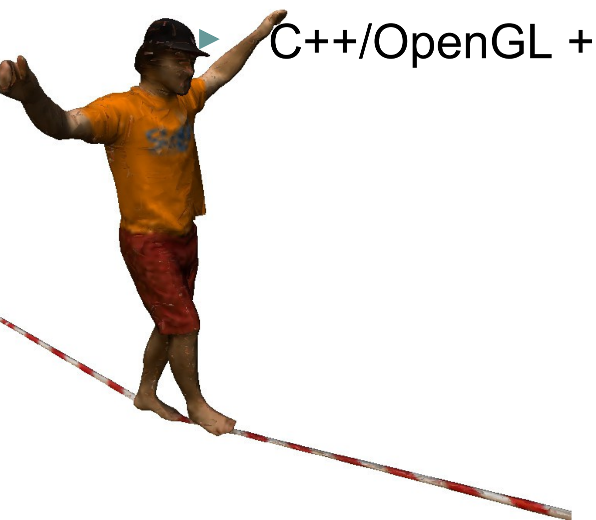
Image indexing and retrieval

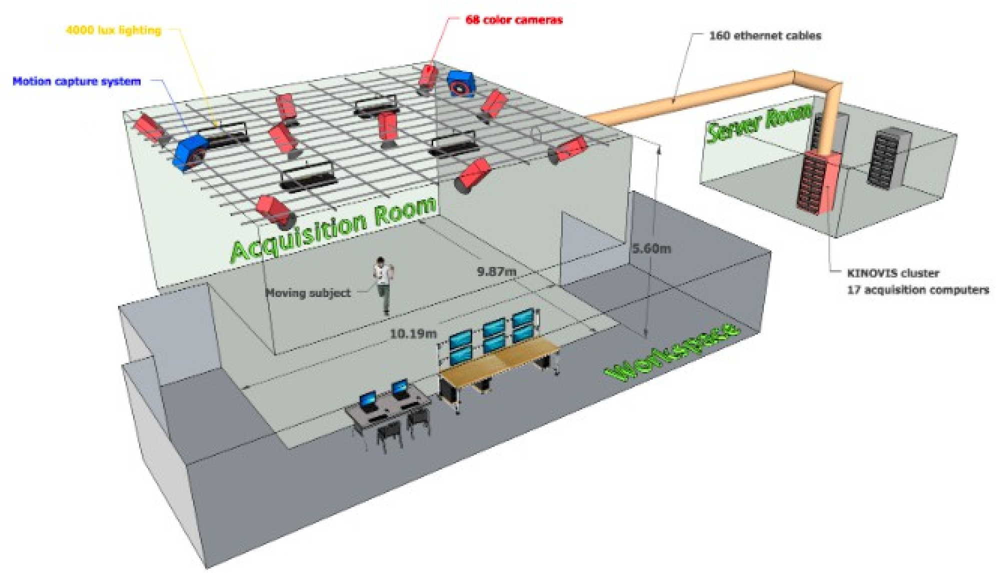
Matthijs Douze

INRIA Grenoble

About...

- Matthijs Douze
  - ENSEEIHT 2000
  - PhD with Vincent Charvillat
  - Engineer at INRIA Grenoble, main subject: large-scale image/video retrieval and classification
- This presentation
  - From “multimedia databases” course at ENSIMAG (2008-)
  - 3 h subset of 18 h → less general
- Internship (nothing to do with image indexing)
  - Real-time 3D reconstruction with 68 calibrated cameras
  - Parallel programming, geometry
  - C++/OpenGL + in-house APIs





Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

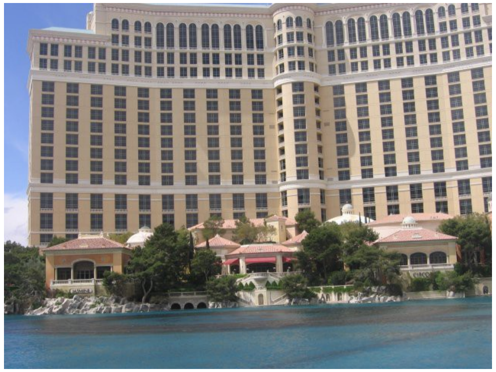
1. Problem statement

Problem setup: Image indexing

- Retrieval of images from a database
  - Input: 1 query image
  - Return images representing the same object/scene
  - Interactive response time (~1s)
  - Various database sizes (100 – 100M)

queries

relevant answers



Types of object recognition

- Same image, edited
  - Cropping/resizing
  - Rotation
  - clutter
  - Etc.

- Different images of the same object
  - Paintings
  - Logos
  - Buildings
  - Etc.

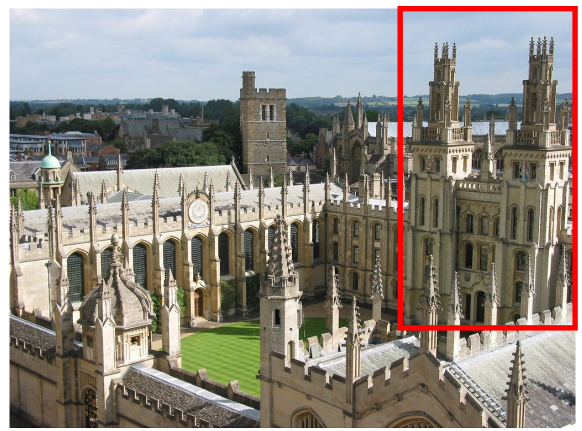
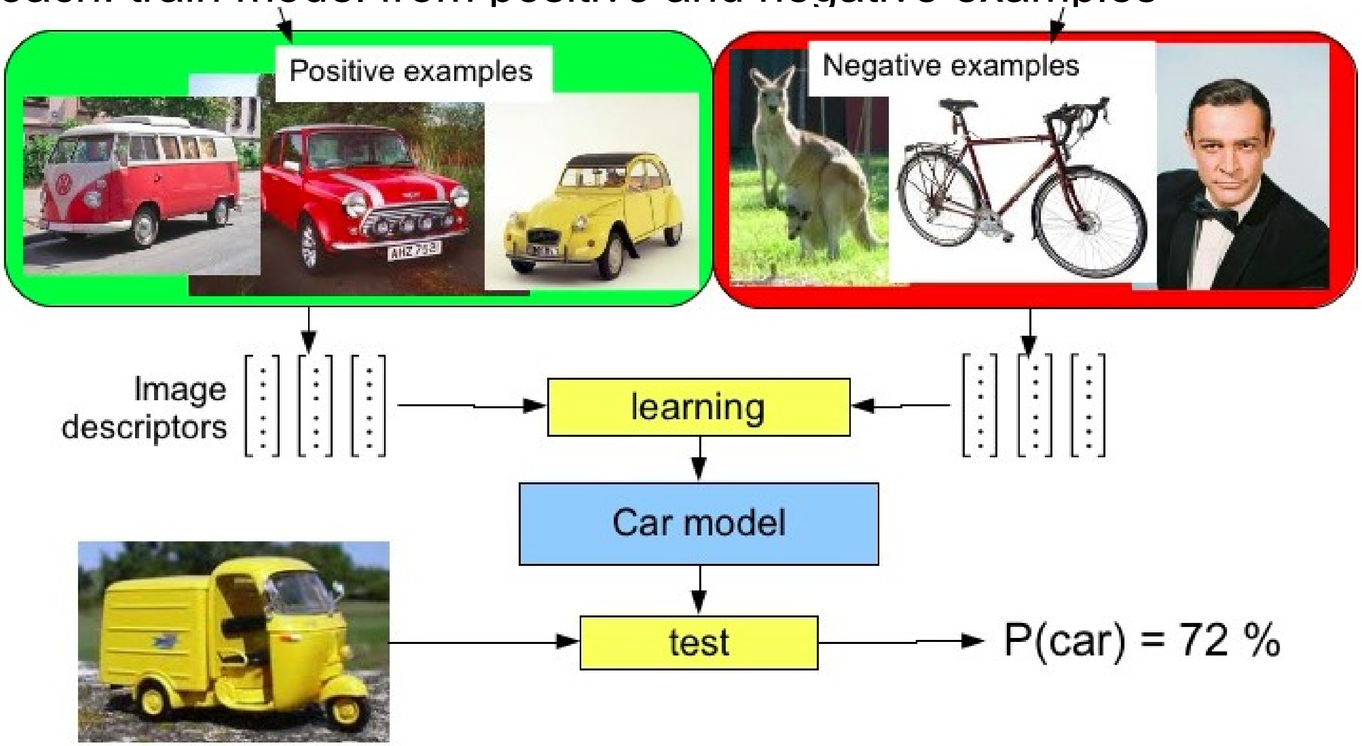


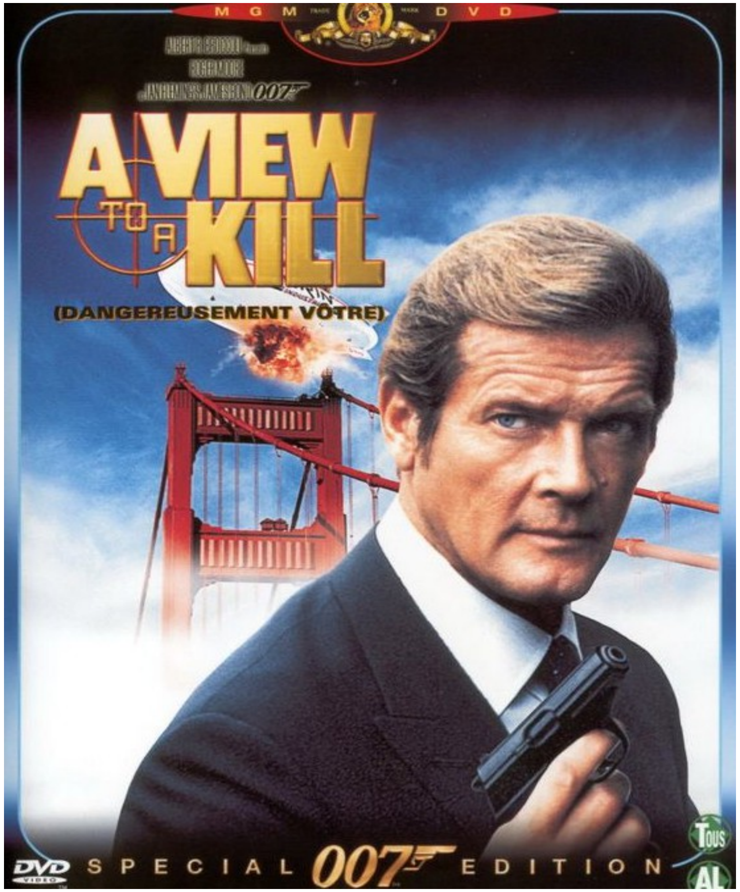
Image classification

- Find “images of cars”
  - Image classification problem
  - Approach: train model from positive and negative examples



- Related to image indexing...
  - But out of scope for this course

What to recognize....



?

?

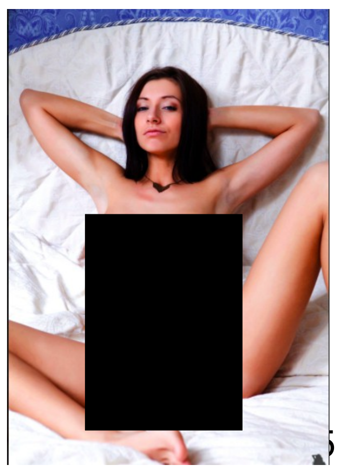
Applications

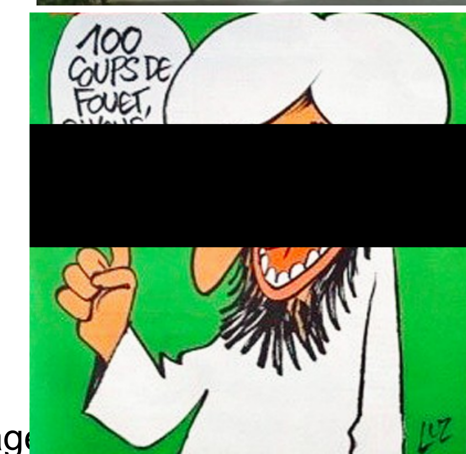
- Use images as web queries
  - Tell me who painted this...
  - Where can I buy this?

- Mobile geo-localization
  - This is what I see, tell me where I am...

- Copyright protection
  - Has my stock picture been used in a magazine?

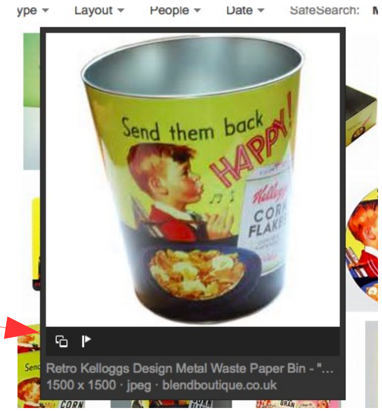
- Tracking illegal pictures





Commercial image databases

- On the web:
  - Bing “image match”



  - Google search by image
  - goggles

  - Tineye.com
- Companies
  - Ltutech.com
  - Kooaba -> Qualcomm Vuforia
  - ...
- Everyone wants to go mobile

Approach

- Indexing
  - Requirement: database fits in RAM

Database image

region extraction
+ SIFT description

$$\begin{bmatrix} 5 \\ 0 \\ \vdots \\ 35 \end{bmatrix} \begin{bmatrix} 34 \\ 6 \\ \vdots \\ 12 \end{bmatrix} \cdots \begin{bmatrix} 14 \\ 20 \\ \vdots \\ 47 \end{bmatrix}$$

Descriptor
compression

Add

database of
Image
descriptors

- Search
  - Requires similarity function between images
  - Requirement: fast!

Query image

region extraction
+ SIFT description

Compute similarity
between query and db descriptors

Result = database sorted by decreasing similarity

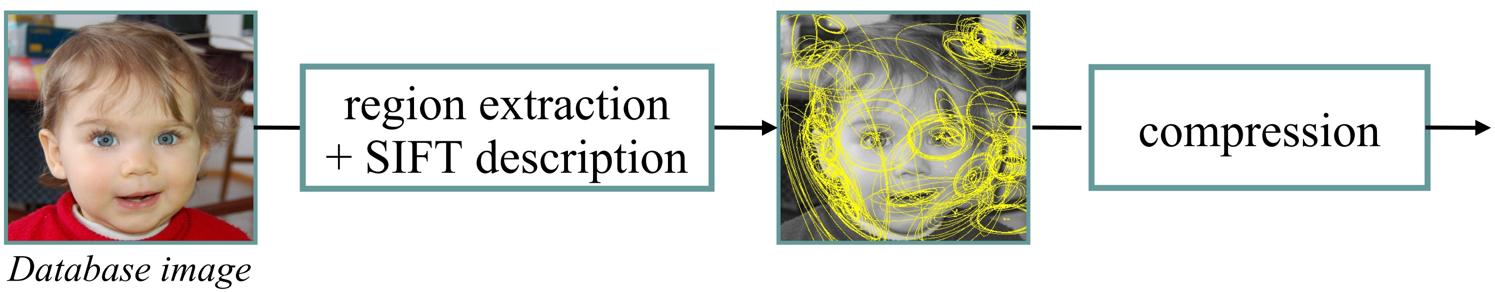
2. Extracting local image descriptors

Global or local descriptors

- Global descriptors:
  - color/texture histograms and statistics
  - GIST descriptors [Torralba & al 08, Douze & al. 09]

→ very limited invariance to scale/rotation/crop

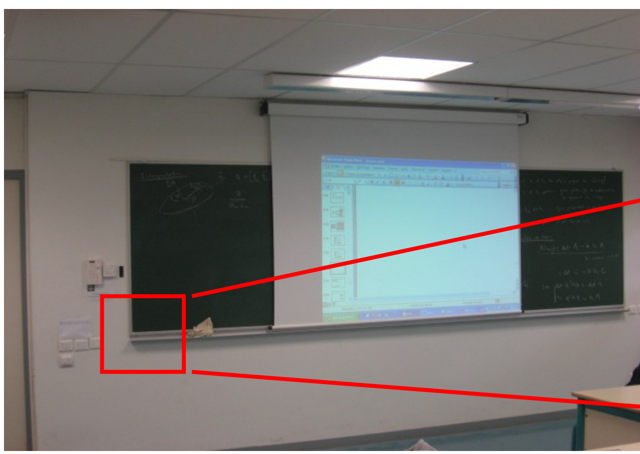
- Local descriptors
  - Detect then describe (this chapter)
  - Invariant to occlusion, clutter
  - Expensive to compute and store (next chapters)

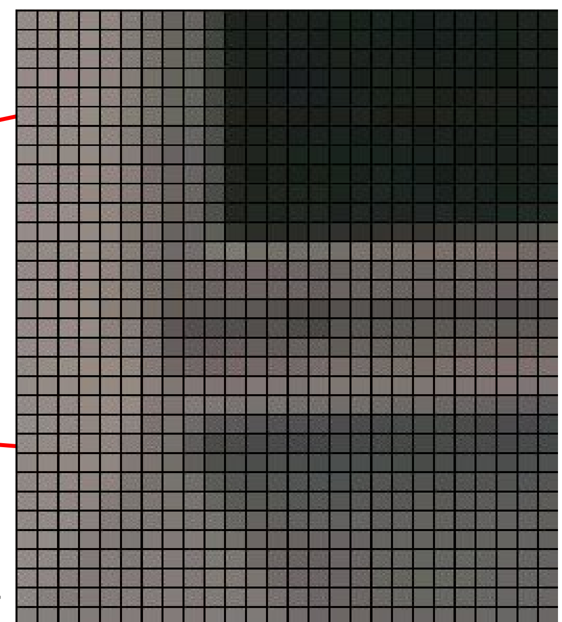


Example : the Harris detector

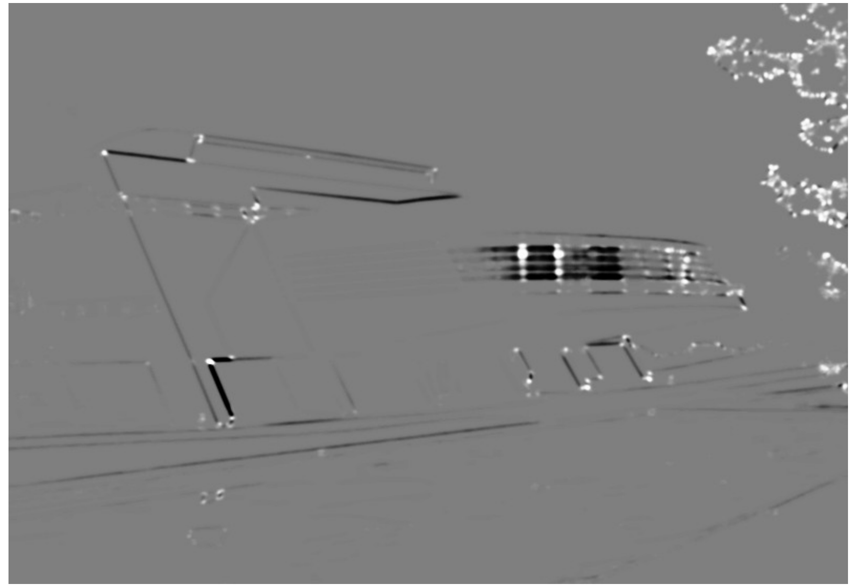
- Typical garadient-based detector
  - Other examples : Hessian, DoG, Laplacian, etc.
  - Counter-example : MSER
- Detects "corners"
  - Easy to reproduce
  - Characteristic location on images
  - Computed on a neighborhood of each image pixel
  - A point is kept if it is la local maximum of the function

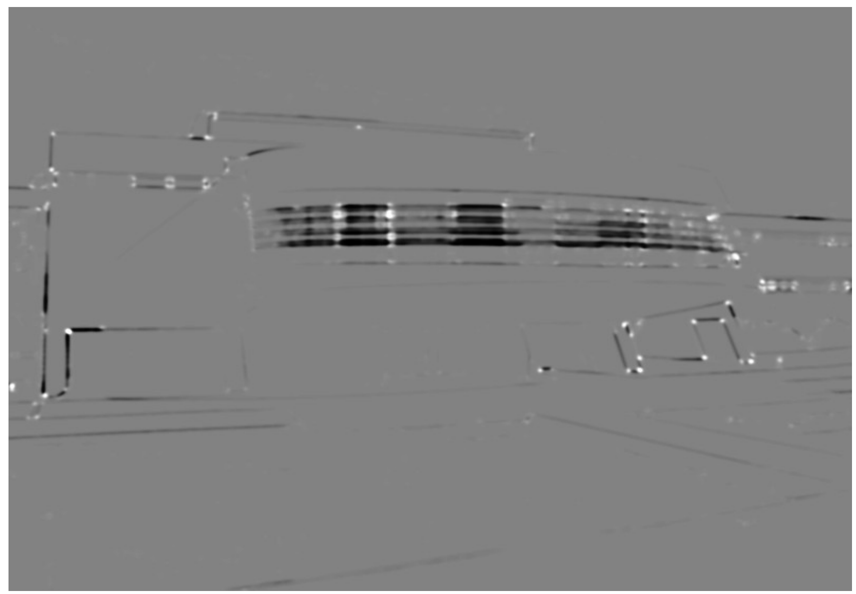
« A Combined Corner and Edge Detector », C. Harris et M. Stephens, 1988





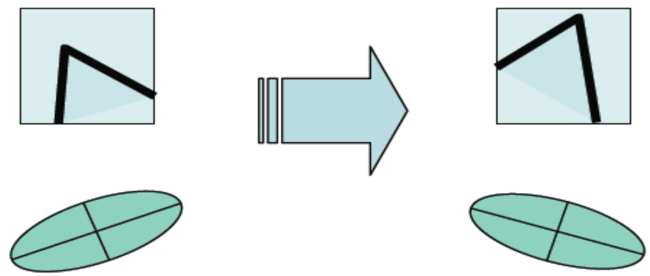
Harris function output





Invariance properties

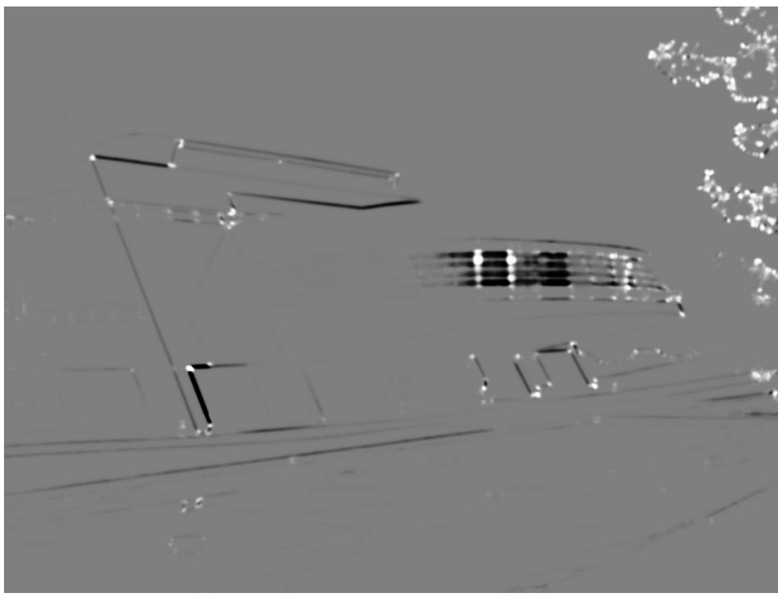
- A point will be detected despite some kind of image/scene transformation
- Invariants: easiest -> hardest to obtain
  - Illumination change
  - Translation
  - Rotation
  - Scale change
  - Blur
  - 3D transform ≃ affine transformation for planar textures



- Opposite property: *discriminance*
  - Tradeoff between invariance and discriminance
  - Example where we would like to be more discriminant:

Invariance to scale

- Harris has a privileged scale
  - Determined by the Gaussian filter size σ
- Multi-scale:
  - Detect at several scales (filter sizes)
  - Select scale with highest response -> maximum selection in 3D *scale-space*

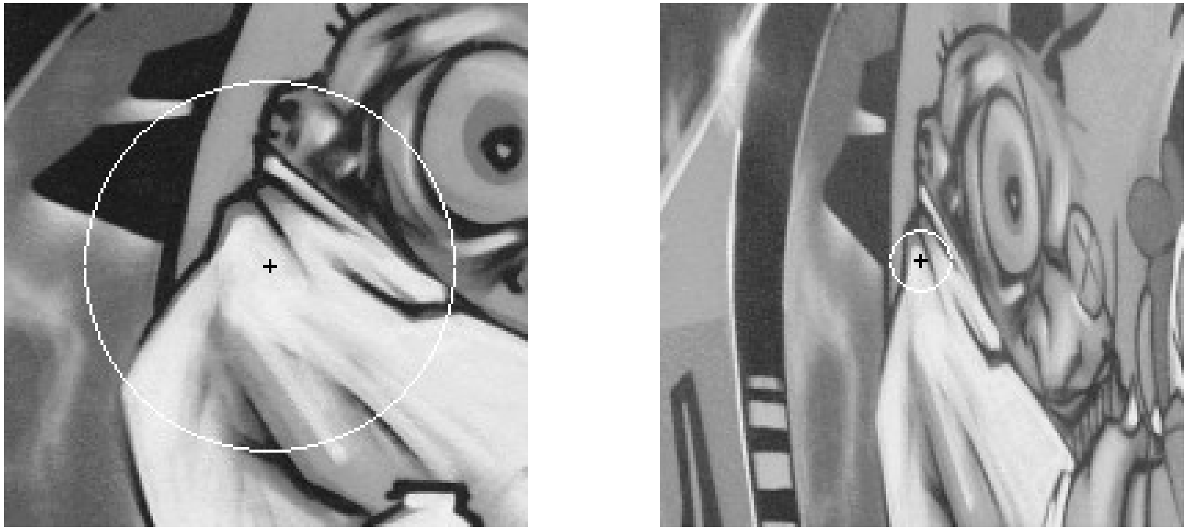


Invariance to affine transformation

- Iterative estimation of an ellipse than aligns with the local graylevel pattern

  - [Mikolajczyk & al, IJCV 05]

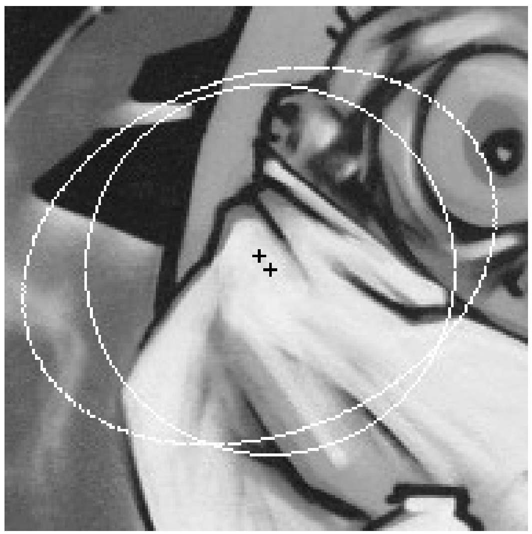
Input points

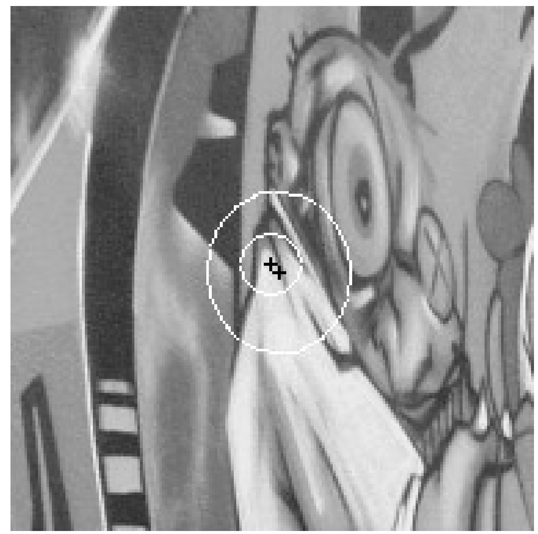


Harris-Affine et Hessian Affine (suite)

- Estimation itérative de la localisation, de l'échelle, du voisinage

Iteration #1

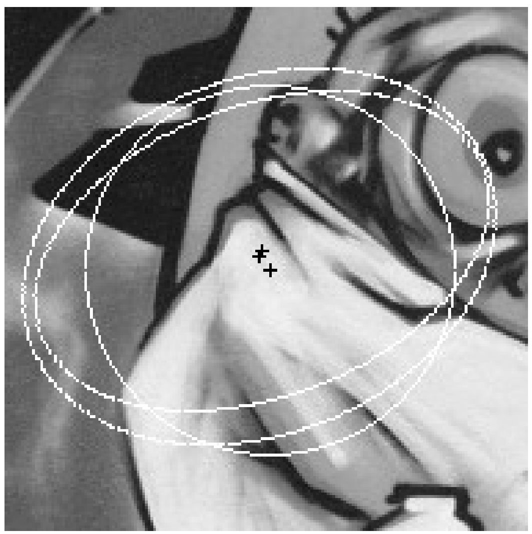




Harris-Affine et Hessian Affine (suite)

- Estimation itérative de la localisation, de l'échelle, du voisinage

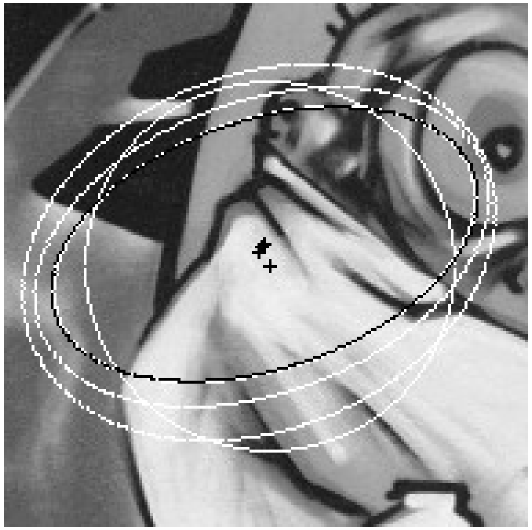
Iteration #2

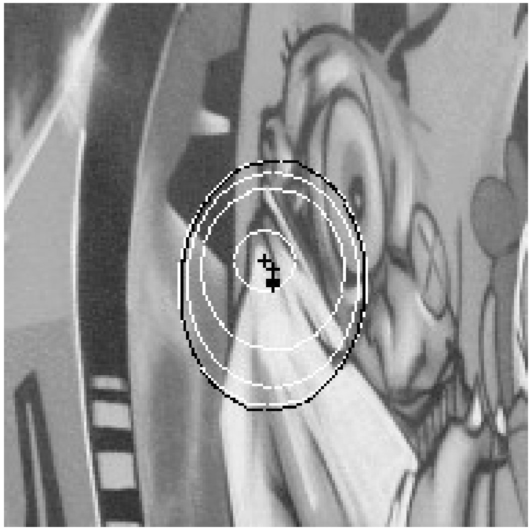


Harris-Affine et Hessian Affine (suite)

- Estimation itérative de la localisation, de l'échelle, du voisinage

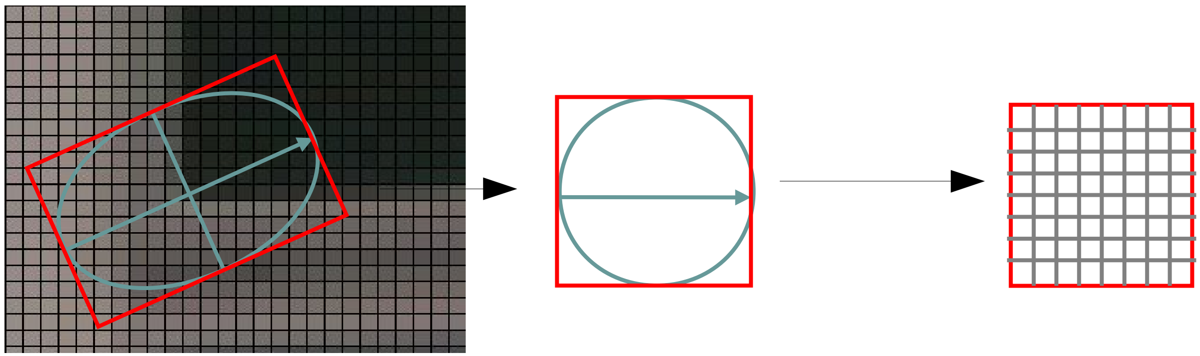
Iteration #3, #4, ...



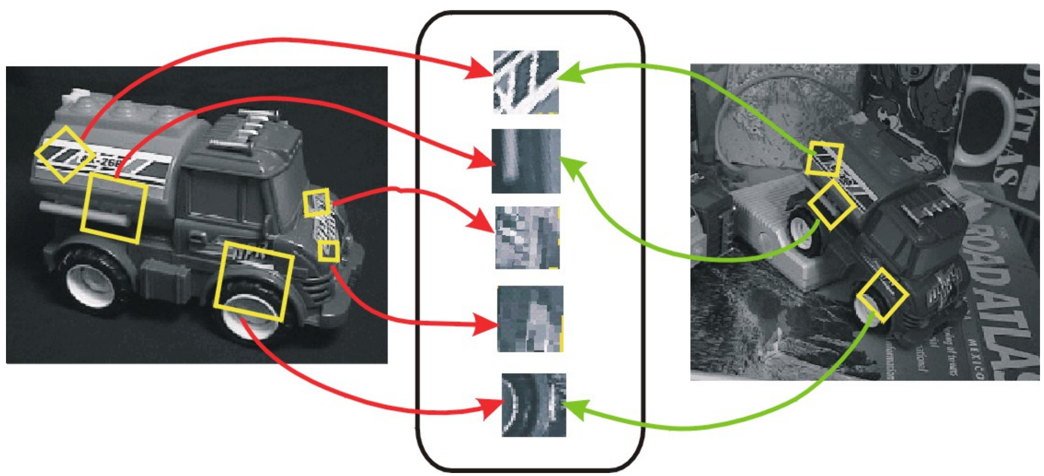


Descriptor computation 1 : normalized patches

- Patch extraction
  - Ellipse mapped to a fixed-size square patch



- Patches from matching images are similar



Descriptor computation 2: SIFT descriptor on a patch

- Histogram of oriented gradients
  - Coarse spatial information
  - Coarse orientation information
- Soft-assign histograms, weighting, normalization
- Output: L2-normalized 128D vector
  - [Lowe, IJCV 04]

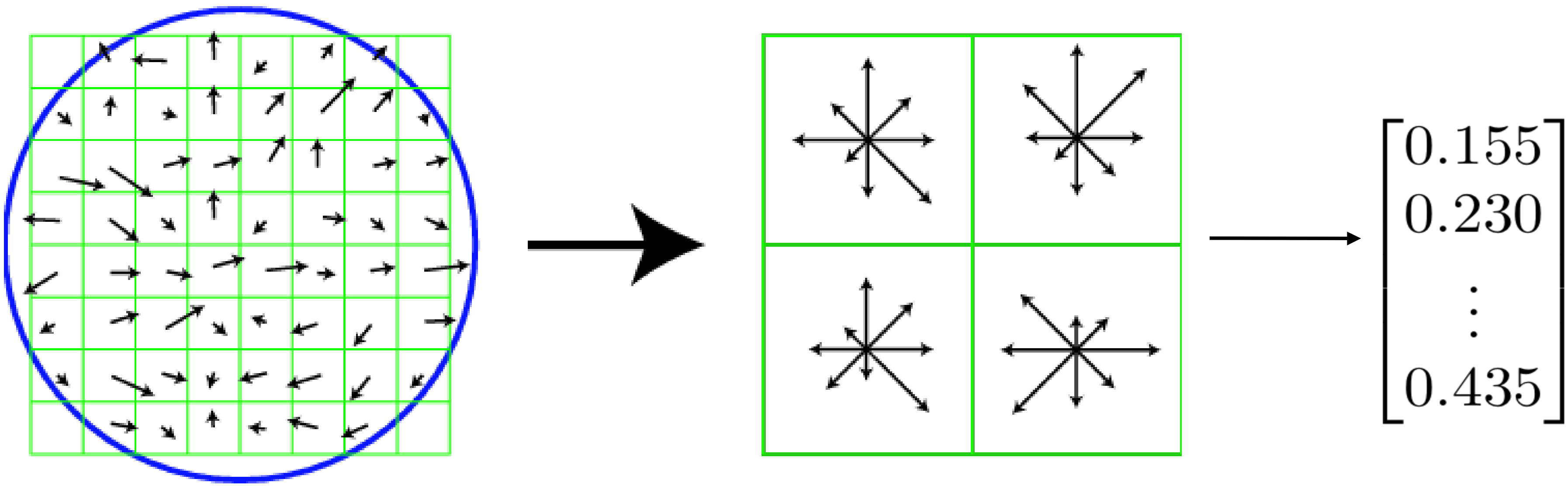
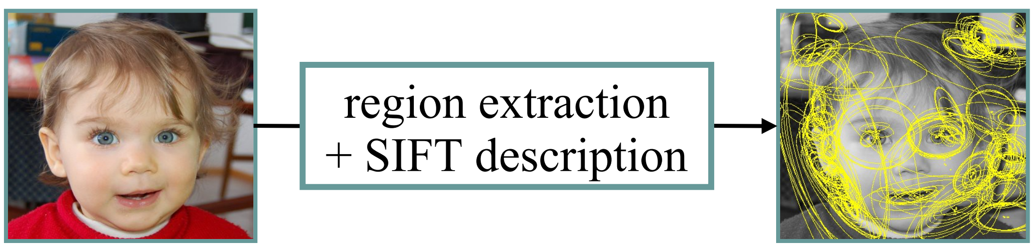


Image gradients

Keypoint descriptor

Ouput: local image descriptors

- n=400-3000 keypoints
  - coordinates, orientation, affine matrix
  - 128 D SIFT descriptor



Database image

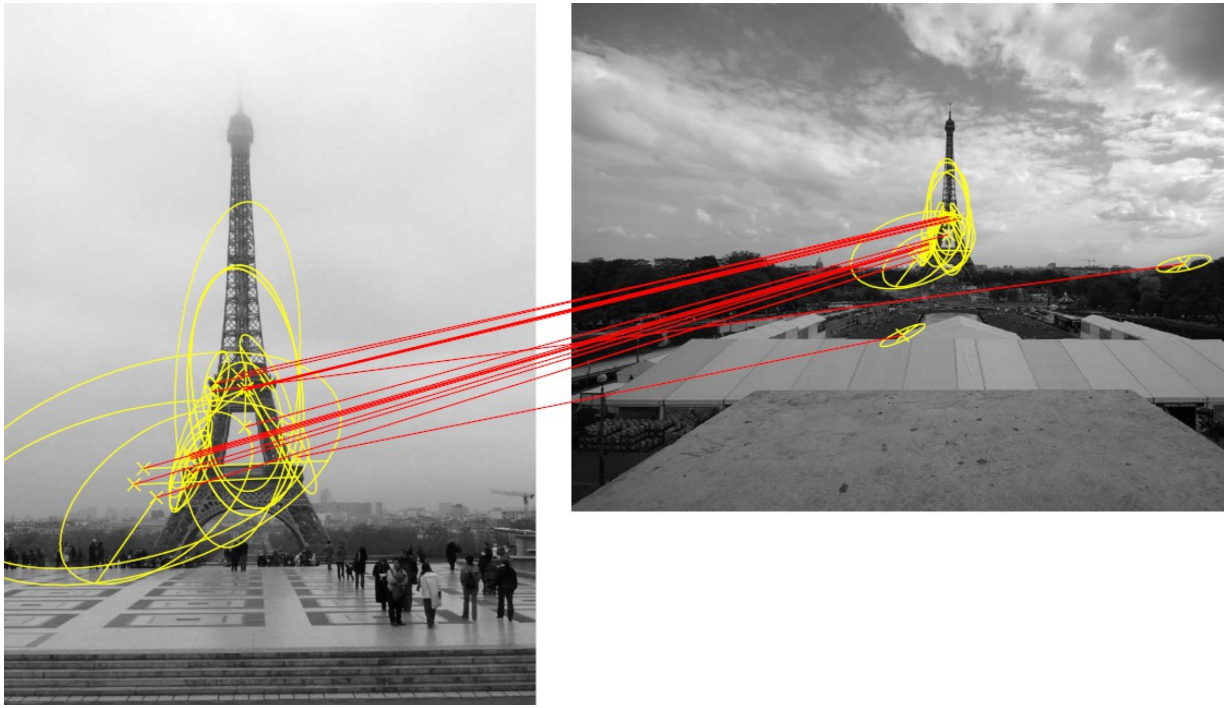
$$\begin{bmatrix} 5 \\ 0 \\ \vdots \\ 35 \end{bmatrix} \begin{bmatrix} 34 \\ 6 \\ \vdots \\ 12 \end{bmatrix} \cdots \begin{bmatrix} 14 \\ 20 \\ \vdots \\ 47 \end{bmatrix}$$

n SIFTs (d=128 dim)

3. Indexing by image matching

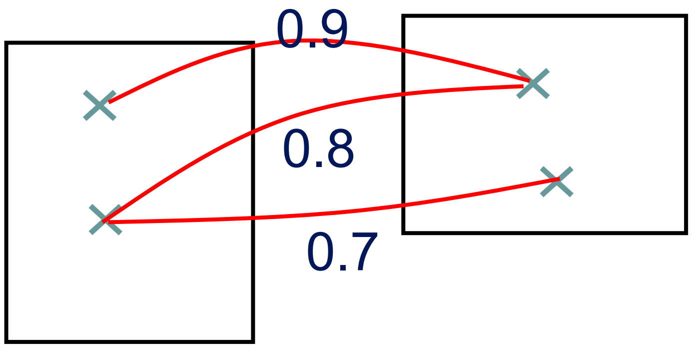
Keypoint matching

- Use descriptors to match points in images

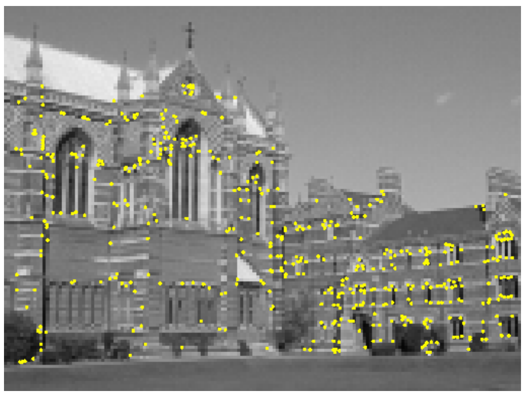


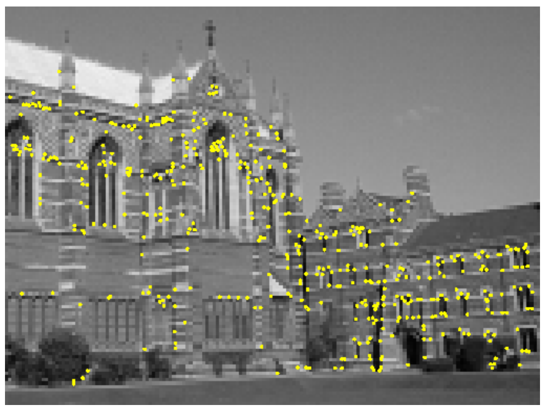
- Eg. for SIFT: compare all pairs of descriptors with L2 distance
  - Exhaustive computation
  - Cost $O(dn^2)$, BLAS
- 1-to-N image comparisons
  - Lowe's criterion

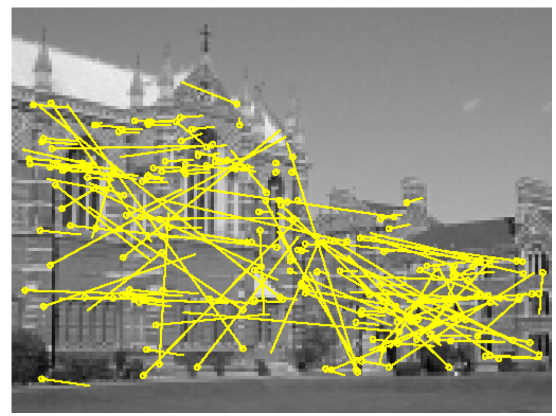
Filtering matches: first approach



- 2 points cannot match the same on the other image
  - Typical for repetitive textures
  - Simple work-around: greedy selection





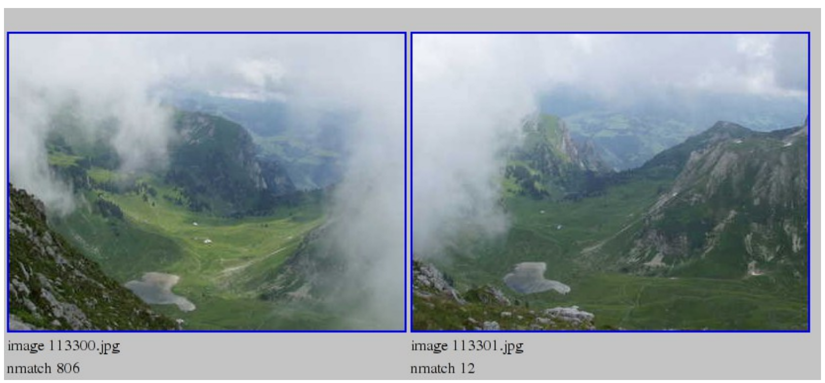


Filtering matches: geometrical constraints

- Geometrical model on point coordinates

  $x' = \mathrm{T}(x, p)$

- Model given by application context:
  - Recognize scanned pictures -> similarity
  - Recognize buildings -> epipolar model
    - in this case implicit model F(x, x', p) = 0
- Often better to use a simpler model than correct one...
  - Fewer parameters
  - easier to estimate (more stable, less expensive)
  - eg. : use 2D affine model to match buildings



Hierarchy of geometrical models (2D ↔ 2D)

	nombre de degré de liberté	invariants géométriques	forme
translation	2	tout, sauf les positions absolues	$\begin{bmatrix} X' \\ Y' \end{bmatrix} = \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} t_X \\ t_Y \end{bmatrix}$
transformée rigide	3	longueur, angle, surface, courbure	$\begin{bmatrix} X' \\ Y' \end{bmatrix} = \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} t_X \\ t_Y \end{bmatrix}$
similitude	4	angle, rapport de longueur	$\begin{bmatrix} X' \\ Y' \end{bmatrix} = s \begin{bmatrix} \cos(\theta) & \sin(\theta) \\ -\sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} t_X \\ t_Y \end{bmatrix}$
transformation affine	6	parallélisme, rapport de surface, rapport de longueur sur une droite, coordonnées barycentriques	$\begin{bmatrix} X' \\ Y' \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} t_X \\ t_Y \end{bmatrix}$
Homographie	8	Birapport	$\begin{bmatrix} X' \\ Y' \end{bmatrix} = \frac{1}{h_{31} X + h_{32} Y + h_{33}} \left(\begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix} + \begin{bmatrix} h_{13} \\ h_{23} \end{bmatrix} \right)$

Filtering matches: estimating model parameters

- Estimate model parameters *p* robustly
  - Input: descriptor matches (many outliers)
  - Output: subset correct matches + model parameters
- Robust estimation
  - RANSAC
  - Hough transform (low-dim models)

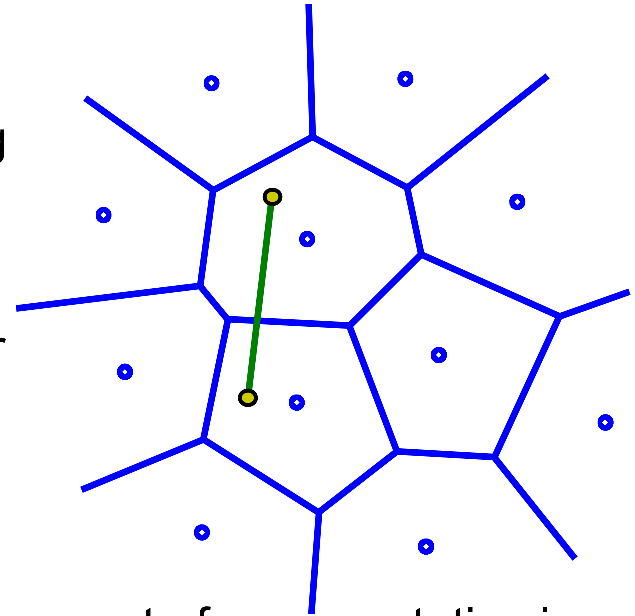
Compute image similarity from keypoint matches

- Basic: number of matching points between the two images
- Per-match weightings:
  - descriptor distances
  - Geometrical matching error
- Per-database image score normalization
  - number of keypoints
  - model likelihood

- In practice: usable for ~10 images...

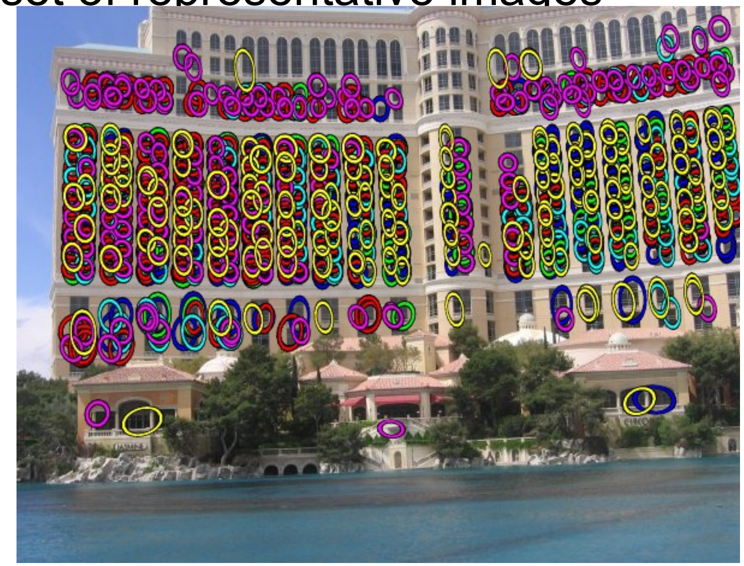
4. Bag-of-words and the inverted file

Scaling up the matching performance



- Drastic simplification of the keypoint matching
  - Direct matching does not scale
  - Local descriptors too large (d=128D)
- Represent each keypoint with a single integer
  - integer obtained by quantization

    $i = q(x)$
  - Nearest-neighbor quantization
  - Quantizer: computed with k-means on a large set of representative images

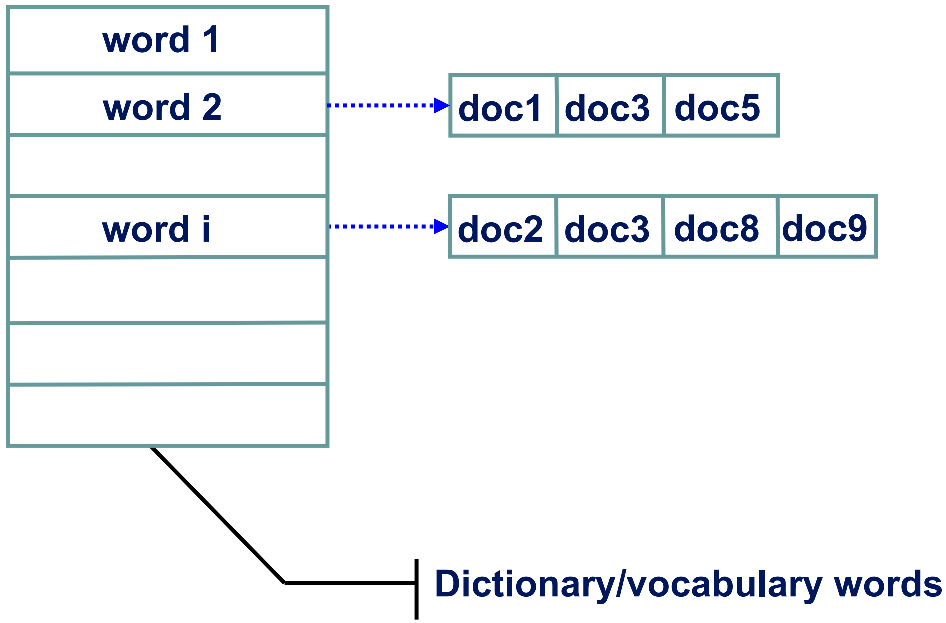


- Matching
  - Keypoint matching = keypoints with the same word
  - Image matching = count matching keypoints
- Quantization index of image descriptor = word in a document
  - Hence the “bag-of-words” term

[« Video Google: A Text Retrieval Approach to Object Matching in Videos », Sivic & Zisserman, ICCV 2003]

The inverted file

- Ususal application context: text indexing



- A word query returns the list of documents containing the word
  - Cost scales linearly with the number of documents to retrieve

Searching in text documents (1)

- Vector model
  - Given a dictionary of size k
  - A text document is represented by a vector $f=(f_1,\ldots,f_i,\ldots f_k) \in \mathbb{R}^k$
  - Each dimension corresponds to a dictionary word
  - f_i = frequency of the word in the document

- In practice, non-discriminant words are removed from the dictionary
  - “the”, “a”, “is”, “them”, etc, are not discriminant enough (stop words)

- Vectors are sparse
  - The dictionary large wrt. Number of words used in document

Searching in text documents (2)

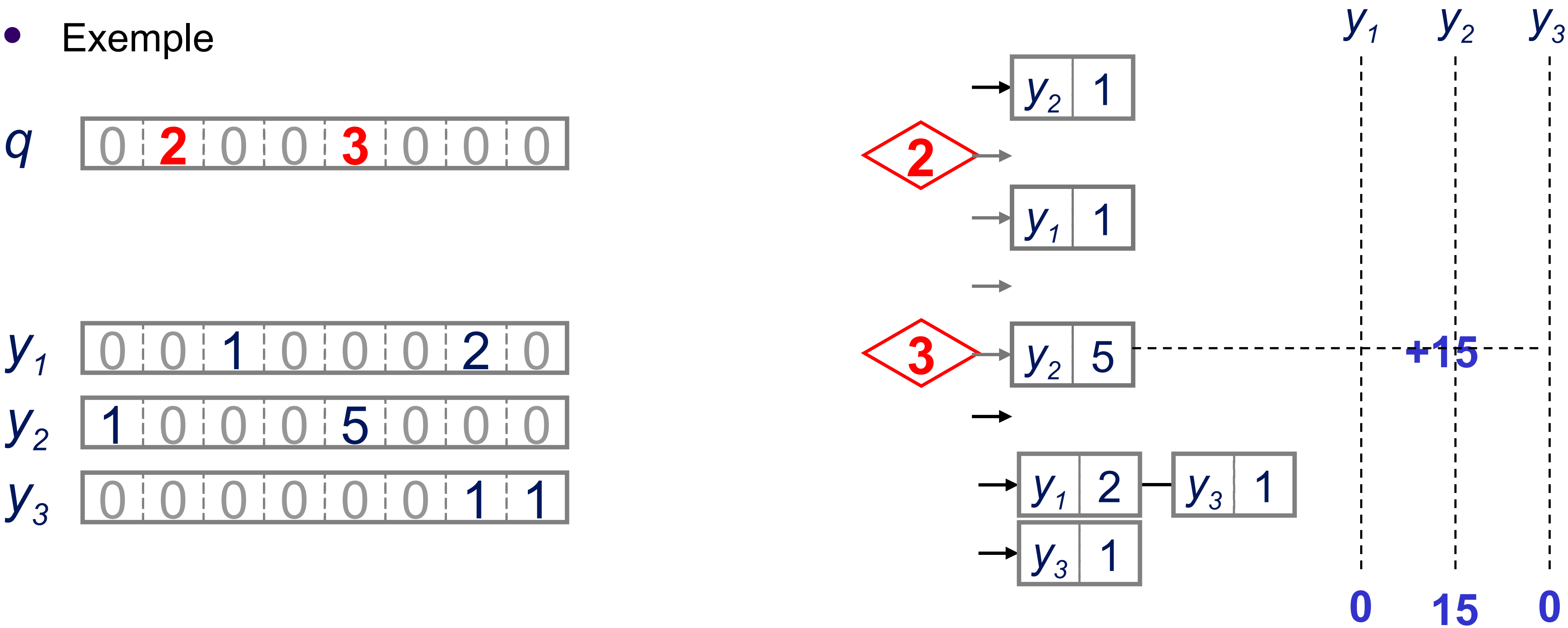
- Example
  - dictionary = {“vélo”, “voiture”, “déplace”, “travail”, “école”, “Rennes”}
  - Documents are vectors in $\mathbb{R}^6$
  - L1 normalized
  - “Rennes est une belle ville. Je me déplace à vélo dans Rennes”

    $f=(1/4,0,1/4,0,0,1/2)^T$

- Searching a document = finding the nearest vectors
  - For a given similarity measure
  - We use the scalar product

Inverted file: distances between sparse vectors

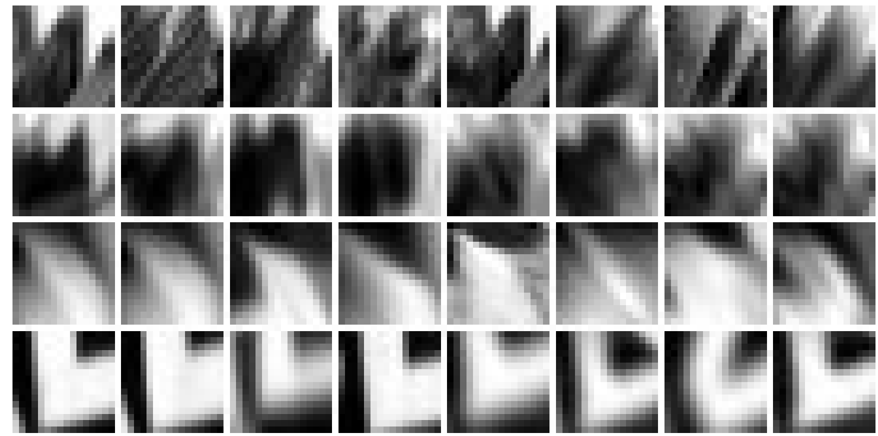
- query q and database Y, all sparse
- Inverted file used to compute scalar product efficiently (works for any L_p distance)
- Exemple



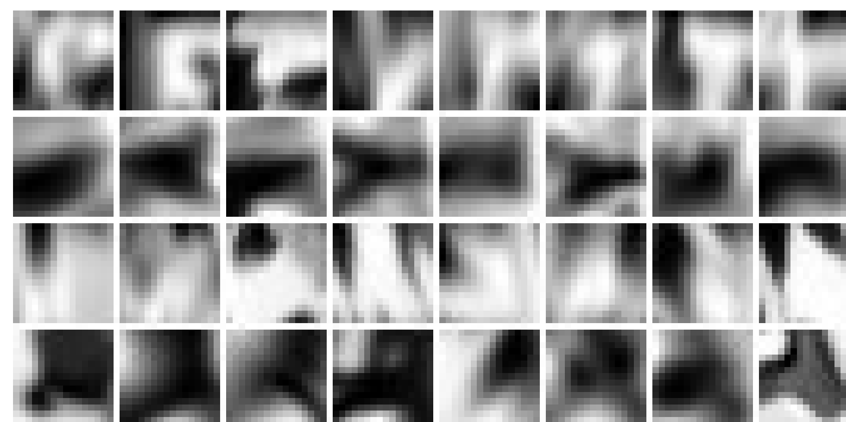
Cost of searching in an inverted file

- Notations
  - k = number of centroids = vocabulary size
  - n = nb of descriptors per image
  - d = dimension of descriptors
  - N = nb of database images
- Storage cost: O(N * n)
- Query quantization cost: O(k * n * d)
- Search cost: O(n^2 * N / k)
  - Assuming k >> n and uniform assignment
- Impact of k:
  - Large = more expensive quantization
  - Large = faster search
  - Large = less invariant

k=200,000



k=20,000



Term frequency – inverse document frequency weighting

- Weighting of vocabulary entries (TFIDF)
  - Same as for text documents
  - Objective: more weight for rare words than for typical ones

Nb occurrences of word *i* in doc d

Nb of words in doc *d*

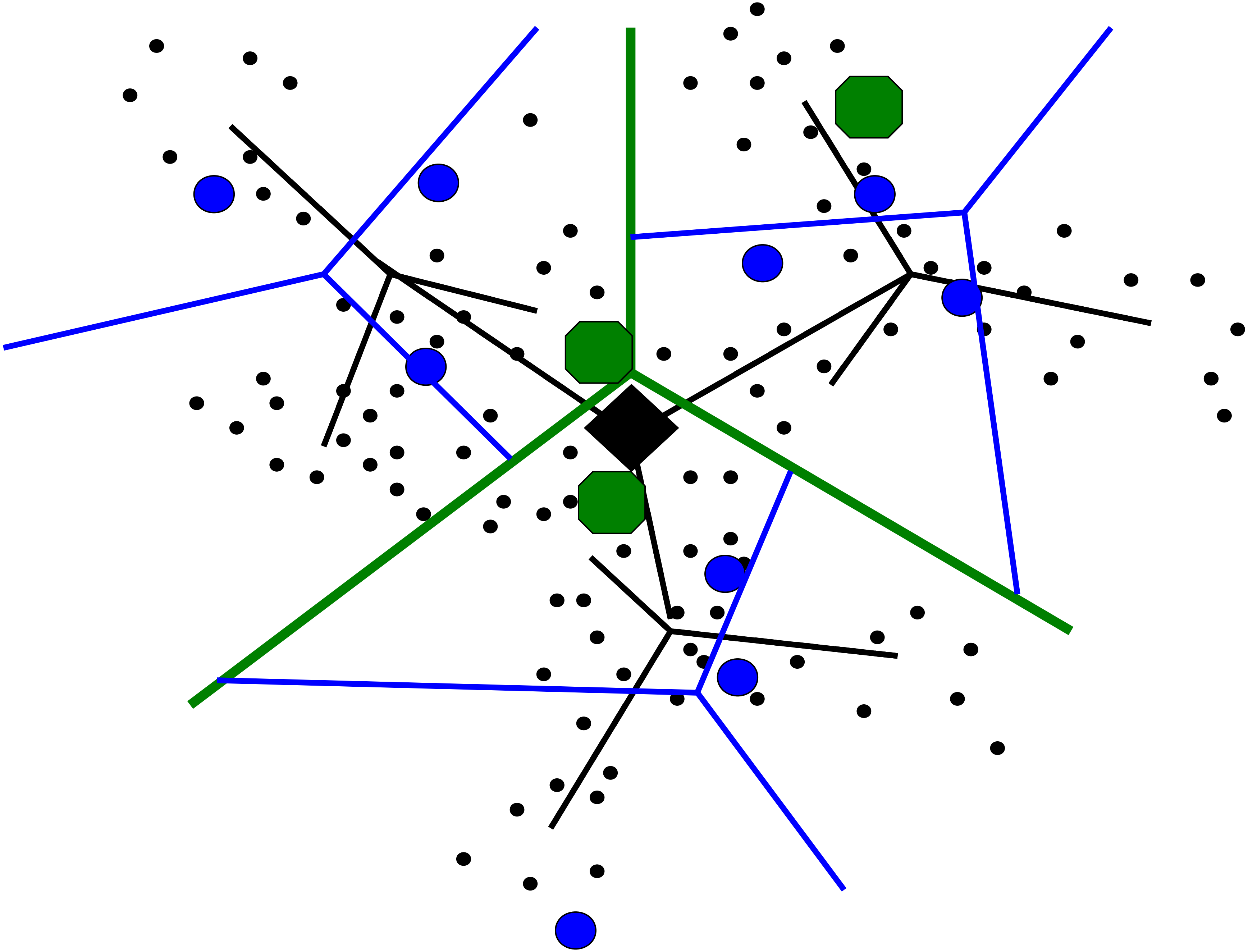
$$t_{id} = \frac{n_{id}}{n_d} \log\left(\frac{N}{n_i}\right)$$

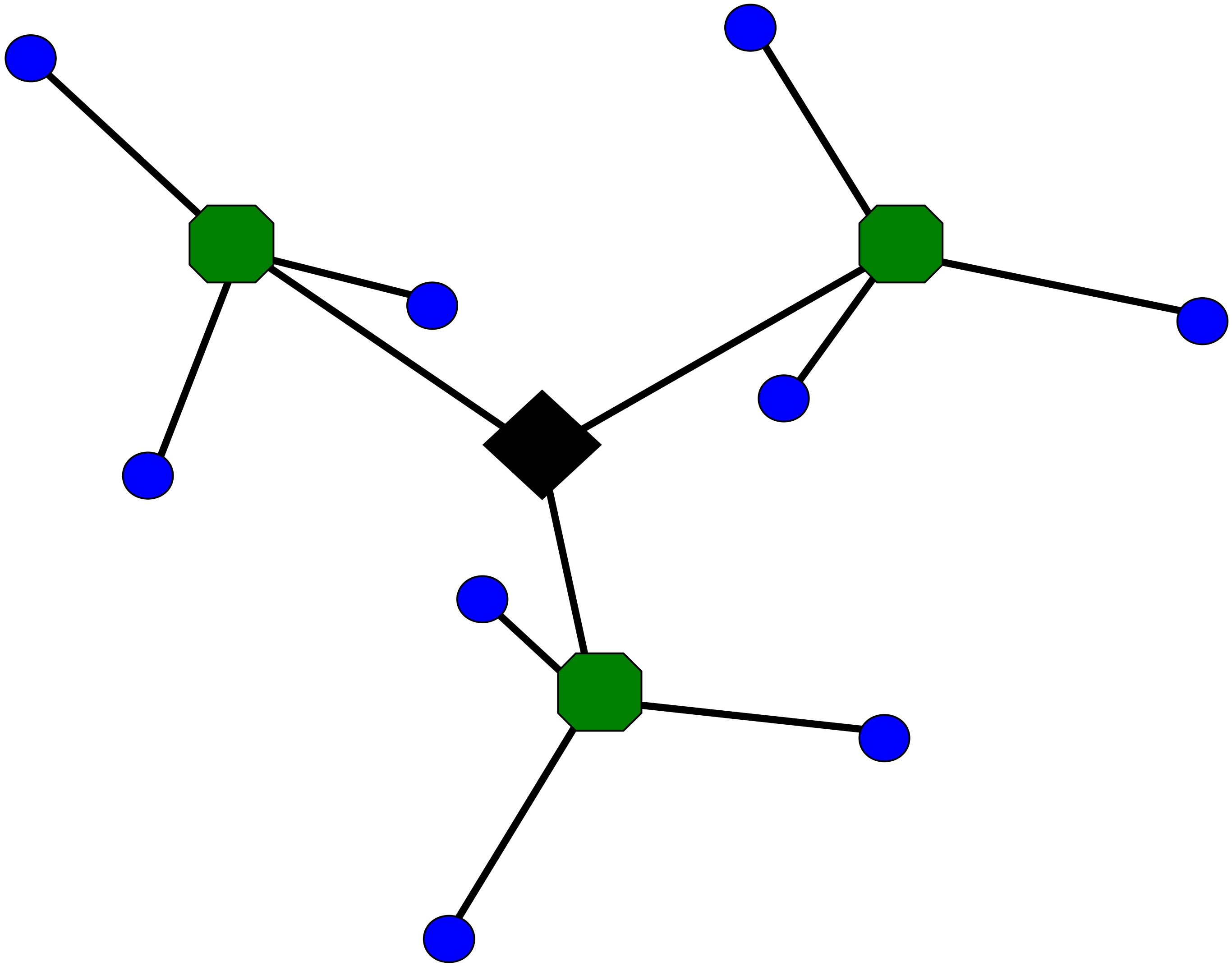
Nb of documents in database

Nb of occurrences of *i* in whole database

Faster quantization

- Larger k is good
  - Faster
  - More discriminant is often good
    - An object is recognizable with as few as 3 keypoint matches
  - Random matches are less likely...
- To speed up quantization: use a hierarchical clustering
  - Apply k-means recursively -> tree
- Vocabularies of up to k=5M

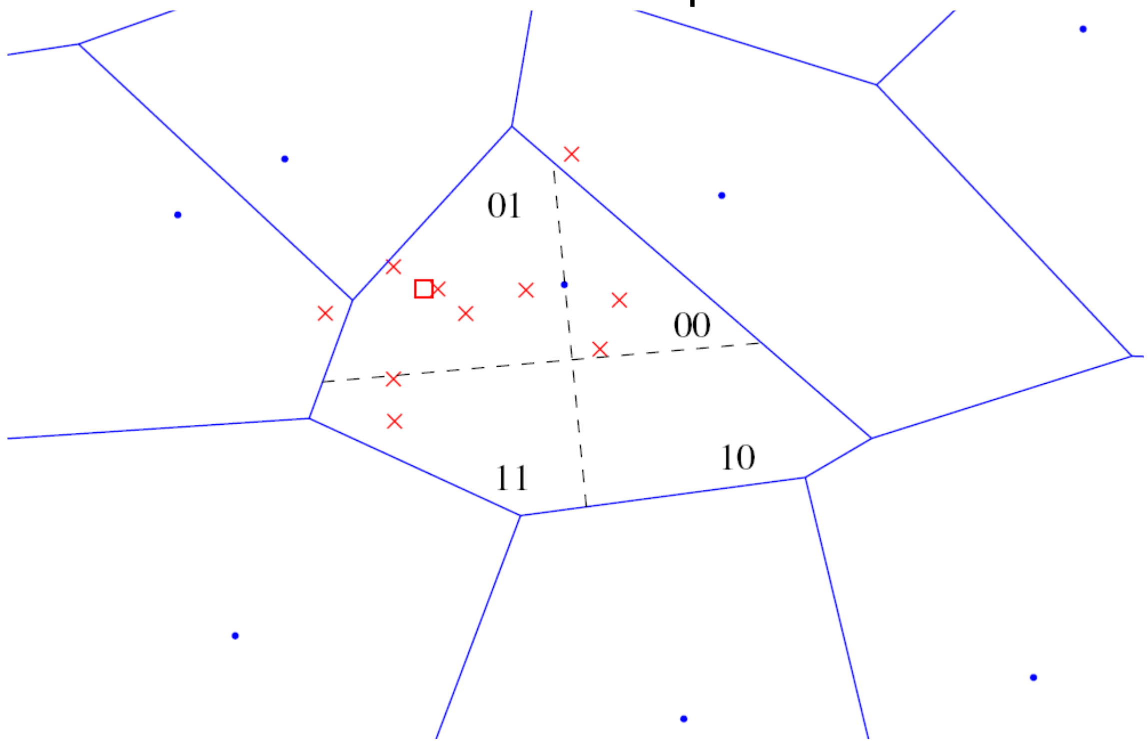




Refine quantization in the inverted file

[Jégou, Douze, Schmid, ECCV 08]
[Tolias, Avritis, Jégou, ICCV 13]

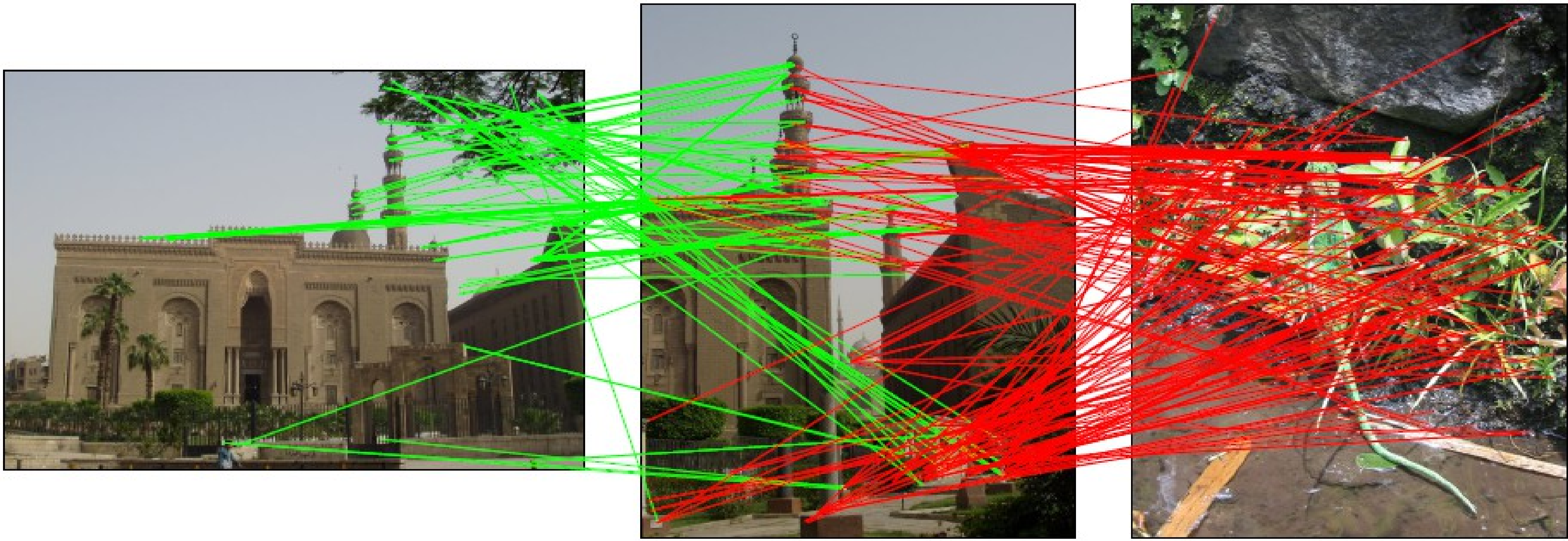
- Basic BoW looses a lot of information about descriptors
- Hamming embedding:
  - 1 entry per SIFT descriptor in inverted file
  - Add a binary signature to the quantization index
  - Compare binary signatures with Hamming distance
  - Filters out 98% of matches -> *faster* than plain BoW



Matching points - 20k word vocabulary

201 matches

240 matches

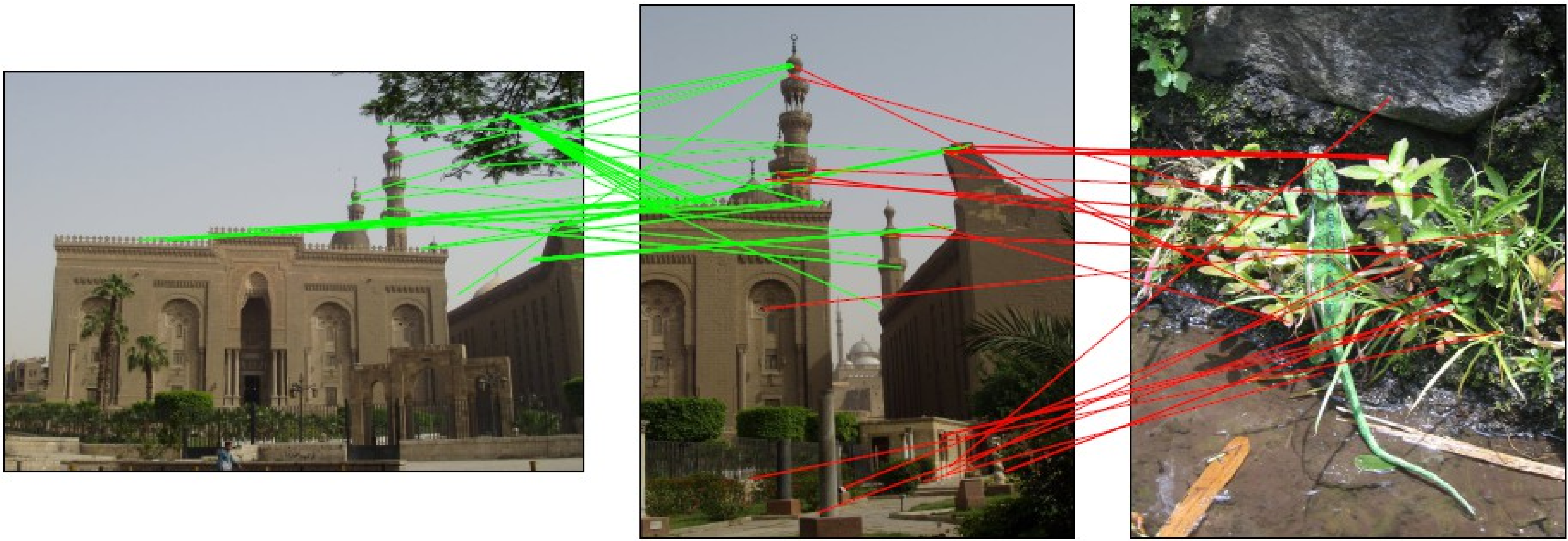


Many matches with the non-corresponding image!

Matching points - 200k word vocabulary

69 matches

35 matches

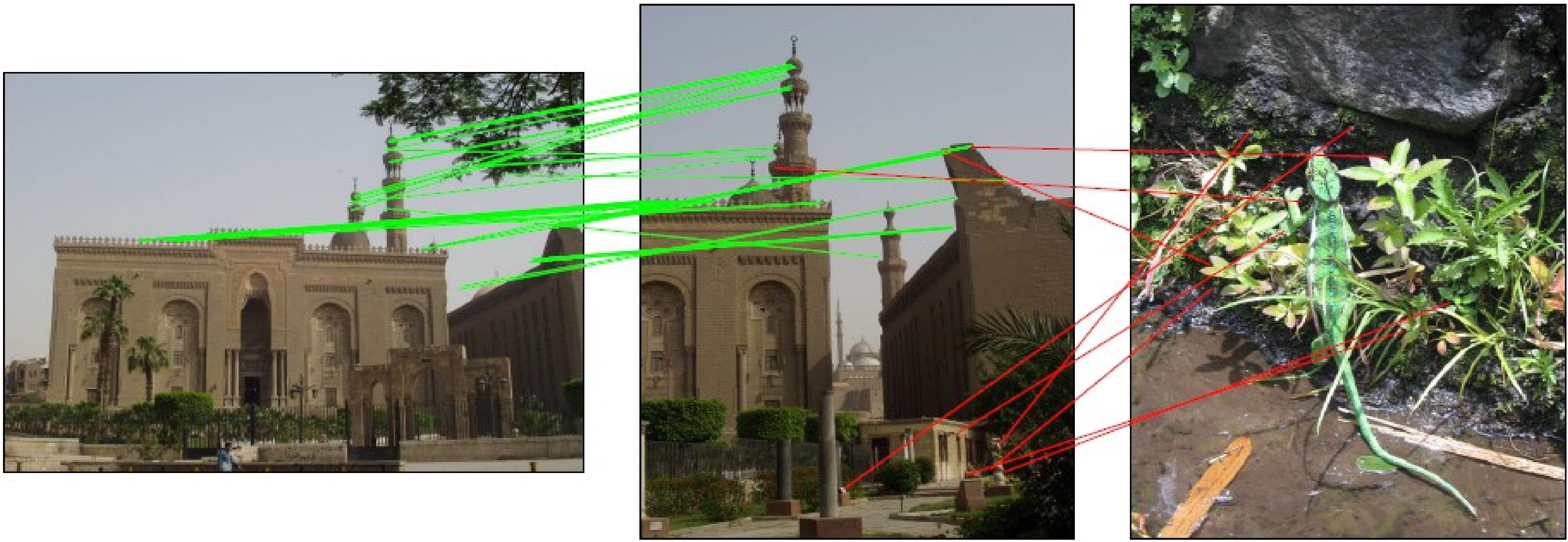


Still many matches with the non-corresponding one

Matching points - 20k word vocabulary + Hamming Embedding

83 matches

8 matches

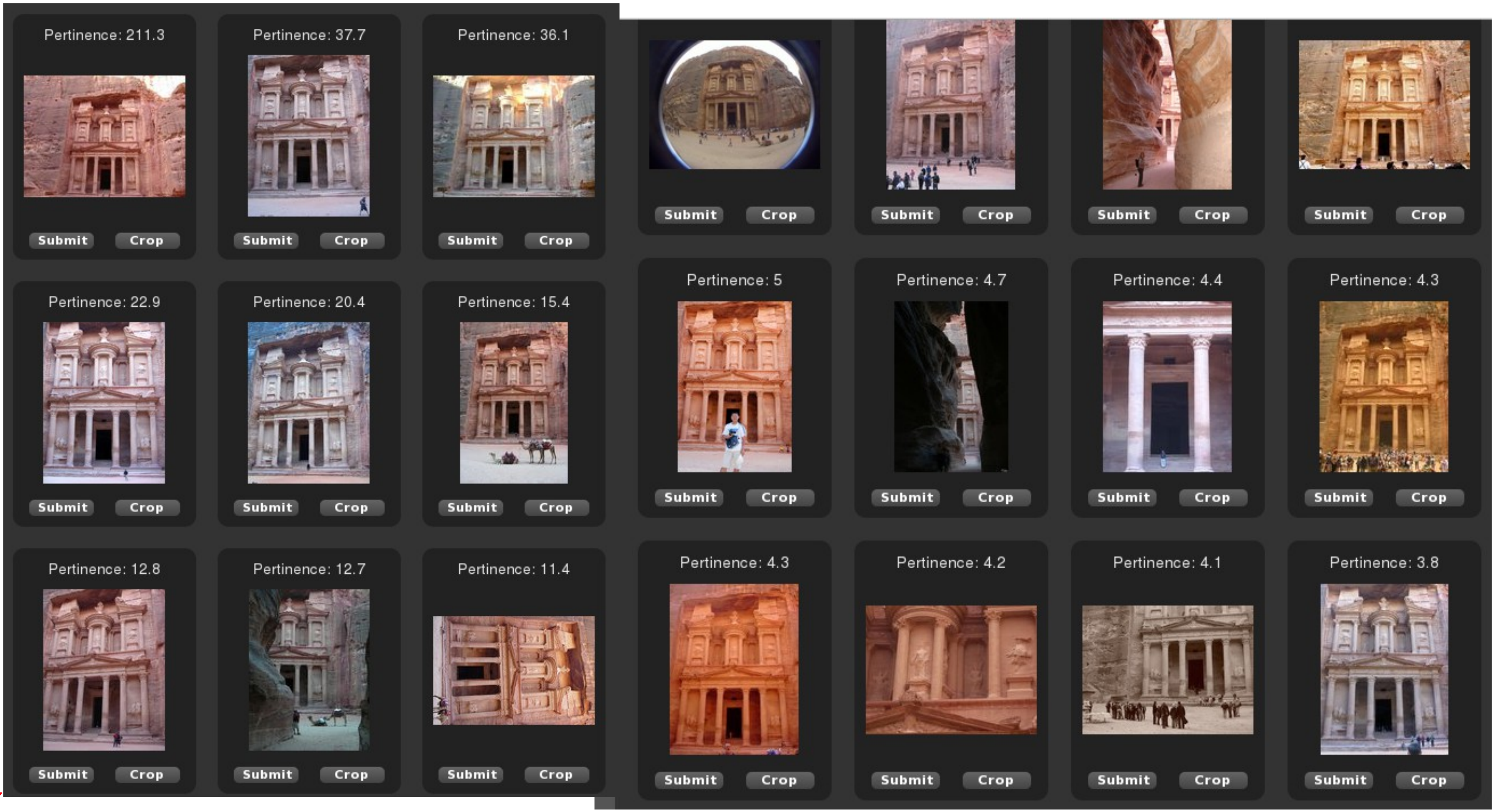


10x more matches with the corresponding image!

Search results (in a 1M-image database)

About BoW + inverted file

- Very effective method
- Works well up to 1-10M images
- See demo at http://bigimbaz.inrialpes.fr



5. Local descriptor aggregation

Bag-of-words is a global descriptor

- The quantized descriptors can be seen as a k-dimensional histogram per image
  - Histogram compared with a dot-product (sometimes L1)
- Sparse encoding
  - Historgram = sparse vector
  - Inverted file = sparse matrix (in compressed-row storage)
  - Search = sparse matrix-vector multiplication

- Improve BoW: represent the SIFTs of an image by a single fixed-size vector:

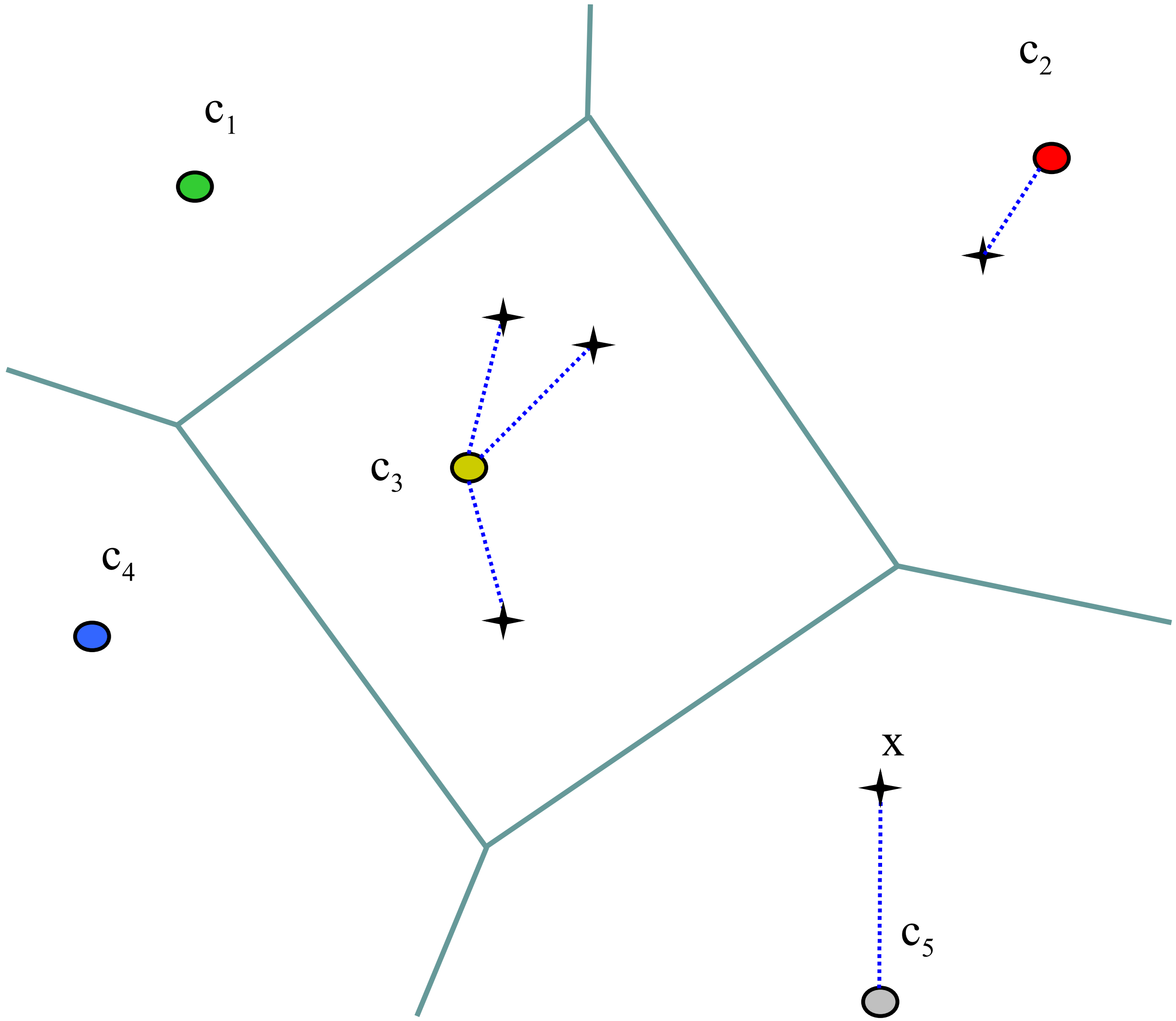
set of *n* local descriptors → 1 vector (size D)

$$\xrightarrow[\textit{SIFT}]{\textit{extract}} \underbrace{\begin{bmatrix}5\\0\\\vdots\\35\end{bmatrix}\begin{bmatrix}34\\6\\\vdots\\12\end{bmatrix}\cdots\begin{bmatrix}14\\20\\\vdots\\47\end{bmatrix}}_{n \textit{ SIFTs (128 dim)}} \xrightarrow[\textit{descriptors}]{\textit{aggregate}} \overset{D}{\begin{bmatrix}-0.234\\0.452\\0.134\\\vdots\\0.001\end{bmatrix}}$$

VLAD : Vector of Locally Aggregated Descriptors

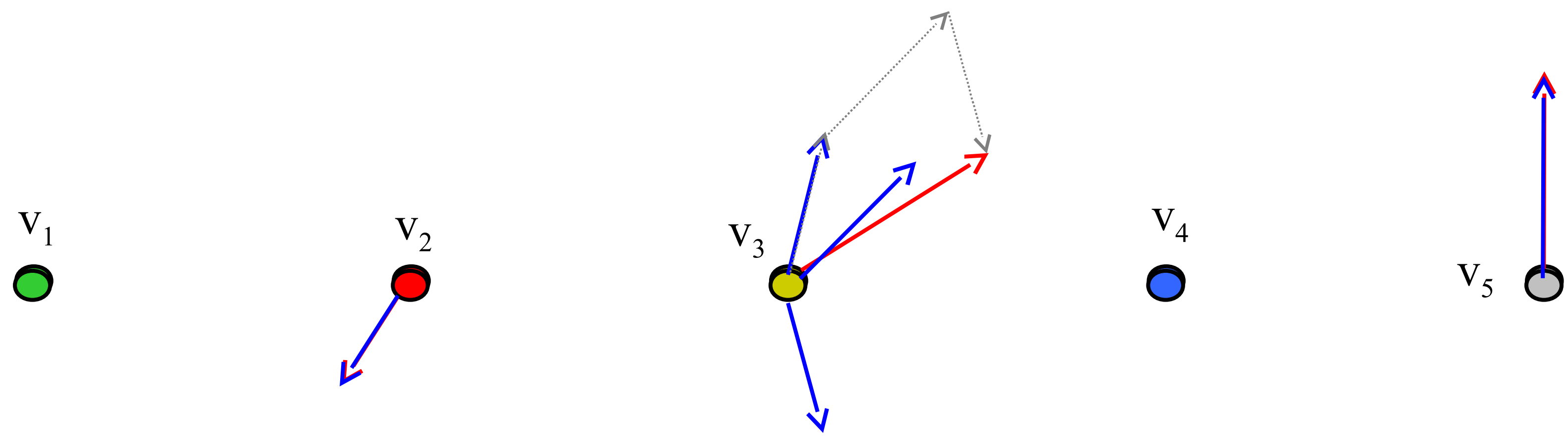
Jégou, Douze, Schmid, Pérez, “aggregating local descriptors into a compact image representation”, CVPR 10

- D-dimensional descriptor space (SIFT: d=128)
- *k* centroids : $c_1,\ldots,c_k$



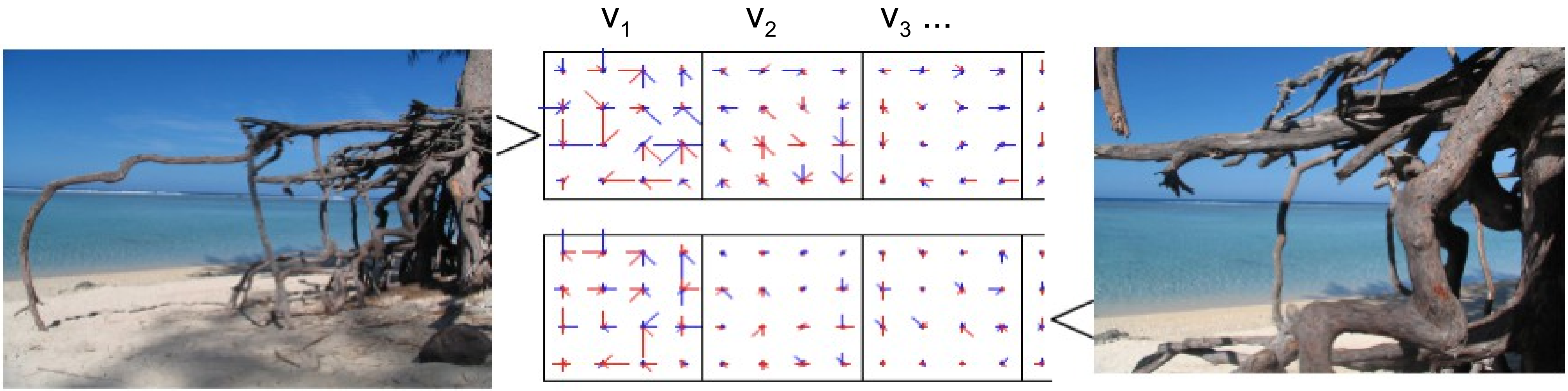
VLAD : Vector of Locally Aggregated Descriptors

- D-dimensional descriptor space (SIFT: D=128)
- k centroids : $c_1,\ldots,c_k$



- Output: $v_1 \ldots v_k$ = descriptor of size k*d
  - Encodes how a SIFT differs from typical SIFTs of its quantization cell
- L2-normalized
- Typical k = 16 or 64 : descriptor in D = 2048 or 8192 dimensions
- Similarity measure = L2 distance.

VLADs for corresponding images

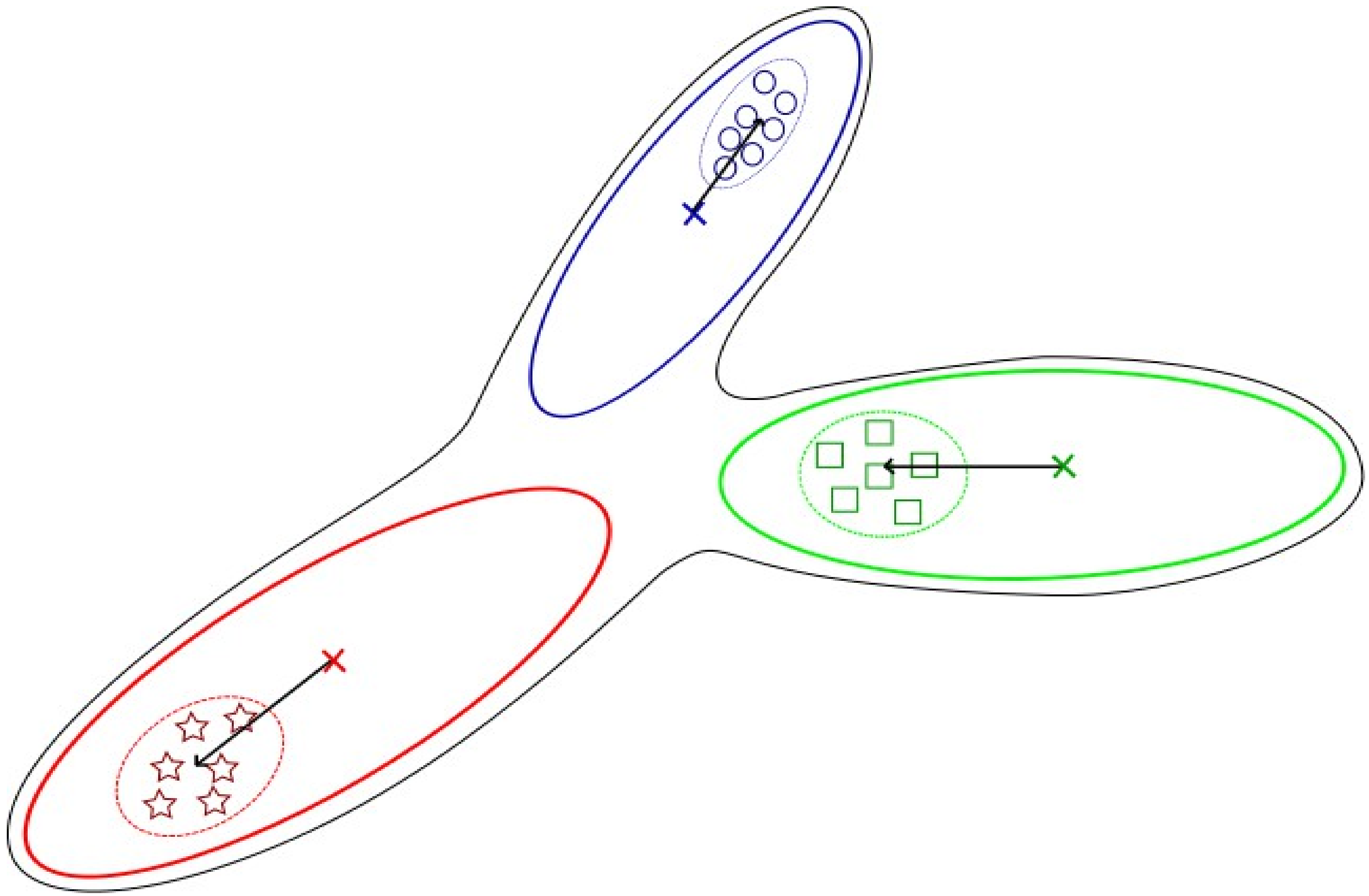


SIFT-like representation per centroid (>0 components: blue, <0 components: red)

- good coincidence of energy & orientations

Fisher vector: a more elaborate version of VLAD

- Based on a Gaussian mixture model
  - Derivative of GMM params at the observed SIFTs



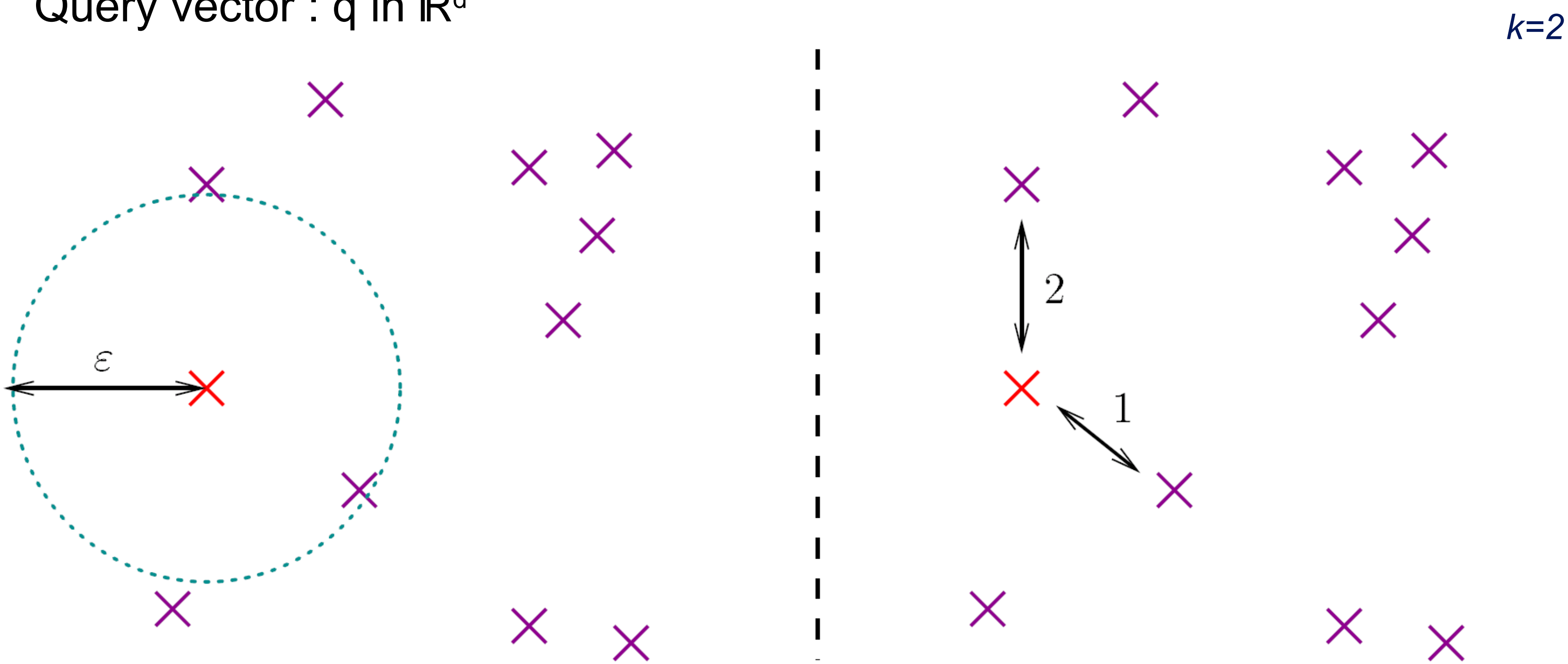
Indexing aggregated descriptors (VLAD and Fisher)

- Descriptors are not sparse
  - Fisher by design
  - VLAD because k >> n does not hold
- Similar to BoW:
  - Vector similarity is dot product (equivalent to L2 distance)
  - Exhaustive search is matrix-vector product: O(D * N)

6. Nearest-neighbor search (low dimension)

Notations

- Database of N vectors : $Y = \{ y_i \in \mathbb{R}^D \}_{i=1..N}$
- Query vector : q in $\mathbb{R}^d$



$N_\varepsilon(q) = \{ y_i \in Y : d(y_i,q) < \varepsilon \}$

$N_k(q) = k\text{-arg-min}_i \, d(y_i,q)$

- We are interested in the later. NB: the nearest-neighbor relation is not symmetric!

Preliminary: finding the k nearest neighbors given computed distances

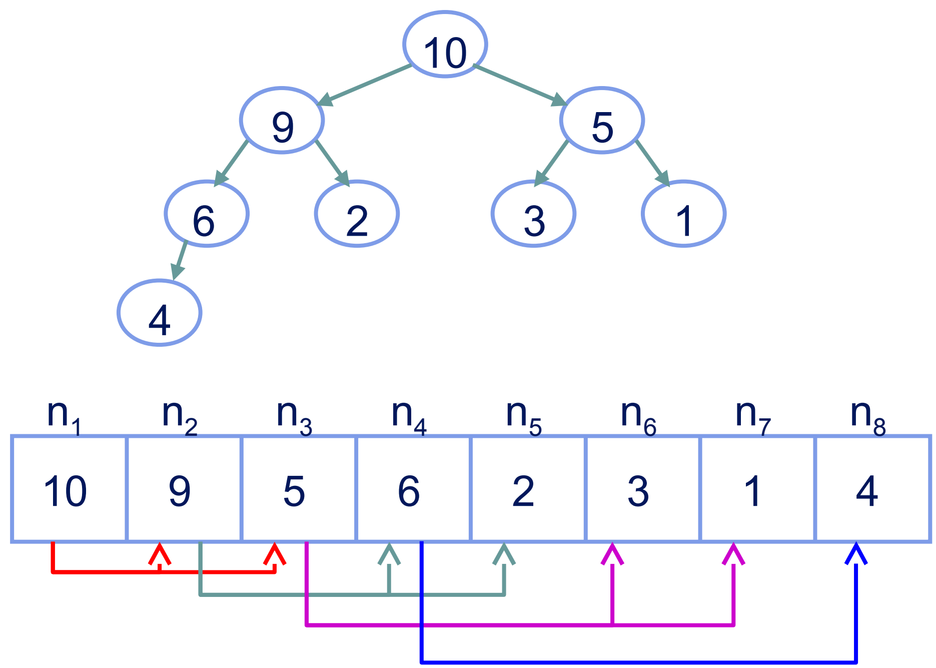
- Pour $N_k(q)$, il faut de plus trouver effectuer l'opération k-arg-min$_i$ $d(q,y_i)$

- Exemple: on veut 3-argmin {1,3,9,4,6,2,10,5}
  - Méthode naïve 1: trier ces distances → O(n log n)
  - Méthode naïve 2: maintenir un tableau des k-plus petits éléments, mis à jour pour chaque nouvelle distance considérée → O(n k)

- Intuitivement, on peut faire mieux…

Max-heap

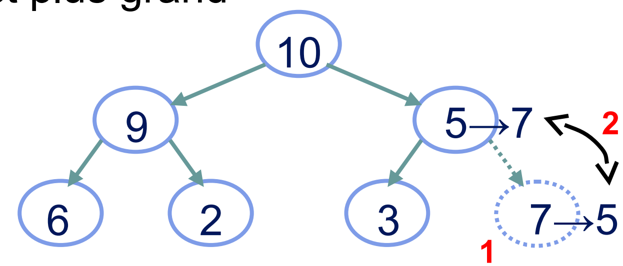
- *Binary max heap*
  - structure d’arbre binaire équilibré
  - dernier niveau rempli de gauche à droite
  - à chaque noeud *n* on associe une valeur v(*n*)
  - propriété : si n_i est un noeud fils de n_j, alors v(n_i) < v(n_j)



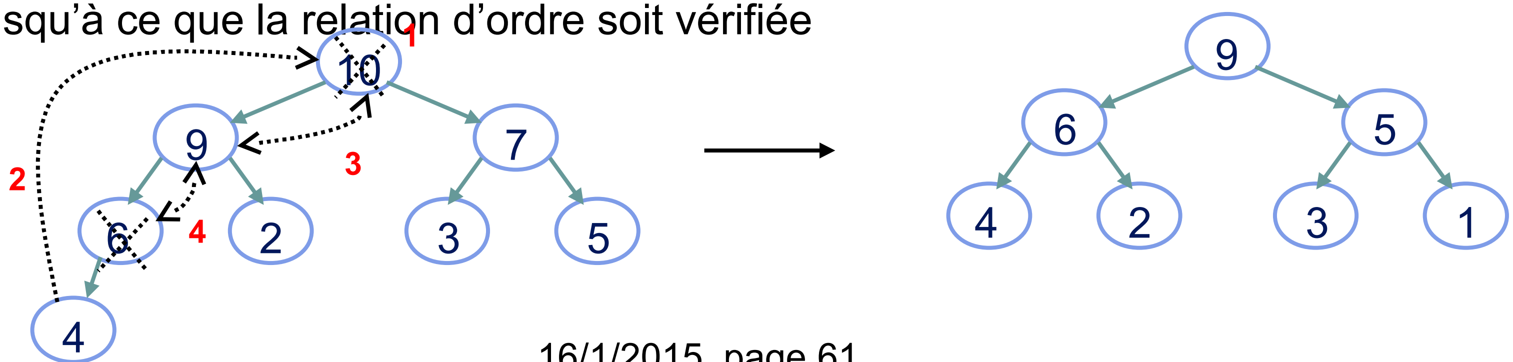
- Remarque : il admet une représentation linéaire simple: n_i a pour père $n_{i/2}$

Max-heap : opérations élémentaires

- **heap_push**: ajout inconditionnel d'un élément dans le heap
  - ajouter le noeud k+1, et y placer le nouvel élément
  - mise à jour (pour garder les propriétés d'ordre) :
    - l'élément inséré remonte : inversion avec son parent s'il est plus grand
    - jusqu'à vérification de la relation d'ordre
    - complexité en O(log k) au pire, mais O(1) en pratique



- **heap_pop**: suppression inconditionnelle de la plus grande valeur
  - on supprime le noeud racine et on le remplace par l'élément du noeud k
  - mise à jour :
    - on descend l'élément : inversion avec le fils le plus grand
    - jusqu'à ce que la relation d'ordre soit vérifiée



Algorithme: Max-heap pour chercher les k plus petites valeurs

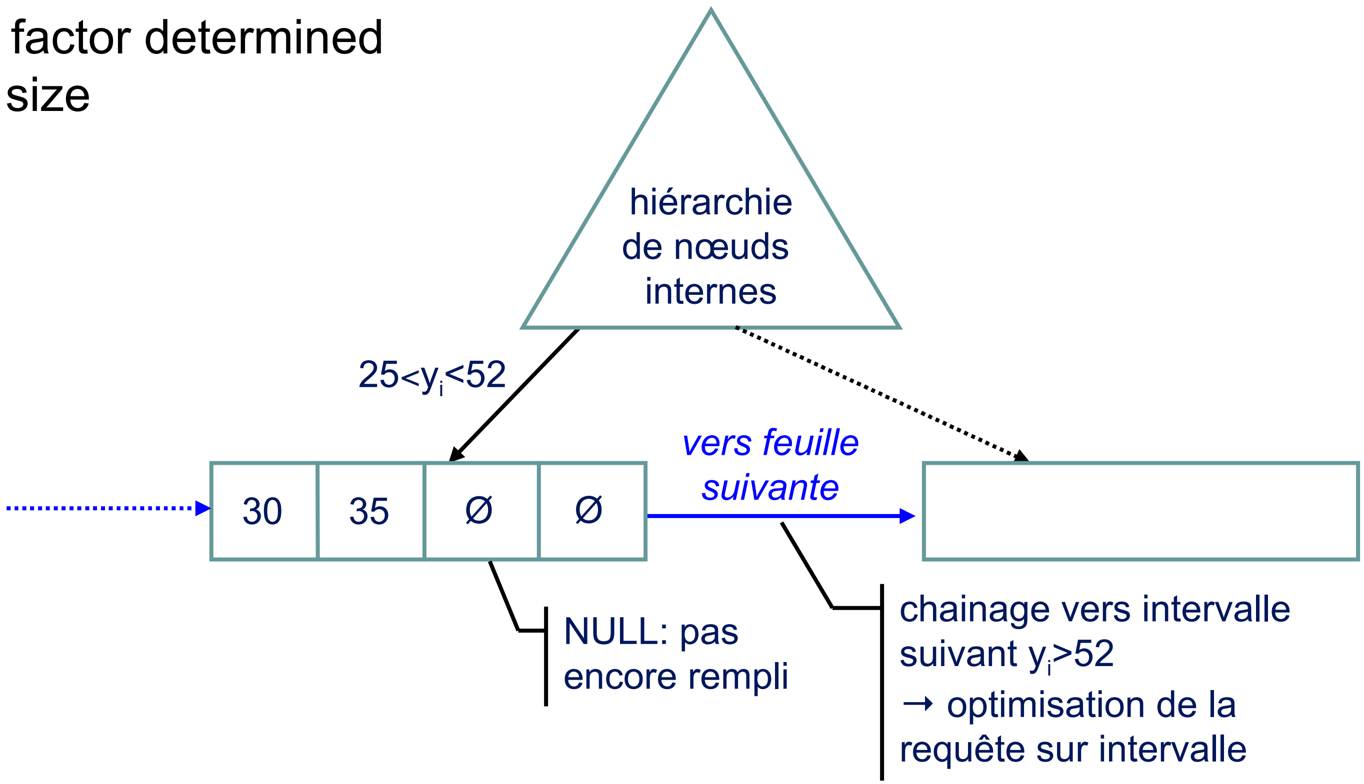
- Pb: on cherche k-argmin$_i$ $\{a_1,\ldots a_i,\ldots a_n\}$

- Initialisation du heap à l'arbre vide
- Pour i=1..n,
  - si l'arbre n'est pas encore de taille k $\rightarrow$ heap_push
  - si l'arbre est déjà de taille k, on compare à la racine
    - si $a_i \geq$ racine $\rightarrow$ on passe à l'élement suivant
    - sinon
      - heap_pop
      - heap_push

- Exemple: 3-argmin {1,3,9,4,6,2,10,5}

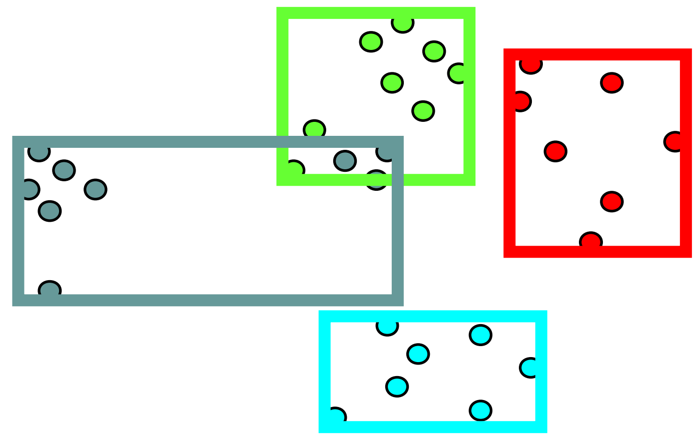
Nearest-neighbor search in 1D

- Take advantage of the total order
  - Sort values
- in standard databases
  - SELECT taille FROM PERSON WHERE taille > 1.70 and taille < 1.90
- Uses a B+ tree
  - Easy to do insertions
  - Branching factor determined disk block size

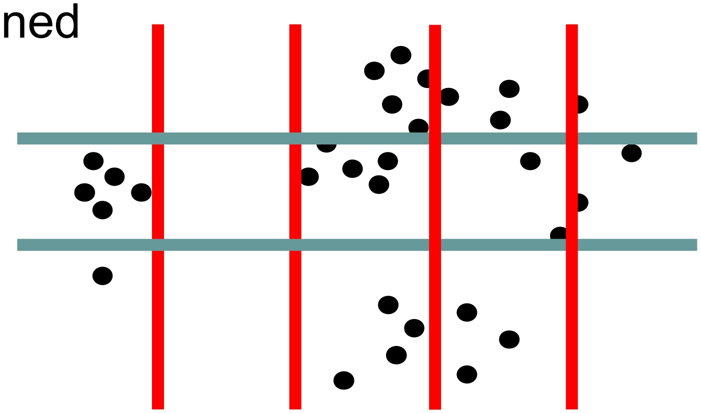


More than 1 dimension

- For D $\geq$ 2, we don't have a total ordering
- Split up space in *cells*
  - Record points for each cell
  - Fewer points than cells
- Two families of splitting policies
  - Data-dependent

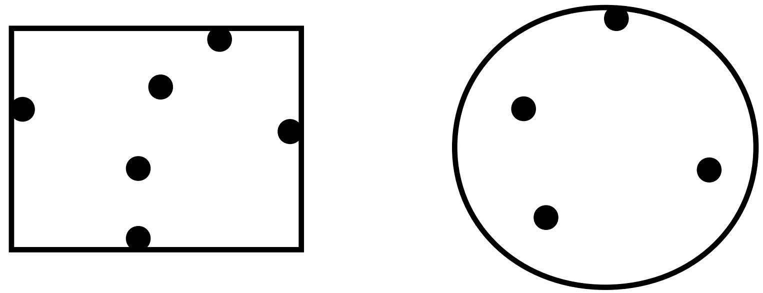


  - pre-defined



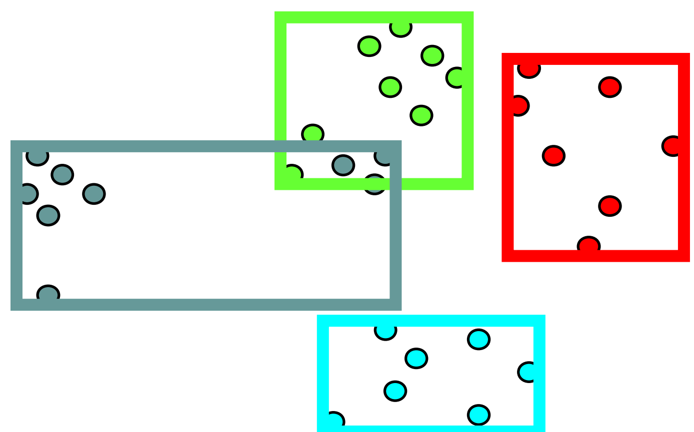
Data dependent

- Bounding hyper-rectangles (2 points) or spheres (1 point and a radius)



- Hyper-rectangles are easier to index, but hyper spheres are more compact
  - Criterion: diameter for given volume
  - Hyper-rectangle: diameter is 5.47 for D=30 and volume = 1
  - Hyper-sphere: 2.86 → more efficient filtering

- Depending on method:
  - Overalpping cells
  - or not



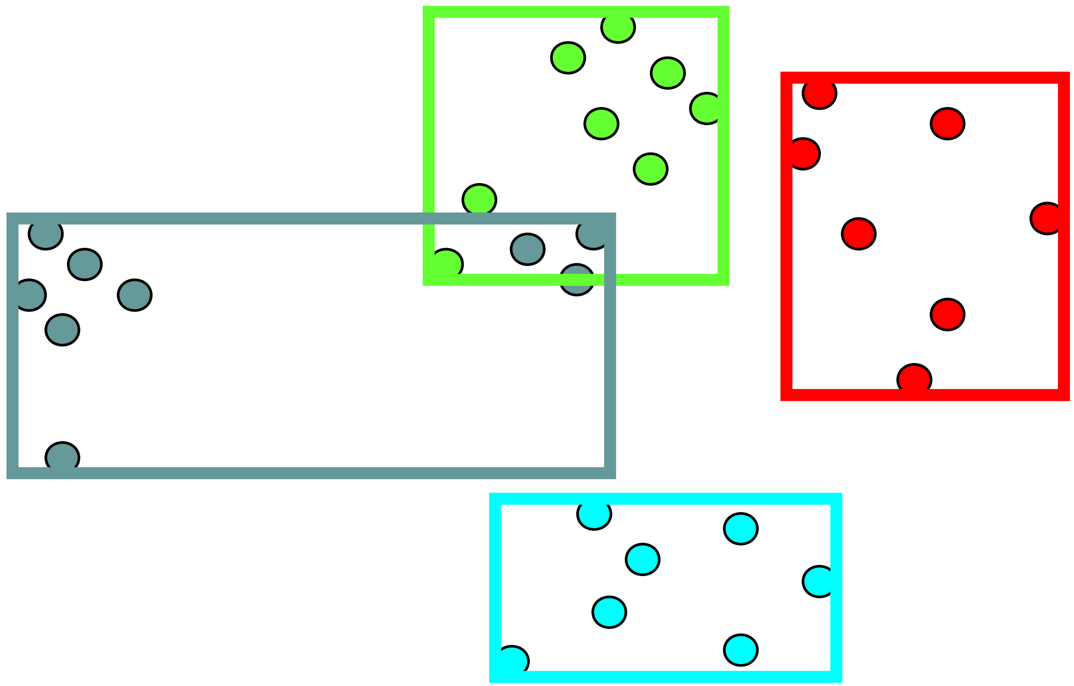
Sur l'utilisation de cellules

- Bien moins de cellules que de descripteurs
  - trouver les cellules les plus proches d'un descripteur requête est efficace
  - donc ce pré-filtrage de la plus grande partie des données apporte *a priori* un gros gain de performance

- Peu de paramètres à associer à chaque cellule
  - hyper-rectangle englobant : deux points
  - sphère : centre et rayon

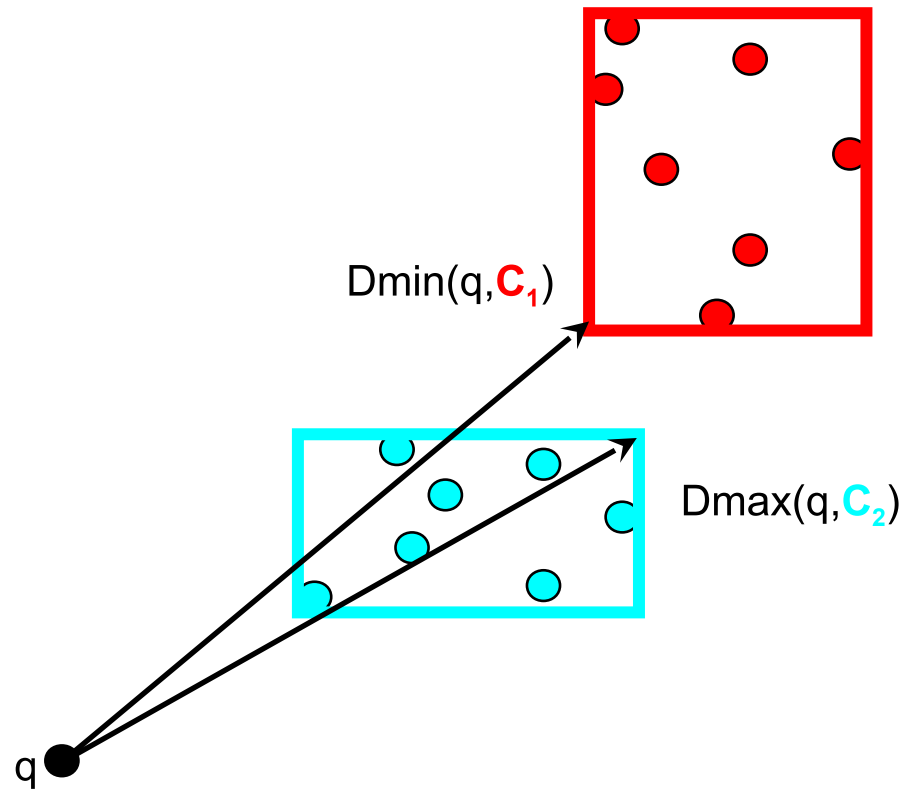
- Qu'est-ce que l'on exploite ?
  - Comparaison de distances

Example with bounding cells



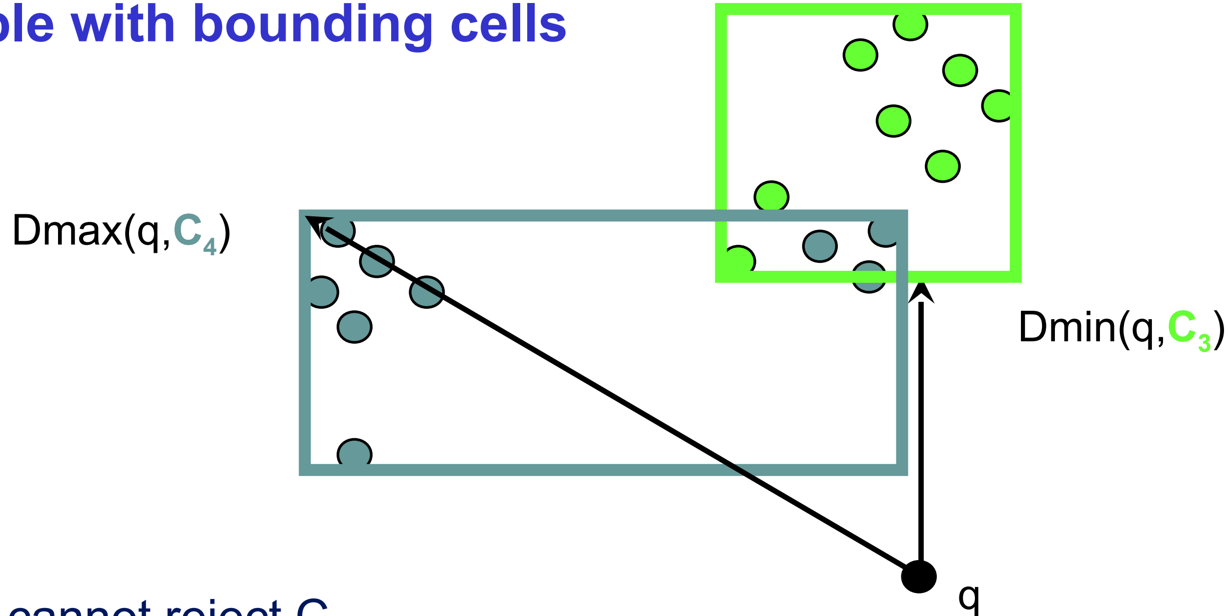
- Searching the 4 nearest neighbors of a point
  - We know the rectangles
  - Not the points inside the rectangles yet

Example with bounding cells



- Cell C_1 can be rejected without accessing its content

Example with bounding cells

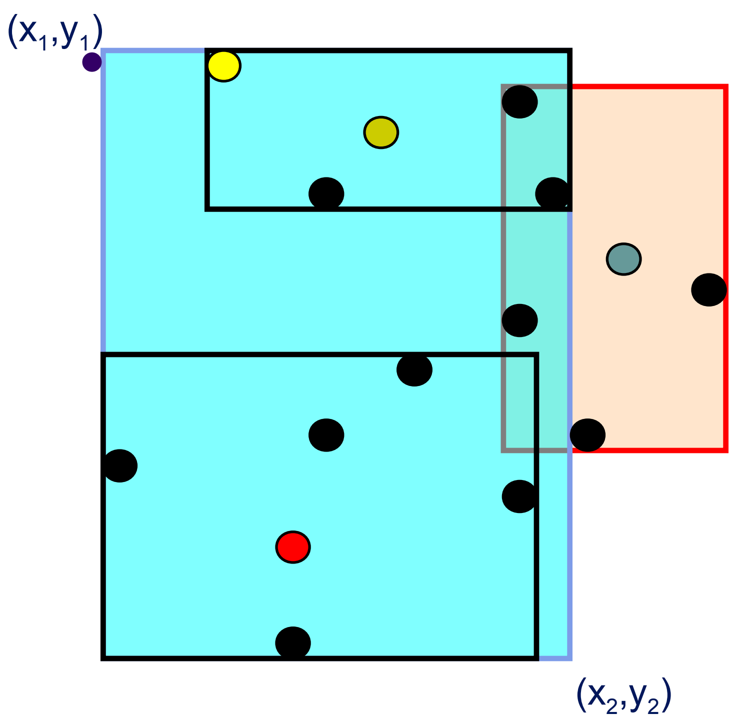


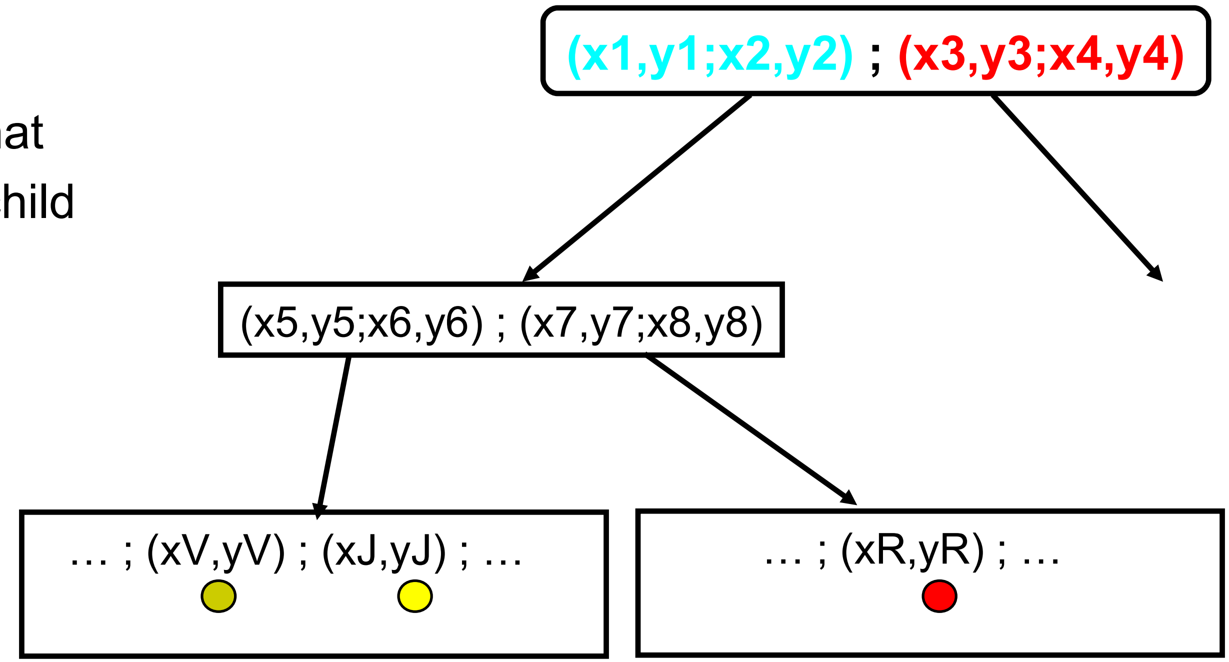
- We cannot reject C_3
  - Its content must be analyzed
  -

- Better to start with nearest cells
  - Obtain distance to points, temporary nearest neighbors
  - These bounds are tighter than the bounds computed from the cell boundaries
  - Access next cells, update bounds, until no candidate cell is left

R-Tree

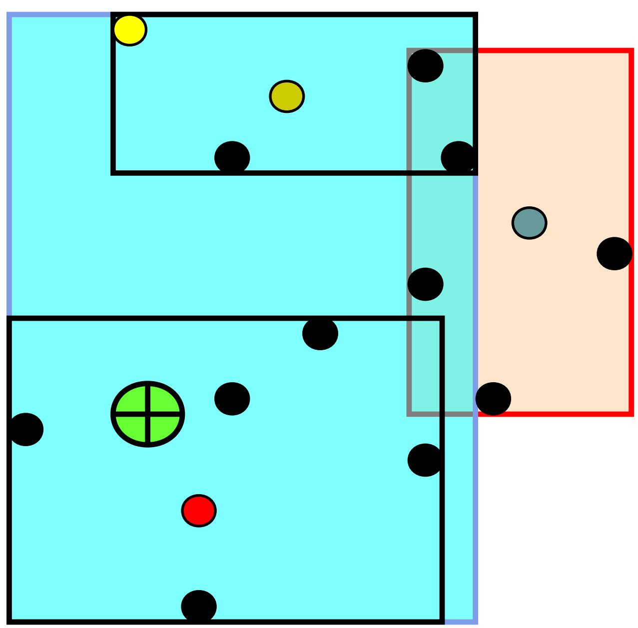
- Guttman, 1984, ACM SIGMOD
- “Extension” of B/B+-Tree
  - Balanced tree
  - Each node is a rectangle that
  - Parent rectangle includes child

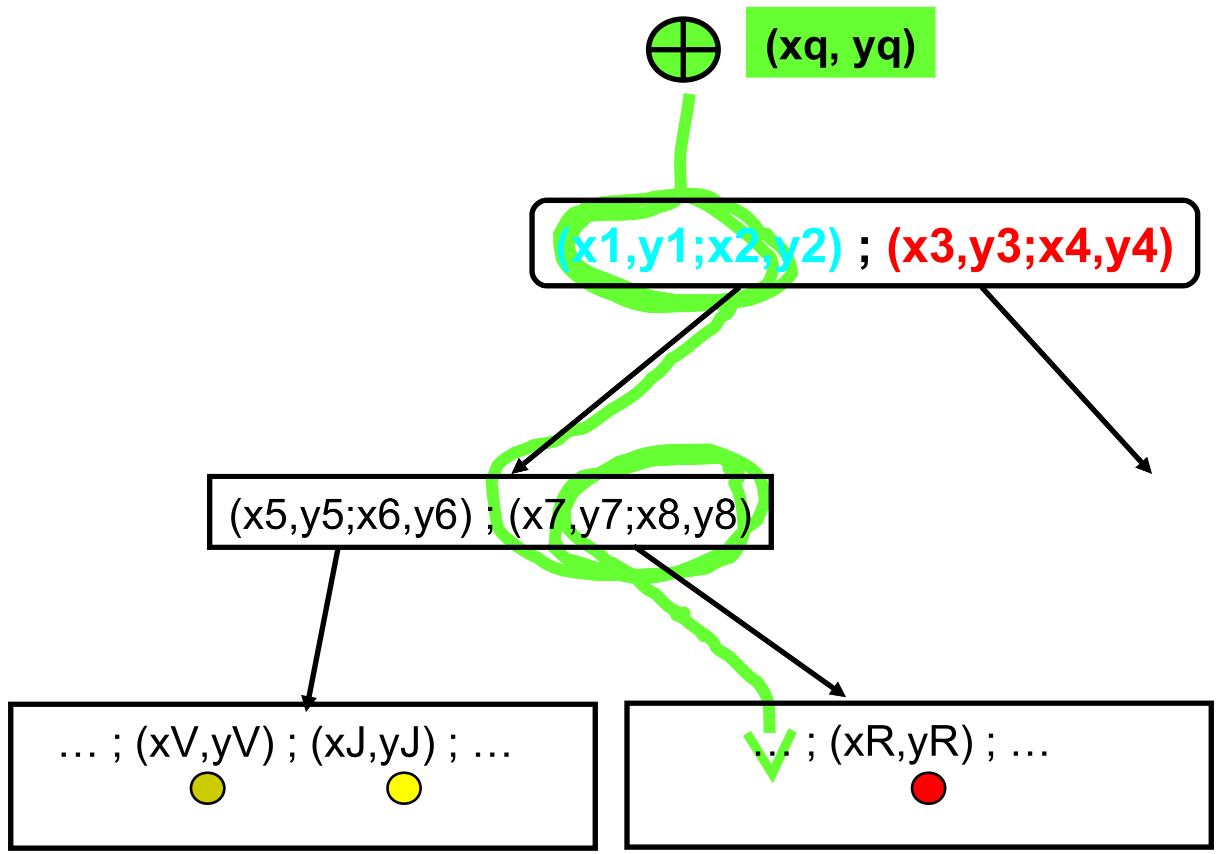




A rectangle includes the child rectangles

R-Tree (suite)





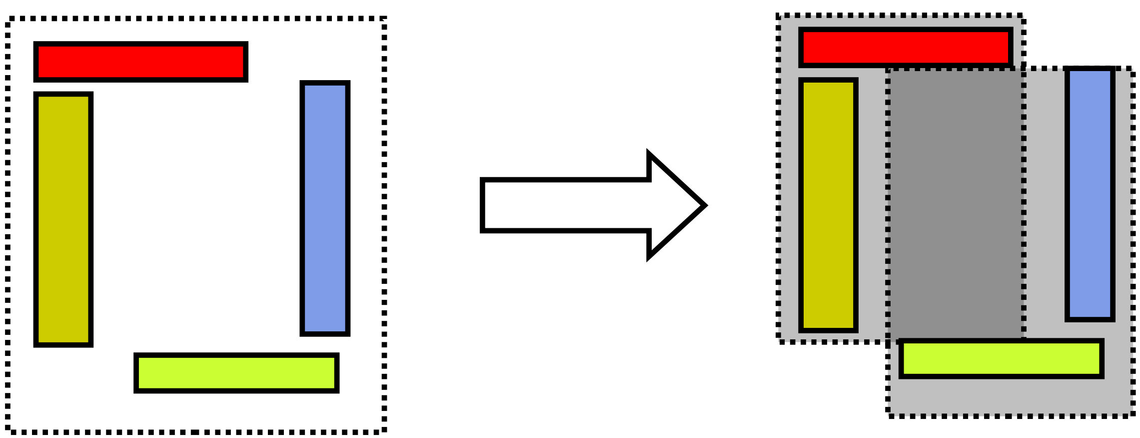
Search goes down the tree using the rectangle coordinates

Query can belong to several regions (≠B+tree)

R-Tree : insertion

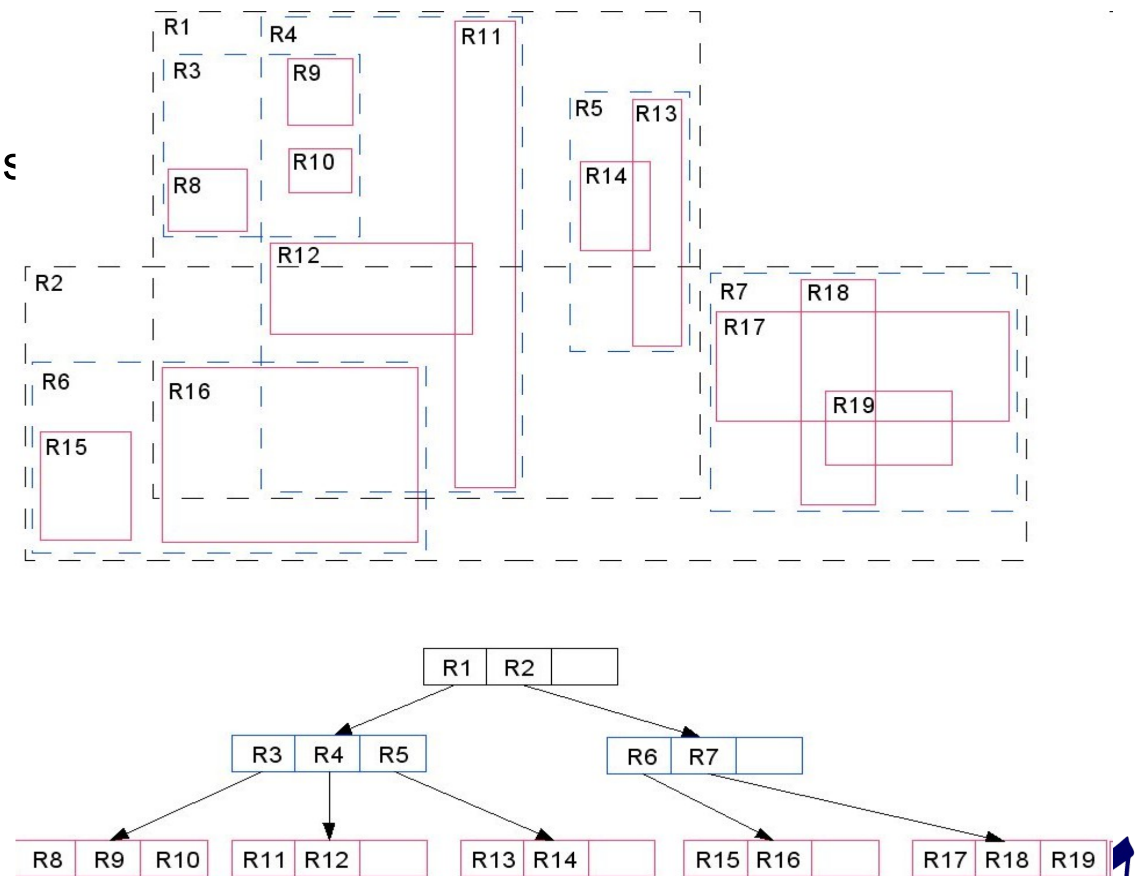
- Vectors can be inserted dynamically
- Traverse tree until leaf
- At each level
  - v ∈ 1 rectangle → no problem
  - v ∈ several rectangles : insertion into smallest
  - v ∈ no rectangle : enlarge rectangle that would grow least

- Branching factor and leaf size is constant
  - Must be split when maximum size is reached
  - problem:



R-Tree : conclusion

- Tree traversal is fast theoretically (log)
- However, in high dimension, the overapping causes few rectangles to be filtered out (end up with exhaustive search)
- Used for geographical information s

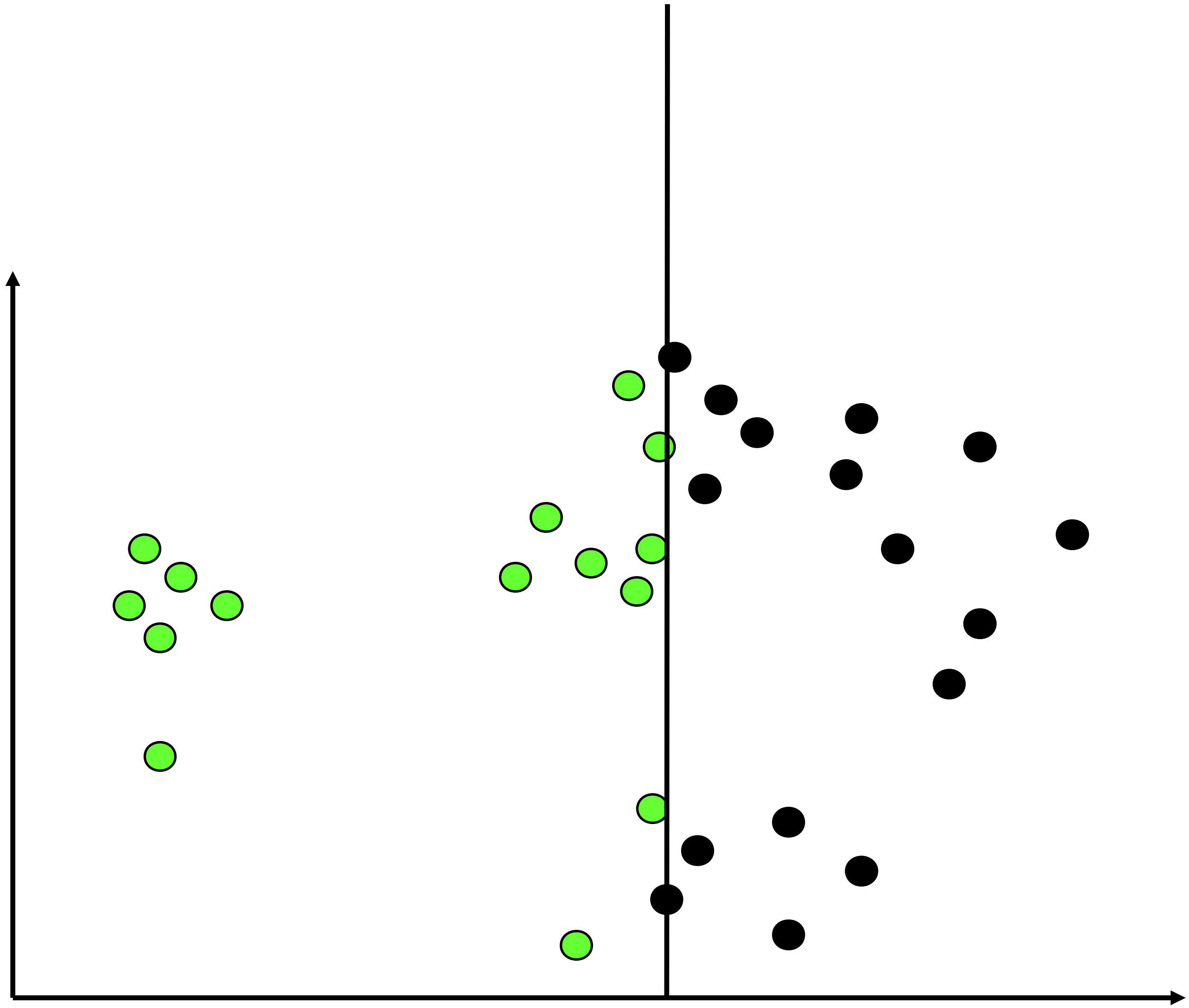


source: wikipedia

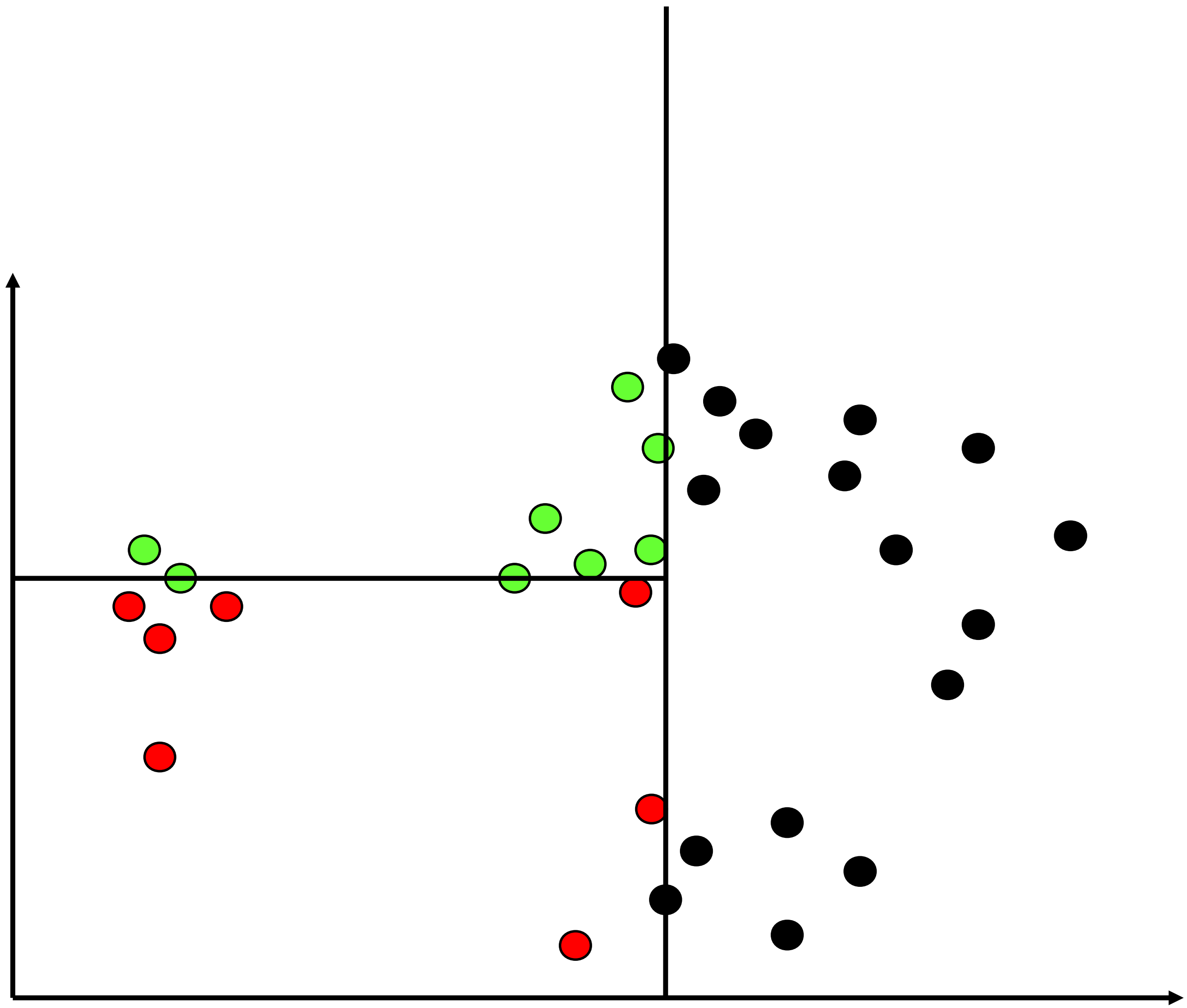
Kd-Tree

- Binary tree
- Popular technique to partition the space of vectors (non-overlapping cells)
- Recursive splitting with hyper-planes
  - Axis-aligned
  - Choice of axis: axis with highest variance
  - Splitting offset = median value of the points on the axis
- Variants
  - Choice of axis
  - Tree arity
  - Not axis aligned...

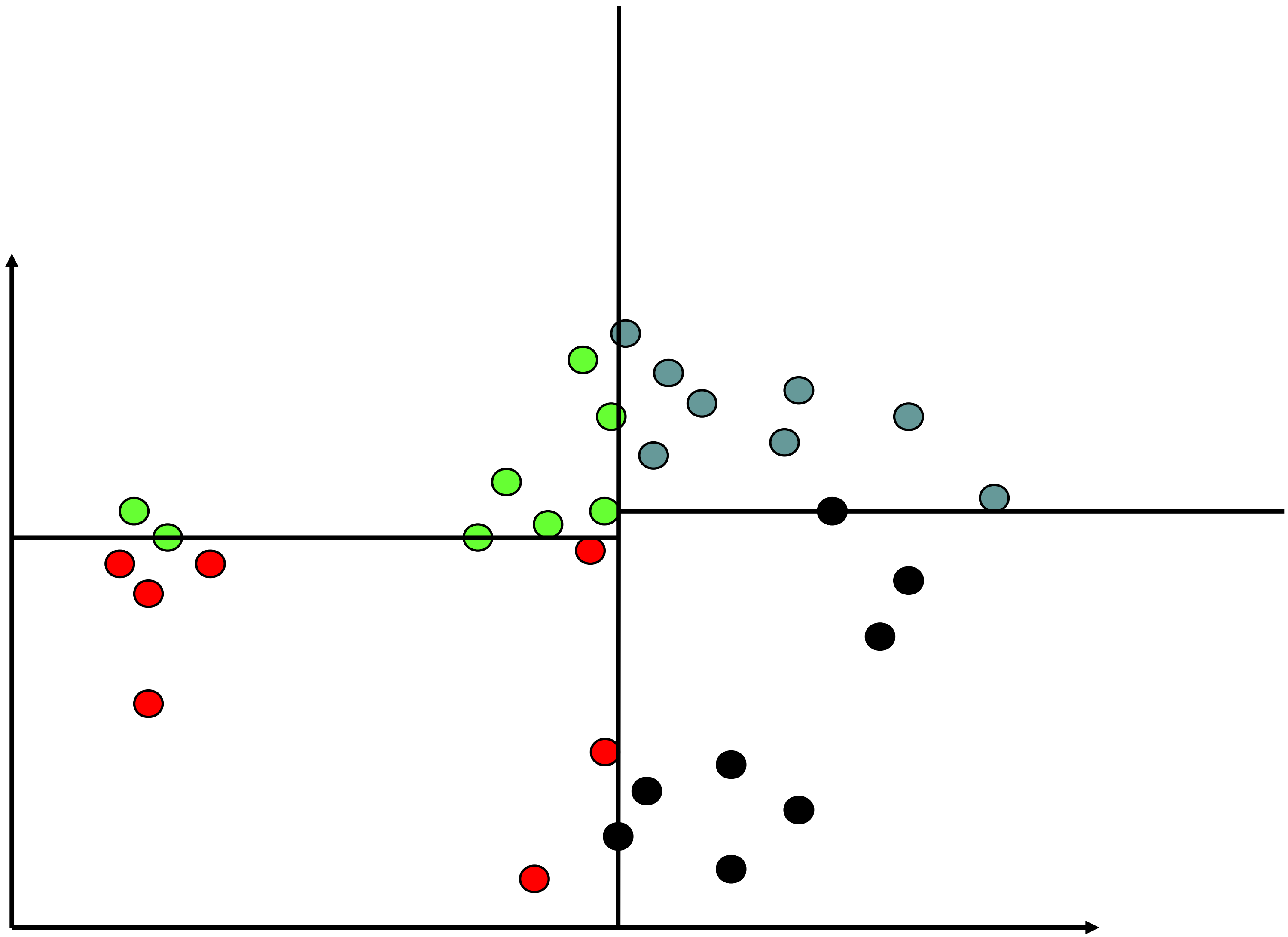
Kd-Tree : construction



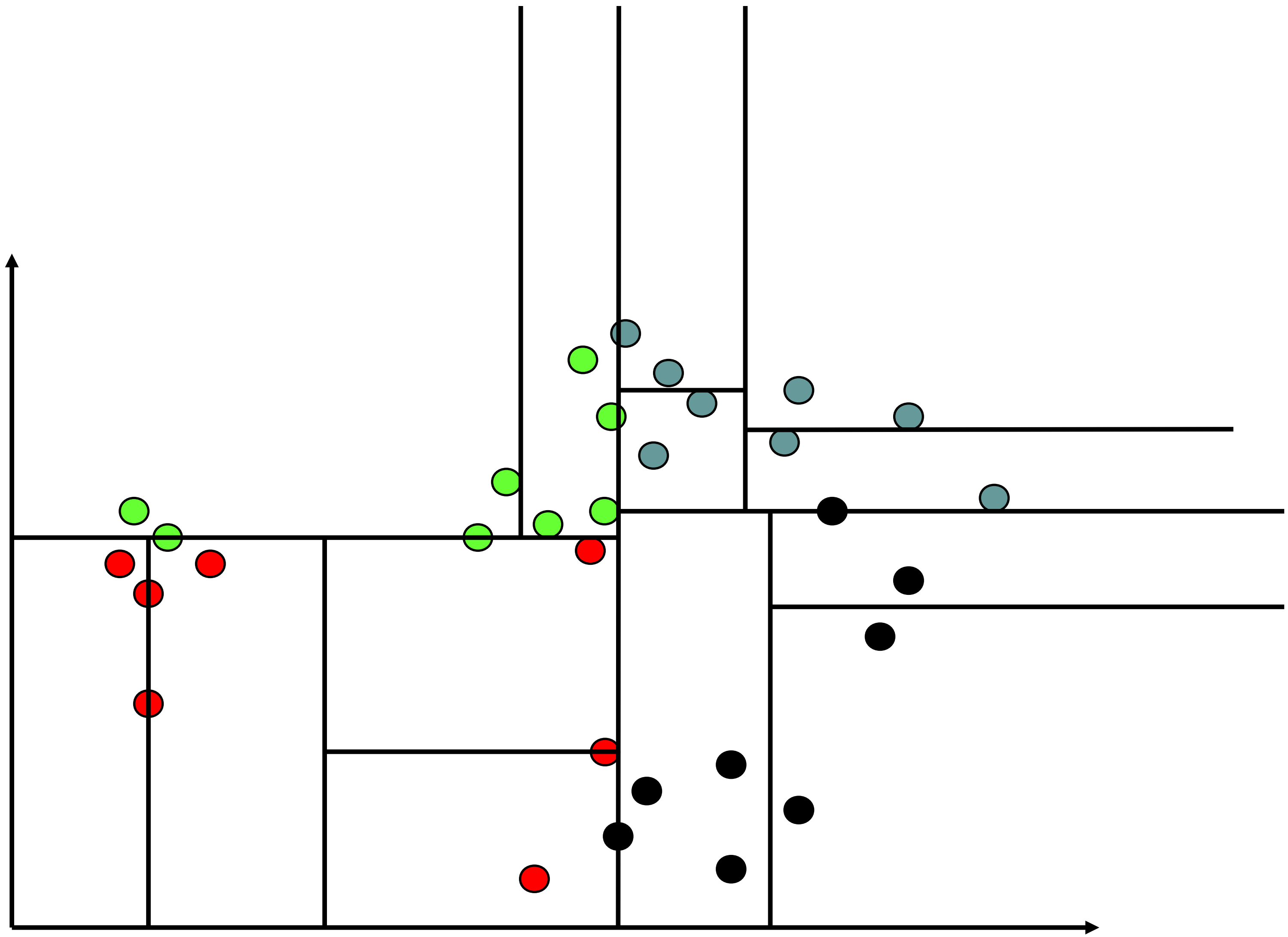
Kd-Tree : construction



Kd-Tree : construction



Kd-Tree : construction



Kd-Tree

- The leaves are a partition the space
  - All cells are disjoint
  - Tree is initially balanced (because of the median)
    - Not true when new elements are inserted
- Binary search tree
  - Traverse tree until leaf (log)
  - Nearest neighbor not necessarily in leaf
- Use NN in leaf → upper bound of true NN distance
- Intersect hyper-sphere of radius NN distance with other cells
  - Update...
  - Branch-and-bound method

- Worst case: the whole tree is explored
  - Often the case in high dimensional spaces

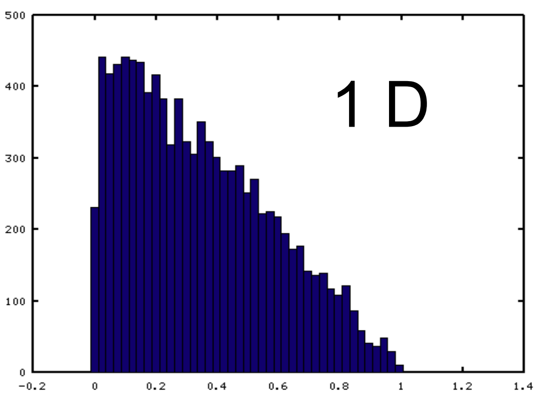
7. Nearest-neighbor search (high dimension)

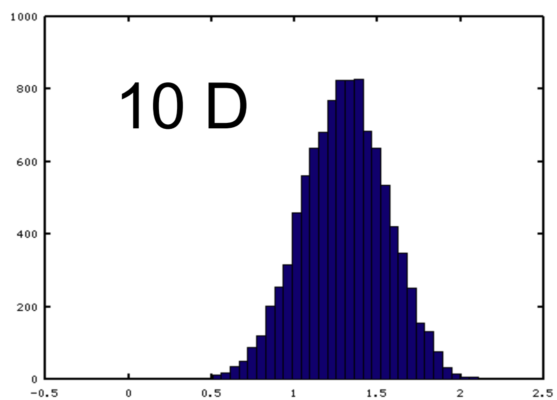
The dimension curse

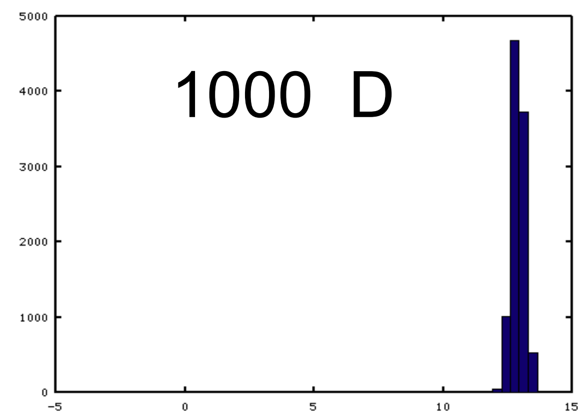
- Methods that work in low dimensions are not effective in high dimensions...
- Due to a few counter-intuitive properies:
  - Vanishing variance
  - Empty space
  - Proximity to boundaries

Vanishing variance

- La distance entre paires de points tend à être identique quand D augmente
  - le plus proche voisin et le point le plus éloigné sont à des distances qui sont presque identiques
  - exemple avec données uniformes:



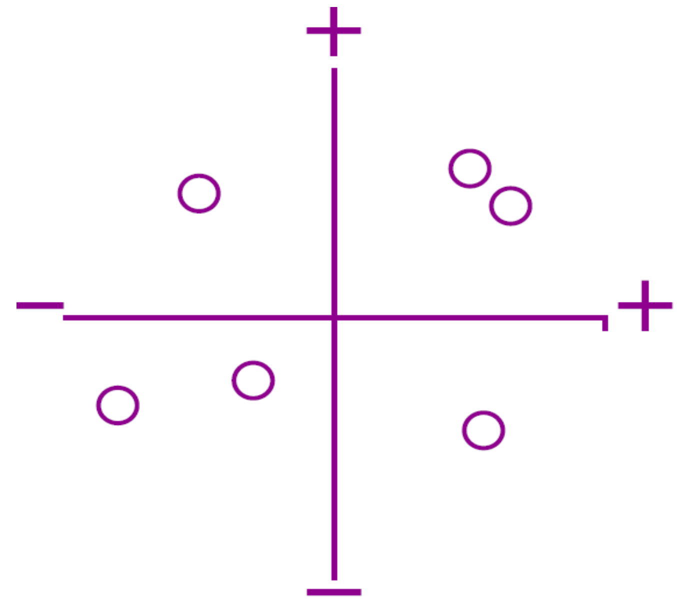




- Conséquence
  - le plus proche voisin devient très instable
  - Comparaisons de distances inefficaces (diamètre + distance)
  - Les jeux de données uniformes ne peuvent pas être indexés efficacement
    - c'est moins vrai pour des données naturelles (ouf !)

Phénomène de l'espace vide

- Cas d'école : partition de l'espace selon le signe des composantes

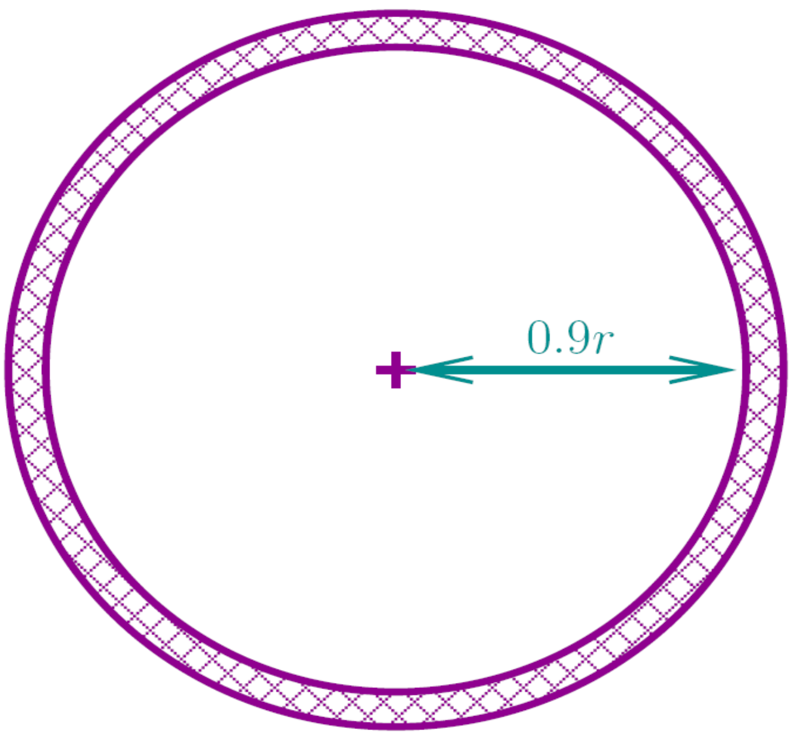


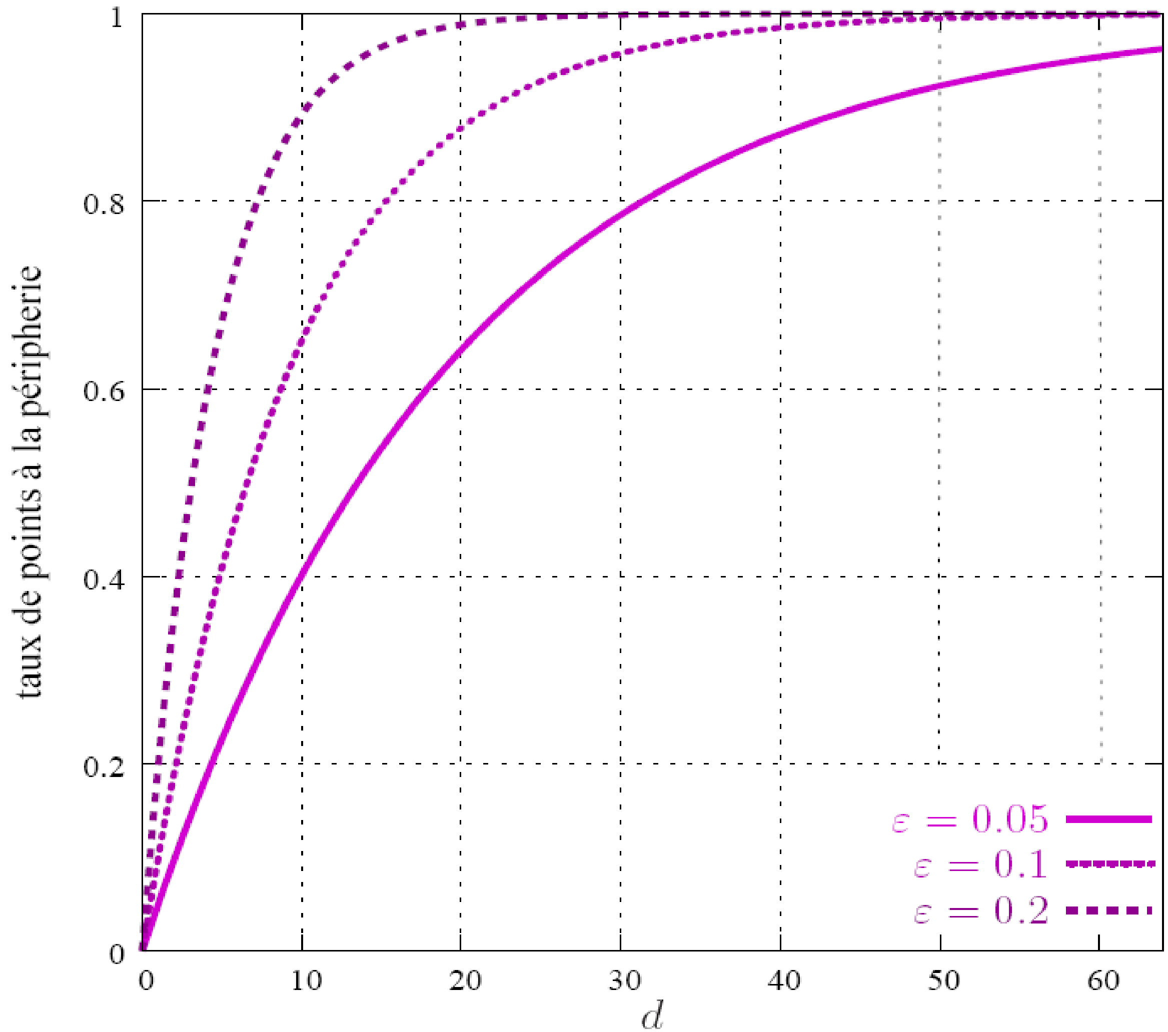
- d=100 → 1.26 10^{30} cellules >> n
- Très peu de cellules sont remplies
  - pour une partition pourtant grossière…
- Ce phénomène est appelé « phénomène de l'espace vide »
  - difficulté pour créer une partition
    - une bonne répartition des points
    - avec une bonne compacité

Tout les vecteurs sont près des frontières

- Pour un partitionnement de l'espace
  - les vecteurs sont très proches des surfaces de séparation avec une très grande probabilité
  - le plus proche voisin d'un point appartient à une cellule différente avec une grande probabilité

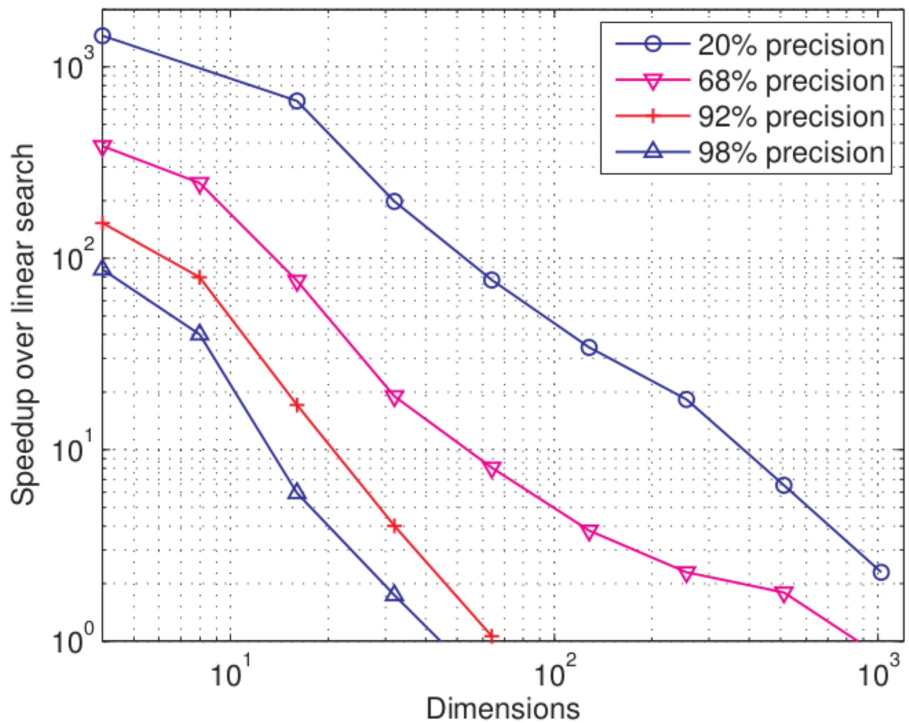
Tout les vecteurs sont près des frontières





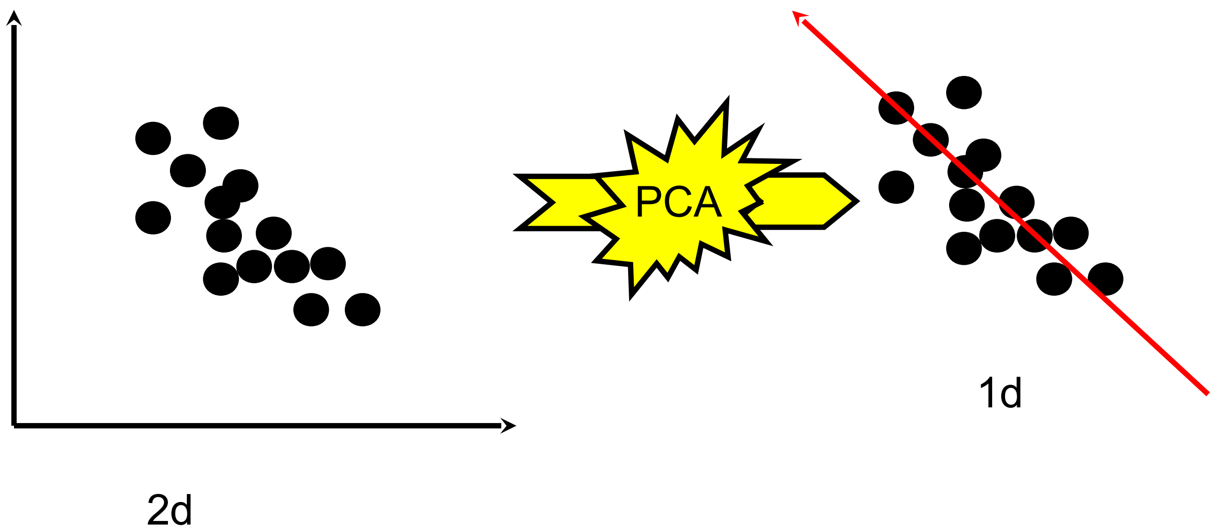
Approximate nearest-neighbor search

- In high dimension
  - there is no exact nearest neighbor search that is faster than linear scan
- What if we give up some precision?
  - The input descriptors are not infinitely accurate...
  - huge speedups can be obtained at a low cost in precision



PCA: dimensionality reduction

- Analyse des relations statistiques entre les différentes composantes
- Pour être capable de reproduire la plus grande partie de l'énergie d'un vecteur avec un nombre plus faible de dimension
  - élimination des axes peu énergétiques



PCA

- Il s'agit d'un changement de base
  - translation (centrage des données) + rotation

- 4 étapes (off-line)
  - centrage des vecteurs
  - calcul de la matrice de covariance
  - calcul des valeurs propres et vecteurs
  - choix des *d'* composantes les plus énergétiques (+ grandes valeurs propres)

- Pour un vecteur, les nouvelles coordonnées sont obtenues par centrage et multiplication du vecteur par la matrice *D' * D* des vecteurs propres conservés

Adaptation of low-dimensional indexing methods: FLANN

[Muja & Lowe, VISAPP 09]

- Tree-based methods
  - KD-tree (Need several of them, with different splitting policies)
  - Hierarchical kd-tree
- Explore tree(s)
  - Use a priority queue to visit a certain number of leaf nodes
  - Pre-select candidat neighbors
  - Filter short-list by computing true L2 distances
    - Requires to keep the whole dataset in RAM (cost O(D*N))
- Automatic selection of parameters for the methods
  - Very easy-to-use software package!

Indexing algorithm: searching with quantization

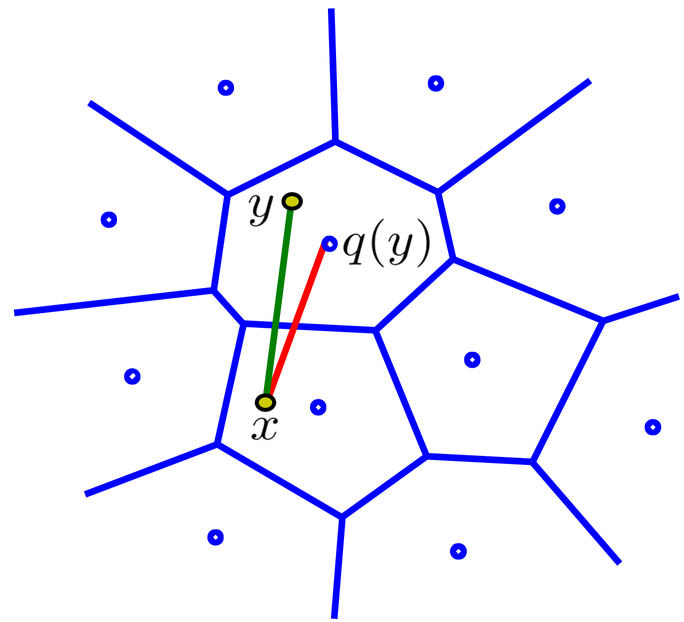
[Jégou & al. PAMI 11]

- Search/Indexing = distance approximation problem
- The distance between a query vector *x* and a database vector y is estimated by

$$d\left(x,y\right)\approx d\left(x,q(y)\right)$$

where q(.) is a quantizer

→ vector-to-code distance



- The choice of the quantizer is critical
  - fine quantizer → need many centroids: typically 64-bit codes → $k=2^{64}$
  - regular (and hierarchical) k-means can not be used

Product quantization for nearest neighbor search

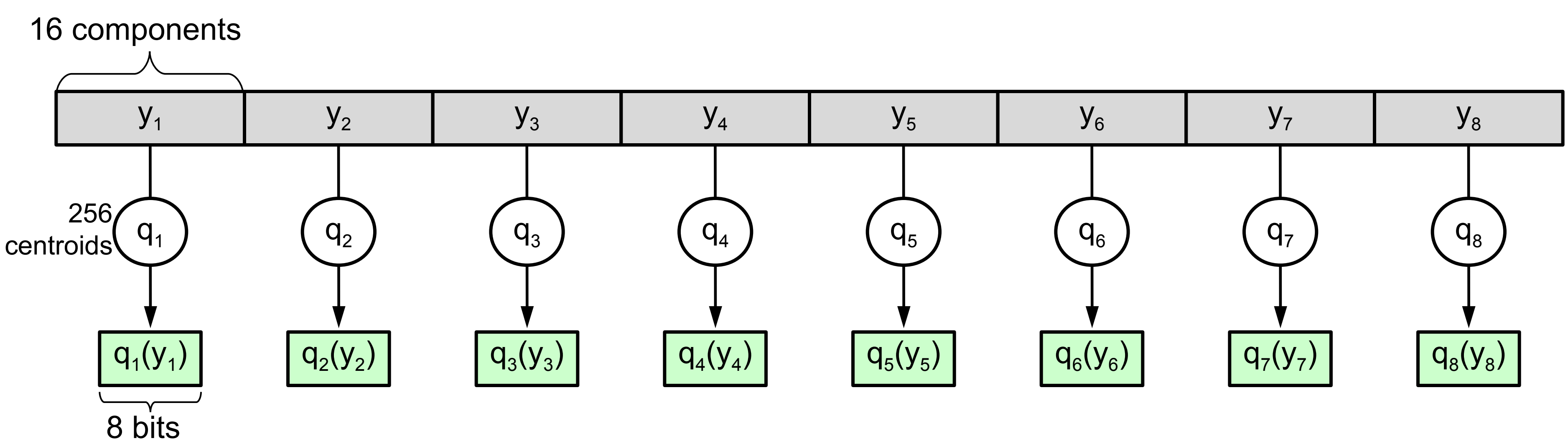
- Vector split into *m* subvectors: $y \rightarrow [y_1 | \ldots | y_m]$

- Subvectors are quantized separately

$$q(y) = [q_1(y_1) | \ldots | q_m(y_m)]$$

where each q_i is learned by *k*-means with a limited number of centroids

- Example: y = 128-dim vector split in 8 subvectors of dimension 16



□ 64-bit quantization index

Product quantization for nearest neighbor search

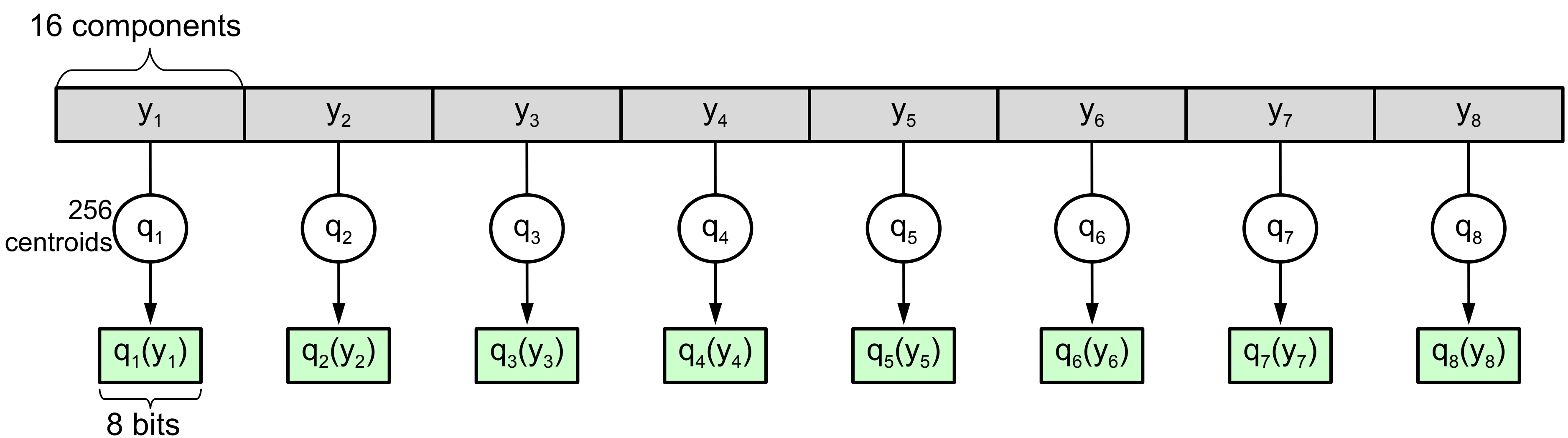
- Vector split into *m* subvectors: $y \longrightarrow [y_1 | \ldots | y_m]$

- Subvectors are quantized separately

$$q(y) = [q_1(y_1) | \ldots | q_m(y_m)]$$

where each q_i is learned by *k*-means with a limited number of centroids

- Example: y = 128-dim vector split in 8 subvectors of dimension 16



⇨ 64-bit quantization index

Product quantizer: asymmetric distance computation (ADC)

- Compute the distance approximation in the compressed domain

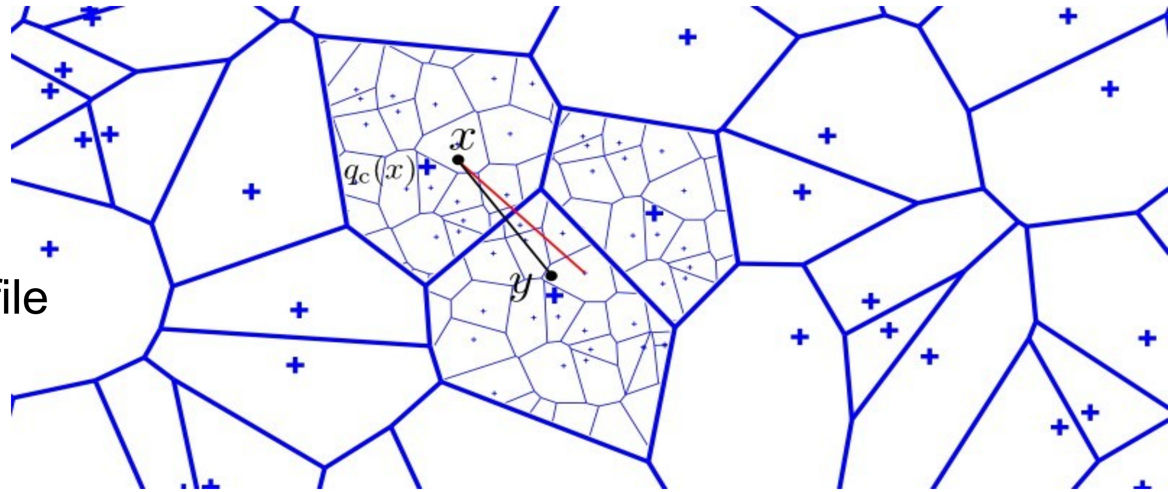
$$d(x,y)^2 \approx \sum_{i=1}^{m} d(x_i, q_i(y_i))^2$$

- To compute distance between query x and many codes
  - compute $d(x_i, c_{i,j})^2$ for each subvector x_i and all possible centroids

  $\rightarrow$ stored in look-up tables
  - for each database code: sum up the elementary squared distances

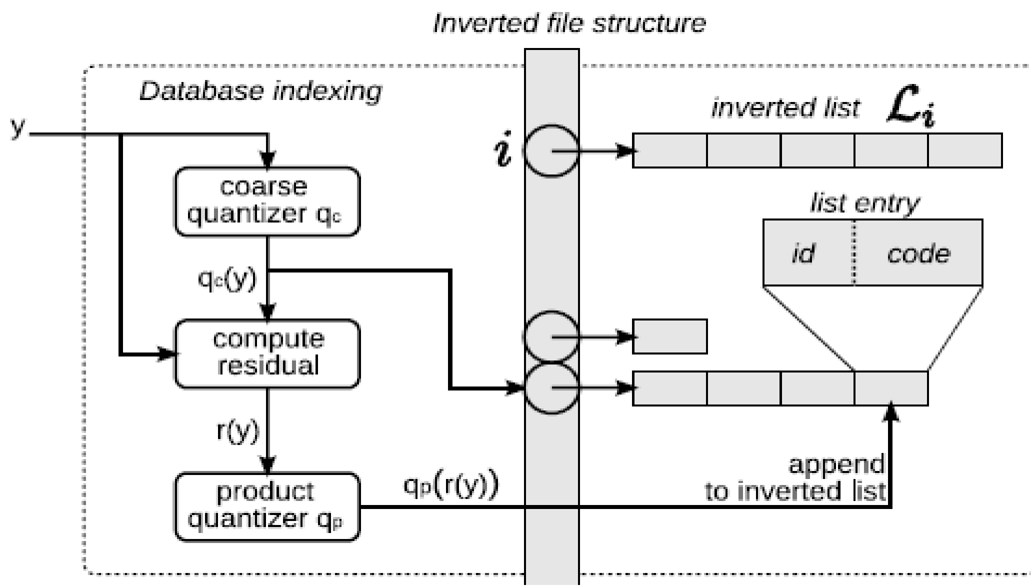
- Each 8x8=64-bits code requires only **m = 8 additions per distance**!
- Verification not mandatory
  - Fine enough distance approximation
  - No need to keep database in RAM

IVFADC: non-exhaustive ADC



- IVFADC
  - Additional quantization level
  - Combination with an inverted file
  - visits 1/128th of the dataset

- Timings for 10 M images
  - Exhaustive search with ADC: 0.286 s
  - Non-exhaustive search with IVFADC: 0.014 s



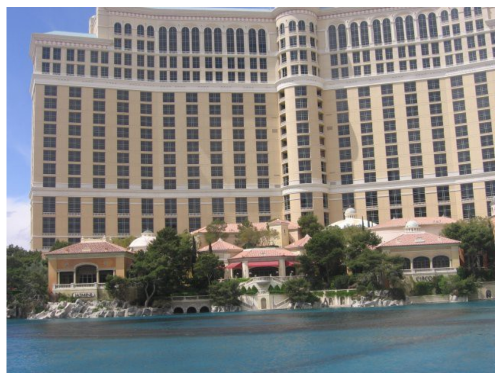
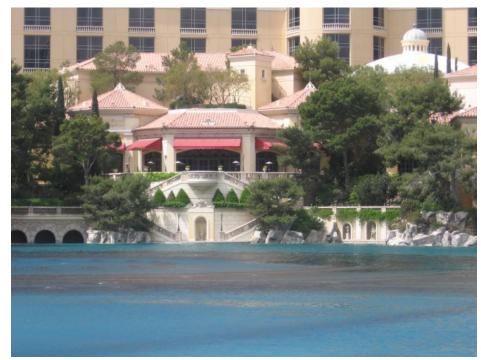
Conclusion

- Product quantization performance
  - Can index 1B images at
  - 20 bytes per image
- Extensions
  - Include temporal component for video [Douze & al. ECCV 2010]
  - More quantization levels [Jégou & al. ICASSP 11] [Babenko & Lempistsky CVPR 11]

8. Results

How to evaluate indexing methods

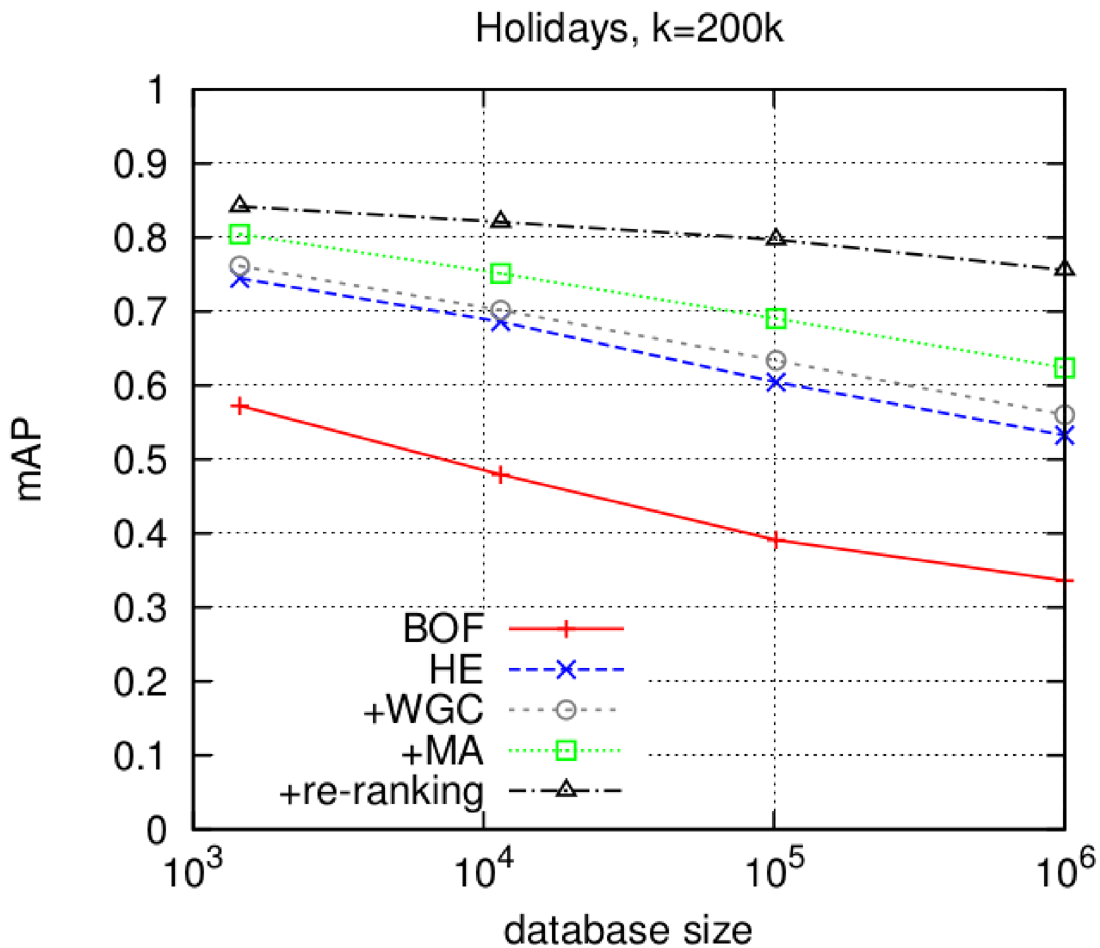
- Groups of matching images
  - One chosen as query
  - Others put in database
  - Add in “distractor” images, unrelated to the groups
- Search the query images
  - Compute score from list of results (precision-recall -> average precision)



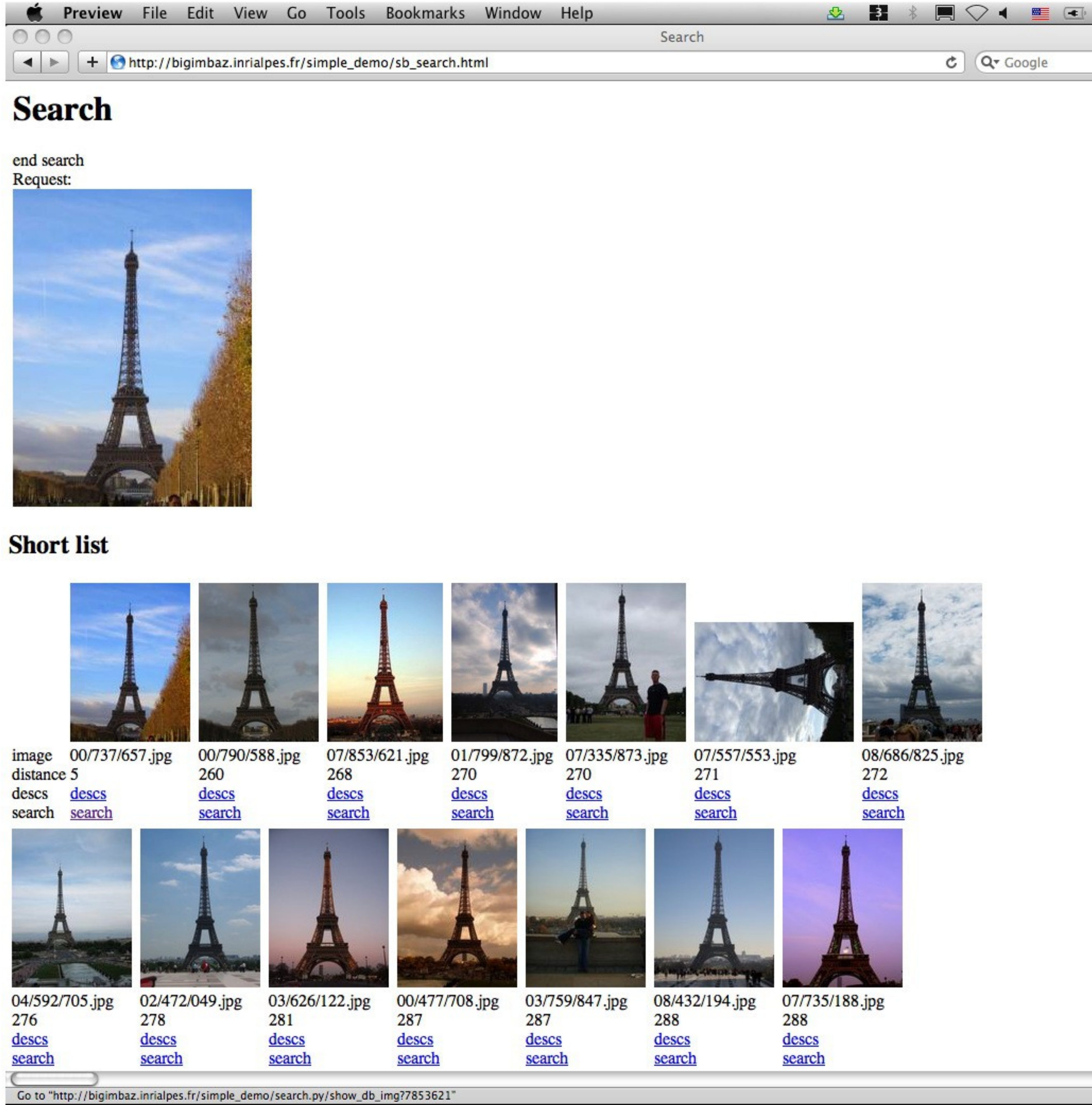

Inverted files

- Up to 1M - 10M images
- Distributed: 90B images [Stewenius & al. ECCV 12]
  - Inverted lists are stored on many different machines
  - Degraded (150 local descriptors / image)

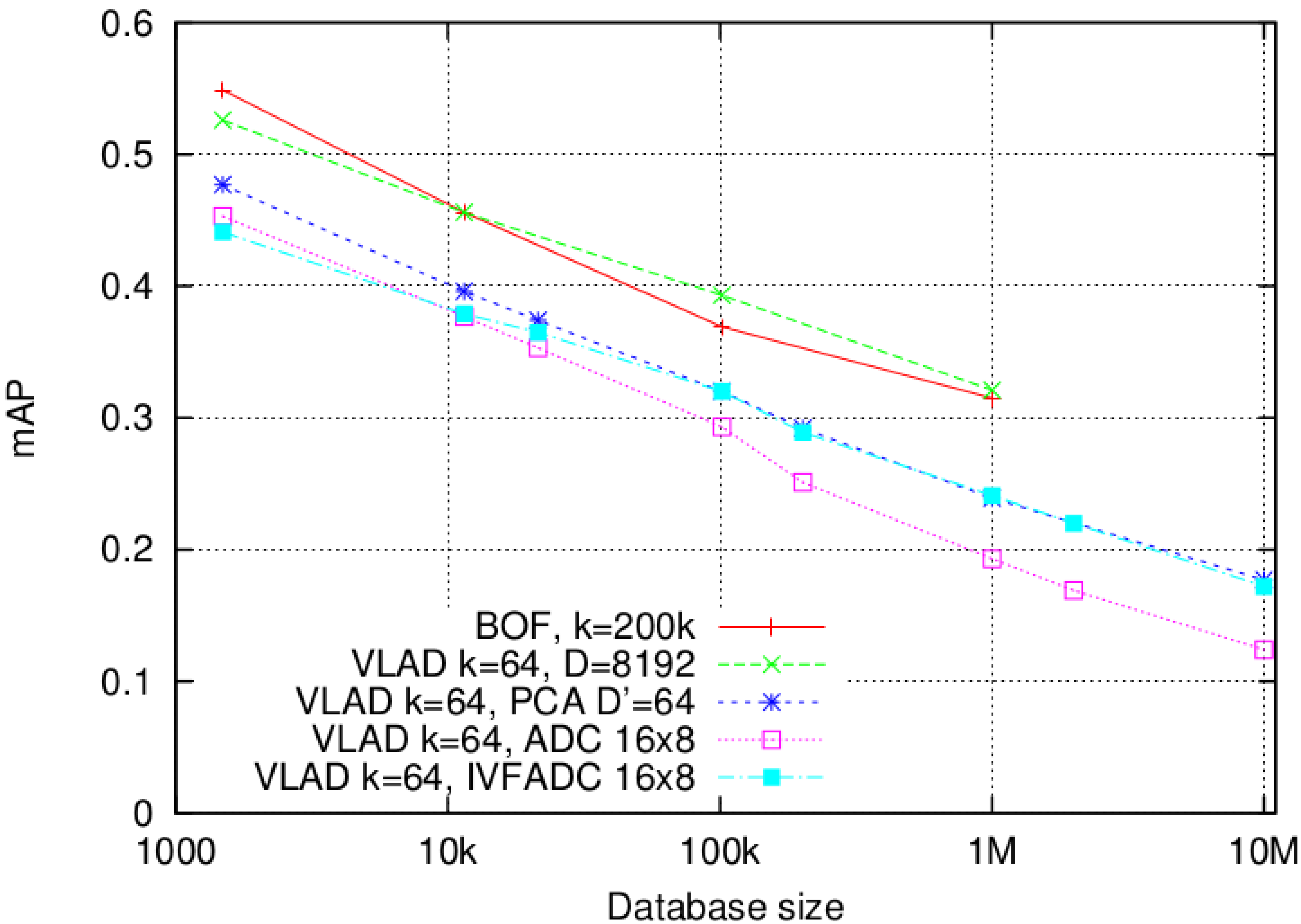


Aggregated descriptors

- Indexing 100M images on a laptop
- Not as robust as inverted file



Example result : plot against database size



Conclusion

- Very active field
- Choose operating point
  - Database size vs. performance
- Software packages
  - For descriptor computation: OpenCV, VLFeat, etc.
  - Product quantization: inverted multi-index
  - Hamming Embedding: Yael

END

Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

Outline

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

VLAD performance and dimensionality reduction

- We compare VLAD descriptors with BoF: INRIA Holidays Dataset (mAP,%)
- Dimension is reduced to from D to D' dimensions with PCA

Aggregator	**k**	**D**	**D'=D (no reduction)**	**D'=128**	**D'=64**
BoF	1,000	1,000	41.4	44.4	43.4
BoF	20,000	20,000	44.6	45.2	44.5
BoF	200,000	200,000	54.9	43.2	41.6
VLAD	16	2,048	49.6	49.5	**49.4**
VLAD	64	8,192	52.6	**51.0**	47.7
VLAD	256	32,768	**57.5**	50.8	47.6

- Observations:
  - performance increases with k
  - VLAD better than BoF for a given descriptor size
  - if small D' needed: choose a smaller k

Outline

Image description with VLAD

Indexing with the product quantizer

Porting to mobile devices

Video indexing

Results on standard datasets

- Datasets
  - University of Kentucky benchmark — score: nb relevant images, max: 4
  - INRIA Holidays dataset — score: mAP (%)

Method	bytes	UKB	Holidays
BoF, k=20,000	10K	2.92	44.6
BoF, k=200,000	12K	3.06	54.9
miniBOF	20	2.07	25.5
miniBOF	160	2.72	40.3
VLAD k=16, ADC	**16**	**2.88**	**46.0**
VLAD k=64, ADC	**64**	**3.10**	**49.5**

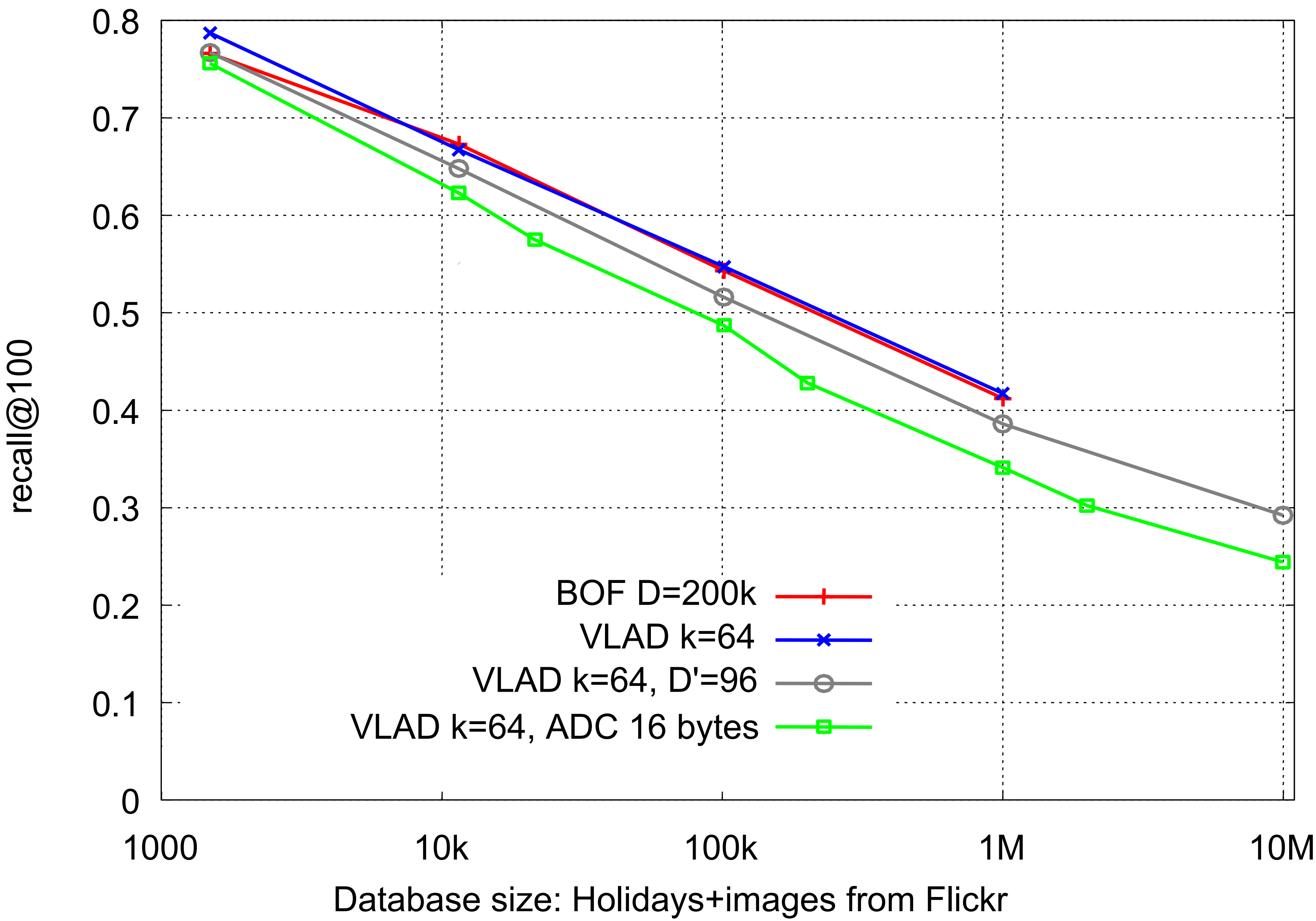
miniBOF: “Packing Bag-of-Features”, ICCV’09

IVFADC: non-exhaustive ADC

- IVFADC
  - Additional quantization level
  - Combination with an inverted file
  - visits 1/128th of the dataset

- Timings for 10 M images
  - Exhaustive search with ADC: 0.286 s
  - Non-exhaustive search with IVFADC: 0.014 s

Large scale experiments (10 million images)



Objective and proposed approach [Jégou & al., CVPR 10]

- Aim: optimizing the trade-off between
  - search speed +
  - memory usage +
  - search quality -

$$\xrightarrow[\textit{SIFT}]{\textit{extract}} \underbrace{\begin{bmatrix}5\\0\\\vdots\\35\end{bmatrix}\begin{bmatrix}34\\6\\\vdots\\12\end{bmatrix}\cdots\begin{bmatrix}14\\20\\\vdots\\47\end{bmatrix}}_{n \textit{ SIFTs (128 dim)}} \xrightarrow[\textit{descriptors}]{\textit{aggregate}} \overset{D}{\begin{bmatrix}-0.234\\0.452\\0.134\\\vdots\\0.001\end{bmatrix}} \xrightarrow[\textit{reduction}]{\textit{dimension}} \overset{D'}{\begin{bmatrix}0.155\\0.230\\\vdots\\0.435\end{bmatrix}} \xrightarrow[\textit{encoding /indexing}]{\textit{vector}} \text{code}$$

- Approach: joint optimization of three stages
  - local descriptor aggregation
  - dimension reduction
  - indexing algorithm

Aggregation of local descriptors

- Problem: represent an image by a single fixed-size vector:

  set of n local descriptors → 1 vector

- Indexing:
  - similarity = distance between aggregated description vectors (preferably L2)
  - search = (approximate) nearest-neighbor search in descriptor space

- Most popular idea: BoF representation [Sivic & Zisserman 03]
  - sparse vector
  - highly dimensional

→ dimensionality reduction harms precision a lot

- Alternative: Fisher Kernels [Perronnin et al 07]
  - non sparse vector
  - excellent results with a small vector dimensionality

  → VLAD is in the spirit of this representation

Outline

Image description with VLAD

Indexing with the product quantizer

Porting to mobile devices

Video indexing

On the mobile

- Indexing on the server:

$$\xrightarrow[\text{SIFT}]{\text{extract}} \underbrace{\begin{bmatrix}5\\0\\\vdots\\35\end{bmatrix} \begin{bmatrix}34\\6\\\vdots\\12\end{bmatrix} \cdots \begin{bmatrix}14\\20\\\vdots\\47\end{bmatrix}}_{n \text{ SIFTs (128 dim)}} \xrightarrow[\text{descriptors}]{\text{aggregate}} \underbrace{\begin{bmatrix}-0.234\\0.452\\0.134\\\vdots\\0.001\end{bmatrix}}_{D} \xrightarrow[\text{reduction}]{\text{dimension}} \underbrace{\begin{bmatrix}0.155\\0.230\\\vdots\\0.435\end{bmatrix}}_{D'} \xrightarrow[\text{server}]{\text{send to}}$$

stage	image	SIFTs	VLAD	VLAD+PCA
data size	300 kB	512 kB	32 kB	384 bytes
computing time (relative)	NA	1.5 s (50 ms for CS-LBP)	5 ms	0.5 ms

- query from mobile
  - relatively cheap to compute
  - small bandwidth

Indexing on the mobile

- The database is stored on the device
- In addition to the previous:
  - database: 20 bytes per image in RAM
  - quantize query (find closest centroids + build look-up tables)
  - scan database to find nearest neighbors
- Adapt algorithms to optimize speed

db size (images)	exhaustive (ADC) / non-exhaust. (IVFADC)	precompute distance tables
<1000	ADC	no
<1M	ADC	yes
>1M	IVFADC	yes

Outline

Image description with VLAD

Indexing with the product quantizer

Porting to mobile devices

Video indexing

Video indexing [Douze & al. ECCV 2010]

- video = image sequence
  - index VLAD descriptors for *all* images (CS-LBP instead of SIFT for speed)
  - temporal verification

- database side: images are grouped in segments
  - 1 VLAD descriptor represents each segment
  - frame represented as refinement w.r.t. this descriptor

- query = seach all frames of the query video

- Frame matches → alignment of query with database video
  - Hough transform on $\delta t = t_q - t_{db}$
  - Output: most likely δt → alignments
  - map back to frame matches to find aligned video segments

Video indexing results

- Comparison with Trecvid 2008 copy detection task
  - 200 h indexed video
  - 2000 queries
  - 10 “attacks” = video editing, clutter, frame dropping, camcording...
  - state of the art: competition results (score = NDCR, lower = better)

transformation	best	ours	rank (/23)
camcording	0.08	0.22	**2**
picture in picture	0.02	0.32	4
insertion of patterns	0.02	0.08	3
strong re-encoding	0.02	0.06	2
geometric attacks	0.07	0.14	2
5 random transformations	0.20	0.54	**2**

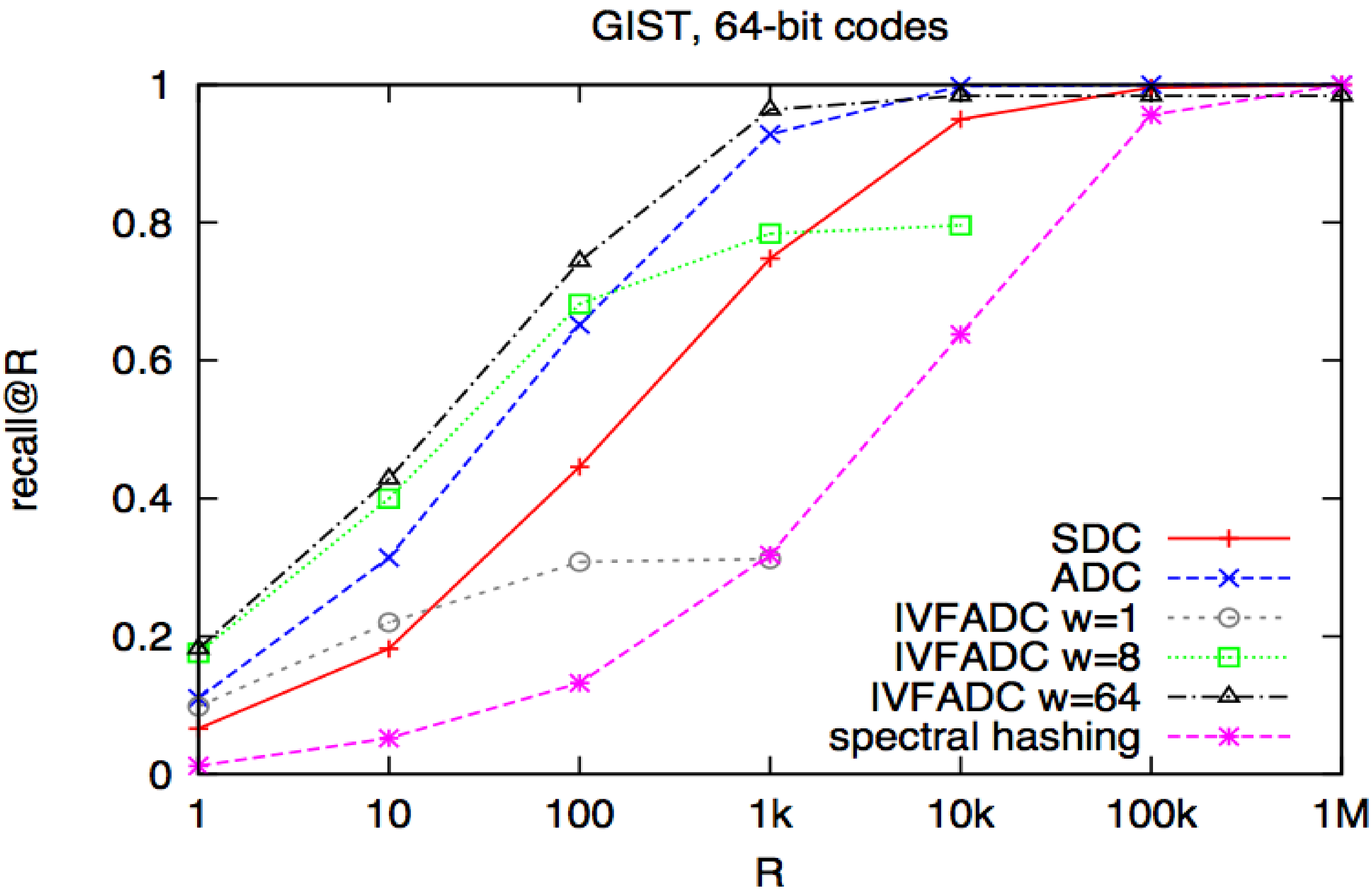
- Observations:
  - Always among 5 first results
  - 5 times faster and 100 times less memory than competing methods
  - Best localization results (due to dense temporal sampling)

Conclusion

- VLAD: compact & discriminative image descriptor
  - aggregation of SIFT, CS-LBP, SURF (ongoing),...
- Product Quantizer: generic indexing method with nearest-neighbor search function
  - works with local descriptors and GIST, audio features (ongoing)...
- Standard image and datasets
  - Holidays (different viewpoints)
  - Copydays (copyright attacks)
- Compatible with mobile applications:
  - compact descriptor, cheap to compute
- Code for VLAD and Product quantizer at http://www.irisa.fr/texmex/people/jegou/src.php
- Demo!

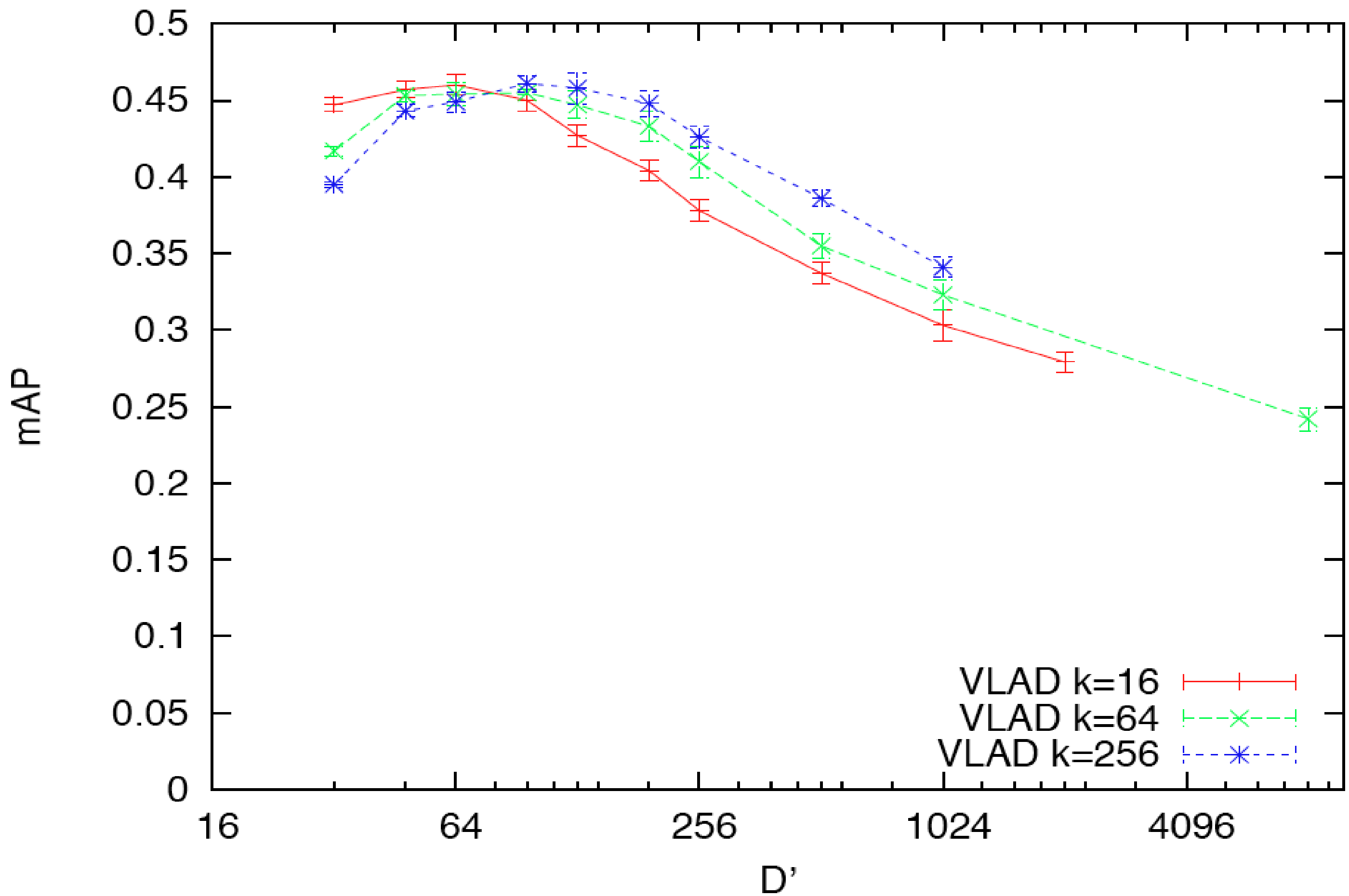
END

Searching with quantization: comparison with spectral Hashing

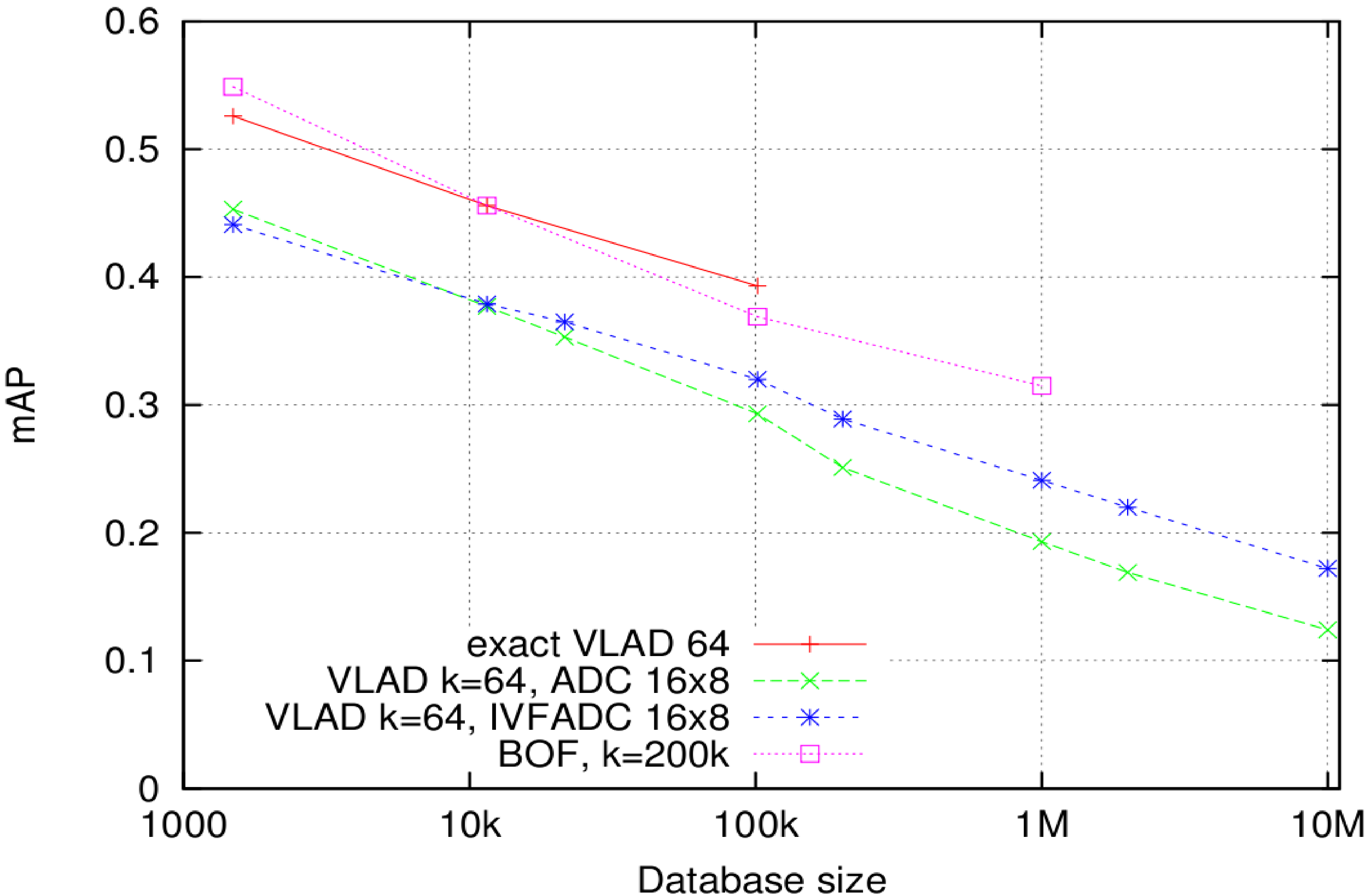


Impact of D’ on image retrieval

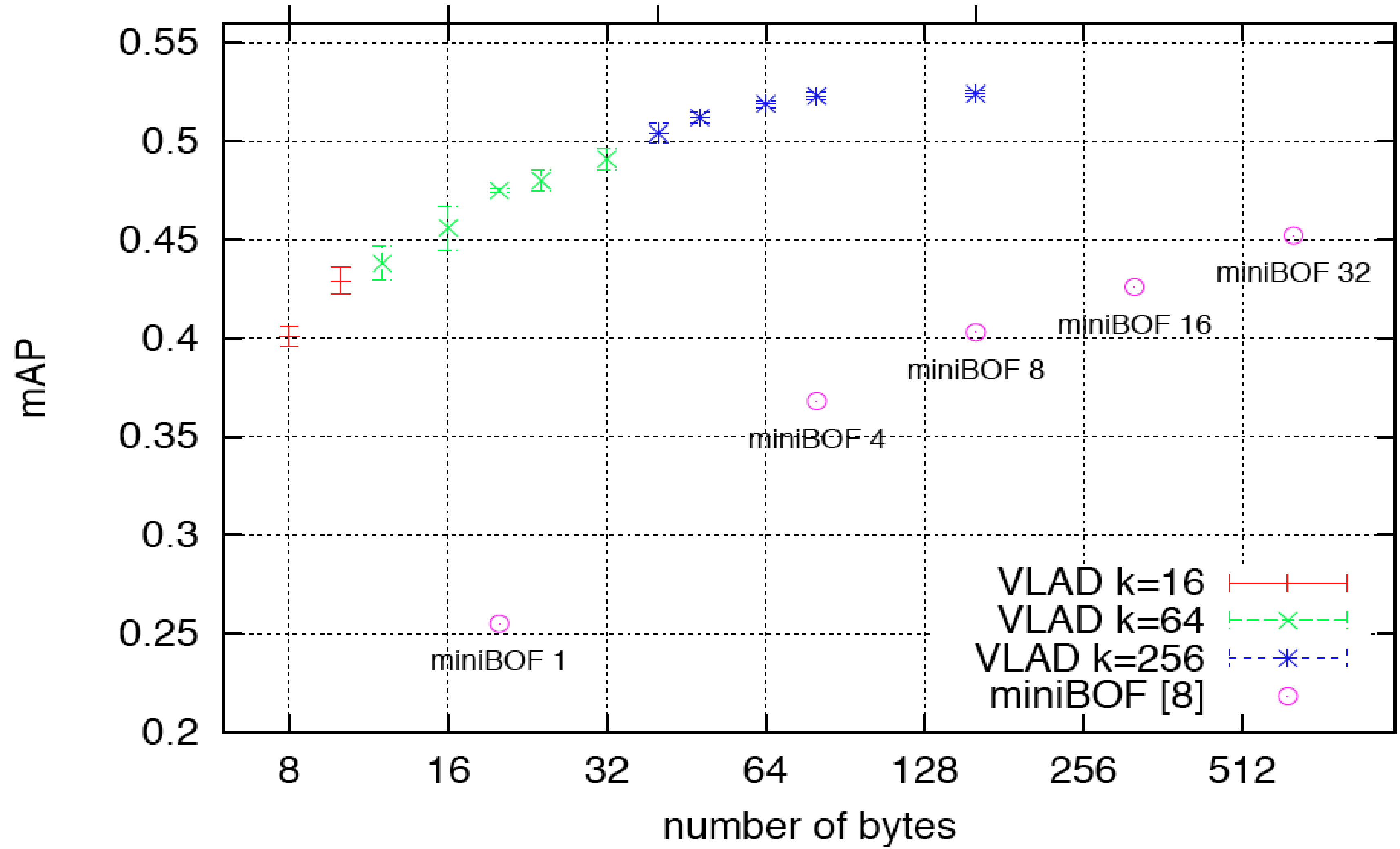
- The best choice of D’ found by minimizing the square error criterion is reasonably consistent with the optimum obtained when measuring the image search quality



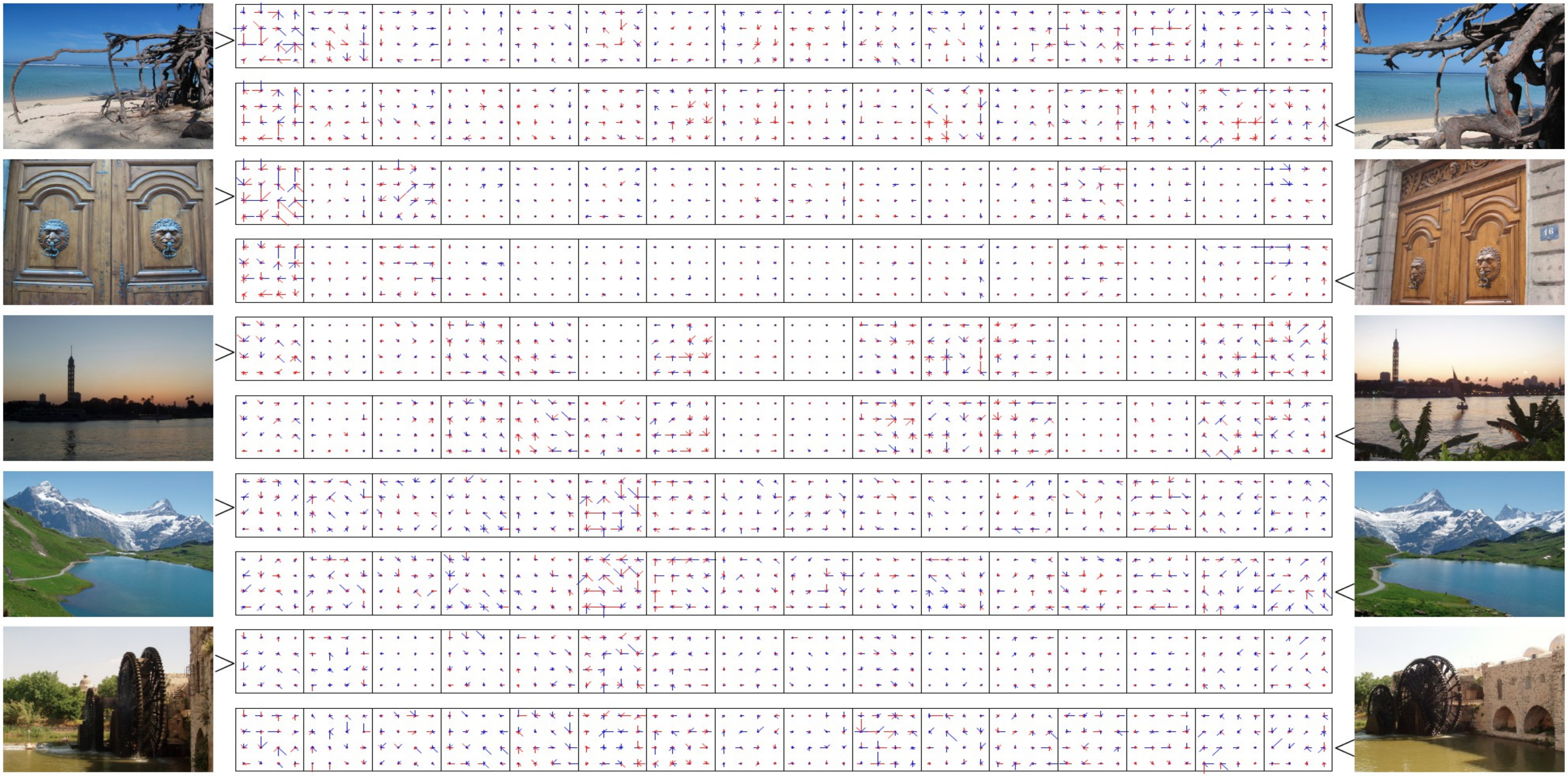
Results on 10 million images



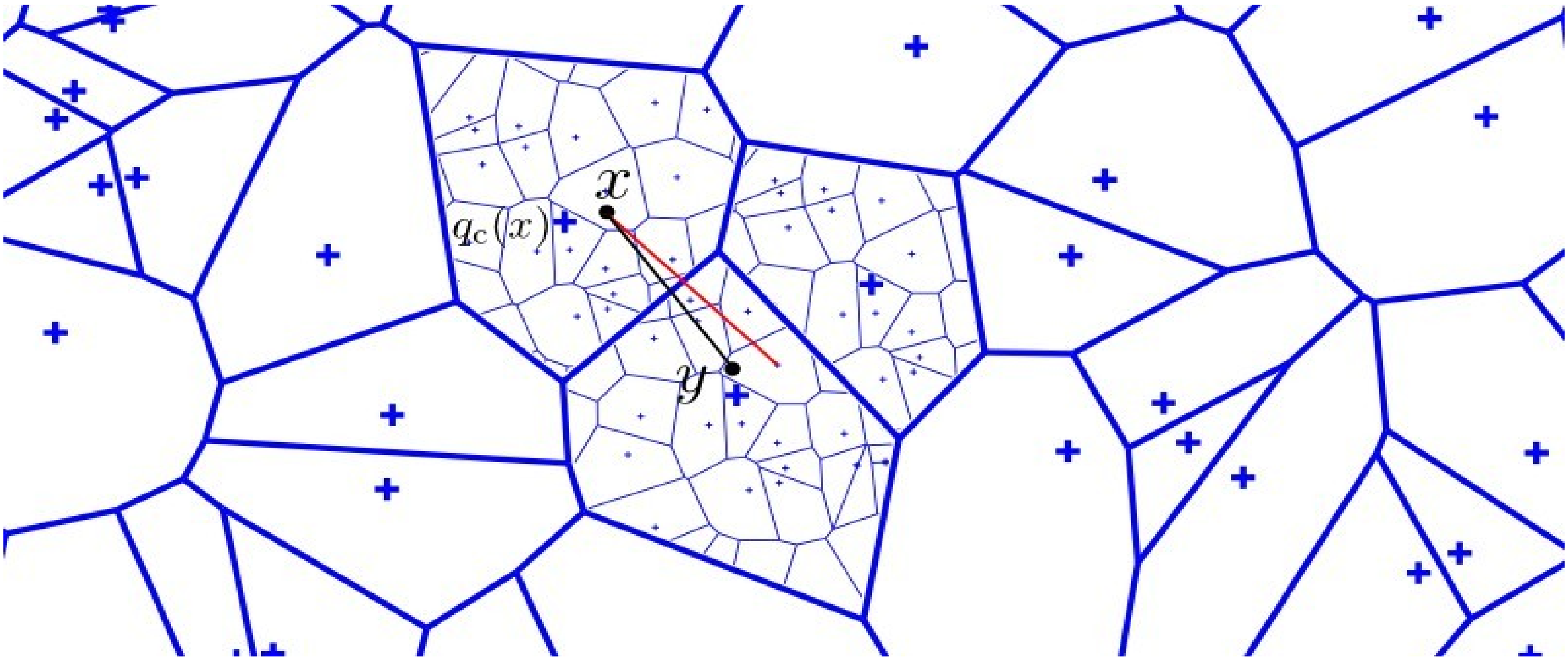
Results: comparison with « Packing BOF » (Holidays dataset)



VLAD: other examples



Combination with an inverted file



Related work on large scale image search

- Global descriptors:
  - GIST descriptors with Spectral Hashing or similar techniques [Torralba & al 08]

→ very limited invariance to scale/rotation/crop: use local descriptors

- Bag-of-features [Sivic & Zisserman 03]
  - Large (hierarchical) vocabularies [Nister Stewenius 06]
  - Improved descriptor representation [Jégou et al 08, Philbin et al 08]
  - Geometry used in index [Jégou et al 08, Perdoc'h et al 09]
  - Query expansion [Chum et al 07]

→ memory tractable for a few million images only

- Efficiency improved by
  - Min-hash and Geometrical min-hash [Chum et al. 07-09]
  - compressing the BoF representation [Jégou et al. 09]

→ But still hundreds of bytes are required to obtain a "reasonable quality"

1. Problem statement

Include geometry in the inverted file

- Problem statement
- Extracting local image descriptors
- Indexing by image matching
- Bag-of-words and the inverted file
- Local descriptor aggregation
- Nearest neighbor search (low dimension)
- Nearest neighbor search (high dimension)
- Results

Including geometry in the inverted file: orientation consistency