Instance level recognition IV: Very large databases

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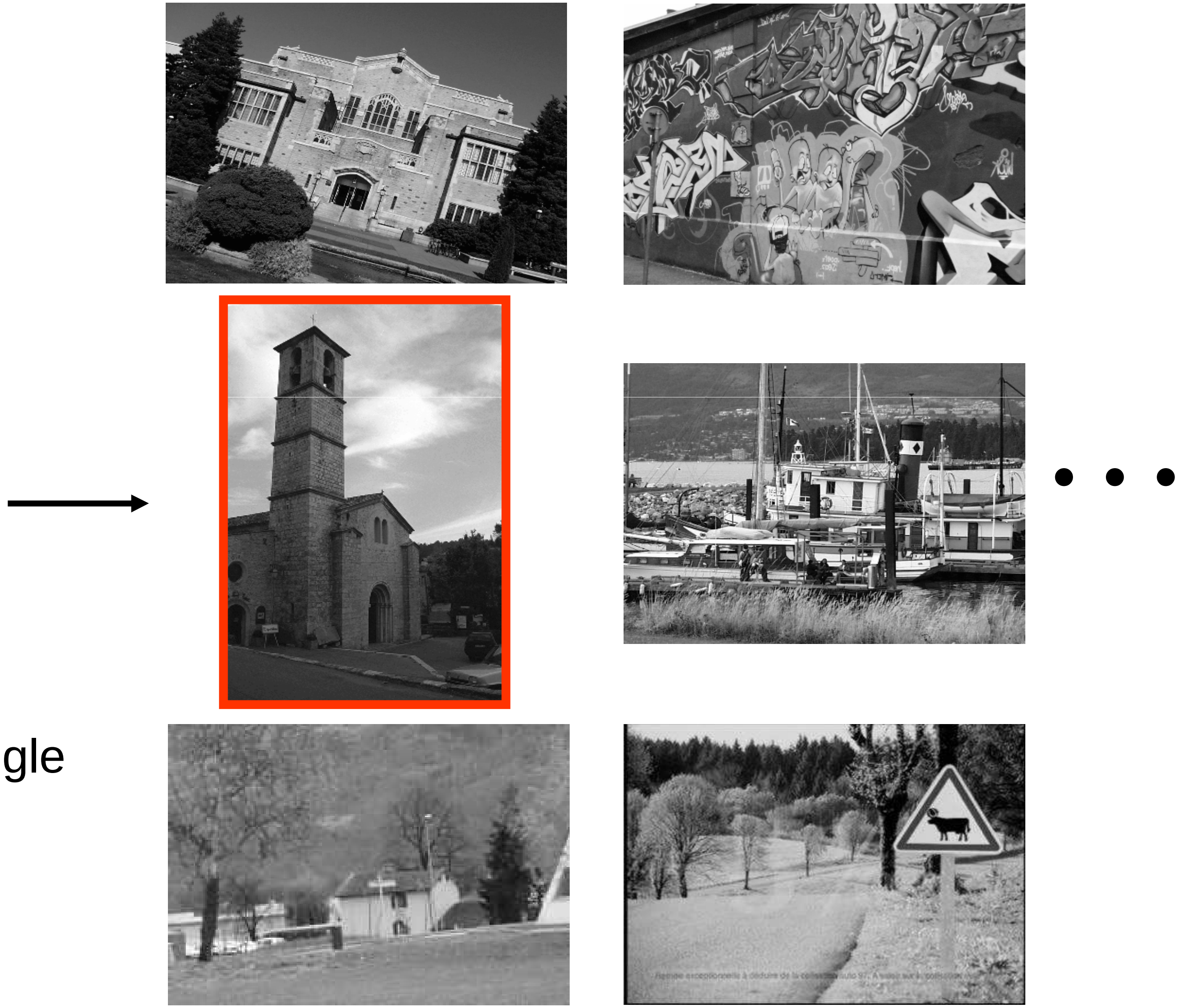
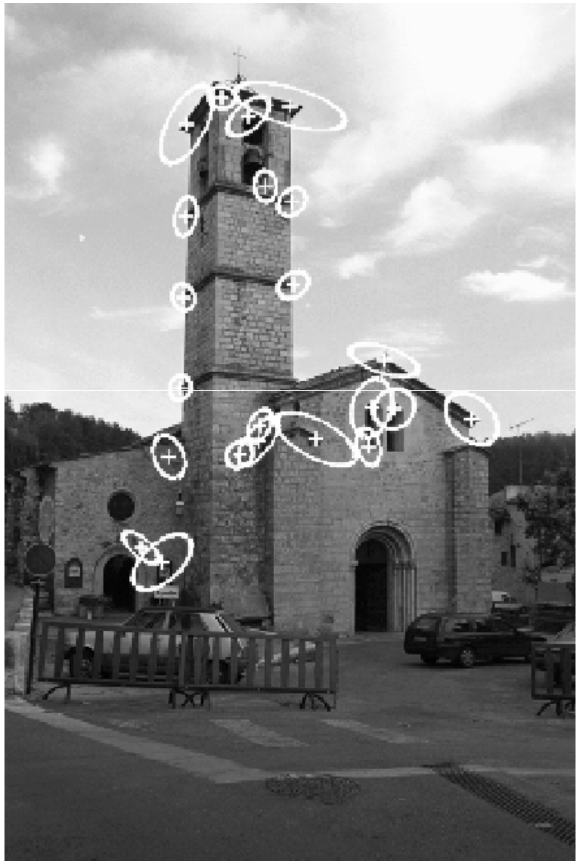
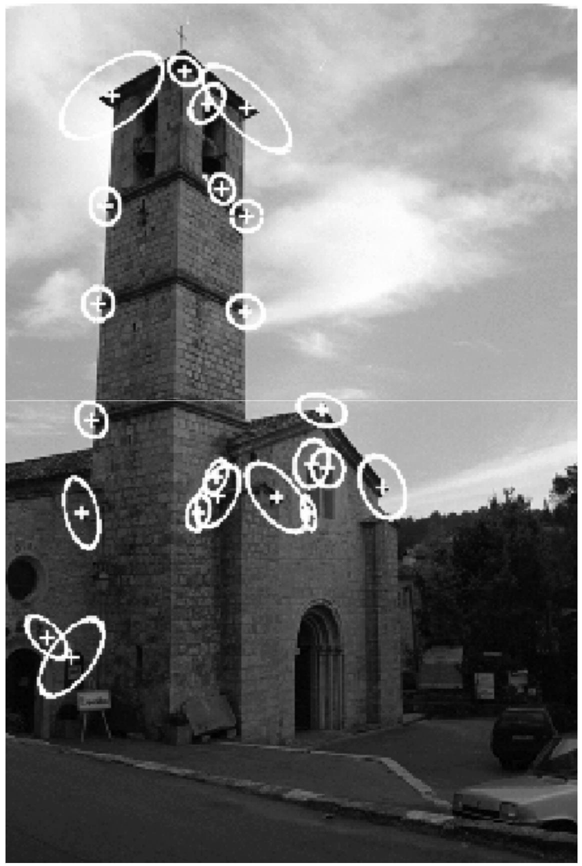
Visual search

change in viewing angle

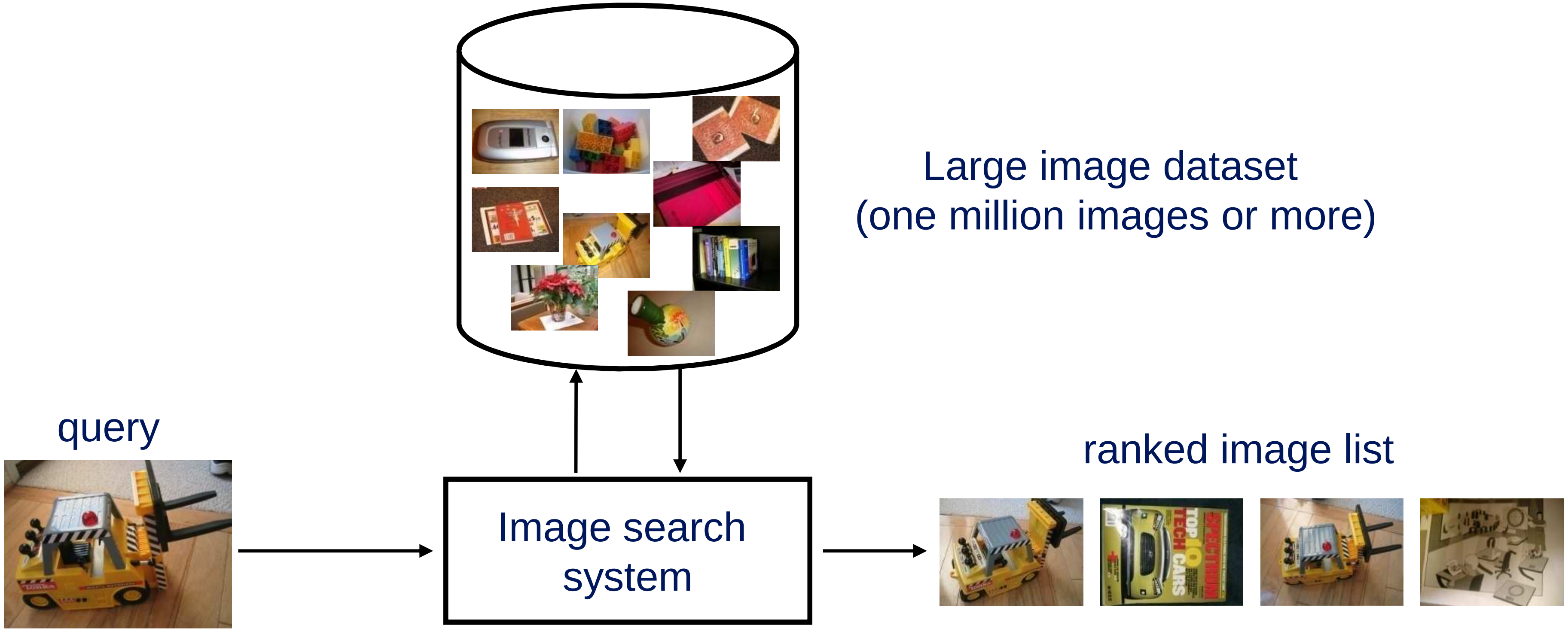


Matches

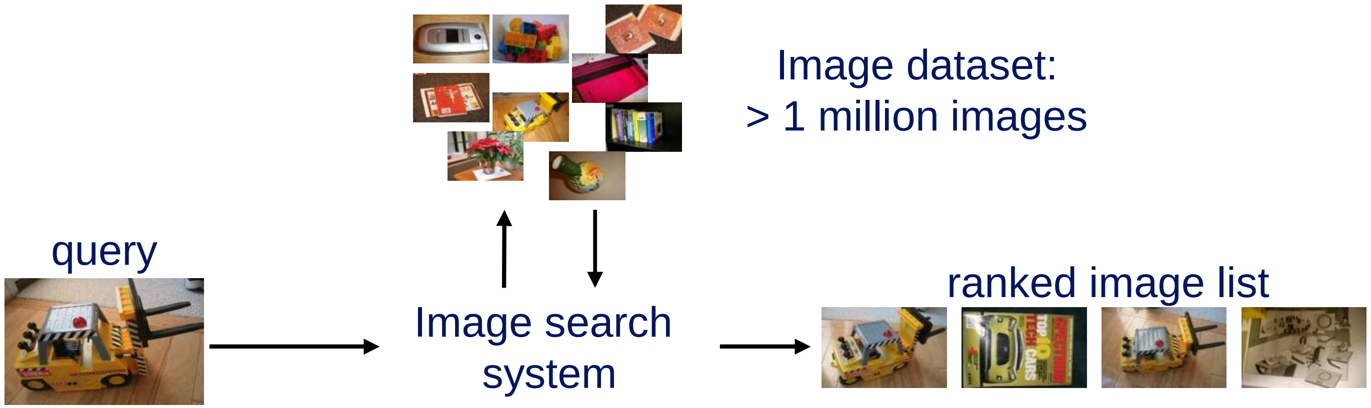
22 correct matches

Image search system for large datasets



- **Issues** for very large databases
  - to reduce the query time
  - to reduce the storage requirements
  - with minimal loss in retrieval accuracy

Large scale object/scene recognition



- Each image described by approximately 2000 descriptors
  - $2 * 10^9$ descriptors to index for one million images!

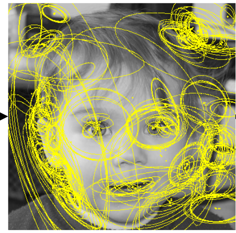
- Database representation in RAM:
  - Size of descriptors : 1 TB, search+memory intractable

Bag-of-features [Sivic&Zisserman'03]

Query image

Harris-Hessian-Laplace regions + SIFT descriptors

Set of SIFT descriptors



centroids (visual words)

Bag-of-features processing +*tf-idf* weighting

sparse frequency vector

- Visual Words
  - 1 word (index) per local descriptor
  - only images ids in inverted file
  - ⇒ 8 GB for a million images, fits in RAM
- Problem
  - Matching approximation

Inverted file

querying

ranked image short-list

Geometric verification

[Chum & al. 2007]

Re-ranked list

Visual words – approximate NN search

- Map descriptors to words by quantizing the feature space
  - Quantize via k-means clustering to obtain visual words
  - Assign descriptors to closest visual words

- Bag-of-features as approximate nearest neighbor search

Descriptor matching with *k*-nearest neighbors

$$f_{k\text{-NN}}(x, y) = \begin{cases} 1 & \text{if } x \text{ is a } k\text{-NN of } y \\ 0 & \text{otherwise} \end{cases}$$

Bag-of-features matching function $f_q(x, y) = \delta_{q(x),q(y)}$

where q(x) is a quantizer, i.e., assignment to a visual word and $\delta_{a,b}$ is the Kronecker operator ($\delta_{a,b}$=1 iff a=b)

Approximate nearest neighbor search evaluation

- ANN algorithms usually returns a short-list of nearest neighbors
  - this short-list is supposed to contain the NN with high probability
  - exact search may be performed to re-order this short-list

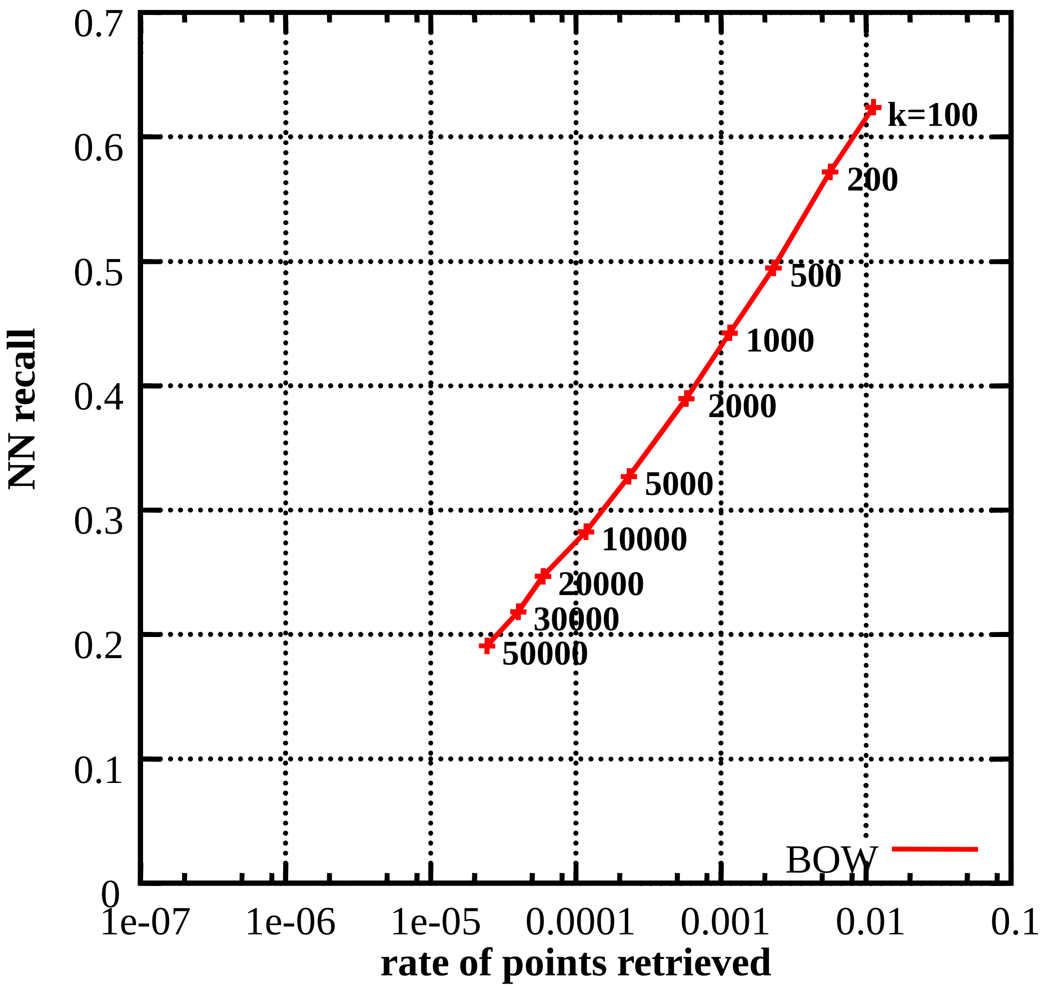
- Proposed quality evaluation of ANN search: trade-off between
  - **Accuracy**: **NN recall** = probability that *the* NN is in this list

    against

  - **Ambiguity removal** = proportion of vectors in the short-list
    - the lower this proportion, the more information we have about the vector
    - the lower this proportion, the lower the complexity if we perform exact search on the short-list

- ANN search algorithms usually have some parameters to handle this trade-off

ANN evaluation of bag-of-features



- ANN algorithms returns a list of potential neighbors

- **Accuracy**: **NN recall** = probability that *the* NN is in this list

- **Ambiguity removal**: = proportion of vectors in the short-list

- In BOF, this trade-off is managed by the number of clusters *k*

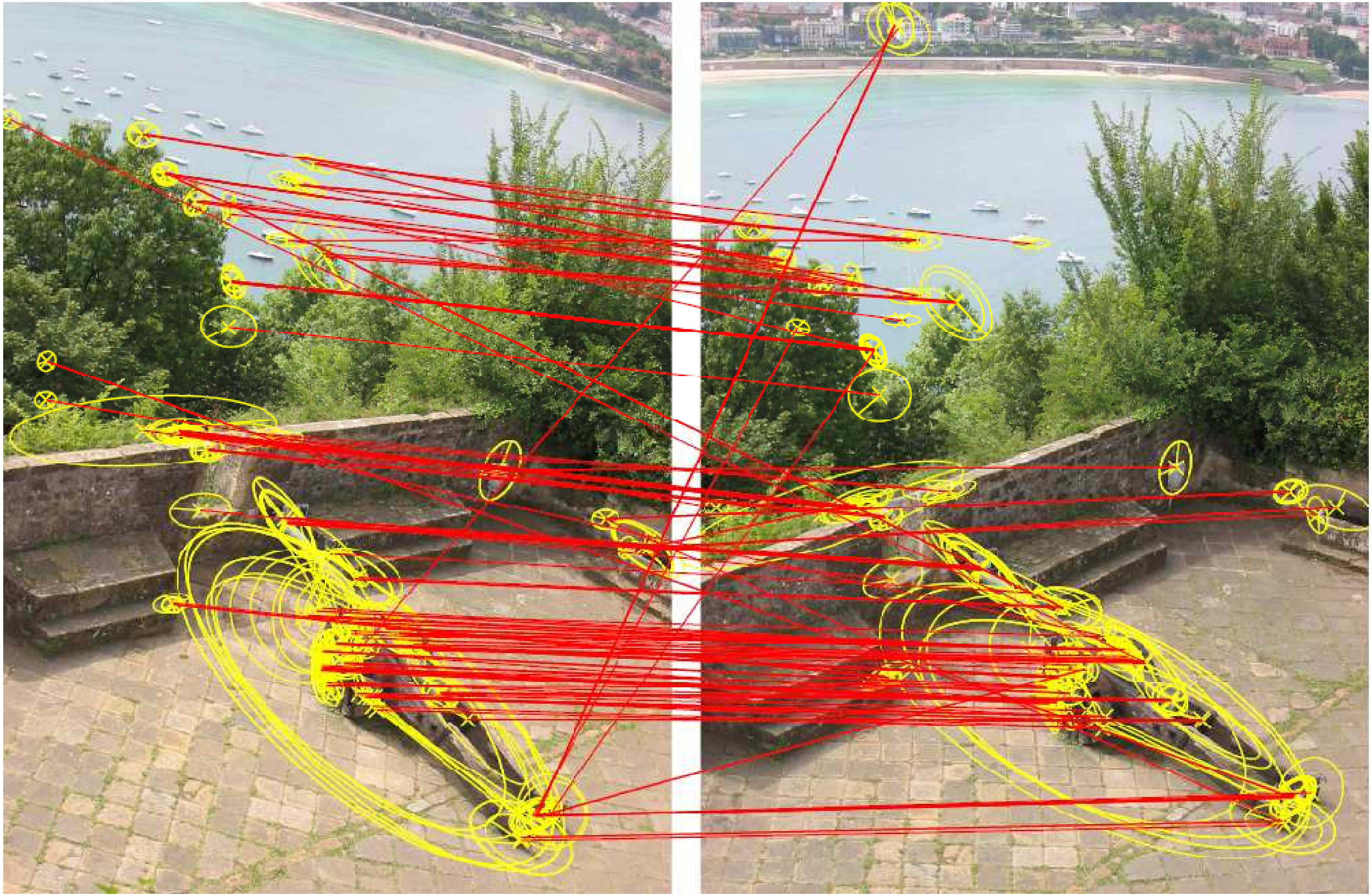
Vocabulary size

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

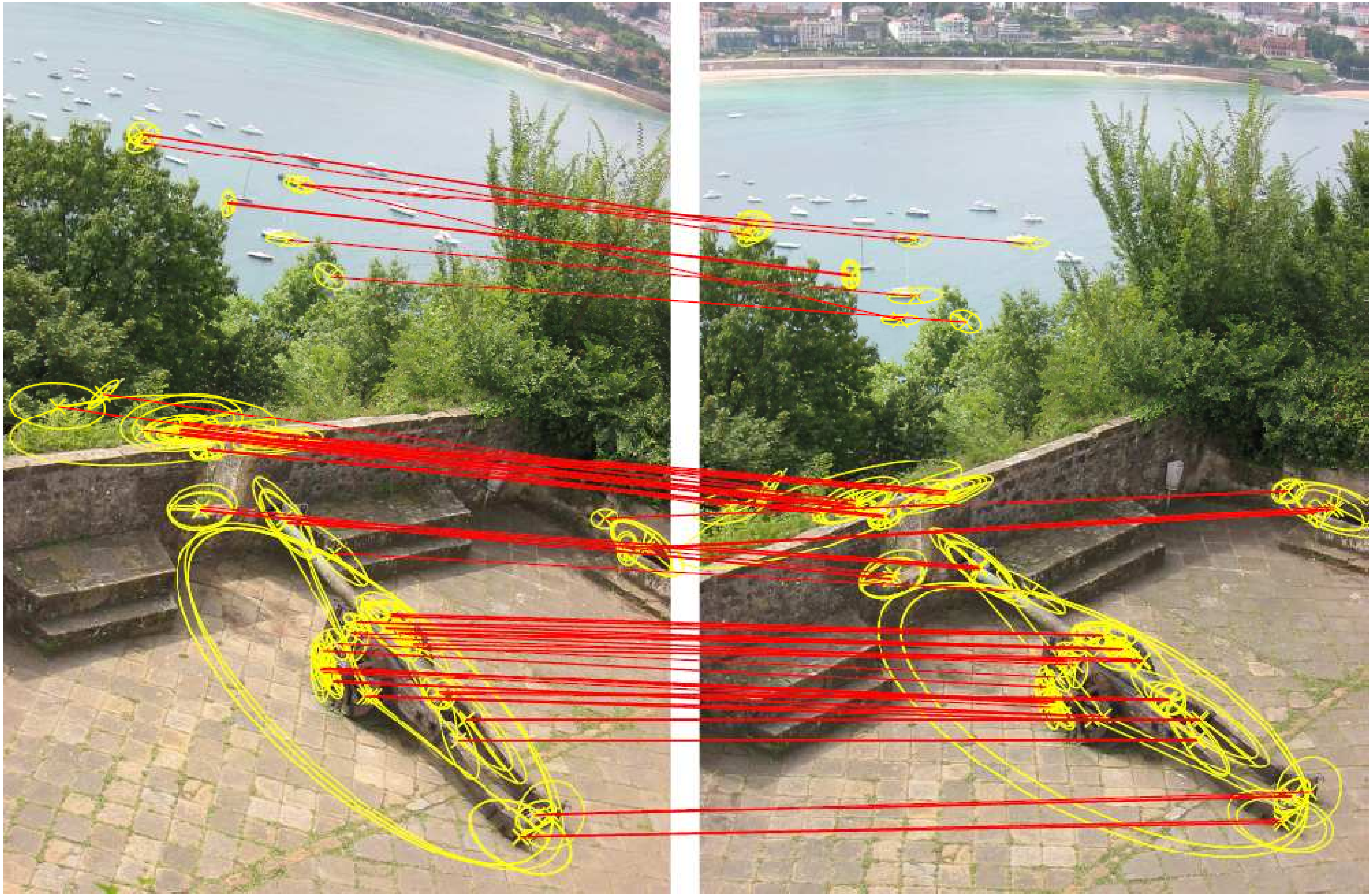
- No good trade-off between “small” and “large” !
  - either the Voronoi cells are too big
  - or these cells can’t absorb the descriptor noise

  $\rightarrow$ intrinsic approximate nearest neighbor search of BOF is not sufficient

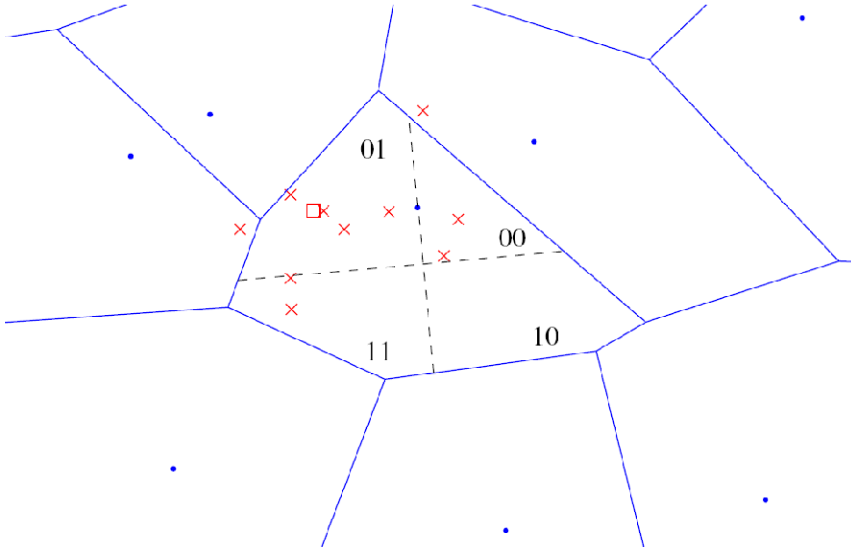
20K visual word: false matches



200K visual word: good matches missed



Hamming Embedding [Jegou et al. ECCV'08]



Representation of a descriptor *x*

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

Two descriptors x and y match iif

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

h(*a*,*b*) Hamming distance

Term frequency – inverse document frequency

- Weighting with tf-idf score: weight visual words based on their frequency

  - Tf: normalized term (word) frequency ti in a document dj

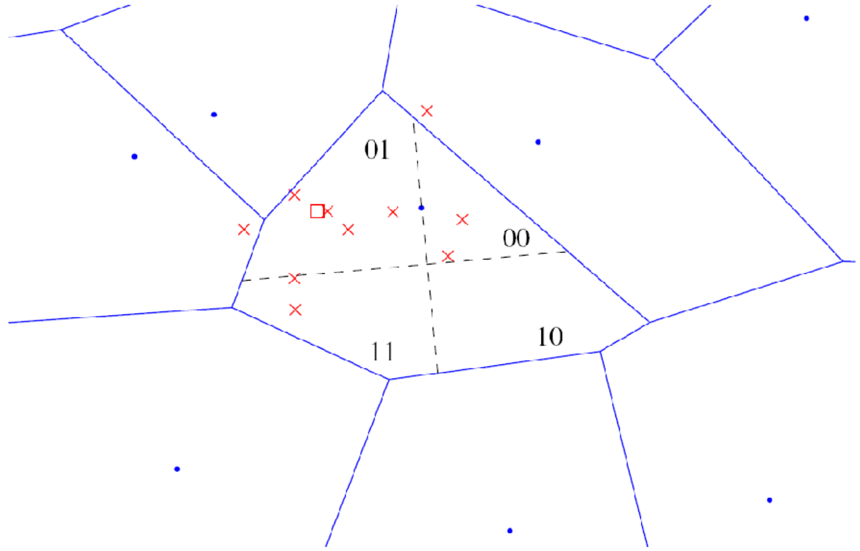
$$tf_{ij} = n_{ij} / \sum_k n_{kj}$$

  - Idf: inverse document frequency, total number of documents divided by number of documents containing the term ti

$$idf_i = \log \frac{|D|}{|\{d : t_i \in d\}|}$$

Tf-Idf: $$tf-idf_{ij} = tf_{ij} \cdot idf_i$$

Hamming Embedding [Jegou et al. ECCV'08]



•Nearest neighbors for Hamming distance ≈ those for Euclidean distance
→ a metric in the embedded space reduces dimensionality curse effects

•Efficiency

– Hamming distance = very few operations
– Fewer random memory accesses: 3 x faster that BOF with same dictionary size!

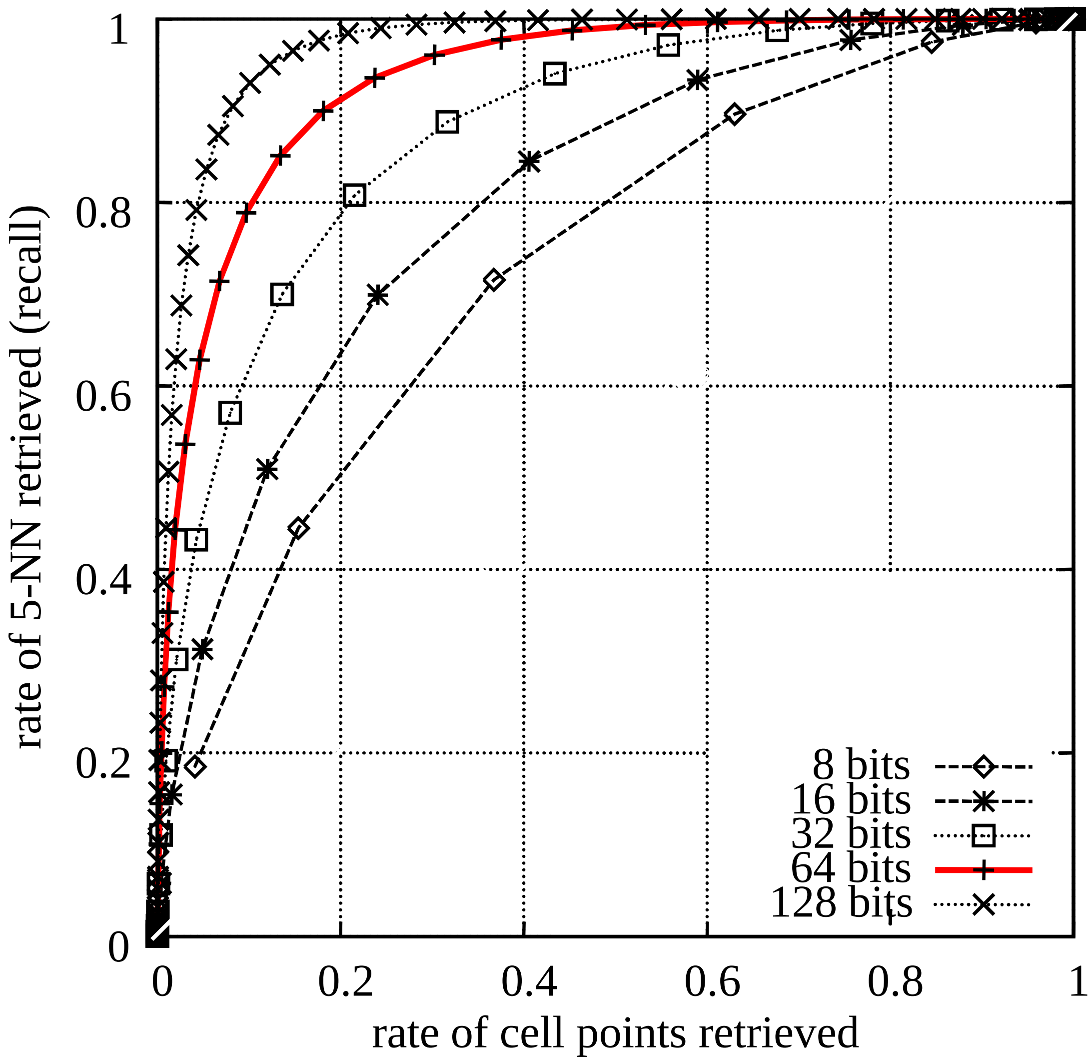
Hamming Embedding

- **Off-line** (given a quantizer)
  - draw an orthogonal projection matrix P of size $d_b \times d$

  $\rightarrow$ this defines d_b random projection directions
  - for each Voronoi cell and projection direction, compute the median value for a learning set

- **On-line**: compute the binary signature b(x) of a given descriptor
  - project x onto the projection directions as $z(x) = (z_1,\ldots z_{db})$
  - $b_i(x) = 1$ if $z_i(x)$ is above the learned median value, otherwise 0

Hamming neighborhood

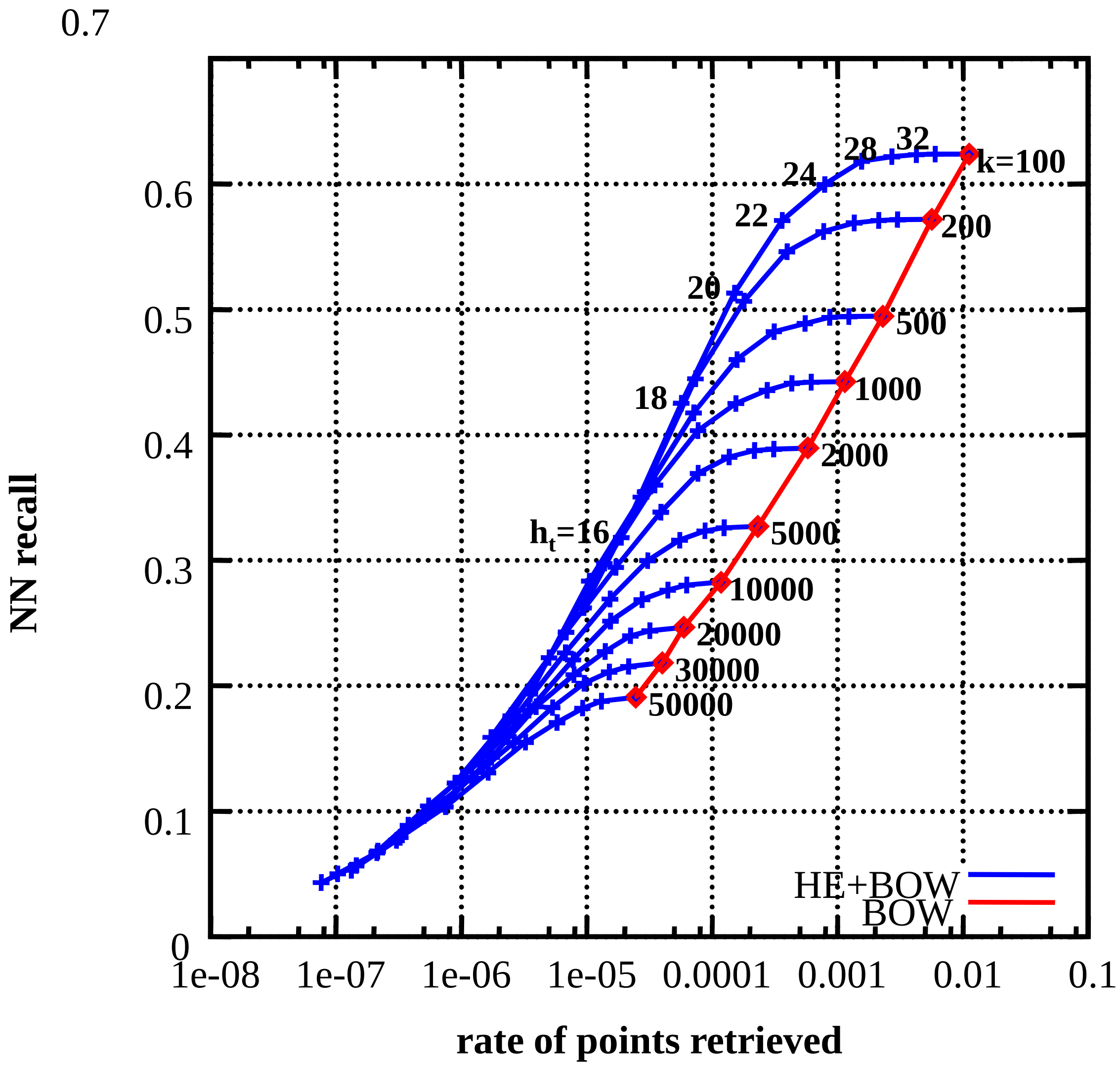


Trade-off between memory usage and accuracy

→More bits yield higher accuracy

In practice, 64 bits (8 byte)

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 ambiguity removal

Matching points - 20k word vocabulary

201 matches

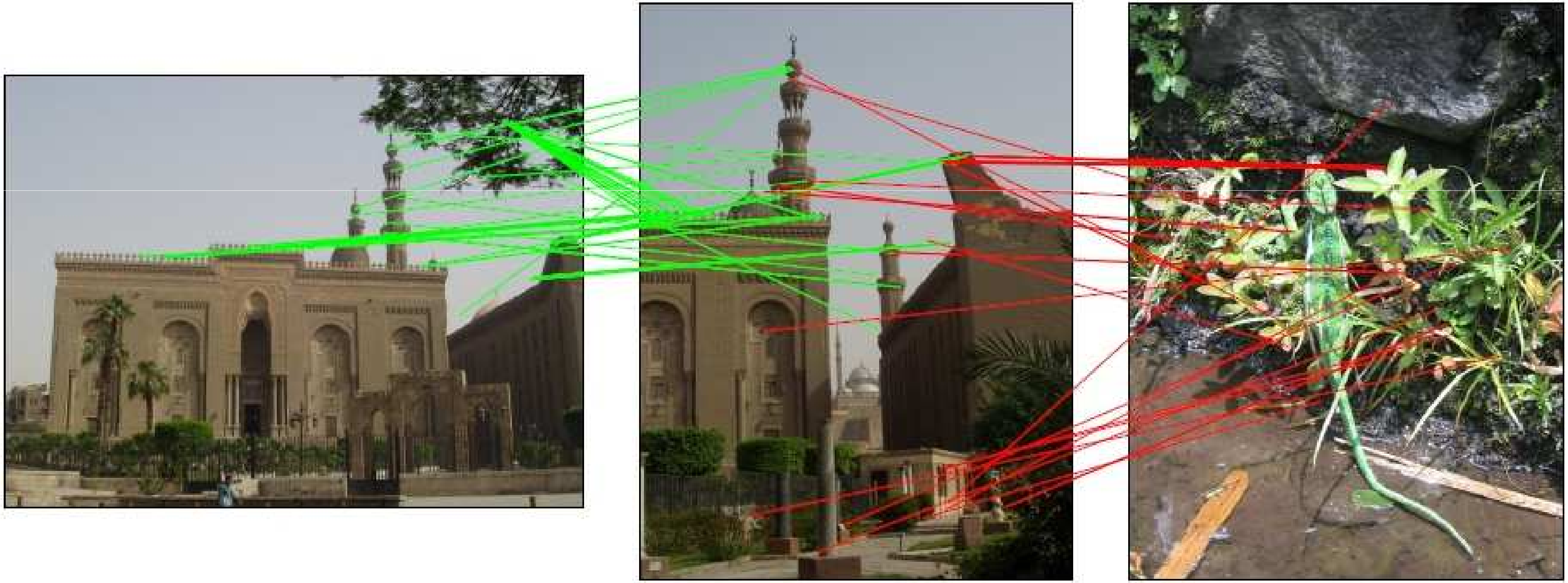
240 matches

Many matches with the non-corresponding image!

Matching points - 200k word vocabulary

69 matches

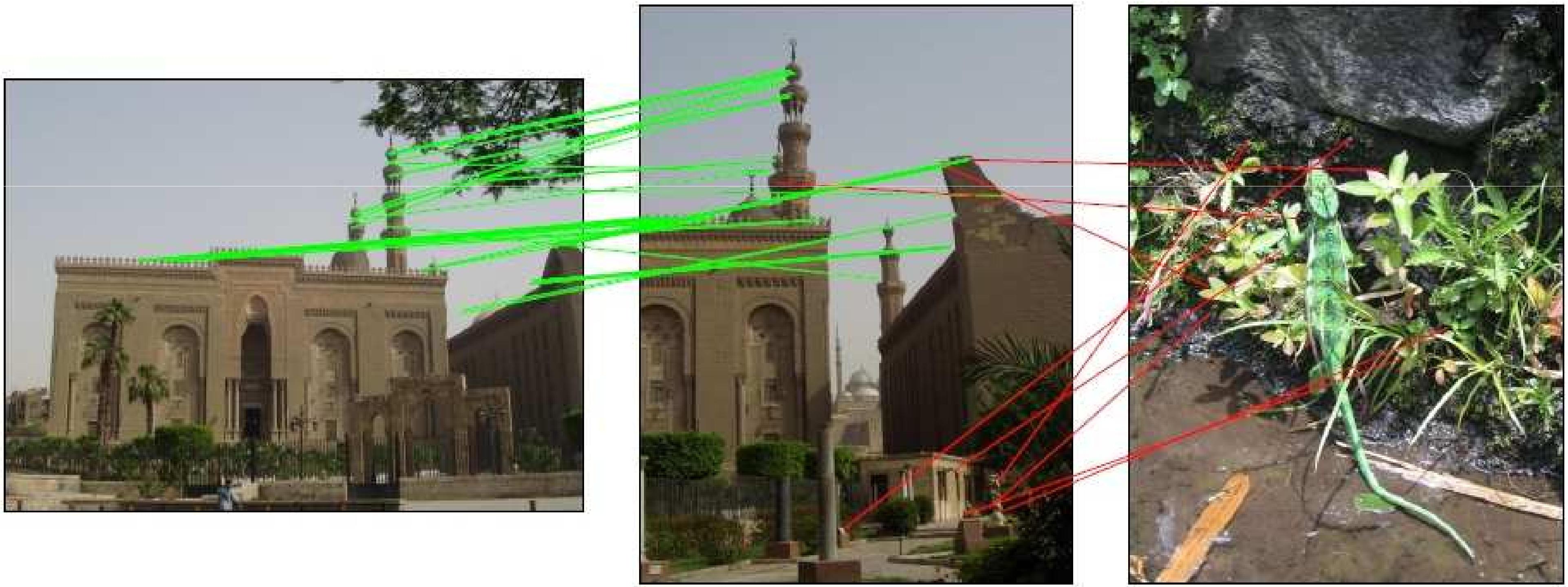
35 matches



Still many matches with the non-corresponding one

Matching points - 20k word vocabulary + HE

83 matches 8 matches



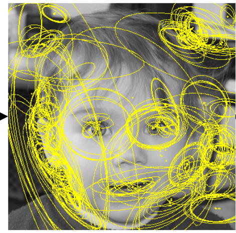
10x more matches with the corresponding image!

Bag-of-features [Sivic&Zisserman'03]

Query image

Harris-Hessian-Laplace regions + SIFT descriptors

Set of SIFT descriptors



centroids (visual words)

Bag-of-features processing *+tf-idf* weighting

sparse frequency vector

Inverted file

querying

ranked image short-list

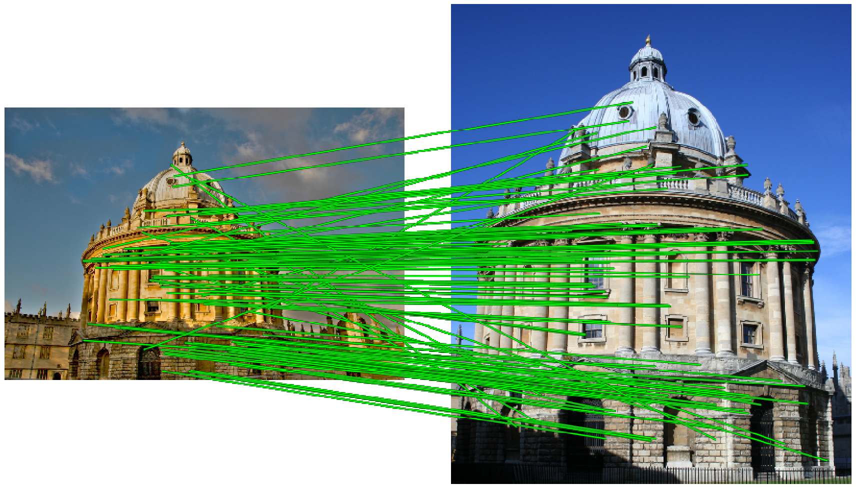
Geometric verification

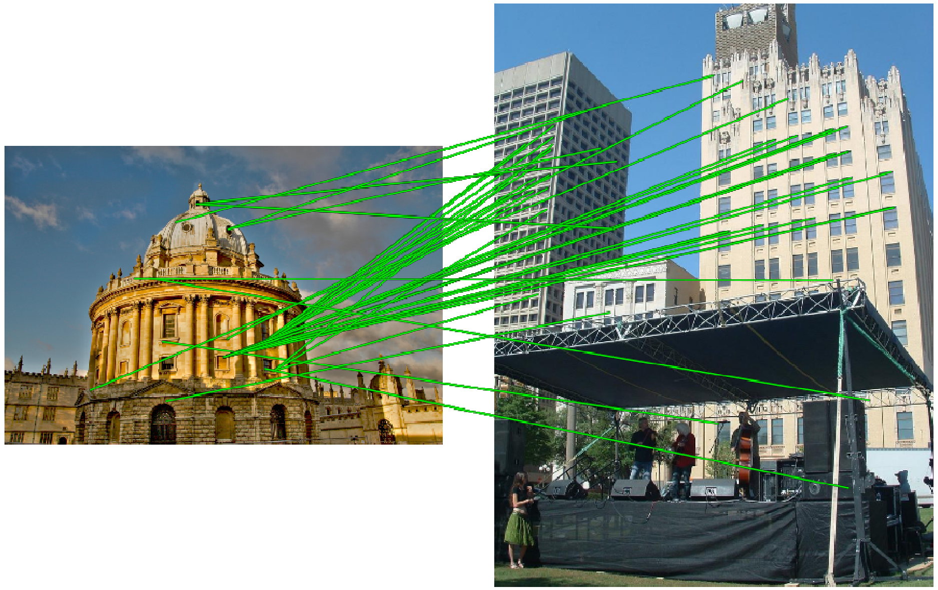
[Chum & al. 2007]

Re-ranked list

Geometric verification

Use the **position** and **shape** of the underlying features to improve retrieval quality

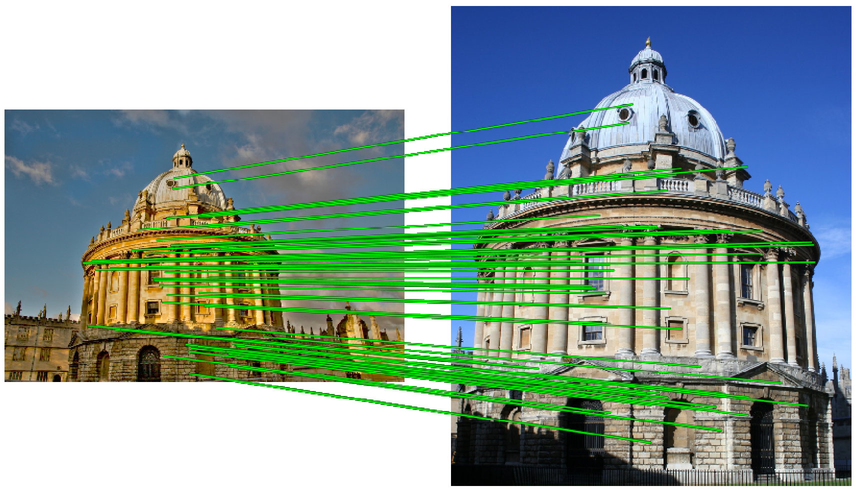




Both images have many matches – which is correct?

Geometric verification

We can measure **spatial consistency** between the query and each result to improve retrieval quality

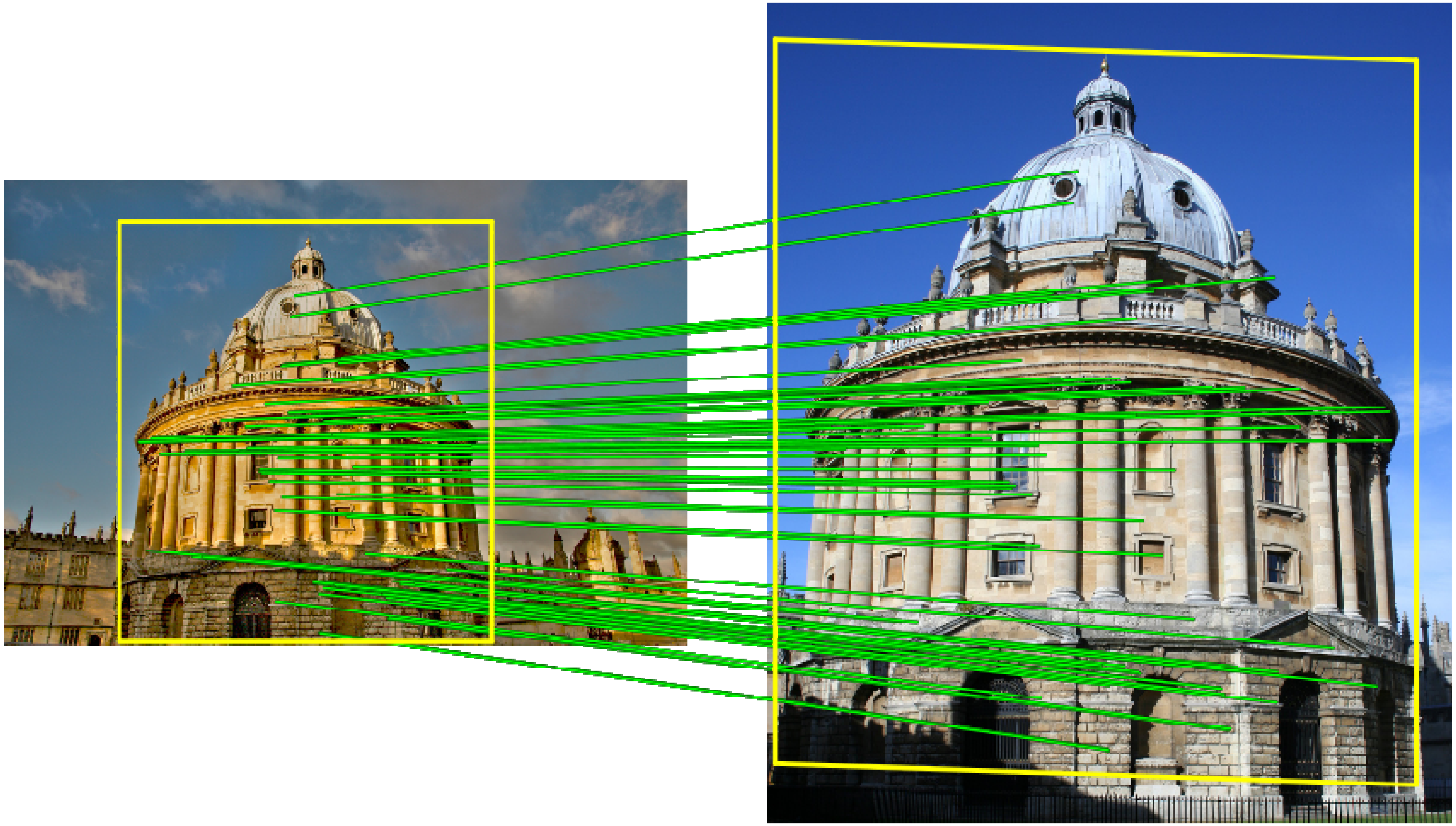


Many spatially consistent matches – **correct result**

Few spatially consistent matches – **incorrect result**

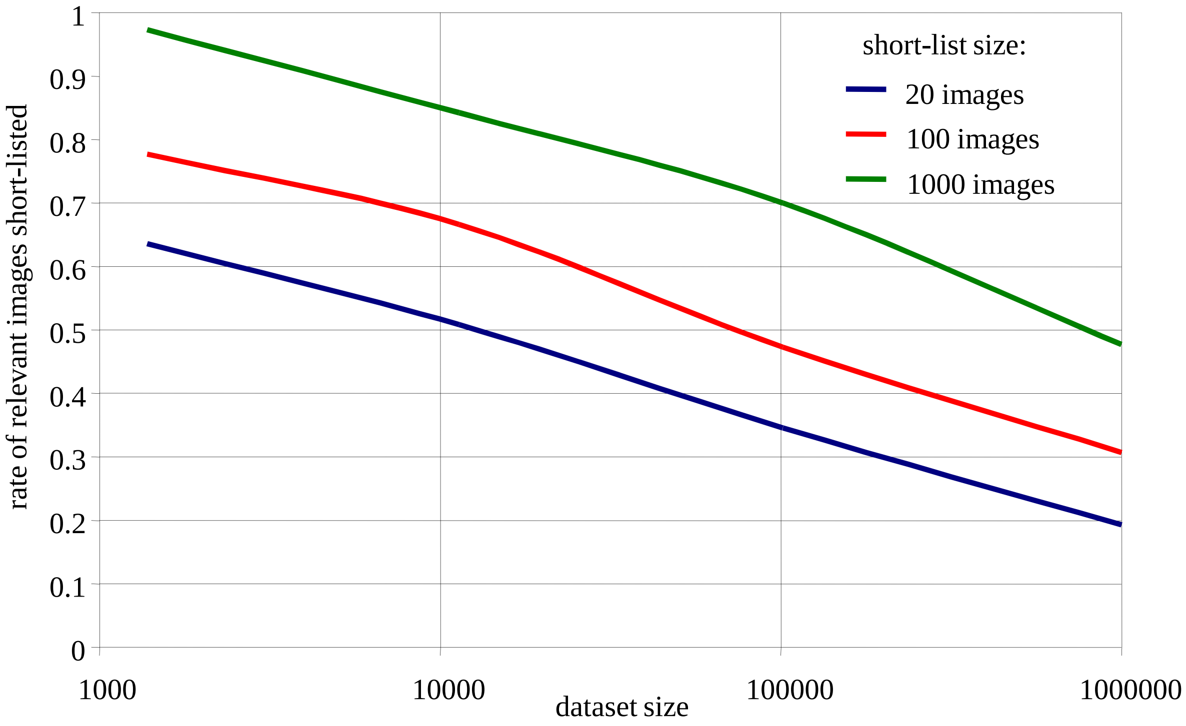
Geometric verification

Gives **localization** of the object



Weak geometry consistency

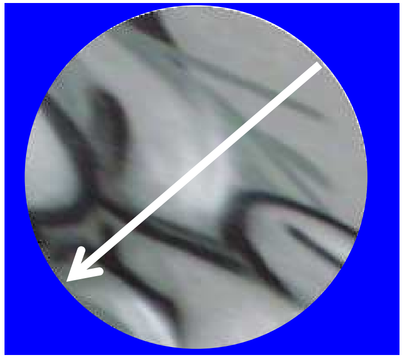
- Re-ranking based on full geometric verification
  - works very well
  - but performed on a short-list only (typically, 100 images)
  - → for very large datasets, the number of distracting images is so high that relevant images are not even short-listed!



Weak geometry consistency

- Weak geometric information used for **all** images (not only the short-list)

- Each invariant interest region detection has a scale and rotation angle associated, here characteristic scale and dominant gradient orientation



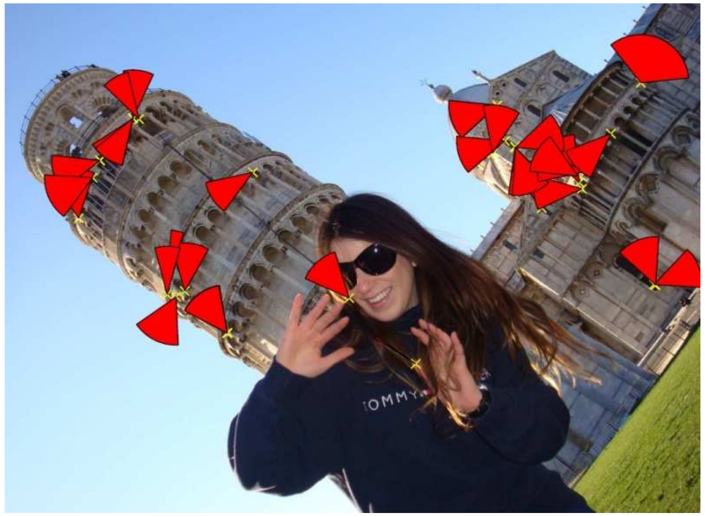
Scale change 2

Rotation angle ca. 20 degrees

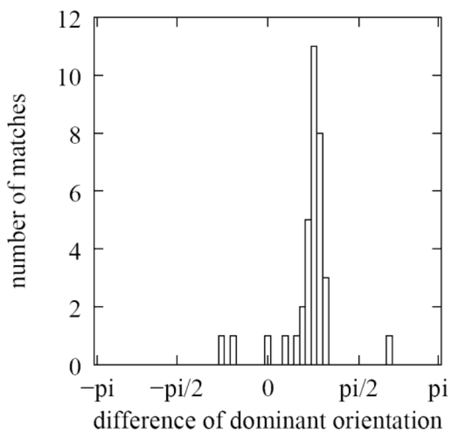
- Each matching pair results in a scale and angle difference

- For the global image scale and rotation changes are roughly consistent

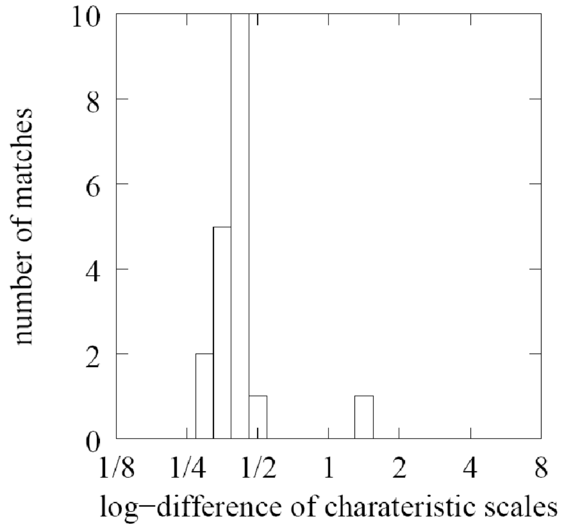
WGC: orientation consistency



Max = rotation angle between images



WGC: scale consistency



Weak geometry consistency

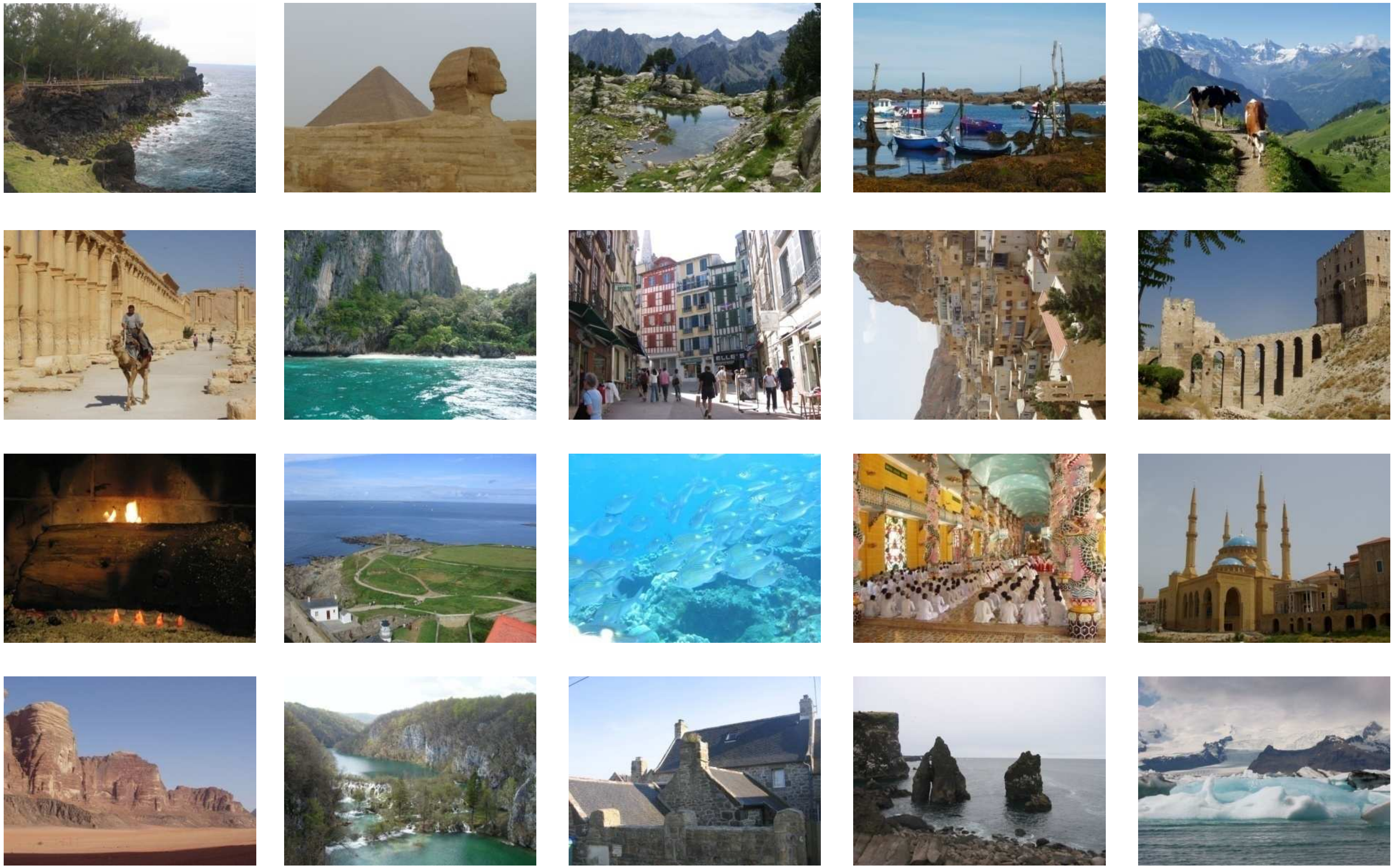
- Integration of the geometric verification into the BOF
  - votes for an image in two quantized subspaces, i.e. for angle & scale
  - these subspace are show to be roughly independent
  - final score: filtering for each parameter (angle and scale)
- Only matches that do agree with the main difference of orientation and scale will be taken into account in the final score
- Re-ranking using full geometric transformation still adds information in a final stage

INRIA holidays dataset

- Evaluation for the INRIA holidays dataset, 1491 images
  - 500 query images + 991 annotated true positives
  - Most images are holiday photos of friends and family
- 1 million & 10 million distractor images from Flickr
- Vocabulary construction on a different Flickr set
- Almost real-time search speed

- Evaluation metric: mean average precision (in [0,1], bigger = better)
  - Average over precision/recall curve

Holiday dataset – example queries



Dataset : Venice Channel

Dataset : San Marco square


Query


Base 1


Base 2


Base 3


Base 4


Base 5

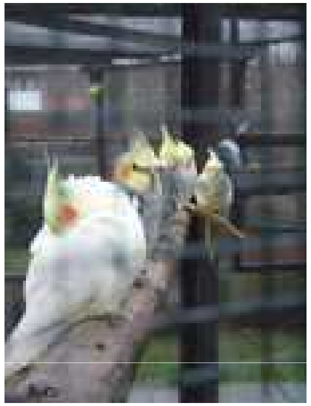

Base 6


Base 7


Base 8


Base 9

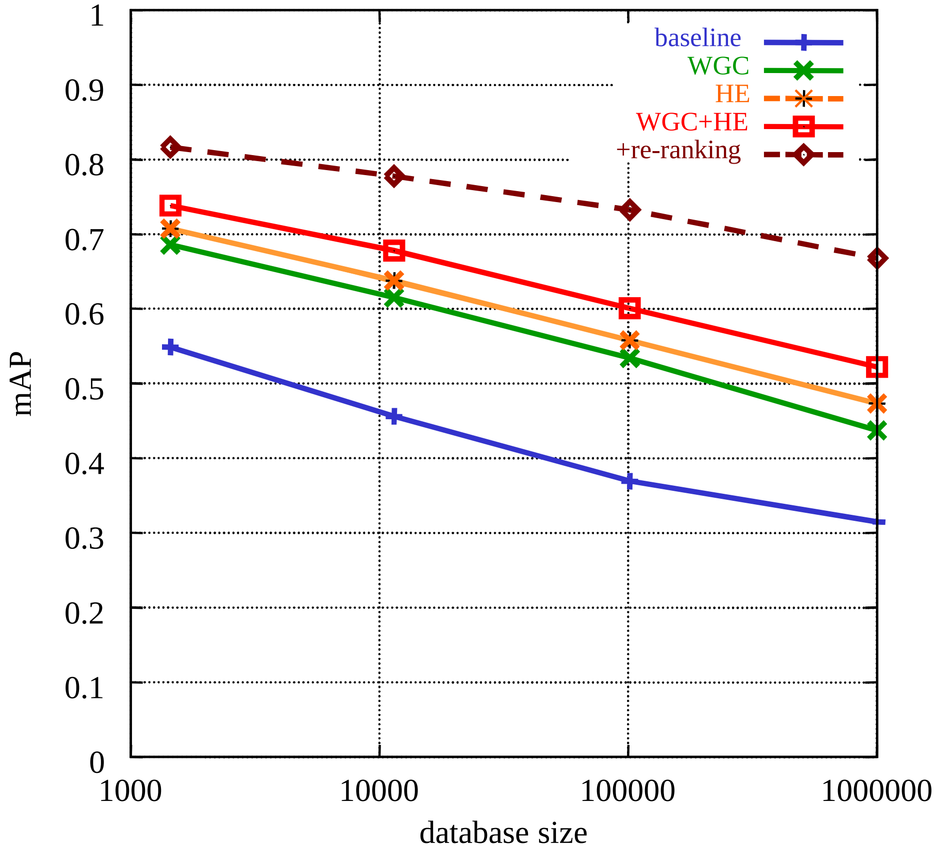
Example distractors - Flickr




Experimental evaluation

- Evaluation on our holidays dataset, 500 query images, 1 million distracter images
- Metric: mean average precision (in [0,1], bigger = better)



Average query time (4 CPU cores)	
Compute descriptors	880 ms
Quantization	600 ms
Search – baseline	**620** ms
Search – WGC	**2110** ms
Search – HE	**200** ms
Search – HE+WGC	**650** ms

Results – Venice Channel

Comparison with the state of the art: Oxford dataset [Philbin et al. CVPR'07]

Evaluation measure:

Mean average precision (mAP)

Comparison with the state of the art: Kentucky dataset [Nister et al. CVPR'06]

4 images per object

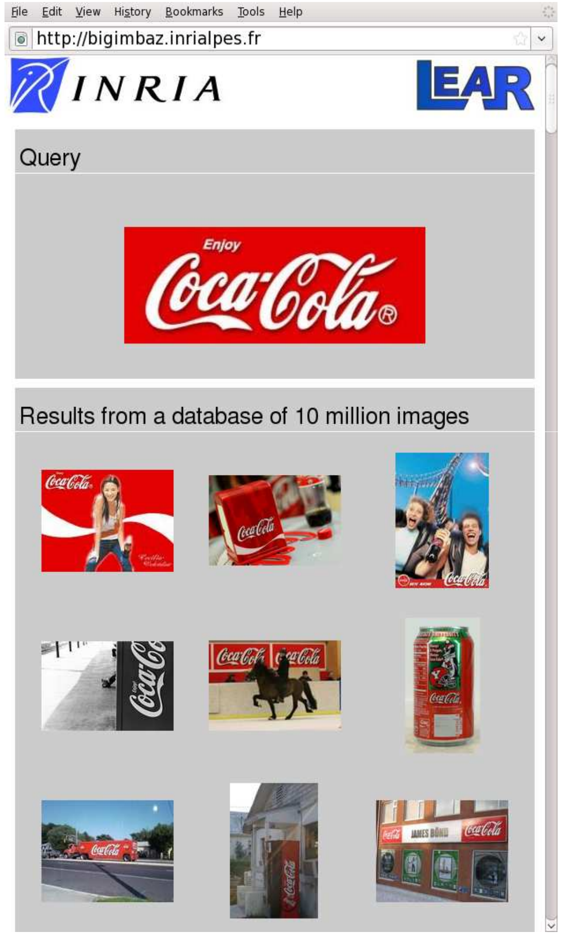
Evaluation measure: among the 4 best retrieval results how many are correct (ranges from 1 to 4)

Comparison with the state of the art

dataset	Oxford		Kentucky	
distractors	0	100K	0	1M
soft assignment [14]	0.493	0.343		
ours	0.615	0.516		
soft + geometrical re-ranking [14]	0.598	0.480		
ours + geometrical re-ranking	0.667	0.591		
soft + query expansion [14]	0.718	0.605		
ours + query expansion	0.747	0.687		
hierarchical vocabulary [6]			3.19	
CDM [11]			3.61	2.93
ours			3.42	3.10
ours + geometrical re-ranking			3.55	3.40

[14] Philbin et al., CVPR’08; [6] Nister et al., CVPR’06; [10] Harzallah et al., CVPR’07

On-line demonstration



Demo at http://bigimbaz.inrialpes.fr

Towards larger databases?

- BOF can handle up to ~10 M d'images
  - with a limited number of descriptors per image
  - 40 GB of RAM
  - search = 2 s

- Web-scale = billions of images
  - With 100 M per machine

    $\longrightarrow$ search = 20 s, RAM = 400 GB

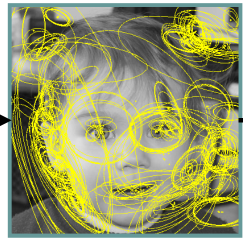
    $\longrightarrow$ not tractable!

Recent approaches for very large scale indexing

Query image

Hessian-Affine regions + SIFT descriptors

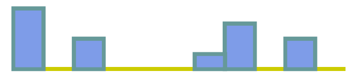
Set of SIFT descriptors



centroids (visual words)

Bag-of-features processing +*tf-idf* weighting

sparse frequency vector



Vector compression

Vector search

ranked image short-list

Geometric verification

Re-ranked list

- Each image is represented by one vector (not necessarily a BOF)

- This vector is compressed to reduce storage requirements

INRIA

Related work on very large scale image search

- Min-hash and geometrical min-hash [Chum et al. 07-09]
- Compressing the BoF representation (miniBof) [Jegou et al. 09]

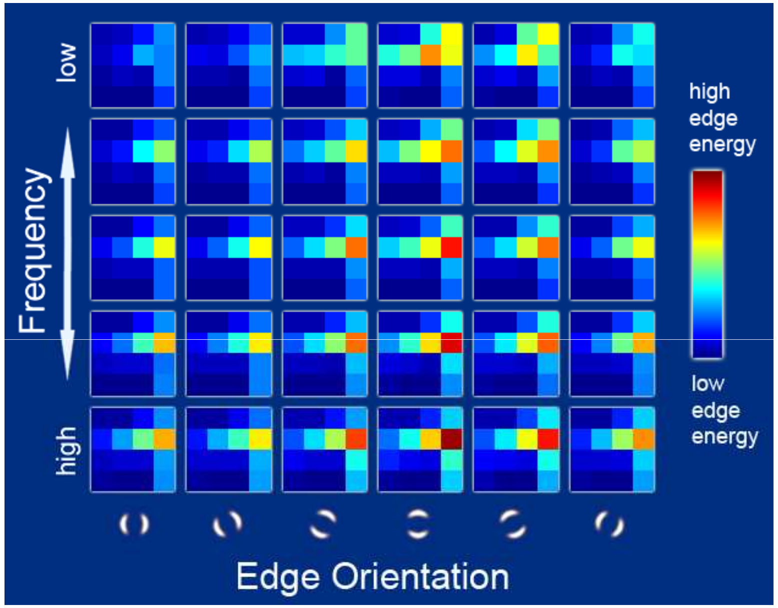
  → these approaches require hundreds of bytes to obtain a “reasonable quality”

- GIST descriptors with Spectral Hashing [Weiss et al.’08]

  → very limited invariance to scale/rotation/crop

Global scene context – GIST descriptor

- The "gist" of a scene: Oliva & Torralba (2001)



- 5 frequency bands and 6 orientations for each image location
- Tiling of the image to describe the image

GIST descriptor + spectral hashing

- The position of the descriptor in the image is encoded in the representation

Gist

Torralba et al. (2003)

- Spectral hashing produces binary codes similar to spectral clusters

Related work on very large scale image search

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  → require hundreds of bytes are required to obtain a “reasonable quality”

- GIST descriptors with Spectral Hashing [Weiss et al.’08]

  → very limited invariance to scale/rotation/crop

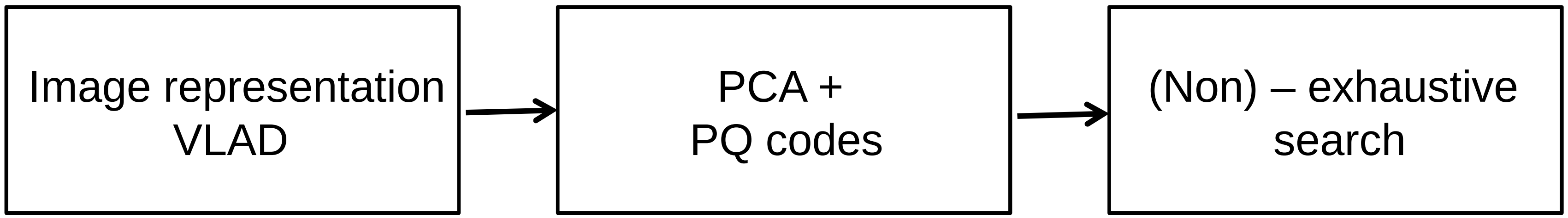
- Aggregating local descriptors into a compact image representation [Jegou &al.‘10]

- Efficient object category recognition using classemes [Torresani et al.’10]

Compact image representation

- Aim: improving the tradeoff between
  - search speed
  - memory usage
  - search quality

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



[H. Jegou et al., Aggregating local desc into a compact image representation, CVPR'10]

Aggregation of local descriptors

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

set of n local descriptors $\rightarrow$ 1 vector

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

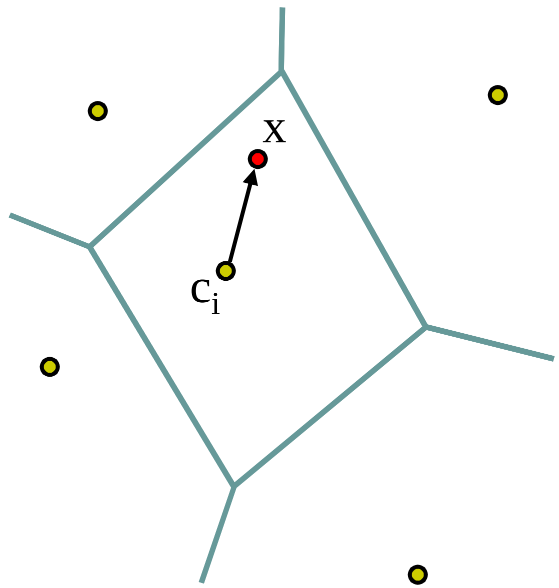
$\rightarrow$ high dimensionality reduction/compression introduces loss

- Alternative : vector of locally aggregated descriptors (VLAD)
  - non sparse vector
  - excellent results with a small vector dimensionality

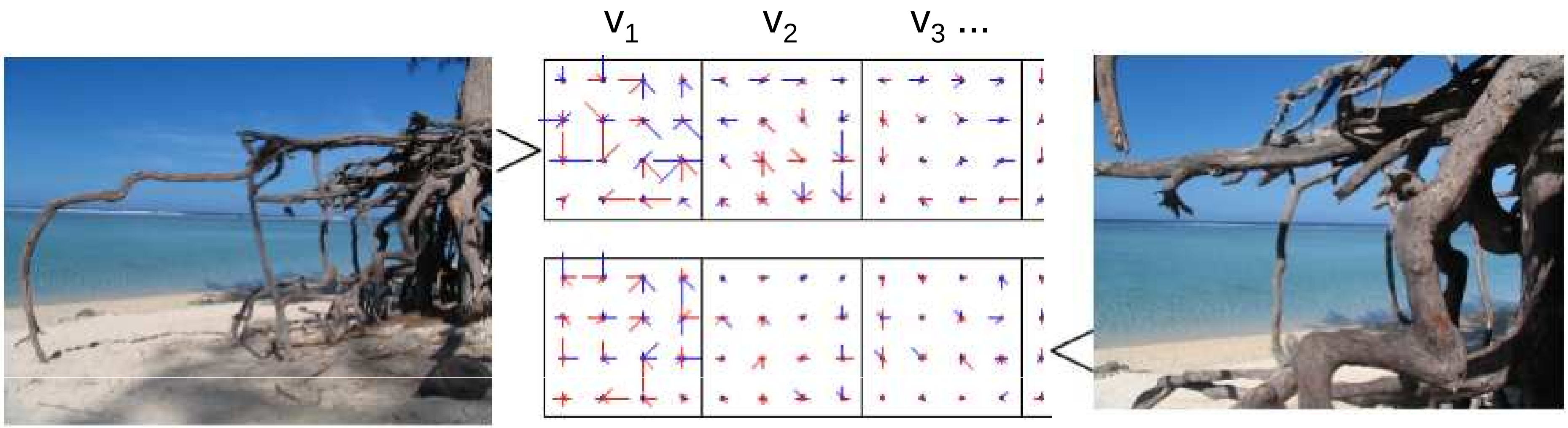
VLAD : vector of locally aggregated descriptors

- Learning: a vector quantifier (*k*-means)
  - output: *k* centroids (visual words): $c_1,\ldots,c_i,\ldots c_k$
  - centroid c_i has dimension *d*
- For a given image
  - assign each descriptor to closest center c_i
  - accumulate (sum) descriptors per cell

    $v_i := v_i + (x - c_i)$
- VLAD (dimension $D = k \times d$)
- The vector is L2-normalized
- Alternative: Fisher vector



VLADs for corresponding images



SIFT-like representation per centroid (+ components: blue, - components: red)

- good coincidence of energy & orientations

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

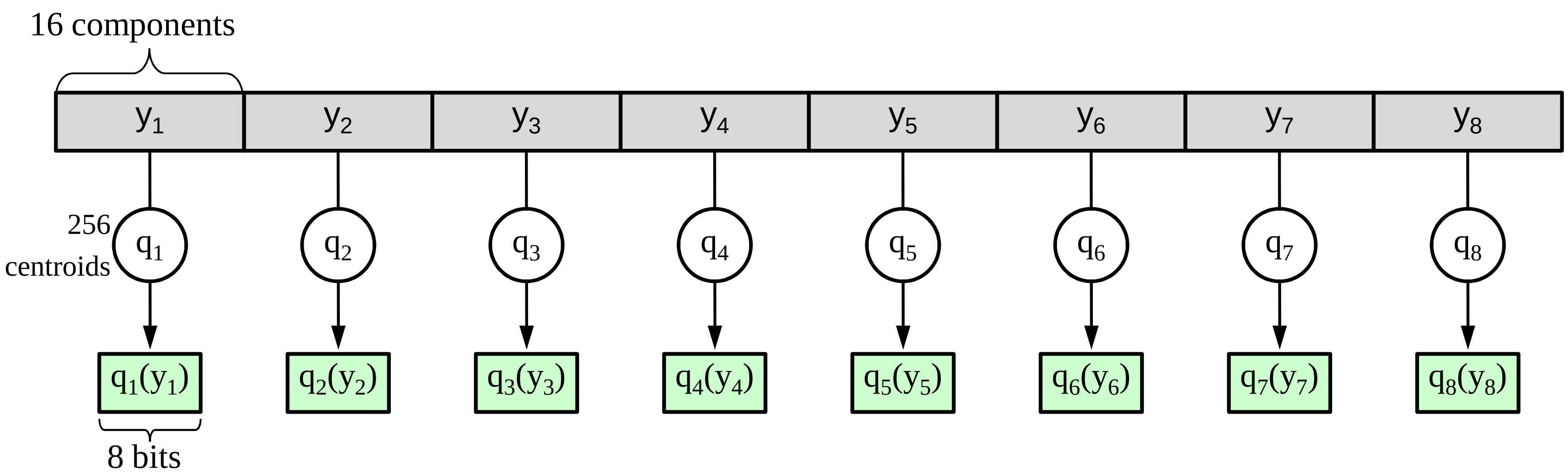
- Observations:
  - VLAD better than BoF for a given descriptor size
    → comparable to Fisher kernels for these operating points
  - Choose a small D if output dimension D' is small

Product quantization for nearest neighbor search

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

- Subvectors are quantized separately by quantizers $q(y) = [q_1(y_1)|\ldots|q_m(y_m)]$
  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
  - each subvector is quantized with 256 centroids -> 8 bit
  - very large codebook 256^8 ~ 1.8x10^19



⇒ 8 subvectors x 8 bits = 64-bit quantization index

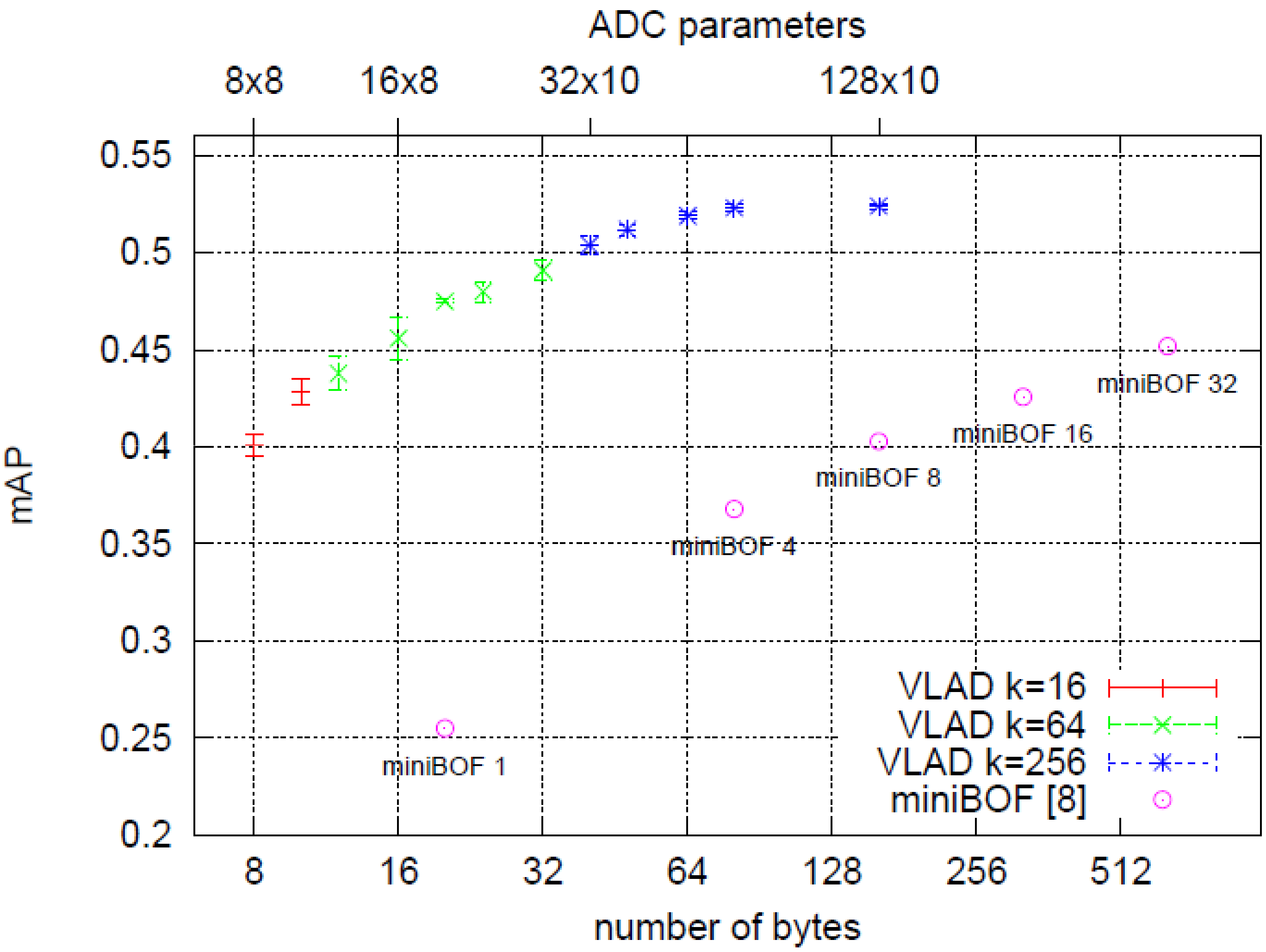
Joint optimization of VLAD and dimension reduction-indexing

- For VLAD
  - The larger *k*, the better the raw search performance
  - But large *k* produce large vectors, that are harder to index

- Optimization of the vocabulary size
  - Fixed output size (in bytes)
  - *D'* computed from *k* via the joint optimization of reduction/indexing
  - Only *k* has to be set

➔ end-to-end parameter optimization

Results on the Holidays dataset with various quantization parameters



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 x 8	**16**	**2.88**	**46.0**
VLAD k=64, ADC 32 x10	**40**	**3.10**	**49.5**

$D'=64$ for $k=16$ and $D'=96$ for $k=64$

ADC (subvectors) x (bits to encode each subvector)

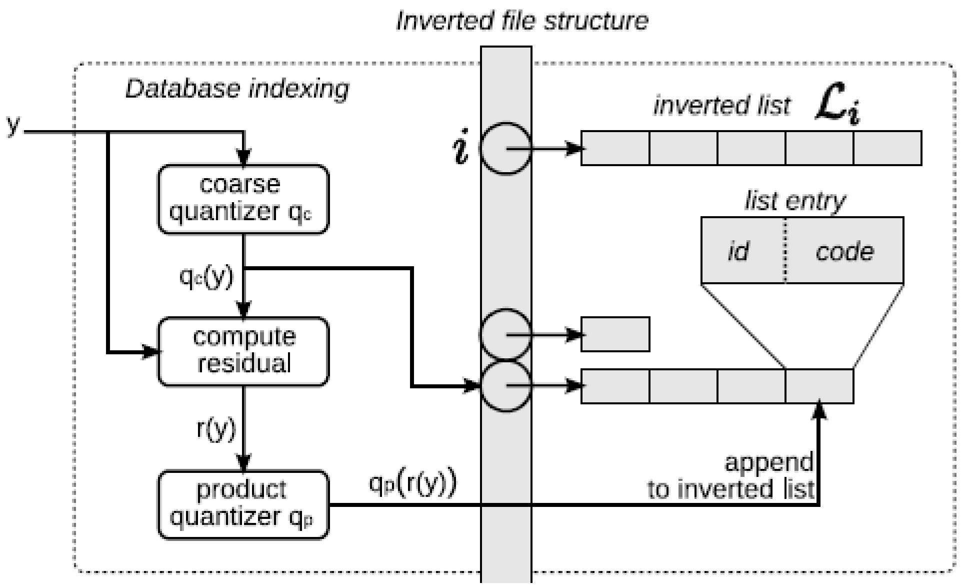
miniBOF: "Packing Bag-of-Features", ICCV'09

Large scale experiments (10 million images)

- Exhaustive search of VLADs, D'=64
  - 4.77s

- With the product quantizer
  - Exhaustive search with ADC: 0.29s
  - Non-exhaustive search with IVFADC: 0.014s

IVFADC -- Combination with an inverted file



Large scale experiments (10 million images)