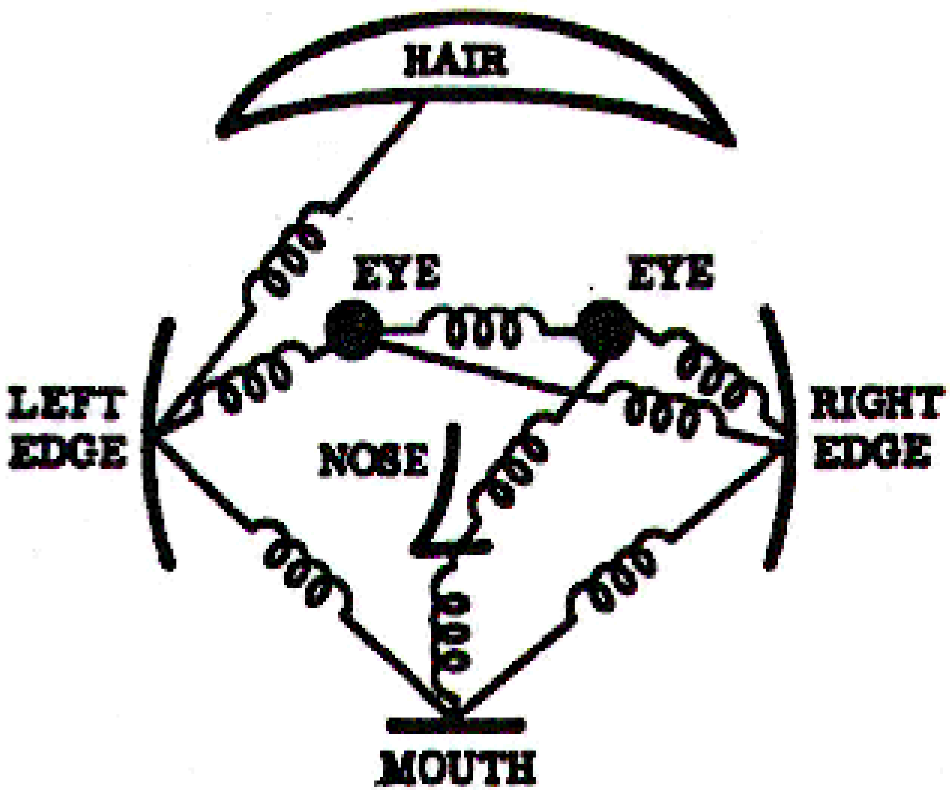
Beyond bags of features: Adding spatial information



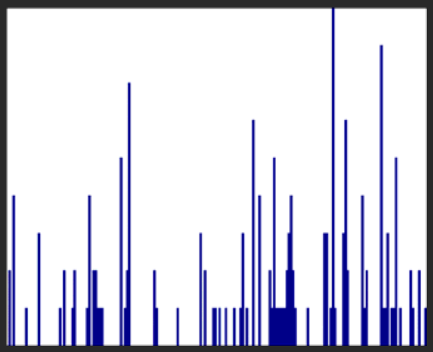
Many slides adapted from Fei-Fei Li, Rob Fergus, and Antonio Torralba

Adding spatial information

- Forming vocabularies from pairs of nearby features – “doublets” or “bigrams”
- Computing bags of features on sub-windows of the whole image
- Using codebooks to vote for object position
- Generative part-based models

Spatial pyramid representation

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

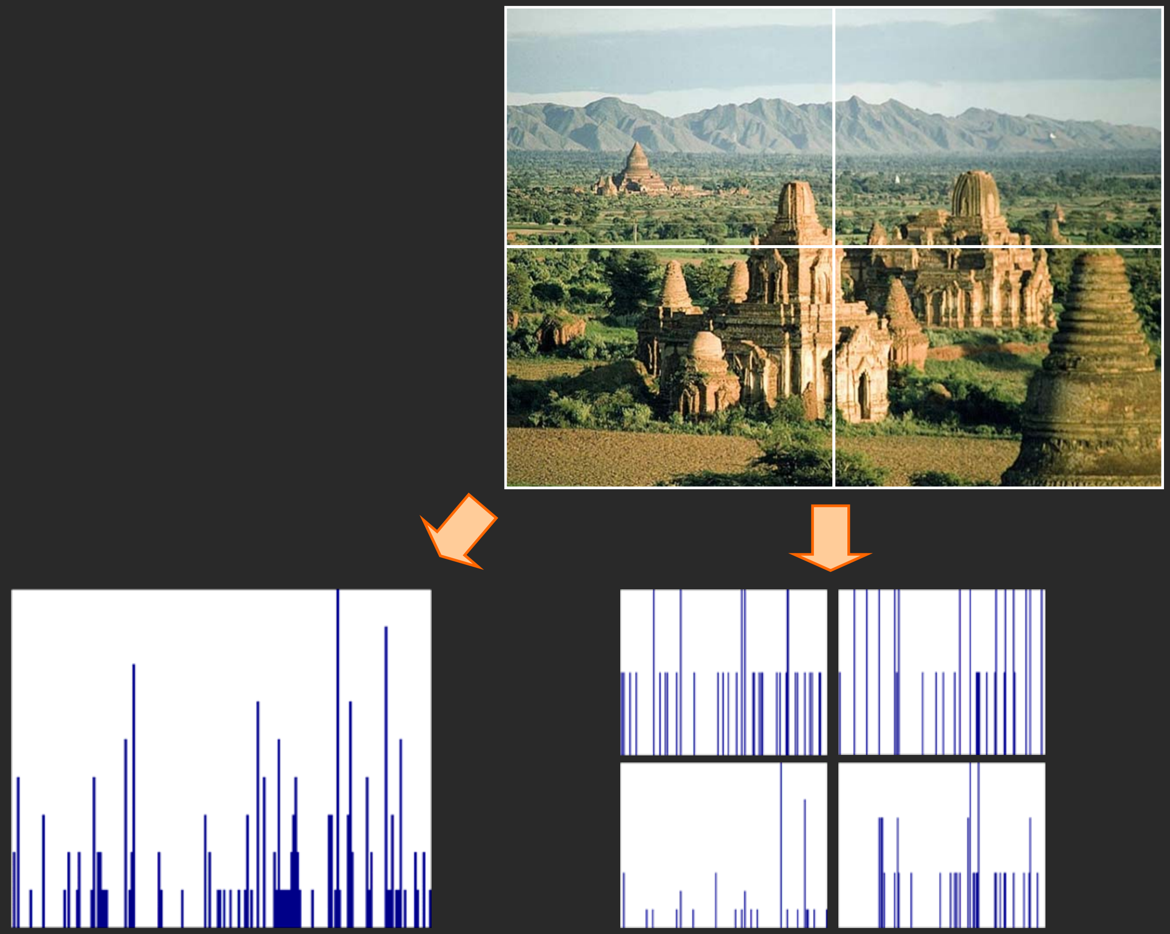


level 0

Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramid representation

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

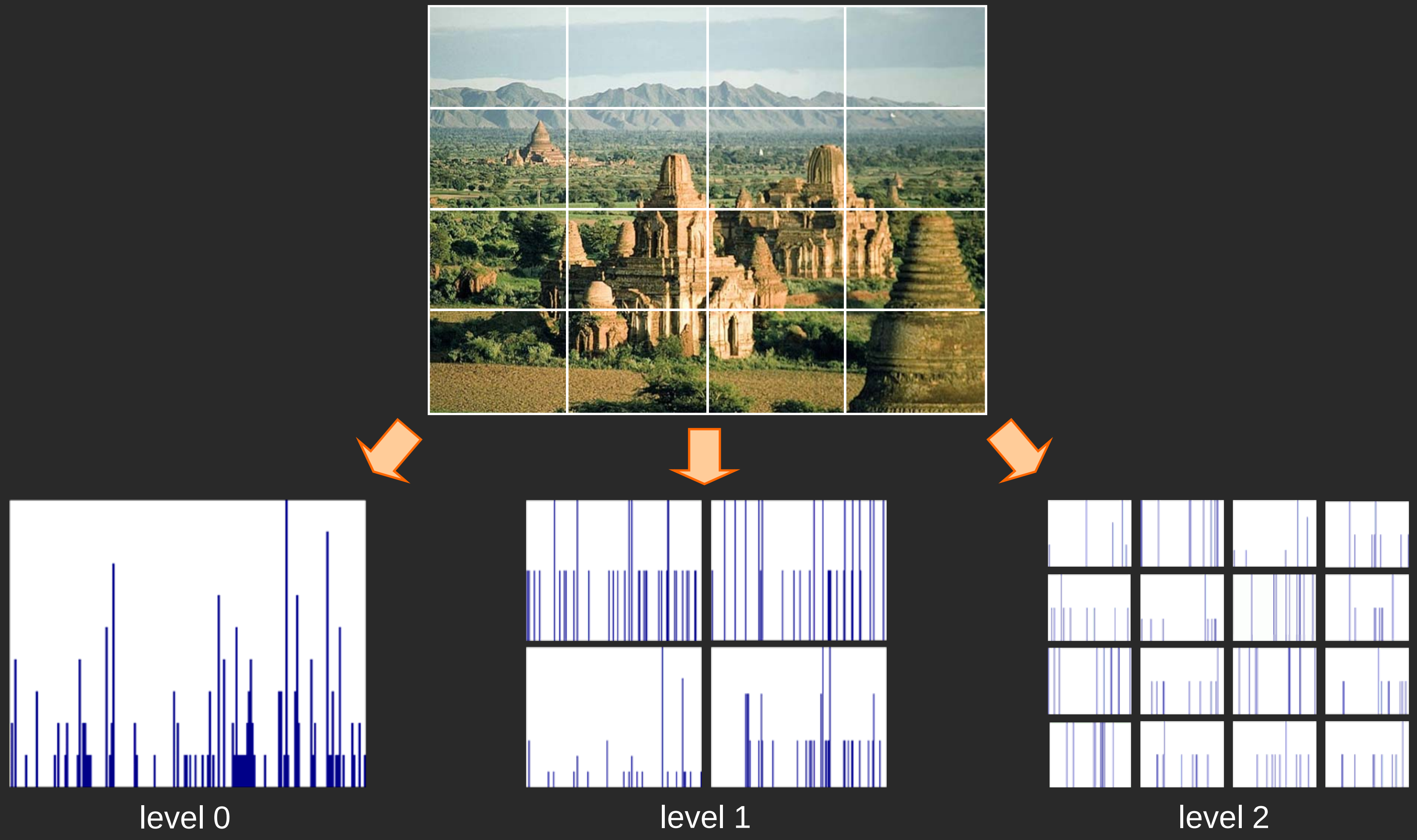


level 0 level 1

Lazebnik, Schmid & Ponce (CVPR 2006)

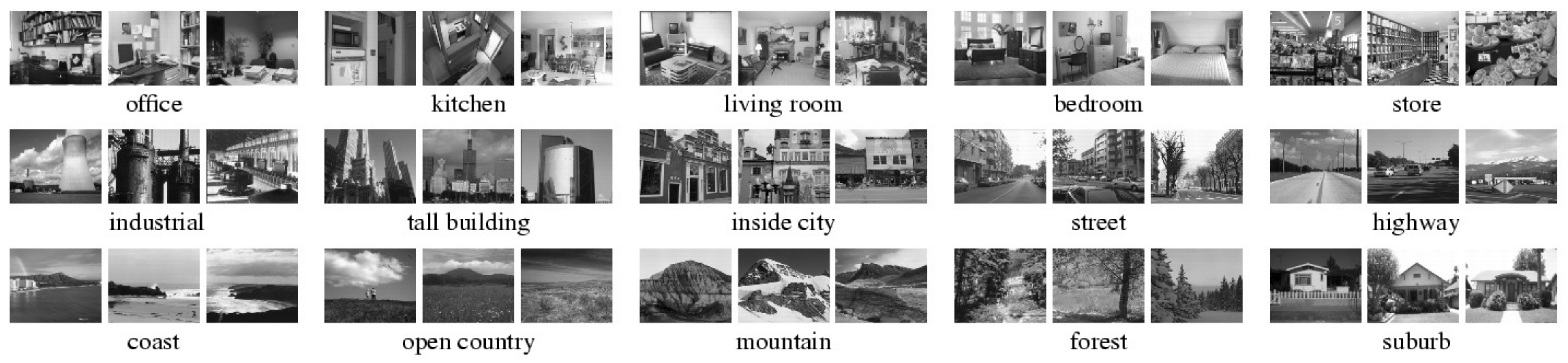
Spatial pyramid representation

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



Lazebnik, Schmid & Ponce (CVPR 2006)

Scene category dataset

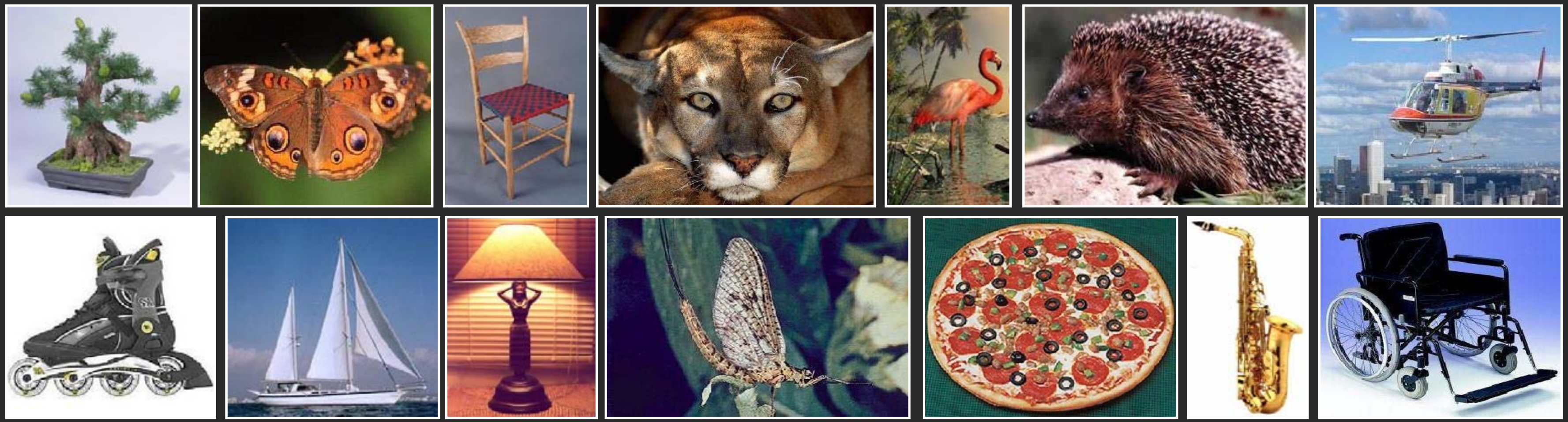


Multi-class classification results
(100 training images per class)

	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

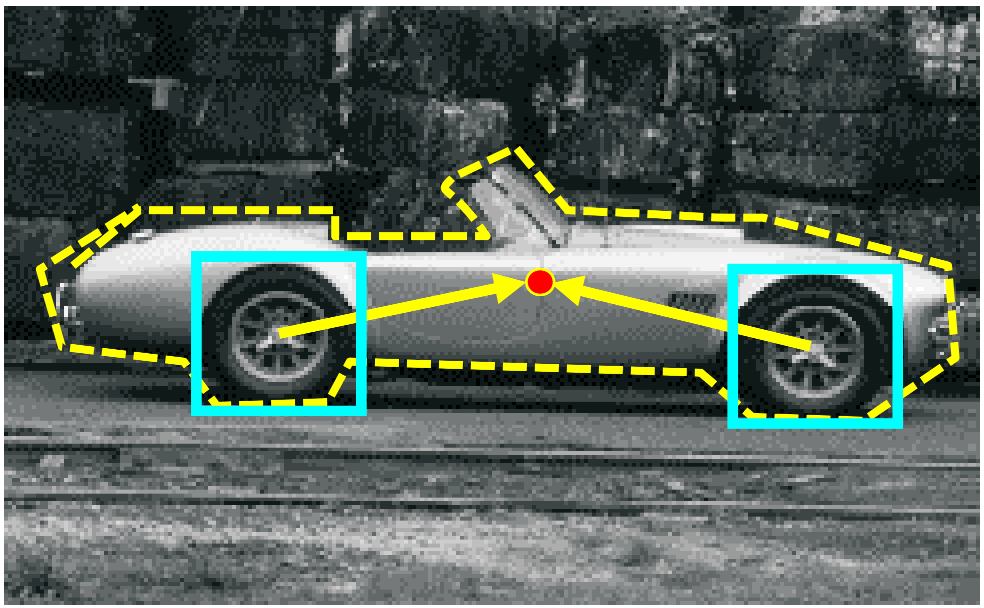


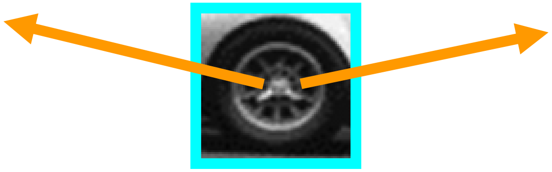
Multi-class classification results (30 training images per class)

	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

Implicit shape models

- Visual codebook is used to index votes for object position





visual codeword with displacement vectors

training image annotated with object localization info

B. Leibe, A. Leonardis, and B. Schiele, [Combined Object Categorization and Segmentation with an Implicit Shape Model](), ECCV Workshop on Statistical Learning in Computer Vision 2004

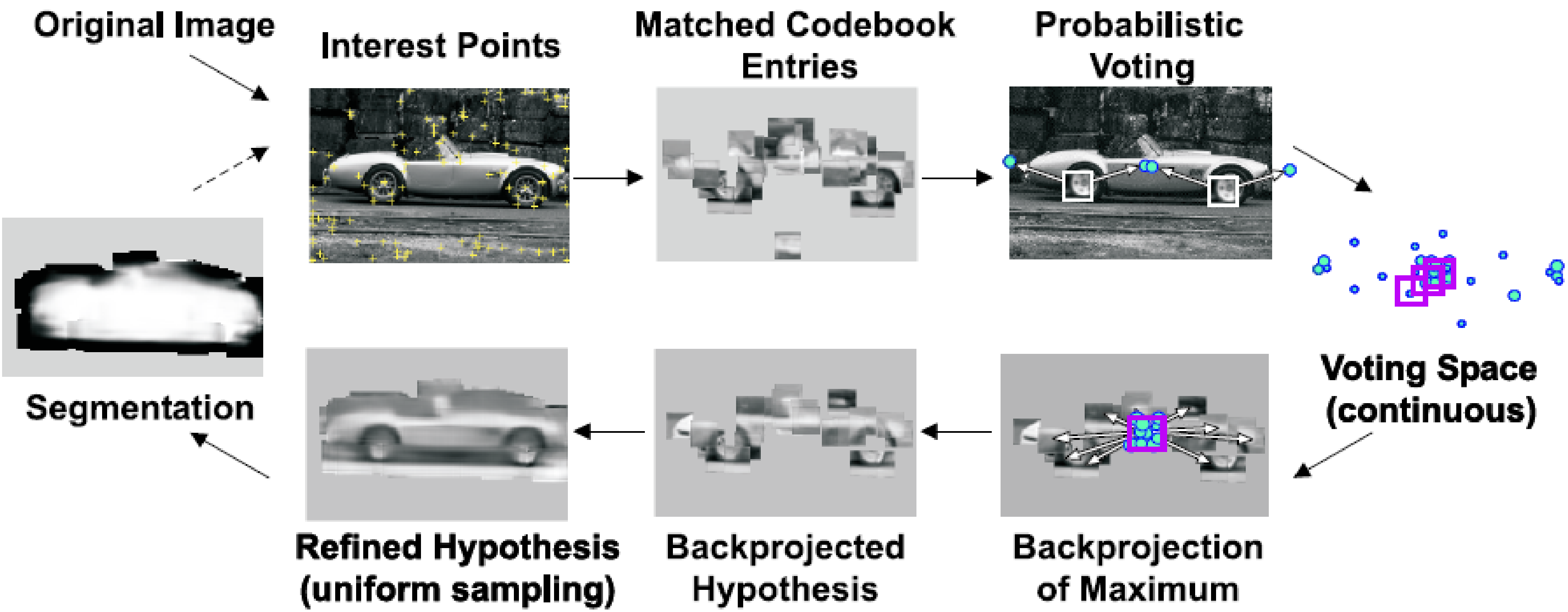
Implicit shape models

- Visual codebook is used to index votes for object position

test image

B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Implicit shape models: Details



B. Leibe, A. Leonardis, and B. Schiele, Combined Object Categorization and Segmentation with an Implicit Shape Model, ECCV Workshop on Statistical Learning in Computer Vision 2004

Generative part-based models

R. Fergus, P. Perona and A. Zisserman, **Object Class Recognition by Unsupervised Scale-Invariant Learning**, CVPR 2003

Probabilistic model

$$P(image \mid object) = P(appearance, shape \mid object)$$

Part descriptors

Part locations

Candidate parts

Probabilistic model

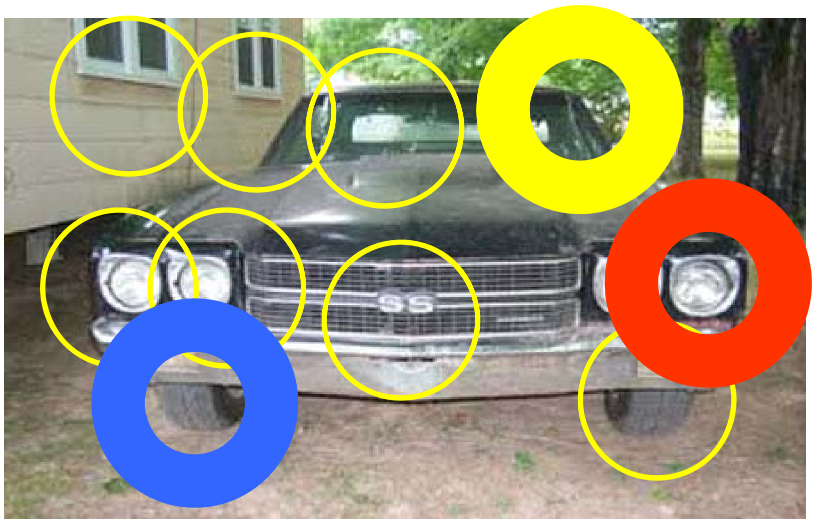
$$P(image \mid object) = P(appearance, shape \mid object)$$

Probabilistic model

$$P(image \mid object) = P(appearance, shape \mid object)$$

$$= \max_h P(appearance \mid h, object)\, p(shape \mid h, object)\, p(h \mid object)$$

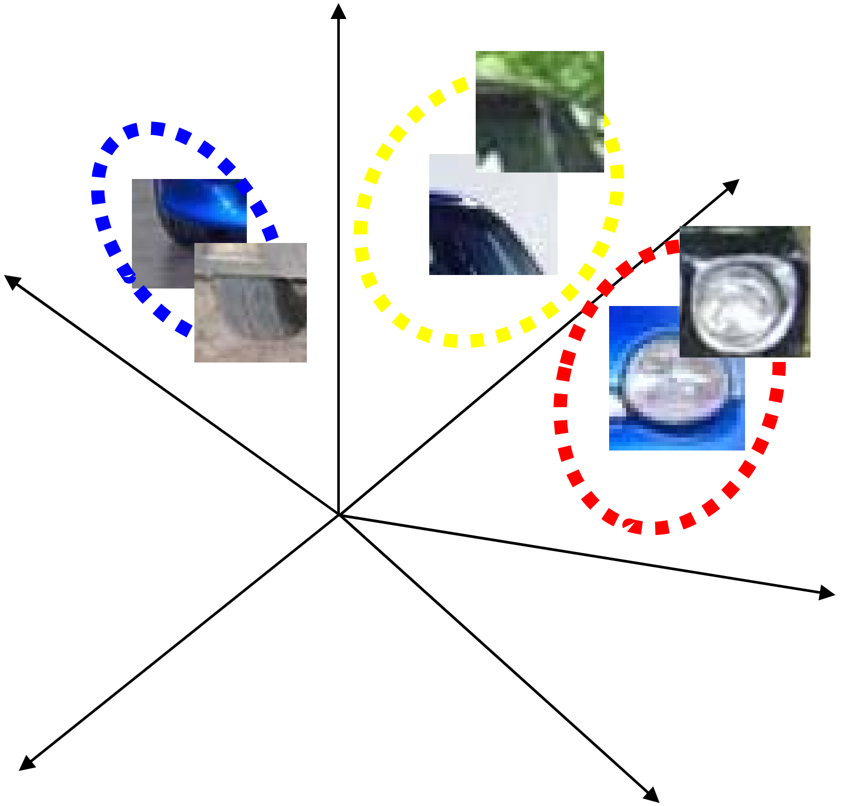
h: assignment of features to parts



Probabilistic model

$$P(image \mid object) = P(appearance, shape \mid object)$$

$$= \max_h \boxed{P(appearance \mid h, object)}\, p(shape \mid h, object)\, p(h \mid object)$$



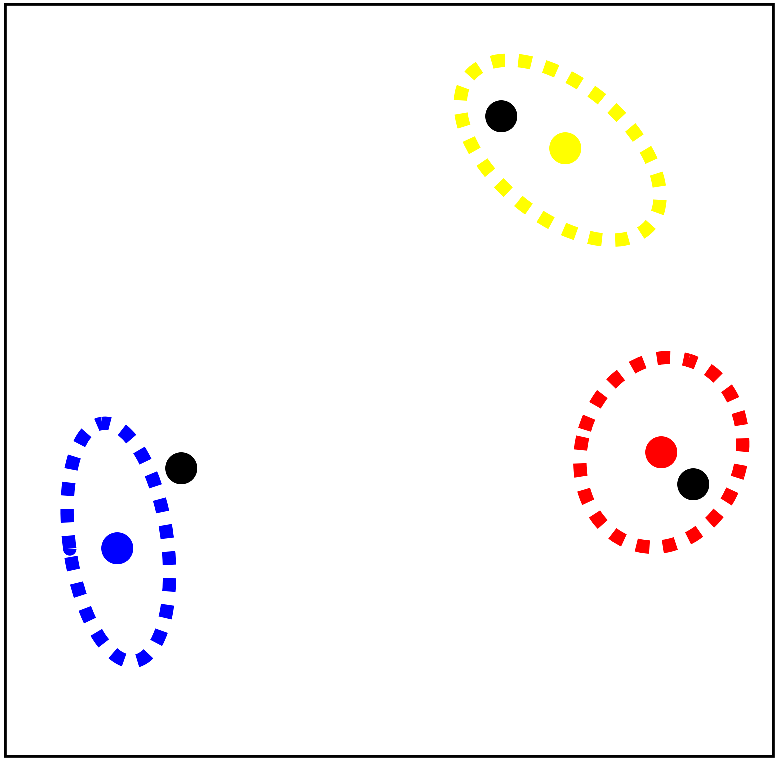
Distribution over patch descriptors

High-dimensional appearance space

Probabilistic model

$$P(image \mid object) = P(appearance, shape \mid object)$$

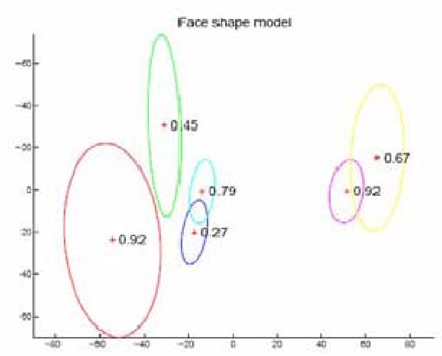
$$= \max_h P(appearance \mid h, object)\, p(shape \mid h, object)\, p(h \mid object)$$



Distribution over joint part positions

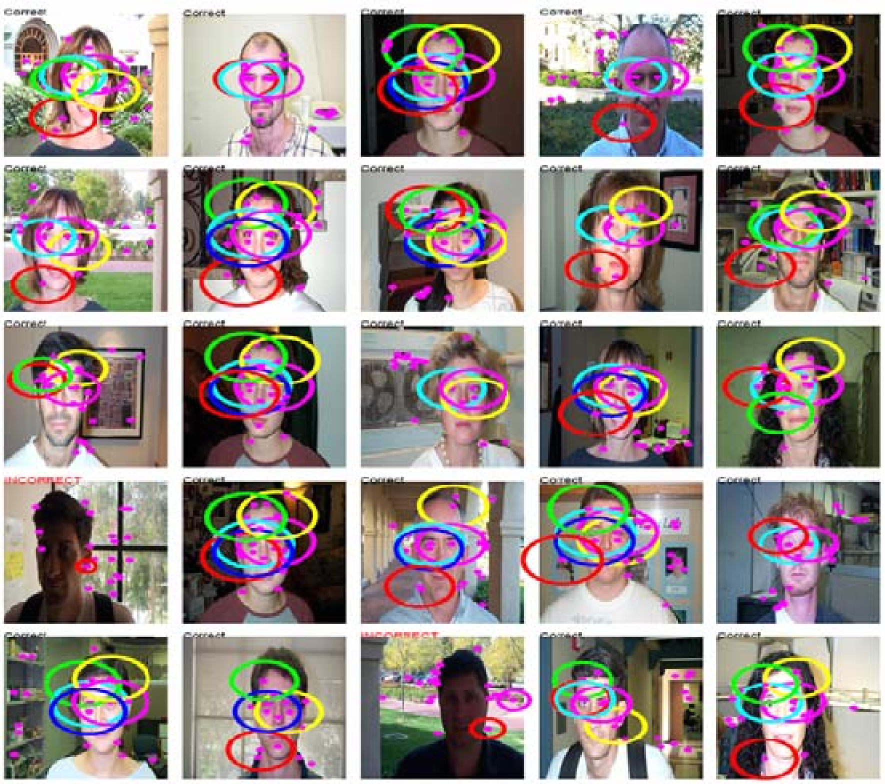
Results: Faces

Face shape model

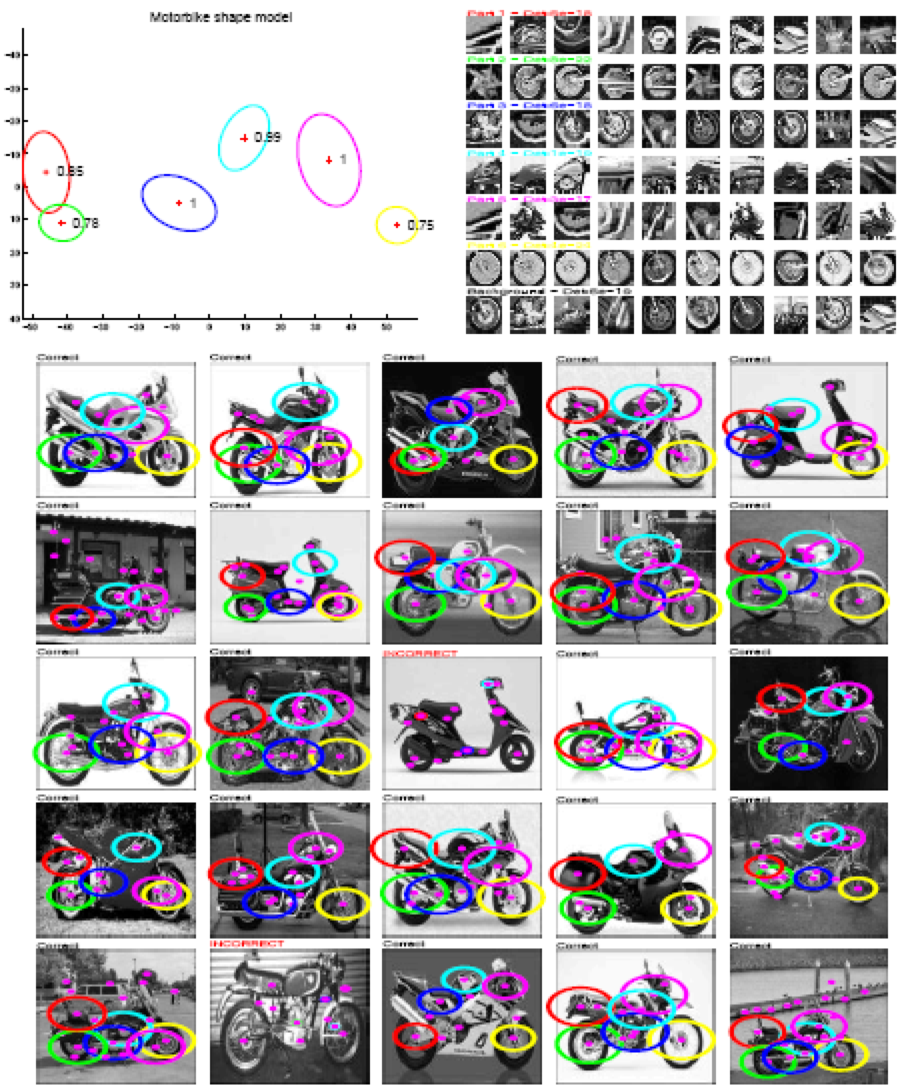


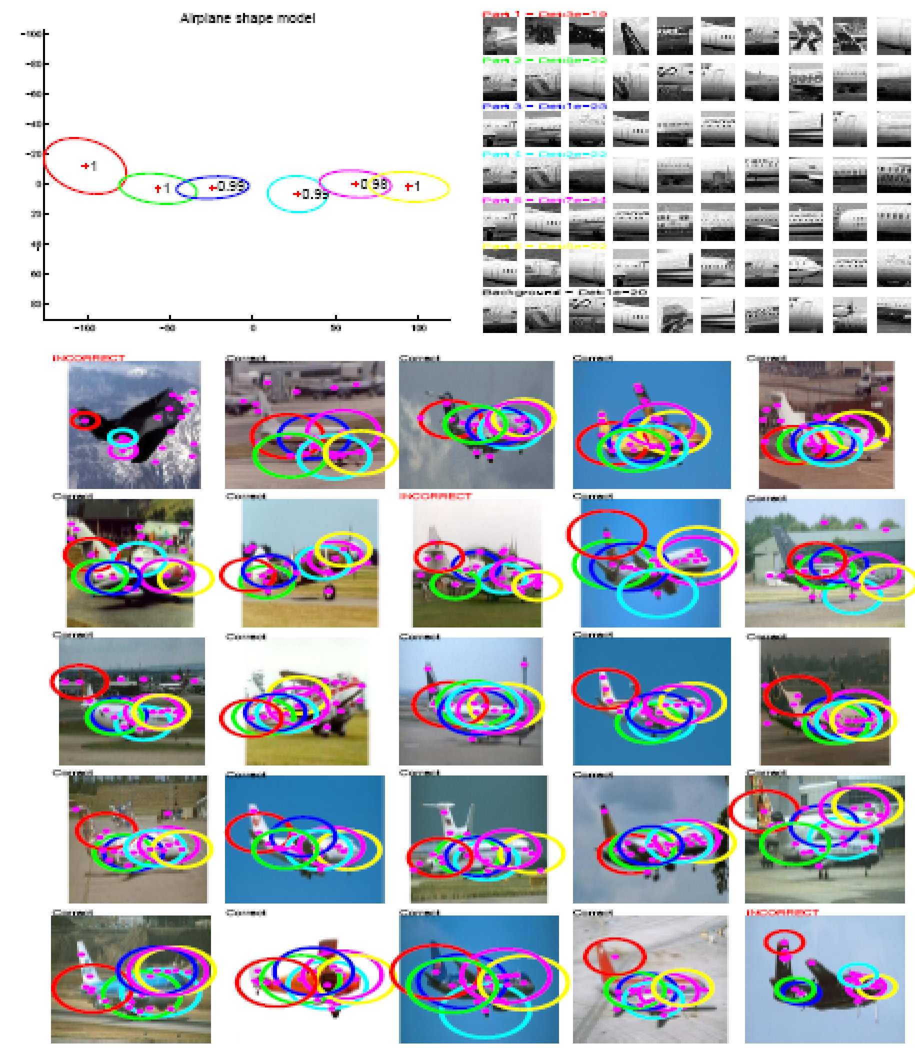
Patch appearance model

Recognition results



Results: Motorbikes and airplanes





Summary: Adding spatial information

- Doublet vocabularies
  - Pro: takes co-occurrences into account, some geometric invariance is preserved
  - Con: too many doublet probabilities to estimate
- Spatial pyramids
  - Pro: simple extension of a bag of features, works very well
  - Con: no geometric invariance, no object localization
- Implicit shape models
  - Pro: can localize object, maintain translation and possibly scale invariance
  - Con: need supervised training data (known object positions and possibly segmentation masks)
- Generative part-based models
  - Pro: very nice conceptually, can be learned from unsegmented images
  - Con: combinatorial hypothesis search problem