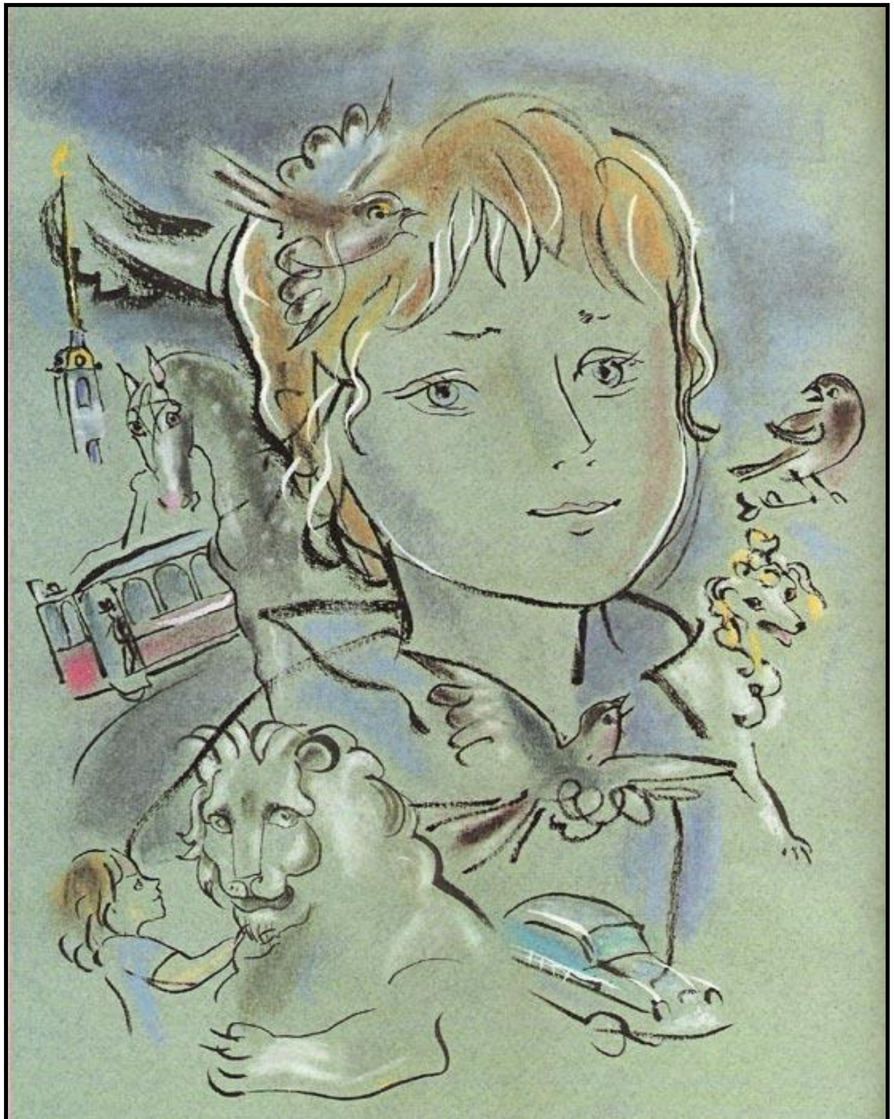
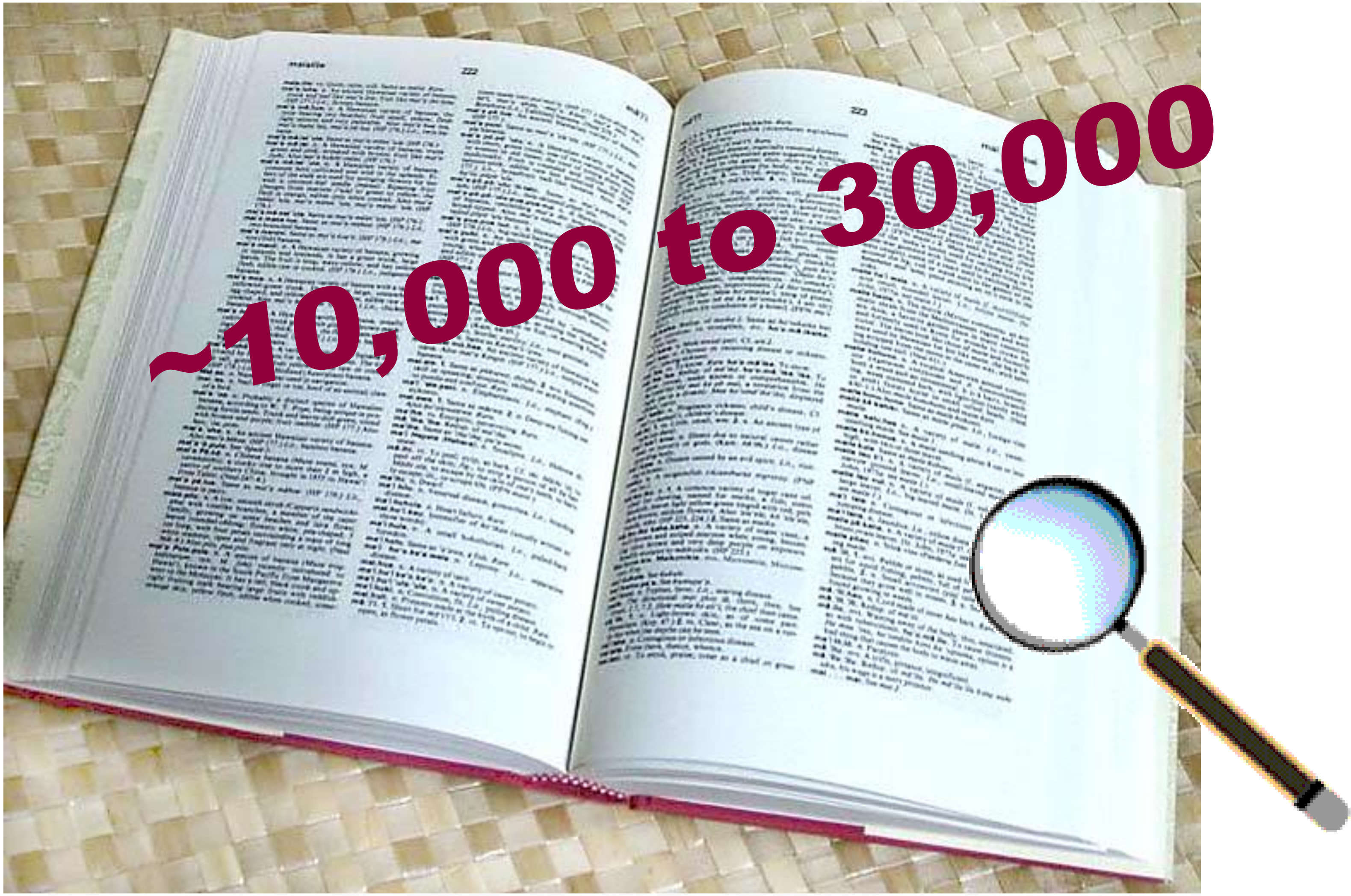
Recognition: Overview and History



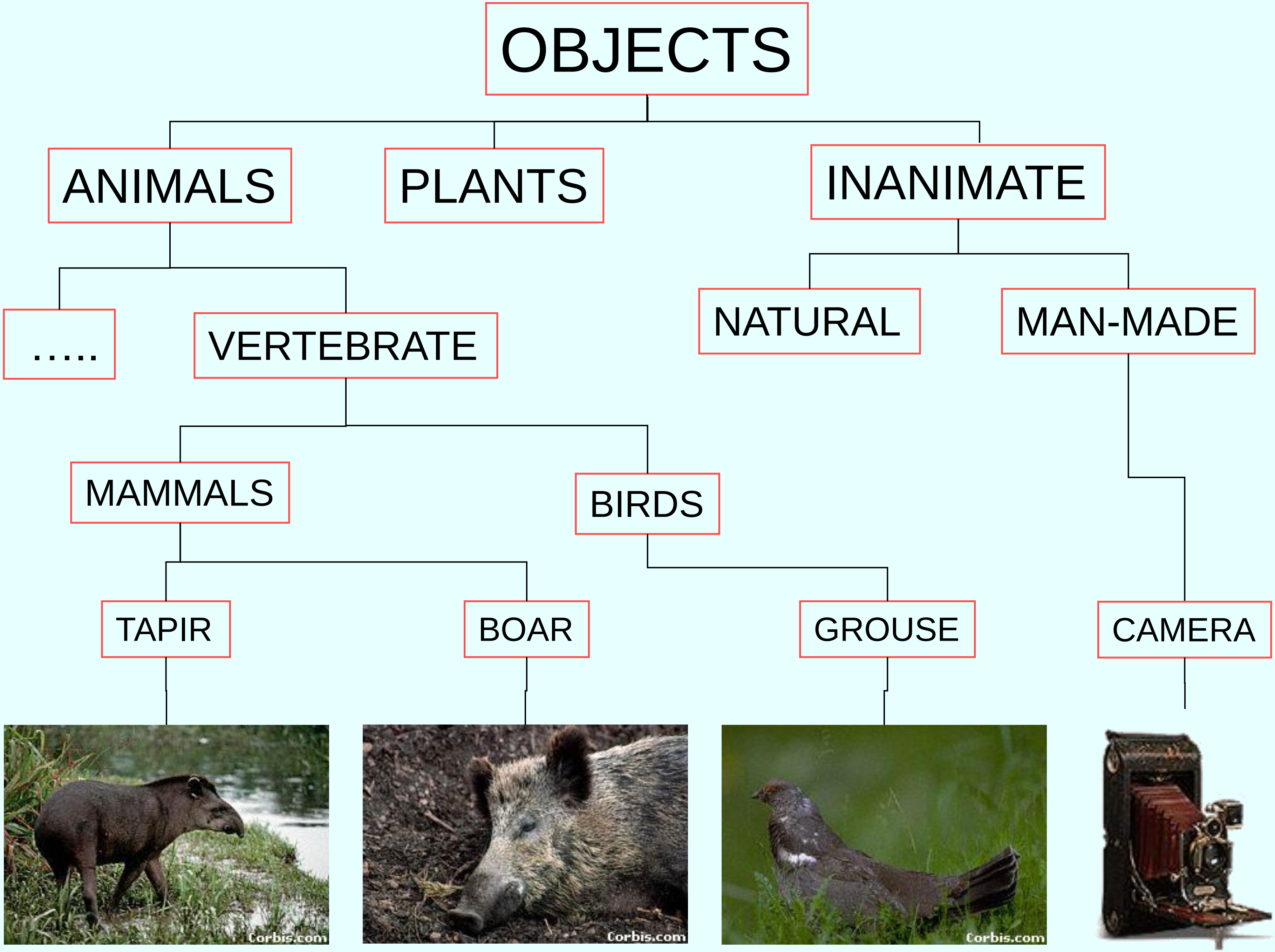
Slides from Lana Lazebnik, Fei-Fei Li, Rob Fergus, Antonio Torralba, and Jean Ponce

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

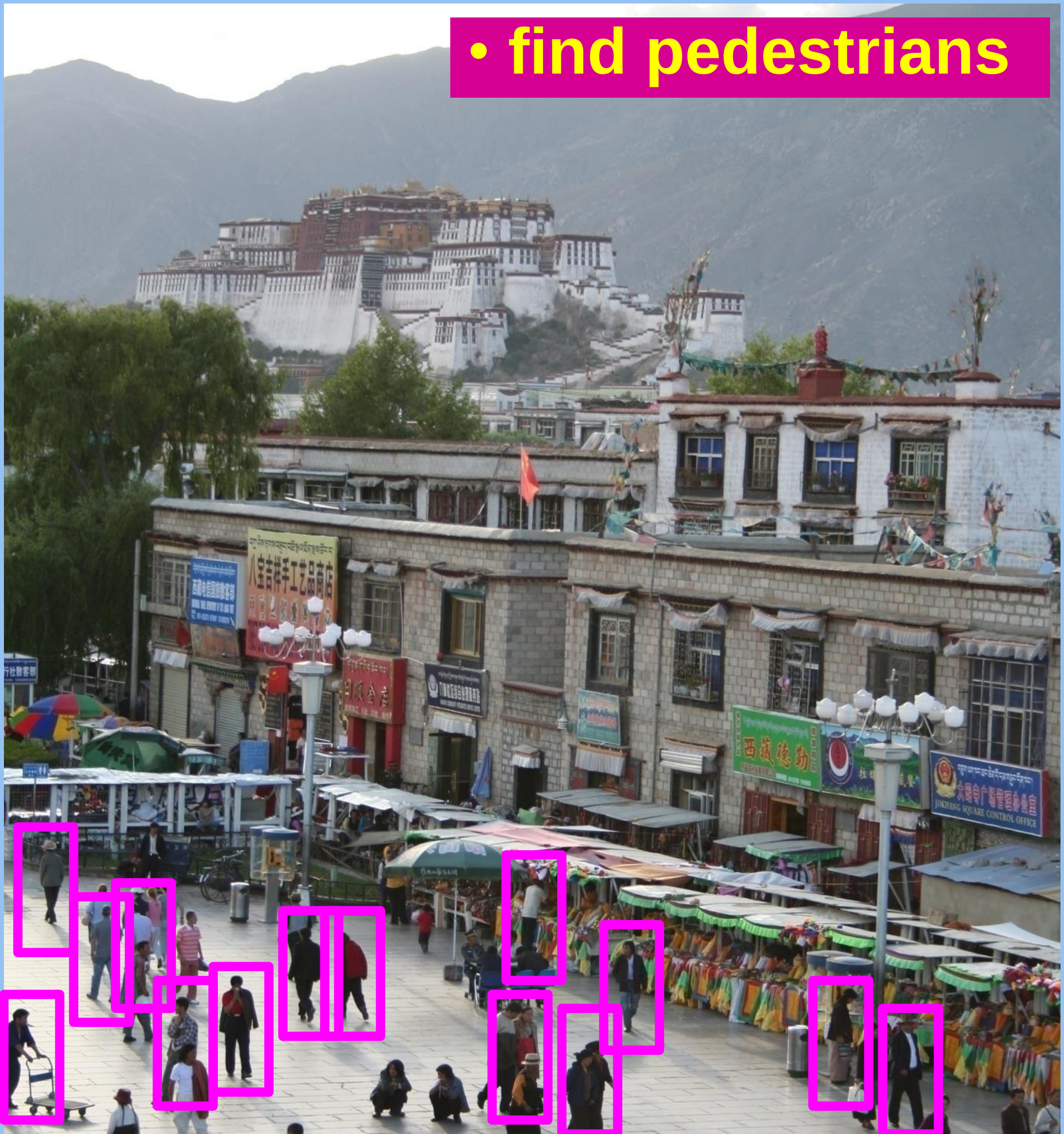

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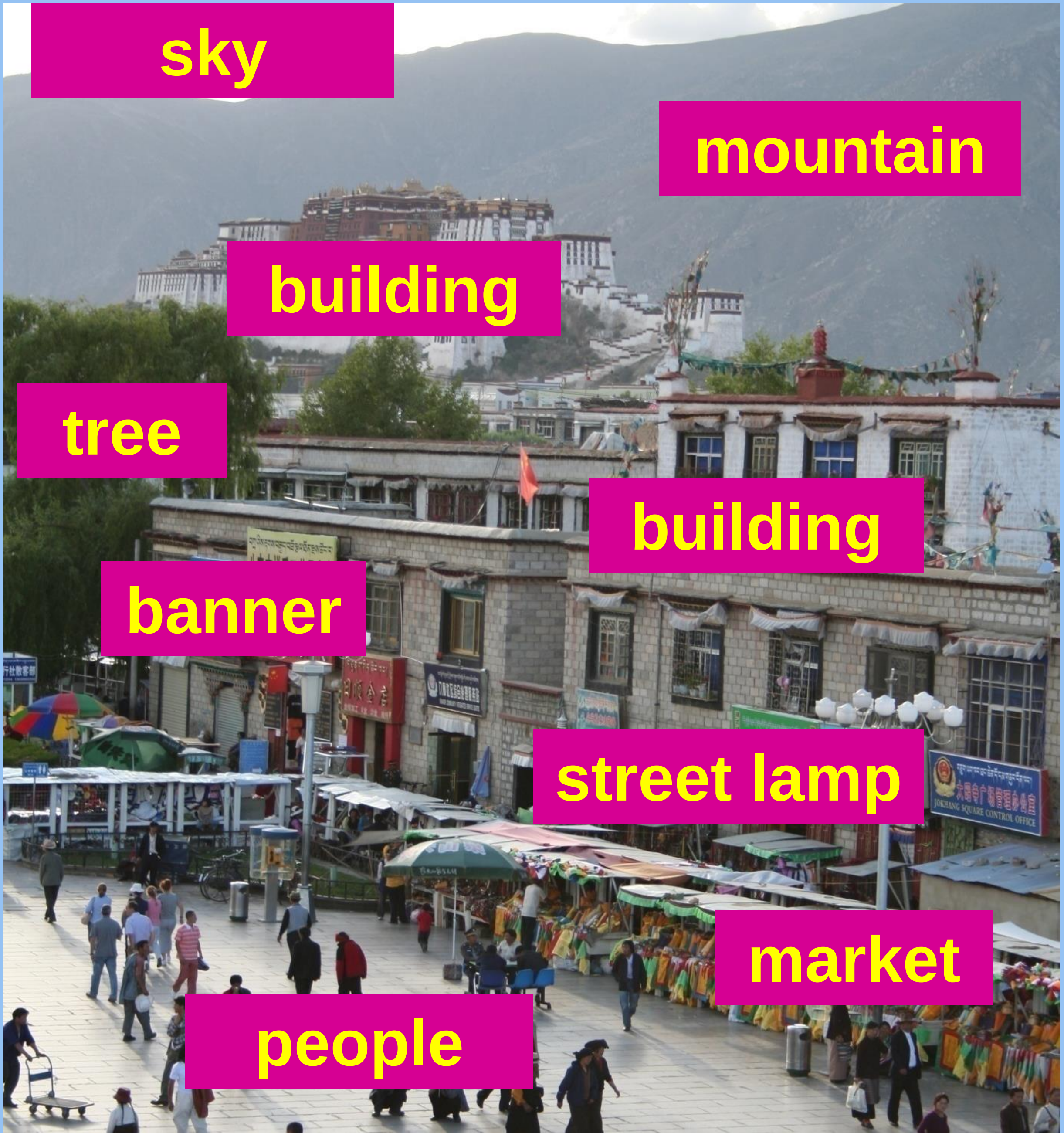
Image parsing / semantic segmentation



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Scene understanding?

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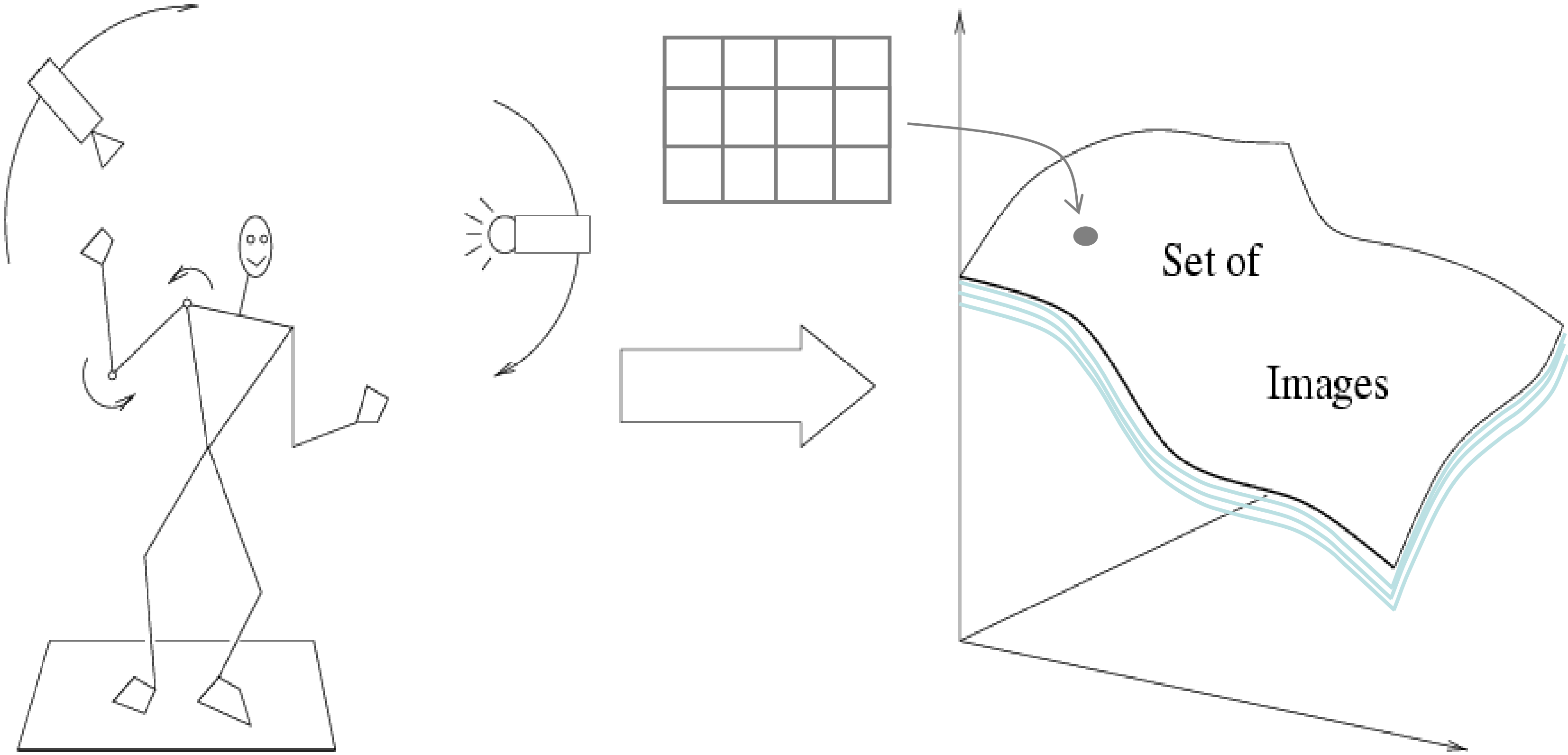
Project 3: Scene recognition with bag of words

http://cs.brown.edu/courses/csci1430/proj3/

Recognition is all about modeling variability



Variability: Camera position
Illumination
Shape parameters

Within-class variations?

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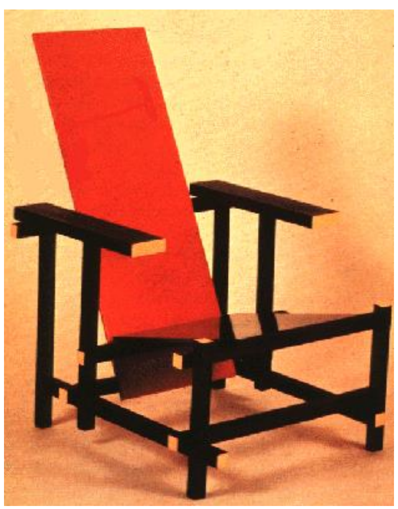
Within-class variations



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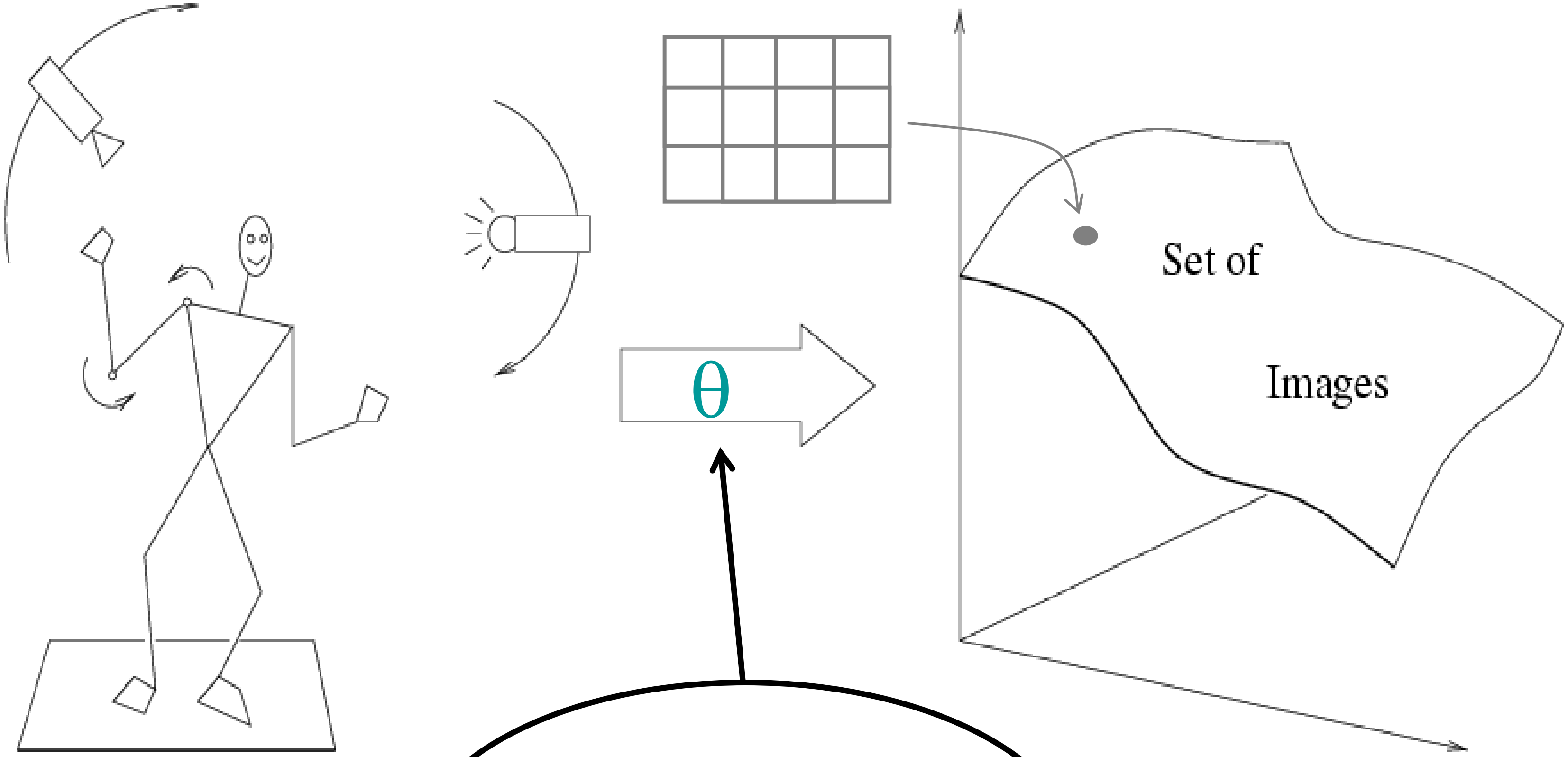
History of ideas in recognition

- 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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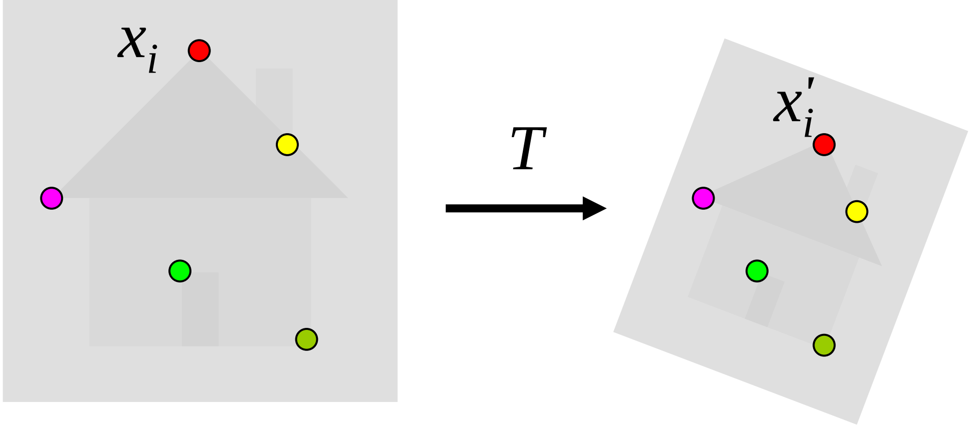
Recall: Alignment

- 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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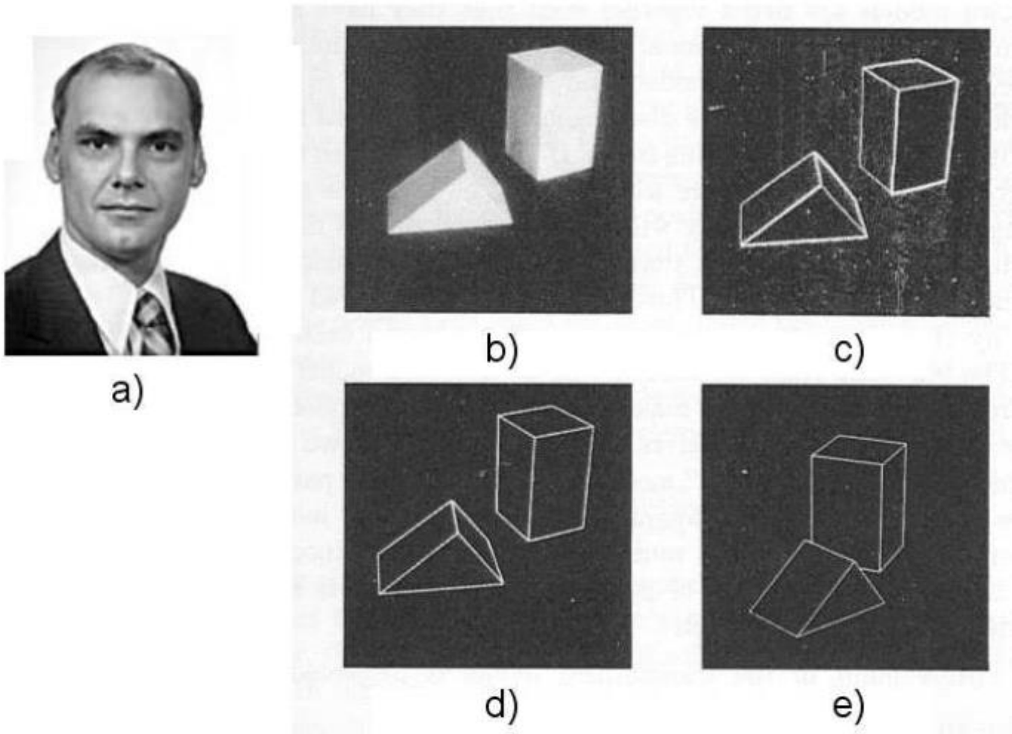
Recognition as an alignment problem: Block world

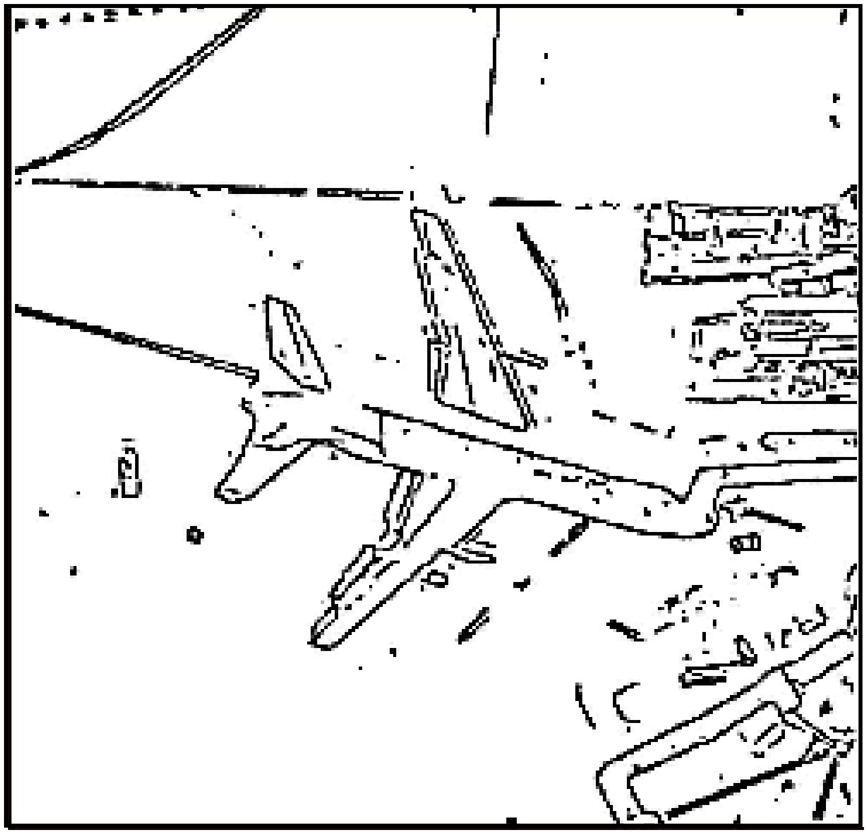


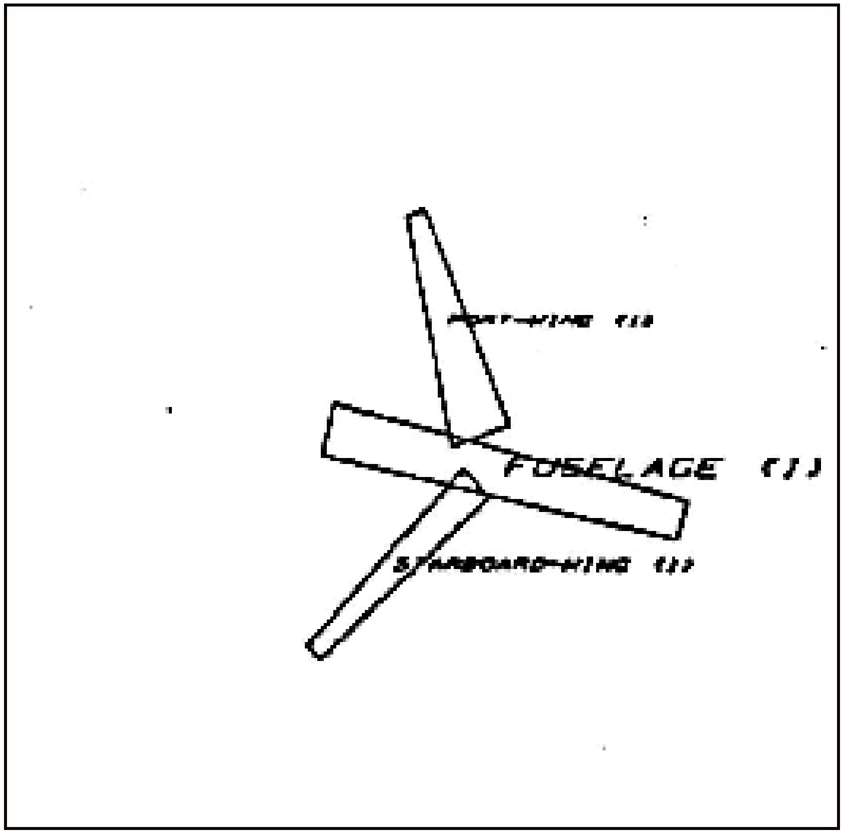
L. G. Roberts, *Machine Perception of Three Dimensional Solids*, Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

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

Representing and recognizing object categories is harder...





ACRONYM (Brooks and Binford, 1981)

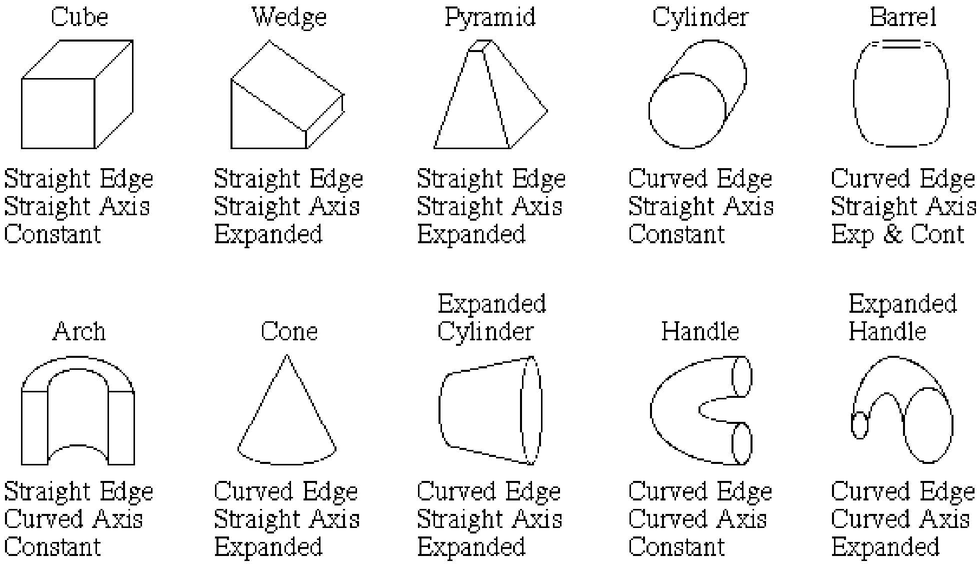
Binford (1971), Nevatia & Binford (1972), Marr & Nishihara (1978)

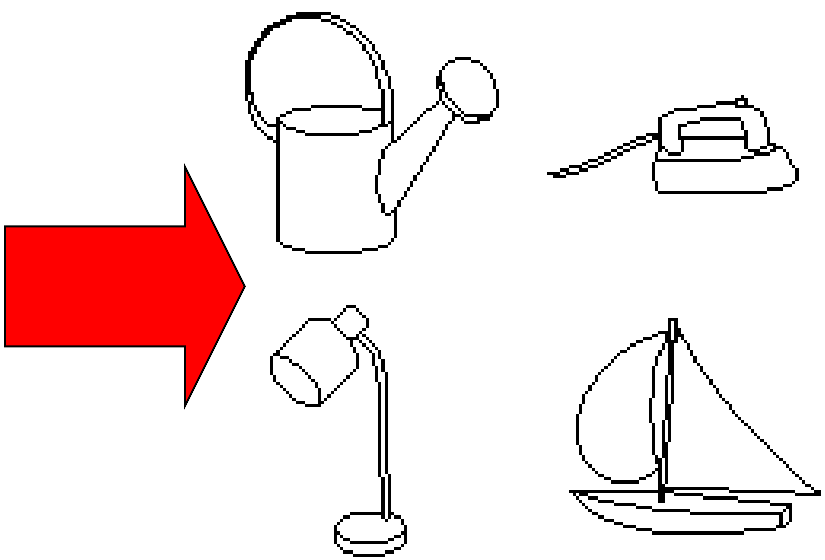
Recognition by components

Biederman (1987)

Primitives (geons)

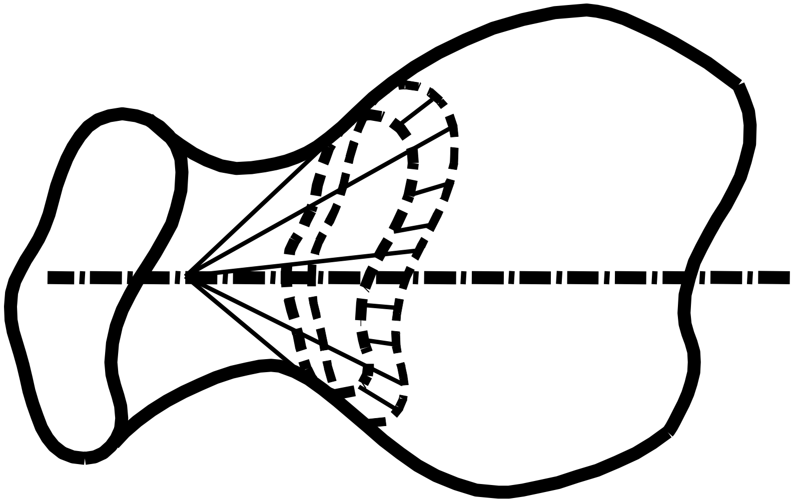
Objects



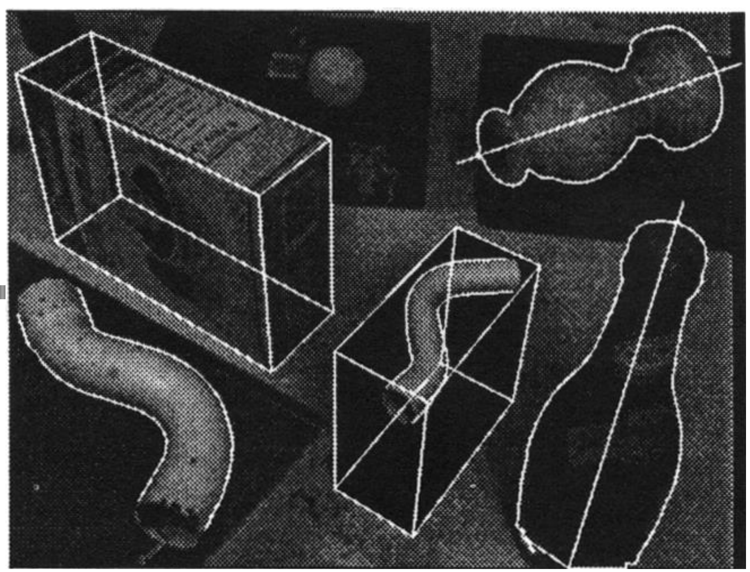


http://en.wikipedia.org/wiki/Recognition_by_Components_Theory

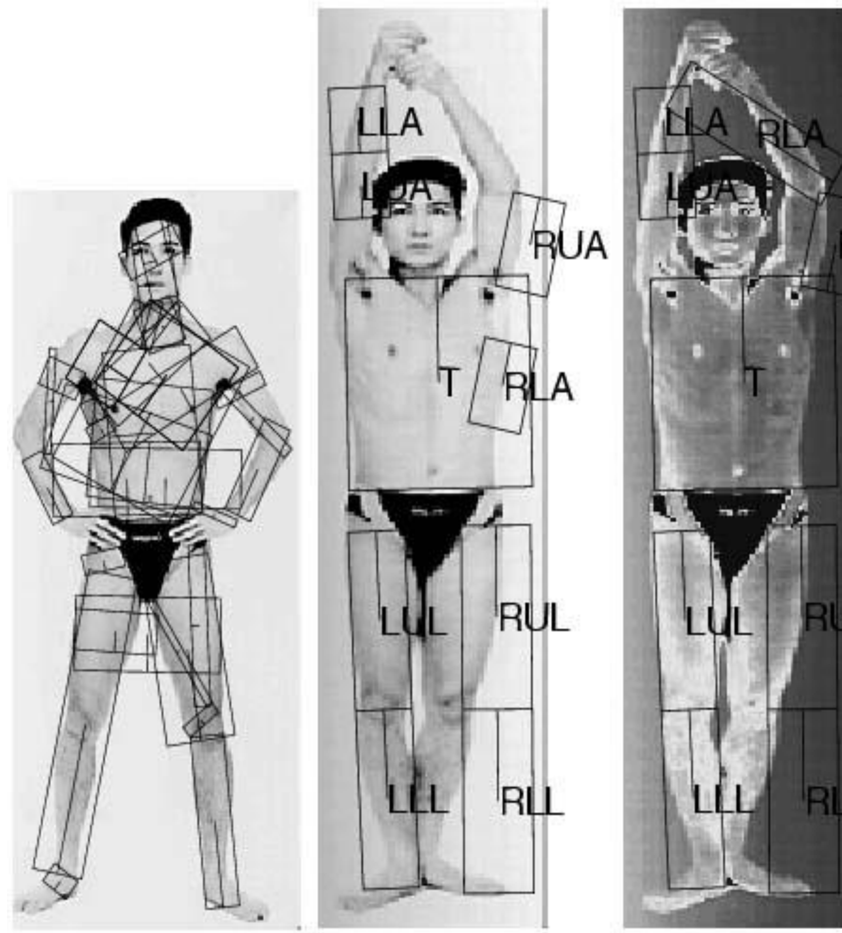
General shape primitives?



Generalized cylinders
Ponce et al. (1989)



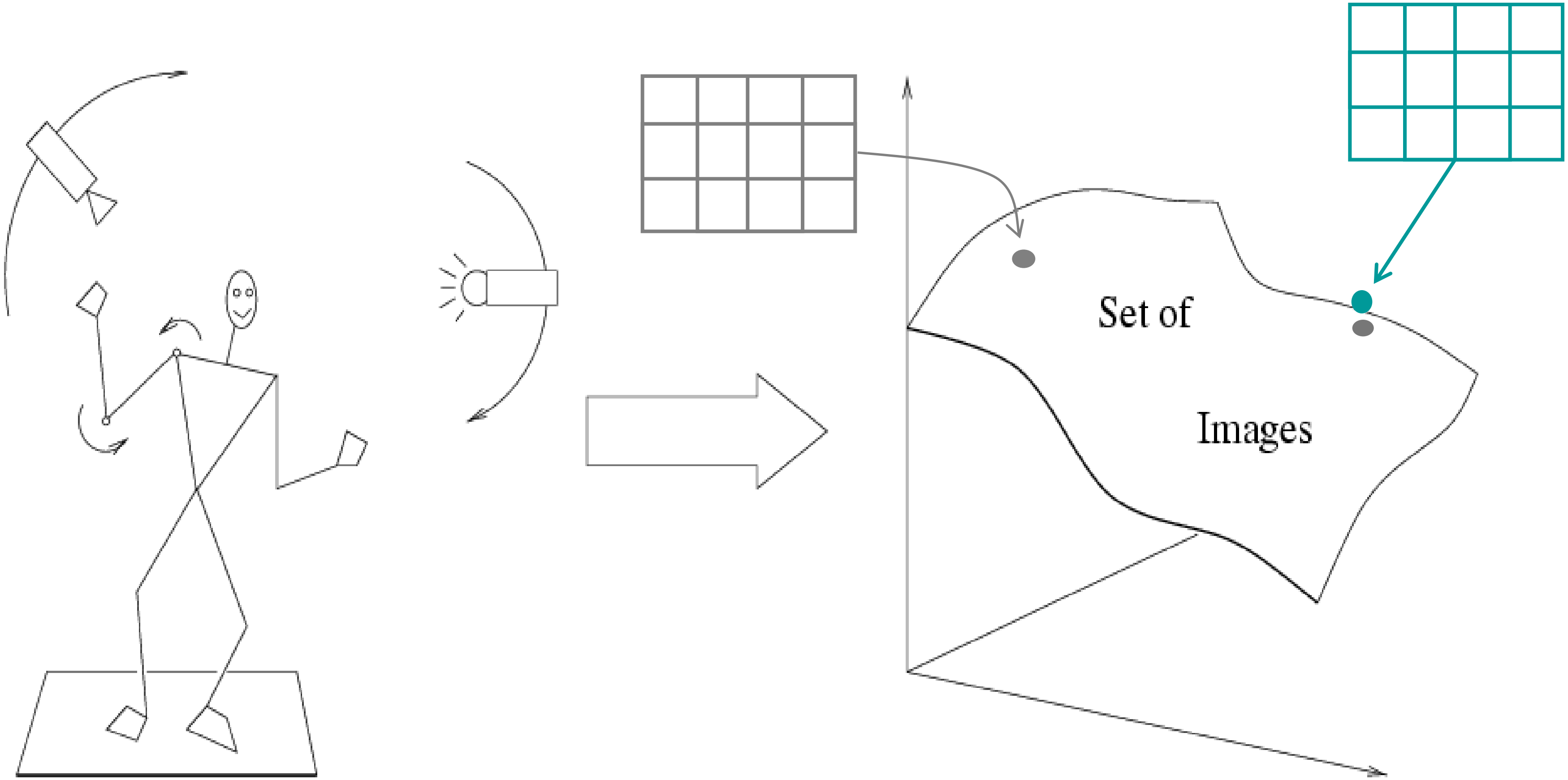
Zisserman et al. (1995)



Forsyth (2000)

History of ideas in recognition

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

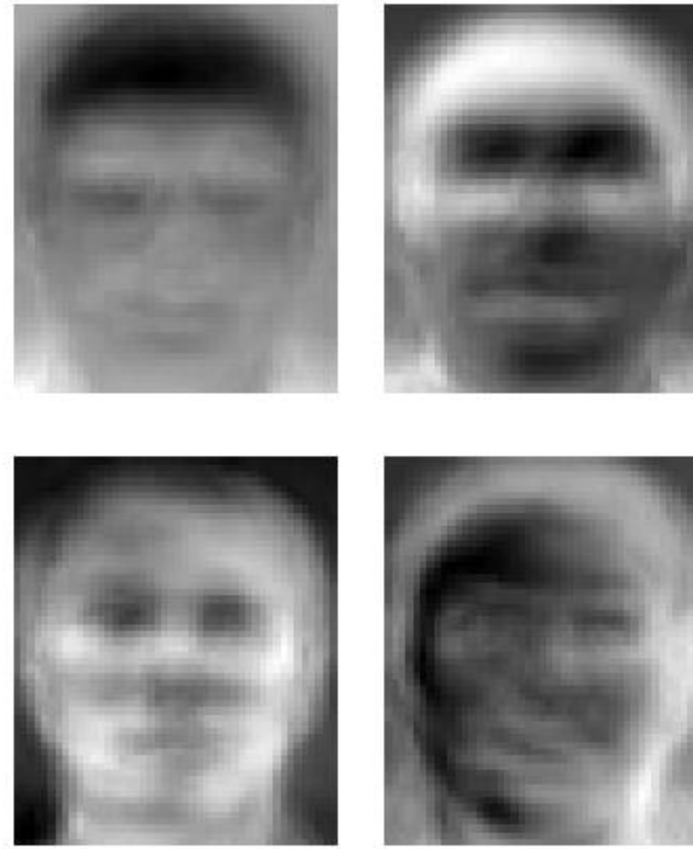


Empirical models of image variability

Appearance-based techniques

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

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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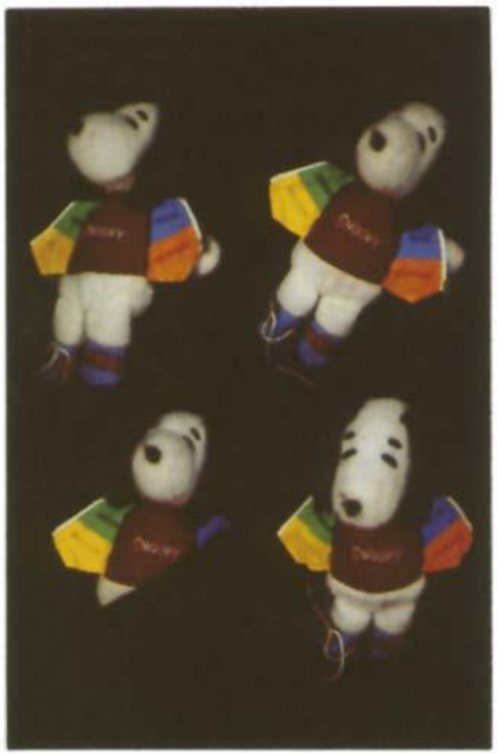
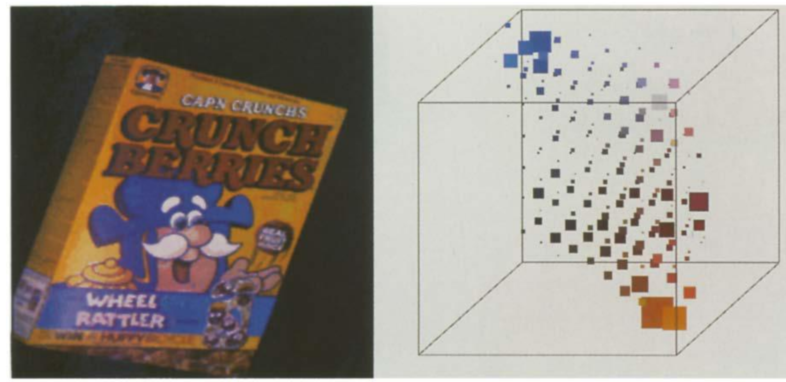
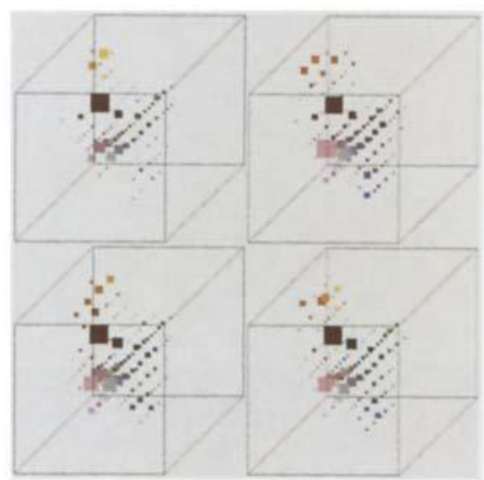
Color Histograms







Swain and Ballard, [Color Indexing](), IJCV 1991.

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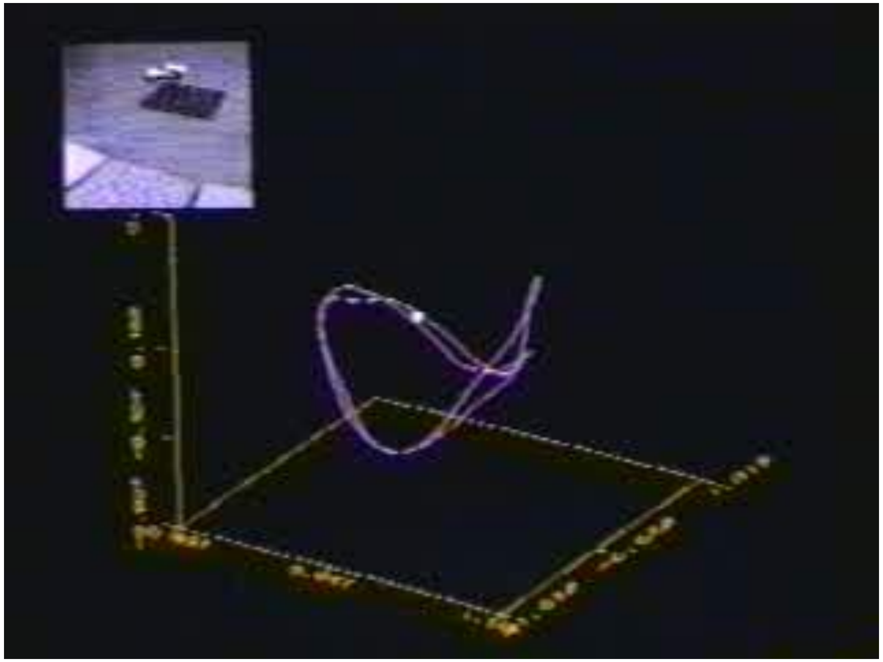
Appearance manifolds



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

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

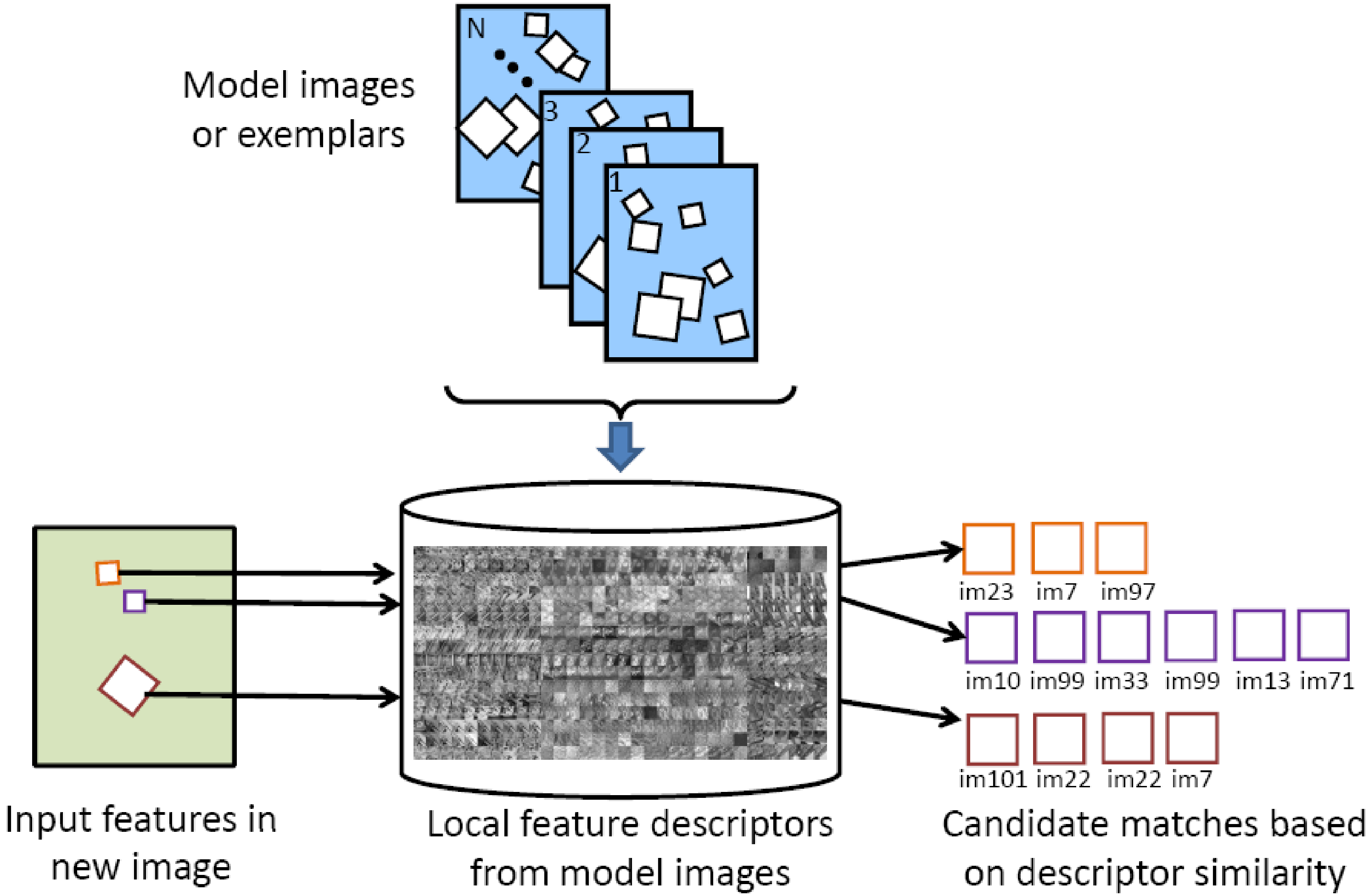
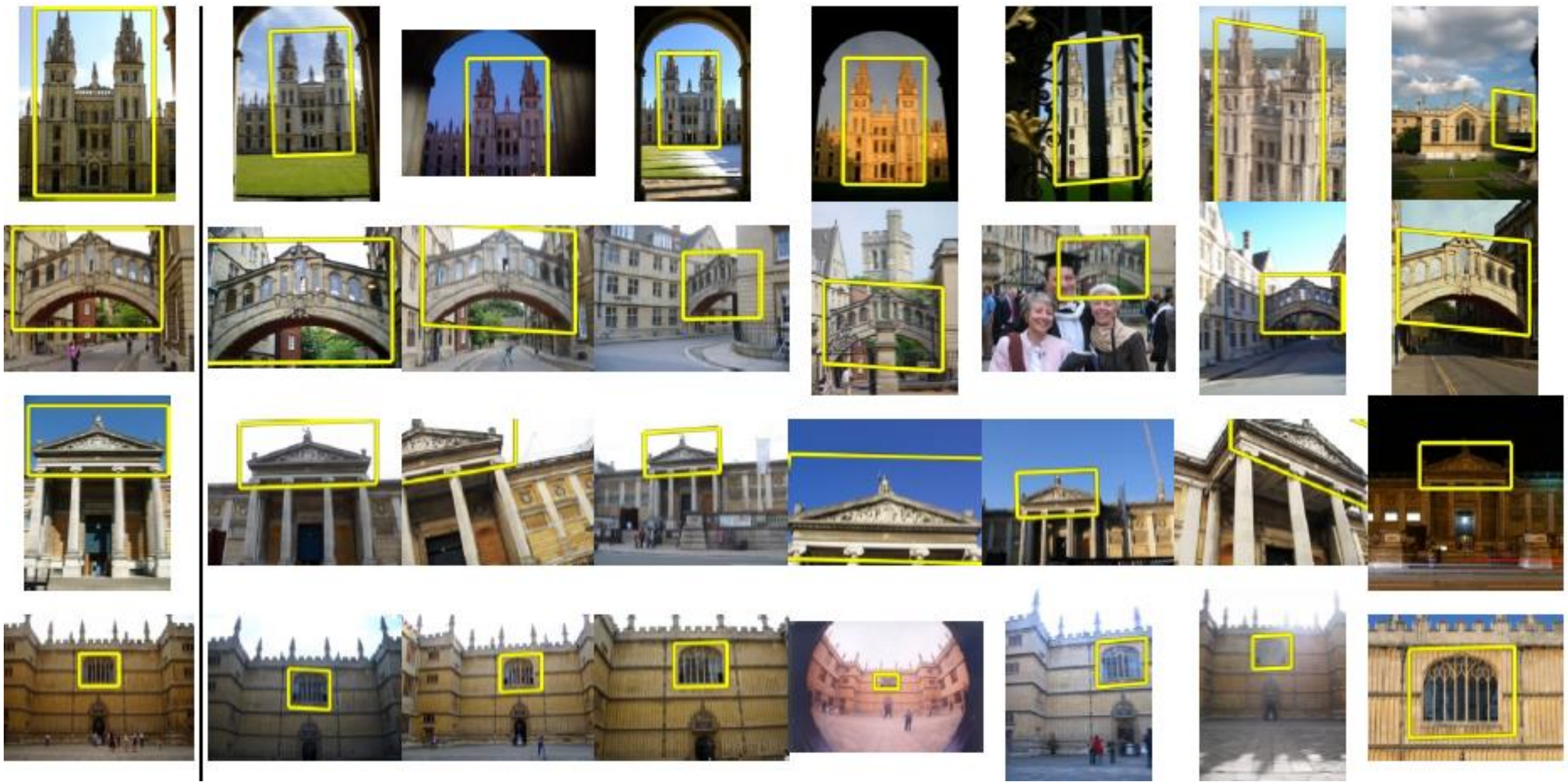


Image credit: K. Grauman and B. Leibe

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

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History of ideas in recognition

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- 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

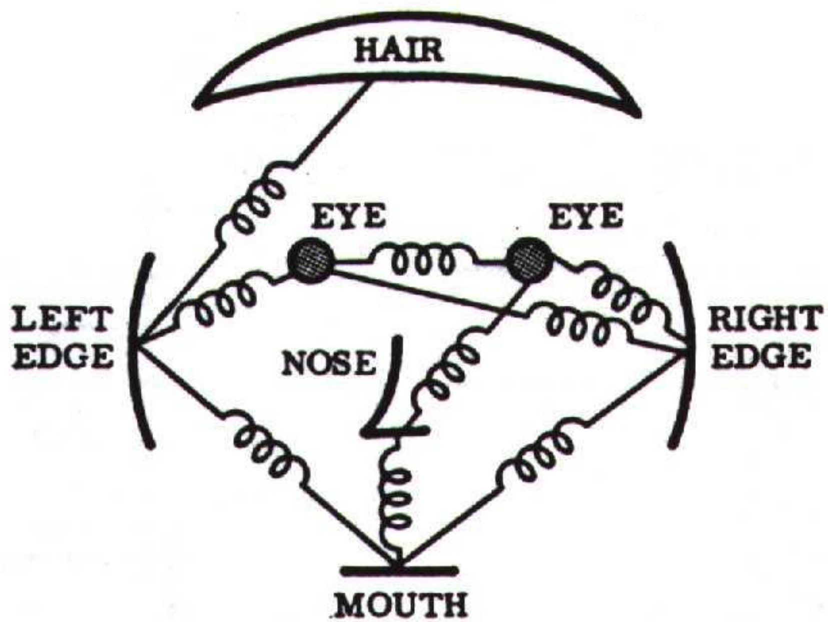


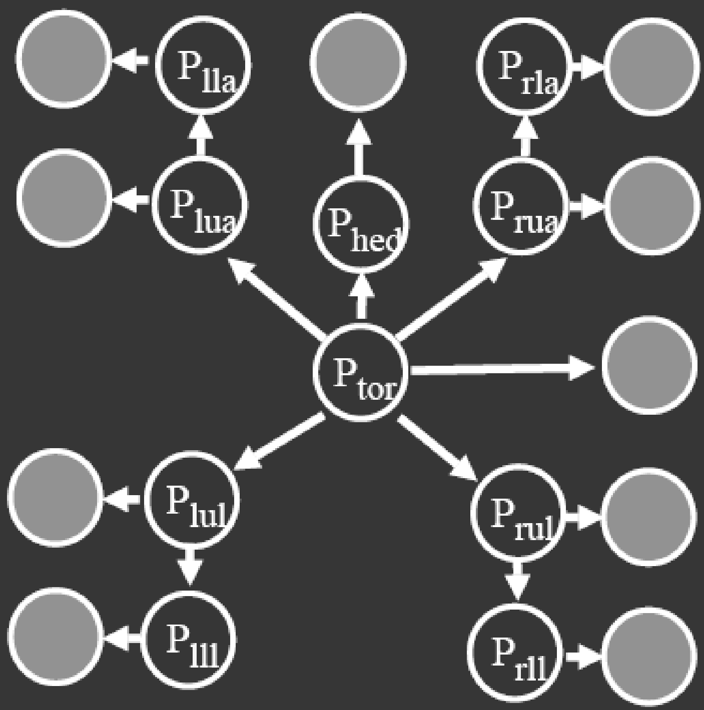
Figure from [Fischler & Elschlager 73]

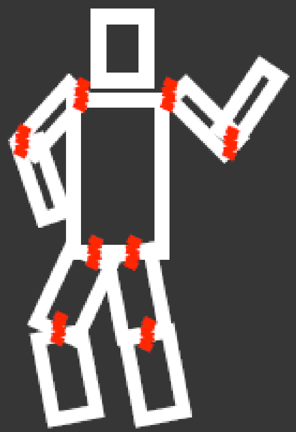
Constellation models

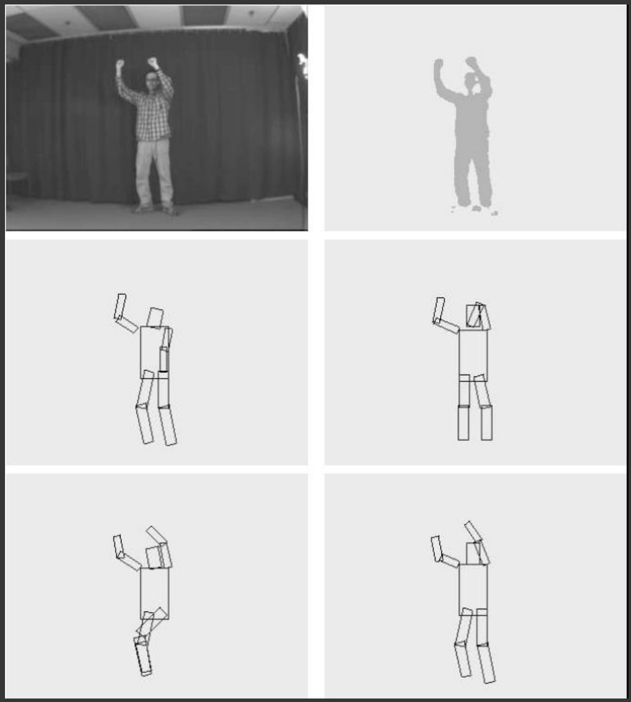
Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

Pictorial structure model

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





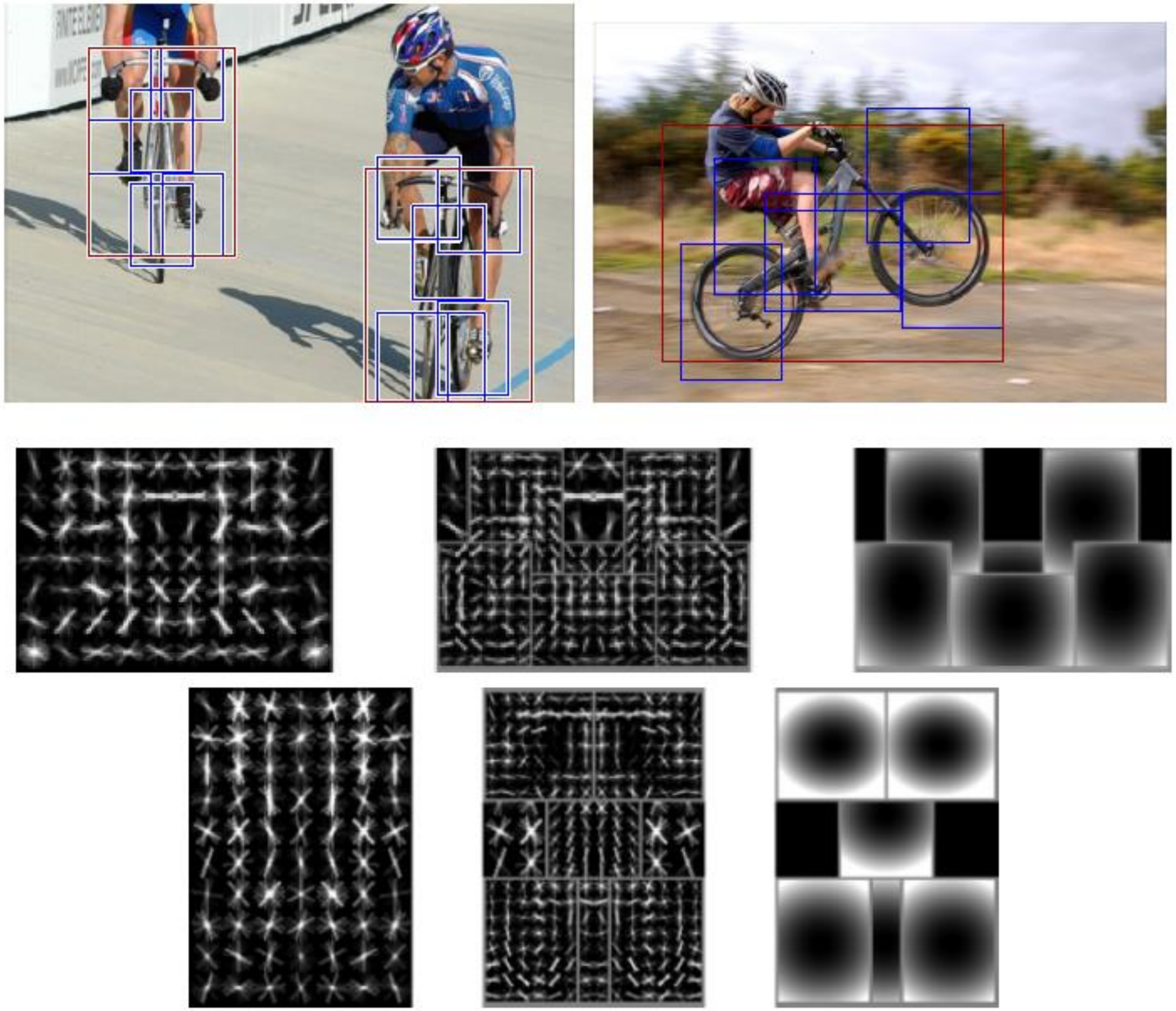


$$\Pr(P_{tor}, P_{arm}, \ldots | Im) \propto \prod_{i,j} \Pr(P_i \mid P_j) \prod_i \Pr(Im(P_i))$$

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

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Bag-of-features models

Object → **Bag of 'words'**

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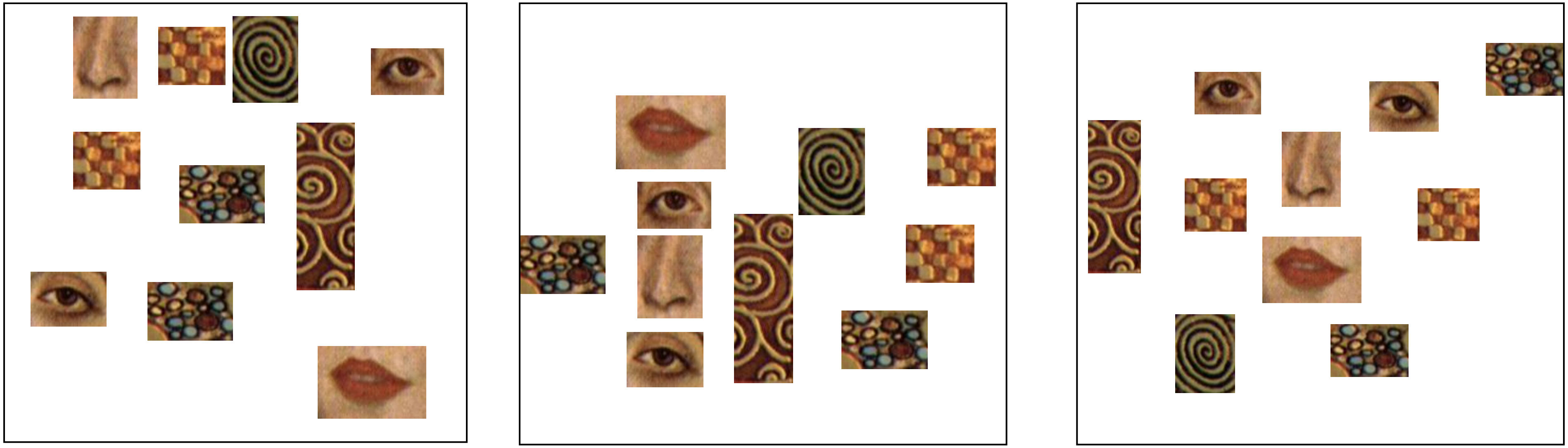
Objects as texture

- All of these are treated as being the same



- No distinction between foreground and background: scene recognition?

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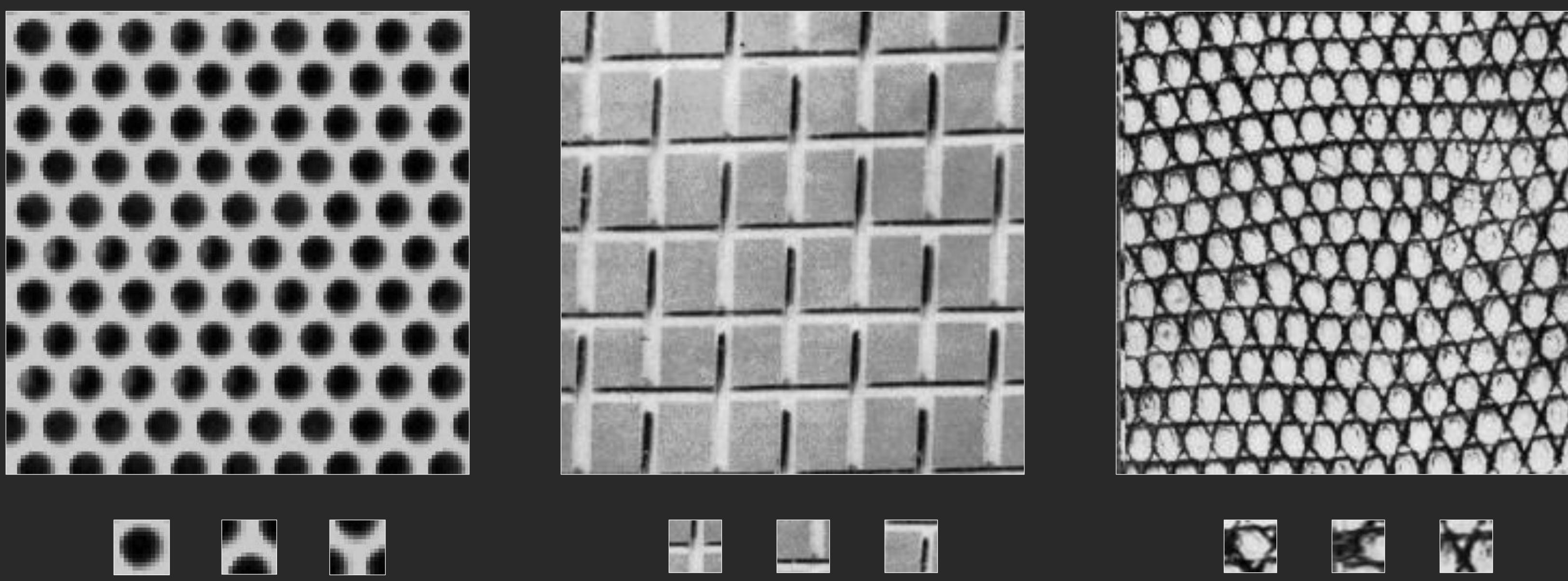
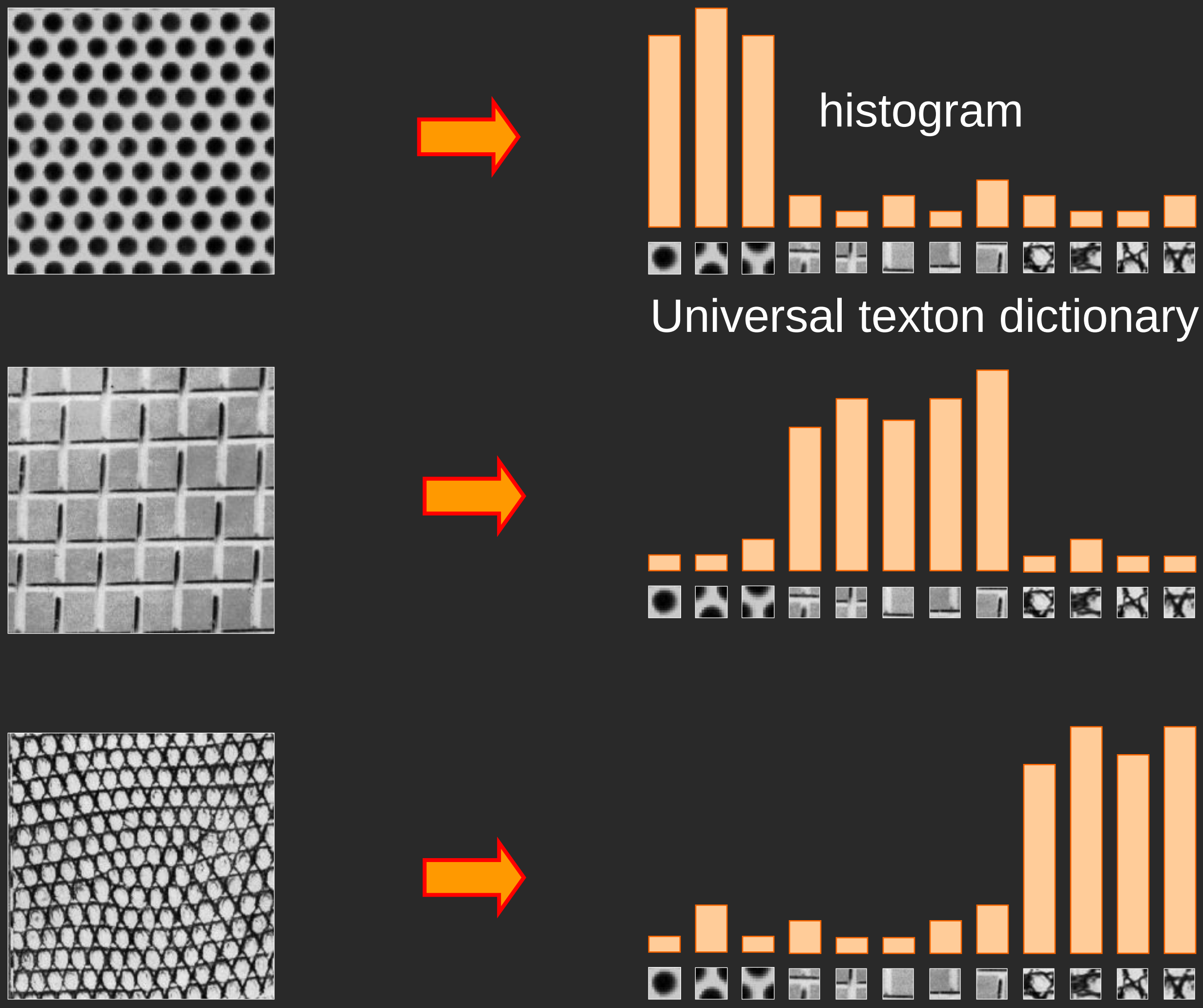
Origin 1: Texture recognition

- 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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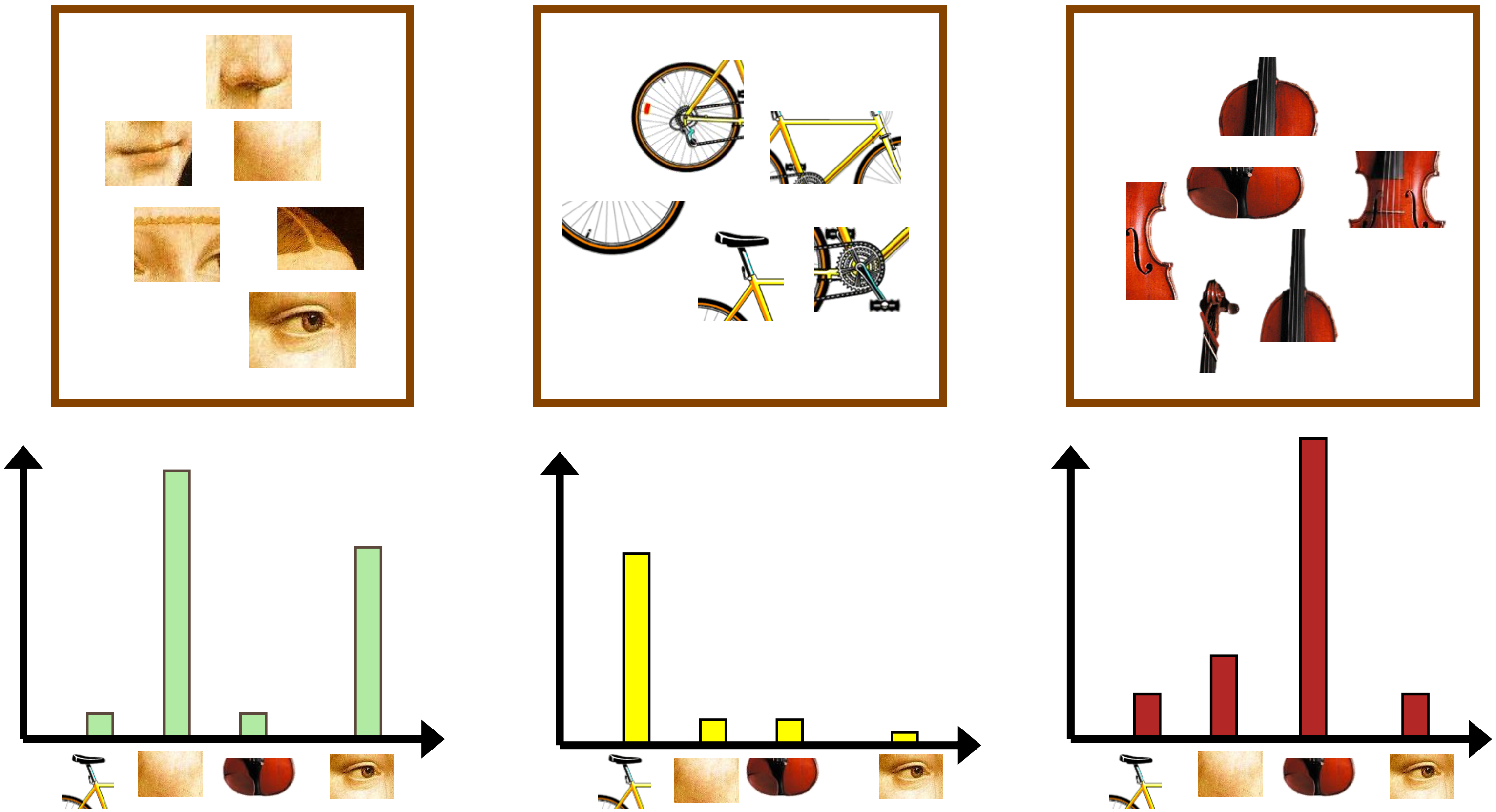
Origin 2: Bag-of-words models

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

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

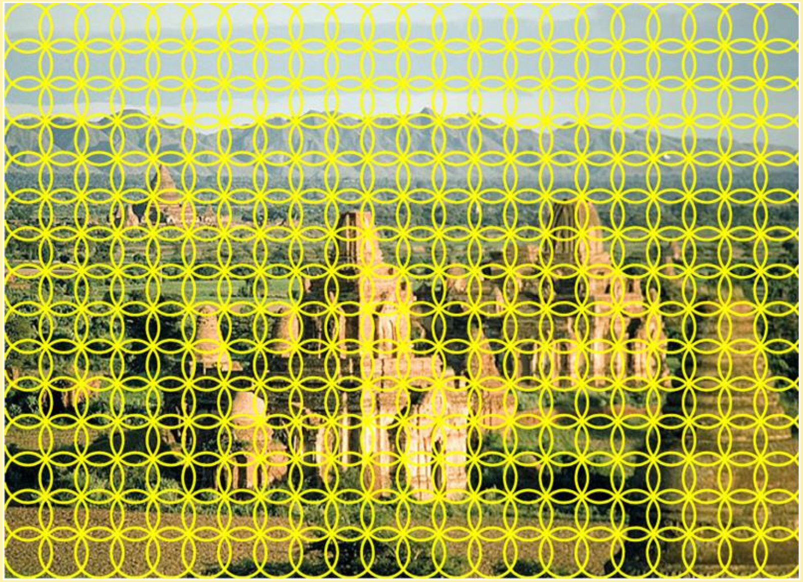
Bag-of-features steps

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

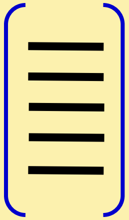


1. Feature extraction

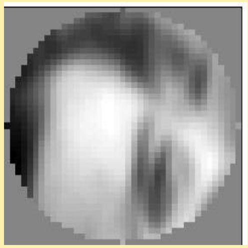
- Regular grid or interest regions



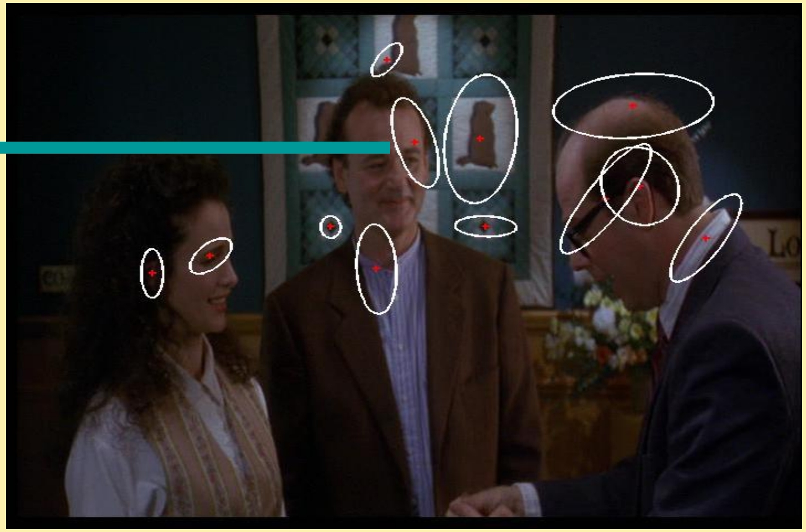
1. Feature extraction



Compute descriptor



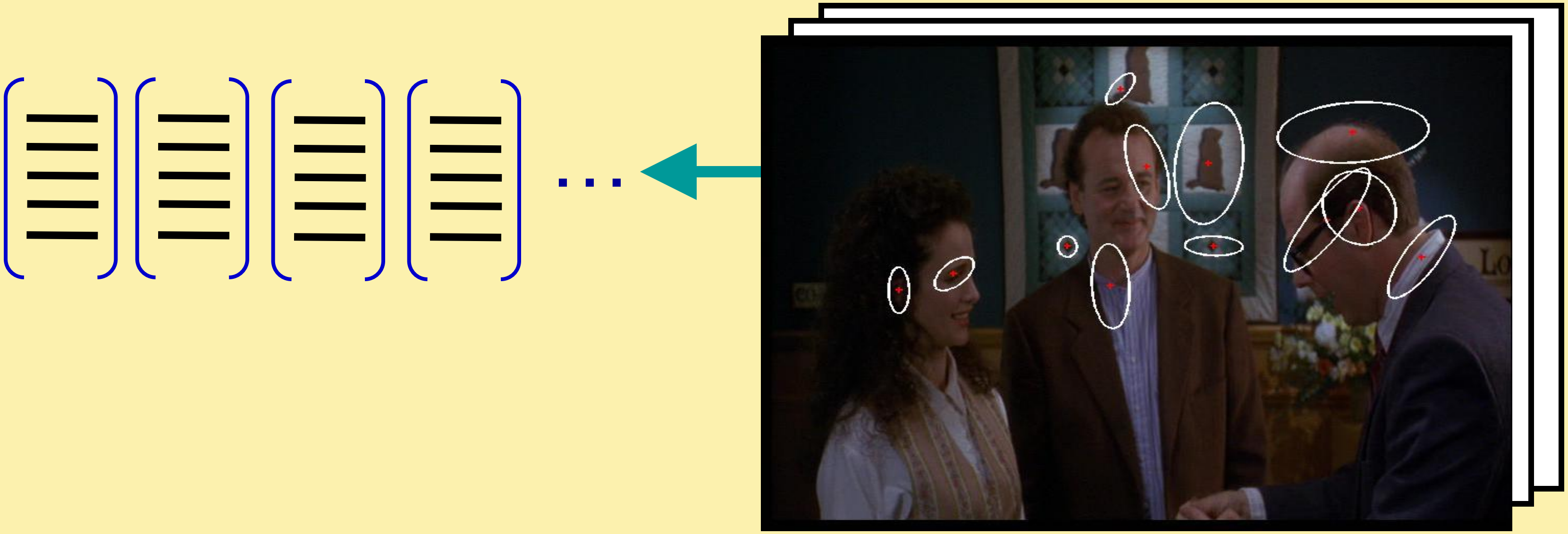
Normalize patch



Detect patches

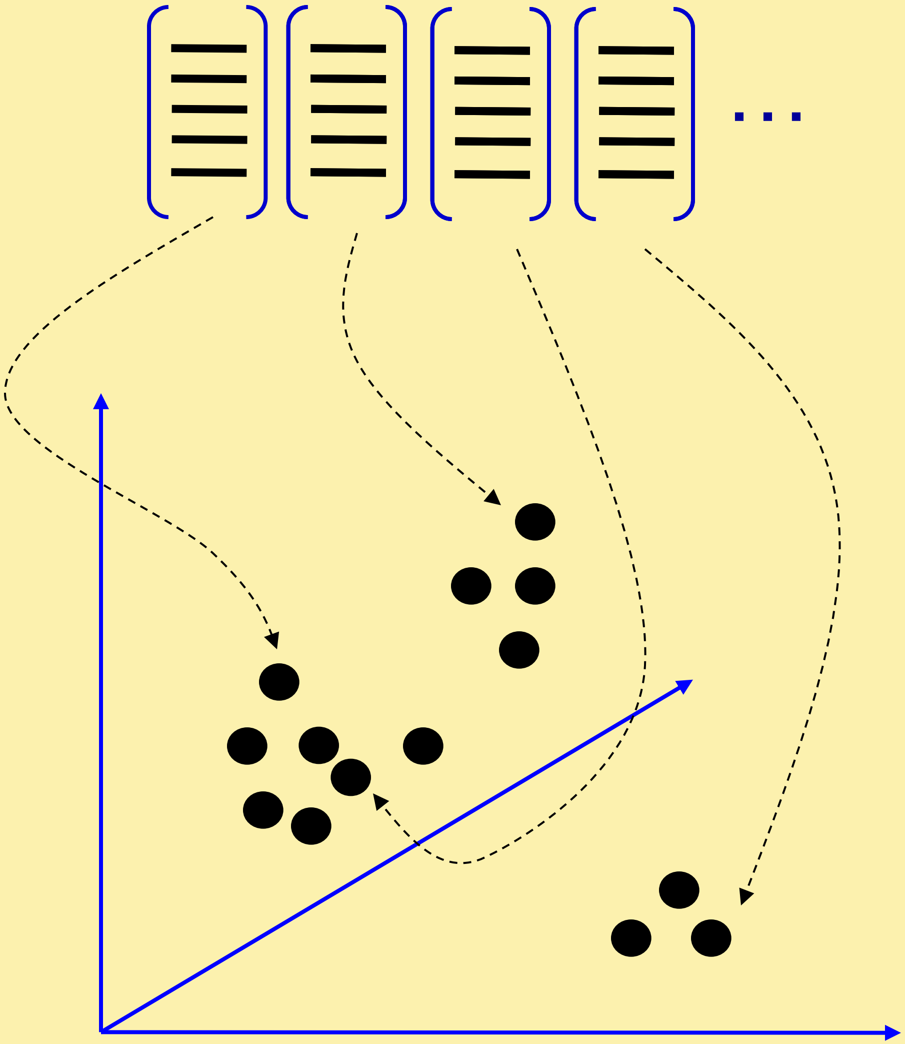
Slide credit: Josef Sivic

1. Feature extraction



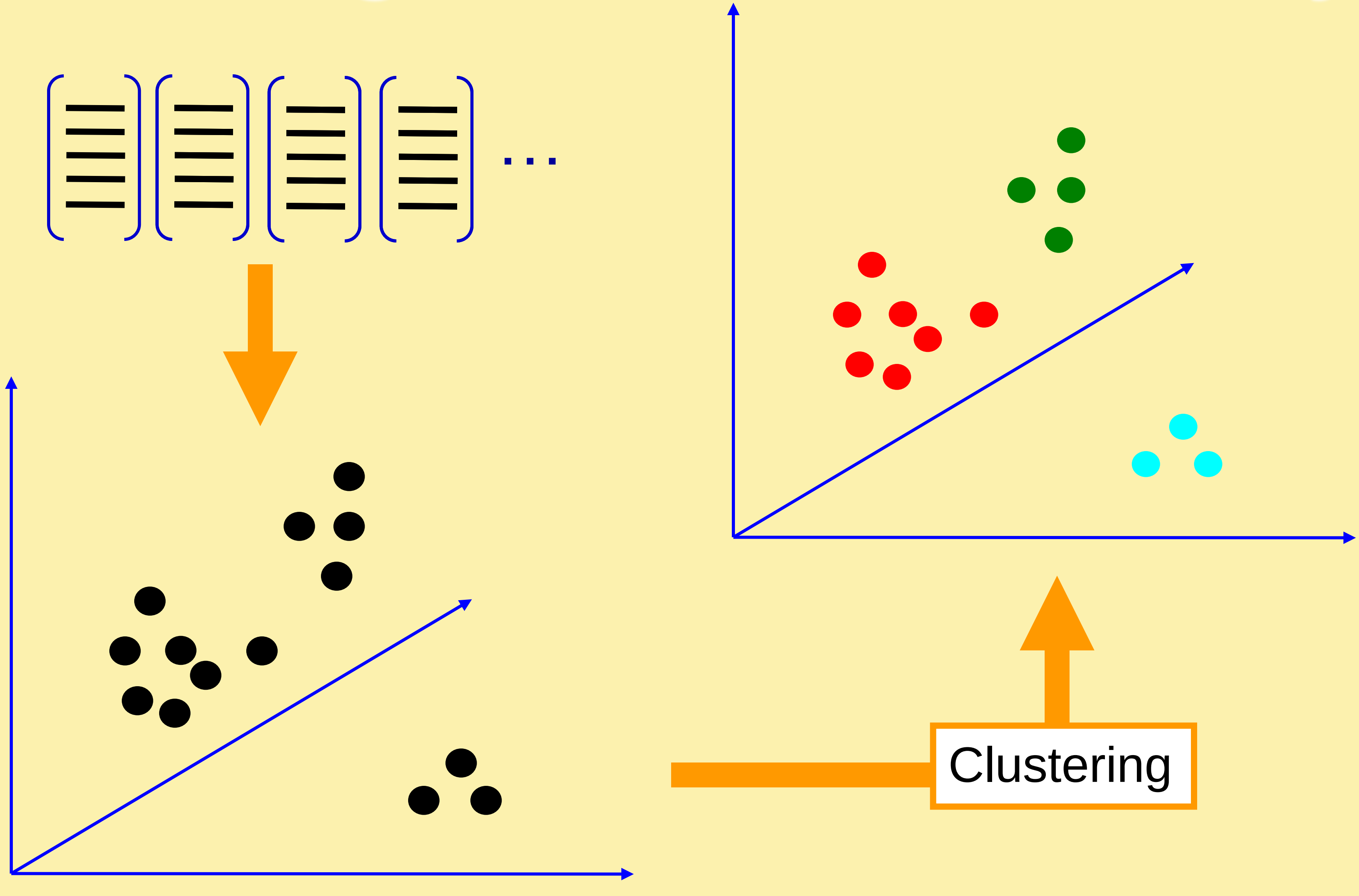
Slide credit: Josef Sivic

2. Learning the visual vocabulary



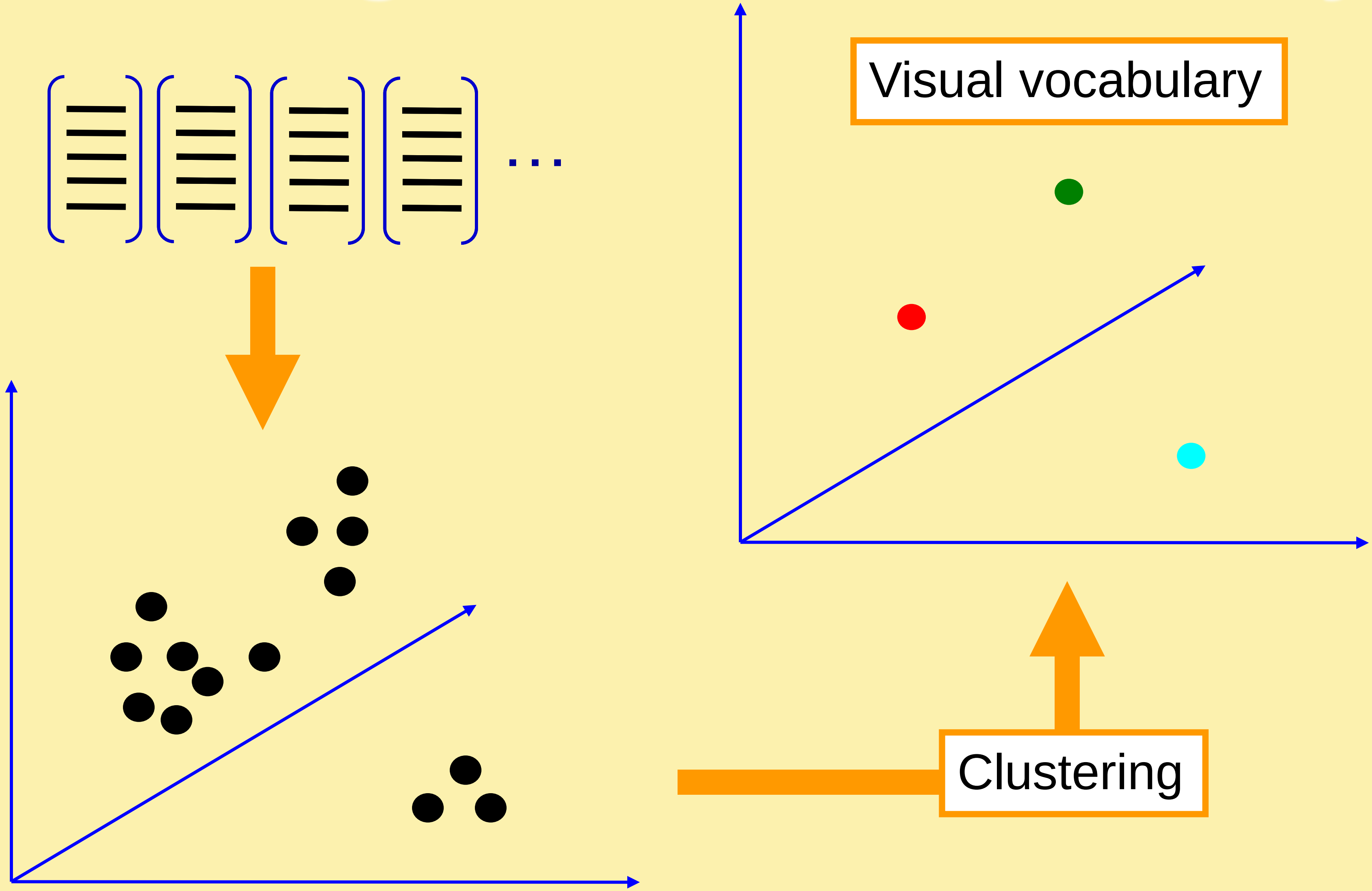
Slide credit: Josef Sivic

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:

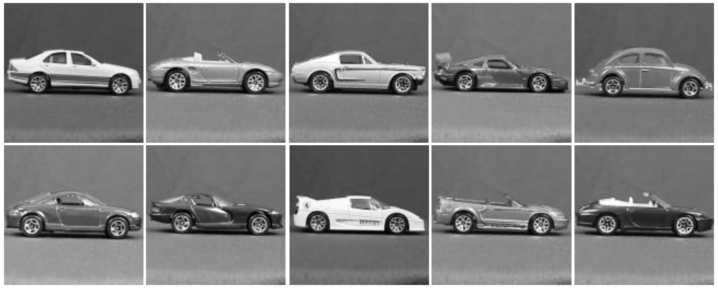
- Randomly initialize K cluster centers
- Iterate until convergence:
  - Assign each data point to the nearest center
  - Recompute each cluster center as the mean of all points assigned to it

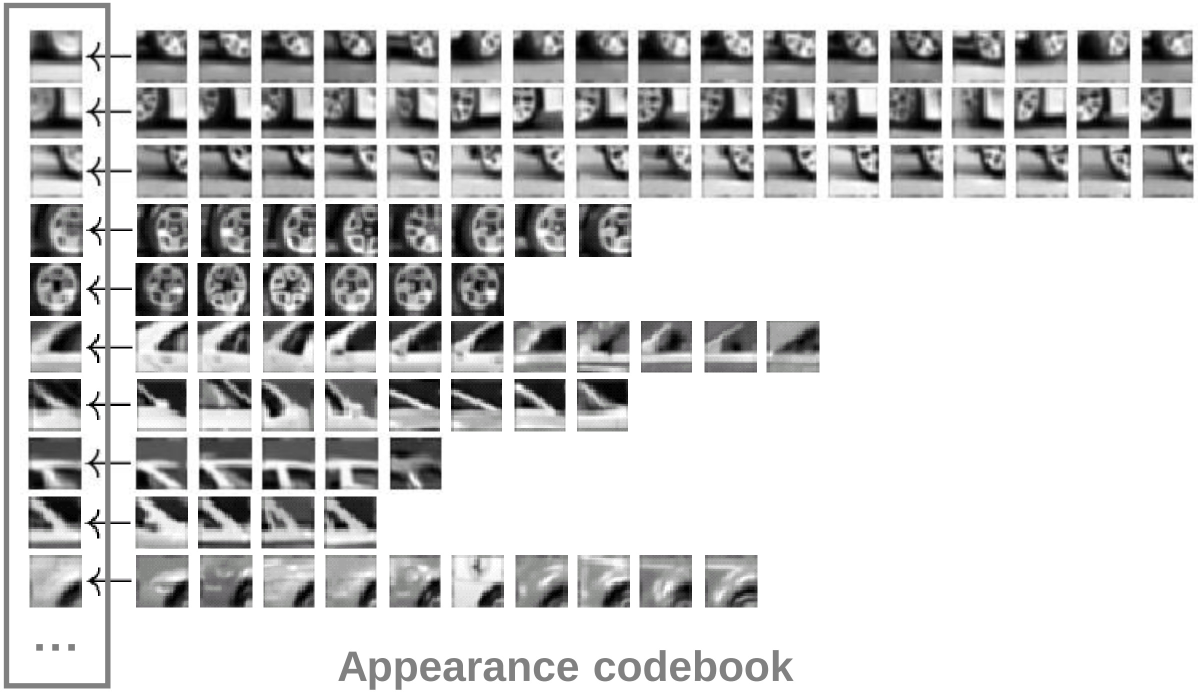
Clustering and vector quantization

- 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

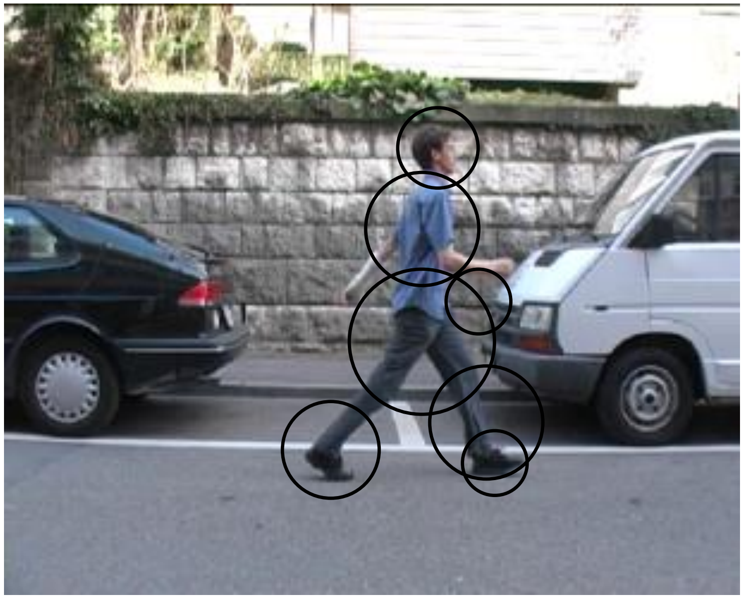


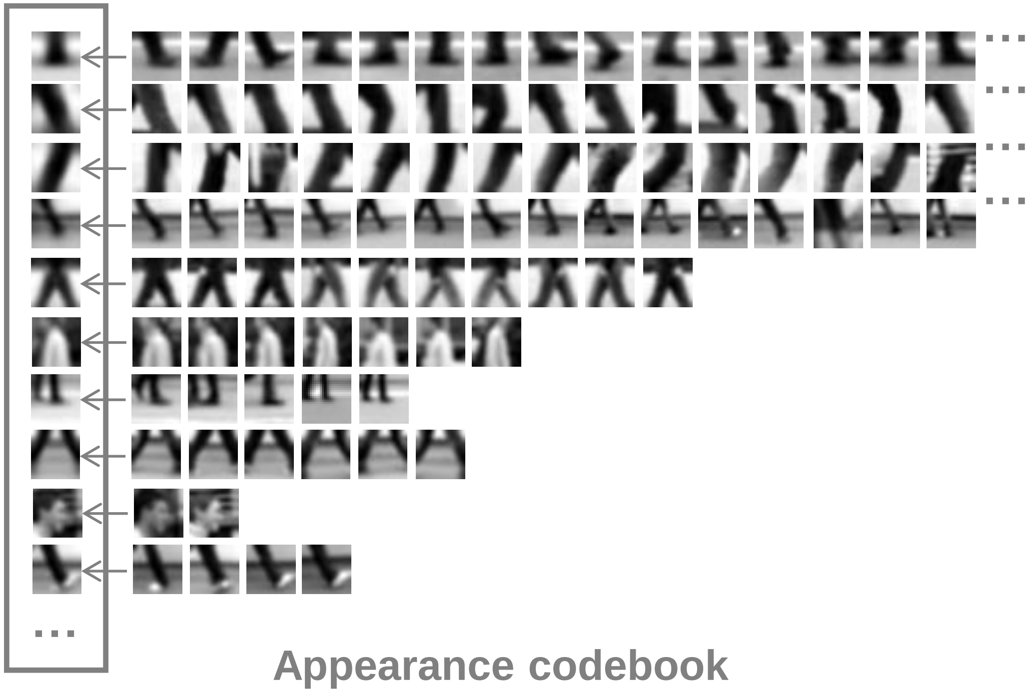


Appearance codebook

Source: B. Leibe

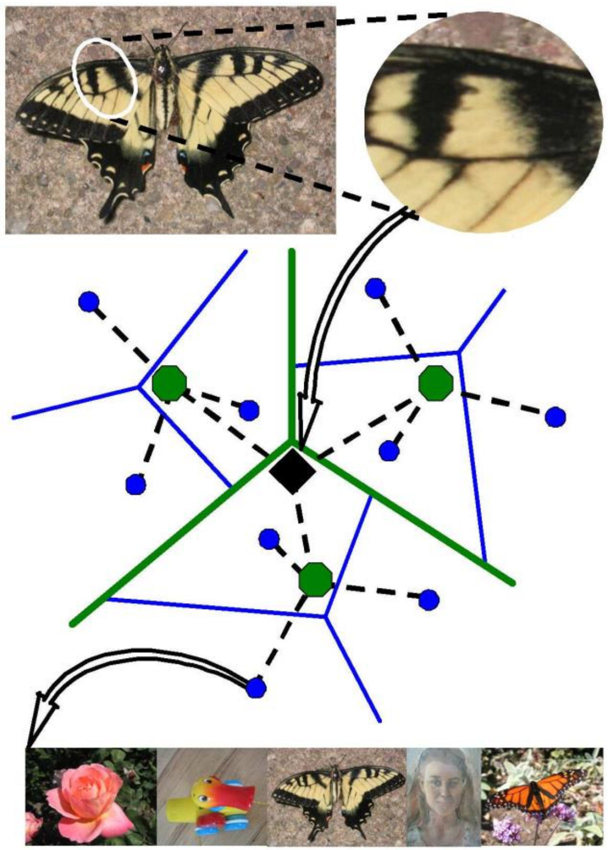
Another codebook



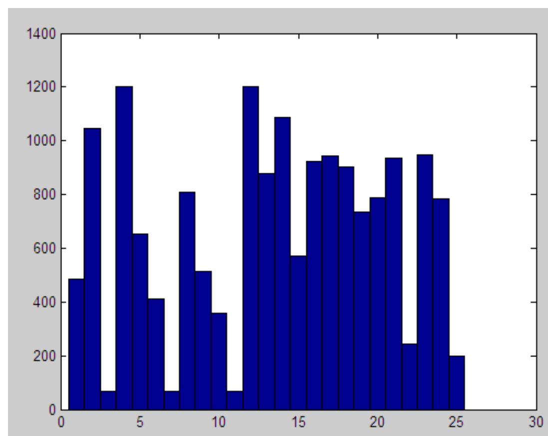


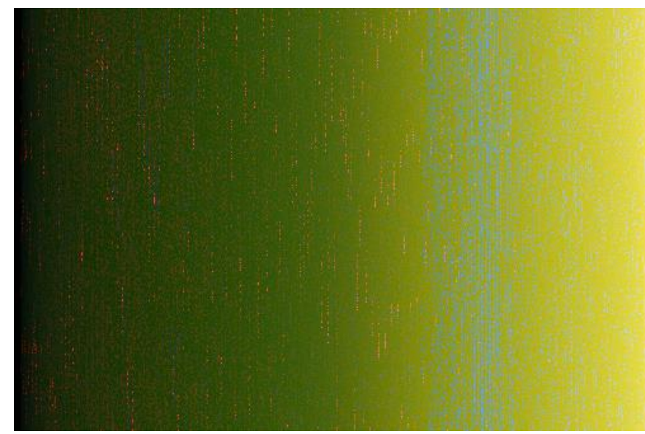
Visual vocabularies: Issues

- 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)



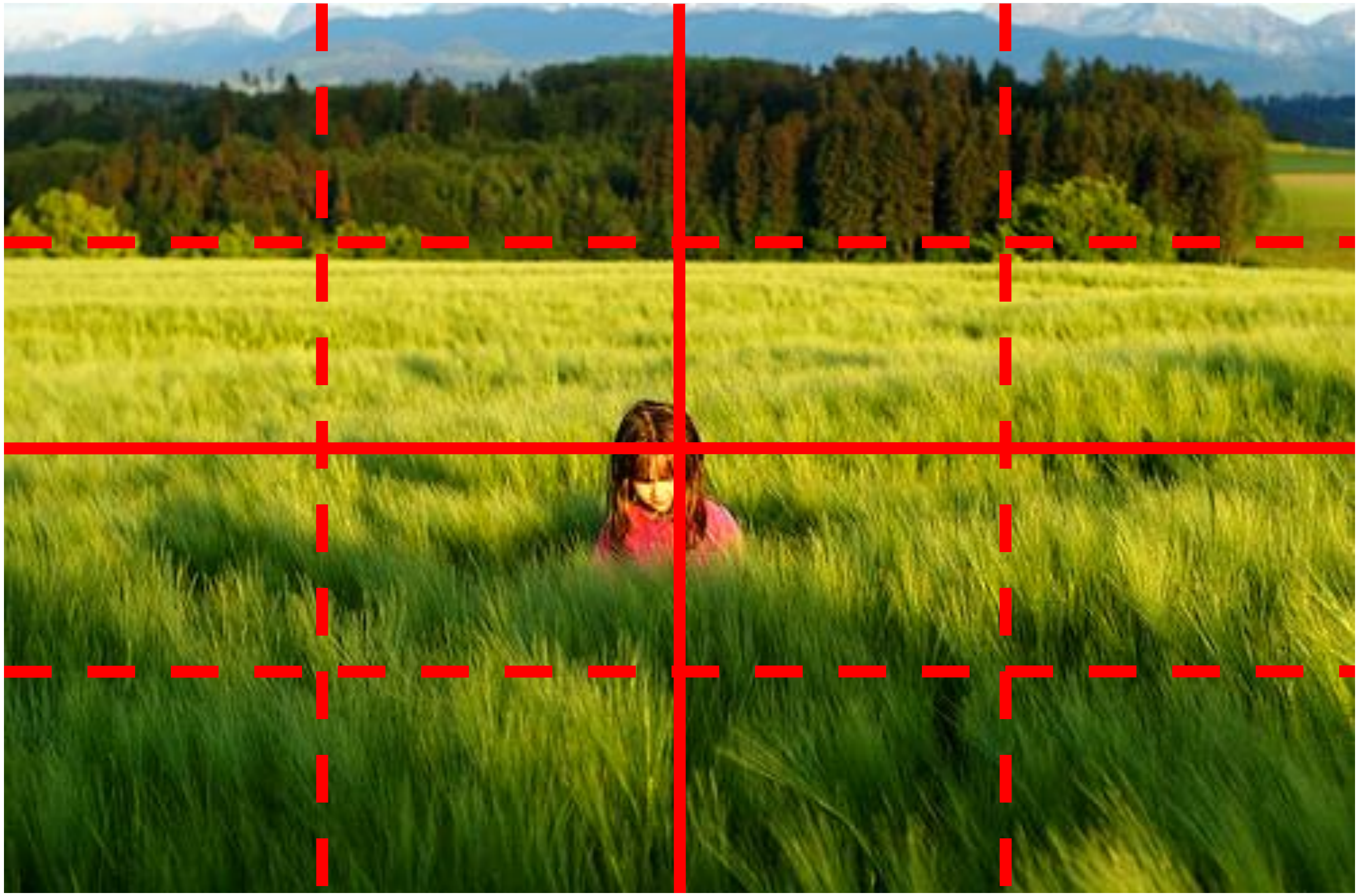
But what about layout?





All of these images have the same color histogram

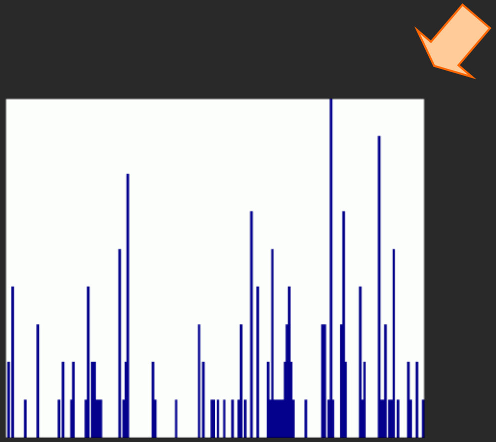
Spatial pyramid



Compute histogram in each spatial bin

Spatial pyramid representation

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

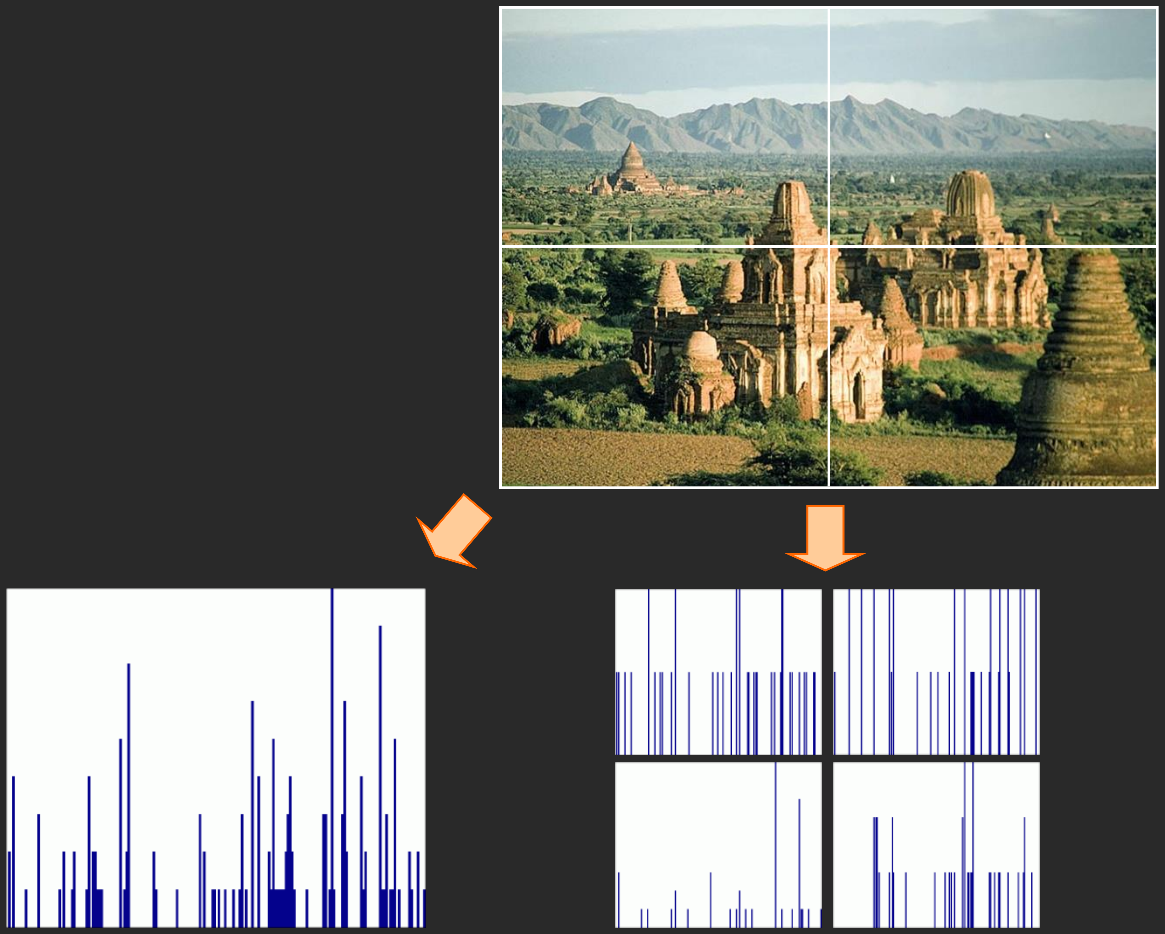


level 0

Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramid representation

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

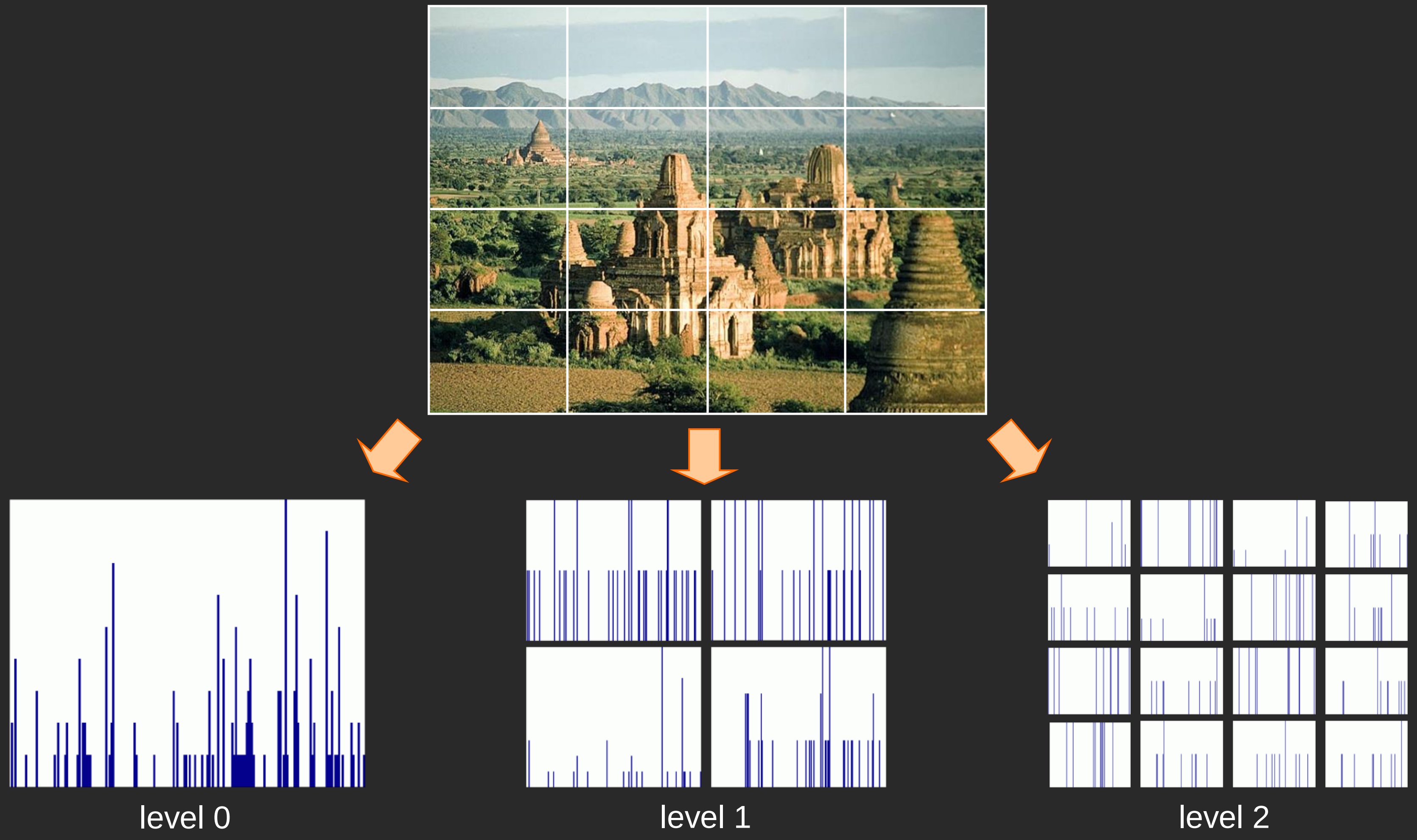


level 0 level 1

Lazebnik, Schmid & Ponce (CVPR 2006)

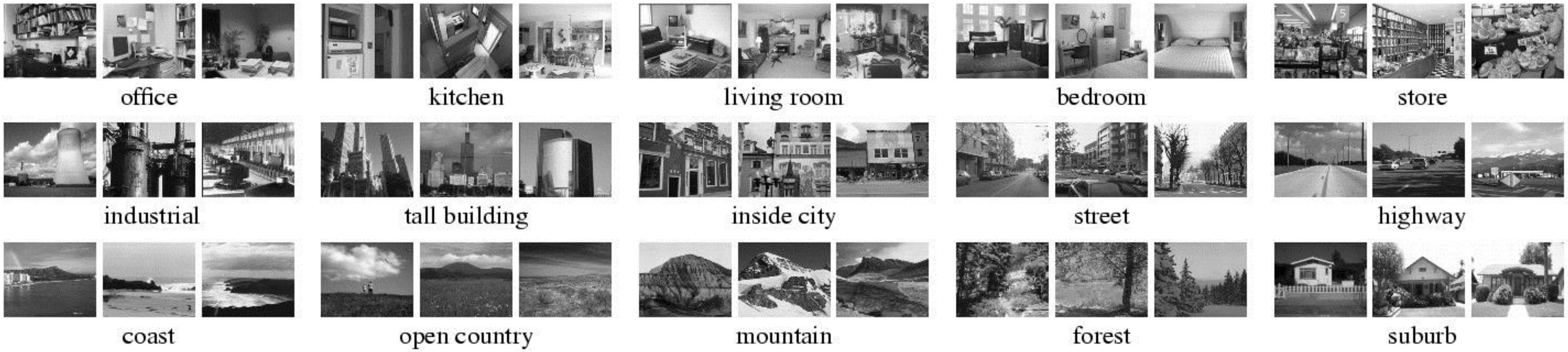
Spatial pyramid representation

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



Lazebnik, Schmid & Ponce (CVPR 2006)

Scene category dataset

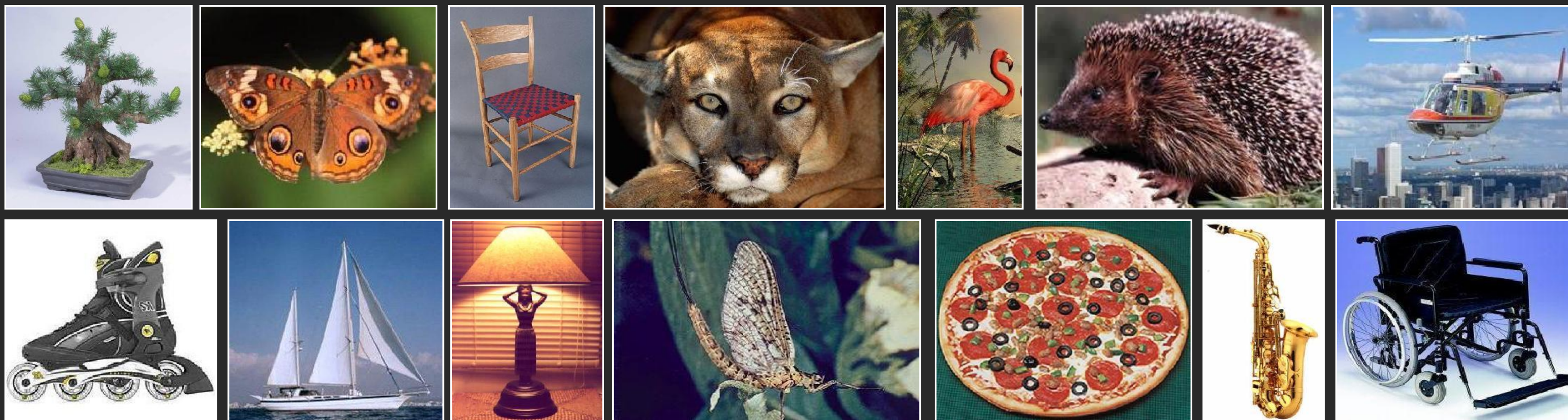


Multi-class classification results
(100 training images per class)

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

Caltech101 dataset

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

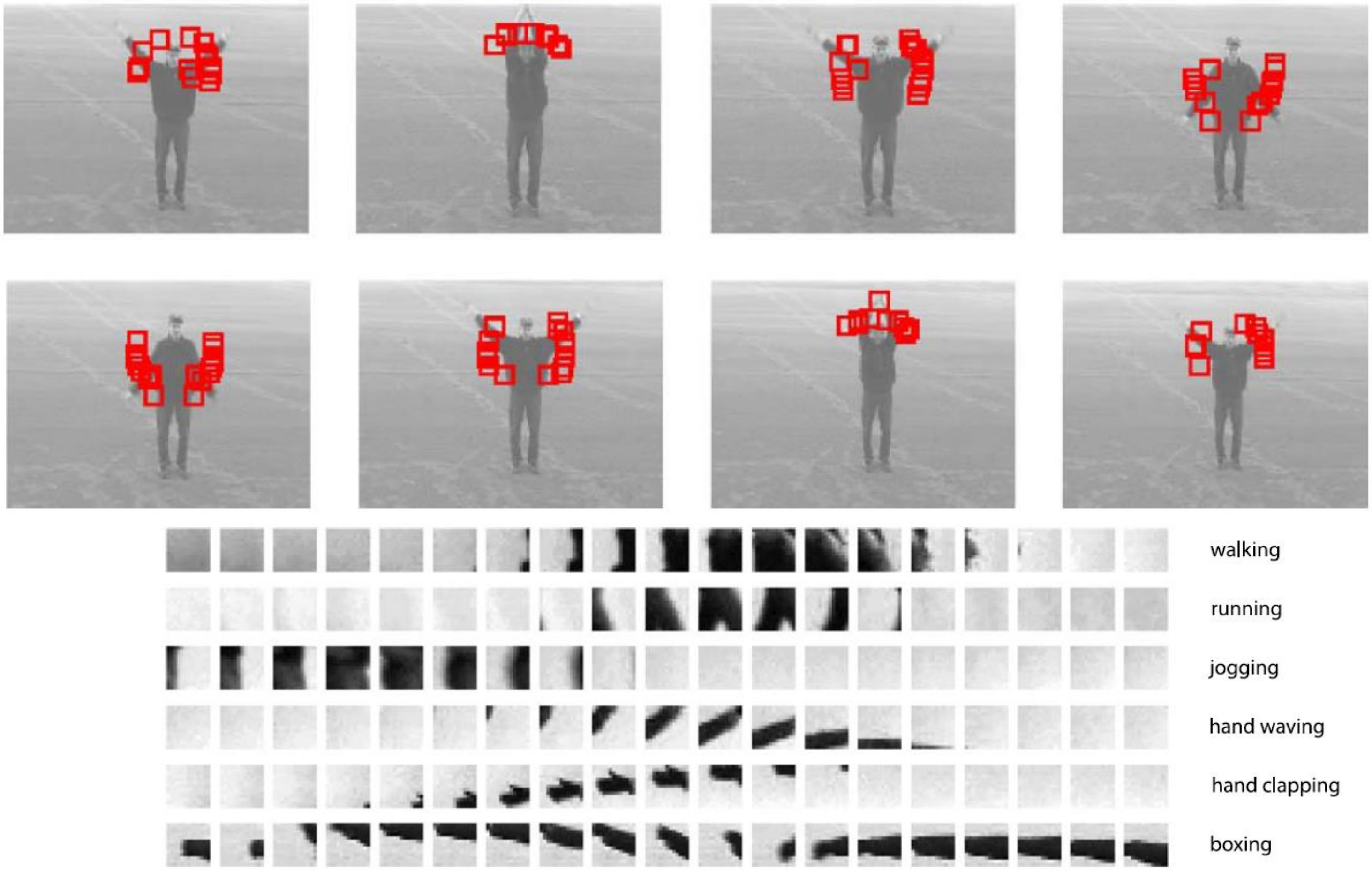


Multi-class classification results (30 training images per class)

	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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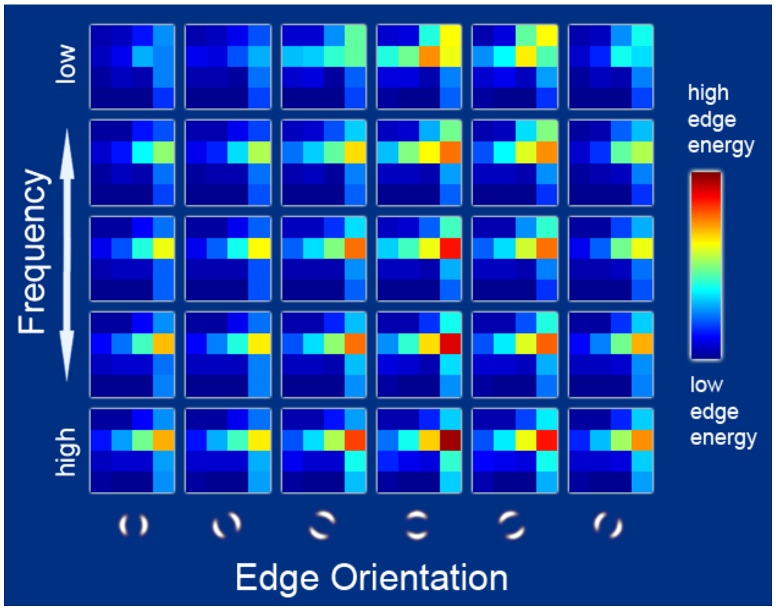
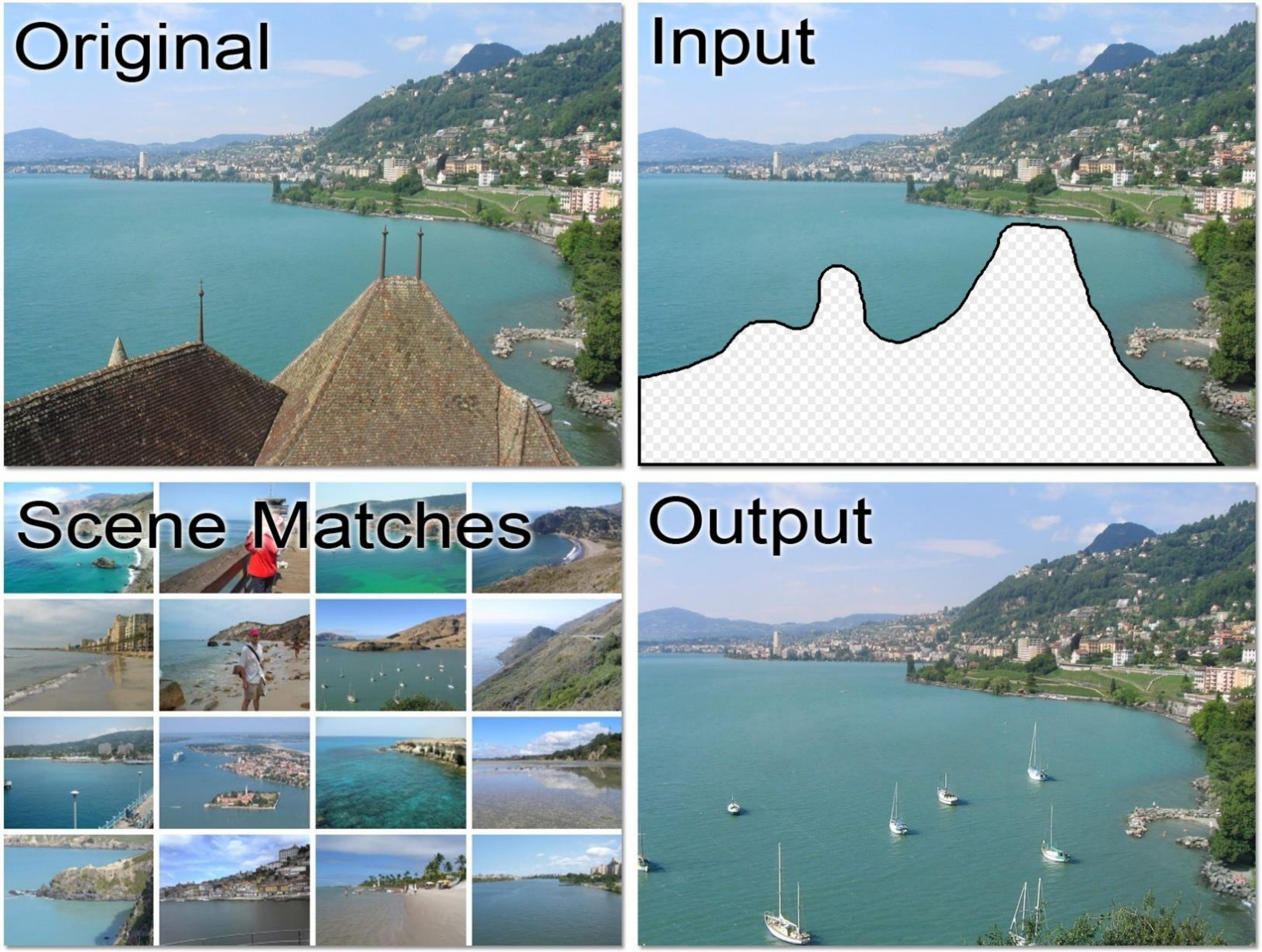
Global scene descriptors

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



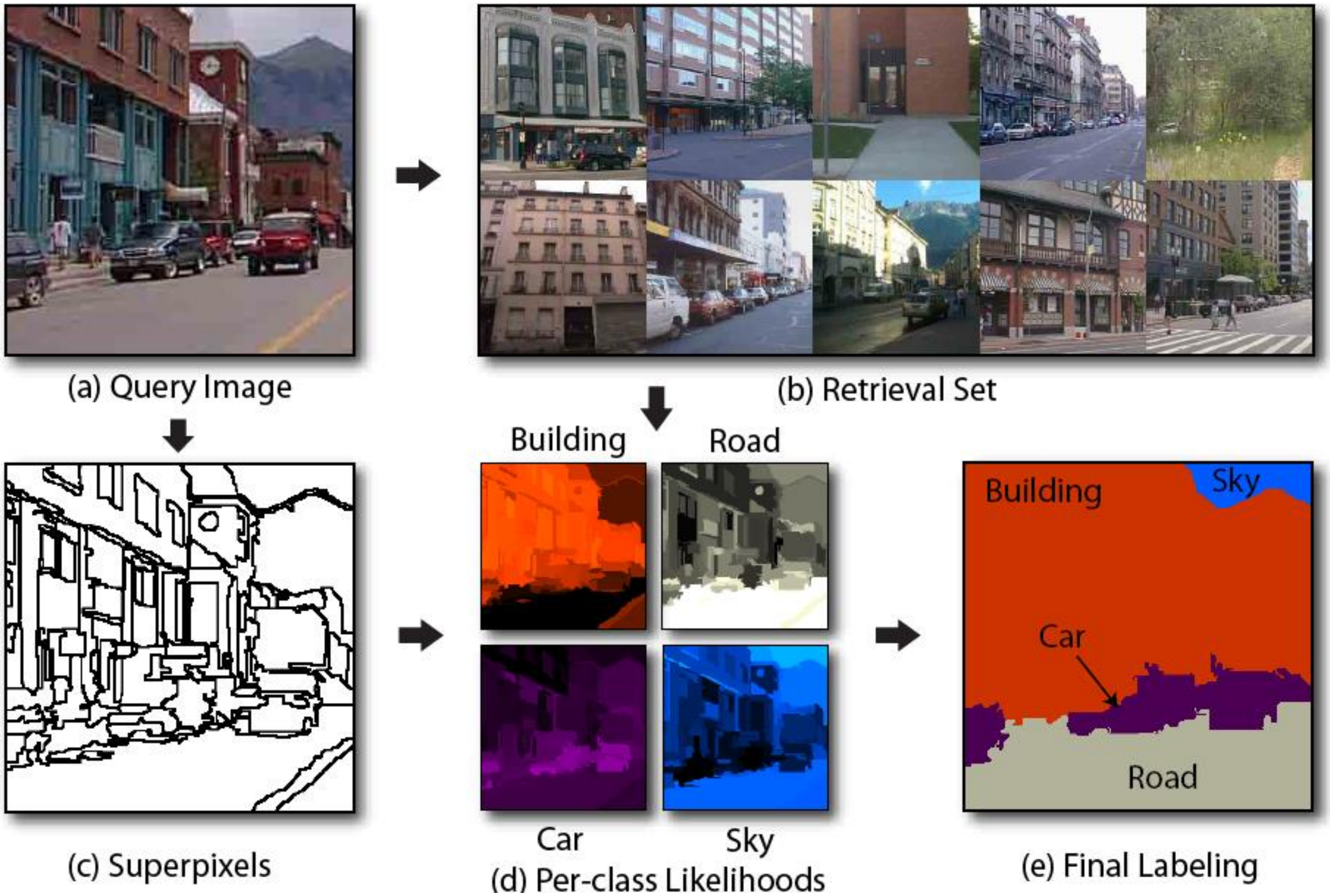
http://people.csail.mit.edu/torralba/code/spatialenvelope/

Data-driven methods



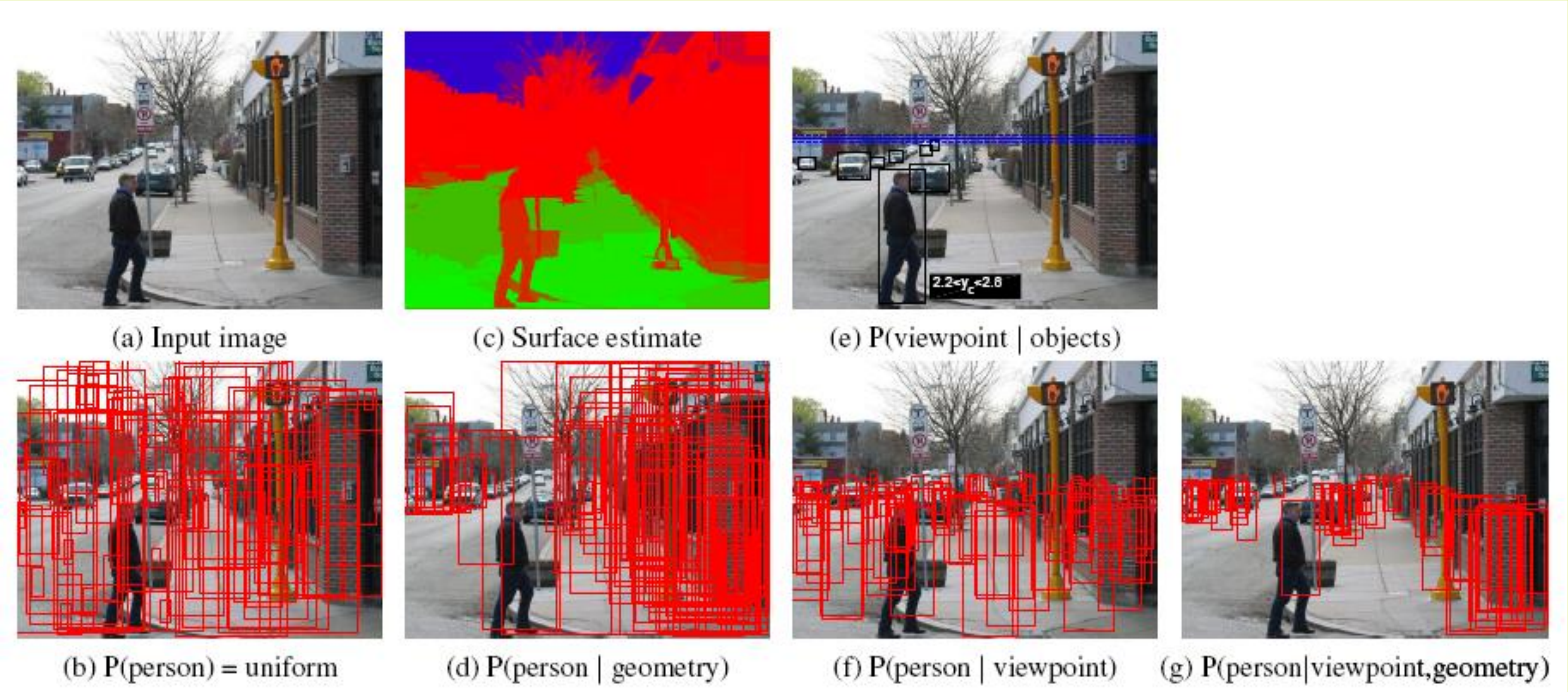
J. Hays and A. Efros, [Scene Completion using Millions of Photographs](), SIGGRAPH 2007

Data-driven methods



J. Tighe and S. Lazebnik, ECCV 2010

Geometric context



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

What “works” today

- Reading license plates, zip codes, checks

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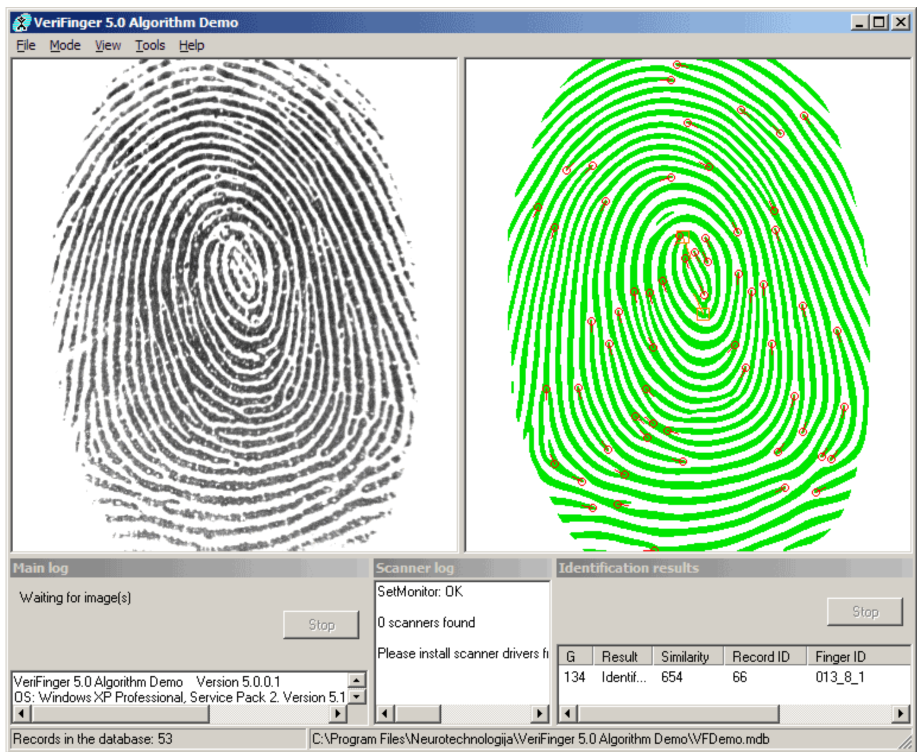
What “works” today

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



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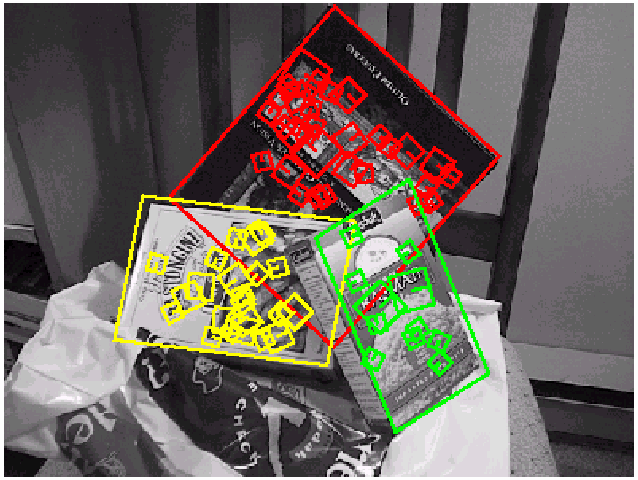
What “works” today

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

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

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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