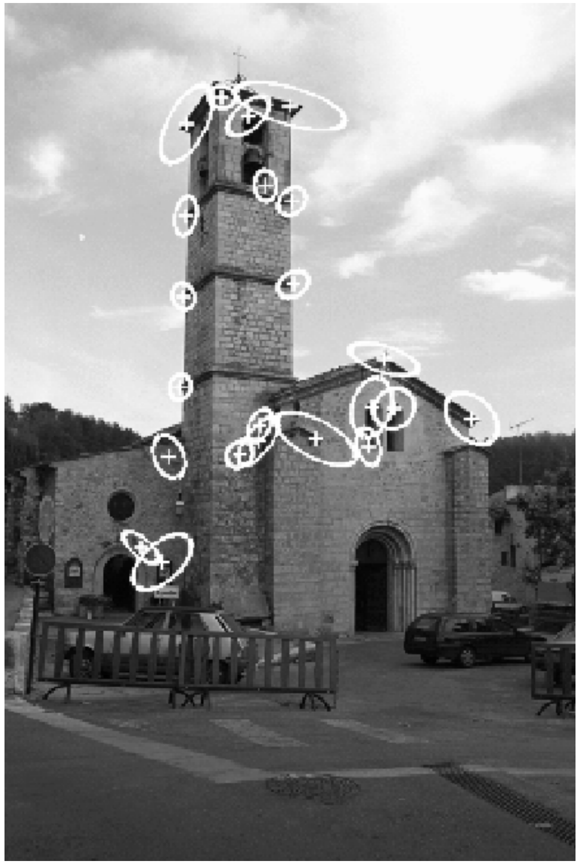
Instance level recognition IV: Very large databases

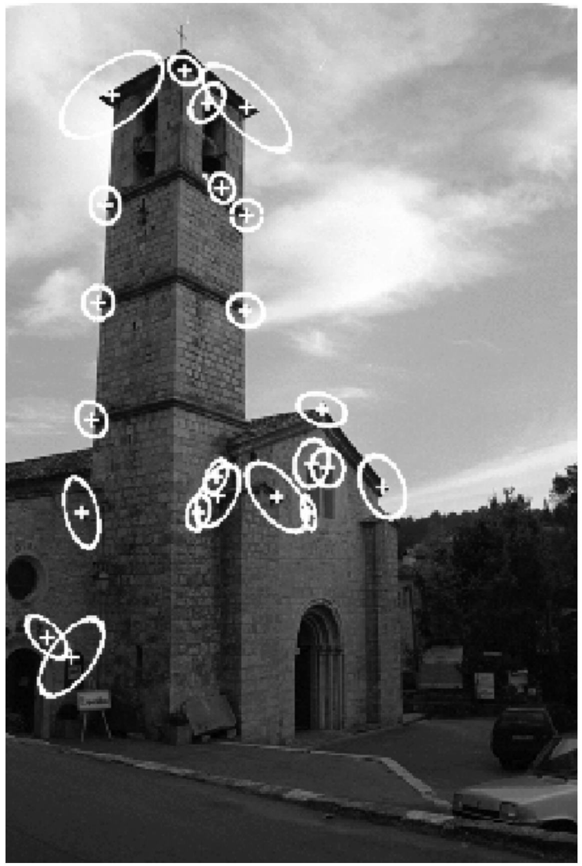
Cordelia Schmid
LEAR – INRIA Grenoble

Visual search

change in viewing angle

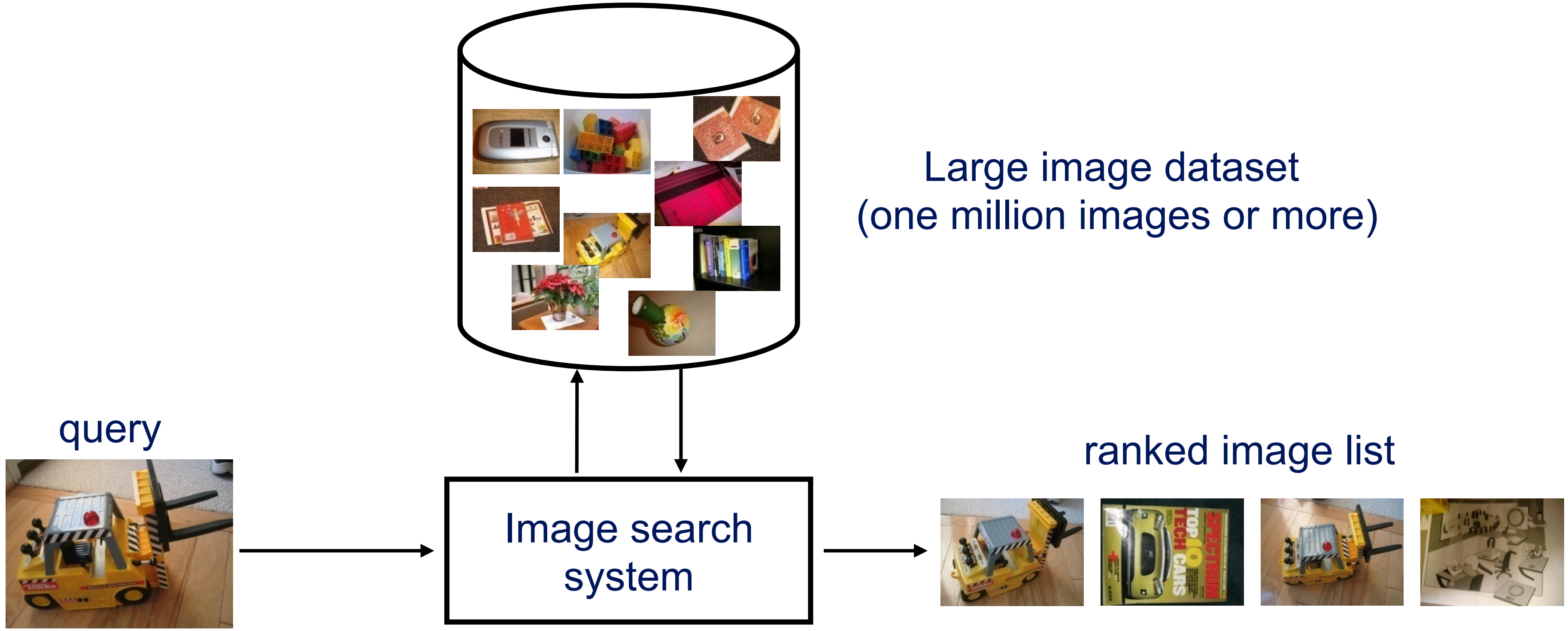
Matches





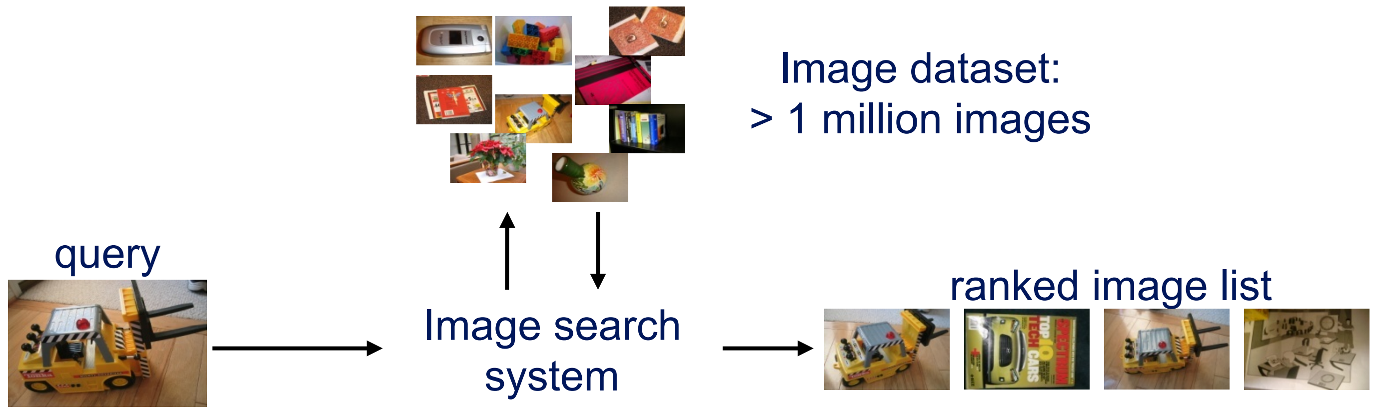
22 correct matches

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!

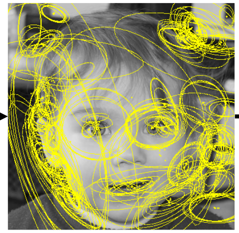
- Database representation in RAM:
  - Size of descriptors : 1 TB, search+memory intractable

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

Inverted file

querying

ranked image short-list

Geometric verification

[Chum & al. 2007]

Re-ranked list

- 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

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

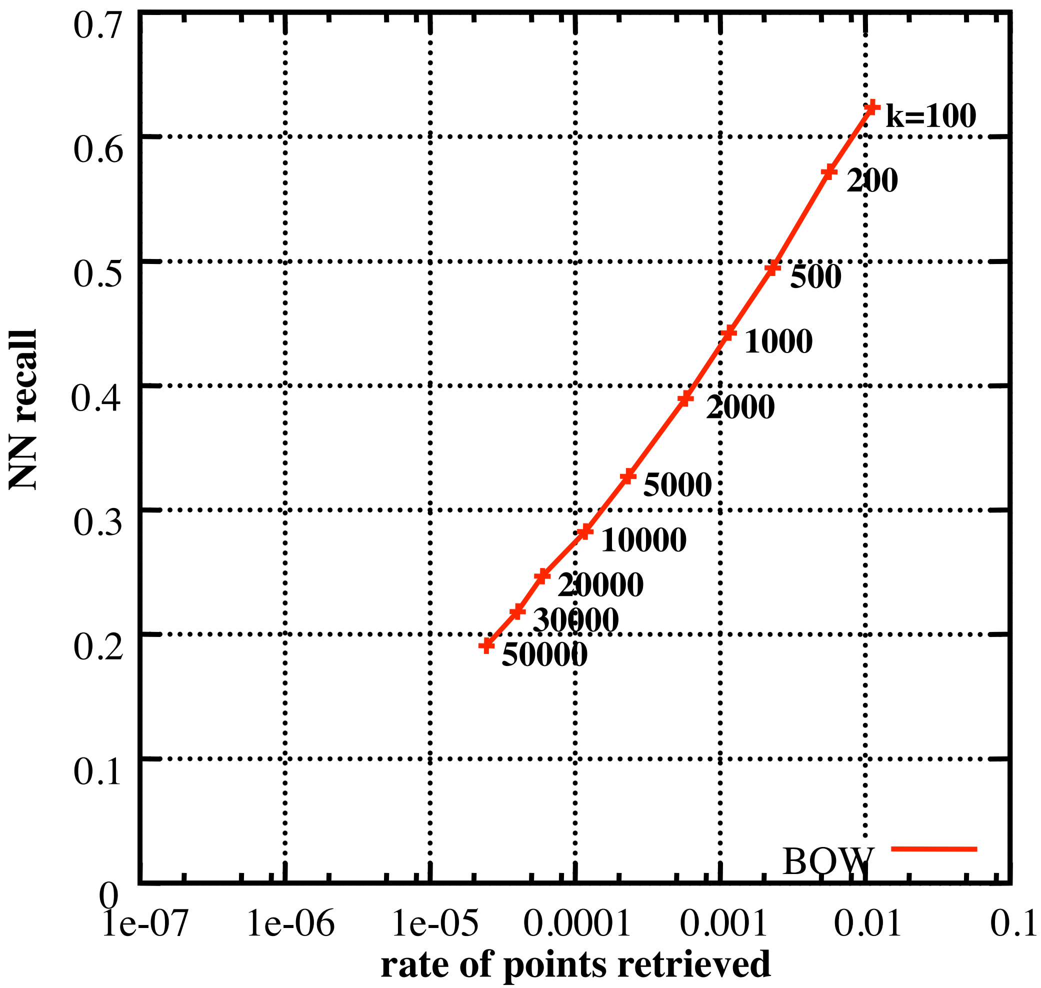
- Proposed quality evaluation of ANN search: trade-off between
  - **Accuracy**: **NN recall** = probability that *the* NN is in this list

    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



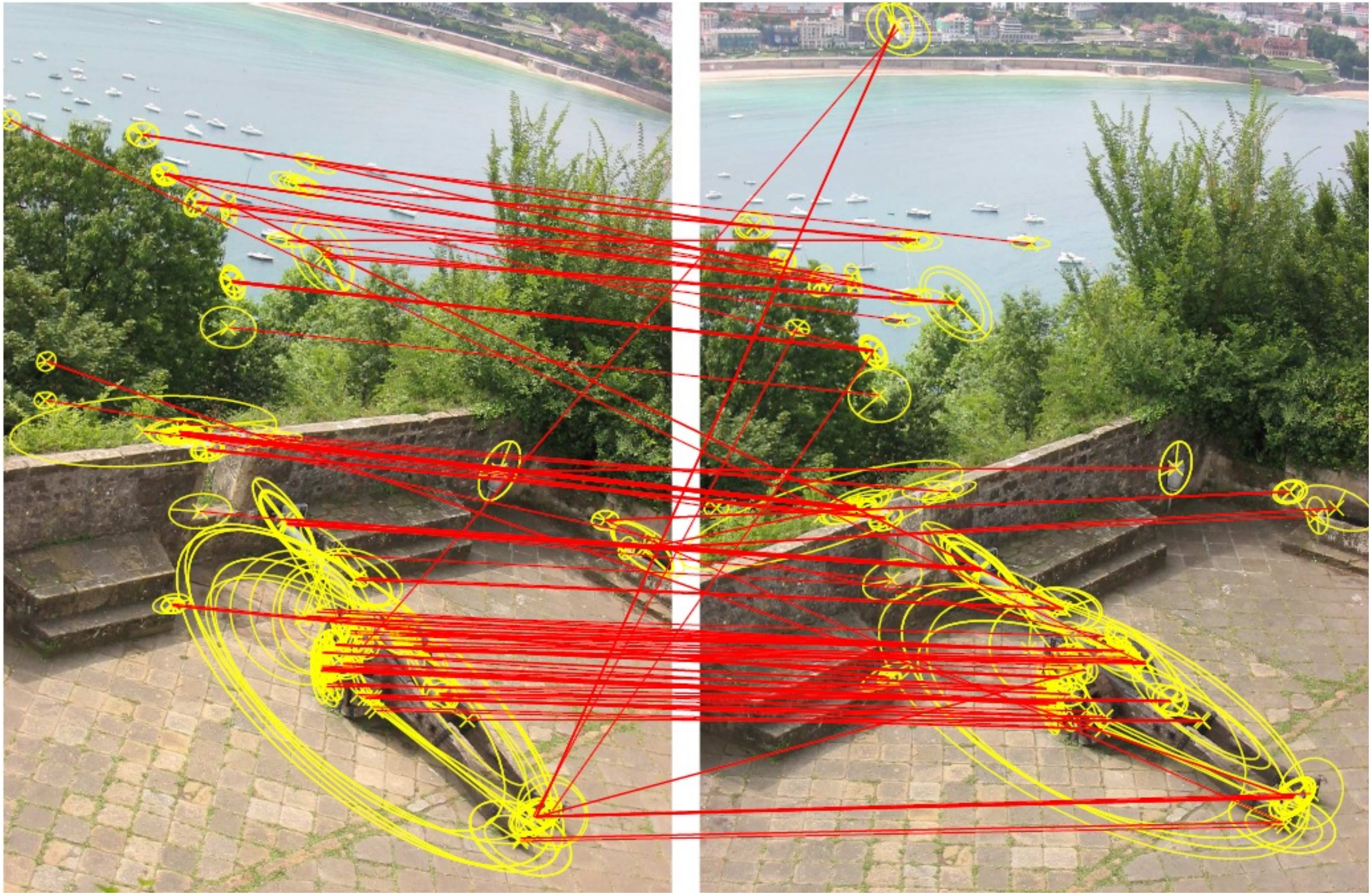
- ANN algorithms returns a list of potential neighbors

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

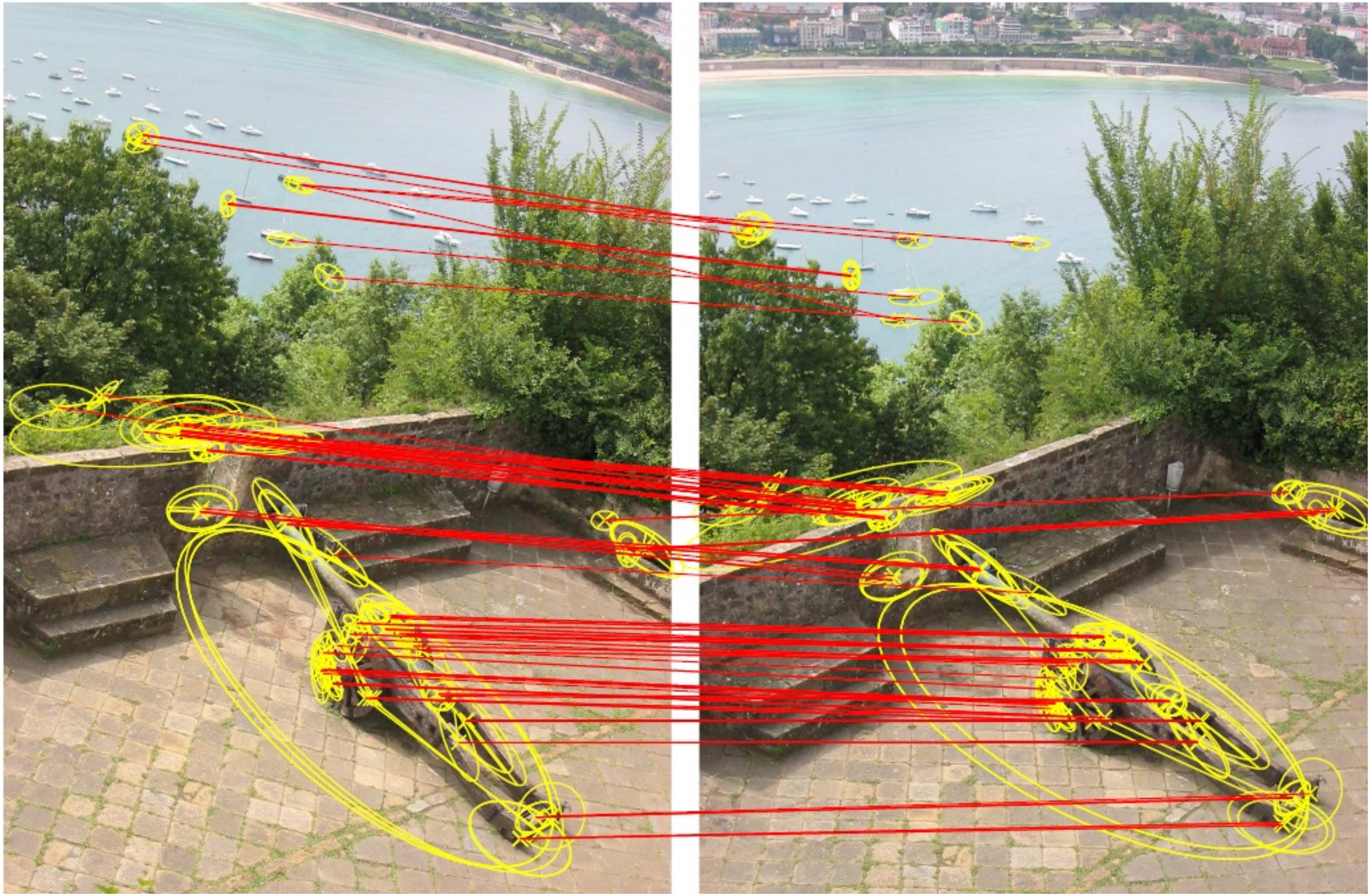
- **Ambiguity removal**: = proportion of vectors in the short-list

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

20K visual word: false matches



200K visual word: good matches missed

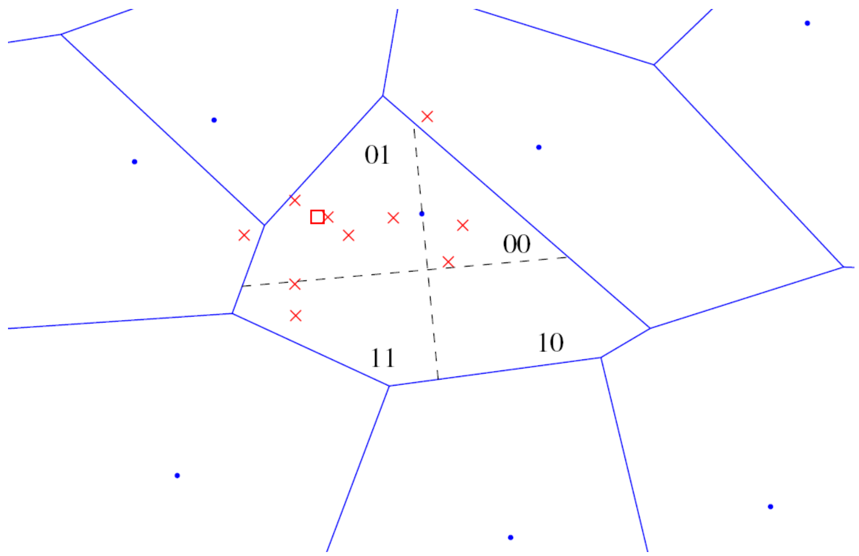


Problem with bag-of-features

- The intrinsic matching scheme performed by BOF is weak
  - for a “small” visual dictionary: too many false matches
  - for a “large” visual dictionary: many 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
  - → intrinsic approximate nearest neighbor search of BOF is not sufficient
  - Possible solutions
    - ➢ Soft assignment [Philbin et al. CVPR’08]
    - ➢ Additional short codes [Jegou et al. ECCV’08]

Hamming Embedding [Jegou et al. ECCV'08]



Representation of a descriptor *x*

– Vector-quantized to *q(x)* as in standard BOF

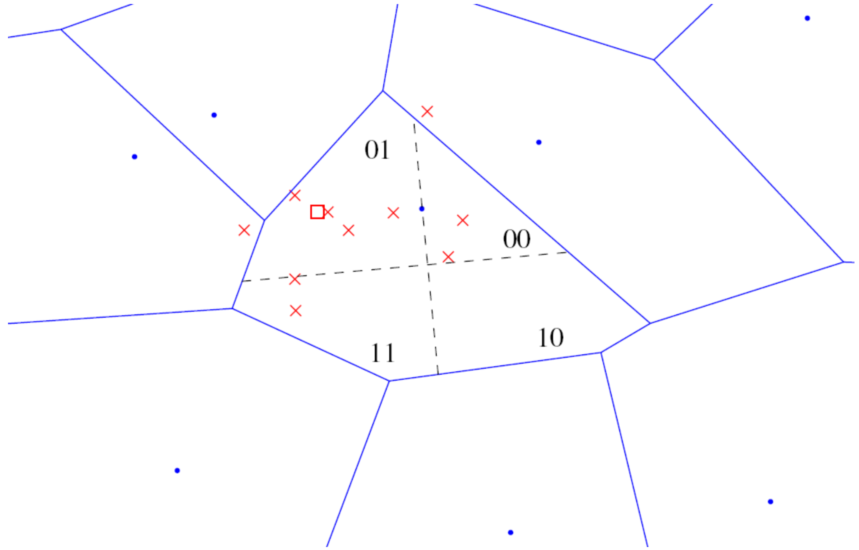
+ short binary vector *b(x)* for an additional localization in the Voronoi cell

Two descriptors x and y match iif

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

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

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

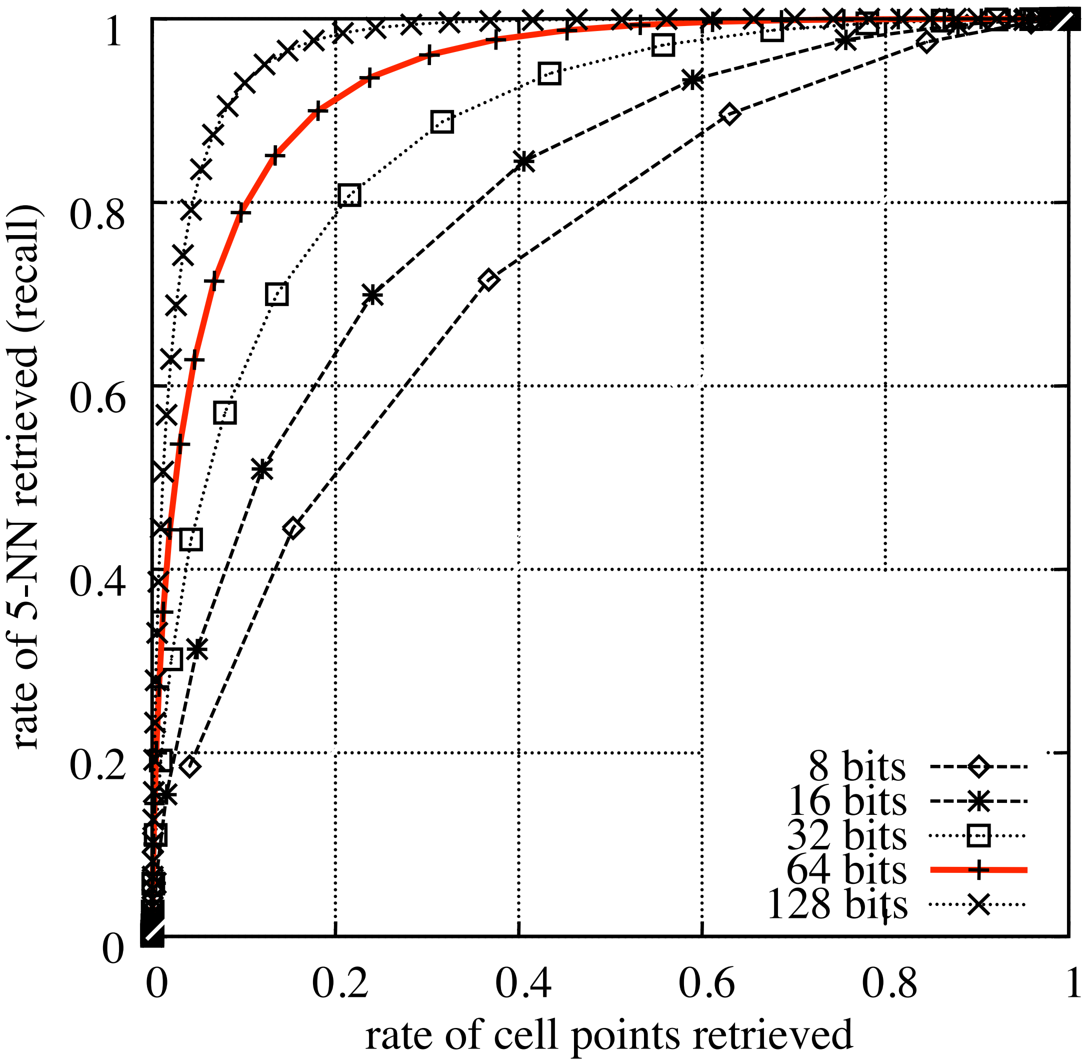
•Efficiency
- Hamming distance = very few operations
- Fewer random memory accesses: 3 x faster that BOF with same dictionary size!

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

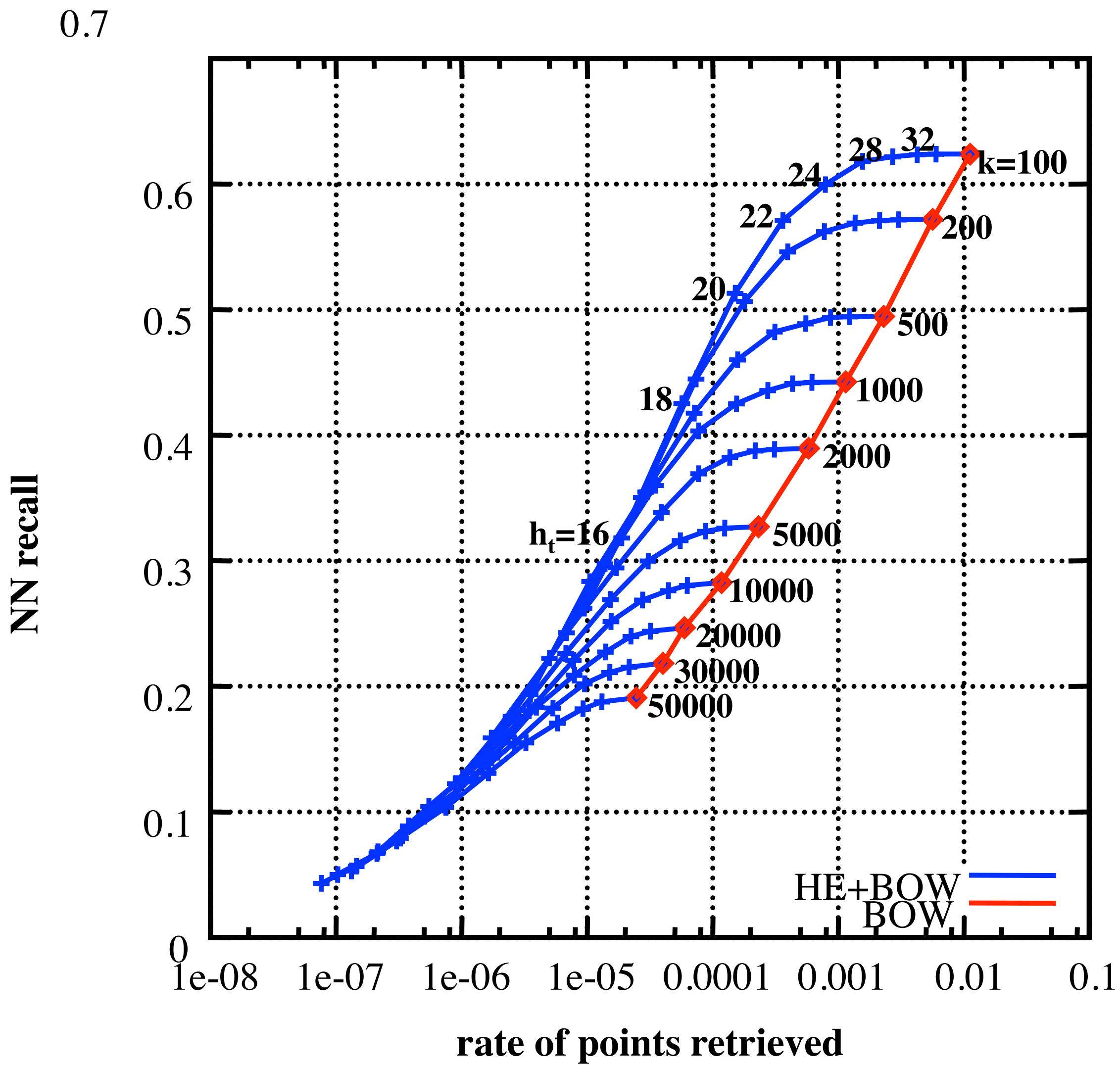


Trade-off between memory usage and accuracy

→More bits yield higher accuracy

In practice, 64 bits (8 byte)

ANN evaluation of Hamming Embedding



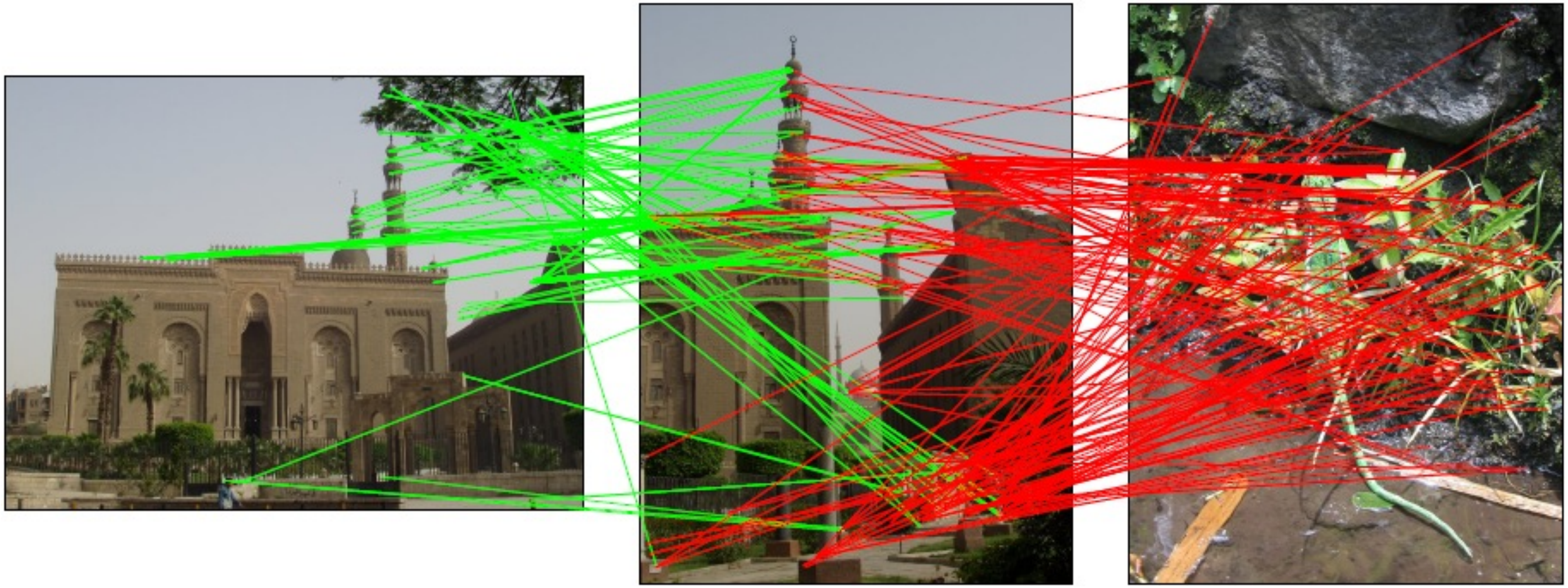
compared to BOW: at least 10 times less points in the short-list for the same level of accuracy

Hamming Embedding provides a much better trade-off between recall and ambiguity removal

Matching points - 20k word vocabulary

201 matches

240 matches

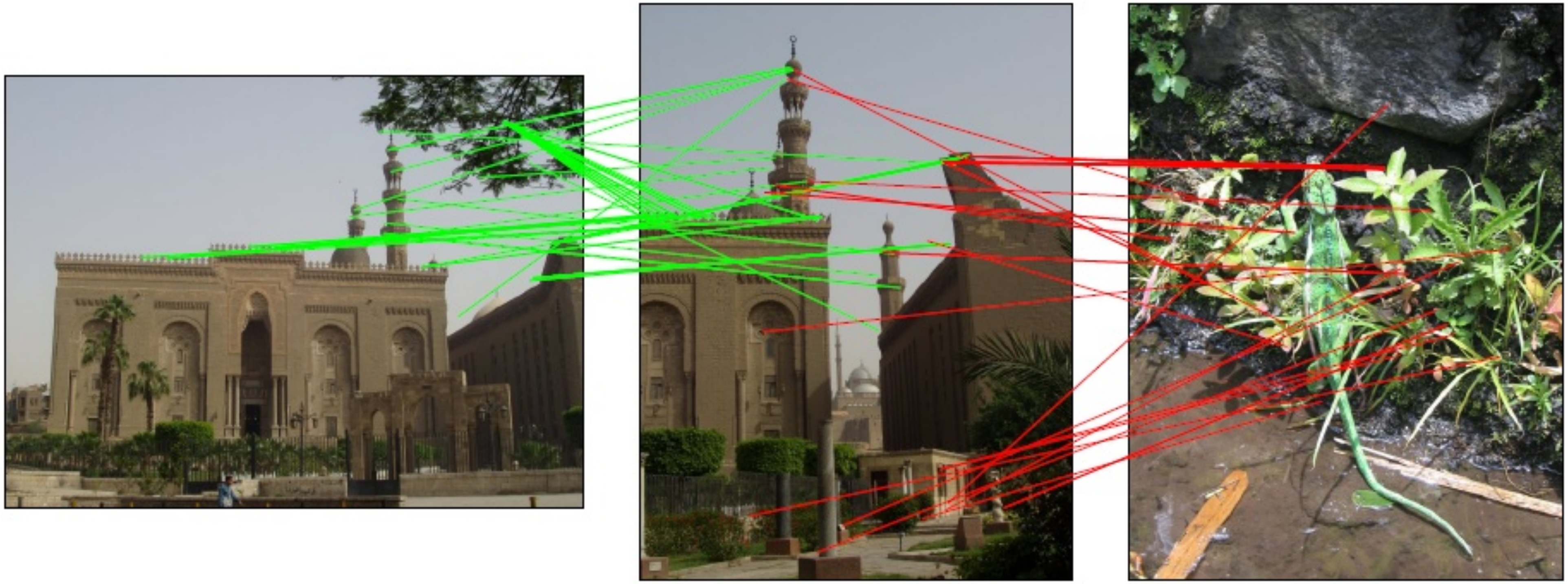


Many matches with the non-corresponding image!

Matching points - 200k word vocabulary

69 matches

35 matches

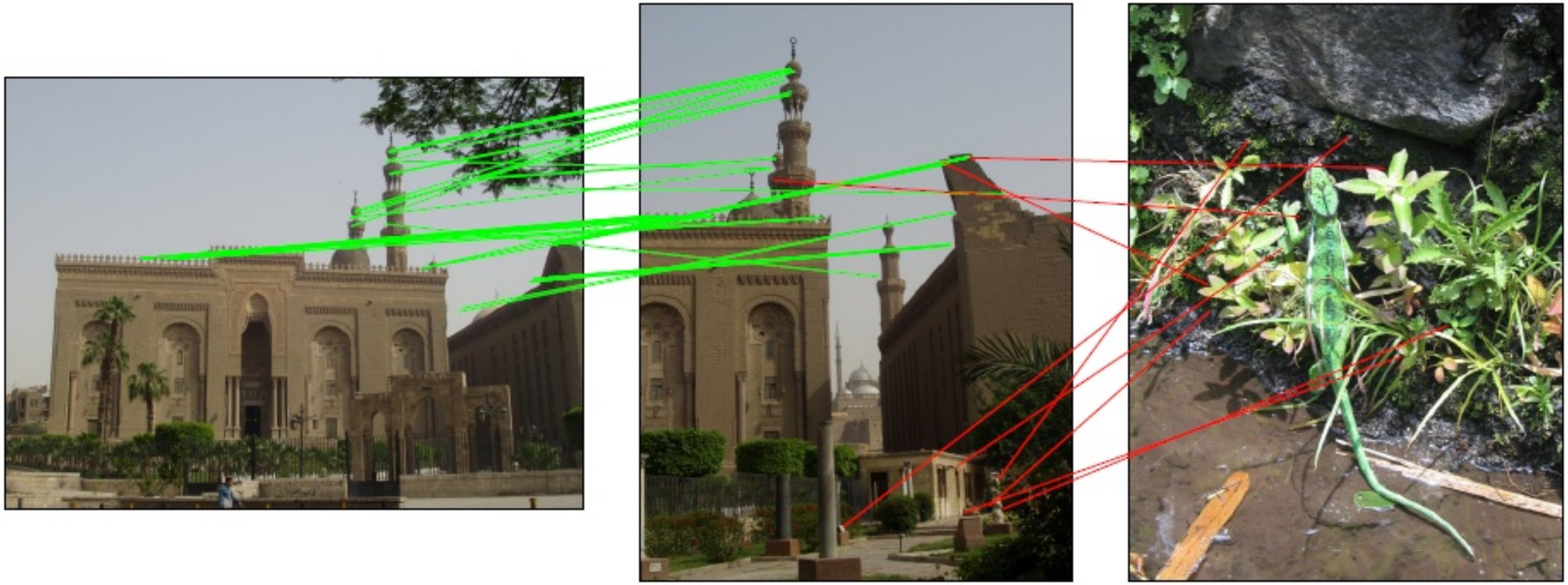


Still many matches with the non-corresponding one

Matching points - 20k word vocabulary + HE

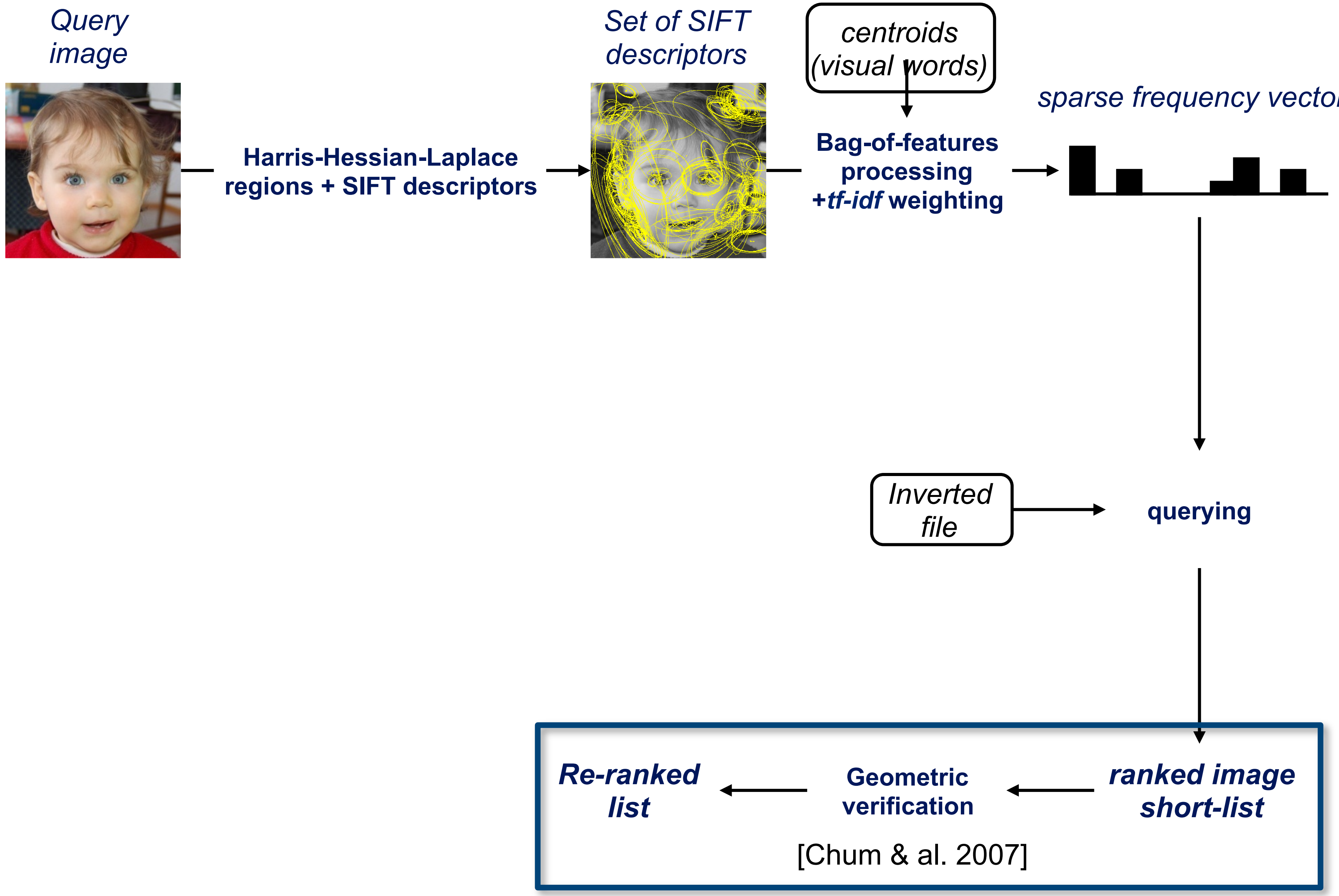
83 matches

8 matches



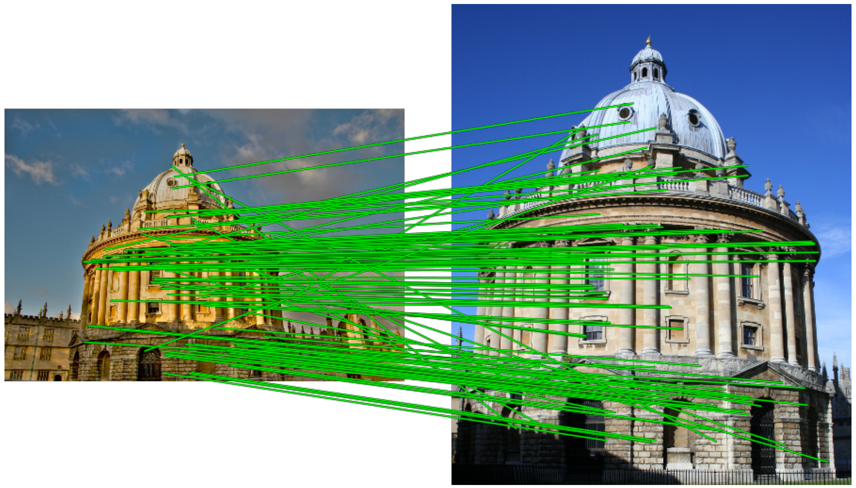
10x more matches with the corresponding image!

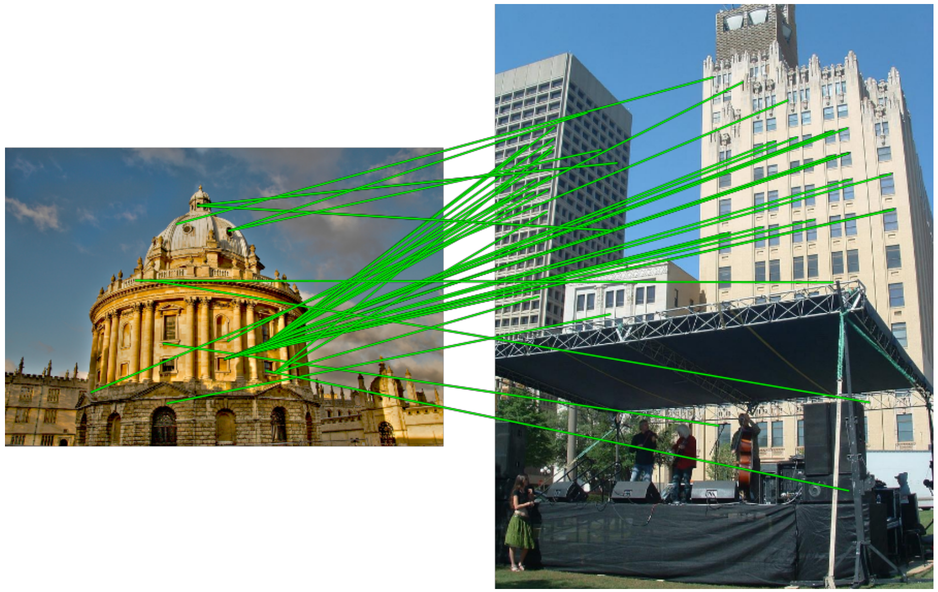
Bag-of-features [Sivic&Zisserman' 03]



Geometric verification

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

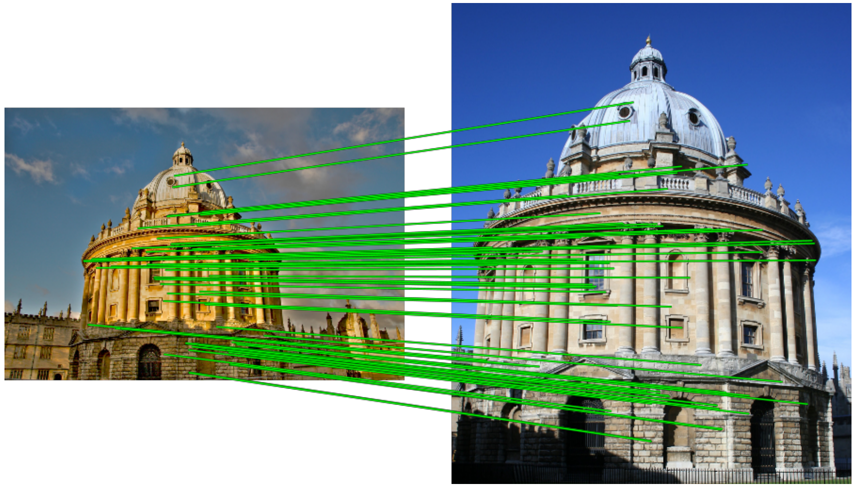




Both images have many matches – which is correct?

Geometric verification

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

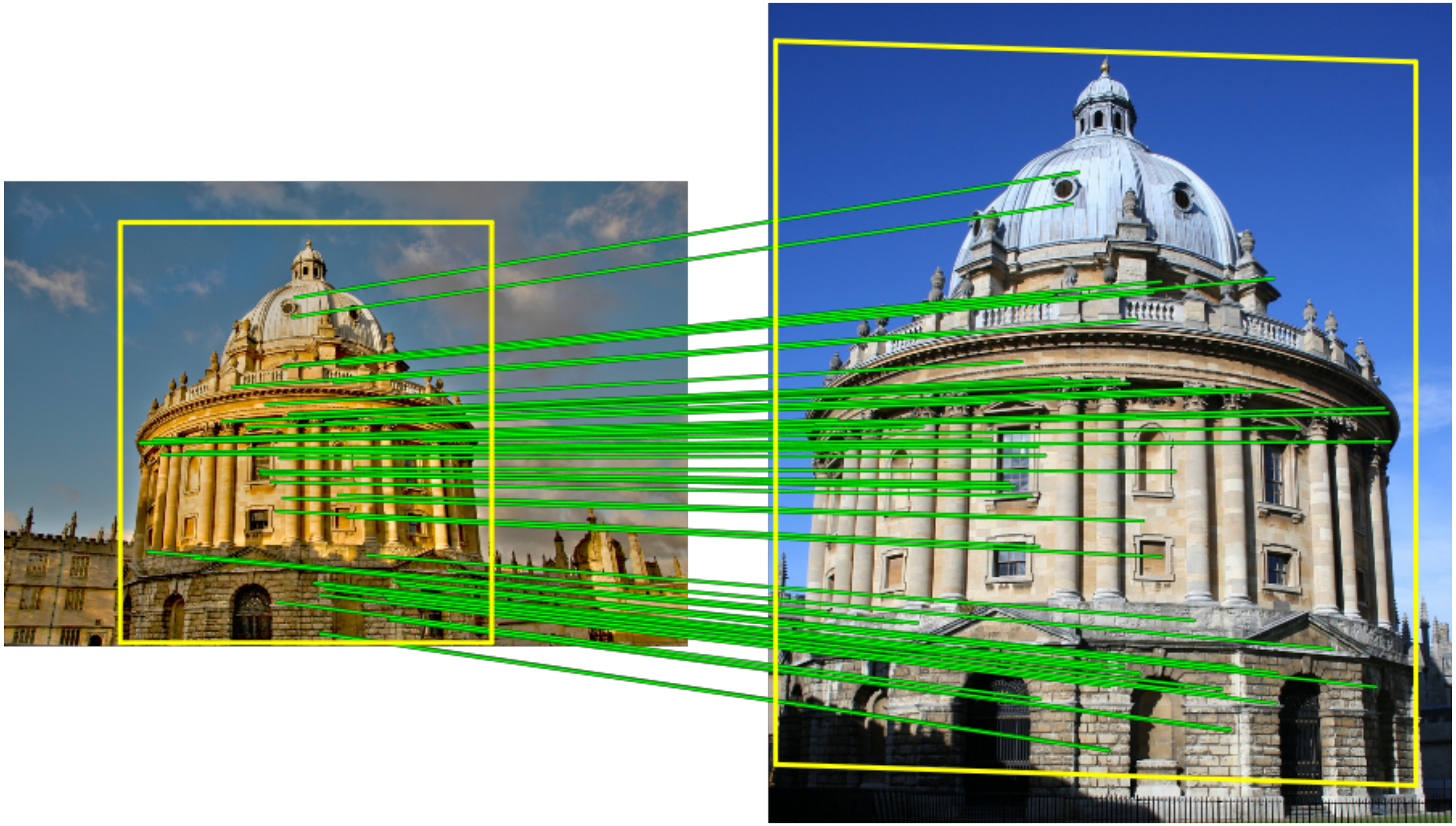


Many spatially consistent matches – **correct result**

Few spatially consistent matches – **incorrect result**

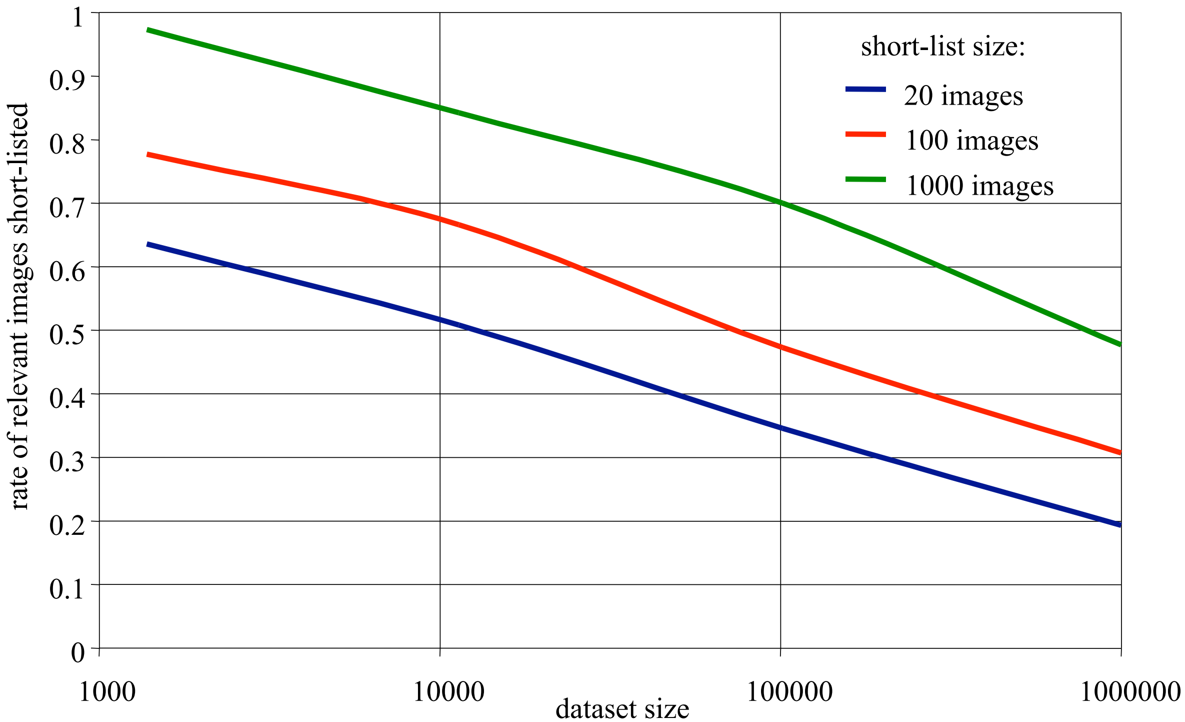
Geometric verification

Gives **localization** of the object



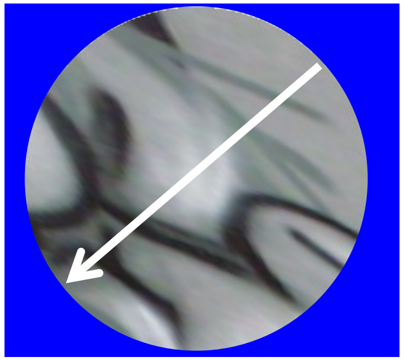
Re-ranking based on geometric verification

- works very well
- but performed on a short-list only (typically, 1000 images)
  → for very large datasets, the number of distracting images is so high that relevant images are not even short-listed!
  → weak geometry



Weak geometry consistency

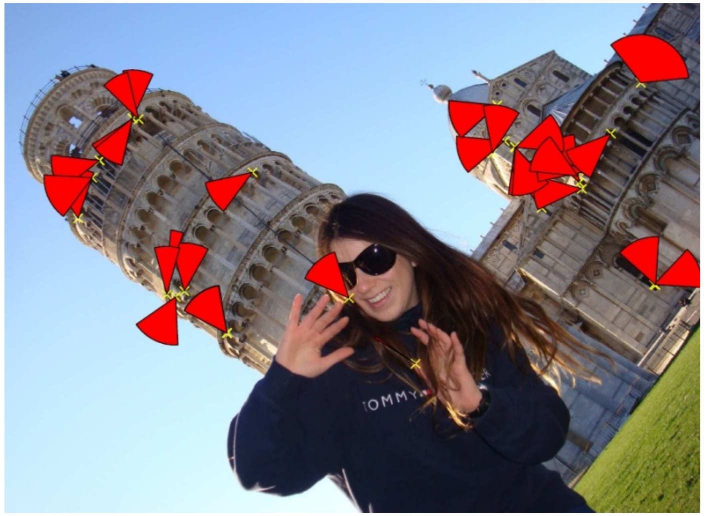
- Weak geometric information used for **all** images (not only the short-list)
- Each invariant interest region detection has a scale and rotation angle associated, here characteristic scale and dominant gradient orientation



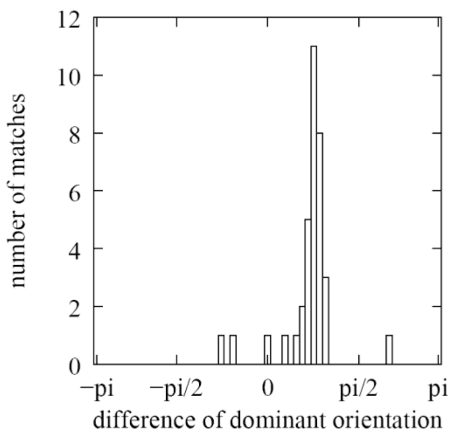
Scale change 2
Rotation angle ca. 20 degrees

- Each matching pair results in a scale and angle difference
- For the global image scale and rotation changes are roughly consistent

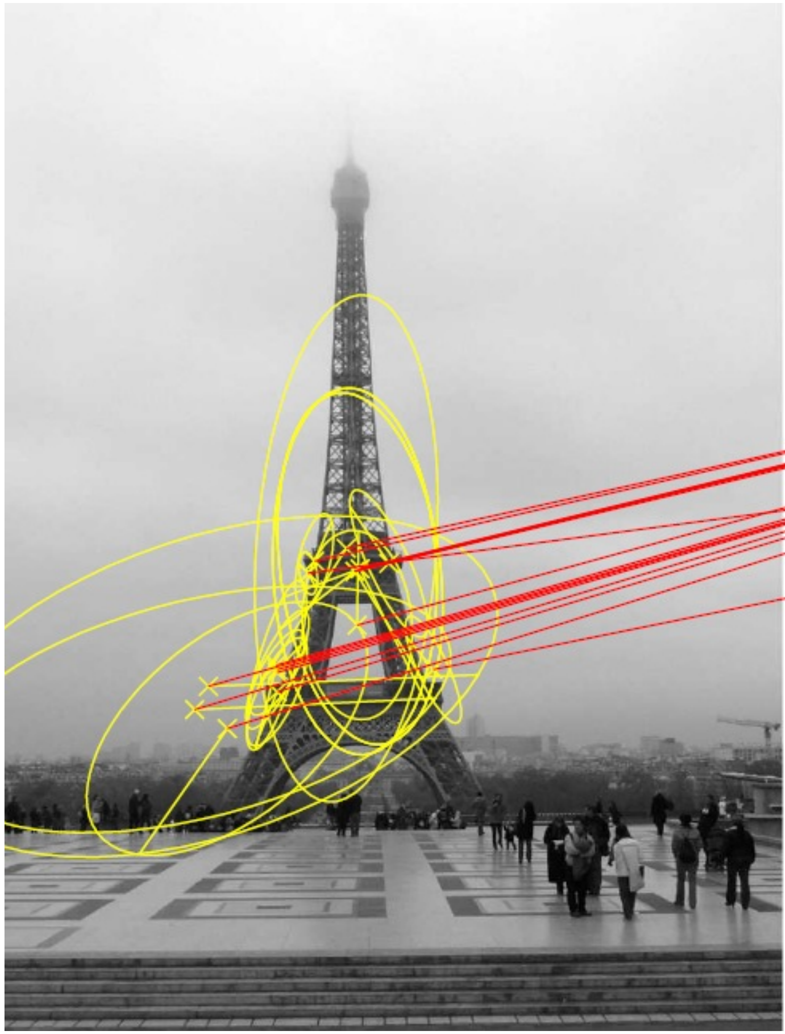
WGC: orientation consistency

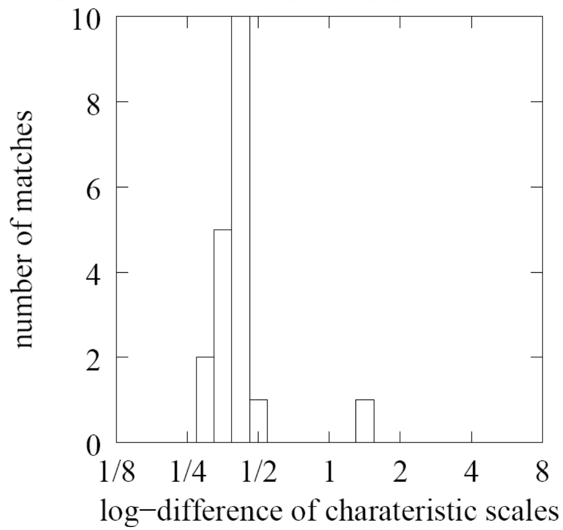


Max = rotation angle between images



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

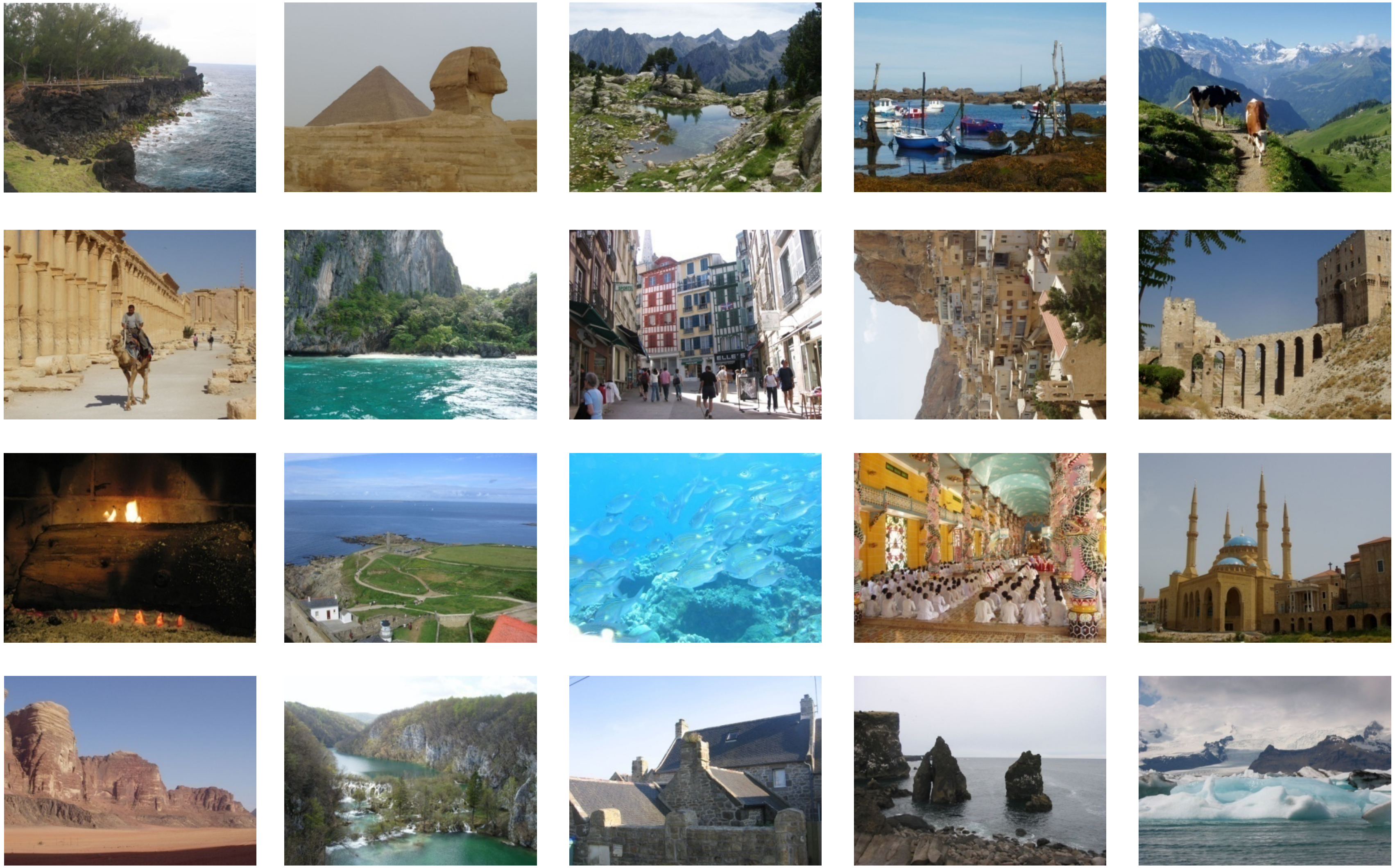
- Re-ranking using full geometric transformation still adds information in a final stage

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

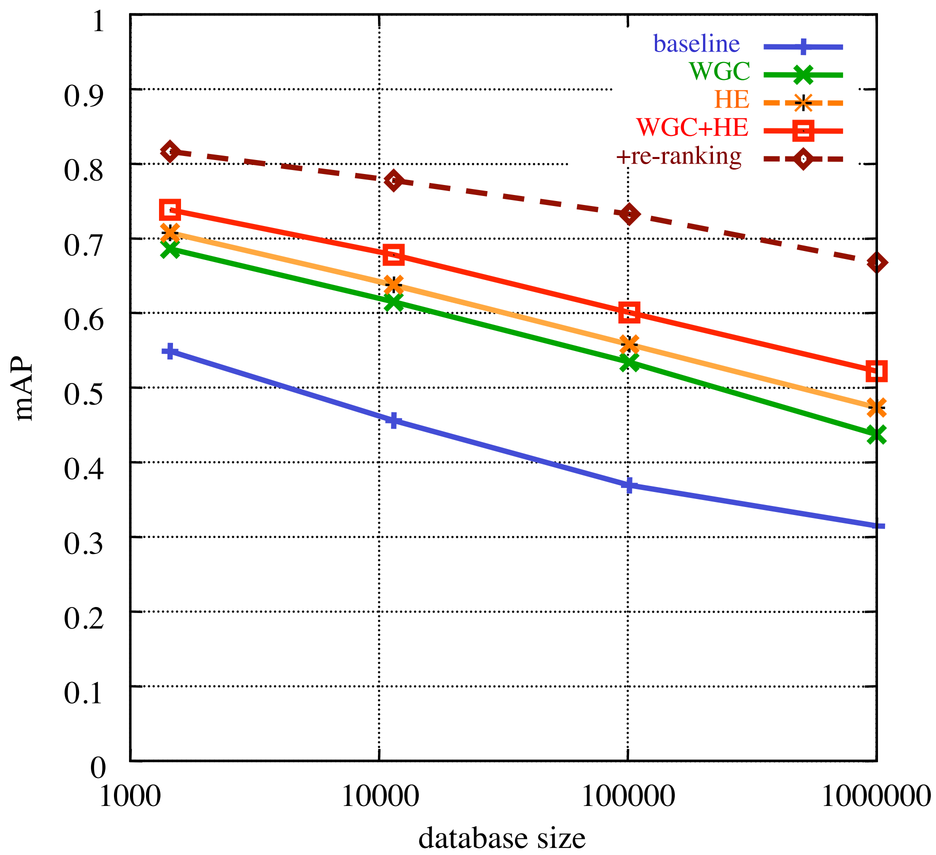

Base 8


Base 9

Example distractors - Flickr

Experimental evaluation

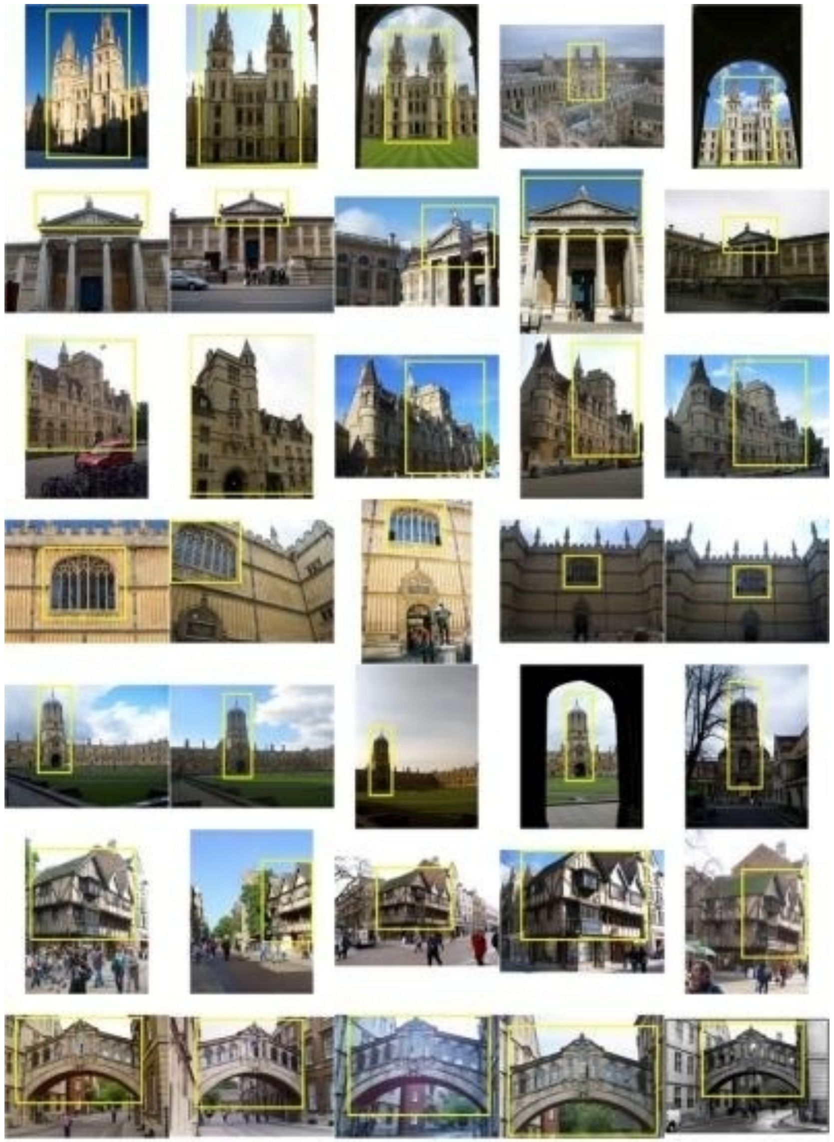
- Evaluation on our holidays dataset, 500 query images, 1 million distracter images
- Metric: mean average precision (in [0,1], bigger = better)



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

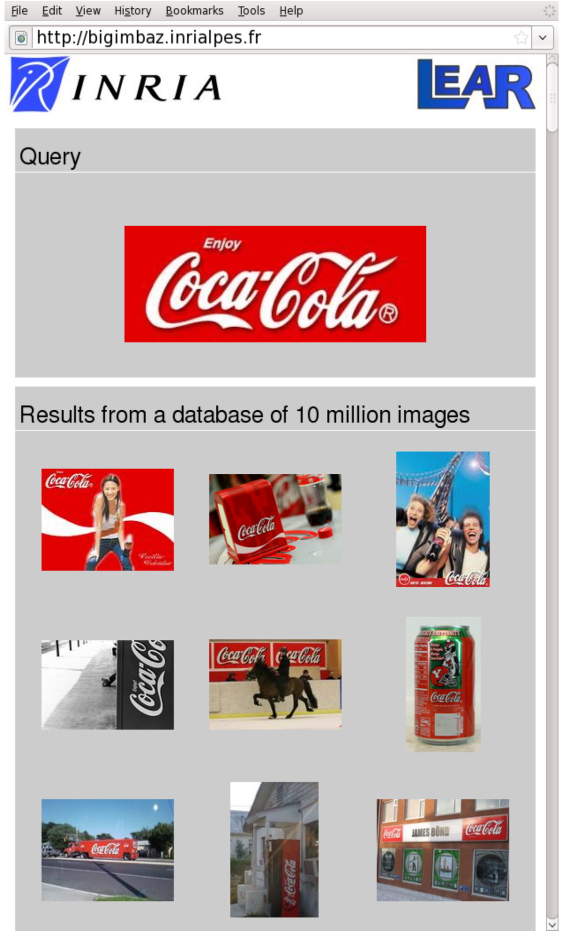
Evaluation measure: among the 4 best retrieval results how many are correct (ranges from 1 to 4)

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

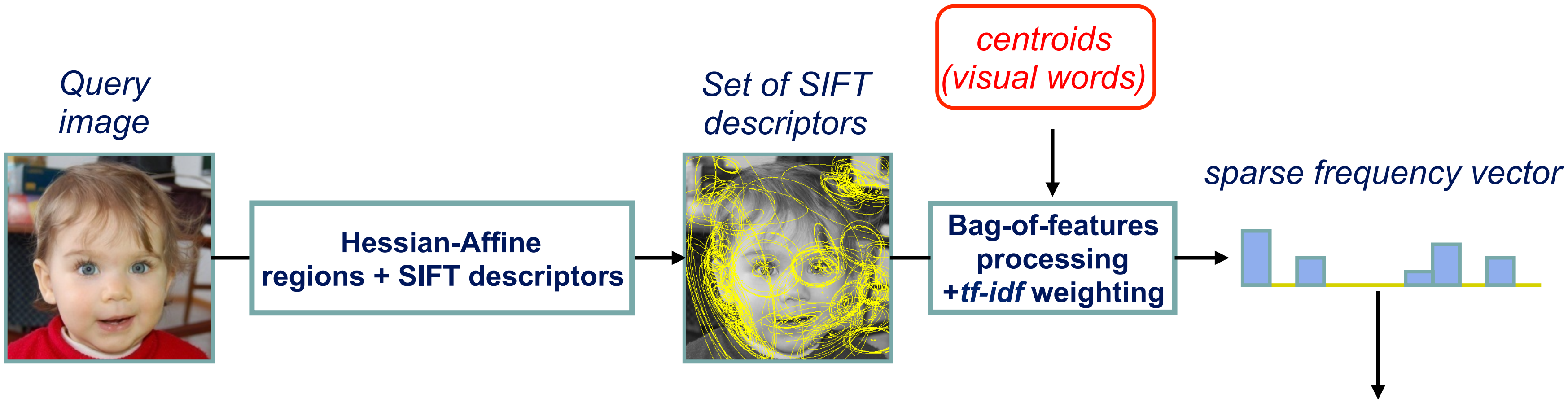


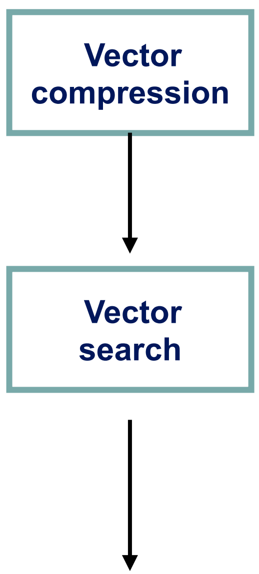
Demo at http://bigimbaz.inrialpes.fr

Towards large-scale image search

- BOF+inverted file can handle up to ~10 millions images
  - with a limited number of descriptors per image → RAM: 40GB
  - search: 2 seconds
- Web-scale = billions of images
  - with 100 M per machine → search: 20 seconds, RAM: 400 GB
  - not tractable
- Solution: represent each image by one compressed vector

Recent approaches for very large scale indexing





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

- This vector is compressed to reduce storage requirements

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]

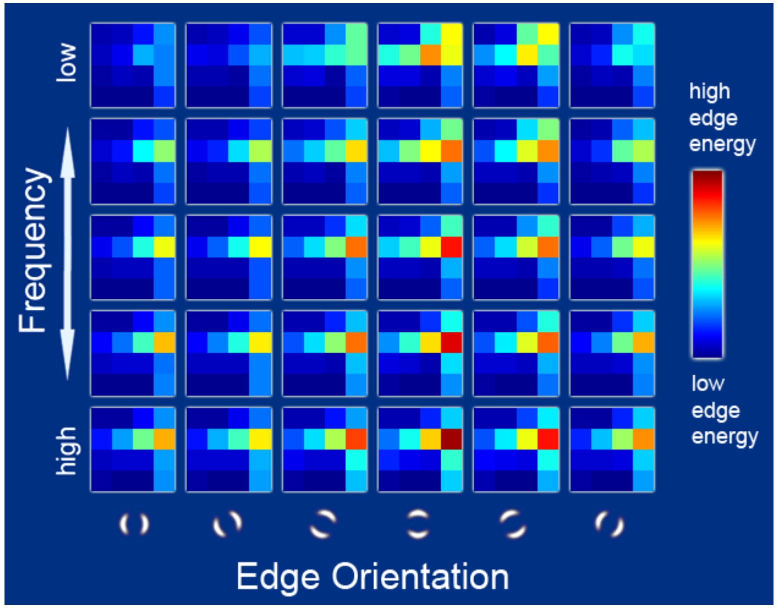
  → these approaches require hundreds of bytes to obtain a “reasonable quality”

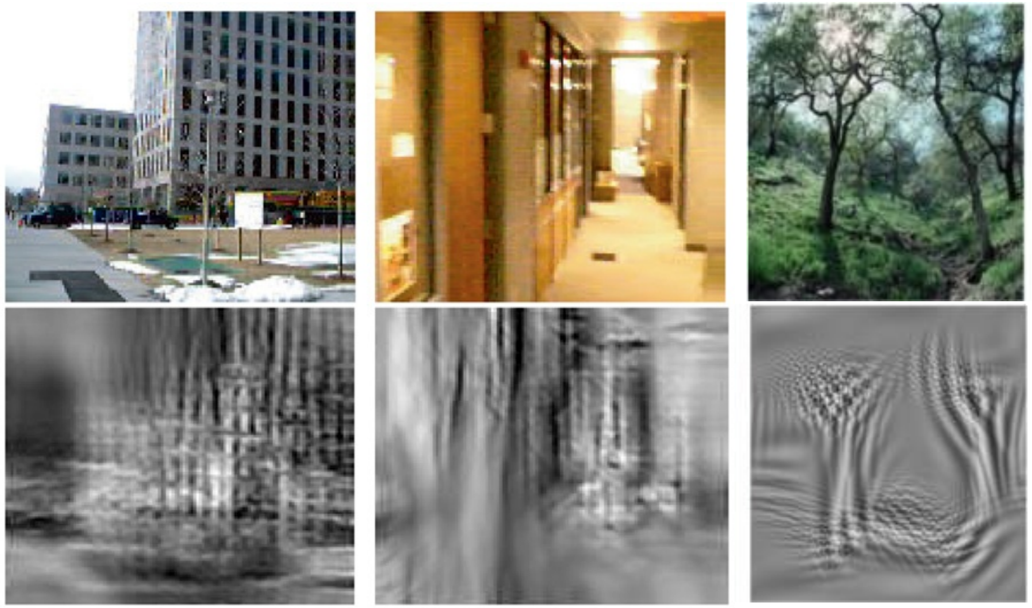
- GIST descriptors with Spectral Hashing [Weiss et al.’08]

  → 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

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

  → 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]

Aggregating local descriptors

- Set of n local descriptors → 1 vector
- Popular approach: bag of features, often with SIFT features
- Recently improved aggregation schemes
  - Fisher vector [Perronnin & Dance '07]
  - VLAD descriptor [Jegou, Douze, Schmid, Perez '10]
  - Supervector [Zhou et al. '10]
  - Sparse coding [Wang et al. '10, Boureau et al.'10]
- Use in very large-scale retrieval and classification

Aggregating local descriptors

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

→ significant dimensionality reduction introduces loss

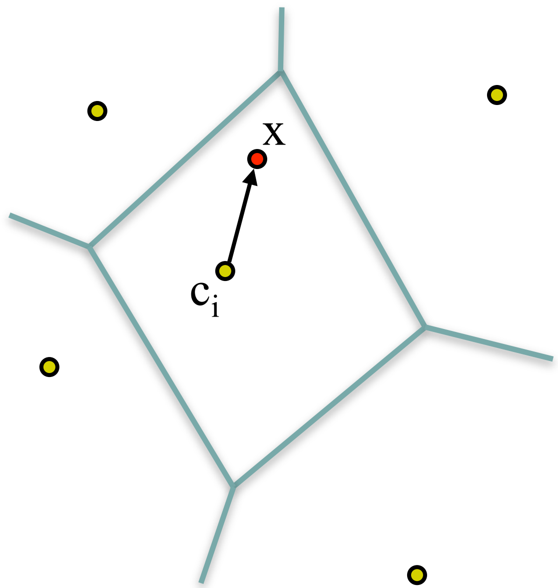
- Vector of locally aggregated descriptors (VLAD) [Jegou et al. 10]
  - non sparse vector
  - fast to compute
  - excellent results with a small vector dimensionality

- Fisher vector [Perronnin & Dance 07]
  - probabilistic version of VLAD
  - initially used for image classification
  - comparable or improved performance over VLAD for image retrieval

VLAD : vector of locally aggregated descriptors

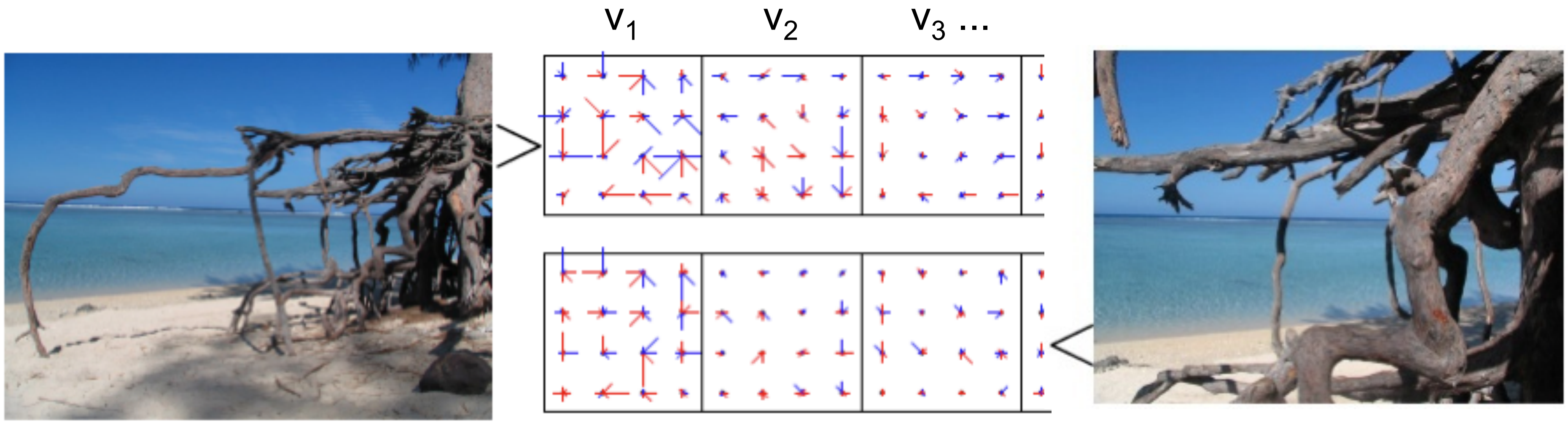
- Determine a vector quantifier (*k*-means)
  - output: *k* centroids (visual words): $c_1, \ldots, c_i, \ldots c_k$
  - centroid c_i has dimension *d*
- For a given image
  - assign each descriptor to closest center c_i
  - accumulate (sum) descriptors per cell

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



[Jegou, Douze, Schmid, Perez, CVPR'10]

VLADs for corresponding images

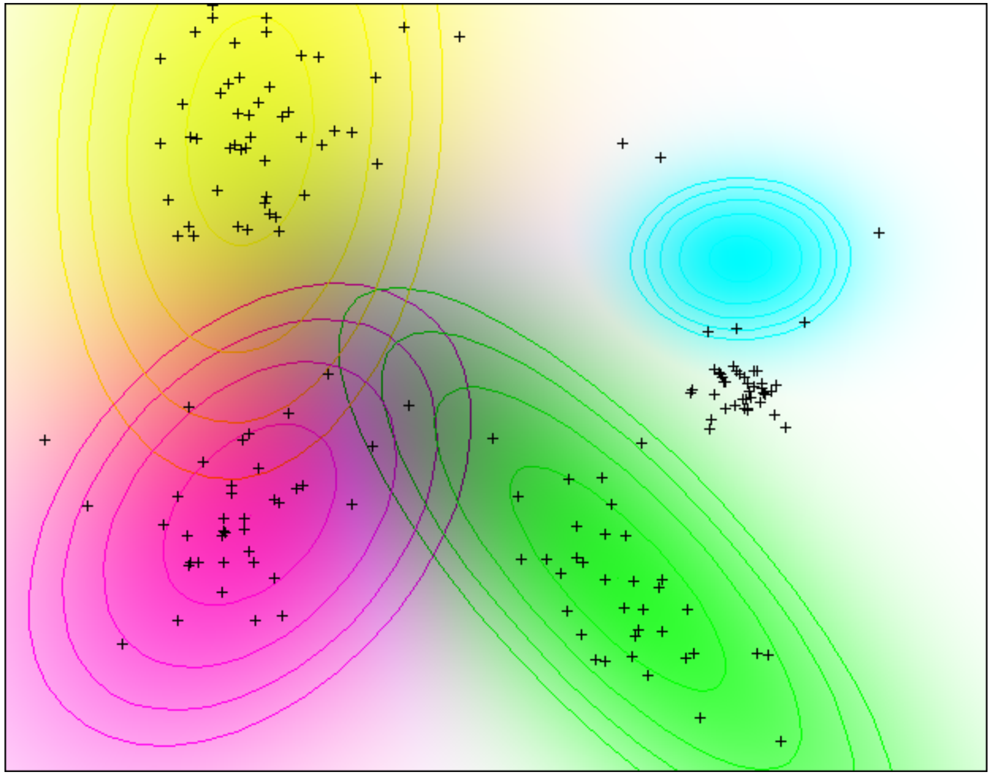


SIFT-like representation per centroid (+ components: blue, - components: red)

- good coincidence of energy & orientations

Fisher vector

- Use a Gaussian Mixture Model as vocabulary
- Statistical measure of the descriptors of the image w.r.t the GMM
- Derivative of likelihood w.r.t. GMM parameters



GMM parameters:

w_i weight

μ_i mean

σ_i co-variance

(diagonal)

Translated cluster →
large derivative on μ_i for this
component

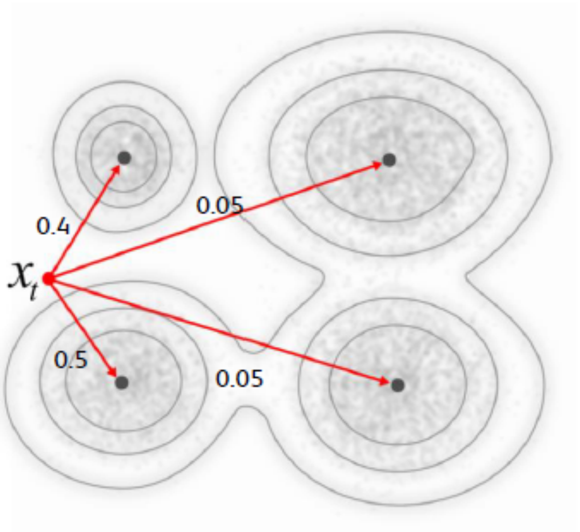
[Perronnin & Dance 07]

Fisher vector

FV formulas:

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

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



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

Fisher Vector = concatenation of per-Gaussian gradient vectors

For image retrieval in our experiments:

- only deviation wrt mean, dim: K*D [K number of Gaussians, D dim of descriptor]
- variance does not improve for comparable vector length

VLAD/Fisher/BOF performance and dimensionality reduction

- We compare Fisher, VLAD and BoF on INRIA Holidays Dataset (mAP %)
- Dimension is reduced to D' dimensions with PCA

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
	256	16 384	58.7	62.1	56.7	54.2	51.3	48.1
GIST		960	36.5					

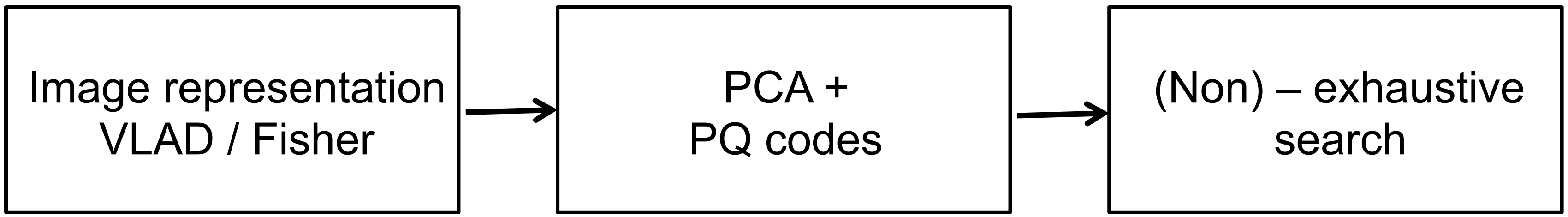
- Observations:
  - Fisher, VLAD better than BoF for a given descriptor size
  - Choose a small D if output dimension D' is small
  - Performance of GIST not competitive

[Jegou, Perronnin, Douze, Sanchez, Perez, Schmid, PAMI'12]

Compact image representation

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

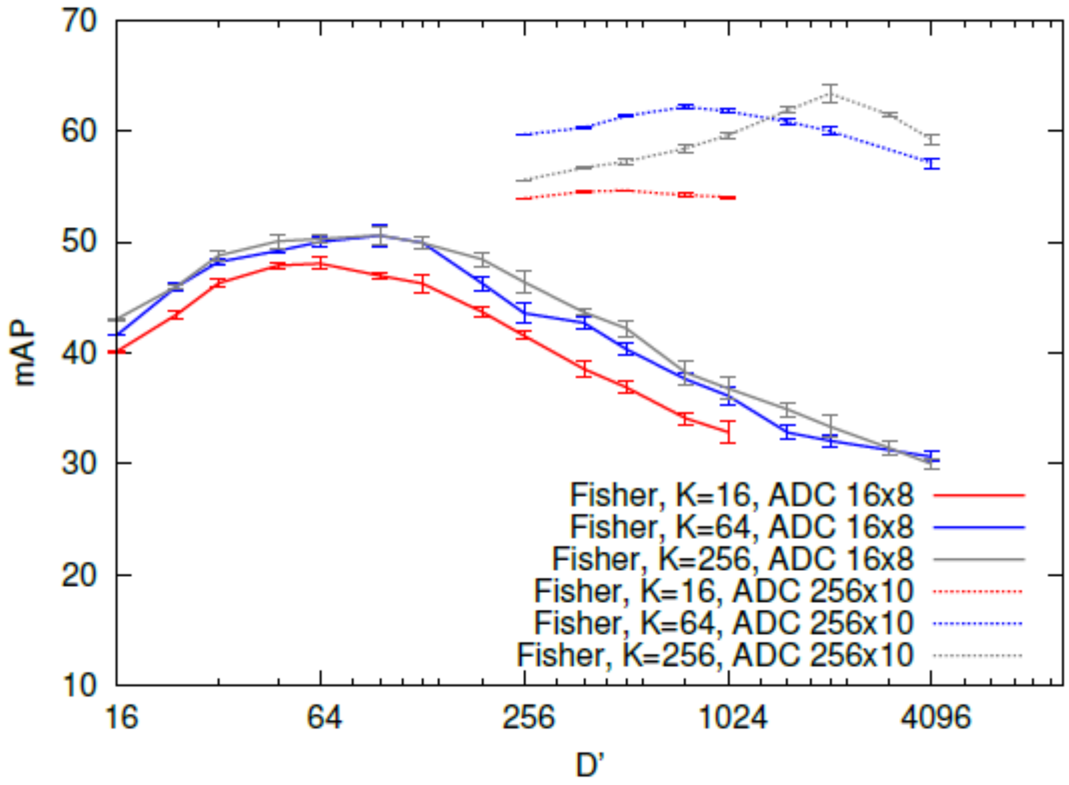
- Approach: joint optimization of three stages
  - local descriptor aggregation
  - dimension reduction
  - indexing algorithm



Optimizing the dimension reduction and quantization together

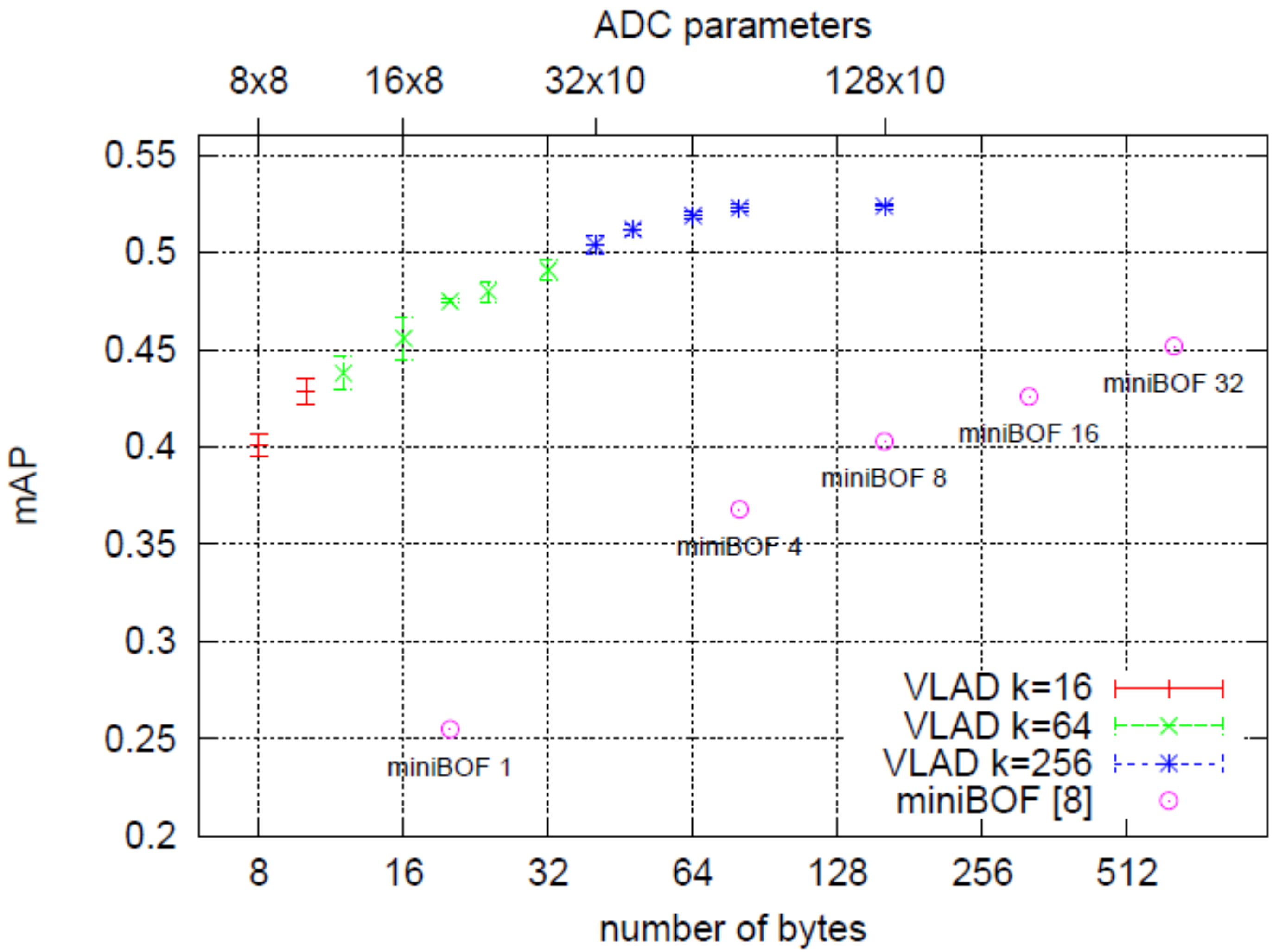
- Fisher vectors undergoes two approximations
  - mean square error from PCA projection
  - mean square error from quantization

- Given k and bytes/image, choose D' minimizing their sum



Results on Holidays dataset:
- there exists an optimal D'
- 16 byte best results for k=64
- 320 byte best results for k=256

Results on the Holidays dataset with various quantization parameters

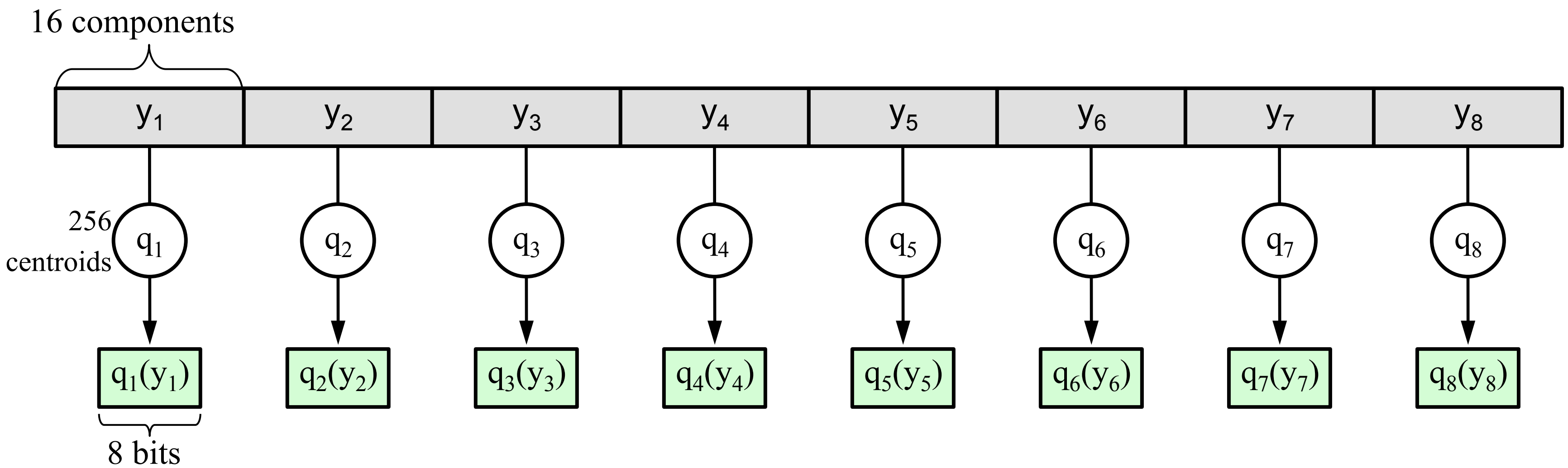


Product quantization for nearest neighbor search

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

- Subvectors are quantized separately by quantizers $q(y) = [q_1(y_1)| \dots |q_m(y_m)]$
  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



$\Rightarrow$ 8 subvectors x 8 bits = 64-bit quantization index

[Jegou, Douze, Schmid, PAMI'11]

Comparison to the state of the art

Method	bytes	UKB	Holidays
BOW, K=20,000	10 364	2.87	43.7
BOW, K=200,000	12 886	2.81	54.0
miniBOF [12]	20	2.07	25.5
	80	2.72	40.3
	160	2.83	42.6
FV K=64, spectral hashing 128 bits	16	2.57	39.4
VLAD, K=16, ADC 16×8 [23]	16	2.88	46.0
VLAD, K=64, ADC 32×10 [23]	40	3.10	49.5
FV K=8, binarized [22]	65	2.79	46.0
FV K=64, binarized [22]	520	3.21	57.4
FV K=64, ADC 16×8 (D'=96)	**16**	**3.10**	**50.6**
FV K=256, ADC 256×10 (D'=2048)	**320**	**3.47**	**63.4**

[12] H. Jégou, M. Douze, and C. Schmid, "Packing bag-of-features," in *ICCV*, September 2009.

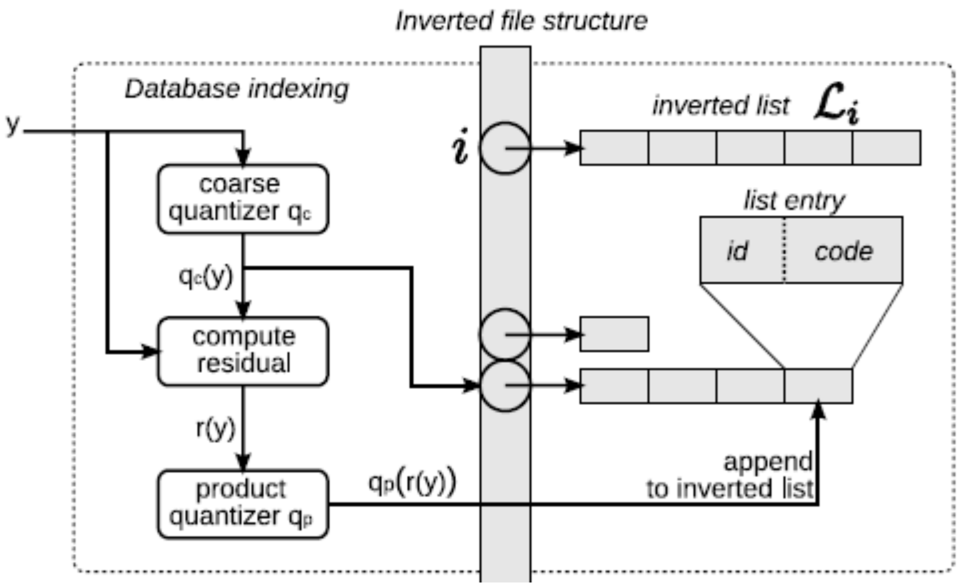
[22] F. Perronnin, Y. Liu, J. Sanchez, and H. Poirier, "Large-scale image retrieval with compressed Fisher vectors," in *CVPR*, June 2010.

[23] H. Jégou, M. Douze, C. Schmid, and P. Pérez, "Aggregating local descriptors into a compact image representation," in *CVPR*, June 2010.

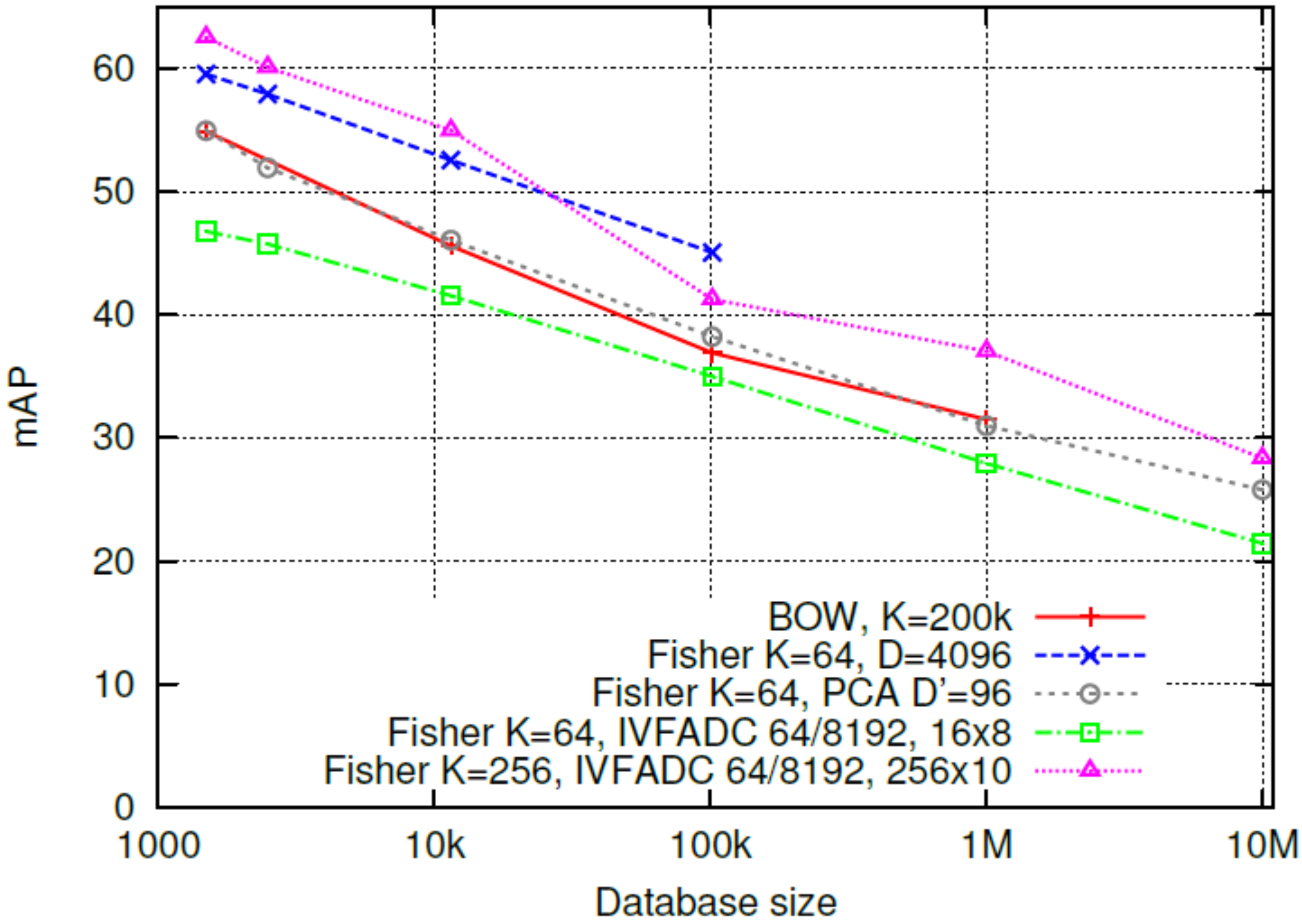
Large scale experiments (10 million images)

- 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)



Timings

IVFADC: 0.02s

Conclusion

- Competitive search accuracy with a few dozen bytes per indexed image

- Tested on 220 million video frames
  - extrapolation for 1 billion images: 20GB RAM, query < 1s on 8 cores

- Code on-line available Software for Fisher computation and PQ-codes
  - http://lear.inrialpes.fr/software