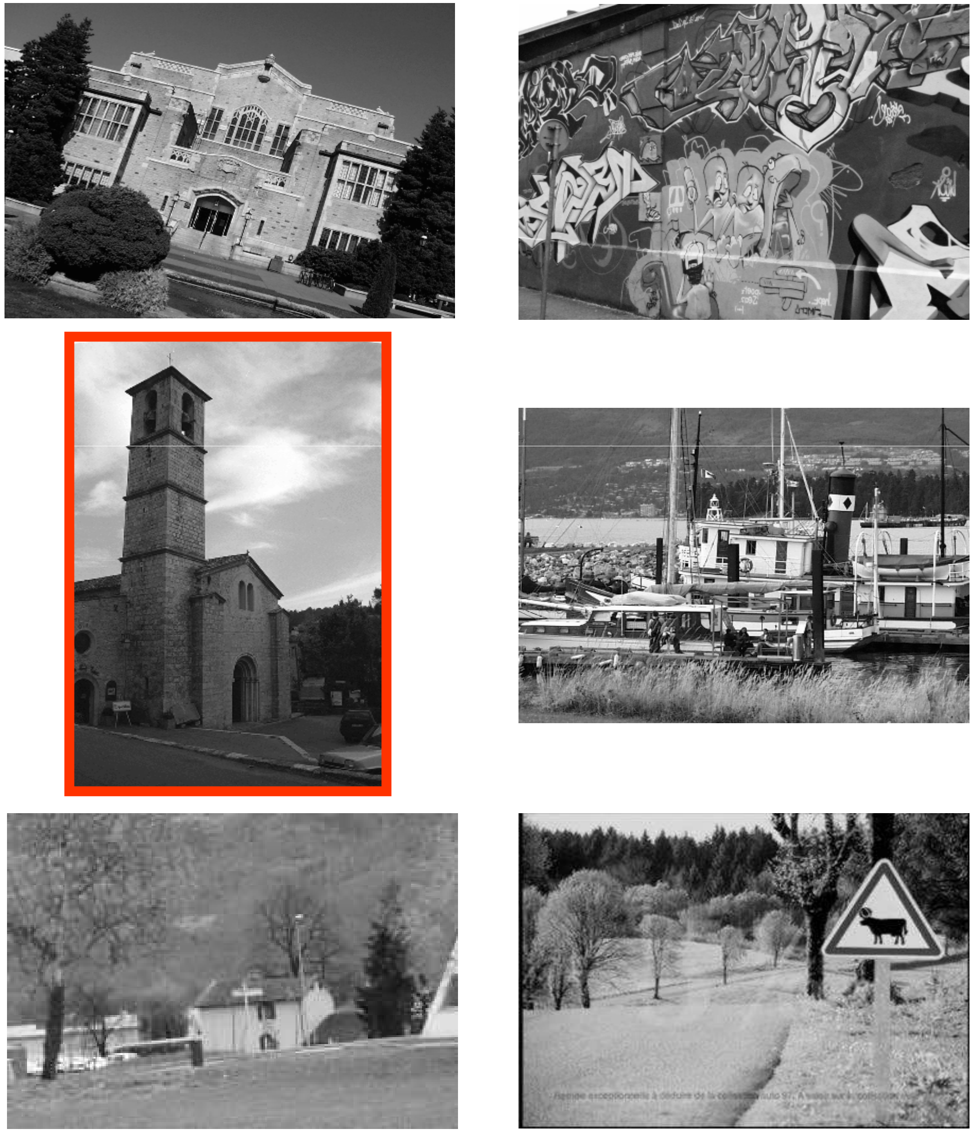
Efficient visual search of local features

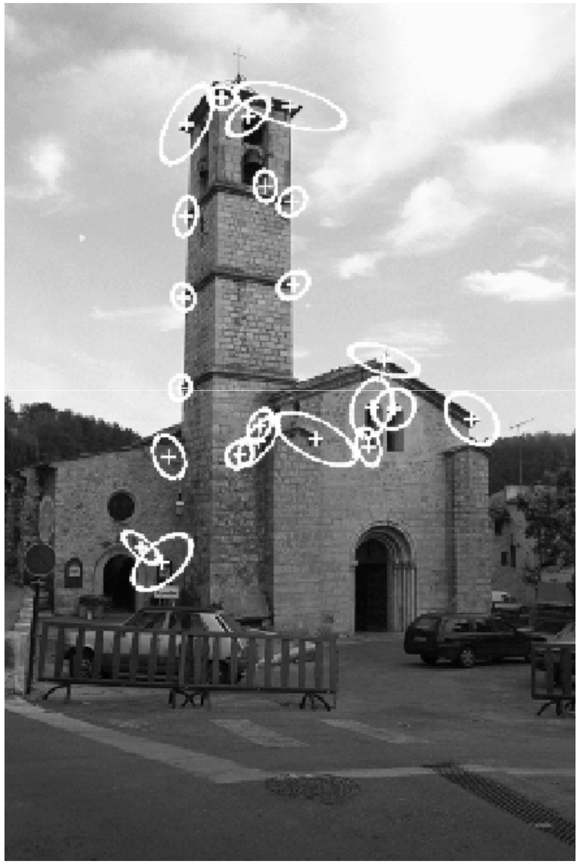
Cordelia Schmid

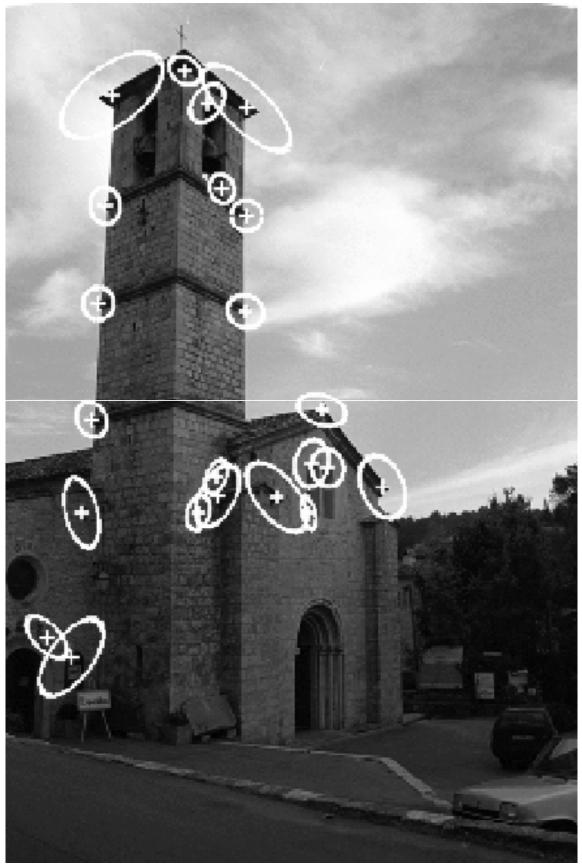
Visual search

change in viewing angle



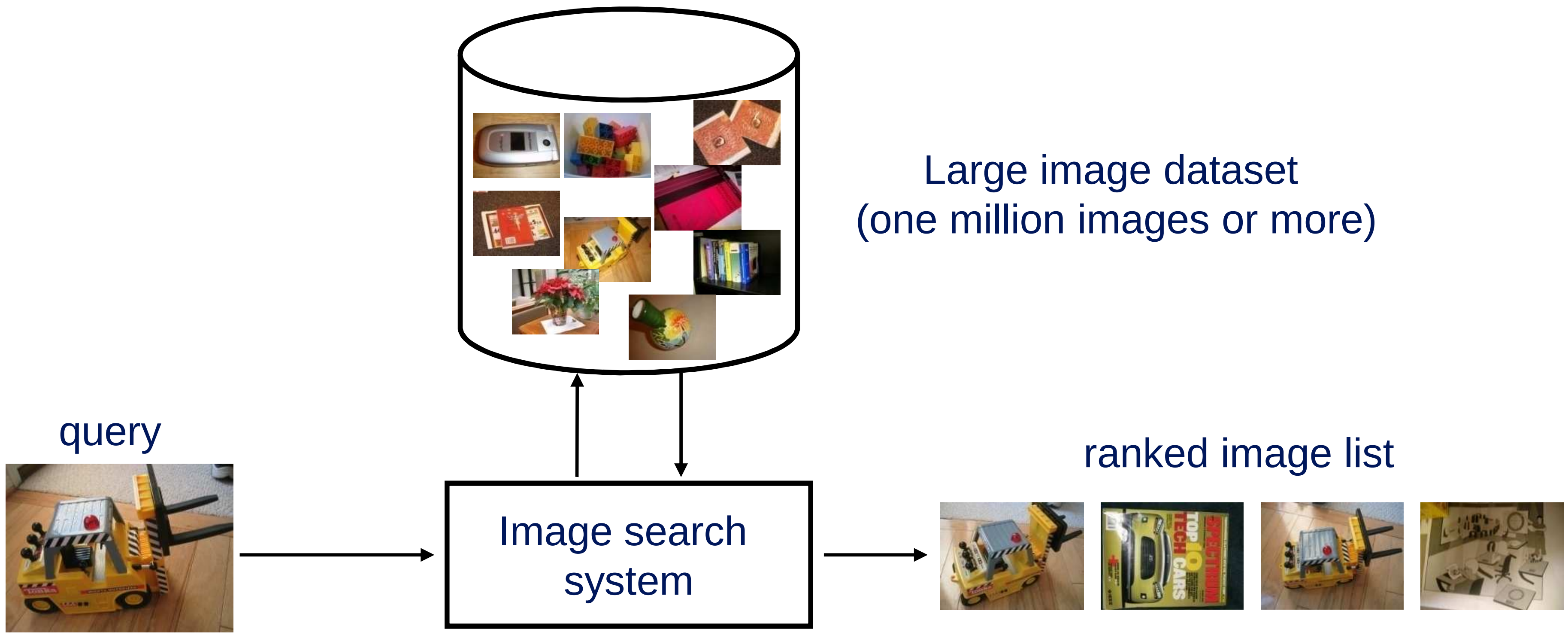
Matches





22 correct matches

Image search system for large datasets



- **Issues** for very large databases
  - to reduce the query time
  - to reduce the storage requirements

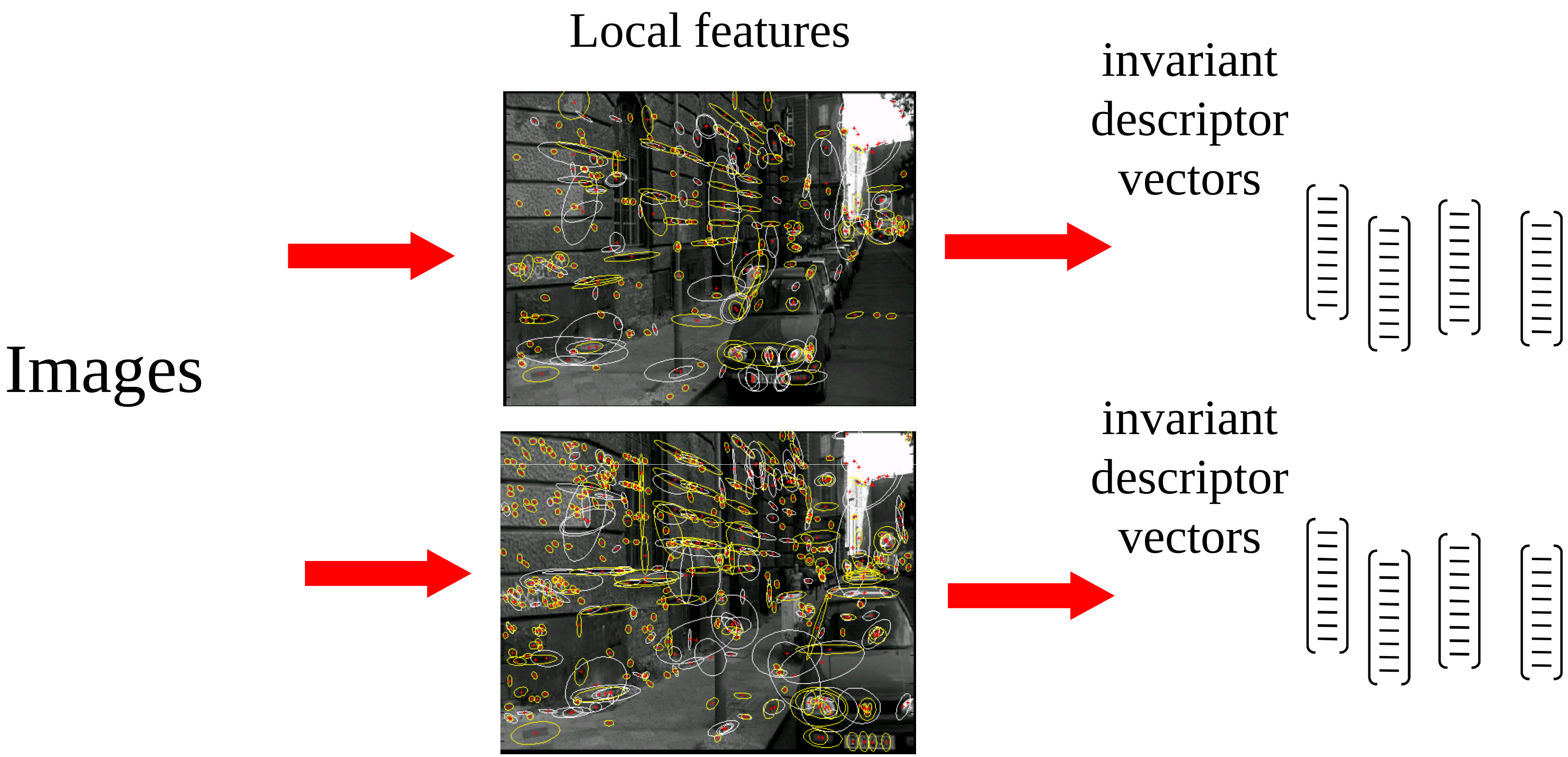
Two strategies

1. Efficient approximate nearest neighbour search on local feature descriptors.

2. Quantize descriptors into a “visual vocabulary” and use efficient techniques from text retrieval.

   (Bag-of-words representation)

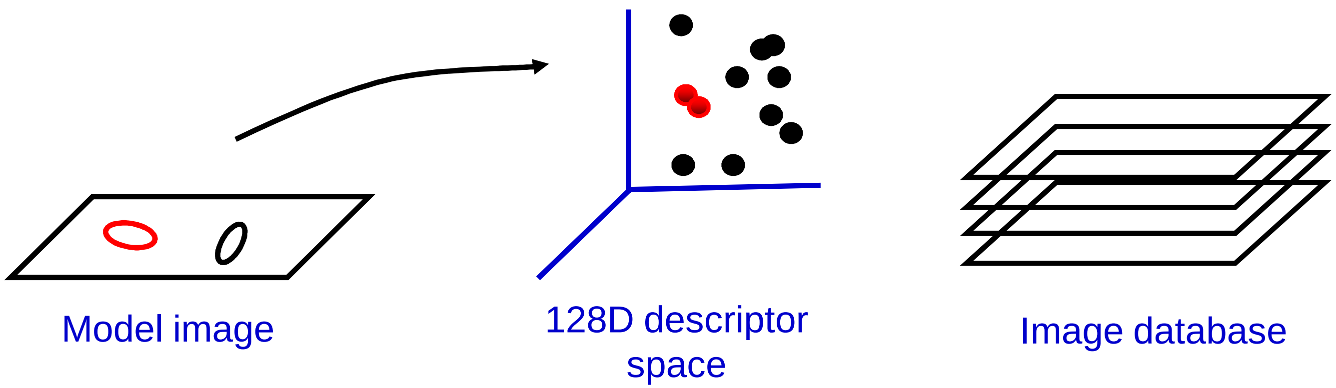
Strategy 1: Efficient approximate NN search



1. Compute local features in each image independently
2. Describe each feature by a descriptor vector
3. Find nearest neighbour vectors between query and database
4. Rank matched images by number of (tentatively) corresponding regions
5. Verify top ranked images based on spatial consistency

Finding nearest neighbour vectors

Establish correspondences between query image and images in the database by **nearest neighbour matching** on SIFT vectors



Solve following problem for all feature vectors, $\mathbf{x}_j \in \mathcal{R}^{128}$, in the query image:

$$\forall j \; NN(j) = \arg\min_i ||\mathbf{x}_i - \mathbf{x}_j||$$

where, $\mathbf{x}_i \in \mathcal{R}^{128}$, are features from all the database images.

Quick look at the complexity of the NN-search

N … images

M … regions per image (~1000)

D … dimension of the descriptor (~128)

Exhaustive linear search: O(M NMD)

Example:

- Matching two images (N=1), each having 1000 SIFT descriptors
  Nearest neighbors search: 0.4 s (2 GHz CPU, implemenation in C)
- Memory footprint: 1000 * 128 = 128kB / image

# of images	CPU time	Memory req.
N = 1,000 …	~7min	(~100MB)
N = 10,000 …	~1h7min	(~ 1GB)
…		
N = 10^7	~115 days	(~ 1TB)
…		
All images on Facebook:		
N = 10^{10} …	~300 years	(~ 1PB)

Nearest-neighbor matching

Solve following problem for all feature vectors, $\mathbf{x_j}$, in the query image:

$$\forall j \; NN(j) = \arg\min_i ||\mathbf{x}_i - \mathbf{x}_j||$$

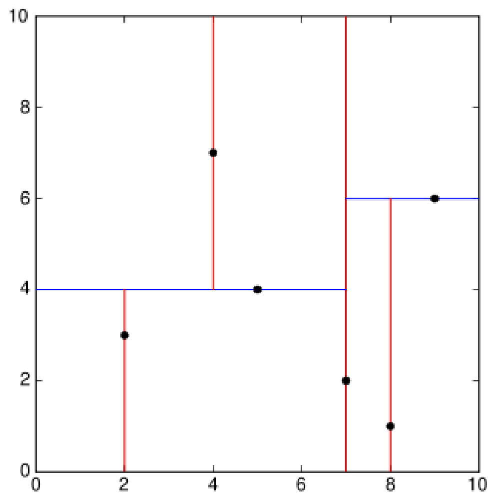
where $\mathbf{x_i}$ are features in database images.

Nearest-neighbour matching is the major computational bottleneck

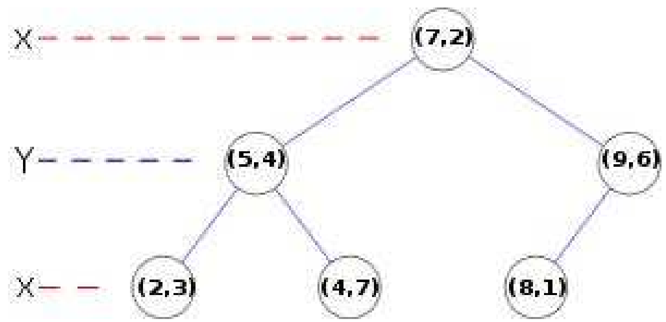
- Linear search performs *dn* operations for *n* features in the database and *d* dimensions
- No exact methods are faster than linear search for d>10
- Approximate methods can be much faster, but at the cost of missing some correct matches. Failure rate gets worse for large datasets.

Approximate nearest neighbour search

- kd-trees (k dim. tree)
- Binary tree in which each node is a k-dimensional point
- Every split is associated with one dimension



kd-tree decomposition



kd-tree

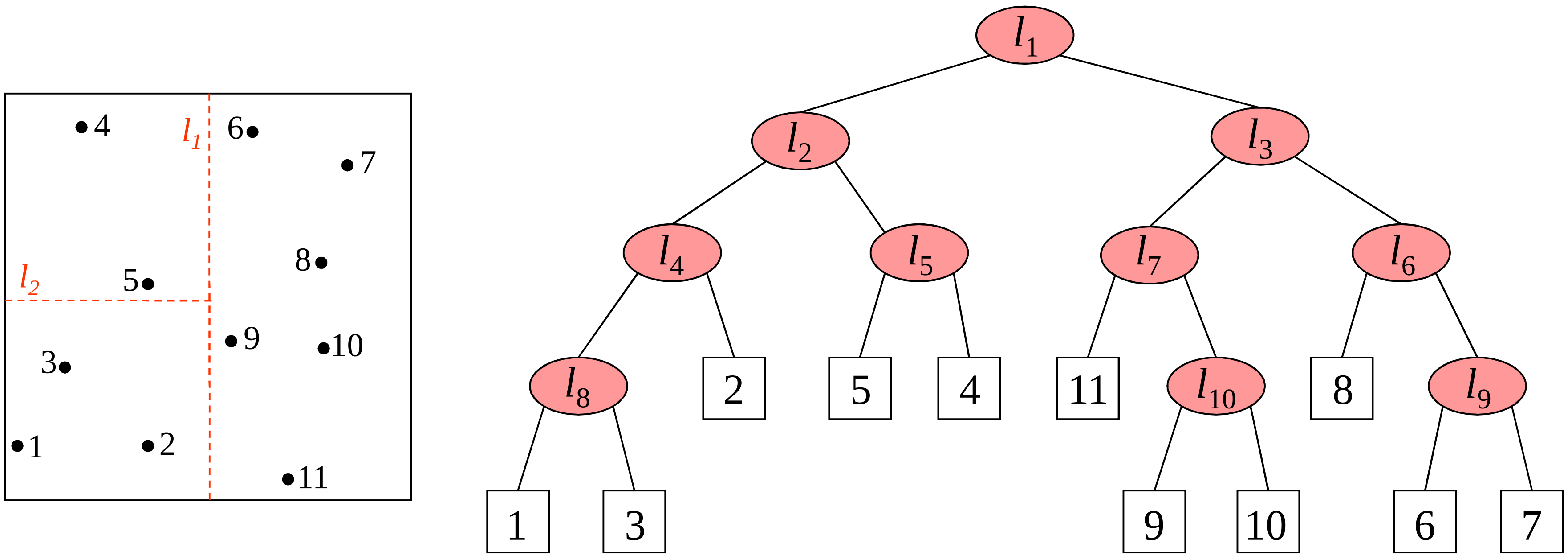
K-d tree

• K-d tree is a binary tree data structure for organizing a set of points

• Each internal node is associated with an axis aligned hyper-plane splitting its associated points into two sub-trees.

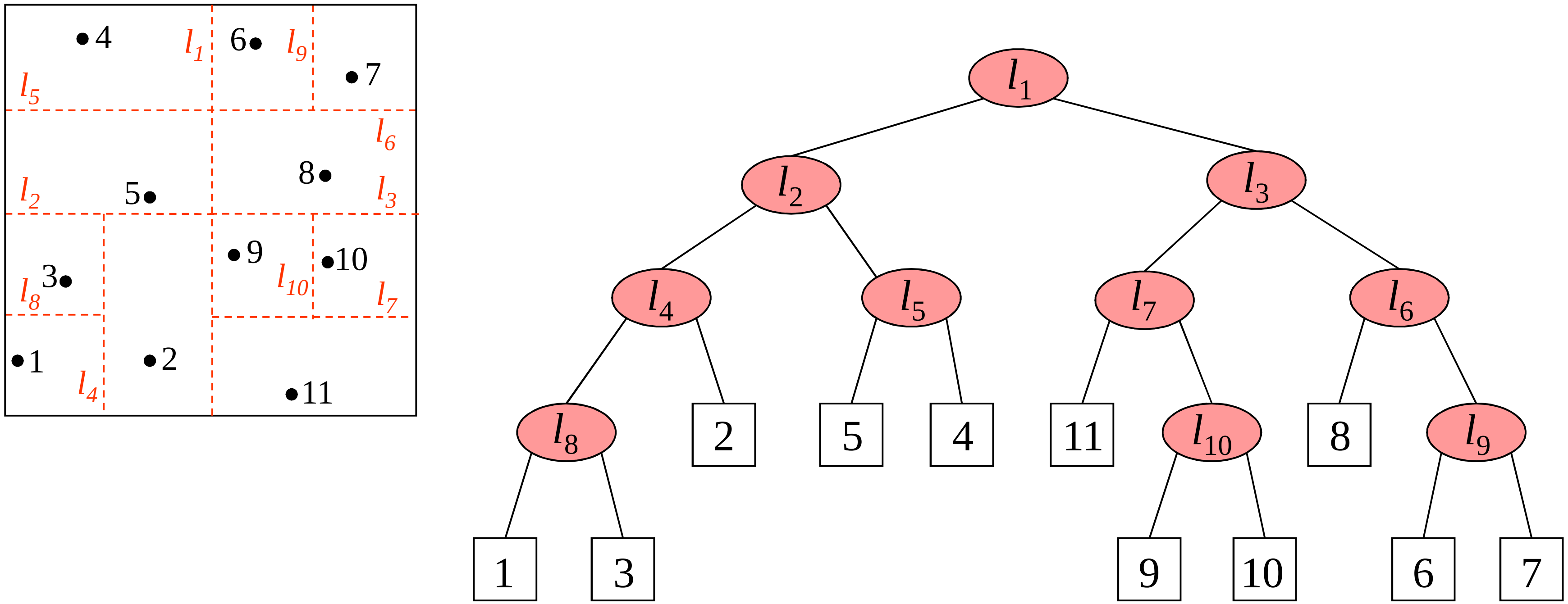
• Dimensions with high variance are chosen first.

• Position of the splitting hyper-plane is chosen as the mean/median of the projected points – balanced tree.

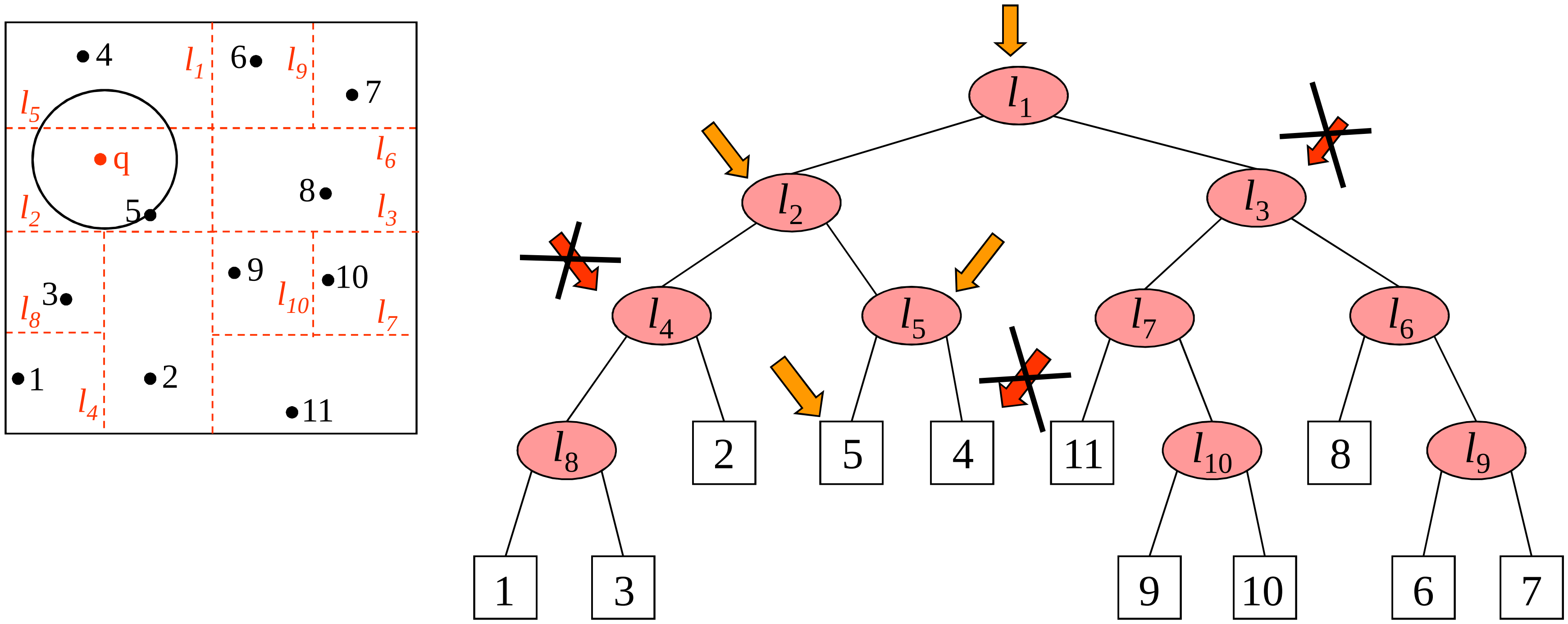


K-d tree construction

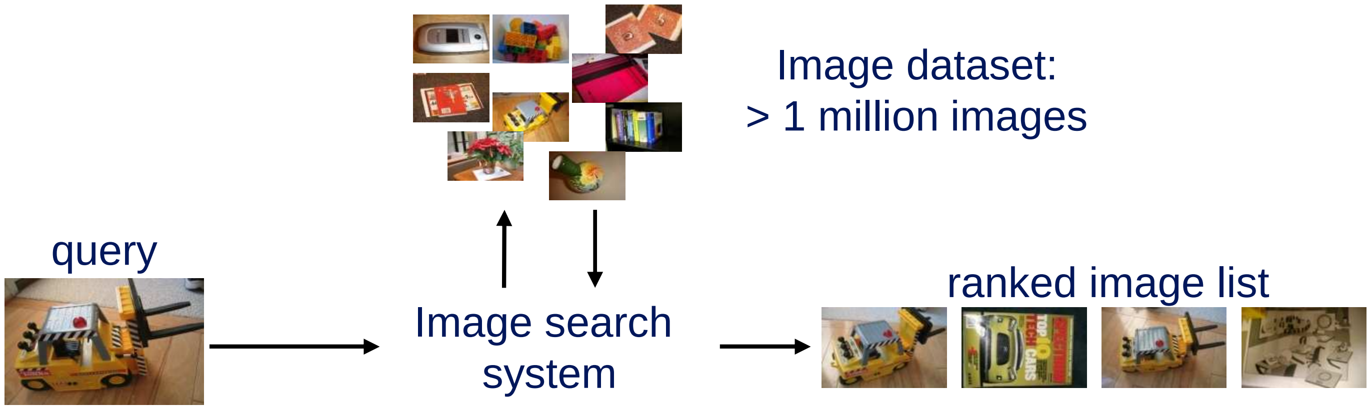
Simple 2D example



K-d tree query



Large scale object/scene recognition



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

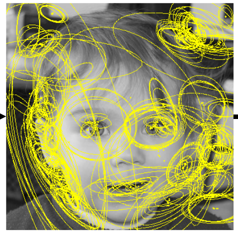
- Database representation in RAM:
  - Size of descriptors : 1 TB, search+memory intractable

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]

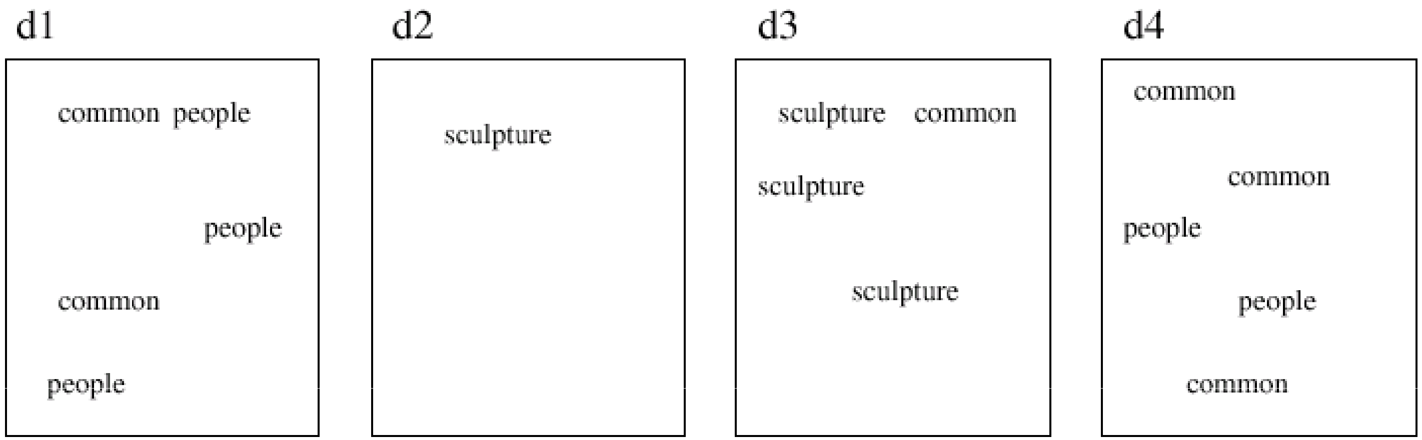
Re-ranked list

- "visual words":
  - 1 "word" (index) per local descriptor
  - only images ids in inverted file

  => 8 GB fits!

Indexing text with inverted files

Document collection:



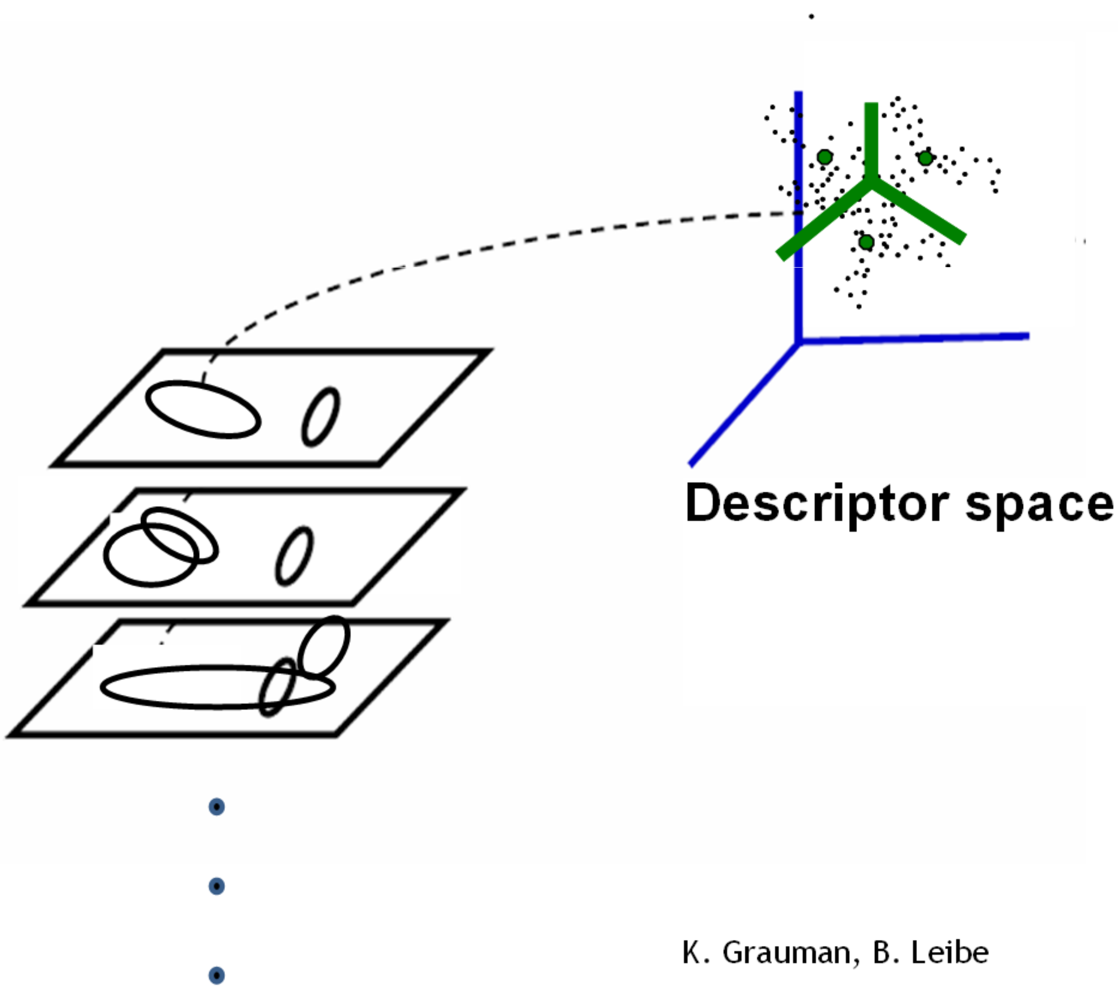
Inverted file:

Term	**List of hits** (occurrences in documents)
People	[d1:hit hit hit], [d4:hit hit] …
Common	[d1:hit hit], [d3: hit], [d4: hit hit hit] …
Sculpture	[d2:hit], [d3: hit hit hit] …

Need to map feature descriptors to “visual words”

Visual words: main idea

Map high-dimensional descriptors to tokens/words by quantizing the feature space

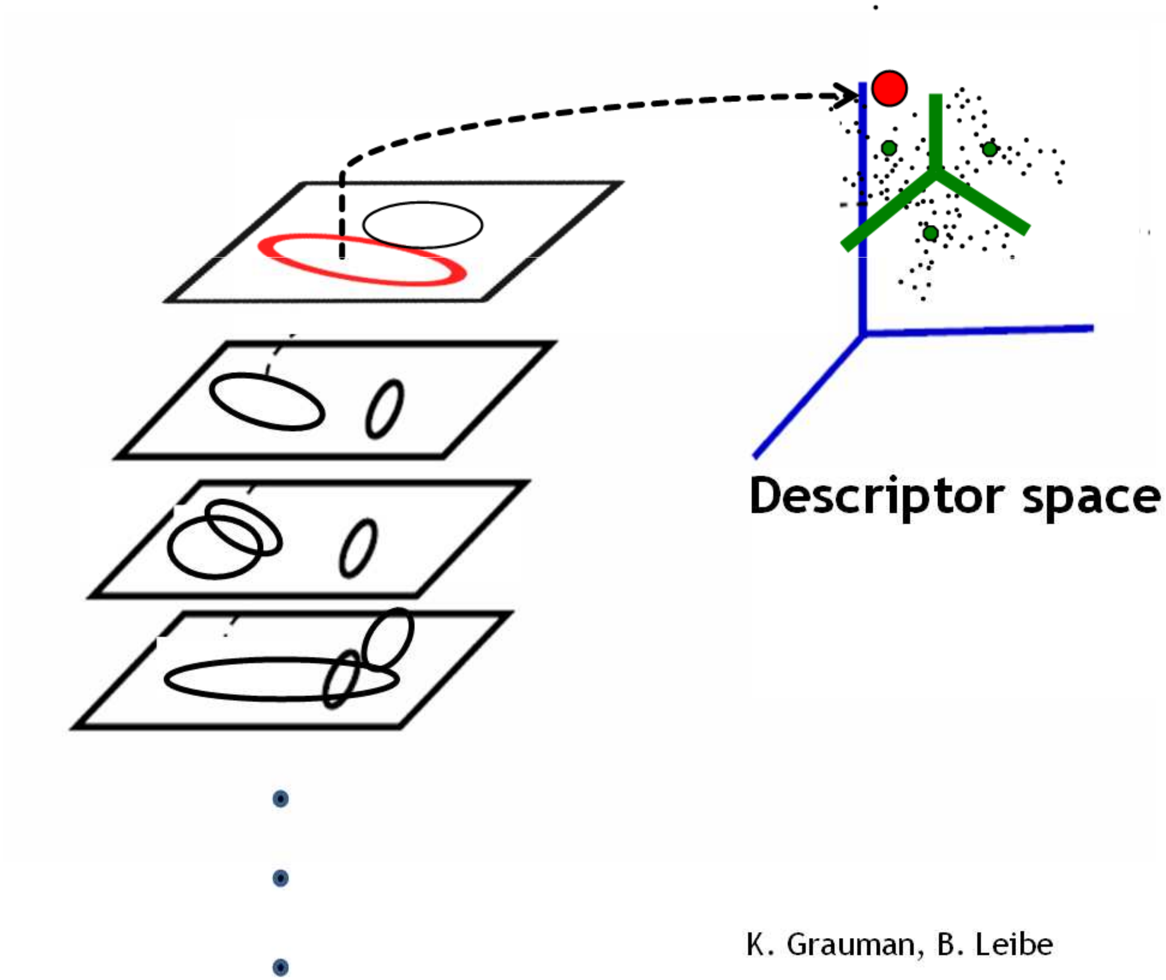


- Quantize via clustering, let cluster centers be the prototype “words”

K. Grauman, B. Leibe

Visual words: main idea

Map high-dimensional descriptors to tokens/words by quantizing the feature space

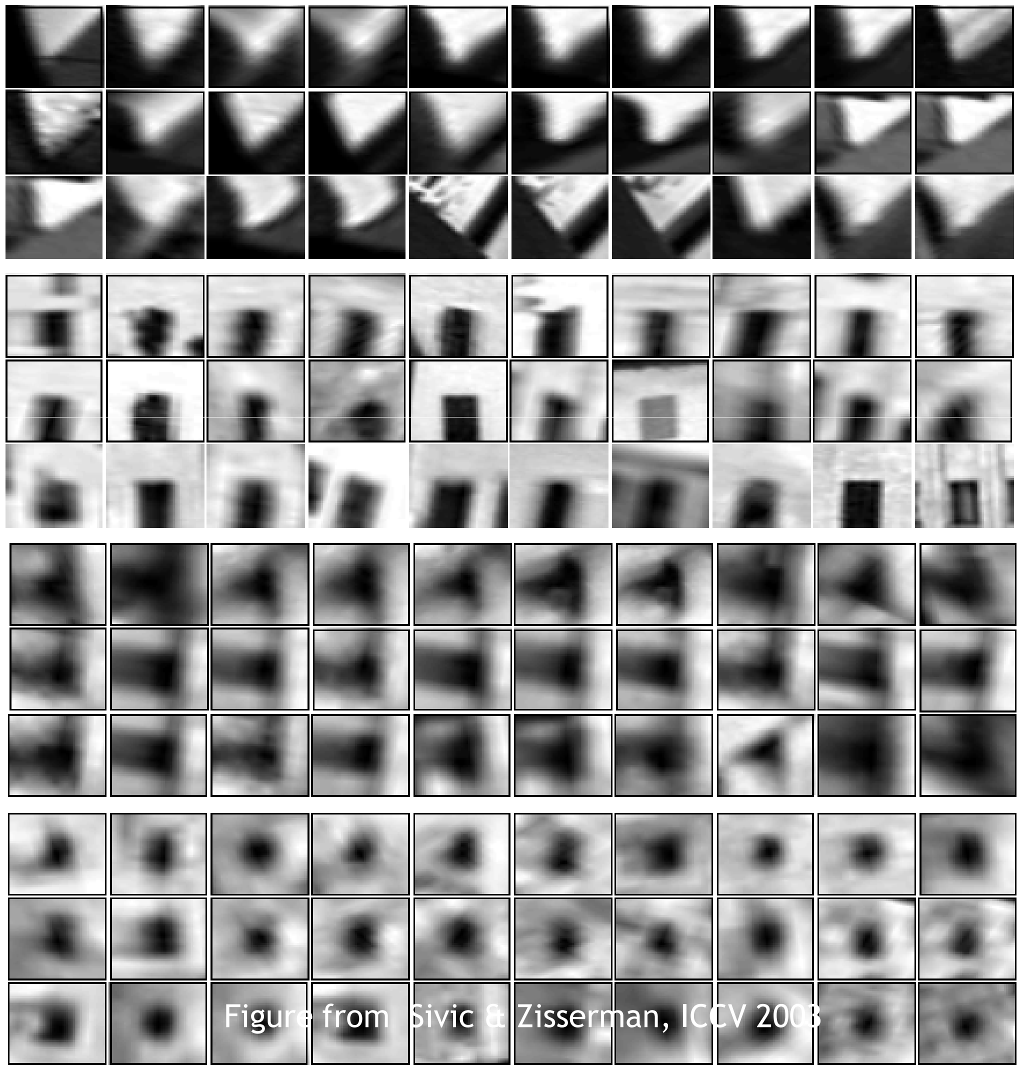


- Determine which word to assign to each new image region by finding the closest cluster center.

K. Grauman, B. Leibe

Visual words

- Example: each group of patches belongs to the same visual word



K-means clustering

- Minimizing sum of squared Euclidean distances between points x_i and their nearest cluster centers

- Algorithm:
  - Randomly initialize K cluster centers
  - Iterate until convergence:
    - Assign each data point to the nearest center
    - Recompute each cluster center as the mean of all points assigned to it

- Local minimum, solution dependent on initialization

- Initialization important, run several times, select best

Inverted file index for images comprised of visual words

frame #5

frame #10

Word number		List of image numbers
1	→	5,10, ...
2	→	10,...
...		...

- Score each image by the number of common visual words (tentative correspondences)
- Dot product between bag-of-features
- Fast for sparse vectors !

Inverted file index for images comprised of visual words

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

    - Tf: normalized term (word) ti frequency 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: $$tf-idf_{ij} = tf_{ij} \cdot idf_i$$

Visual words

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

- Bag-of-features as approximate nearest neighbor search

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

  where q(x) is a quantizer, i.e., assignment to 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

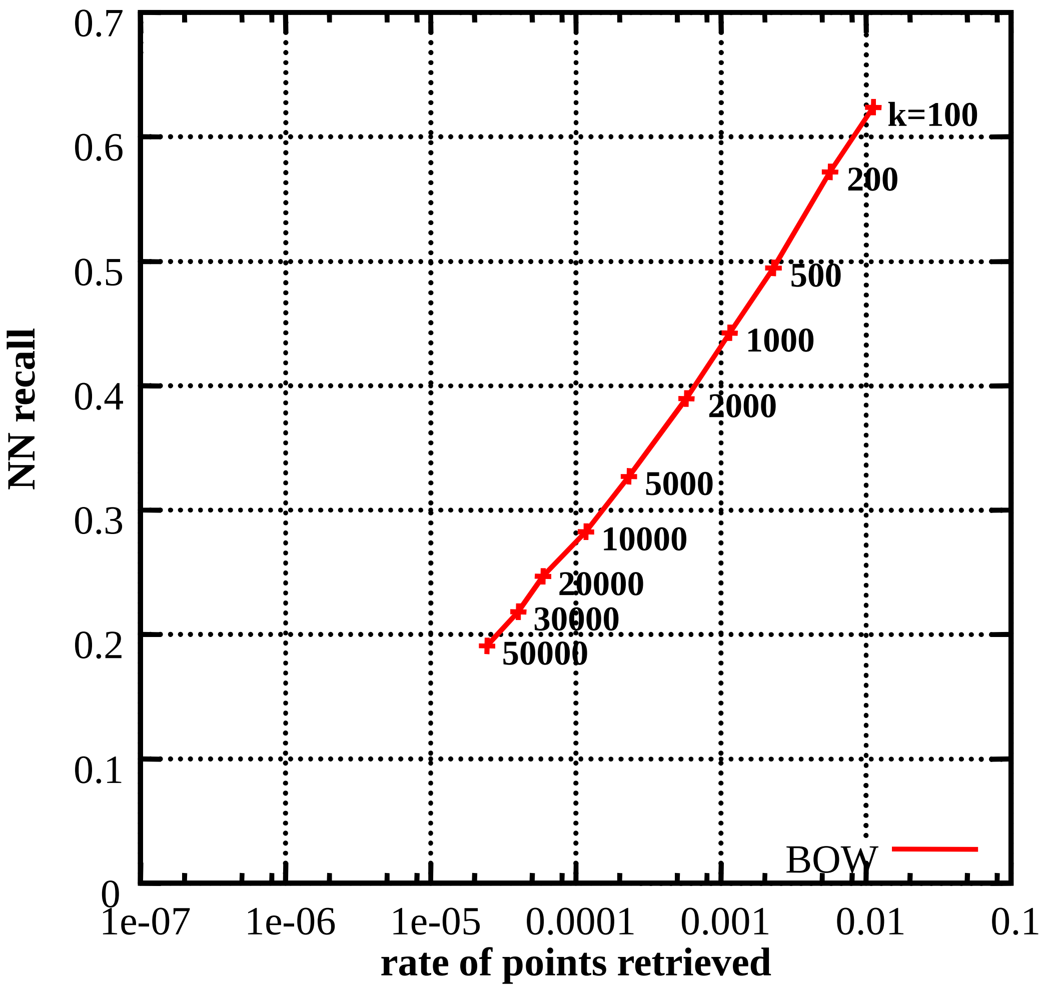
- Proposed quality evaluation of ANN search: trade-off between
  - **Accuracy**: **NN recall** = probability that *the* NN is in this list

    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*

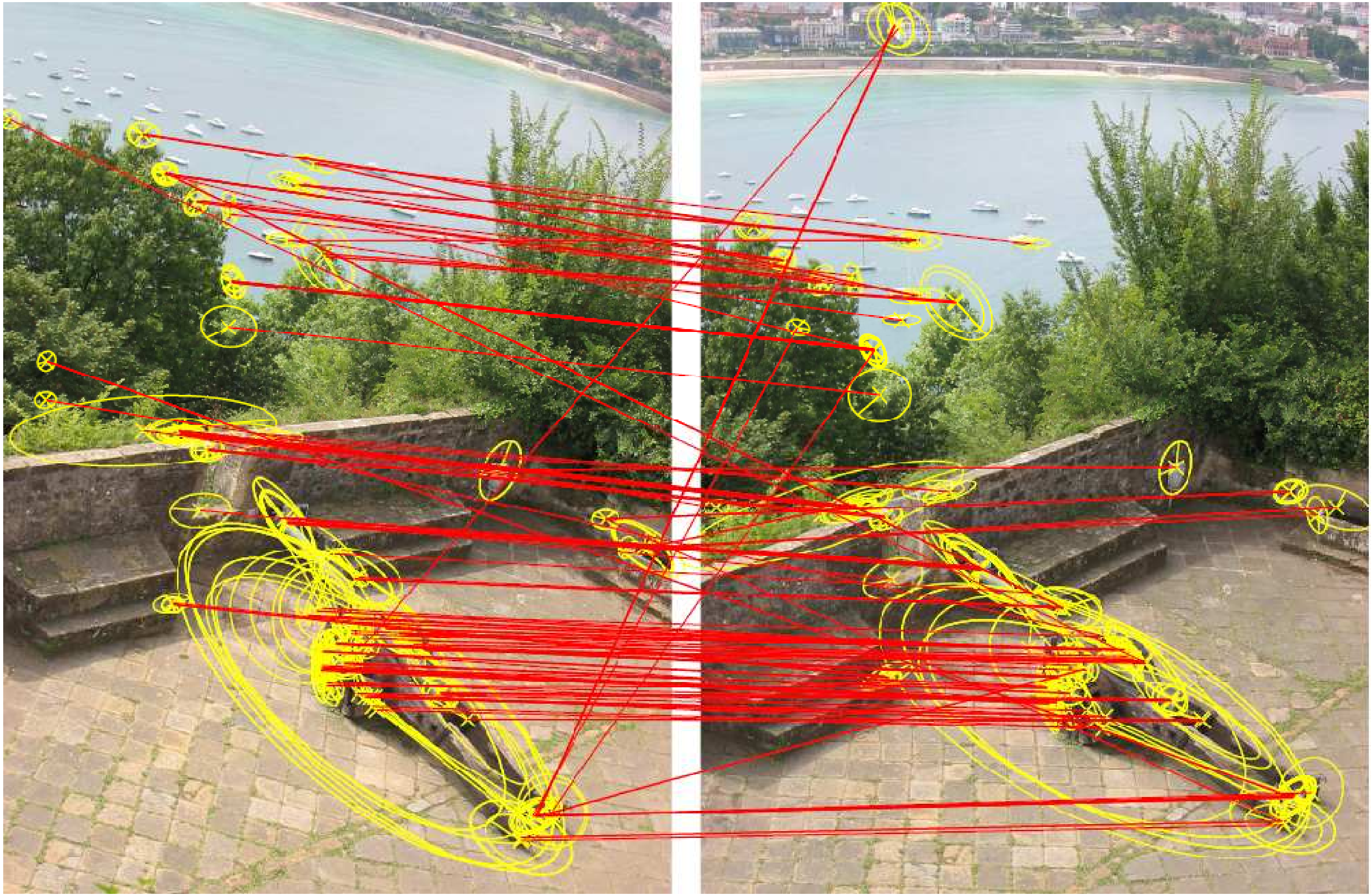
Vocabulary size

- 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

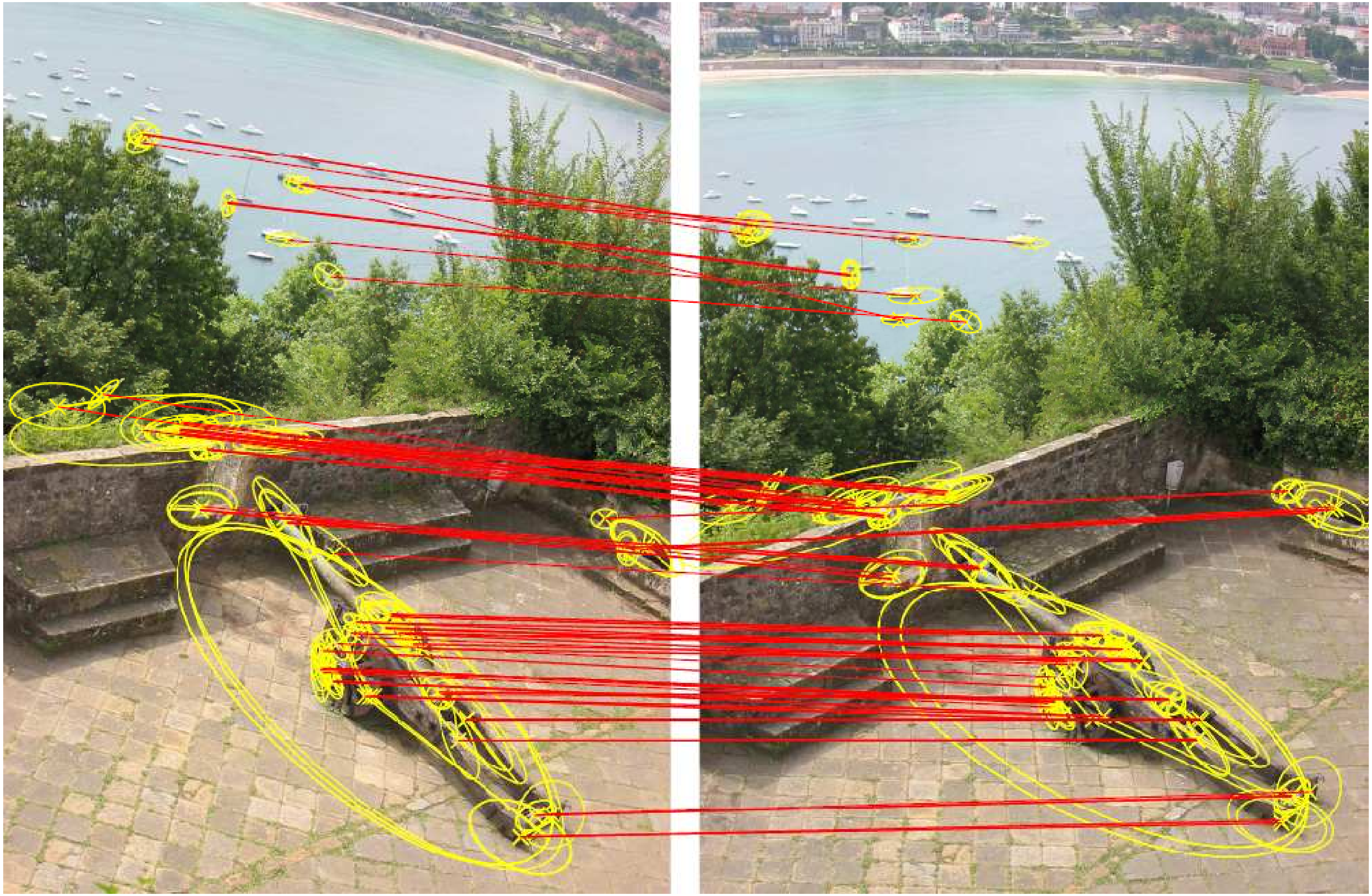
- No good trade-off between “small” and “large” !
  - either the Voronoi cells are too big
  - or these cells can’t absorb the descriptor noise

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

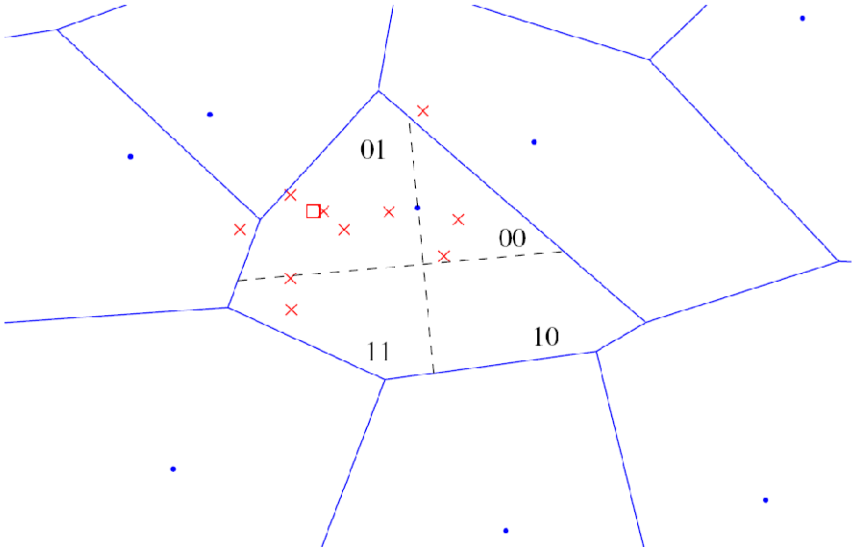
20K visual word: false matches



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

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

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

Hamming Embedding

- Nearest neighbors for Hamming distance $\approx$ those for Euclidean distance
$\rightarrow$ a metric in the embedded space reduces dimensionality curse effects

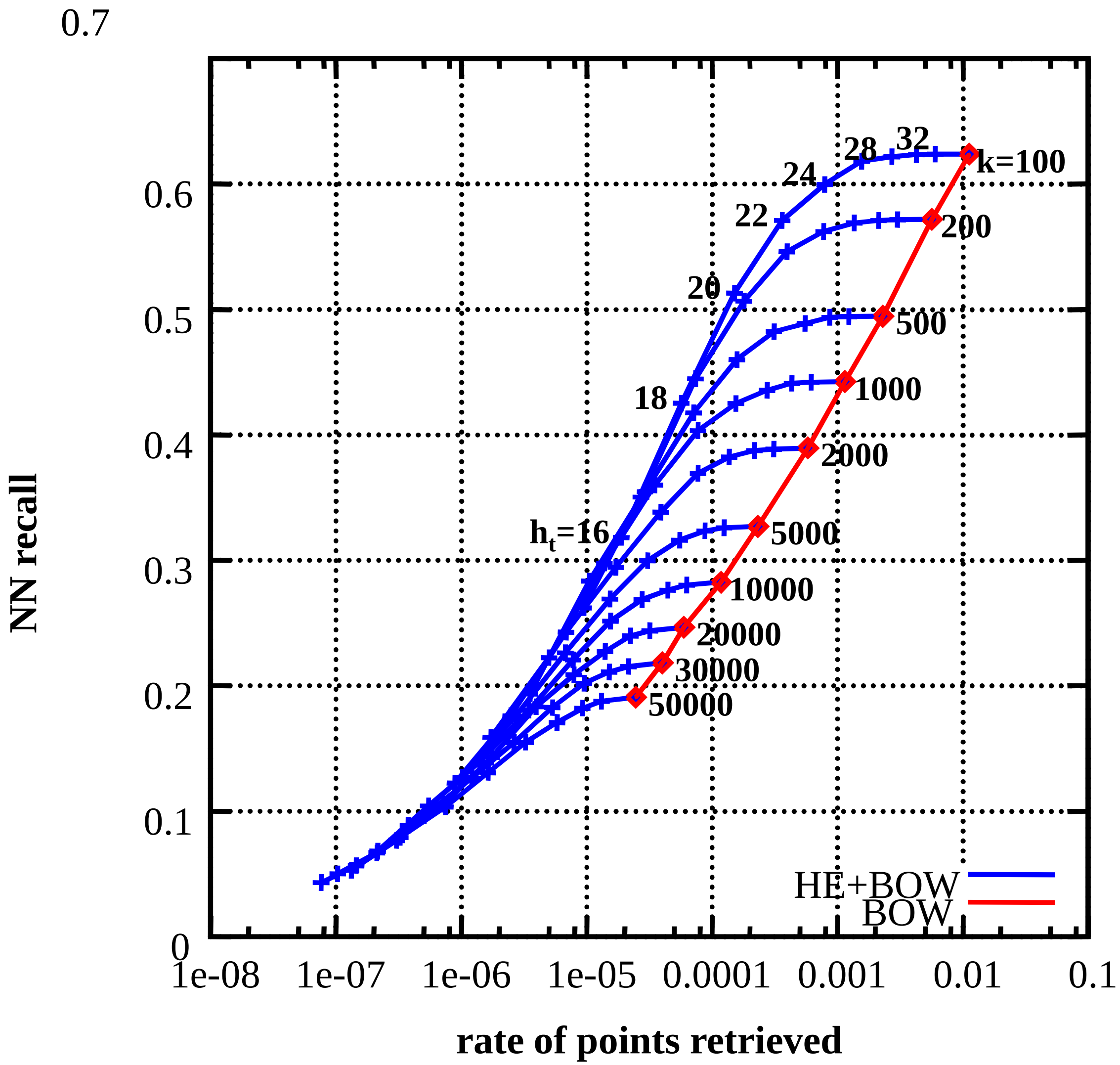
- Efficiency
  - Hamming distance = very few operations
  - Fewer random memory accesses: 3 x faster that BOF with same dictionary size!

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

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

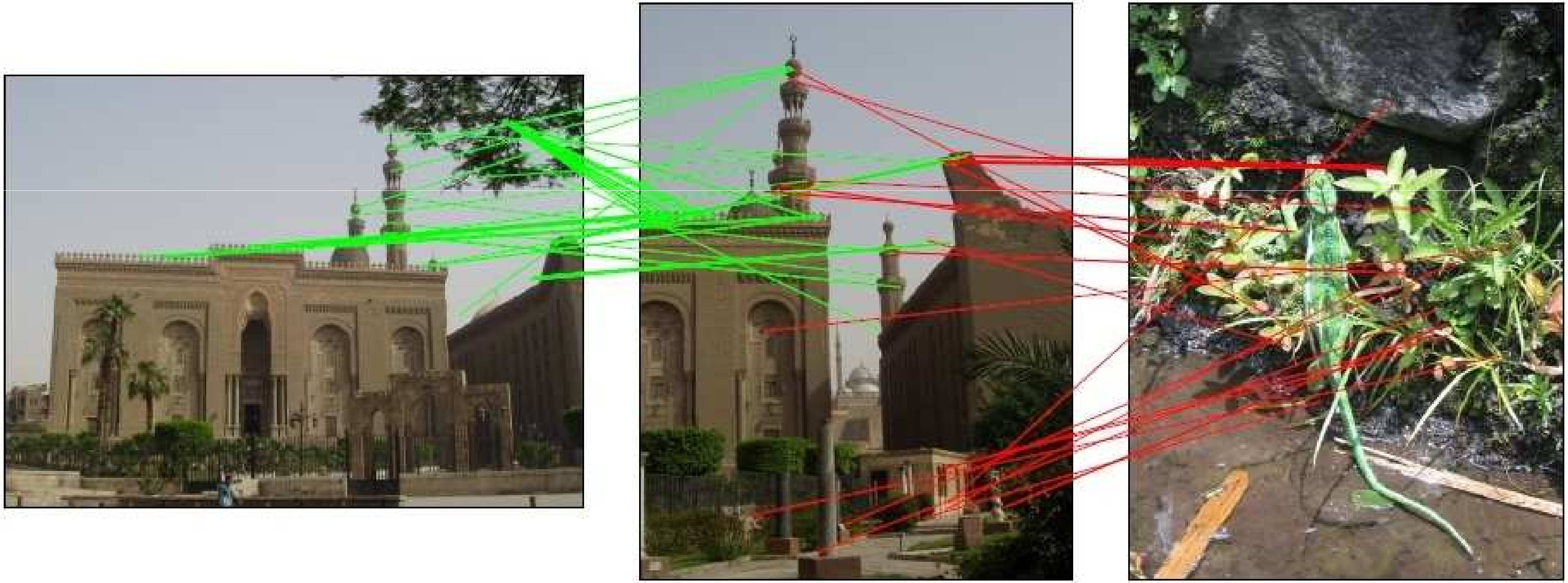
240 matches

Many matches with the non-corresponding image!

Matching points - 200k word vocabulary

69 matches

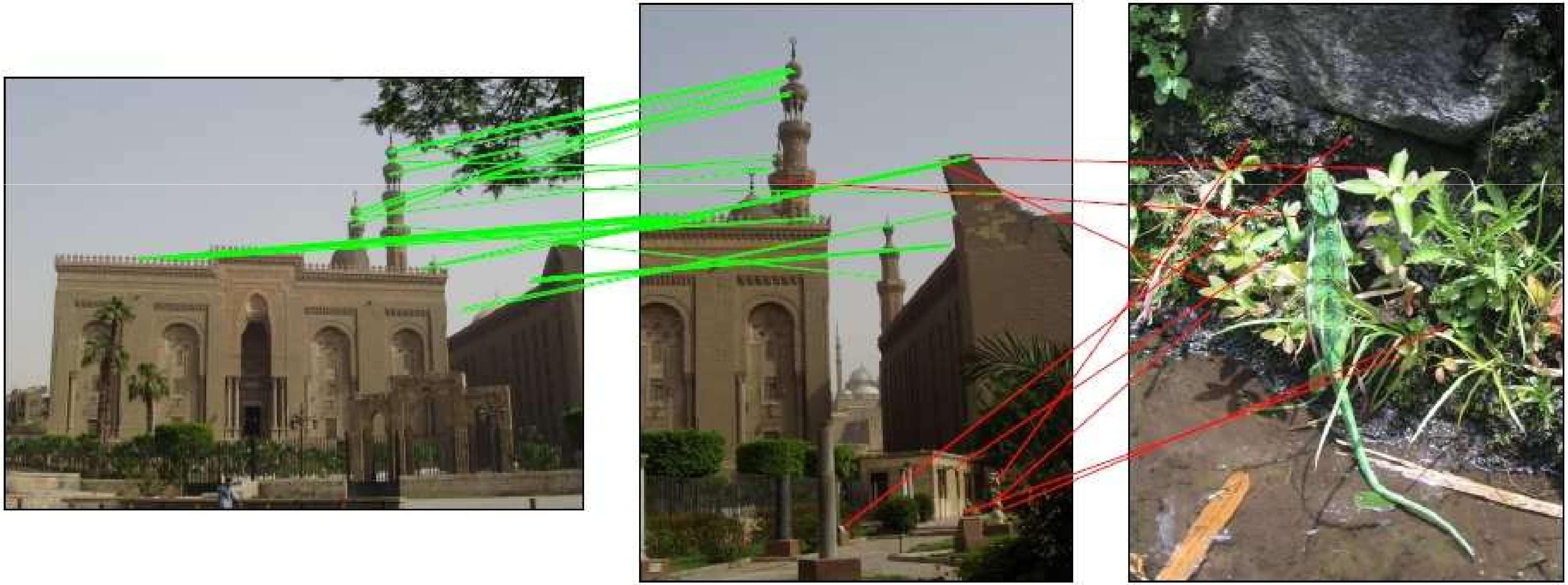
35 matches



Still many matches with the non-corresponding one

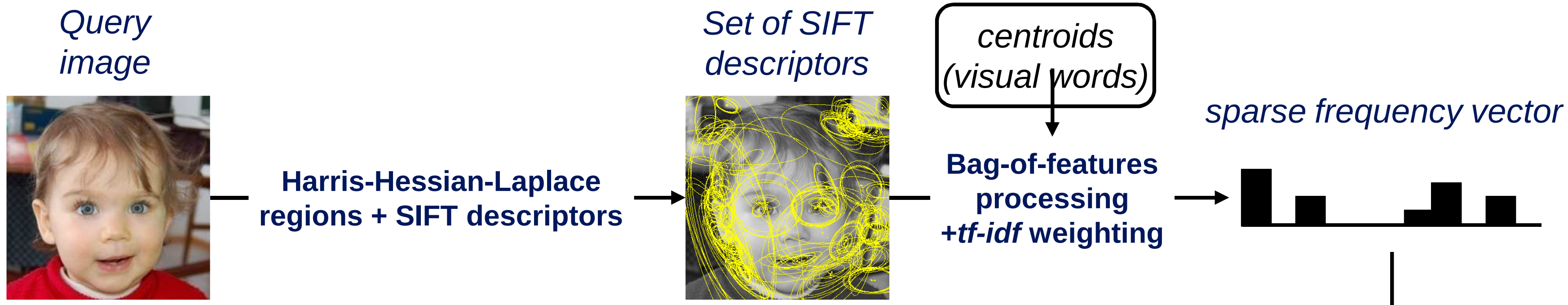
Matching points - 20k word vocabulary + HE

83 matches 8 matches



10x more matches with the corresponding image!

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



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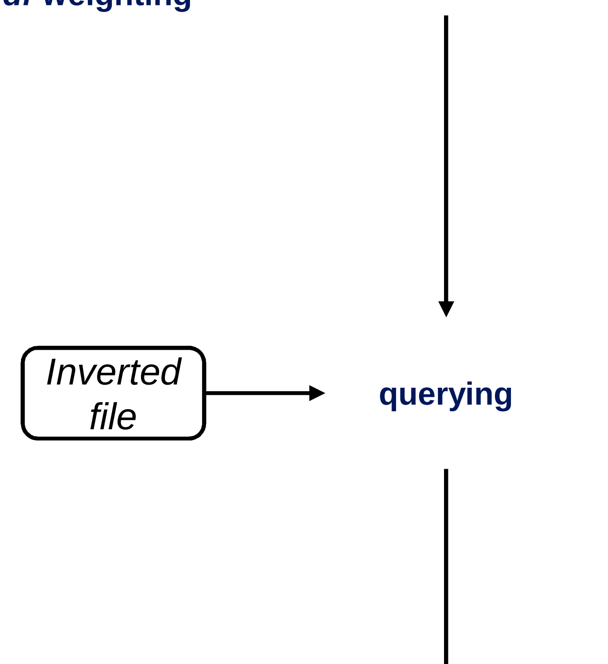
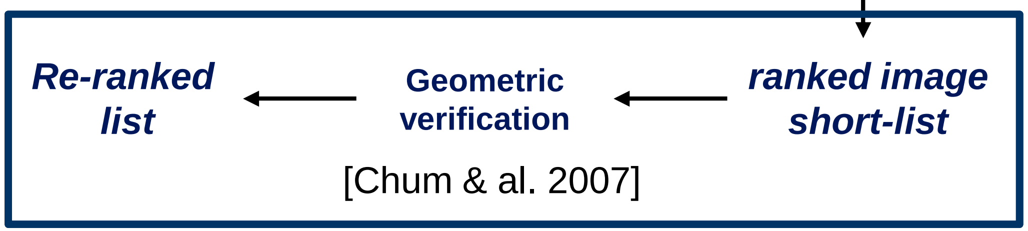
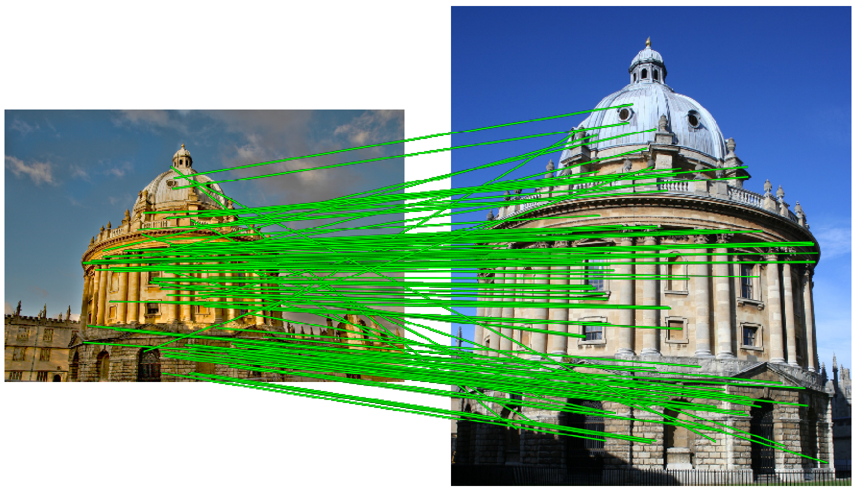
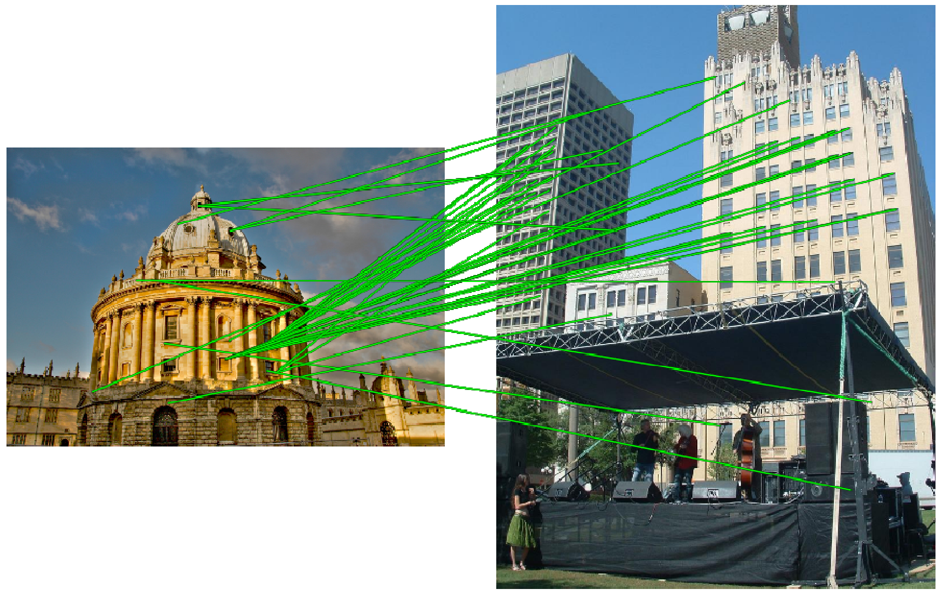




Geometric verification

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

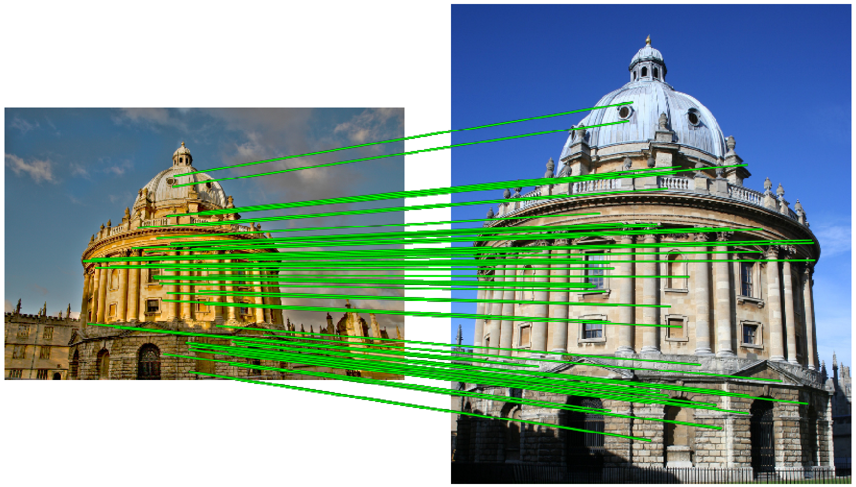




Both images have many matches – which is correct?

Geometric verification

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

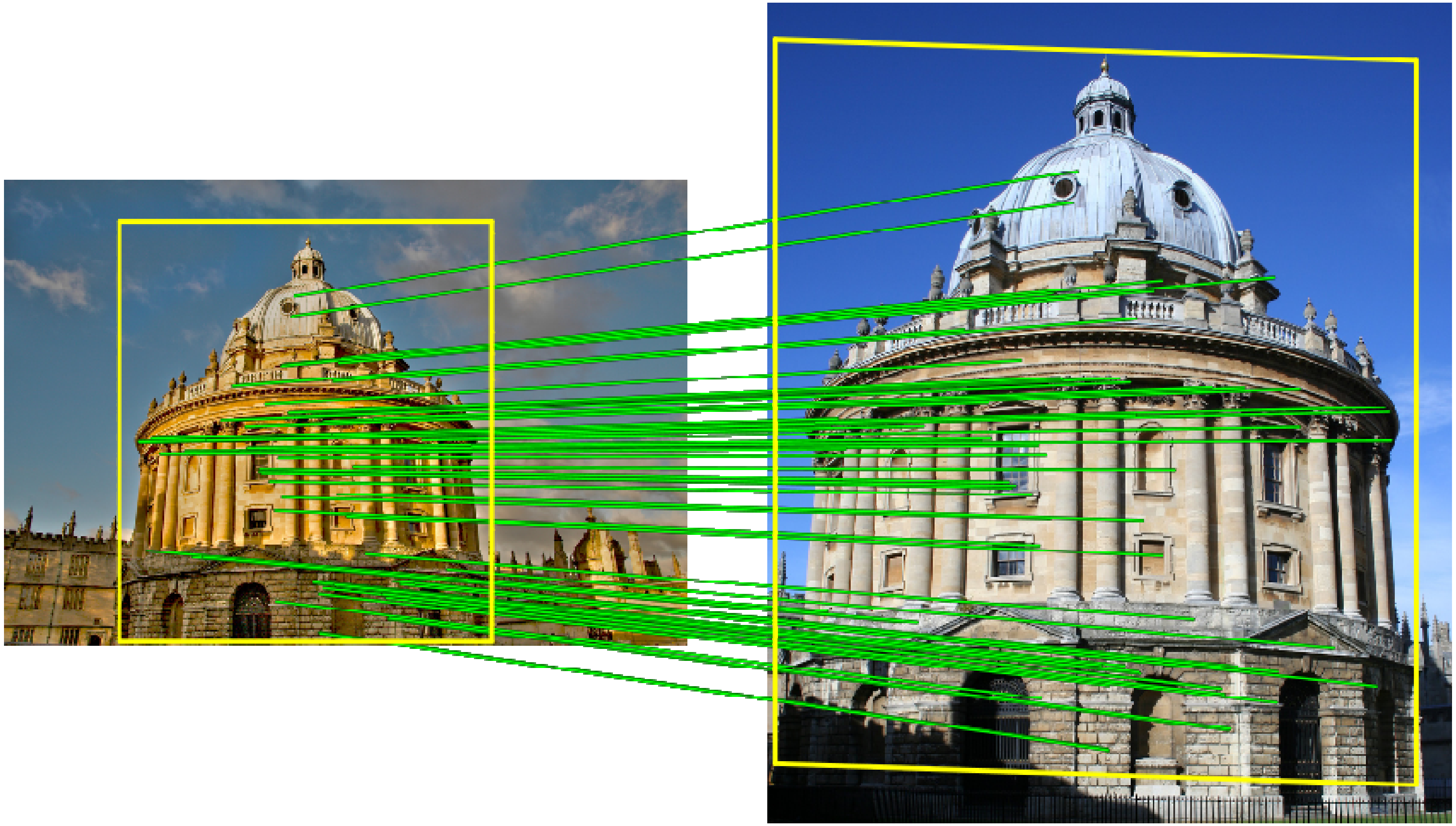


Many spatially consistent matches – **correct result**

Few spatially consistent matches – **incorrect result**

Geometric verification

Gives **localization** of the object

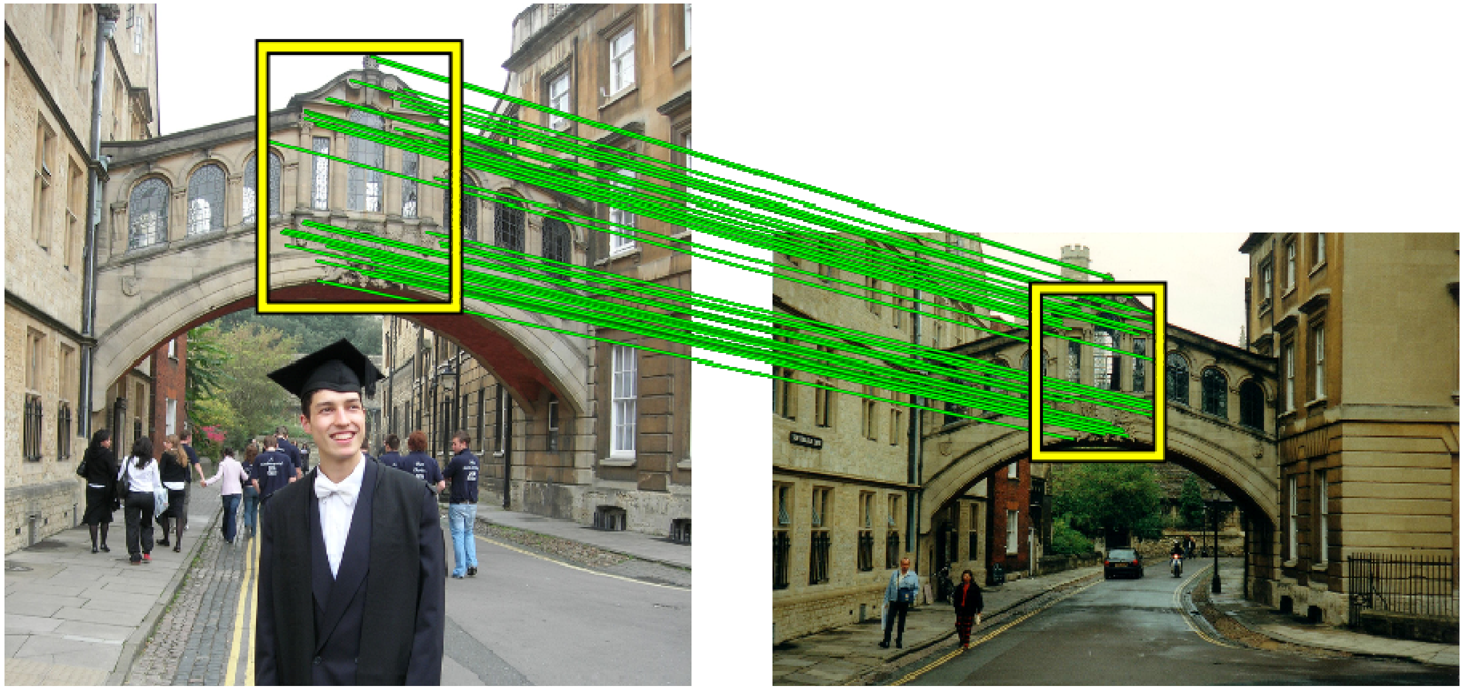


Geometric verification

- Remove outliers, matches contain a high number of incorrect ones
- Estimate geometric transformation
- Robust strategies
  - RANSAC
  - Hough transform

Example: estimating 2D affine transformation

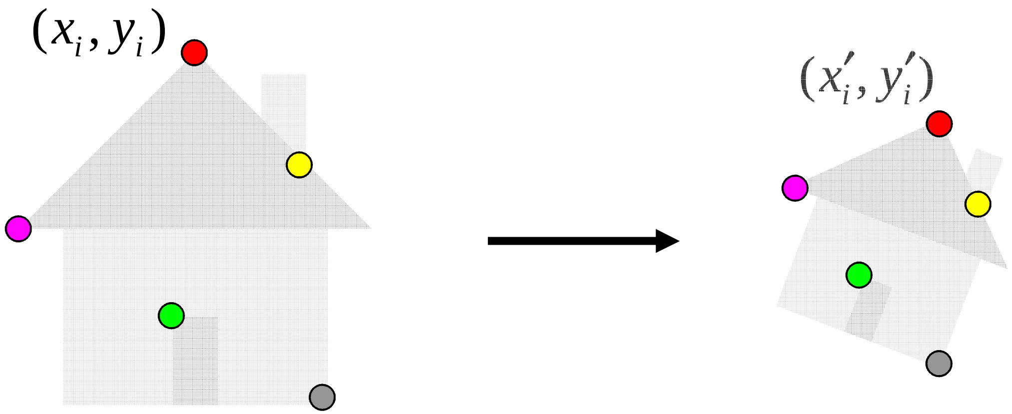
- Simple fitting procedure (linear least squares)
- Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras
- Can be used to initialize fitting for more complex models



Matches consistent with an affine transformation

Fitting an affine transformation

Assume we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

Fitting an affine transformation

$$\begin{bmatrix} & & \mathrm{L} & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \mathrm{L} & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \mathrm{L} \\ x_i' \\ y_i' \\ \mathrm{L} \end{bmatrix}$$

Linear system with six unknowns

Each match gives us two linearly independent equations: need at least three to solve for the transformation parameters