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

...

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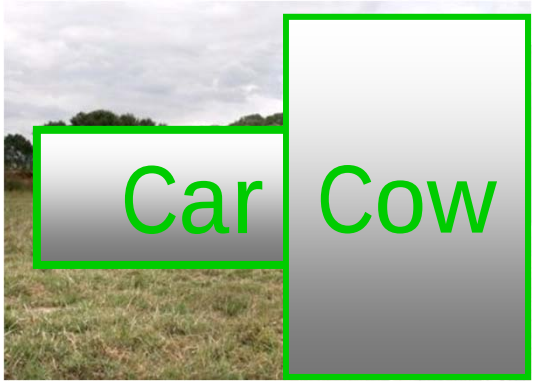
Horse: not present
...

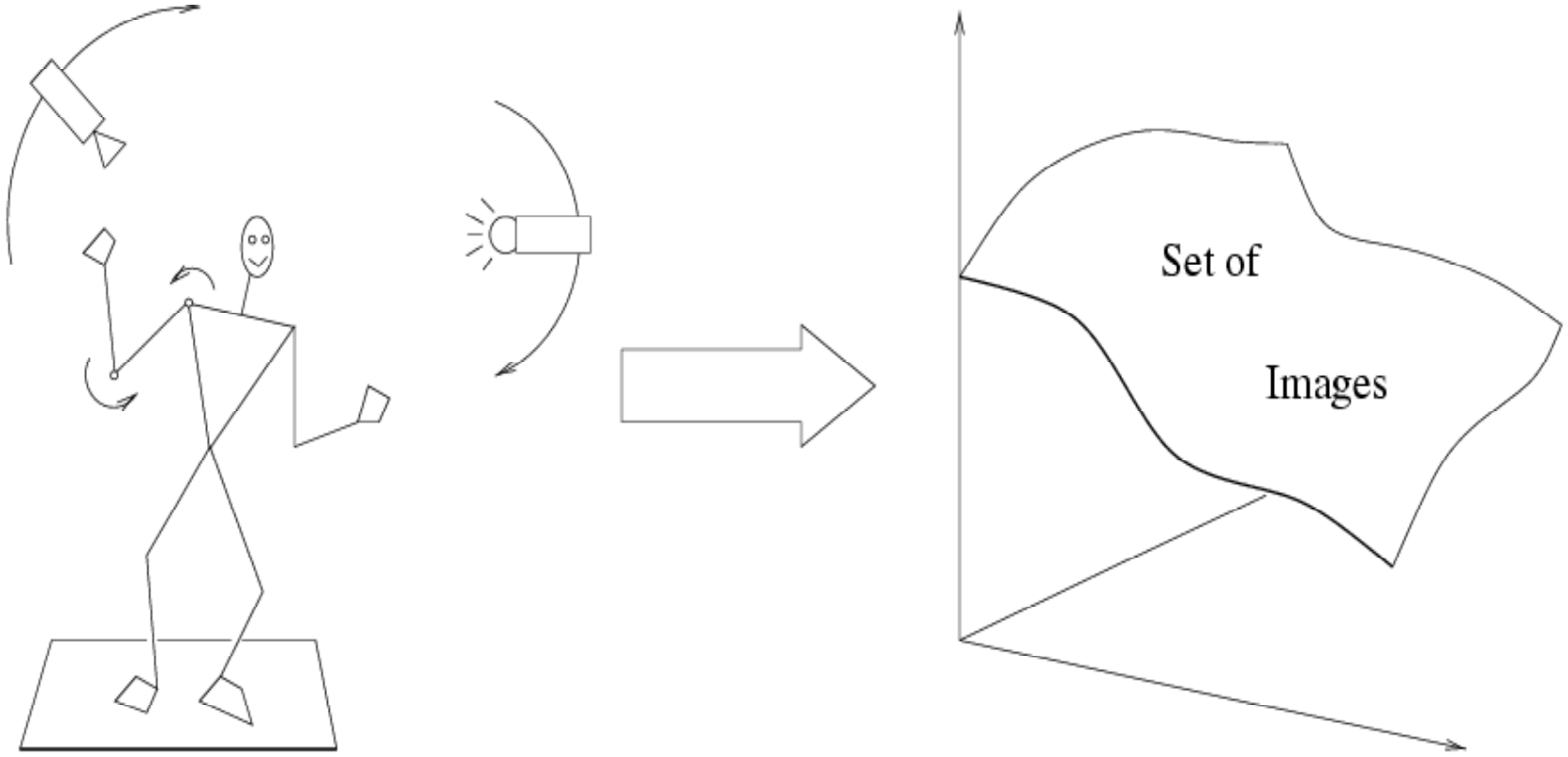
- Object localization: define the location and the category



Location

Category

Difficulties: within object variations



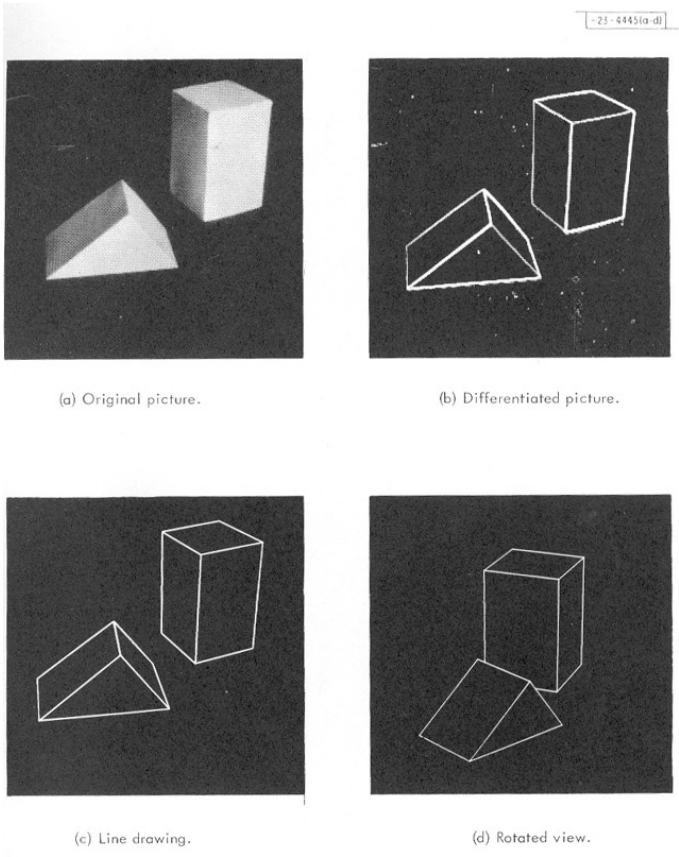
Variability: Camera position, Illumination,Internal parameters

⇒ Within-object variations

Difficulties: within-class variations

Why machine learning?

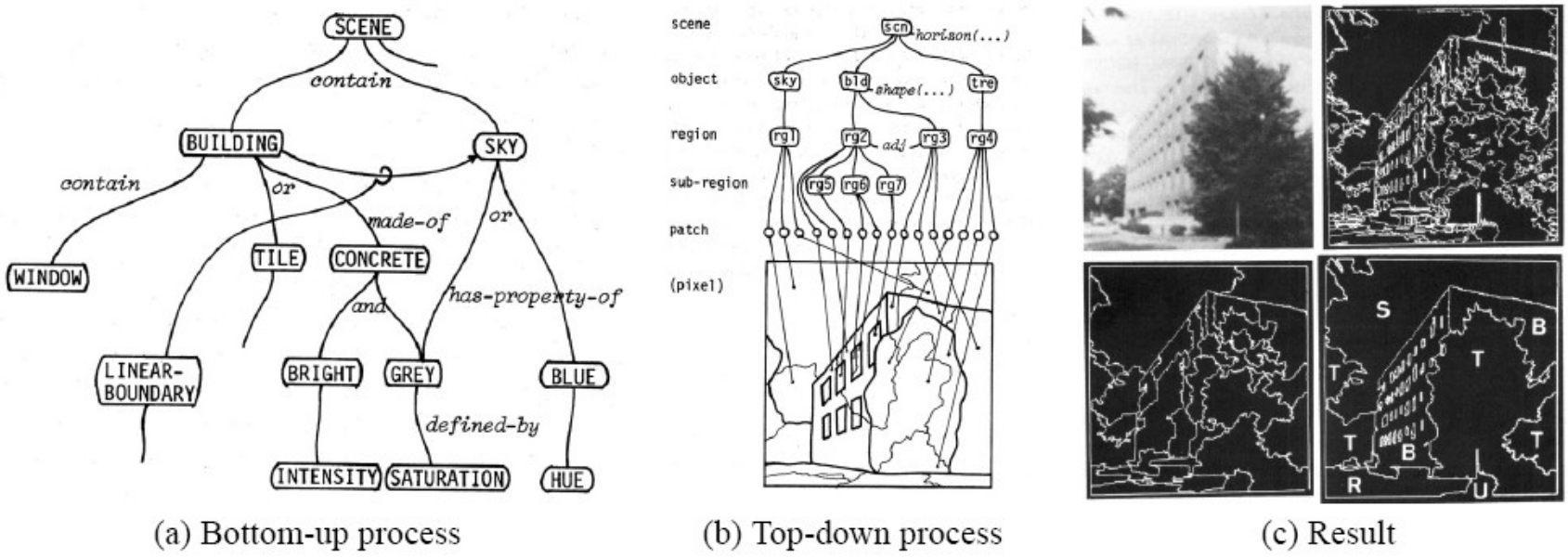
- Early approaches: simple features + handcrafted models
- Can handle only few images, simples tasks



L. G. Roberts, *Machine Perception of Three Dimensional Solids,* Ph.D. thesis, MIT Department of Electrical Engineering, 1963.

Why machine learning?

- Early approaches: manual programming of rules
- Tedious, limited and does not take into accout the data



(a) Bottom-up process (b) Top-down process (c) Result

Figure 3. A system developed in 1978 by Ohta, Kanade and Sakai [33, 32] for knowledge-based interpretation of outdoor natural scenes. The system is able to label an image (c) into semantic classes: S-sky, T-tree, R-road, B-building, U-unknown.

Y. Ohta, T. Kanade, and T. Sakai, "An Analysis System for Scenes Containing objects with Substructures," *International Joint Conference on Pattern Recognition*, 1978.

Why machine learning?

- Today lots of data, complex tasks

Internet images,
personal photo albums

Movies, news, sports

- Instead of trying to encode rules directly, learn them from examples of inputs and desired outputs

Types of learning problems

- Supervised
  - Classification
  - Regression
- Unsupervised
- Semi-supervised
- Active learning
- Self-supervised learning
- ….

Supervised learning

- Given training examples of inputs and corresponding outputs, produce the “correct” outputs for new inputs

- Two main scenarios:

  - **Classification:** outputs are discrete variables (category labels). Learn a decision boundary that separates one class from the other.

  - **Regression:** also known as “curve fitting” or “function approximation.” Learn a continuous input-output mapping from examples (possibly noisy).

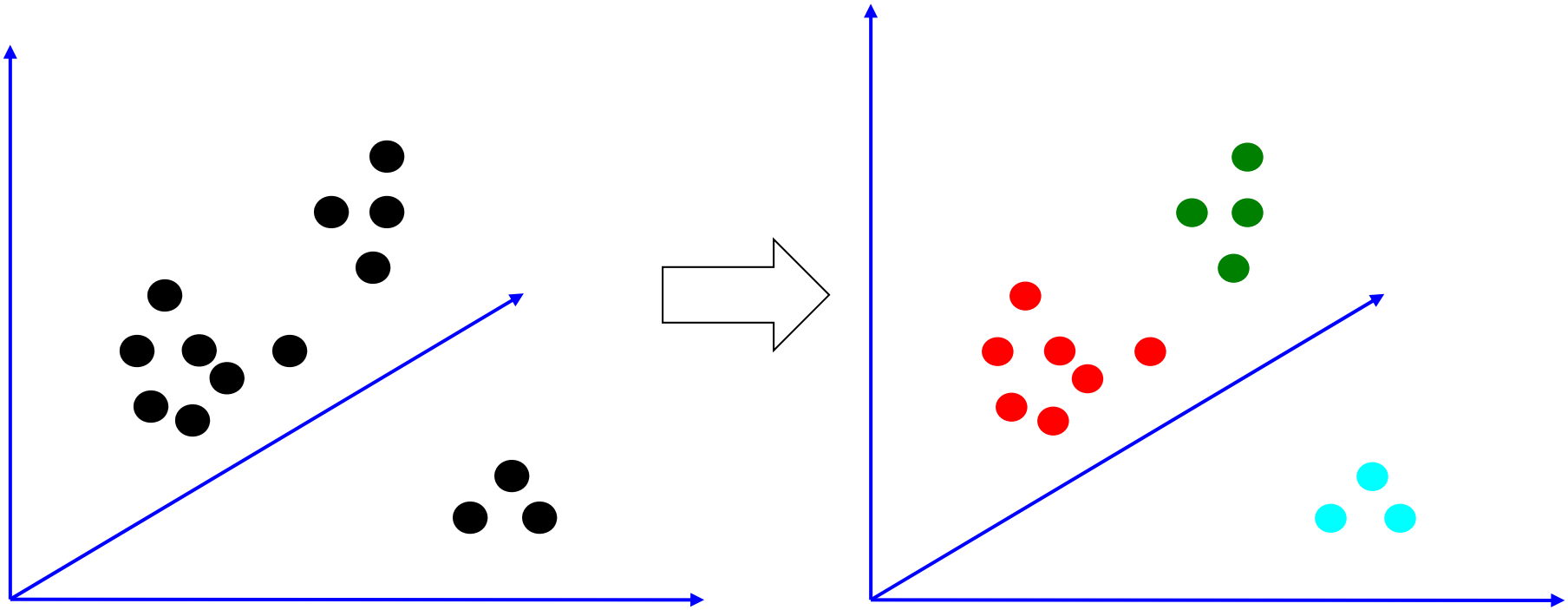
Unsupervised Learning

- Given only *unlabeled* data as input, learn some sort of structure.

- The objective is often more vague or subjective than in supervised learning. This is more an exploratory/descriptive data analysis.

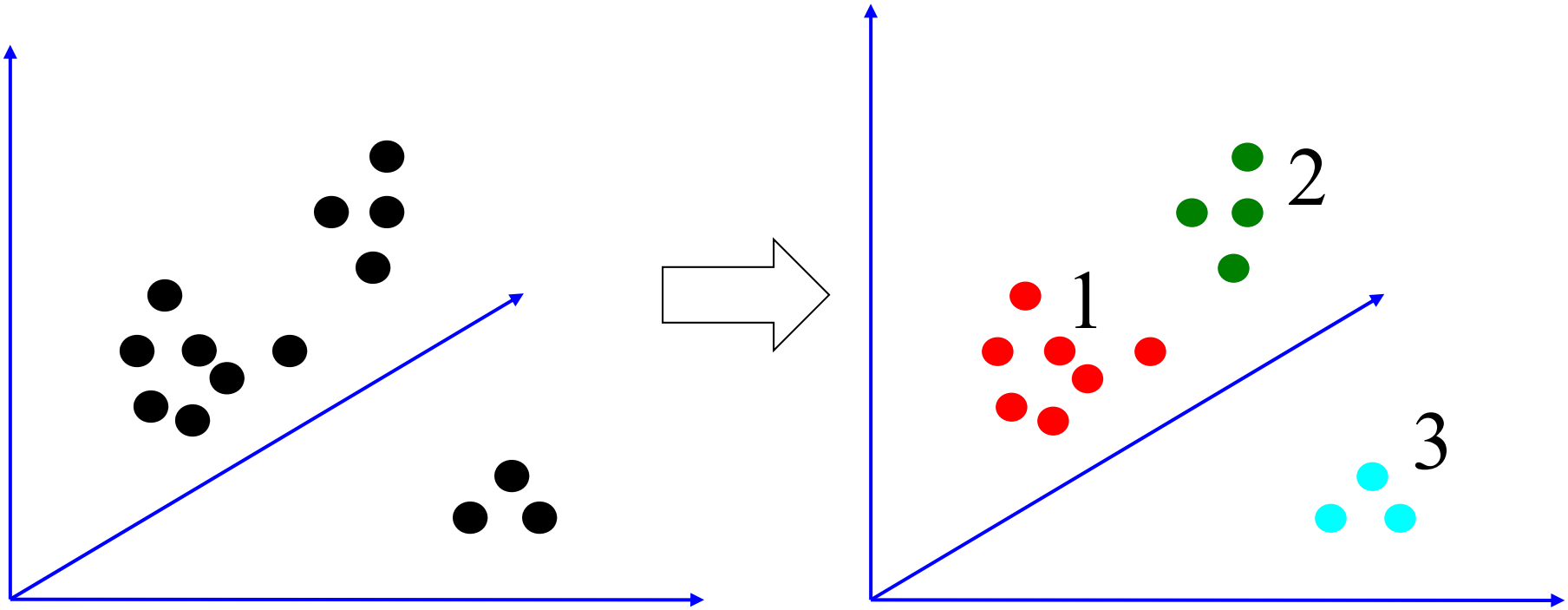
Unsupervised Learning

- **Clustering**
  - Discover groups of “similar” data points



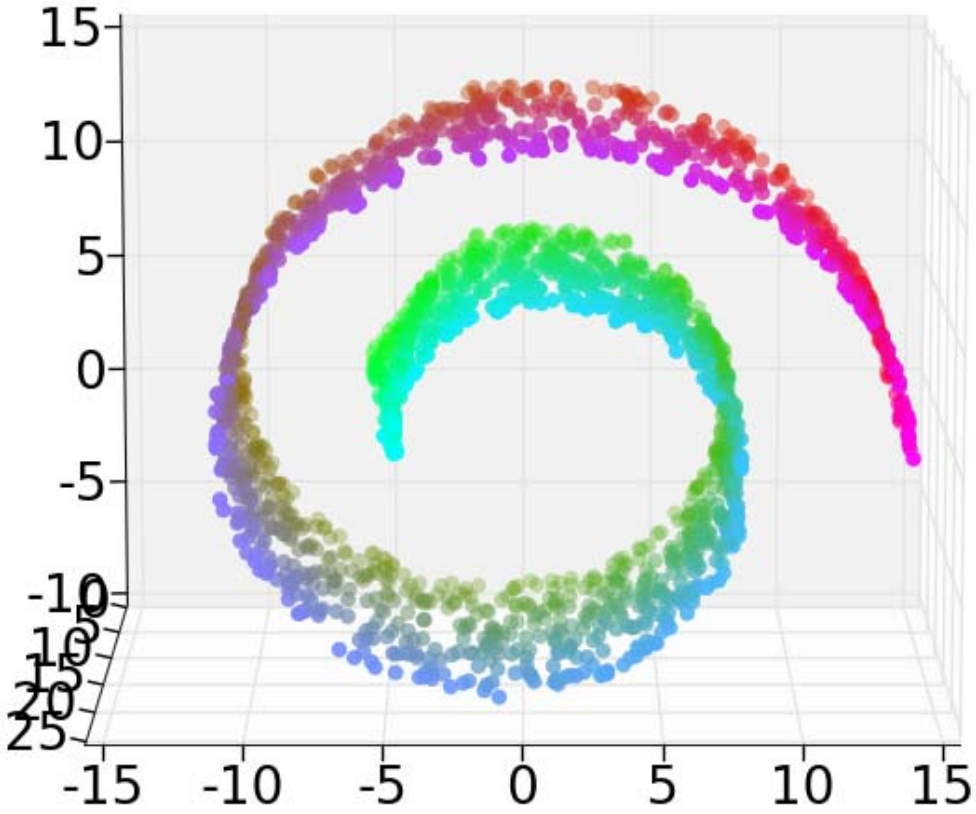
Unsupervised Learning

- **Quantization**
  - Map a continuous input to a discrete (more compact) output



Unsupervised Learning

- **Dimensionality reduction, manifold learning**
  - Discover a lower-dimensional surface on which the data lives



Other types of learning

- **Semi-supervised learning:** lots of data is available, but only small portion is labeled (e.g. since labeling is expensive)

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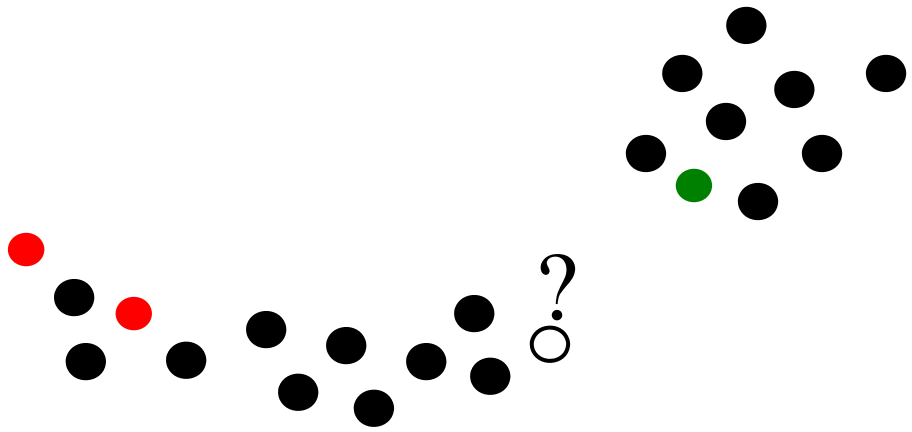
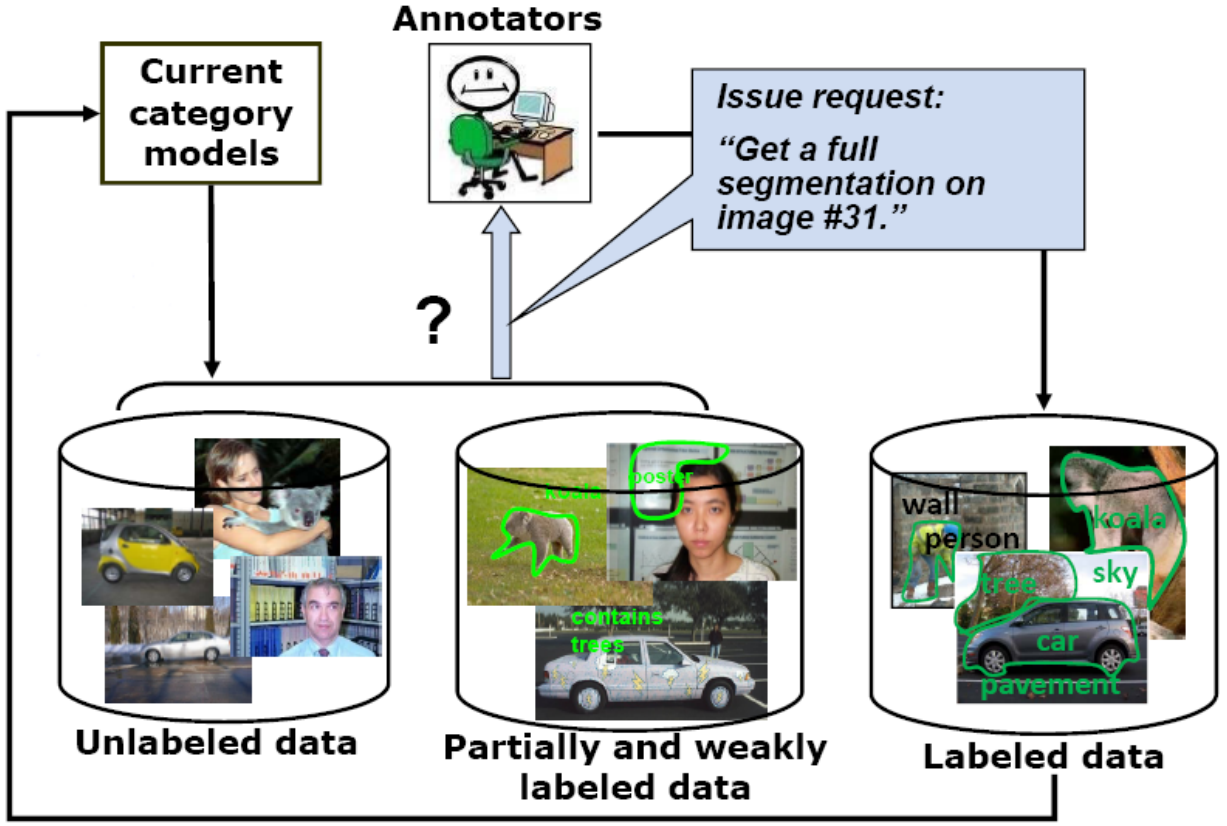
- **Semi-supervised learning:** lots of data is available, but only small portion is labeled (e.g. since labeling is expensive)
  - Why is learning from labeled and unlabeled data better than learning from labeled data alone?



Other types of learning

- **Active learning:** the learning algorithm can choose its own training examples, or ask a “teacher” for an answer on selected inputs



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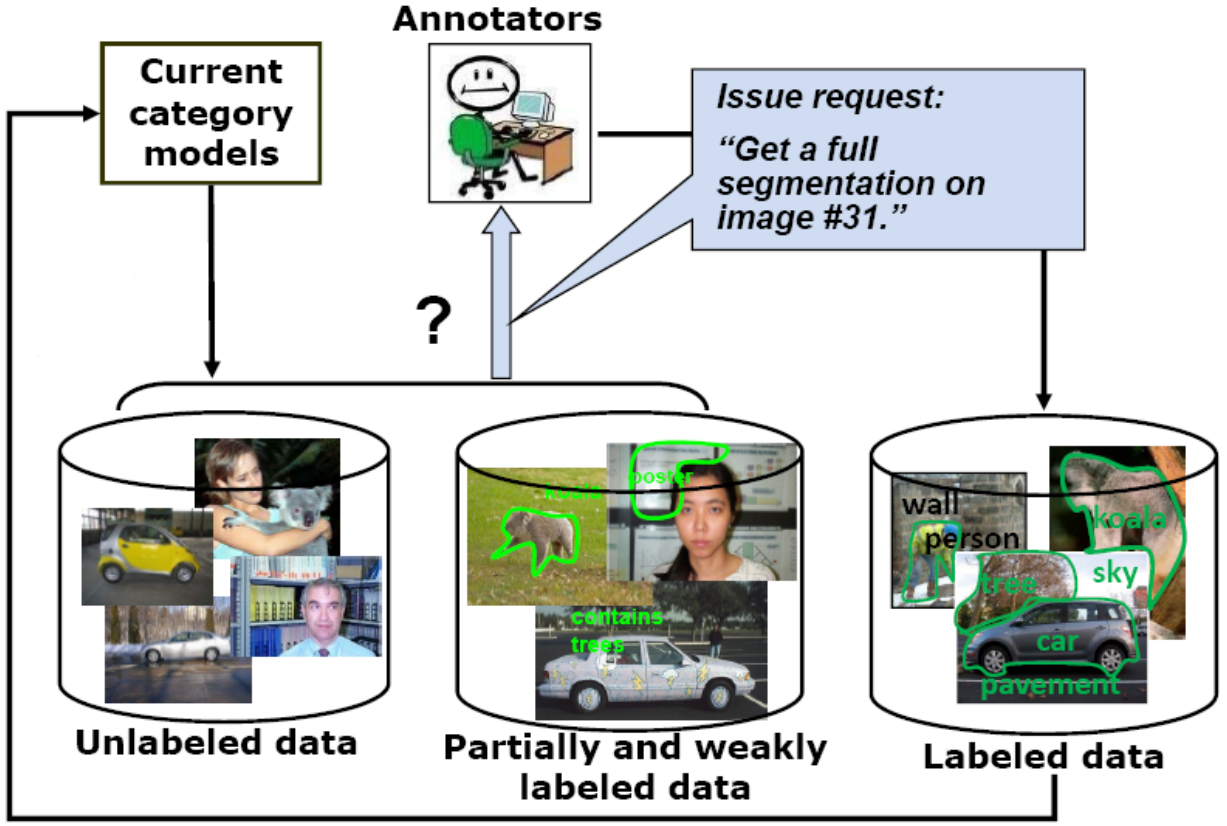
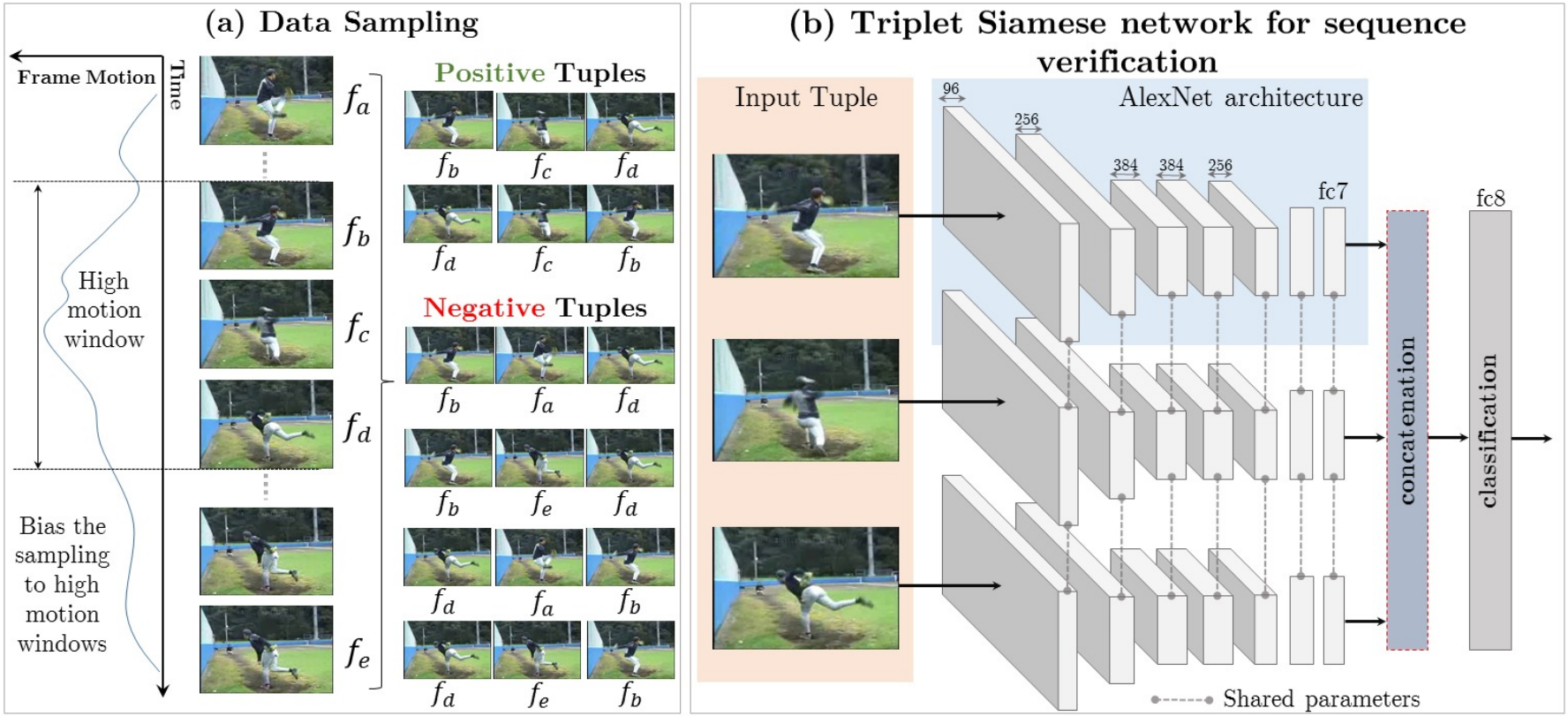


Other types of learning

- **Self-supervised learning:** regularities in the data are used for learning



[I. Misra 2016]

Category recognition

- Image classification: assigning a class label to the image

Car: present
Cow: present
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- Supervised scenario: given a set of training images

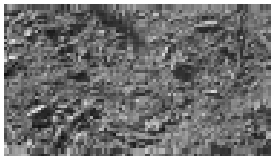
Image classification

- Given

  Positive training images containing an object class



  Negative training images that don't



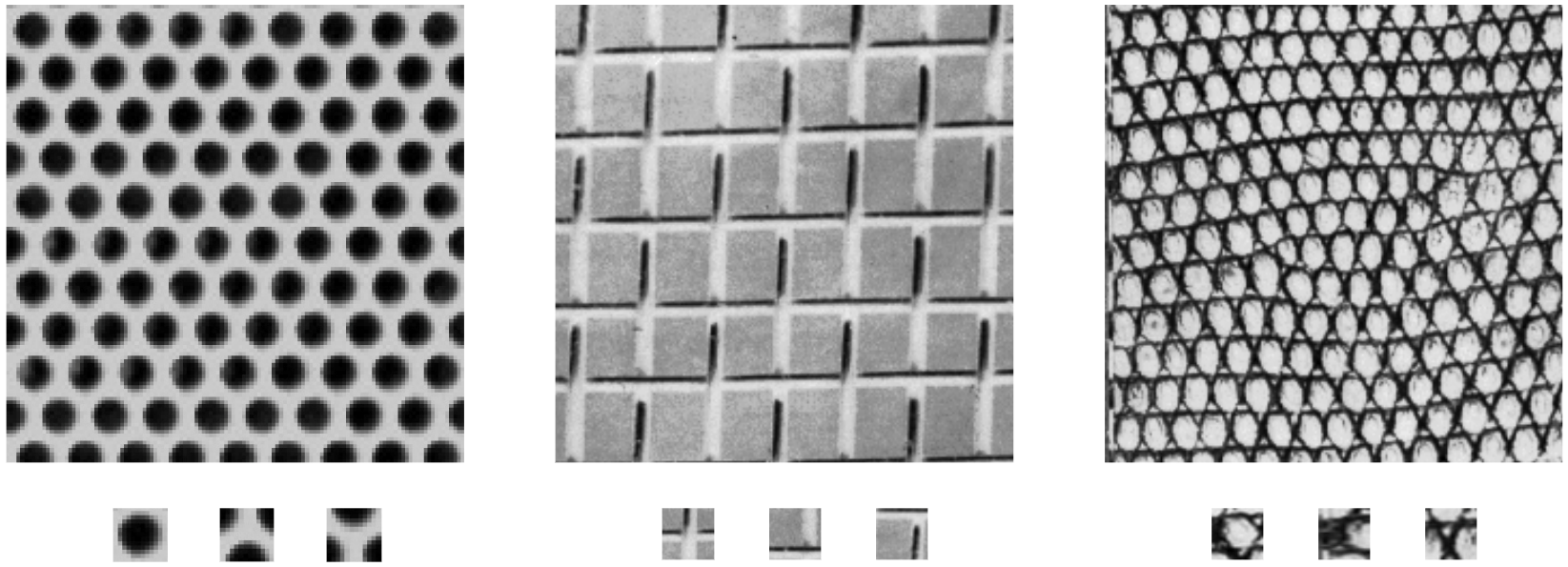
- Classify

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

?

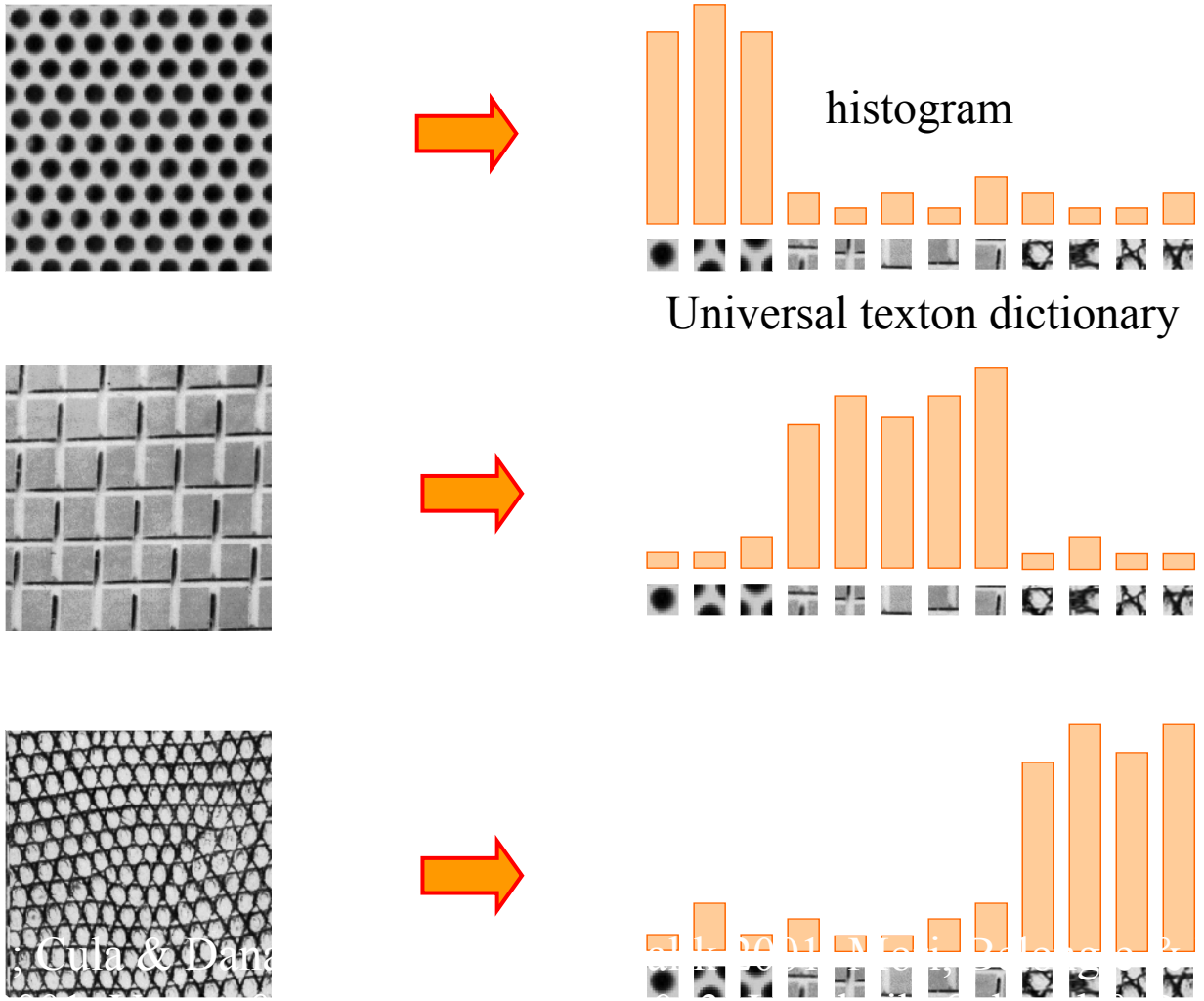
Bag-of-features for image classification

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

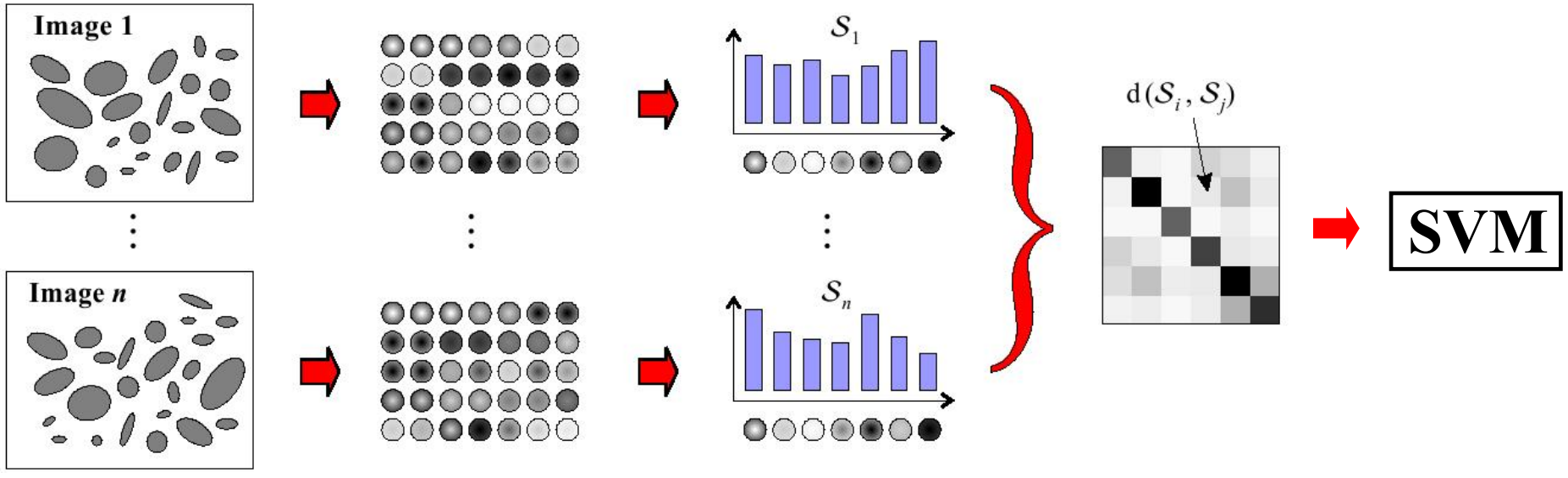


Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001
Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

Texture recognition

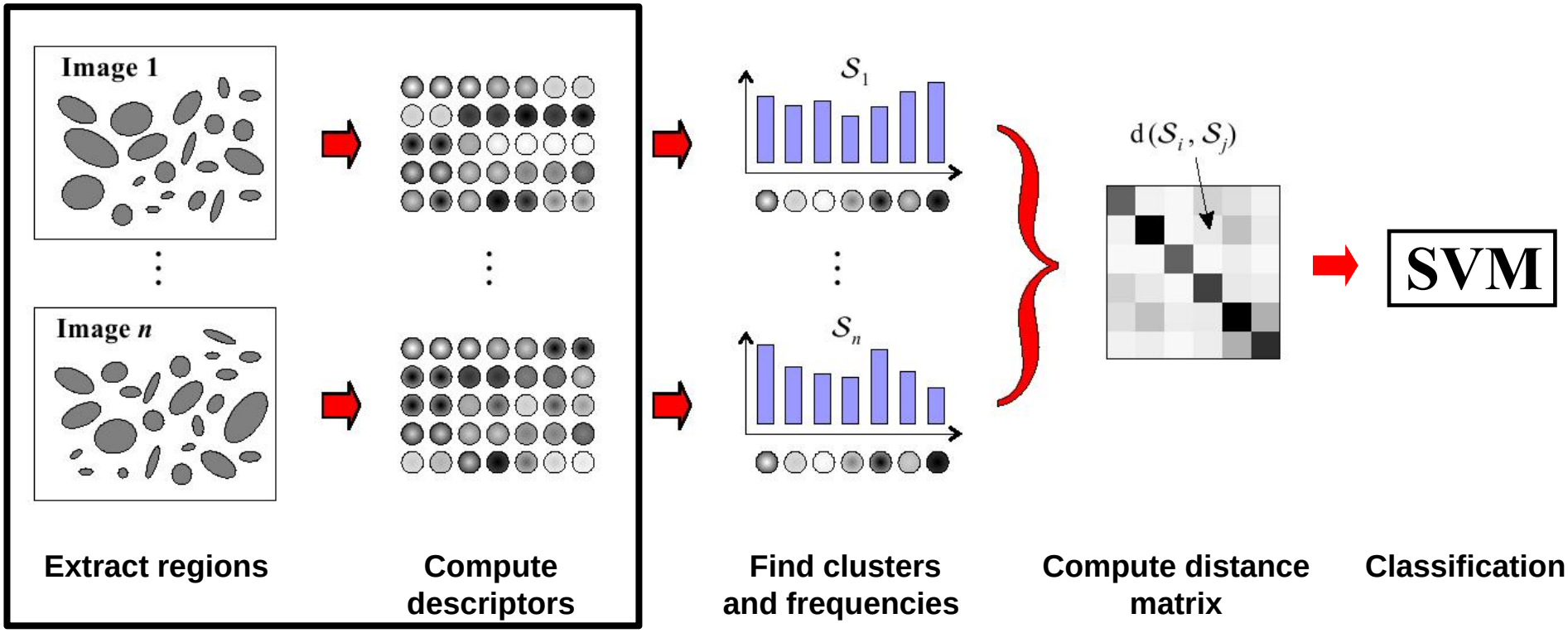


Bag-of-features for image classification



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

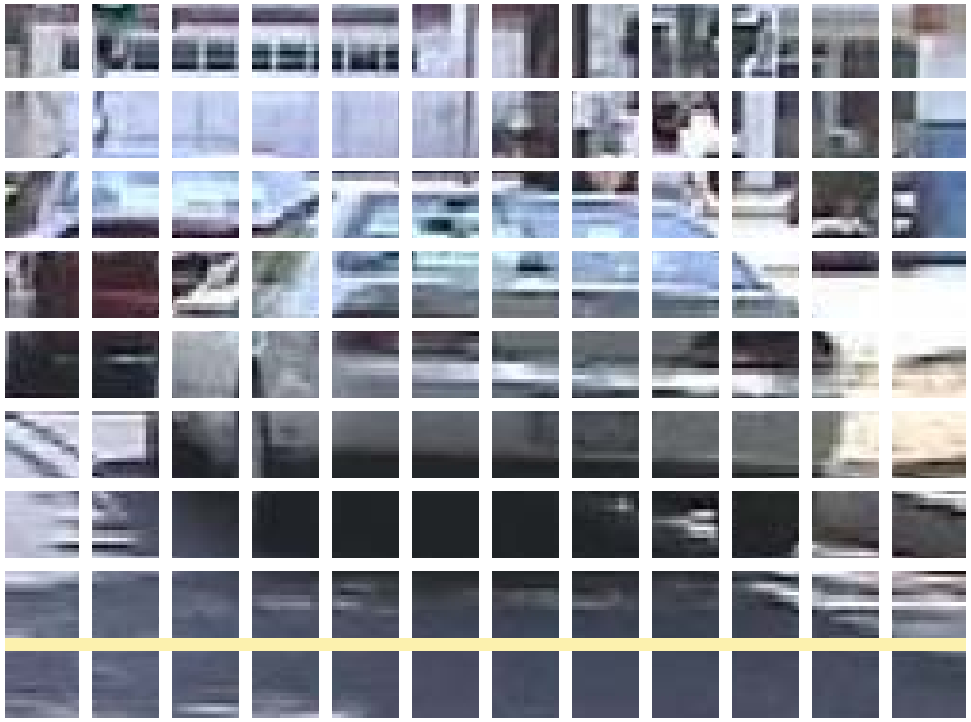
Bag-of-features for image classification



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

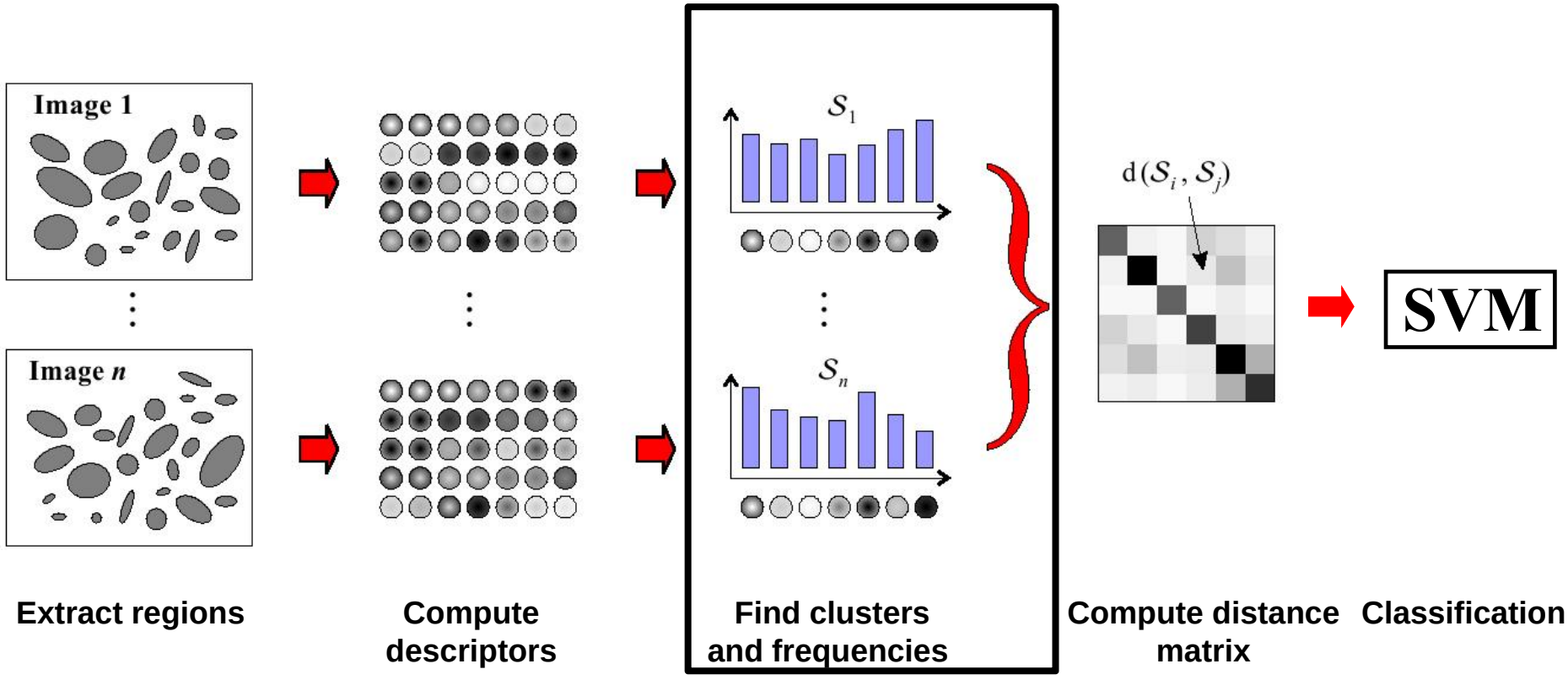


- Multi-scale dense grid: extraction of small overlapping patches at multiple scales

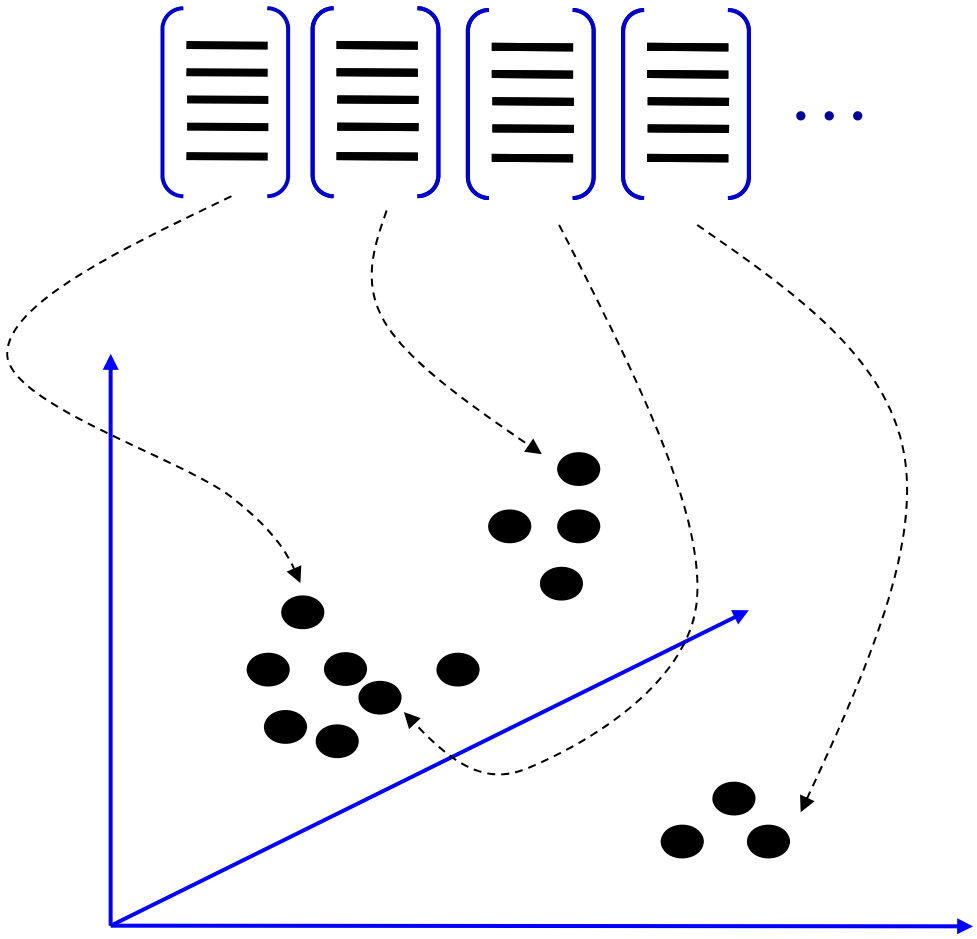
-Computation of the SIFT descriptor for each grid cells

-Exp.: Horizontal/vertical step size 3-6 pixel, scaling factor of 1.2 per level

Bag-of-features for image classification



Step 2: Quantization



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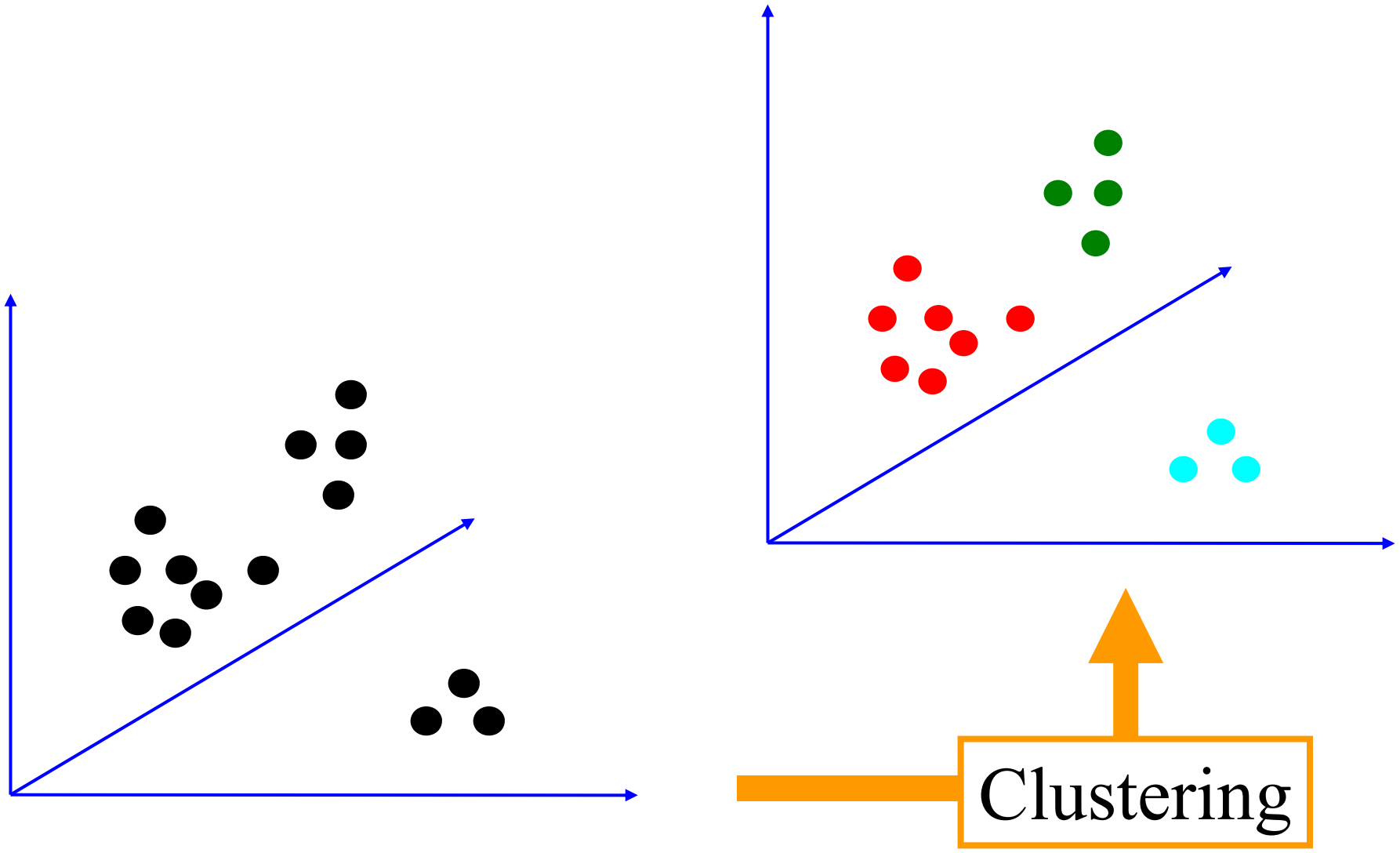

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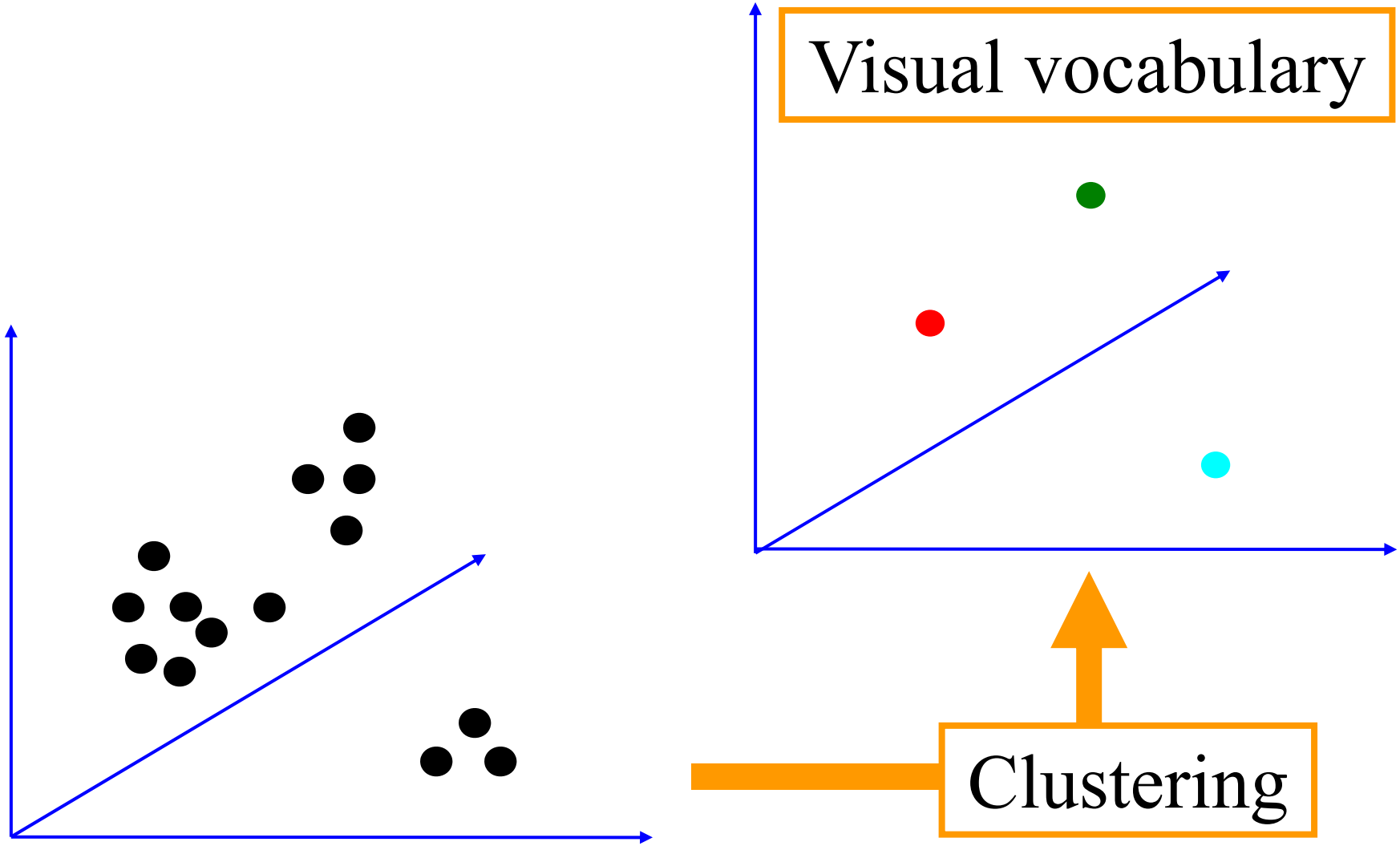
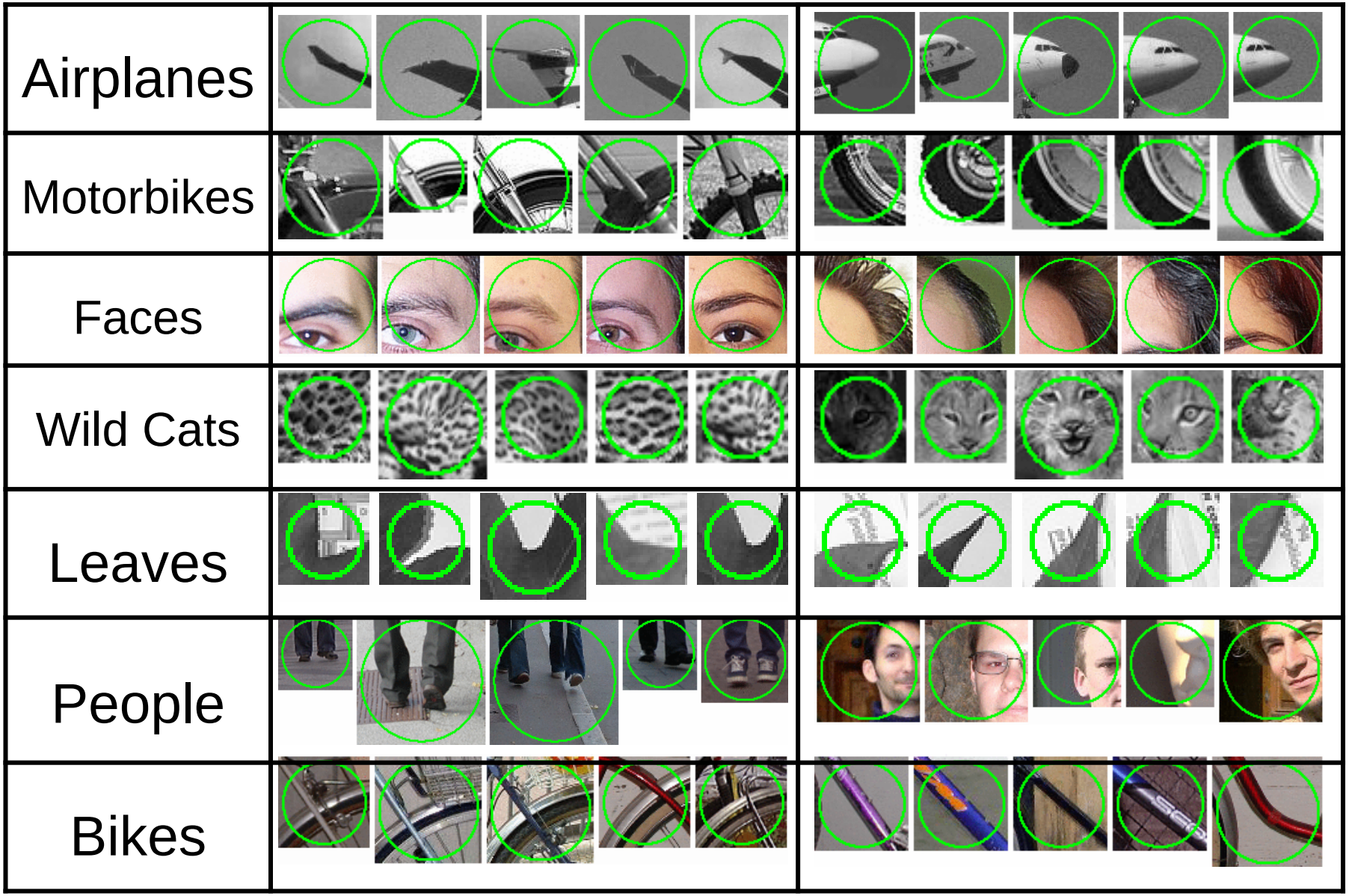


Examples for visual words



Step 2: Quantization

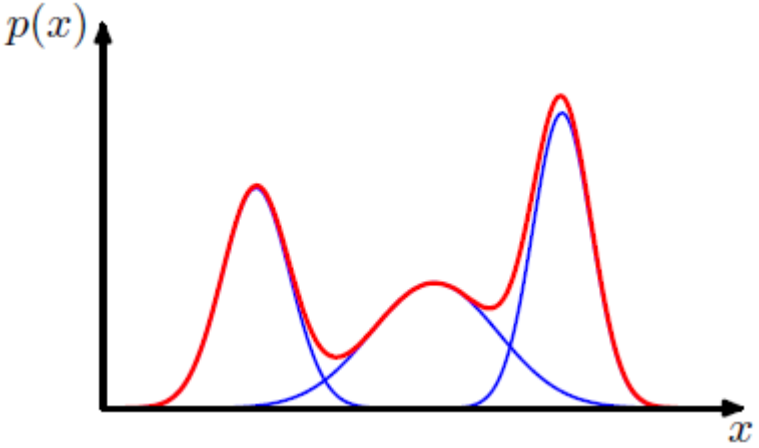
- Cluster descriptors
  - K-means
  - Gaussian mixture model
- Assign each visual word to a cluster
  - Hard or soft assignment
- Build frequency histogram

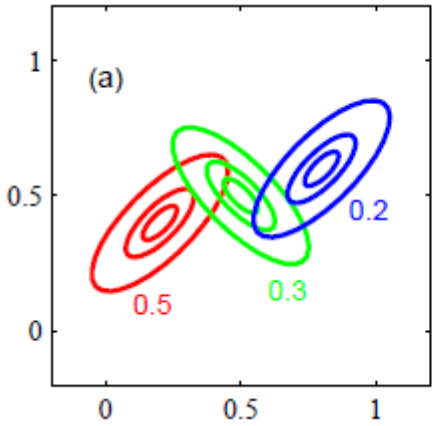
Gaussian mixture model (GMM)

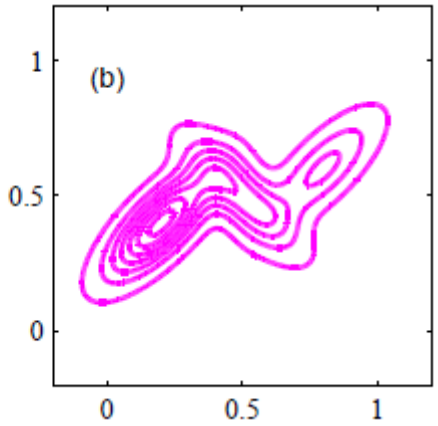
- Mixture of Gaussians: weighted sum of Gaussians

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

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



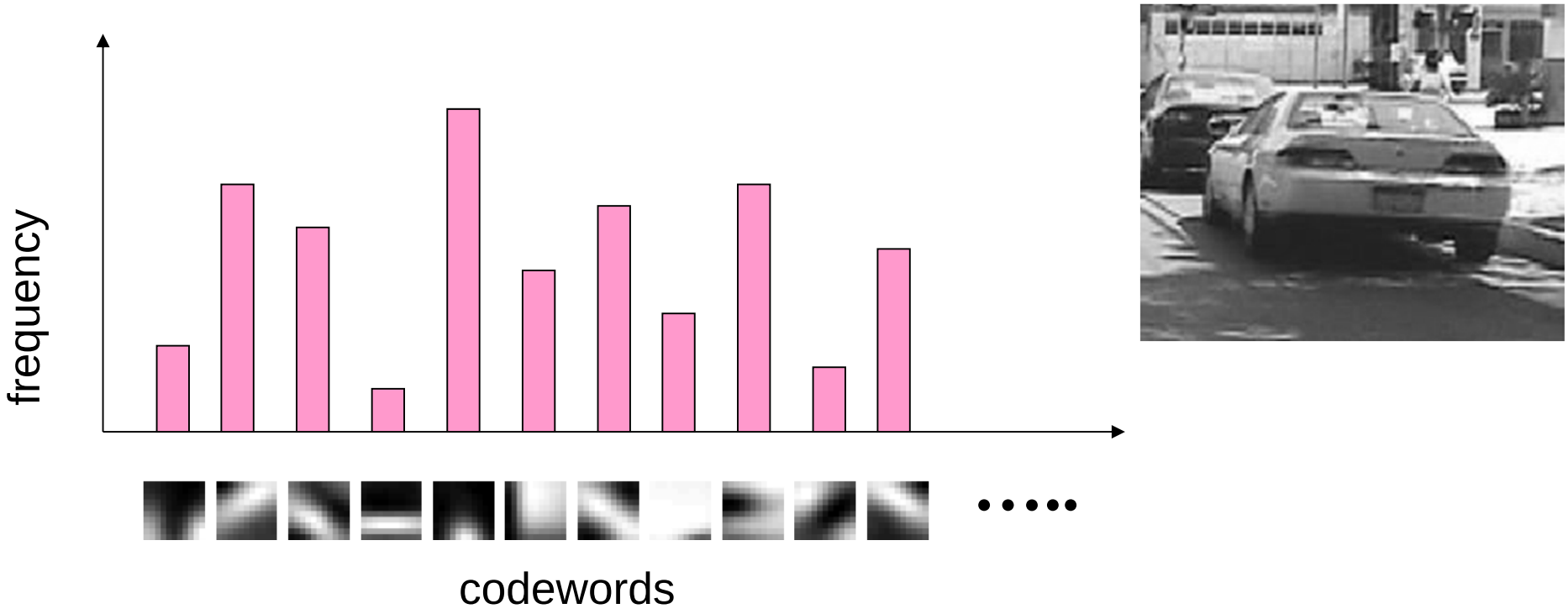




Hard or soft assignment

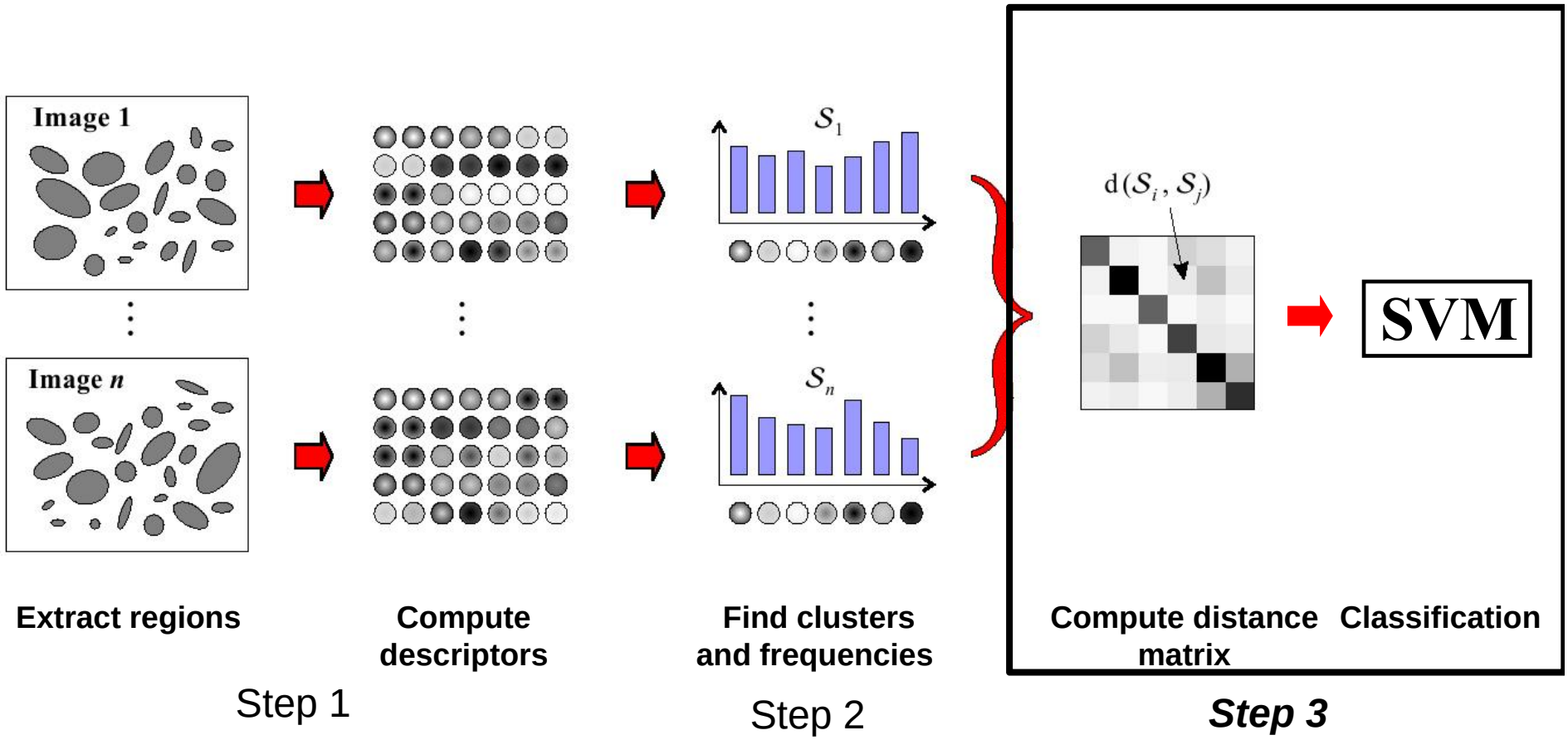
- K-means → hard assignment
  - Assign to the closest cluster center
  - Count number of descriptors assigned to a center
- Gaussian mixture model → soft assignment
  - Estimate distance to all centers
  - Sum over number of descriptors
- Represent image by a frequency histogram

Image representation



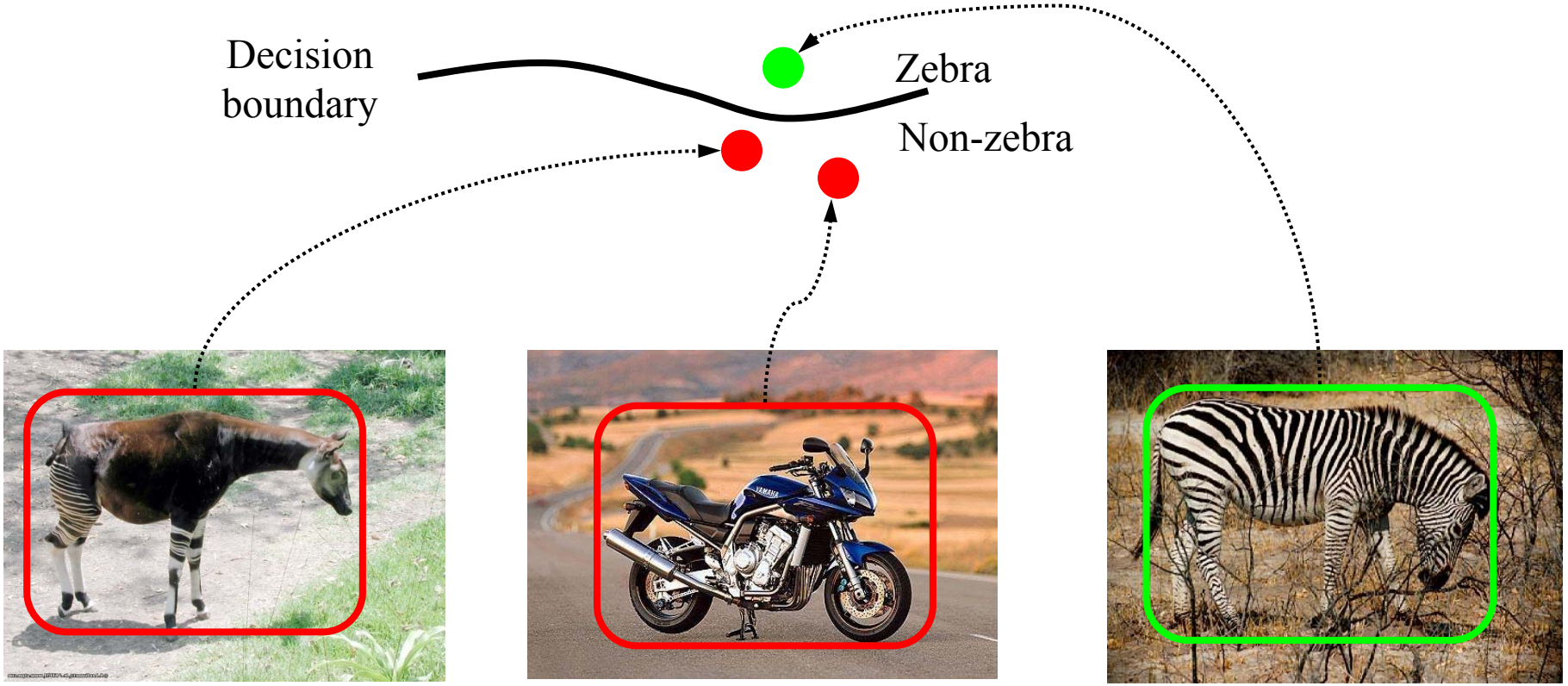
- each image is represented by a vector, typically 1000-4000 dimension, normalization with L2 norm
- fine grained – represent model instances
- coarse grained – represent object categories

Bag-of-features for image classification



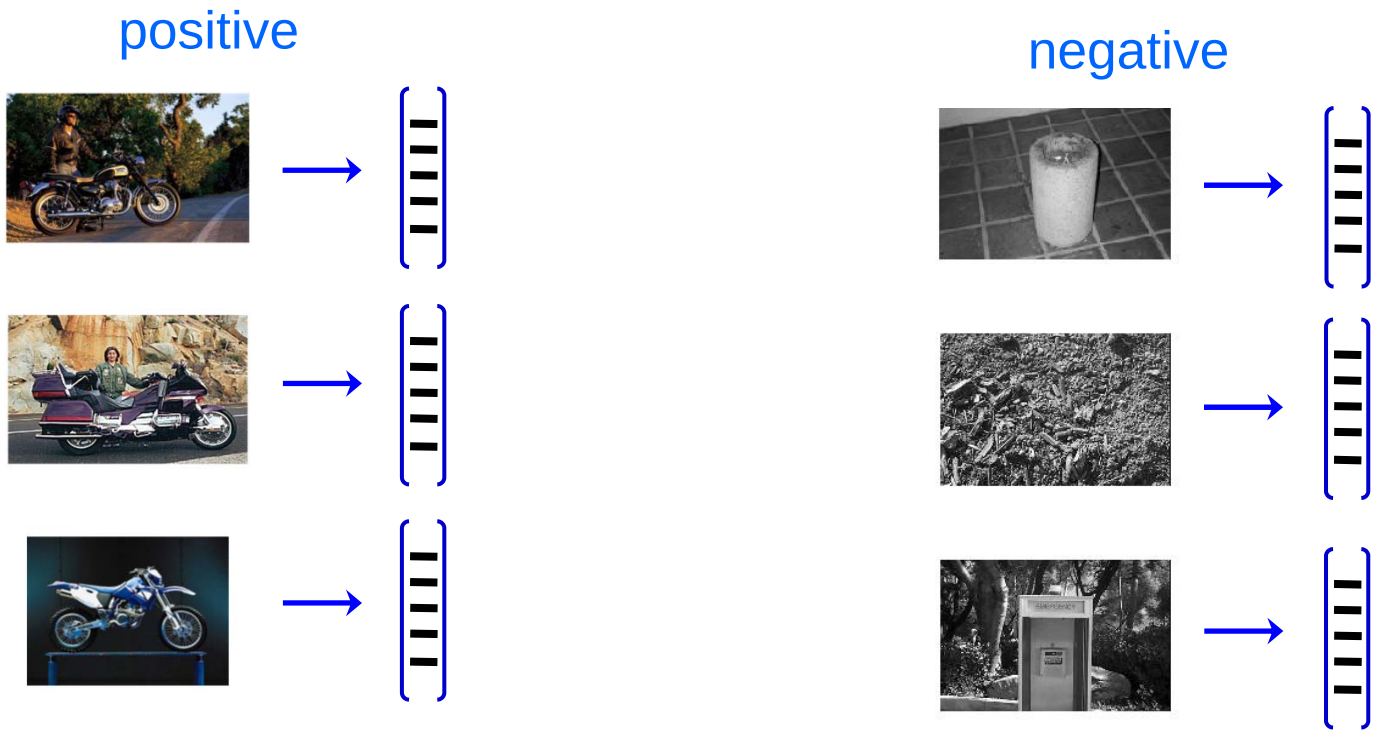
Step 3: Classification

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



Training data

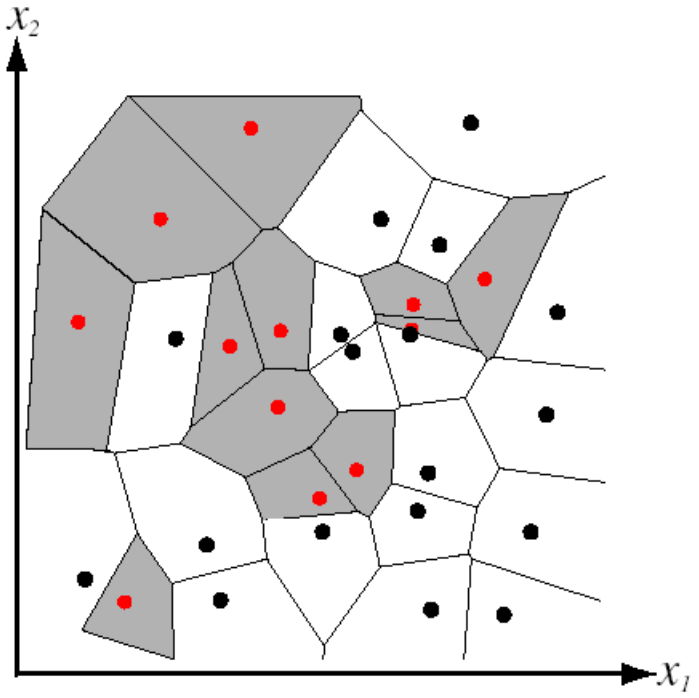
Vectors are histograms, one from each training image



Train classifier,e.g.SVM

Nearest Neighbor Classifier

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

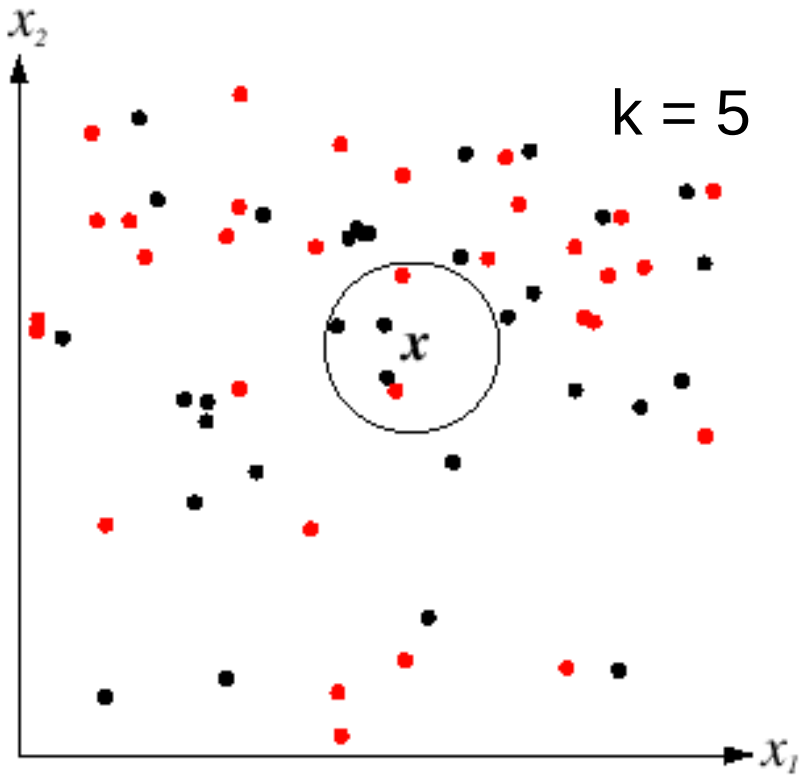


from Duda *et al.*

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

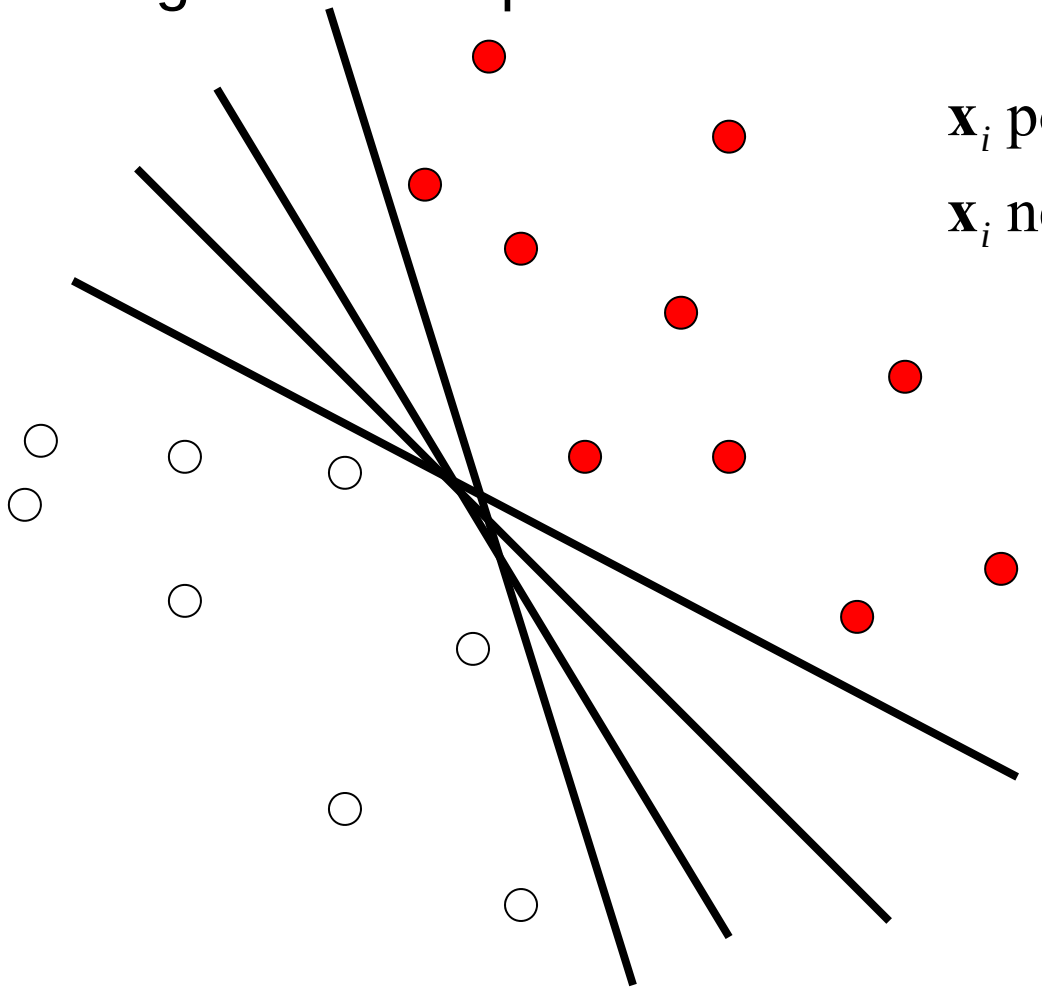


Nearest Neighbor Classifier

- 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



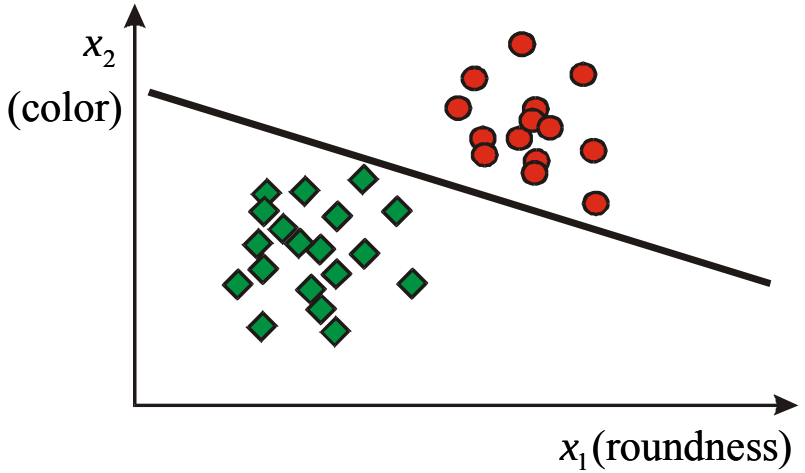
$$\mathbf{x}_i \text{ positive}: \quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 0$$

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

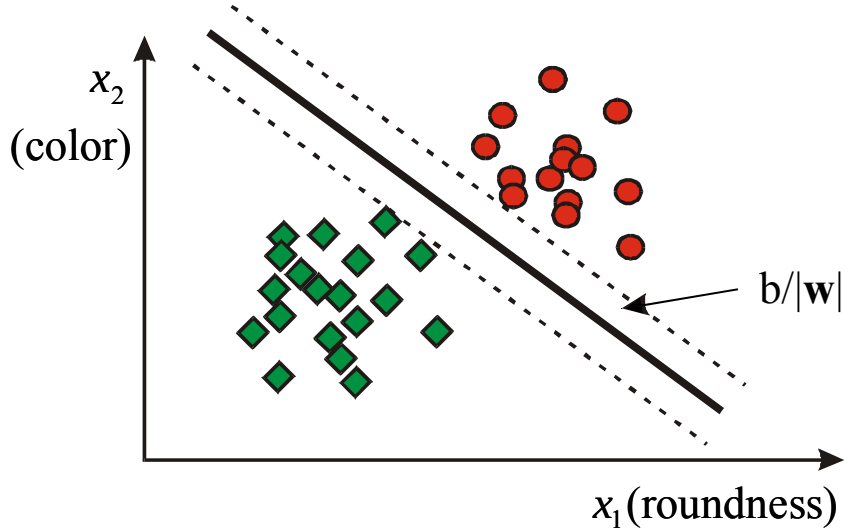
Which hyperplane is best?

Linear classifiers - margin

- Generalization is not good in this case:

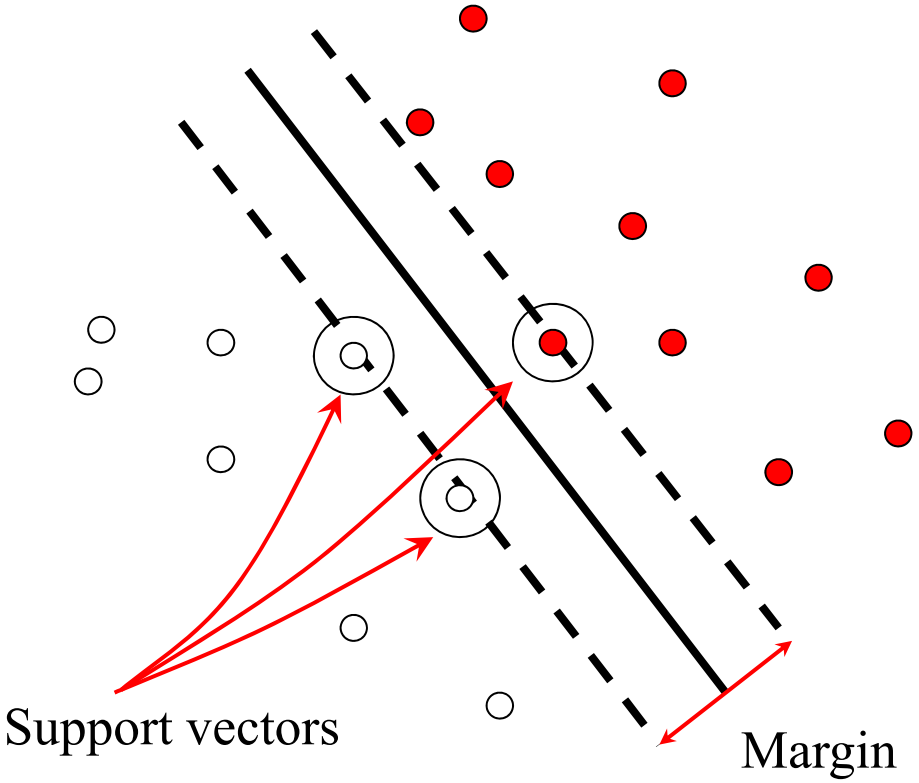


- Better if a margin is introduced:



Support vector machines

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



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

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

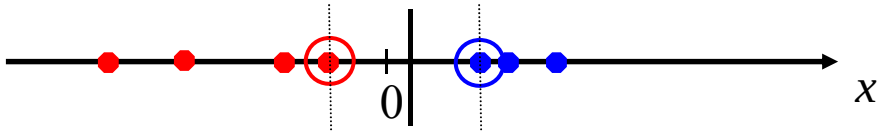
For support vectors: $\mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Data not perfectly separable, introduction of slack variable

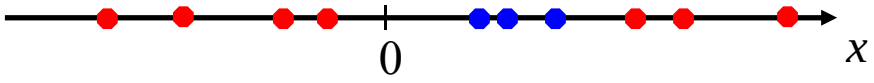
$$y^{(i)}(w^T x^{(i)} + b) \quad \geq \quad 1 - \xi_i$$

Nonlinear SVMs

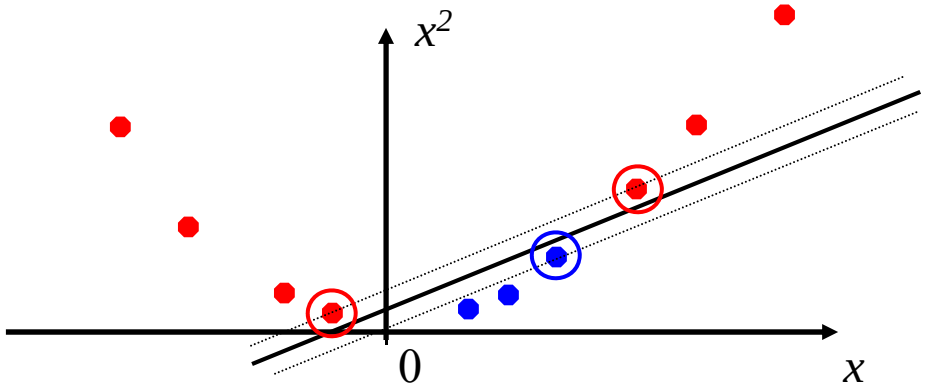
- Datasets that are linearly separable work out great:



- But what if the dataset is just too hard?

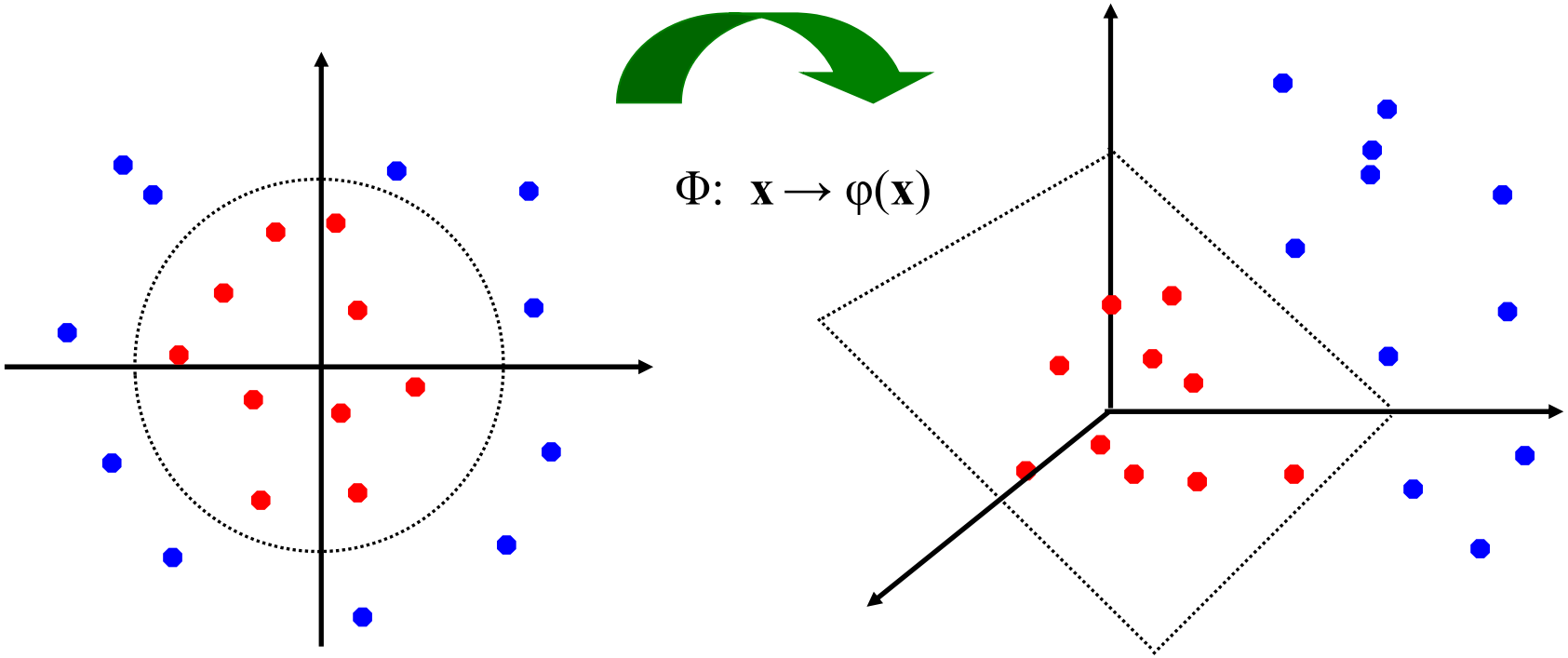


- We can map it to a higher-dimensional space:



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 $\boldsymbol{\varphi}(\mathbf{x})$, define a kernel function K such that

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

- 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

- 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

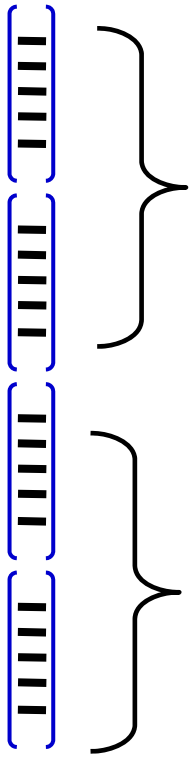
- Mutil-class formulations exist, but they are not widely used in practice. It is more common to obtain multi-class SVMs by combining two-class SVMs in various ways.

- 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

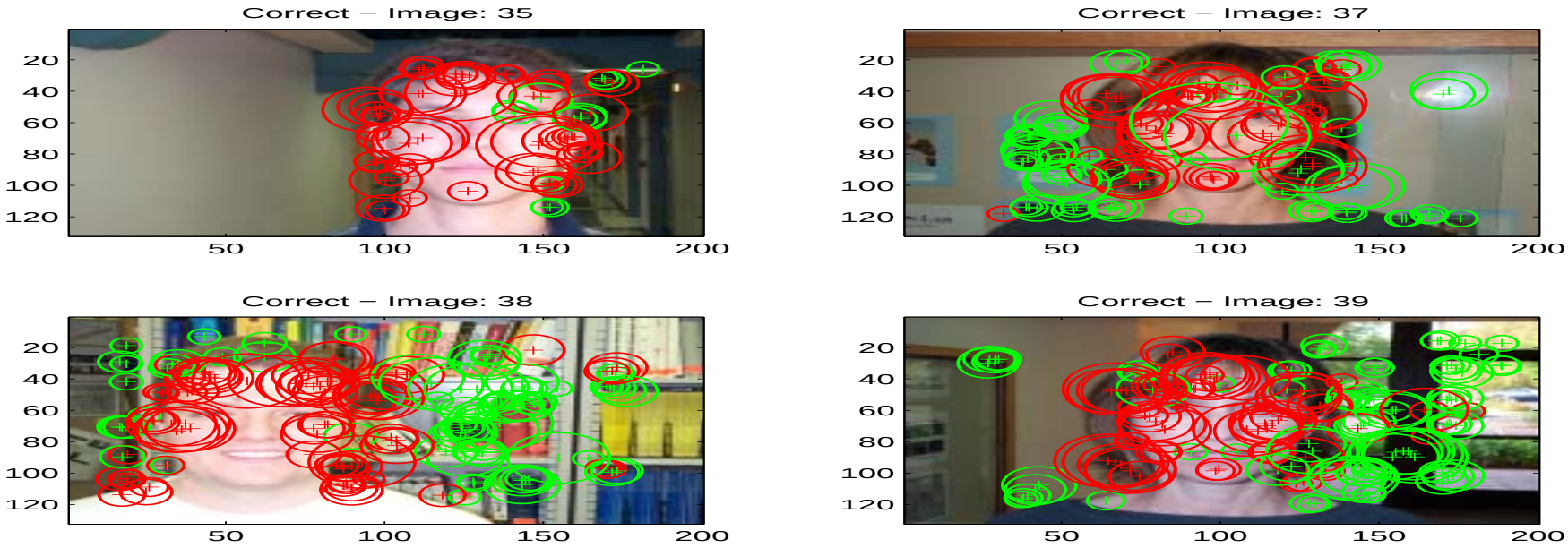


foreground words – high weight

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)

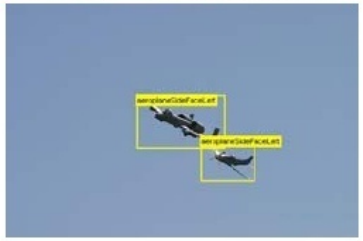
- PASCAL VOC [05-12] datasets

- 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

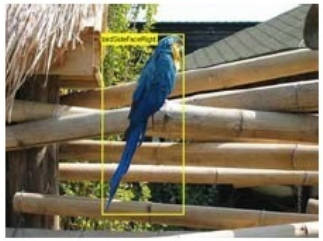
PASCAL 2007 dataset

Aeroplane

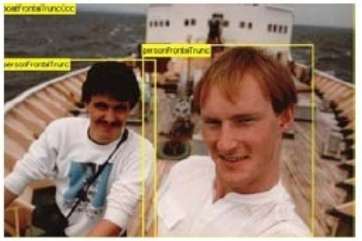


Bicycle

Bird



Boat



Bottle

Bus

Car

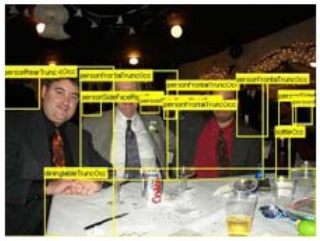
Cat

Chair

Cow

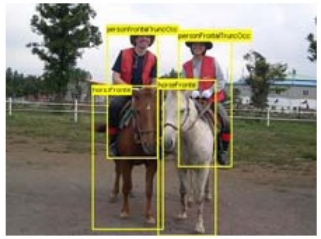
PASCAL 2007 dataset

Dining Table

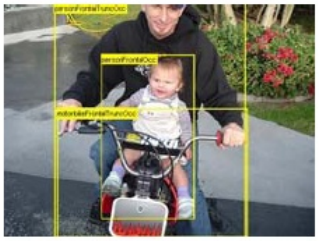


Dog

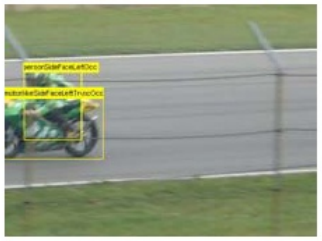
Horse



Motorbike

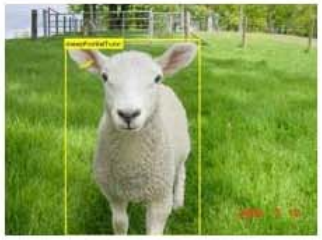


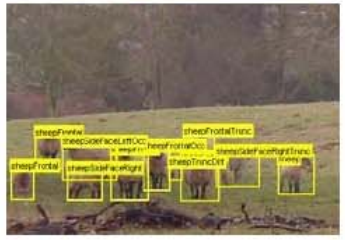
Person



Potted Plant

Sheep

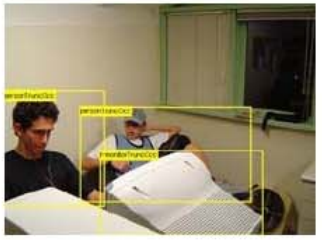




Sofa

Train

TV/Monitor



ImageNet: large-scale image classification dataset

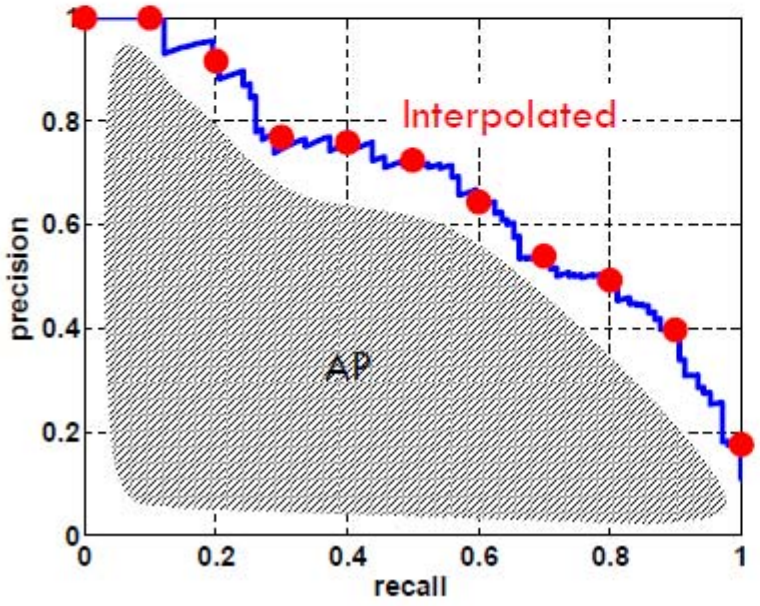
IMAGENET has 14M images from 22k classes

Standard Subsets

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

Evaluation

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



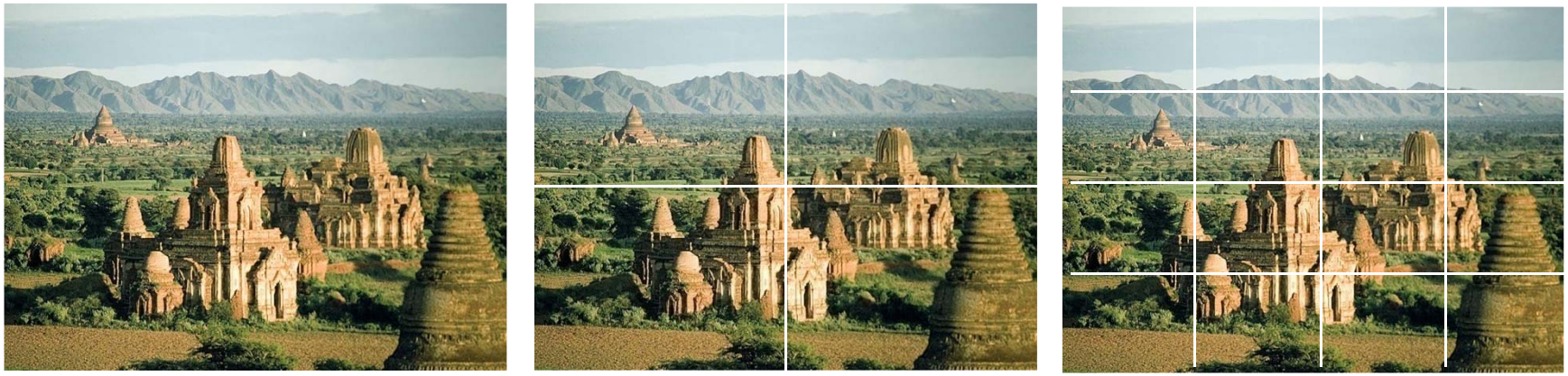
- A good score requires both high recall and high precision
- Application-independent
- Penalizes methods giving high precision but low recall

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

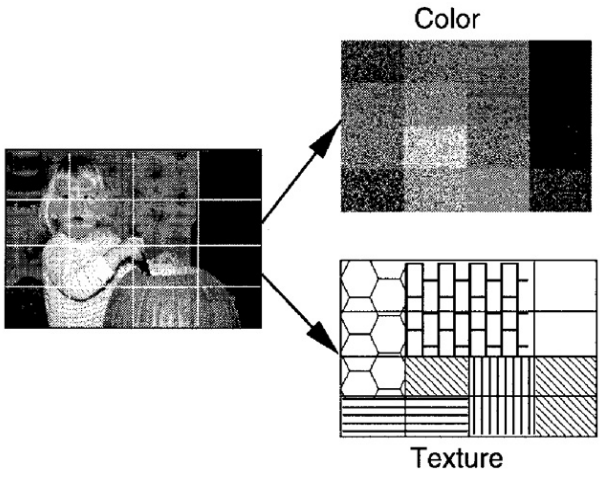


[Lazebnik, Schmid & Ponce, CVPR 2006]

Related work

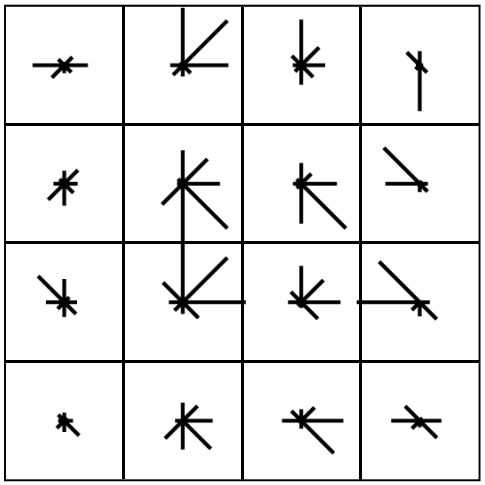
Similar approaches:

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



Szummer & Picard (1997)

SIFT

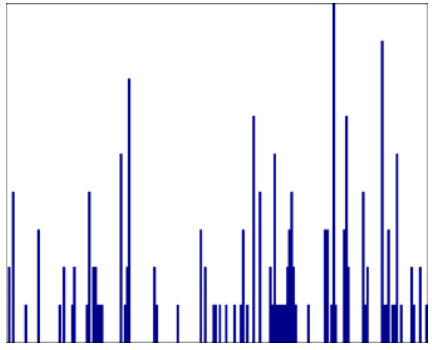


Lowe (1999, 2004)

Gist

Torralba et al. (2003)

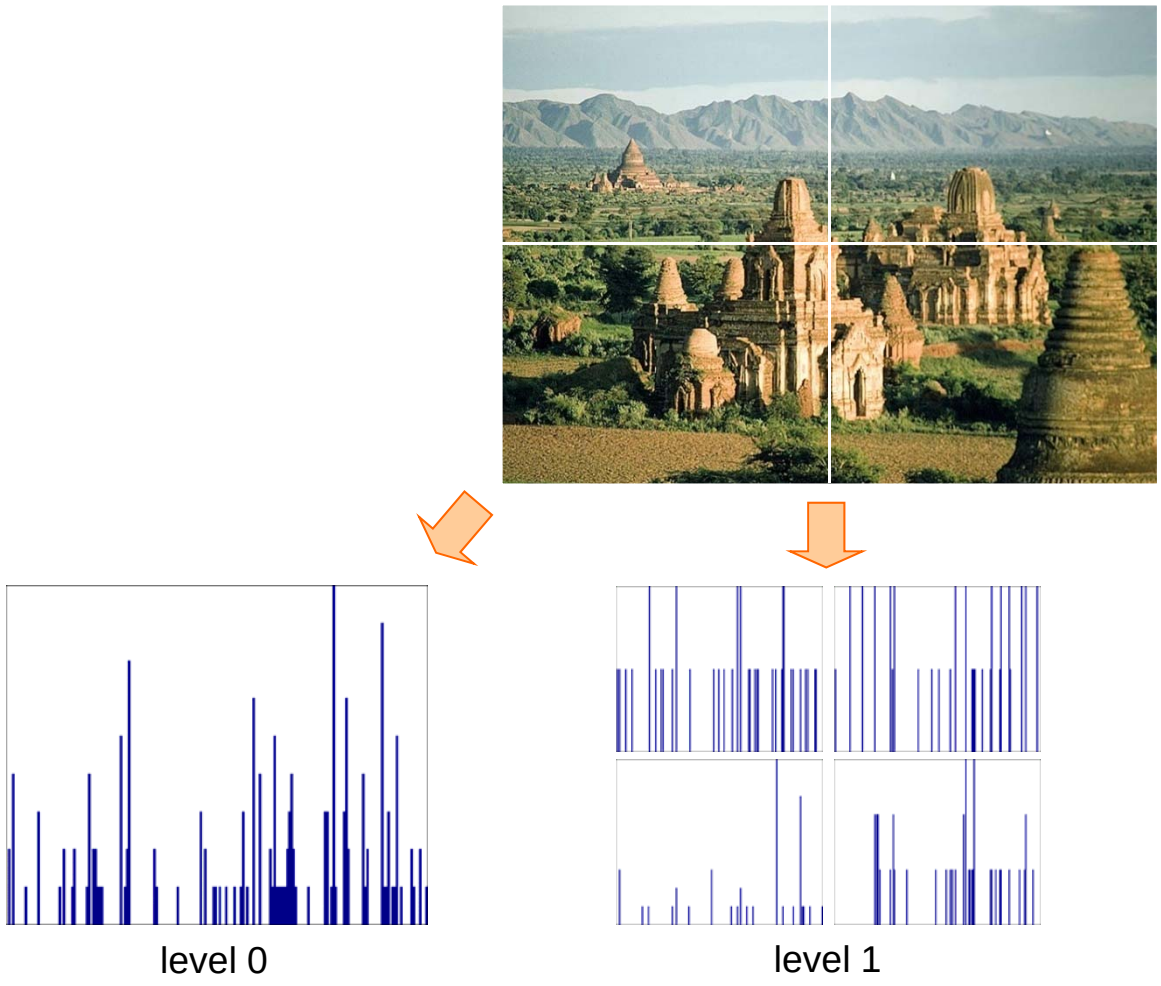
Spatial pyramid representation



level 0

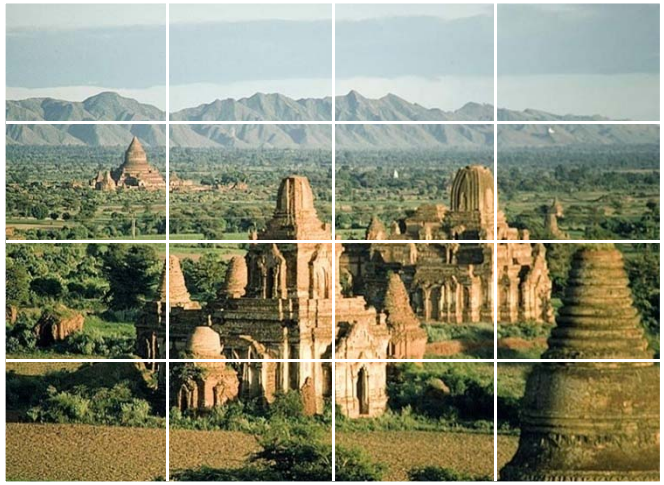
Locally orderless representation at several levels of spatial resolution

Spatial pyramid representation

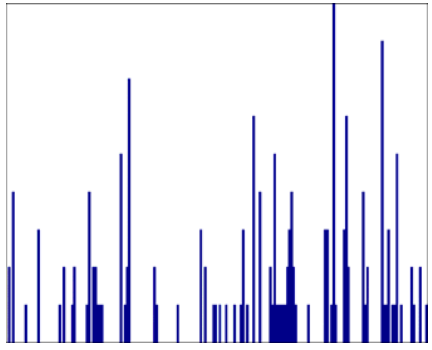


Locally orderless representation at several levels of spatial resolution

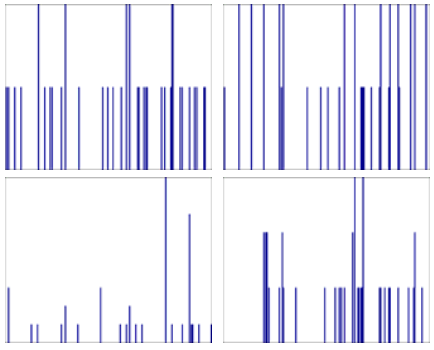
Spatial pyramid representation



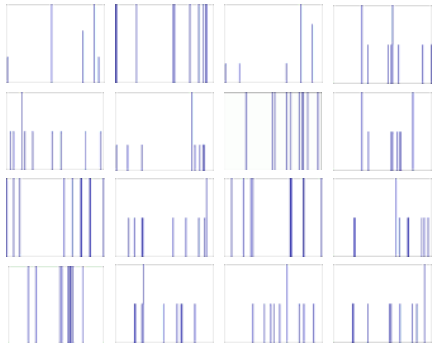
Locally orderless representation at several levels of spatial resolution



level 0

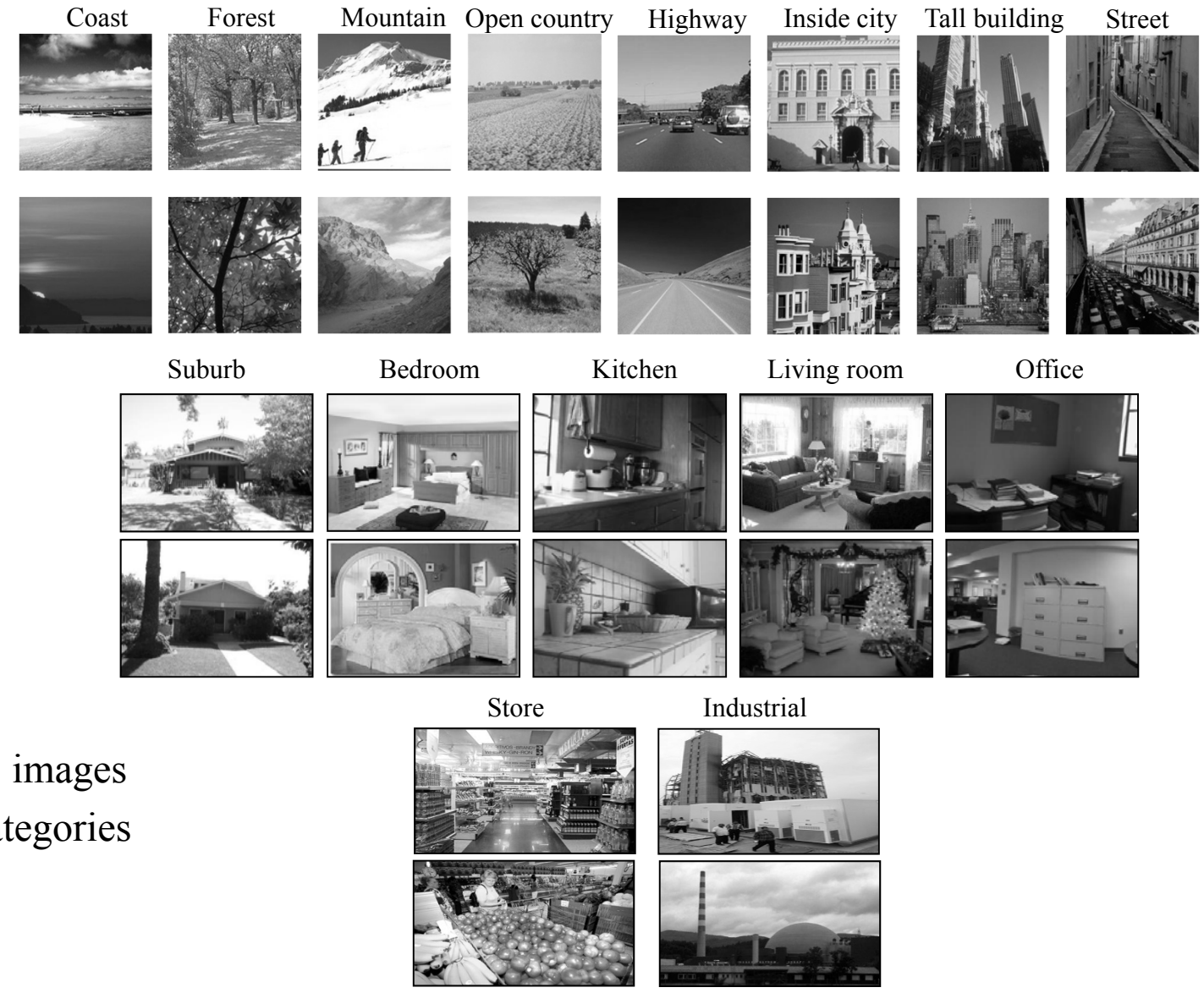


level 1



level 2

Scene dataset [Labzenik et al.'06]



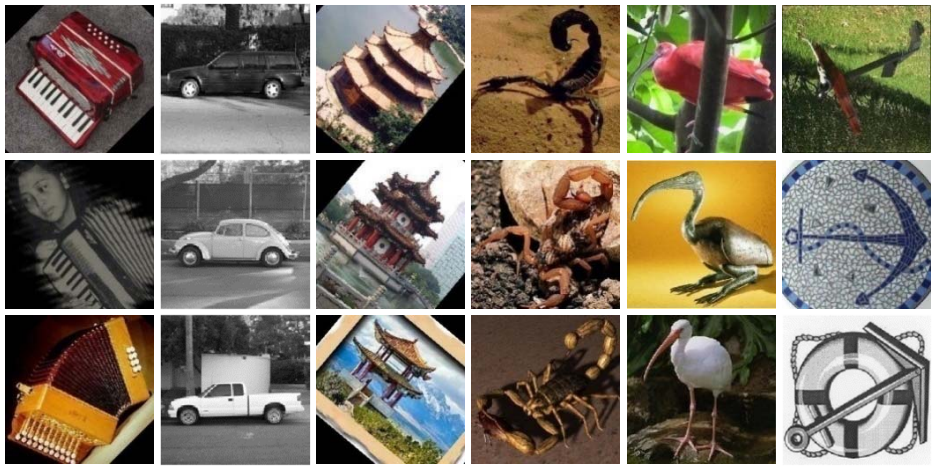
4385 images

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


minaret (97.6%)


windsor chair (94.6%)


joshua tree (87.9%)


okapi (87.8%)


cougar body (27.6%)


beaver (27.5%)


crocodile (25.0%)


ant (25.0%)

- 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]

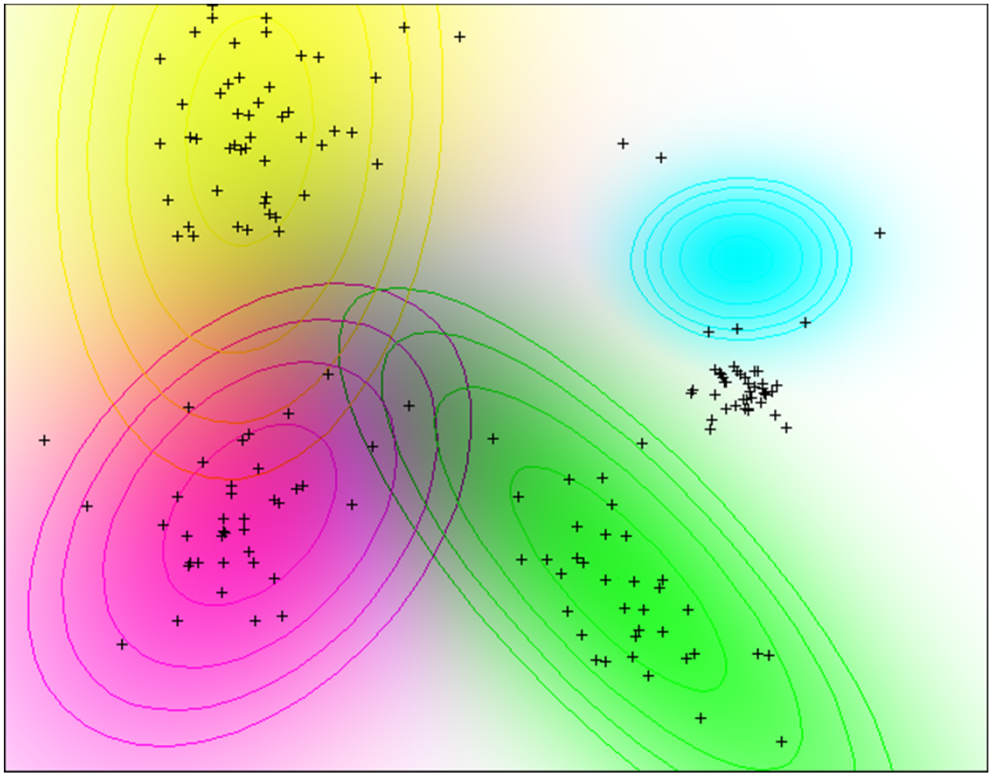
Recent extensions

- 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

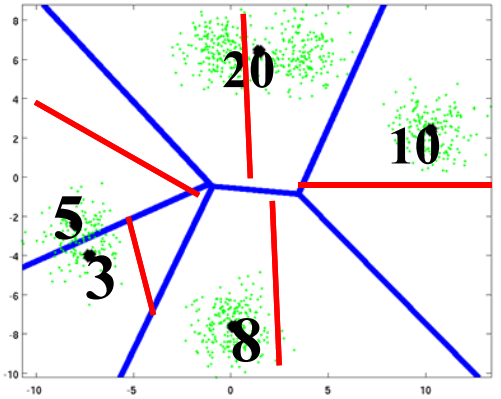
σ_i co-variance (diagonal)

Translated cluster → large derivative on μ_i for this component

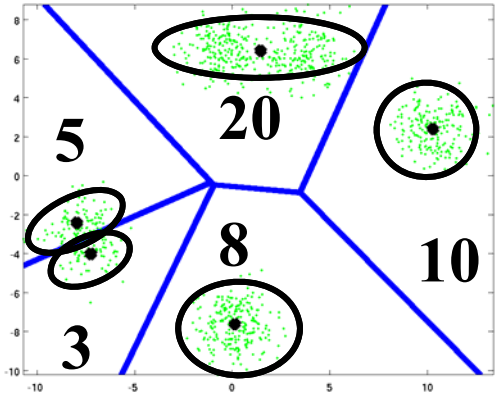
[Perronnin & Dance 07]

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

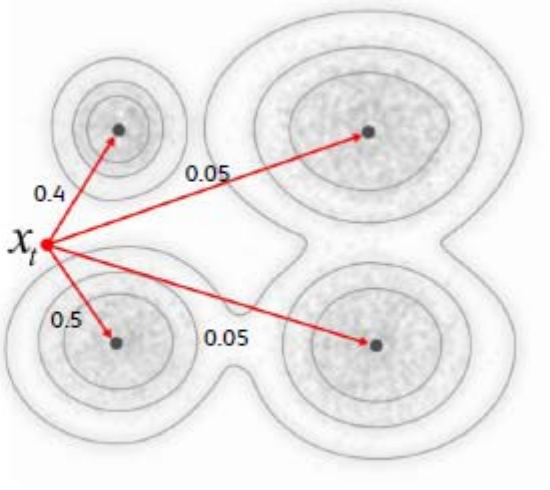
$X = \{x_t, t = 1 \ldots T\}$ is the set of T i.i.d. D-dim local descriptors (e.g. SIFT) extracted from an image:

$u_\lambda(x) = \sum_{i=1}^{K} w_i u_i(x)$ 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:

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

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

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 % → FV = 57.7 % → √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

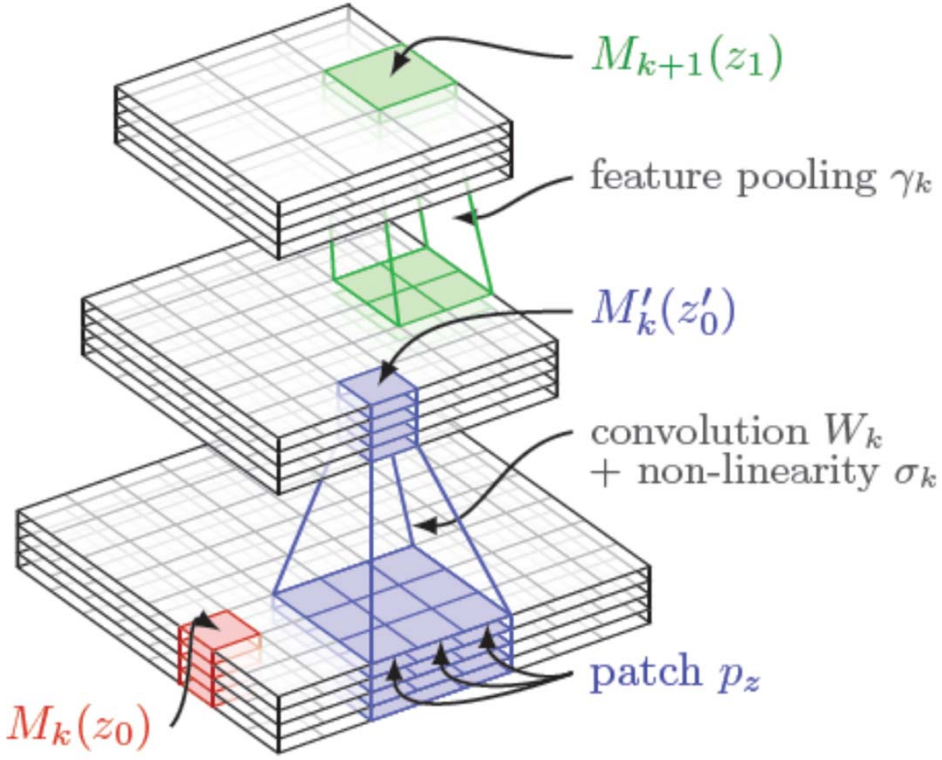
IMAGENET has 14M images from 22k classes

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]

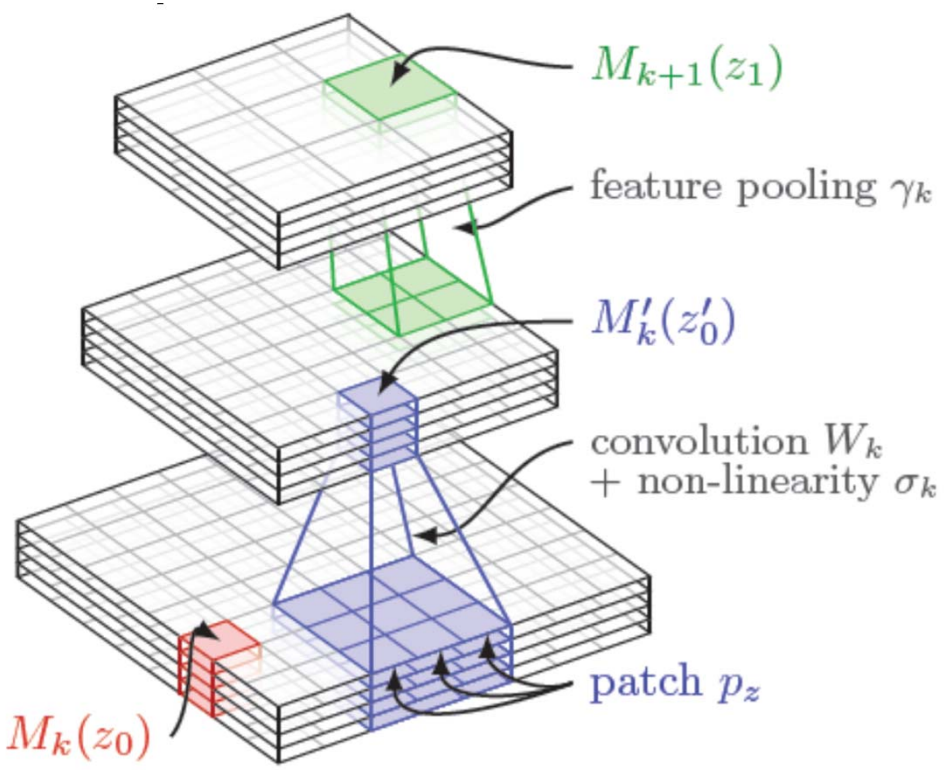
Deep convolutional neural networks

- Convolutional neural network – one layer



Deep convolutional neural networks

- Convolutional neural network – one layer

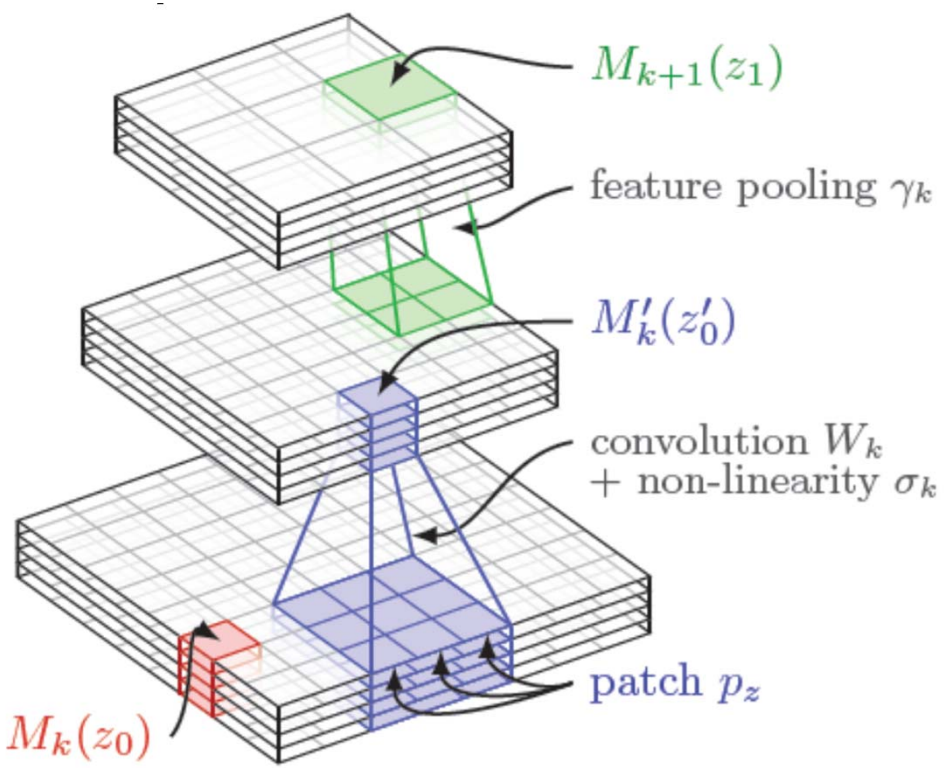


Convolutions:

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

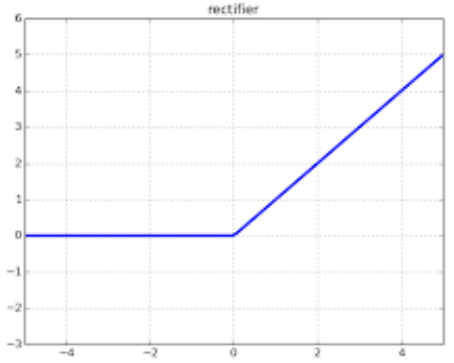
Deep convolutional neural networks

- Convolutional neural network – one layer



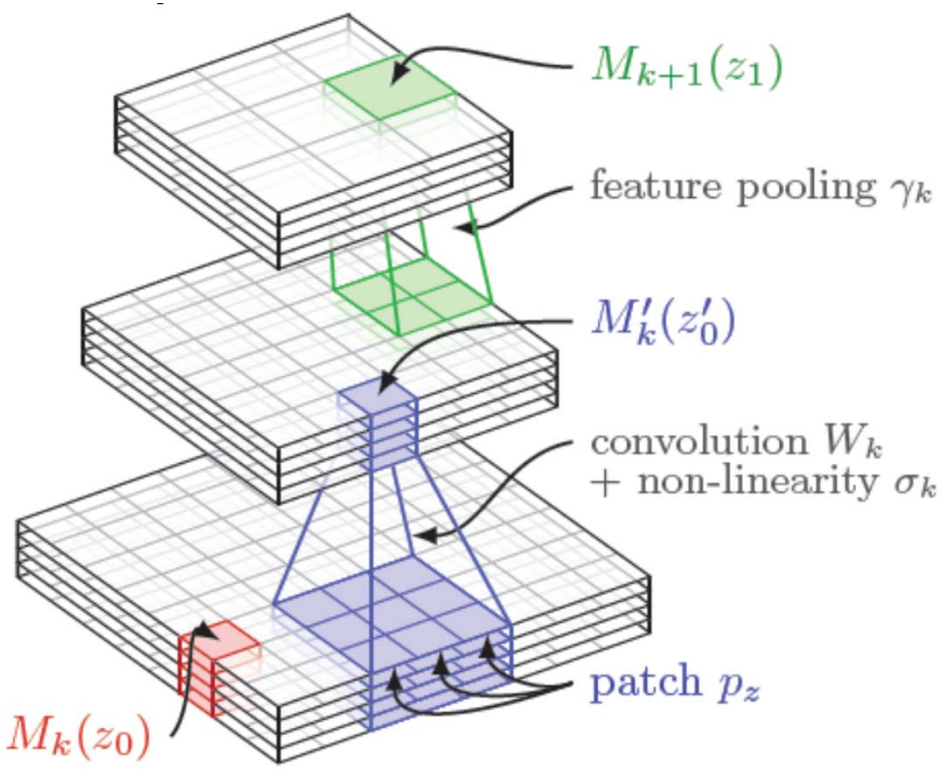
Non-linearity:

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



Deep convolutional neural networks

- Convolutional neural network – one layer

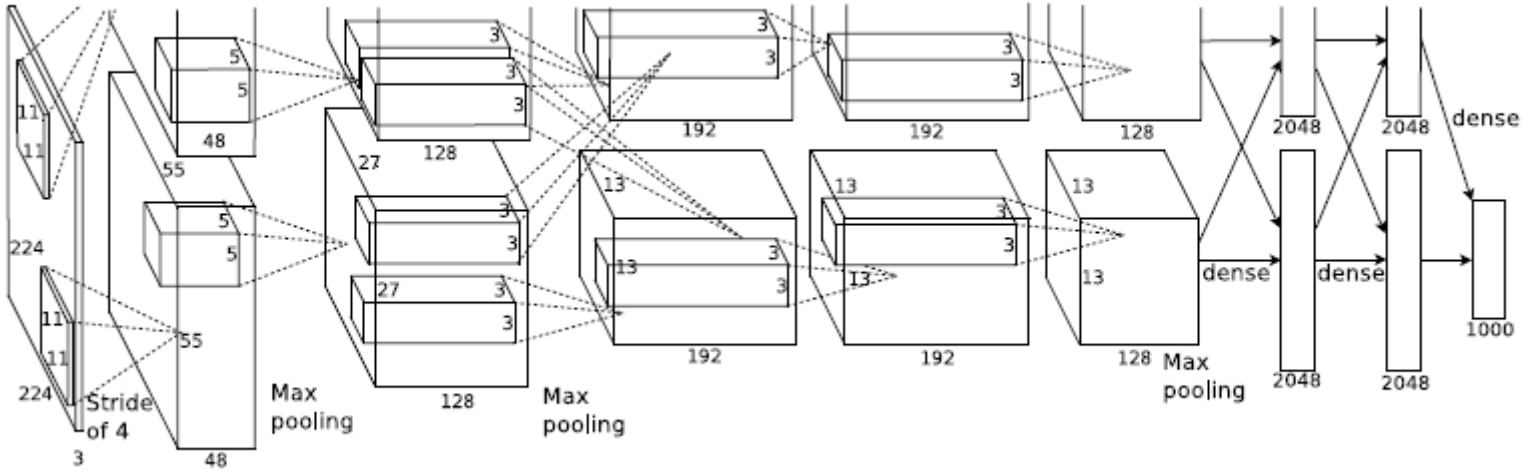


Spatial feature pooling:

- 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

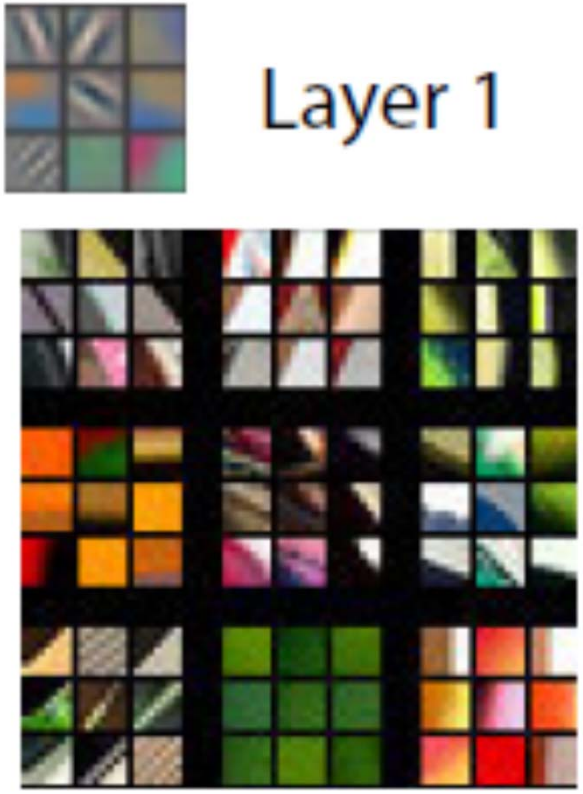
Deep convolutional neural networks

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

(a) Star Anise (b) Geyser (c) Pulp Magazine (d) Carrycot

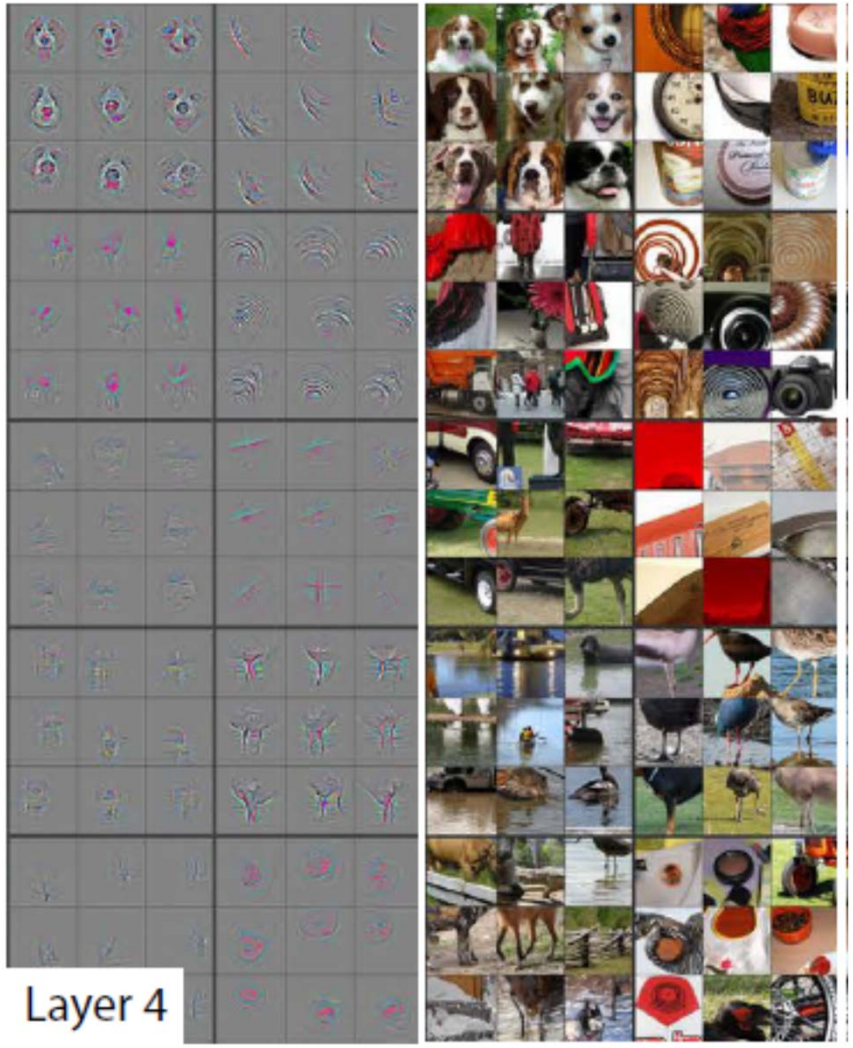
(e) European gallinule (f) Sea Snake (g) Paintbrush (h) Mountain Tent

Visualization of the convolution filters



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

Visualization of the convolution filters



Top nine activations