Bag-of-features for category classification

Cordelia Schmid

Category recognition

- Image classification: assigning a class label to the image

Car: present
Cow: present
Bike: not present
Horse: not present
...

Category recognition

- Image classification: assigning a class label to the image

Car: present
Cow: present
Bike: not present
Horse: not present
...

- Object localization: define the location and the category

Location
Category

Category recognition

- Image classification: assigning a class label to the image

Car: present
Cow: present
Bike: not present
Horse: not present
...

- Supervised scenario: given a set of training images

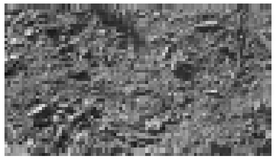
Image classification

- Given

  Positive training images containing an object class



  Negative training images that don't



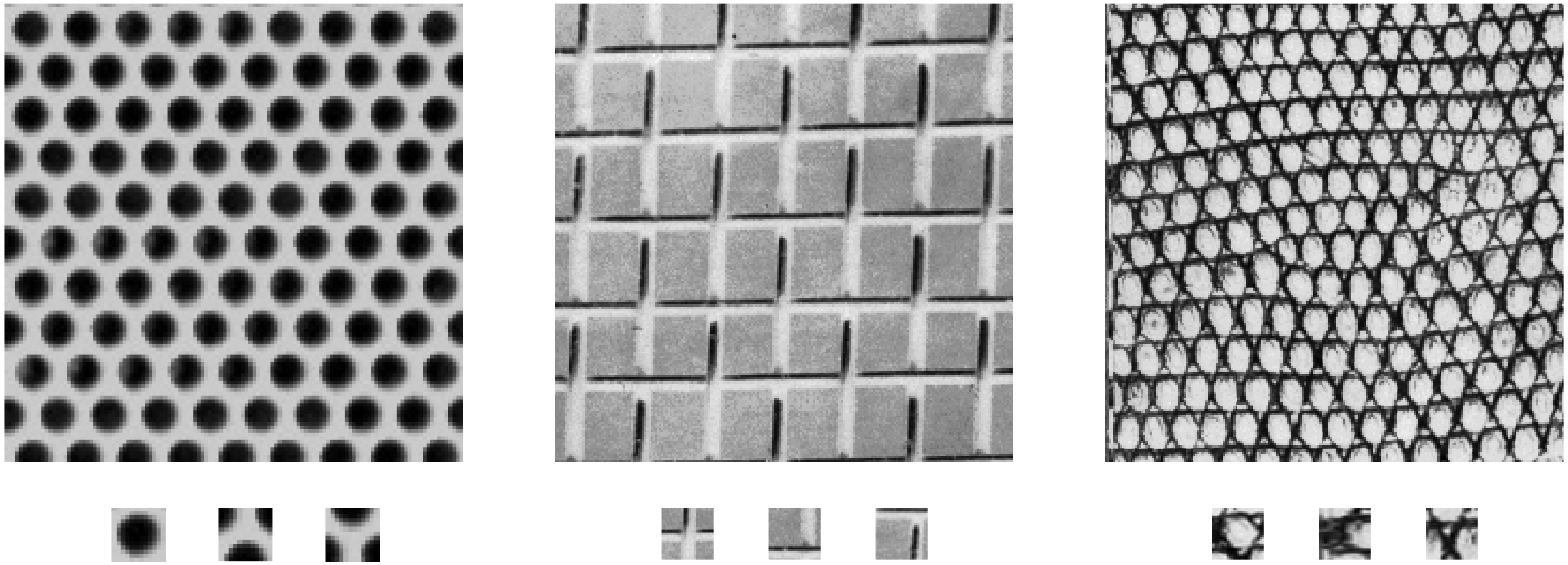
- Classify

  A test image as to whether it contains the object class or not

?

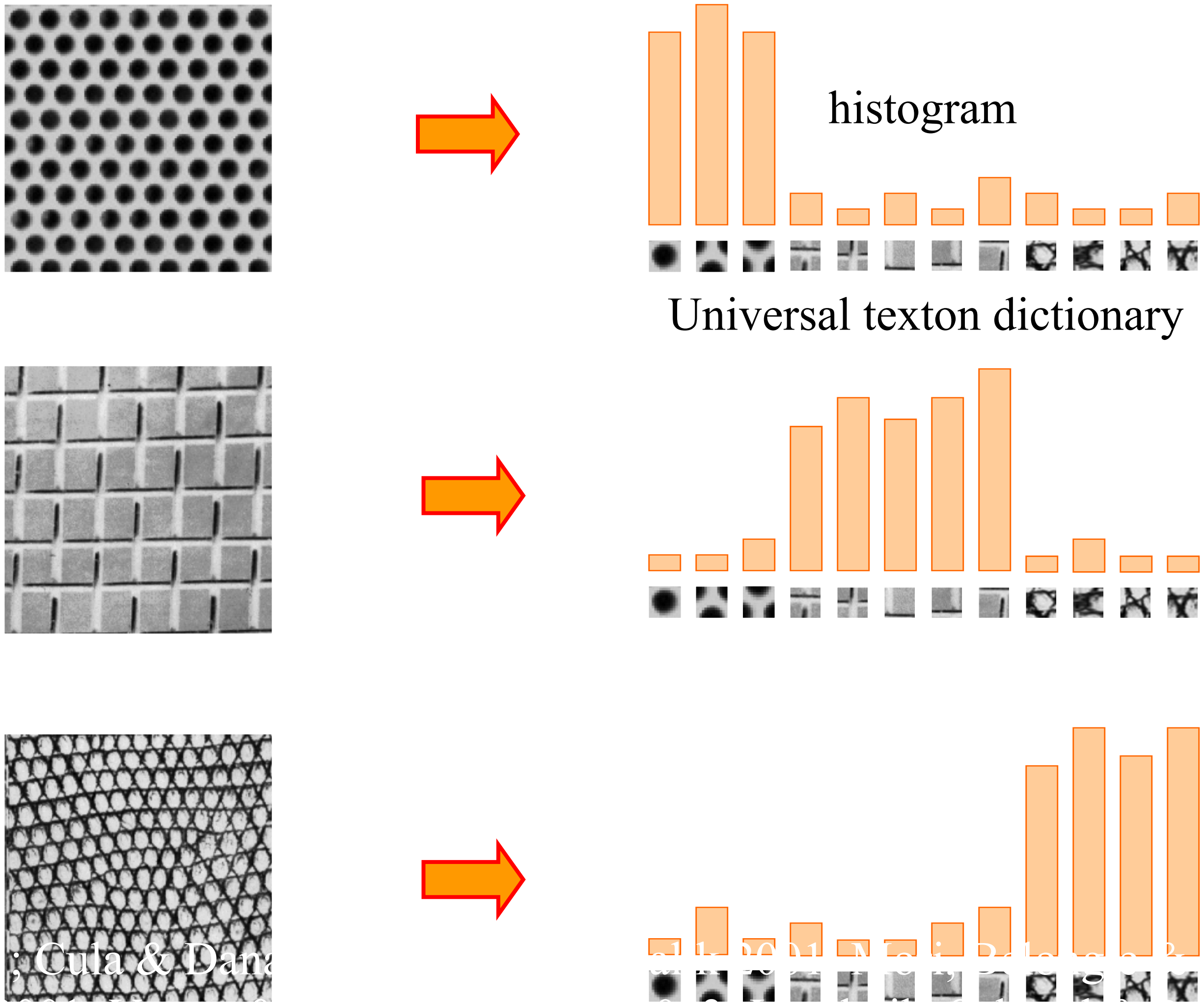
Bag-of-features for image classification

- Origin: texture recognition
  - Texture is characterized by the repetition of basic elements or *textons*

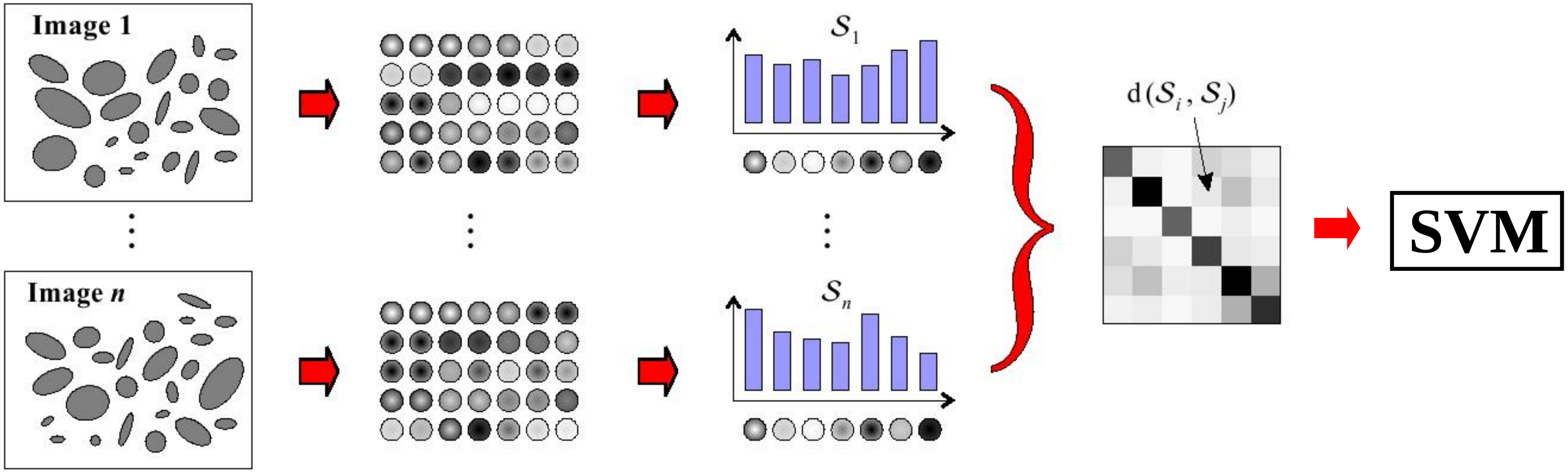


Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001
Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Texture recognition



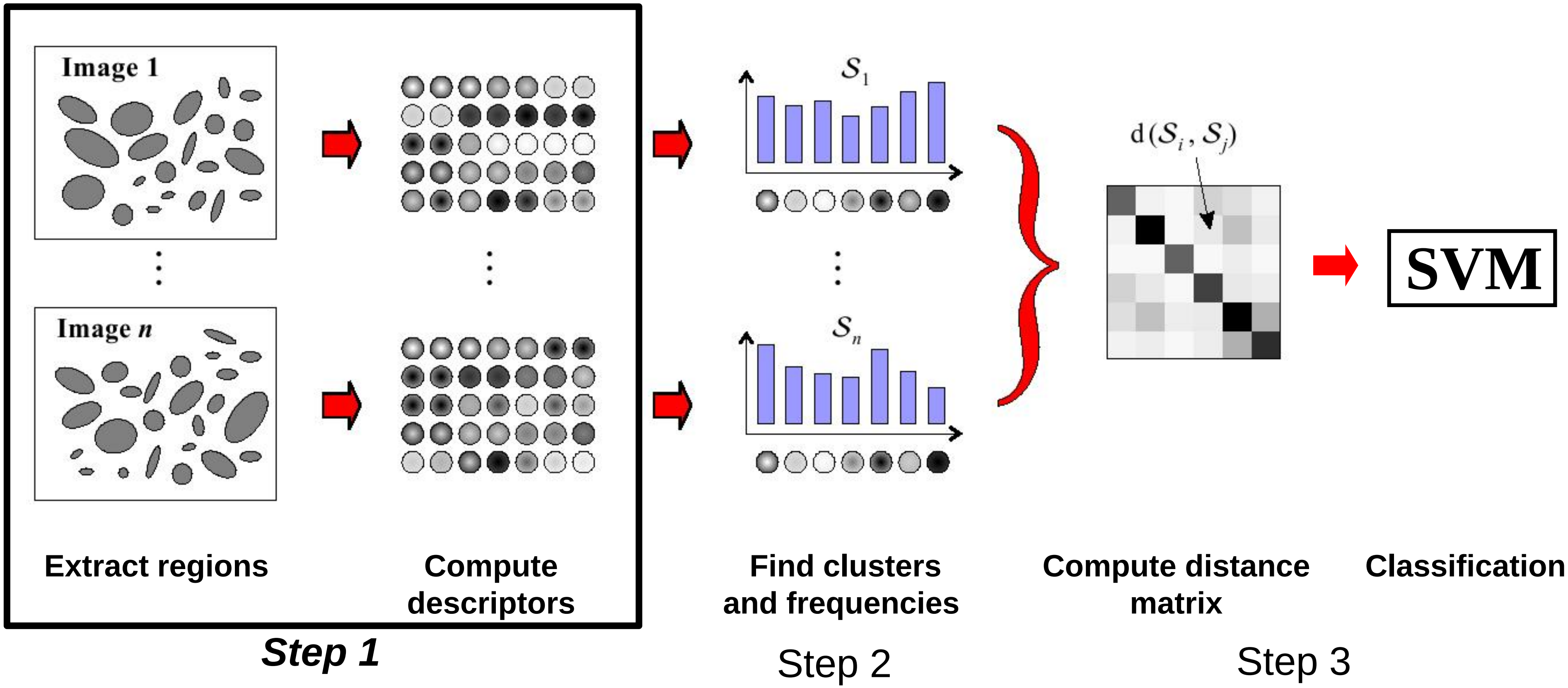
Bag-of-features for image classification



Extract regions | **Compute descriptors** | **Find clusters and frequencies** | **Compute distance matrix** | **Classification**

[Csurka et al. WS'2004], [Nowak et al. ECCV'06], [Zhang et al. IJCV'07]

Bag-of-features for image classification



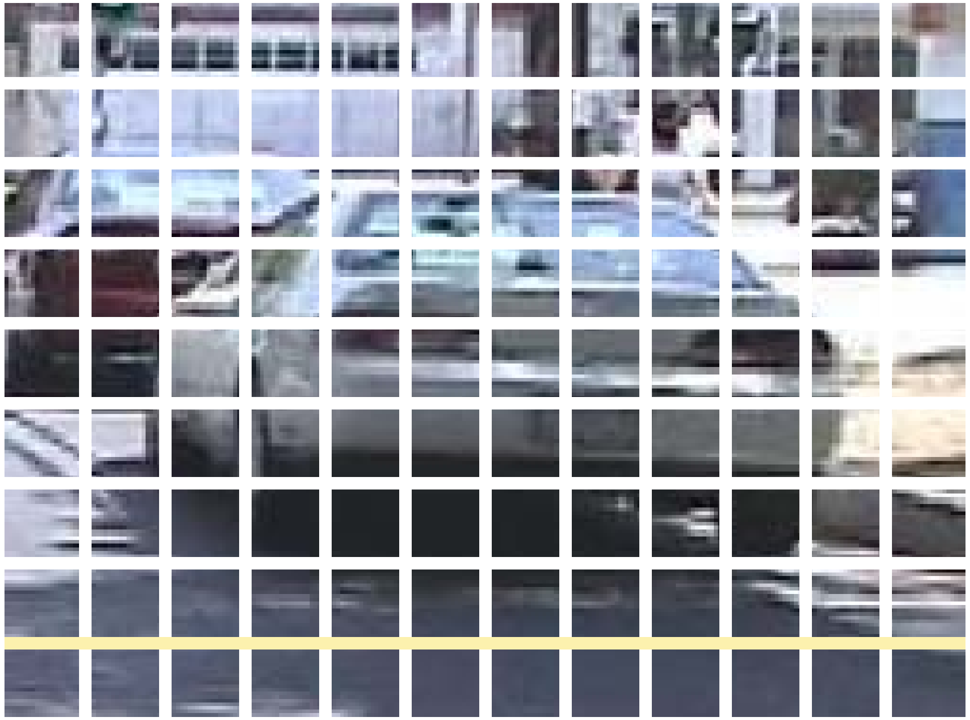
Step 1: feature extraction

- Scale-invariant image regions + SIFT
  - Affine invariant regions give “too” much invariance
  - Rotation invariance for many realistic collections “too” much invariance

- Dense descriptors
  - Improve results in the context of categories (for most categories)
  - Interest points do not necessarily capture “all” features

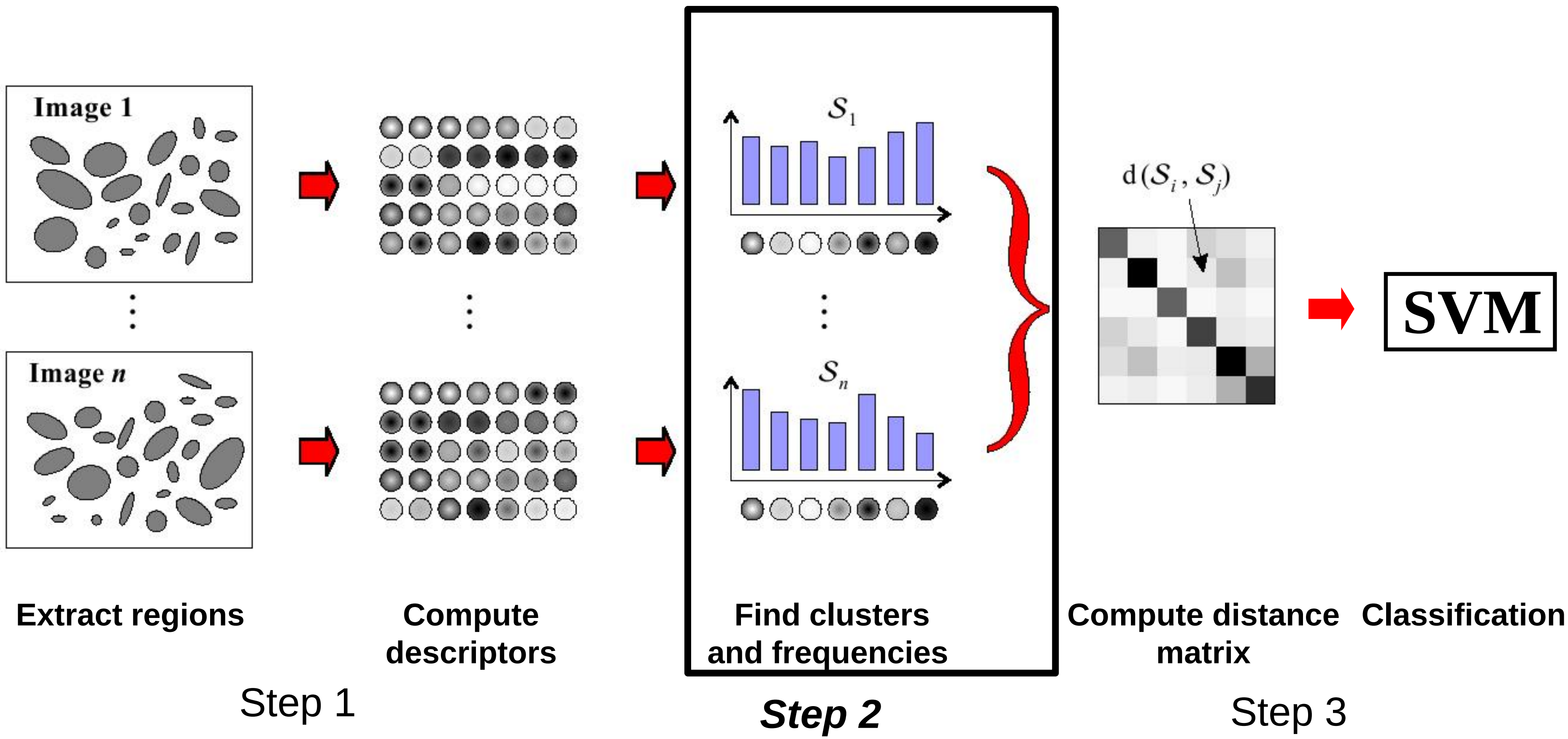
- Color-based descriptors

Dense features

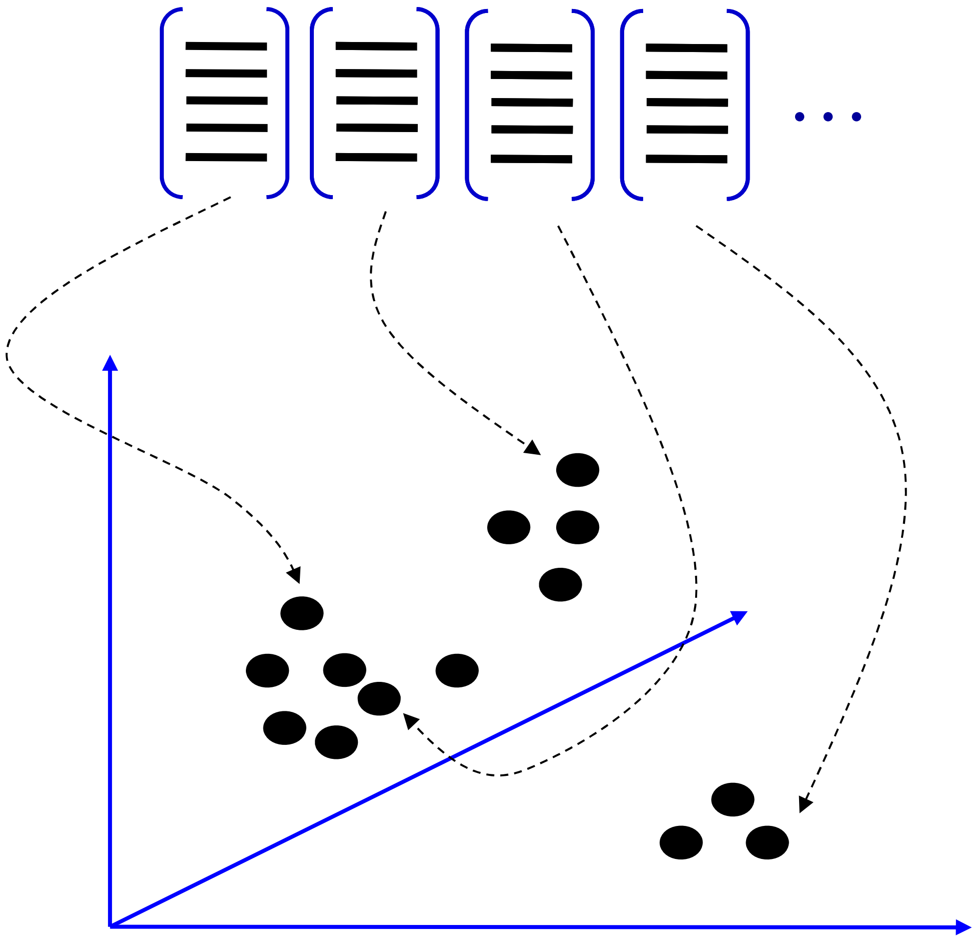


- Multi-scale dense grid: extraction of small overlapping patches at multiple scales
-Computation of the SIFT descriptor for each grid cells
-Exp.: Horizontal/vertical step size 3-6 pixel, scaling factor of 1.2 per level

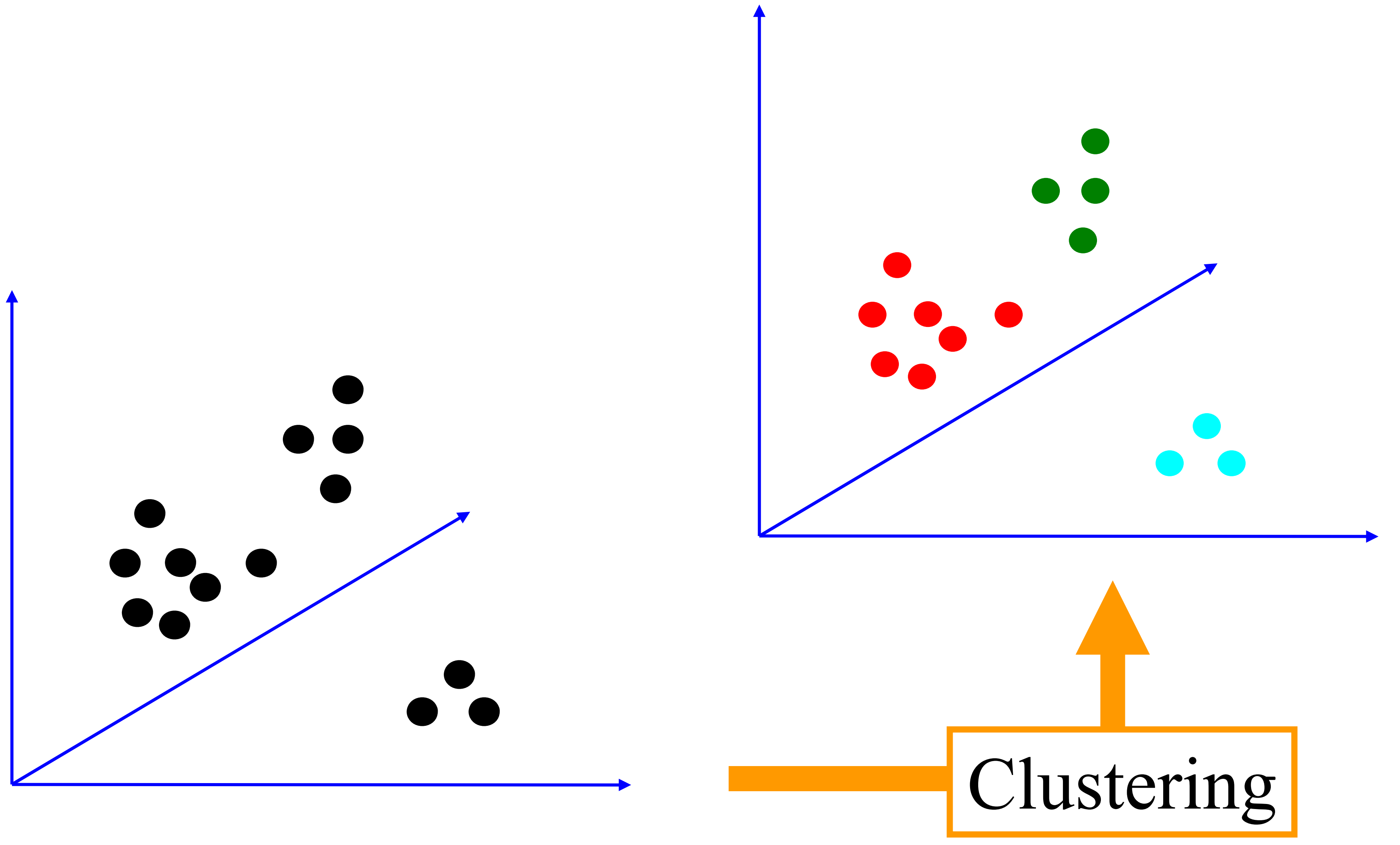
Bag-of-features for image classification



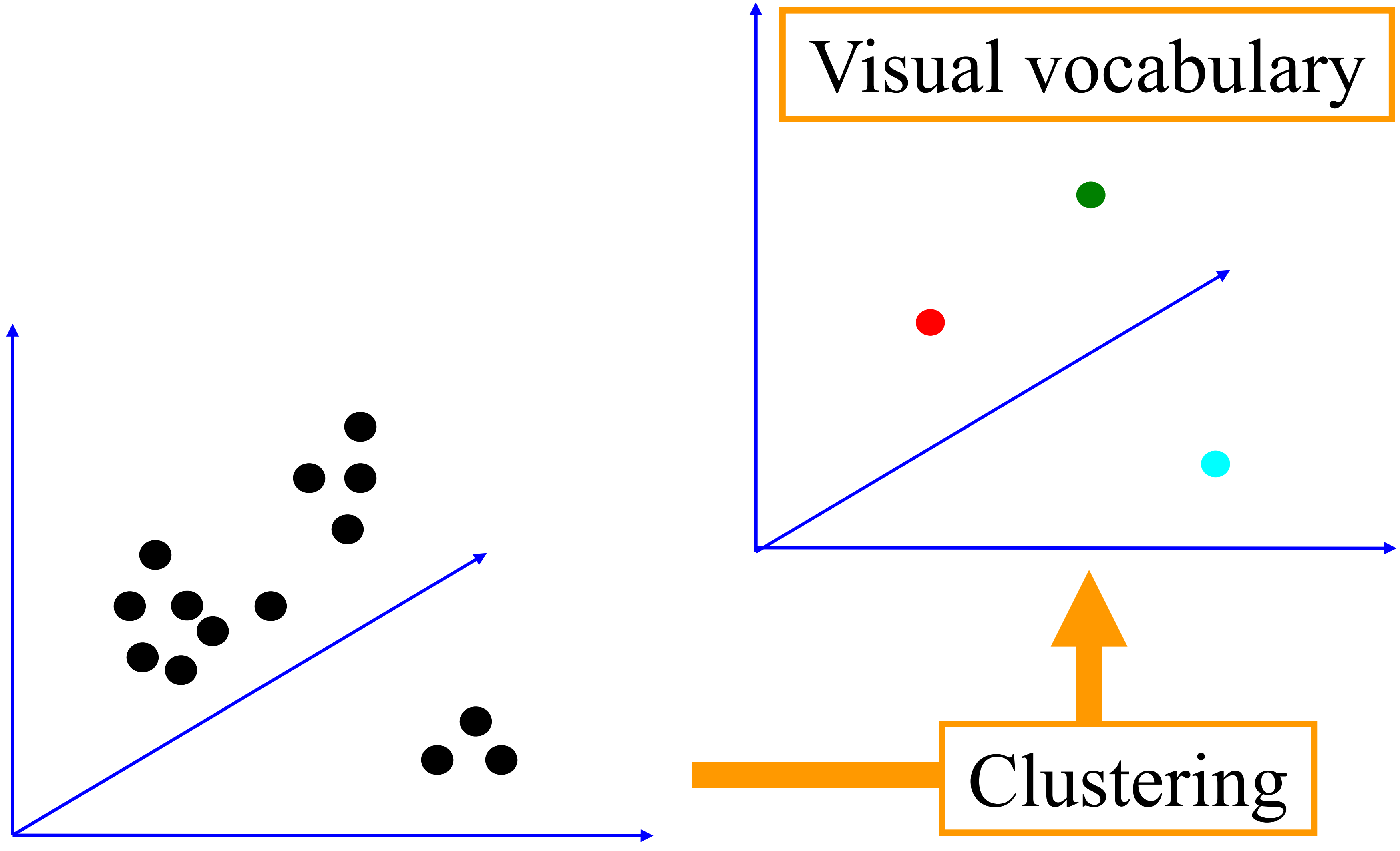
Step 2: Quantization



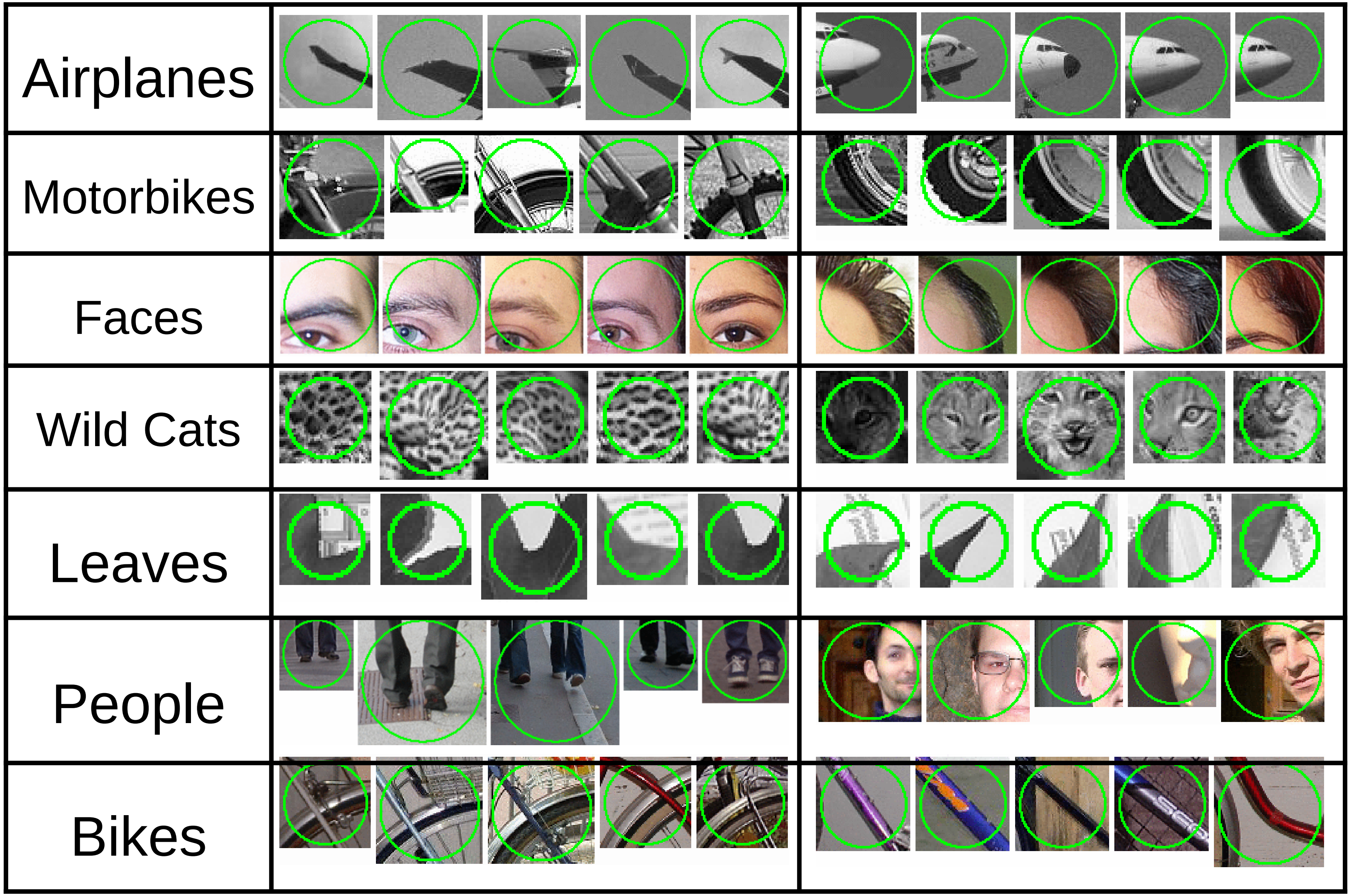
Step 2:Quantization



Step 2: Quantization



Examples for visual words



Step 2: Quantization

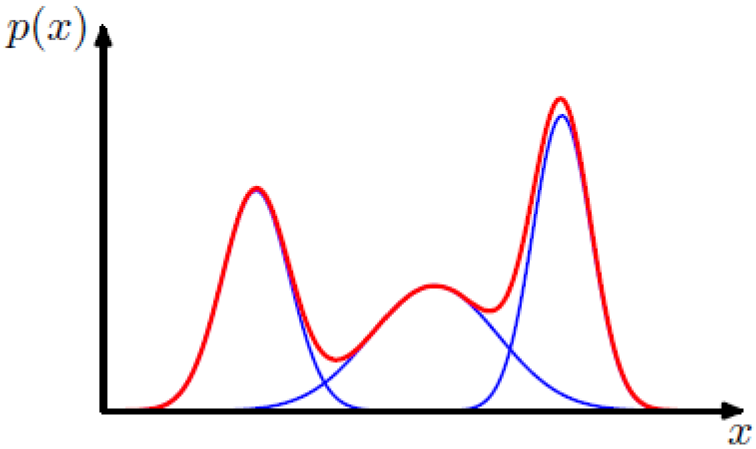
- Cluster descriptors
  - K-means
  - Gaussian mixture model
- Assign each visual word to a cluster
  - Hard or soft assignment
- Build frequency histogram

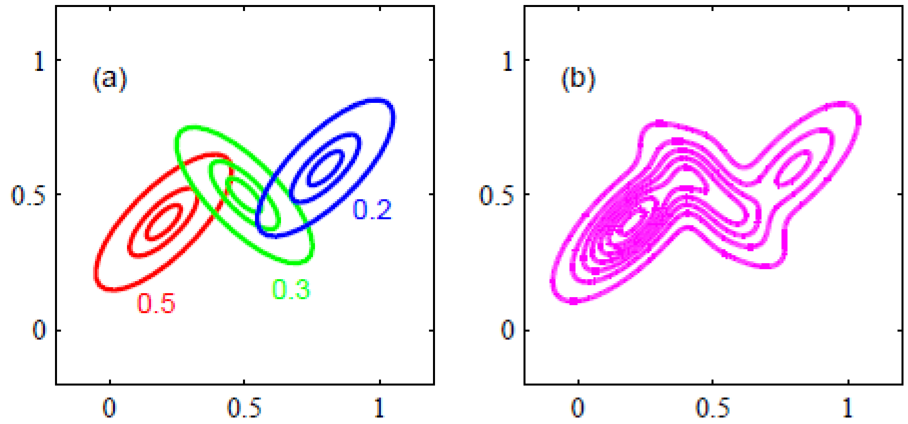
Gaussian mixture model (GMM)

- Mixture of Gaussians: weighted sum of Gaussians

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \, \mathcal{N}(\mathbf{x}; \boldsymbol{\mu}_k, \Sigma_k)$$

where $\mathcal{N}(\mathbf{x}; \boldsymbol{\mu}, \Sigma) = (2\pi)^{(-d/2)} |\Sigma|^{-1/2} \exp\left(-\frac{1}{2}(\mathbf{x} - \boldsymbol{\mu})^\top \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right)$

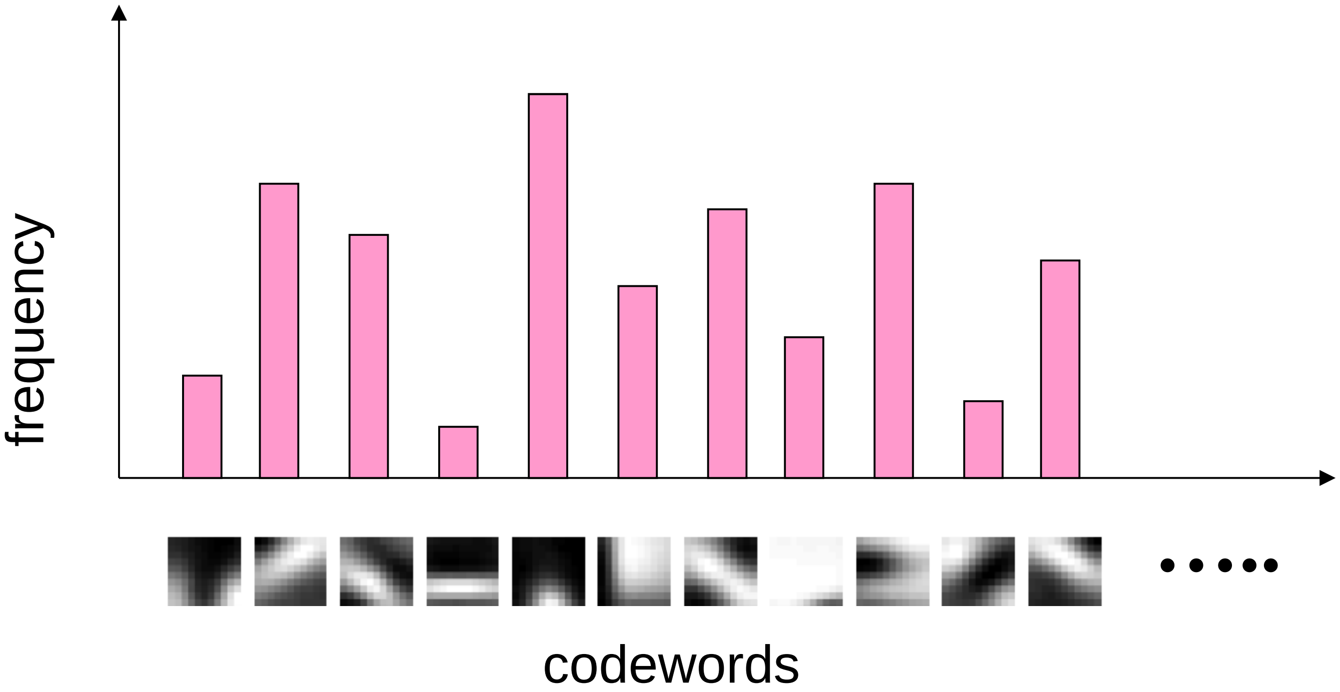




Hard or soft assignment

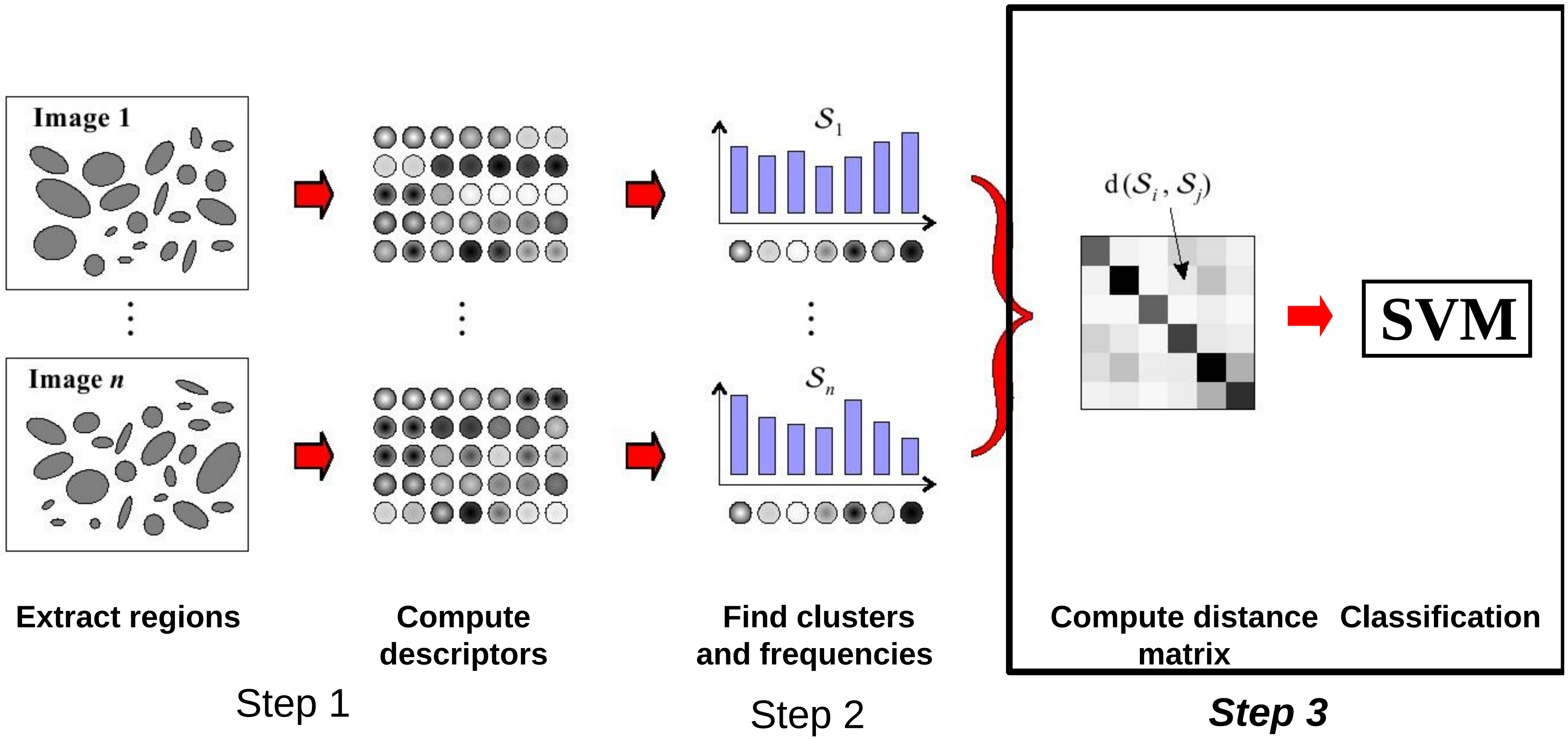
- K-means → hard assignment
  - Assign to the closest cluster center
  - Count number of descriptors assigned to a center
- Gaussian mixture model → soft assignment
  - Estimate distance to all centers
  - Sum over number of descriptors
- Represent image by a frequency histogram

Image representation



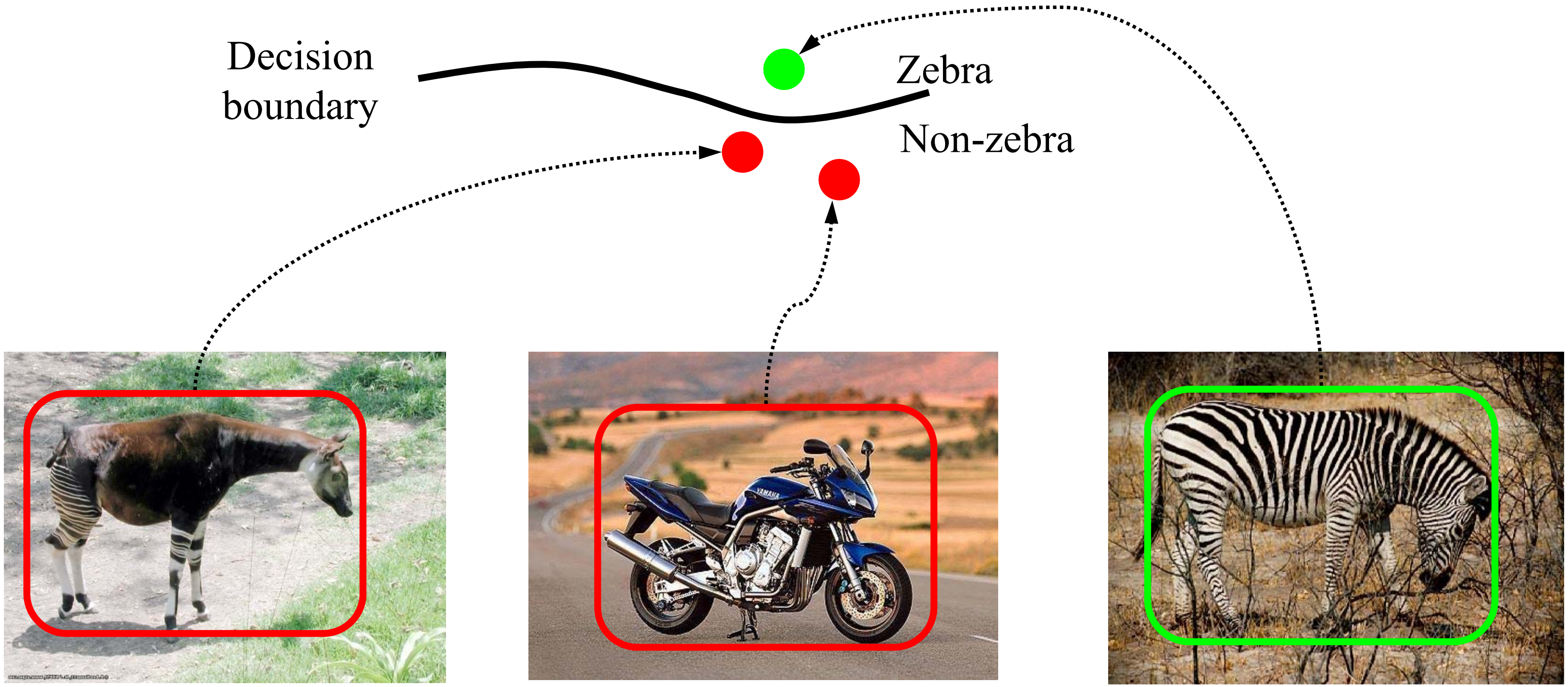
- each image is represented by a vector, typically 1000-4000 dimension, normalization with L2 norm
- fine grained – represent model instances
- coarse grained – represent object categories

Bag-of-features for image classification



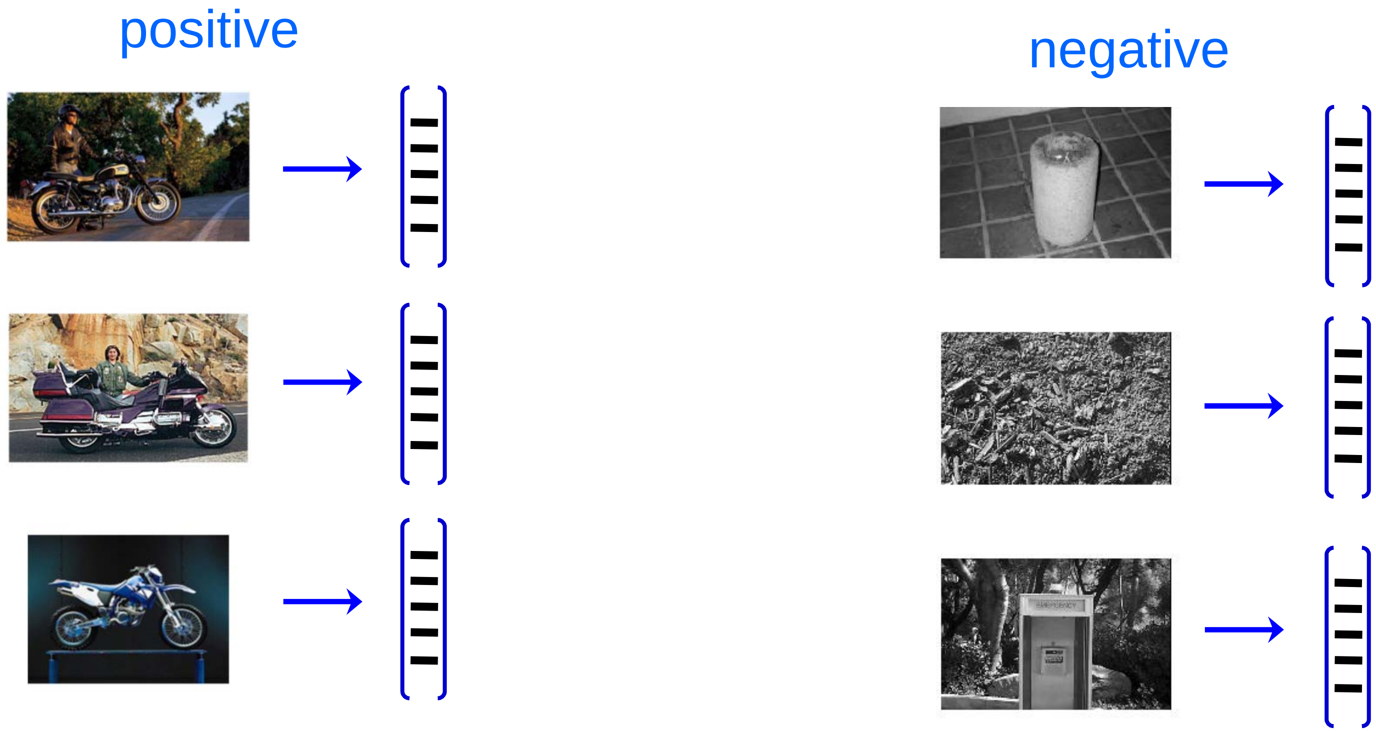
Step 3: Classification

- Learn a decision rule (classifier) assigning bag-of-features representations of images to different classes



Training data

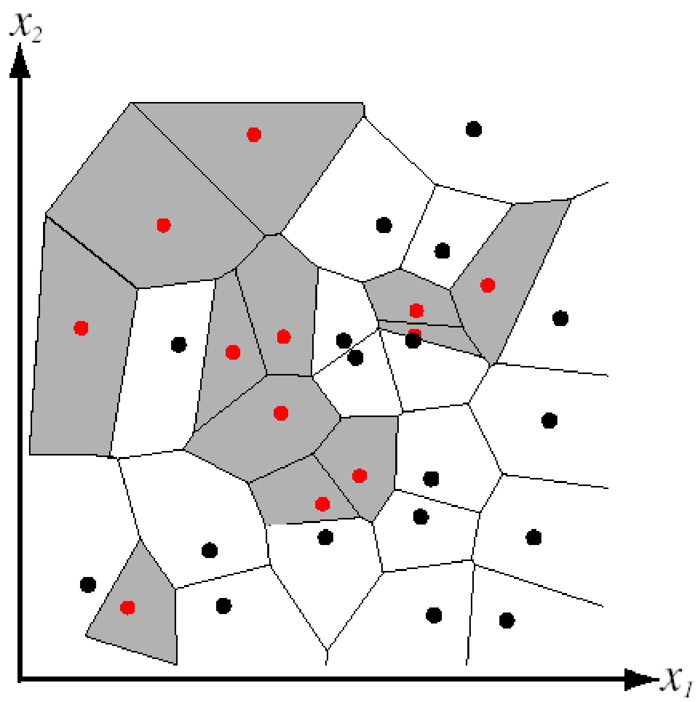
Vectors are histograms, one from each training image



Train classifier,e.g.SVM

Nearest Neighbor Classifier

- Assign label of nearest training data point to each test data point

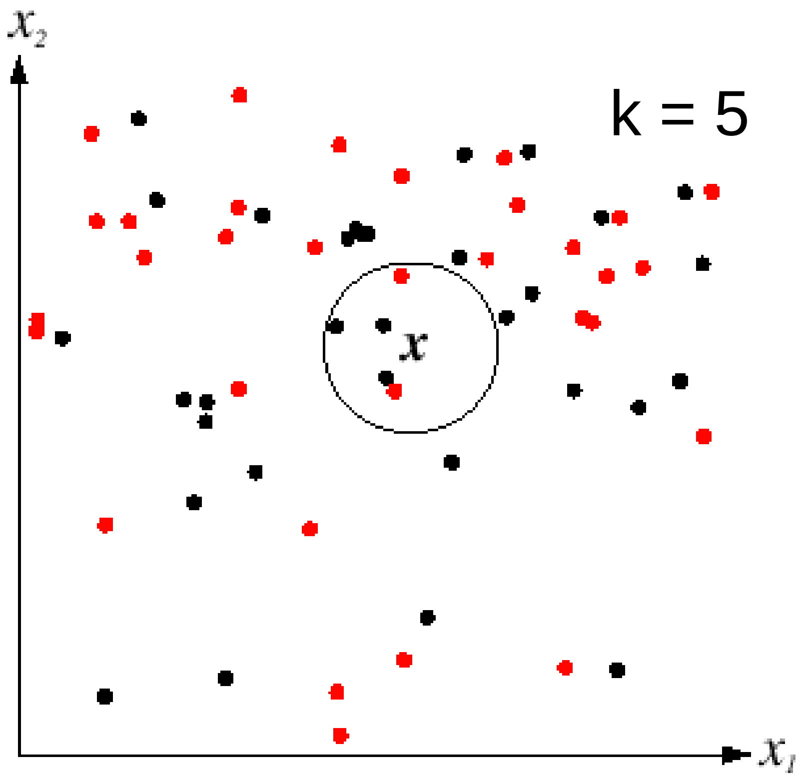


from Duda *et al.*

Voronoi partitioning of feature space
for 2-categories and 2-D data

k-Nearest Neighbors

- For a new point, find the k closest points from the training data
- Labels of the k points “vote” to classify

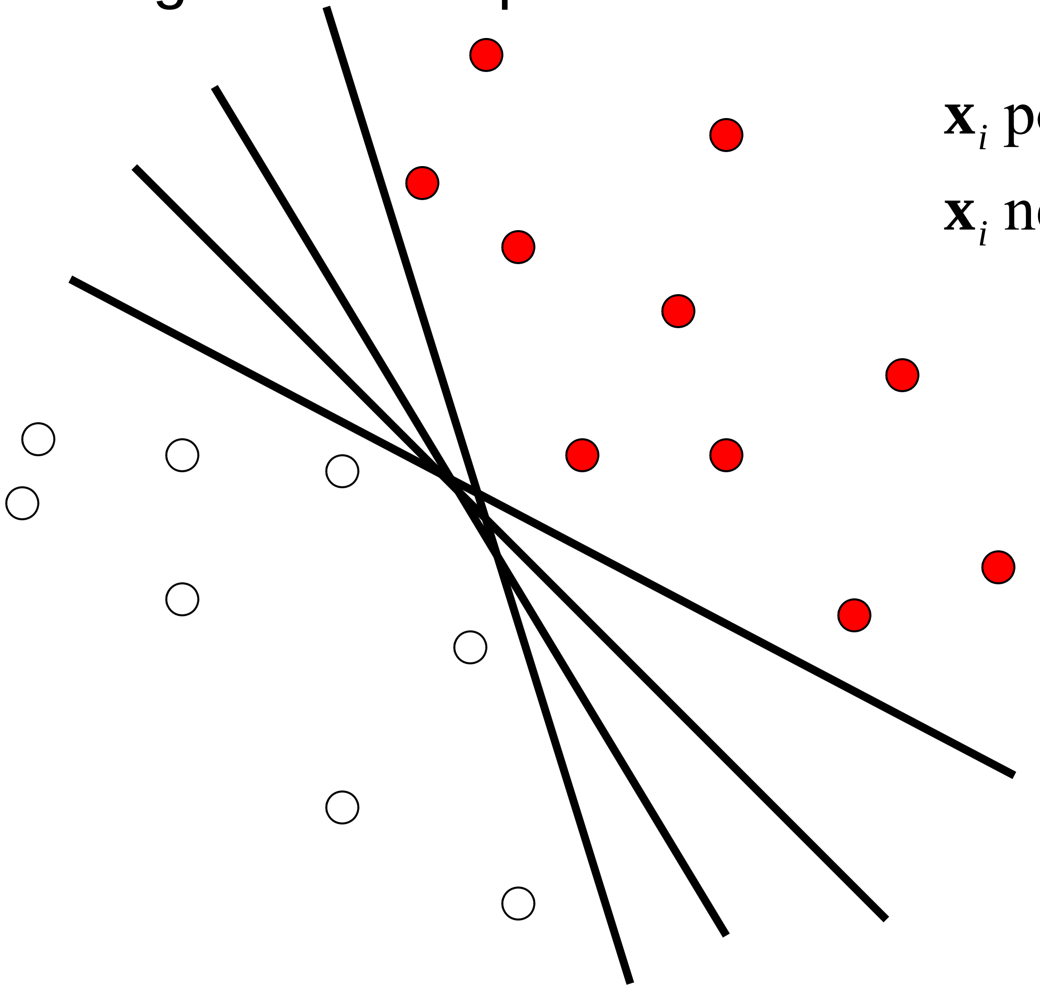


Nearest Neighbor Classifier

- For each test data point : assign label of nearest training data point
- K-nearest neighbors: labels of the k nearest points, vote to classify
- Works well provided there is lots of data and the distance function is good

Linear classifiers

- Find linear function (*hyperplane*) to separate positive and negative examples



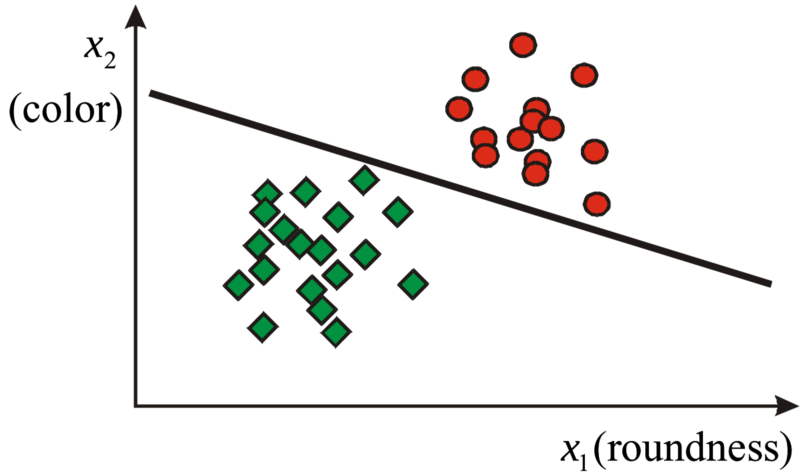
$$\mathbf{x}_i \text{ positive}: \quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$$

$$\mathbf{x}_i \text{ negative}: \quad \mathbf{x}_i \cdot \mathbf{w} + b < 0$$

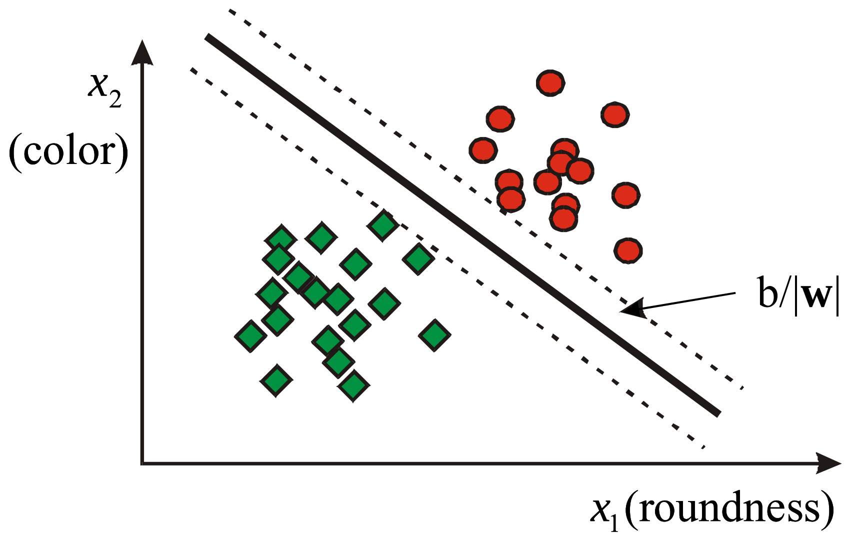
Which hyperplane
is best?

Linear classifiers - margin

- Generalization is not good in this case:

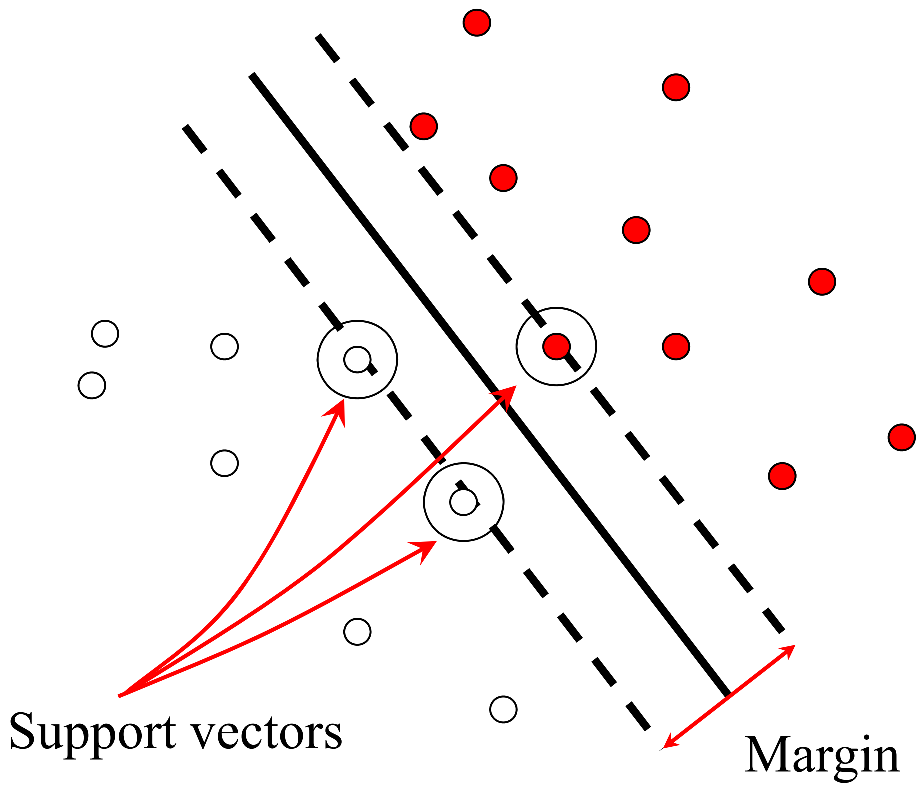


- Better if a margin is introduced:



Support vector machines

- Find hyperplane that maximizes the *margin* between the positive and negative examples



$\mathbf{x}_i$ positive $(y_i = 1)$: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 1$

$\mathbf{x}_i$ negative $(y_i = -1)$: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

For support vectors: $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Data not perfectly separable, introduction of slack variable

$$y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i$$

Kernels for bags of features

- Hellinger kernel $K(h_1, h_2) = \sum_{i=1}^{N} \sqrt{h_1(i) h_2(i)}$
- Histogram intersection kernel $I(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$
- Generalized Gaussian kernel $K(h_1, h_2) = \exp\left(-\frac{1}{A} D(h_1, h_2)^2 \right)$
- *D* can be Euclidean distance, χ^2 distance etc.

$$D_{\chi^2}(h_1, h_2) = \sum_{i=1}^{N} \frac{\left(h_1(i) - h_2(i)\right)^2}{h_1(i) + h_2(i)}$$

Multi-class SVMs

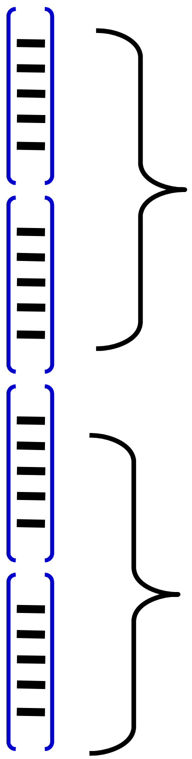
- Mutil-class formulations exist, but they are not widely used in practice. It is more common to obtain multi-class SVMs by combining two-class SVMs in various ways.

- One versus all:
  - Training: learn an SVM for each class versus the others
  - Testing: apply each SVM to test example and assign to it the class of the SVM that returns the highest decision value

- One versus one:
  - Training: learn an SVM for each pair of classes
  - Testing: each learned SVM “votes” for a class to assign to the test example

Why does SVM learning work?

- Learns foreground and background visual words

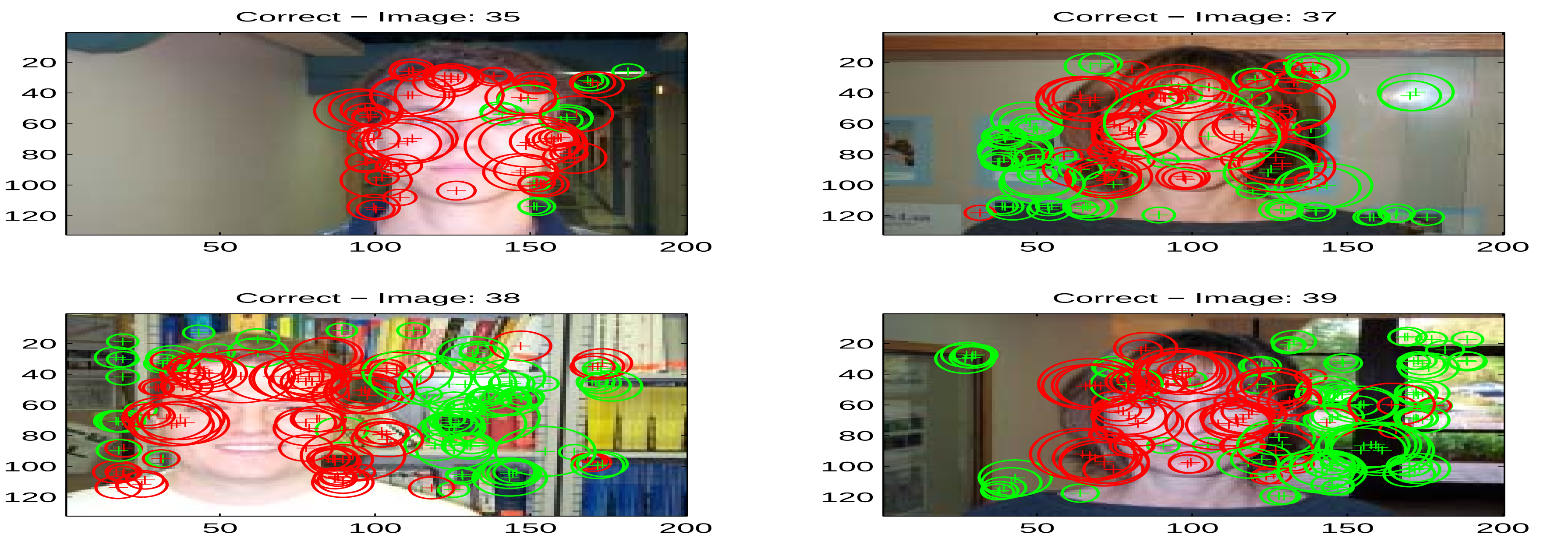


foreground words – high weight

background words – low weight

Illustration

Localization according to visual word probability



foreground word more probable

background word more probable

Bag-of-features for image classification

- Excellent results in the presence of background clutter

bikes books building cars people phones trees

Examples for misclassified images

Books- misclassified into faces, faces, buildings

Buildings- misclassified into faces, trees, trees

Cars- misclassified into buildings, phones, phones

Bag of visual words summary

- Advantages:
  - largely unaffected by position and orientation of object in image
  - fixed length vector irrespective of number of detections
  - very successful in classifying images according to the objects they contain

- Disadvantages:
  - no explicit use of configuration of visual word positions
  - poor at localizing objects within an image
  - no explicit image understanding

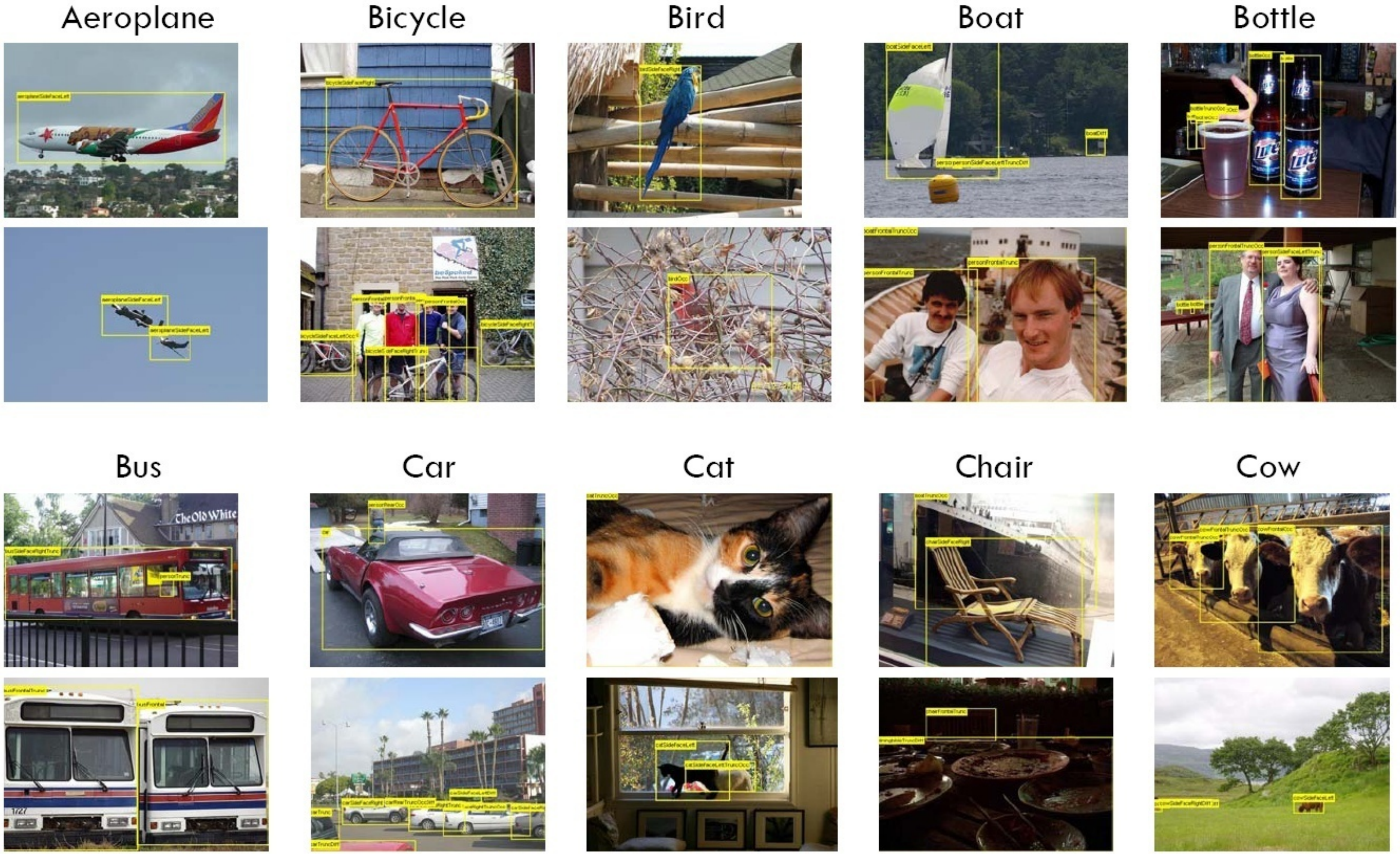
Evaluation of image classification (object localization)

- PASCAL VOC [05-12] datasets

- PASCAL VOC 2007
  - Training *and* test dataset available
  - Used to report state-of-the-art results
  - Collected January 2007 from Flickr
  - 500 000 images downloaded and random subset selected
  - 20 classes manually annotated
  - Class labels per image + bounding boxes
  - 5011 training images, 4952 test images
  - Exhaustive annotation with the 20 classes

- Evaluation measure: average precision

PASCAL 2007 dataset



PASCAL 2007 dataset

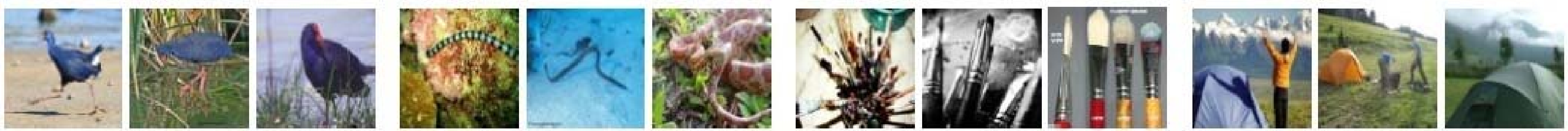
ImageNet: large-scale image classification dataset

IMAGENET has 14M images from 22k classes

Standard Subsets

- ImageNet Large Scale Visual Recognition Challenge 2010 (ILSVRC)
  - 1000 classes and 1.4M images
- ImageNet10K dataset
  - 10184 classes and ~ 9 M images

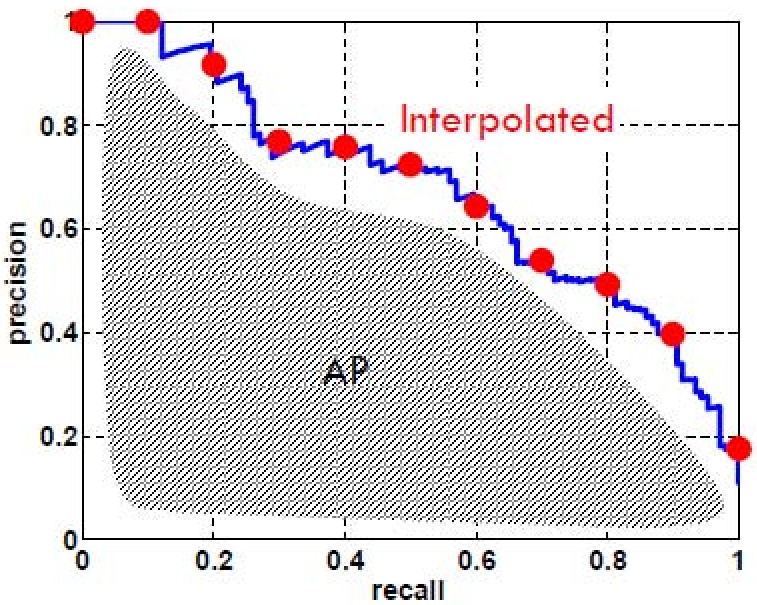
(a) Star Anise (92.45%) (b) Geyser (85.45%) (c) Pulp Magazine (83.01%) (d) Carrycot (81.48%)



(e) European gallinule (15.00%) (f) Sea Snake (10.00 %) (g) Paintbrush (4.68 %) (h) Mountain Tent (0.00%)

Evaluation

- Average Precision [TREC] averages precision over the entire range of recall
  - Curve interpolated to reduce influence of “outliers”



- A good score requires both high recall and high precision
- Application-independent
- Penalizes methods giving high precision but low recall

Spatial pyramid matching

- Add spatial information to the bag-of-features

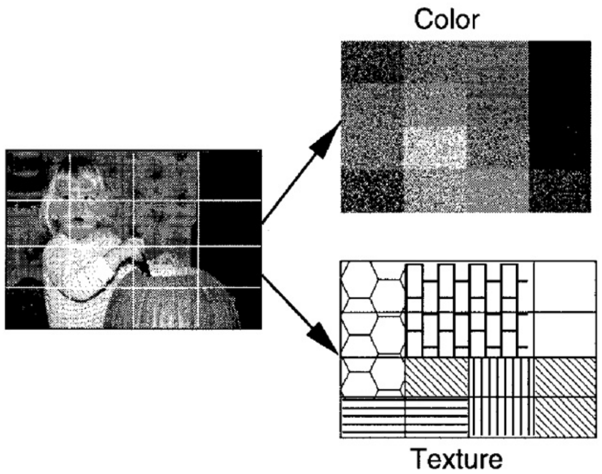
- Perform matching in 2D image space

[Lazebnik, Schmid & Ponce, CVPR 2006]

Related work

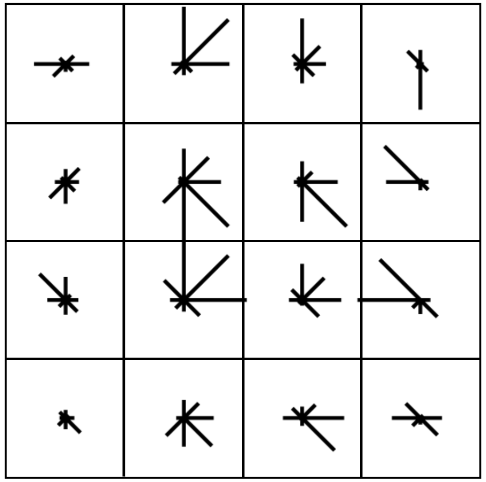
Similar approaches:

- Subblock description [Szummer & Picard, 1997]
- SIFT [Lowe, 1999]
- GIST [Torralba et al., 2003]



Szummer & Picard (1997)

SIFT

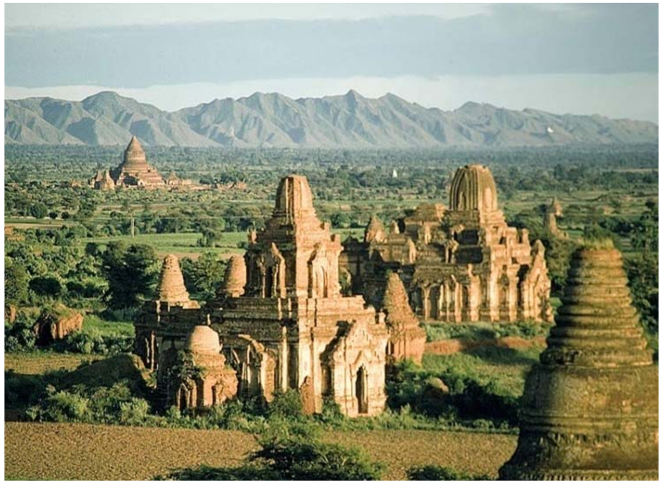


Lowe (1999, 2004)

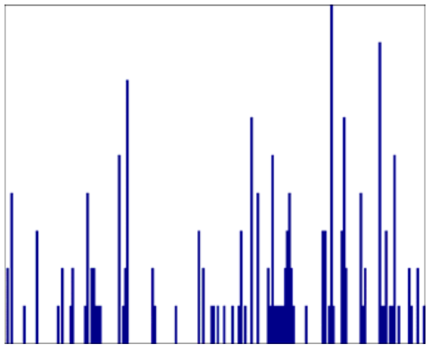
Gist

Torralba et al. (2003)

Spatial pyramid representation

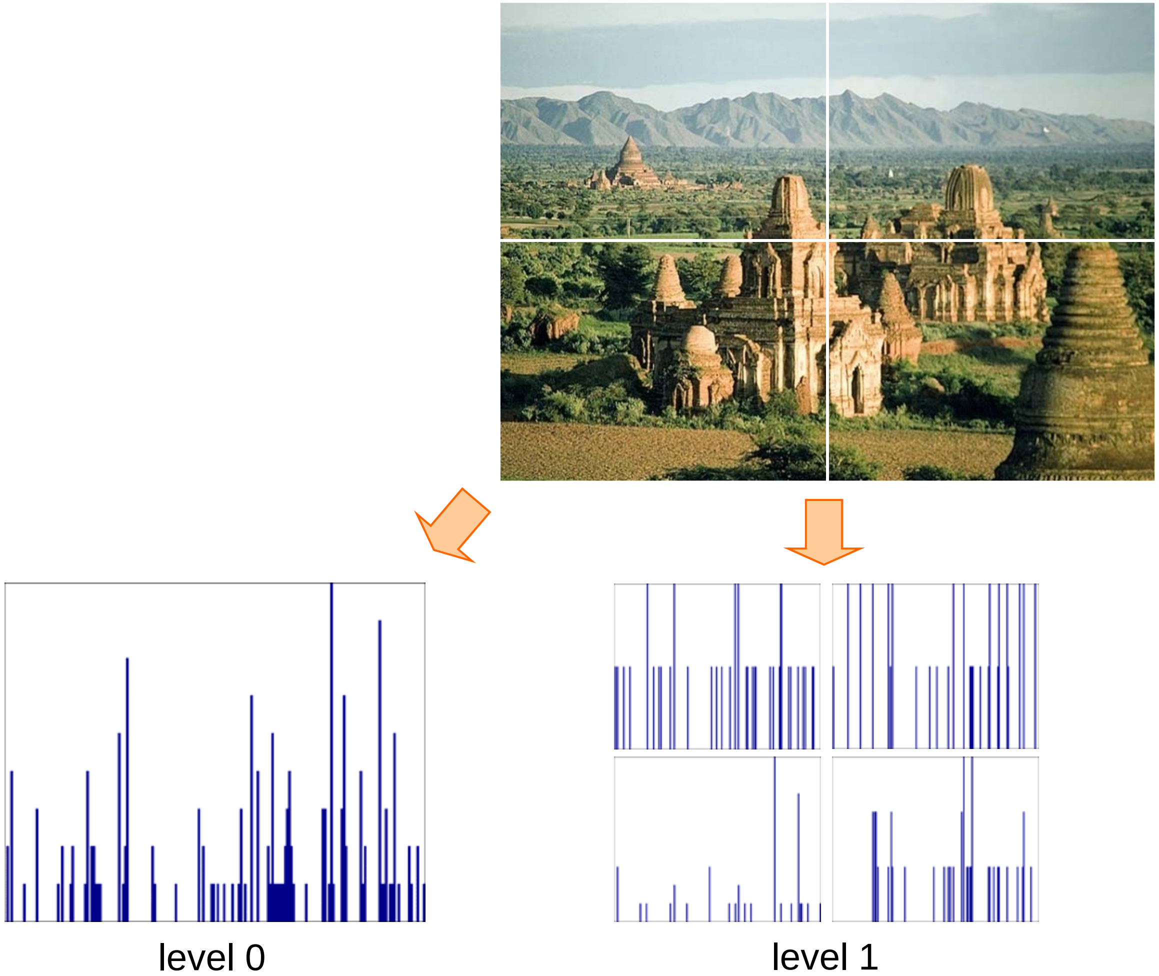


Locally orderless representation at several levels of spatial resolution



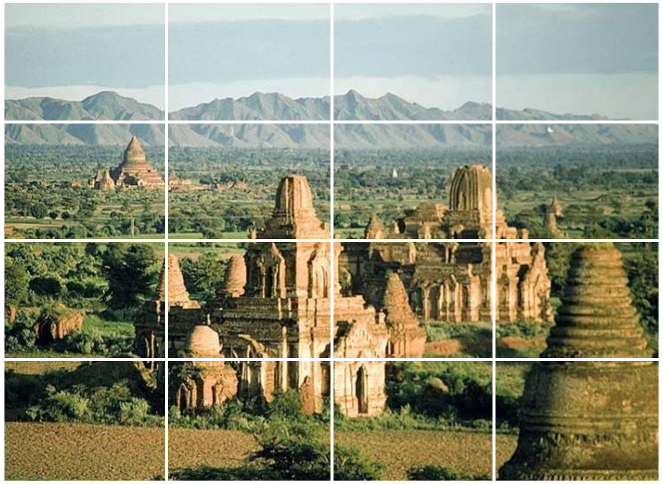
level 0

Spatial pyramid representation

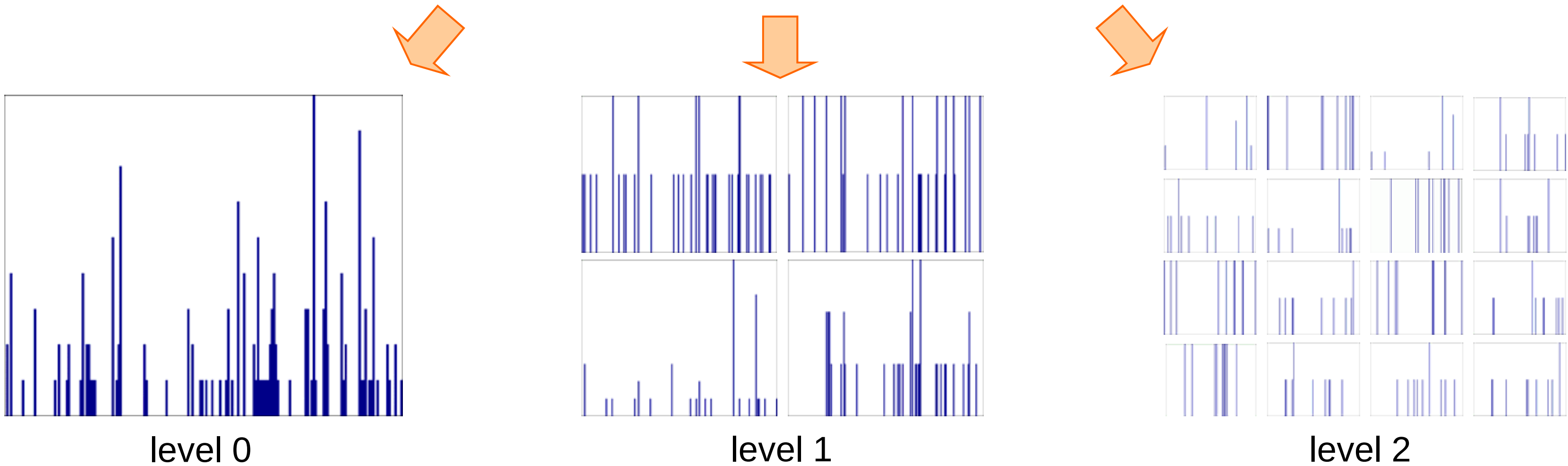


Locally orderless representation at several levels of spatial resolution

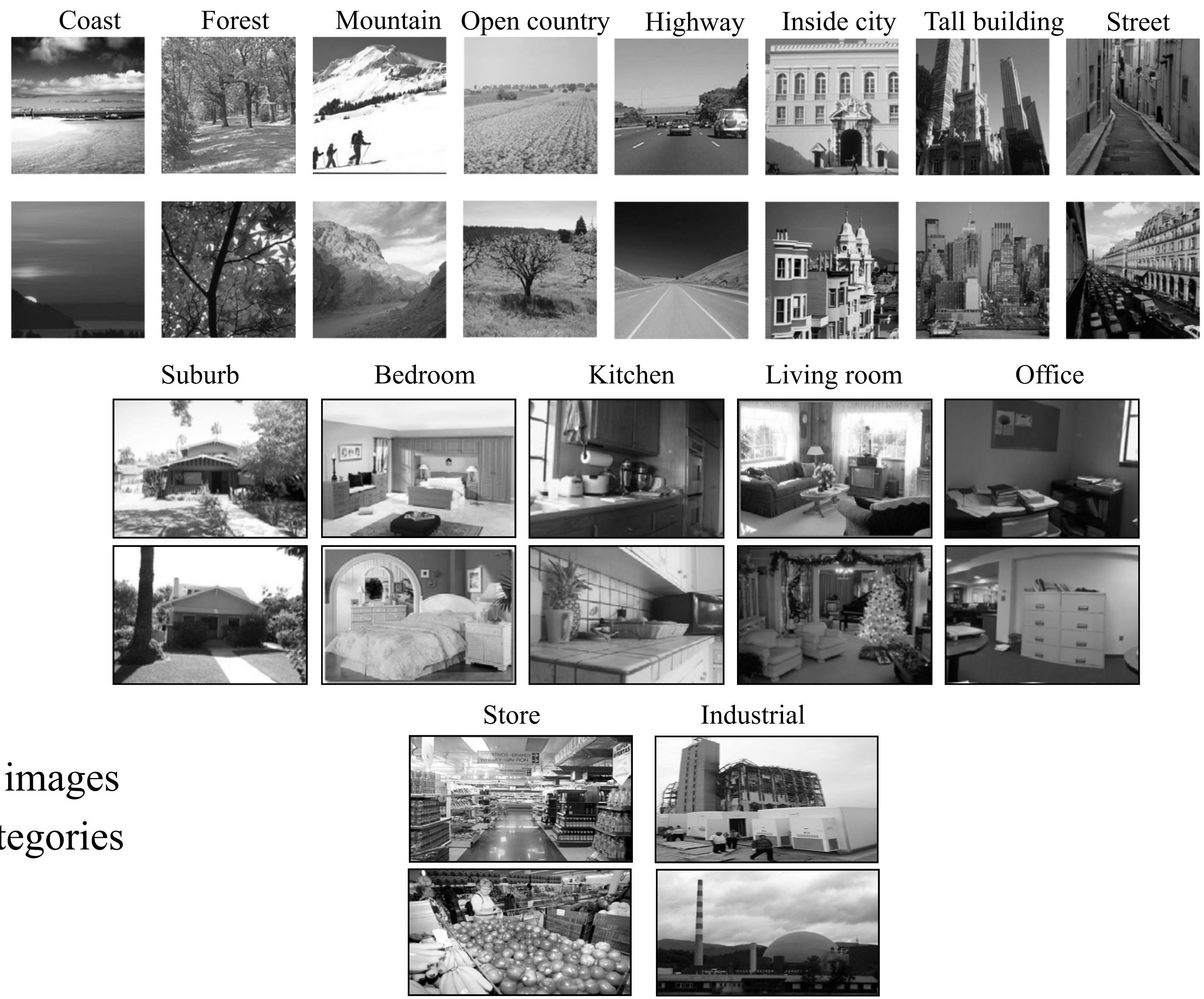
Spatial pyramid representation



Locally orderless representation at several levels of spatial resolution



Scene dataset [Labzenik et al.’06]



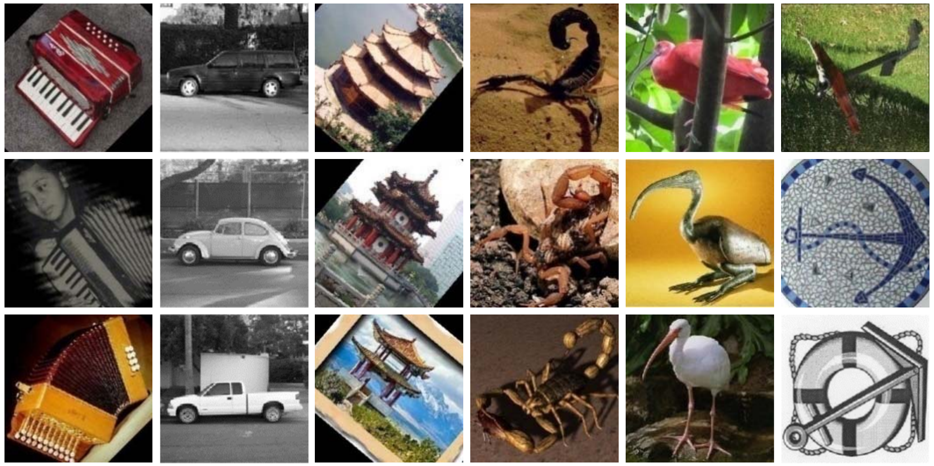
4385 images

15 categories

Scene classification

L	Single-level	Pyramid
0(1x1)	**72.2±0.6**	
1(2x2)	**77.9±0.6**	**79.0 ±0.5**
2(4x4)	**79.4±0.3**	***81.1 ±0.3***
3(8x8)	**77.2±0.4**	**80.7 ±0.3**

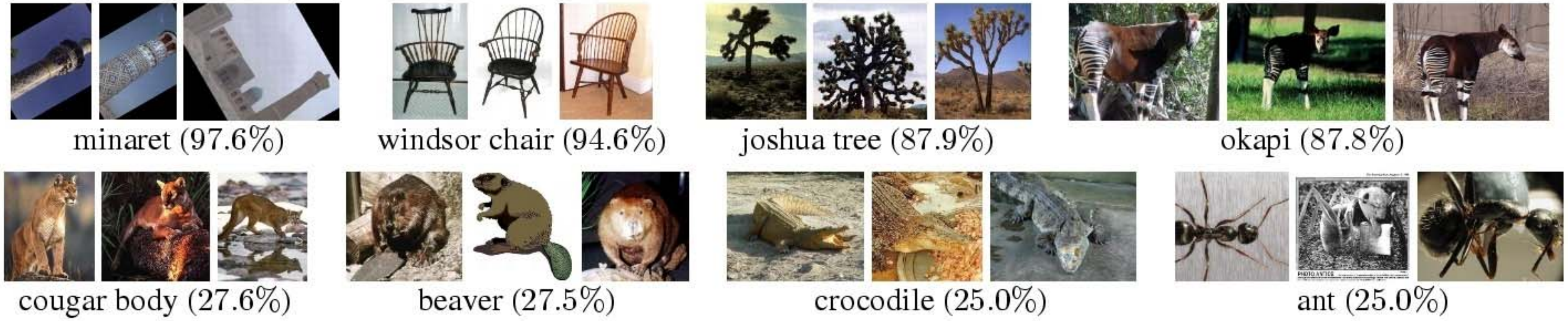
Category classification – CalTech101



L	Single-level	Pyramid
0(1x1)	**41.2±1.2**	
1(2x2)	**55.9±0.9**	**57.0 ±0.8**
2(4x4)	**63.6±0.9**	***64.6 ±0.8***
3(8x8)	**60.3±0.9**	**64.6 ±0.7**

CalTech101

Easiest and hardest classes



- Sources of difficulty:
  - Lack of texture
  - Camouflage
  - Thin, articulated limbs
  - Highly deformable shape

Evaluation BoF – spatial

Image classification results on PASCAL’07 train/val set

(SH, Lap, MSD) x (SIFT,SIFTC) spatial layout	AP
1	0.53
2x2	0.52
3x1	0.52
1,2x2,3x1	0.54

Spatial layout not dominant for PASCAL’07 dataset

Combination improves average results, i.e., it is appropriate for some classes

Discussion

- Summary
  - Spatial pyramid representation: appearance of local image patches + coarse global position information
  - Substantial improvement over bag of features
  - Depends on the similarity of image layout

- Recent extensions
  - Flexible, object-centered grid
    - Shape masks [Marszalek'12] => additional annotations
  - Weakly supervised localization of objects
    - [Russakovsky et al.'12, Oquab'14, Cinbis'16]

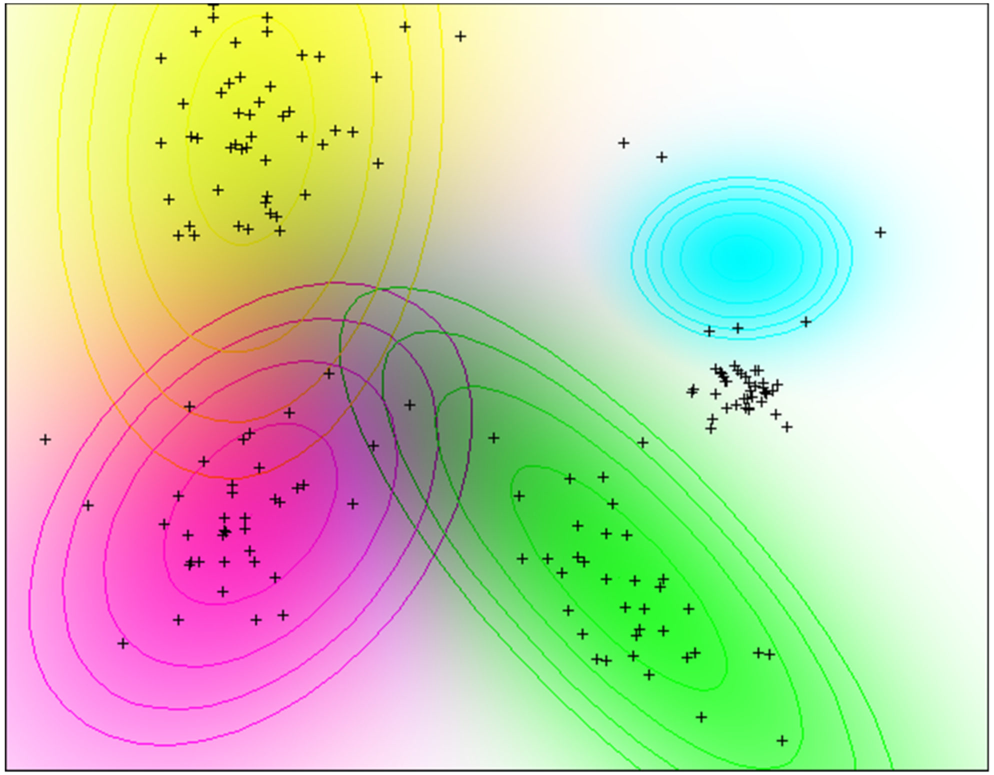
Extensions

- Improved aggregation schemes, such as the Fisher vector, Perronnin et al., ECCV'10
  - More discriminative descriptor, power normalization, linear SVM

- ImageNet classification with deep convolutional neural networks, Krizhevsky, Sutskever, Hinton, NIPS 2012

Fisher vector

- Use a Gaussian Mixture Model as vocabulary
- Statistical measure of the descriptors of the image w.r.t the GMM
- Derivative of likelihood w.r.t. GMM parameters



GMM parameters:

w_i weight

μ_i mean

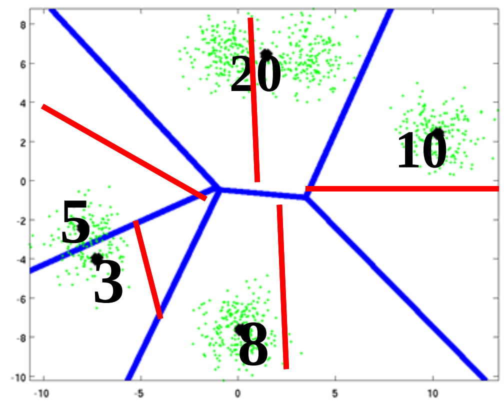
σ_i co-variance (diagonal)

Translated cluster →
large derivative on μ_i for this
component

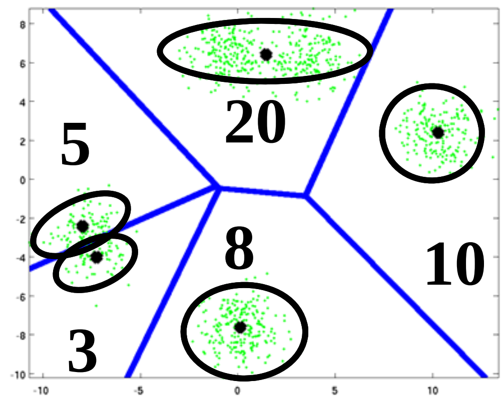
[Perronnin & Dance 07]

Fisher vector image representation

- Mixture of Gaussian/ k-means stores nbr of points per cell



- Fisher vector adds 1st & 2nd order moments
  - More precise description of regions assigned to cluster
  - Fewer clusters needed for same accuracy
  - Per cluster store: mean and variance of data in cell
  - Representation 2D times larger, at same computational cost
  - High dimensional, robust representation



Fisher vector image representation

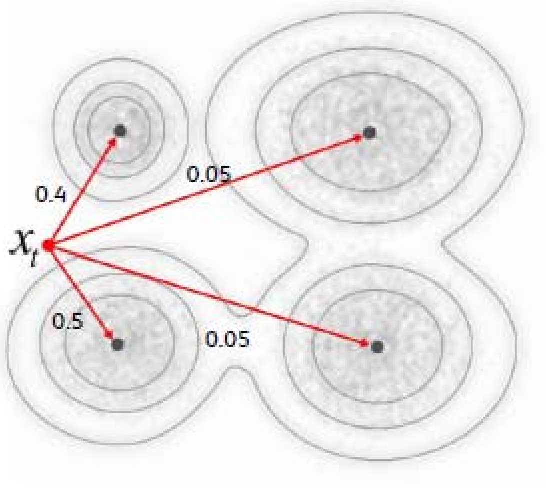
$X = \{x_t, t = 1 \dots T\}$ is the set of T i.i.d. D-dim local descriptors (e.g. SIFT) extracted from an image:

$u_\lambda(x) = \sum_{i=1}^{K} w_i u_i(x)$ is a Gaussian Mixture Model (GMM) with parameters $\lambda = \{w_i, \mu_i, \Sigma_i, i = 1 \dots N\}$ trained on a large set of local descriptors: a **visual vocabulary**

FV formulas:

$$\mathcal{G}^X_{\mu,i} = \frac{1}{T\sqrt{w_i}} \sum_{t=1}^{T} \gamma_t(i) \left(\frac{x_t - \mu_i}{\sigma_i} \right)$$

$$\mathcal{G}^X_{\sigma,i} = \frac{1}{T\sqrt{2w_i}} \sum_{t=1}^{T} \gamma_t(i) \left[\frac{(x_t - \mu_i)^2}{\sigma_i^2} - 1 \right]$$



$\gamma_t(i)$ = soft-assignment of patch x_t to Gaussian i

Fisher Vector = concatenation of per-Gaussian gradient vectors

Relation to BOF

FV formulas:

$$\boxed{\begin{aligned}\mathcal{G}^X_{\mu,i} &= \frac{1}{T\sqrt{w_i}}\sum_{t=1}^{T}\gamma_t(i)\left(\frac{x_t-\mu_i}{\sigma_i}\right)\\ \mathcal{G}^X_{\sigma,i} &= \frac{1}{T\sqrt{2w_i}}\sum_{t=1}^{T}\gamma_t(i)\left[\frac{(x_t-\mu_i)^2}{\sigma_i^2}-1\right]\end{aligned}}$$

Soft BOV formula:

$$\frac{1}{T}\sum_{t=1}^{T}\gamma_t(i)$$

Like the (original) BOV the FV is an average of local statistics.

The FV extends the BOV and includes higher-order statistics (up to 2nd order)

Results on VOC 2007: BOV = 43.6 % $\rightarrow$ FV = 57.7 % $\rightarrow$ √FV = 62.1 %

Large-scale image classification

- Image classification: assigning a class label to the image

Car: present
Cow: present
Bike: not present
Horse: not present
...

- What makes it large-scale?
  - number of images
  - number of classes
  - dimensionality of descriptor

IMAGENET has 14M images from 22k classes

Current state of the art – image classification

- Deep convolutional neural networks
- Convolutional networks [LeCun'98 …]
- AlexNet [Krizhevsky'12]
- VGG Net [Simonyan'14]
- Google Inception [Szegedy'15]
- ResNet [He'16]