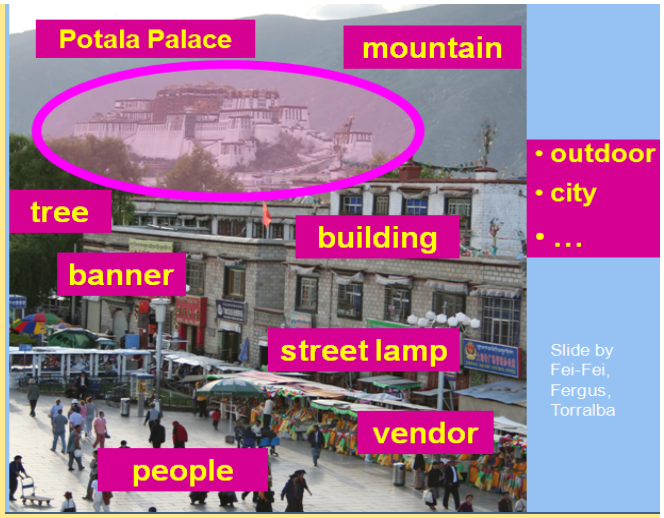
Course Outline

1. Computer Vision Introduction (1): Visual (local) feature detection and description **(2): Bag of Word Image representation**
2. Classification: Datasets, benchmarks and evaluation, Linear classification (SVM)

From Bag of features to Bag of Words



1. **Introduction to Bag of Words**
2. Dictionary computation
3. Coding of local descriptors
4. Image signature computation: pooling
5. Whole recognition pipeline

Bag of Feature (BoF) Model

Image

(features)

Bag of Words repsentation

- BoF
  - Local signatures: not a scalable representation
  - Not a *semantic* representation

- Model to represent images for categorization: « **Bag of Words BoW »**
- BoW model computed from BoF (Bag of features)

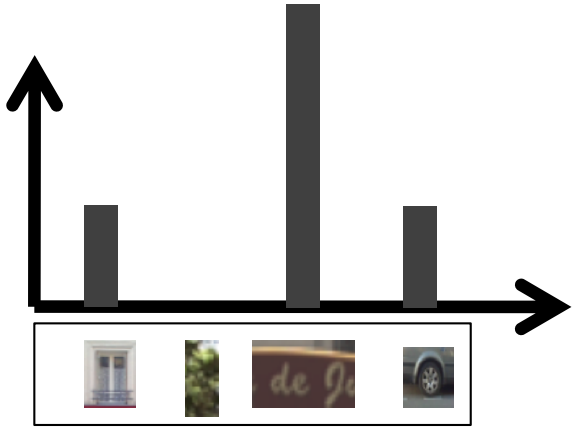
Bag of Words (BoW) model: basic explication with textual representation and color indexing

Comparing 2 docs using visual/color/word occurrences

Bag of Visual Words (BoW)

(features)

BoW : histogram on visual dictionary



Questions:

1. Which dictionary ?
2. How to project the BoF onto the dico
3. How to compute the histogram?

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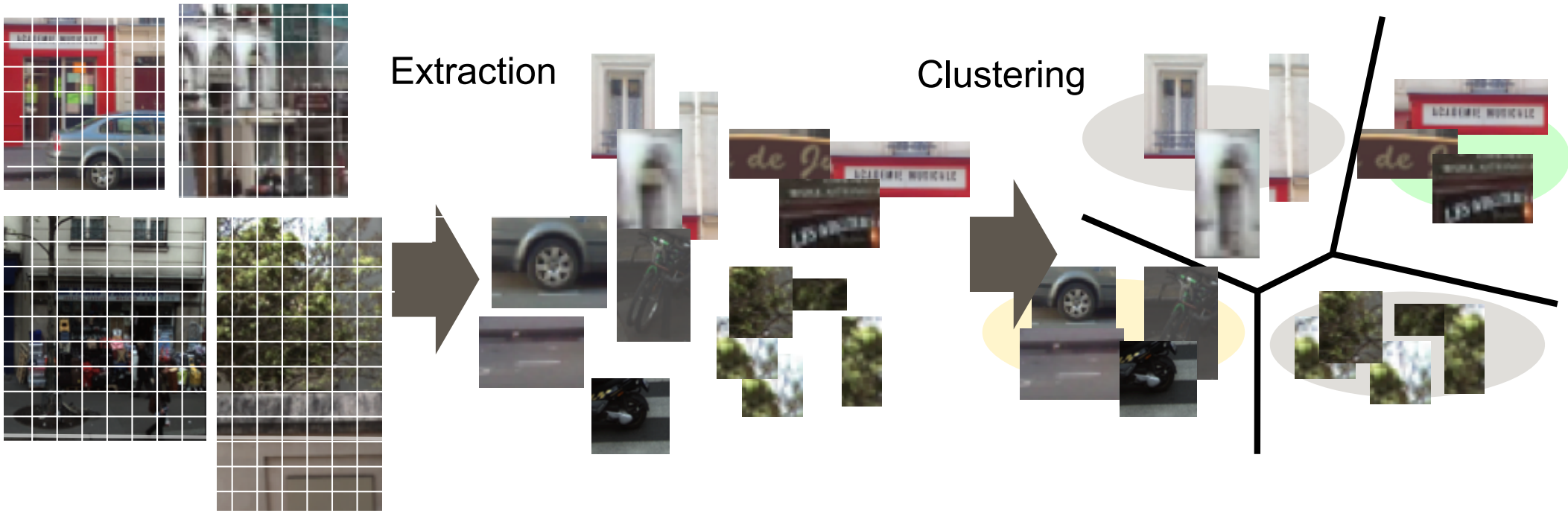
3 steps for BoWs

Step 1 : dico computation

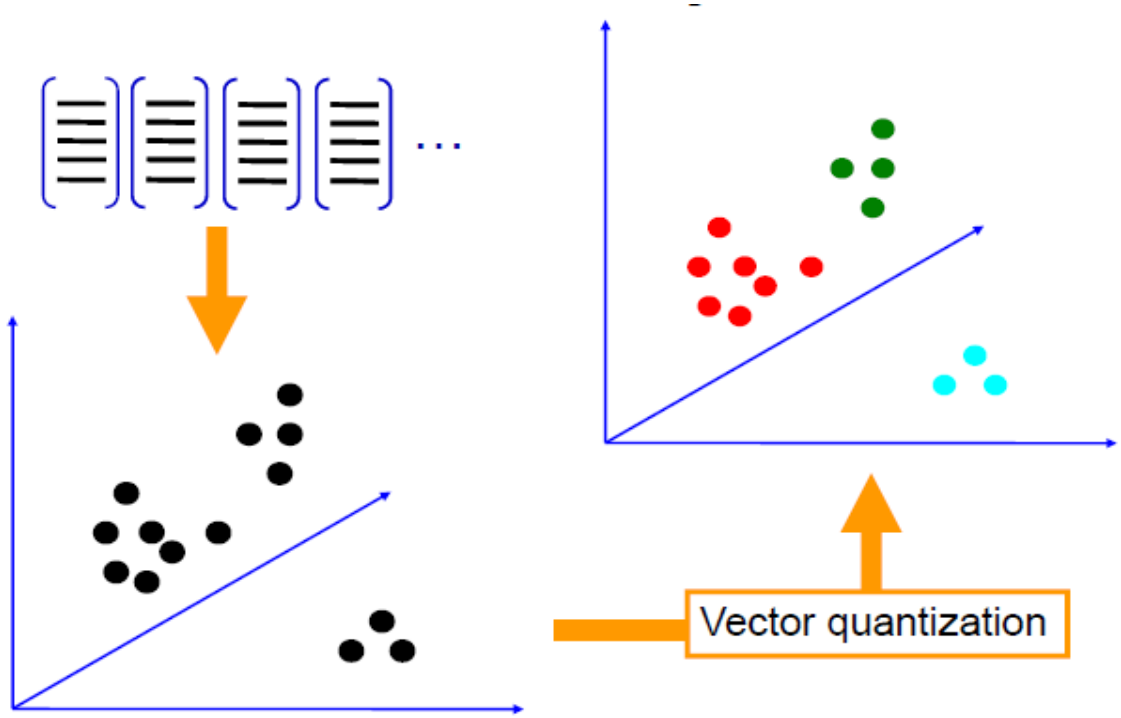
1. Extraction of local features (pattern/visual words) in images
   - Training dataset in classification
   - Image dataset in retrieval
2. Clustering of feature space



Training set but no labels => UNSUPERVISED Learning

Step 1 : dico computation

- Many algorithms for clustering :
  - K-Means
  - Vectorial Quantization
  - Gaussian Mixture Models
  - …



Clustering with K clusters

Input: set of n points $\{x_j\}_n$ in R^d

Goal: find a set of K (K<<n) points $w=\{w_k\}_K$
that give a approximation of the n input points,
ie. minimizing mean square error C(w):

$$C(w) = \sum_{i=1}^{n} \min_k \|x_i - w_k\|^2$$

At k fixed, complexity is $O(n^{(Kd+1)}\log n)$

A lot of strategies to approximate the global optimization problem

Clustering with K clusters

$$C(w) = \sum_{i=1}^{n} \min_{k} \|x_i - w_k\|^2$$

***K-means* Algorithm:**

Init K centers (c_k) by sampling K points w_k in R^d

$$\min_{k} \|x_i - w_k\|^2$$

1. (Re)assign each point x_i to the cluster s_i with the center w_{si} so that dist(x_i, w_{si}) is less than dist from x_i to any other clusters

$$\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2$$

2. Move all w_k inside each cluster as the new barycenter from all the points assigned to the cluster k (equ. to minimize the corresponding mean square error)
3. Go to step 1 if some points changed clusters during the last iteration

Output: the set of the final K cluster centers $\{c_k = w_k\}$

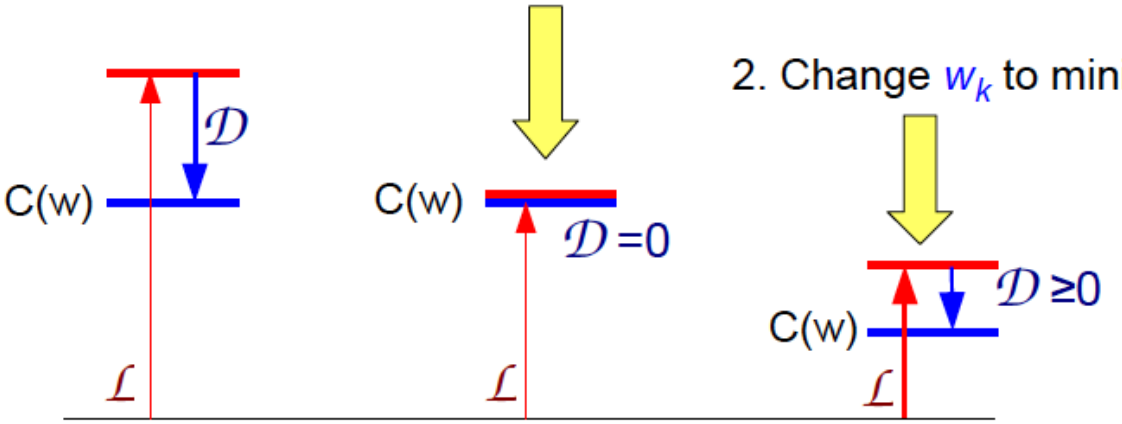
K-means : why it is successful ?

Consider an arbitrary cluster assignment s_i.

$$C(w) = \sum_{i=1}^{n} \min_k \|x_i - w_k\|^2 = \underbrace{\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2}_{\mathcal{L}(s,w)} - \underbrace{\sum_{i=1}^{n} \|x_i - w_{s_i}\|^2 - \min_k \|x_i - w_k\|^2}_{\mathcal{D}(s,w) \geq 0}$$

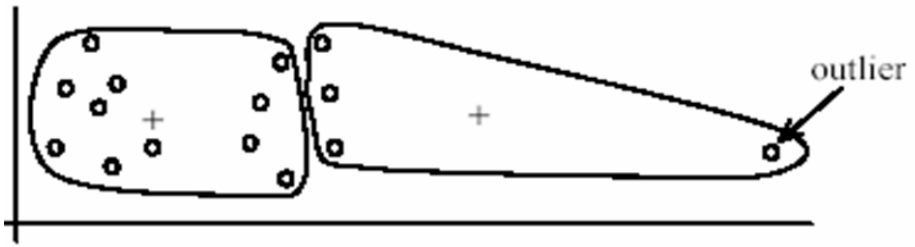
1. Change s_i to minimize $\mathcal{D}$ leaving C(w) unchanged.

2. Change w_k to minimize $\mathcal{L}$. Meanwhile $\mathcal{D}$ can only increase.



Clustering

- K-means :
  - Pros
    - Simplicity
    - Convergence (local min)
  - Cons
    - Memory-intensive
    - Depending on K
    - Sensitive to initialization
    - Sensitive to artifacts
    - Limited to spherical clusters
    - Concentration of clusters to areas with high densities of points (Alternatives : radial based methods)



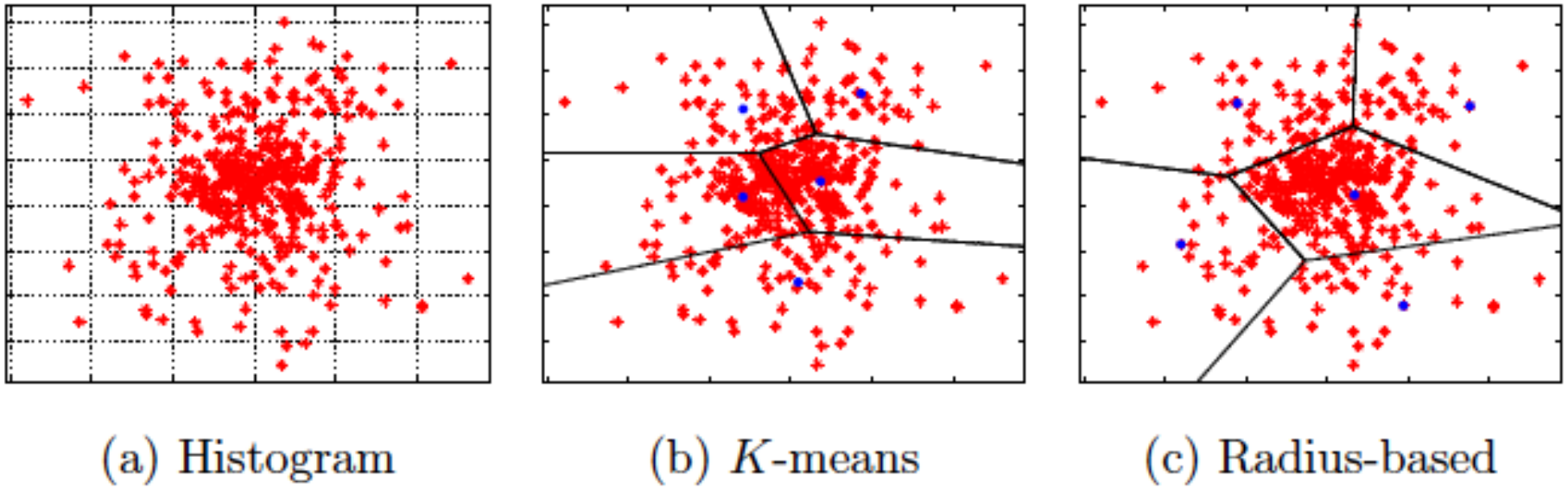
(A): Undesirable clusters

(B): Ideal clusters

- K-Means deeply used in practice

Clustering

- Uniform / K-means / radius-based :



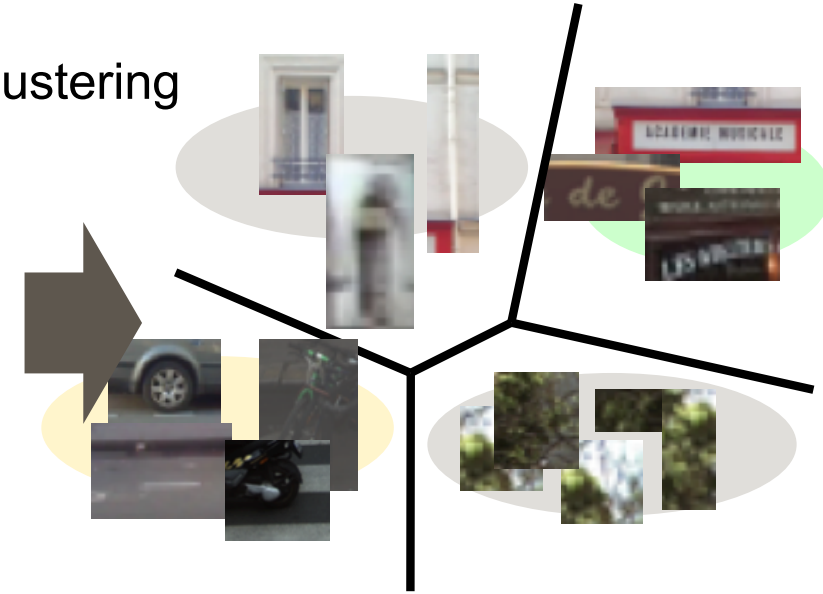
(a) Histogram (b) K-means (c) Radius-based

- *Radius-based clustering assigns all features within a fixed radius of similarity r to one cluster.*

Visual words

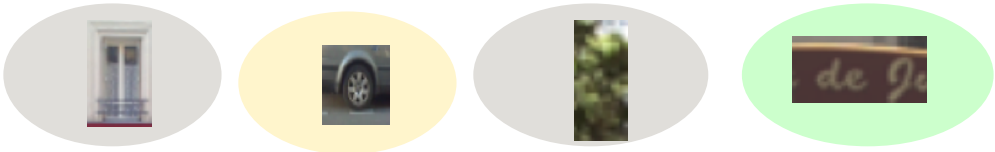
Extraction

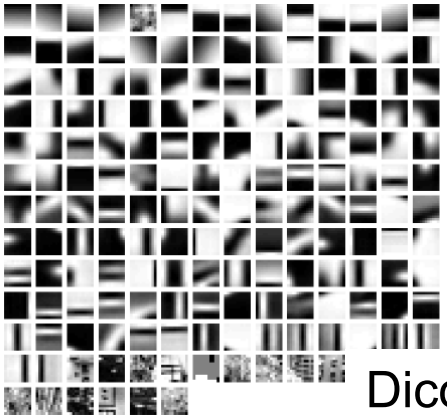
Clustering



Formation du dico

Centers = dico. Visual words





Dico examples

Plan

1. Introduction to Bag of Words
2. Dictionary computation
3. **Coding of local descriptors**
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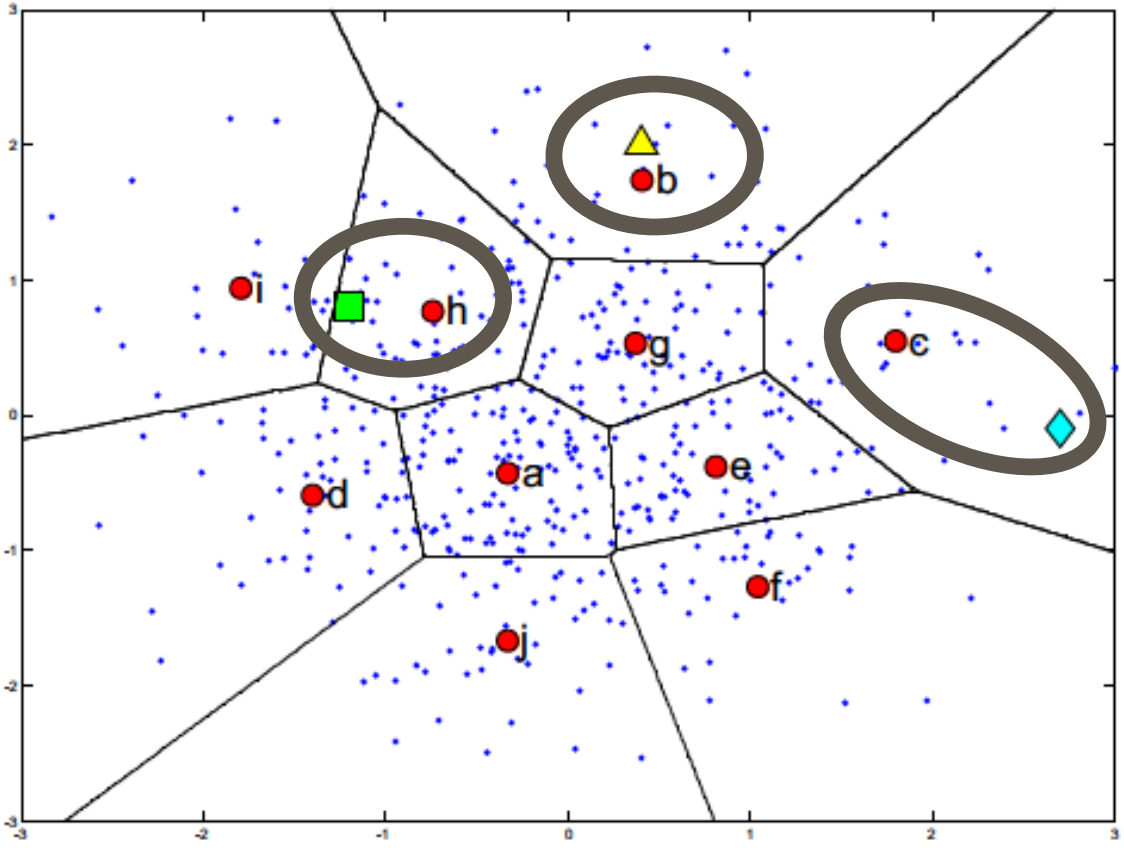
Step 2 : BoW image signature

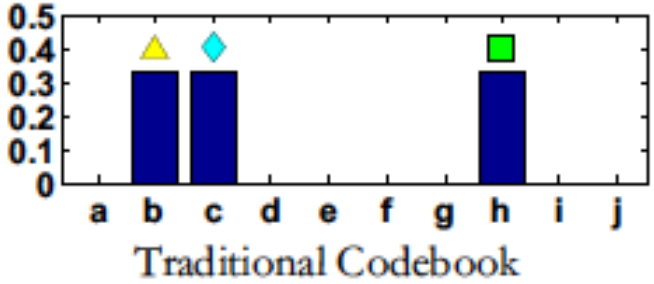
- For each image:
  - For each local feature: find the closest visual word
  - Increase the corresponding bin in histogram

- Image signature (global Index):
  - Vector (histogram)
  - M=K dimension = dico size
  - Each term represents a Likelihood to get this visual word

Projection to dictionary

- Original BoW strategy: **hard assignement/coding**
  - Find the closest cluster for each feature
  - Assign a fix weight (*e.g.* 1)





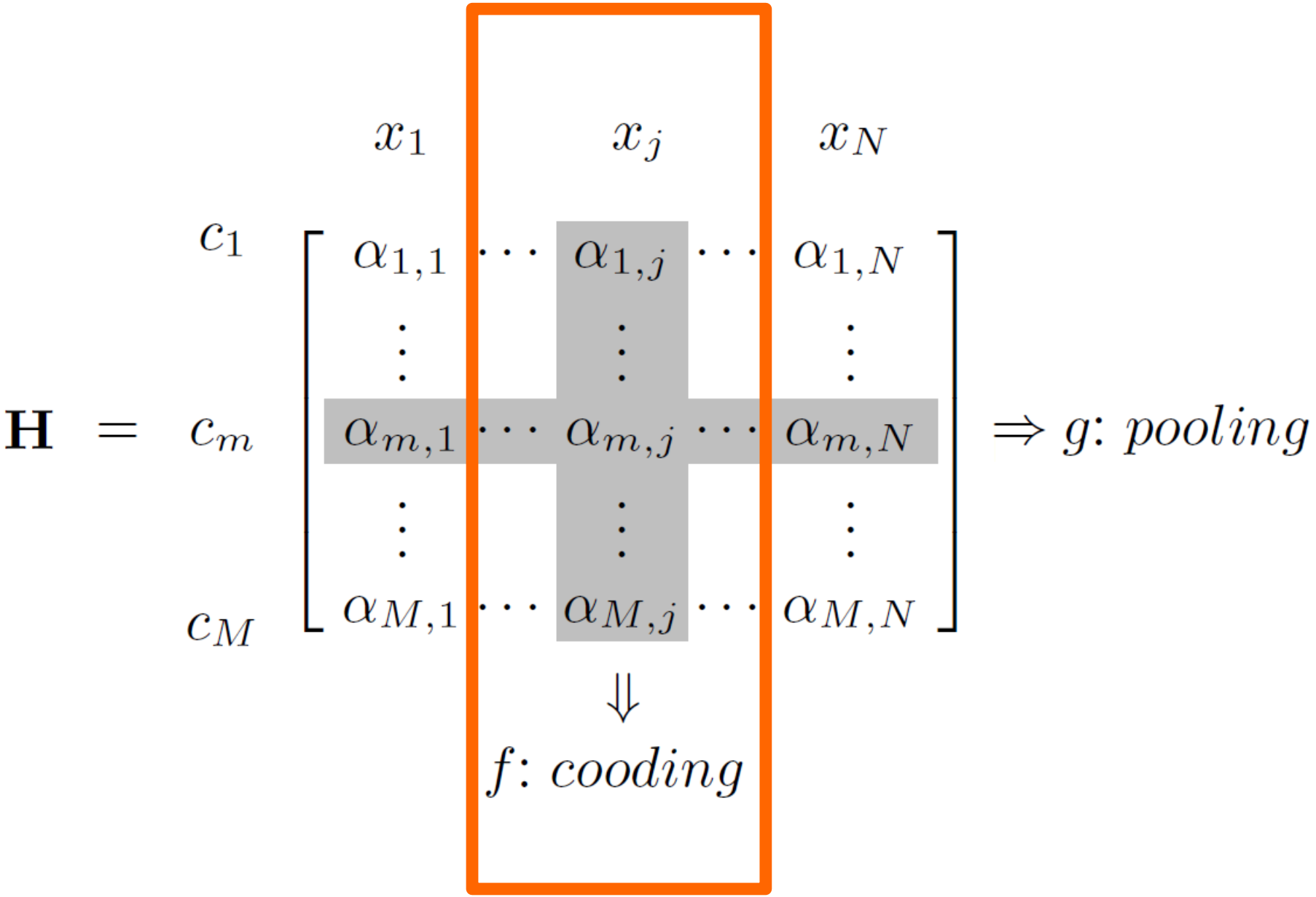
Notations:

- Image data : $\mathbf{X} = \left\{ x_j \in \mathbb{R}^d \right\}, j \in \{1; N\}$
- Centers : $\mathbf{C} = \{C_m\},\ m \in \{1; M\}$
- Coding :

$$\begin{aligned} f : \mathbb{R}^d &\longrightarrow \mathbb{R}^M \\ x_j &\longrightarrow f(x_j) = \alpha_{\mathbf{j}} = \{\alpha_{m,j}\}, \quad m \in \{1; M\} \end{aligned}$$

Hard coding: $f = f_Q$ assigns a constant weight to its closest center:

$$f_Q(x_j)[m] = \begin{cases} 1 & \text{if } m = \underset{k \in \{1;M\}}{\operatorname{argmin}} \|x_j - c_k\|^2 \\ 0 & \text{otherwise} \end{cases}$$


x_1
x_j
x_N
c_1
c_m
c_M
$\mathbf{H} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,j} & \cdots & \alpha_{1,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,j} & \cdots & \alpha_{m,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{M,1} & \cdots & \alpha_{M,j} & \cdots & \alpha_{M,N} \end{bmatrix}$
$\Rightarrow g$: pooling
$\Downarrow$
f: cooding

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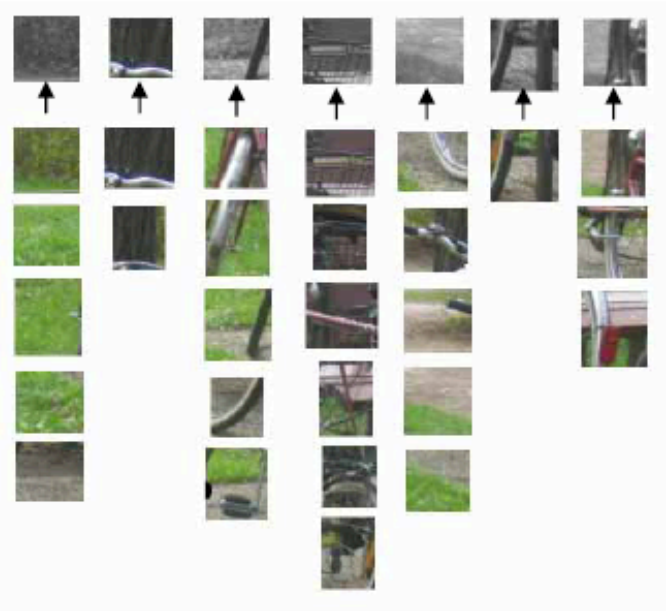
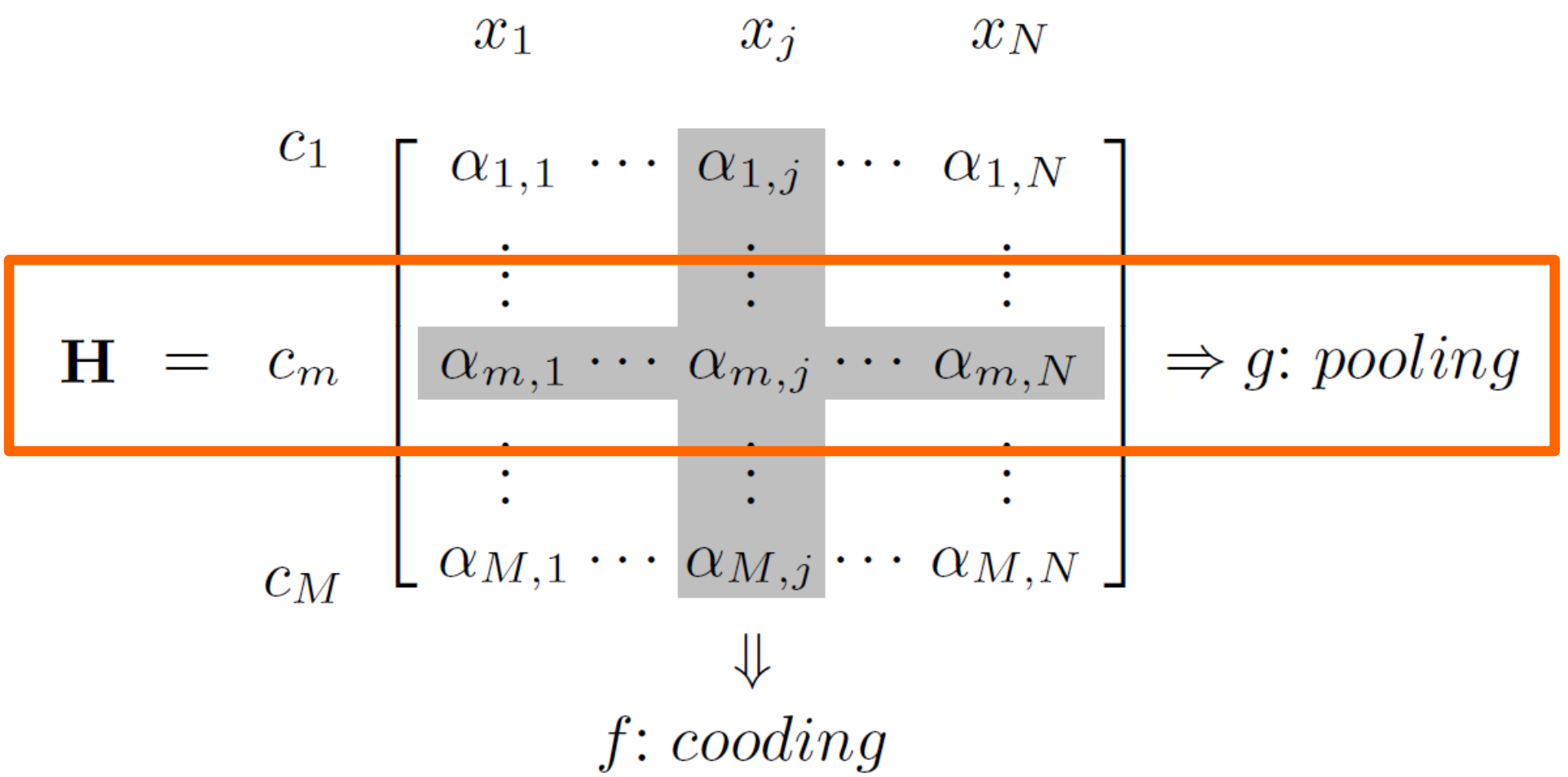
Aggregating projections => global image index

- Global Index: image likelihood to get each visual word
- Several strategies to aggregate the projections: **pooling**

$$g : \mathbb{R}^N \longrightarrow \mathbb{R}$$

$$\alpha_{\mathbf{m}} = \{\alpha_{m,j}\}, j \in \{1; N\} \longrightarrow g(\alpha_m) = z_m$$



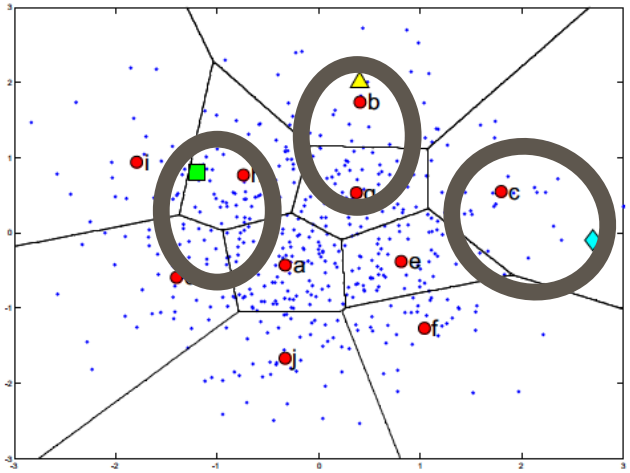

x_1 x_j x_N
c_1
c_m
c_M
$\mathbf{H} = \begin{bmatrix} \alpha_{1,1} & \cdots & \alpha_{1,j} & \cdots & \alpha_{1,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{m,1} & \cdots & \alpha_{m,j} & \cdots & \alpha_{m,N} \\ \vdots & & \vdots & & \vdots \\ \alpha_{M,1} & \cdots & \alpha_{M,j} & \cdots & \alpha_{M,N} \end{bmatrix}$
$\Rightarrow g$: pooling
$\Downarrow$
f: cooding

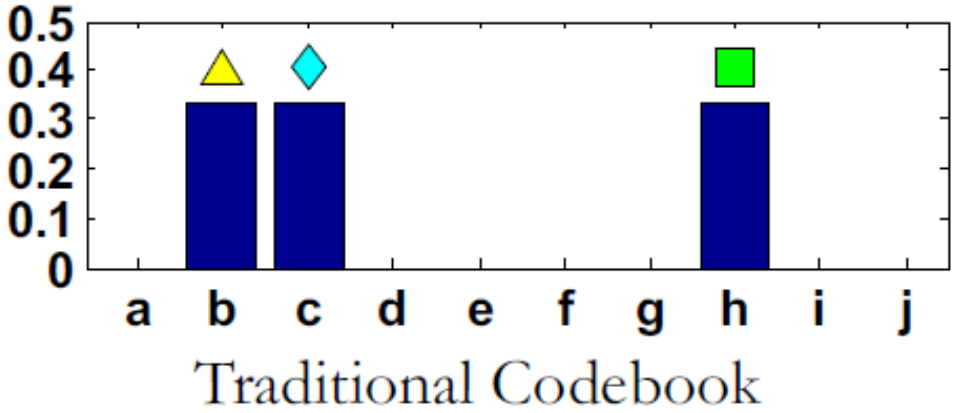
Aggregating projections => global image index

- **Sum pooling** : initial BoW strategy (just counting occurrences of words in the document)

Classical BoW = **hard coding + sum pooling**

1. Find the closest cluster for each feature
2. Assign a fix weight (*e.g.* 1) to this cluster





Aggregating projections => global image index

- BoW Sum pooling:

$$z_m = g(\alpha_m) = \sum_{j=1}^{N} \alpha_{m,j} = \sum_{j=1}^{N} f_Q(x_j)[m]$$

$$z_m = \sum_{j=1}^{N} \begin{cases} 1 & \text{if } m = \underset{k \in \{1;M\}}{\operatorname{argmin}} \|x_j - c_k\|^2 \\ 0 & \text{otherwise} \end{cases}$$

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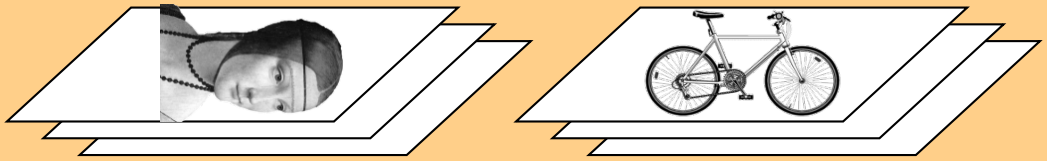
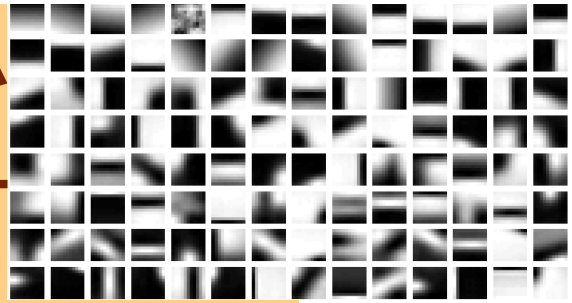
Representation



2.

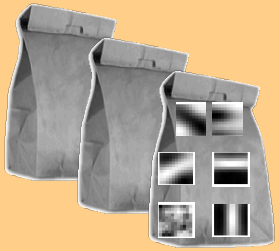
codewords dictionary

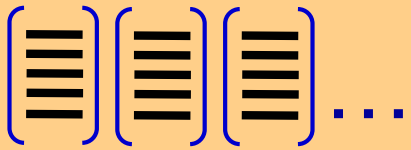


1. feature detection & representation

image representation

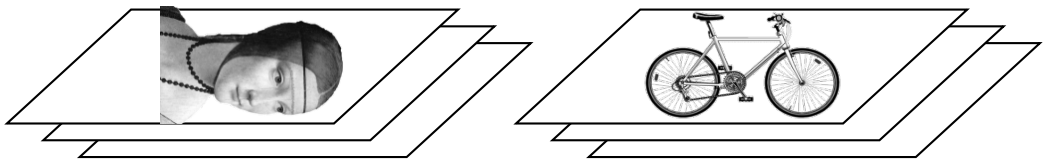
3.





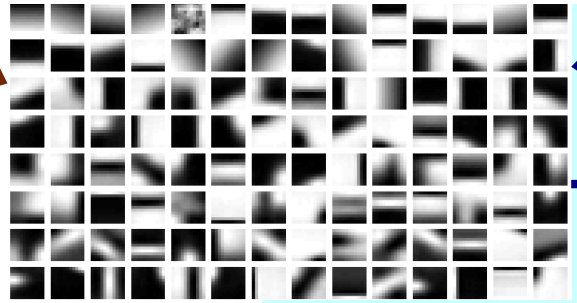
Representation

Learning and Recognition

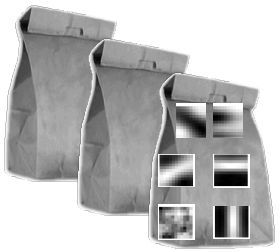


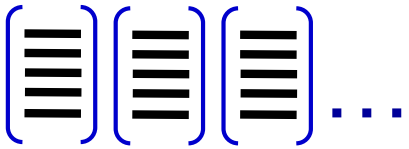
1. feature detection & representation

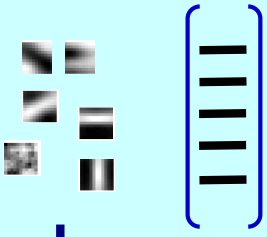
2. codewords dictionary



3.







4.

category models (and/or) classifiers

category decision

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