Bag-of-features
for category classification

Cordelia Schmid

Category recognition

- Image classification: assigning a class label to the image

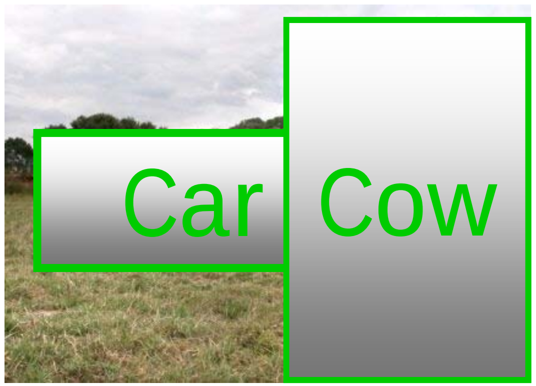
Car: present
Cow: present
Bike: not present
Horse: not present
...

Category recognition

- Image classification: assigning a class label to the image

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

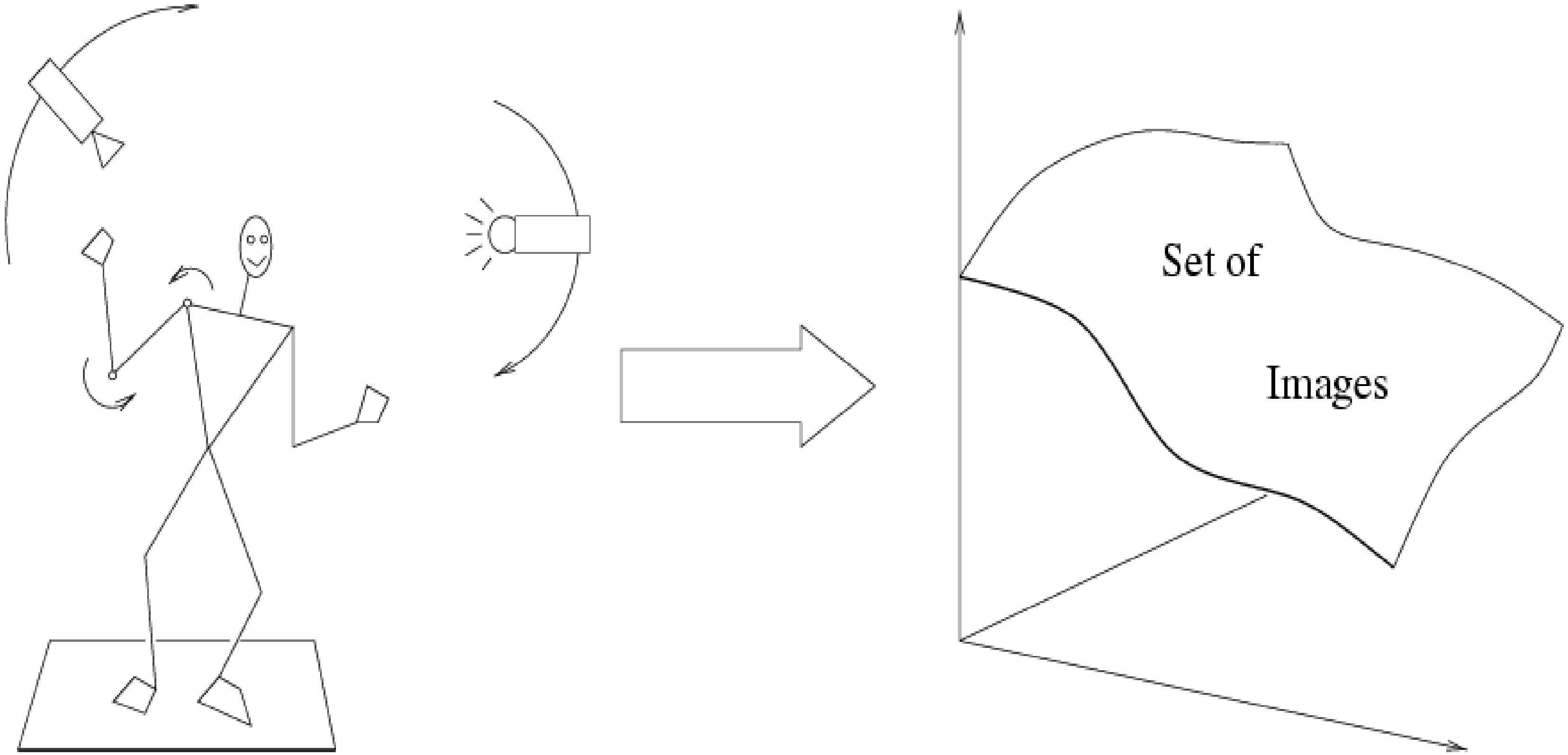
- Object localization: define the location and the category



Location

Category

Difficulties: within object variations



Variability: Camera position, Illumination,Internal parameters

Within-object variations

Difficulties: within-class variations






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

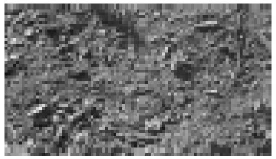
Image classification

- Given

    Positive training images containing an object class

    Negative training images that don't

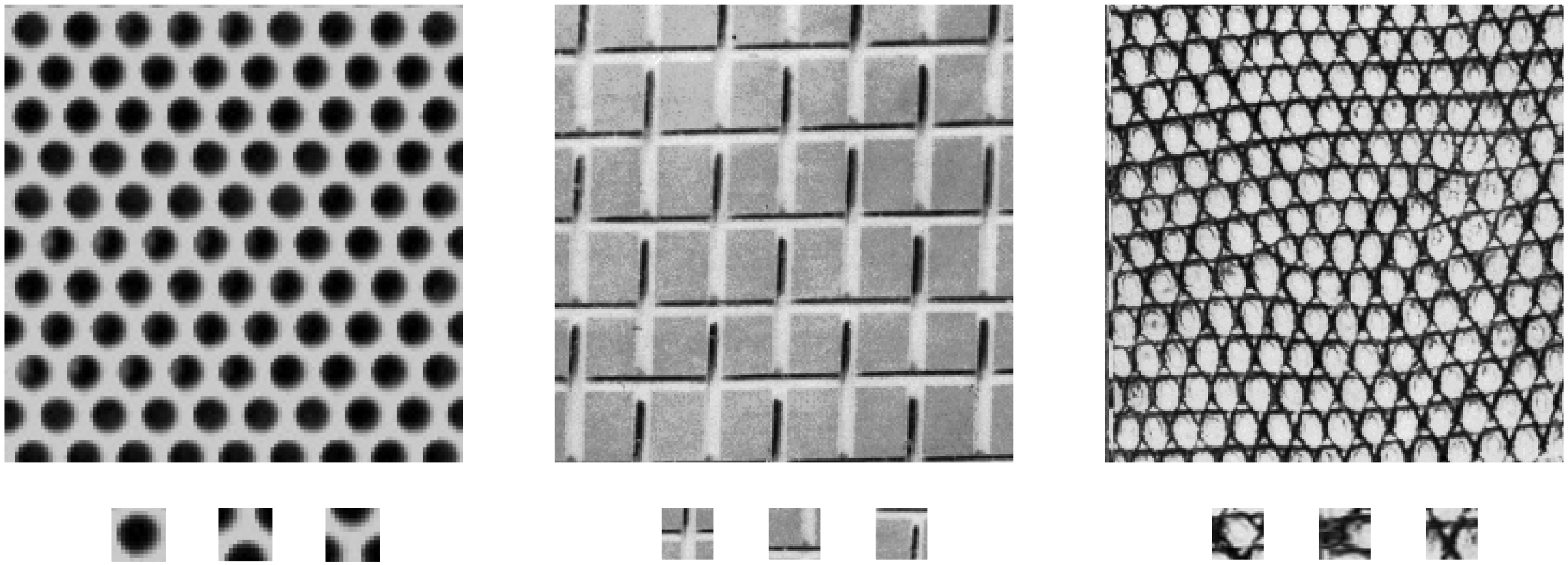
- Classify

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

?

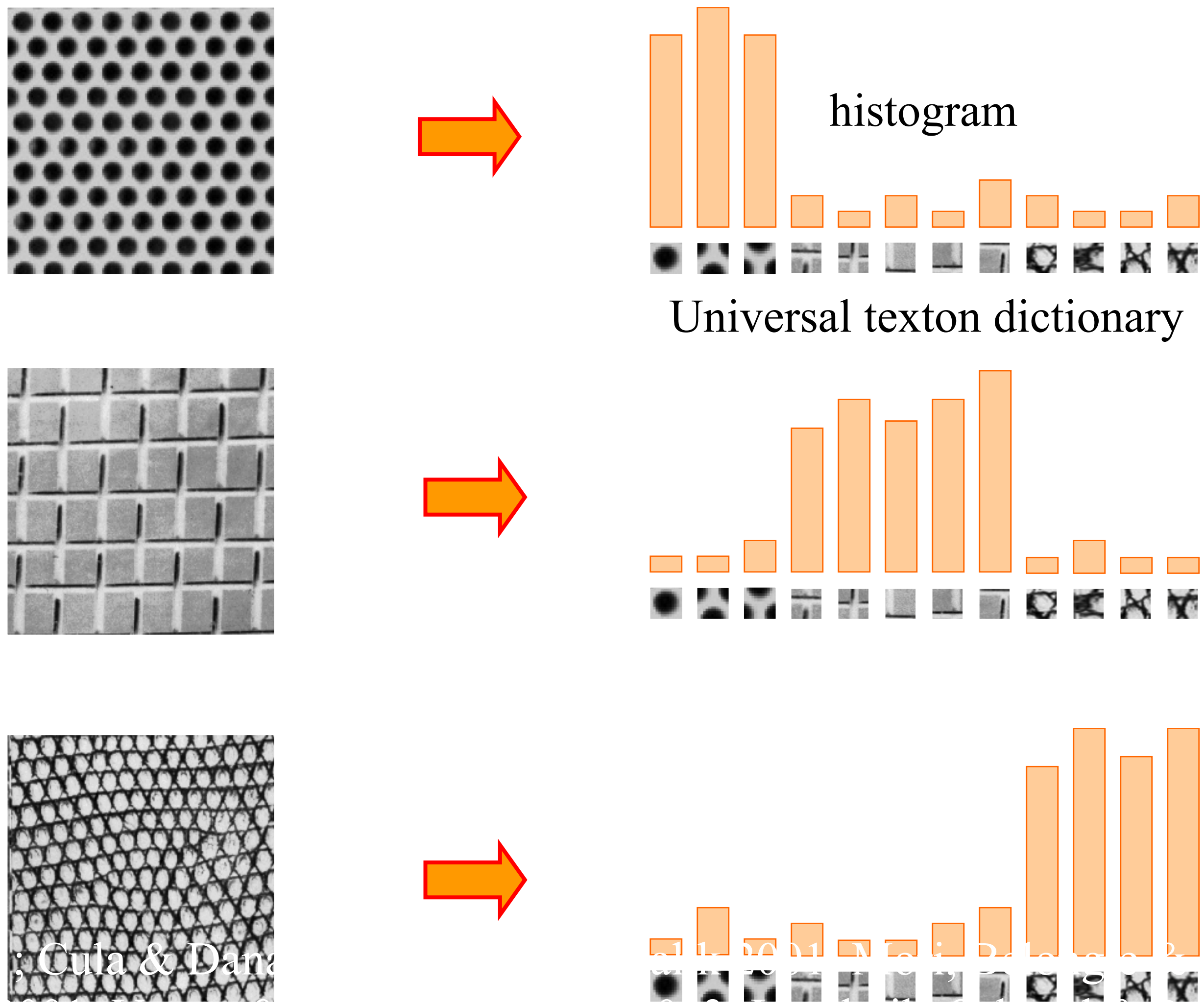
Bag-of-features for image classification

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

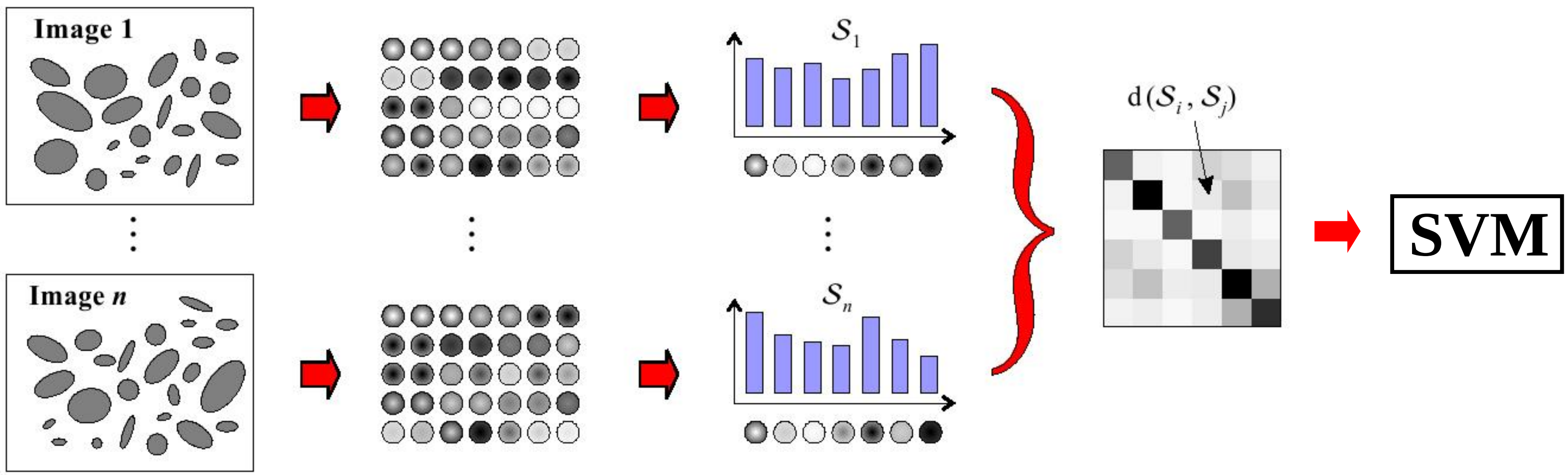


Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001
Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Texture recognition



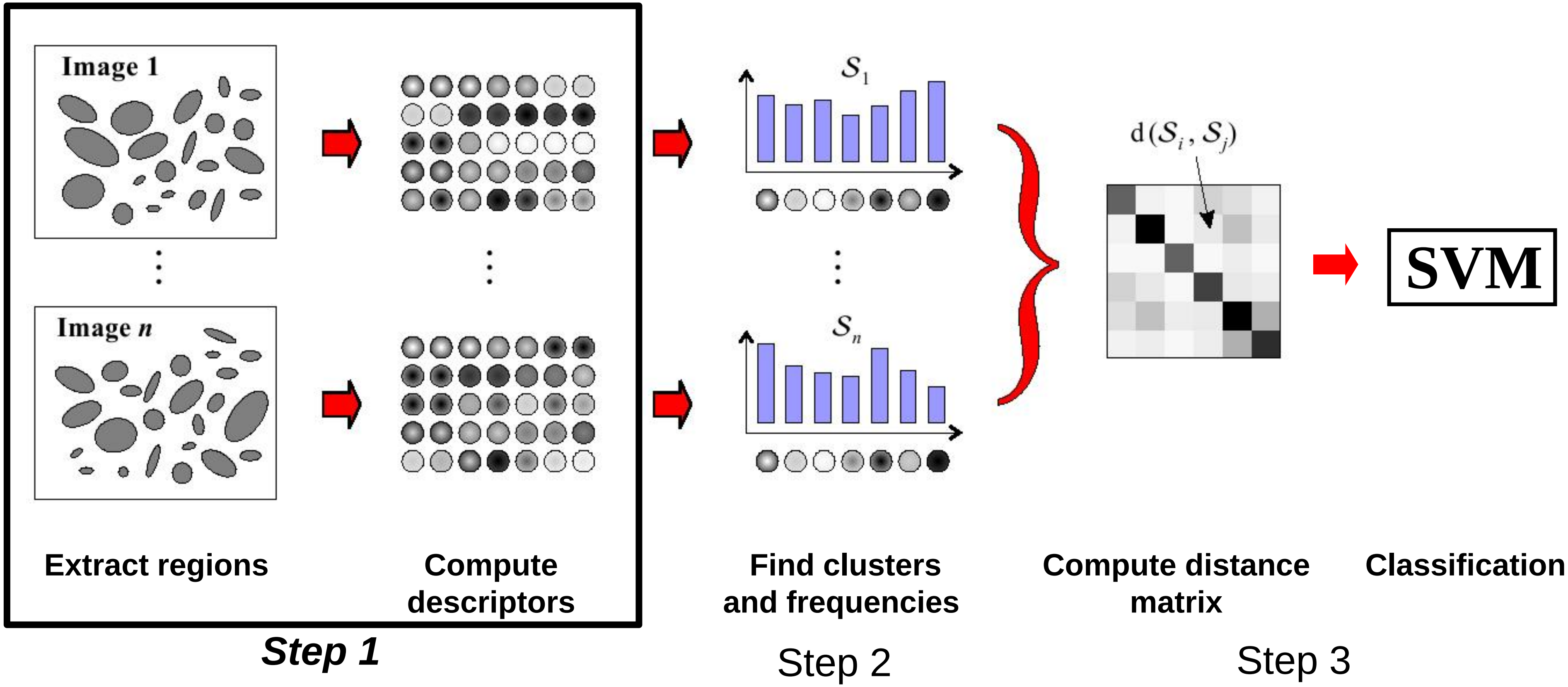
Bag-of-features for image classification



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]

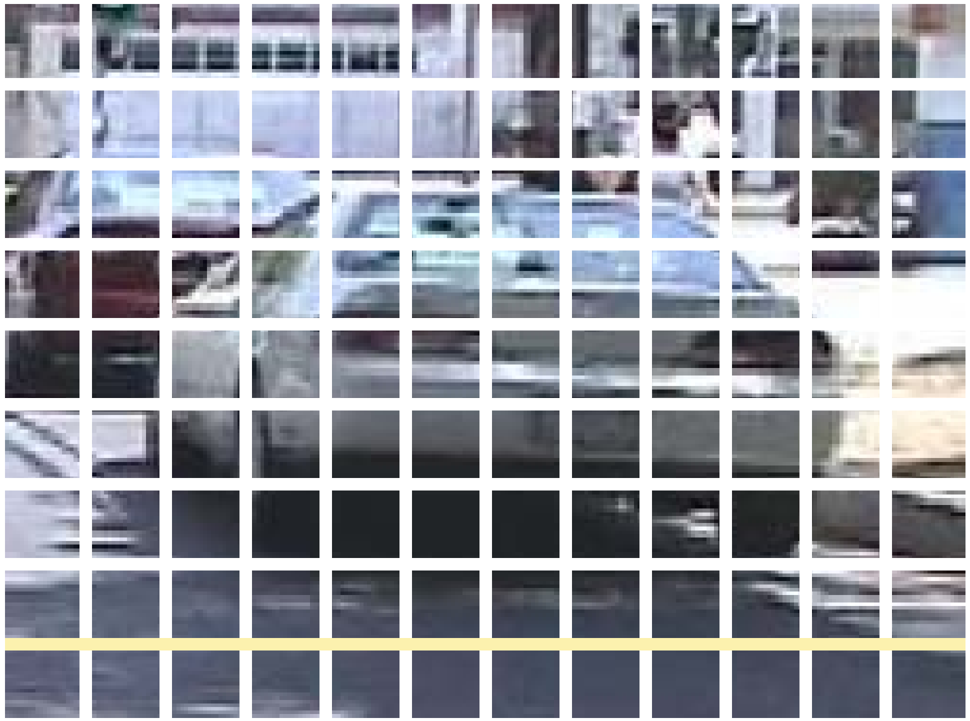
Bag-of-features for image classification



Step 1: feature extraction

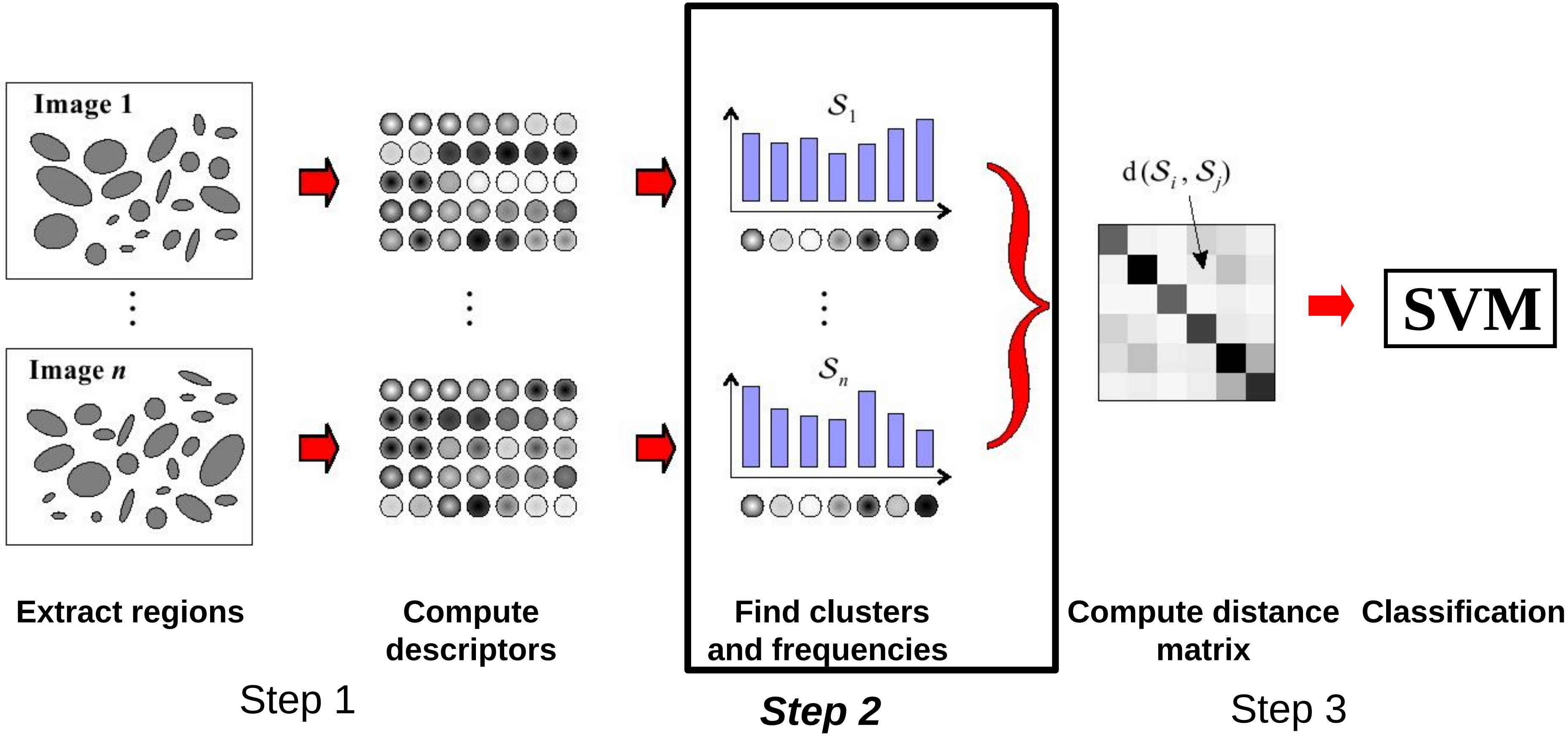
- Scale-invariant image regions + SIFT
  - Affine invariant regions give “too” much invariance
  - Rotation invariance for many realistic collections “too” much invariance
- Dense descriptors
  - Improve results in the context of categories (for most categories)
  - Interest points do not necessarily capture “all” features
- Color-based descriptors

Dense features

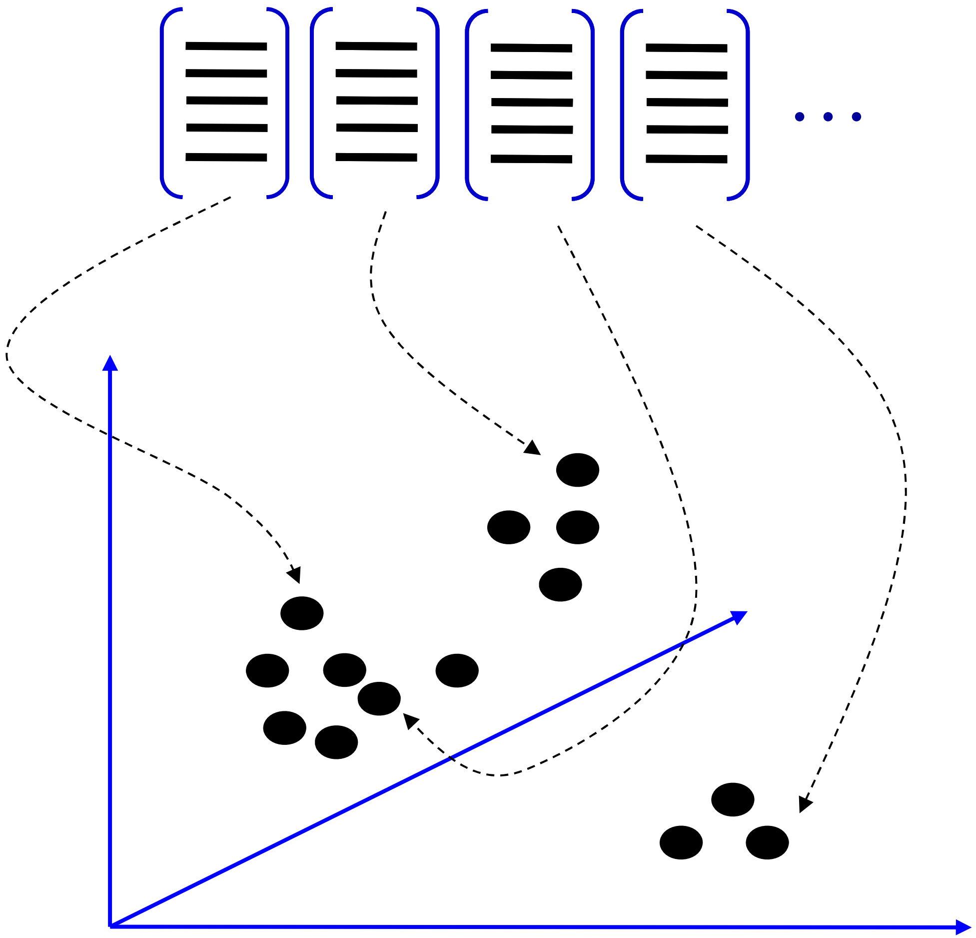


- Multi-scale dense grid: extraction of small overlapping patches at multiple scales
- Computation of the SIFT descriptor for each grid cells
- Exp.: Horizontal/vertical step size 3-6 pixel, scaling factor of 1.2 per level

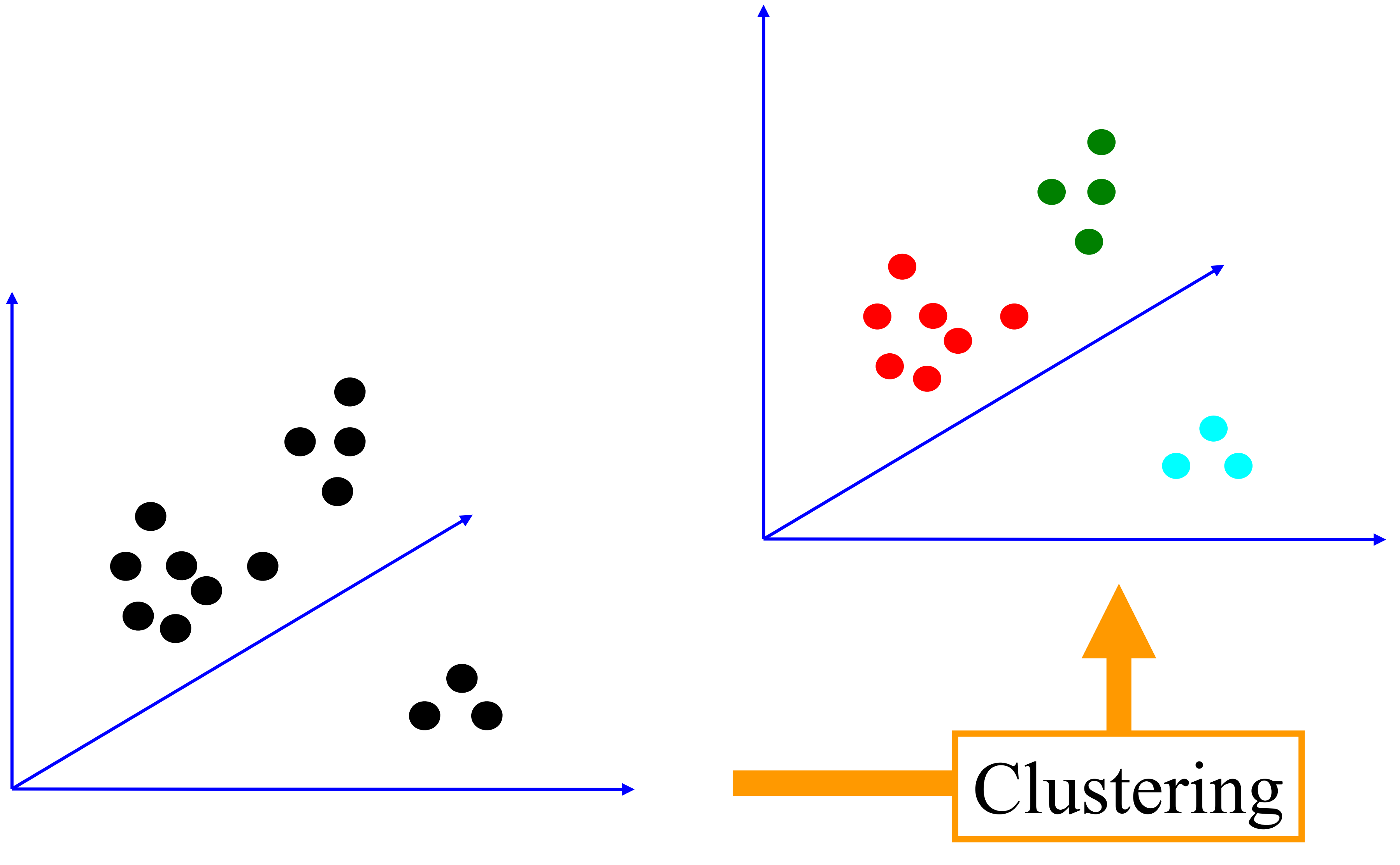
Bag-of-features for image classification



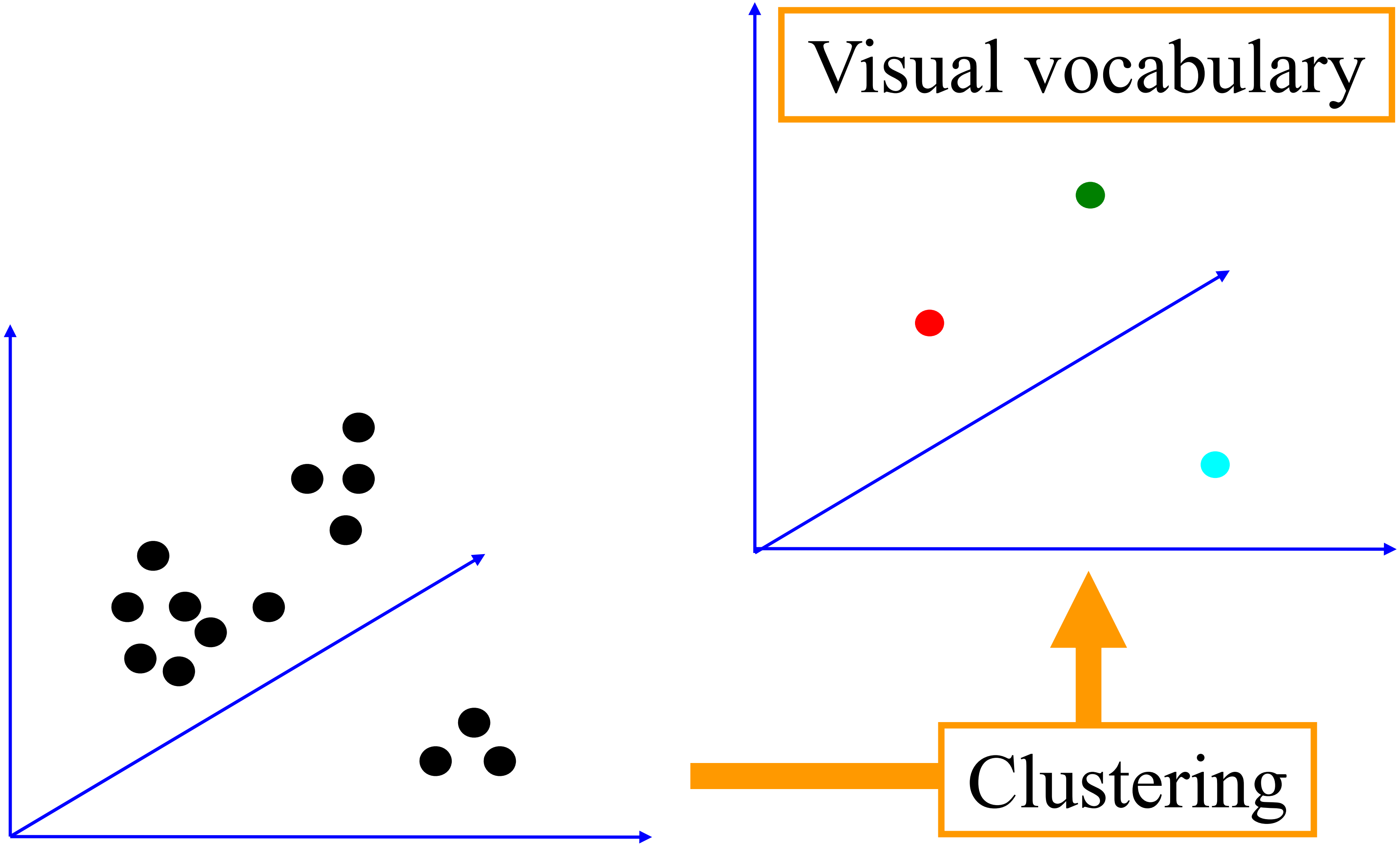
Step 2: Quantization



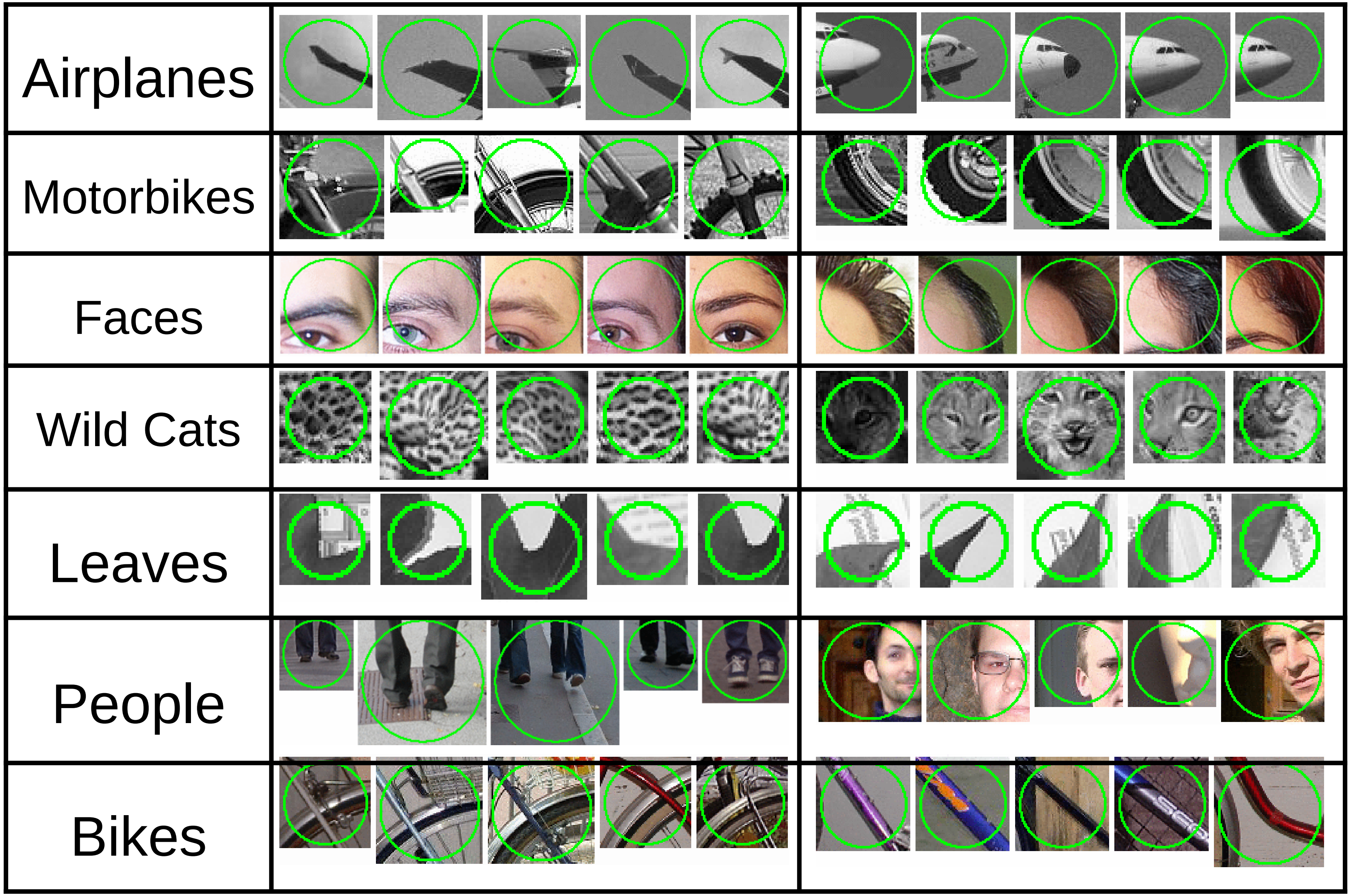
Step 2:Quantization



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

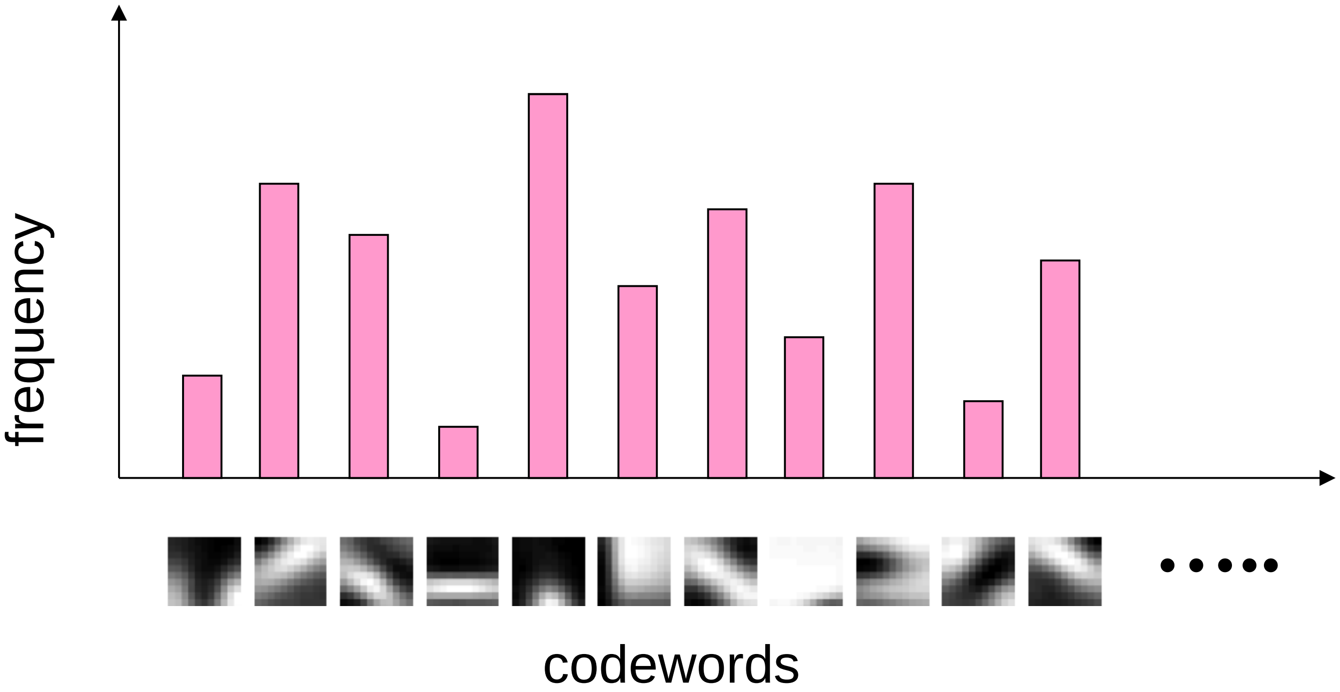
Hard or soft assignment

- 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

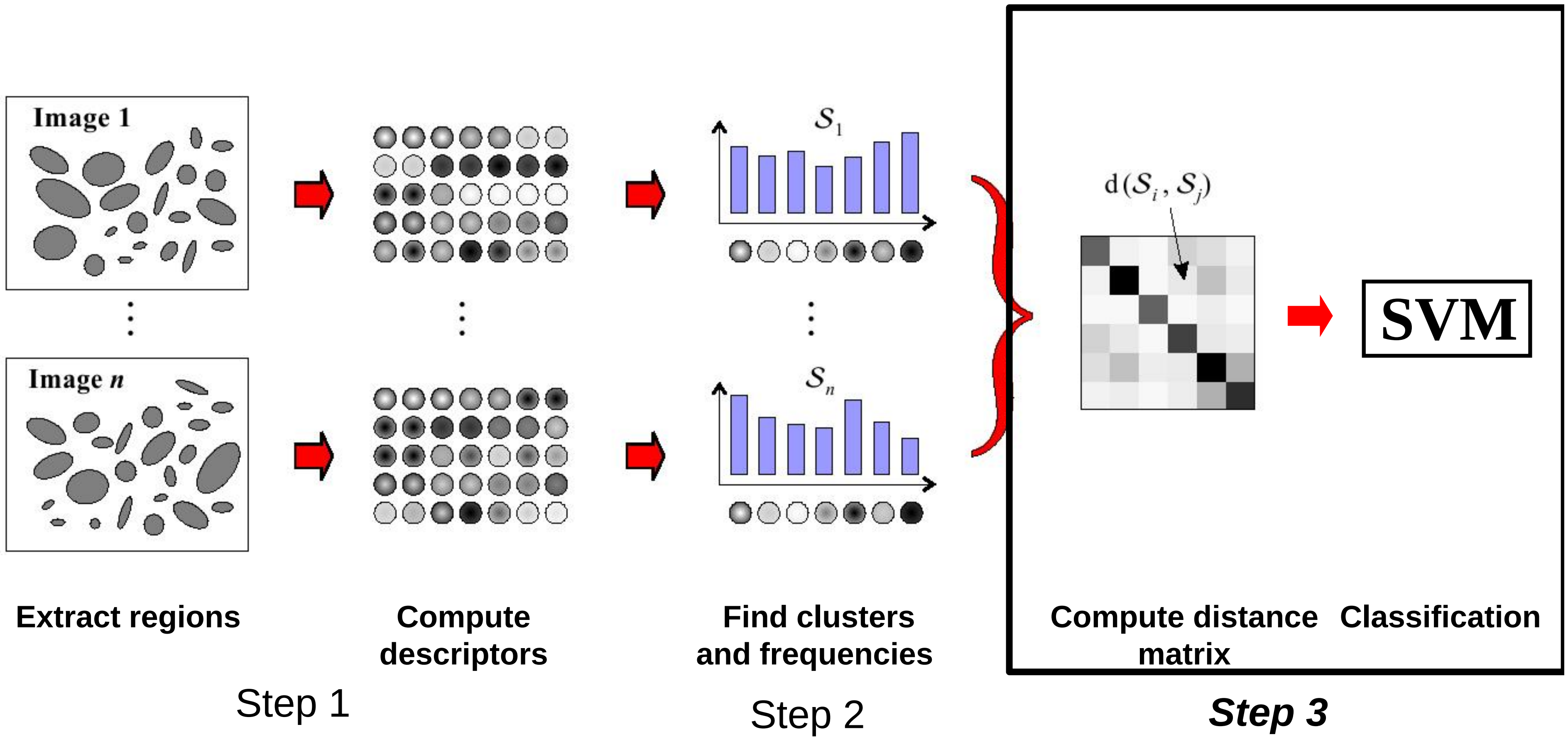


• each image is represented by a vector, typically 1000-4000 dimension, normalization with L2 norm

• fine grained – represent model instances

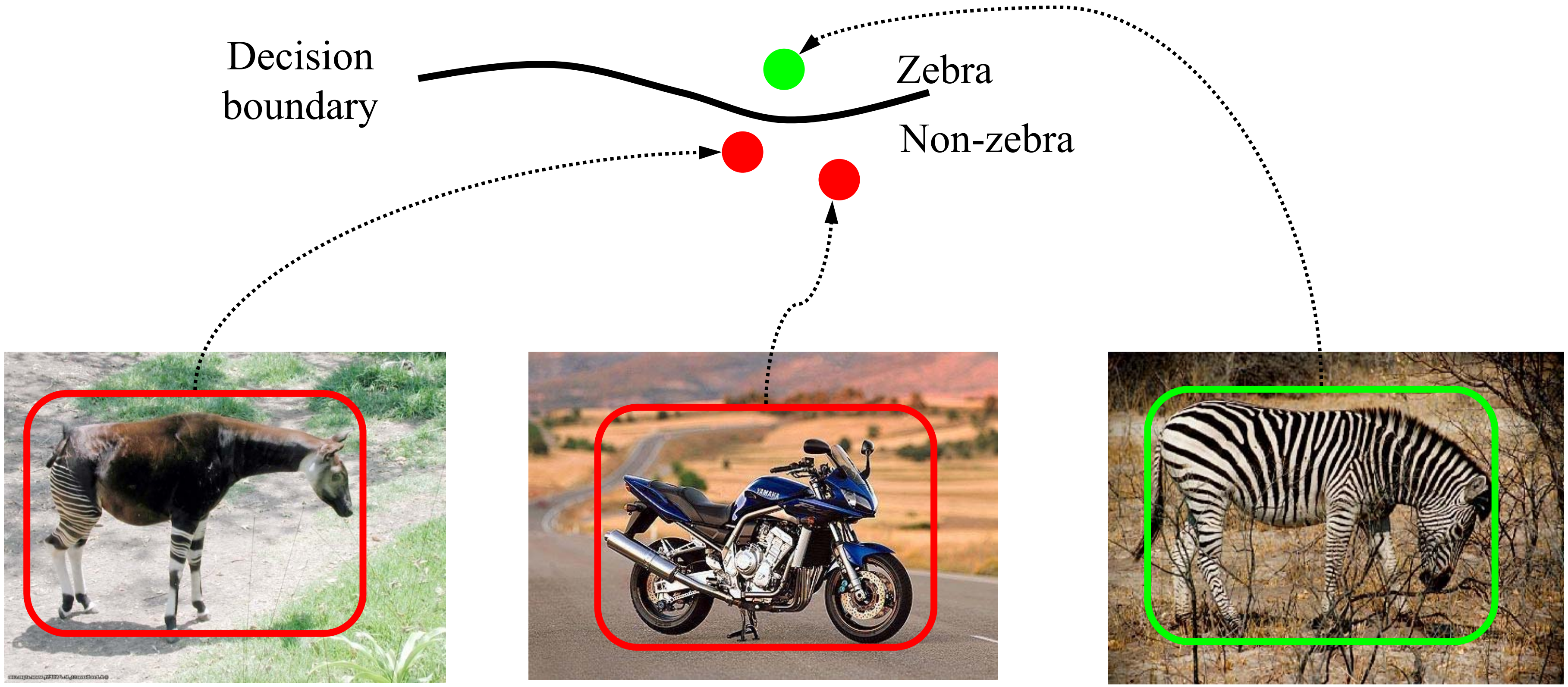
• coarse grained – represent object categories

Bag-of-features for image classification



Step 3: Classification

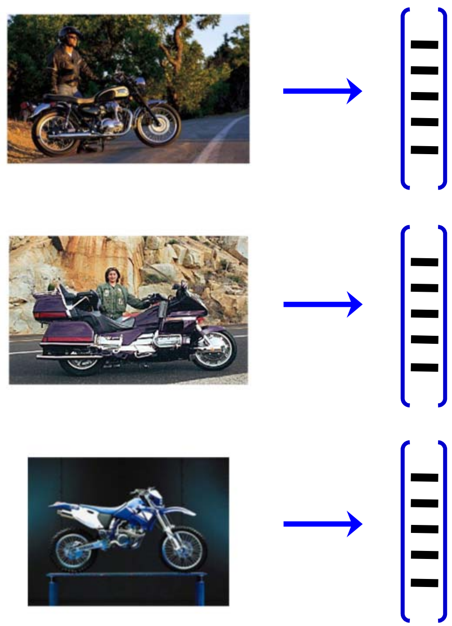
- Learn a decision rule (classifier) assigning bag-of-features representations of images to different classes



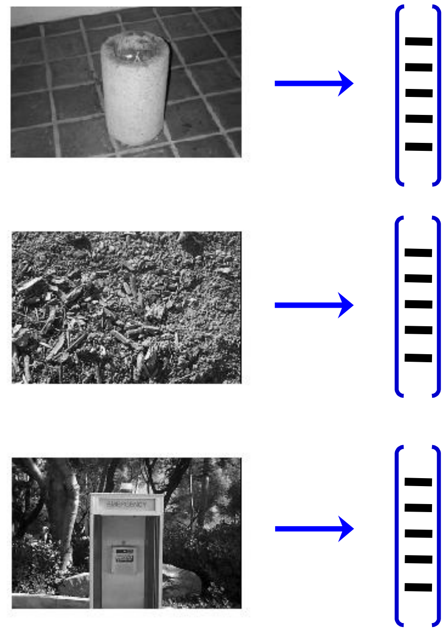
Training data

Vectors are histograms, one from each training image

positive



negative



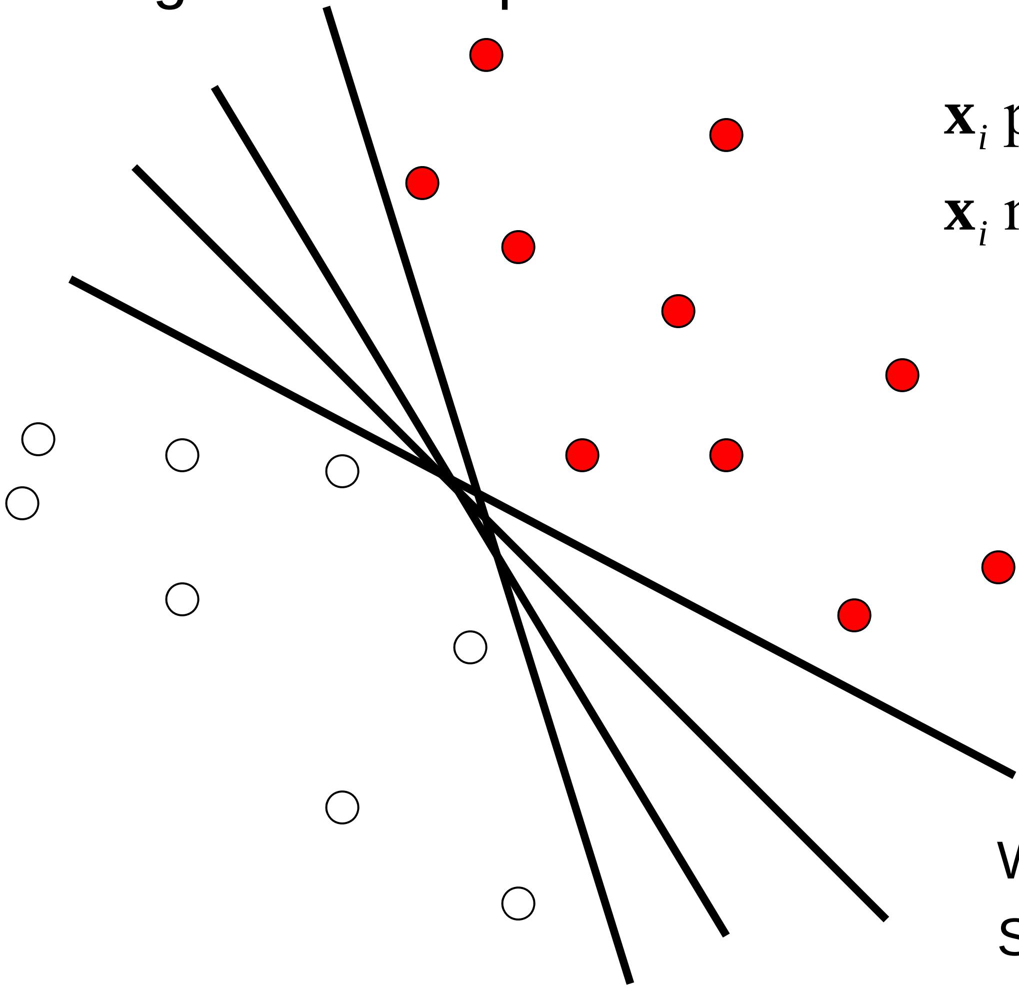
Train classifier,e.g.SVM

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?

Support Vector Machine (SVM)

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

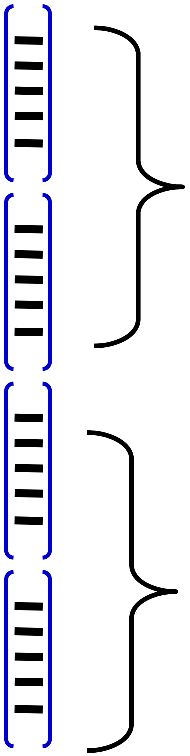
- Mutli-class formulations exist, but they are not widely used in practice. It is more common to obtain multi-class SVMs by combining two-class SVMs in various ways.

- 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

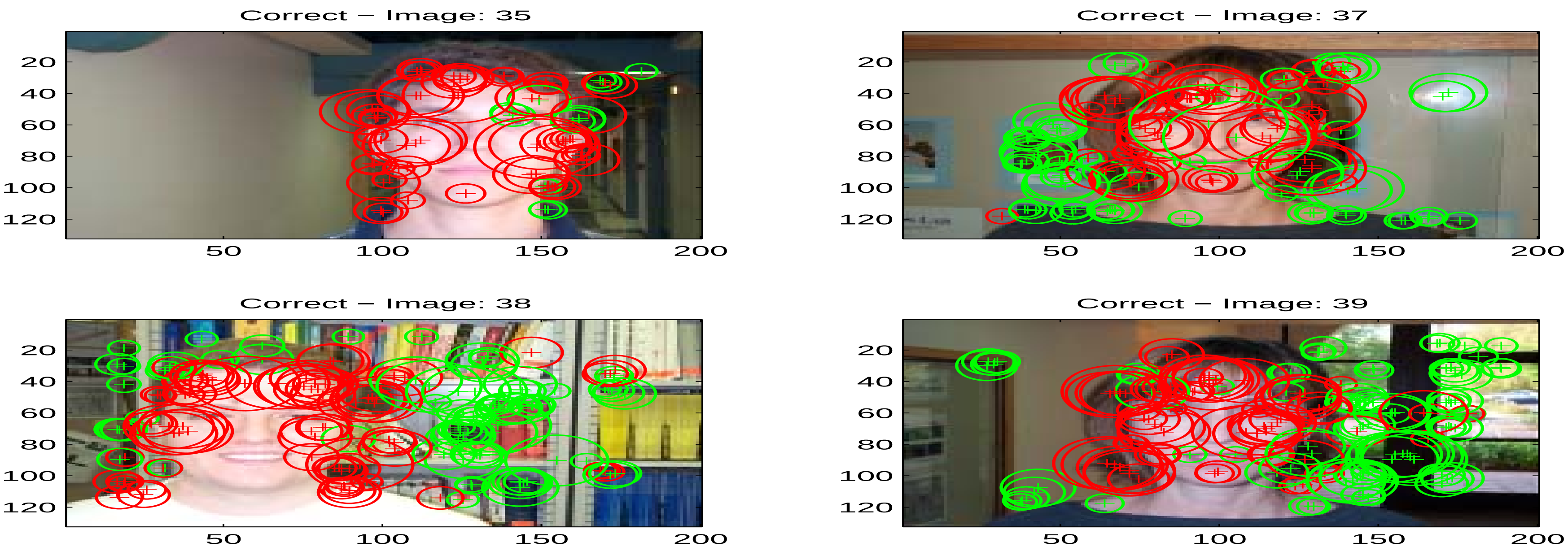


foreground words – high weight

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

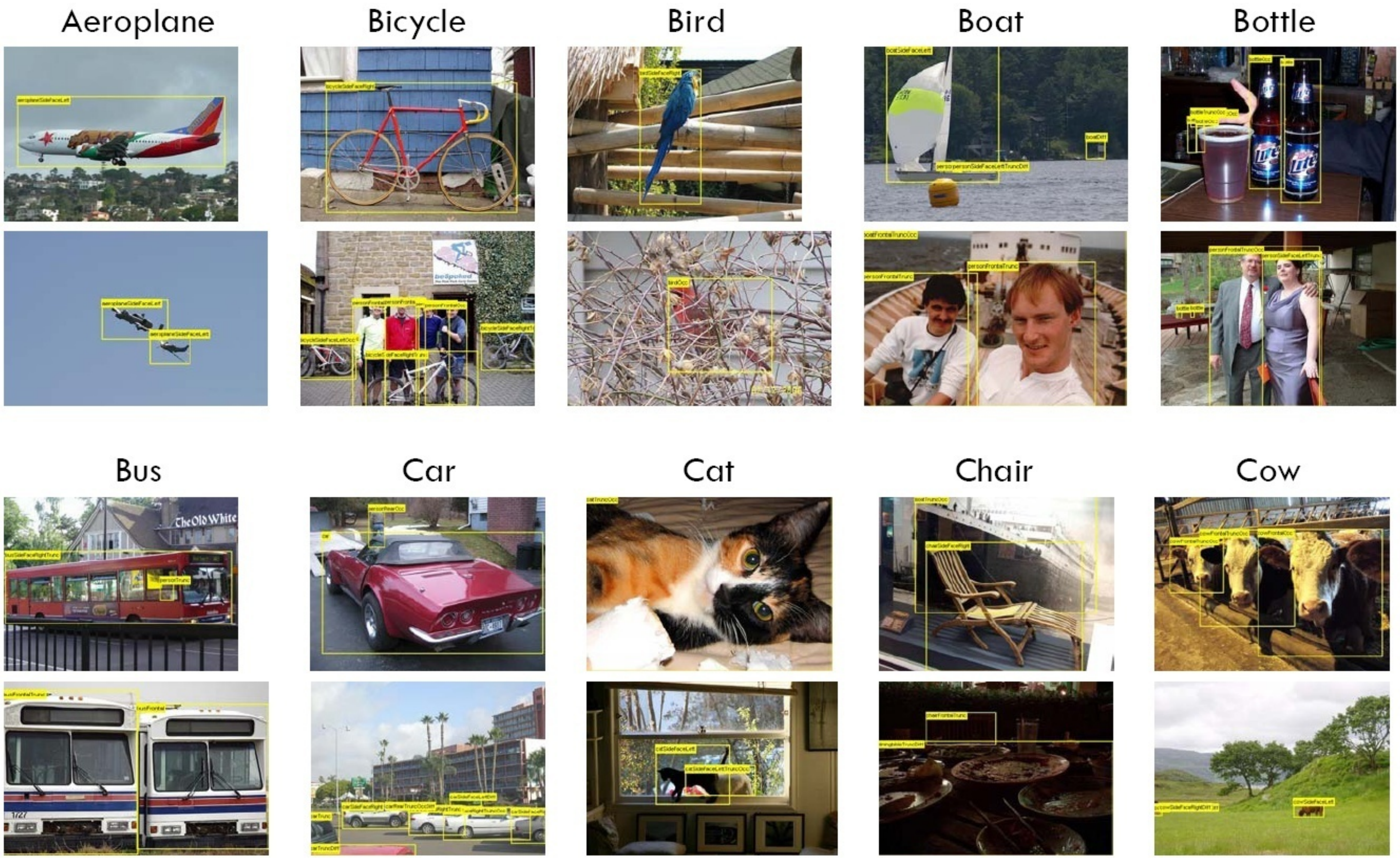
Evaluation of image classification (object localization)

- 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

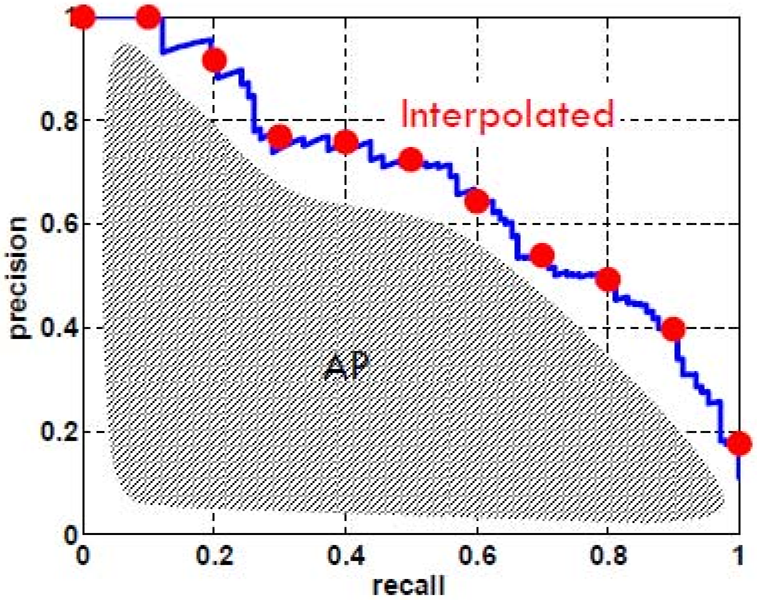
- ImageNet Large Scale Visual Recognition Challenge 2010 (ILSVRC)
  - 1000 classes and 1.4M images
- ImageNet10K dataset
  - 10184 classes and ~ 9 M images

(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

Results for PASCAL 2007

- Winner of PASCAL 2007 [Marszalek et al.] : mAP 59.4
  - Combining several channels with non-linear SVM and Gaussian kernel
- Multiple kernel learning [Yang et al. 2009] : mAP 62.2
  - Combination of several features, Group-based MKL approach
- Object localization & classification [Harzallah et al.'09] : mAP 63.5
  - Use detection results to improve classification
- Adding objectness boxes [Sanchez at al.'12] : mAP 66.3
- Convolutional Neural Networks [Oquab et al.'14] : mAP 77.7

Spatial pyramid matching

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

[Lazebnik, Schmid & Ponce, CVPR 2006]

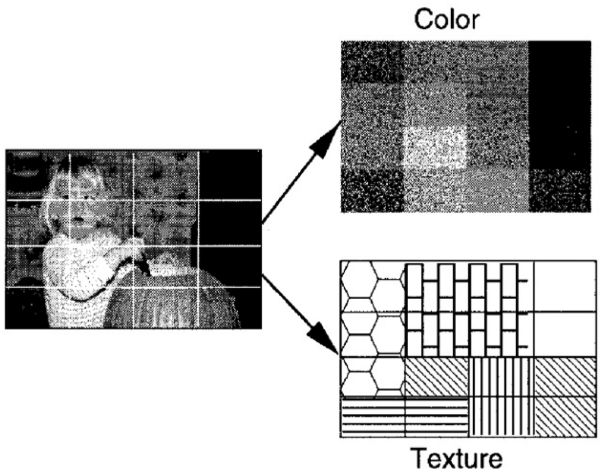
Related work

Similar approaches:

Subblock description [Szummer & Picard, 1997]

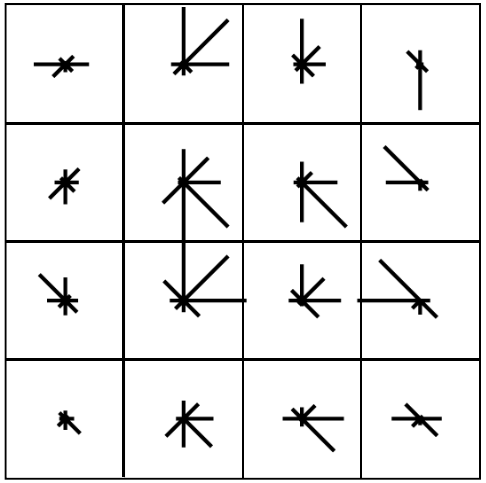
SIFT [Lowe, 1999]

GIST [Torralba et al., 2003]



Szummer & Picard (1997)

SIFT

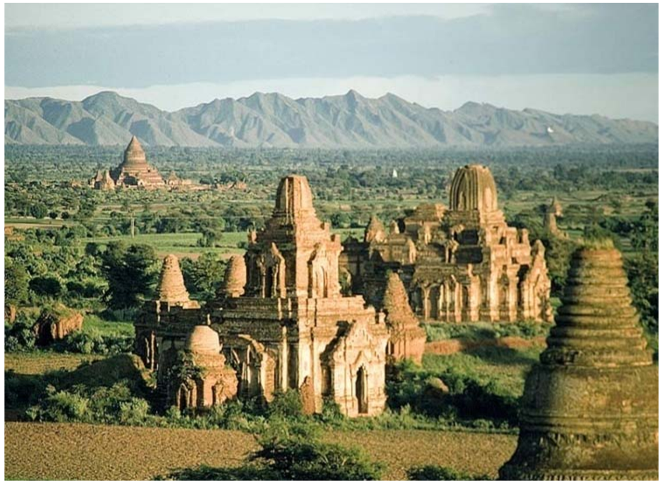


Lowe (1999, 2004)

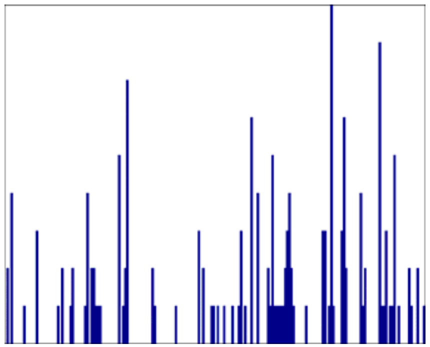
Gist

Torralba et al. (2003)

Spatial pyramid representation

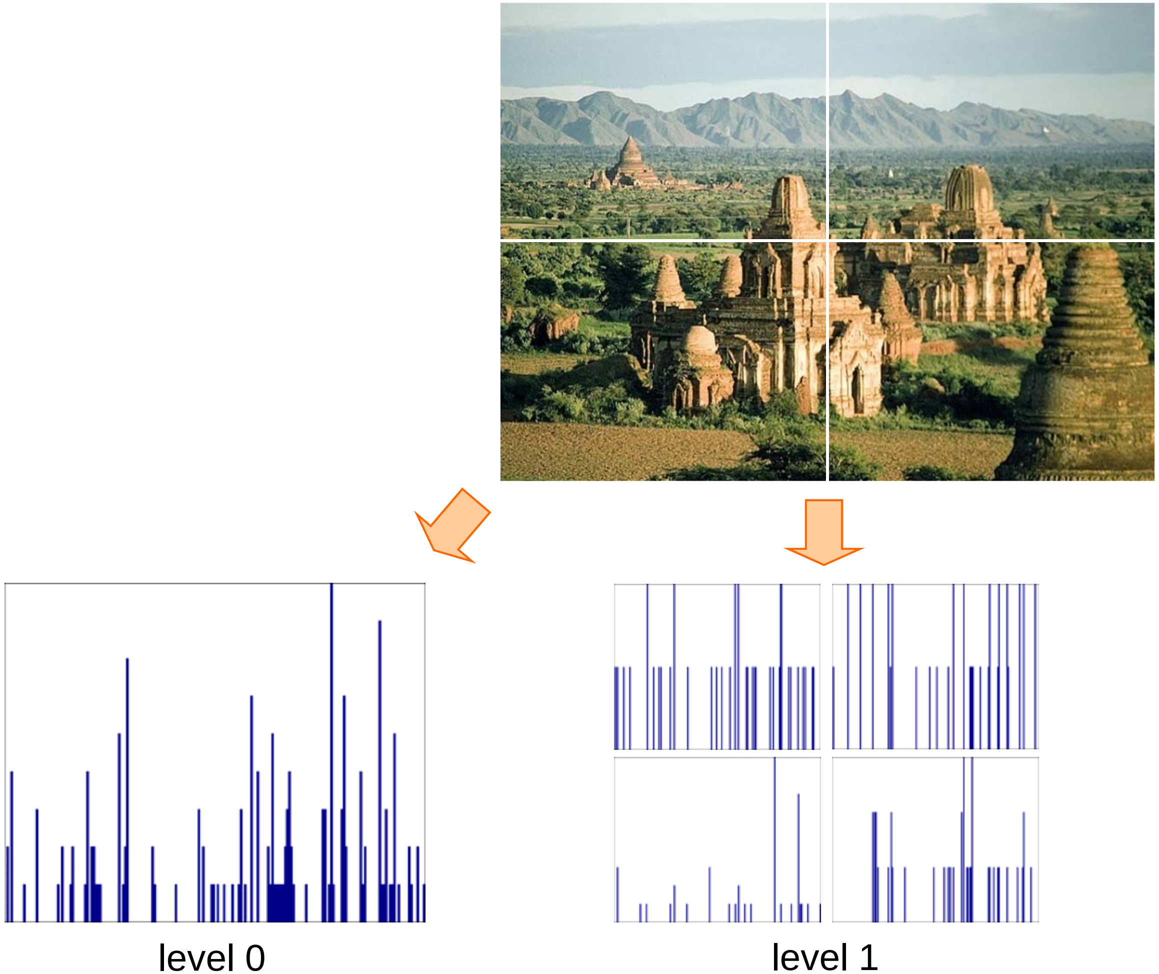


Locally orderless representation at several levels of spatial resolution



level 0

Spatial pyramid representation



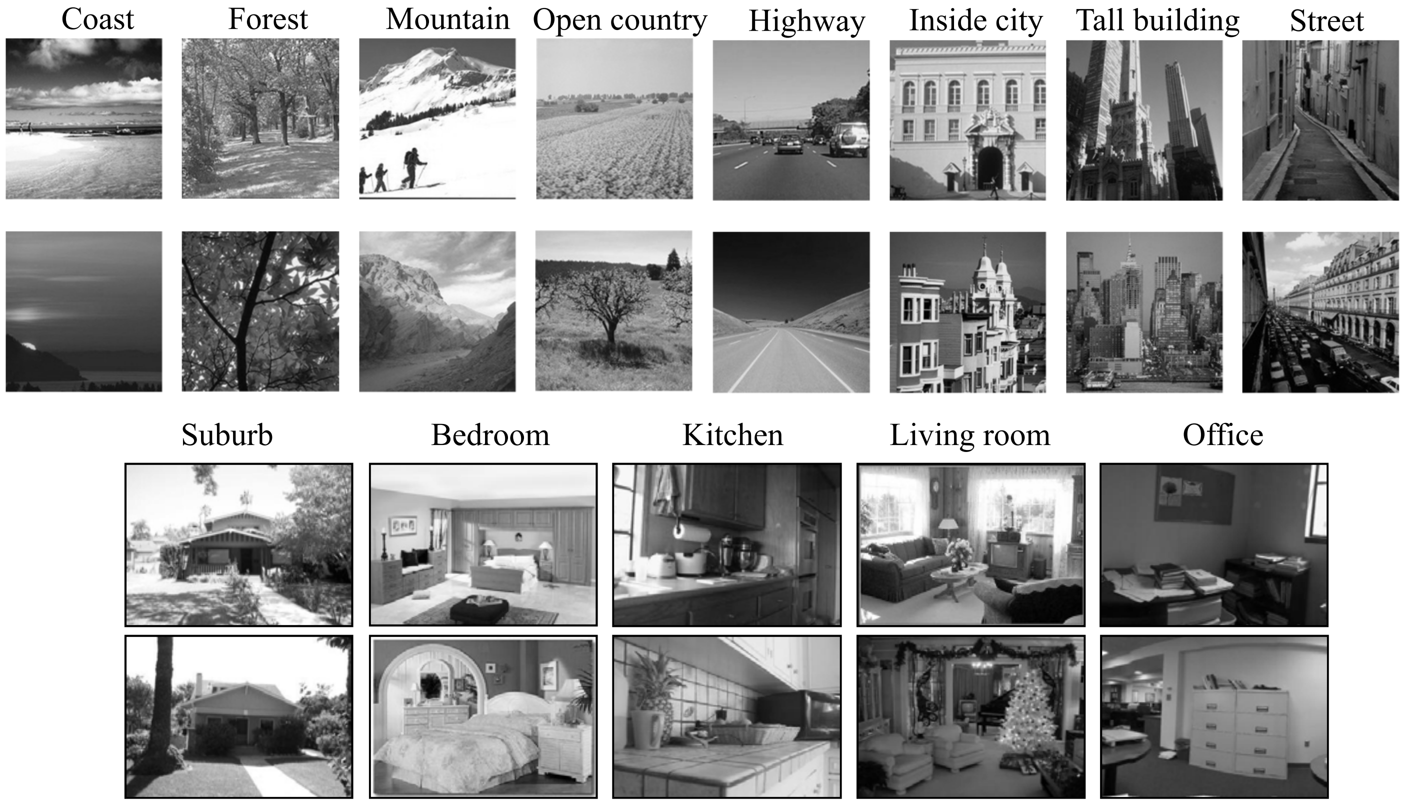
Locally orderless representation at several levels of spatial resolution

Spatial pyramid representation

Locally orderless representation at several levels of spatial resolution

level 0 level 1 level 2

Scene dataset [Labzenik et al.’06]



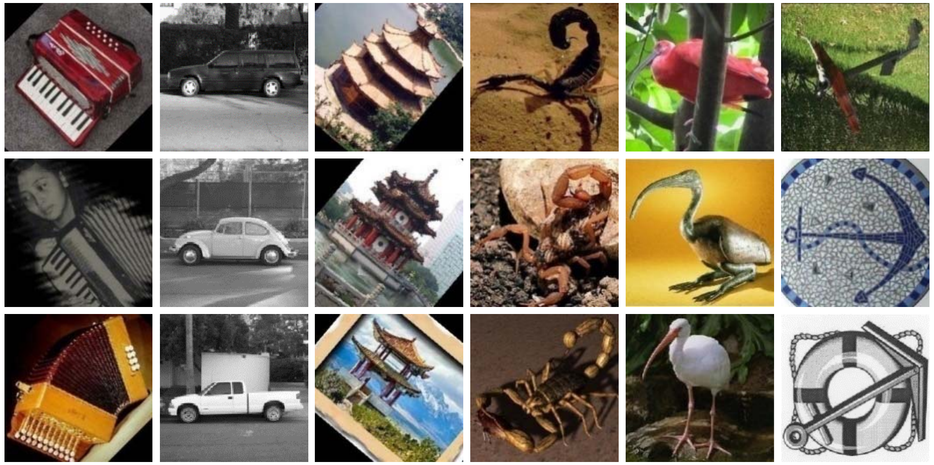
4385 images

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**

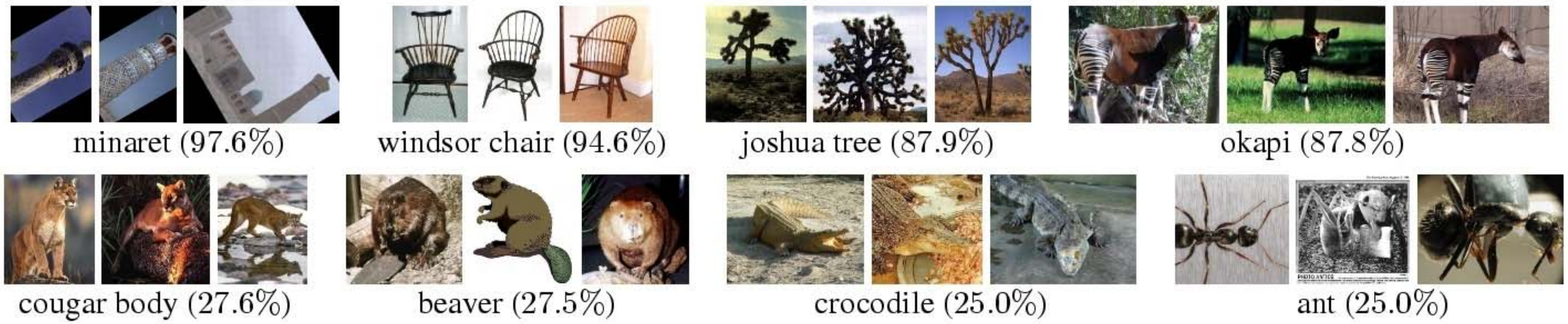
Category classification – CalTech101



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

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

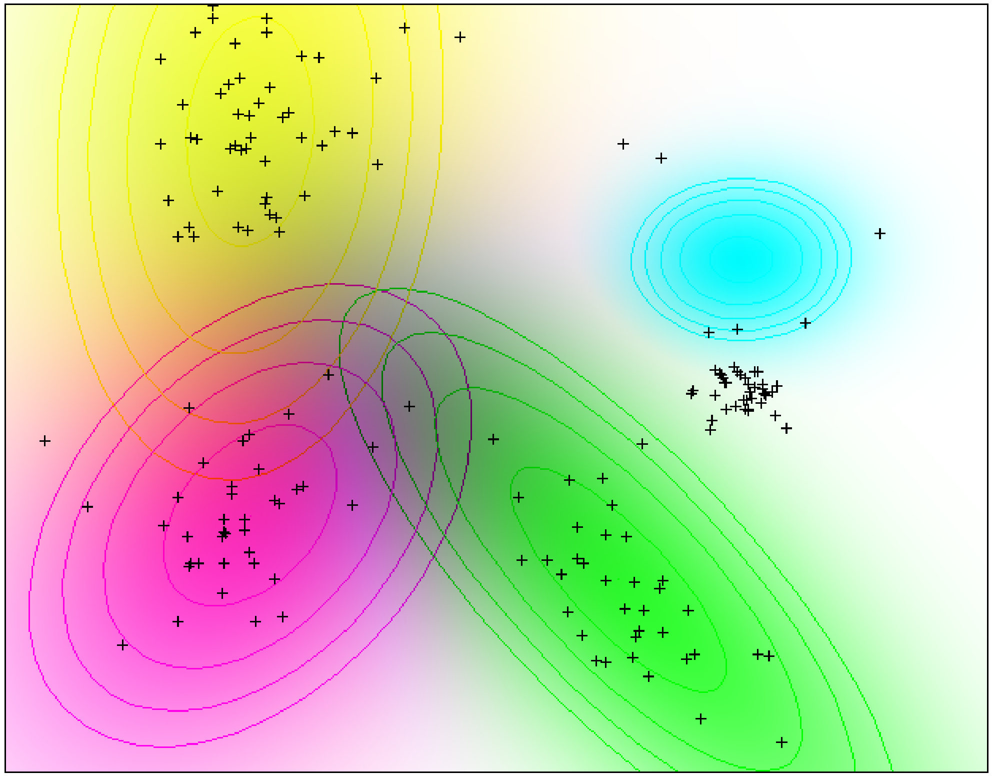
- Recent extensions
  - Flexible, object-centered grid
    - Shape masks [Marszalek'12] => additional annotations
  - Weakly supervised localization of objects
    - [Russakovsky et al.'12, Oquab'14, Cinbis'16]

Recent 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

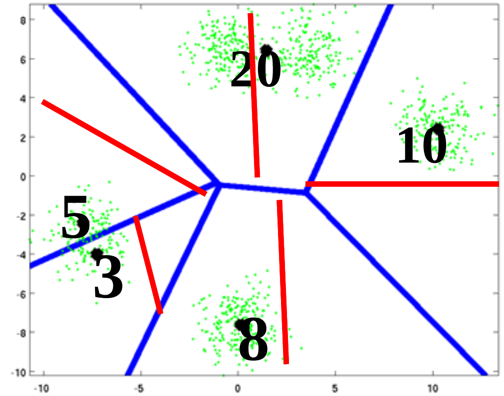
σ_i co-variance (diagonal)

Translated cluster →
large derivative on μ_i for this
component

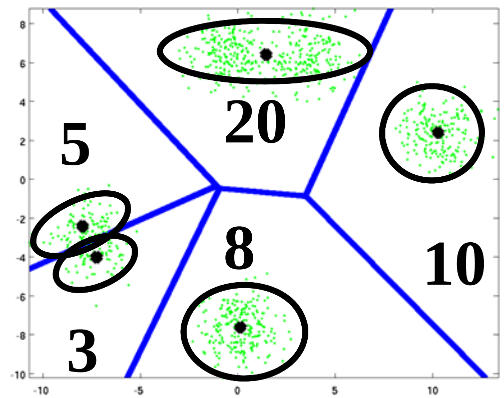
[Perronnin & Dance 07]

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

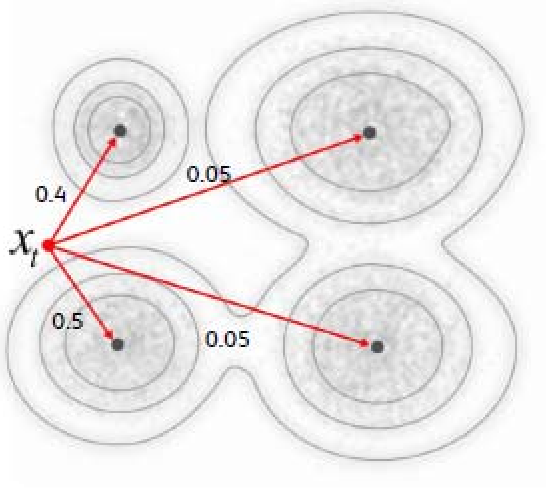
$X = \{x_t, t = 1 \ldots T\}$ is the set of T i.i.d. D-dim local descriptors (e.g. SIFT) extracted from an image:

$u_\lambda(x) = \sum_{i=1}^{K} w_i u_i(x)$ is a Gaussian Mixture Model (GMM) with parameters $\lambda = \{w_i, \mu_i, \Sigma_i, i = 1 \ldots N\}$ 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:

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

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

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

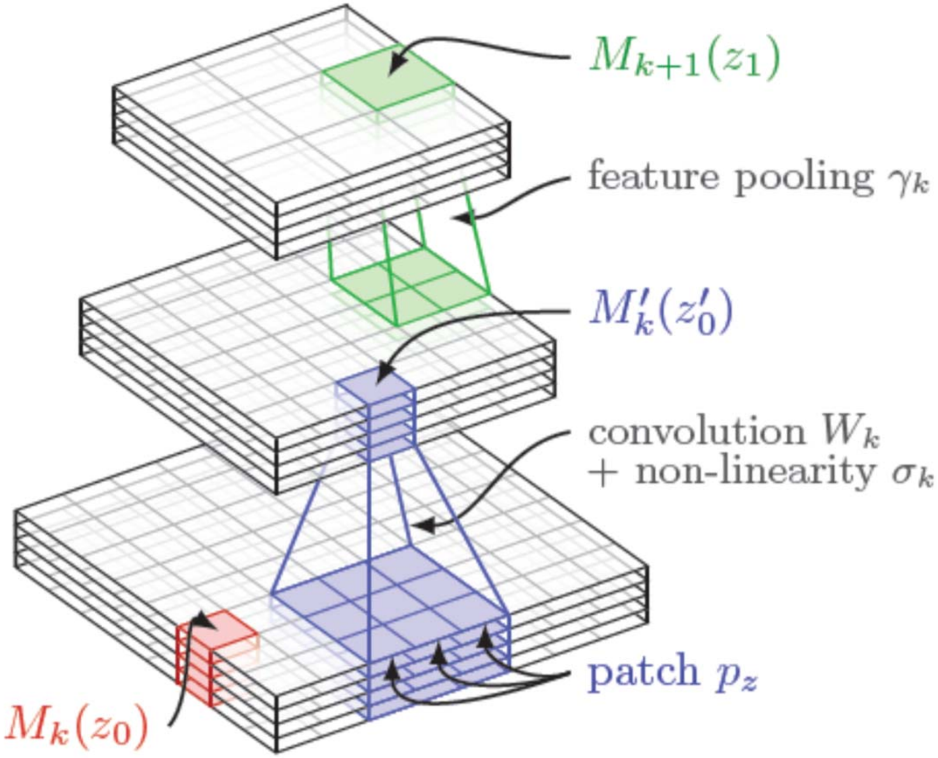
IMAGENET has 14M images from 22k classes

Current state of the art – image classification

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

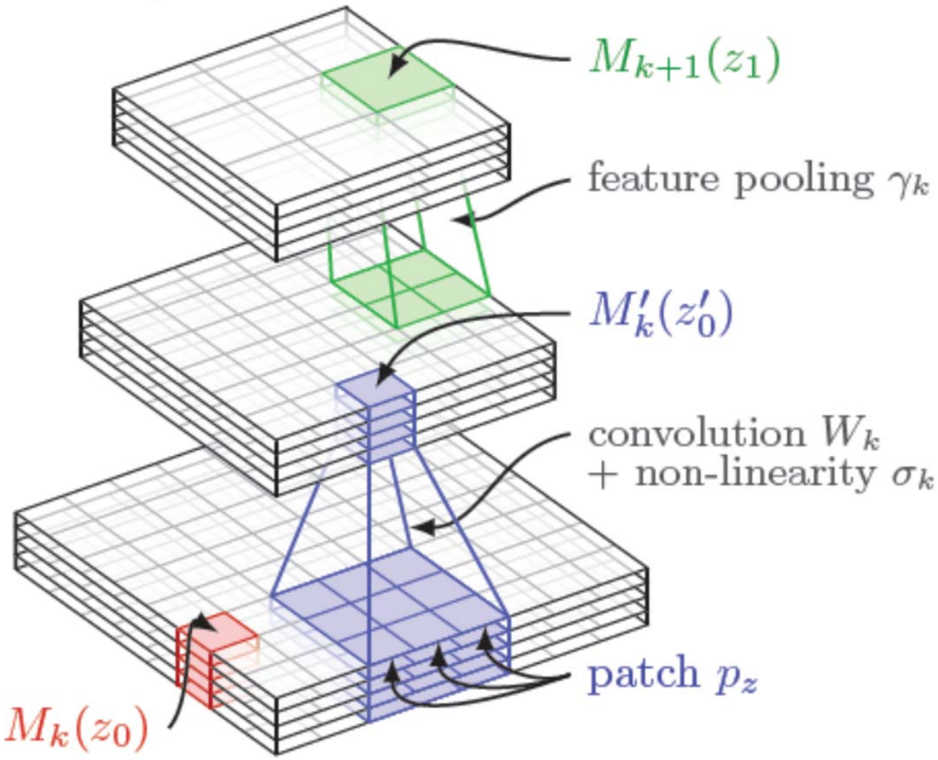
Deep convolutional neural networks

- Convolutional neural network – one layer



Deep convolutional neural networks

- Convolutional neural network – one layer

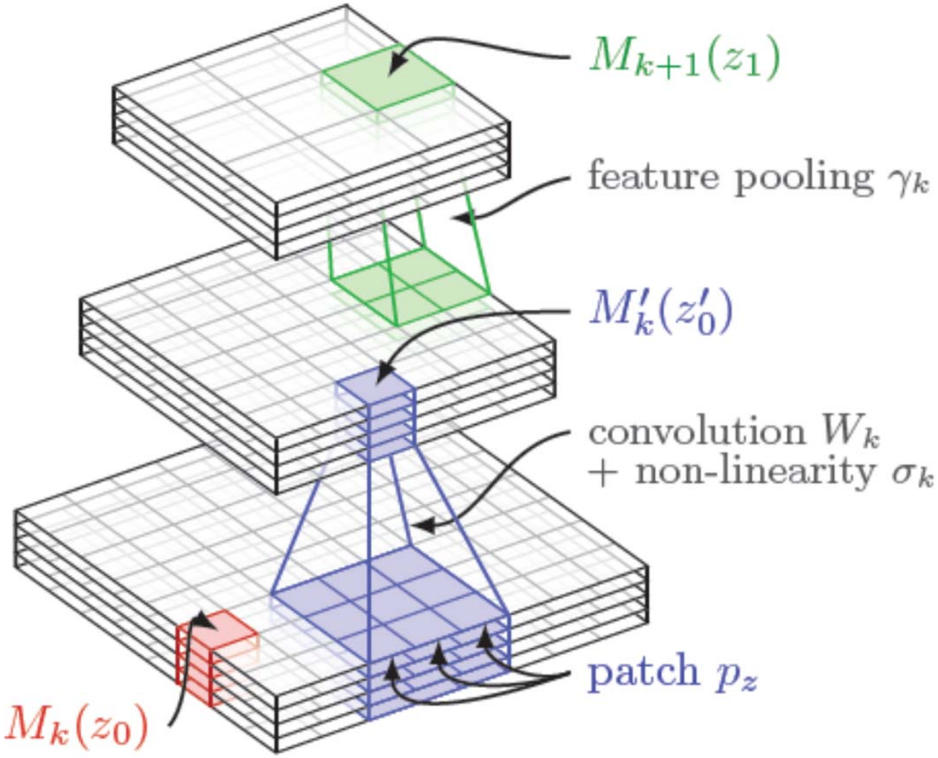


Convolutions:

- Learn convolutional filters
- Translation invariant
- Several filters at each layer
- From simple to complex filters

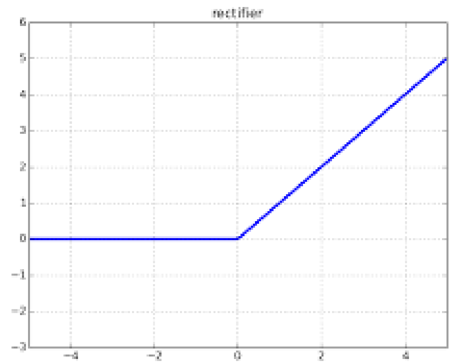
Deep convolutional neural networks

- Convolutional neural network – one layer



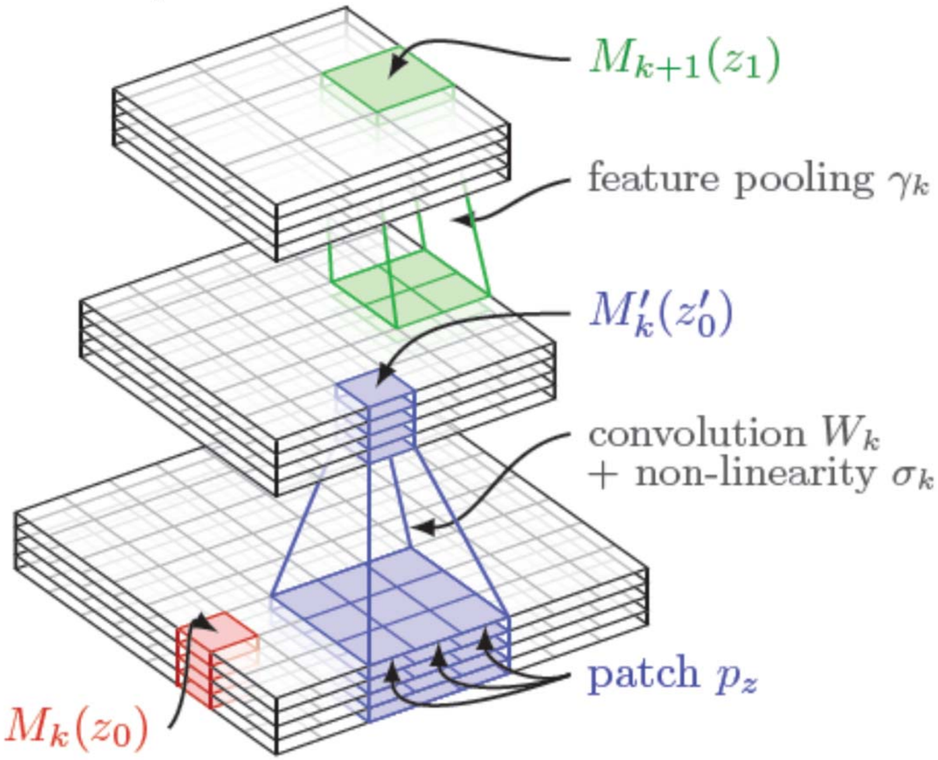
Non-linearity:

- Sigmoid
- Rectified linear unit (ReLU)
  - Simplifies backpropagation
  - Makes learning faster
  - Avoid saturation issues



Deep convolutional neural networks

- Convolutional neural network – one layer

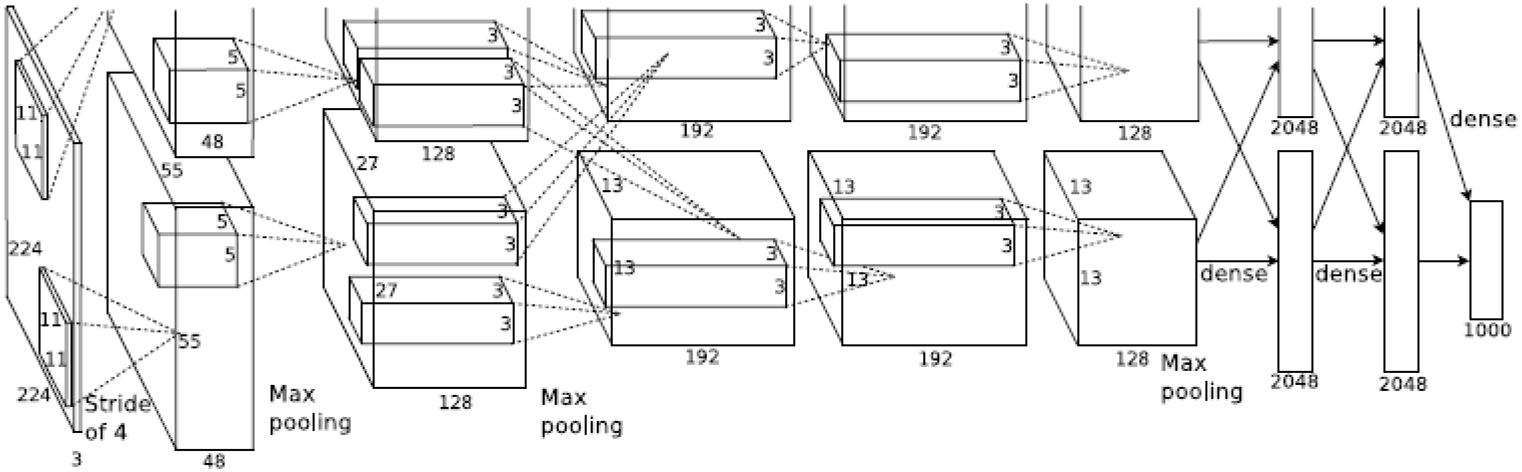


Spatial feature pooling:

- Average or maximum
- Invariance to small transformations
- Larger receptive fields

Deep convolutional neural networks

- First 5 layers: convolutional layer, last 2: full connected
- Large model (7 hidden layers, 650k units, 60M parameters)
- Requires large training set (ImageNet)
- GPU implementation (50x speed up over CPU)

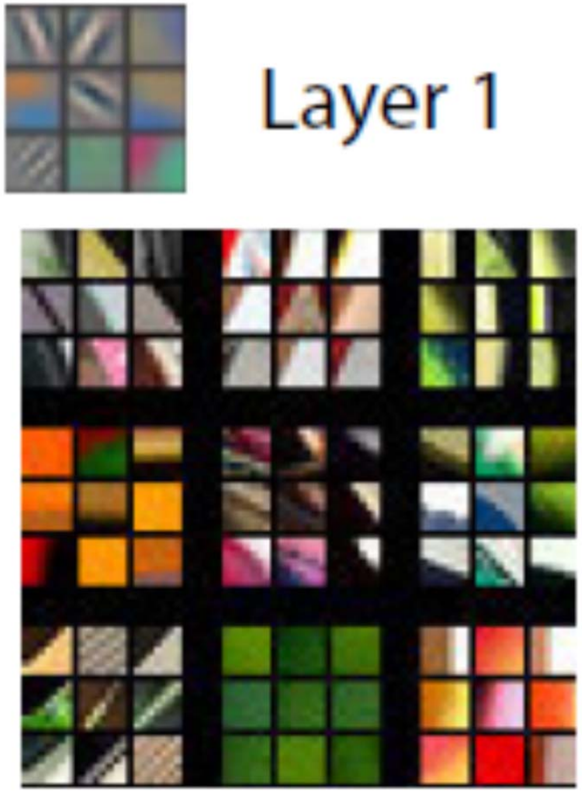


Krizhevsky, Sutskever, Hinton, *ImageNet classification with deep convolutional neural networks*, NIPS'12

Deep convolutional neural networks

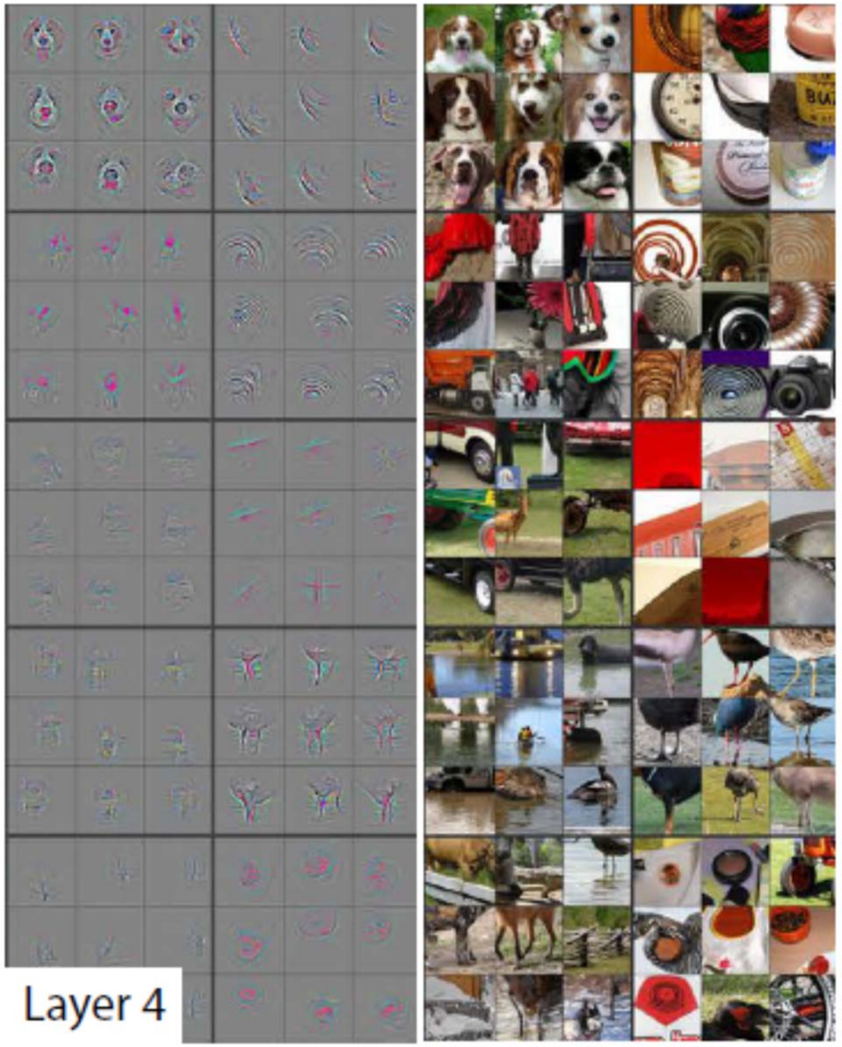
- State of the art result on ImageNet challenge
  - 1000 categories and 1.2 million images

Visualization of the convolution filters



Zeiler and Fergus, *Visualizing and Understanding Convolutional Networks*, ECCV’14

Visualization of the convolution filters



Top nine activations