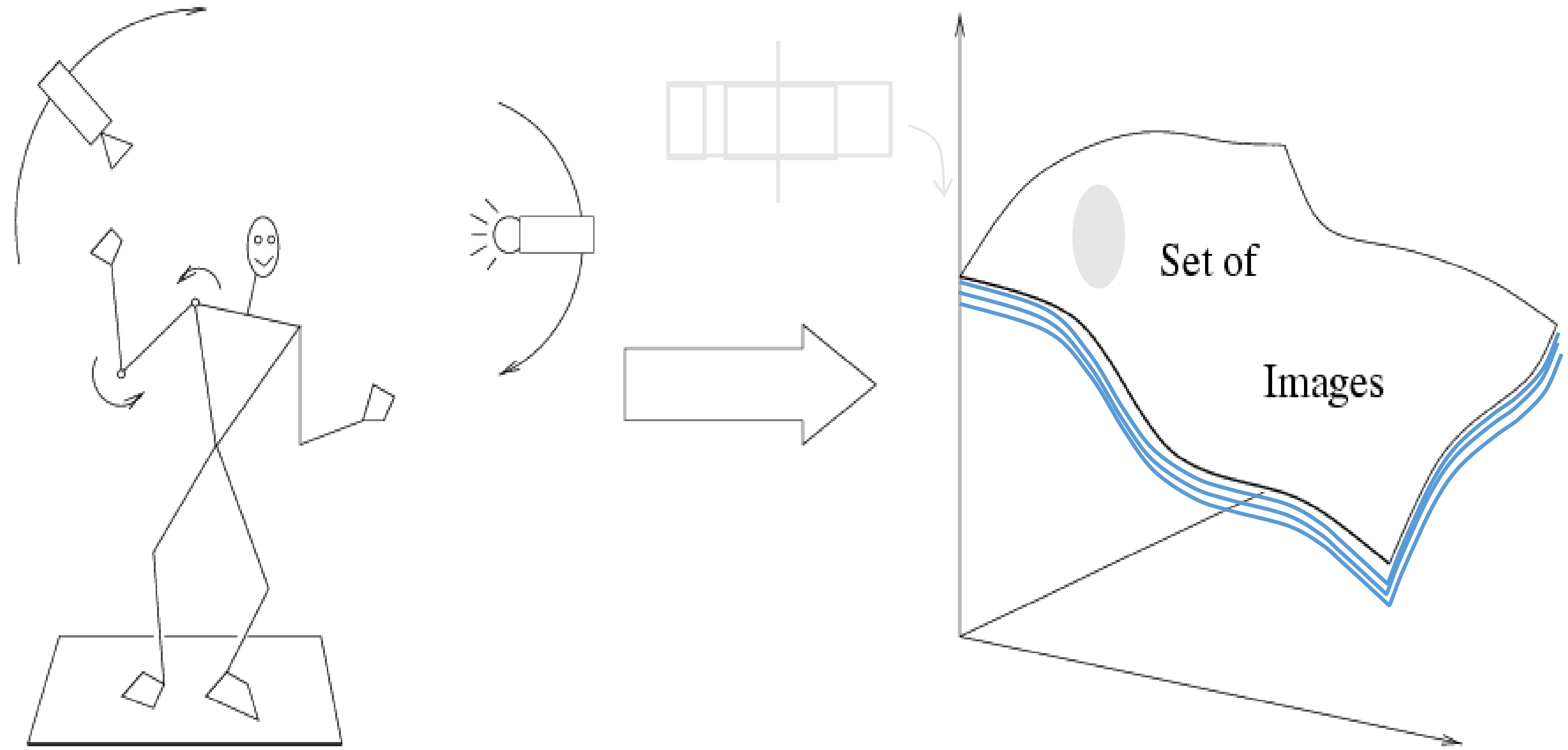
Bag of Visual Words for Image Representation

Jianping Fan
Department of Computer Science
UNC-Charlotte

Course Website:
http://webpages.uncc.edu/jfan/itcs5152.html

Recognition is all about modeling variability

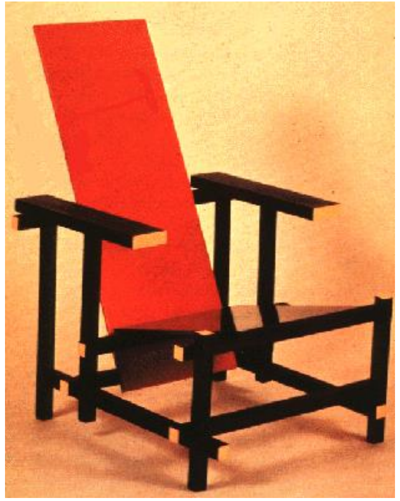


Variability: Camera position
Illumination
Shape parameters

Within-class variations?

Svetlana Lazebnik

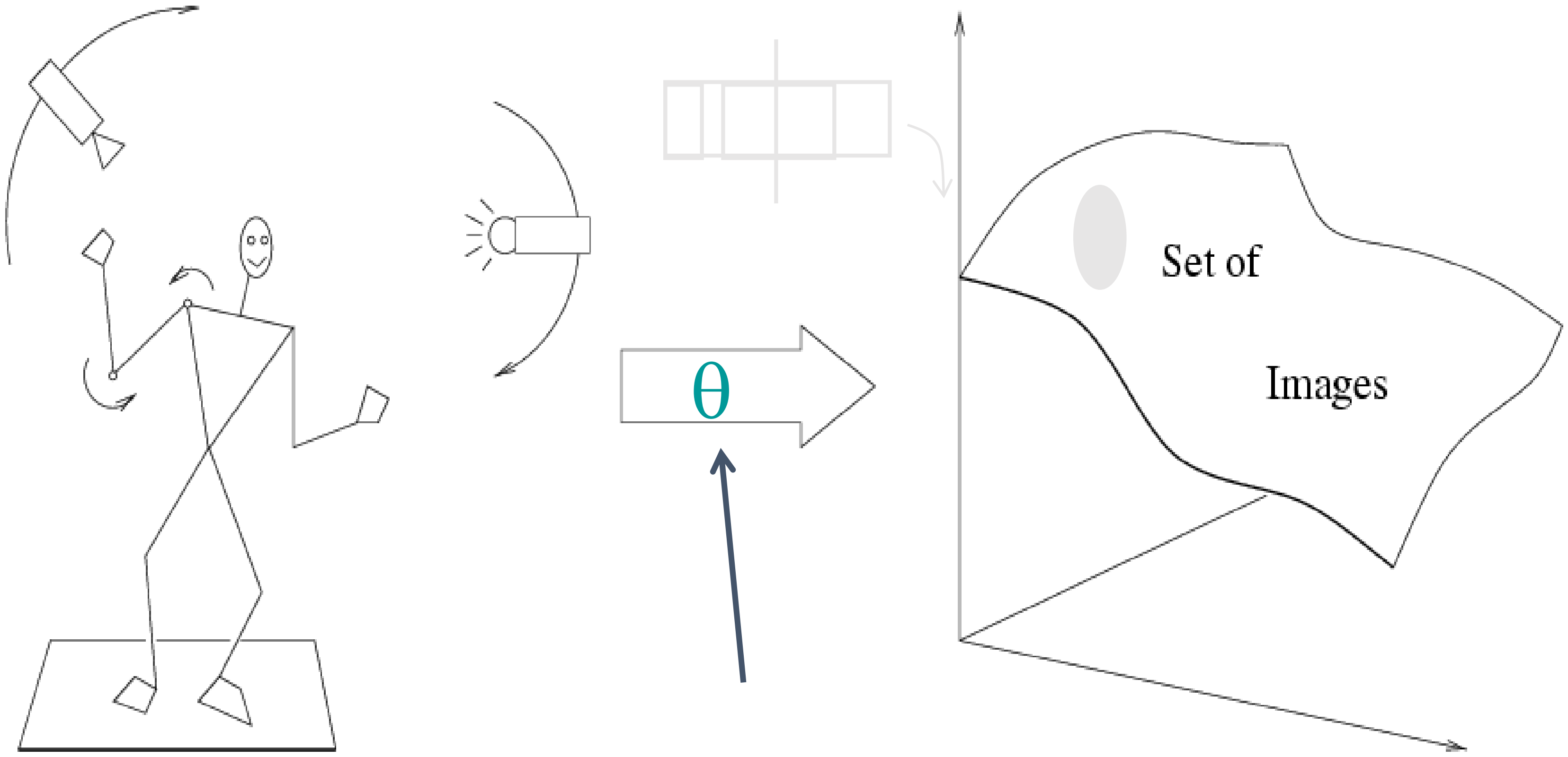
Within-class variations



Svetlana Lazebnik

History of ideas in recognition

- 1960s – early 1990s: the geometric era



Variability: θ Camera position
Illumination

Alignment

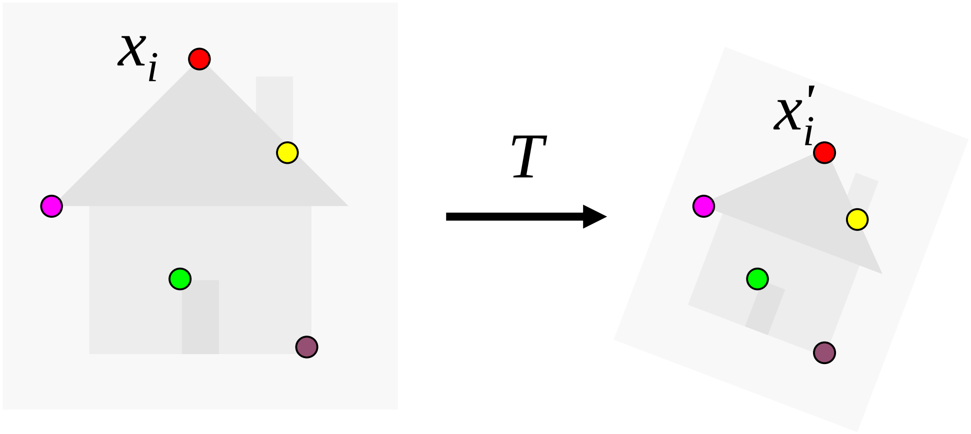
Shape: assumed known

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

Svetlana Lazebnik

Recall: Alignment

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



Find transformation *T* that minimizes

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

Svetlana Lazebnik

Recognition as an alignment problem: Block world

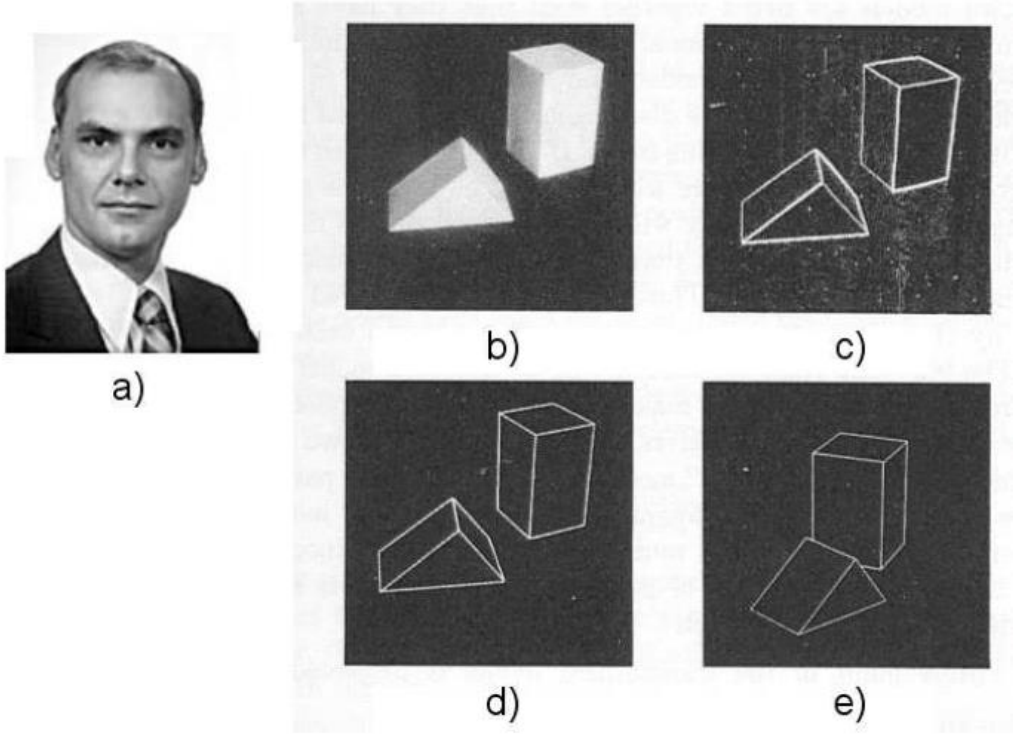
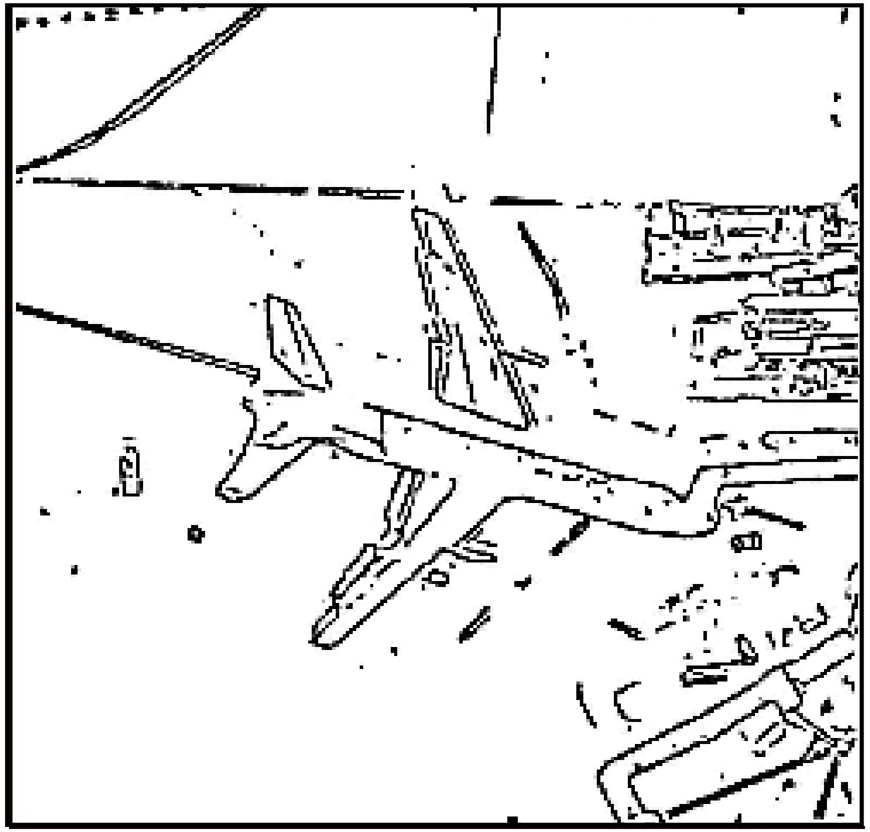


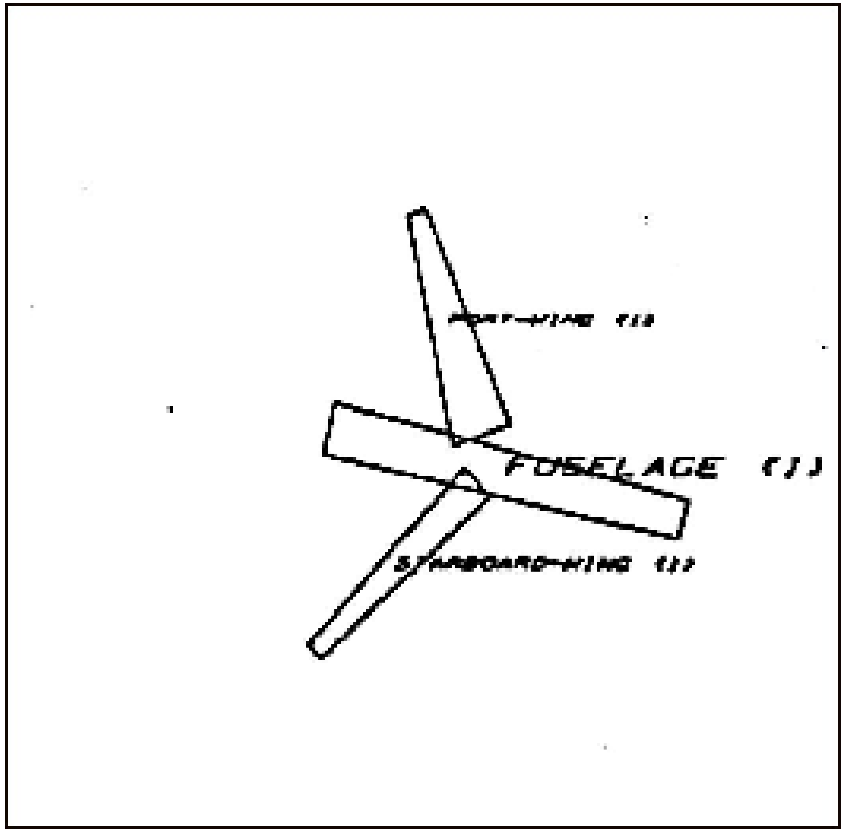
Fig. 1. A system for recognizing 3-d polyhedral scenes. a) L.G. Roberts. b)A blocks world scene. c)Detected edges using a 2x2 gradient operator. d) A 3-d polyhedral description of the scene, formed automatically from the single image. e) The 3-d scene displayed with a viewpoint different from the original 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

Representing and recognizing object categories is harder...





ACRONYM (Brooks and Binford, 1981)

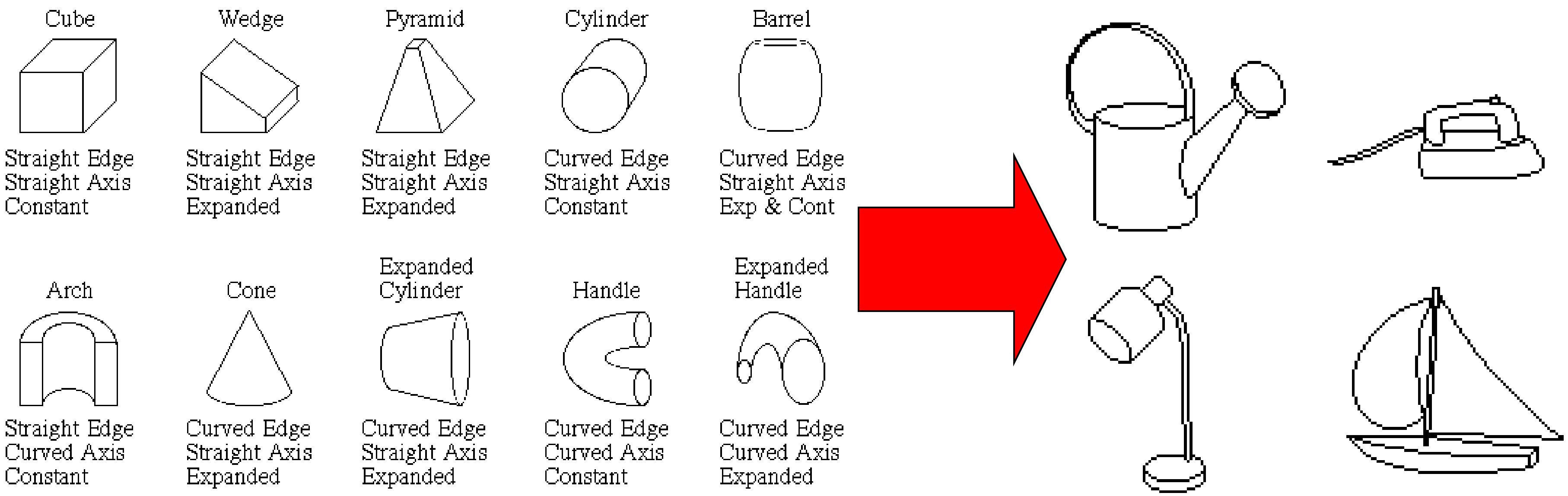
Binford (1971), Nevatia & Binford (1972), Marr & Nishihara (1978)

Recognition by components

Biederman (1987)

Primitives (geons)

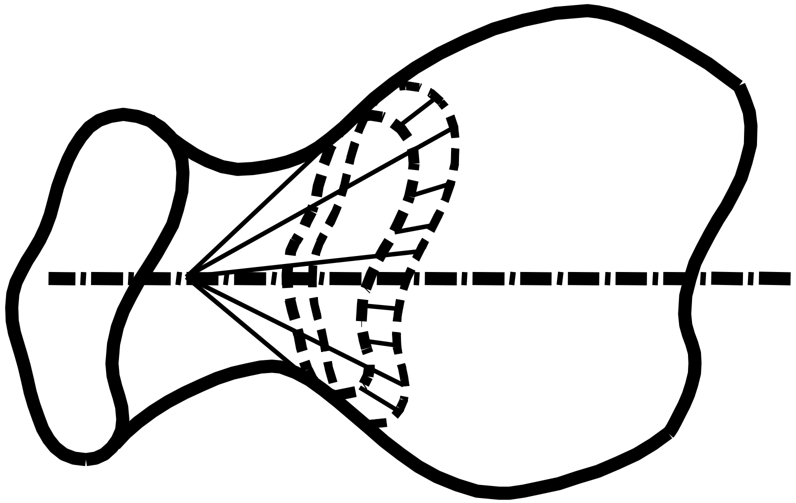
Objects



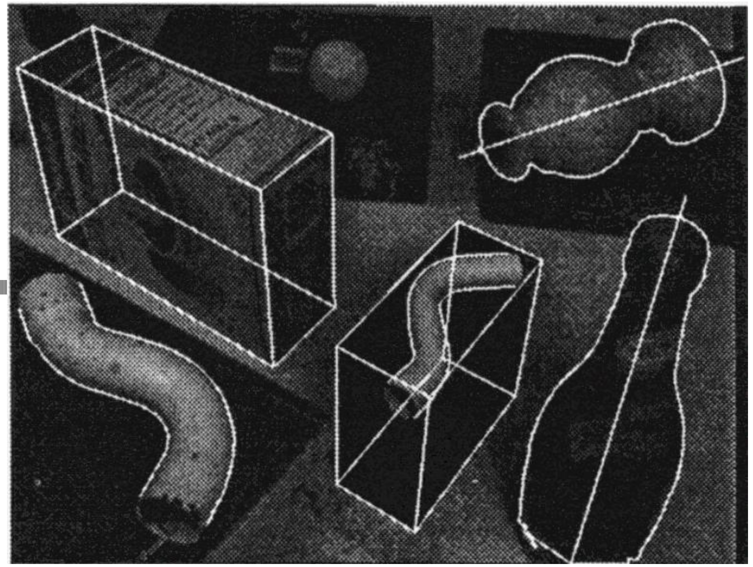
http://en.wikipedia.org/wiki/Recognition_by_Components_Theory

Svetlana Lazebnik

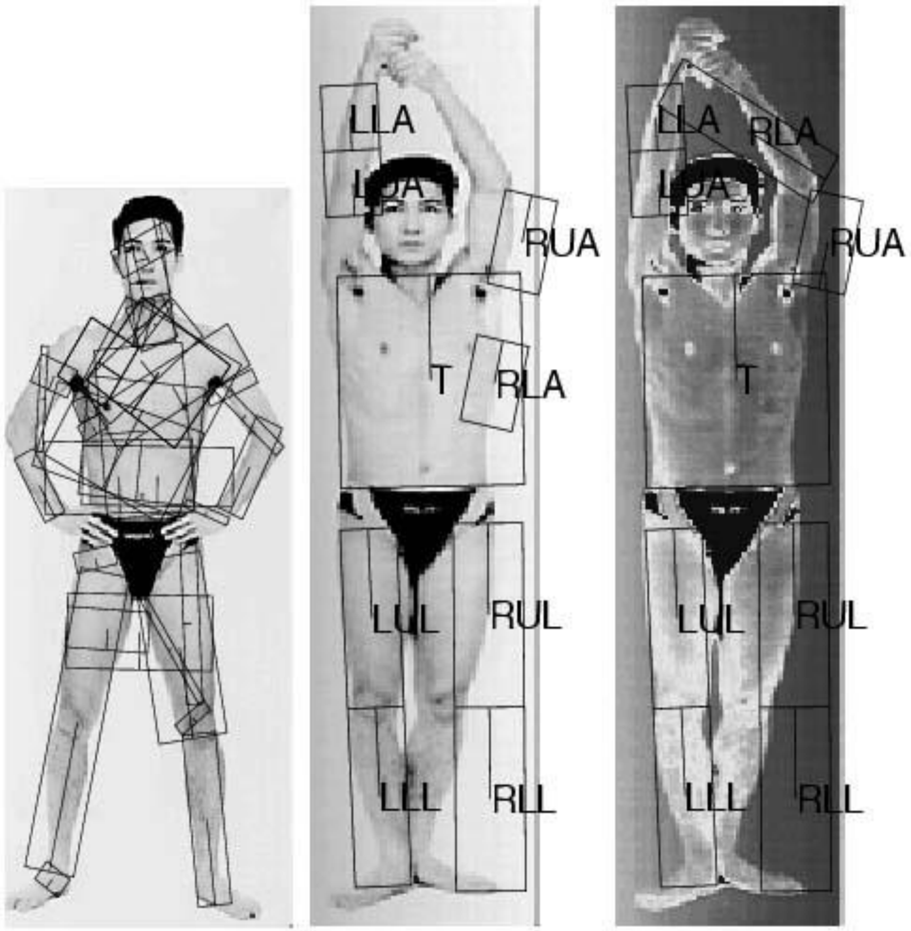
General shape primitives?



Generalized cylinders
Ponce et al. (1989)



Zisserman et al. (1995)



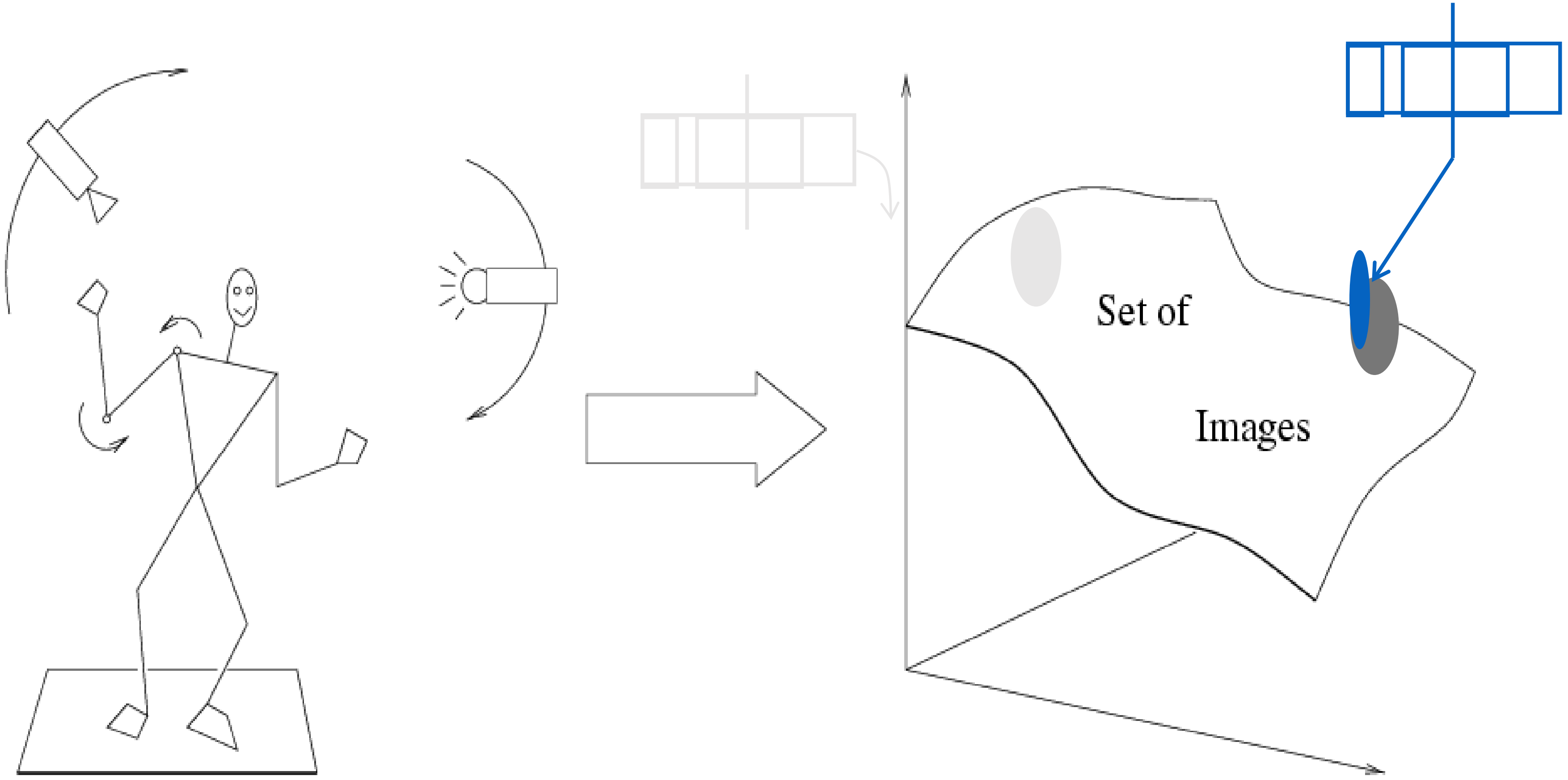
Forsyth (2000)

Svetlana Lazebnik

History of ideas in recognition

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

Svetlana Lazebnik

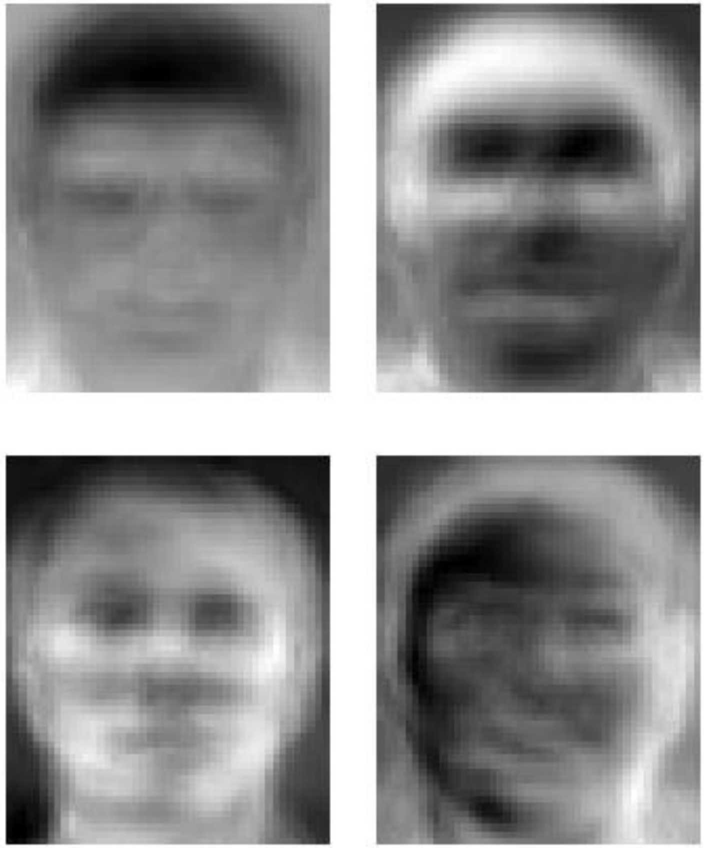


Empirical models of image variability

Appearance-based techniques

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

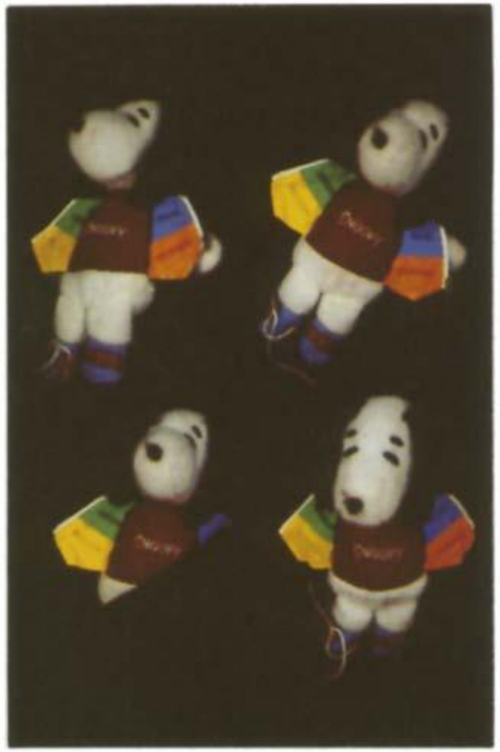
Eigenfaces (Turk & Pentland, 1991)

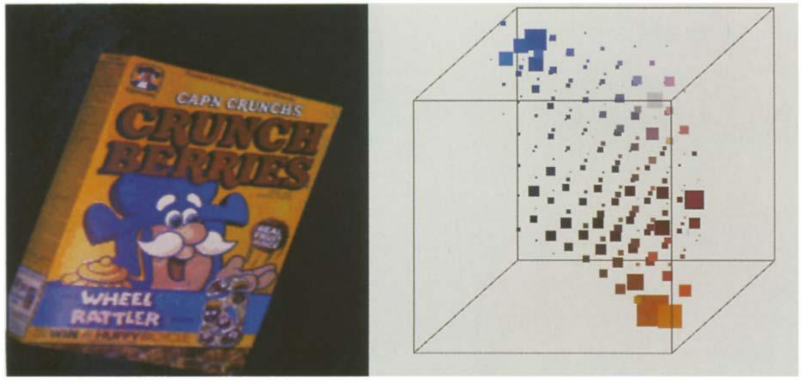


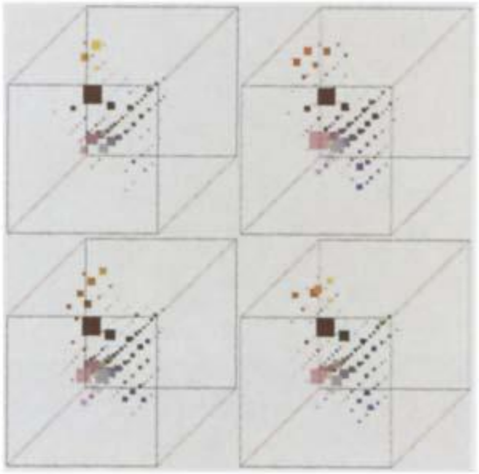
Experimental	Correct/Unknown Recognition Percentage		
Condition	Lighting	Orientation	Scale
Forced classification	96/0	85/0	64/0
Forced 100% accuracy	100/19	100/39	100/60
Forced 20% unknown rate	100/20	94/20	74/20

Svetlana Lazebnik

Color Histograms







Swain and Ballard, Color Indexing, IJCV 1991.

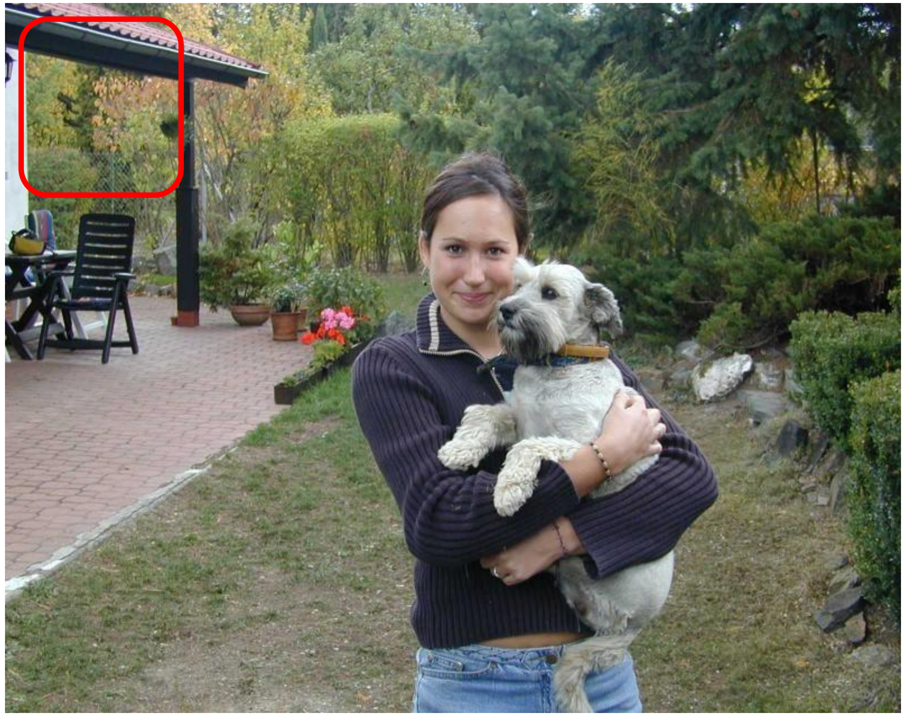
Svetlana Lazebnik

History of ideas in recognition

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

Svetlana Lazebnik

Sliding window approaches



History of ideas in recognition

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

Svetlana Lazebnik

Local features for object instance recognition

D. Lowe (1999, 2004)

Large-scale image search

Combining local features, indexing, and spatial constraints

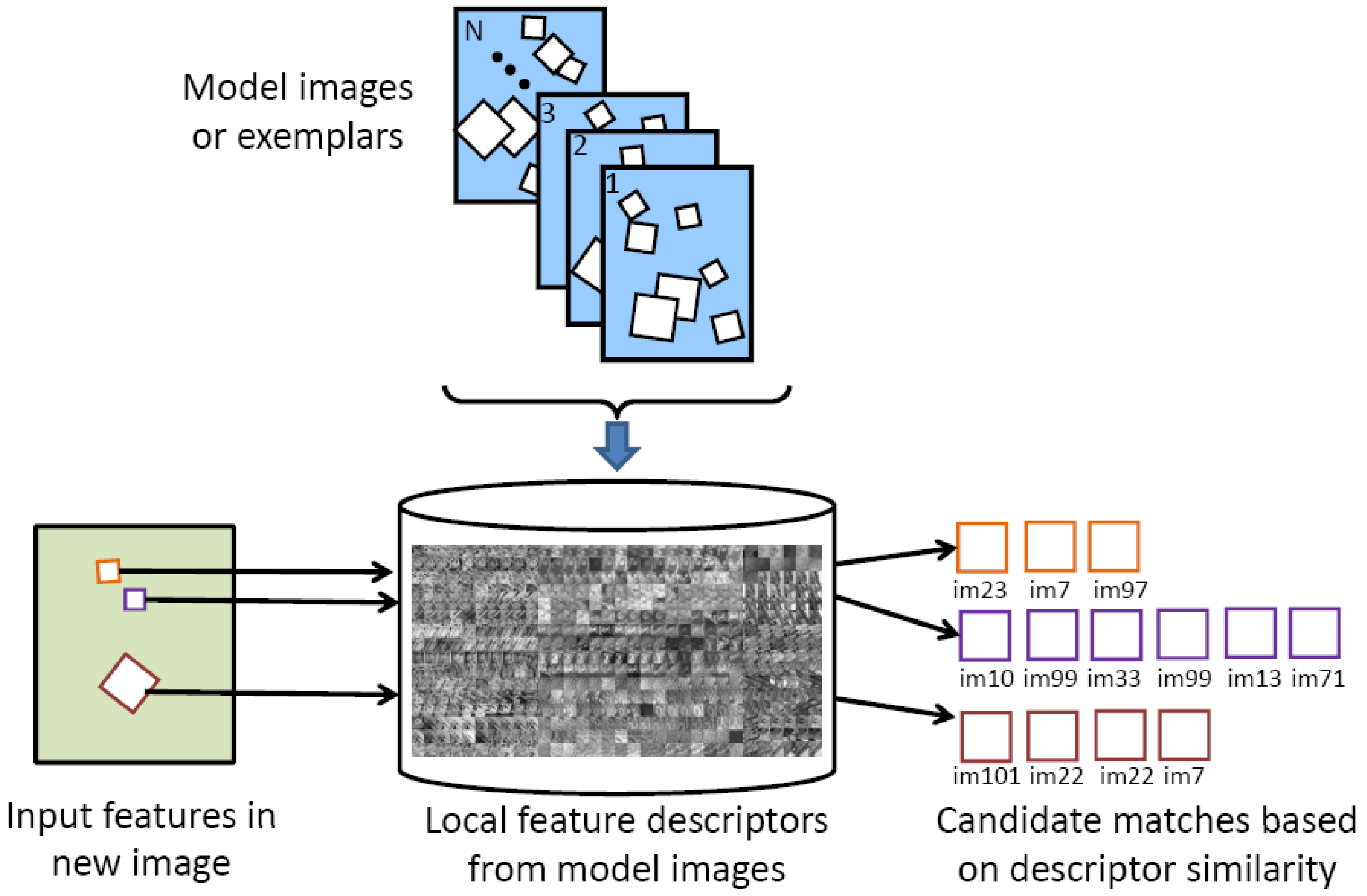
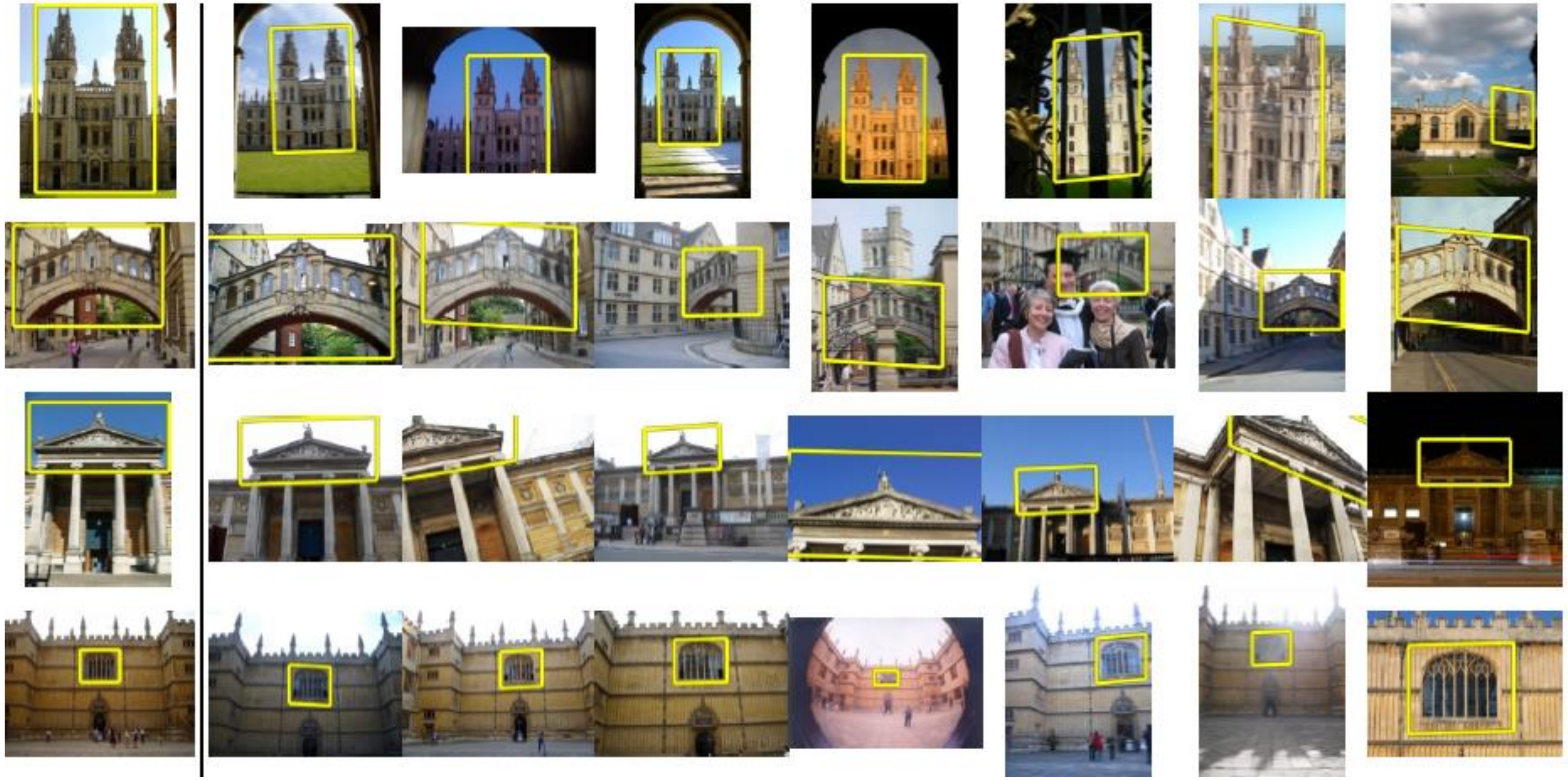


Image credit: K. Grauman and B. Leibe

Large-scale image search

Combining local features, indexing, and spatial constraints



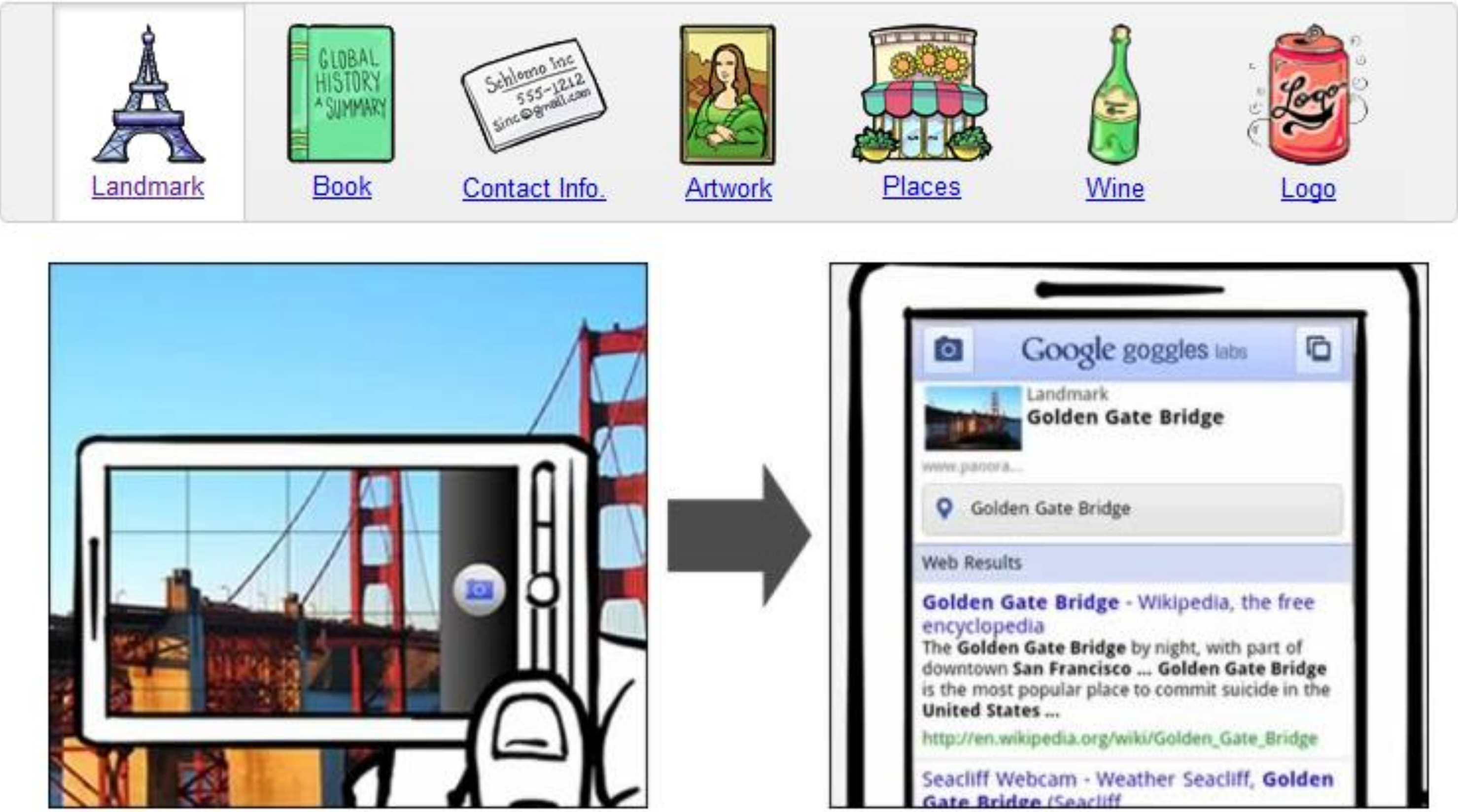
Philbin et al. '07

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)

Svetlana Lazebnik

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

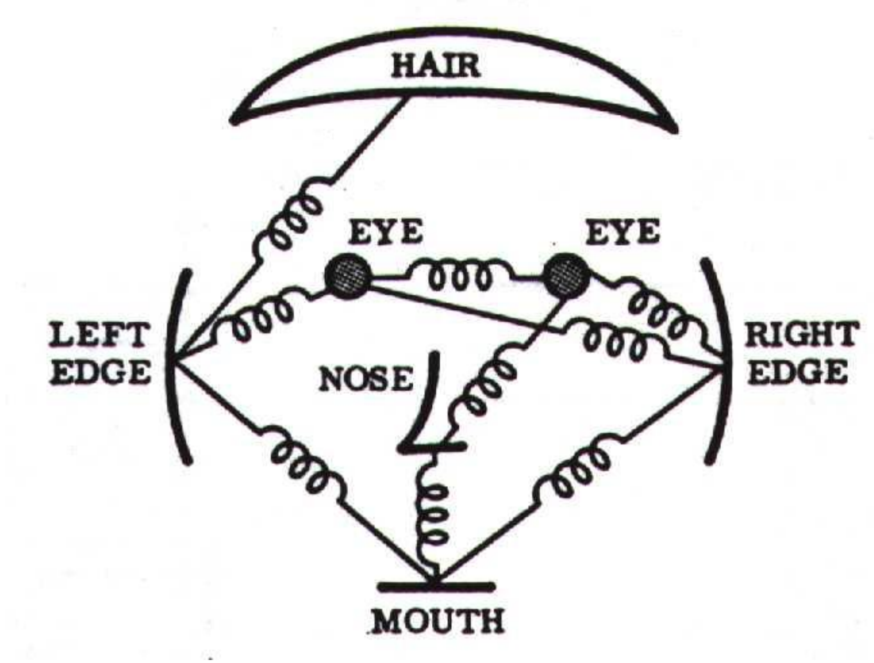


Figure from [Fischler & Elschlager 73]

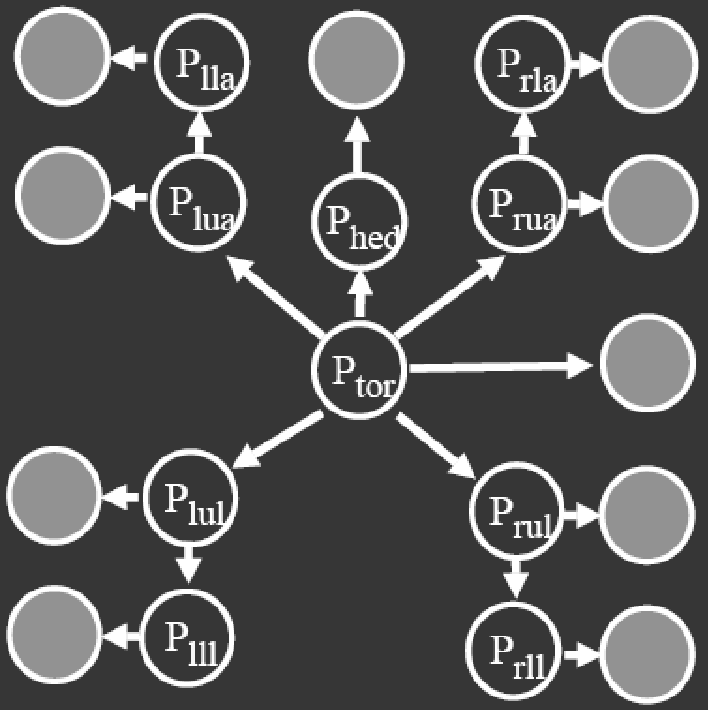
Constellation models

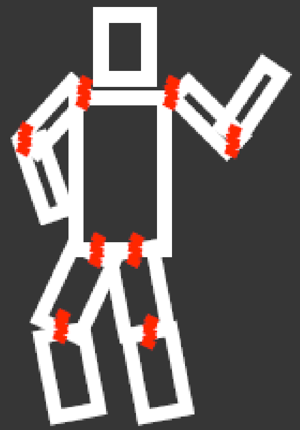
Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

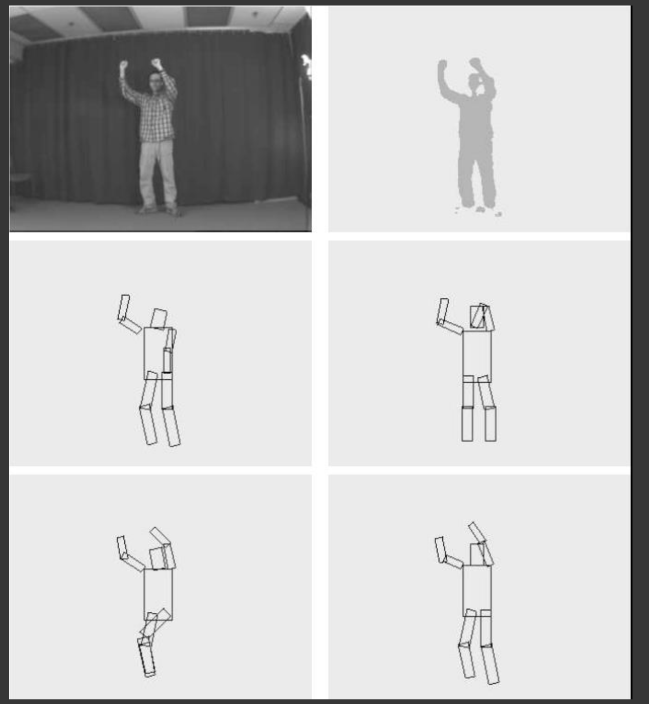
Re

Pictorial structure model

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





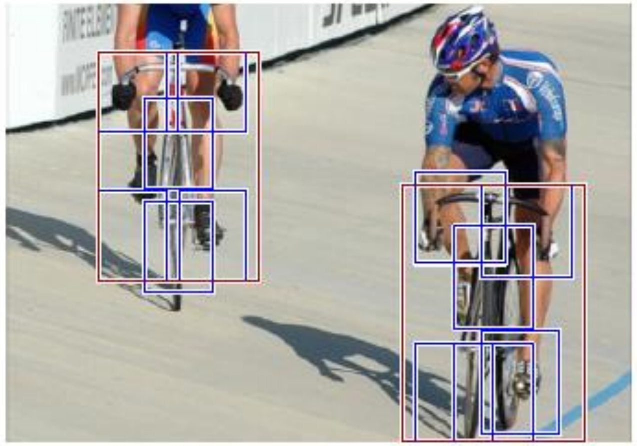


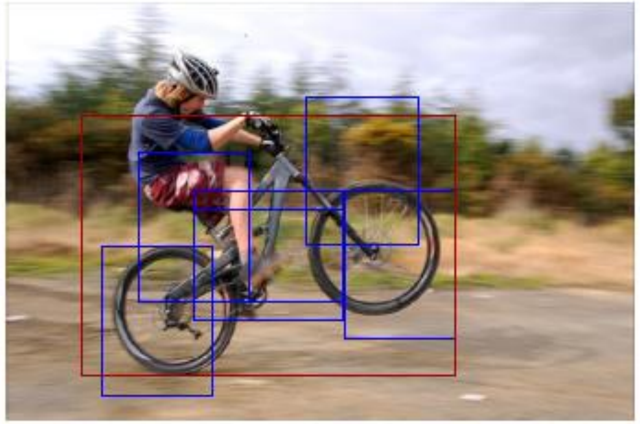
$$\Pr(P_{tor}, P_{arm}, \ldots | \mathrm{Im}) \propto \prod_{i,j} \Pr(P_i \mid P_j) \prod_i \Pr(\mathrm{Im}(P_i))$$

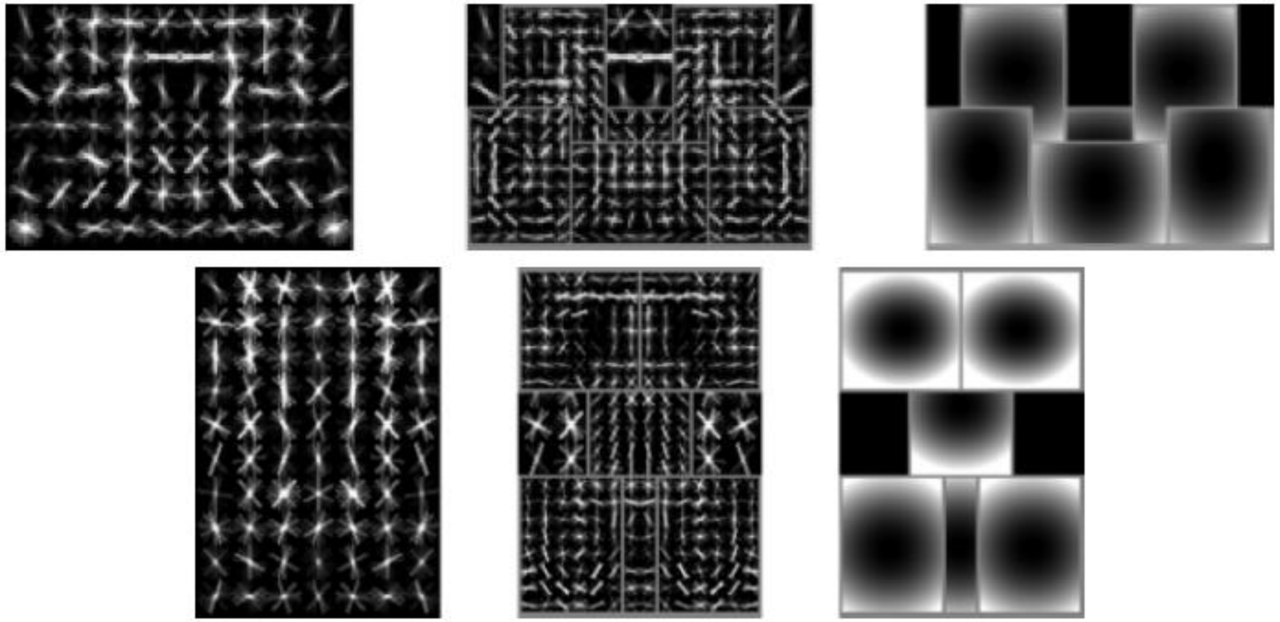
part geometry

part appearance

Discriminatively trained part-based models







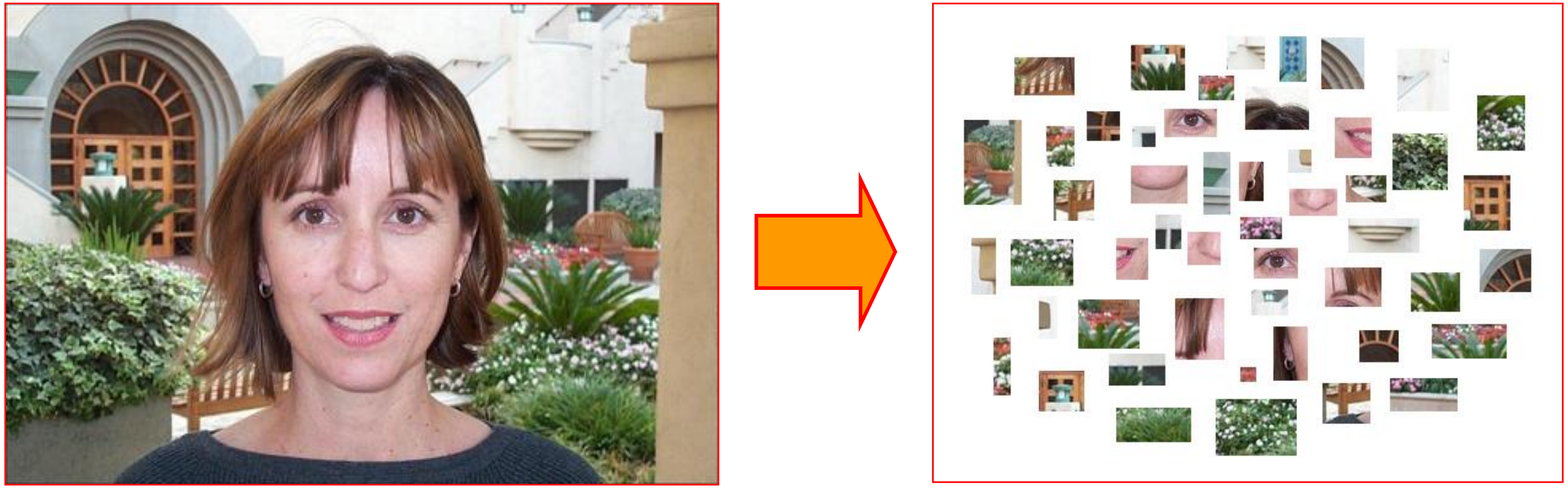
P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, ["Object Detection with Discriminatively Trained Part-Based Models,"]() PAMI 2009

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

Svetlana Lazebnik

Bag-of-features models



Svetlana Lazebnik

Bag-of-features models

Object → **Bag of ‘words’**

Svetlana Lazebnik

Objects as texture

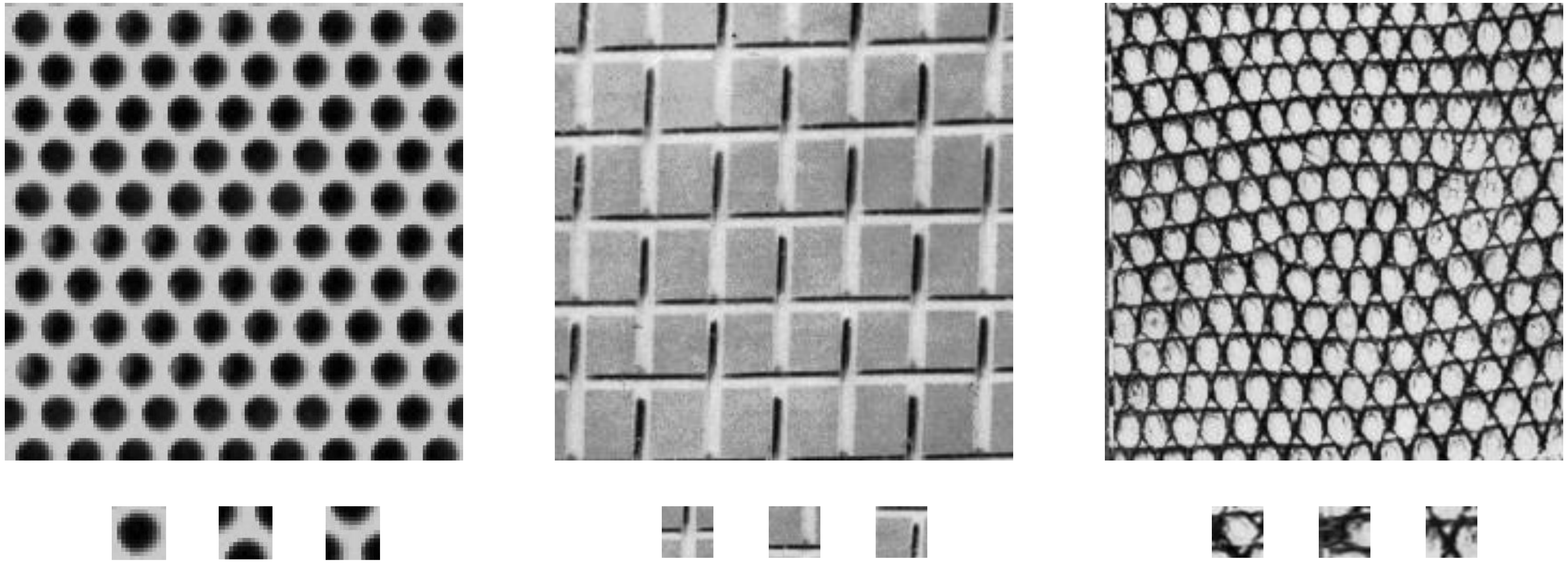
- All of these are treated as being the same

- No distinction between foreground and background: scene recognition?

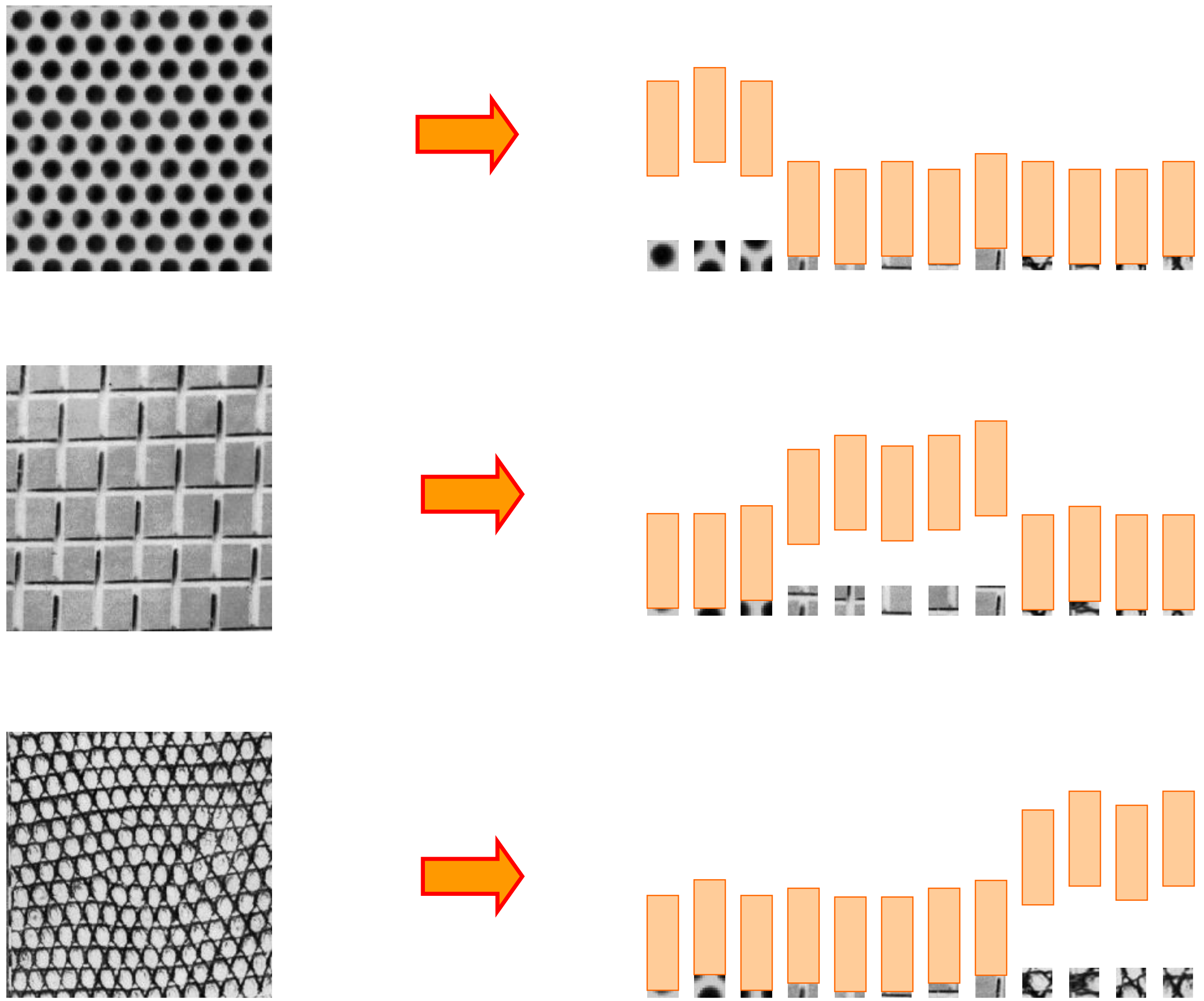
Svetlana Lazebnik

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



Origin 1: Texture recognition



Origin 2: Bag-of-words models

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

Origin 2: Bag-of-words models

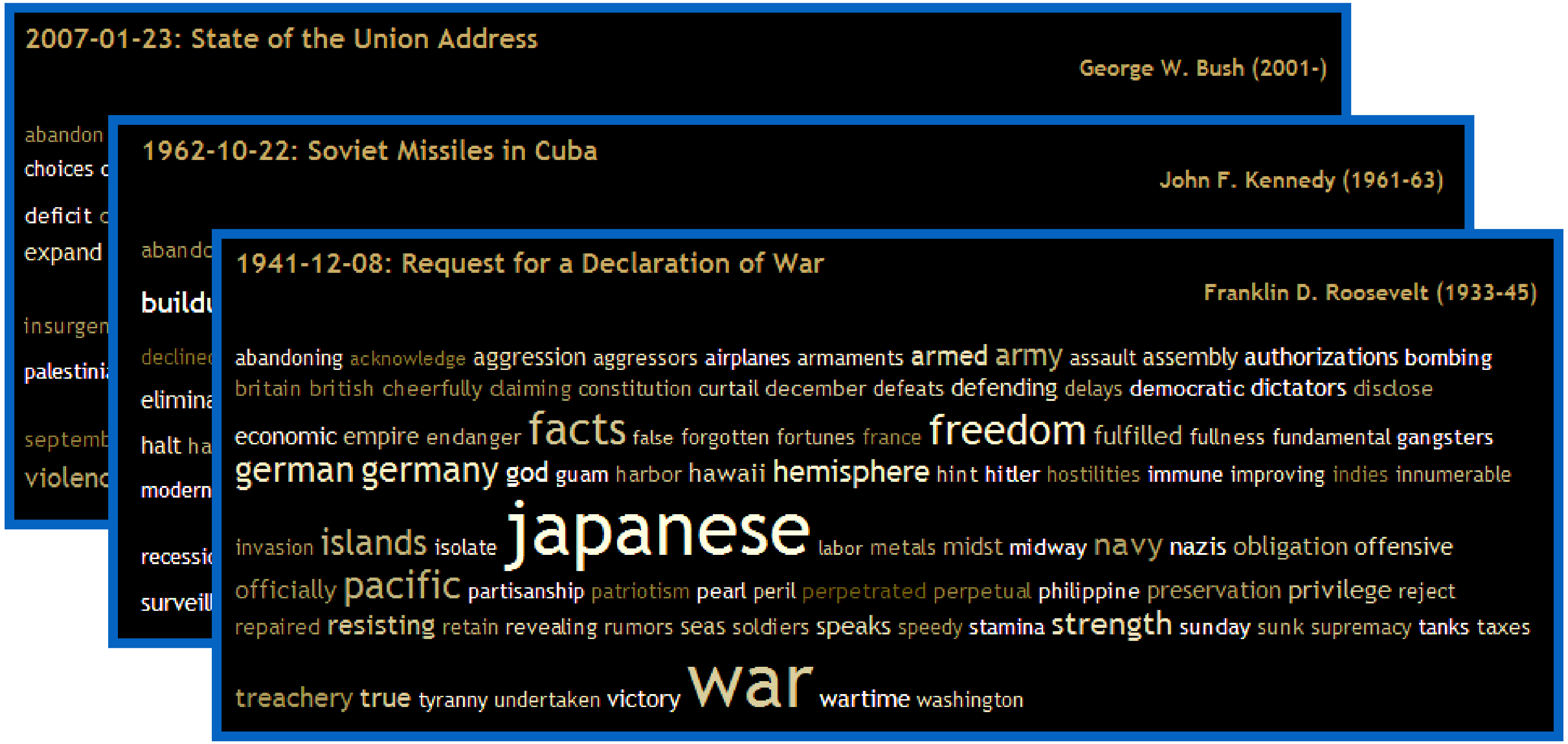
- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

Origin 2: Bag-of-words models

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

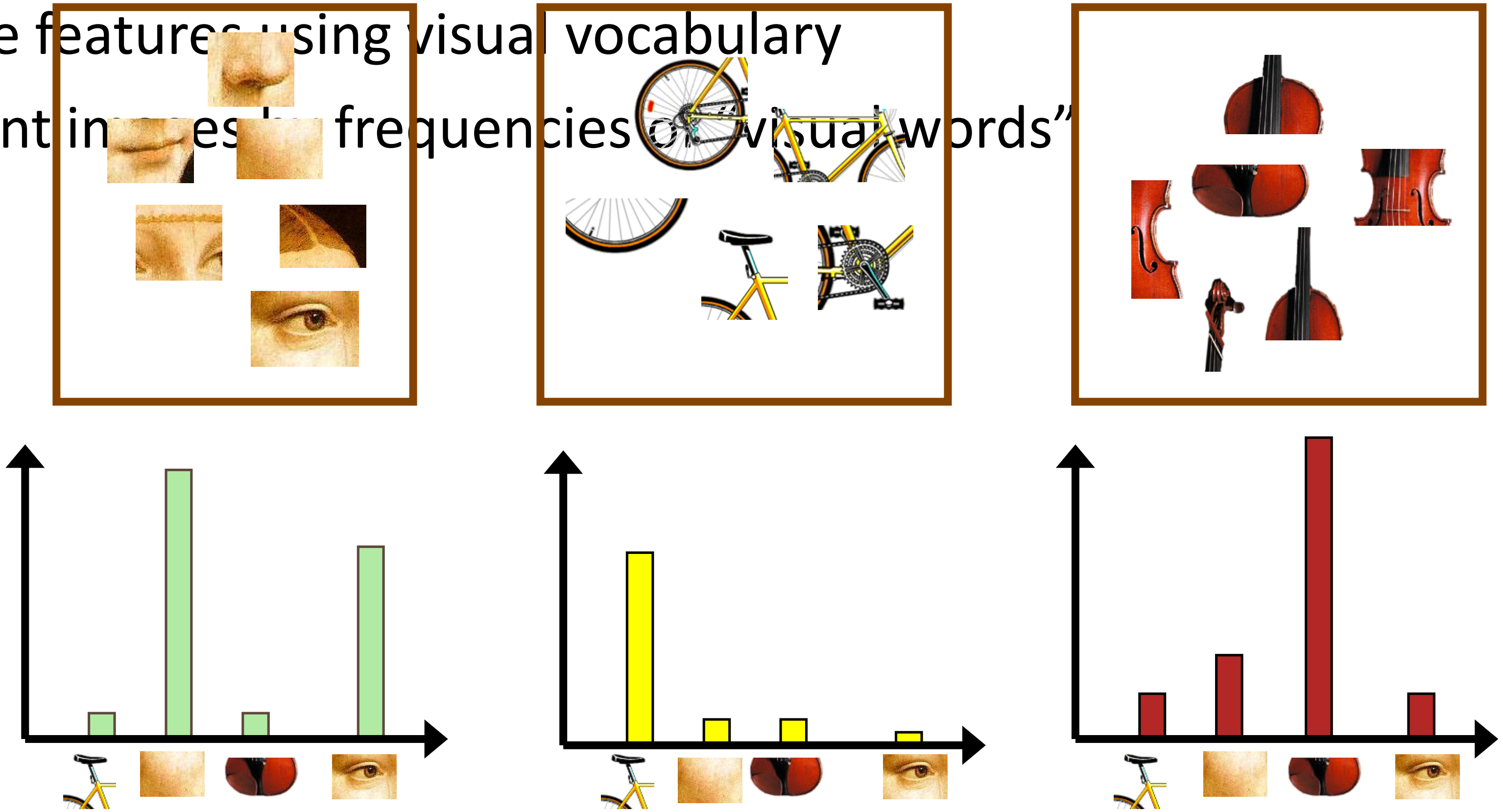
Origin 2: Bag-of-words models

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



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”

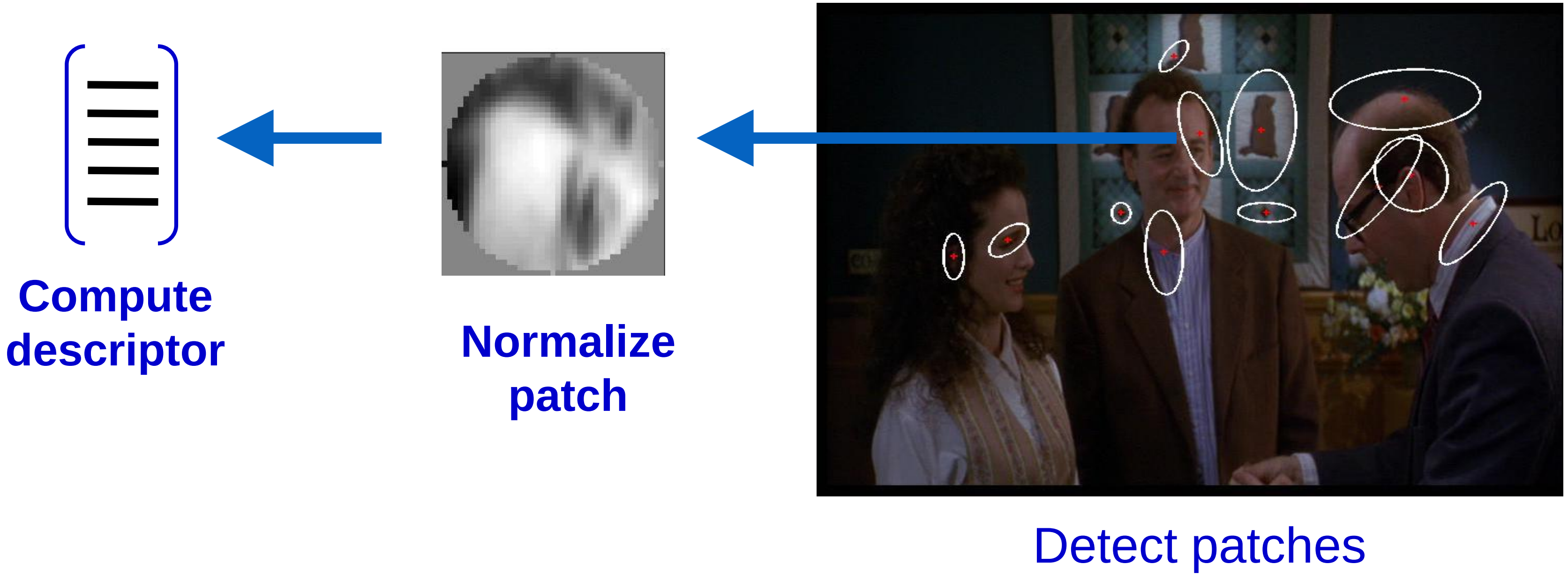


1. Feature extraction

- Regular grid or interest regions

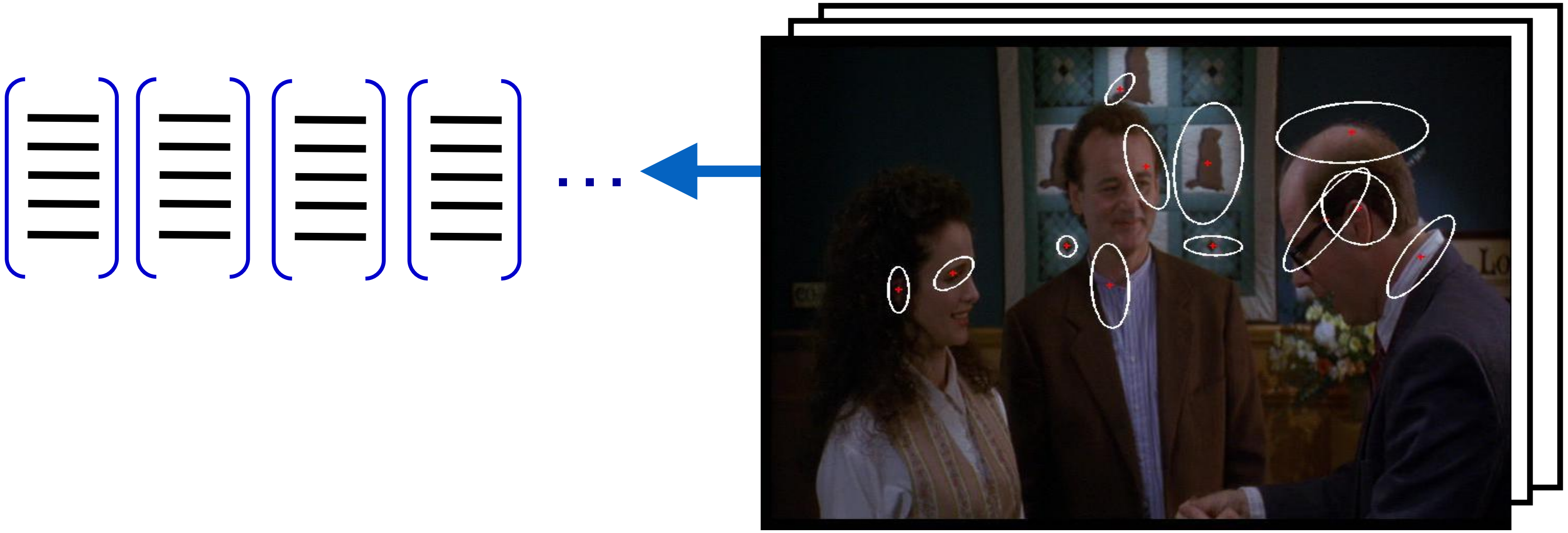
 

1. Feature extraction



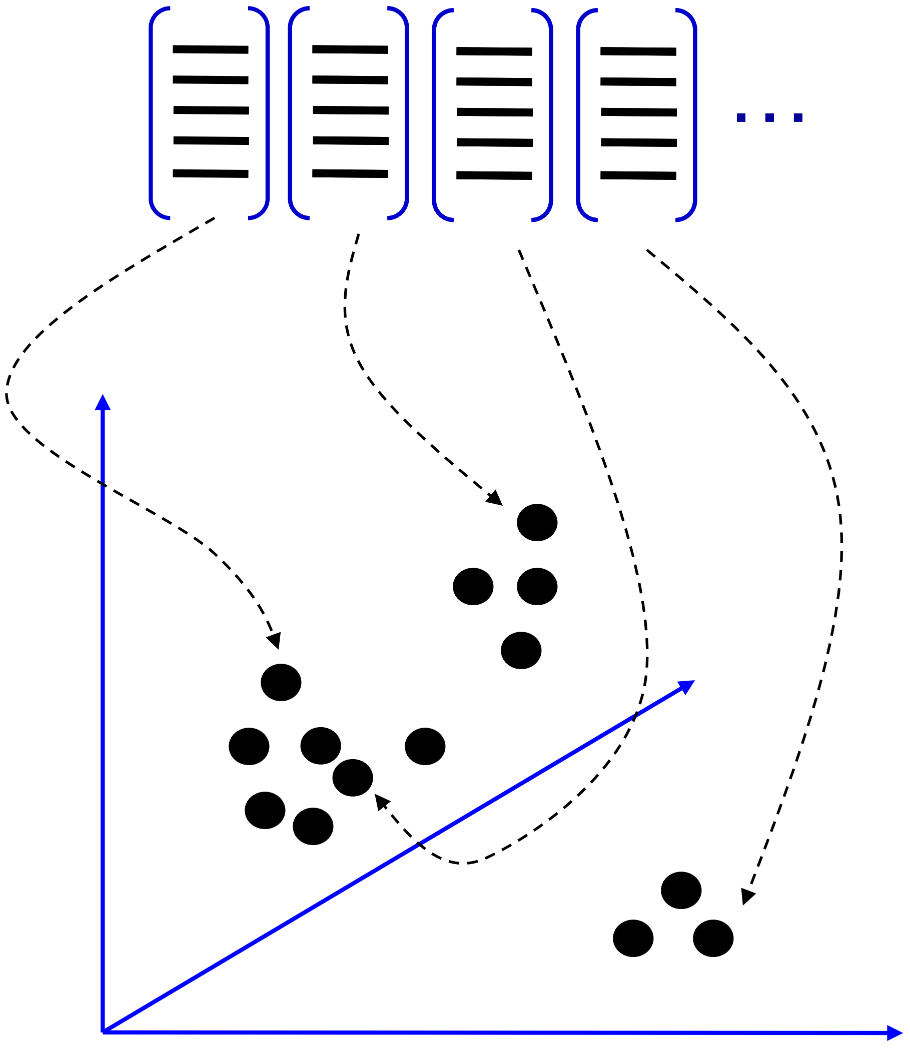
Slide credit: Josef Sivic

1. Feature extraction



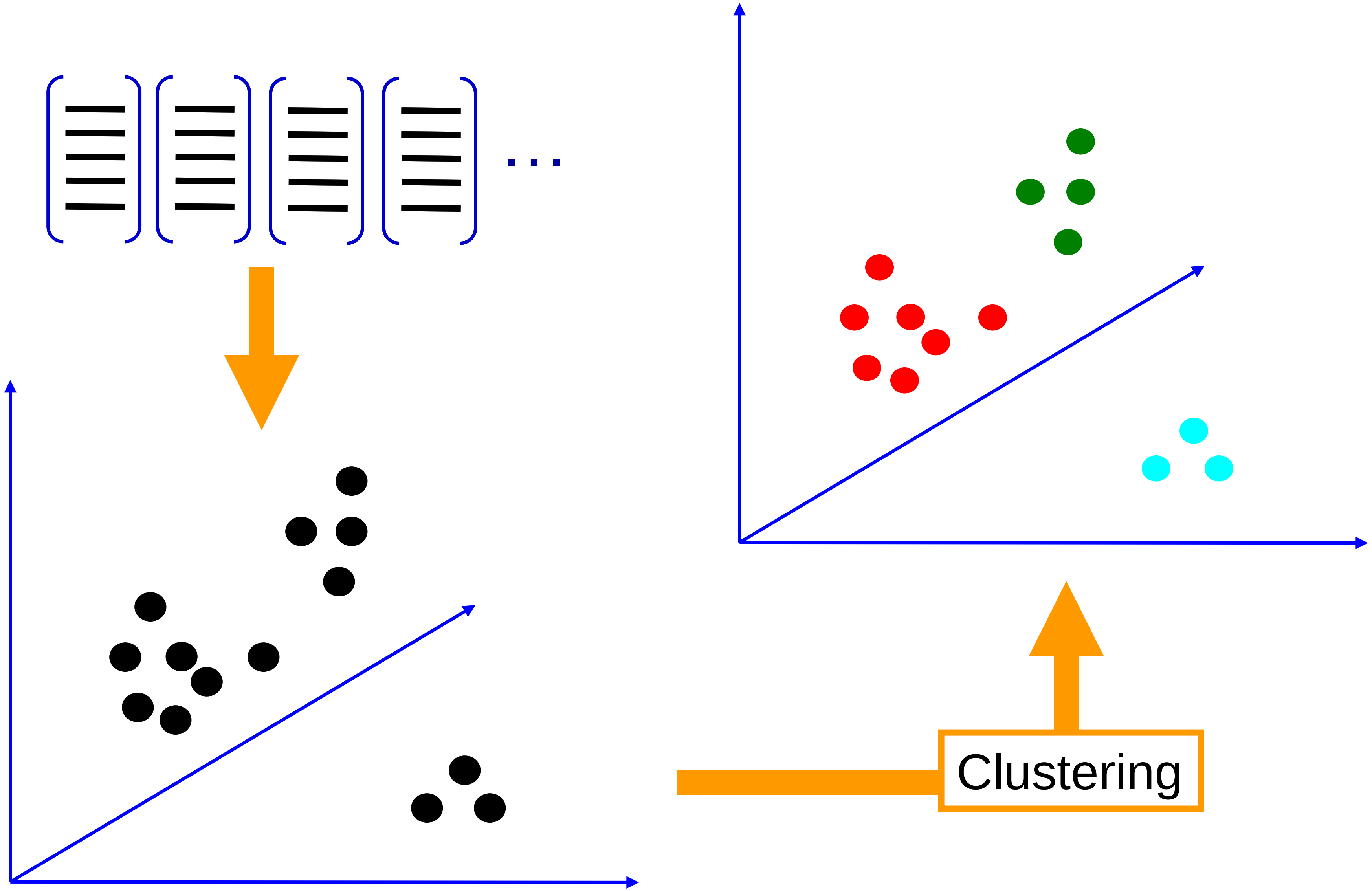
Slide credit: Josef Sivic

2. Learning the visual vocabulary



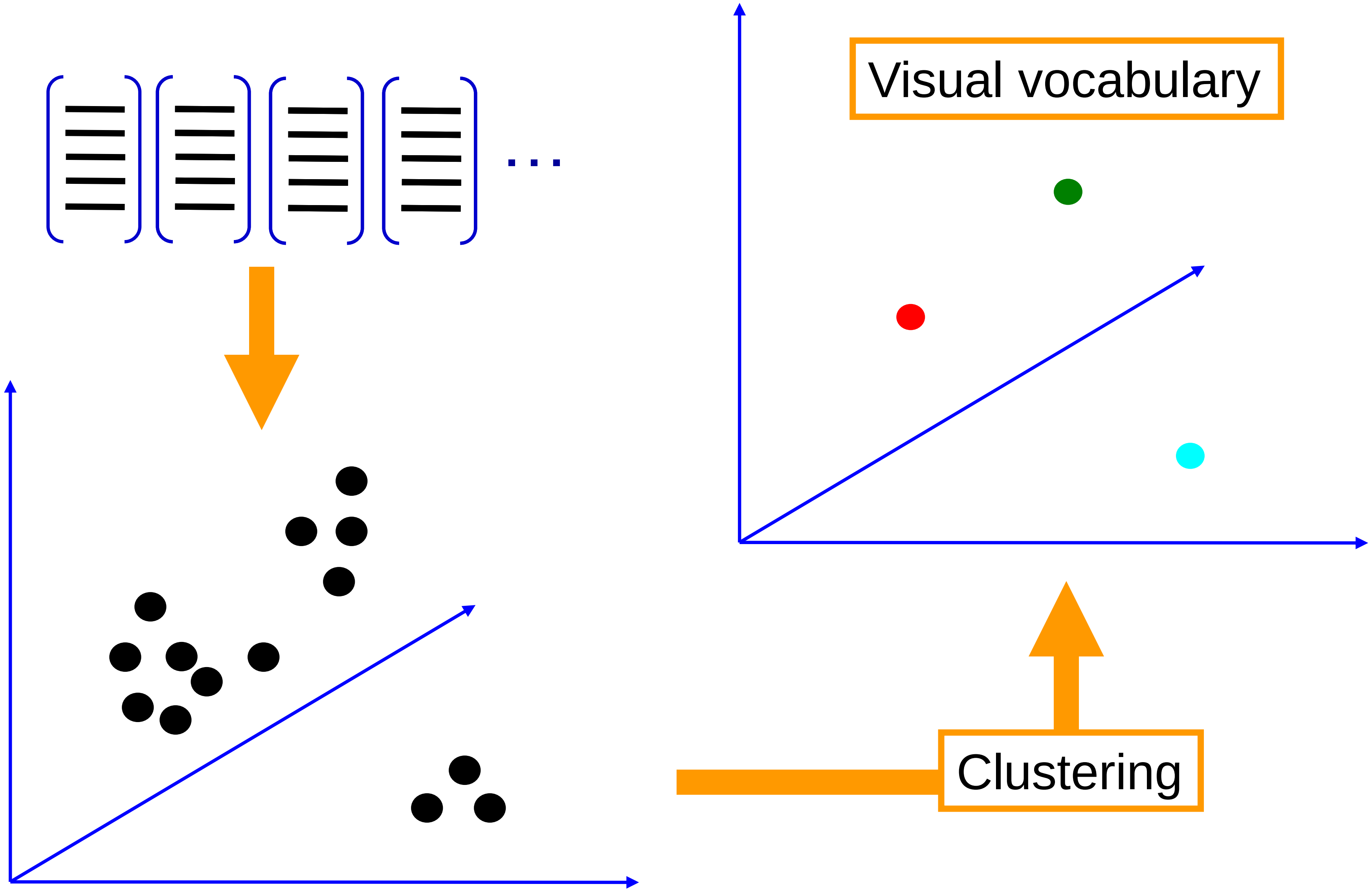
Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

2. Learning the visual vocabulary



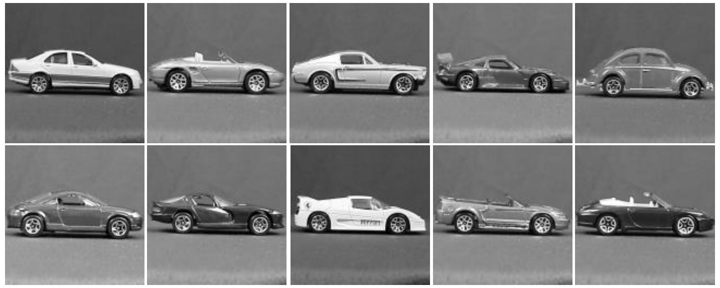
Slide credit: Josef Sivic

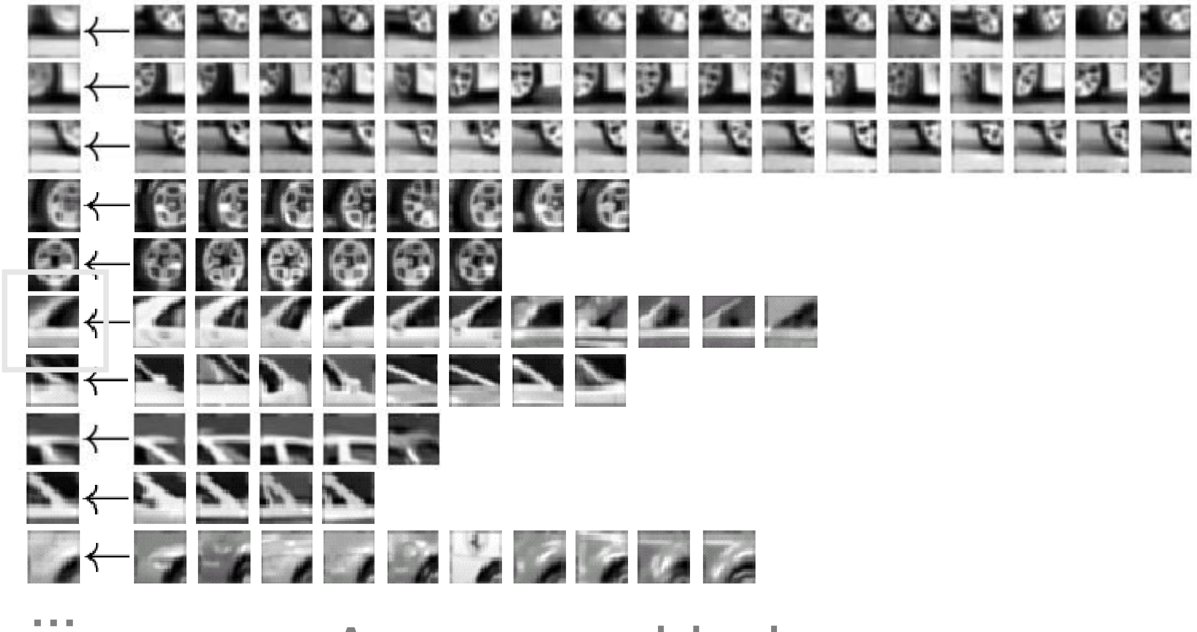
Clustering and vector quantization

- 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



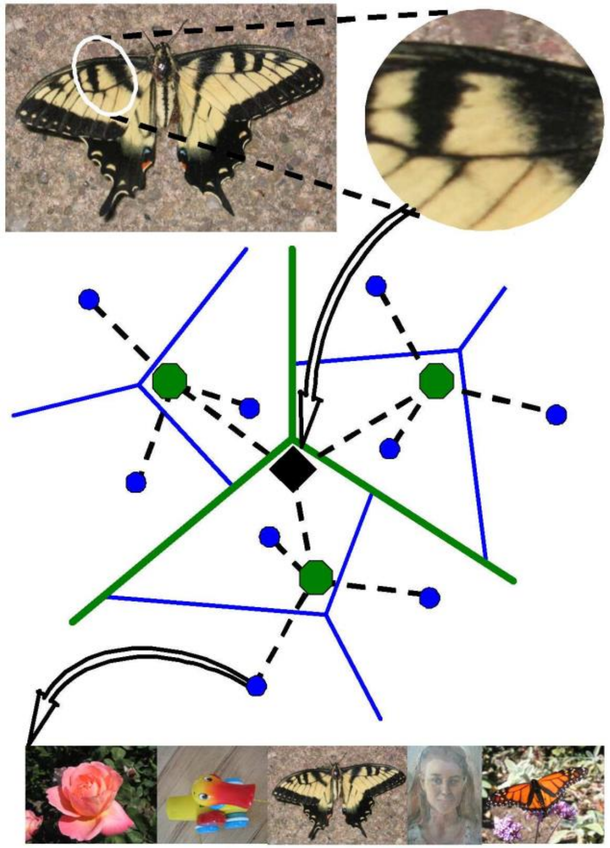


Appearance codebook

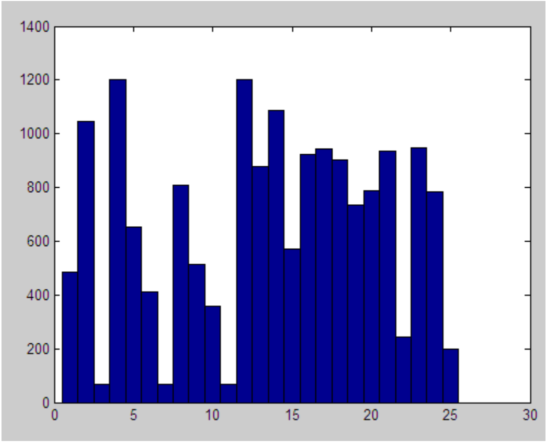
Source: B. Leibe

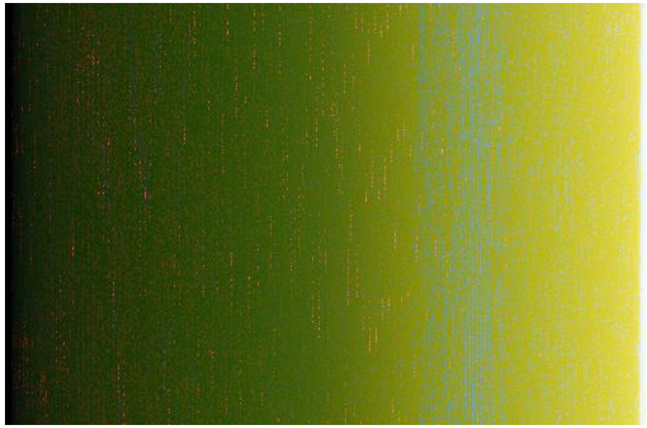
Visual vocabularies: Issues

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



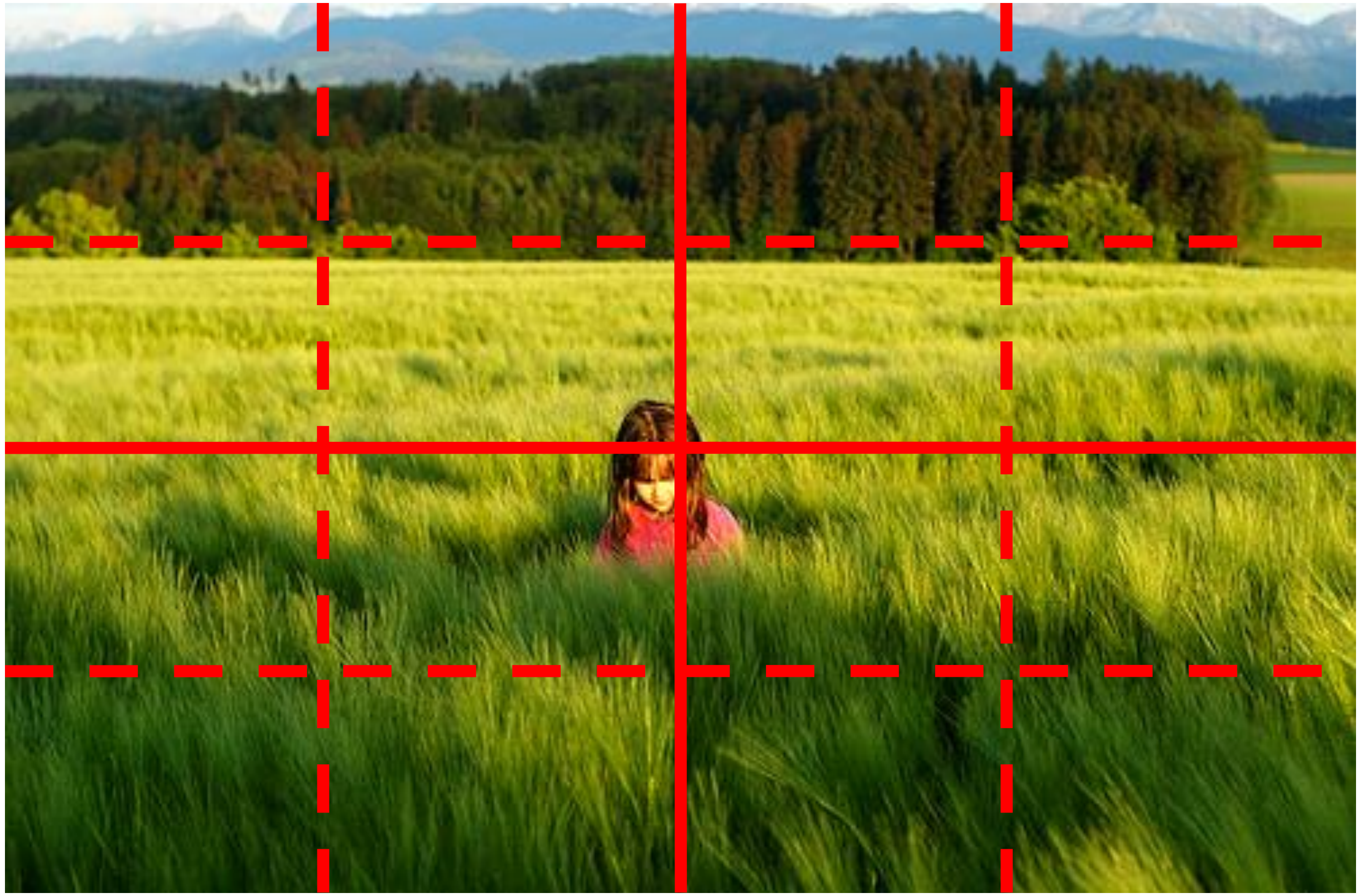
But what about layout?





All of these images have the same color histogram

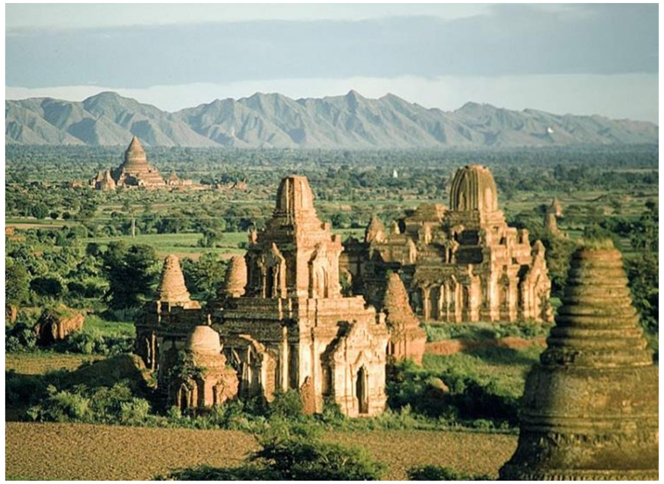
Spatial pyramid

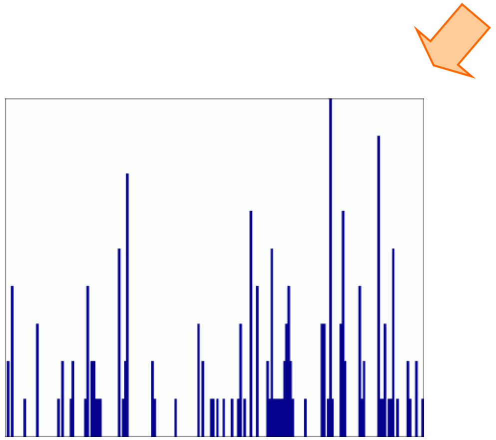


Compute histogram in each spatial bin

Spatial pyramid representation

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

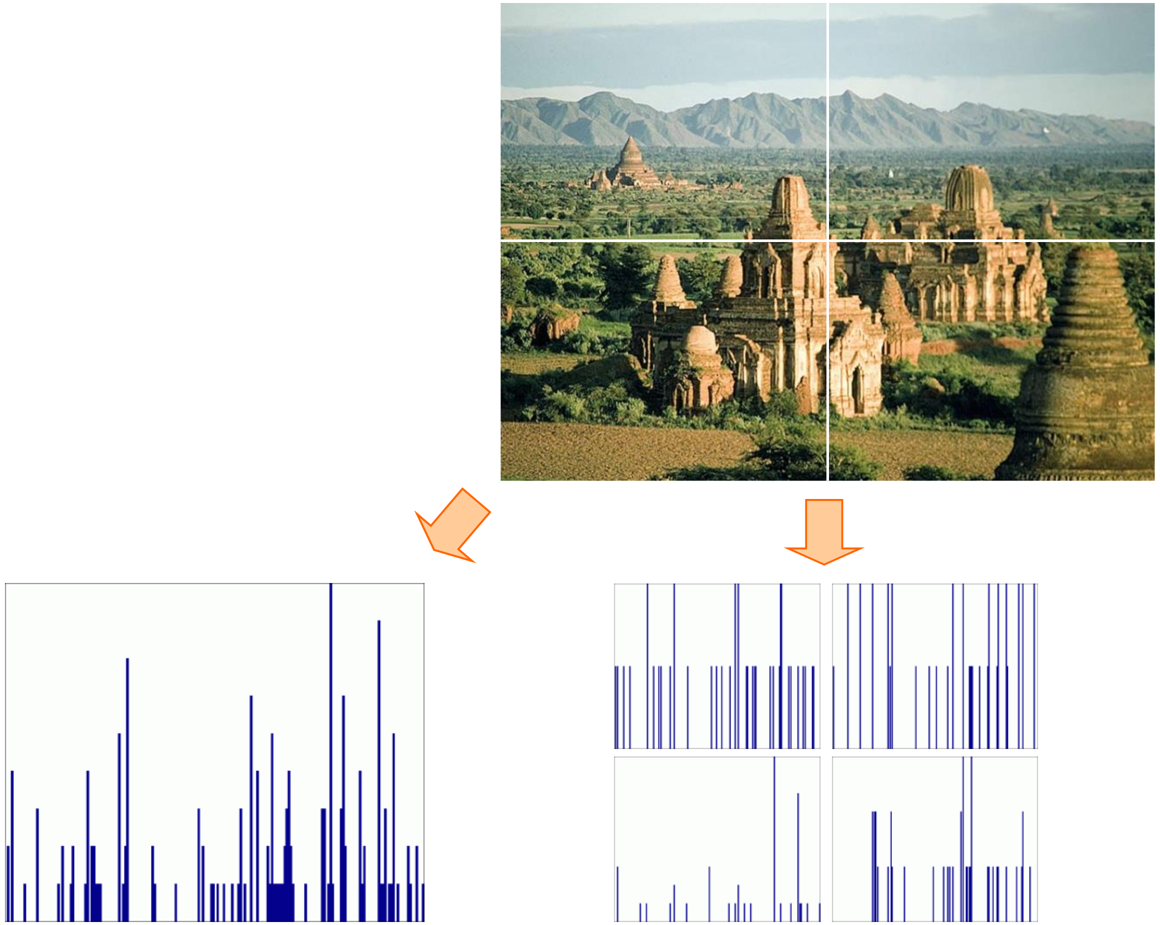




Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramid representation

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



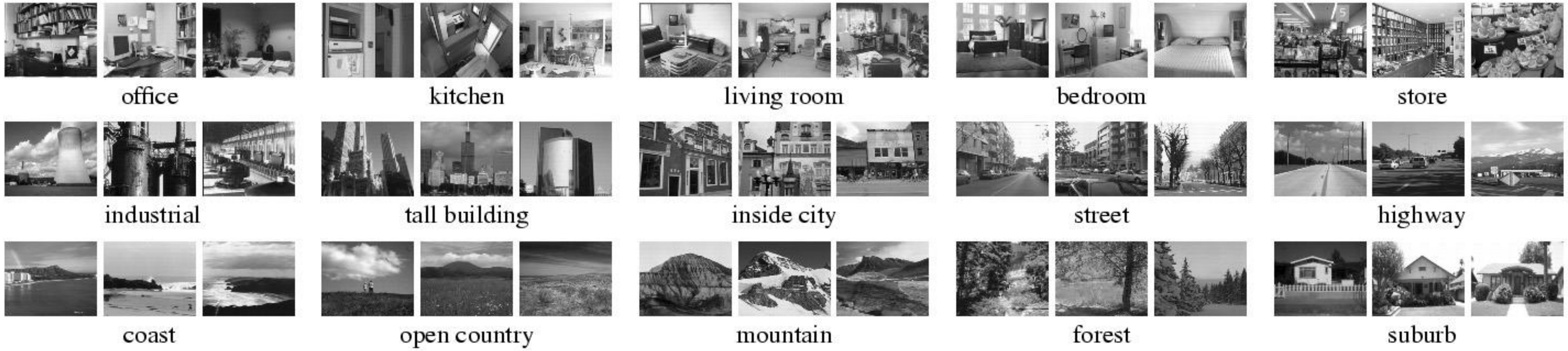
Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramid representation

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

Lazebnik, Schmid & Ponce (CVPR 2006)

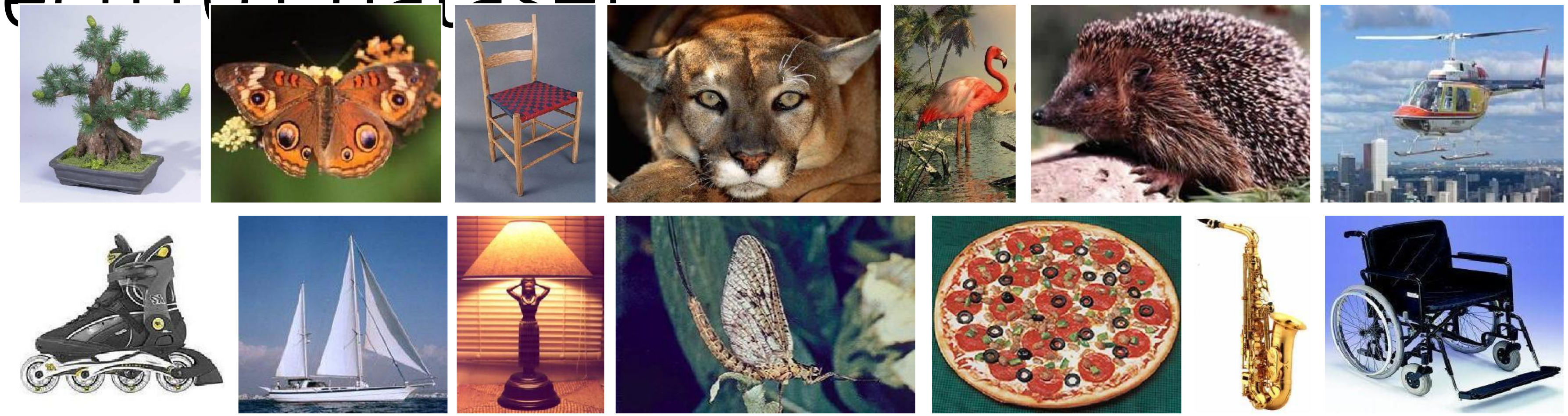
Sce



Multi-class classification results

	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

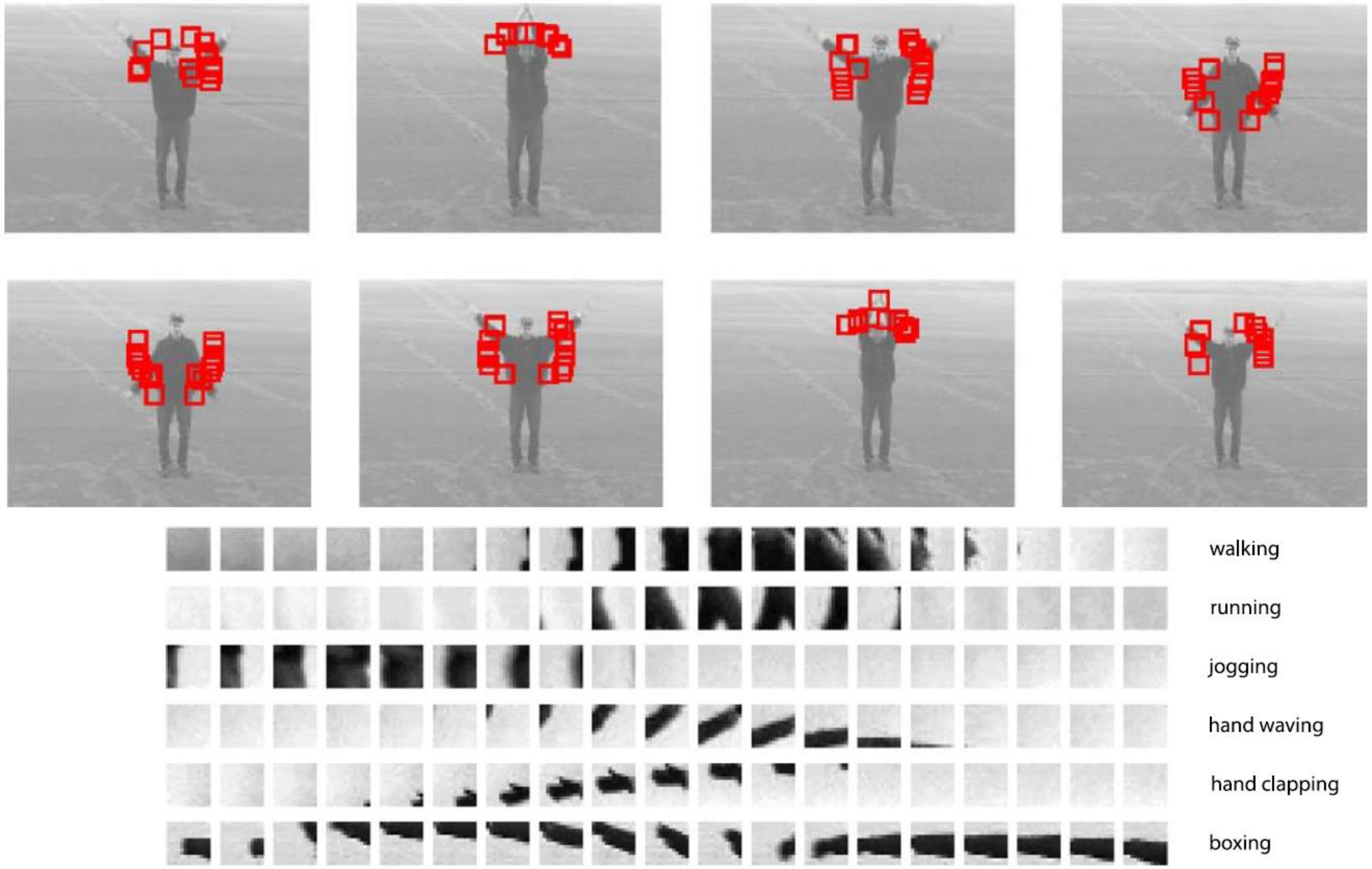


Multi-class classification results (30 training images per class)

	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, context, *deep learning*

Svetlana Lazebnik