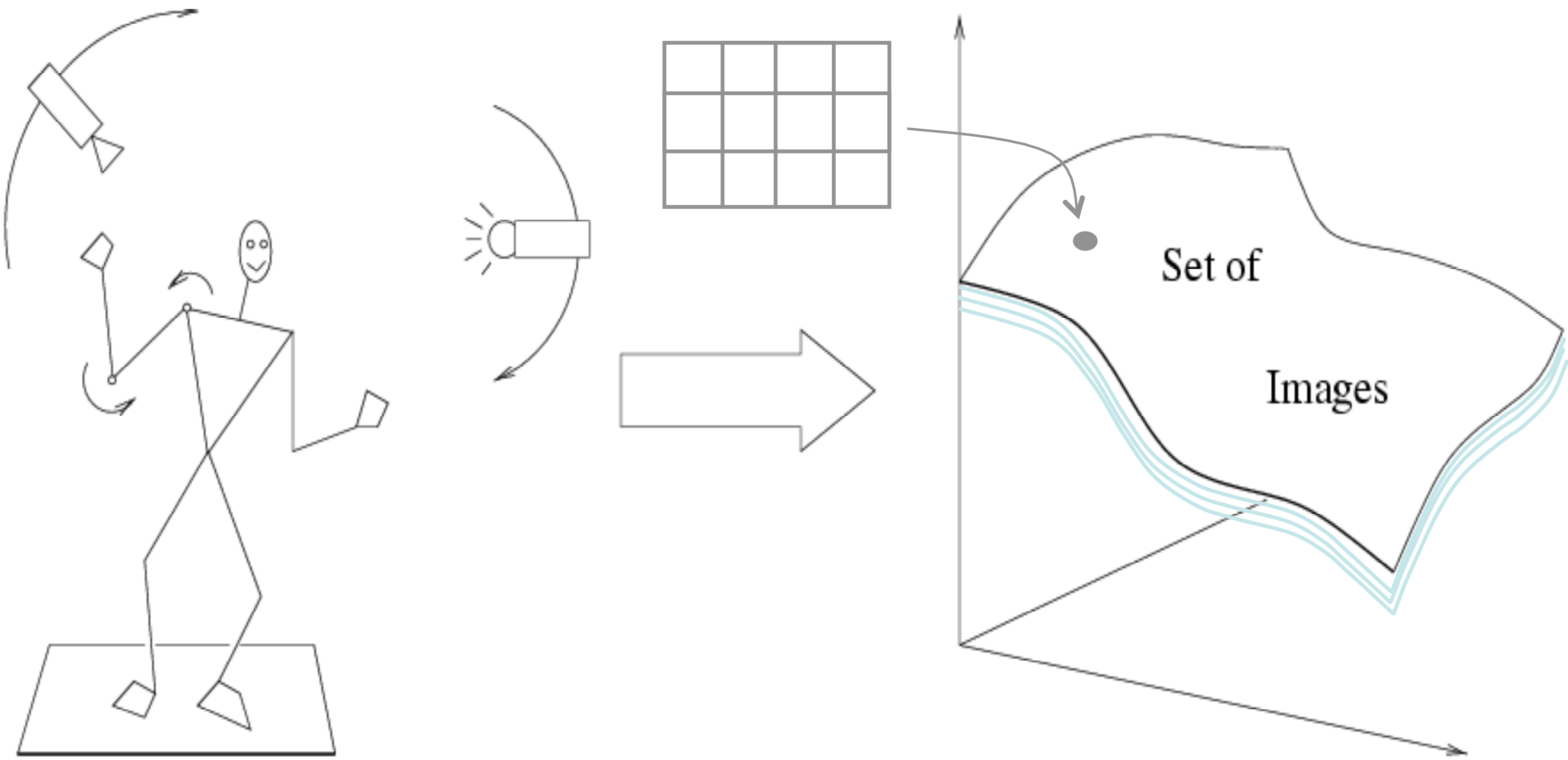
Recognition is all about modeling variability



Variability: Camera position
Illumination
Shape parameters

Within-class variations?

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Within-class variations

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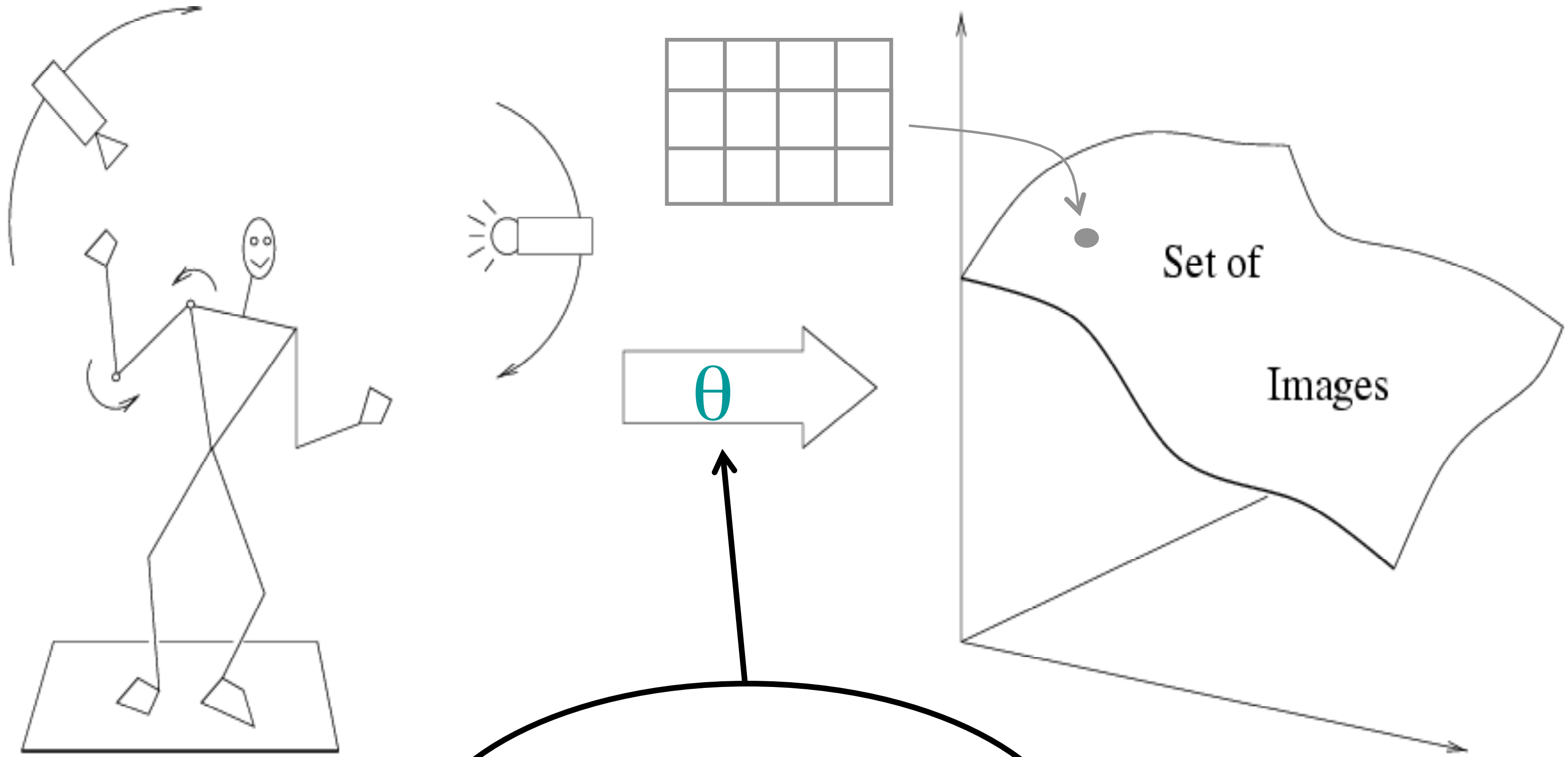
History of ideas in recognition

- 1960s – early 1990s: the geometric era



Variability: Camera position
Illumination

Alignment

Shape: assumed known

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

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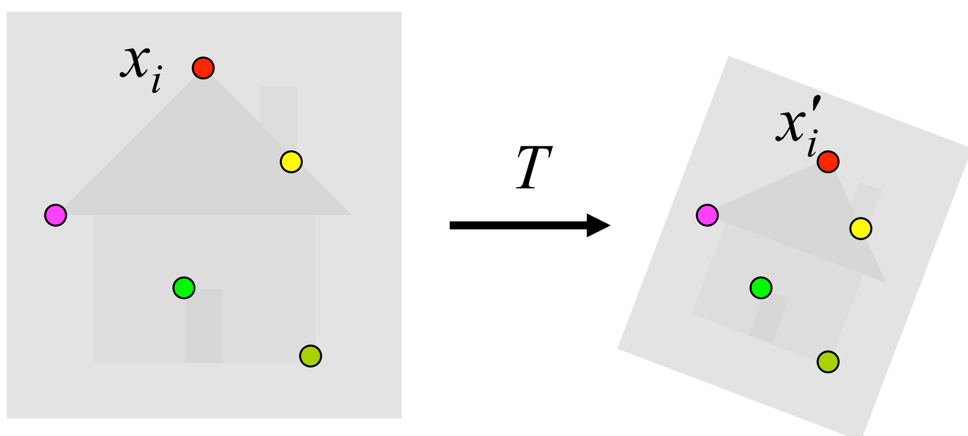
Recall: Alignment

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



Find transformation T that minimizes

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

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Recognition as an alignment problem: Block world

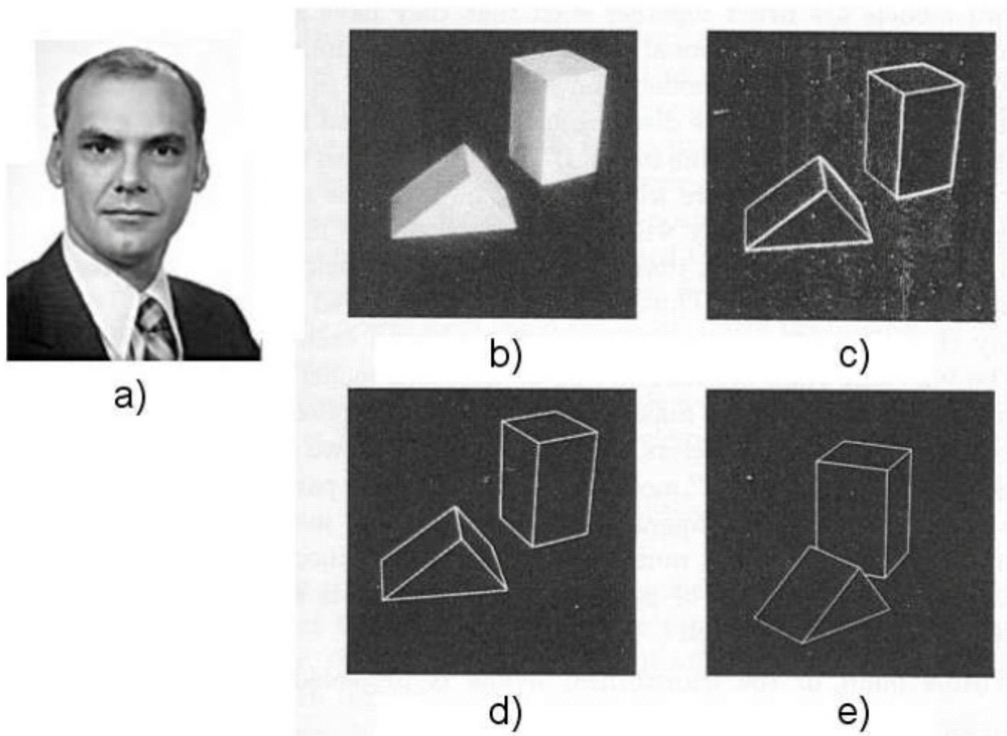
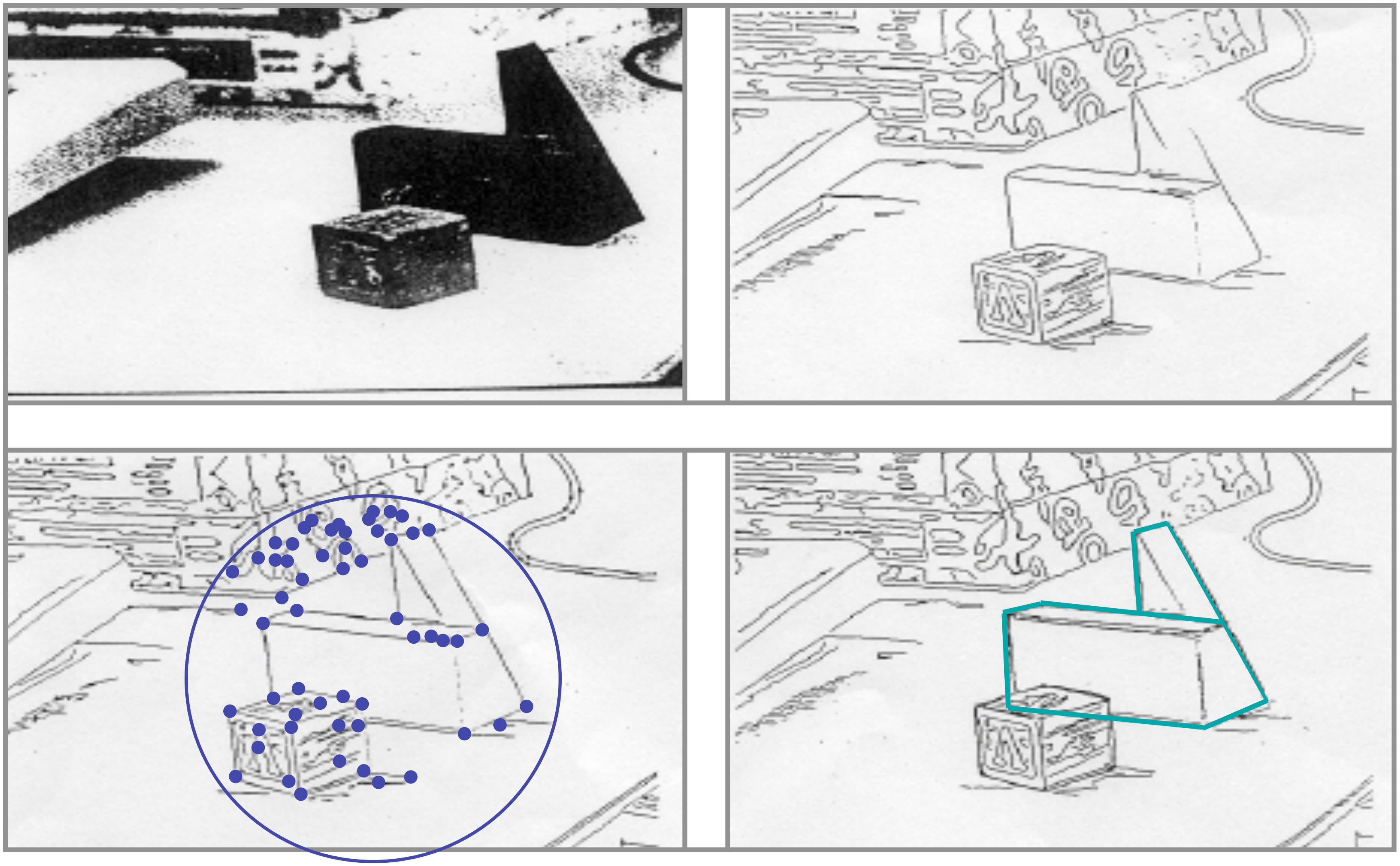


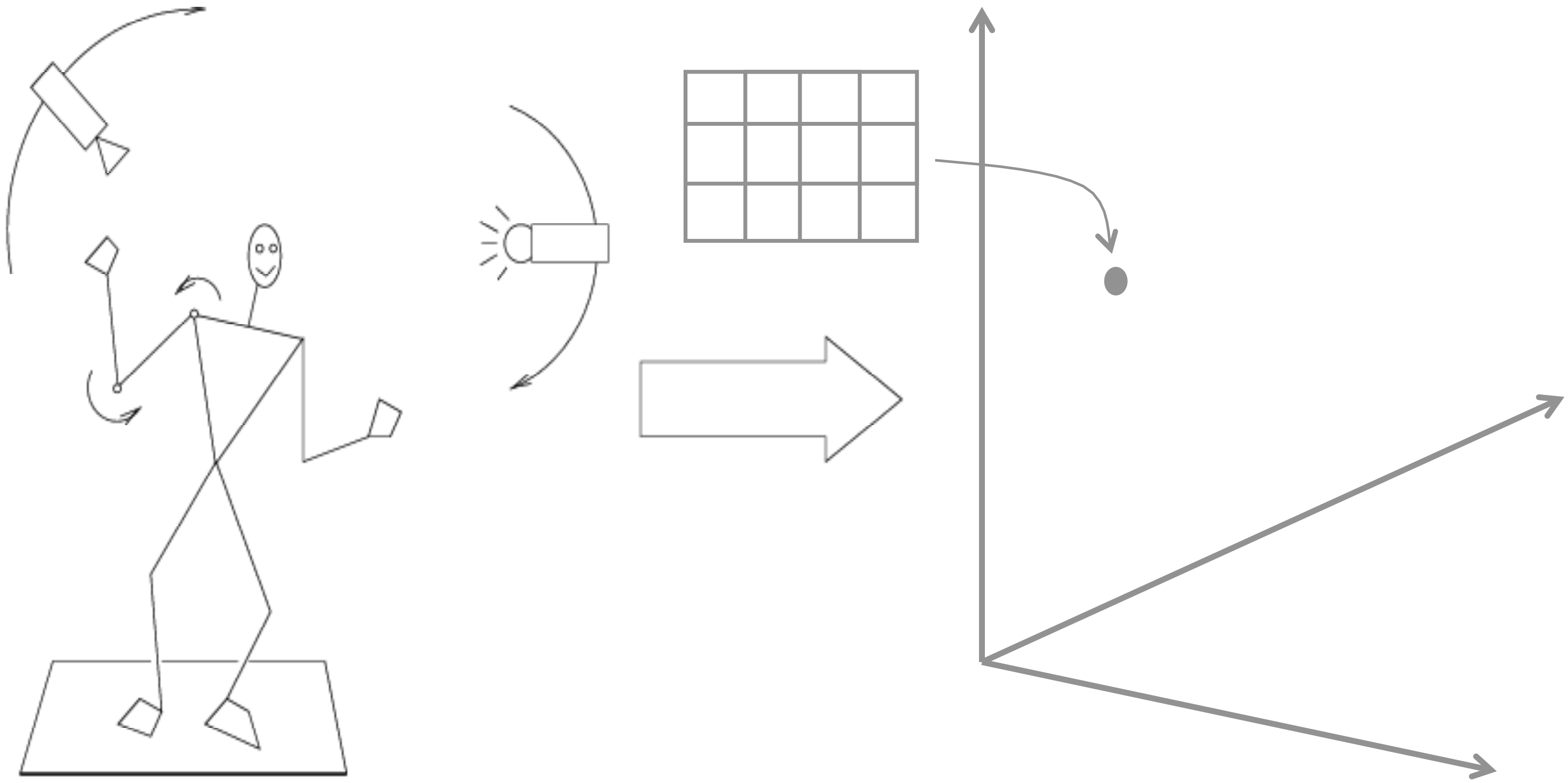
Fig. 1. A system for recognizing 3-d polyhedral scenes. a) L.G. Roberts. b)A blocks world scene. c)Detected edges using a 2x2 gradient operator. d) A 3-d polyhedral description of the scene, formed automatically from the single image. e) The 3-d scene displayed with a viewpoint different from the original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

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

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

Alignment: Huttenlocher & Ullman (1987)





~~Variability~~ **Invariance to:** Camera position
Illumination
Internal parameters

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

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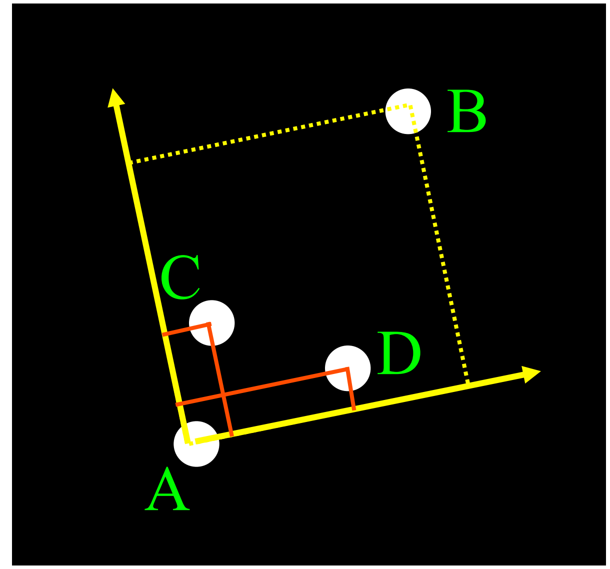
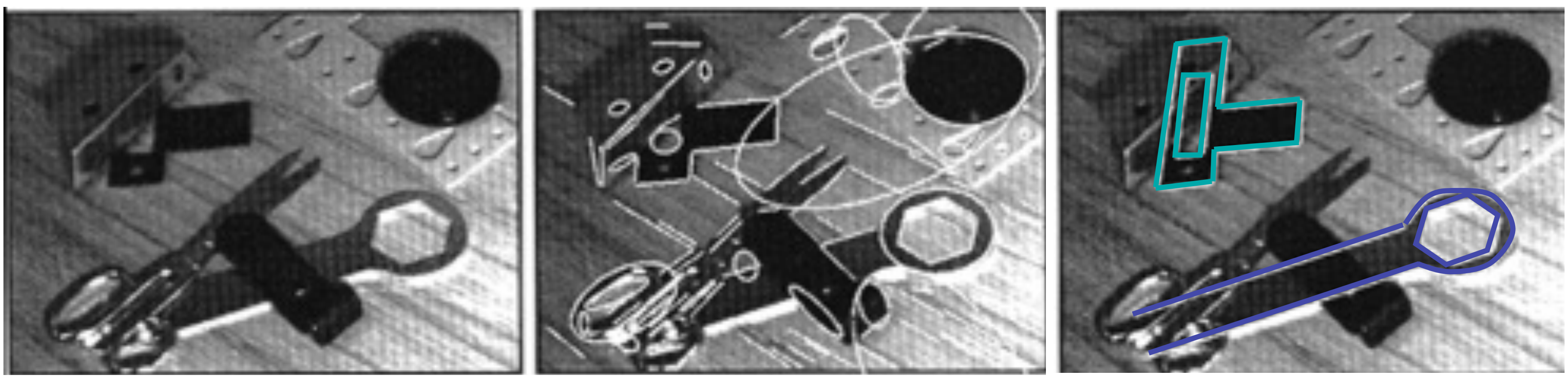
Example: invariant to similarity transformations computed from four points

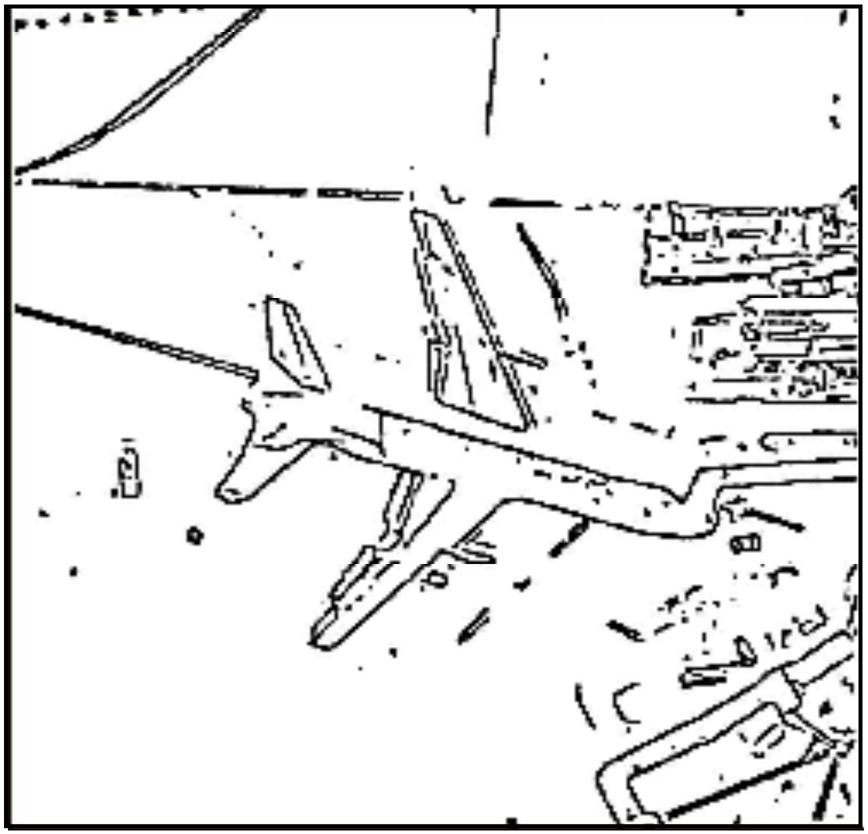


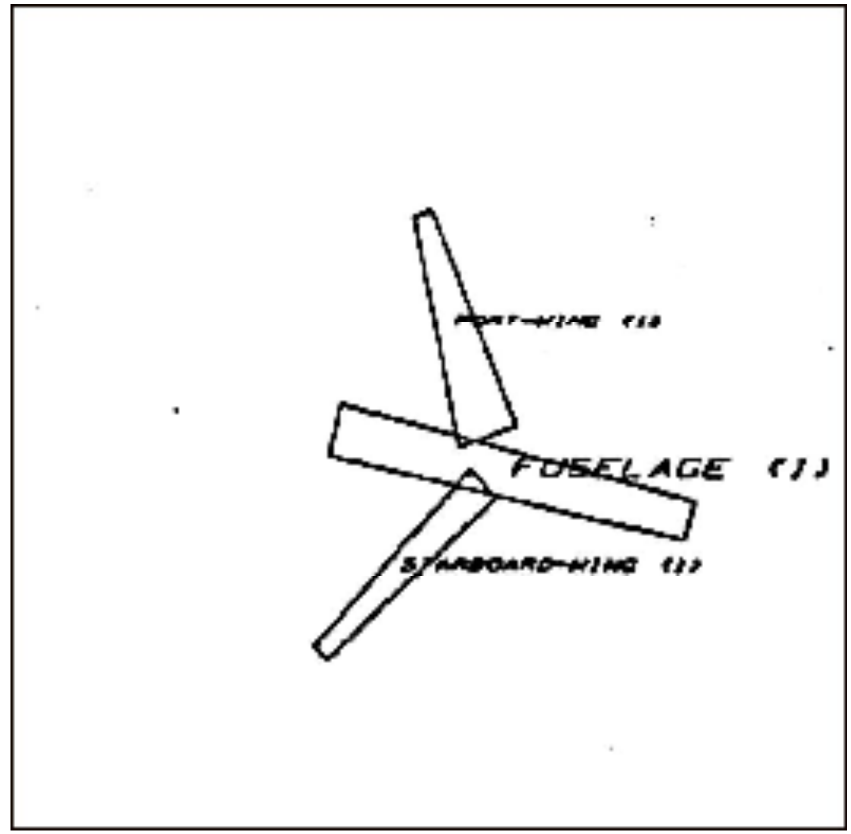
Projective invariants (Rothwell et al., 1992):



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

Representing and recognizing object categories is harder...





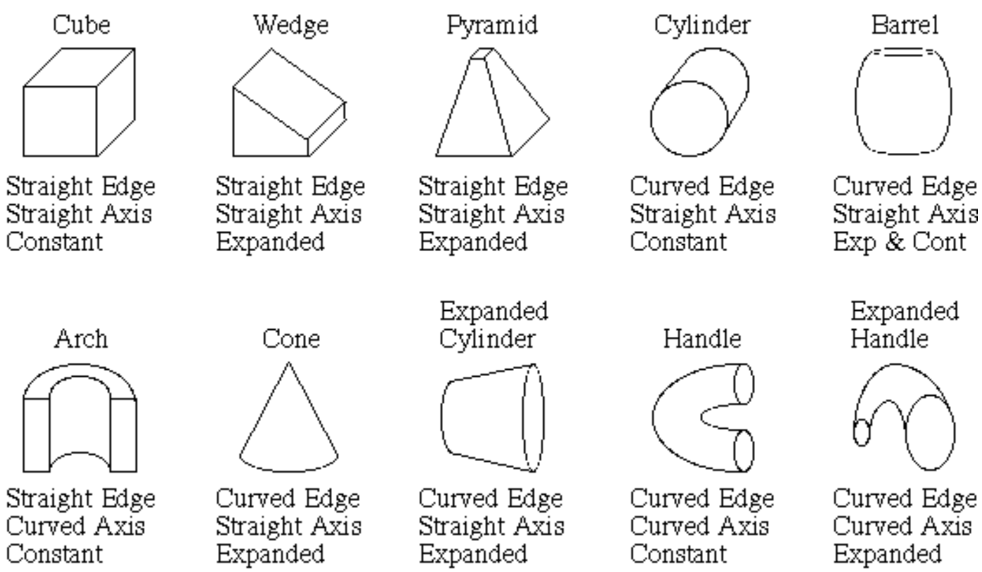
ACRONYM (Brooks and Binford, 1981)

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

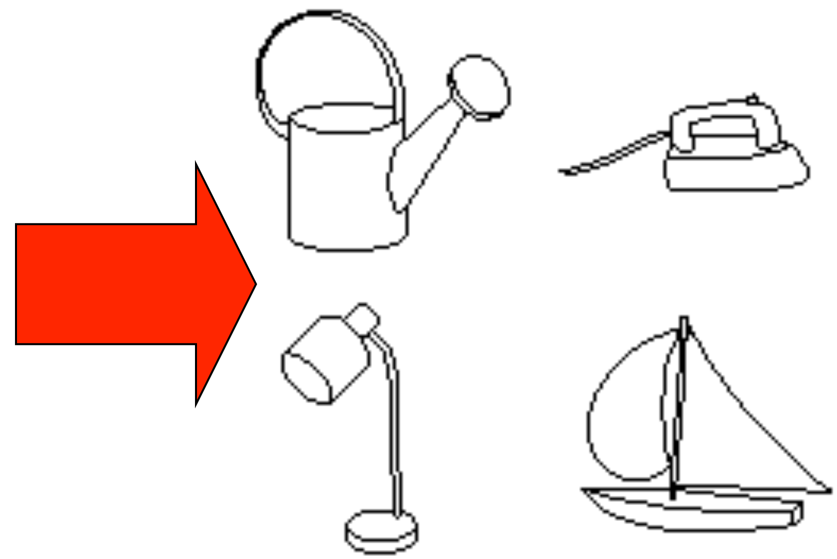
Recognition by components

Biederman (1987)

Primitives (geons)



Objects



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

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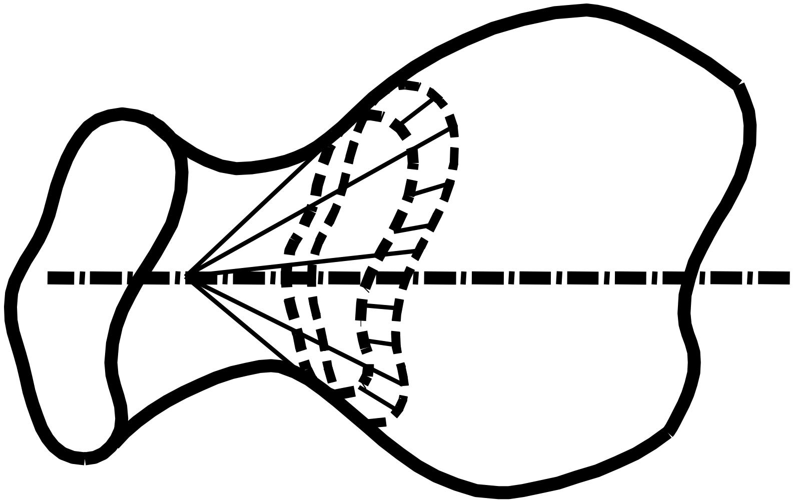
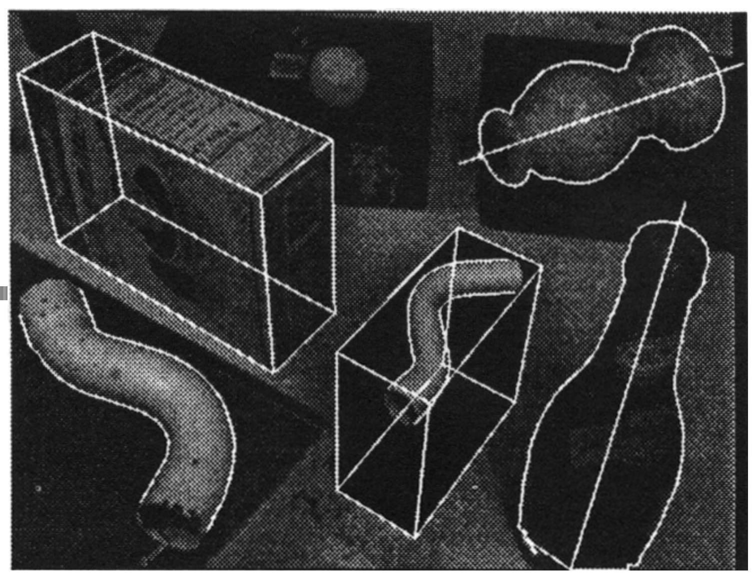
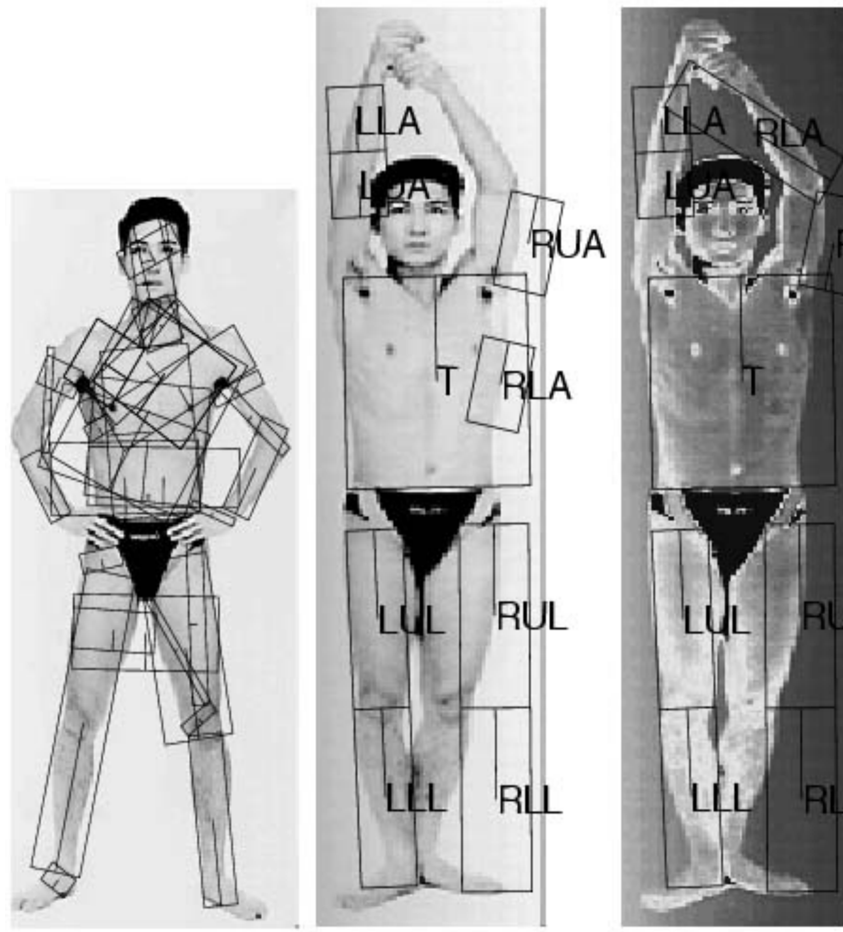
General shape primitives?



Generalized cylinders
Ponce et al. (1989)



Zisserman et al. (1995)



Forsyth (2000)

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History of ideas in recognition

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

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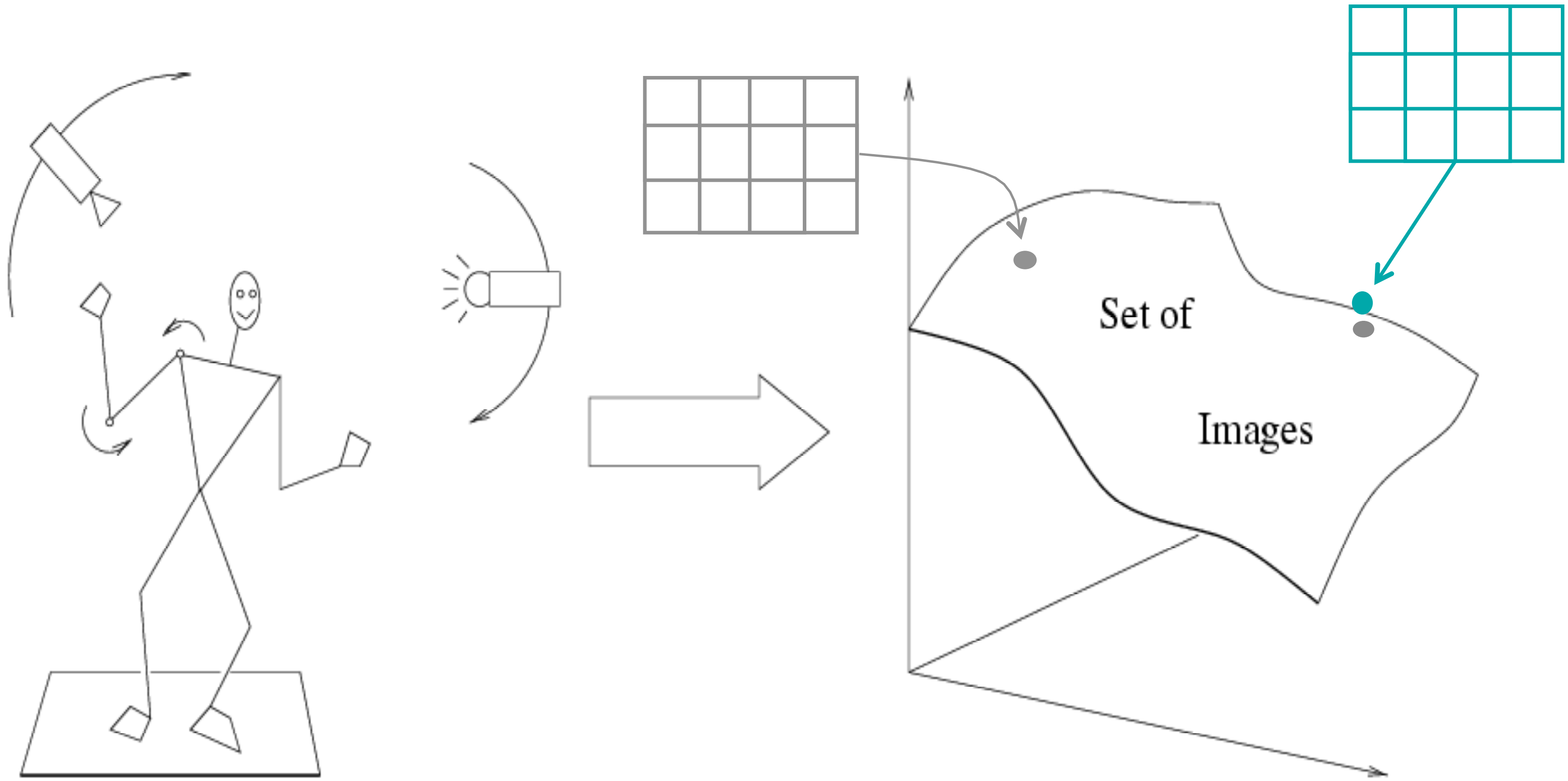

Empirical models of image variability

Appearance-based techniques

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

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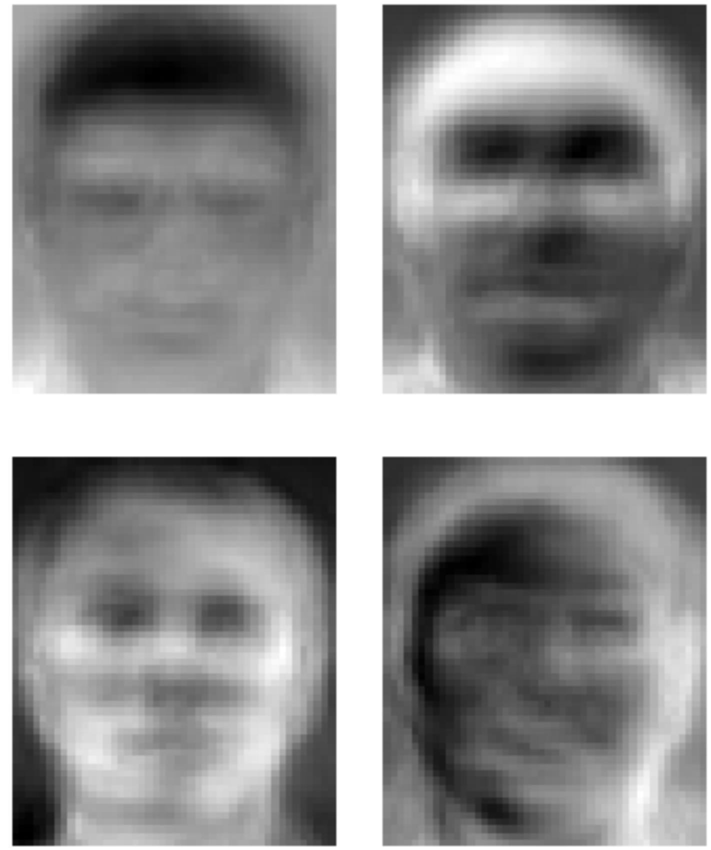
Eigenfaces (Turk & Pentland, 1991)



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

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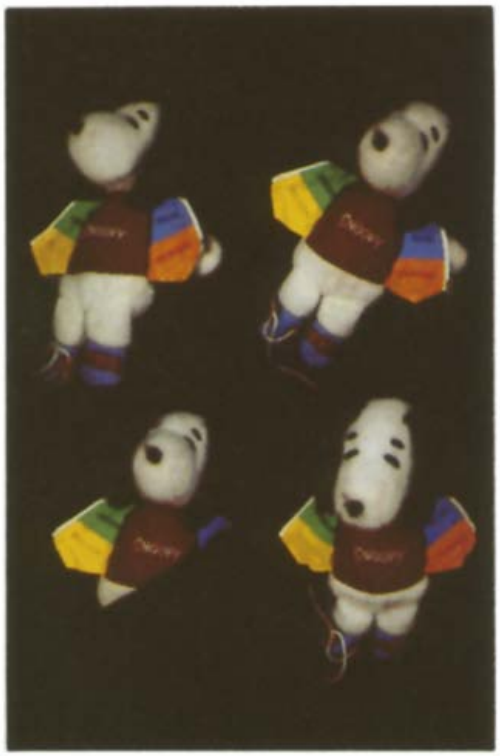
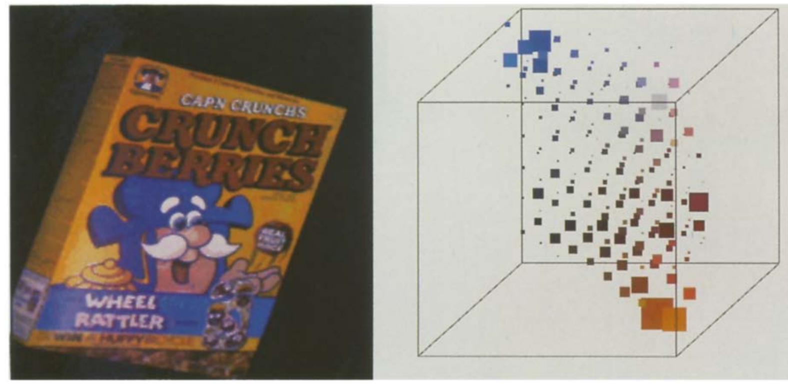
Color Histograms





Swain and Ballard, Color Indexing, IJCV 1991.

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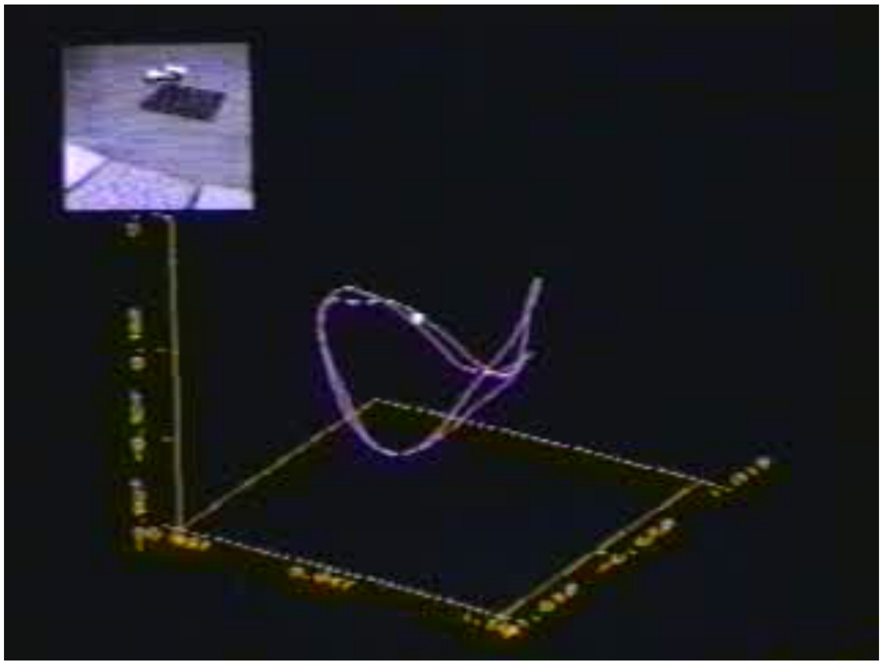
Appearance manifolds



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

Limitations of global appearance models

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

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History of ideas in recognition

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

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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 object instance recognition

D. Lowe (1999, 2004)

Large-scale image search

Combining local features, indexing, and spatial constraints

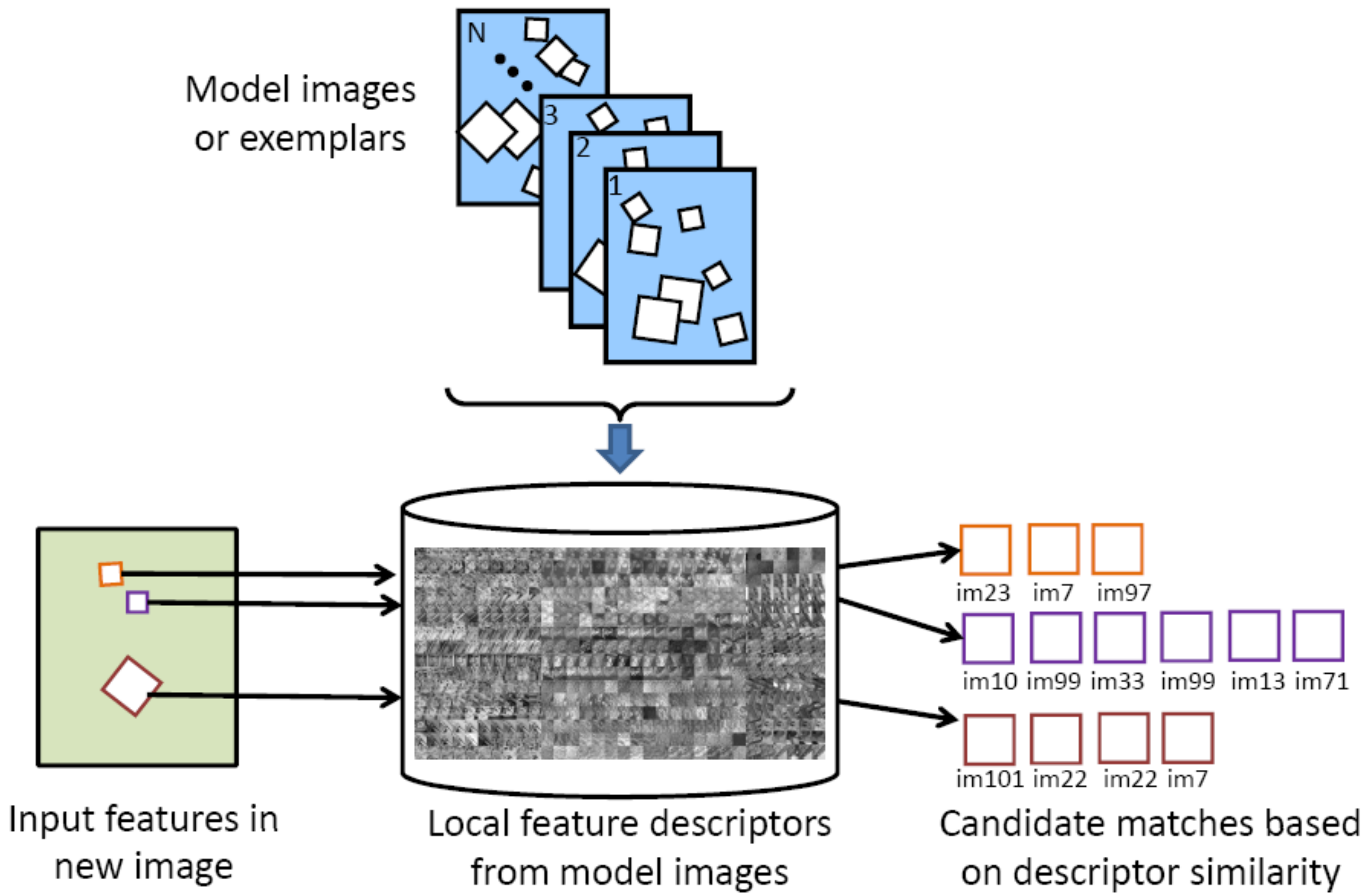


Image credit: K. Grauman and B. Leibe

Large-scale image search

Combining local features, indexing, and spatial constraints

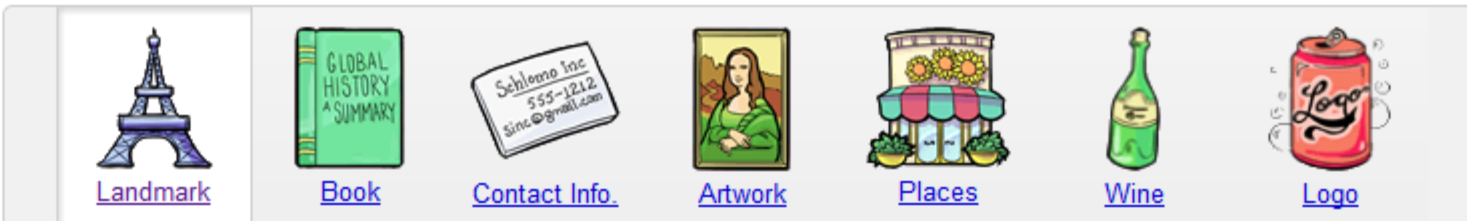
Philbin et al. '07

Large-scale image search

Combining local features, indexing, and spatial constraints

Google Goggles in Action

Click the icons below to see the different ways Google Goggles can be used.



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

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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

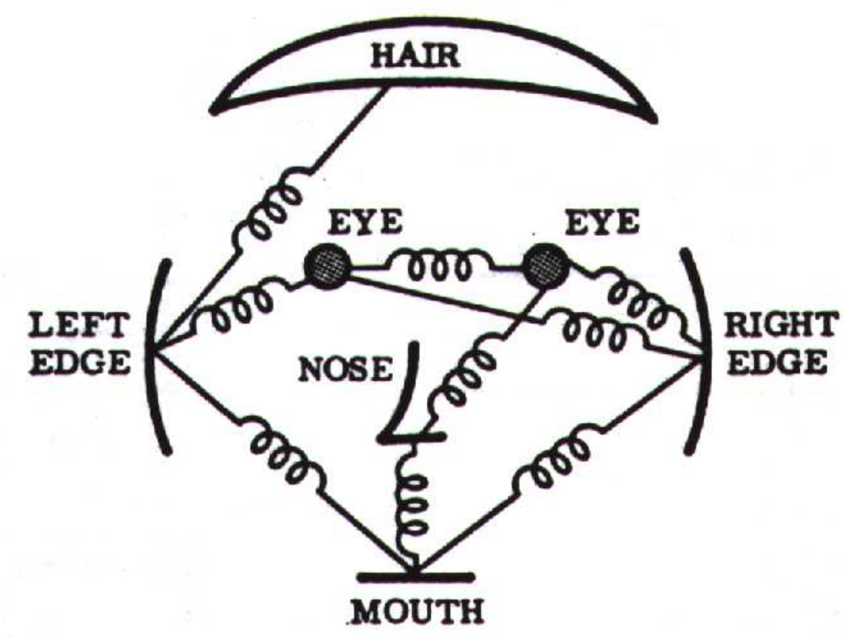


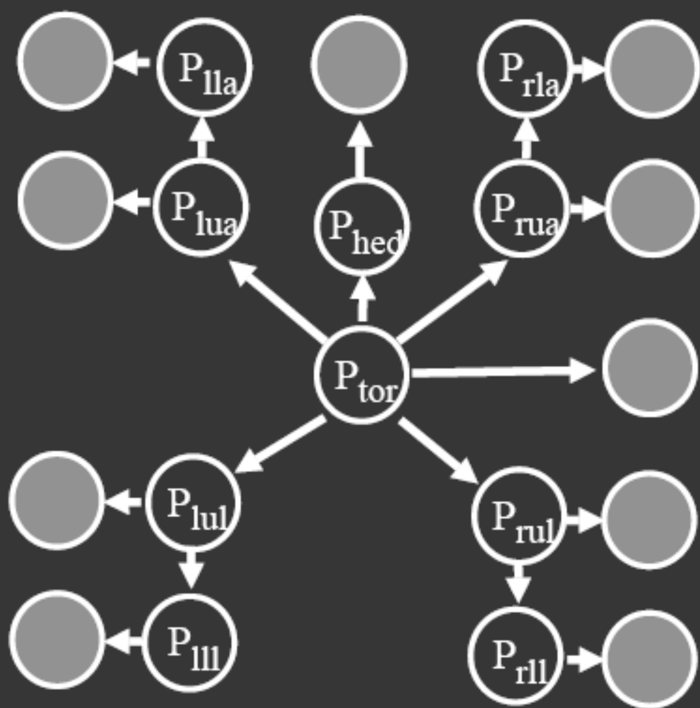
Figure from [Fischler & Elschlager 73]

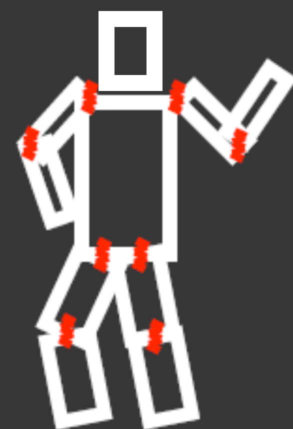
Constellation models

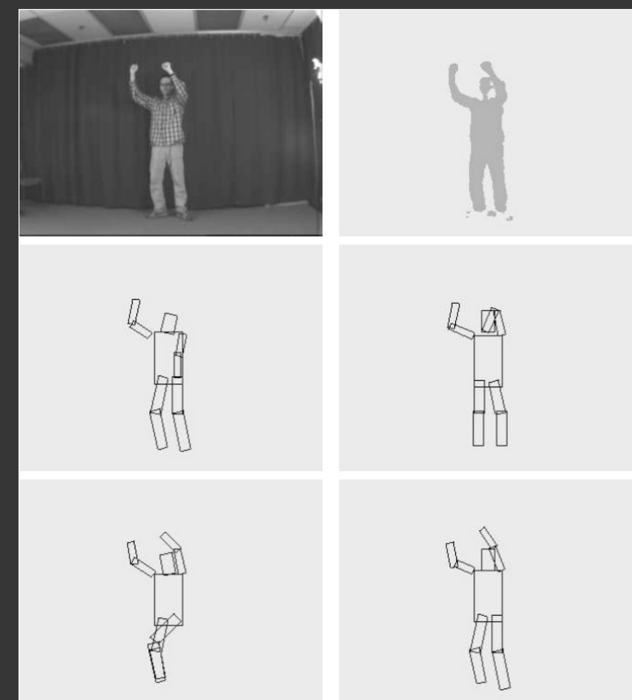
Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

Pictorial structure model

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





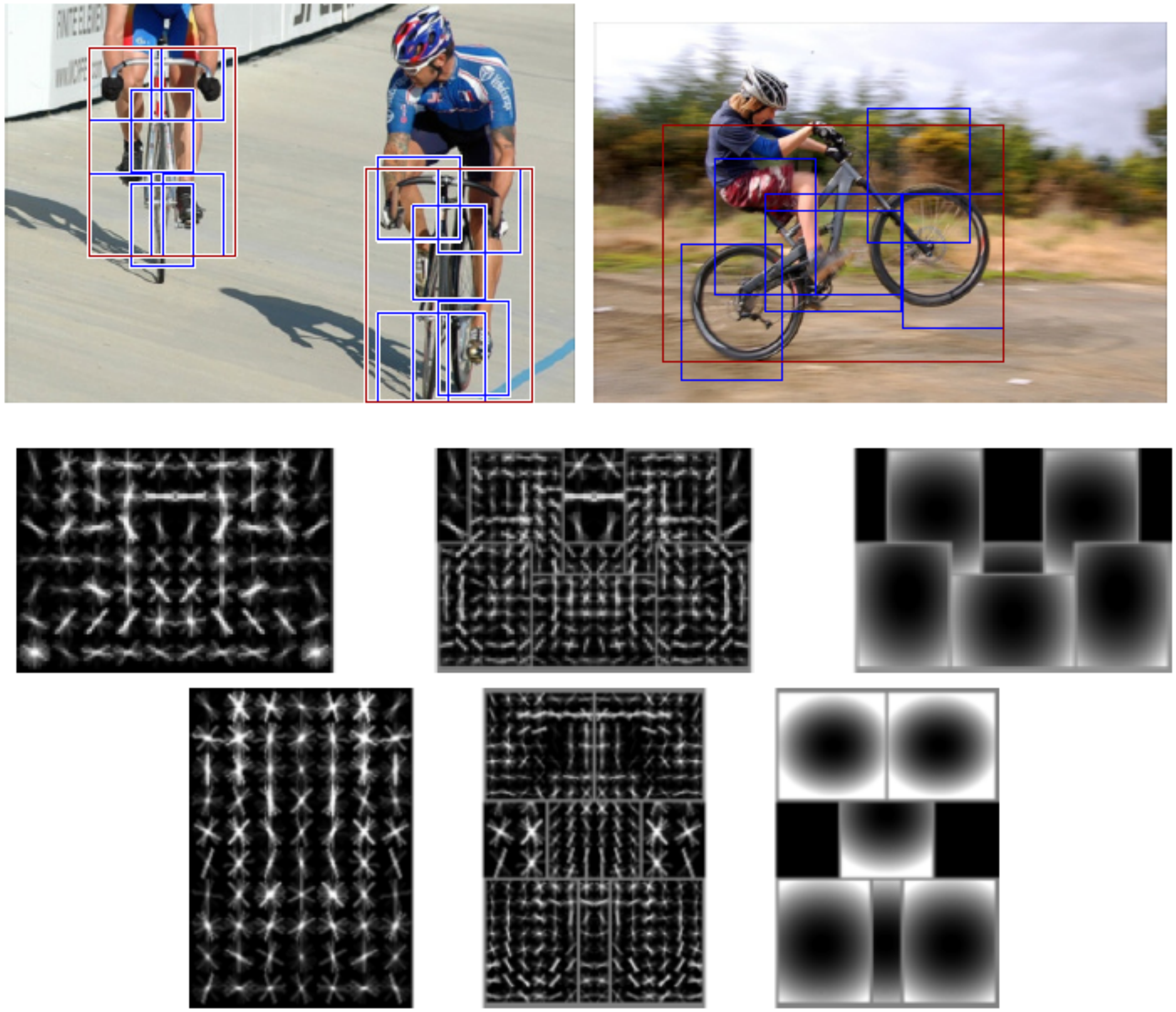


$$\Pr(P_{tor}, P_{arm}, \ldots | \mathrm{Im}) \propto \prod_{i,j} \Pr(P_i \mid P_j) \prod_{i} \Pr(\mathrm{Im}(P_i))$$

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

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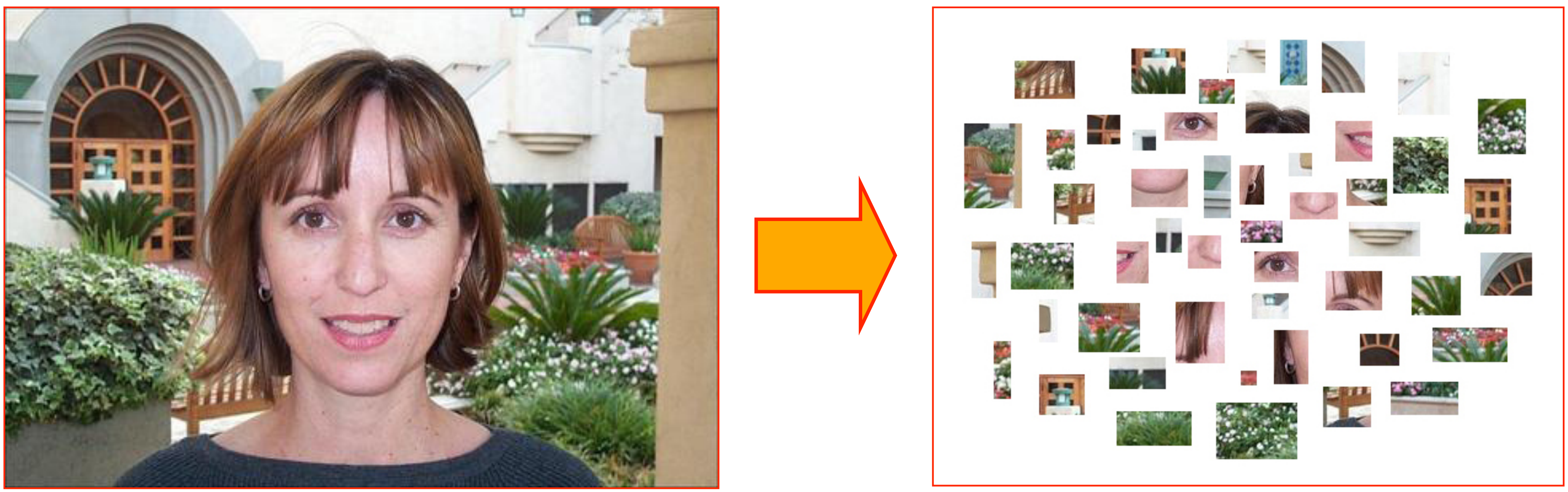
Bag-of-features models



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Bag-of-features models

Object → **Bag of ‘words’**

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Objects as texture

- All of these are treated as being the same

- No distinction between foreground and background: scene recognition?

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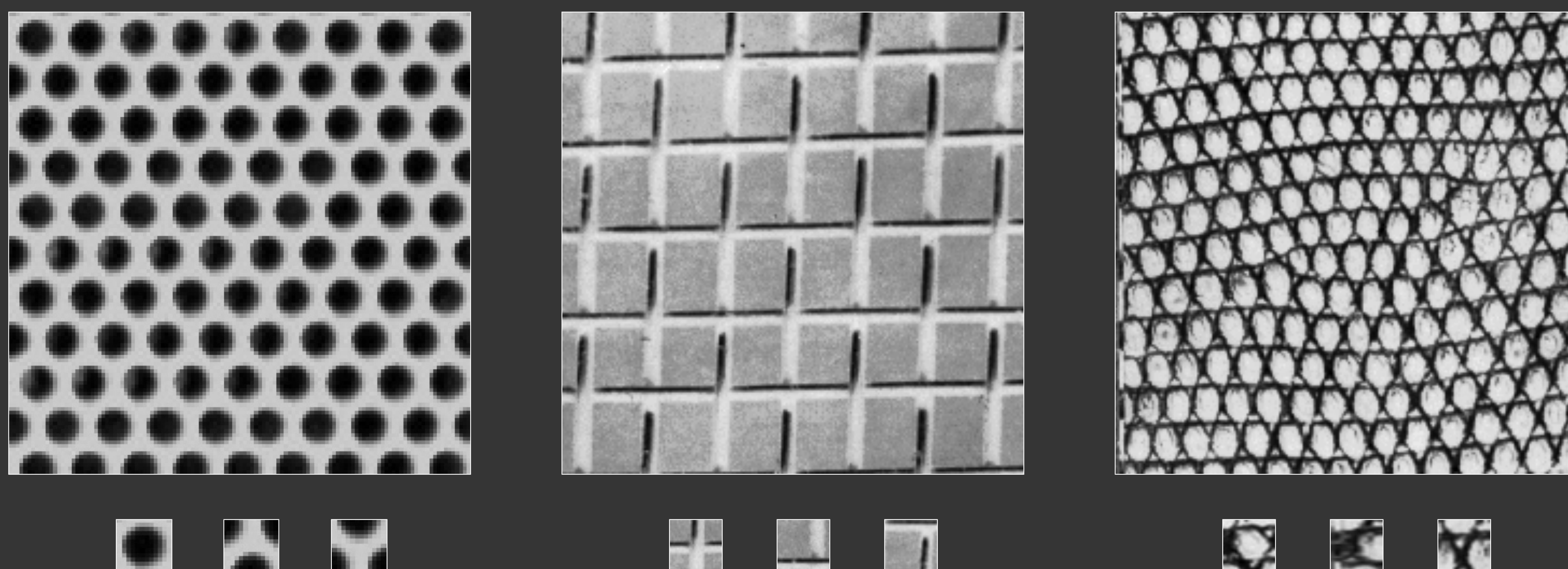
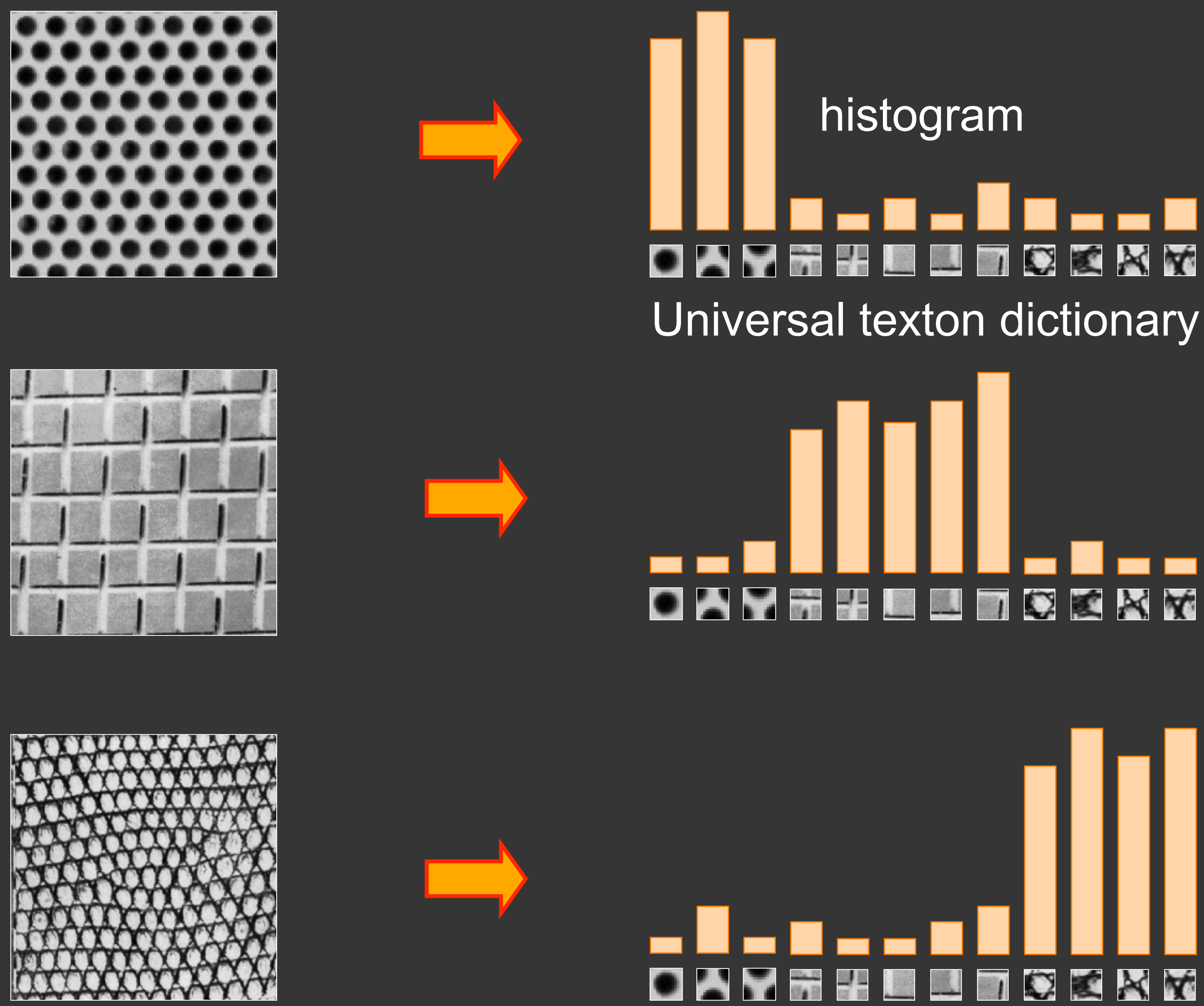
Origin 1: Texture recognition

- Texture is characterized by the repetition of basic elements or *textons*
- For stochastic textures, it is the identity of the textons, not their spatial arrangement, that matters



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)

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

Origin 2: Bag-of-words models

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

US Presidential Speeches Tag Cloud
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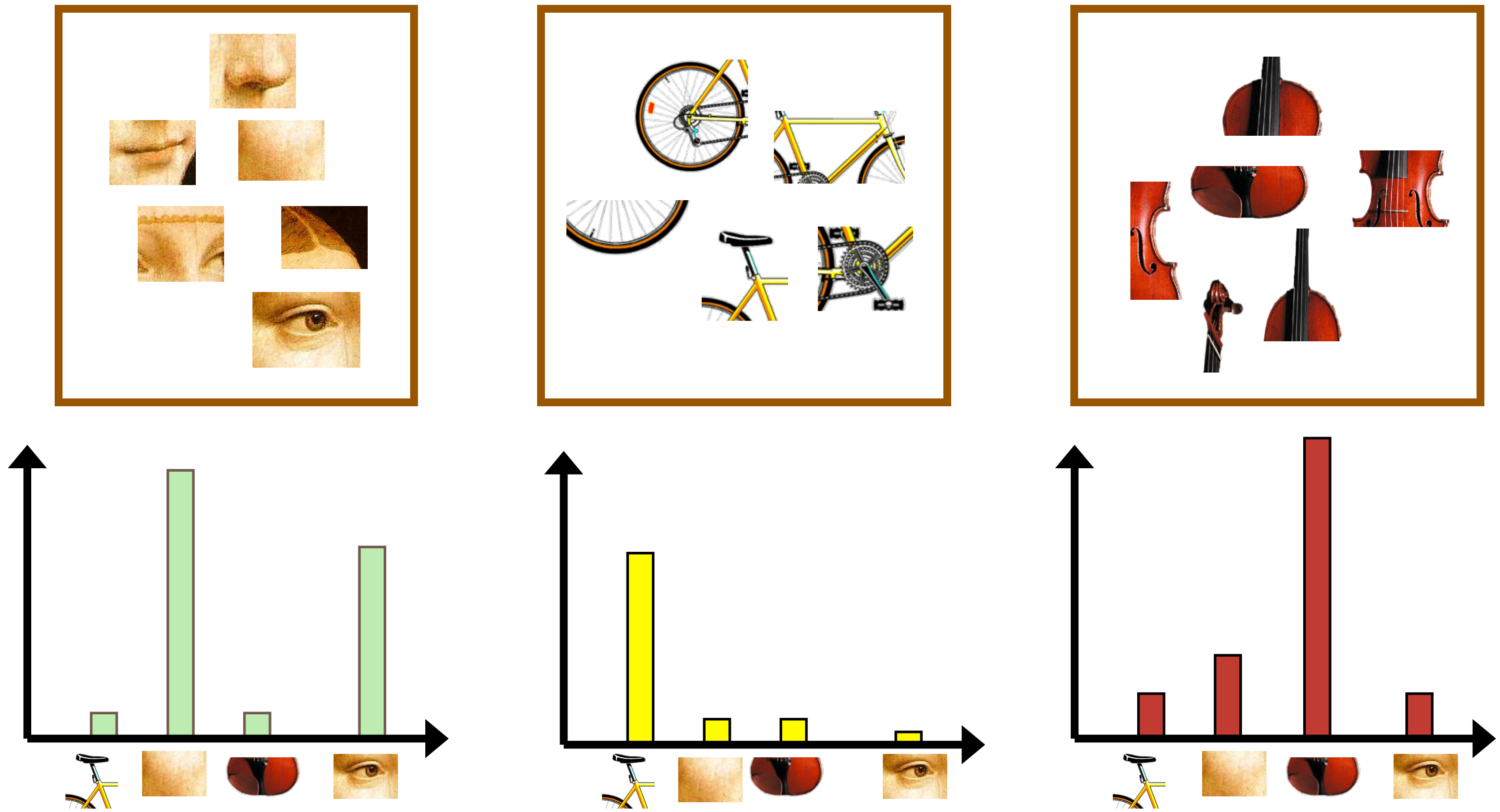
Origin 2: Bag-of-words models

- 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

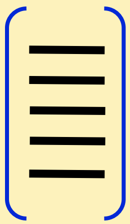
1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



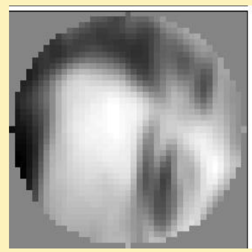
1. Feature extraction

- Regular grid or interest regions

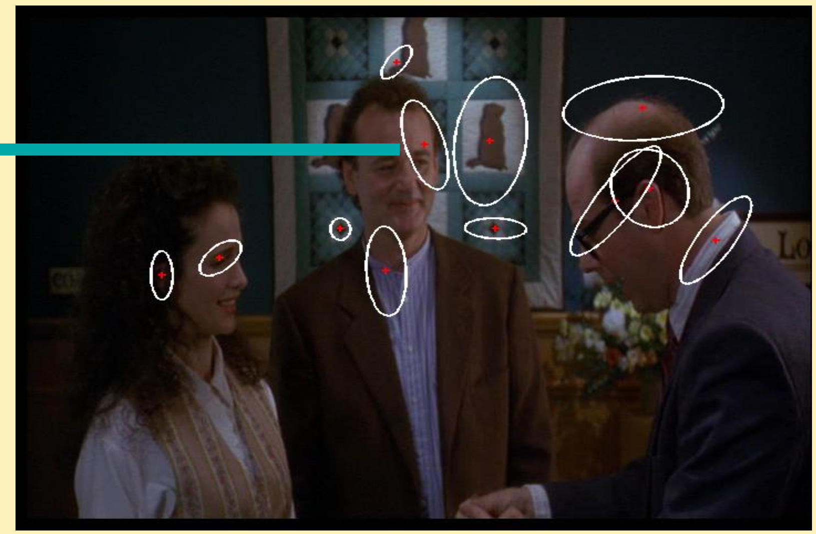
1. Feature extraction



Compute descriptor



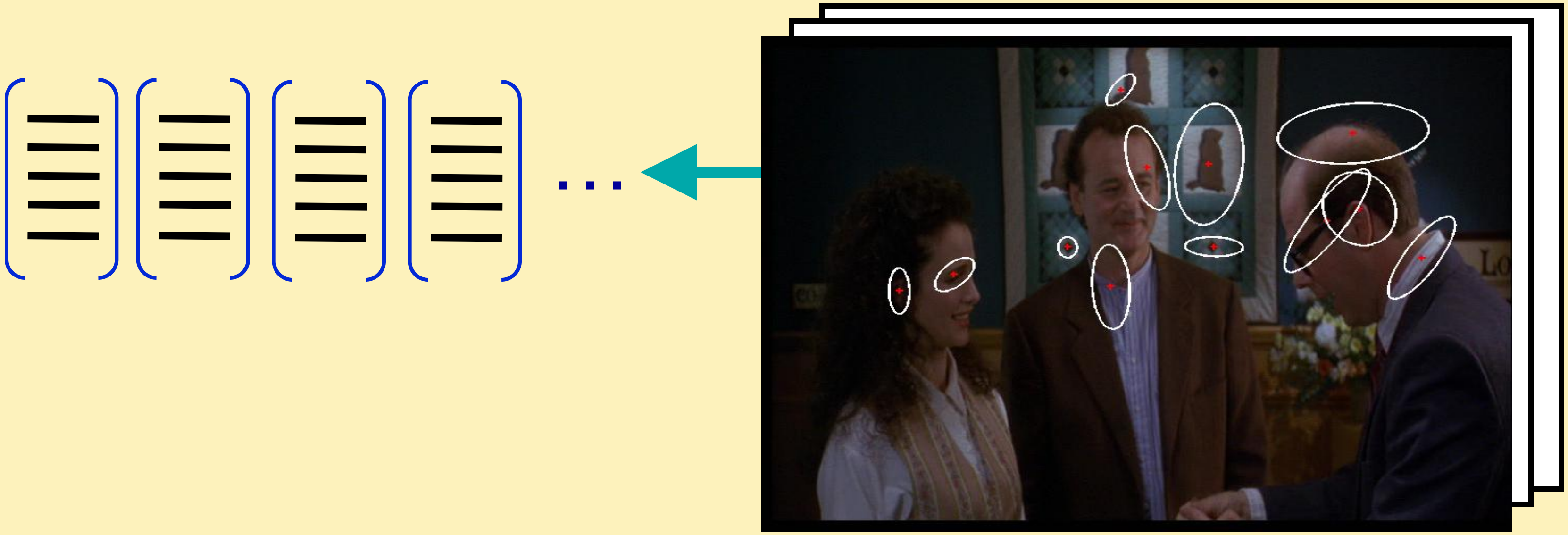
Normalize patch



Detect patches

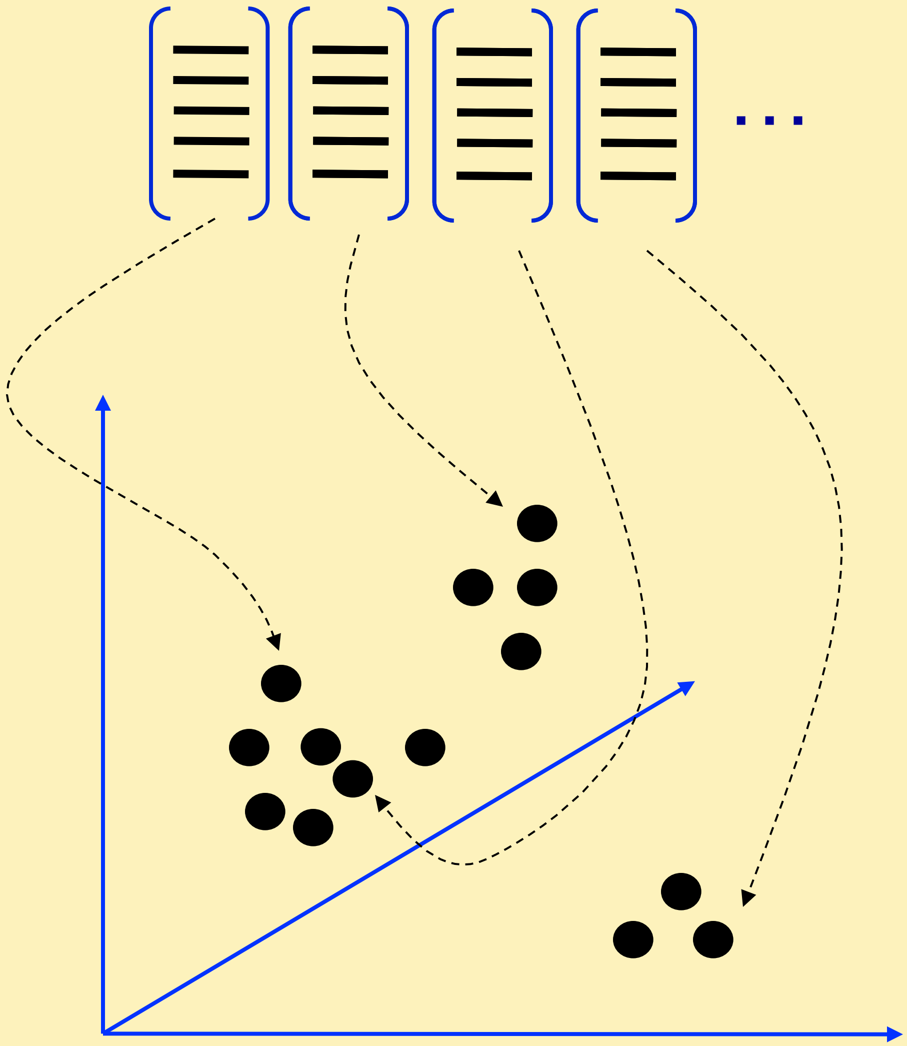
Slide credit: Josef Sivic

1. Feature extraction



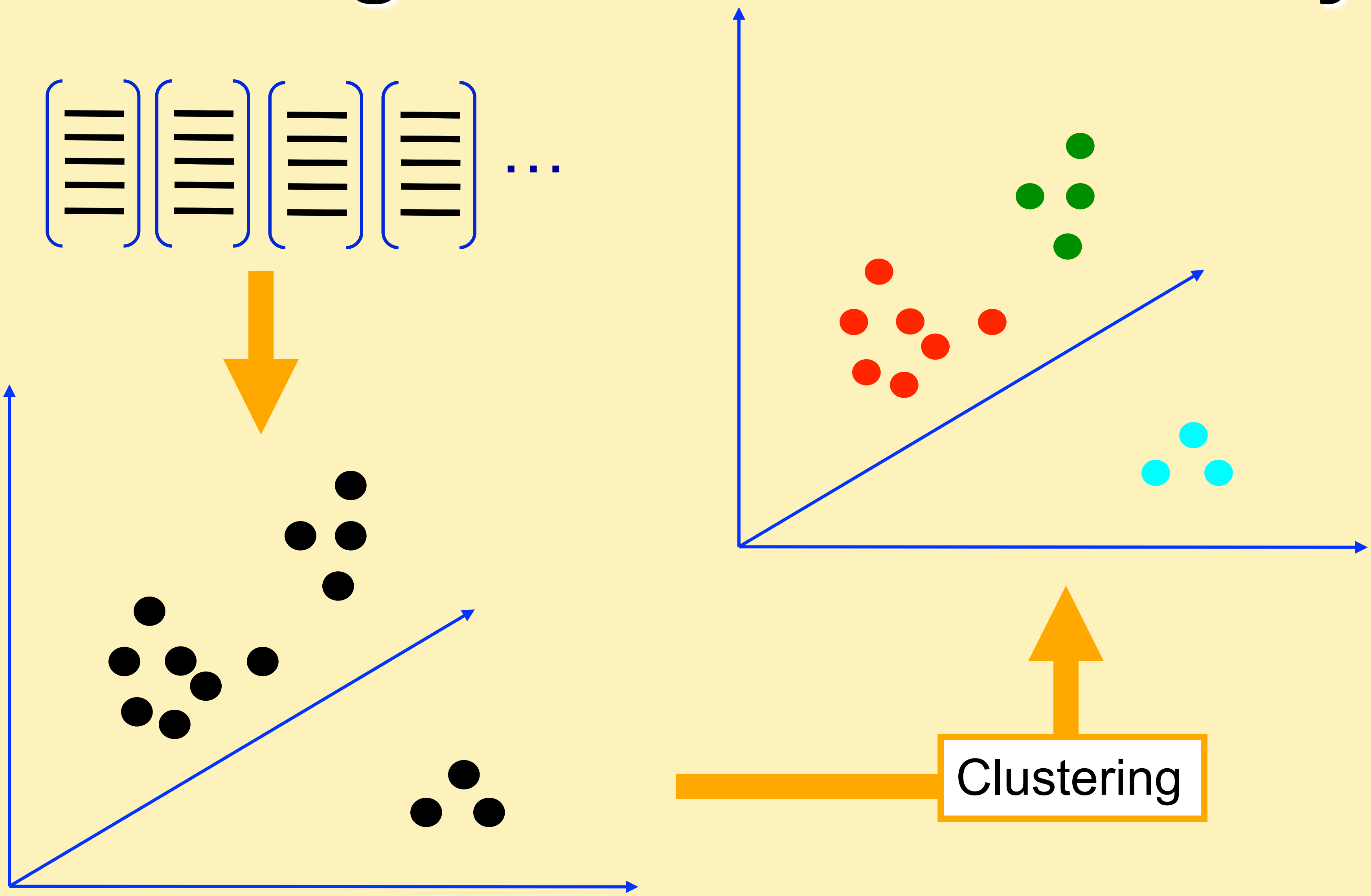
Slide credit: Josef Sivic

2. Learning the visual vocabulary



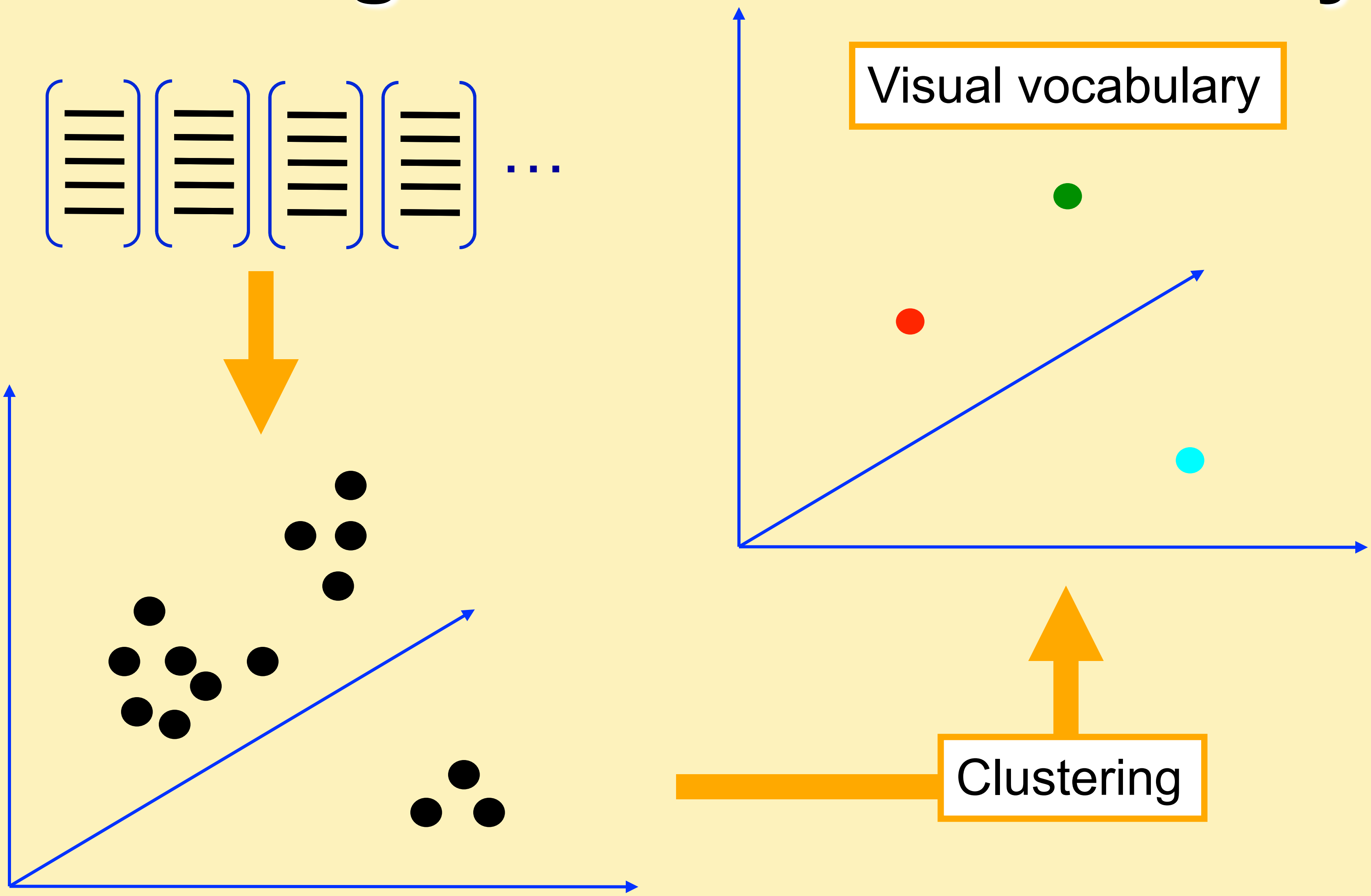
Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

K-means clustering

- Want to minimize sum of squared Euclidean distances between points x_i and their nearest cluster centers m_k

$$D(X,M) = \sum_{\text{cluster } k} \sum_{\substack{\text{point } i \text{ in} \\ \text{cluster } k}} (x_i - m_k)^2$$

Algorithm:

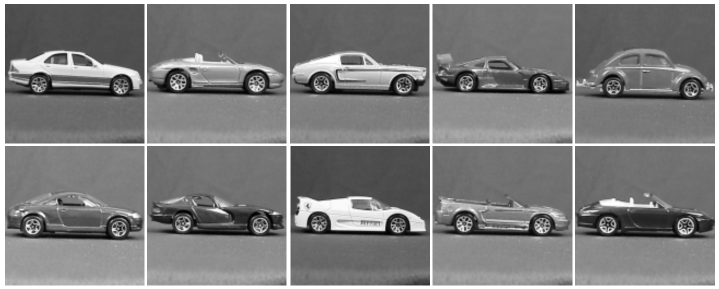
- Randomly initialize K cluster centers
- Iterate until convergence:
  - Assign each data point to the nearest center
  - Recompute each cluster center as the mean of all points assigned to it

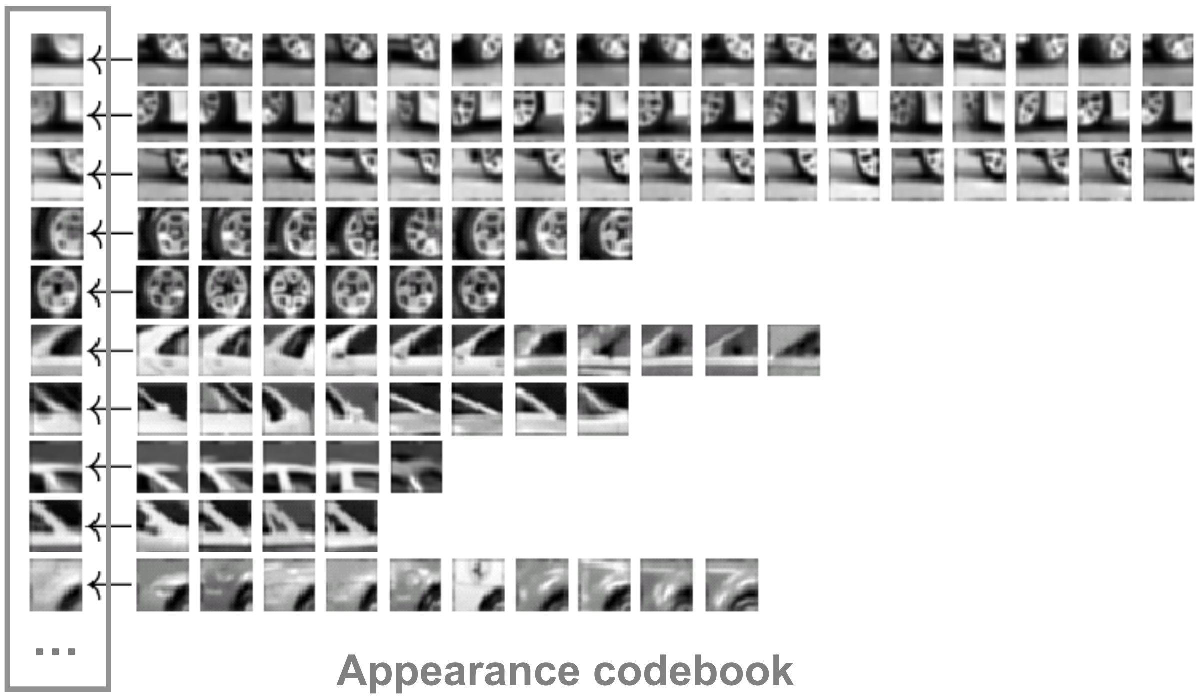
Clustering and vector quantization

- Clustering is a common method for learning a visual vocabulary or codebook
  - Unsupervised learning process
  - Each cluster center produced by k-means becomes a codevector
  - Codebook can be learned on separate training set
  - Provided 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

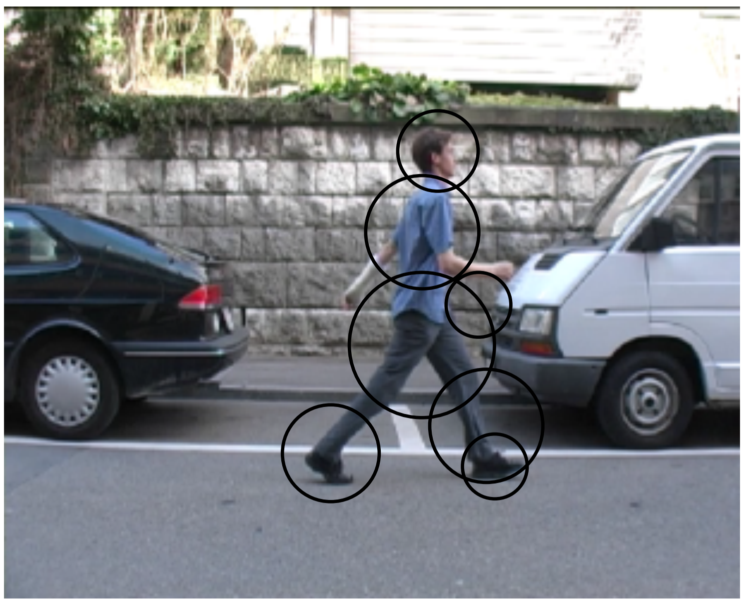




Appearance codebook

Source: B. Leibe

Another codebook

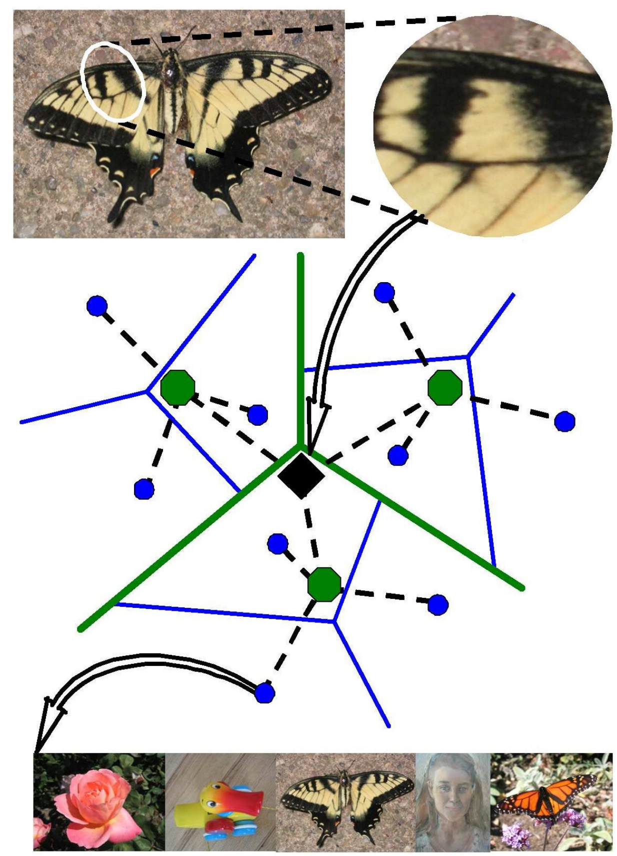


Appearance codebook

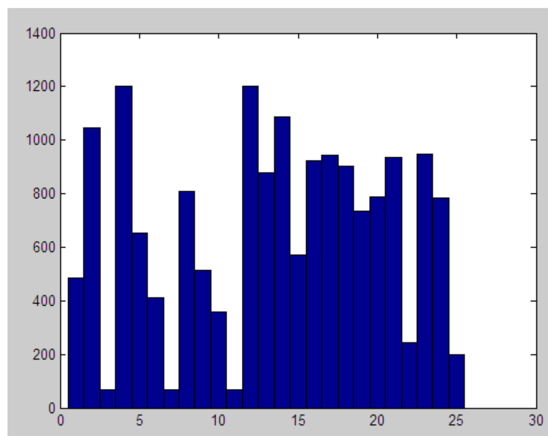
Source: B. Leibe

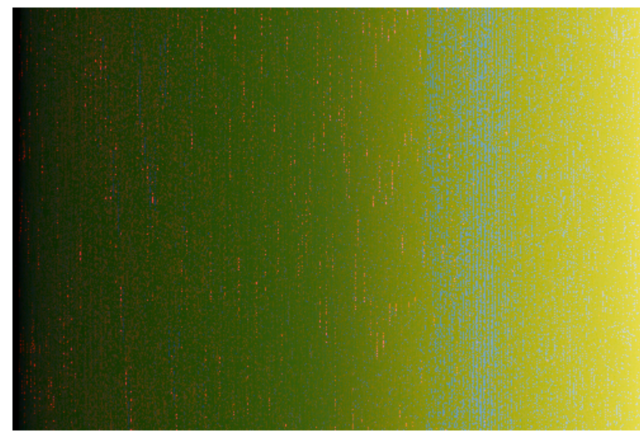
Visual vocabularies: Issues

- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
- Computational efficiency
  - Vocabulary trees
    (Nister & Stewenius, 2006)



But what about layout?





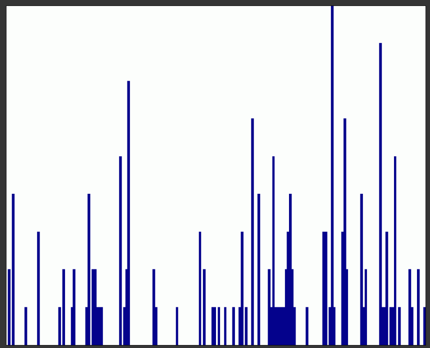
All of these images have the same color histogram

Spatial pyramid

Compute histogram in each spatial bin

Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution

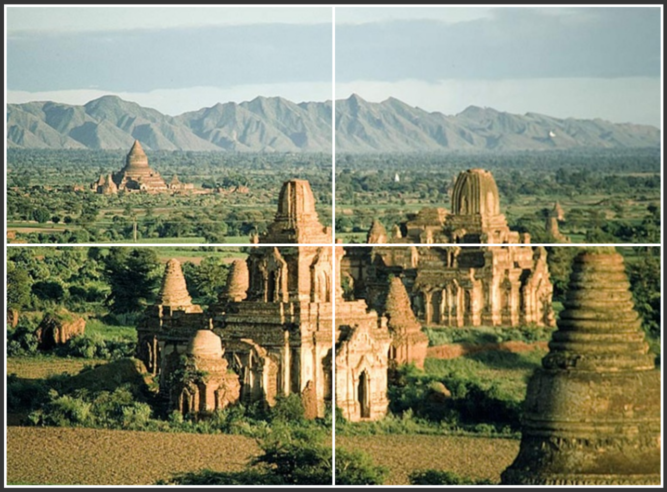


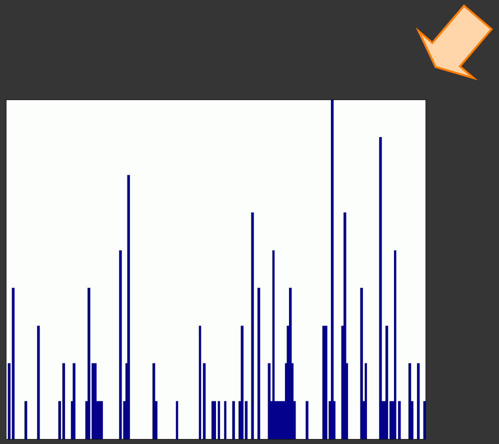
level 0

Lazebnik, Schmid & Ponce (CVPR 2006)

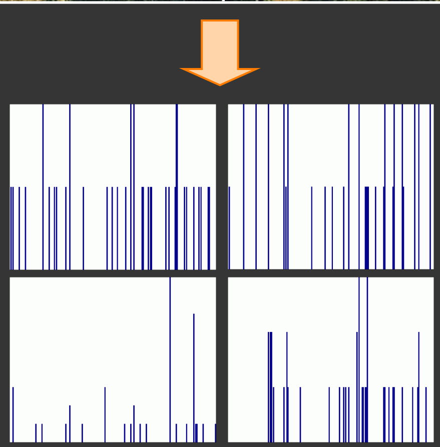
Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution





level 0

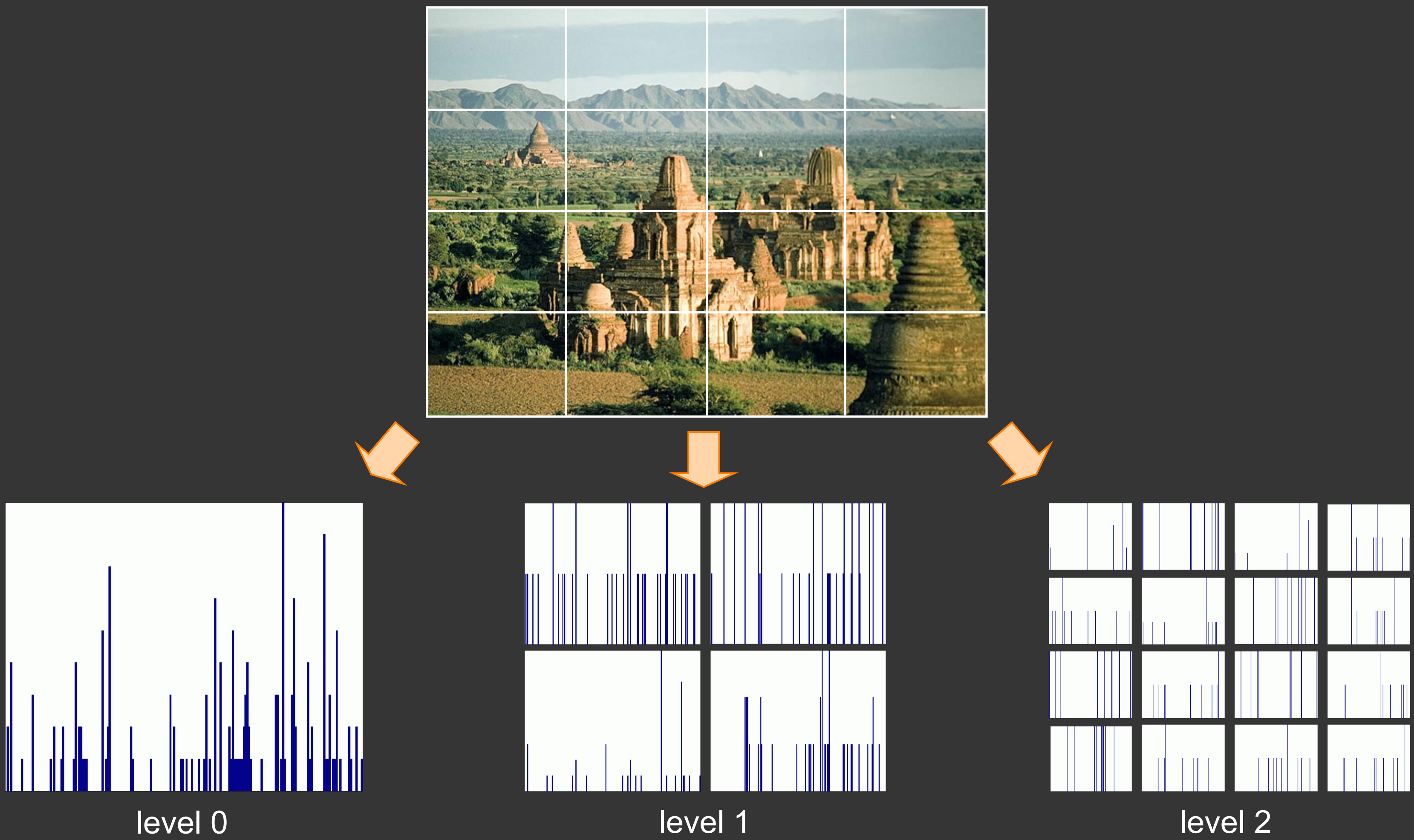


level 1

Lazebnik, Schmid & Ponce (CVPR 2006)

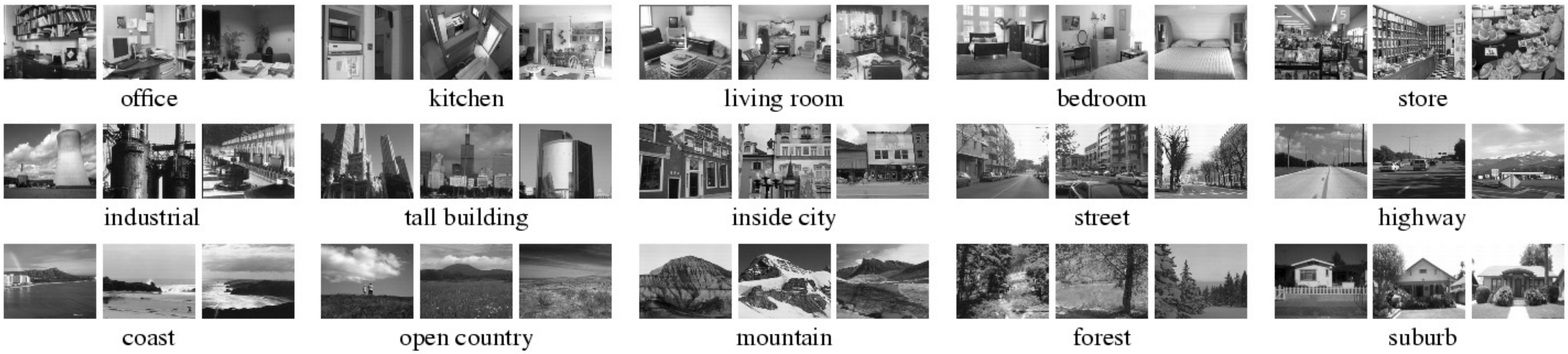
Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution



Lazebnik, Schmid & Ponce (CVPR 2006)

Scene category dataset

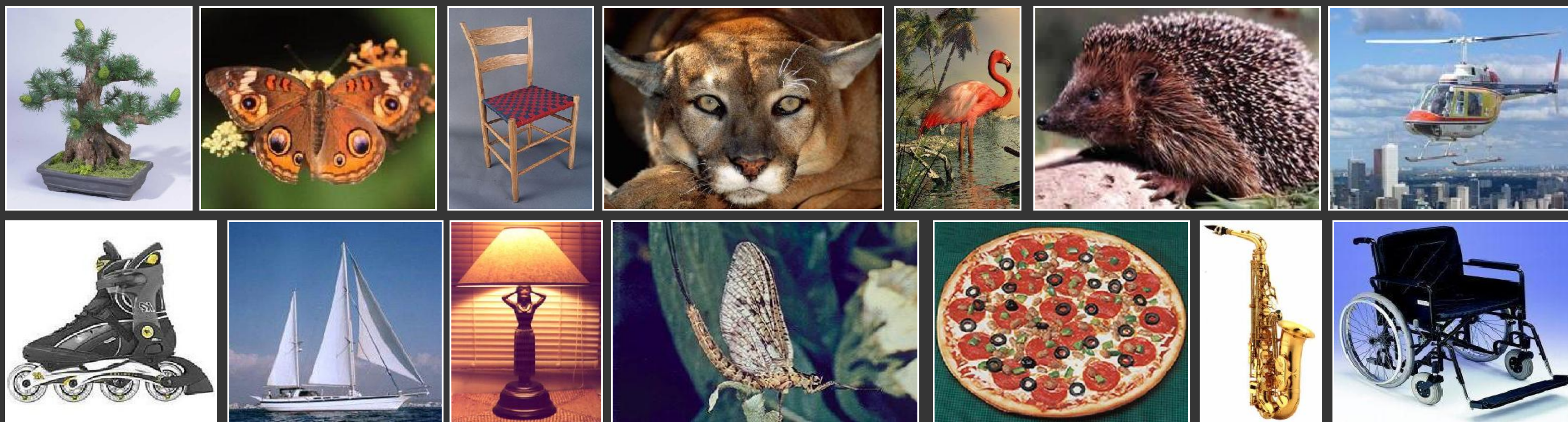


Multi-class classification results
(100 training images per class)

Level	Weak features (vocabulary size: 16) Single-level	Weak features (vocabulary size: 16) Pyramid	Strong features (vocabulary size: 200) Single-level	Strong features (vocabulary size: 200) Pyramid
0 (1×1)	45.3 $\pm$0.5		72.2 $\pm$0.6	
1 (2×2)	53.6 $\pm$0.3	56.2 $\pm$0.6	77.9 $\pm$0.6	79.0 $\pm$0.5
2 (4×4)	61.7 $\pm$0.6	64.7 $\pm$0.7	79.4 $\pm$0.3	**81.1** $\pm$0.3
3 (8×8)	63.3 $\pm$0.8	**66.8** $\pm$0.6	77.2 $\pm$0.4	80.7 $\pm$0.3

Caltech101 dataset

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

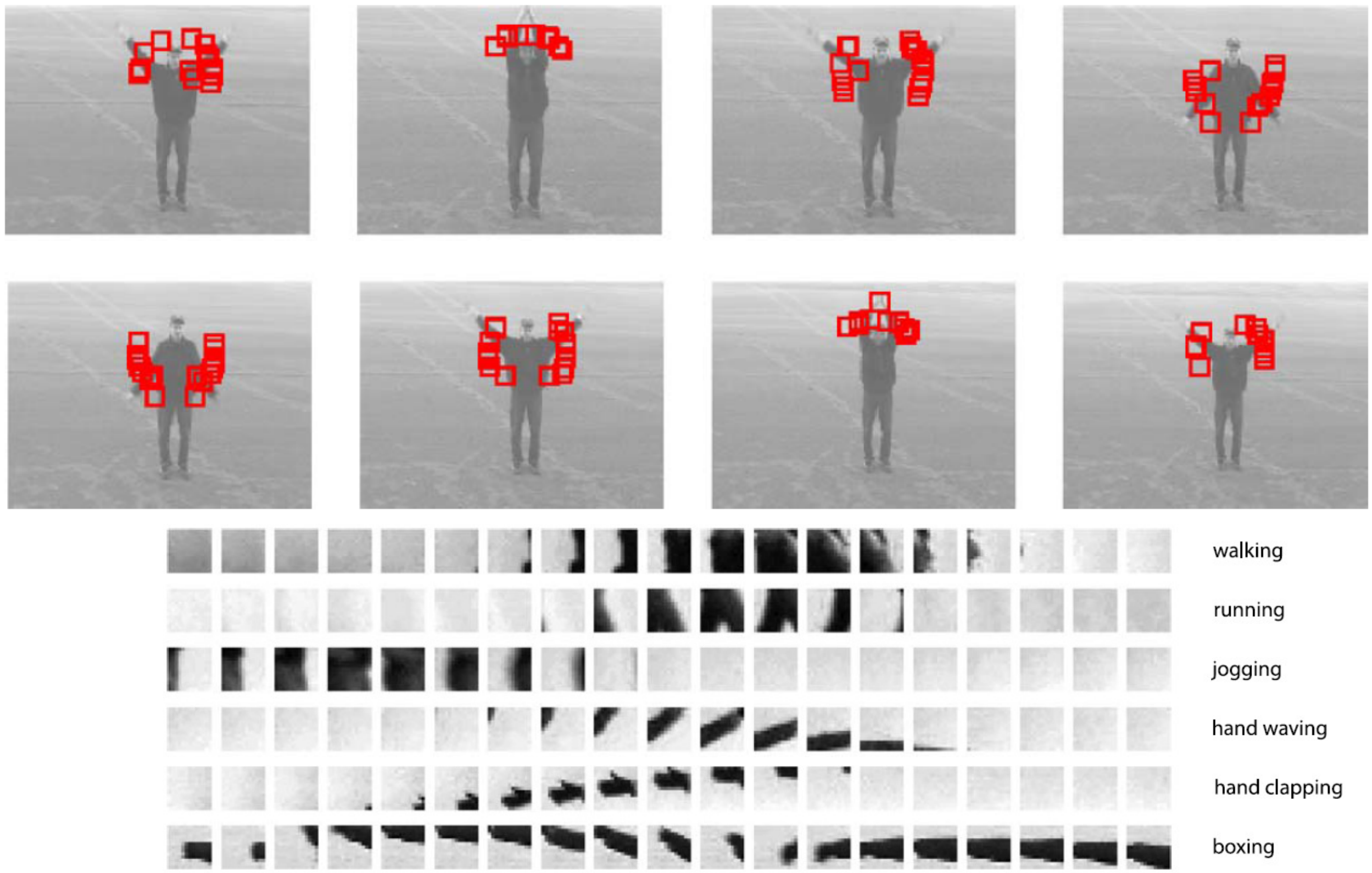


Multi-class classification results (30 training images per class)

	Weak features (16)		Strong features (200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0	15.5 ±0.9		41.2 ±1.2	
1	31.4 ±1.2	32.8 ±1.3	55.9 ±0.9	57.0 ±0.8
2	47.2 ±1.1	49.3 ±1.4	63.6 ±0.9	**64.6** ±0.8
3	52.2 ±0.8	**54.0** ±1.1	60.3 ±0.9	64.6 ±0.7

Bags of features for action recognition

Space-time interest points



Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, **Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words**, IJCV 2008.

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
- Present trends: combination of local and global methods, data-driven methods, context

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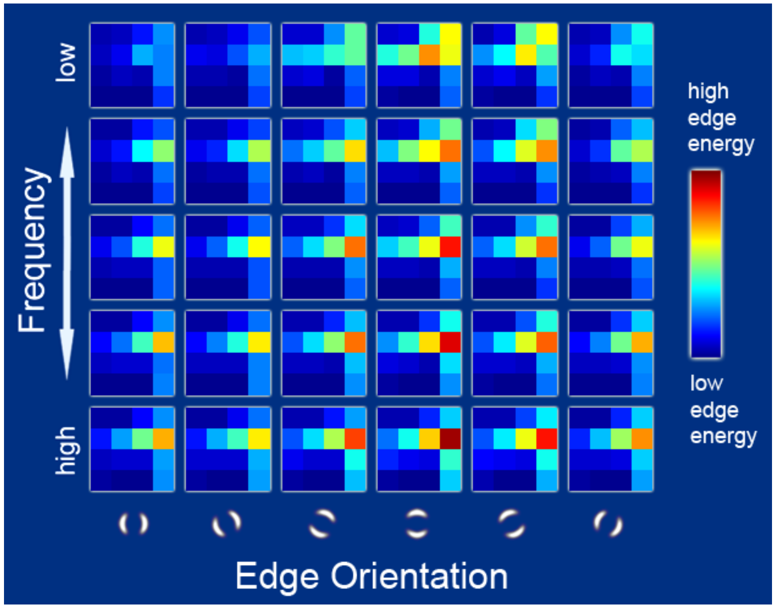
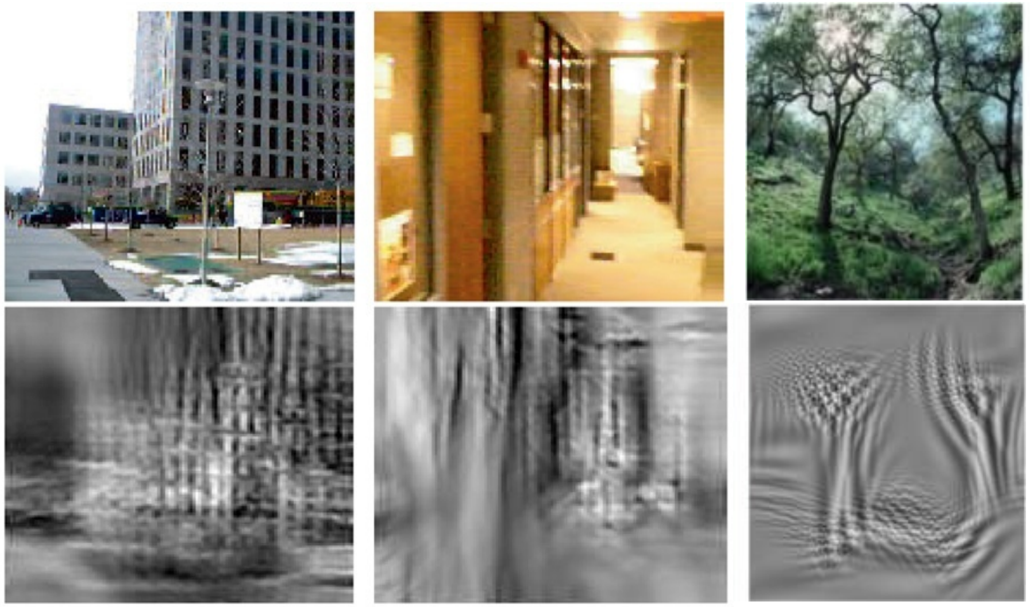
Global scene descriptors

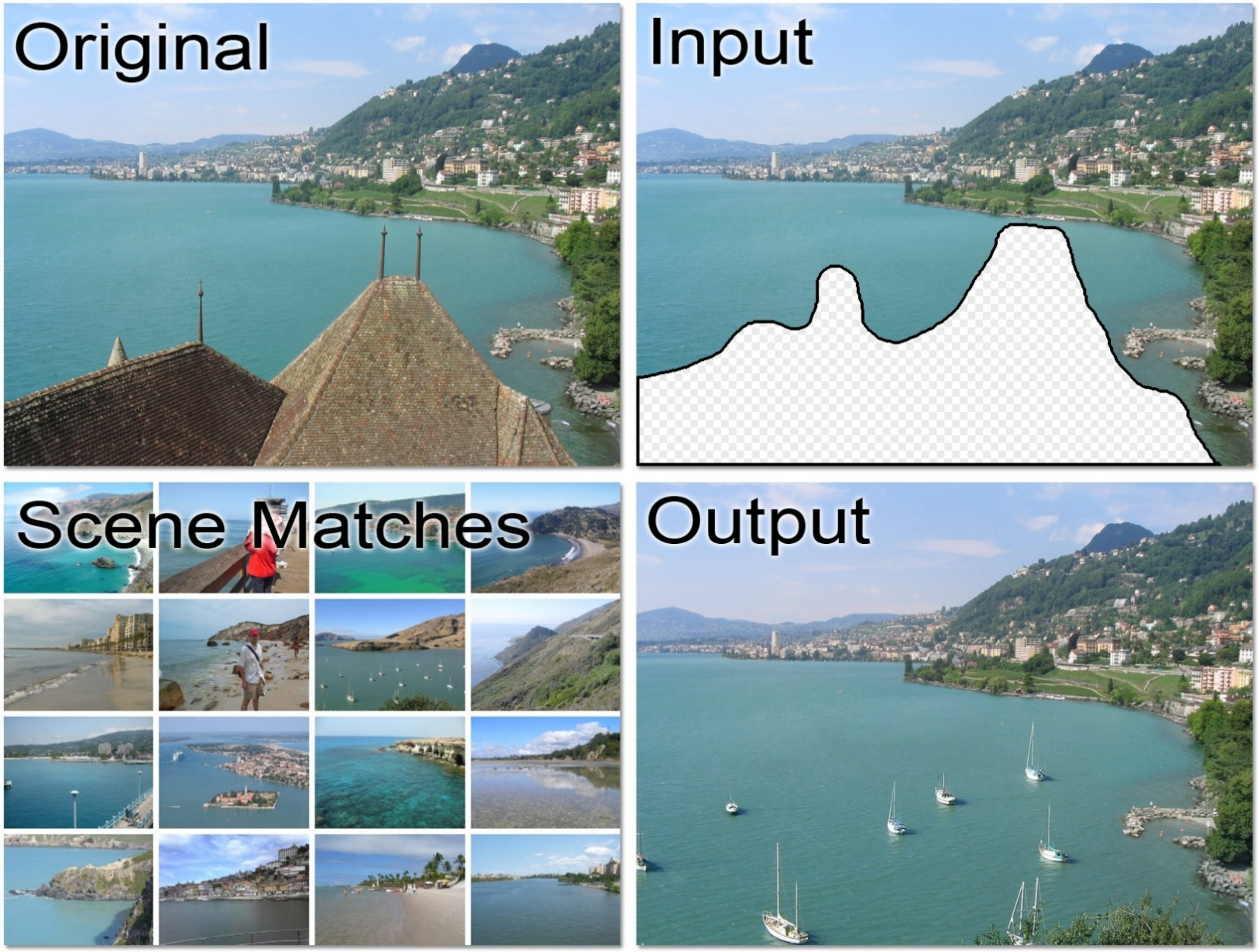
- The "gist" of a scene: Oliva & Torralba (2001)





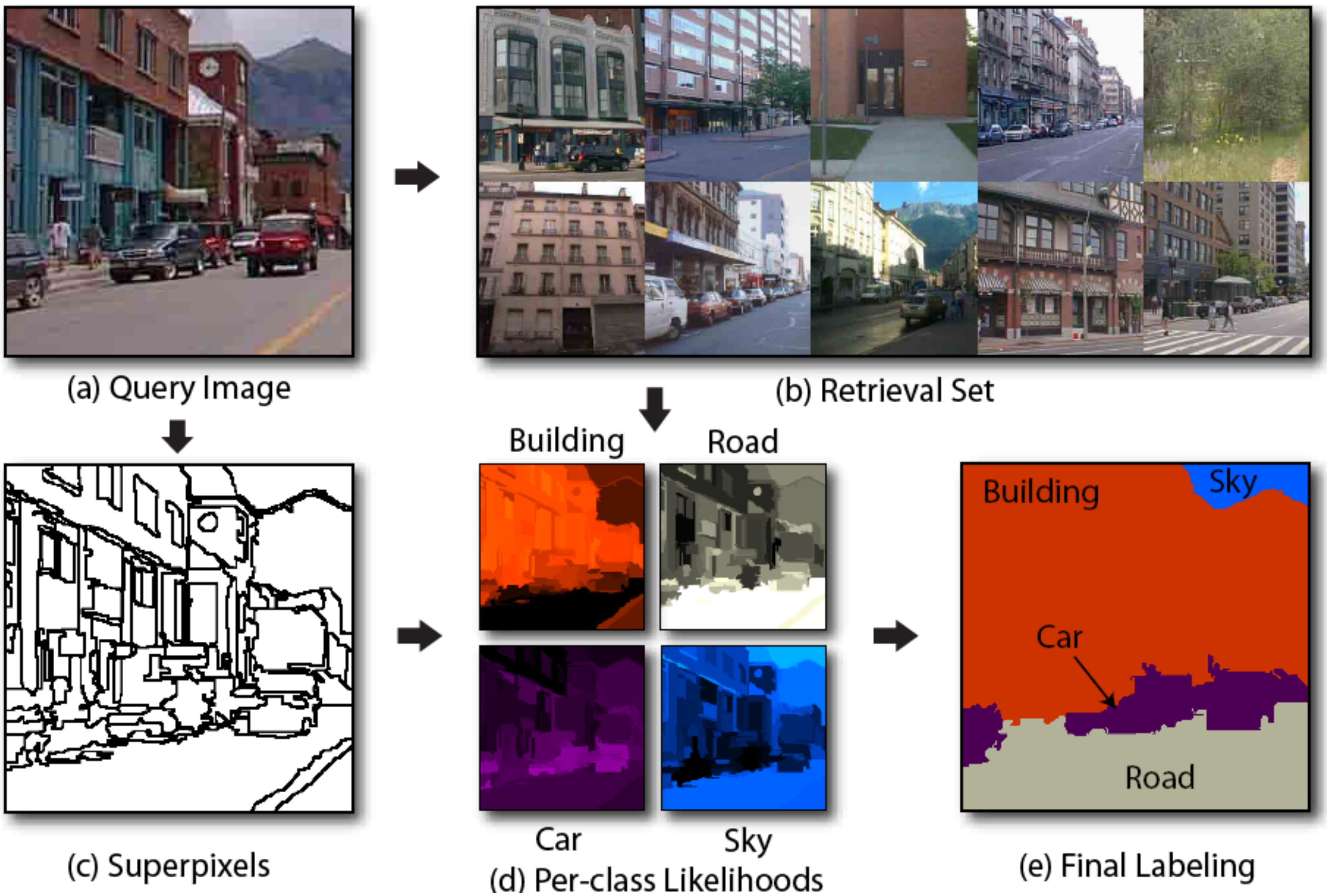
http://people.csail.mit.edu/torralba/code/spatialenvelope/

Data-driven methods



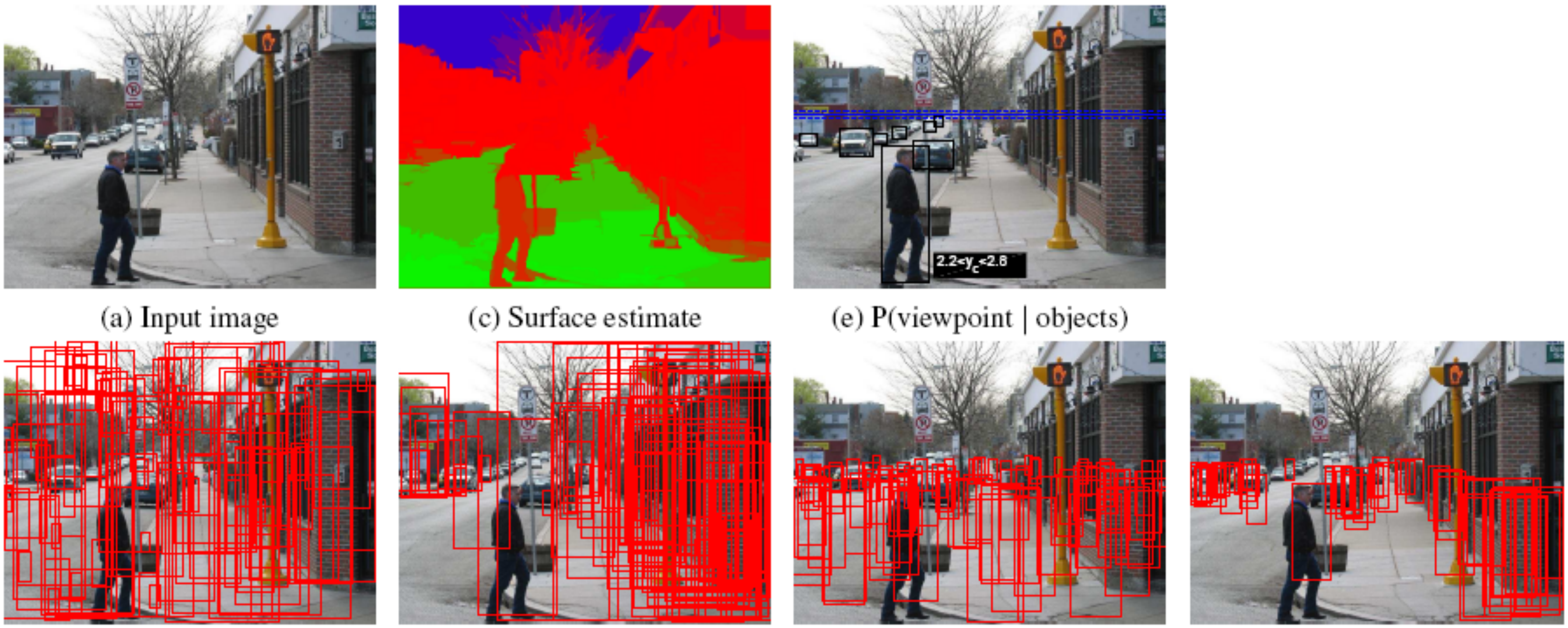
J. Hays and A. Efros, [Scene Completion using Millions of Photographs](), SIGGRAPH 2007

Data-driven methods



J. Tighe and S. Lazebnik, ECCV 2010

Geometric context



(a) Input image (c) Surface estimate (e) P(viewpoint | objects)
(b) P(person) = uniform (d) P(person | geometry) (f) P(person | viewpoint) (g) P(person|viewpoint,geometry)

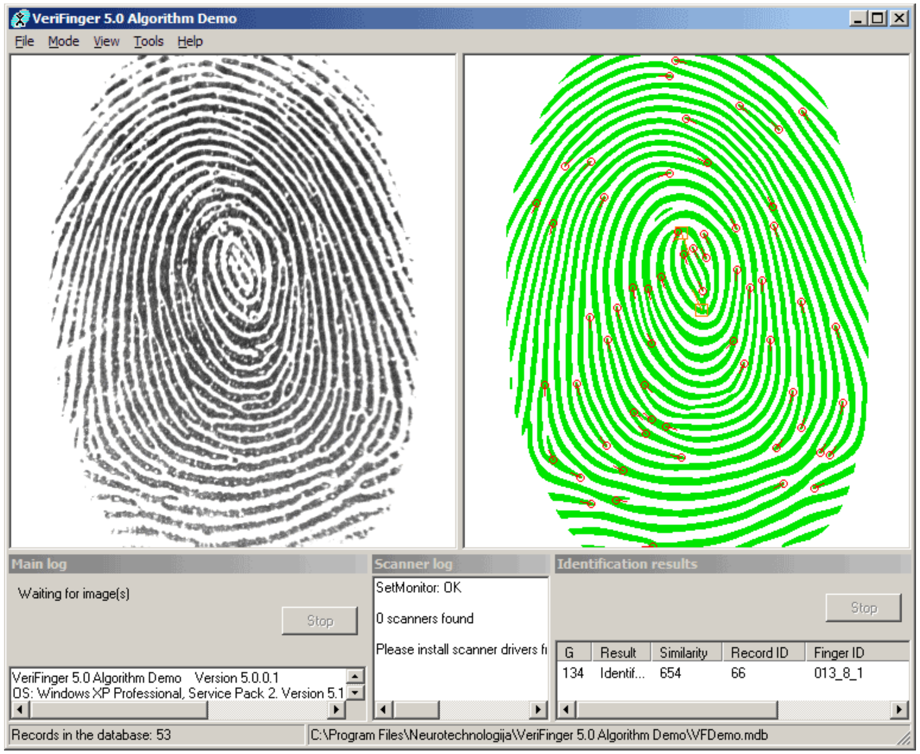
D. Hoiem, A. Efros, and M. Herbert.
Putting Objects in Perspective. CVPR 2006.

What “works” today

- Reading license plates, zip codes, checks

What "works" today

- Reading license plates, zip codes, checks
- Fingerprint recognition



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What "works" today

- Reading license plates, zip codes, checks
- Fingerprint recognition
- Face detection

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

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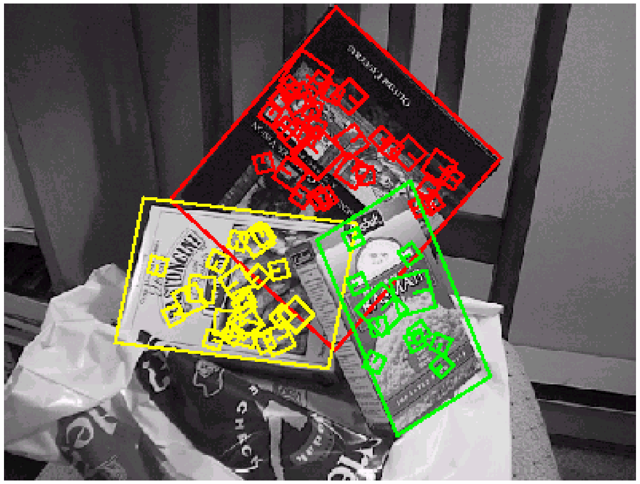
What "works" today

- Reading license plates, zip codes, checks
- Fingerprint recognition
- Face detection
- Recognition of flat textured objects (CD covers, book covers, etc.)



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