Bag-of-features for category classification

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INRIA

LEAR

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

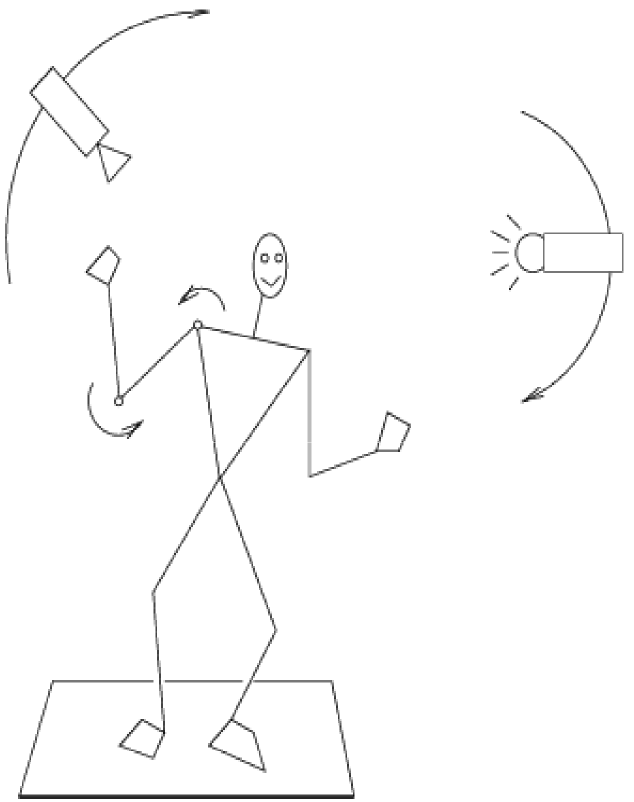
Car: present
Cow: present
Bike: not present
Horse: not present
…

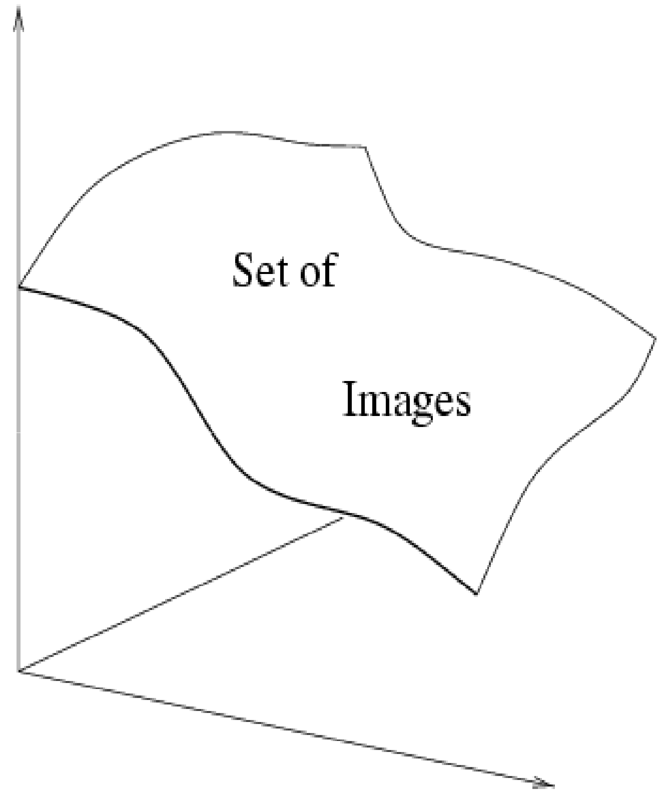
- Object localization: define the location and the category

Location

Category

Difficulties: within object variations





Variability: Camera position, Illumination,Internal parameters

Within-object variations

Difficulties: within class variations





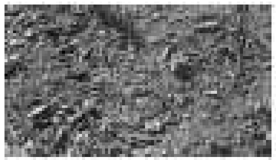

Image classification

- Given

  Positive training images containing an object class



  Negative training images that don’t



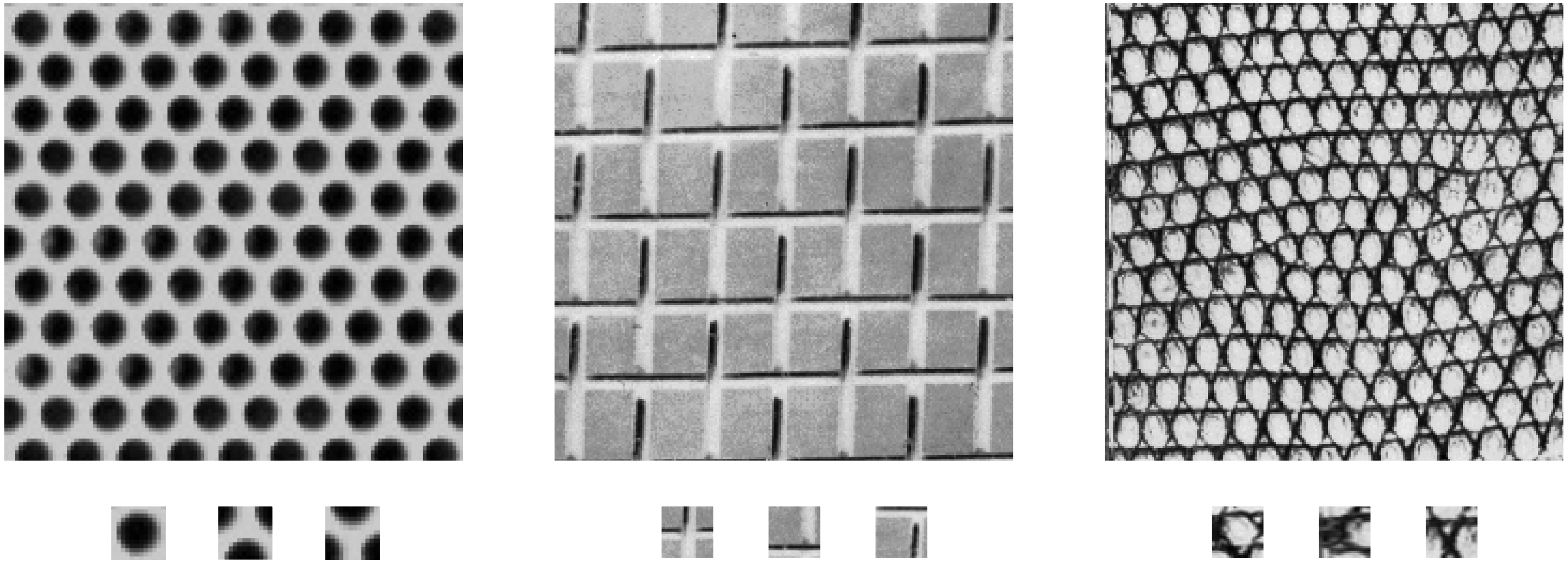
- Classify

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

?

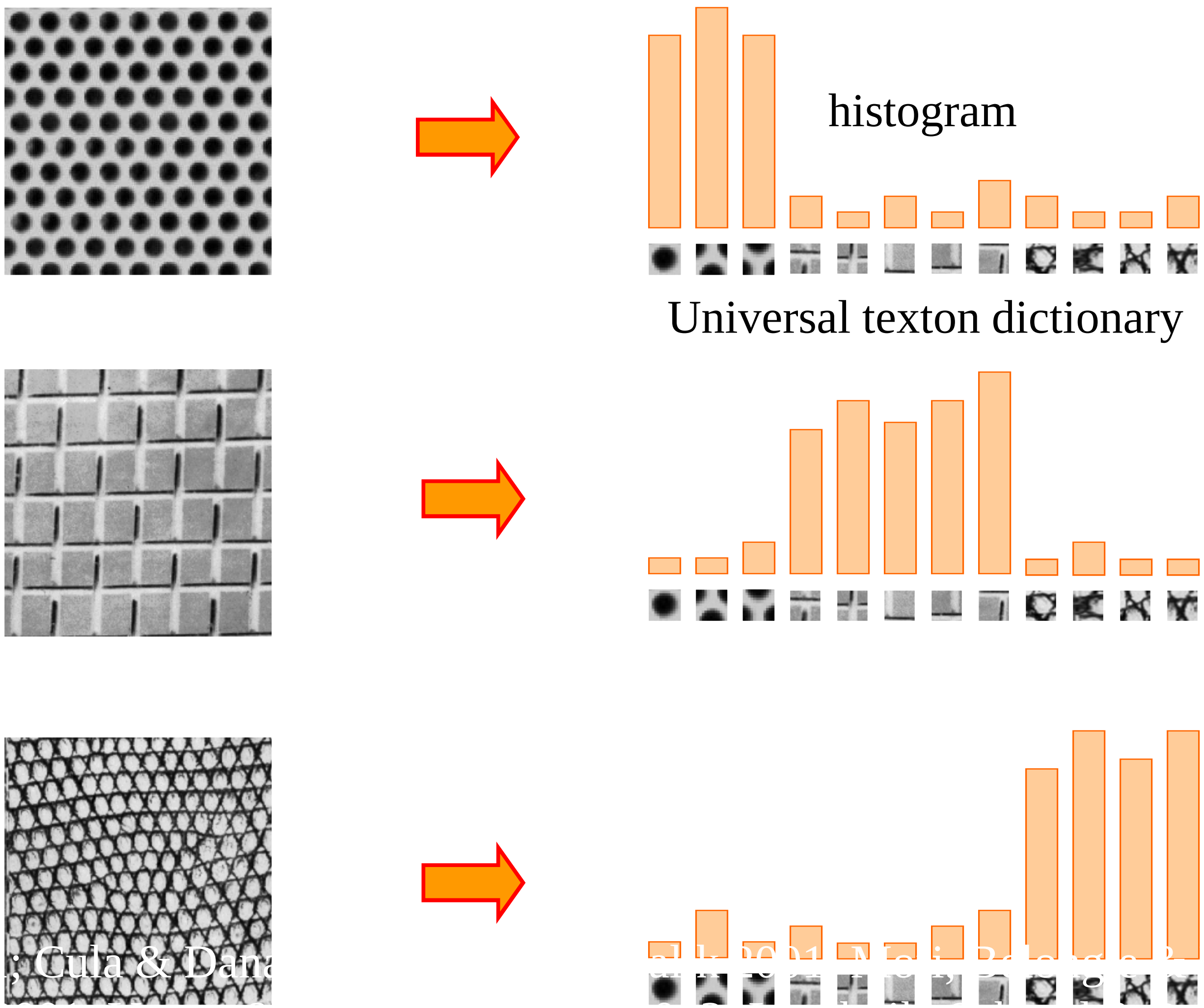
Bag-of-features – Origin: texture recognition

- Texture is characterized by the repetition of basic elements or *textons*



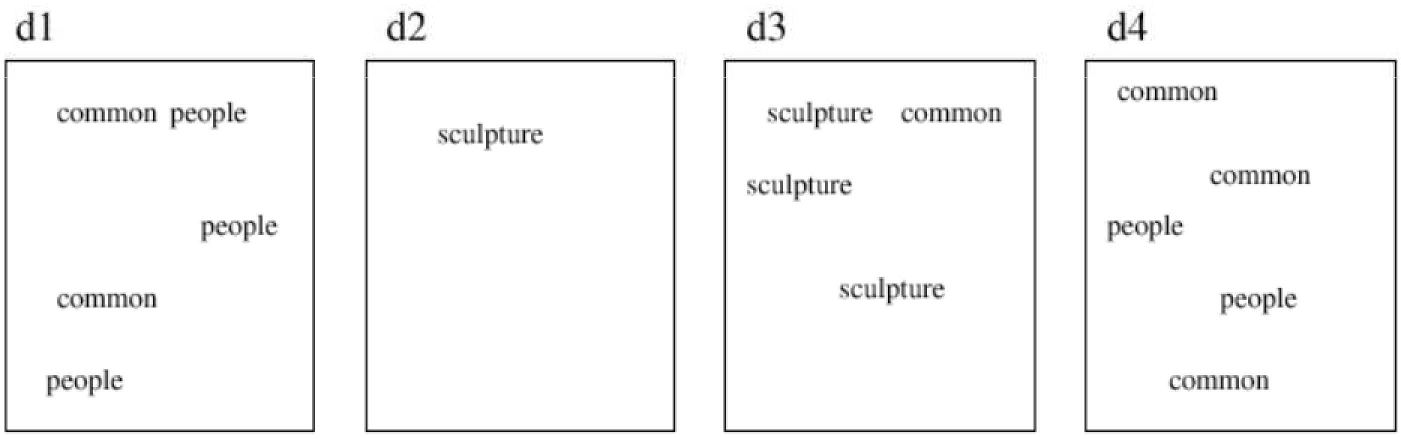
Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001
Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Bag-of-features – Origin: texture recognition



Bag-of-features – Origin: bag-of-words (text)

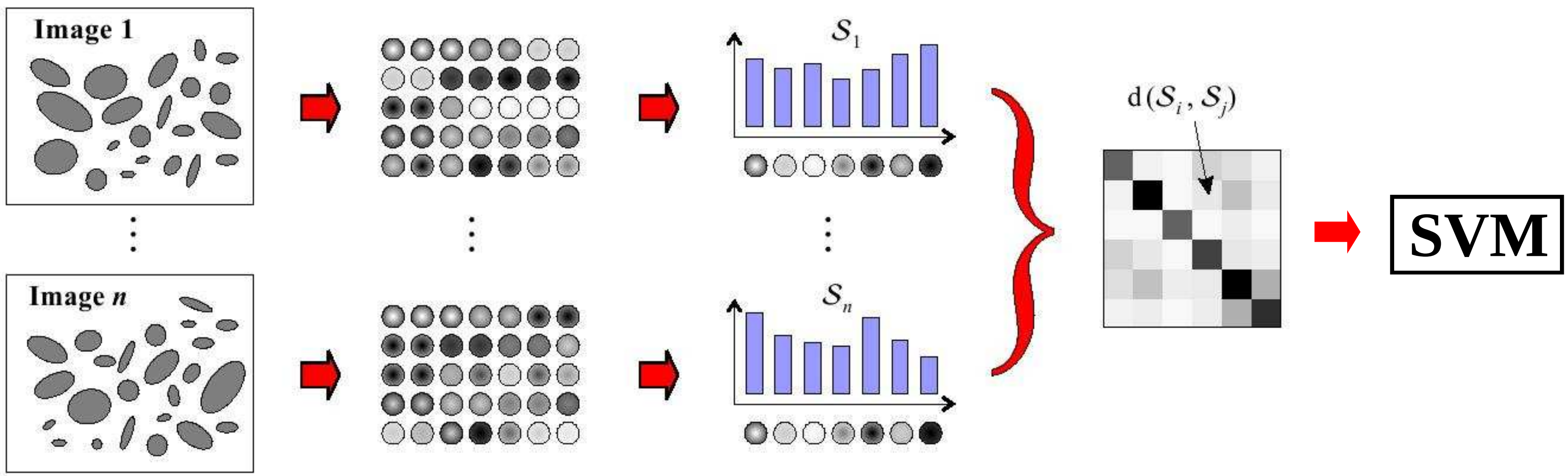
- Orderless document representation: frequencies of words from a dictionary
- Classification to determine document categories



Bag-of-words

Common	2	0	1	3
People	3	0	0	2
Sculpture	0	1	3	0
…	…	…	…	…

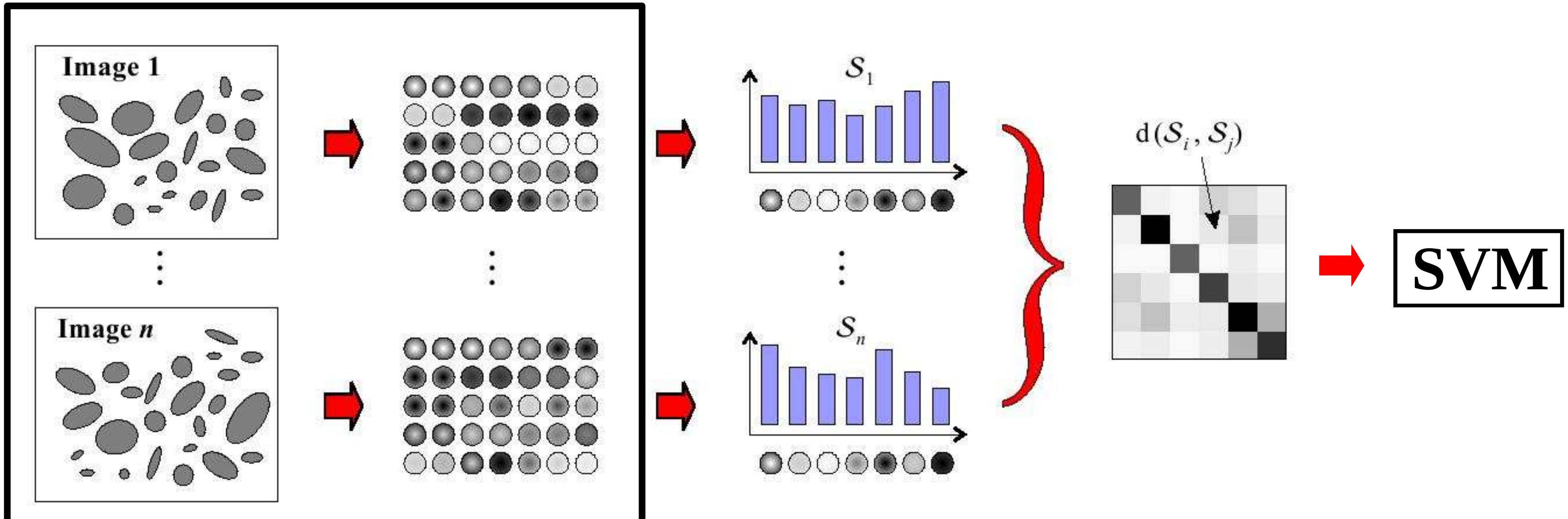
Bag-of-features for image classification



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

[Csurka et al., ECCV Workshop'04], [Nowak,Jurie&Triggs,ECCV'06], [Zhang,Marszalek,Lazebnik&Schmid,IJCV'07]

Bag-of-features for image classification



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

Step 1 Step 2 Step 3

Step 1: feature extraction

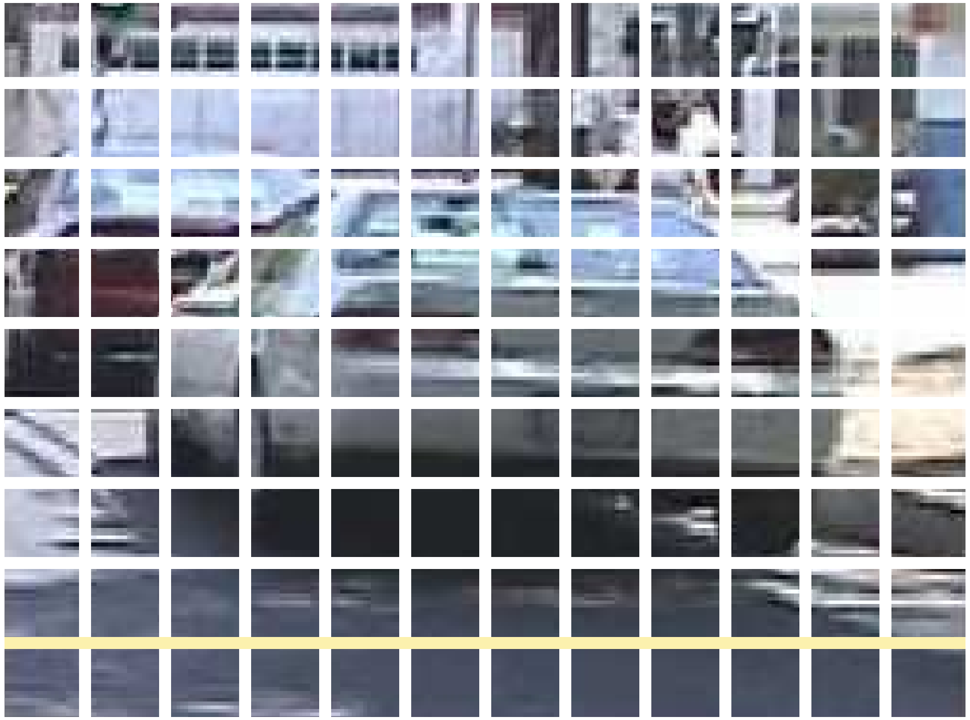
- Scale-invariant image regions + SIFT (see previous lecture)
  - Affine invariant regions give “too” much invariance
  - Rotation invariance for many realistic collections “too” much invariance

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

- Color-based descriptors

- Shape-based descriptors

Dense features

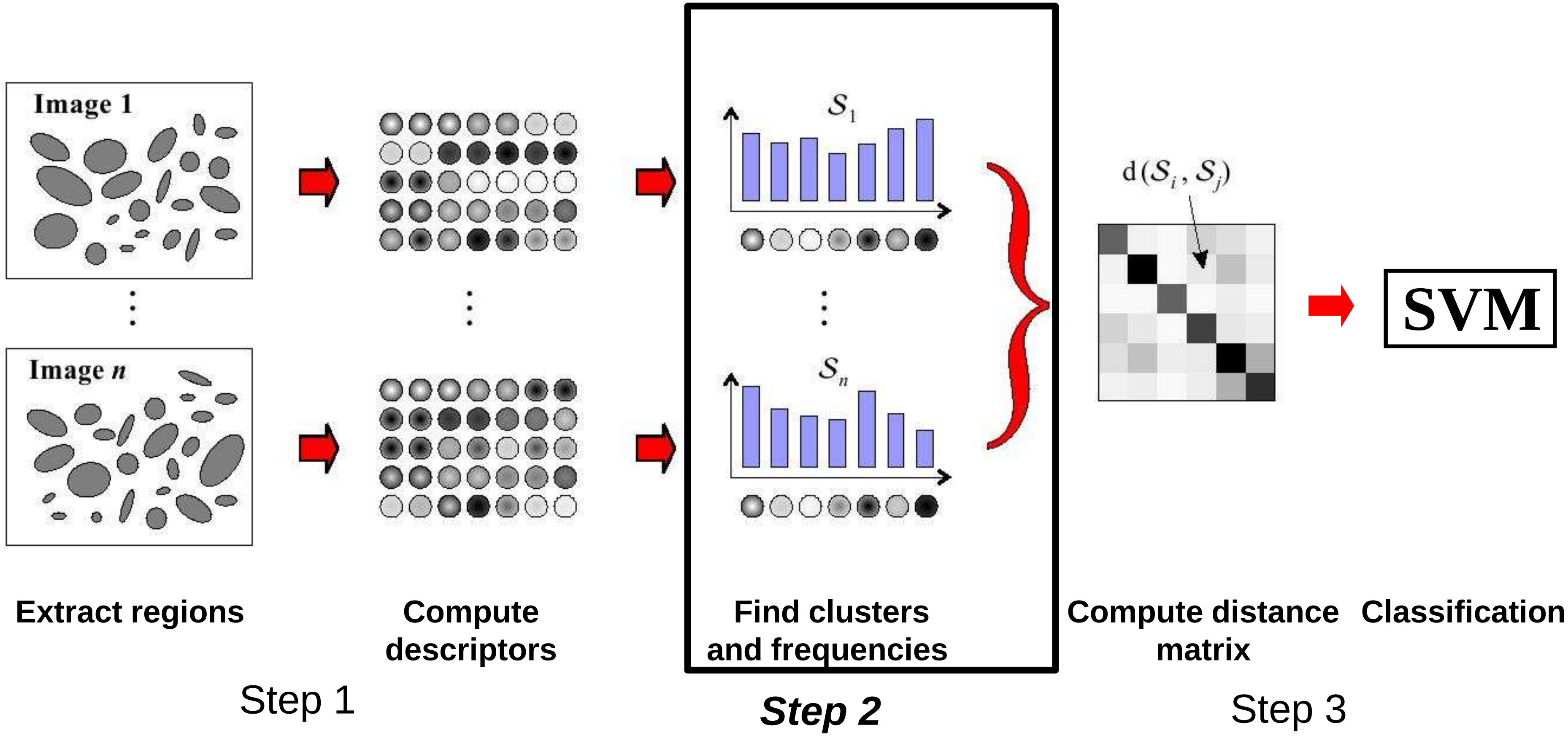


- Multi-scale dense grid: extraction of small overlapping patches at multiple scales

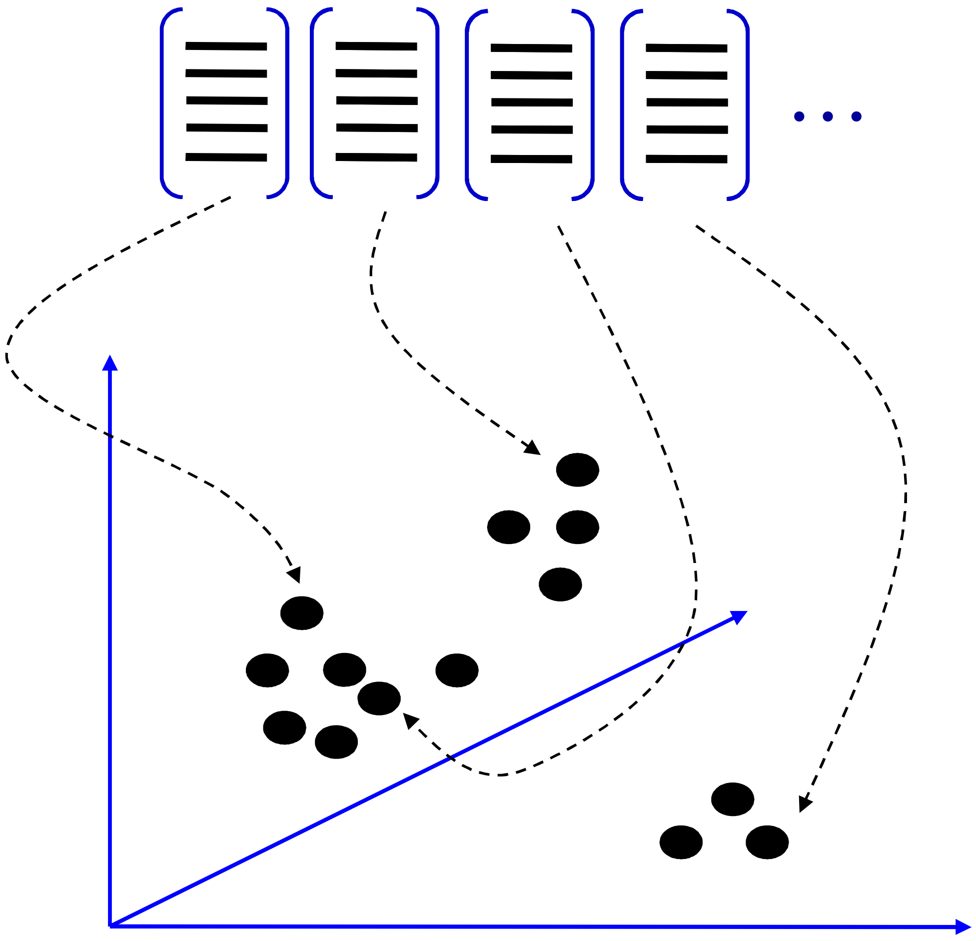
-Computation of the SIFT descriptor for each grid cells

-Exp.: Horizontal/vertical step size 6 pixel, scaling factor of 1.2 per level

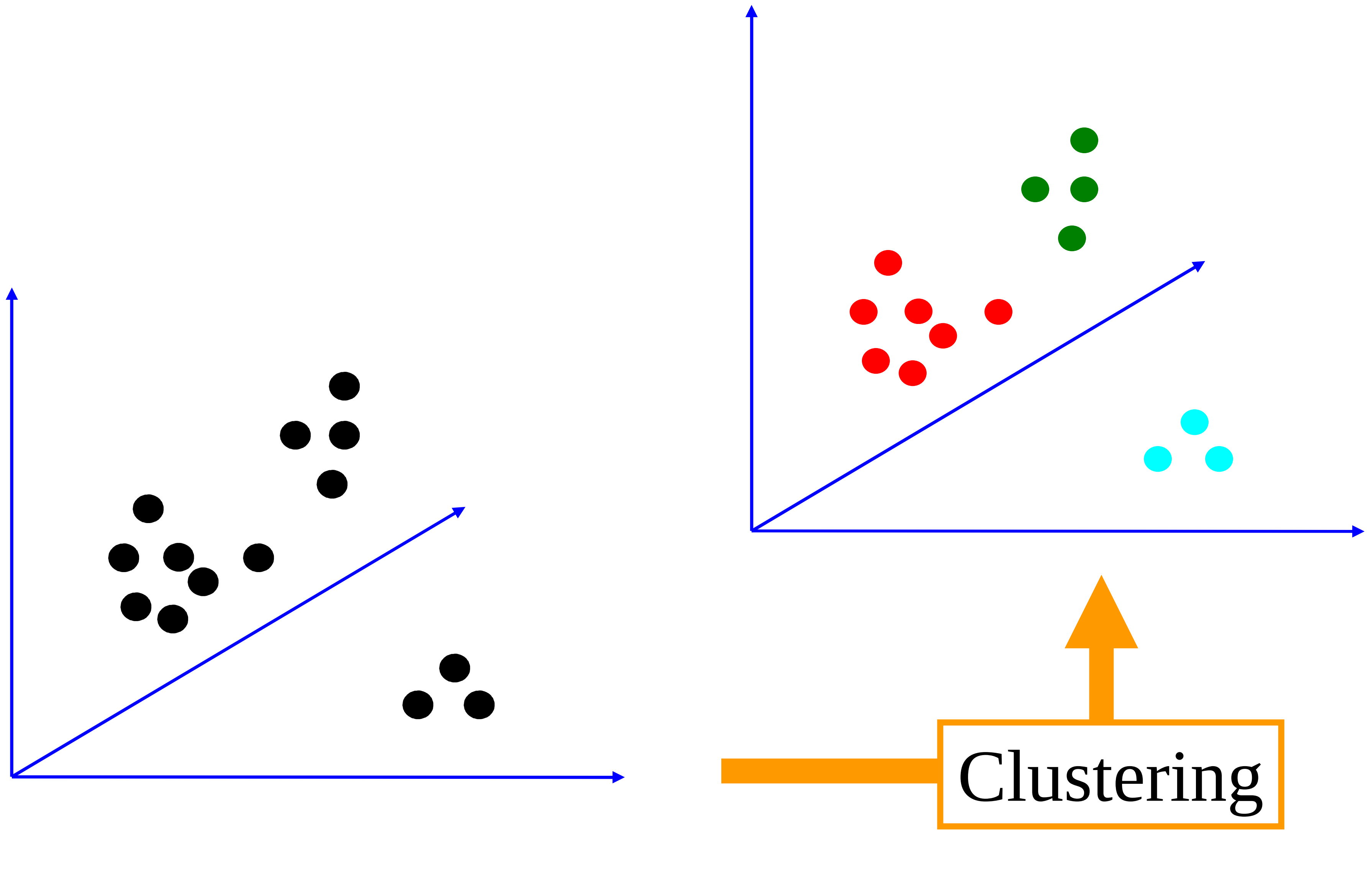
Bag-of-features for image classification



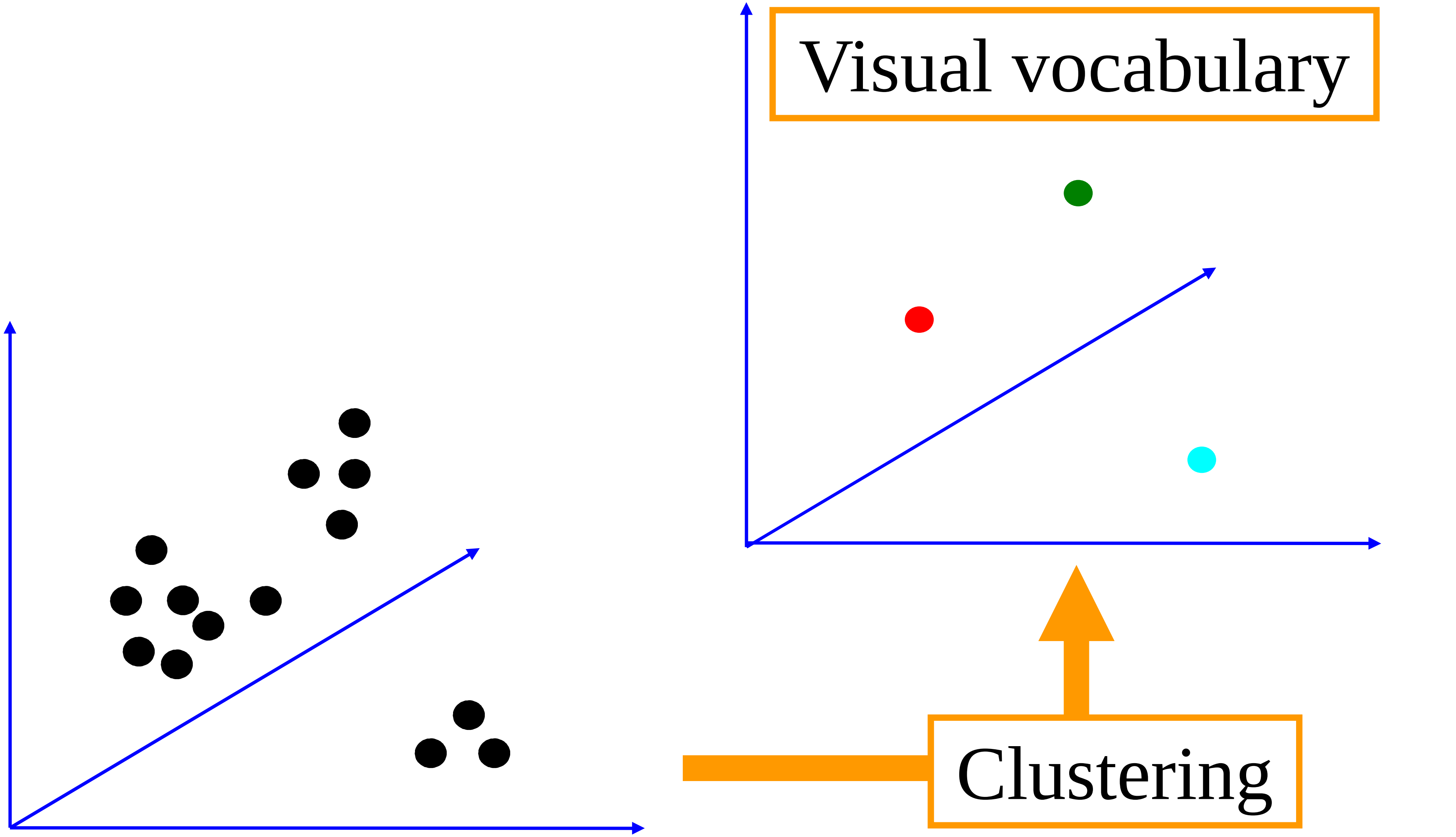
Step 2: Quantization



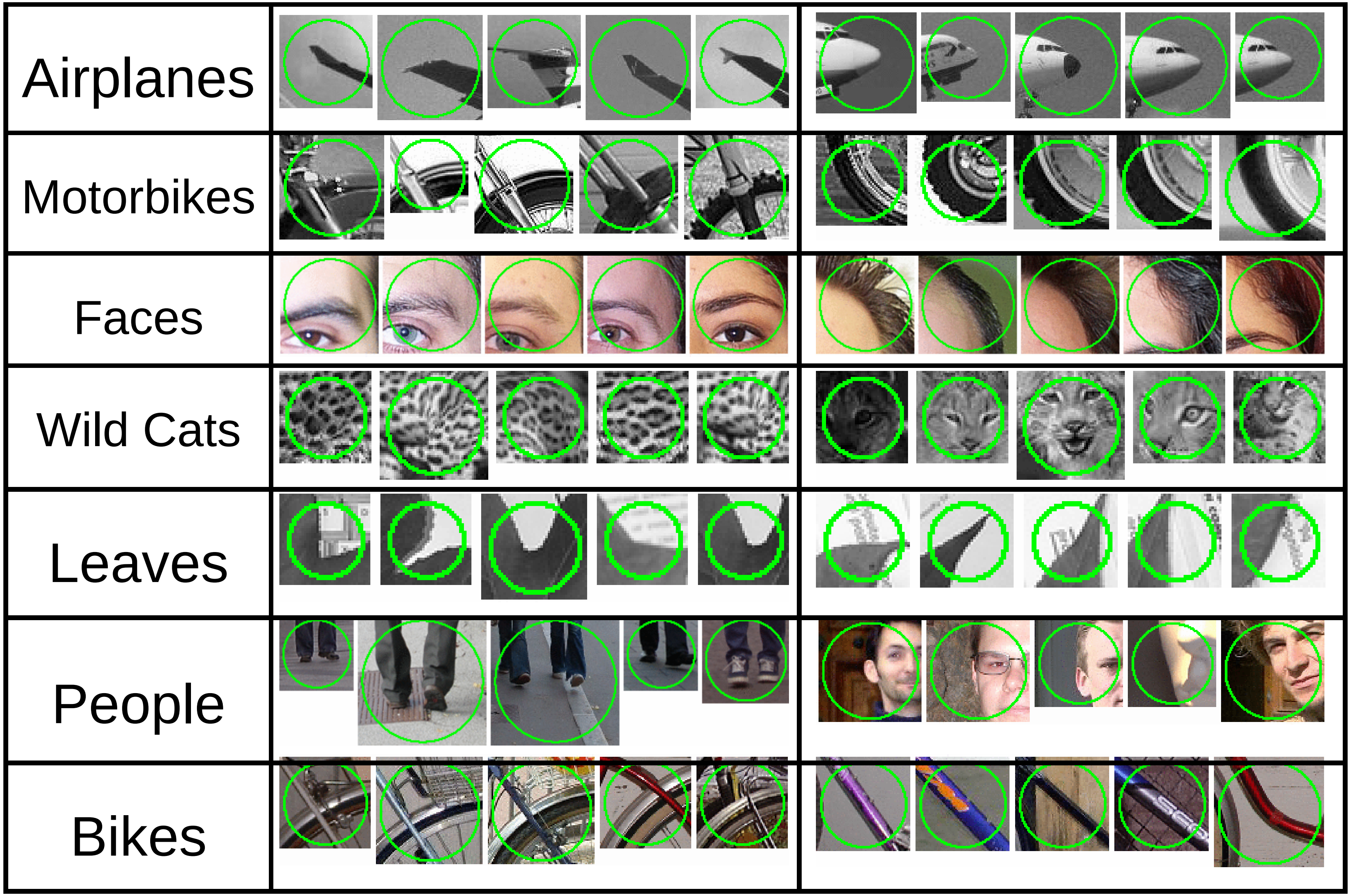
Step 2:Quantization



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

K-means clustering

- Minimizing sum of squared Euclidean distances between points x_i and their nearest cluster centers

- 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

- Local minimum, solution dependent on initialization

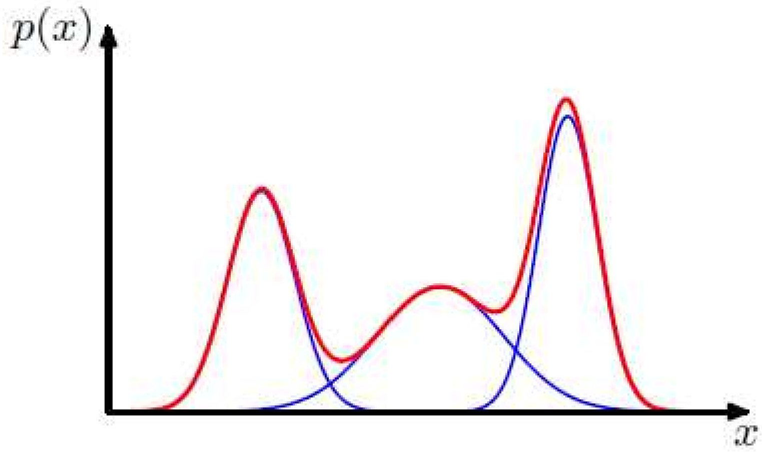
- Initialization important, run several times, select best

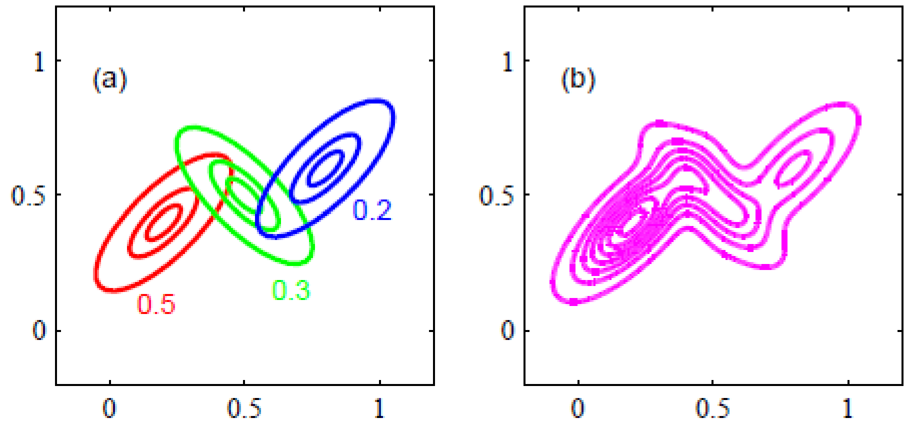
Gaussian mixture model (GMM)

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

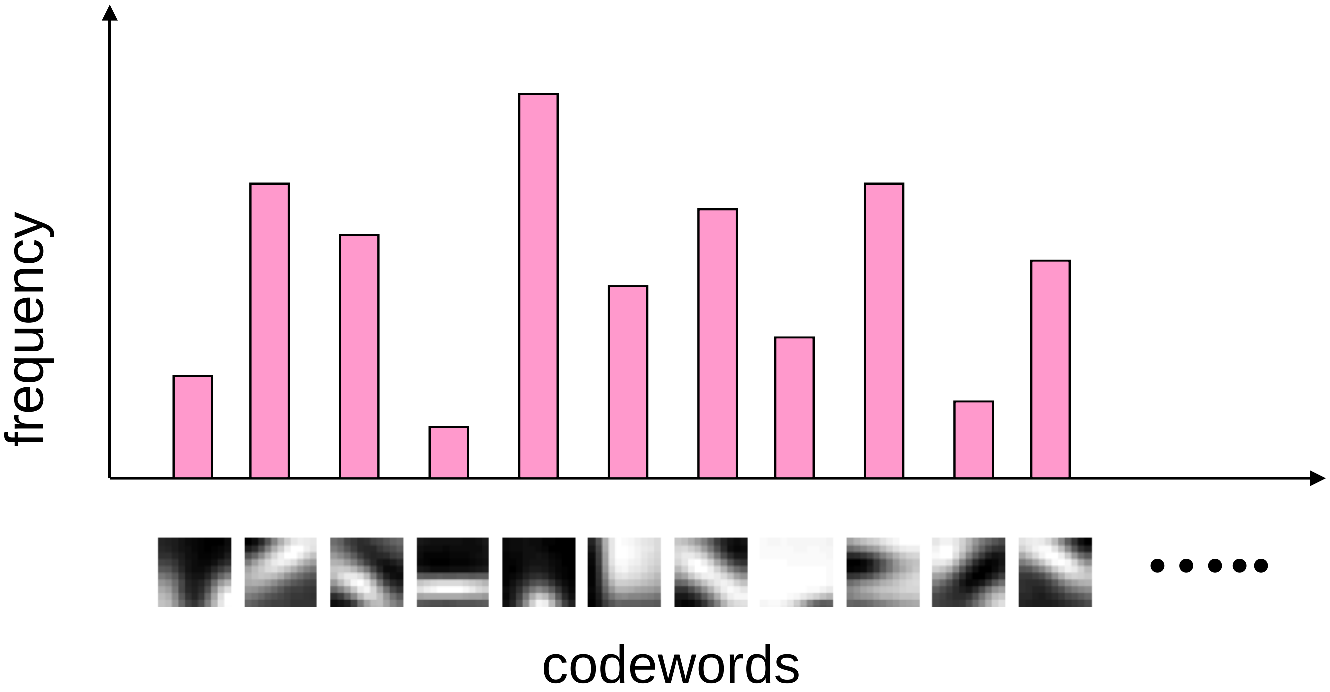




Hard or soft assignment

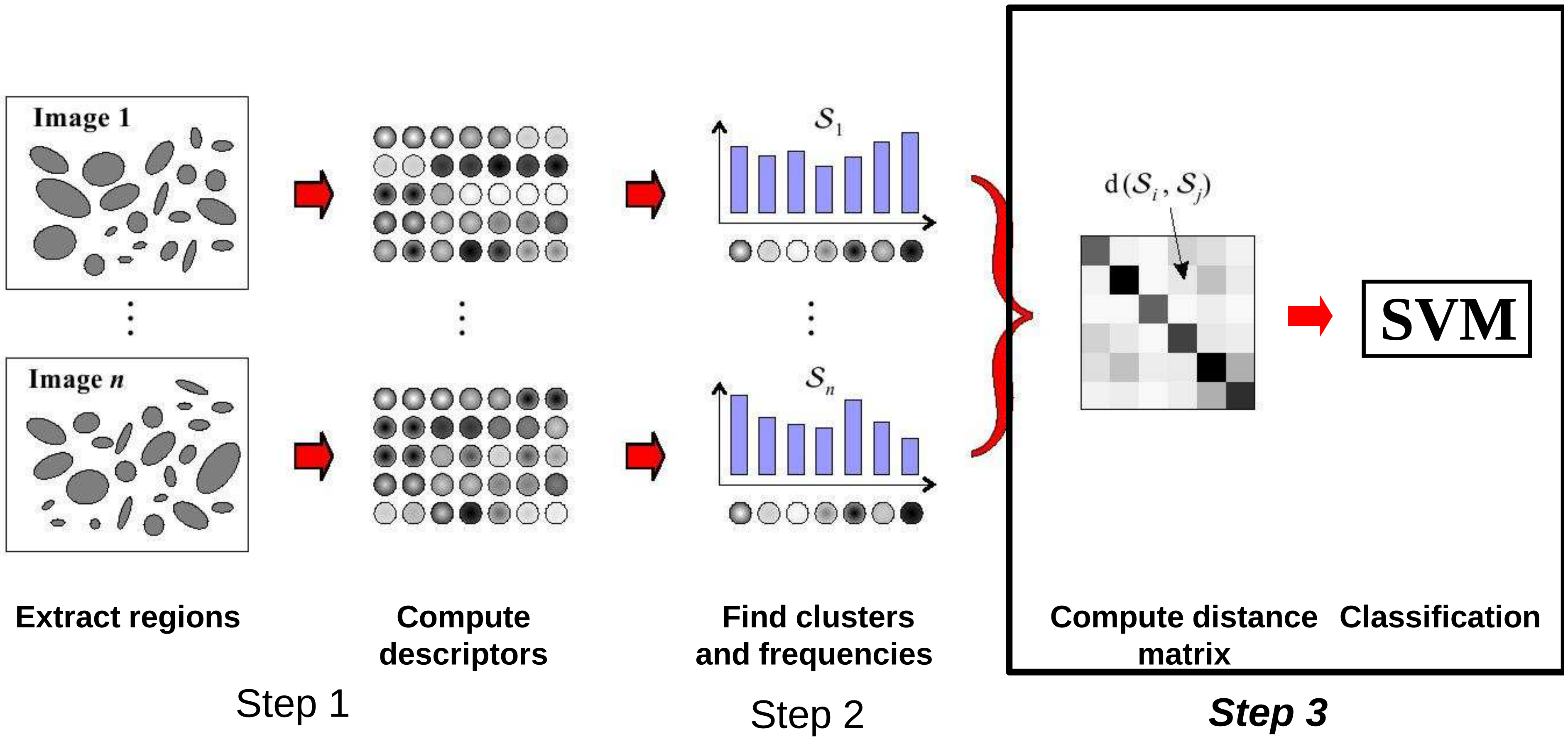
- K-means → hard assignment
  - Assign to the closest cluster center
  - Count number of descriptors assigned to a center
- Gaussian mixture model → soft assignment
  - Estimate distance to all centers
  - Sum over number of descriptors
- Represent image by a frequency histogram

Image representation



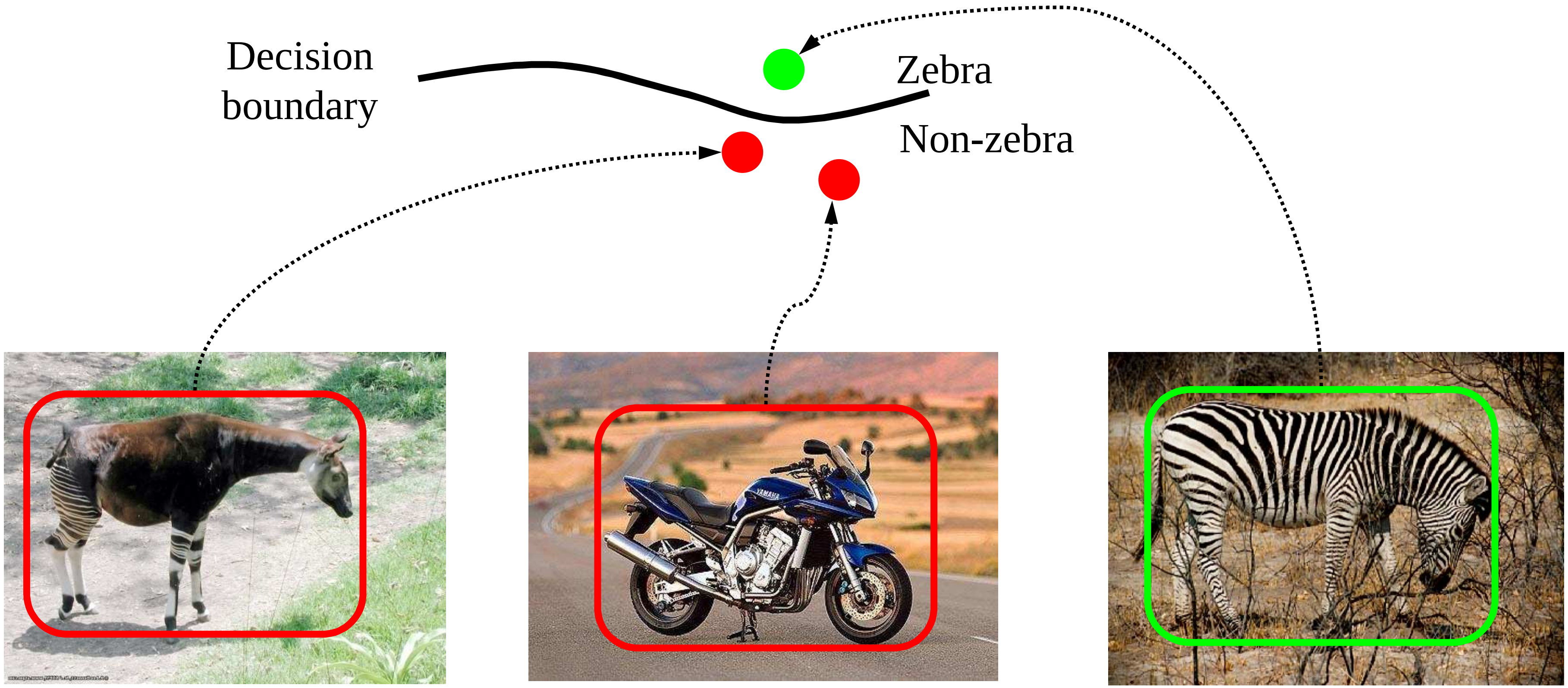
- each image is represented by a vector, typically 1000-4000 dimension, normalization with L1/L2 norm
- fine grained – represent model instances
- coarse grained – represent object categories

Bag-of-features for image classification



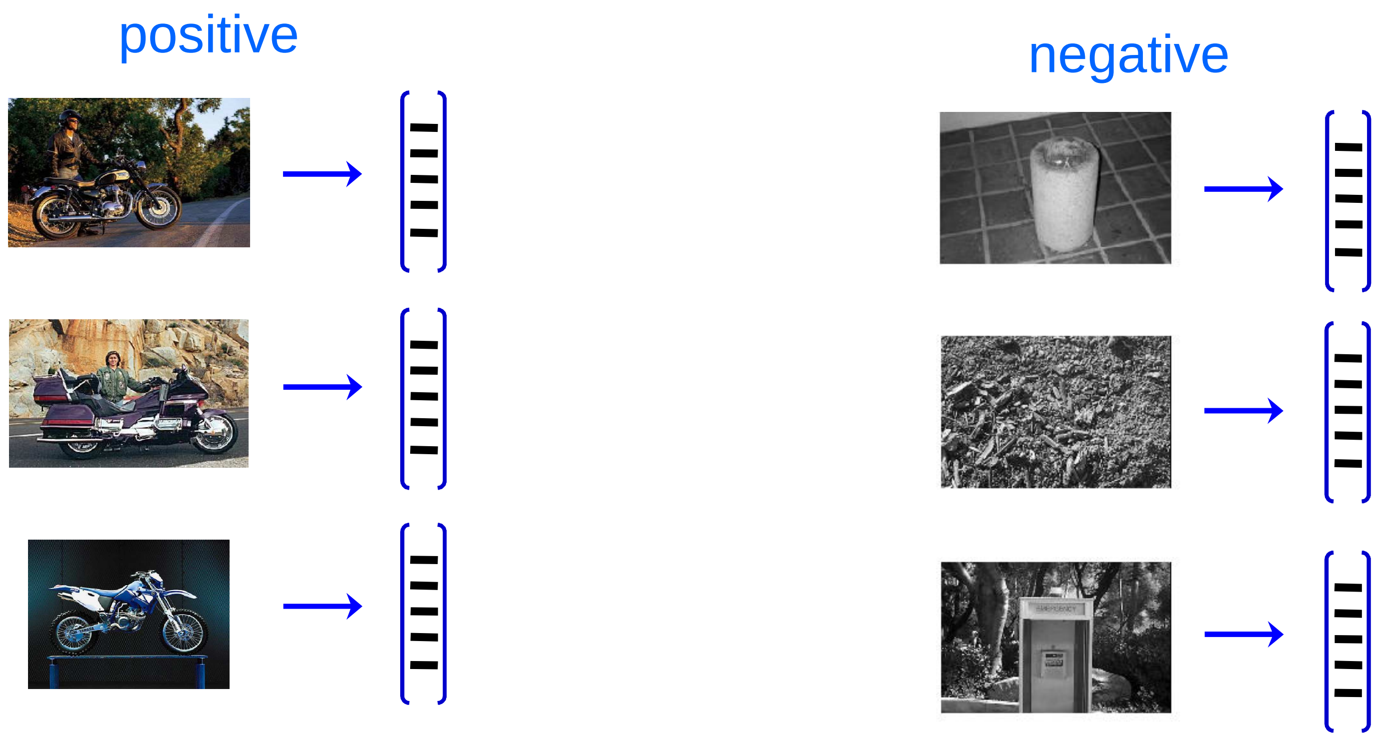
Step 3: Classification

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



Training data

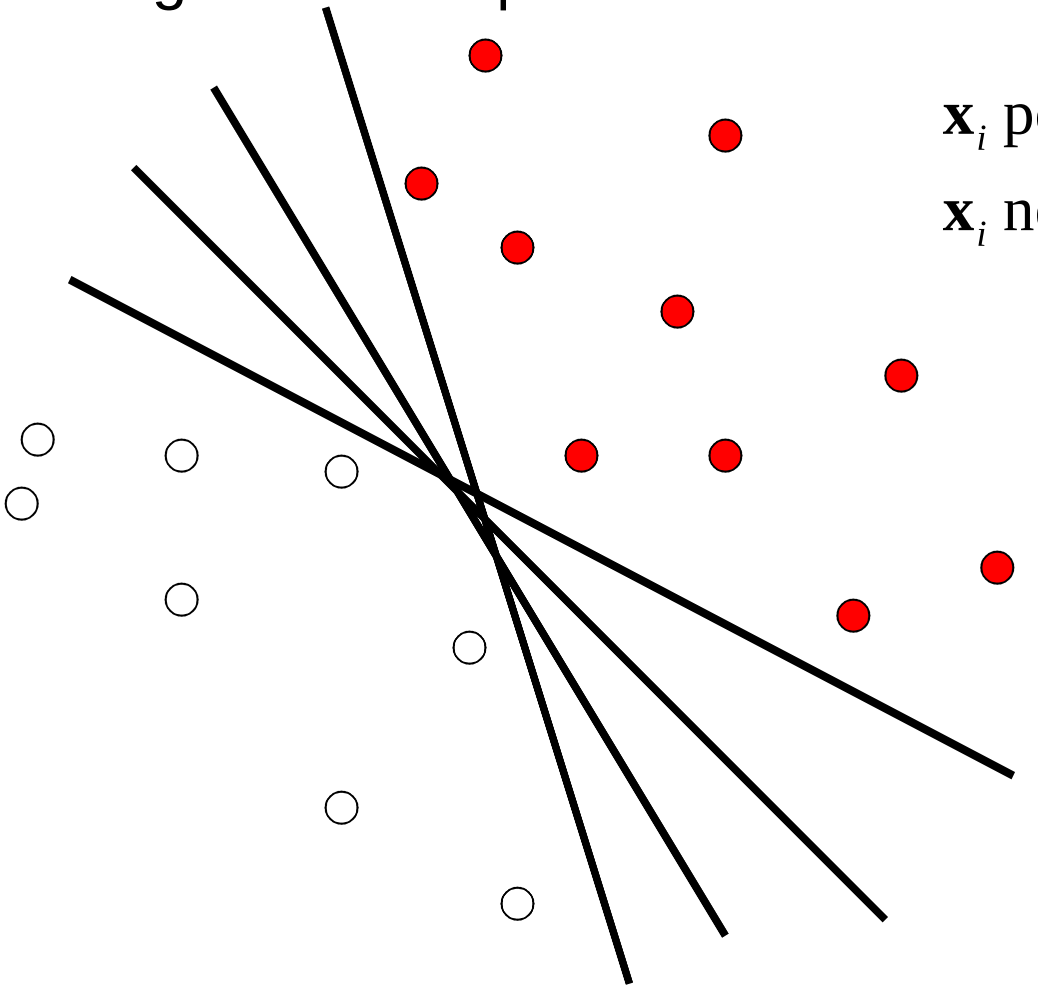
Vectors are histograms, one from each training image



Train classifier,e.g.SVM

Linear classifiers

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



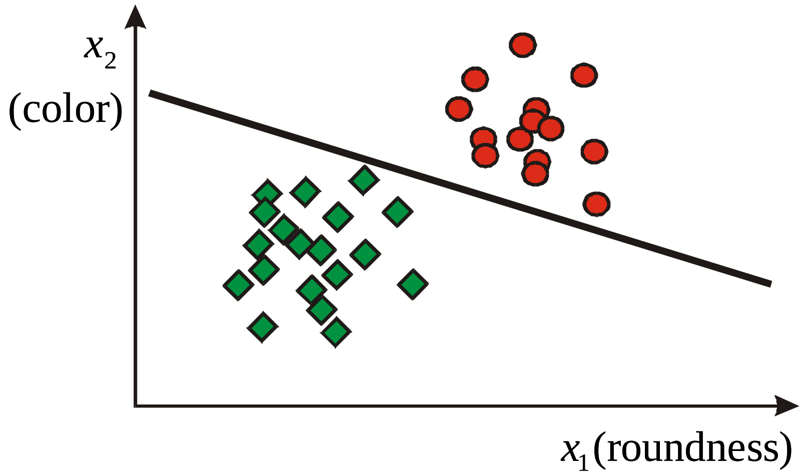
$$\mathbf{x}_i \text{ positive}: \quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$$

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

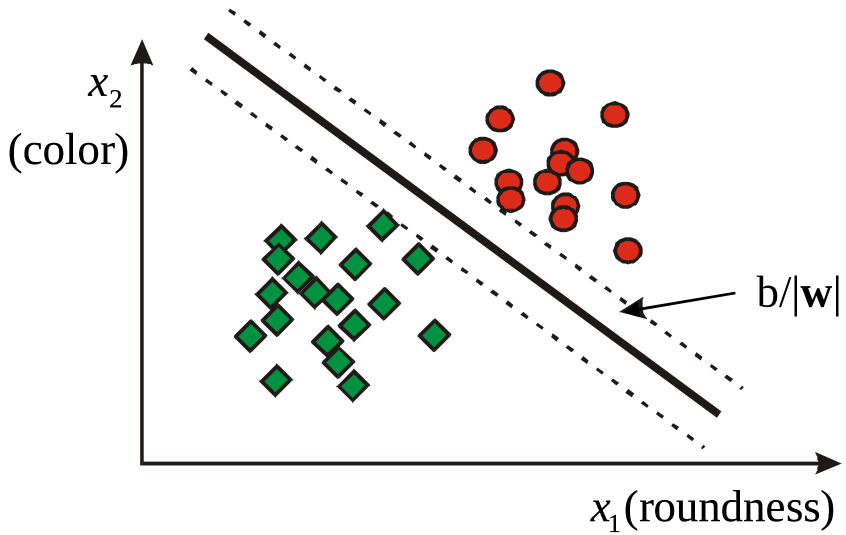
Which hyperplane
is best?

Linear classifiers - margin

- Generalization is not good in this case:

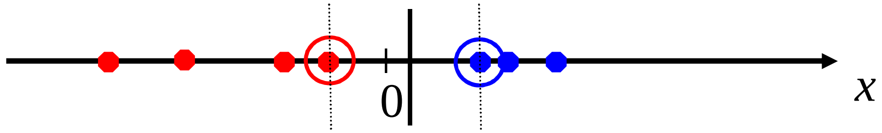


- Better if a margin is introduced:

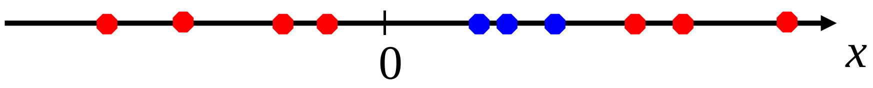


Nonlinear SVMs

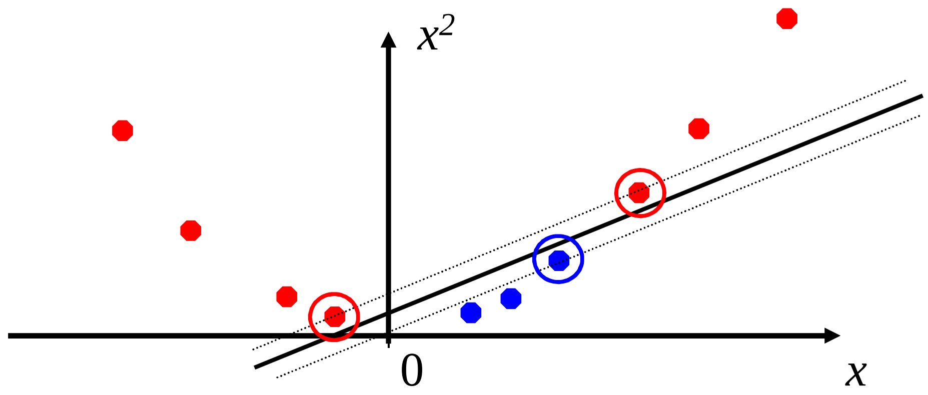
- Datasets that are linearly separable work out great:



- But what if the dataset is just too hard?

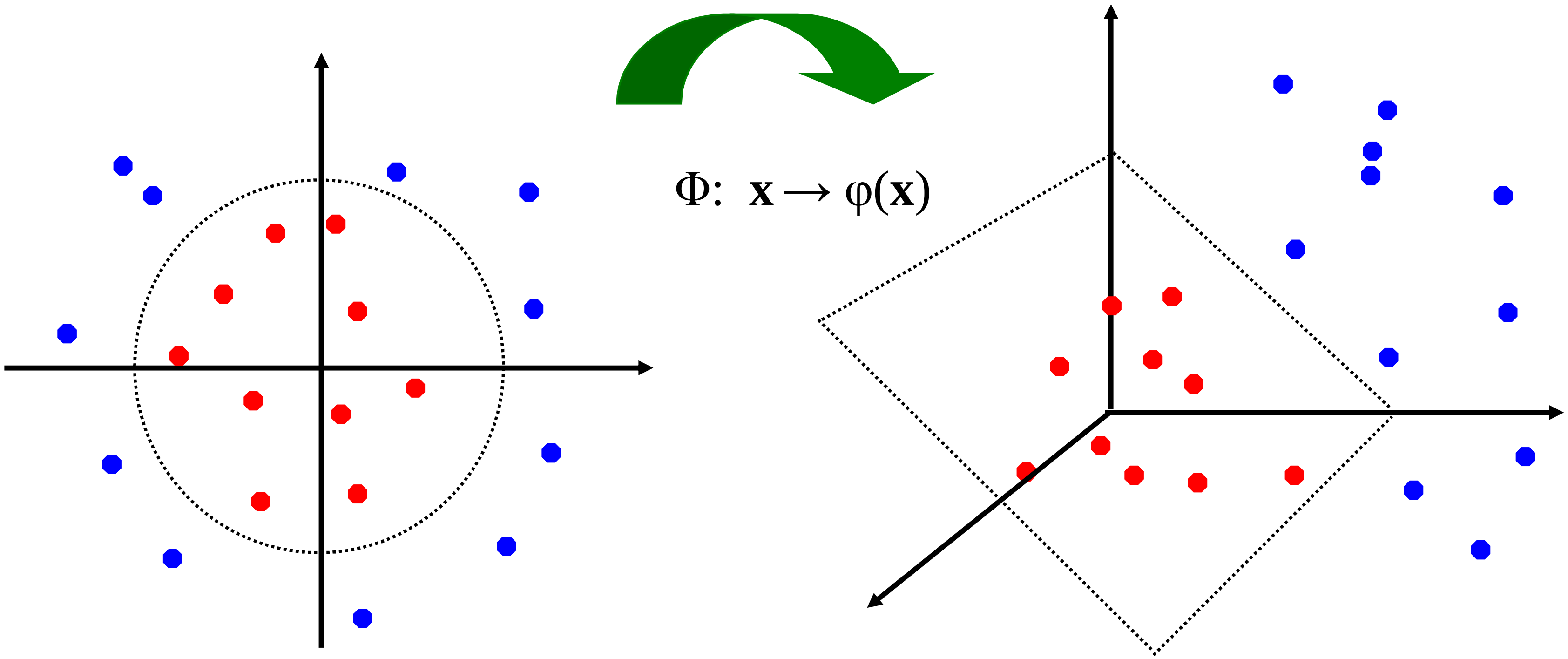


- We can map it to a higher-dimensional space:



Nonlinear SVMs

- General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable:



Nonlinear SVMs

- *The kernel trick*: instead of explicitly computing the lifting transformation $\varphi(\mathbf{x})$, define a kernel function K such that

$$K(\mathbf{x}_i, \mathbf{x}_j) = \varphi(\mathbf{x}_i) \cdot \varphi(\mathbf{x}_j)$$

- This gives a nonlinear decision boundary in the original feature space:

$$\sum_i \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b$$

Kernels for bags of features

- 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 → RBF kernel
- D can be χ^2 distance $D(h_1, h_2) = \sum_{i=1}^{N} \frac{\left(h_1(i) - h_2(i)\right)^2}{h_1(i) + h_2(i)}$
- Earth mover's distance

Earth Mover's Distance

- Each image is represented by a *signature S* consisting of a set of *centers* $\{m_i\}$ and *weights* $\{w_i\}$
- Centers can be codewords from universal vocabulary, clusters of features in the image, or individual features (in which case quantization is not required)
- Earth Mover's Distance has the form

$$EMD(S_1, S_2) = \sum_{i,j} \frac{f_{ij}\, d(m_{1i}, m_{2j})}{f_{ij}}$$

where the *flows* f_{ij} are given by the solution of a *transportation problem*

Combining features

- SVM with multi-channel chi-square kernel

$$K(H_i, H_j) = \exp\left(- \sum_{c \in \mathcal{C}} \frac{1}{A_c} D_c(H_i, H_j) \right)$$

  - Channel *c* is a combination of detector, descriptor
  - $D_c(H_i, H_j)$ is the chi-square distance between histograms

$$D_c(H_1, H_2) = \frac{1}{2} \sum_{i=1}^{m} [(h_{1i} - h_{2i})^2 / (h_{1i} + h_{2i})]$$

  - A_c is the mean value of the distances between all training sample
  - Extension: learning of the weights, for example with Multiple Kernel Learning (MKL)

J. Zhang, M. Marszalek, S. Lazebnik and C. Schmid. Local features and kernels for classification of texture and object categories: a comprehensive study, IJCV 2007.

Multi-class SVMs

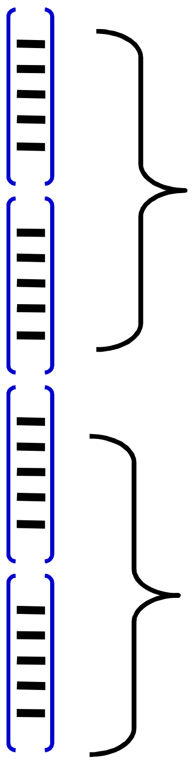
- Various direct formulations exist, but they are not widely used in practice. It is more common to obtain multi-class SVMs by combining two-class SVMs in various ways.

- 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

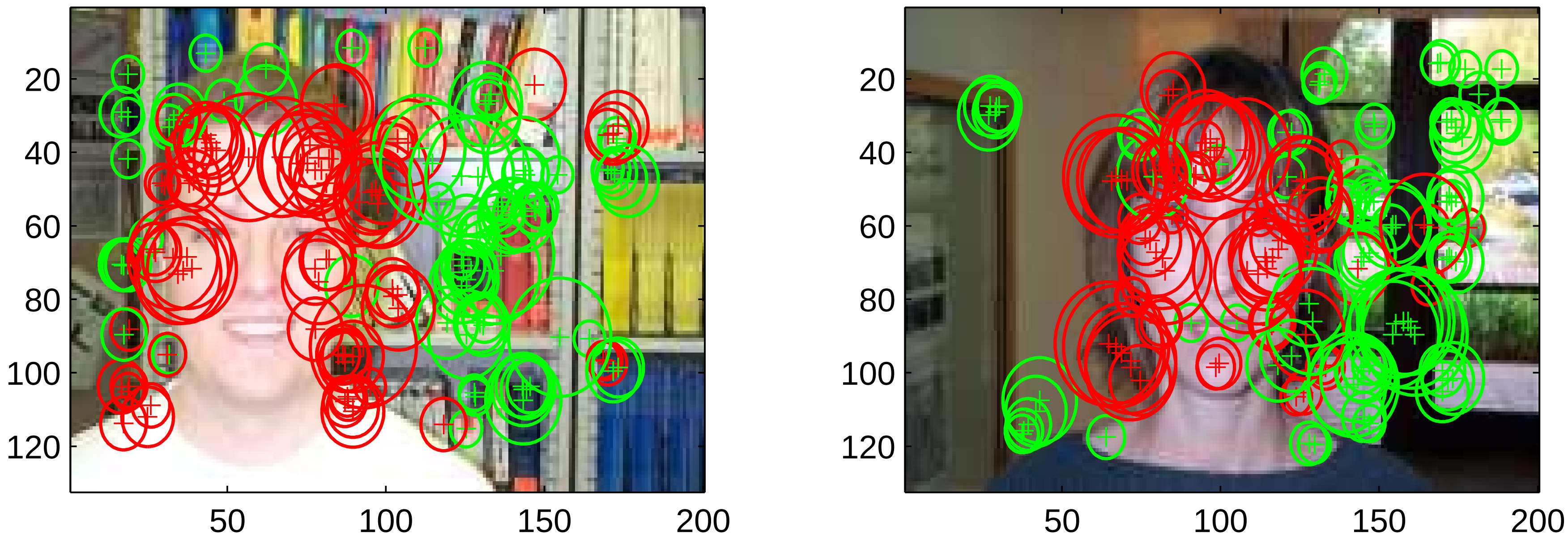


foreground words – high weight

background words – low weight

Illustration

Localization according to visual word probability



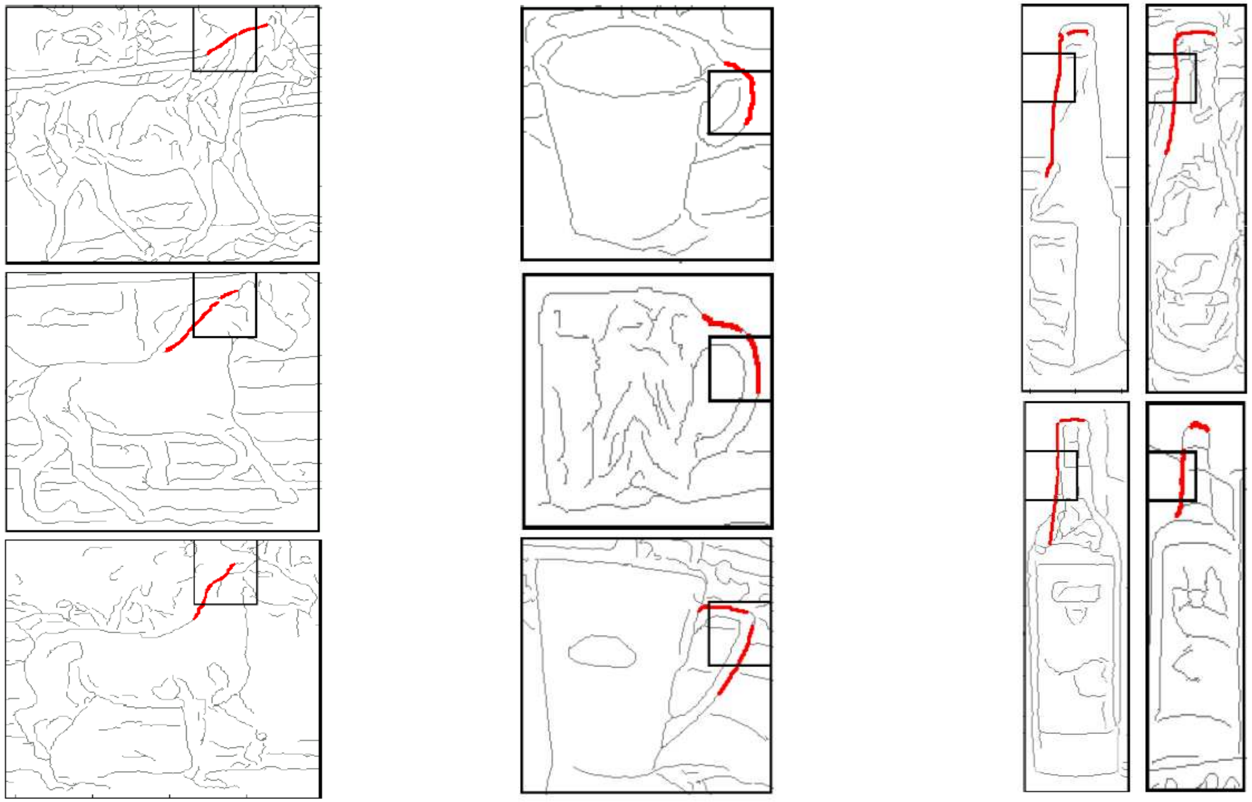
foreground word more probable

background word more probable

Illustration

A linear SVM trained from positive and negative window descriptors

A few of the highest weighted descriptor vector dimensions (= 'PAS + tile')



+ lie on object boundary (= local shape structures common to many training exemplars)

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

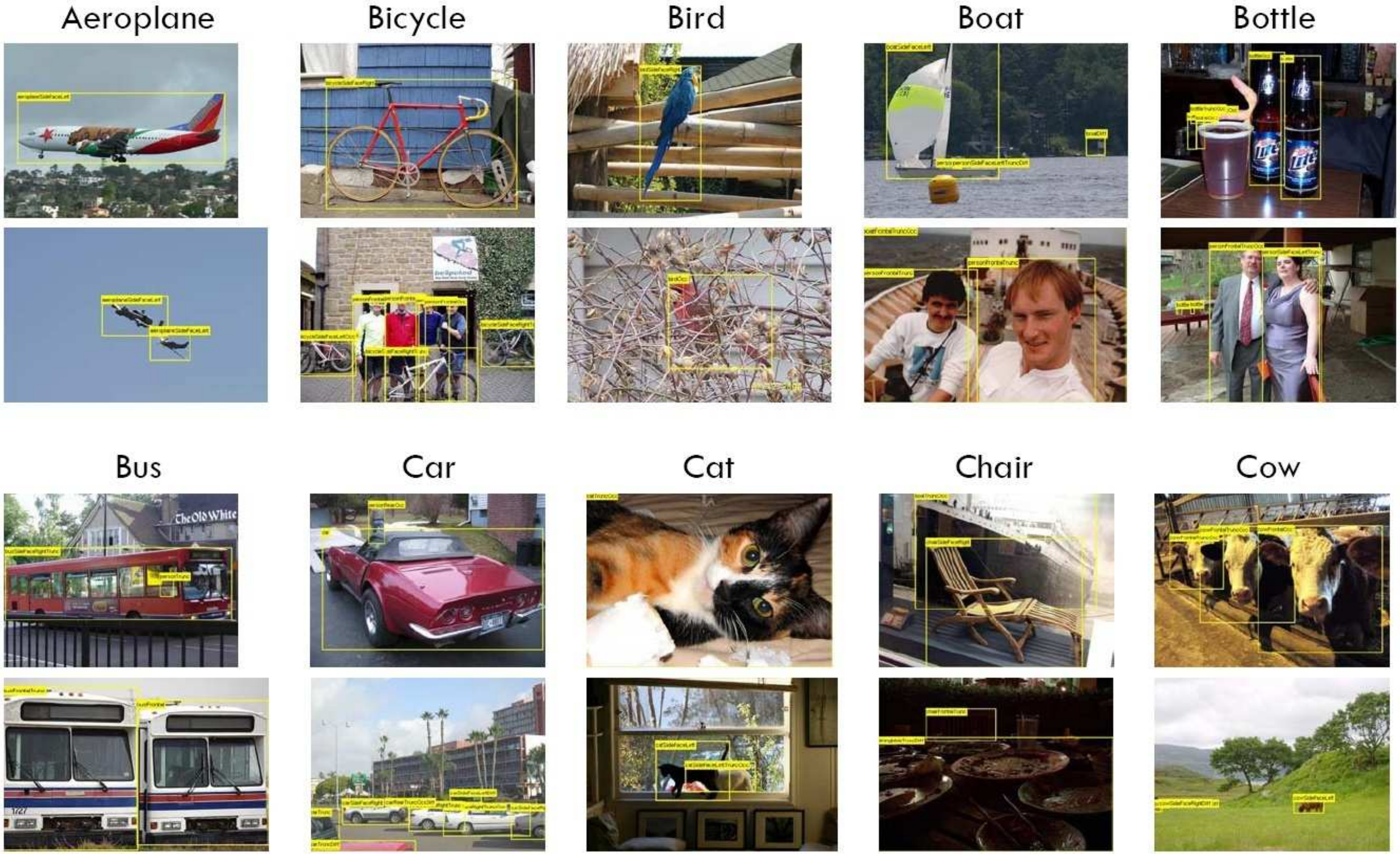
Evaluation of image classification

- PASCAL VOC [05-10] datasets

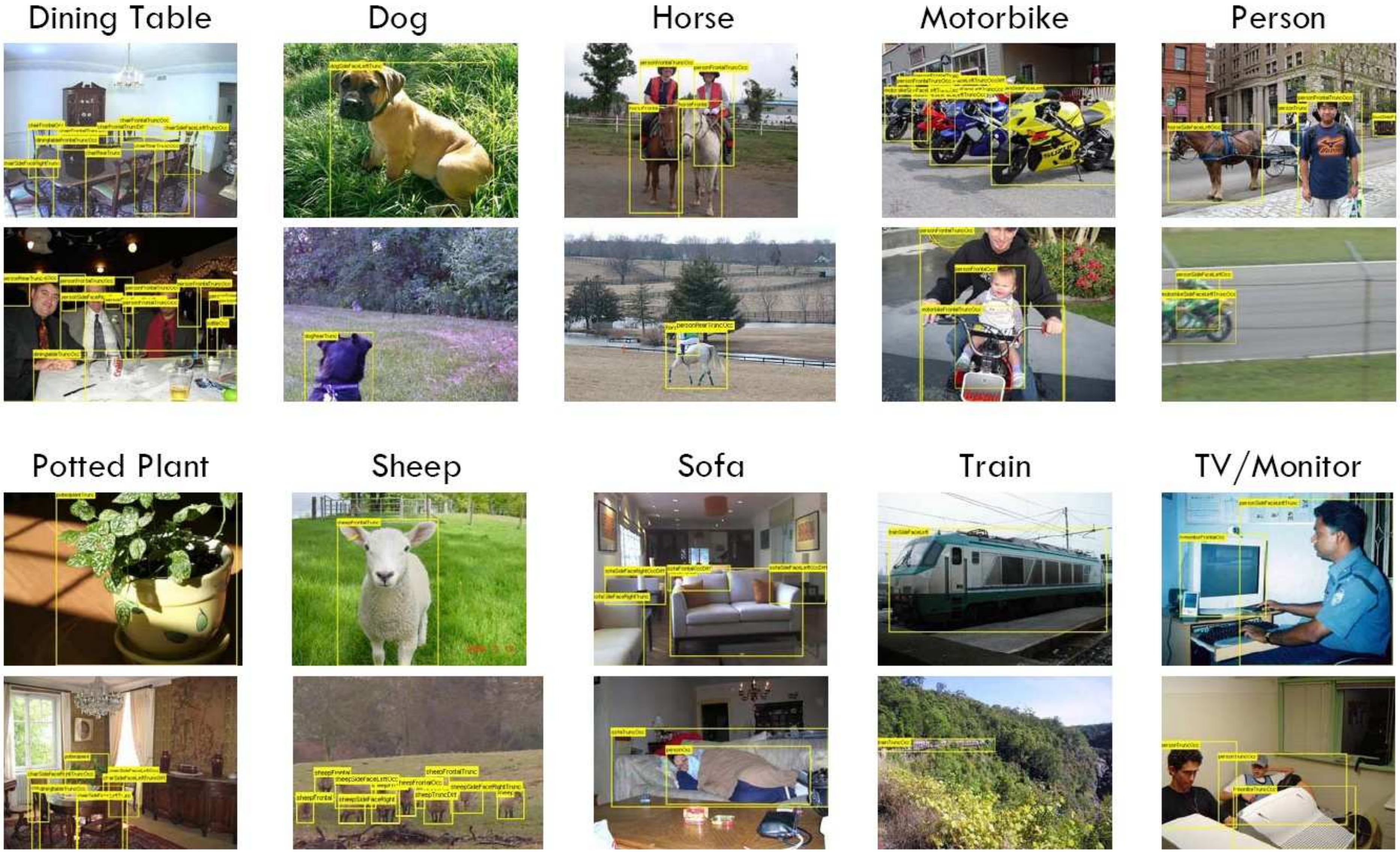
- PASCAL VOC 2007
  - Training *and* test dataset available
  - Used to report state-of-the-art results
  - Collected January 2007 from Flickr
  - 500 000 images downloaded and random subset selected
  - 20 classes
  - Class labels per image + bounding boxes
  - 5011 training images, 4952 test images

- Evaluation measure: average precision

PASCAL 2007 dataset

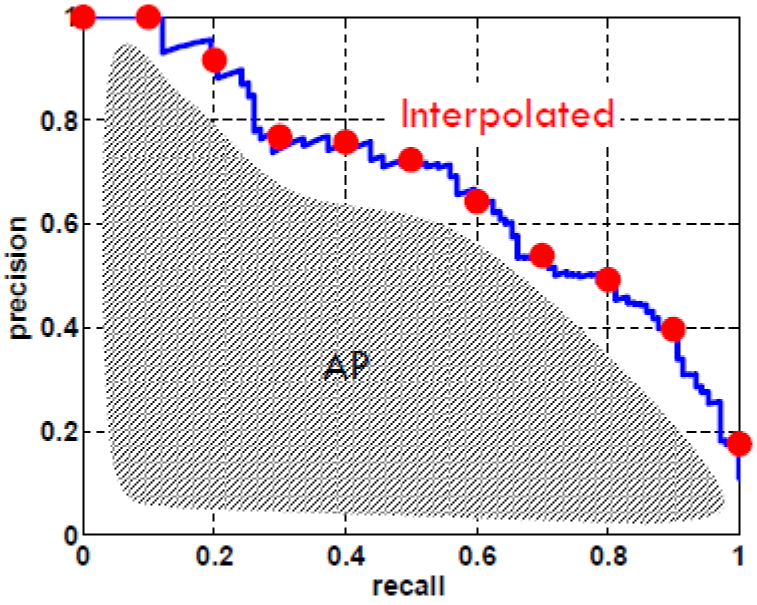


PASCAL 2007 dataset



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

Results for PASCAL 2007

- Winner of PASCAL 2007 [Marszalek et al.] : mAP 59.4
  - Combination of several different channels (dense + interest points, SIFT + color descriptors, spatial grids)
  - Non-linear SVM with Gaussian kernel
- Multiple kernel learning [Yang et al. 2009] : mAP 62.2
  - Combination of several features
  - Group-based MKL approach
- Combining object localization and classification [Harzallah et al.'09] : mAP 63.5
  - Use detection results to improve classification
- …..

Comparison interest point - dense

Image classification results on PASCAL'07 train/val set

Method: bag-of-features + χ^2 -SVM classifier

	AP
(SHarris + Lap) x SIFT	0.452
MSDense x SIFT	0.489
(SHarris + Lap + MSDense) x SIFT	0.515

Dense is on average a bit better!

IP and dense are complementary, combination improves results.

Comparison interest point - dense

Image classification results on PASCAL'07 train/val set for individual categories

	(SHarris + Lap) x SIFT	MSDense x SIFT
Bicycle	**0.534**	0.443
PottedPlant	**0.234**	0.167
Bird	0.342	**0.497**
Boat	0.482	**0.622**

Results are category dependent!

Spatial pyramid matching

- Add spatial information to the bag-of-features
- Perform matching in 2D image space

[Lazebnik, Schmid & Ponce, CVPR 2006]

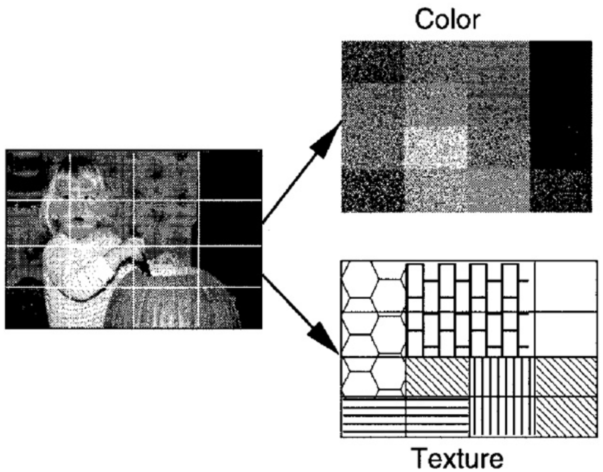
Related work

Similar approaches:

Subblock description [Szummer & Picard, 1997]

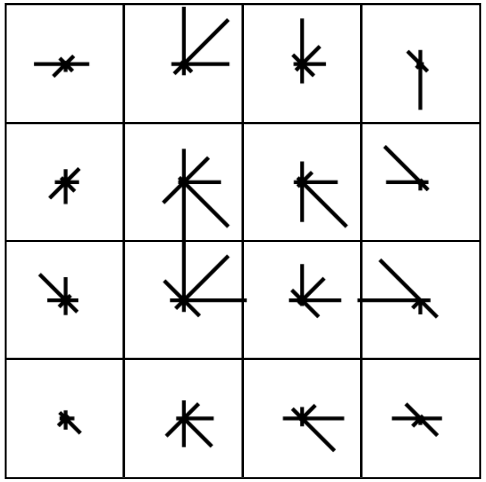
SIFT [Lowe, 1999]

GIST [Torralba et al., 2003]



Szummer & Picard (1997)

SIFT

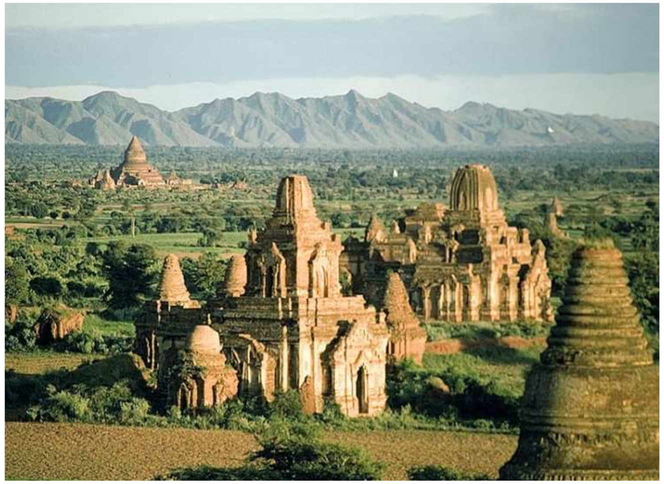


Lowe (1999, 2004)

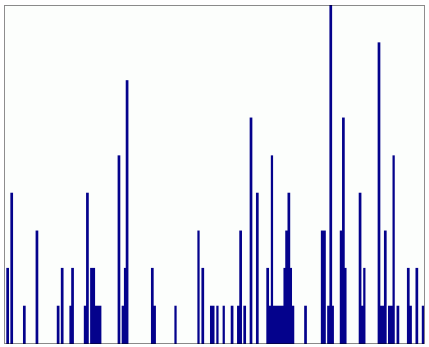
Gist

Torralba et al. (2003)

Spatial pyramid representation

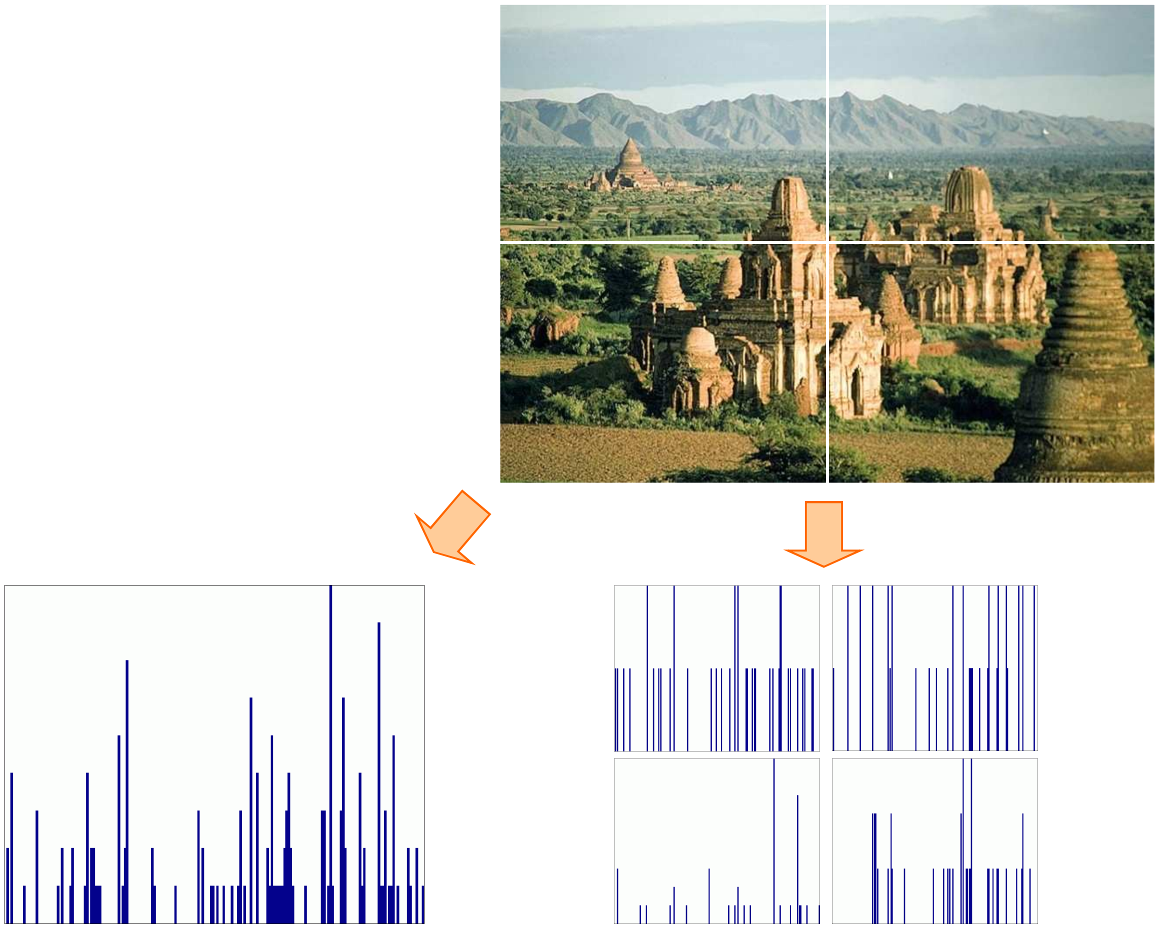


Locally orderless representation at several levels of spatial resolution



level 0

Spatial pyramid representation

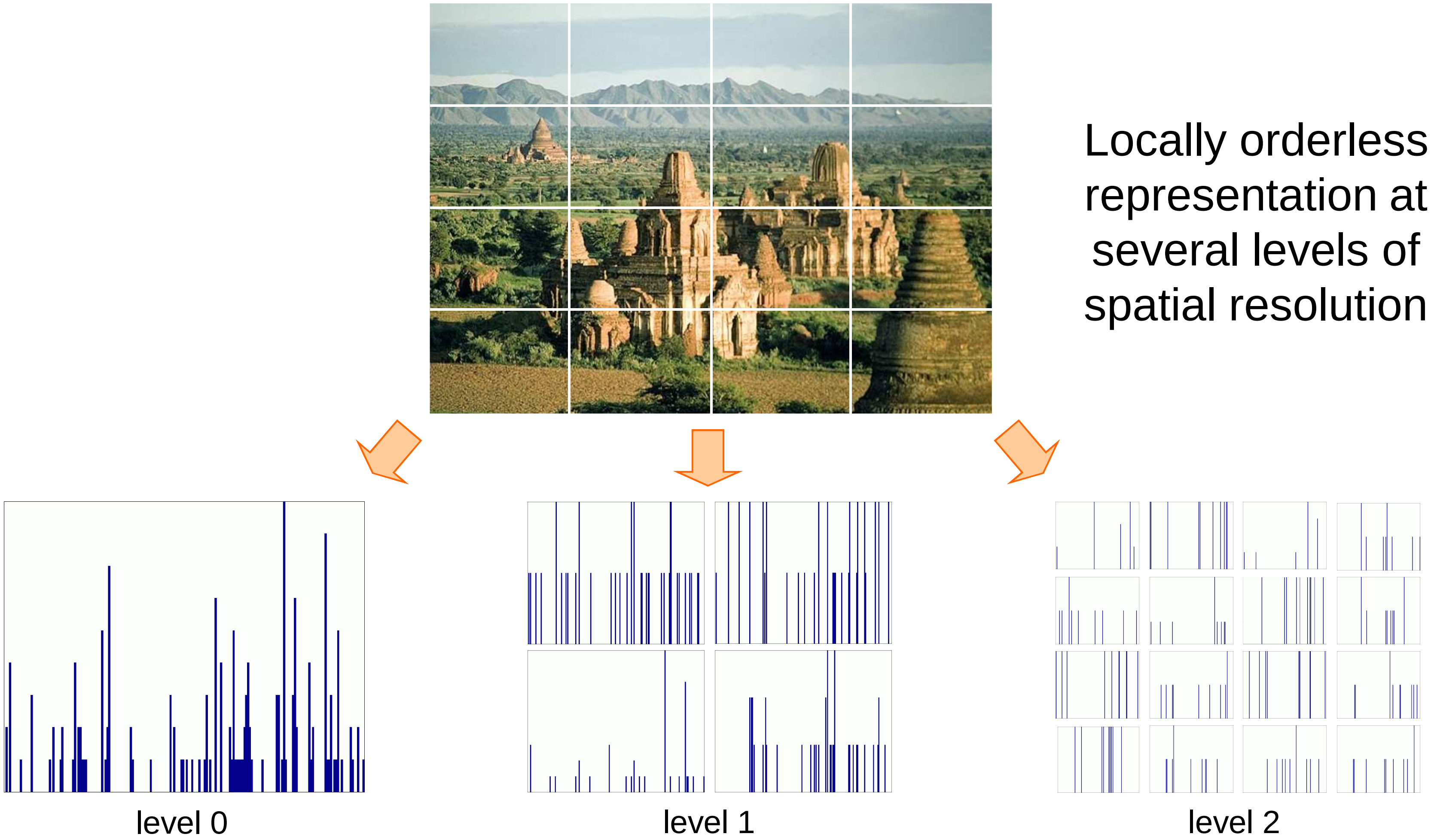


level 0 level 1

Locally orderless representation at several levels of spatial resolution

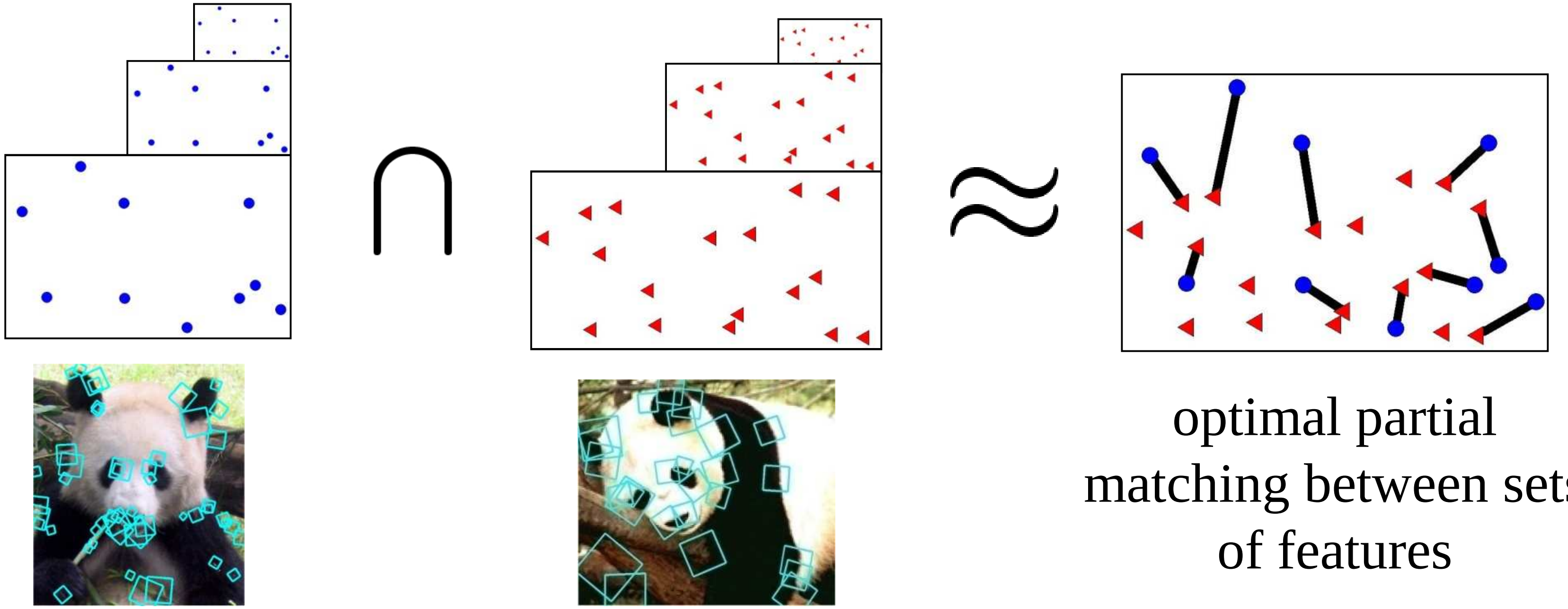
Spatial pyramid representation

Locally orderless representation at several levels of spatial resolution



Pyramid match kernel

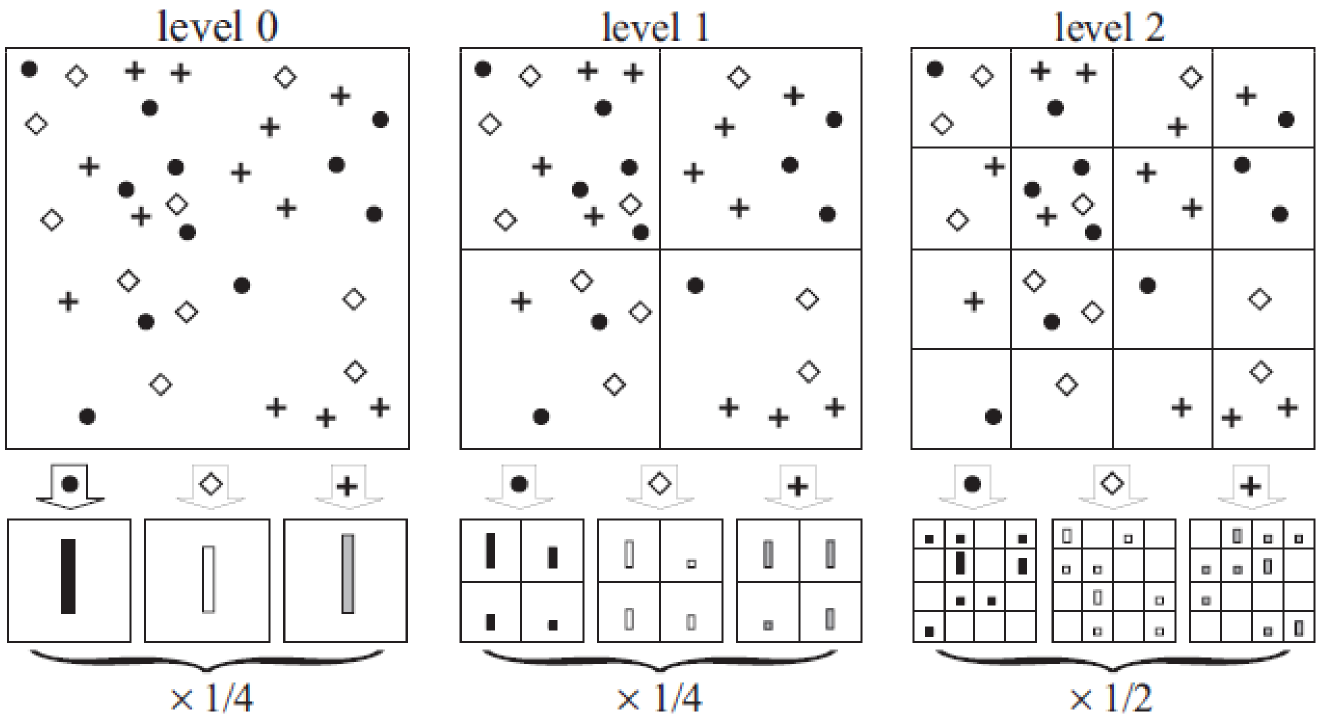
- Weighted sum of histogram intersections at multiple resolutions (linear in the number of features instead of cubic)



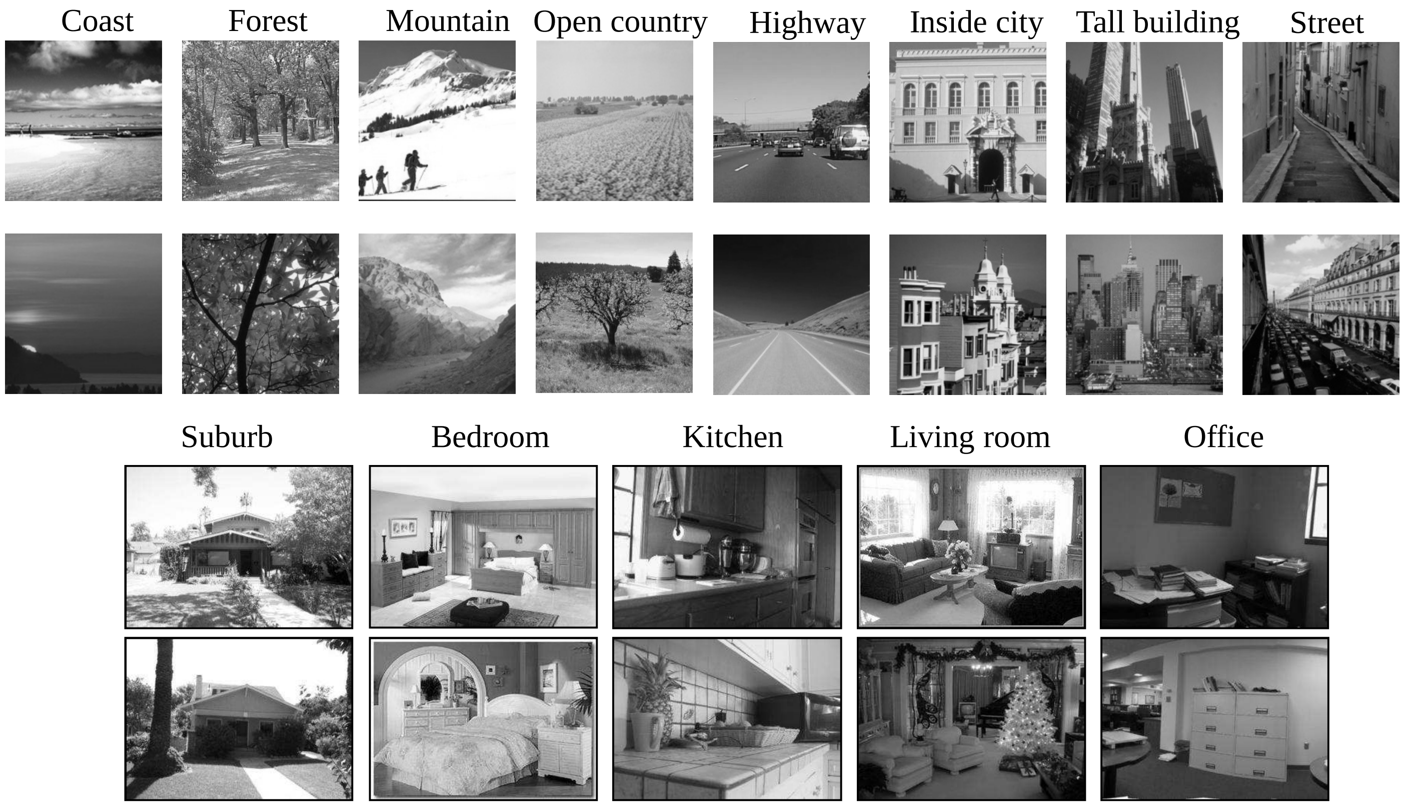
optimal partial matching between sets of features

Spatial pyramid matching

- Combination of spatial levels with pyramid match kernel
  [Grauman & Darell'05]
- Intersect histograms, more weight to finer grids



Scene dataset [Labzenik et al.'06]



4385 images

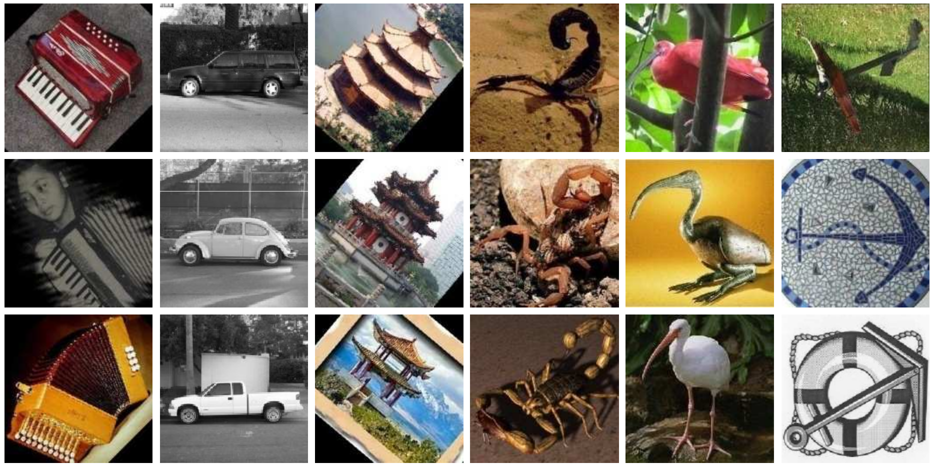
15 categories

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

Retrieval examples

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**

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

Evaluation BoF - spatial

Image classification results on PASCAL'07 train/val set for individual categories

	1	3x1
Sheep	**0.339**	0.256
Bird	**0.539**	0.484
DiningTable	0.455	**0.502**
Train	0.724	**0.745**

Results are category dependent!

➔ Combination helps somewhat

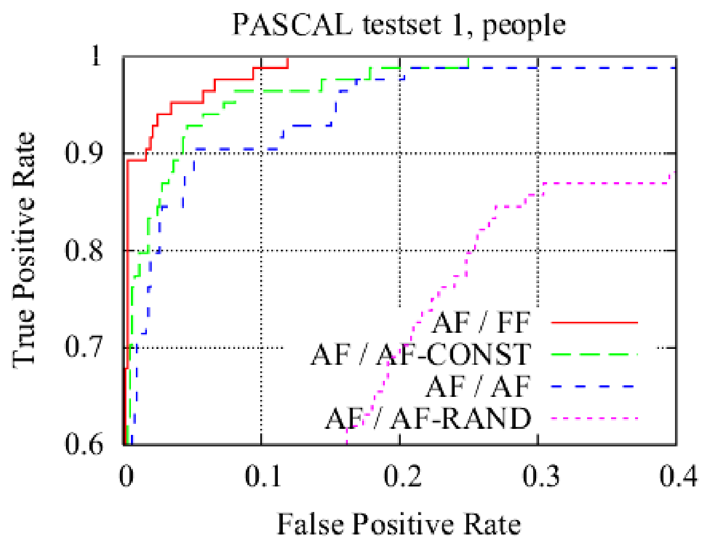
Discussion

- 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

- Extensions
  - Flexible, object-centered grid

Motivation

- Evaluating the influence of background features [J. Zhang et al., IJCV'07]
  - Train and test on different combinations of foreground and background by separating features based on bounding boxes



Training: original training set

Testing: different combinations foreground + background features

Best results when testing with foreground features only

Approach

- Better to train on a “harder” dataset with background clutter and test on an easier one without background clutter

- Spatial weighting for bag-of-features [Marszalek & Schmid, CVPR’06]
  - weight features by the likelihood of belonging to the object
  - determine likelihood based on shape masks

Masks for spatial weighting

For each test feature:

- Select closest training features + corresponding masks
(training requires segmented images or bounding boxes)

- Align mask based on local co-ordinates system
(transformation between training and test co-ordinate systems)

Sum masks weighted by matching distance

three features agree on object localization,
the object has higher weights

Weight histogram features with the strength of the final mask

Example masks for spatial weighting

Classification for PASCAL dataset

	Zhang et al.	Spatial weighting	Gain
bikes	74.8	76.8	+2.0
cars	75.8	76.8	+1.0
motorbikes	78.8	79.3	+0.5
people	76.9	77.9	+1.0

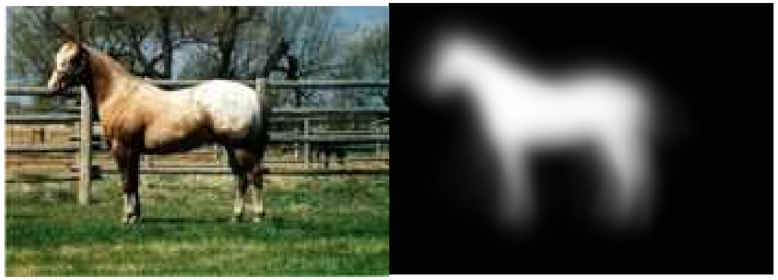
Equal error rates for PASCAL'06 test set 2

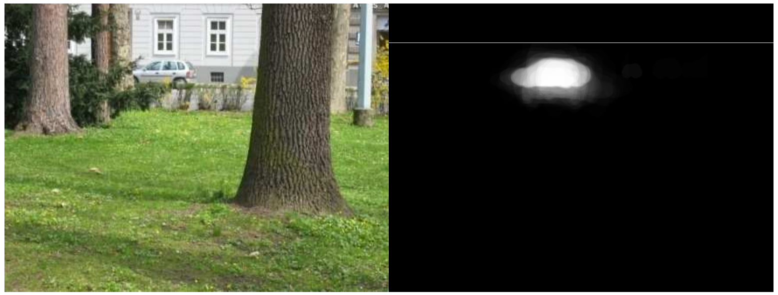
Extension to localization

- Cast hypothesis
  - Aligning the mask based on matching features
- Evaluate each hypothesis
  - SVM for local features
- Merge hypothesis to produce localization decisions
  - Online clustering of similar hypothesis, rejection of weak ones

[Marszalek & Schmid, CVPR 2007]

Localization results



Discussion

- Including spatial information improves results
- Importance of flexible modeling of spatial information
  - coarse global position information
  - object based models

Recent extensions

- Linear Spatial Pyramid Matching Using Sparse Coding for Image Classification. J. Yang et al., CVPR'09.
  - Local coordinate coding, linear SVM, excellent results in last year's PASCAL challenge
- Learning Mid-level features for recognition, Y. Boureau et al., CVPR'10.
  - Use of sparse coding techniques and max pooling

Recent extensions

- Efficient Additive Kernels via Explicit Feature Maps, A. Vedaldi and Zisserman, CVPR’10.
  - approximation by linear kernels

- Improving the Fisher Kernel for Large-Scale Image Classification, Perronnin et al., ECCV’10
  - More discriminative descriptor, power normalization, linear SVM