Large / larger-scale image search
Introduction

Hervé Jégou, INRIA

Special Acknowledgments to
Florent Perronnin, Matthijs Douze, Cordelia Schmid, Patrick Pérez, Ondrej Chum

General outline

PART I: Introduction

- **Applications and datasets**
- Image description and matching

PART II: Large-scale image search

- The bag-of-word representation and some extensions

PART III: Larger-scale image search

- Novel aggregation mechanisms
- Efficient indexing

Conclusions

Image search

Scenario: Query-by-example:

On a large (largest) scale:

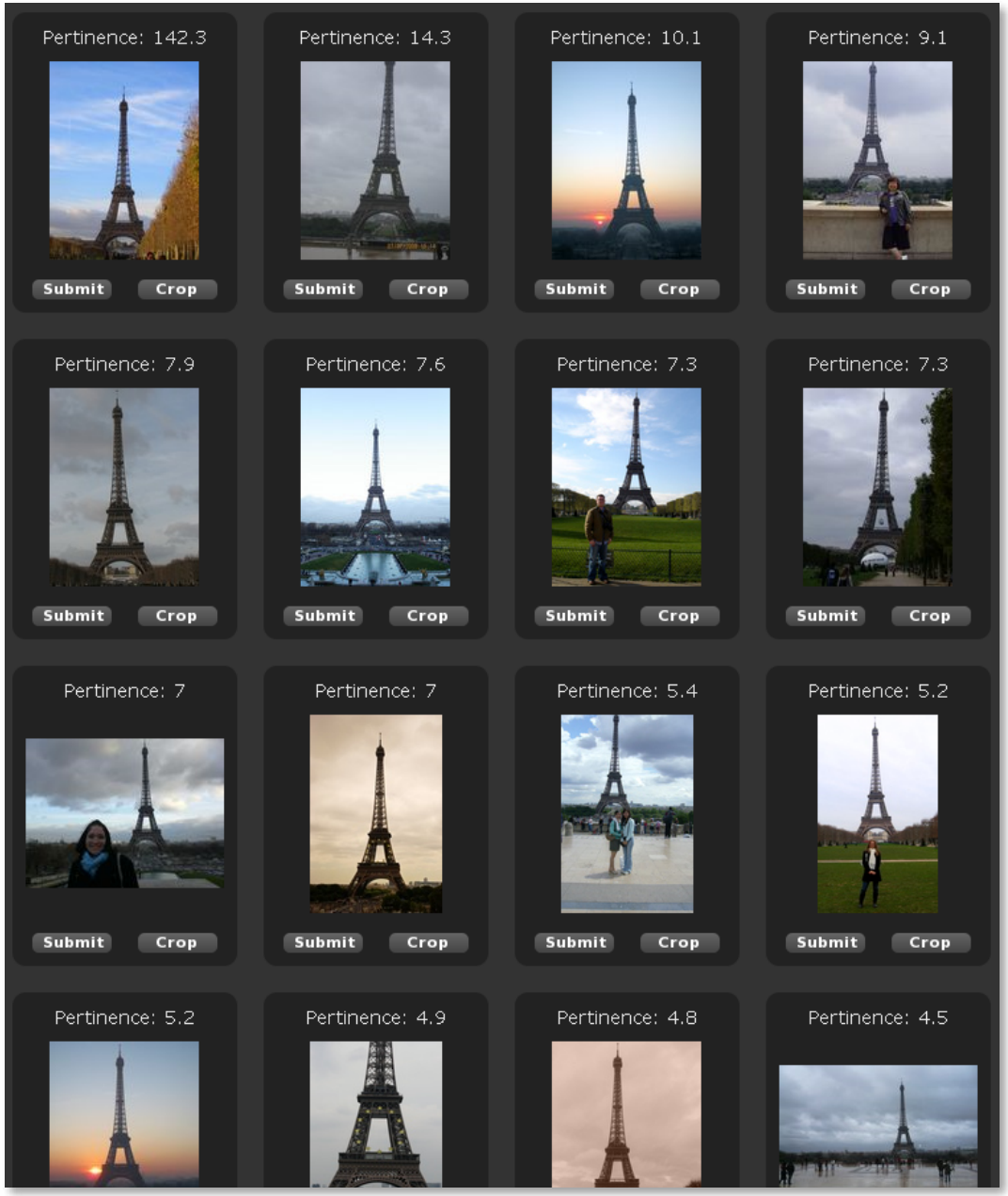
- short response time
- Millions to **billions** of images

Visual Search

- Inria's BigImBaz (2008-)

  http://bigimbaz.inrialpes.fr/

10 millions images on a big server



Visual Search

- TinEye.com

194 Results

Searched over **1.9305 billion** images in 2.106 seconds.

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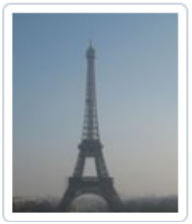

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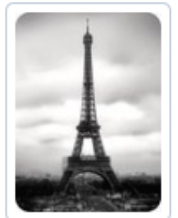

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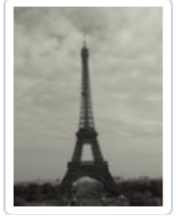

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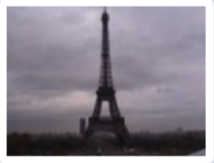

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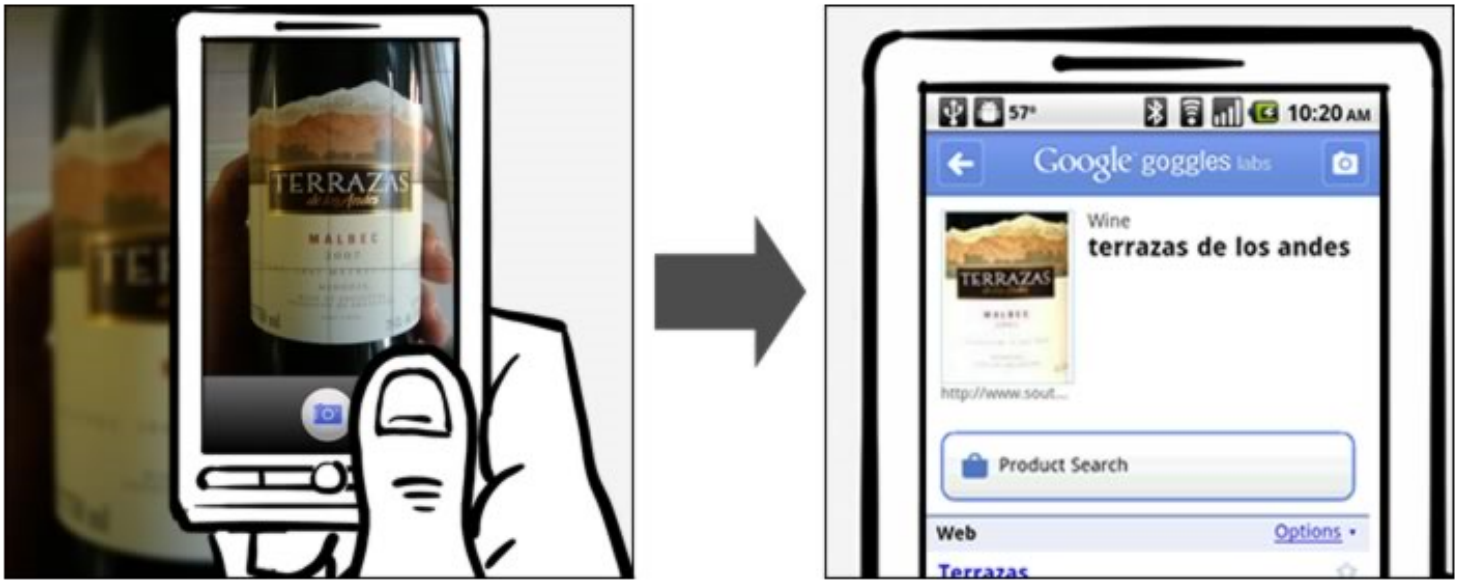
Visual Search

- Google's goggles on Android



Scalability for the image search problem

Scalable systems with Global descriptors (image-level)

- QBIC'95: 7.5K (but in 1995!)
- Cortina: Quack et al. – ACMM'04
  3 million images (10M)
- Torralba et al. – CVPR'08
  12.9M – 74ms with 30bit codes
- Douze et al.'2009 – CIVR'09
  110 million images – 180ms

Scalable systems local descriptors (object instance)

- Sivic et al. – CVPR'03: "Video-Google"
  5k images
- Joly et al. – CIVR'03
  6M video keyframes – 120M descriptors
- Nister et al. – CVPR'06
  50k images (then 1M images)
- J. et al. – CVPR'10
  10M images (then 100M)

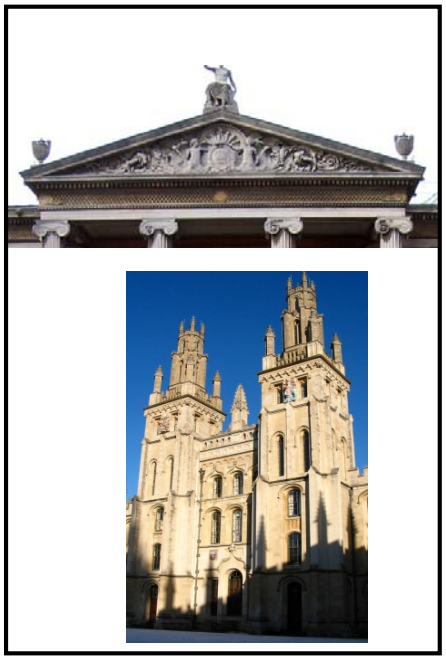
Datasets – Oxford5k/Paris6k

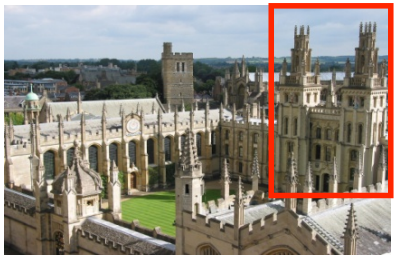
Oxford5k dataset: find images of the same famous building

55 queries (11*5 buildings), varying number of relevant results (6-221)

Oxford105K = Oxford5k + a image set of 100k “distractors” for large scale tests

Queries





Some images to be found

Philbin, Chum, Isard, Sivic and Zisserman,

« Object retrieval with large vocabularies and fast spatial matching », ICCV’07

Datasets– Holidays

INRIA Holidays dataset: 1491 shots of personal Holiday snapshot

500 queries, each associated with a small number of results 1-11 results

1 million distracting images (with some “false false” positives)

Hervé Jégou, Matthijs Douze and Cordelia Schmid

Hamming Embedding and Weak Geometric consistency for large-scale image search, ECCV'08

Univ. Kentucky object recognition benchmark

Nister & Stewenius 2006

2550 objects, represented each by 4 images

10200 images in total

Images shot for the purpose of the benchmark

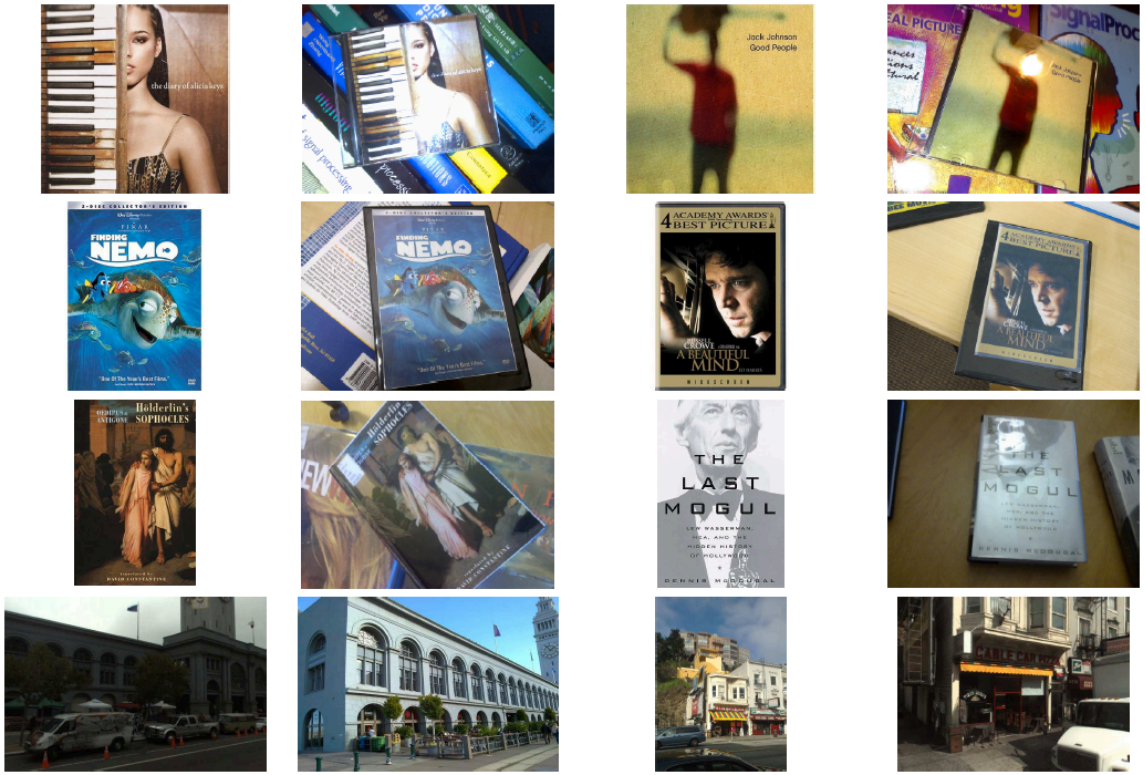
Each query is submitted in turn

Typical performance measure: average number of images returned in first 4 positions

Datasets – Stanford Mobile

Stanford Mobile Visual dataset:

- 1200 reference images
- 3000 queries: images shot by mobile devices (queries) – of lower quality



Tutorial: large scale image search
Image description & matching

Hervé Jégou, INRIA

informatics mathematics

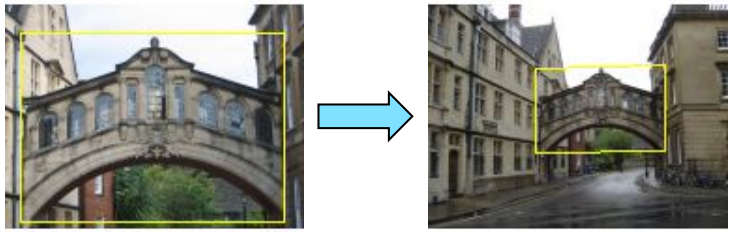
General Outline

- PART I: Introduction
  - Applications and datasets
  - **Image description and matching**
- PART II: Large-scale image search
  - The bag-of-word representation and some extension
- PART III: Larger-scale image search
  - Novel aggregation mechanisms
  - Efficient indexing
- Conclusions

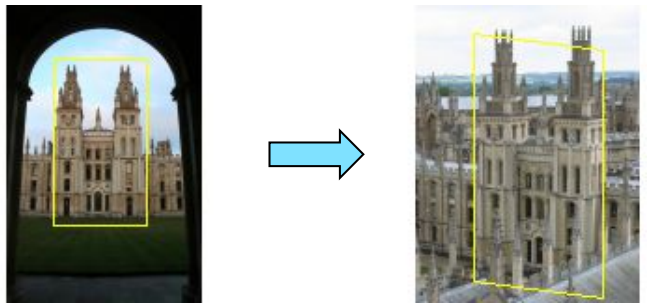
Image description

- Image processing : analysis step (=description)
  - Convert an image to a mathematical representation
  - Similar images have the “similar” representations, but not dissimilar ones

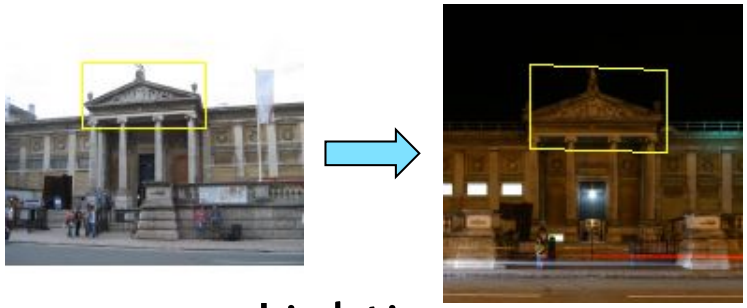
- Difficulty: Finding the object despite possibly large changes in scale, viewpoint, lighting and partial occlusion
  ⇨ needs **invariant description**



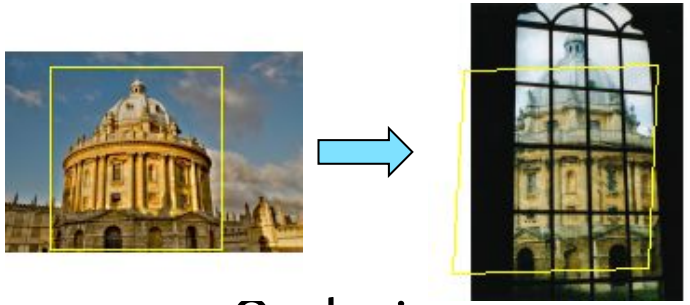
Scale



Viewpoint



Lighting

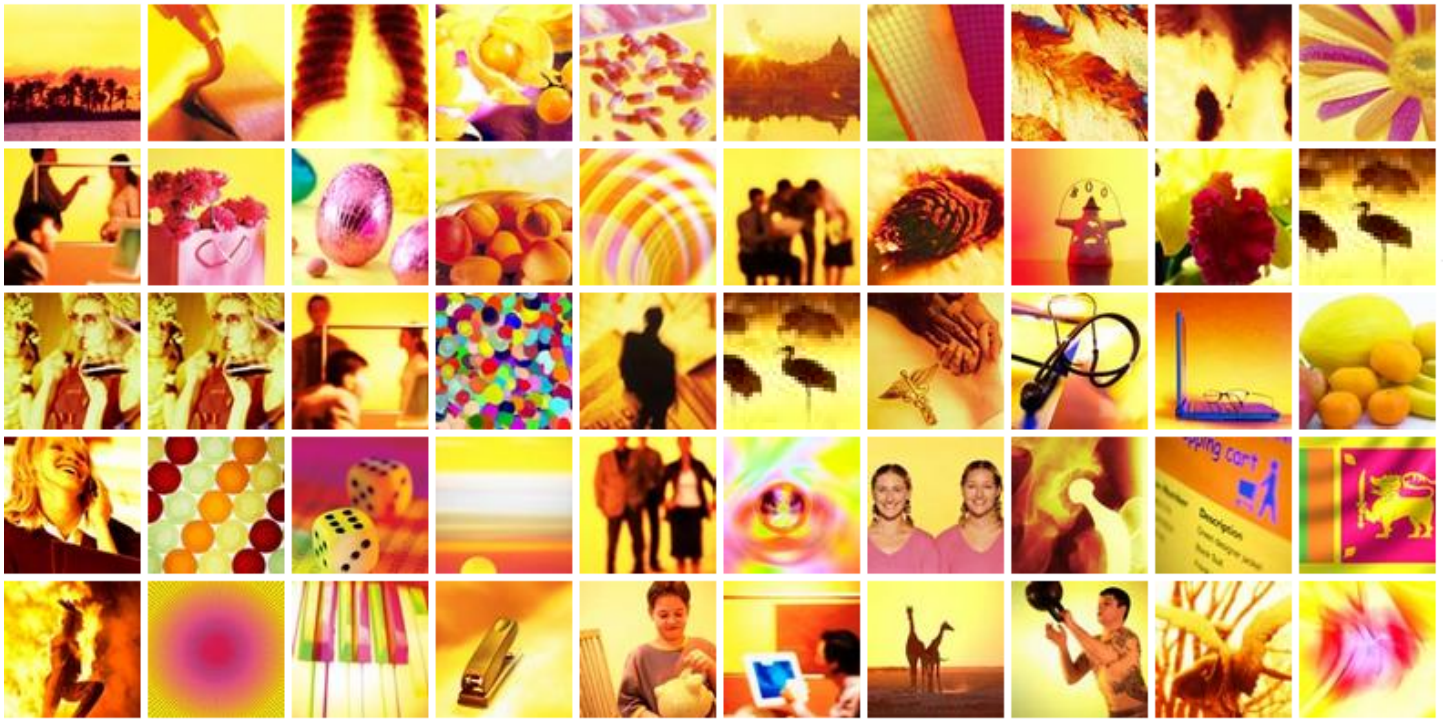


Occlusion

Image description

- Image processing : analysis step (=description)
  - Convert an image to a mathematical representation
  - Similar images have the “similar” representations, but not dissimilar ones

- But the representation should be discriminative enough
  ⇨ careful selection of what should be invariant for the application



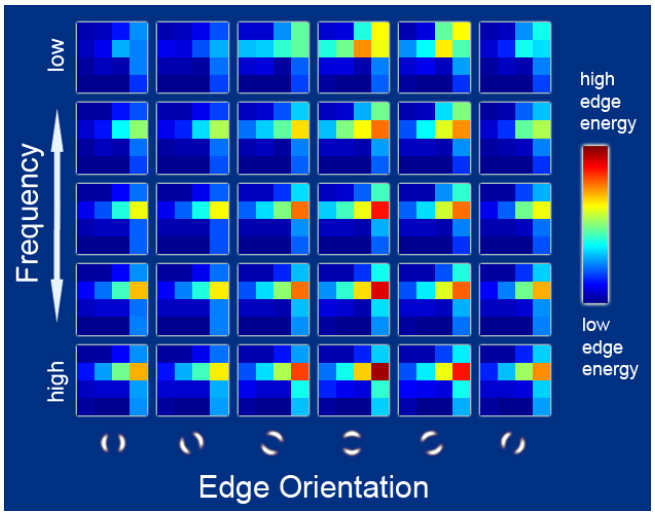
http://labs.ideeinc.com/multicolour/

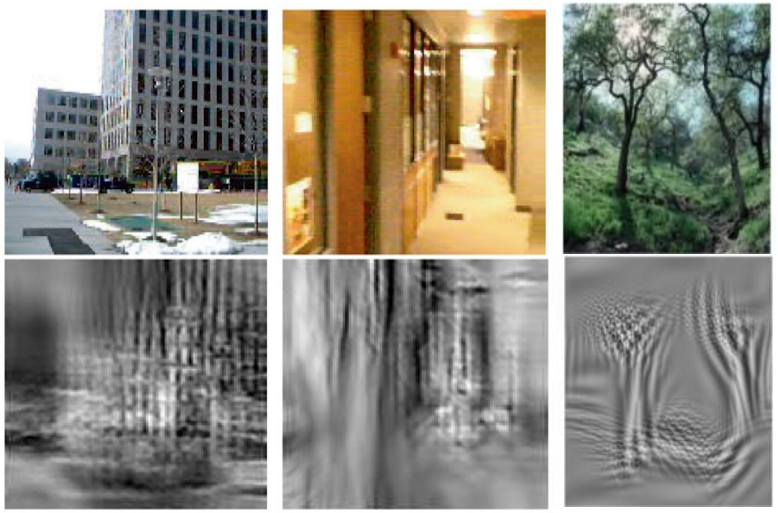
Global descriptors

- Highly scalable: 1 vector matched with a set of N database vectors

- Color Histogram, e.g.: [Swain 91]
  - High invariance to many transformation
  - But limited discriminative power

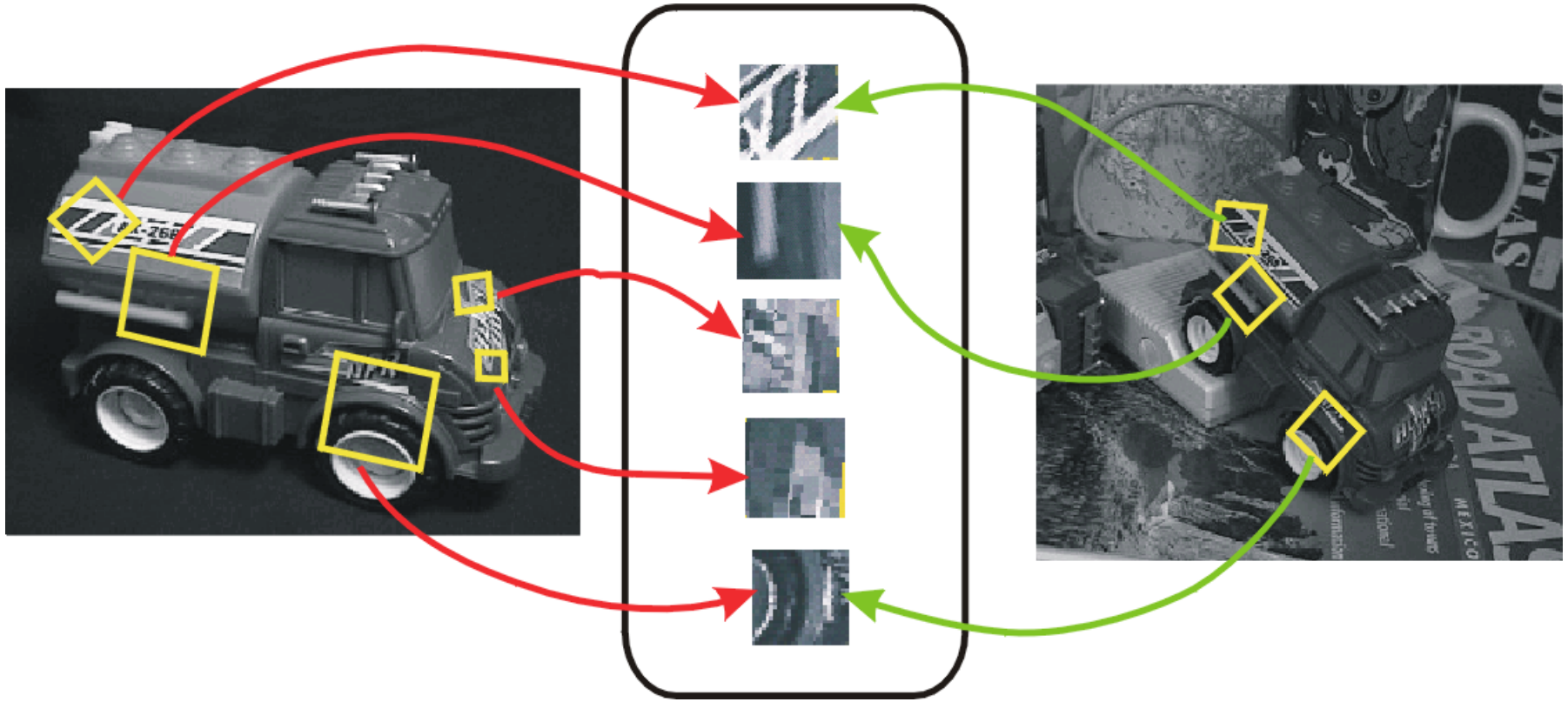
- The “gist” of a scene [Oliva 01]
  - Several frequency bands and orientations for each image location
  - Tiling of the image, for example 4x4, and at different resolution





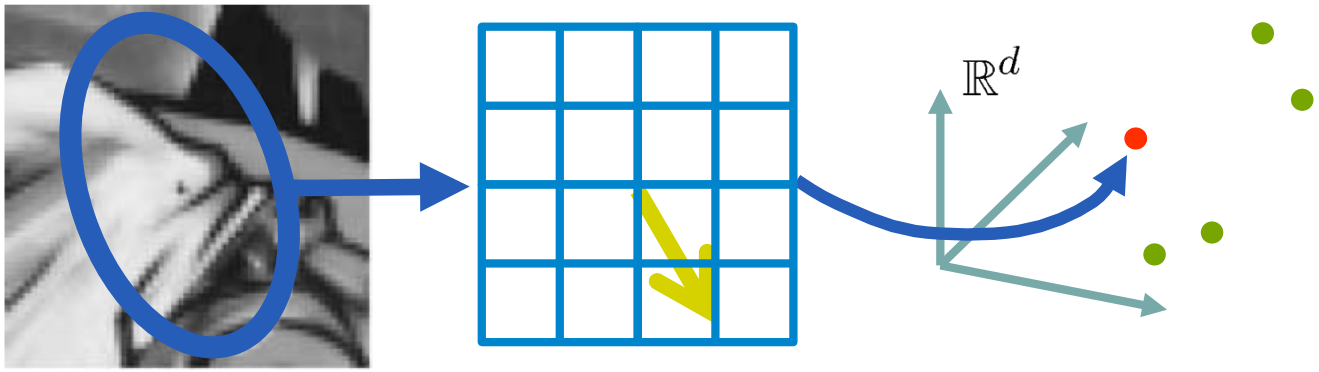
Matching local descriptors [Lowe04]

- Image content is transformed into local features that are invariant to geometric and photometric transformations



Local description: image detector

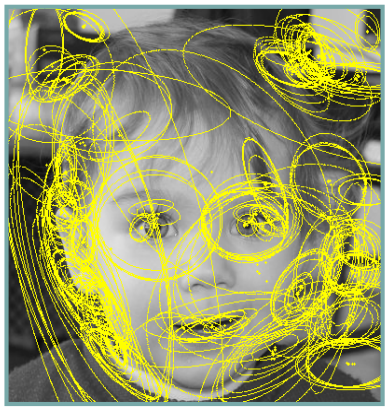
- The detector provides the desired invariance to transformations



[Lowe, IJCV 2004]

- Popular detectors:
  - MSER: Wide-baseline matching [Matas 02]
  - Difference of Gaussian [Lowe 99]
  - Hessian-Affine [Mikolajczyk 01]

- Renewed interest for dense descriptors
  - [Leung 99, Fei-Fei 05, Lazebnik 06]
  - Mainly for Image classification
  - But also for image/scene/object retrieval
    E.g., [Gordo 12] at CVPR'12



Local image descriptor

- Description of patch
  - After orientation/scale/photometric normalization

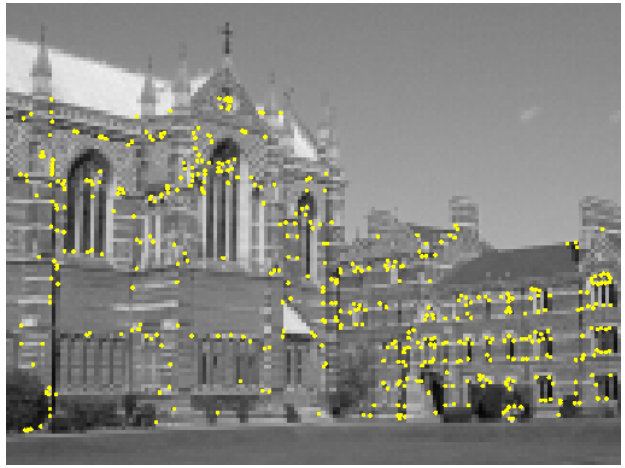
- SIFT [Lowe 99]
  - 8 orientations of the gradient
  - 4x4 spatial grid ⇨ 128 dimensions
  - Normalized to L2-norm one, compared with Euclidean distance
  - Component-wise “Power-law” [Jain’12, Arandjelovic 12]

- Most descriptors derive from SIFT:
  - More efficient: SURF [Bay 08]
  - More compact: many, e.g., DAISY
  - With color: [Burghouts 09]

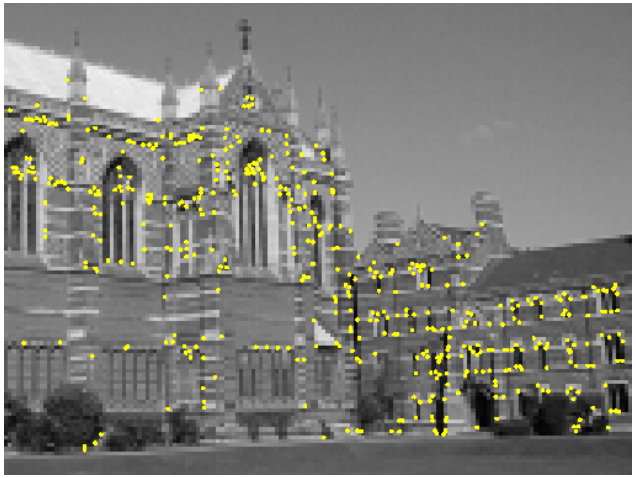
- Learned descriptors [Winder’07, Brown’10]
  - Used training sets of 1) matching and 2) non-matching patches

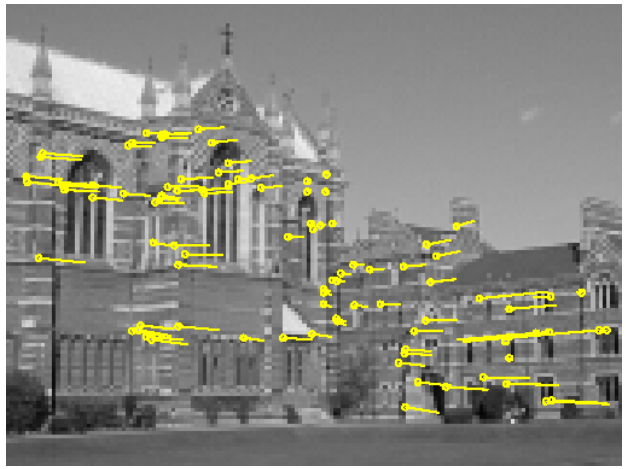
Geometric matching with local descriptors

- Use a global geometrical constraint to filter out the outliers



Interest points extracted with Harris detector (~ 500 points)



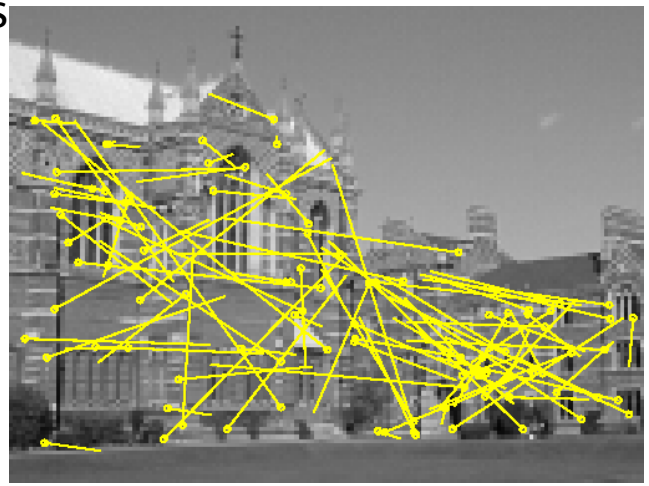


Match points using descriptors

99 inliers

⇨ score

89 outliers



- Precise matching, but not scalable (100—1000 images)

Large-scale image search
Bag-of-words and extensions

Hervé Jégou, INRIA

Inria informatics mathematics

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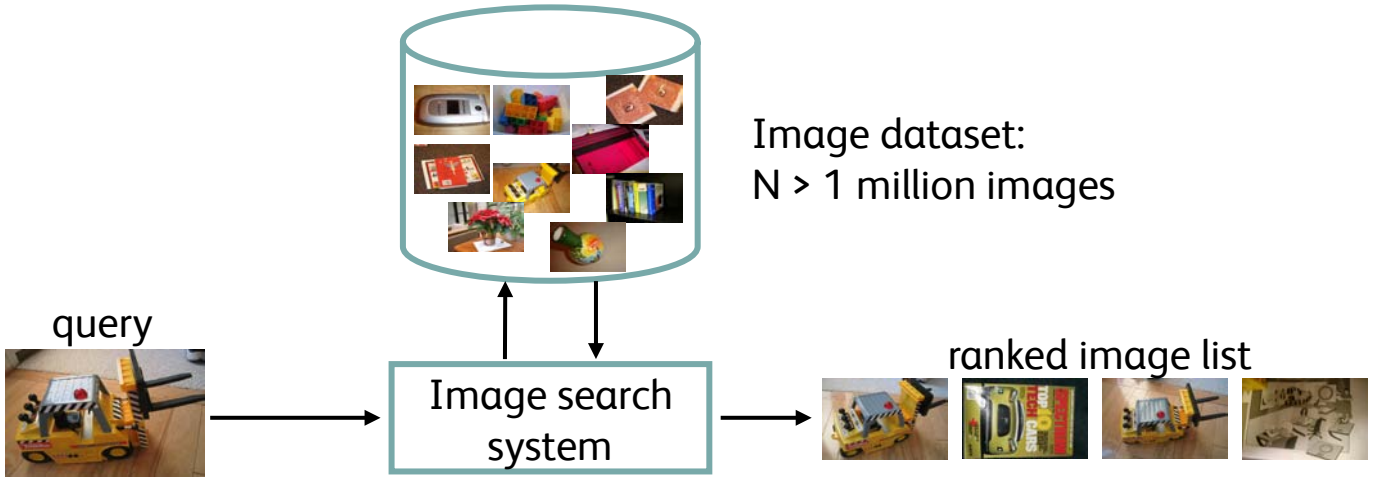
Direct matching: the complexity issue



- Assume an image described by m=1000 descriptors (dimension d=128)
  - N*m=1 billion descriptors to index
- Database representation in RAM: 128 GB with 1 byte per dimension
- Search: $\mathbf{m^2}$* N * d elementary operations
  - i.e., > 10^{14} ⇨ computationally not tractable
  - The quadratic term m^2: severely impacts the efficiency

Bag-of-visual-words

- The BOV representation
  - First introduced for texture classification [Malik'99]

- "Video-Google paper" – Sivic and Zisserman, ICCV'2003
  - Mimick a text retrieval system for image/video retrieval
  - High retrieval efficiency and excellent recognition performance

- "Visual categorization with bag of keypoints" – Dance'04
  - Show its interest when used jointly with a (kernelized) SVM

- Key idea: n local descriptor describing the image → 1 vector
  - sparse vectors ⇨ efficient comparison
  - **inherits invariance** of the local descriptors

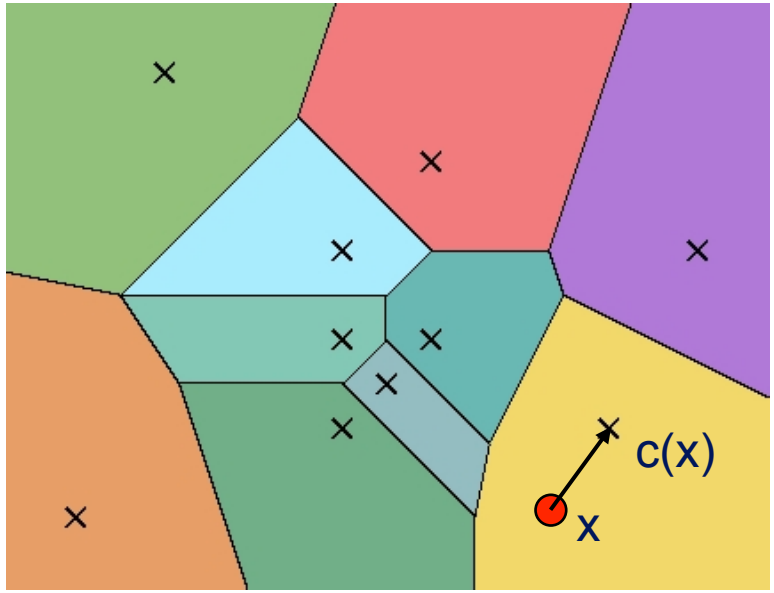
Bag-of-visual words

- The goal: “put the images into words”, namely visual words
  - Input local descriptors are continuous
  - Need to define what a “visual word is”
  - Done by a quantizer q

$$q: \mathbb{R}^d \rightarrow \omega$$

$$x \rightarrow c(x) \in \omega$$

  - q is typically a k-means



- ω is called a “visual dictionary”, of size k
  - A local descriptor is assigned to its nearest neighbor

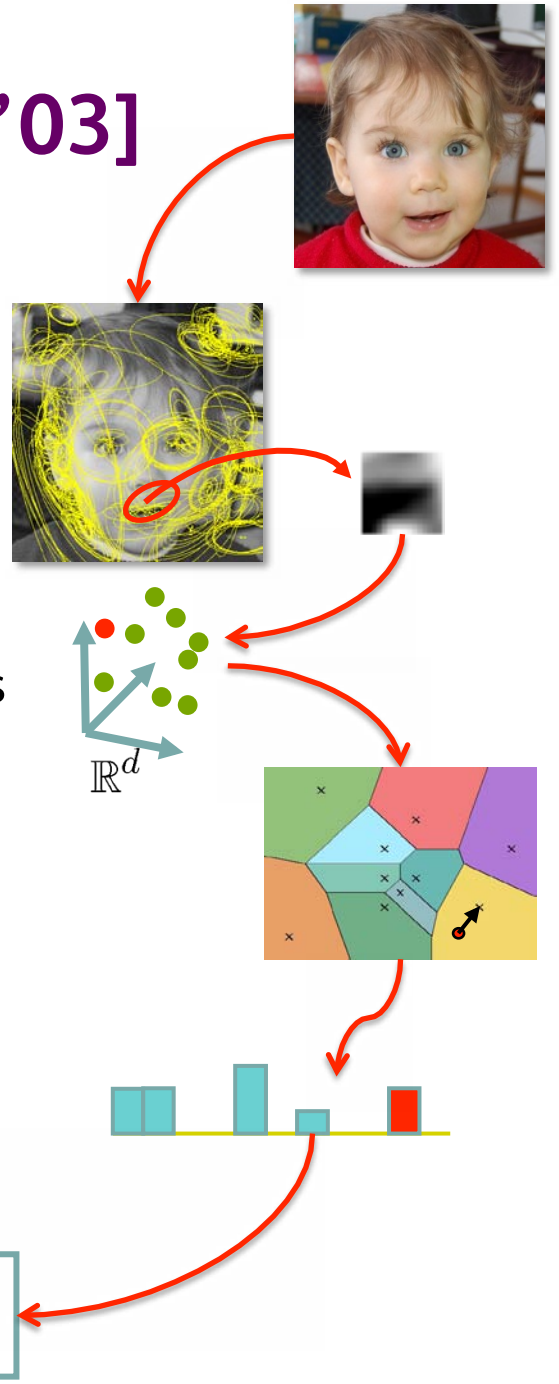
$$q(x) = \arg\min_{w \in \omega} \|x-w\|^2$$

  - Quantization is lossy: we can not get back to the original descriptor
  - But much more compact: typically 2-4 bytes/descriptor

Video Google [Sivic & Zisserman'03]

- Extract local descriptors
  - Detector
  - Describe the patch
- Quantize all descriptors
  - Subsequently compute the vector of frequencies
  - Weight by IDF (rare = more important)

    ⇨ TF-IDF vectors
- Search similar vectors
- Optionally: Re-ranking

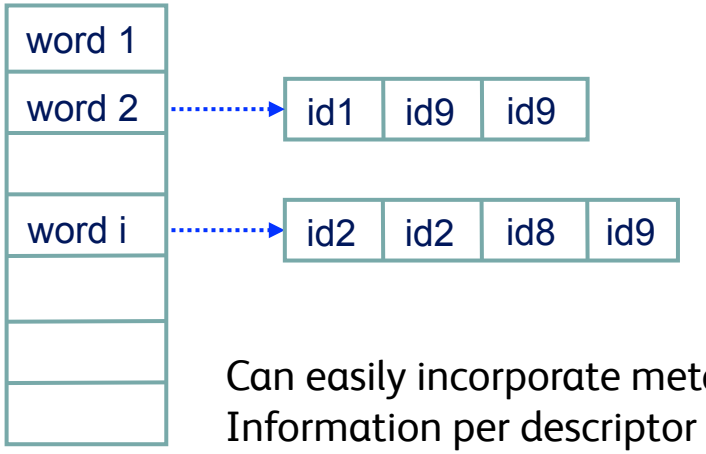


Inverted file

- Set of lists
  - That stores the sparse vector components
  - Use to compute the cosine similarity (or any Lp-norm, see [Nister 06])

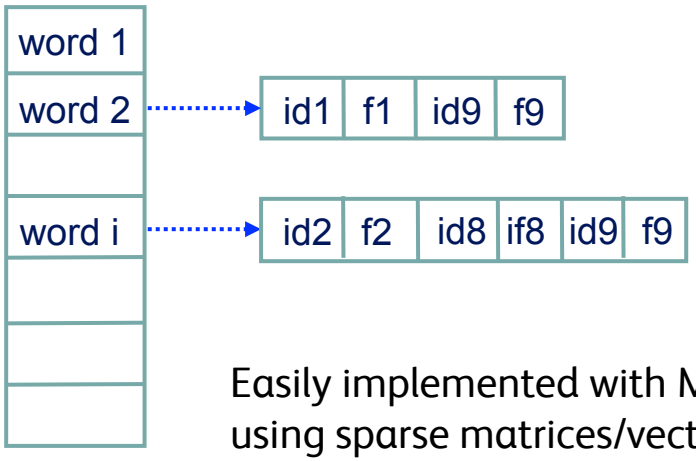
- Two implementations

store one image id per descriptor



Can easily incorporate meta Information per descriptor (geometry, bundled features, etc)

Store image id+nb of descriptors



Easily implemented with Matlab using sparse matrices/vectors

- Complexity: approximated by the number of visited items

Interest of the voting interpretation

- And the corresponding implementation of the inverted file

- Easy extended to incorporate
  - A better matching method [J'08]
  - Partial Geometrical information [J'08, Zhao 10, …]
  - Neighborhood information [Wu 09]
  - … any method that requires to handle individual descriptors

Inverted file – Complexity

- Denote
  - p_i = P(assign a descriptor to word i)
  - N = number of image in database
  - m = average # of descriptors / image

⇨ The expected length of List i is given by: $N*m*p_i$

- The expected cost is : $N.m^2 \sum_{i=1}^{k} p_i^2$

- Clusters of variable sizes negatively impacts this cost [Nister 06]
  - Imbalance factor: $k \sum_i {p_i}^2$
  - measures the divergence from (optimal) uniform distribution (=1)

- Strategies proposed to balance the clusters [Tavenard 11]

  → but these impact the search quality

Inverted file – Complexity

- Complexity is **linear** in the number of images
  - but small constant, in order of m/k
    E.g., C=0.01

- **Memory usage** of an inverted file
  - 1 million images ≈ 8 GB (depending on m)
  - Can be compressed [J'09], "Packing bag-of-features"
    - As previously proposed for text search engines [Zobel'06, Zhang'08]

Inverted file – Boosting efficiency

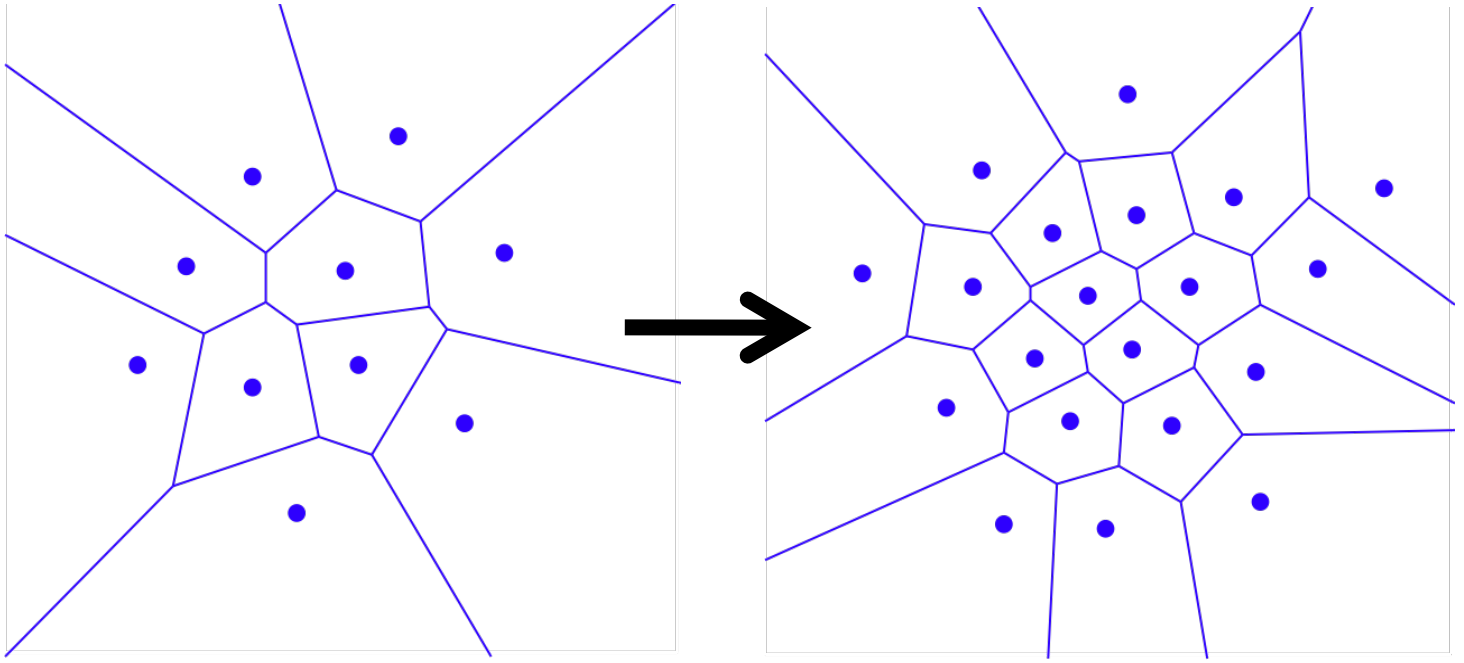
- **Stop-words**
  - Method used in Text retrieval to discard uninformative words
  - In image search: remove the s most frequent ones [Sivic 03]
  - Impact on efficiency: assuming p_i in decreasing order

    replace $N.m^2 \sum_{i=1}^{k} p_i^2$ by $N.m^2 \sum_{i=s+1}^{k} p_i^2$

  - But most frequent **visual** words are not that uninformative

Inverted file – Boosting efficiency

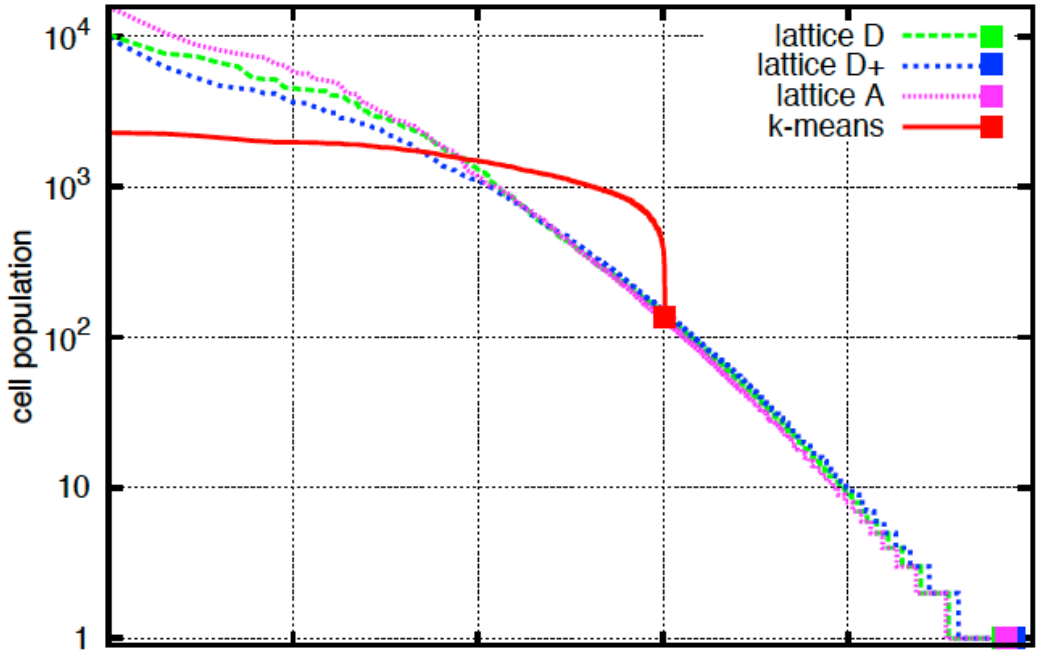
- **Large vocabularies**
  - Unlike in text, **we decide** the vocabulary size by choosing k
    → for search quality and/or efficiency
  - Querying complexity: linear in 1/k
  - Efficiency boosted by using a very large dictionary [Nister 06]



Large vocabularies: assignment cost

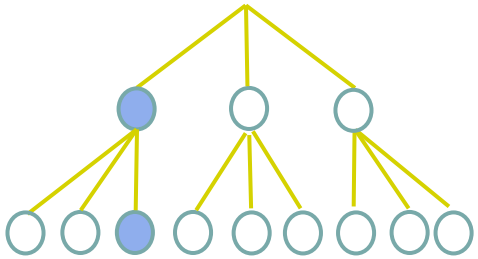
- Large vocabularies are preferred [Nister 06]: high retrieval efficiency
  - But increased assignment cost, e.g., for k-means: $C(k) = C_1 \times k + \frac{C_2}{k}$

- Structured quantizers: low quantization cost even for huge vocabularies
  - Grid lattice quantizer [Tuytelaars 07]
  - But poor performance in retrieval [Philbin 08]
  - And very unbalanced [Pauleve 10]:



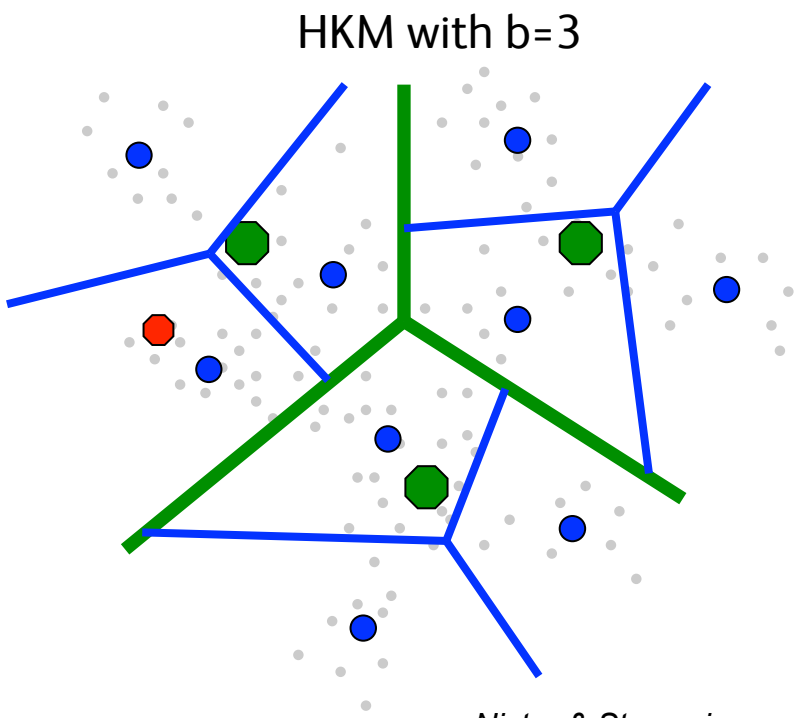
Large vocabularies with learned quantizer

- Hierarchical k-means [Nister 06]
  - K-means tree of height h



  - Branching factor b: $k = b^h$
  - Assignment Complexity:

$$\mathcal{O}(dhb) = \mathcal{O}(dhk^{\frac{1}{h}})$$



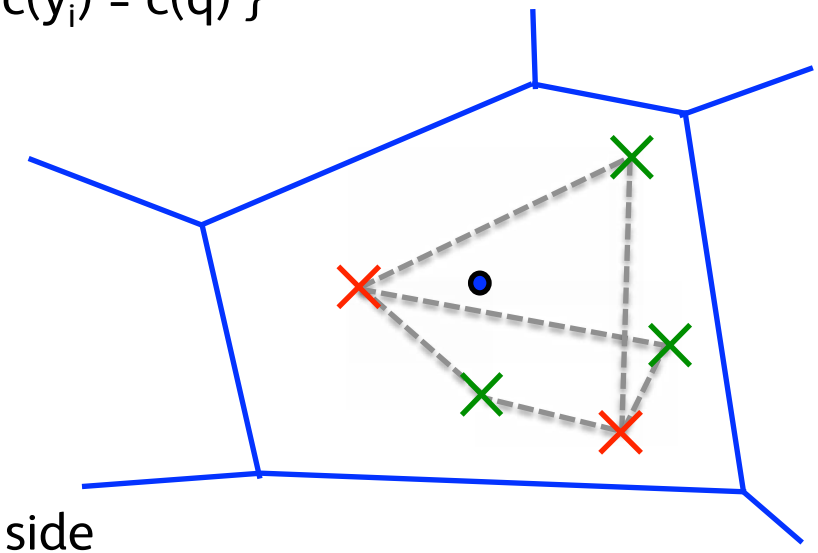
Nister & Stewenius

- Approximate k-means [Philbin 07]
  - Based on approximate nearest neighbor search
  - With parallel tree structures
  - See later in this tutorial

Bag-of-words : another interpretation

- « Visual words » are a view of mind
- BOV ≈ **approximate k-NN search+voting**
  - Implicitly define the neighborhood N(x) of a vector x as

$$N(x) = \{ y_i \text{ in } Y : c(y_i) = c(q) \}$$



- But, let assume:
  - 2 descriptors in query
  - 3 descriptors on database side

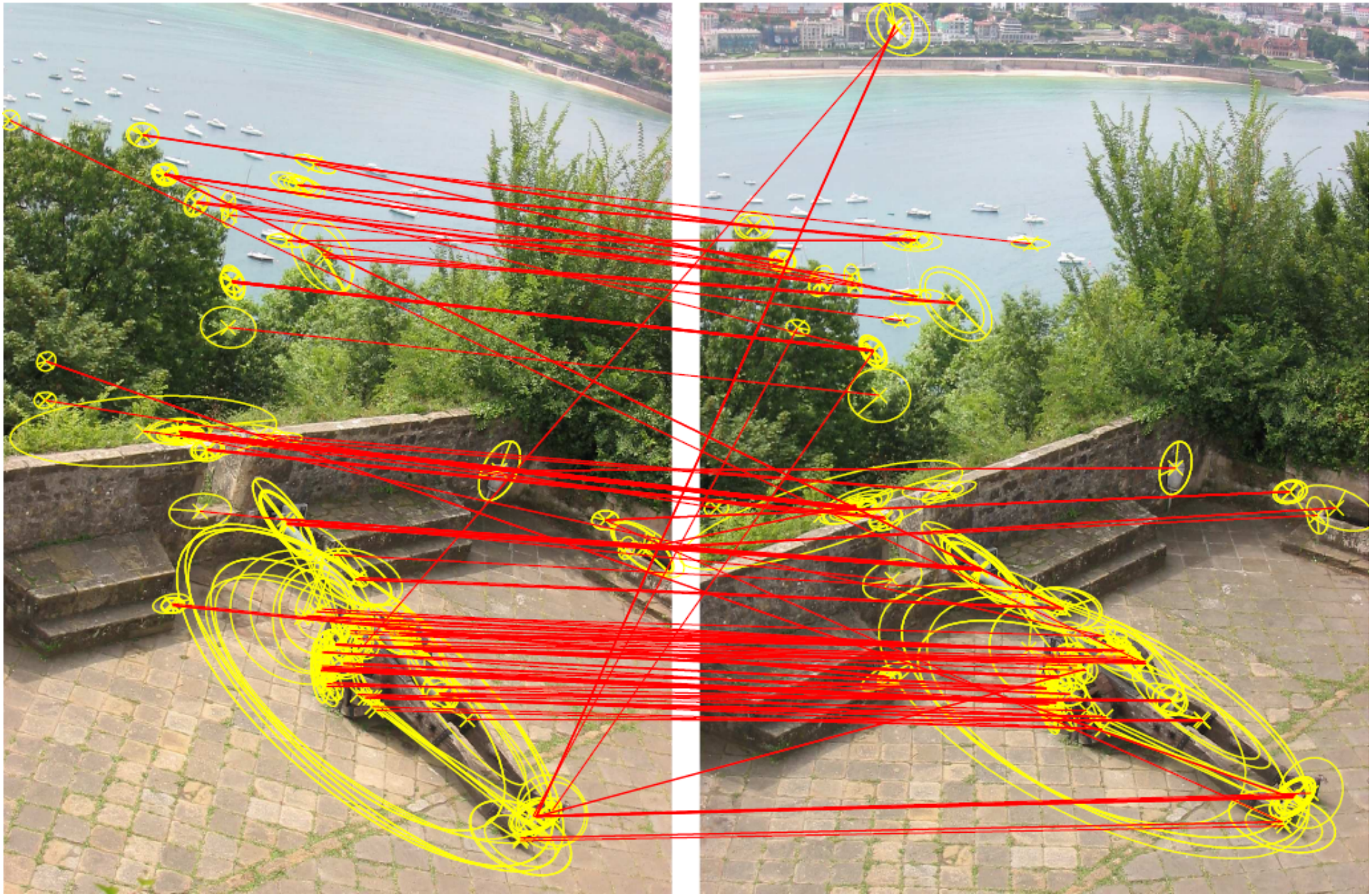
⇨ 6 votes for 2x3 descriptors

= contribution to the cosine similarity

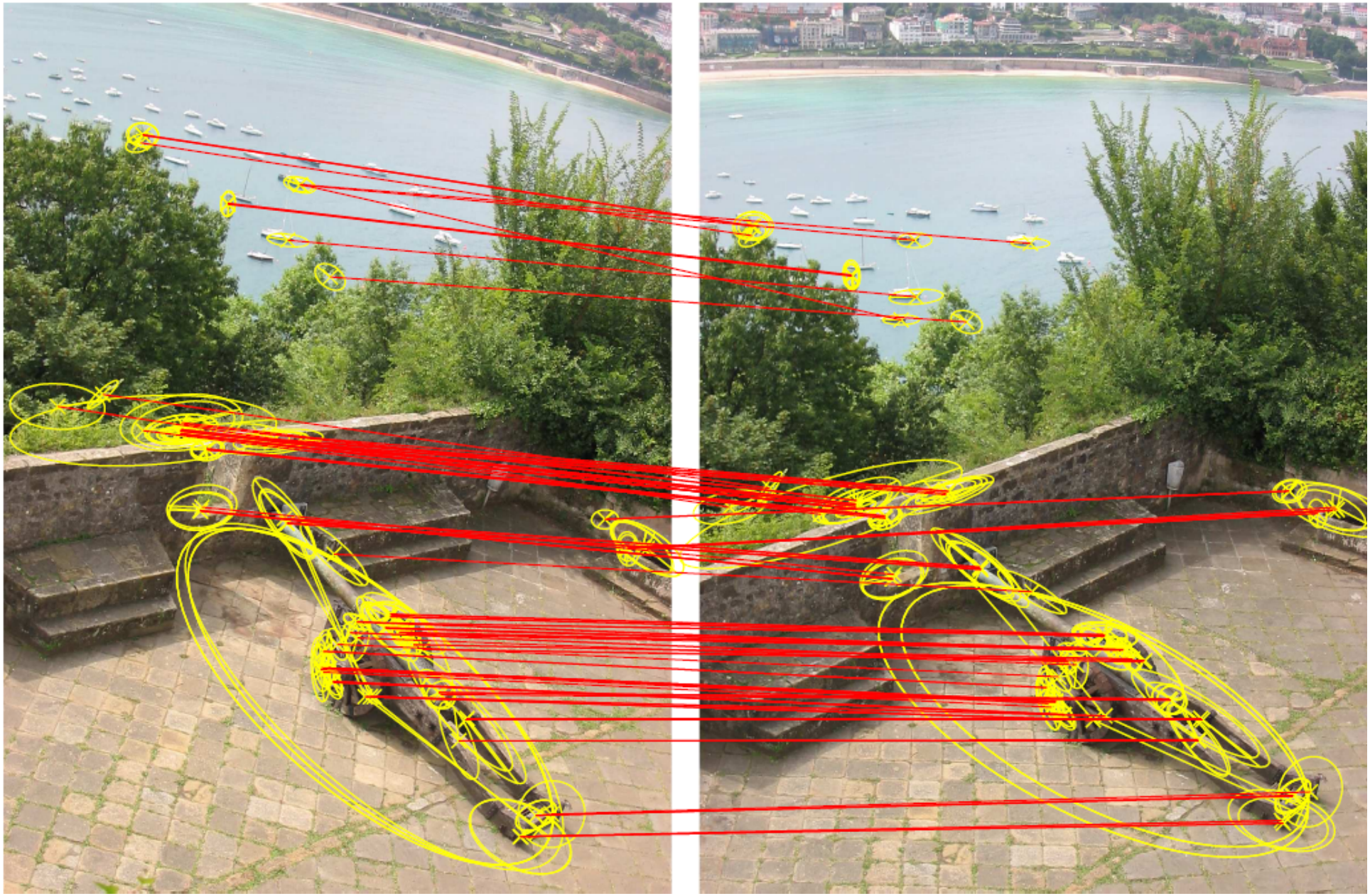
- Partial solution: pre-process BOV with **component-wise square rooting**

  ⇨ Linear contribution w.r.t the number of matches

Compromise on vocabulary size: k=20000



Compromise on vocabulary size: k=200000

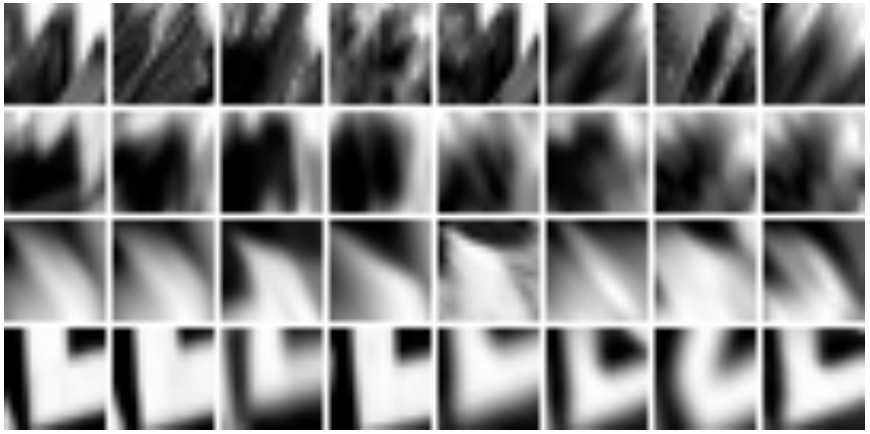


Impact of the vocabulary size on accuracy

- The intrinsic matching scheme performed by BOV is **weak**
  - for a “small” visual dictionary: too many false matches
  - for a “large” visual dictionary: complexity, true matches are missed

k=1,000

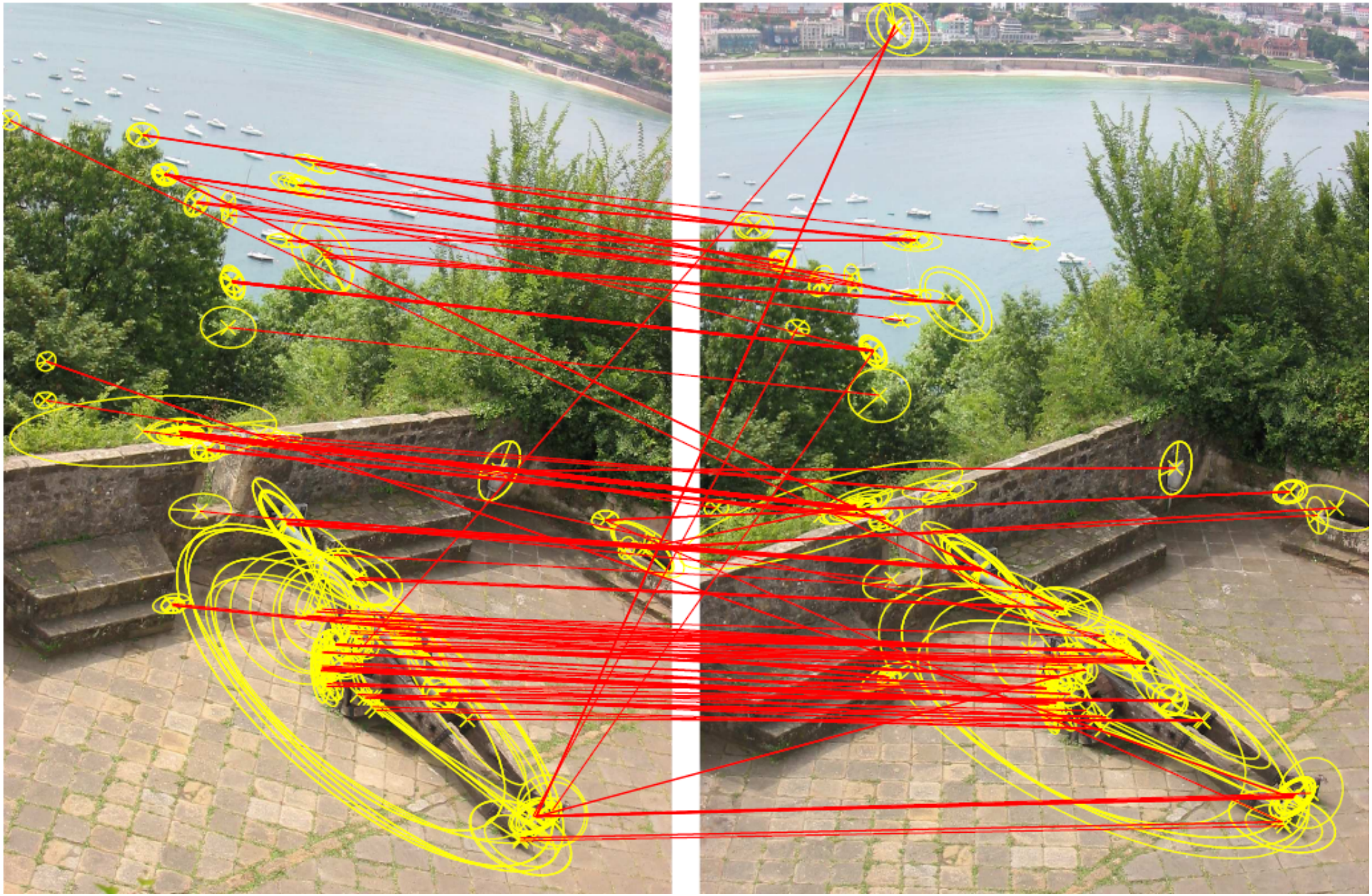
k=200,000



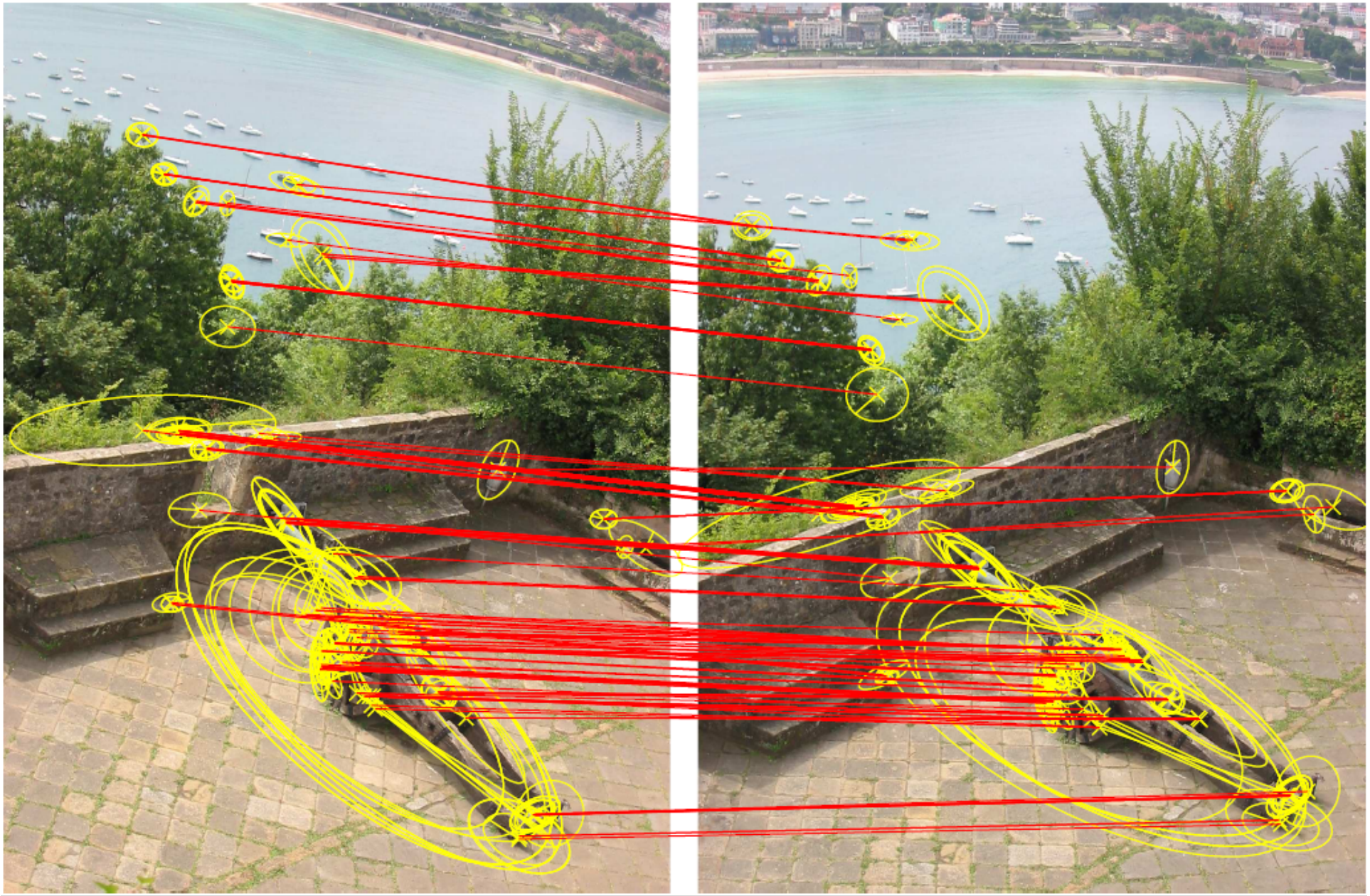
- No good trade-off between “small” and “large” !
  - Intrinsic matching method of BOV is relatively poor in all cases

- Partially solved by multiple [J’07] or soft assignment [Philbin 08]
  - Preferably on query side only [J’09, Arandjelovic’12] to save memory

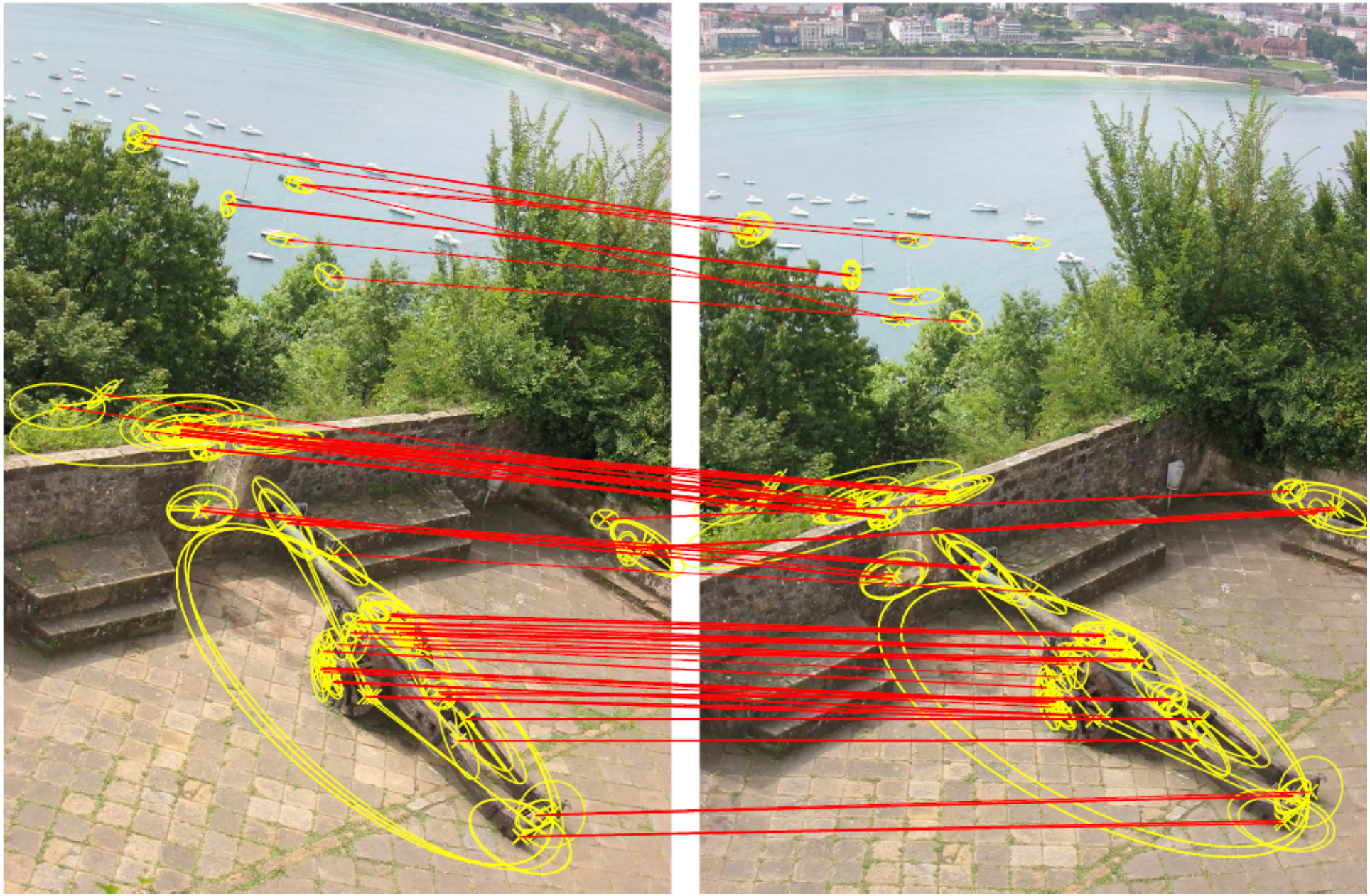
Compromise on vocabulary size: k=20000



But with a better matching method (HE)…

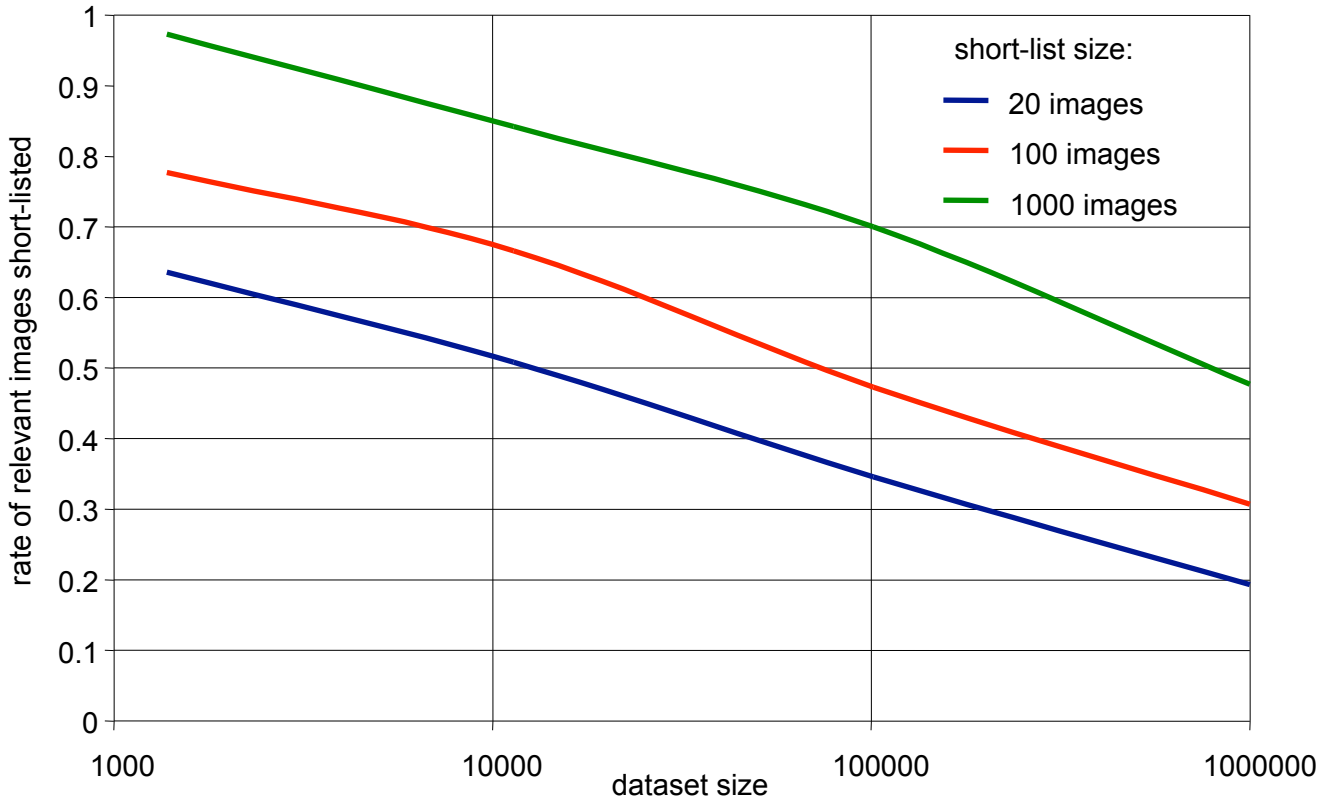


Compromise on vocabulary size: k=200000



Geometrical verification

- Re-ranking based on full geometric verification [Philbin 07]
  - works very well but **very costly**
  - Applied to a short-list only (typically, 100 images)
  - → for very large datasets, the number of distracting images is so high that relevant images are not even short-listed!



BOV search in 1M images – ranks

Query

BOV 2

BOV 5890

BOV 43064

Geometrical verification on a large scale

- Important activity on the topic
  - Weak geometry consistency [Jegou 08]
  - Geometrical Min-hash [Chum 09]
  - Bundling features [Wu 09]
  - Spatial inverted file [Lin 10]
  - …

- In classification
  - Most of these methods does not correspond to a vector model
  - not useable for classification with SVM
  - Geometry in classification: spatial pyramid matching [Lazebnik 06]

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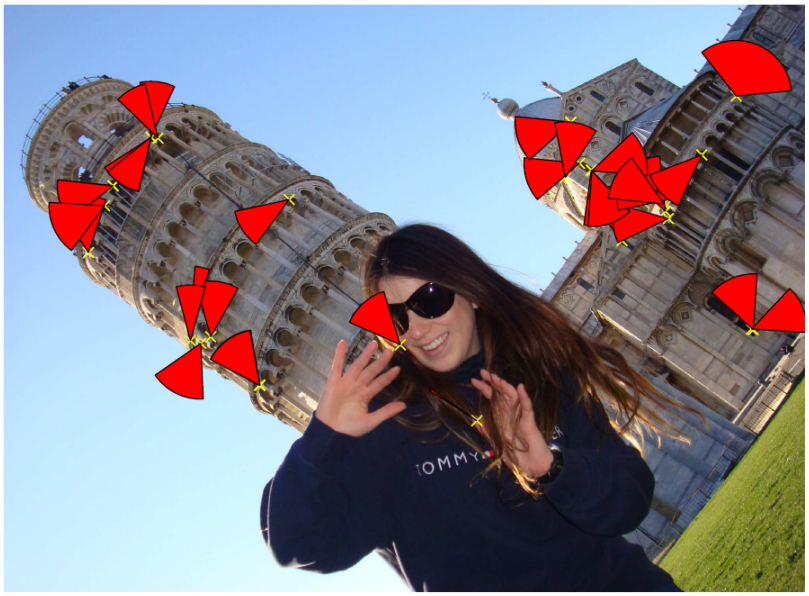
Weak Geometry consistency

- WGC is a Hough transform
  - But do estimate a full geometrical transformation
  - **Separately estimate scalar quantities**: rotation angle and log-scale
  - Just used to filter out the outliers

- Implementation
  - Store quantized dominant orientation and detector log-scale
    → directly in the inverted file
  - Two small hough histograms to collect the votes (16–32 bins/image)

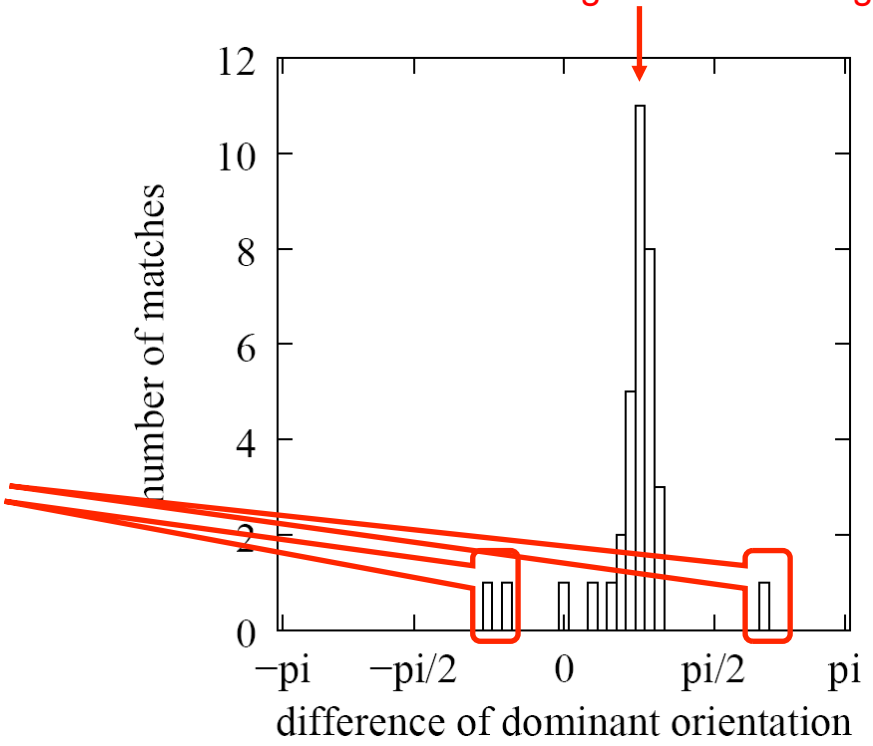
- **Variation: Enhanced Weak Geometry consistency** [Zhao 10]
  - a.k.a visual phrases [Zhang 11]
  - Deal with the translation (instead of angle/scale)

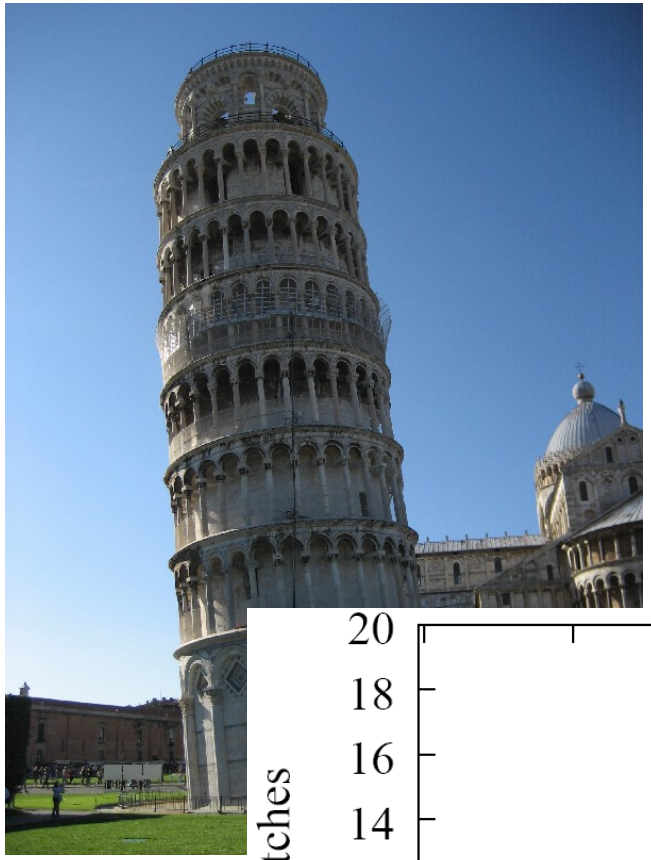
Weak geometric consistency



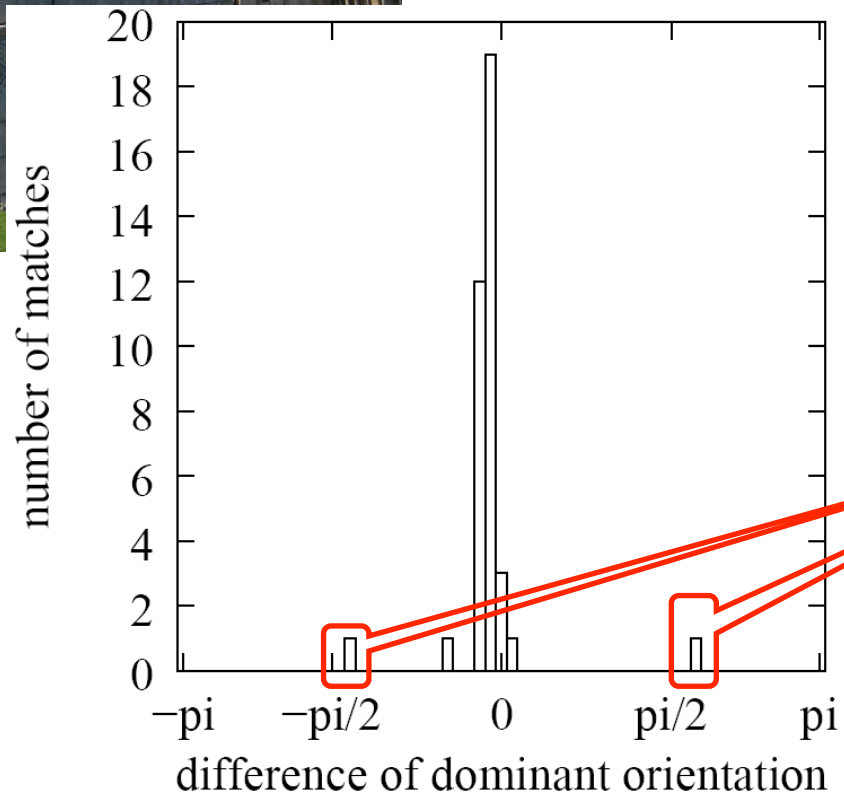
FILTERED!

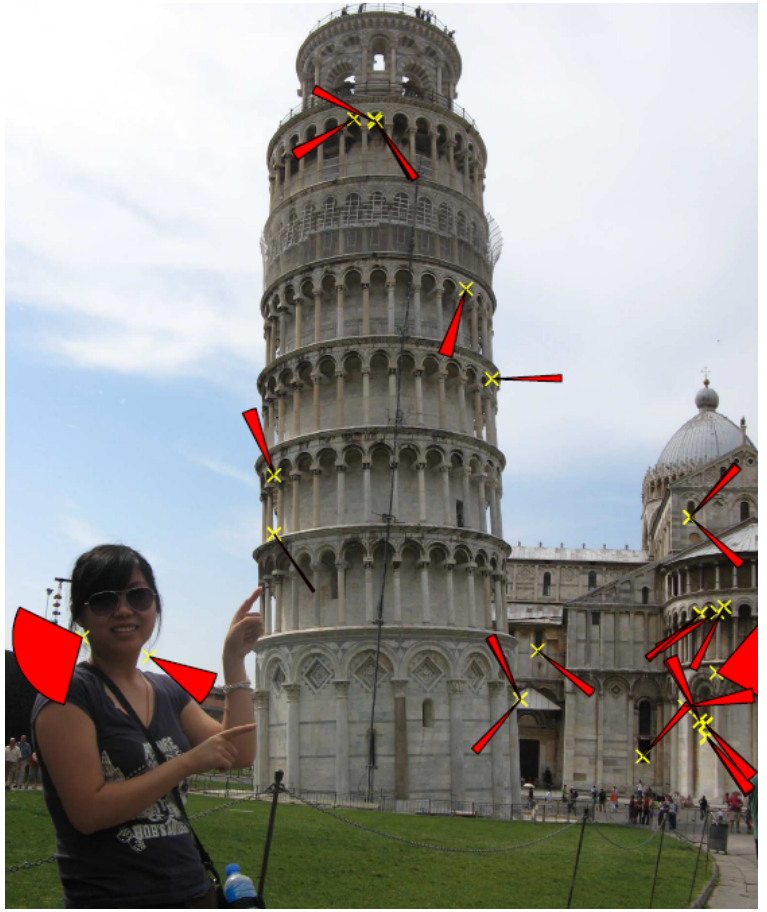
Max = rotation angle between images





PEAK





FILTERED!

Large scale: BOV search in 1M images

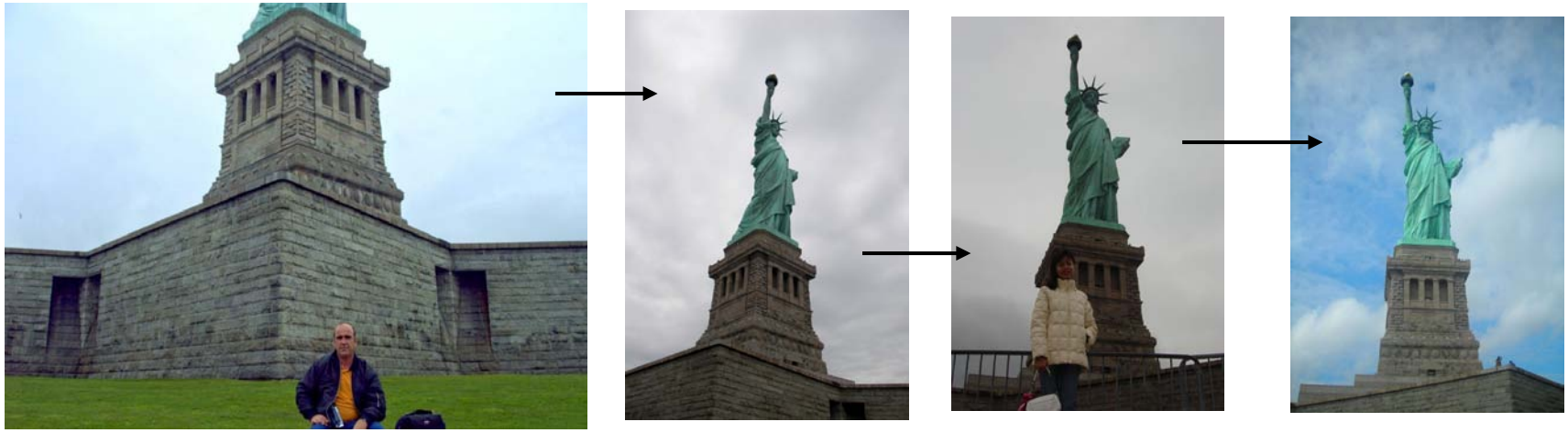
Query

BOV 2
HE+WGC 1

BOV 5890
HE+WGC 4

BOV 43064
HE+WGC 5

Query expansion in visual search



- [Chum 07], “Total Recall”, ICCV 07
  - Process the list of results
  - If some images are good (verified by spatial verification), use them
  - To process some other **augmented** queries

- Discriminative query expansion [Arandjelovic 12]
  - Learn a classifier on-the-fly

Bag-of-words: concluding comments

- Practical solution: same ingredients as in text can be used
  - vector model especially interesting in classification
    → useable with strong classifiers, in particular SVM
  - query expansion [Chum'07]
  - Or handle statistical phenomenons, e.g.,
    - Burstiness [Jegou'09]
    - Co-occurences [Chum'10]

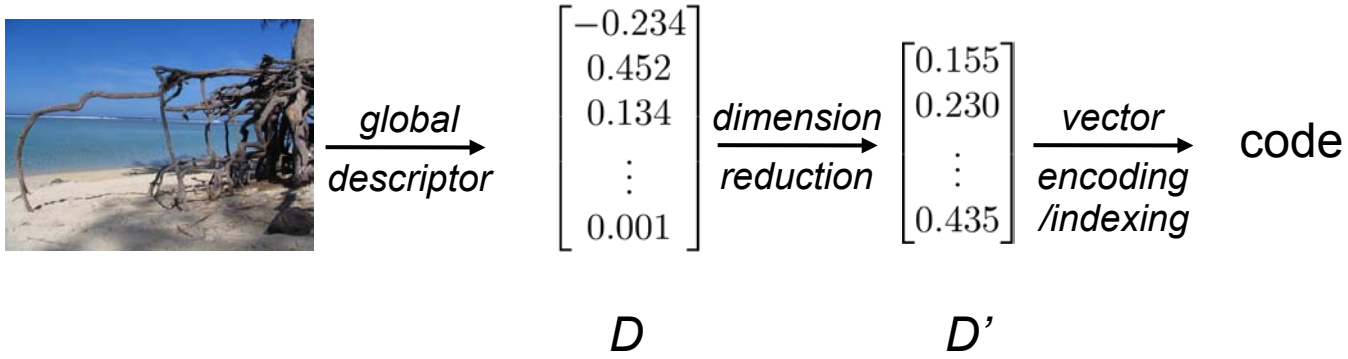
- With appropriate extension, state-of-the-art:
  - Hamming Embedding
  - Re-ranking with spatial verification
  - Query-expansion

Questions ?

Towards larger scale

- BOV Limited to about **a few million images** on a server (memory!)

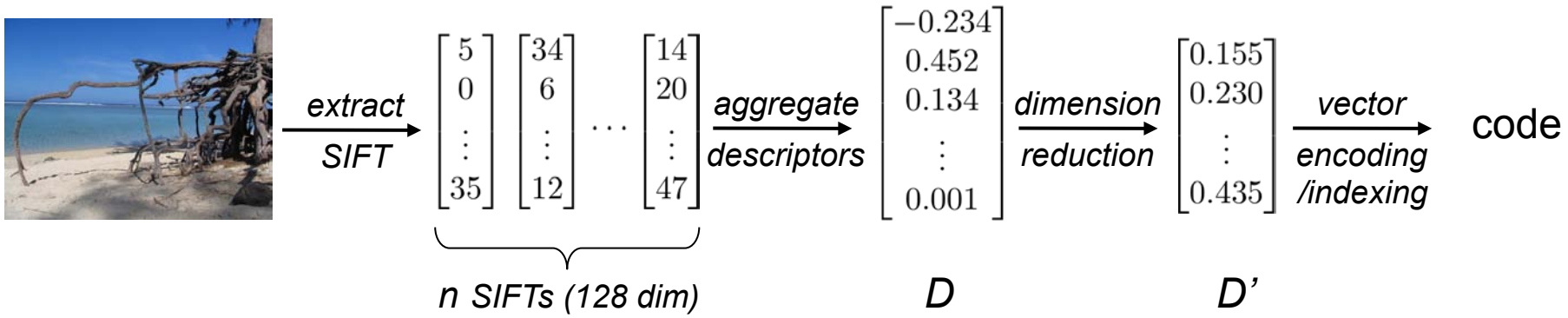
- **To scale more**, one may use
  - global descriptors
  - With a subsequent coding technique



- "Small codes and large databases for recognition [Torralba'08]
  - Very compact binary codes (32-256 bits)
  - Yet limited invariance

Towards larger scale

- BOV Limited to about **a few million images** on a server (memory!)
- **To scale more**, need to jointly optimize: quality, speed, memory
- Approach: joint optimization of three stages
  - local descriptor aggregation
  - dimension reduction
  - indexing algorithm



Larger-scale visual recognition
Novel aggregation mechanisms

Hervé Jégou, INRIA

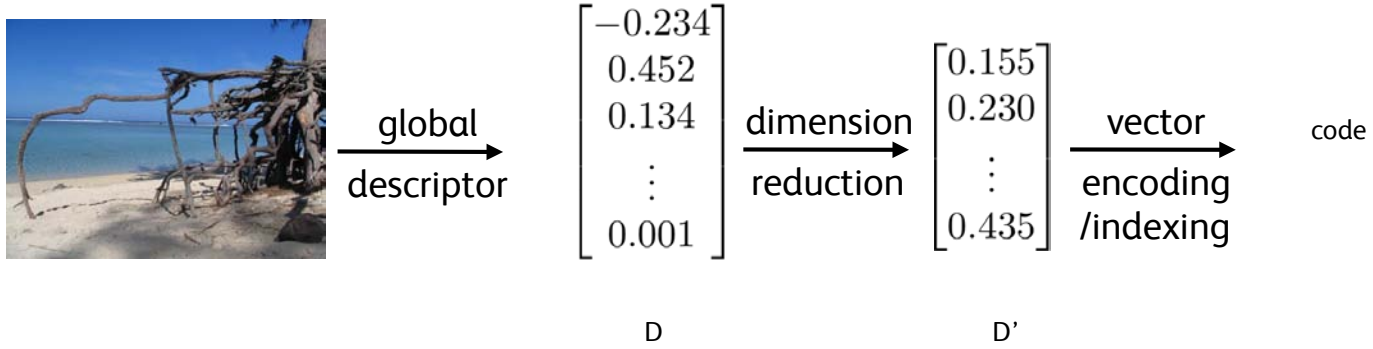
Inria informatics mathematics

Towards larger scale

BOV Limited to about **a few million images** on a server (memory!)

To scale more, one may use

- Global descriptors
- With a subsequent coding technique



"Small codes and large databases for recognition [Torralba'08]

- Very compact binary codes (32-256 bits)
- Yet limited invariance

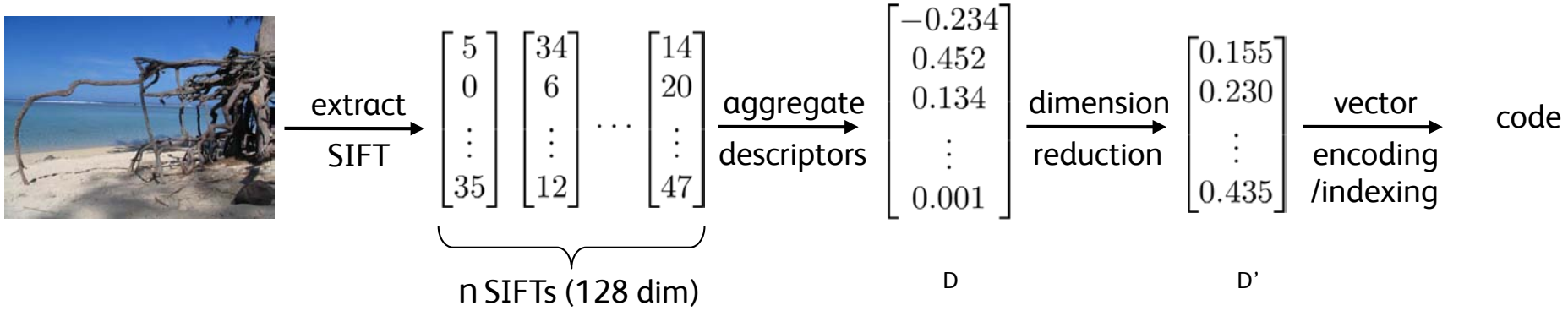
Towards larger scale

With a representation based on local descriptors

To scale more, need to jointly optimize: quality, speed, memory

Approach: joint optimization of three stages

- local descriptor aggregation
- dimension reduction
- indexing algorithm



Outline

PART I: Introduction

- Applications and datasets
- Image description and matching

PART II: Large-scale image search

- The bag-of-word representation and some extension

PART III: Larger-scale image search

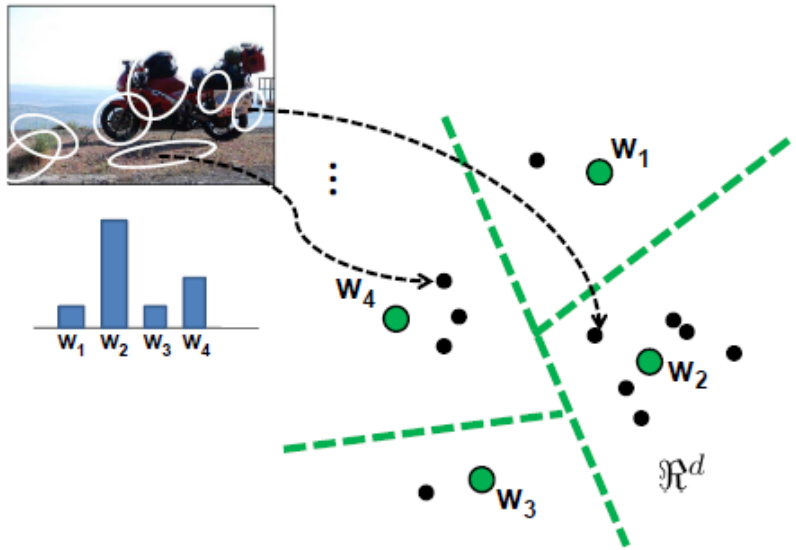
- **Novel aggregation mechanisms**
- Efficient indexing

Conclusions

Motivation for new aggregation mechanisms

BOV is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**?



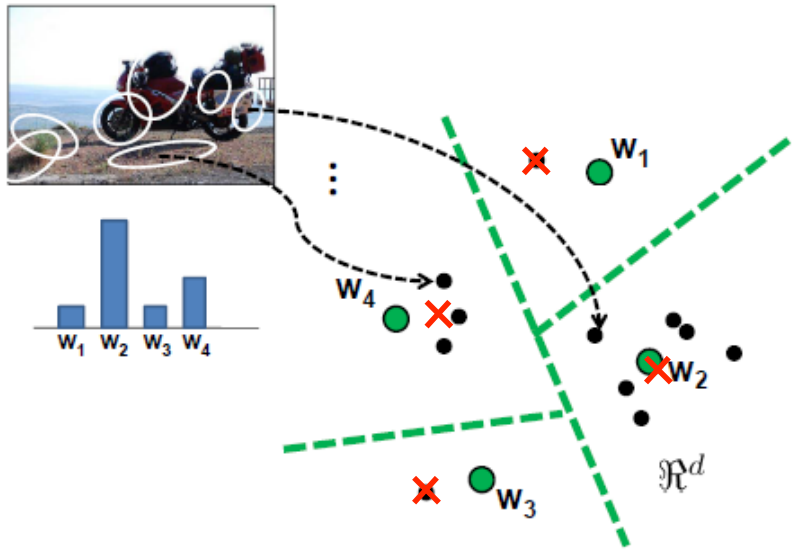
http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

BOV is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**? For instance:

mean of local descriptors ×



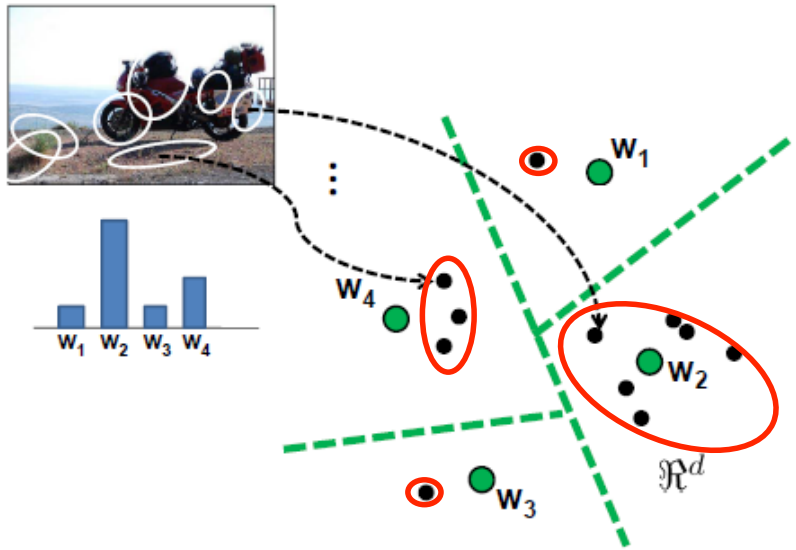
http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

BOV is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**? For instance:

- mean of local descriptors
- (co)variance of local descriptors

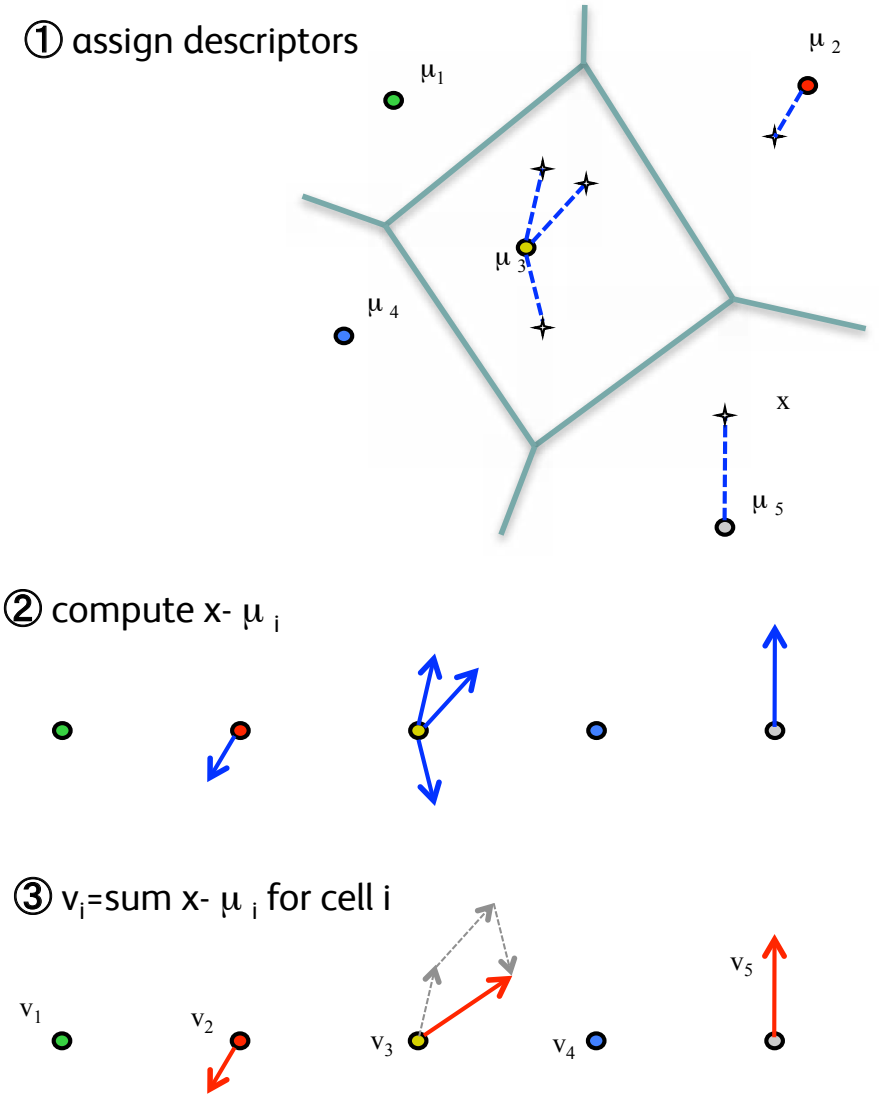


http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

A first example: the VLAD

Given a codebook $\{\mu_i, i = 1 \dots N\}$,
e.g. learned with K-means, and a set of local descriptors $X = \{x_t, t = 1 \dots T\}$:

- ① assign: $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$
- ②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$
- concatenate v_i's + ℓ_2 normalize



Jégou, Douze, Schmid and Pérez, "Aggregating local descriptors into a compact image representation", CVPR'10.

A first example: the VLAD

A graphical representation of $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$

Jégou, Douze, Schmid and Pérez, “Aggregating local descriptors into a compact image representation”, CVPR’10.

The Fisher vector

Score function

Given a likelihood function u_λ with parameters λ, the **score function** of a given sample X is given by:

$$G_\lambda^X = \nabla_\lambda \log u_\lambda(X)$$

→ Fixed-length vector whose **dimensionality depends only on # parameters**.

Intuition: direction in which the parameters λ of the model should we modified to better fit the data.

The Fisher vector

Fisher information matrix

Fisher information matrix (FIM) or negative Hessian:

$$F_\lambda = E_{x \sim u_\lambda} \left[\nabla_\lambda \log u_\lambda(x) \nabla_\lambda \log u_\lambda(x)' \right]$$

Measure similarity between using the **Fisher Kernel (FK)**:

$$K(X, Y) = G_\lambda^{X\prime} F_\lambda^{-1} G_\lambda^Y$$

Jaakkola and Haussler, "Exploiting generative models in discriminative classifiers", NIPS'98.

→ can be interpreted as a score whitening

The Fisher information matrix can be decomposed as $F_\lambda^{-1} = L_\lambda' L_\lambda$

and the FK can be rewritten as a dot product between **Fisher Vectors** (FV):

$$\mathcal{G}_\lambda^X = L_\lambda G_\lambda^X$$

The Fisher vector

Application to images

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

$$G_\lambda^X = \frac{1}{T} \sum_{t=1}^{T} \nabla_\lambda \log u_\lambda(x_t)$$

→ **average pooling** is a direct consequence of independence assumption

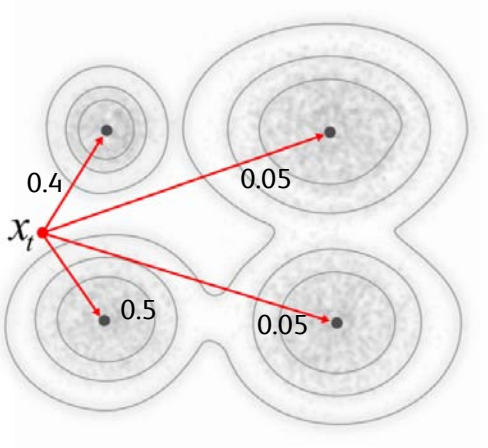
$u_\lambda(x) = \sum_{i=1}^{K} w_i u_i(x)$ is a Gaussian Mixture Model (GMM)
with parameters $\lambda = \{w_i, \mu_i, \Sigma_i, i = 1 \dots N\}$ trained on a large set of local descriptors
→ a probabilistic **visual vocabulary**

Perronnin and Dance, "Fisher kernels on visual categories for image categorization", CVPR'07.

The Fisher vector

Relationship with the BOV

FV formulas:



Perronnin and Dance, “Fisher kernels on visual categories for image categorization”, CVPR’07.

The Fisher vector

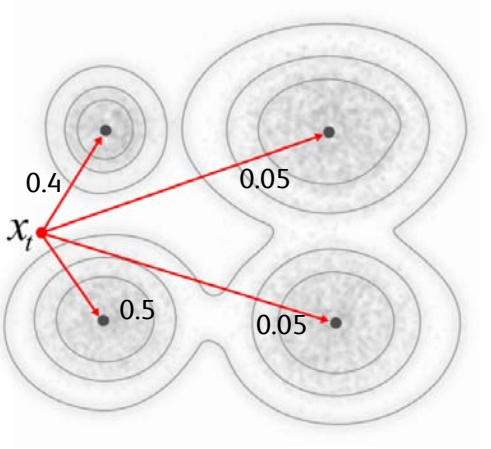
Relationship with the BOV

FV formulas:

- gradient wrt to w

≈ $\boxed{\frac{1}{T}\sum_{t=1}^{T}\gamma_t(i)}$

→ **soft BOV**



$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

Perronnin and Dance, “Fisher kernels on visual categories for image categorization”, CVPR’07.

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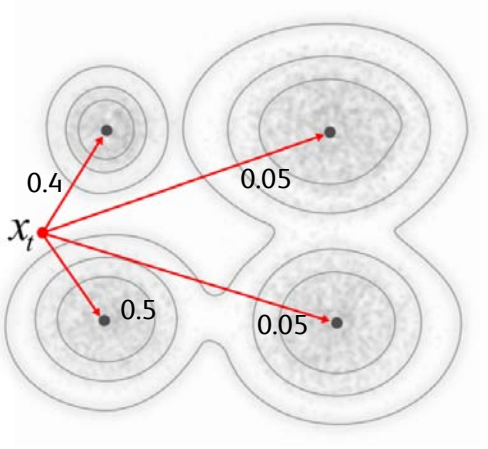


- gradient wrt to μ and σ

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

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

$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

→ compared to BOV, include **higher-order statistics** (up to order 2)

Let us denote: D = feature dim, N = # Gaussians

- BOV = N-dim
- FV = 2DN-dim

Perronnin and Dance, "Fisher kernels on visual categories for image categorization", CVPR'07.

The Fisher vector

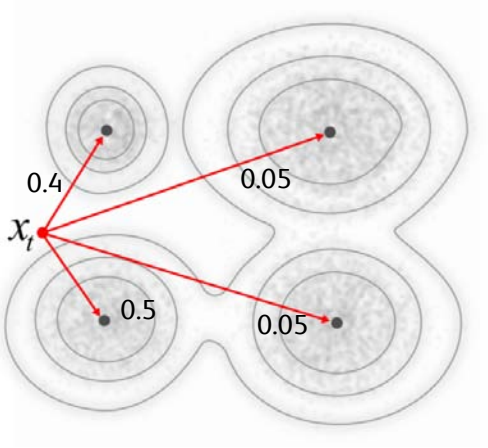
Relationship with the BOV

FV formulas:

- gradient wrt to w

≈ $\frac{1}{T}\sum_{t=1}^{T}\gamma_t(i)$

→ **soft BOV**



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$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

→ compared to BOV, include **higher-order statistics** (up to order 2)

→ FV **much higher-dim** than BOV for a **given visual vocabulary size**

→ FV **much faster to compute** than BOV for a **given feature dim**

Perronnin and Dance, "Fisher kernels on visual categories for image categorization", CVPR'07.

The Fisher vector

Dimensionality reduction on local descriptors

Perform PCA on local descriptors:

→ uncorrelated features are more consistent with diagonal assumption of covariance matrices in GMM

→ FK performs whitening and enhances low-energy (possibly noisy) dimensions

The Fisher vector

Dimensionality reduction on local descriptors

Perform PCA on local descriptors:

→ uncorrelated features are more consistent with diagonal assumption of covariance matrices in GMM

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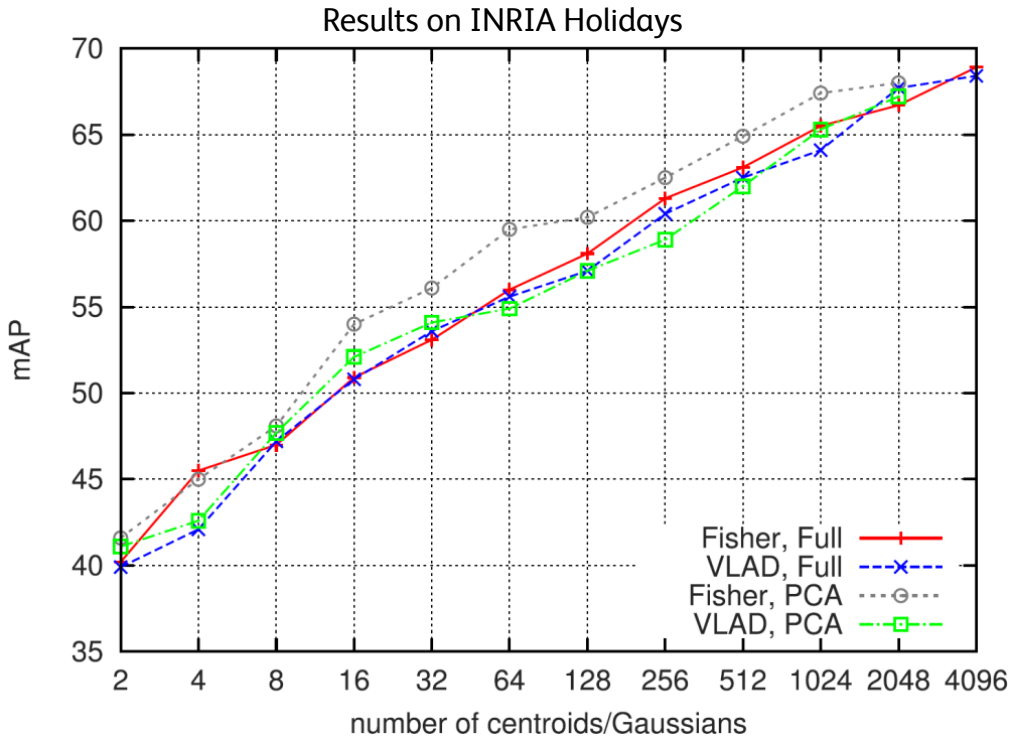

Jégou, Perronnin, Douze, Sánchez, Pérez and Schmid, "Aggregating local descriptors into compact codes", TPAMI'12.

The Fisher vector: power-law

As in BOV, the Fisher vector representation suffers from

1) Over-counting similar pattern

2) Bursty visual elements [J'09]

Effective solution: Signed component-wise Power-law

$$f(z) = \text{sign}(z)|z|^{\alpha} \text{ with } 0 \leq \alpha \leq 1$$

(with α=0.5 by default)

Perronnin, Sánchez and Mensink, "Improving the Fisher kernel for large-scale image classification", ECCV'10.

Relationship between VLAD and Fisher

→ The VLAD can be viewed as a non-probabilistic version of the FV:

→ replace GMM clustering by k-means

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

Main differences: in contrast to VLAD, Fisher

- Performs **soft assignment** of descriptors
- Implicitly **whiten** the components
- High-order statistics are included

→ extension of the VLAD to include 2nd order statistics: VLAT

Picard and Gosselin, "Improving image similarity with vectors of locally aggregated tensors", ICIP '11.

Remark on the supervector [Zhou 11]: **SV ≈ BOV + VLAD**

Examples
Retrieval

Example on Holidays:

From: Jégou, Perronnin, Douze, Sánchez, Pérez and Schmid, "Aggregating local descriptors into compact codes", TPAMI'12.

Descriptor	K	D	Holidays (mAP)					
			$D' = D$	$\rightarrow D'$=2048	$\rightarrow D'$=512	$\rightarrow D'$=128	$\rightarrow D'$=64	$\rightarrow D'$=32
BOW	1 000	1 000	40.1		43.5	44.4	43.4	40.8
	20 000	20 000	43.7	41.8	44.9	45.2	44.4	41.8
Fisher (μ)	16	1 024	54.0		54.6	52.3	49.9	46.6
	64	4 096	59.5	60.7	61.0	56.5	52.0	48.0
	256	16 384	62.5	62.6	57.0	53.8	50.6	48.6
VLAD	16	1 024	52.0		52.7	52.6	50.5	47.7
	64	4 096	55.6	57.6	59.8	55.7	52.3	48.4
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→ soft assignment + whitening of FV helps when number of Gaussians ↑

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→ second order statistics are not essential for retrieval

→ even for the same feature dim, the FV/VLAD can beat the BOV

→ soft assignment + whitening of FV helps when number of Gaussians ↑

→ after dim-reduction however, the FV and VLAD perform similarly

Packages for Fisher vectors

The INRIA package (VLAD also available):
http://lear.inrialpes.fr/src/inria_fisher/

The Oxford package:
http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/

Questions?

Larger-scale visual recognition
Efficient matching

Hervé Jégou, INRIA

informatics mathematics

General outline

- PART I: Introduction
  - Applications and datasets
  - Image description and matching
- PART II: Large-scale image search
  - The bag-of-word representation and some extension
- **PART III: Larger-scale image search**
  - Novel aggregation mechanisms
  - **Efficient indexing**
- Conclusions

Efficient matching: outline

- **Preliminary**
- Locality Sensitive Hashing: the two modes
- Hamming Embedding
- Searching with Product Quantization

Finding neighbors

- Nearest neighbor search is a critical step in object recognition
  - To compute the image descriptor itself
    E.g., assignment with k-means to a large vocabulary
  - To find the most similar images/patches in a database
  - For instance, the closest one w.r.t to Euclidean distance:

$$\mathrm{NN}(x) = \arg\min_{y \in \mathcal{Y}} ||x - y||^2$$

- Problems:
  - costly operation of exact exhaustive search: O(n*d)
  - High-dimensional vectors: for exact search the best approach is the naïve exhaustive comparison

The cost of (efficient) exact matching

- But what about the actual timings ? With an efficient implementation!

- Finding the 10-NN of 1000 distinct queries in 1 million vectors
  - Assuming 128-D Euclidean descriptors
  - i.e., 1 billion distances, computed on a 8-core machine

Poll: How much time?

The cost of (efficient) exact matching

- But what about the actual timings ? With an efficient implementation!

- Finding the 10-NN of 1000 distinct queries in 1 million vectors
  - Assuming 128-D Euclidean descriptors
  - i.e., 1 billion distances, computed on a 8-core machine

  5.5 seconds

- Assigning 2000 SIFTs to a visual vocabulary of size k=100,000
  - 1.2 second

Need for approximate nearest neighbors

- 1 million images, 1000 descriptors per image
  - 1 billion distances per local descriptor
  - 10^{12} distances in total
  - 1 hour 30 minutes to perform the query for Euclidean vectors

- To improve the scalability:
  - We allow to find the nearest neighbors in probability only:
    Approximate nearest neighbor (ANN) search

- Three (contradictory) performance criteria for ANN schemes
  - search quality (retrieved vectors are actual nearest neighbors)
  - speed
  - memory usage

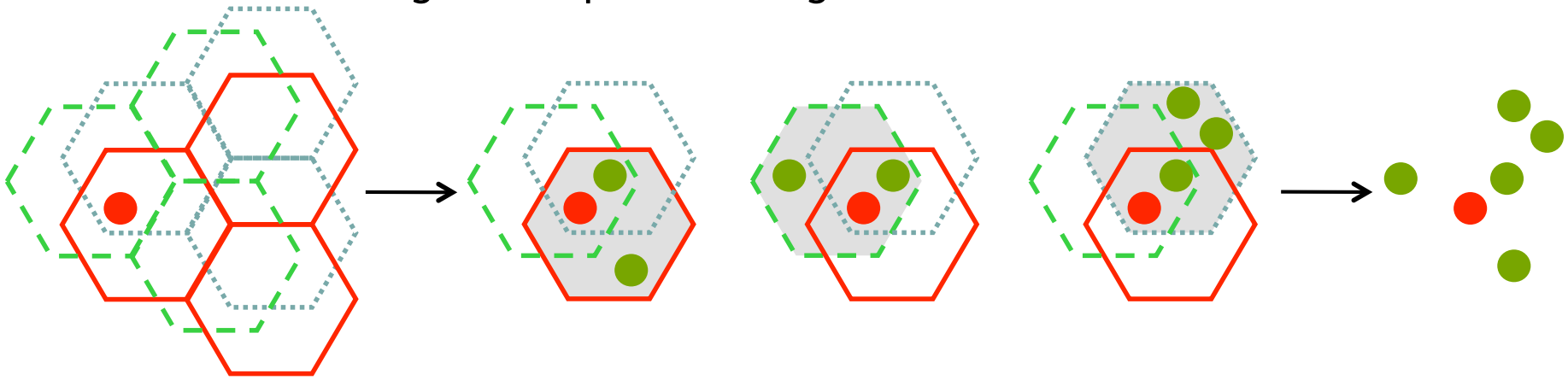
Efficient matching: outline

- Preliminary
- **Locality Sensitive Hashing: the two modes**
- Hamming Embedding
- Searching with Product Quantization

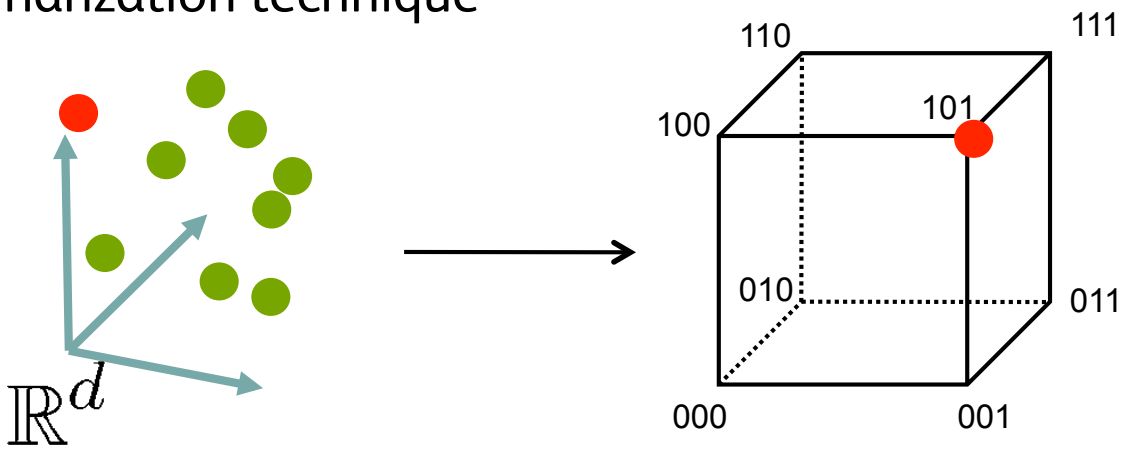
Locality Sensitive Hashing (LSH)

- Most known ANN technique [Charikar 98, Gionis 99, Datar 04,…]

- But “LSH” is associated with two distinct search algorithms
  - As an indexing technique involving several hash functions

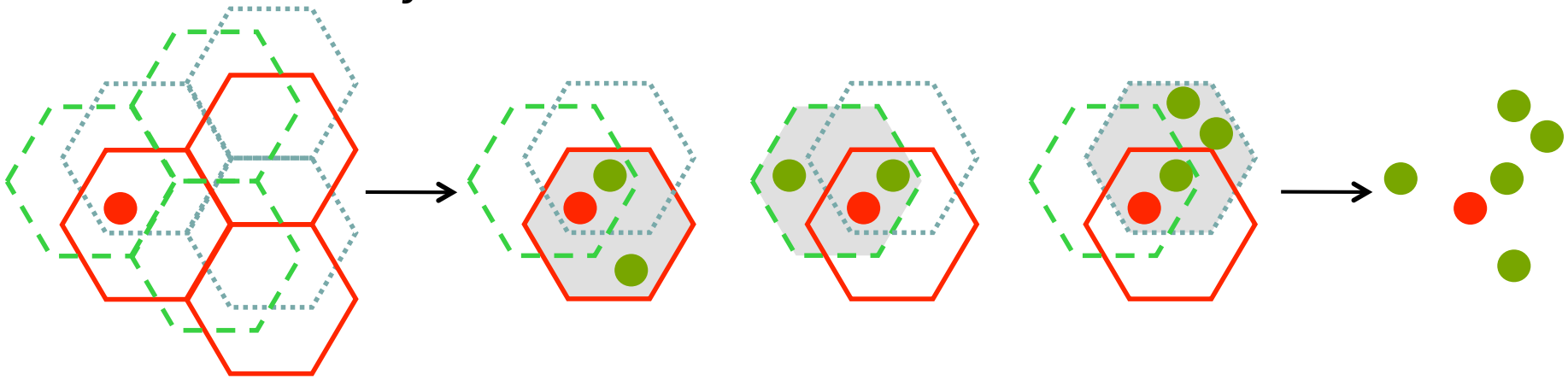


  - As a binarization technique



LSH – partitioning technique

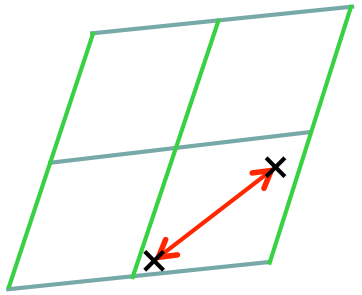
- General idea:
  - Define m hash functions in parallel
  - Each vector: associated with m distinct hash keys
  - Each hash key is associated with a hash table



- At query time:
  - Compute the hash keys associated with the query
  - For each hash function, retrieve all the database vectors assigned to the same key (for this hash function)
  - Compute the exact distance on this short-list

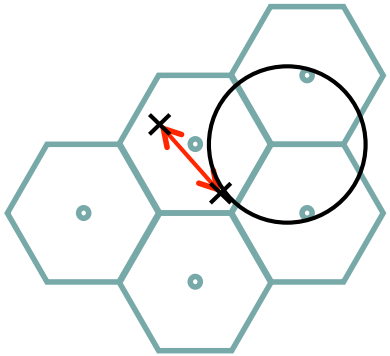
What kind of hash functions/partitions ?

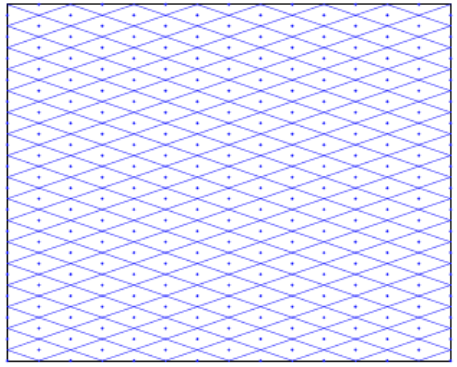
- Any hash function can be used in LSH
  - Just need a set of functions $f_j : \mathbb{R}^d \to \mathbb{K}$



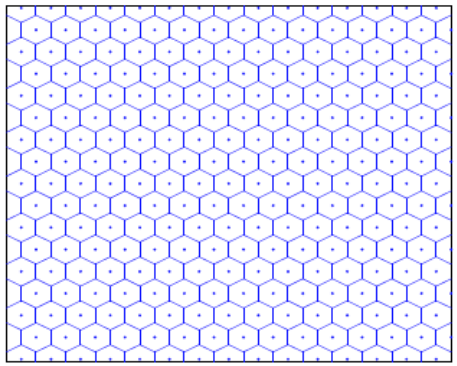
- Usually, random projection + scalar quantization

- Could be
  - Structured lattice quantizers [Andoni'06, J'08]
  - k-means, Hierarchical k-means, KD-trees

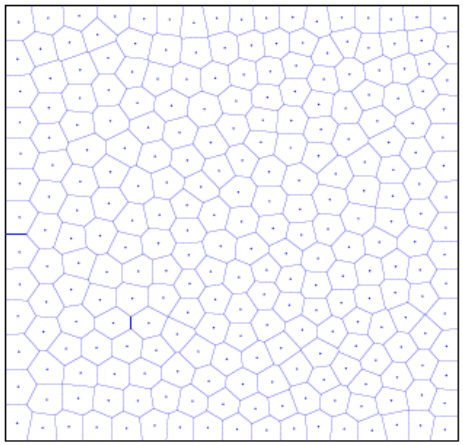




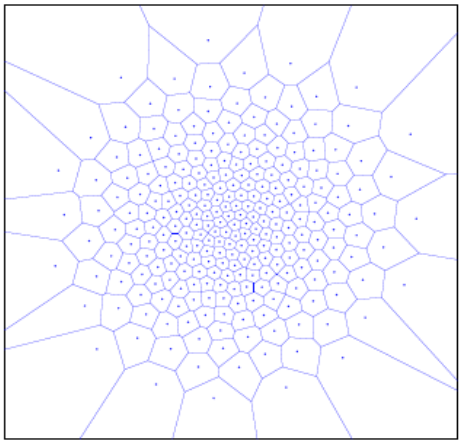
(a) Random projections



(b) A_2 lattice



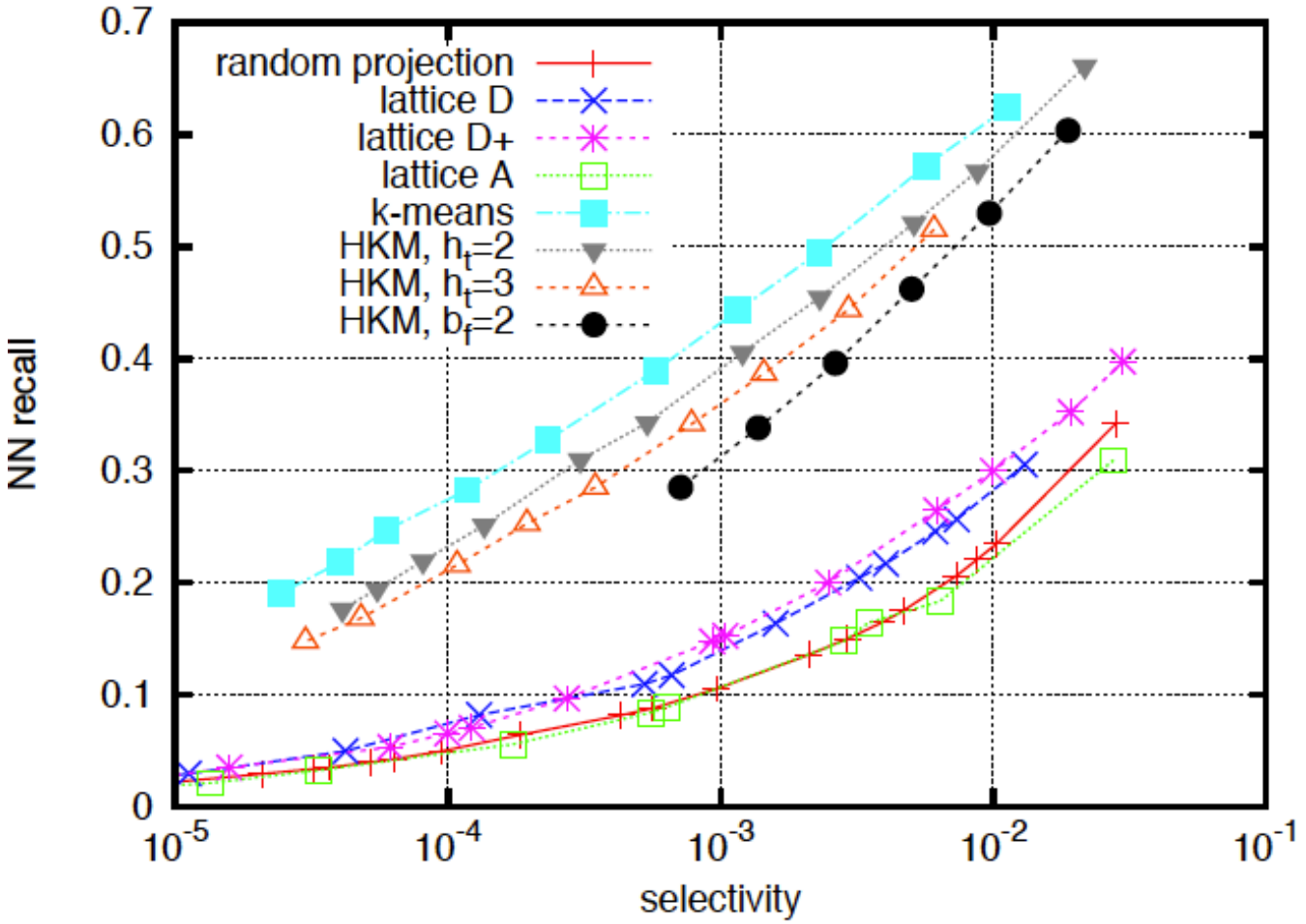
(c) k-means
Uniform distribution



(d) k-means
Gaussian distribution

Hash functions – Structured *vs* Learned

- Learned quantizers are better than structured quantizers
- Evaluation search quality for a **single** hash function [Pauleve'10]:



- HKM : loss compared with k-means

Multi-probe LSH

- But multiple hash functions use a lot of memory
  - Per vector and per hash table: at least an id

- Multi-probe LSH [Lv 07]
  - Use less hash functions (possibly 1)
  - But probe several (closest) cells per hash function

    ⇨ save a lot of memory
  - Similar in spirit to Multiple-assignment with BOV

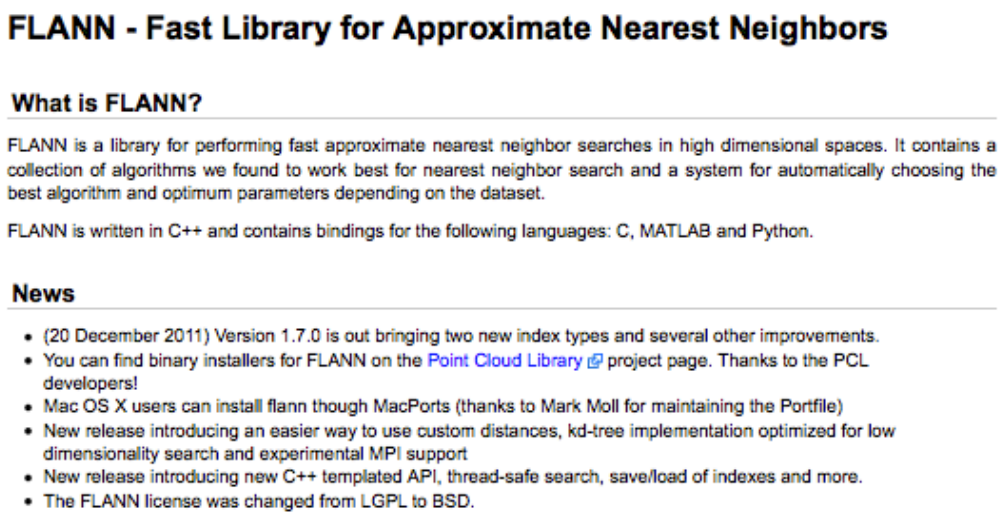
FLANN

- ANN package described in Muja's VISAPP paper [Muja 09]
  - Multiple kd-tree or k-means tree
  - With auto-tuning under given constraints

    Remark: self-tuned LSH proposed in [Dong 07]
  - Still high memory requirement for large vector sets

- Excellent package: high integration quality and interface!

- See http://www.cs.ubc.ca/~mariusm/index.php/FLANN/FLANN



FLANN - Fast Library for Approximate Nearest Neighbors

What is FLANN?

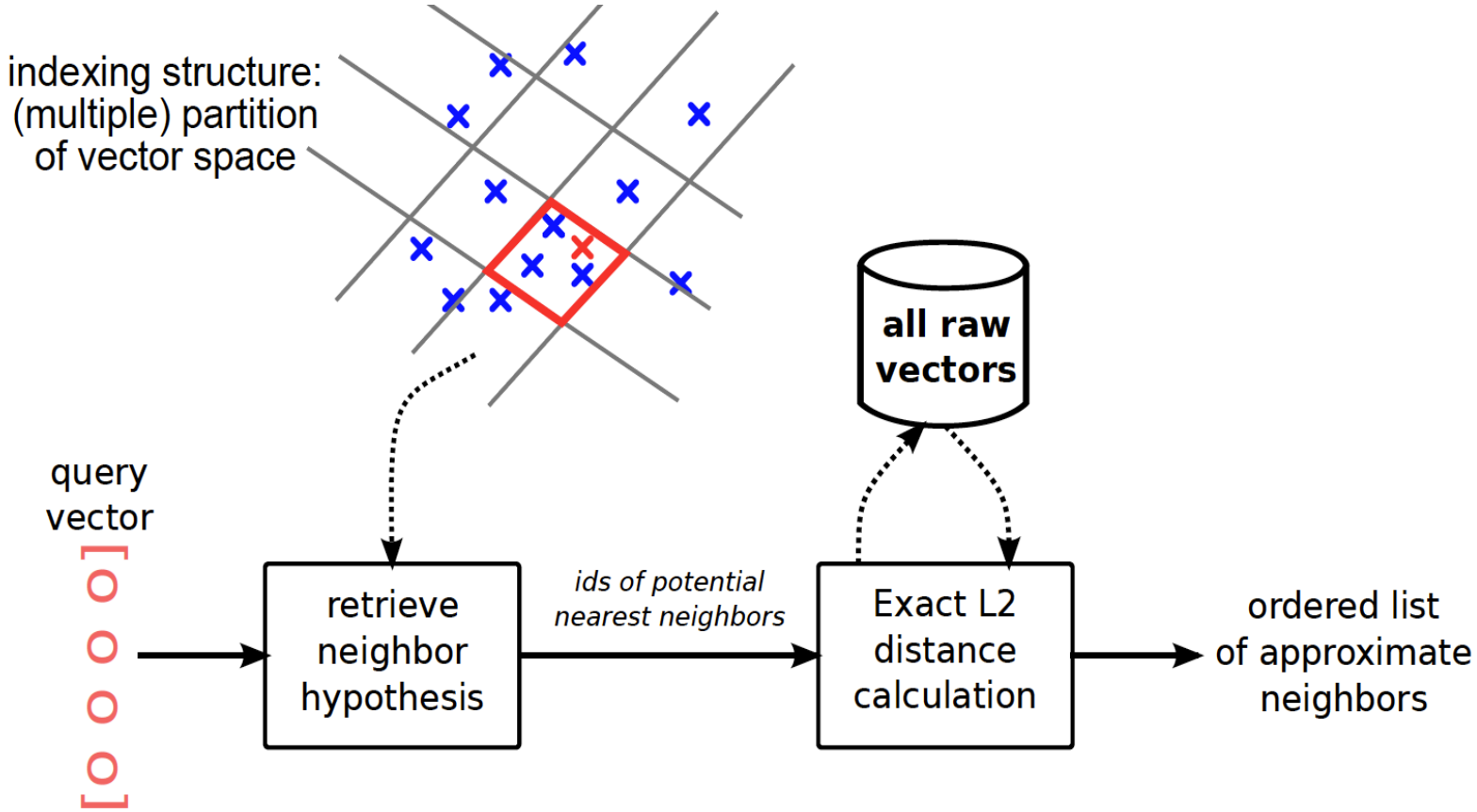
FLANN is a library for performing fast approximate nearest neighbor searches in high dimensional spaces. It contains a collection of algorithms we found to work best for nearest neighbor search and a system for automatically choosing the best algorithm and optimum parameters depending on the dataset.

FLANN is written in C++ and contains bindings for the following languages: C, MATLAB and Python.

News

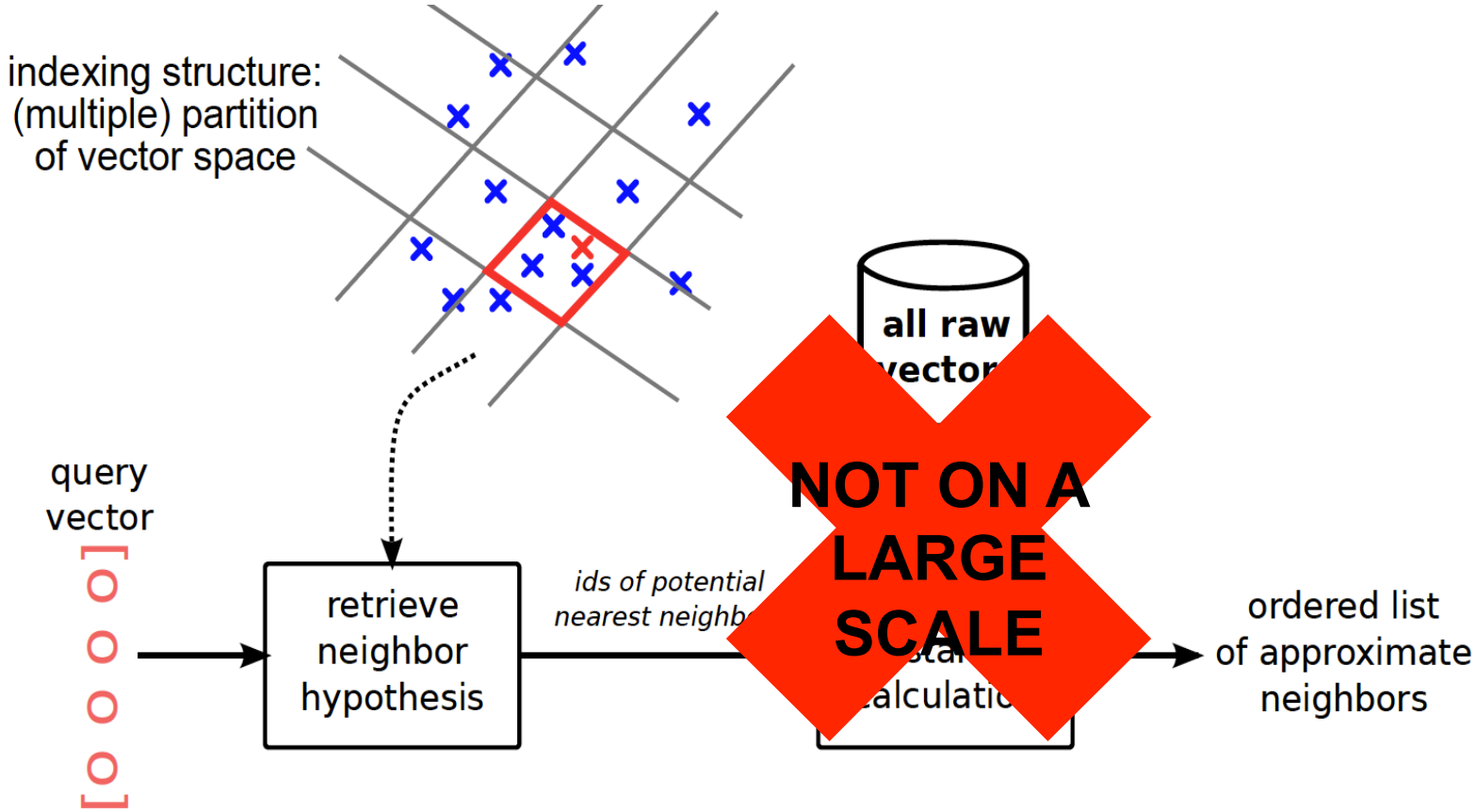
- (20 December 2011) Version 1.7.0 is out bringing two new index types and several other improvements.
- You can find binary installers for FLANN on the Point Cloud Library project page. Thanks to the PCL developers!
- Mac OS X users can install flann though MacPorts (thanks to Mark Moll for maintaining the Portfile)
- New release introducing an easier way to use custom distances, kd-tree implementation optimized for low dimensionality search and experimental MPI support
- New release introducing new C++ templated API, thread-safe search, save/load of indexes and more.
- The FLANN license was changed from LGPL to BSD.

Issue for large scale: final verification



- For this second ("re-ranking") stage, we need raw descriptors, i.e.,
  - either huge amount of memory → 128GB for 1 billion SIFTs
  - either to perform disk accesses → severely impacts efficiency

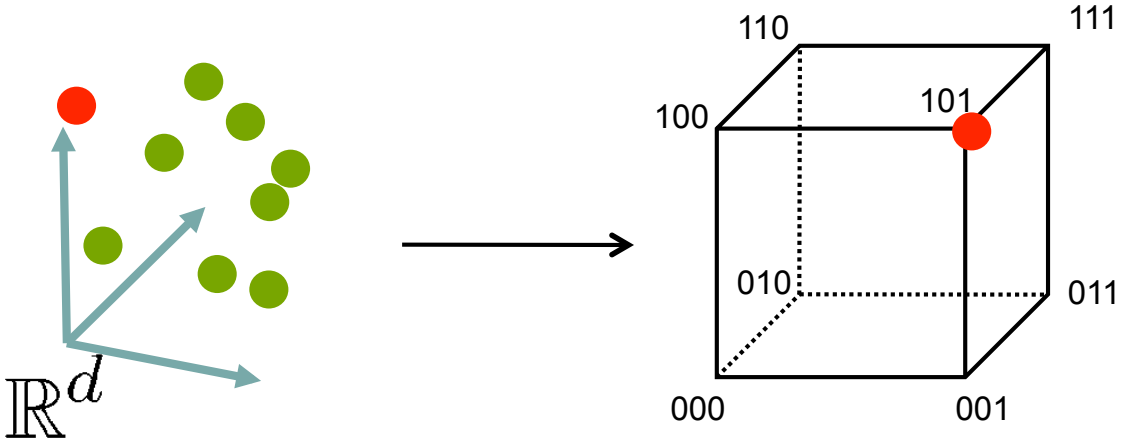
Issue for large scale: final verification



- Some techniques –like BOV– keep all vectors (no verification)

- Better: use very short codes for the filtering stage
  - Hamming Embedding [J'08] or Product Quantization [J'11]

LSH for binarization [Charikar' 98, J.'08, Weiss'09, etc]



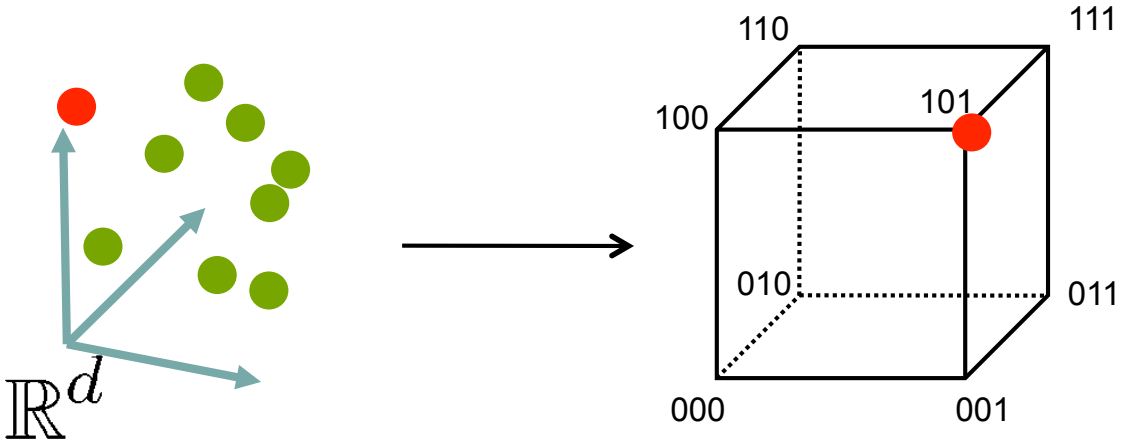
- Idea: design/learn a function mapping the original space into the compact Hamming space:

$$e : \mathbb{R}^d \rightarrow \{0,1\}^D$$
$$x \rightarrow e(x)$$

- Objective: neighborhood in the Hamming space try to reflect original neighborhood $\arg\min_i h\left(e(x), e(y_i)\right) \approx \arg\min_i d(x, y)$

- Advantages: compact descriptor, fast comparison

LSH for binarization [Charikar' 98, J.'08, Weiss'09, etc]



- Given B random projection direction a_i
- Compute a binary code from a vector x as

$$b_i(x) = \text{sign } a_i^\top x$$

$$b(x) = (b_1(x), \ldots, b_B(x))$$

- Spectral Hashing: theoretical framework for finding hash functions
- In practice: PCA + binarization on the different axis (based on variance)

LSH: the two modes – approximate guidelines

Partitioning technique

- **Sublinear/non exhaustive** search
- Several hash indexes (integer)
- **Large memory overhead**
  - Hash table overhead (store ids)
- Need original vectors for re-ranking
  - **Need a lot of memory**
  - **Or to access the disk**
- Interesting when (e.g., FLANN)
  - Not too large dimensionality
  - Dataset small enough (memory)
- Very good variants/software (FLANN)

Binarization technique

- **Linear** search
- Produce a binary code per vector
- **Very compact**
  - bit-vectors, concatenated (no ids)
- **Very fast comparison**
  - Hamming distance (popcnt SSE4)
  - 1 billion comparisons/second
- Interesting
  - For **very high-dimensional** vectors
  - When memory is critical
- Simple to implement. Very active problems with many variants

LSH: the two modes – approximate guidelines

Partitioning technique

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- Dataset small enough (memory)
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Typical usage:

Searching local descriptors

Typical usage:

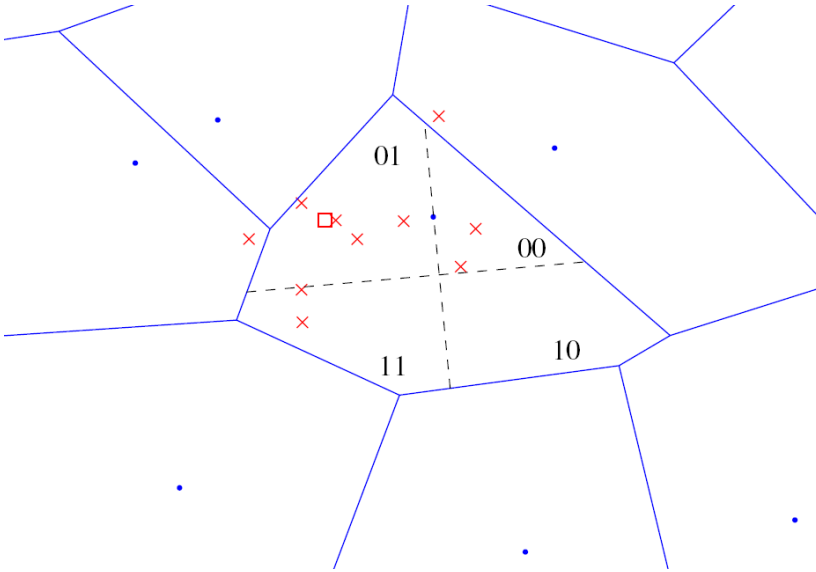
Index global (or aggregated) descriptors

Outline

- Preliminary
- Locality Sensitive Hashing: the two modes
- **Hamming Embedding**
- Searching with Product Quantization

Hamming Embedding

- Introduced as an extension of BOV [J'08]



- Combination of
  - A partitioning technique (k-means)
  - A binary code that refine the descriptor

Representation of a descriptor x

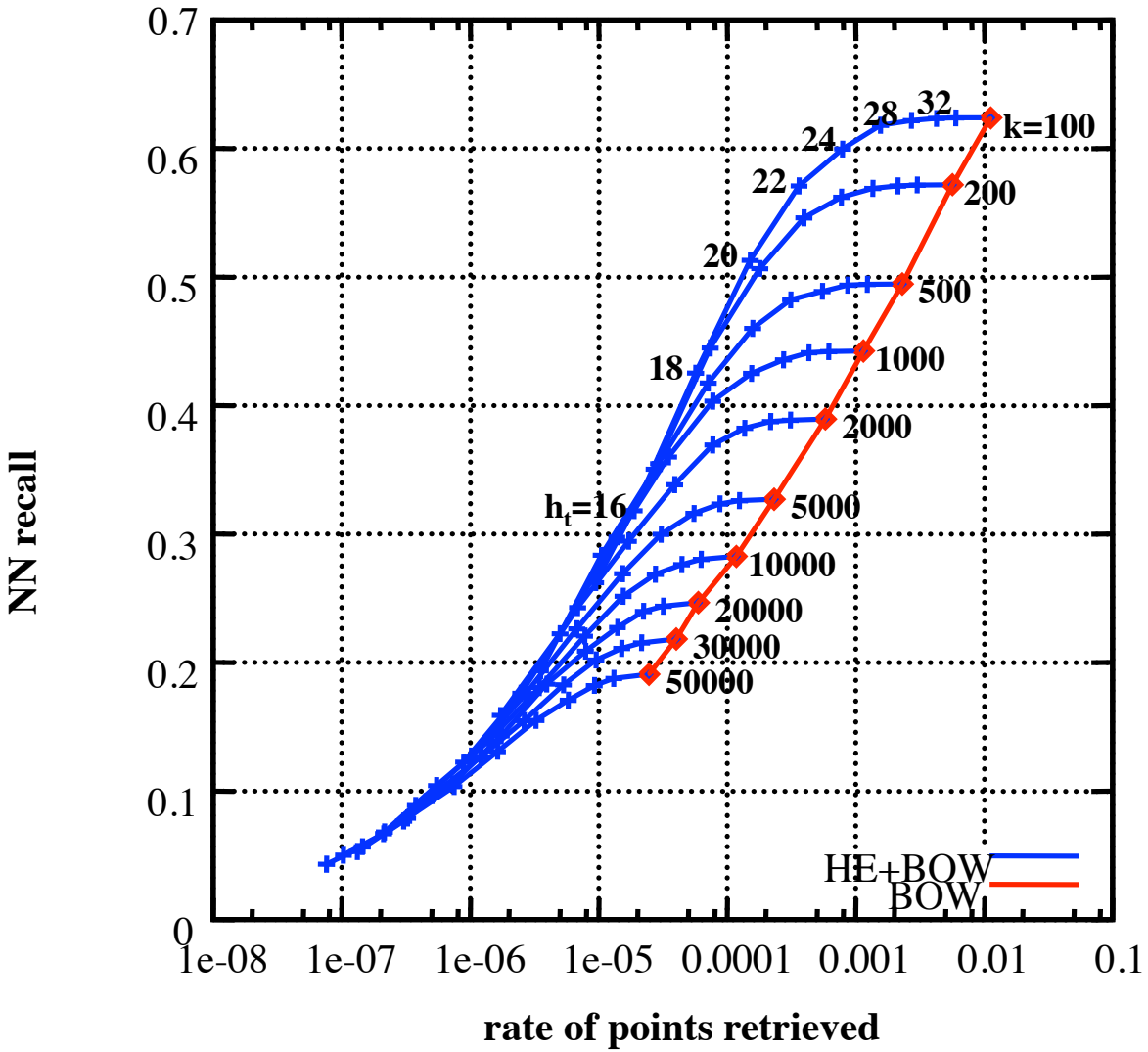
- Vector-quantized to q(x) as in standard BOV
- \+ short binary vector b(x) for an additional localization in the Voronoi cell

- Two descriptors x and y match iif

$$f_{\mathrm{HE}}(x,y) = \begin{cases} (\text{tf-idf}(q(x)))^2 & \text{if } q(x) = q(y) \\ & \quad \text{and } h\left(b(x), b(y)\right) \leq h_t \\ 0 & \text{otherwise} \end{cases}$$

Where h(.,.) denotes the Hamming distance

ANN evaluation of Hamming Embedding



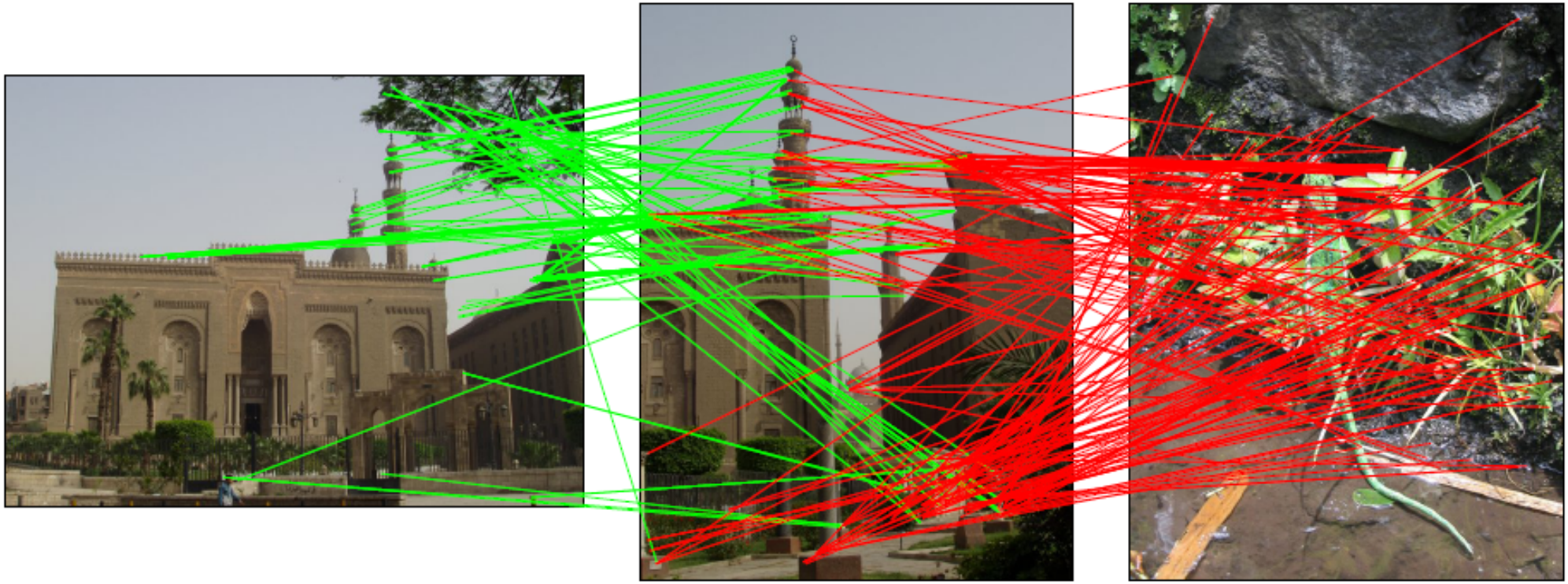
compared to BOW: at least 10 times less points in the short-list for the same level of accuracy

Hamming Embedding provides a much better trade-off between recall and remove false positives

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 + HE

83 matches

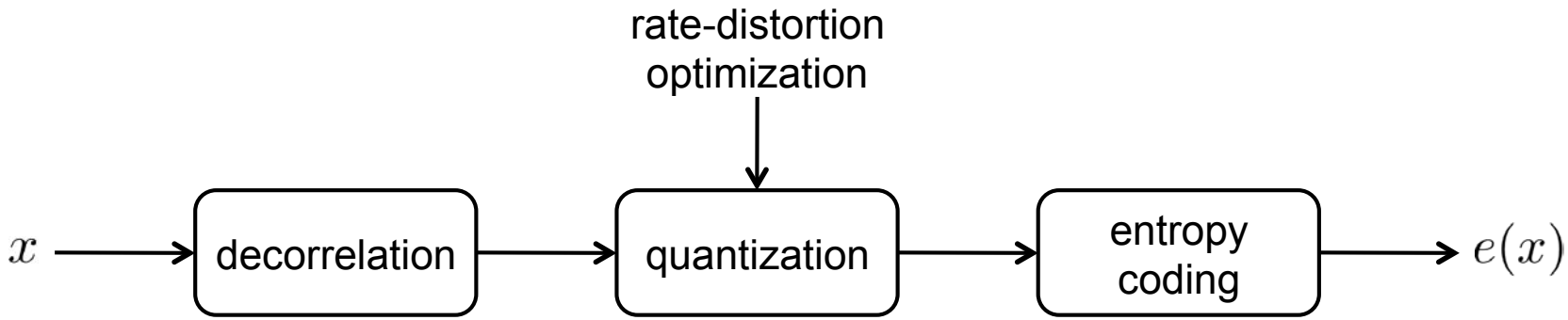
8 matches

10x more matches with the corresponding image!

Outline

- Preliminary
- Locality Sensitive Hashing: the two modes
- Hamming Embedding
- **Searching with Product Quantization**

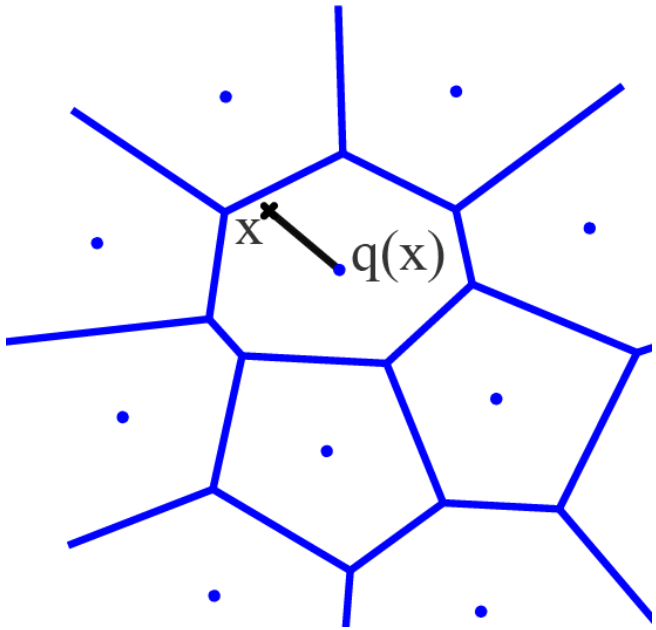
A typical source coding system



- Simple source coding system:
  - Decorrelation, e.g., PCA
  - Quantization
  - Entropy coding

- To a code e(x) is associated a unique reconstruction value q(x)
  ⇨ i.e., the visual word

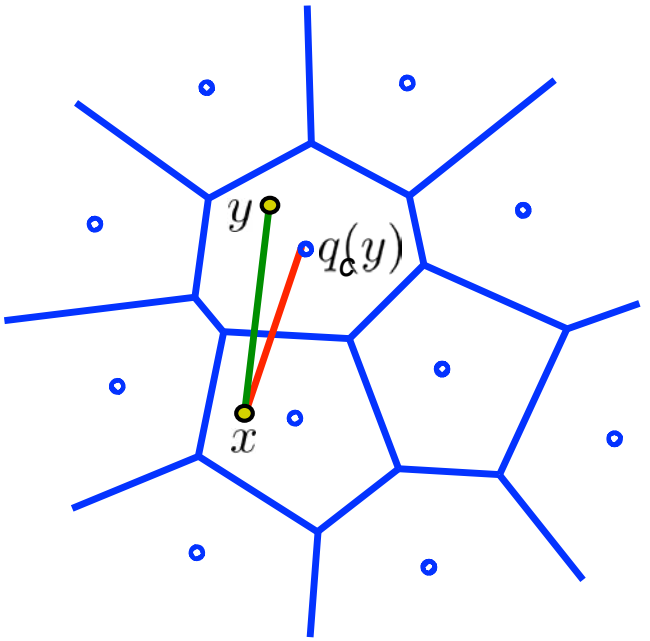
- Focus on quantization (lossy step)



Relationship between Reconstruction and Distance estimation

- Assume y quantized to $q_c(y)$
  x is a query vector

- If we estimate the distance by
$$d(x, y) \approx d(x, q_c(y))$$



- Then we can show that:

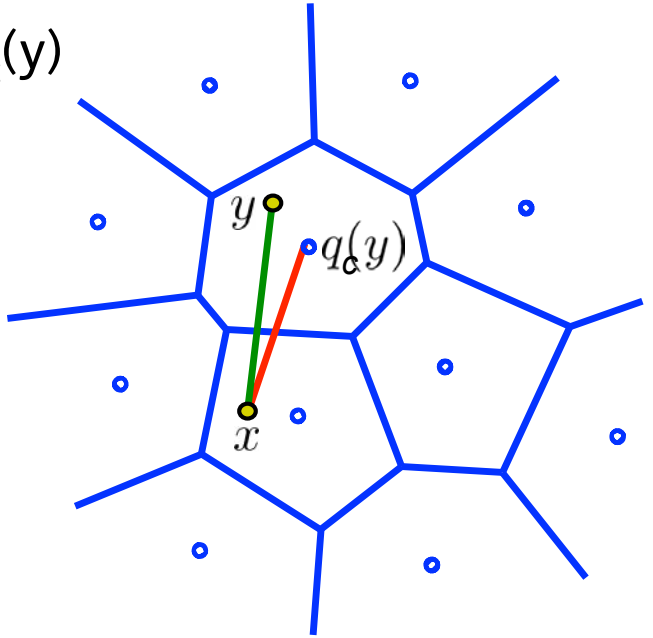
$$\mathbb{E}_Y[(d(x,y) - d(x,q_c(y)))^2] \leq \mathbb{E}_Y[(y - q_c(y))^2] = \mathrm{MSE}$$

i.e., the error on the square distance is statistically bounded by the quantization error

Searching with quantization [J'11]

- Main idea: compressed representation of the database vectors
  - Each database vector y is represented by $q_c(y)$ where $q_c(.)$ is a **product quantizer**

$$d(x, y) \approx d(x, q_c(y))$$



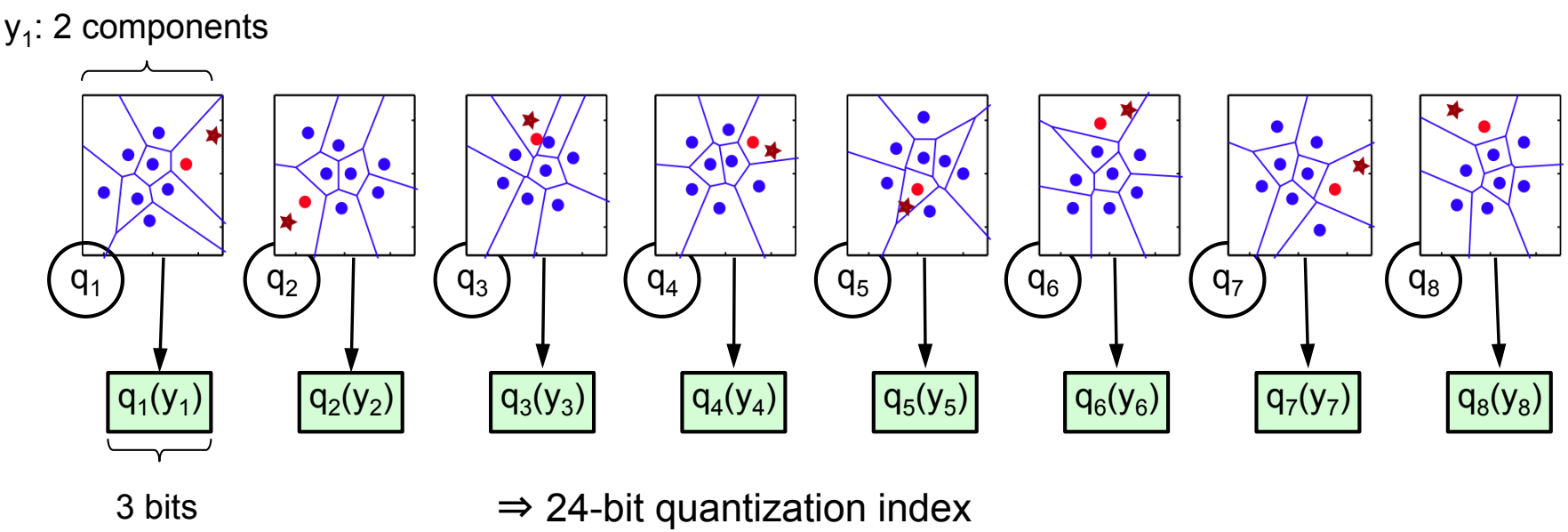
- Search = distance approximation problem

- **The key**: Estimate the distances **in the compressed domain** such that
  - Quantization is fast enough
  - Quantization is precise, i.e., many different possible indexes (ex: 2^{64})

- Regular k-means is not appropriate: not for k=2^{64} centroids

Product Quantizer

- Vector split into m subvectors: $y \rightarrow \left[y_1 | \ldots | y_m\right]$
- Subvectors are quantized separately
- Example: y = 16-dim vector split in 8 subvectors of dimension 16



- In practice: 8 bits/subquantizer (256 centroids),
  - SIFT: m=4-16
  - VLAD/Fisher: 4-128 bytes per indexed vector

Asymmetric distance computation (ADC)

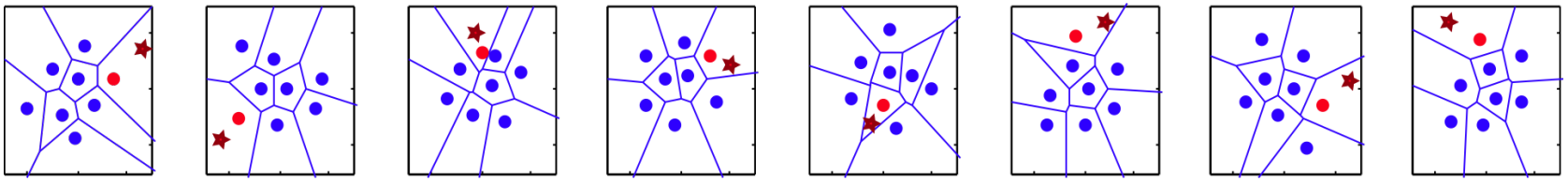
- Compute the square distance approximation in the compressed domain

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

- 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

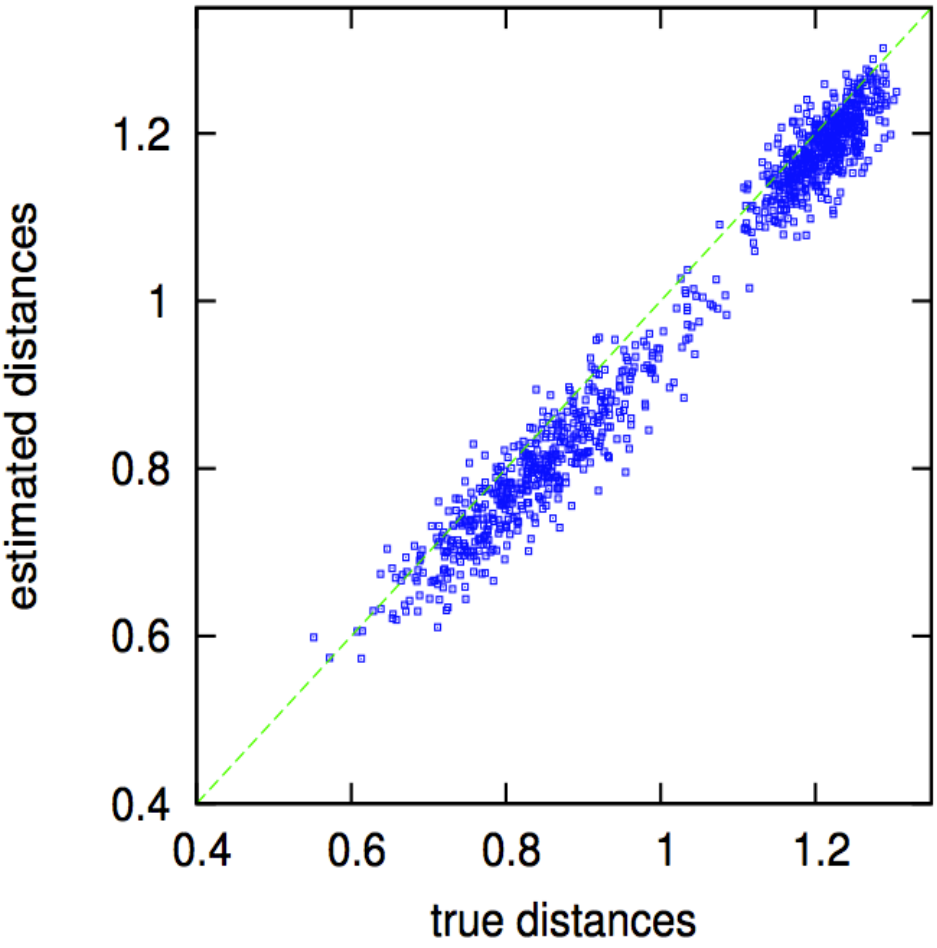
  → stored in look-up tables

  → fixed cost for quantization
  - for each database code: sum the elementary square distances



- Each 8x8=64-bits code requires only **m=8 additions per distance**
- IVFADC: combination with an inverted file to avoid exhaustive search

Estimated distances versus true distances



Combination with an inverted file system

ALGORITHM

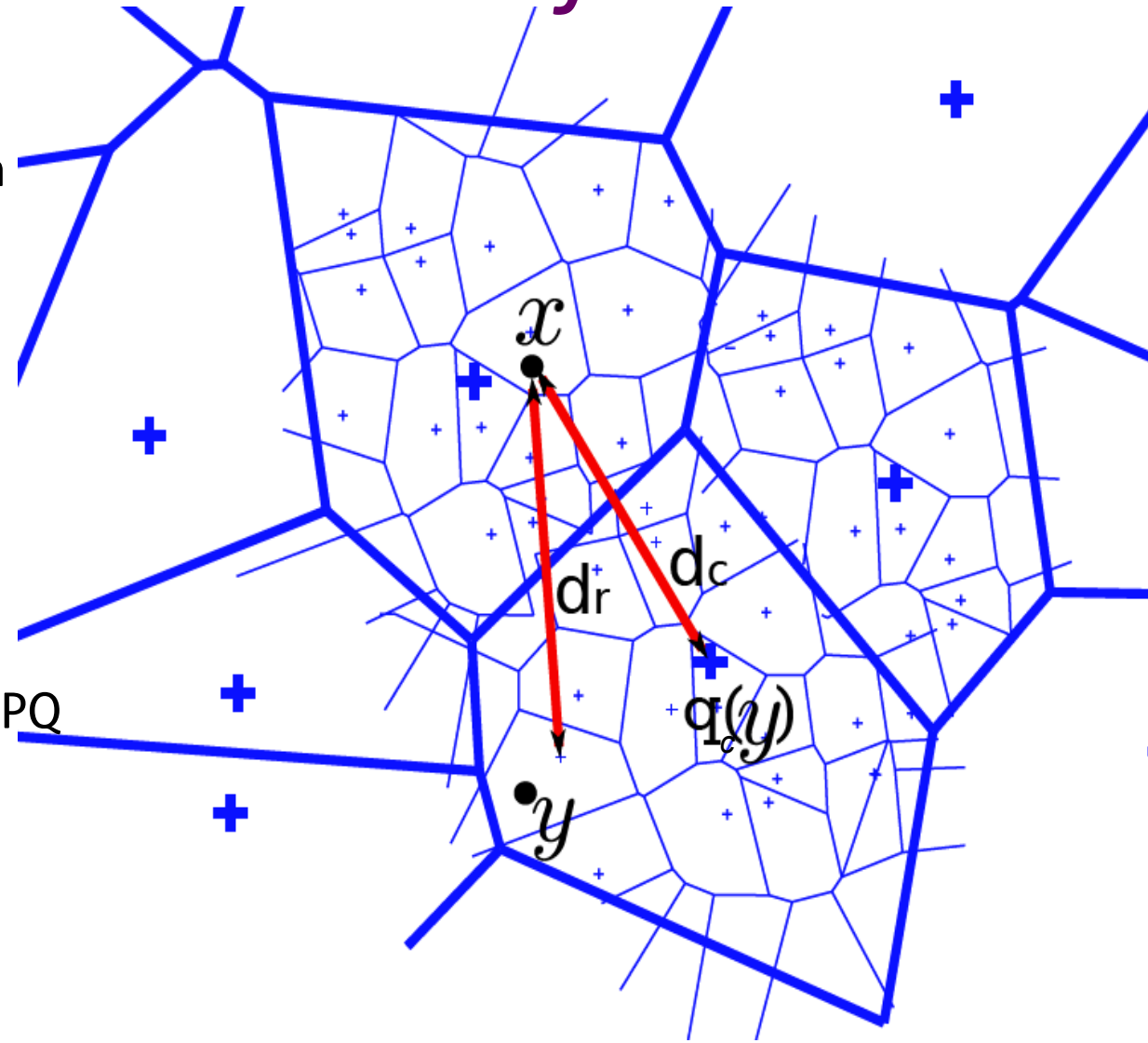
① Coarse k-means hash function

Select k' closest centroids c_i and corresponding cells

② Compute the **residual vector** $x-c_i$ of the query vector

③ Encode the residual vector by PQ

④ Apply the PQ search method. Distance is approximated by $d(x,y) = d(x-c_i, q(y-c_i))$

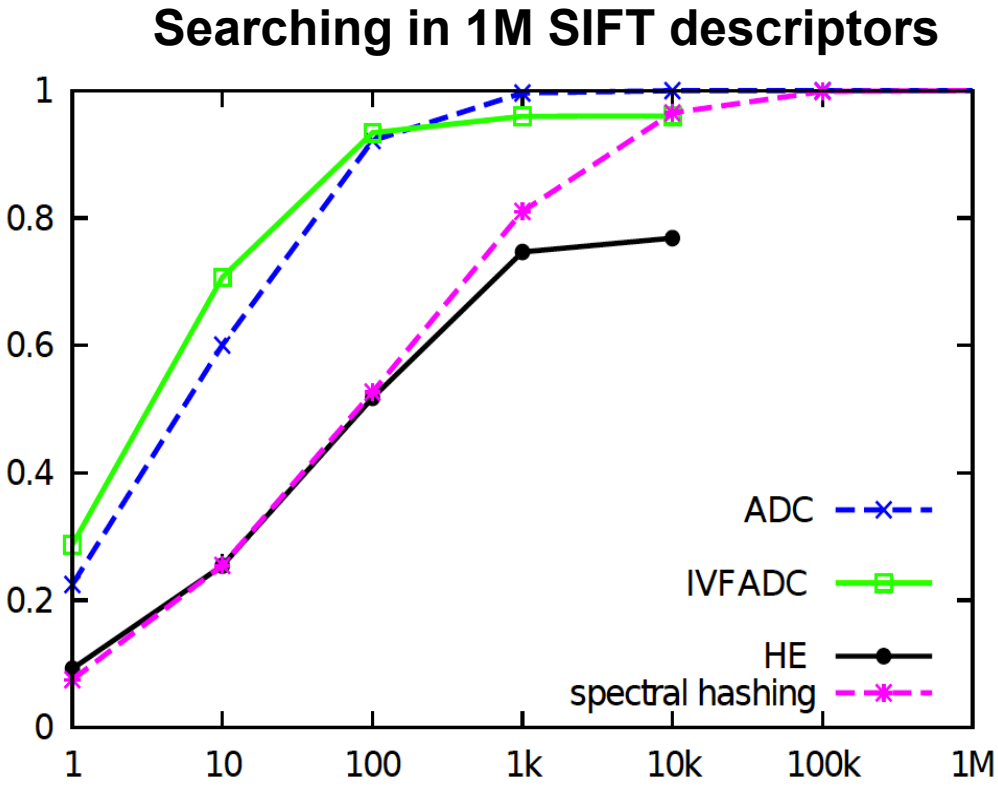


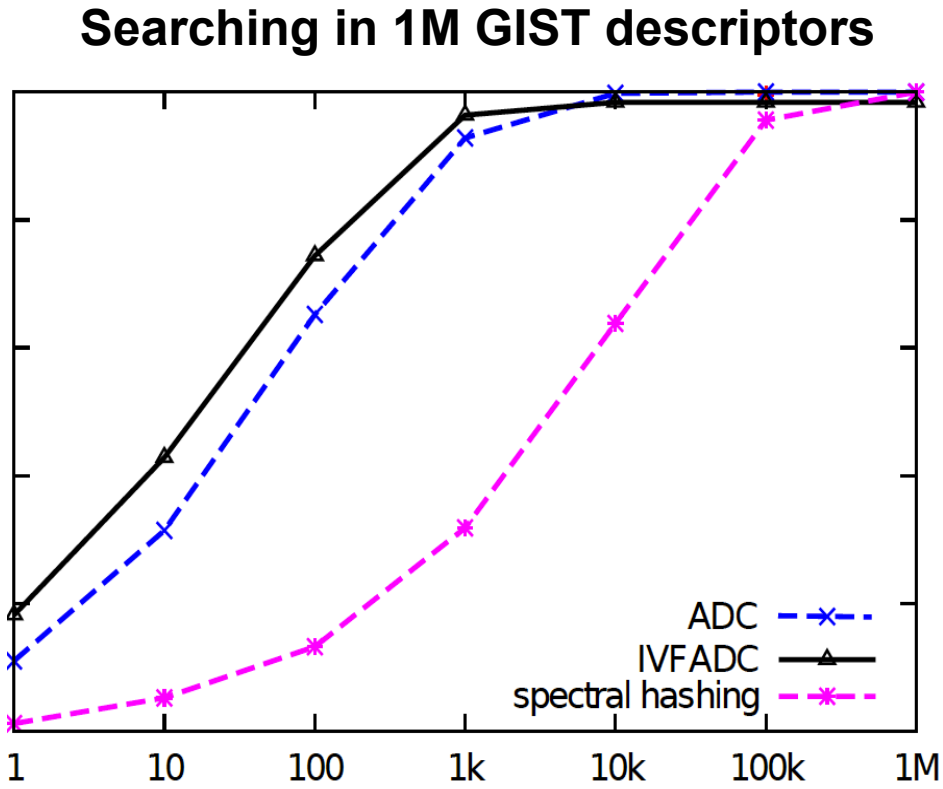
Example timing: 3.5 ms per vector for a search in 2 billion vectors

Performance evaluation

- Comparison with other memory efficient approximate neighbor search techniques, i.e., binarization techniques
  - Spectral Hashing [Weiss 09] – exhaustive search
  - Hamming Embedding [J'08] – non exhaustive search

- Performance measured by searching 1M vector (recall@R, varying R)





Product Quantization: some applications

- PQ search was first proposed for searching local descriptors [J'09-11], i.e., to replace bag-of-words or Hamming Embedding

- [J'10]: Encoding a global image representation (Vlad/Fisher)

- [Gammeter et al'10]: Fast geometrical re-ranking with local descriptors

- [Perronnin et al.'11]: Large scale classification (Imagenet)
  - Combined with Stochastic Gradient Descent SVM
  - Decompression on-the-fly when feeding the classifier
  - Won the ILSVRC competition in 2011

- **Wider scope than pure search: Approximation of the inner product**
  - Learning in the PQ-compressed domain [Vedaldi'12, Harchaoui'12]

Concluding remarks

Nearest neighbor search is a key component of image indexing systems
Must be considered jointly with the image representation!

Product quantization-based approach offers

- Competitive search accuracy
- Compact footprint: few bytes per indexed vector

Tested

- on local image descriptors (up to 2 billions)
- global or aggregated descriptors (200 millions)
- audio, text descriptors
- any descriptor compared with L2 distance/Cosine (and actually more)

Toy Matlab package available on my web page

Larger-scale visual recognition
Conclusion

Hervé Jégou, INRIA

informatics mathematics

General outline

PART I: Introduction

- Applications and datasets
- Image description and matching

PART II: Large-scale image search

- The bag-of-word representation and some extension

PART III: Larger-scale image search

- Novel aggregation mechanisms
- Efficient indexing

Conclusion

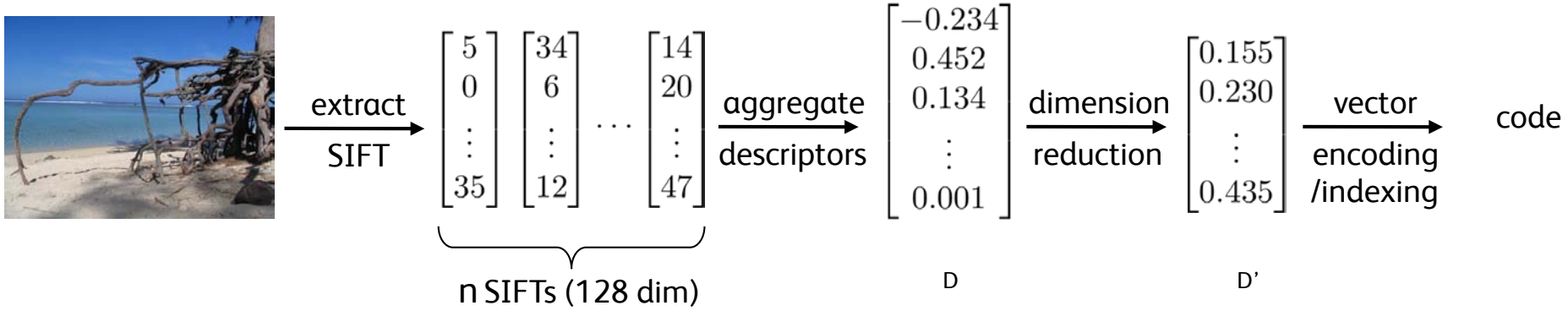
Large-/larger-scale image search

Large-scale (1-5 millions): BOV is still state-of-the-art with proper extensions

- Improved matching extension (Soft assignment, Hamming Embedding, …)
- Re-ranking with spatial verification, or integrated geometry
- Query-expansion

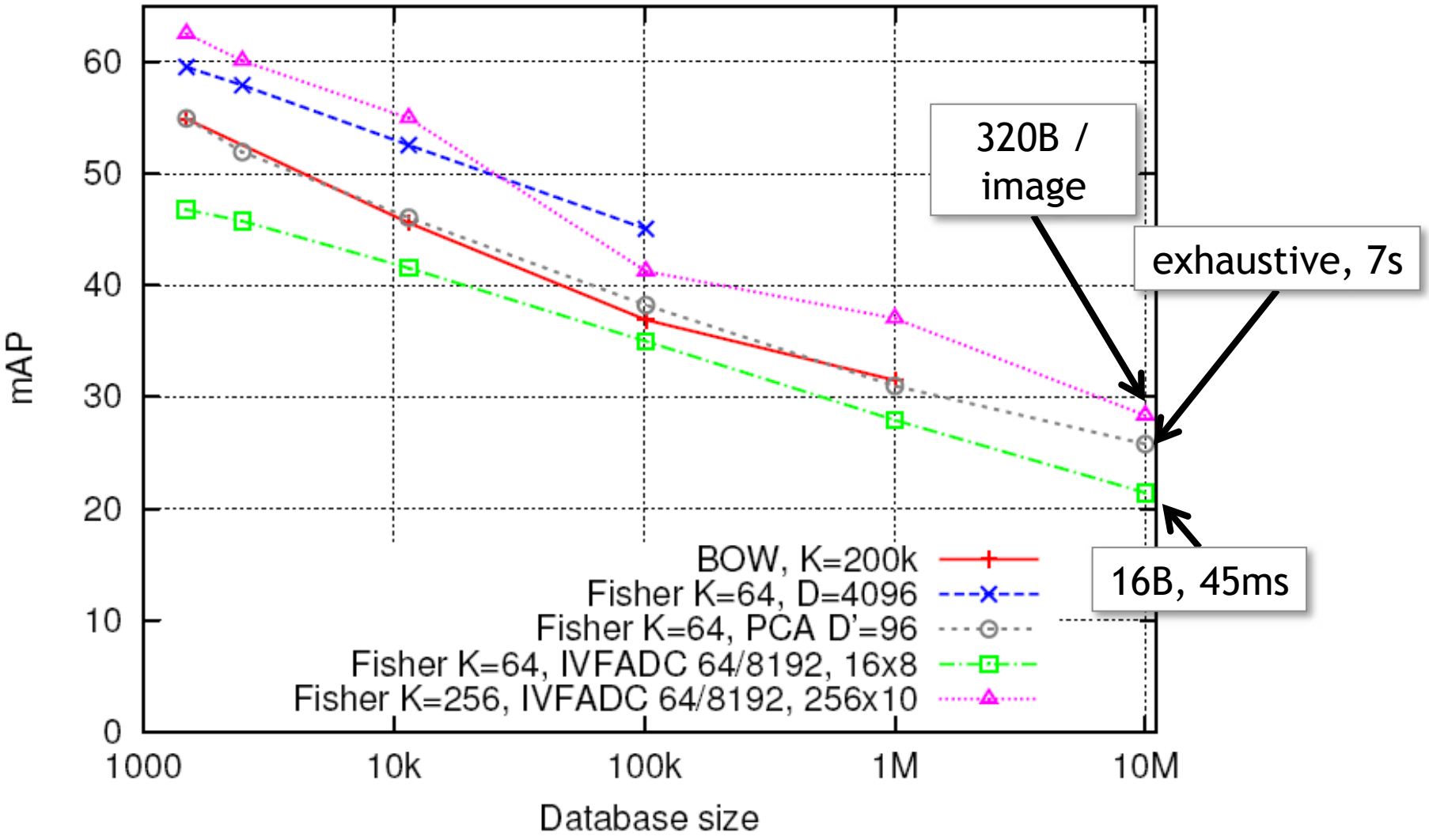
Larger-scale (100M-1B+): historically global descriptors, but better to use

- SIFT extraction (better: **dense**)
- An improved aggregation mechanisms – The Fisher kernel (or variants)
- An efficient indexing technique – Product quantization



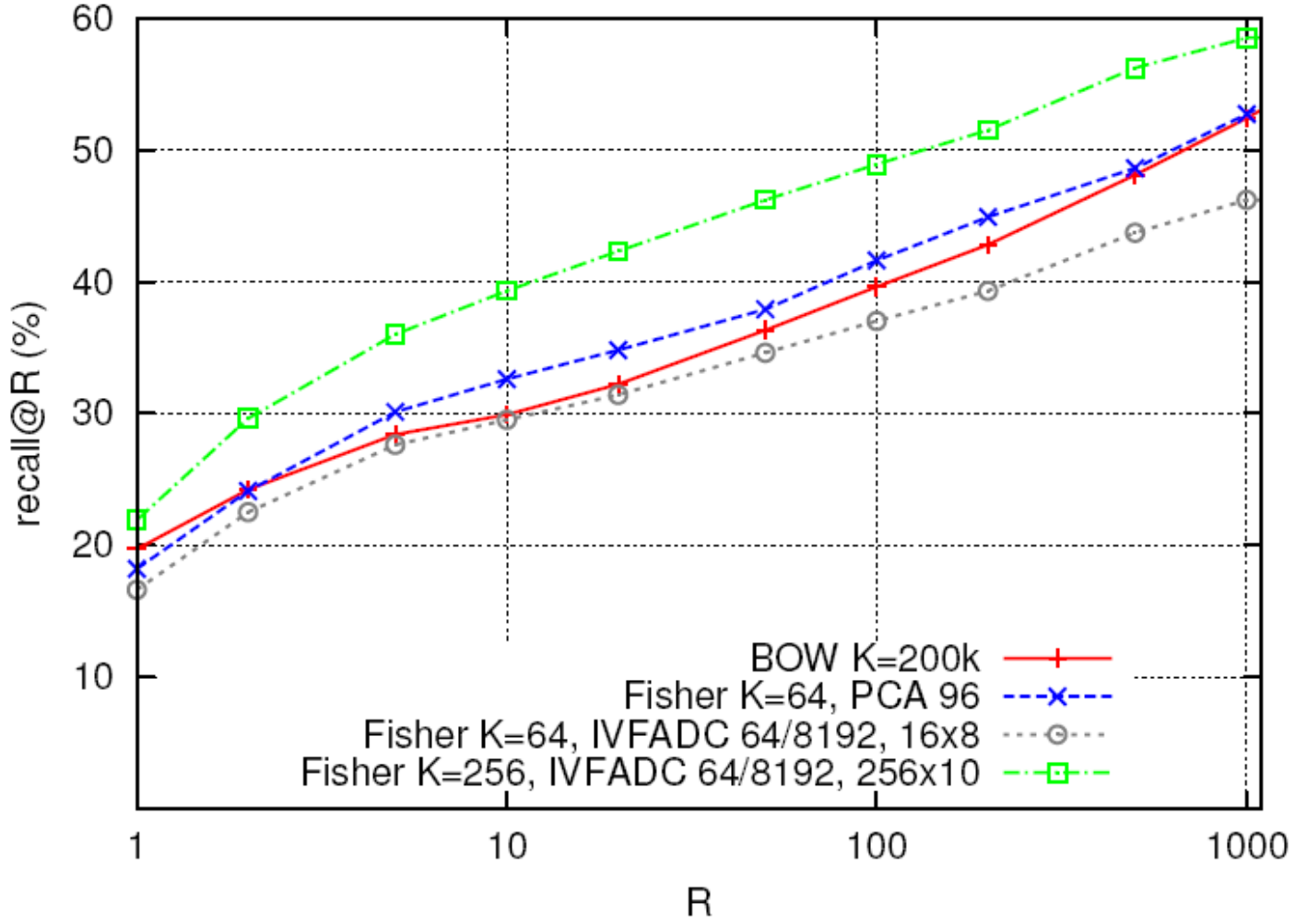
Large Scale Experiments

Holidays + up to 10M distractors from Flickr



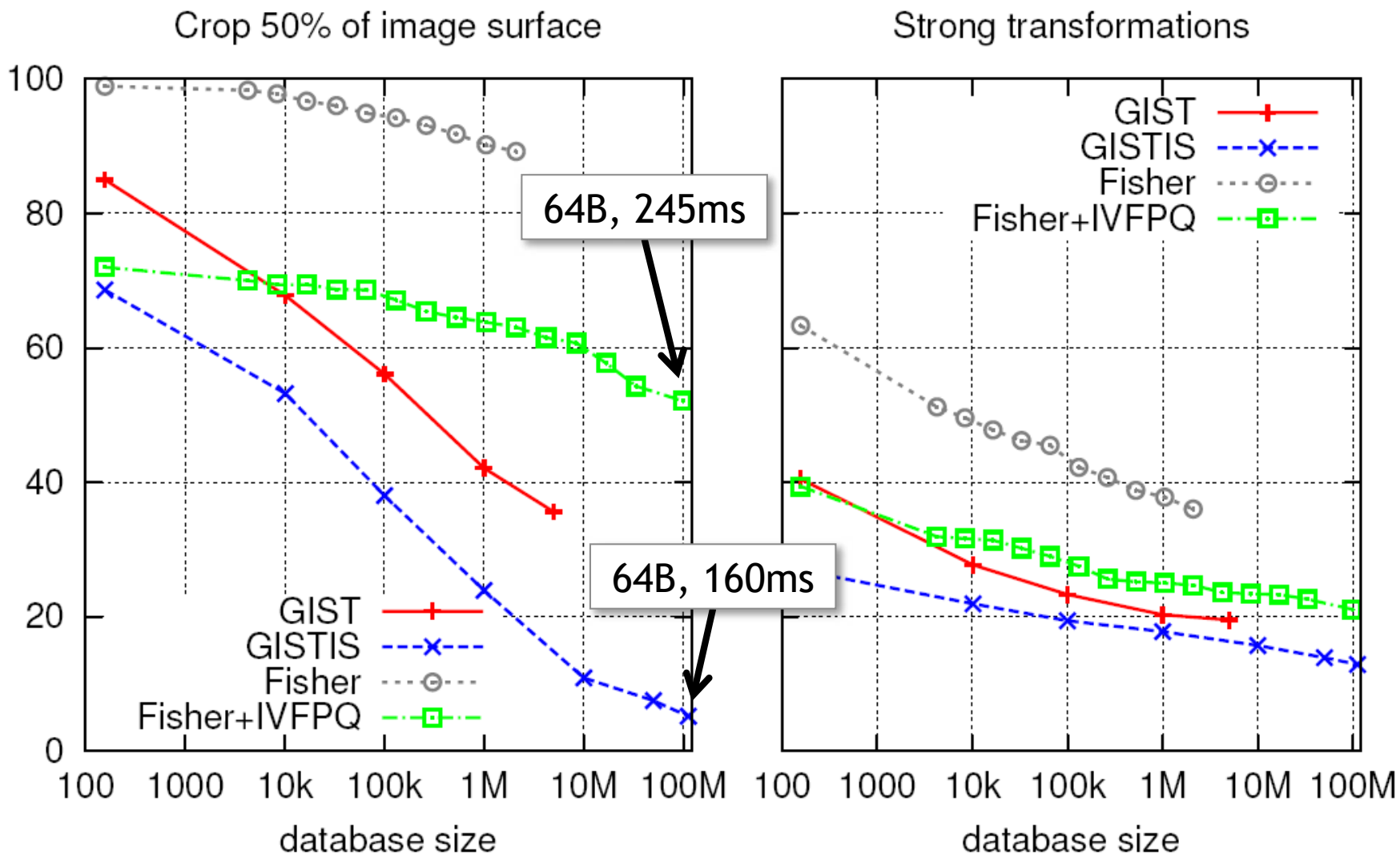
Large Scale Experiments

Short list quality in 10M images



Very Large Scale Experiments

Copydays + 100M distractors from Exalead (copy detection setup)



Final note: search *vs* classification

Query-by-example retrieval of images/objects/location/etc:

Classification / annotation:

PASCAL VOC 2007

person
dog
…

Convergence of large-scale retrieval and classification:

→ retrieval: more and more machine learning

→ classification: more and more cost aware

General conclusions

Tools to handle large-scale datasets:

→ image representations: scaling the BOV, extensions

→ including higher order statistics (VLAD, FV)

→ scalable matching: compressed-domain indexing

Very large-scale image search does not necessarily require gigantic resources:

→ searching in 100M images in 250ms on a single processor