Multimedia Indexing and Retrieval

Visual content representation and retrieval

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Outline

- Introduction
- Query by example versus search
- Descriptors
- Classification, fusion, post-processing ...
- Conclusion

Introduction

Multimedia Retrieval

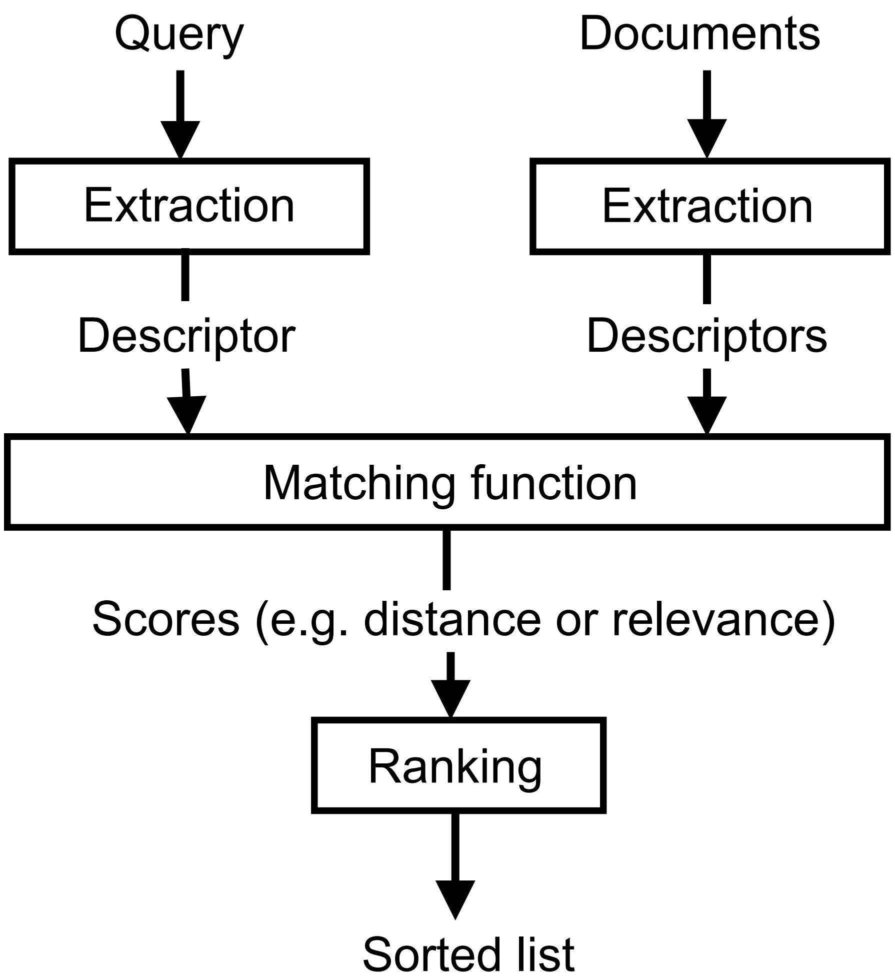
- User need $\rightarrow$ retrieved documents
- Images, audio, video
- Retrieval of full documents or passages (e.g. shots)

- Search paradigms:
  - Surrounding text $\rightarrow$ may be missing, inaccurate or incomplete
  - Query by example $\rightarrow$ need for what you are precisely looking for
  - Content based search (using keywords or concepts)
    $\rightarrow$ need for *content-based indexing* $\rightarrow$ "semantic gap problem"
  - Combinations including feedback

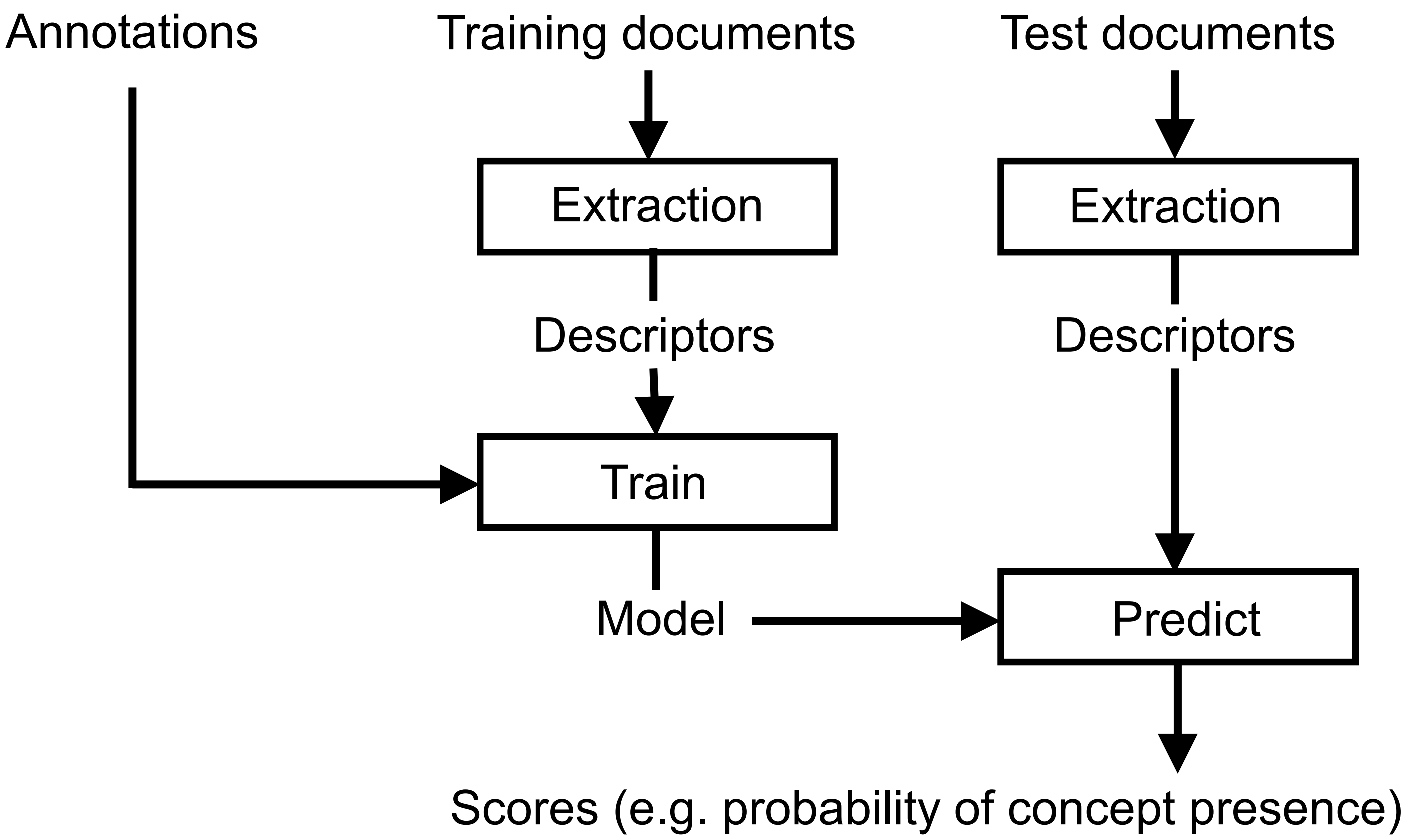
- Need for specific interfaces

Retrieval (query by examples) versus indexing (for enabling query by key words / concepts)

Query BY Example (QBE)



Content based indexing by supervised learning



Descriptors

Descriptors

- “Engineered” descriptors
  - Color
  - Texture
  - Shape
  - Points of interest
  - Motion
  - Semantic
  - Local versus global
  - …
- Learned descriptors
  - Deep learning
  - Auto encoders
  - …

Histograms - general form

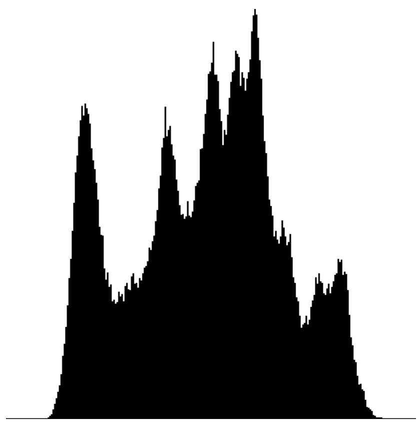
- A fixed set of *disjoint categories* (or *bins*), numbered from 1 to K.
- A set of *observations* that fall into these categories
- The histogram is the vector of K values $h[k]$ with $h[k]$ corresponding to the number of observations that fell into the category k.
- By default, the $h[k]$ are integer values but they can also be turned into real numbers and normalized so that the h vector length is equal to 1 considering either the L_1 or L_2 norm
- Histograms can be computed for several sets of observations using the same set of categories producing one vector of values for each input set

Histograms – text example

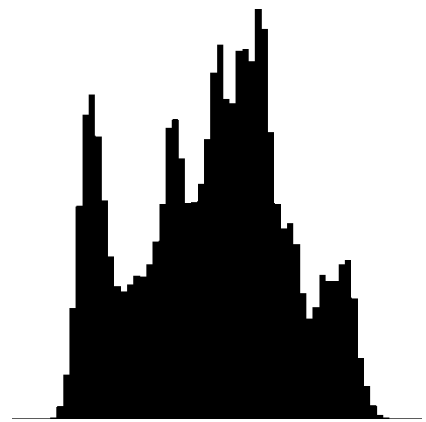
- A vector of term frequencies (tf) is an histogram
- The categories are the index terms
- The observations are the terms in the documents that are also in the index
- A tf.idf representation corresponds to a weighting of the bins, less relevant in multimedia since histograms bins are more symmetrical by construction (e.g. built by K-means partitioning)

Image intensity histogram

- The set of categories are the possible intensity values with 8-bit coding, ranging from 0 (black) to 255 (white) or ranges of these intensity values



256-bin

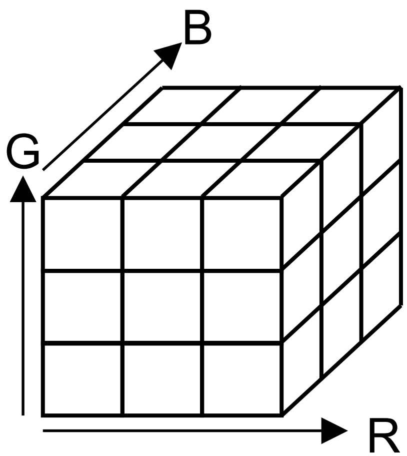


64-bin

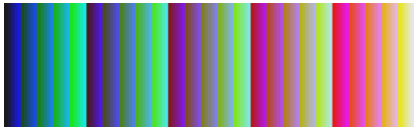
16-bin

Image color histogram

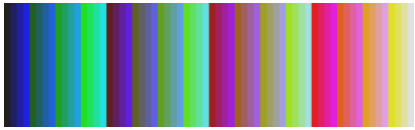
- The set of categories are ranges of possible color values
- A common choice is a per component decomposition resulting in a set of parallelepipeds



Representations with the parallelepipeds' center colors:



5×5×5-bin
125-bin



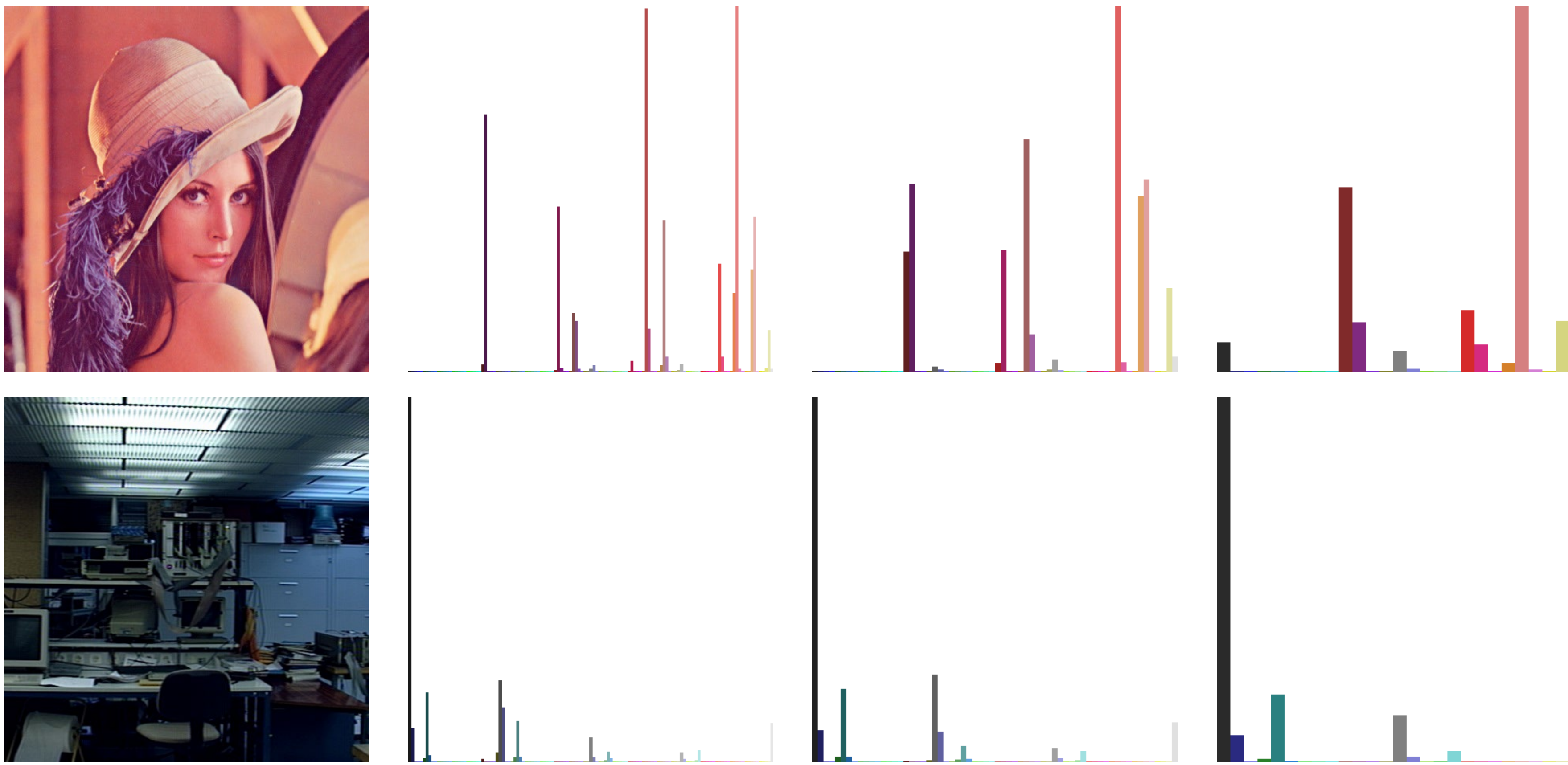
4×4×4-bin
64-bin

3×3×3-bin
27-bin

- Any color space can be chosen (YUV, HSV, LAB …)
- Any number of bins can be chosen for each dimension
- The partition does not need to be in parallelepipeds

Image color histogram

- The set of categories are ranges of possible color values



5×5×5-bin
125-bin

4×4×4-bin
64-bin

3×3×3-bin
27-bin

Image histograms

- Rather invariant to image size if normalized to unit vector length with L_1 or L_2 norm
- Rather invariant to content displacements or symmetries
- NOT invariant to illuminations changes, gain and offset normalization may be needed
- Histograms are distributions, better compared using a $\chi 2$ distance that Euclidean one:

$$d(x, y) = \sum_i \frac{(x_i - y_i)^2}{x_i + y_i}$$

- Earth Mover Distance (EMD) can be even better
- Alternatively, taking the square root of the histogram elements can make the Euclidean distance suitable

Image histograms

- Can be computed on the whole image,
- Can be computed by blocks:
  - One (mono or multidimensional) histogram per image block,
  - The descriptor is the concatenation of the histograms of the different blocks.
  - Typically : 4×4 complementary blocks but non symmetrical and/or non complementary choices are also possible. For instance: 2×2 + 1×3 + 1×1
- Size problem $\rightarrow$ only a few bins per dimension or a lot of bins in total

Image normalization

- Objective : to become more robust again illumination changes before extracting the descriptors.
- Gain and offset normalization: enforce a mean and a variance value by applying the same affine transform to all the color components, non-linear variants.
- Histogram equalization: enforce an as flat as possible histogram for the luminance component by applying the same increasing and continuous function to all the color components.
- Color normalization: enforce a normalization which is similar to the one performed by the human visual: “global” and highly non linear.

Texture descriptors

- Computed on the luminance component only
- Frequential composition or local variability
- Fourier transforms
- Gabor filters
- Neuronal filters
- Co-occurrence matrices
- Normalization possible.

Gabor transforms

(Circular) Gabor filter of direction θ, of wavelength λ and of extension σ :

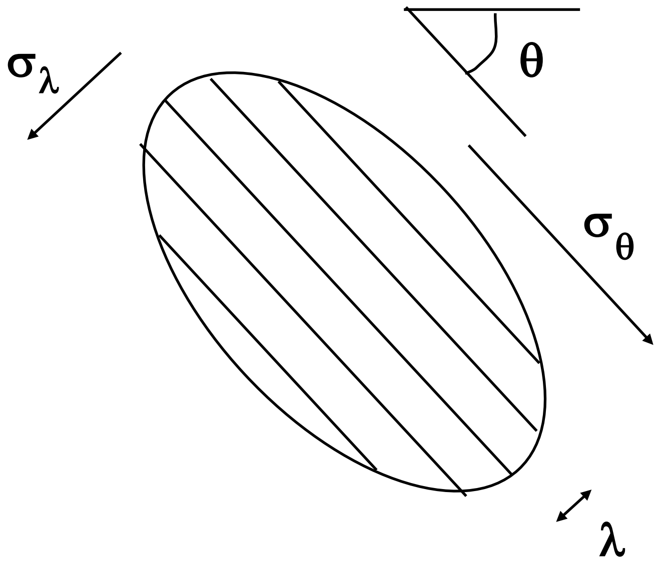
$$g(\sigma,\theta,\lambda,I,i,j) = \frac{1}{2\pi\sigma^2} \sum_{k,l} e^{-\left(\frac{k^2+l^2}{2\sigma^2}\right)} . e^{2\pi\mathbf{i}\left(\frac{k.cos\theta+l.sin\theta}{\lambda}\right)} . I(i+k,j+l)$$

Energy of the image through this filter:

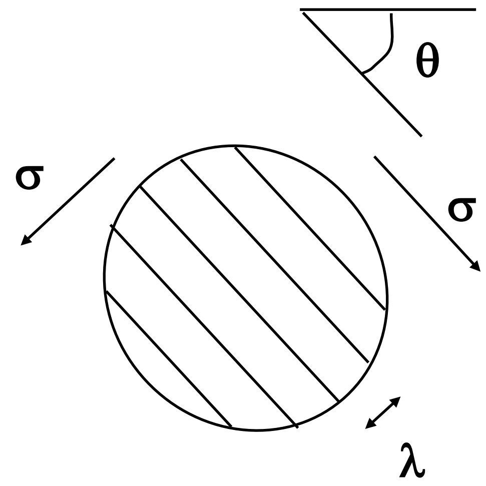
$$E_g(\sigma,\theta,\lambda,I)^2 = \frac{1}{N} \sum_{i,j} \mid g(\sigma,\theta,\lambda,I,i,j) \mid^2$$

Gabor transforms

Elliptic:

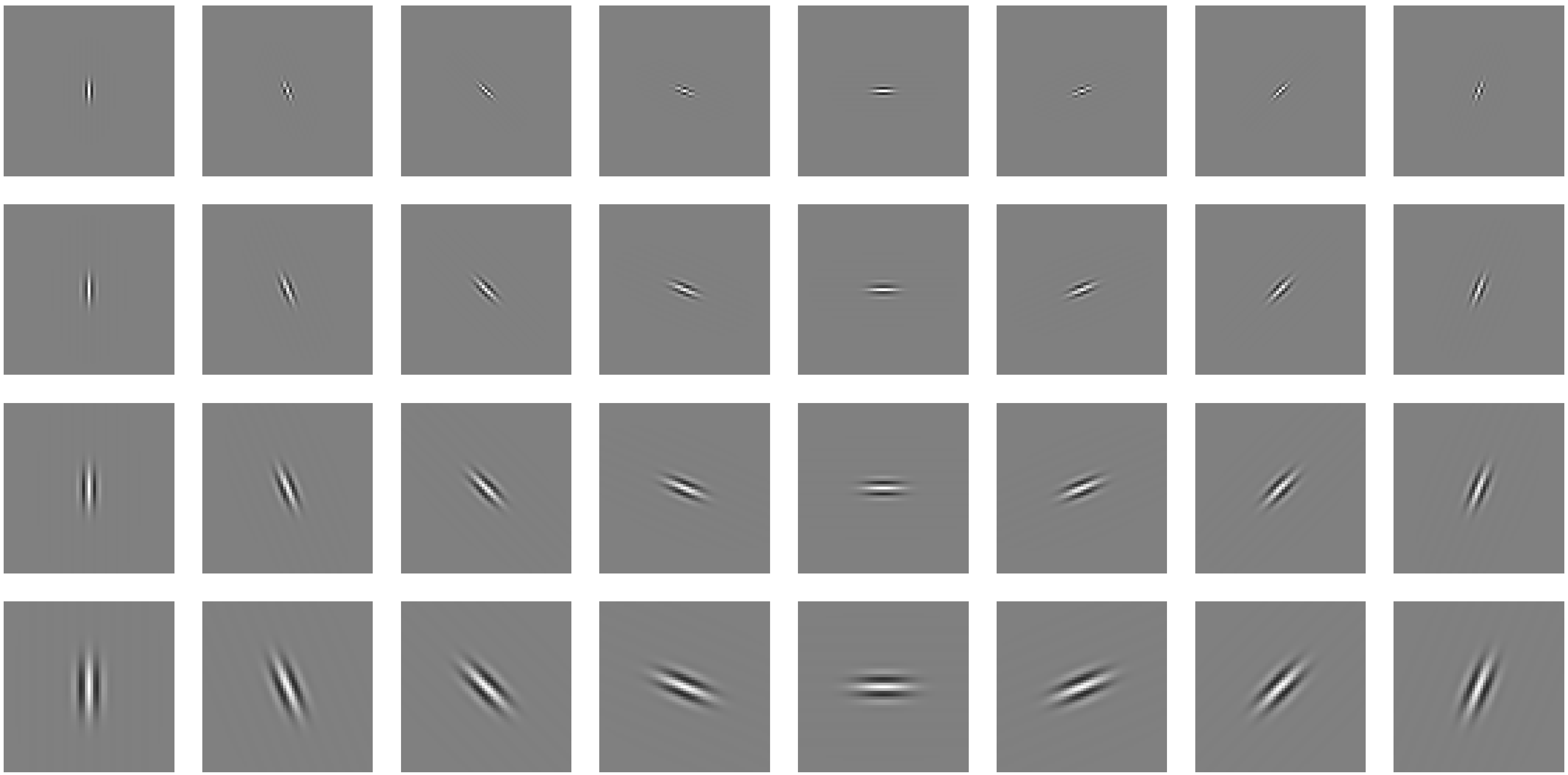


Circular:



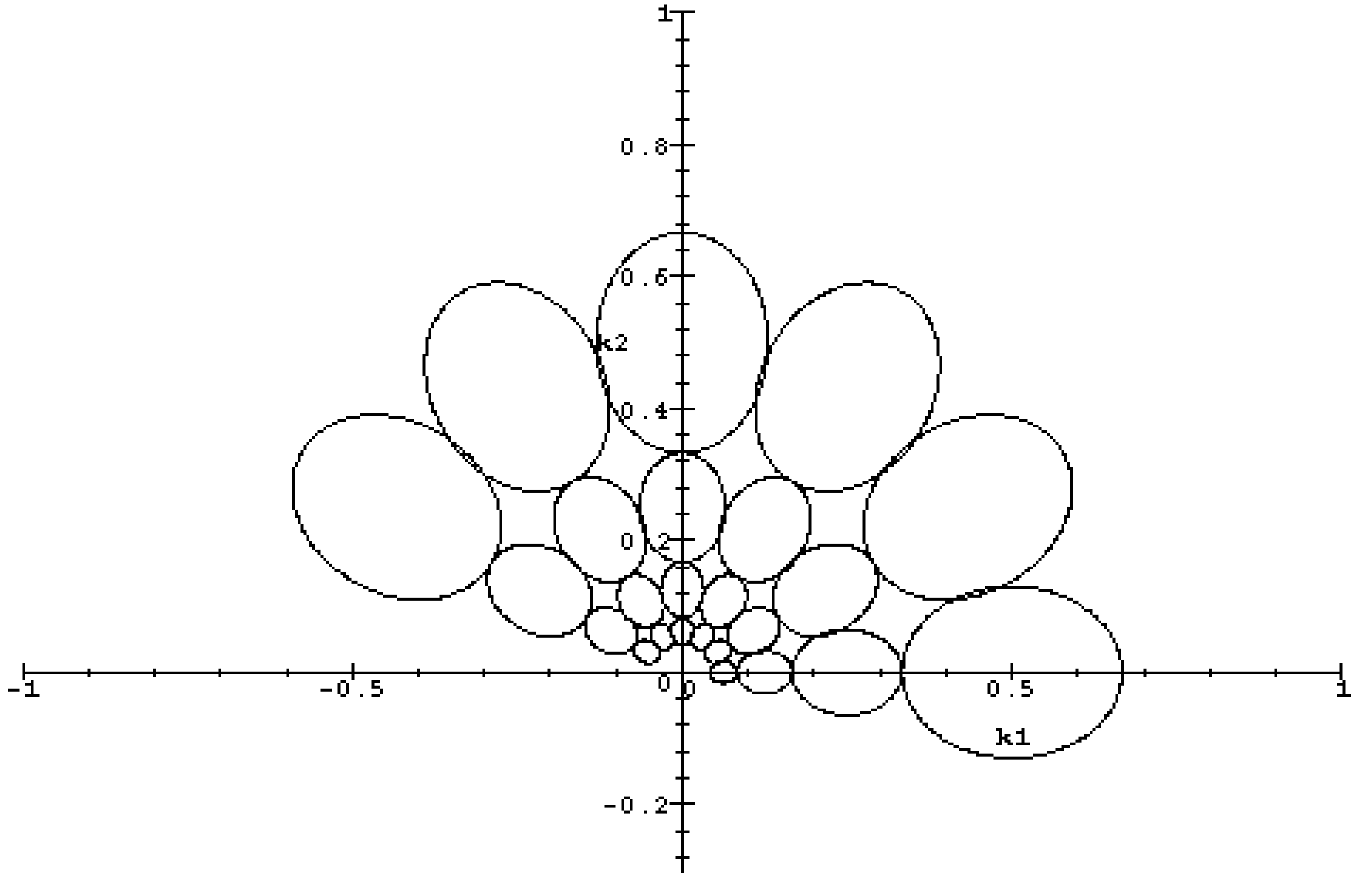
Gabor Filters

Example of elliptic filters with 8 orientations and 4 scales



Gabor filters in Fourier space

Elliptic filters with 6 orientations and 4 scales in the frequential domain (Fourier space)



Gabor transforms

- Circular:
  - scale λ, angle θ, variance σ,
  - σ multiple of λ, typically : $\sigma = 1.25\ \lambda$,
    (“same number” of wavelength whatever the λ value)
- Elliptic:
  - scale λ, angle θ, variances σ_λ and $\sigma_{\theta,}$
  - σ_λ and σ_θ multiples of λ, typically : $\sigma_\lambda = 0.8\ \lambda$ et $\sigma_\theta = 1.6\ \lambda$,
- 2 independent variables:
  - scale λ : N values (typically 4 to 8) on a logarithmic scale (typical ratio of $\sqrt{2}$ to 2)
  - angle θ : P values (typically 8),
  - $N.P$ elements in the descriptor,

Selection of points of interest

- “High curvature” points or “corners”,
- “Singular” points of the I[i][j] surface,
- Extracted using various filters:
  - Computation of the spatial derivatives at several scales,
  - Convolution with derivatives of Gaussians,
  - Harris-Laplace detector.
- Interest points are selected, filtered and described
- 2D (image): Scale Invariant Feature Transform (SIFT) [Lowe, 2004]
- 3D (video): Space-Time Interest Points (STIP) [Laptev, 2005]
- Variable number of points per image or per video shot $\rightarrow$ need for aggregation

Spatial derivatives on images

- First derivative: $f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$
- Discrete version: $f'(x) \sim \frac{f(x+1) - f(x)}{1}$
- Symmetrized discrete version: $f'(x) \sim \frac{f(x+1) - f(x-1)}{2}$
- First derivatives of $I(x, y)$:

$$\frac{\partial I}{\partial x}(x, y) \sim \frac{I(x+1,y) - I(x-1,y)}{2} \qquad \frac{\partial I}{\partial y}(x, y) \sim \frac{I(x,y+1) - I(x,y-1)}{2}$$

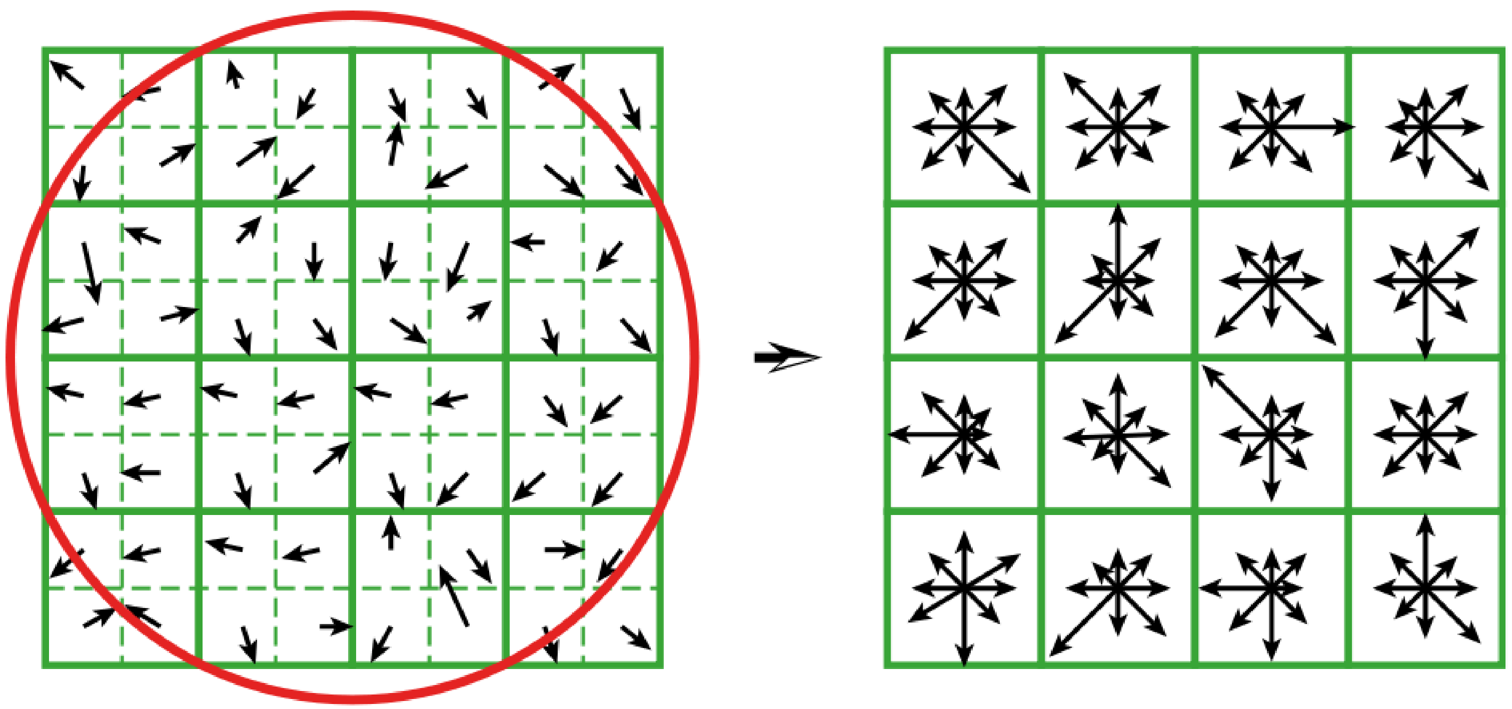
- Second derivatives of $I(x, y)$:

$$\frac{\partial^2 I}{\partial x^2}(x, y) \sim \frac{I(x+1,y) + I(x-1,y) - 2I(x,y)}{1} \quad \ldots$$

- Use of convolutions for both computation and smoothing of derivatives

Descriptors of points of interest

- SIFT descriptor: Histogram of gradient directions:
  8 bins times 4 x 4 blocks in a neighborhood of the point.
- Neighborhoods are scaled according to the detector output



Local versus global descriptors

- Global descriptors: single vector for a whole image
- Local descriptors: one vector for each pixel, image patch, image block shot 3D patch … e.g. SIFT or STIP
- Need for a single vector of fixed length far any image and with comparable components across images
- *Aggregation* of local descriptors → global descriptor

Aggregation of local descriptors

- Building of a single global descriptor
- Homogeneous with the local descriptor:
  - max or average pooling
- Heterogeneous with the local descriptor:
  - Histogramming according to clusters in the local descriptor space [Sivic, 2003][Cusrka, 2004]
  - Gaussian Mixture Models (GMM)
  - Fisher Vectors (FV) [Perronnin, 2006],Vectors of Locally Aggregated Descriptors (VLAD) [Jégou, 2010] or Tensors (VLAT) [Gosselin, 2011], Supervectors

Clustering

- Given a set (x_i) of N data points in a metric space
- Find a set (c_j) of K centers
- Minimizing the representation square error:

$$E = \sum_i \left(\min_j \left(d(x_i, c_j)^2 \right) \right)$$

- Direct search not possible
- Use heuristics for finding good local minima
- Cluster j = subset (part) of the data space which is closest to center c_j than to any other center
- The set of clusters is a partition of the data space
- This partition is *adapted* to the training data

K-means Clustering

- Given a set (x_i) of N data points in a metric space
- Randomly select a set (c_j) of K centers
- Repeat until convergence (no change in centers):
  - for each x_i data point, $i = 1 \ldots N$:
    - find the nearest center $\quad c_j \ : \ j = \arg\min d(x_i, c_k)$
    - assign the x_i data point to the cluster $j \quad x_i \to c_j$
  - for each cluster, $j = 1 \ldots K$:
    - set the new center c_j as the mean of all x_i data point previously assigned to the cluster j : or to a random value if no data point is assigned $\quad c_j = \frac{\sum_{x_i \to c_j} x_i}{\sum_{x_i \to c_j} 1}$
- Complexity: O(#iterations × #clusters × #points × #dimensions)

K-means Clustering

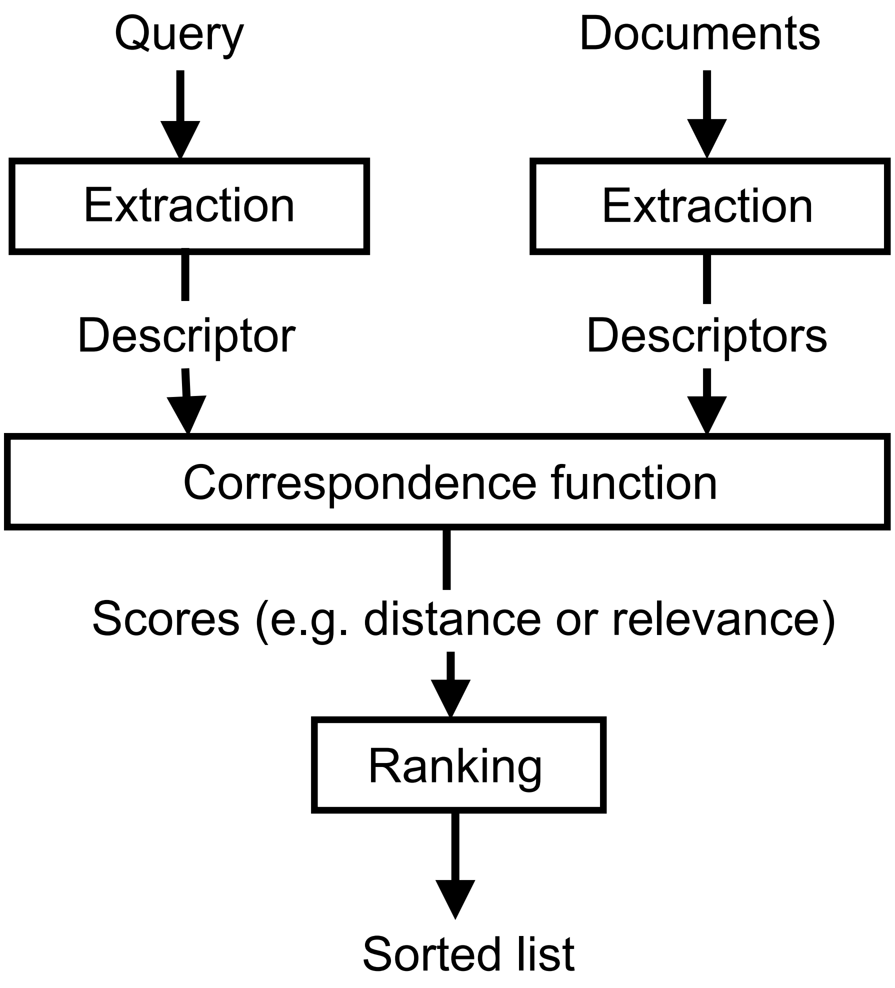
- K-means is relatively fast and efficient compared to alternate and more complex methods
- The final result depends upon the choice of the initial centers; it is always possible to run it many times with different initial conditions and select the one obtaining the smallest representation error
- Tends do produce clusters of comparable size
- Convergence is guaranteed but it may take a large number of iterations and only a local minimum is guaranteed
- For practical applications, a full convergence is not necessary and does not make a big difference

Hierarchical K-means Clustering

- Hierarchical K means may be faster (both for the clustering and the mapping) but less accurate
- The hierarchical structure of the set of clusters may be useful for some applications
- Two main strategies:
  - Recursively split all the clusters into a (small) fixed number of sub-clusters (e.g. recursive dichotomy) starting with a single cluster ($\rightarrow$ regular n-ary tree)
  - Recursively split in two parts only the biggest cluster into sub-clusters ($\rightarrow$ irregular binary tree)
- Hierarchical mapping: recursive search of the closest center from the coarsest to the finest grain.

Retrieval, indexing and fusion

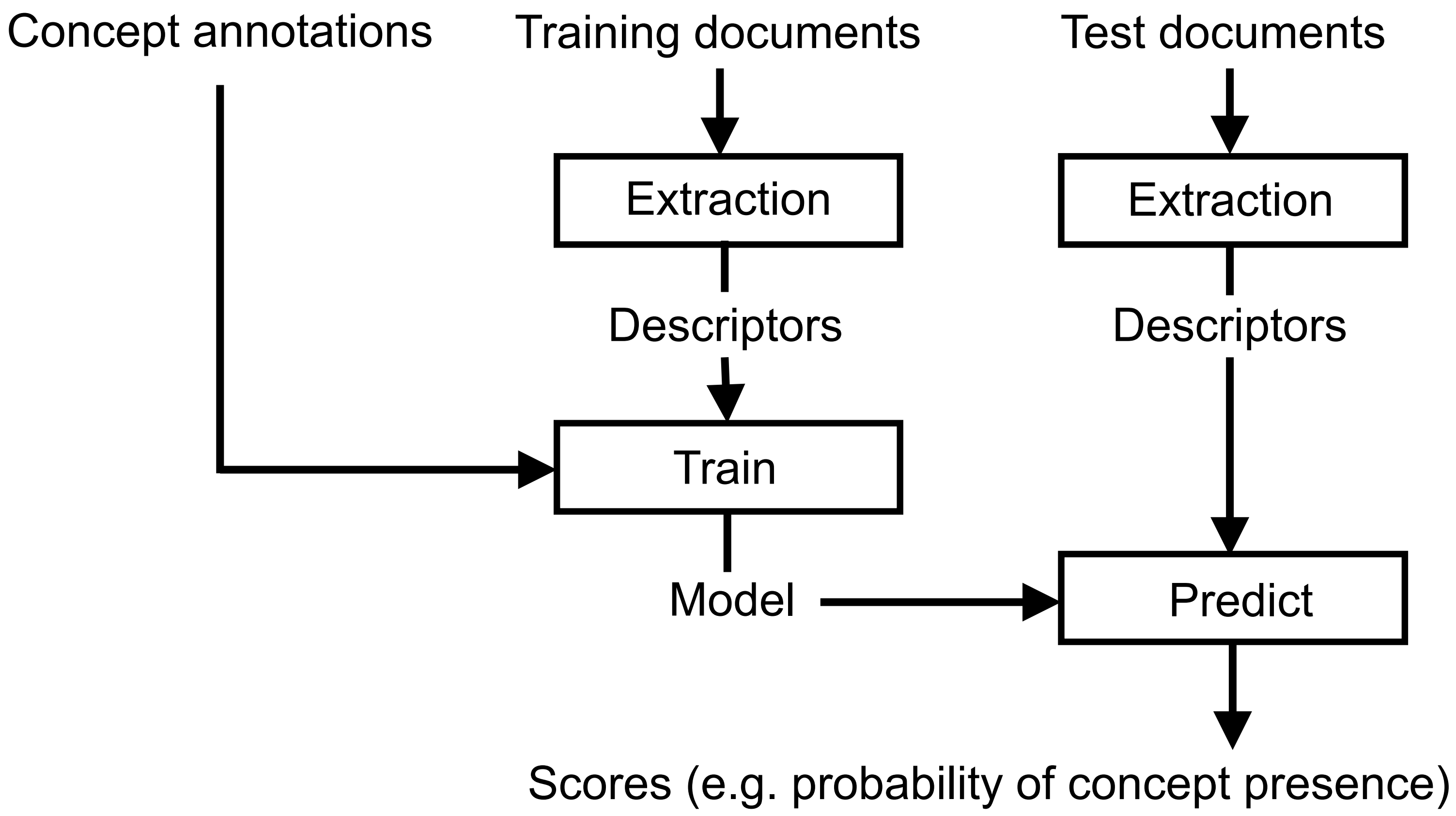
Query BY Example



Query BY Example

- Single query sample:
  - χ^2, EMD or histogram intersection for histograms
  - Euclidian Distance : searching for identities
  - Angle between vectors : searching for similarities robust to illumination changes (for some other descriptors, e.g. Gabor transforms)
- Multiple queries or relevance feedback:
  - Linear combination of distances with different weights for positively and negatively marked samples [Rocchio, 1971]
  - Supervised learning from the marked samples (active learning)
  - Rely also on the choice of a distance between global descriptions
- Direct matching and scoring between sets of local descriptors:
  - Costly but good for searching specific instances rather than general categories

Content based indexing by supervised learning



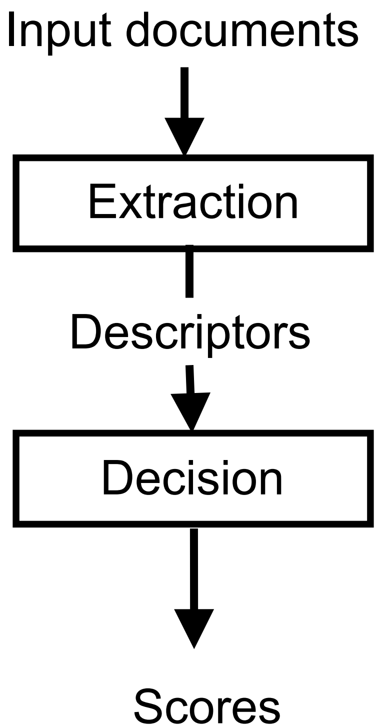
Content based indexing by supervised learning

- Training from annotated collections:
  - LSCOM-TRECVid for videos
  - Pascal VOC or ImageNet for still images
  - Many others, e.g. Hollywood2 for actions in movies
- Use of supervised learning methods:
  - Support Vector Machines (SVM), linear or RBF
  - K nearest neighbors (KNN)
  - Neural Networks (NN), Multi-Layer Perceptrons (MLP)
  - Many others again
  - Adaptations for highly imbalanced data sets
- Fusion if several descriptors and/or several learning methods are simultaneously used.

Fusion

- Several possible descriptors
- Several possible classifiers or correspondence functions
- Early versus late fusion [Snoek, 2005]
  - Early: concatenation of normalized descriptors
  - Late: combination of classification scores
- Kernel fusion [Ayache, 2007]
  - Fusion of kernels in RBF-based (e.g. SVM) learning methods
- These fusion methods are also applicable to query by example

Common processing, single descriptor



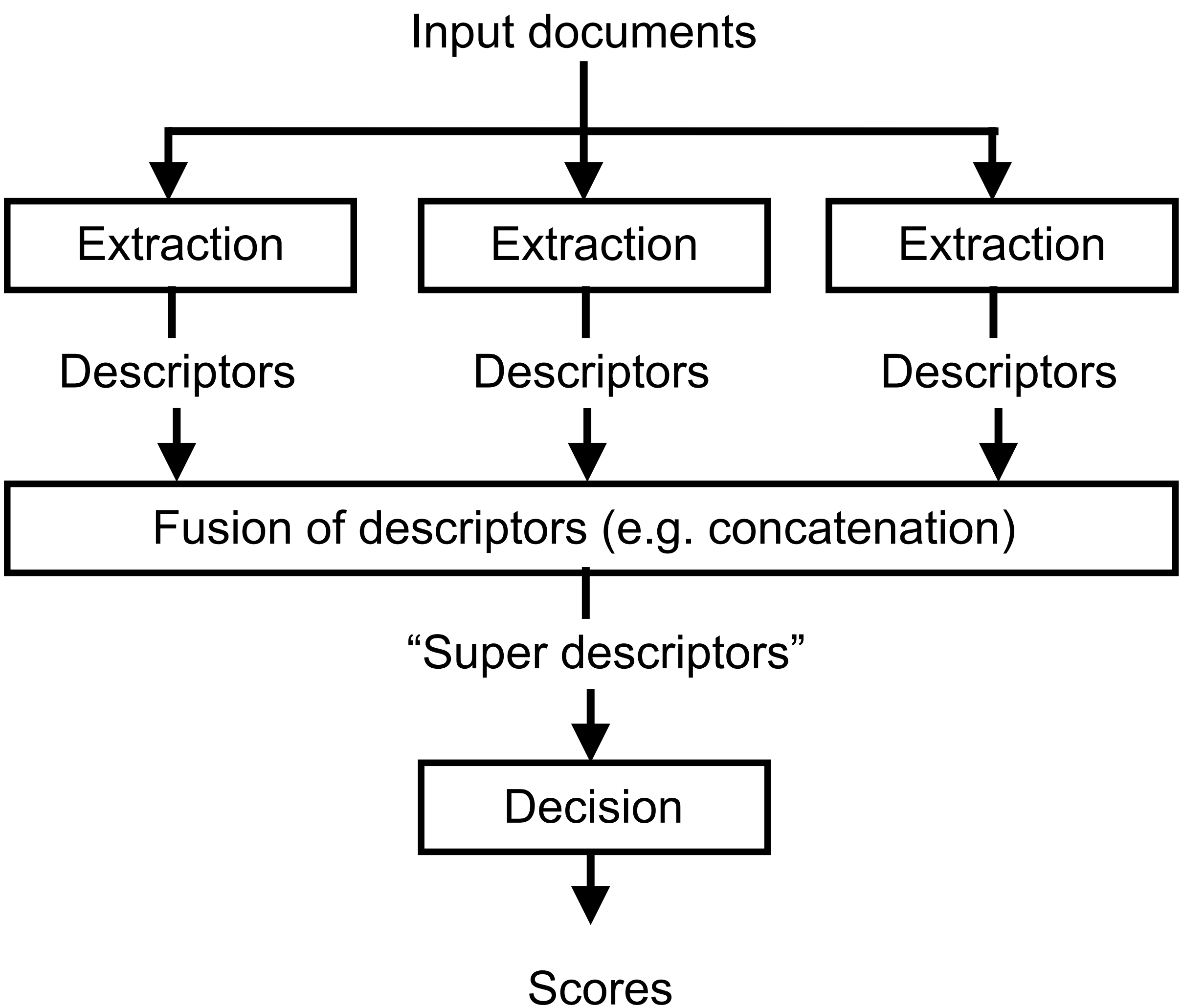
Query,
search collection,
training collection,
test collection …

Color, texture,
bag of SIFTs …

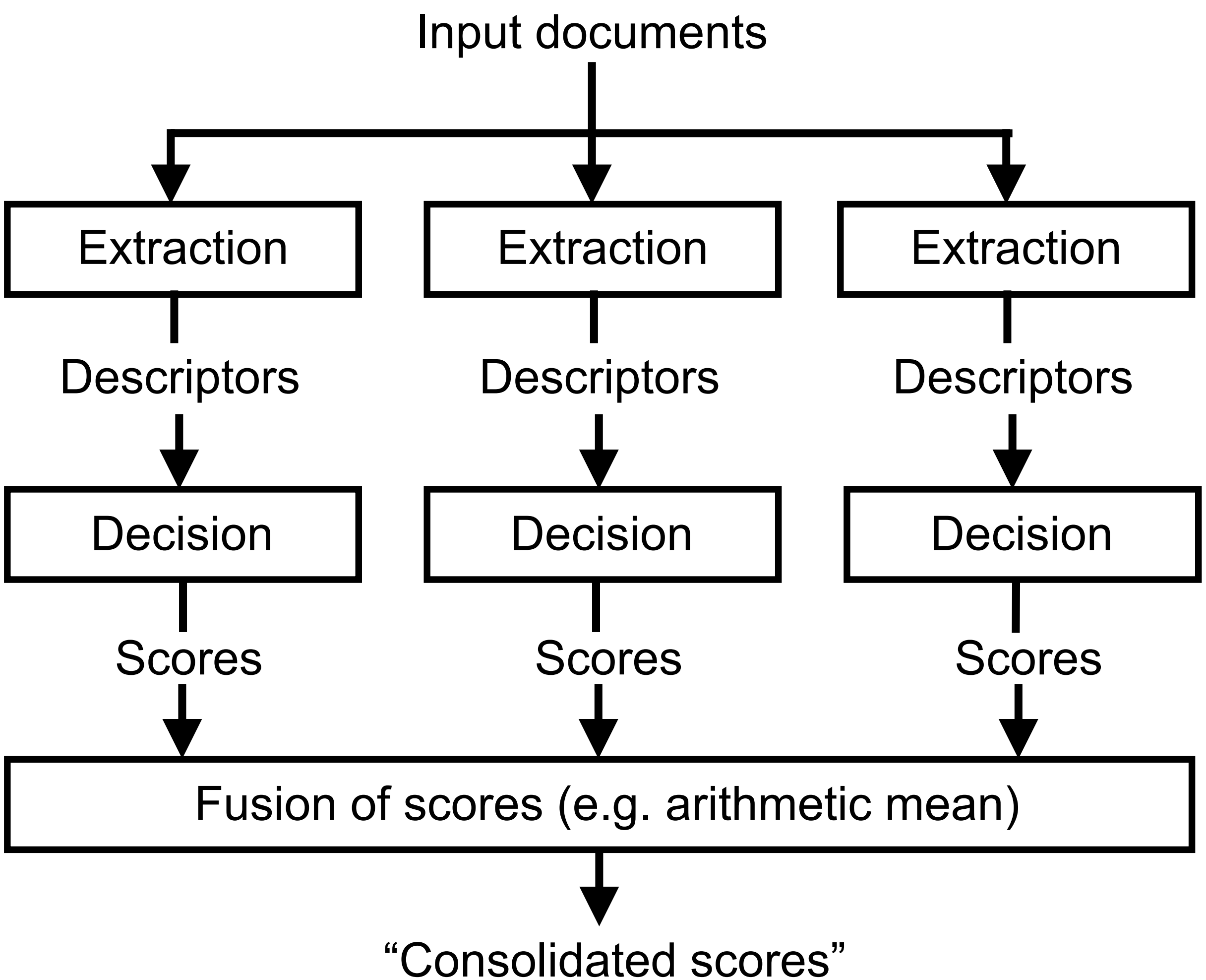
Correspondence function,
train / predict

Similarity measure,
probability of presence

Common processing, multiple descriptors, single decision (early fusion)



Common processing, multiple descriptors, multiple decision (late fusion)



Conclusion

Search at the signal level: conclusion

- Representation by different types of descriptors and evaluation of relevance by various functions,
- A single type: results from poor to average,
- Several types simultaneously: results from average to good with possible domain adaptation
- Possibility to adjust the compromise quality - performance - general - size of the database

- Most of this is obsolete since DL breakthrough