Large-scale Geometry

geometric relations between corresponding features in (pairs of) images for large scale retrieval

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CVPR 2013: Tutorial on Large Scale Visual Recognition

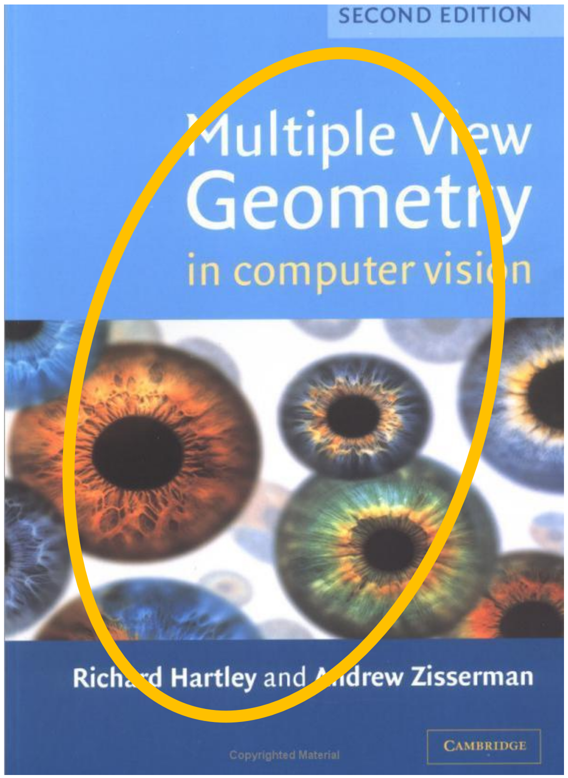
Outline

- Semi-local constraints
- Global constraints
    - Voting
    - RANSAC
- Applications
    - Query expansion
    - Browsing image collections
- Storing the geometry

Semi-local Geometry

- Tentative correspondence verification
- Geometric min-Hash

Semi-local Geometry vs Large Features



Good for:
- Large planar objects
- No occlusions

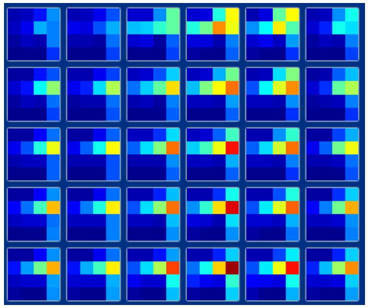
Robustness to:
- viewpoint change
- depth discontinuities
- background change
- partial occlusion

Repeatability of Feature Sets: Translation and Occlusion

Probabilities that features 'survive' viewpoint change, occlusion, etc are not independent.

Global Descriptors over Region of Interest

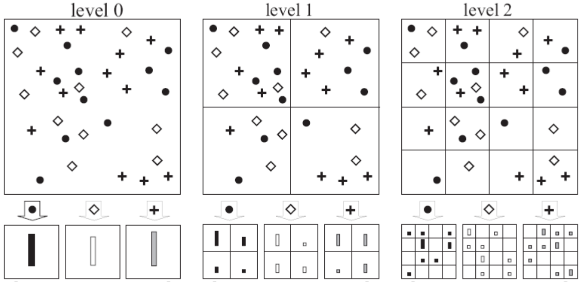
GIST



Oliva, Torralba: Modeling the shape of the scene: a holistic representation of the spatial envelope, IJCV 2001

Deselaers, Alexe, Ferrari:Weakly Supervised Localization and Learning with Generic Knowledge, IJCV 2012

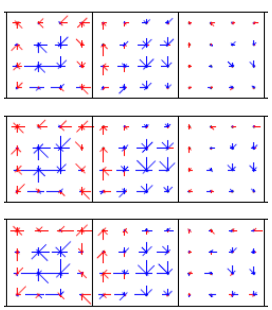
Spatial pyramid



Lazebnik, Schmid, Ponce: Beyond BoF: Spatial Pyramid Matching for Recognizing Natural Scene Categories. CVPR'06

Chum and Zisserman: An Exemplar Model for Learning Object Classes, CVPR 2007

VLAD

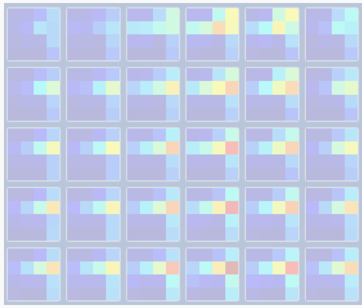


Jégou, Douze, Schmid, and Pérez : Aggregating local descriptors into a compact image representation, CVPR'10

Arandjelovic and Zisserman: All about VLAD, CVPR'13

Global Descriptors over Region of Interest

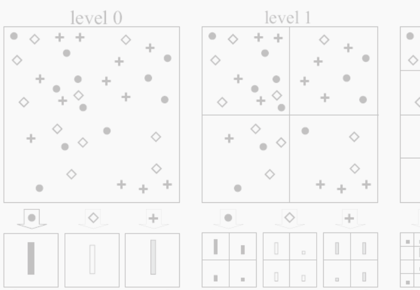
GIST



f the scene: a
envelope, IJCV 2001

ervised Localization
e, IJCV 2012

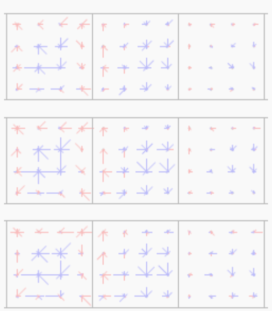
Spatial pyramid



: Spatial Pyramid
ne Categories.

odel for Learning

VLAD



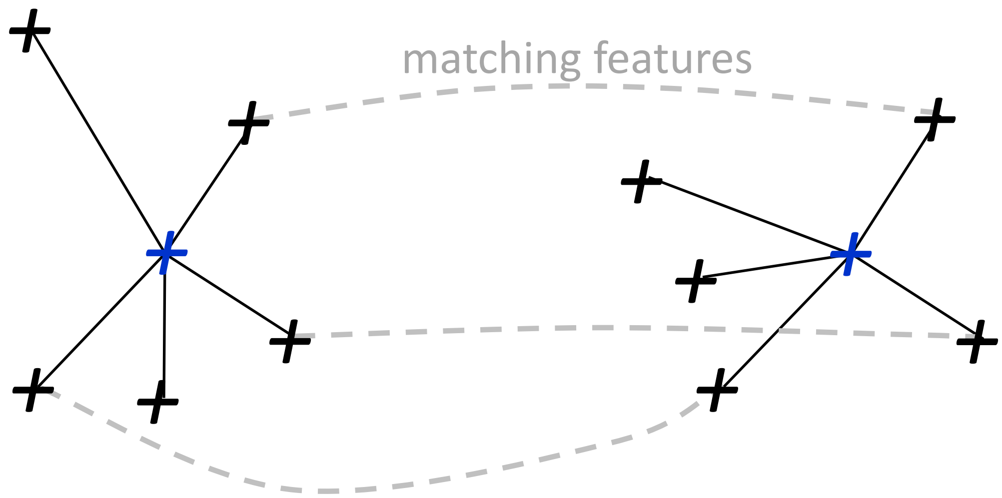
gregating local
resentation, CVPR'10

t VLAD, CVPR'13

Local Geometric Constraints

Idea: verify a tentative match “+“ by comparing neighboring features

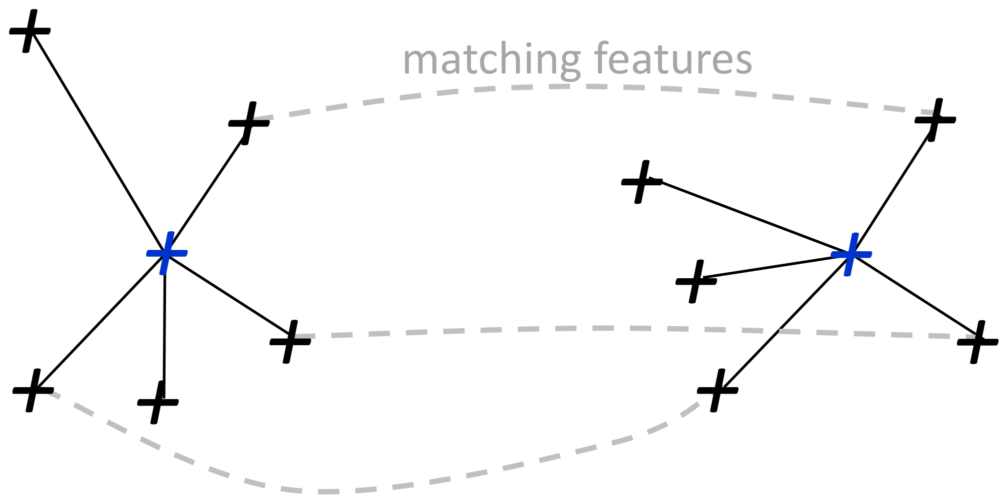
[Schmid and Mohr: Local Greyvalue Invariants for Image Retrieval. PAMI 1997]



matching appearance and locality

used in [Sivic and Zisserman: Video Google, ICCV 2003]

Local Geometric Constraints



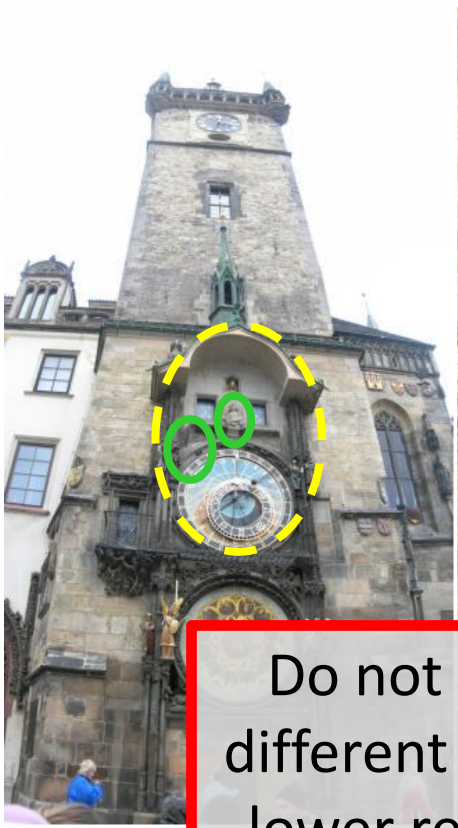
Neighbouring features:

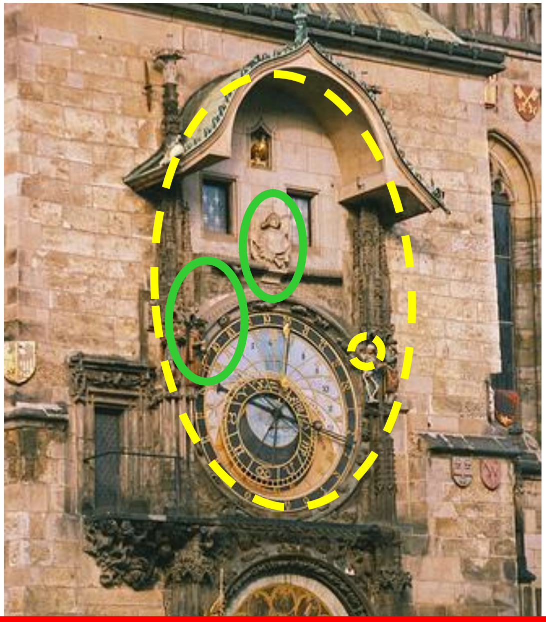
- n nearest
- within an absolute distance
- within a relative distance
- also limited to a similar scale

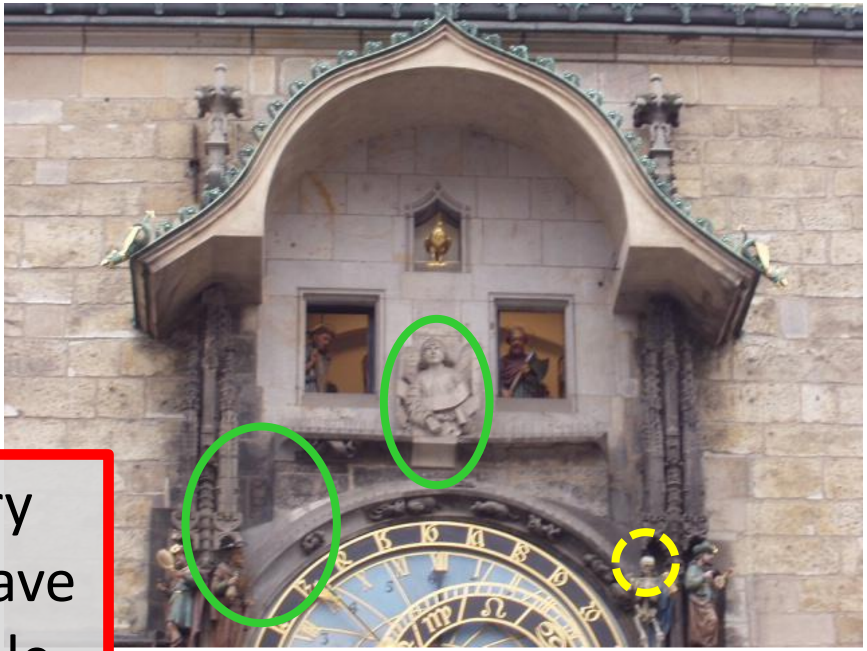
Constraints (rigidity):

- presence (local BoF)
- similar angles
- similar distances
- combination

Repeatability of Feature Sets: Scale Change



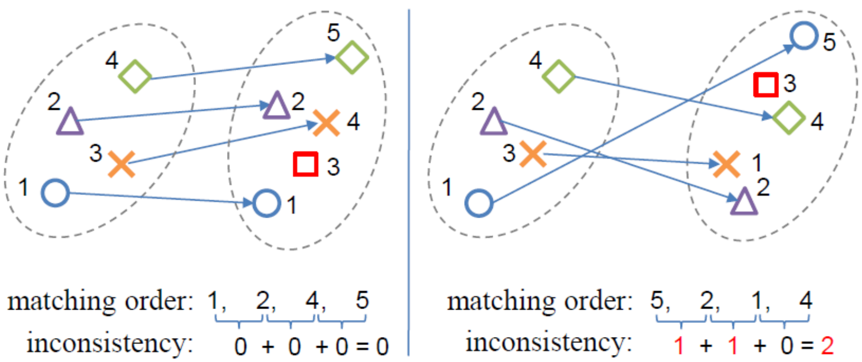


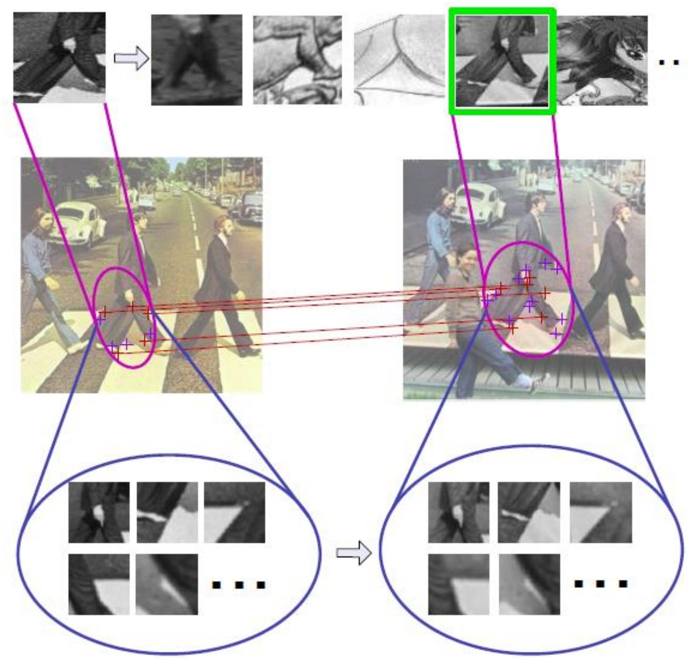


Do not group features of very different scale. Such groups have lower repeatability under scale change.

Data driven neighbourhood

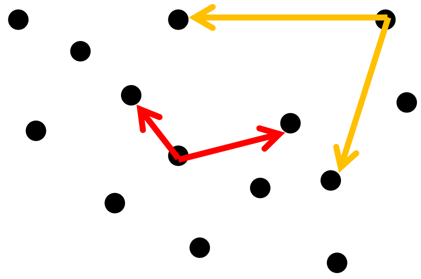
- Segments / regions (MSER) define neighbourhood
- Feature points (DoG)
- Order of projection to x and y
- Efficiently in the posting list





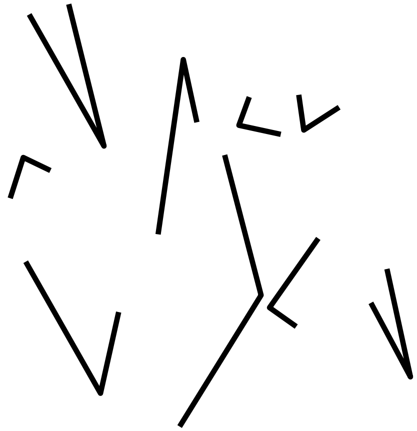
Zhong Wu, Qifa Ke, Michael Isard, and Jian Sun:
Bundling Features for Large Scale Partial-Duplicate Web Image Search, CVPR '09

Geometric Hashing
(the geometry is the descriptor)



- define coordinate system by (triplets of) points
- express other points in the coordinate system
- combinatorially many

Lamdan, Wolfson: Geometric hashing: A general and efficient model-based recognition scheme, ICCV 1988



- use regions that define a coordinate system
- express other regions in the coordinate system
- use spatial and scale neighbourhood

Chum and Matas: Geometric Hashing with LAFs, CVPR 2006

STAROPRAMEN
1
STAROČESKÁ HOSPŮDKA
2
3
DJ's
CLUB
4
5
6
7
8

Geometric min-Hash

min-Hash

min-Hash is an efficient representation of a set A_i

$$m(\mathcal{A}_i, f) = \arg\min_{X \in \mathcal{A}_i} f(X)$$

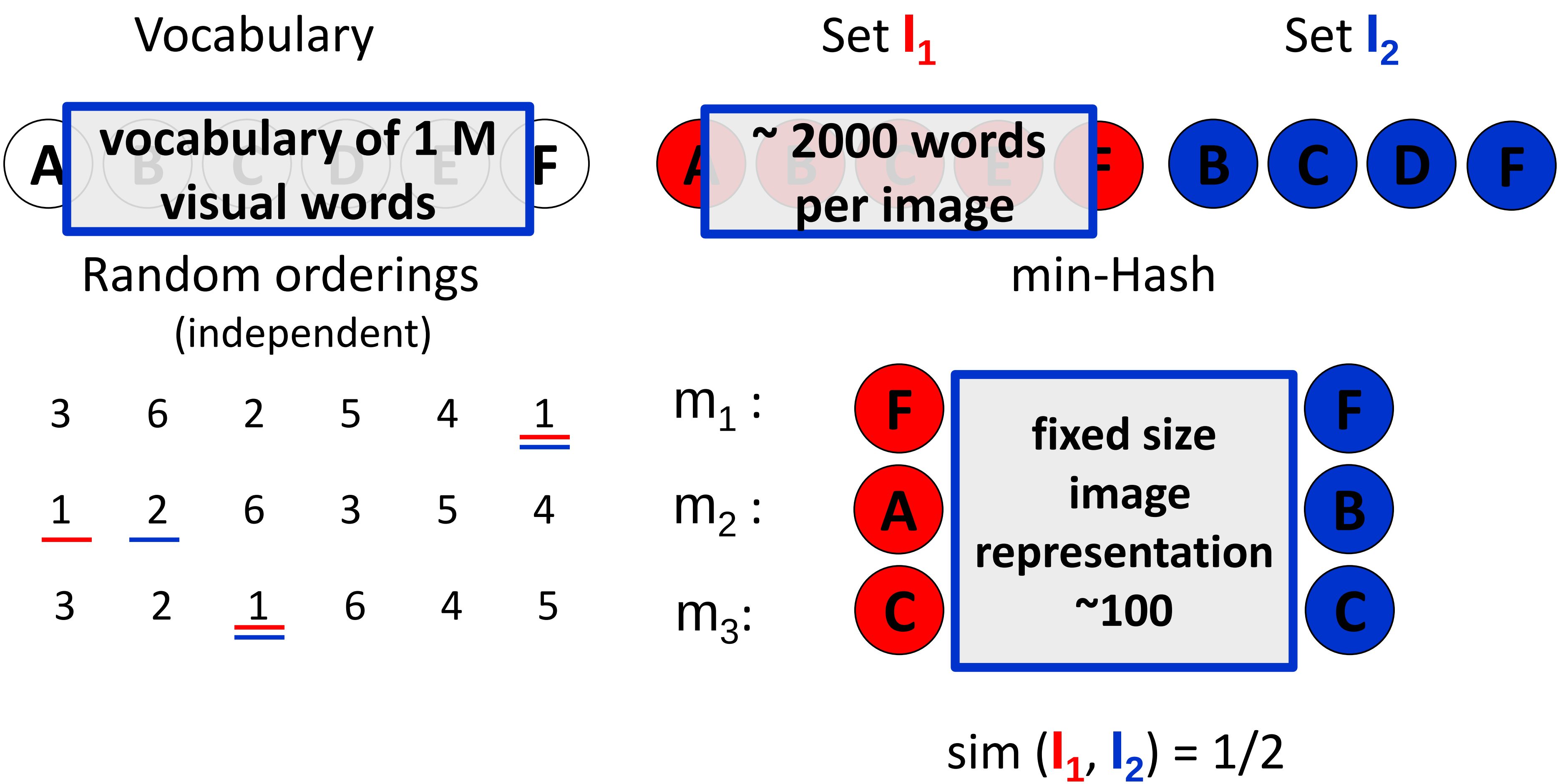
set of visual words   hash function   visual word

min-Hash is a locality sensitive hashing (LSH) function m that selects an element (visual word) $m(A_i)$ from each set A_i of visual words detected in image *i* so that

$$P\{m(\mathcal{I}_1) == m(\mathcal{I}_2)\} = \frac{|\mathcal{I}_1 \cap \mathcal{I}_2|}{|\mathcal{I}_1 \cup \mathcal{I}_2|}$$

Image similarity $\quad \mathrm{sim}(\mathcal{I}_1, \mathcal{I}_2) = \frac{|\mathcal{I}_1 \cap \mathcal{I}_2|}{|\mathcal{I}_1 \cup \mathcal{I}_2|}$

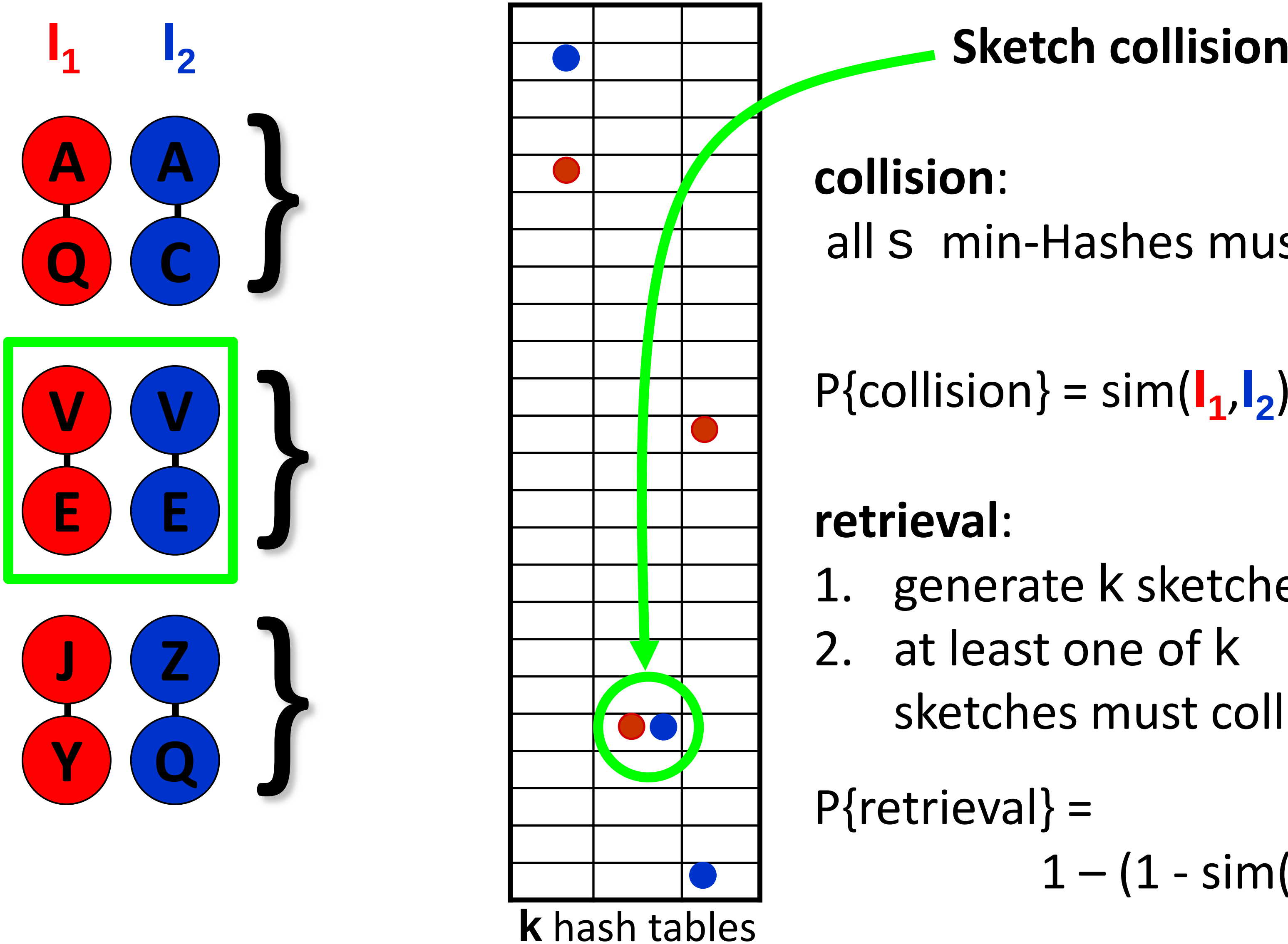
min-Hash



Estimated similarity of I_1 and I_2 from 3 min-Hashes = 2/3

Seed Generation: min-Hash Retrieval

a sketch = **s**-tuple of min-Hashes



collision:
all s min-Hashes must agree

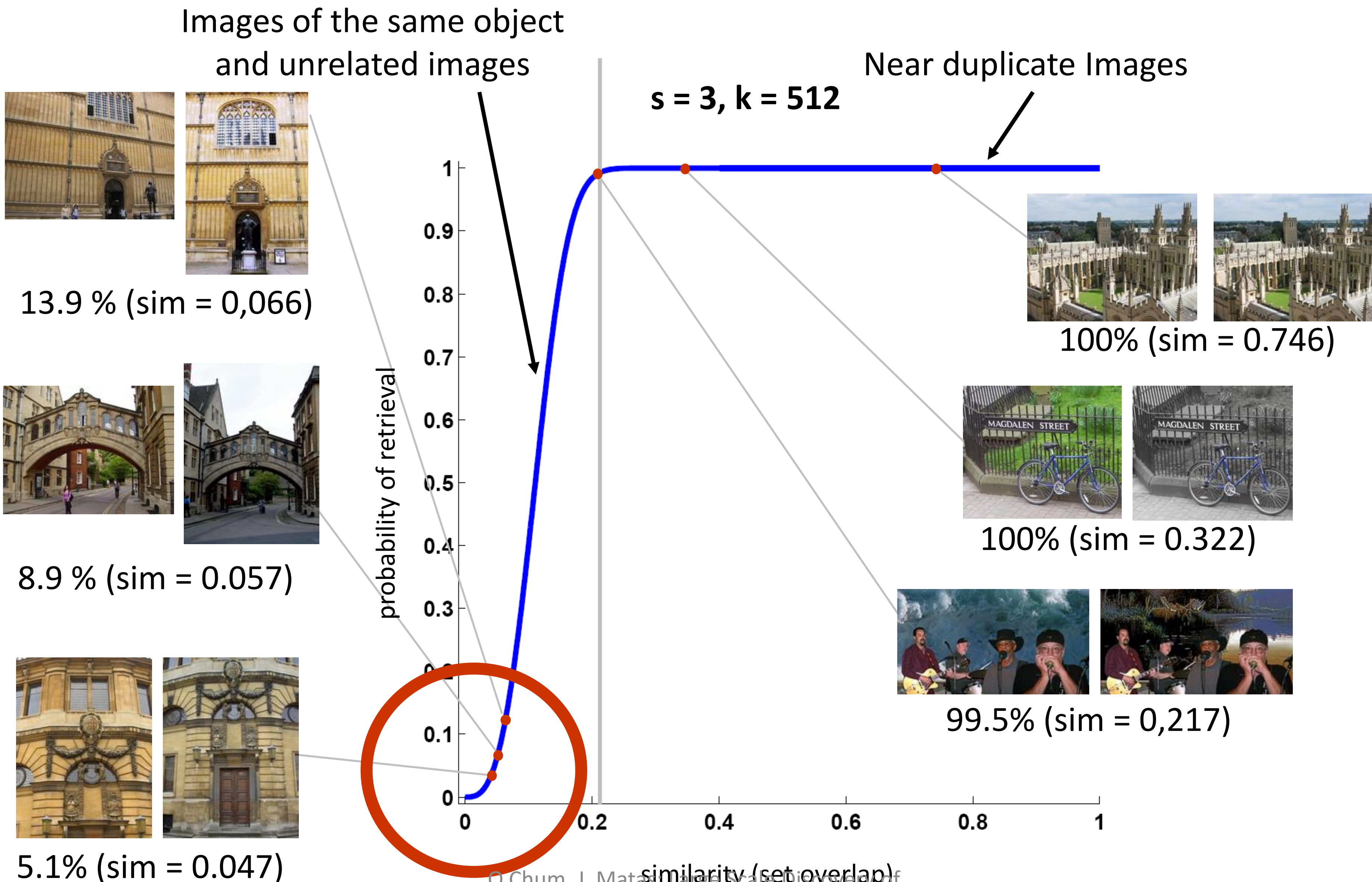
$P\{\text{collision}\} = \text{sim}(I_1, I_2)^s$

retrieval:

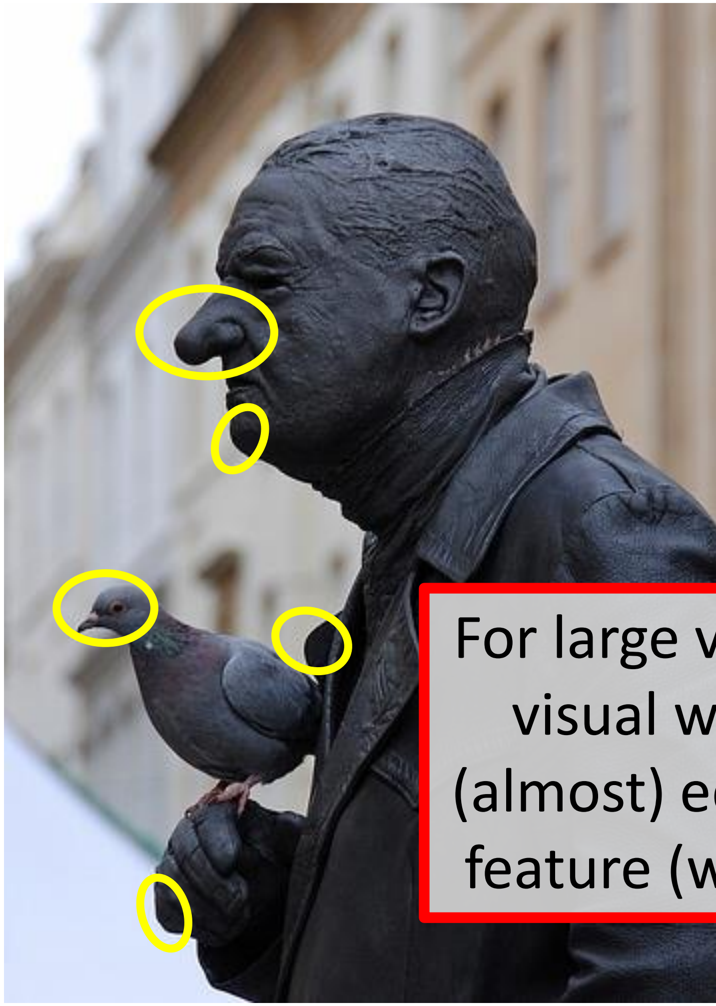
1. generate k sketches
2. at least one of k sketches must collide

$P\{\text{retrieval}\} = 1 - (1 - \text{sim}(I_1, I_2)^s)^k$

Probability of Retrieving an Image Pair



Vocabulary Size and Set Representation



Small vocabulary (1k visual words)

Large vocabulary (1M visual words)

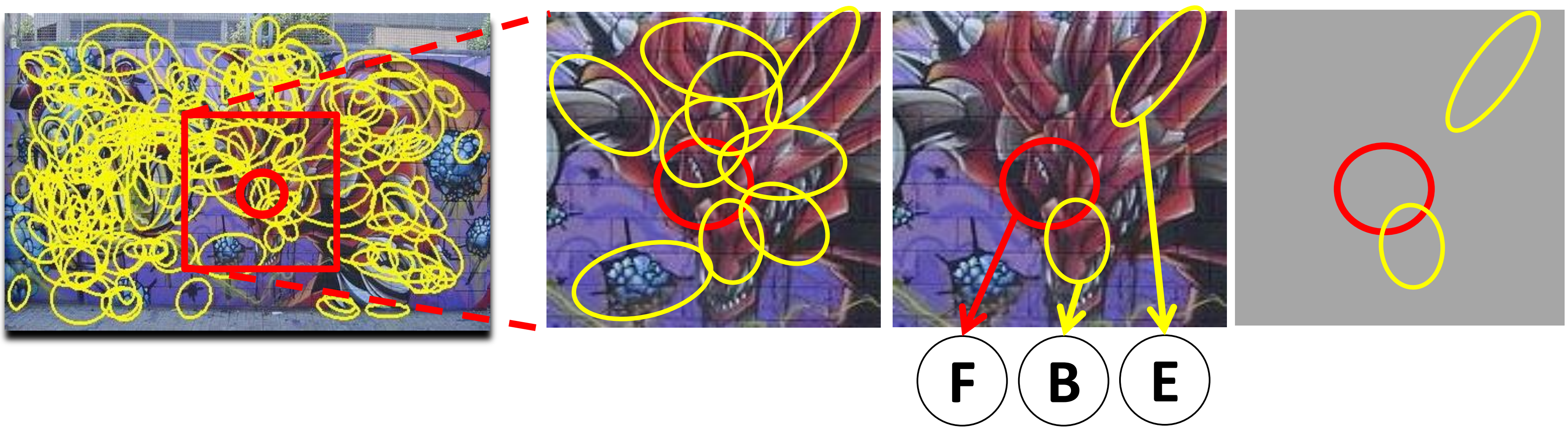
For large vocabularies selecting a visual word from an image is (almost) equivalent to selecting a feature (with location and scale)

On a 100k dataset of images, 95% of features have a unique visual word in an image

Geometric min-Hash algorithm

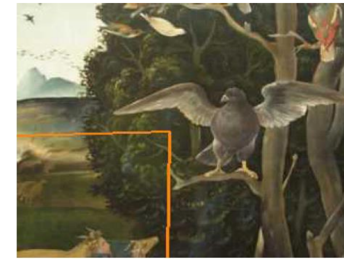
1. Keep features with unique visual word in the image
2. Obtain the “central feature” by min-Hash
3. Select scale and spatial neighbourhood of the central feature
4. Select secondary min-Hash(es) from the neighbourhood
5. Relative pose of the sketch features is a geometric invariant (as in geometric hashing)

Sketch of GmH: s-tuple of visual words + geometric invariant



Geometric vs. Standard min-Hash

- Higher true positives
  - View point change
  - Severe occlusion
  - Scale change
  - Object on a different background

Sketches s=2, k =5000

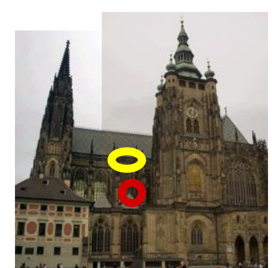
GmH: 37 collisions **mH: 4 collisions**

- Lower false positives
  - Additional geometric invariant (part of the hash key or verification)
  - Lower probability random sketch collisions (next slide)

Sketches s=2, k =5000

GmH: 0 collisions **mH: 4 collisions**

- Faster spatial verification
  - Sketch collision defines geometric transformation



Overlap of Random Sets

False positive = sketch collision of two random images

The probability of two random sets I_1 and I_2 having a common min-Hash (*i.e.* the average overlap of two random sets)

$$\frac{\min(|\mathcal{I}_1|, |\mathcal{I}_2|)}{2w} \leq \mathrm{E}\left(\frac{|\mathcal{I}_1 \cap \mathcal{I}_2|}{|\mathcal{I}_1 \cup \mathcal{I}_2|}\right) \leq \frac{\min(|\mathcal{I}_1|, |\mathcal{I}_2|)}{w}$$

where w is the size of the vocabulary

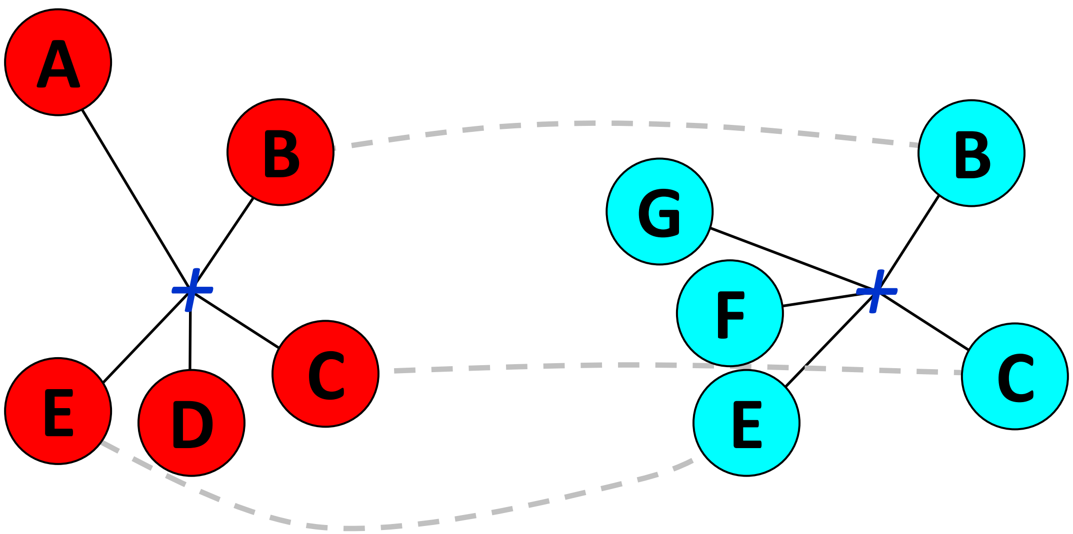
The smaller the sets, the smaller probability of random collision

- Min-Hash: features in the whole image
- Geometric min-Hash: only small subset of the image

Geometric min-Hash as Local Geometric Constraints

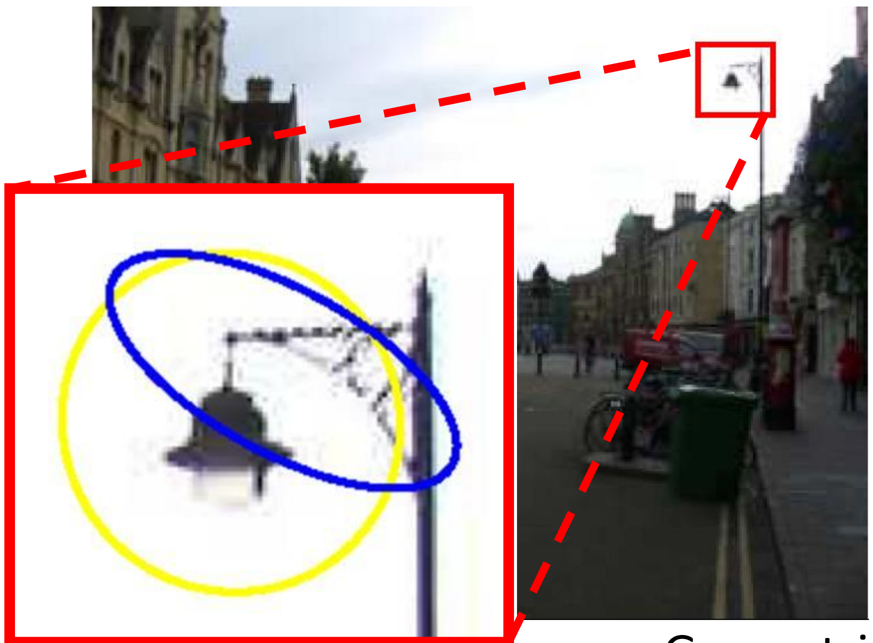
Idea: verify a tentative match "+" by comparing neighboring features

[Schmid and Mohr: Local Greyvalue Invariants for Image Retrieval. PAMI 1997]



Geometric min-Hash is an implicit, robust, constant-time matching of local neighborhood

Object Discovery



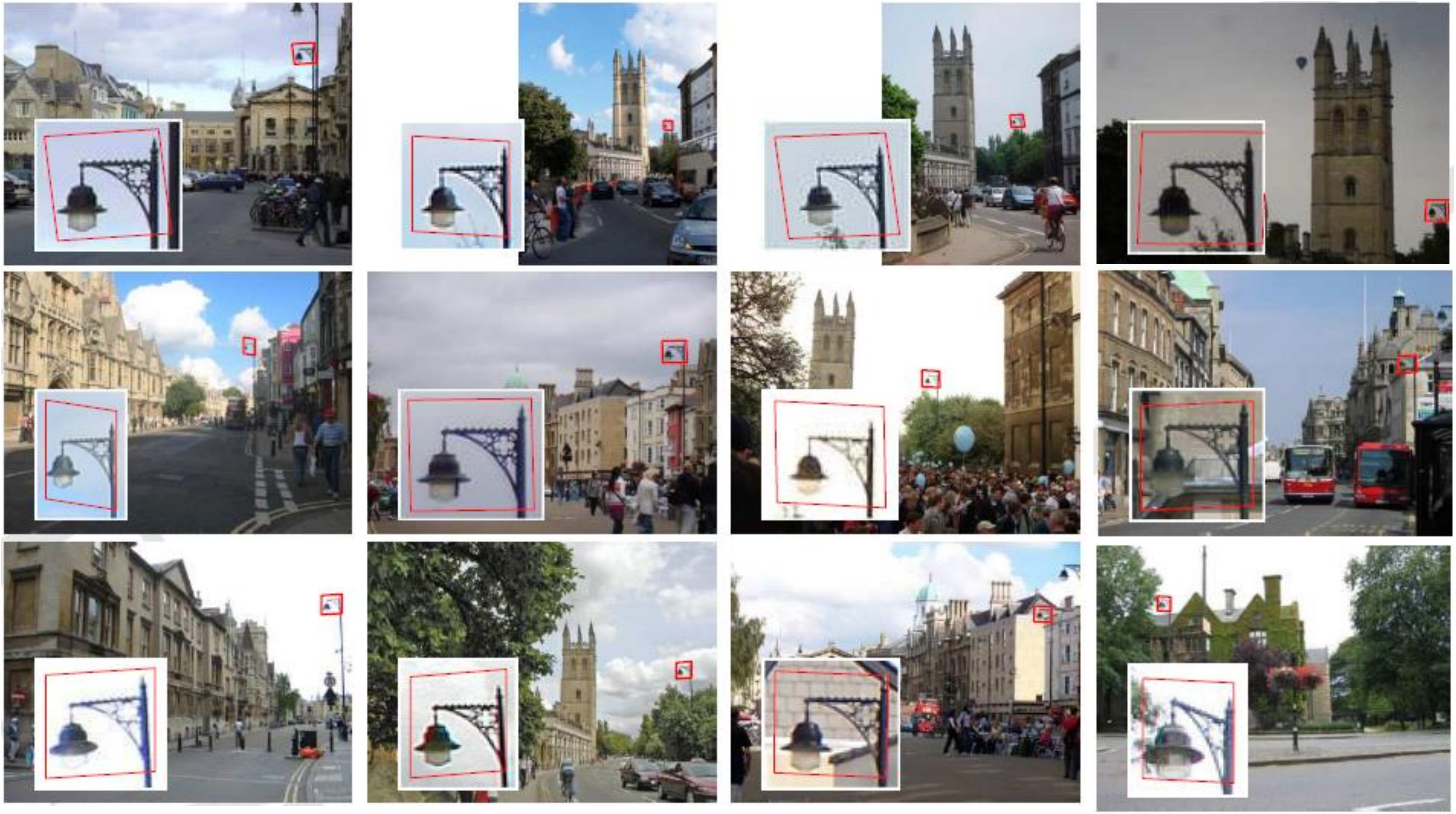
Geometric min-Hash
sketch collision
s = 2, k = 256

Verification by co-segmentation critical for small objects

[Cech, Matas, Perdoch CVPR 08], code available on WWW
[Ferrari, Tuytelaars,Van Gool, ECCV 2004]

Object Discovery

Other instances of the discovered object by (sub)image retrieval



Global Geometry

- Voting in the parameter space
- RANSAC

Robust Estimation: Hough vs. RANSAC

Voting:

- discretized parameter space
- votes for parameters consistent with the measurements
- more votes higher support

+ multiple models
+ can be very fast
- memory demanding
- distances measured in the parameter space

RANSAC:

- hypothesize and verify loop

- randomized (unless you try it all)
- typically slower than voting
+ no extra memory required
+ measures distances in pixels!

Geometric Re-ranking

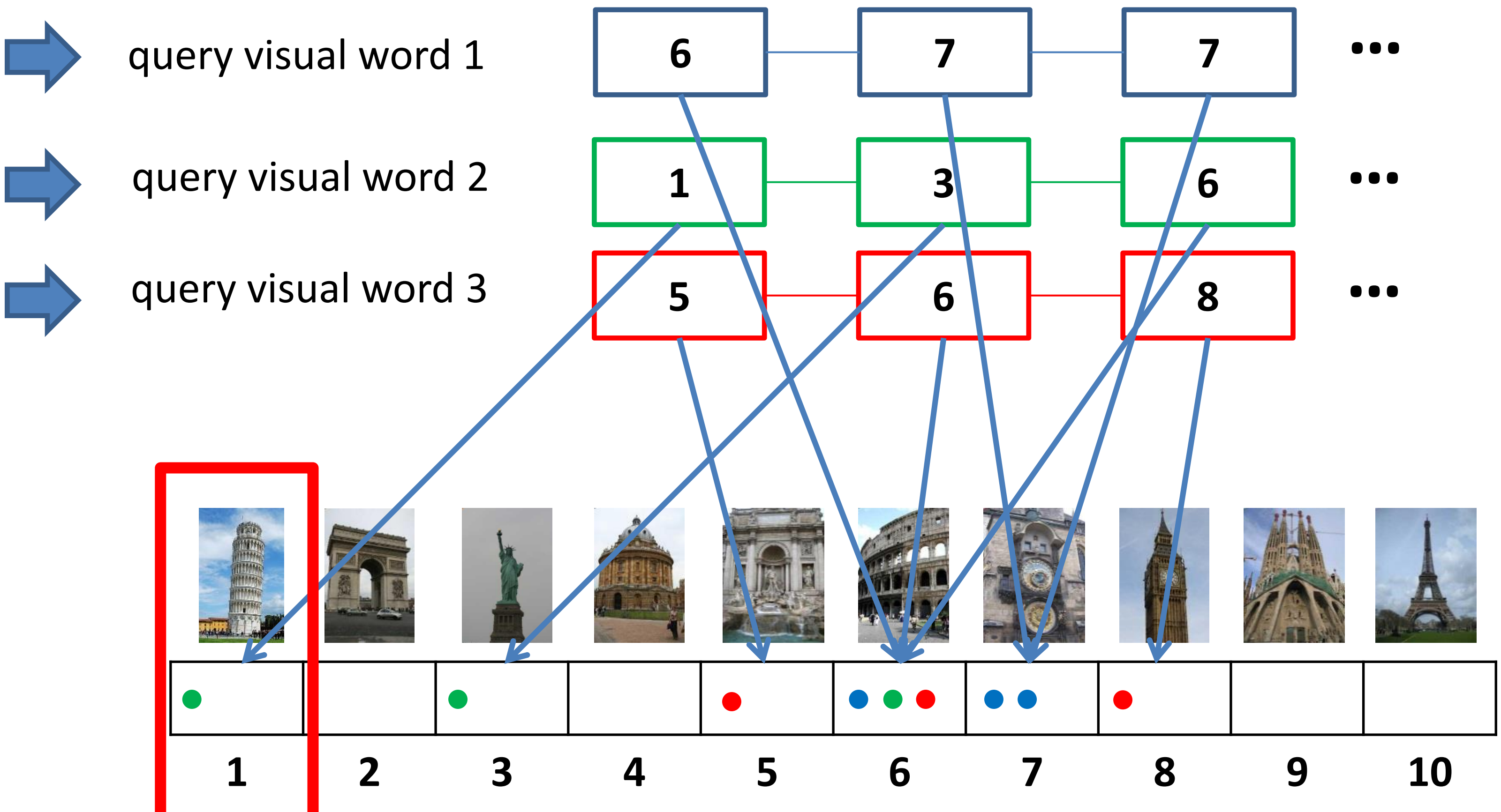
1. Perform ranking without geometric information
   - BoW
   - VLAD
2. Re-rank top ranked images (removing false positives)
   - RANSAC

Sivic, Zisserman: Video Google, ICCV 2003

Philbin, Chum, Isard, Sivic, Zisserman: Object retrieval with large vocabularies and fast spatial matching, CVPR'07

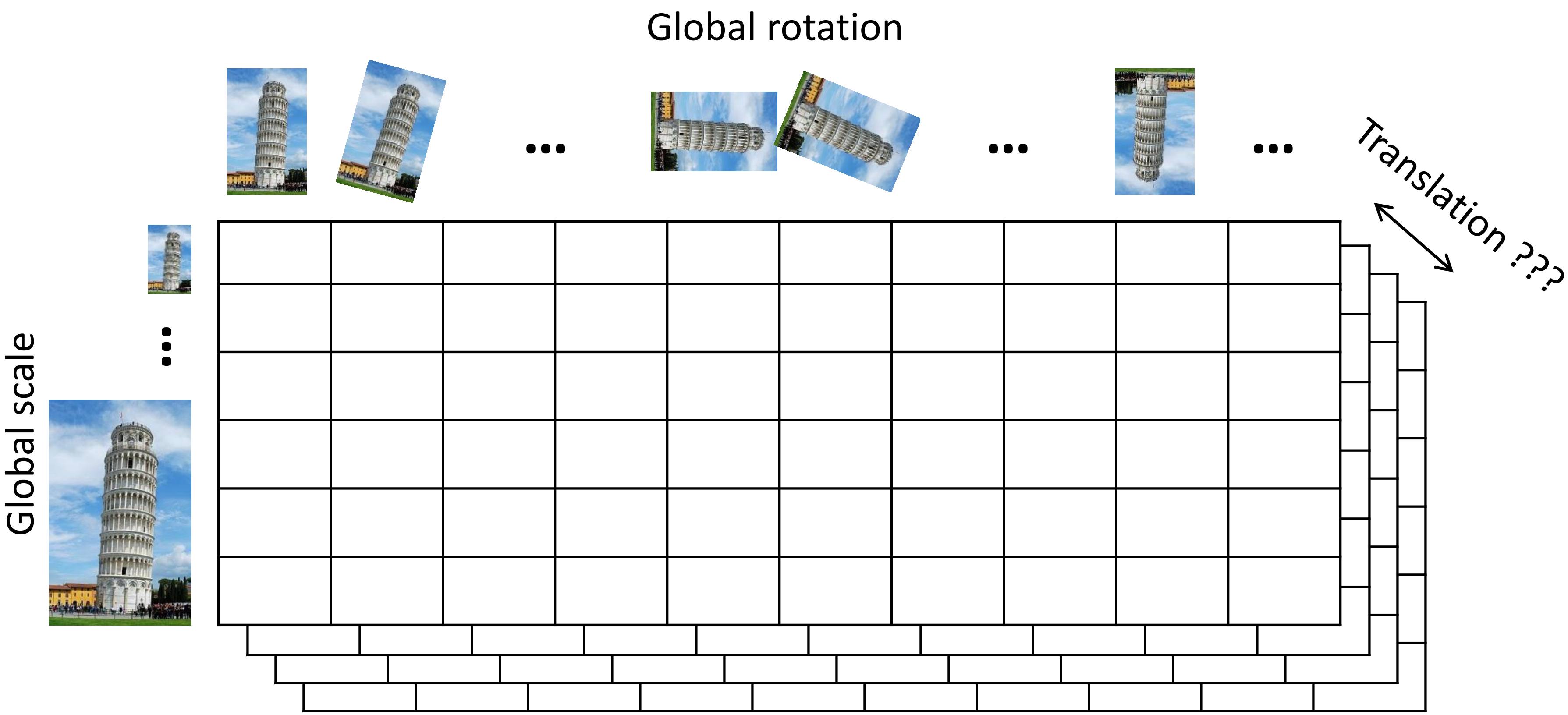
BoW and Inverted File

$$\text{score} = \frac{q^\top x}{||x||}$$



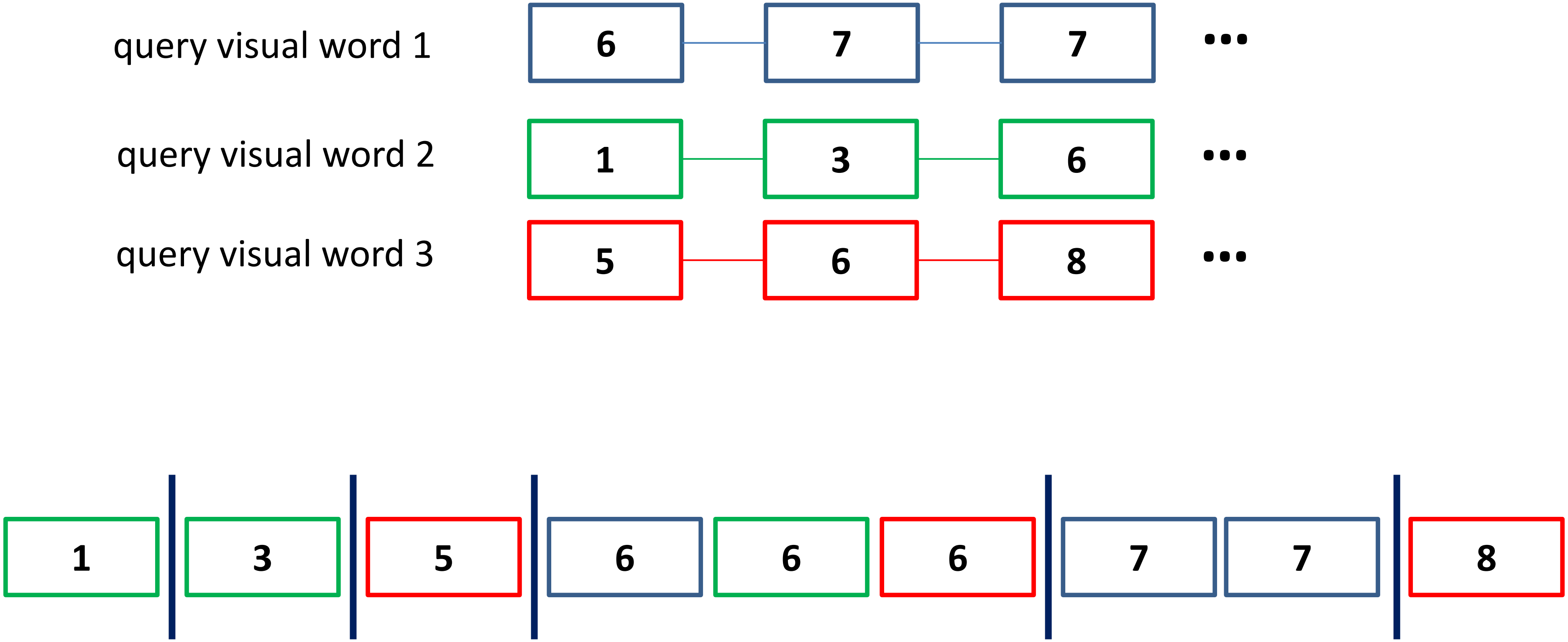
Weak Geometry Constraints

Jégou, Douze, Schmid: Hamming Embedding and
Weak Geometric consistency for large-scale image search, ECCV’08, IJCV’10;
(use margins over rotation and scale rather than the whole table)

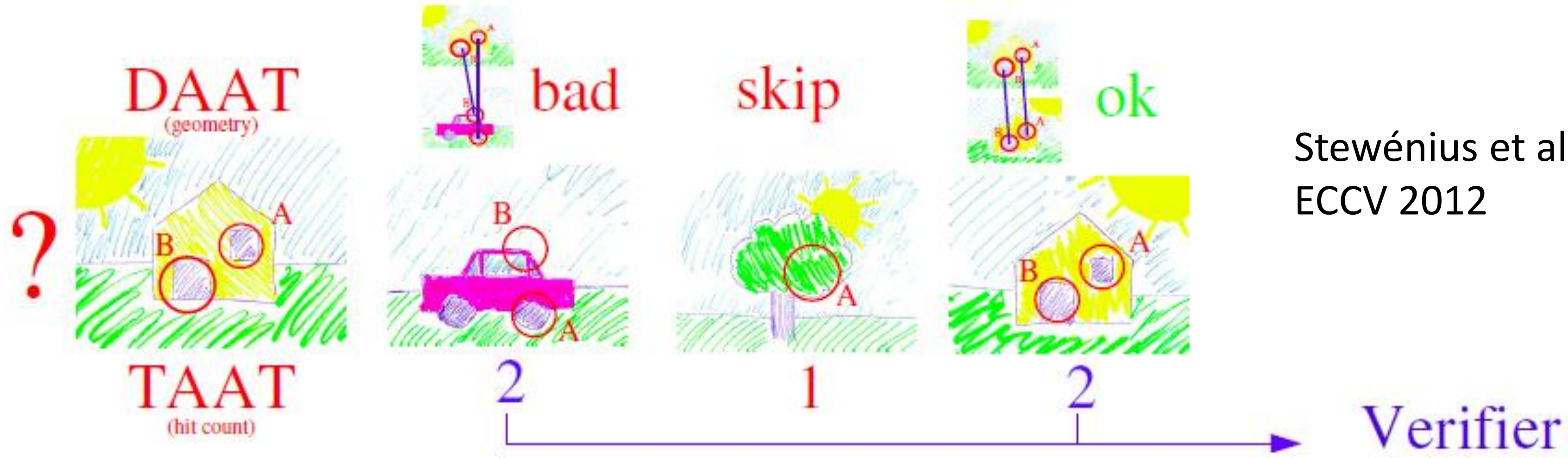


Exhaustive Geometric Verification

Stewénius, Gunderson, Pilet:
Size matters: exhaustive geometric verification for image retrieval, ECCV 2012



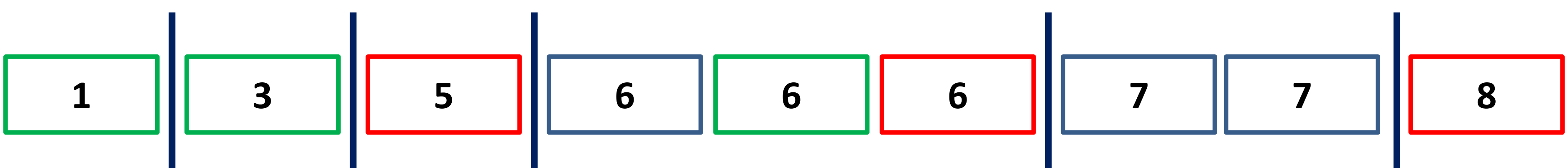
Exhaustive Geometric Verification



Stewénius et al., ECCV 2012

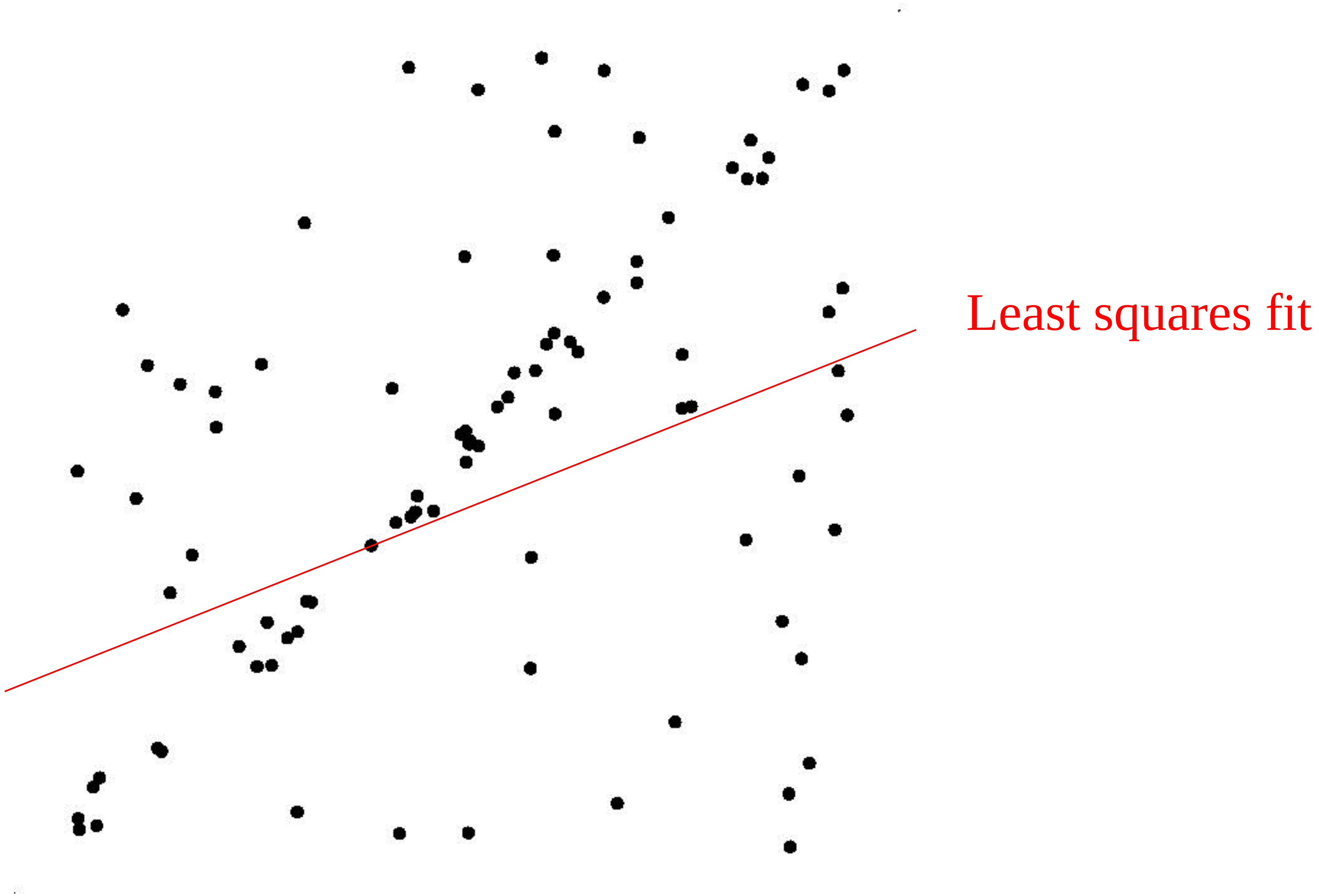
- Costs time: *log* (number of posting lists involved)
- Efficient merging with fixed tree structure
- Any kind of spatial verification can be used
- Images with too few matches are rejected directly

Combined with small number of features per image and very large vocabularies gives impressive massive-scale results

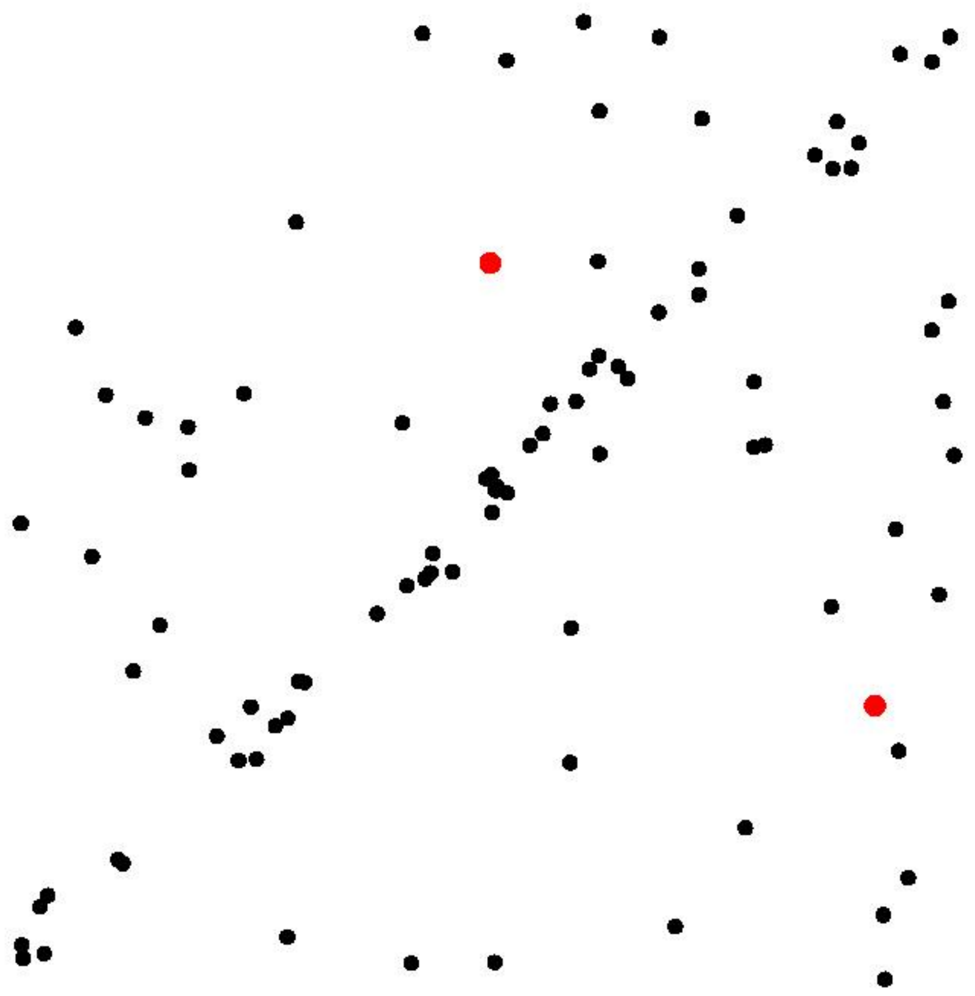


RANSAC

Fitting a Line

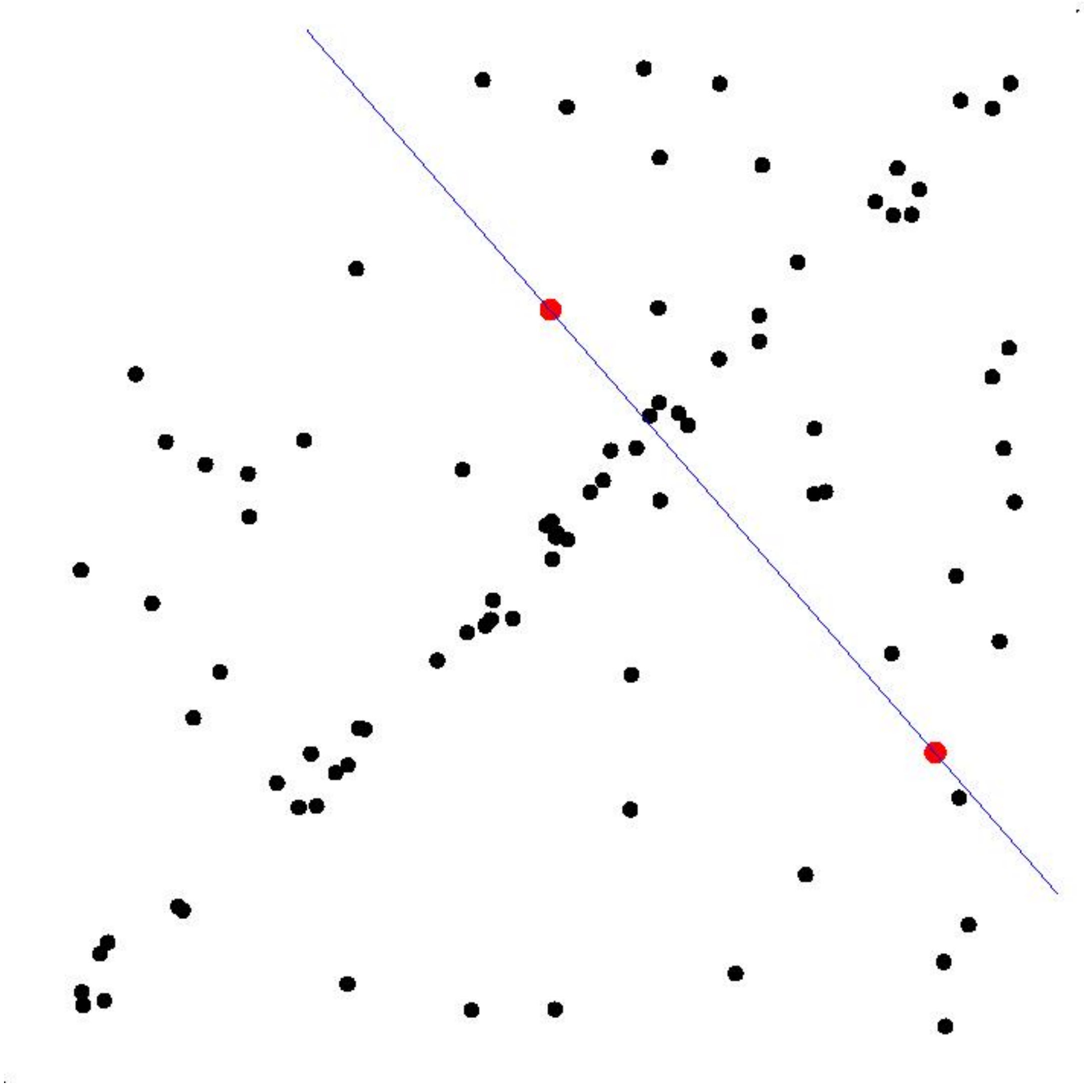


RANSAC



• **Select sample of m points at random**

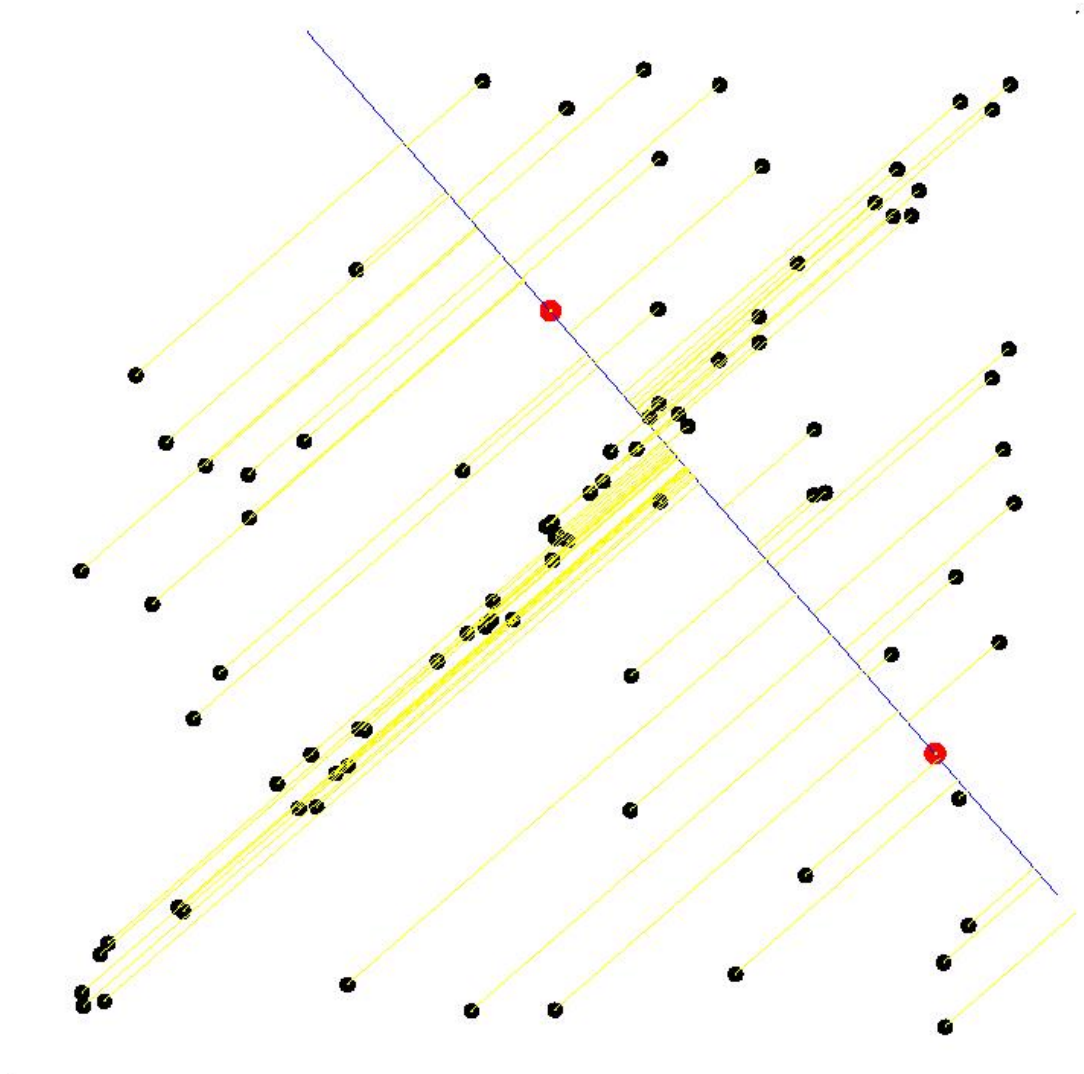
RANSAC



- Select sample of m points at random

- **Calculate model parameters that fit the data in the sample**

RANSAC

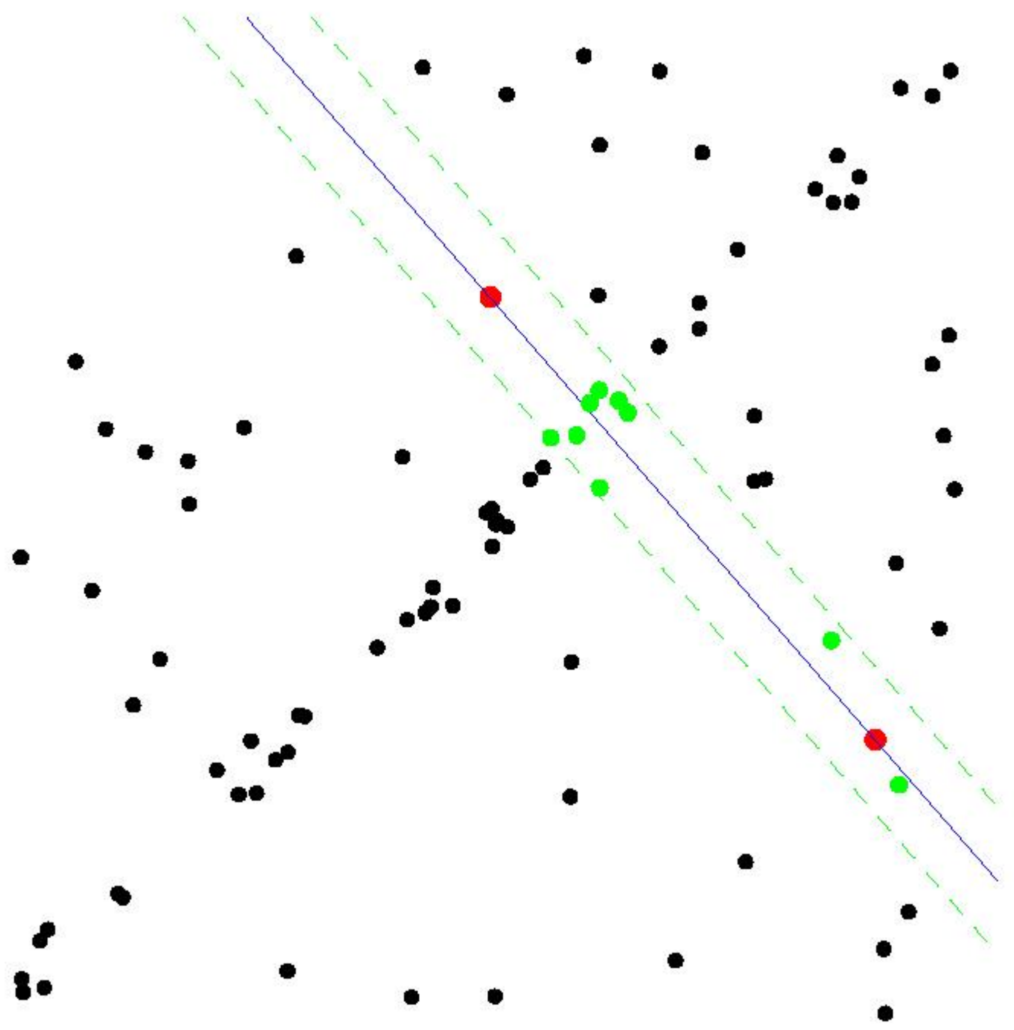


• Select sample of m points at random

• Calculate model parameters that fit the data in the sample

• Calculate error function for each data point

RANSAC



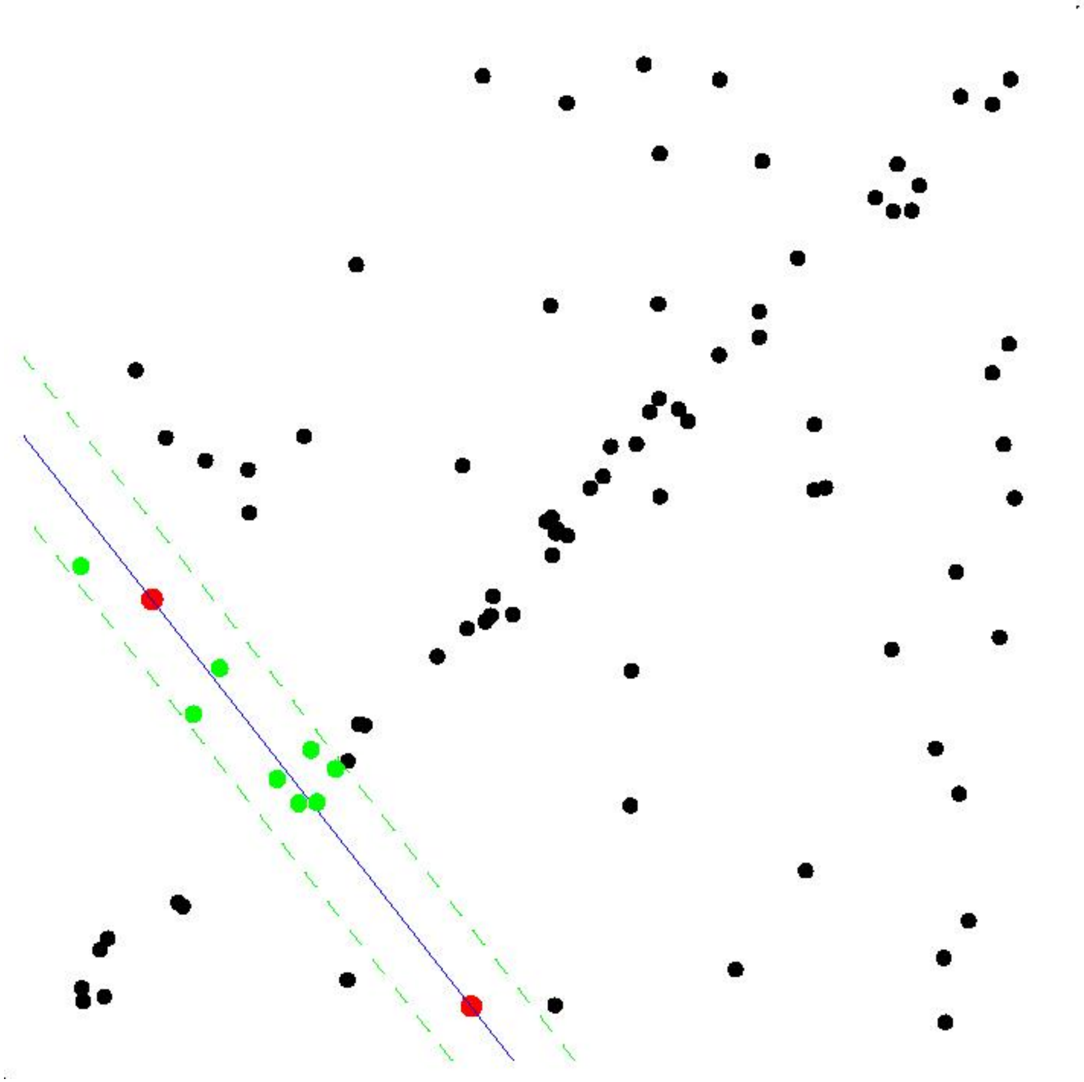
• Select sample of m points at random

• Calculate model parameters that fit the data in the sample

• Calculate error function for each data point

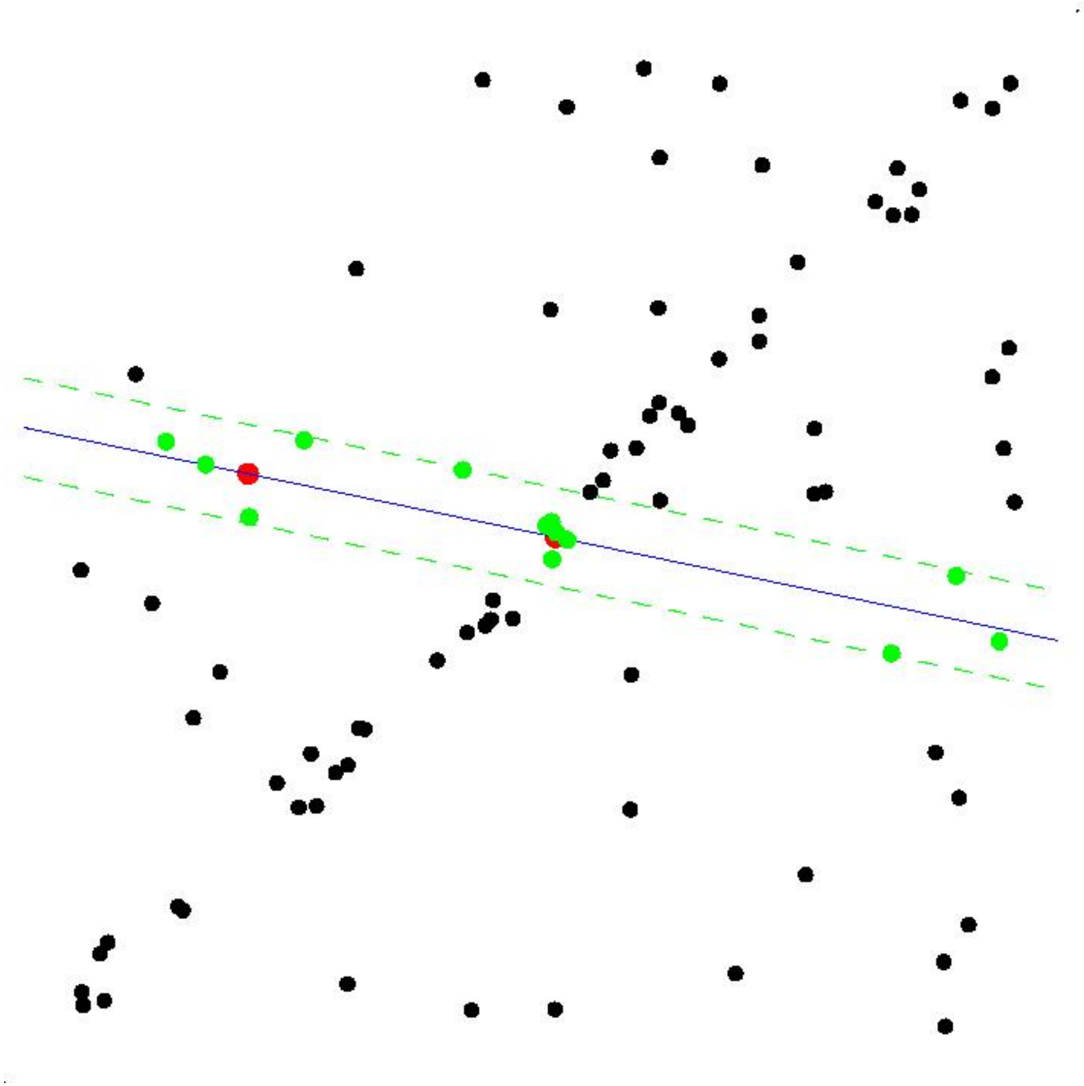
• Select data that support current hypothesis

RANSAC



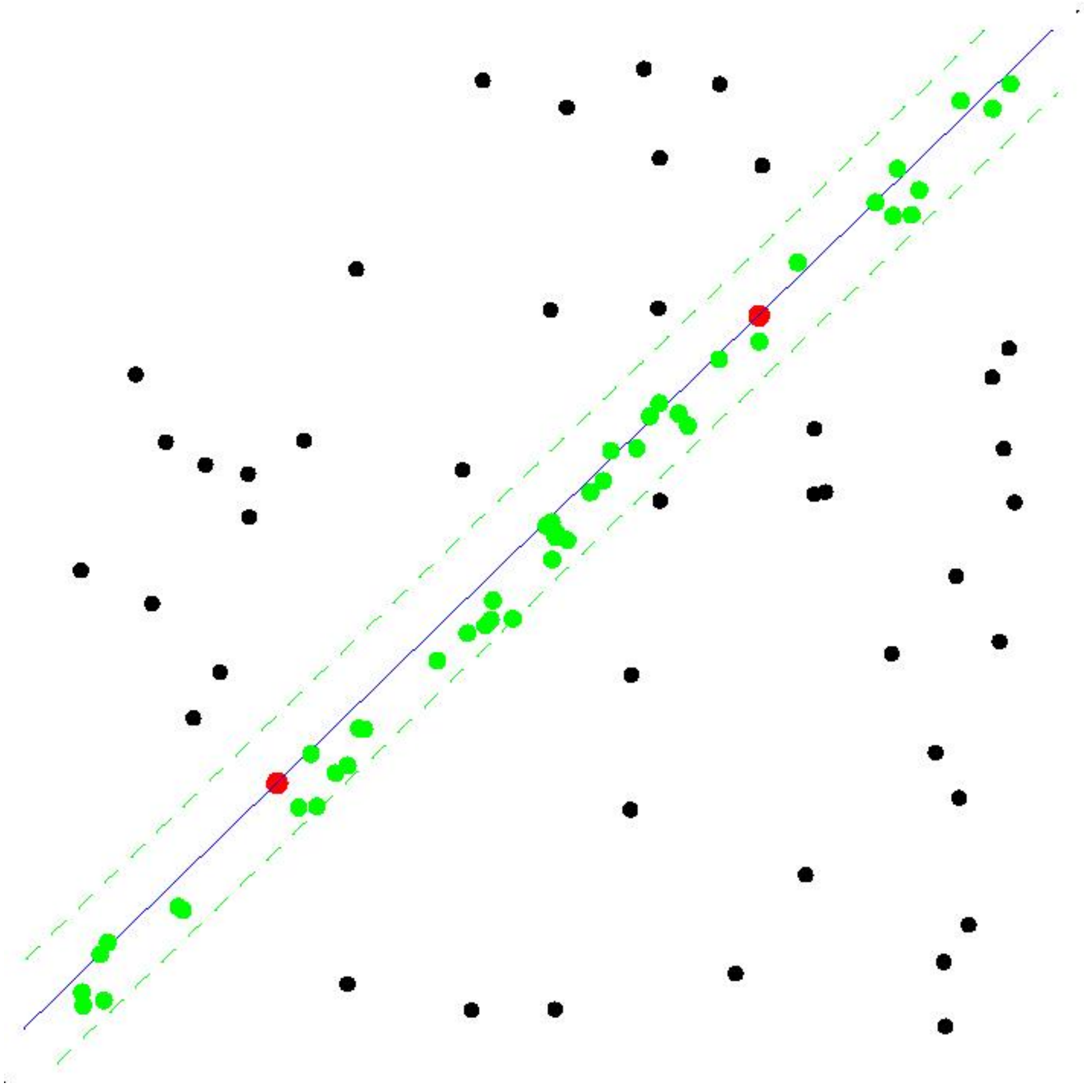
- Select sample of m points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that support current hypothesis
- **Repeat sampling**

RANSAC



- Select sample of m points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that support current hypothesis
- **Repeat sampling**

RANSAC



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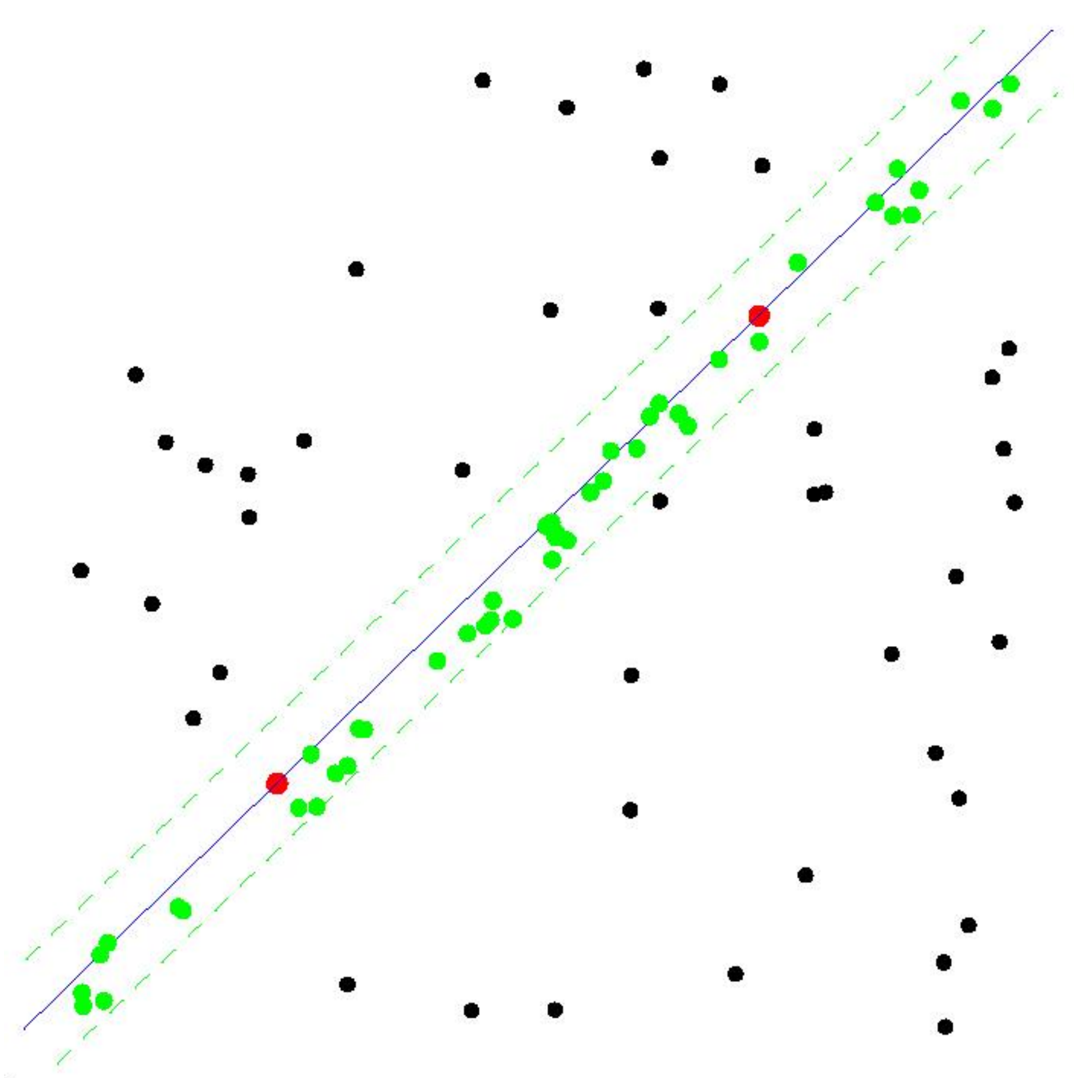
RANSAC



$$k = \frac{\log(1-p)}{\log\left(1- \frac{I^m}{N^m}\right)}$$

k … number of samples drawn

m … minimal sample size

N … number of data points

I … time to compute a single model

p … confidence in the solution (.95)

How Many Samples

$I\ /\ N$ [%]

Size of the sample m

	15%	20%	30%	40%	50%	70%
2	132	73	32	17	10	4
4	5916	1871	368	116	46	11
7	$1.75 \cdot 10^6$	$2.34 \cdot 10^5$	$1.37 \cdot 10^4$	1827	382	35
8	$1.17 \cdot 10^7$	$1.17 \cdot 10^6$	$4.57 \cdot 10^4$	4570	765	50
12	$2.31 \cdot 10^{10}$	$7.31 \cdot 10^8$	$5.64 \cdot 10^6$	$1.79 \cdot 10^5$	$1.23 \cdot 10^4$	215
18	$2.08 \cdot 10^{15}$	$1.14 \cdot 10^{13}$	$7.73 \cdot 10^9$	$4.36 \cdot 10^7$	$7.85 \cdot 10^5$	1838
30	∞	∞	$1.35 \cdot 10^{16}$	$2.60 \cdot 10^{12}$	$3.22 \cdot 10^9$	$1.33 \cdot 10^5$
40	∞	∞	∞	$2.70 \cdot 10^{16}$	$3.29 \cdot 10^{12}$	$4.71 \cdot 10^6$

RANSAC [Fischler, Bolles '81]

In: $U = \{x_i\}$ set of data points, $|U| = N$

$f(S) : S \rightarrow p$ function f computes model parameters p given a sample S from U

$\rho(p, x)$ the cost function for a single data point x

Out: p^* p^*, parameters of the model maximizing the cost function

k := 0

Repeat until P{better solution exists} < η (a function of C^* and no. of steps k)

k := k + 1

I. Hypothesis

(1) select randomly set $S_k \subset U$, sample size $|S_k| = m$

(2) compute parameters $p_k = f(S_k)$

II. Verification

(3) compute cost $C_k = \sum_{x \in U} \rho(p_k, x)$

(4) if $C^* < C_k$ then $C^* := C_k$, $p^* := p_k$

end

Advanced RANSAC

In: $U = \{x_i\}$ set of data points, $|U| = N$

$f(S) : S \rightarrow p$ function f computes model parameters p given a sample S from U

$\rho(p, x)$ the cost function for a single data point x

Out: p^* p^*, parameters of the model maximizing the cost function

k := 0

Repeat until P{better solution exists} < η (a function of C^* and no. of steps k)

k := k + 1

I. Hypothesis

(1) select randomly set $S_k \subset U$, sample size $|S_k| = m$

(2) compute parameters $p_k = f(S_k)$

II. Verification

(3) compute cost $C_k = \sum_{x \in U} \rho(p_k, x)$

(4) if $C^* < C_k$ then $C^* := C_k$, $p^* := p_k$

end

Preemptive scoring

Non-uniform sampling

Error scale estimation

Randomized verification

Improving precision

Potential degeneracy tests

*SAC

RANSAC [Fischler'81], **MLESAC** [Torr'00], **R-RANSAC** [Chum'02], **NAPSAC** [Myatt'02], **Guided MLESAC** [Tordoff'02], **LO-RANSAC** [Chum'03], **Preemtive RANSAC** [Nister'03], **PROSAC** [Chum'05], **RANSAC with bail-out** [Capel'05], **DegenSAC** [Chum'05], **WaldSAC** [Matas'05], **QDEGSAC** [Frahm'06], **GASAC** [Rodehorst'06], **ARRSAC** [Raguram'08] **GroupSAC** [Ni'09], **Cov-RANSAC** [Raguram'09], **...**

Lebeda, Matas, and Chum: **Fixing the Locally Optimized RANSAC**, BMVC 2012

images, data, executables:
http://cmp.felk.cvut.cz/software/LO-RANSAC/index.xhtml

Raguram, Chum, Pollefeys, Matas, Frahm:
"**USAC: A Universal Framework for Random Sample Consensus**", PAMI 2013

code, data:
http://cs.unc.edu/~rraguram/usac/

Minimal Samples

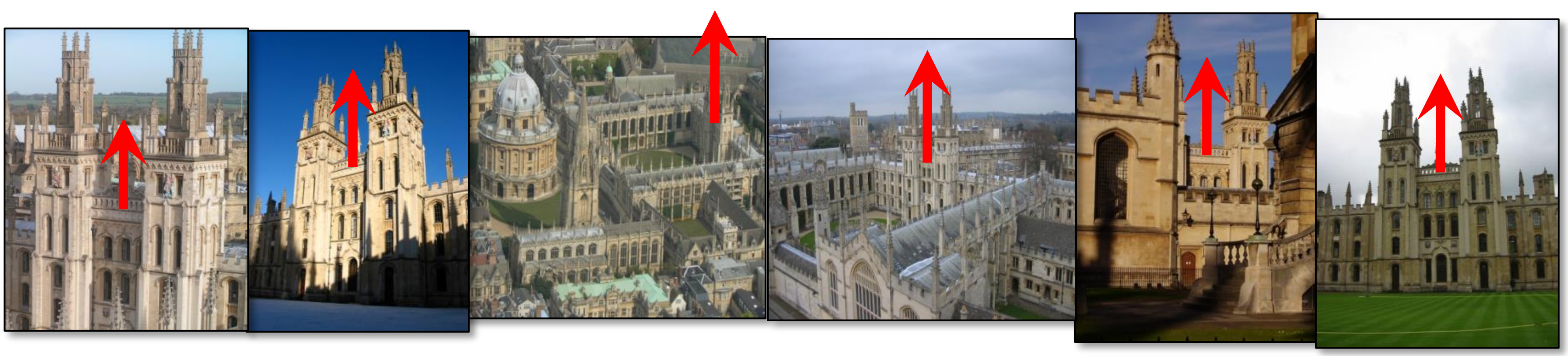
Single Correspondence Models

Point	Translation
Point + scale	Translation and isotropic scale
Point + scale + orientation	Similarity
Ellipse + orientation	Affine transformation

Ellipse correspondence and a gravity vector

Philbin et al.: Object retrieval with large vocabularies and fast spatial matching, CVPR’07 (using rotationally invariant descriptors)

Perdoch, Chum, Matas: Efficient Representation of Local Geometry for Large Scale Object Retrieval, CVPR 2009 (using rotationally variant descriptors)



Gravity Vector Assumption

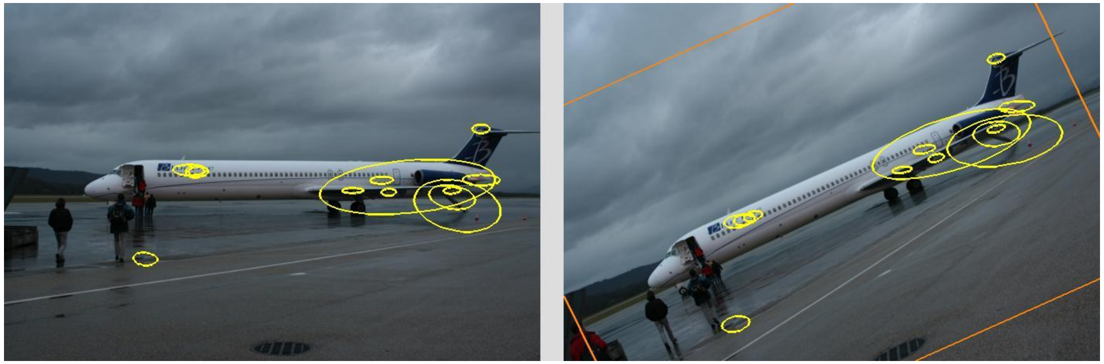
- Performance comparison

mAP	Oxford5K vocab.				Paris vocab.			
	Ox5K		Ox105K		Ox5K		Ox105K	
Dominant orient.	0.772	0.887*	0.687	0.844*	0.592	0.733*	0.501	0.637*
Gravity vector	0.786	0.900*	0.723	0.852*	0.635	0.782*	0.572	0.725*

*with query expansion.

  – SIFT dominant orientation [Lowe'04] produces 50% more descriptors.

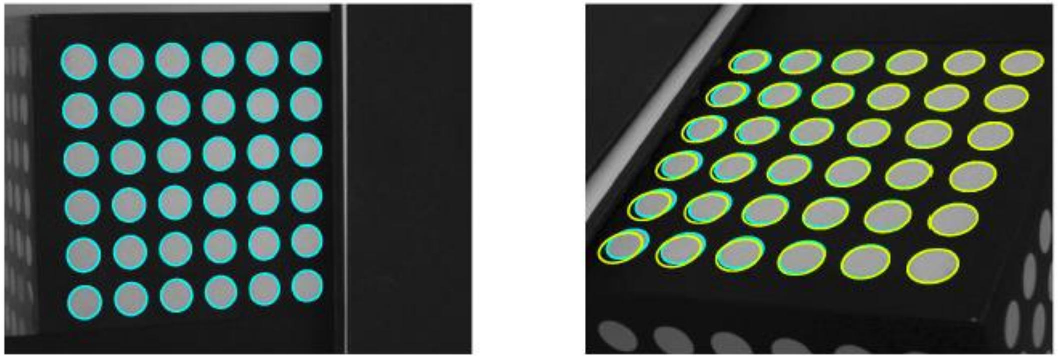
- Robustness of gravity vector assumption



  – Robustness of SIFT to small imprecision in orientation.
  – Correct final geometry due to LO-step in RANSAC.

Planar Homography

from Two or More Elliptical Correspondences



four hypotheses

Kannala, Salo and Heikkilä: Algorithms for computing a planar homography from conics in correspondence, BMVC 2006

Matlab code available: http://www.ee.oulu.fi/~jkannala/bmvc.html

single hypothesis

Chum, Matas: Homography Estimation from Correspondence of Two Local Elliptical Features, ICPR 2012

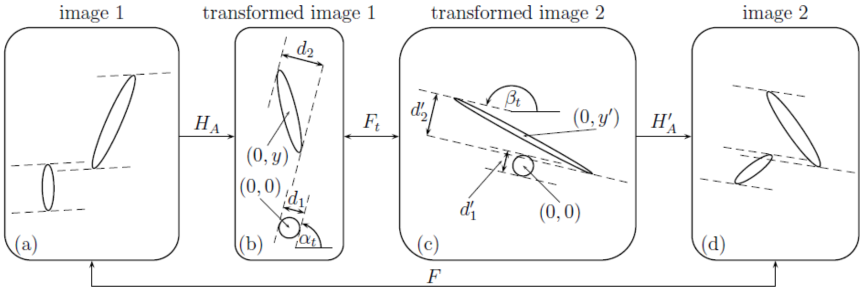
Matlab code available: http://cmp.felk.cvut.cz/~chum/code/ell2h.html

More Models …

- Camera rotation around optical center
- Homography 7 DoF
- Fully defined by a derivative in a point
- Derivative approx. by a single ellipse + orientation correspondence

Koeser, Beder, Koch: Conjugate Rotation: Parameterization and Estimation from an Affine Feature Correspondence, CVPR 2008

Affine epipolar geometry estimated from two elliptical correspondences



four hypotheses

Arandjelovic, Zisserman: Efficient Image Retrieval for 3D Structures , BMVC 2010

Points vs. Regions

Points

- more precise models from good all-inlier samples
- more often exhibit degenerate cases
- lower probability of hitting a all-inlier sample (longer RANSAC)

Regions

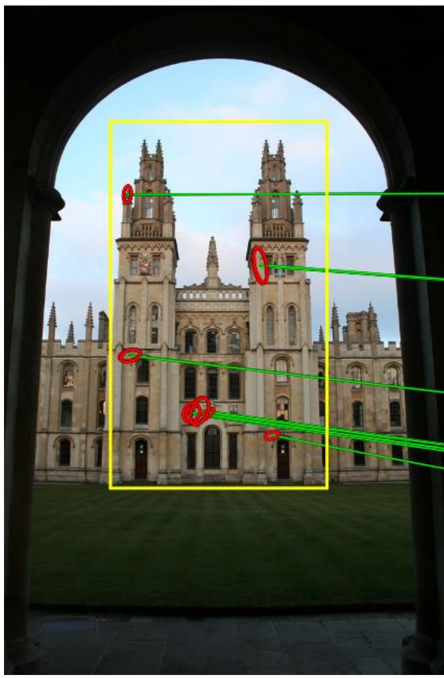
- less precise models from good all-inlier samples
  (model from a single correspondence extrapolates everywhere)
- less often generates degenerate model
- much faster RANSAC (especially with loose thresholds)

Application
Query Expansion

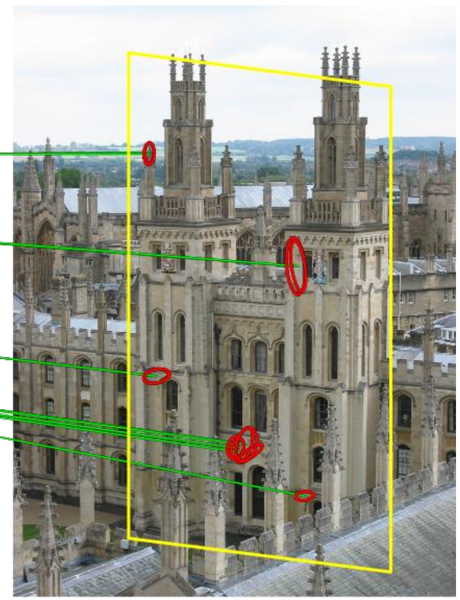
Query Expansion

Chum, Philbin, Sivic, Isard, Zisserman: Total Recall..., ICCV 2007

Query Expansion Step by Step



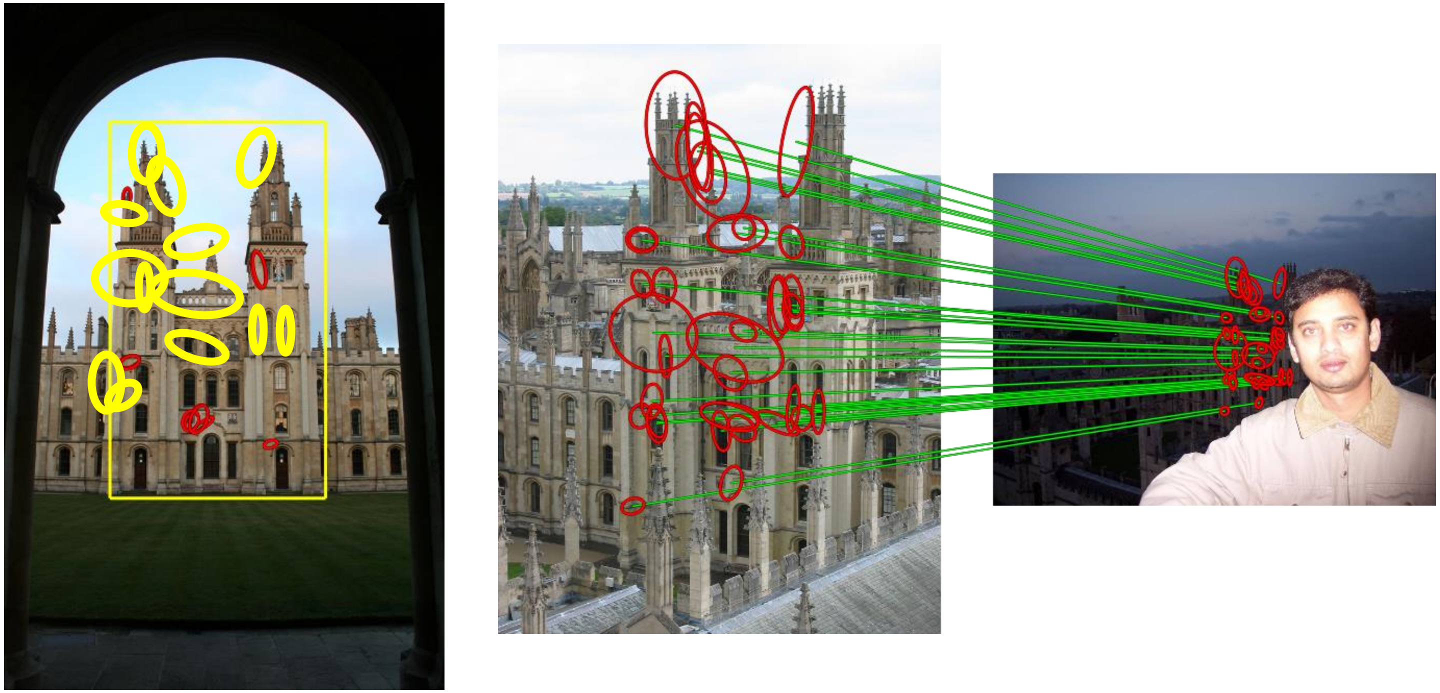
Query Image



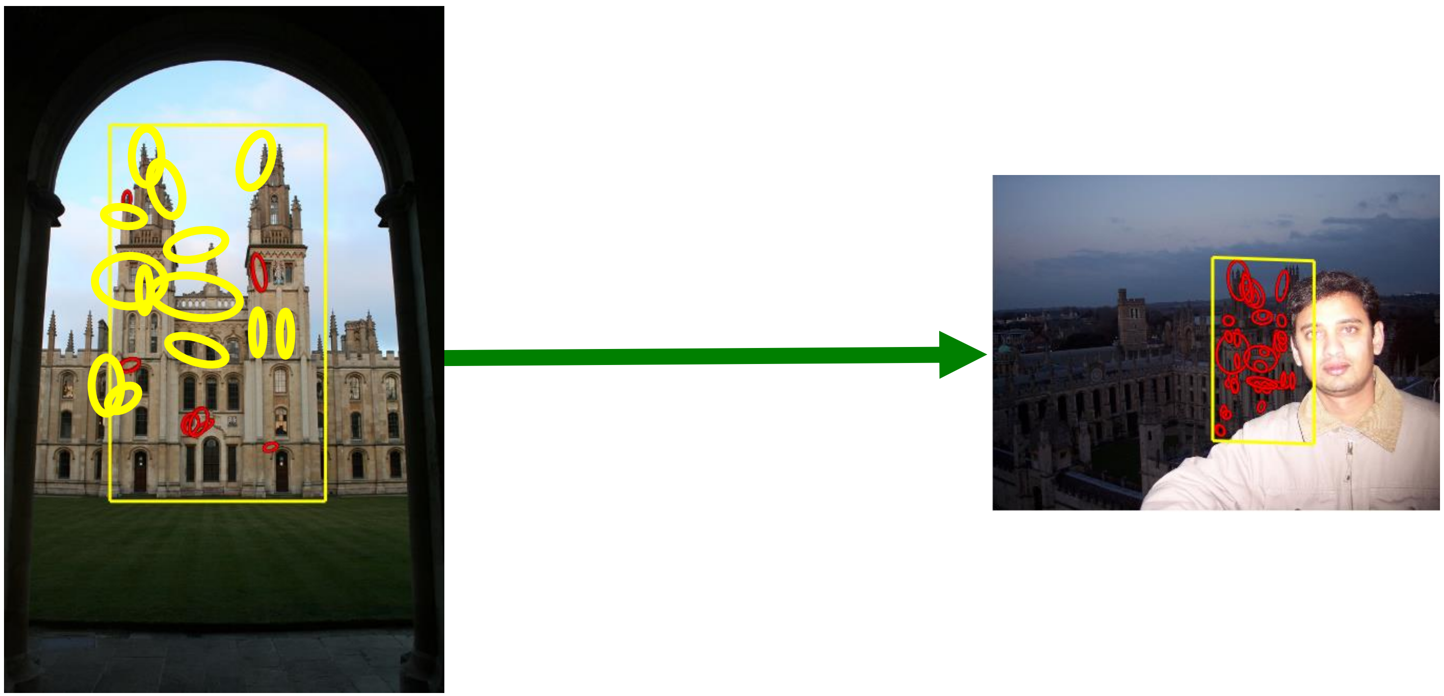
Retrieved image

Originally not retrieved

Query Expansion Step by Step



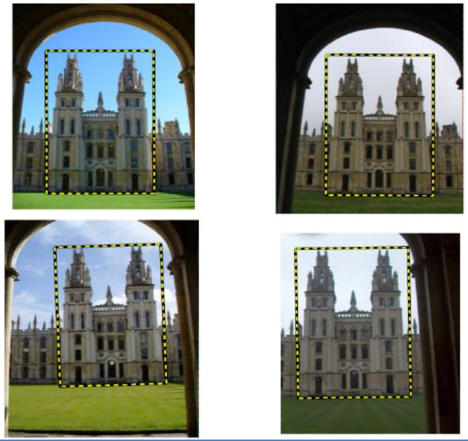
Query Expansion Step by Step

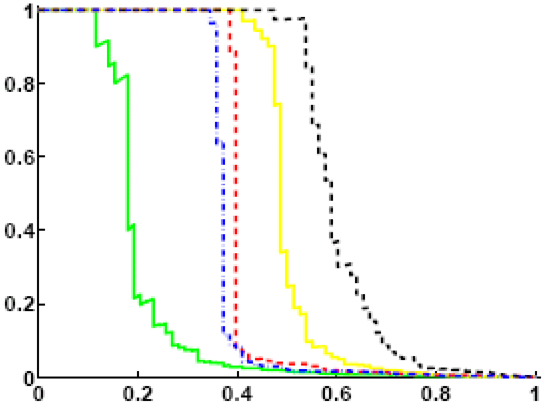


Query Expansion Results

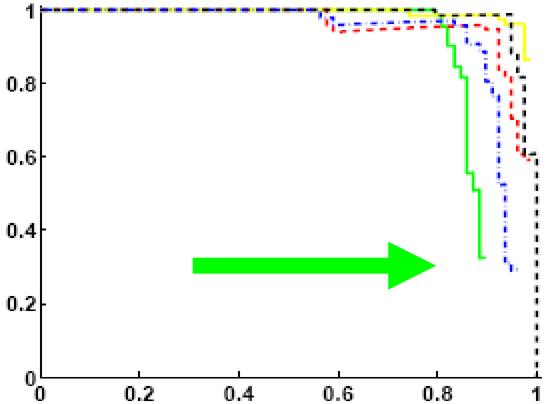
Query image

Original results (good)



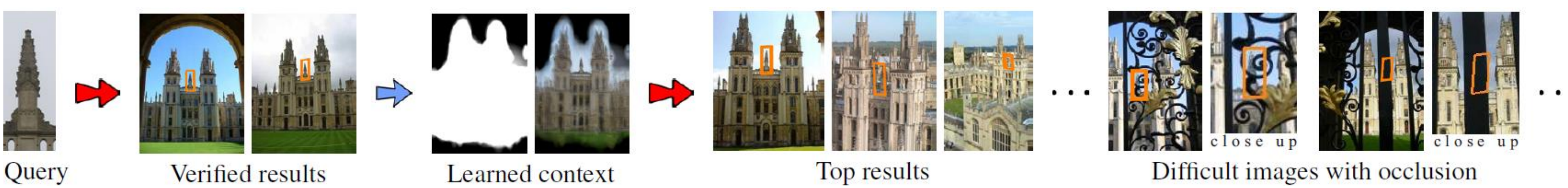


Expanded results (better)



Context expansion

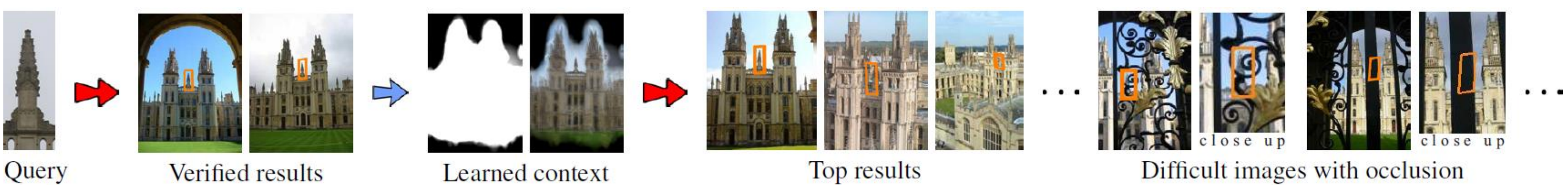
• the model of the object is grown beyond the boundaries of the initial query,
• a feature added into the model that is not inside the context is inactive until confirmed by feature(s) from another image with the same visual word and similar geometry.
• Once a feature is confirmed, it adds the neighbourhood around its center to the context.



Chum, Mikulik, Perdoch, Matas: Total Recall II: Query Expansion Revisited, CVPR 2011

Context expansion

• the mode object is gro the
initial quer
• a feature nto the mod t is
inactive un rmed by feat th
the same w rd and simil
• Once a fe confirmed, i und
its center t ntext.

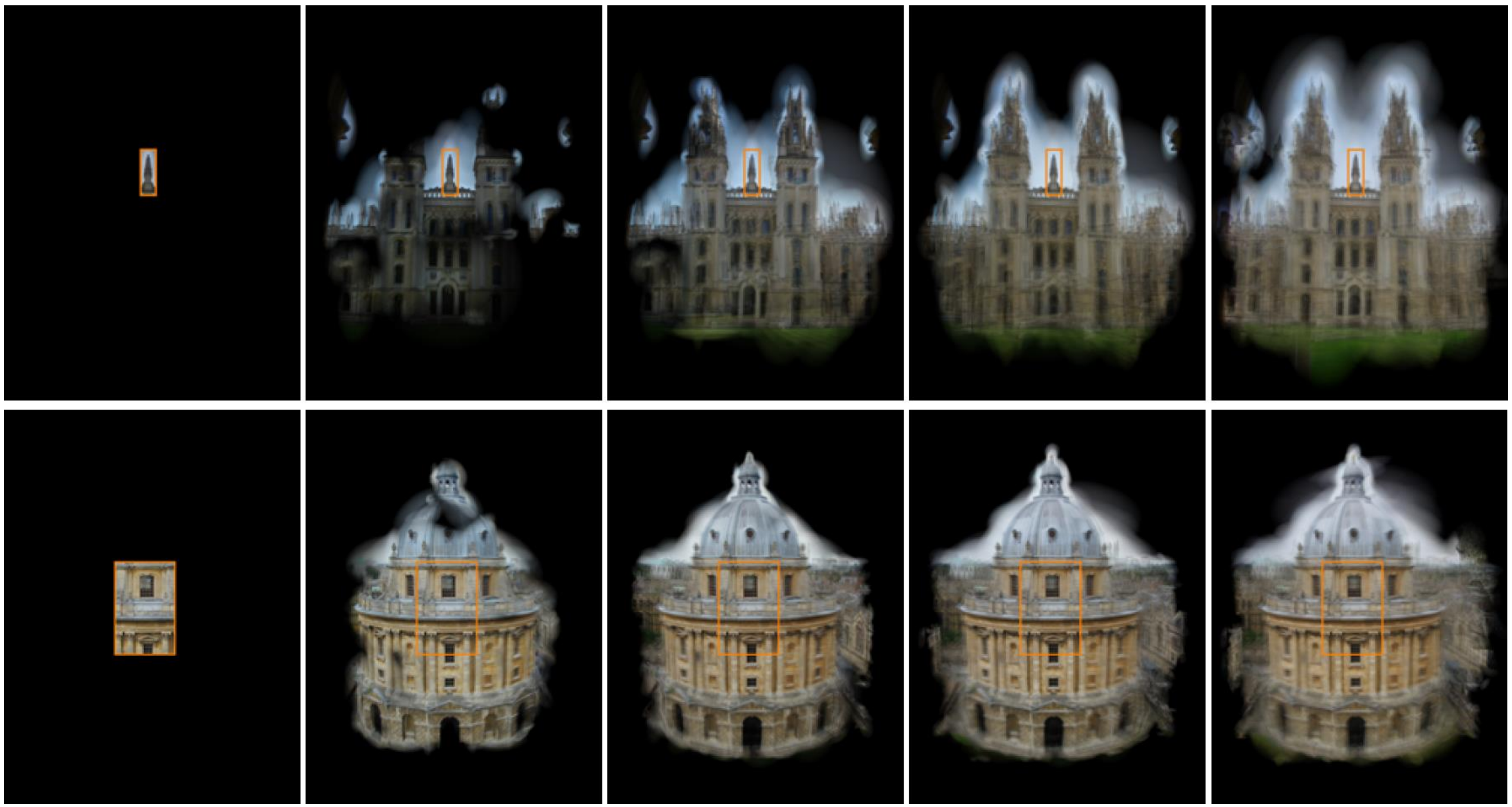


Chum, Mikulik, Perdoch, Matas: Total Recall II: Query Expansion Revisited, CVPR 2011

Learning the Context

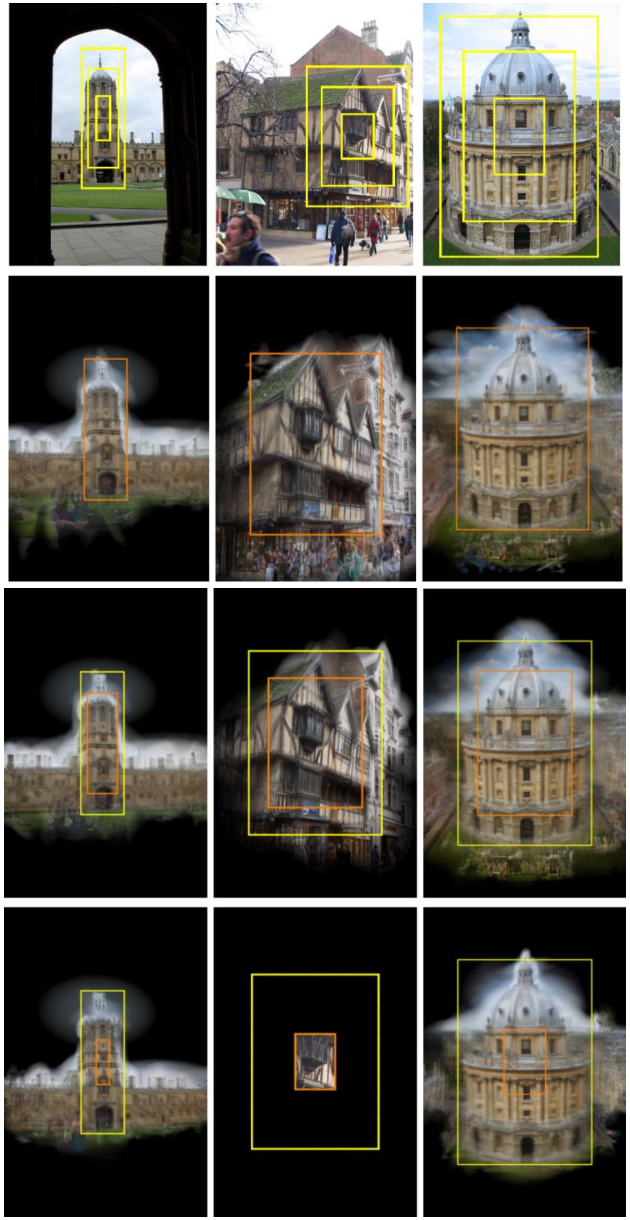
Feature patches back-projected into the context from spatially verified images.

The query



2 5 10 20

How Much Do We Need to See?



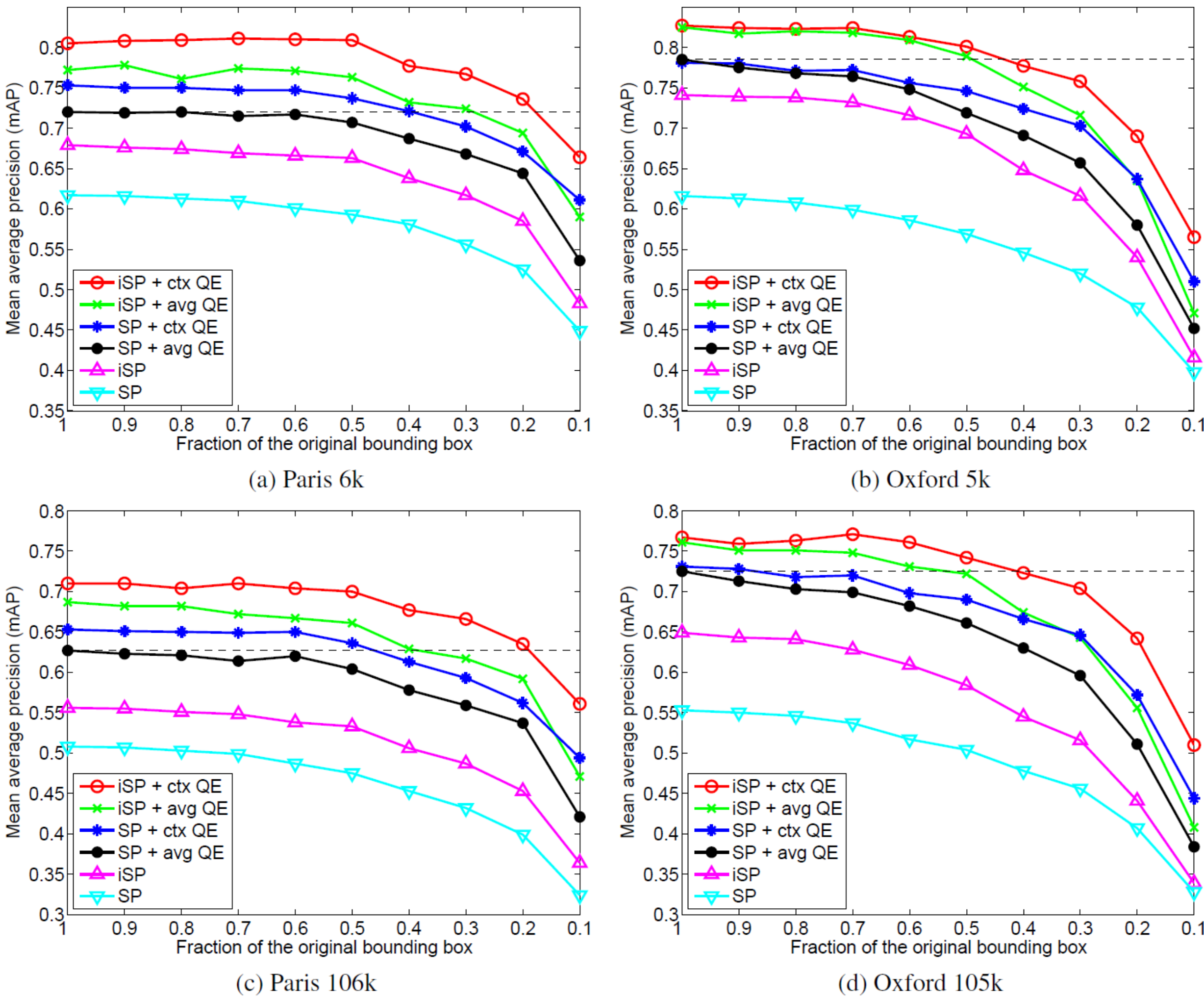
Oxford landmarks – 3 queries
100%, 50%, and 10% of the query bounding box

Context learned from the full bounding box

Context learned from 50% of the bounding box

Context learned from 10% of the bounding box

Effects of decreasing the query bounding-box size



(a) Paris 6k
(b) Oxford 5k
(c) Paris 106k
(d) Oxford 105k

Baseline:
spatial verification + full bounding box

Context QE at the baseline performance needs only:

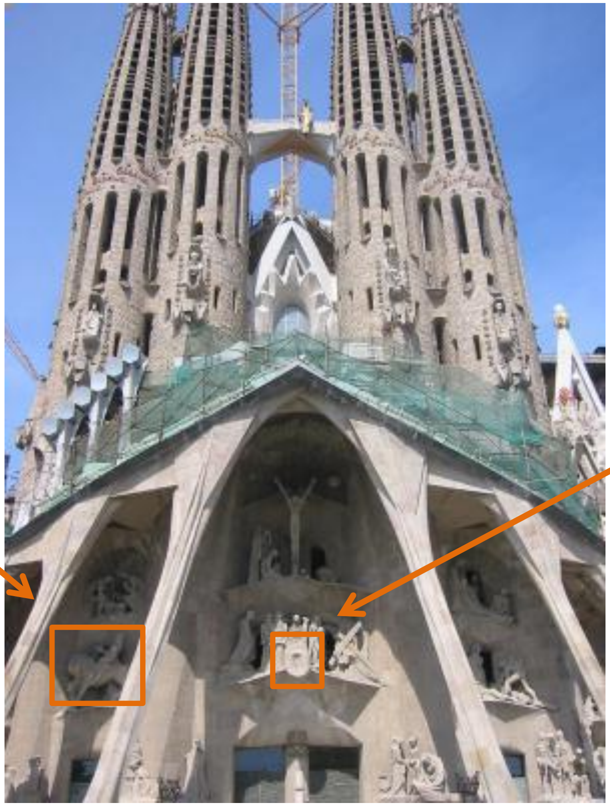
- 20% of the BB on the Paris dataset
- 40% of the BB on the Oxford dataset

Application
Browsing Image Collections

Retrieval for Browsing

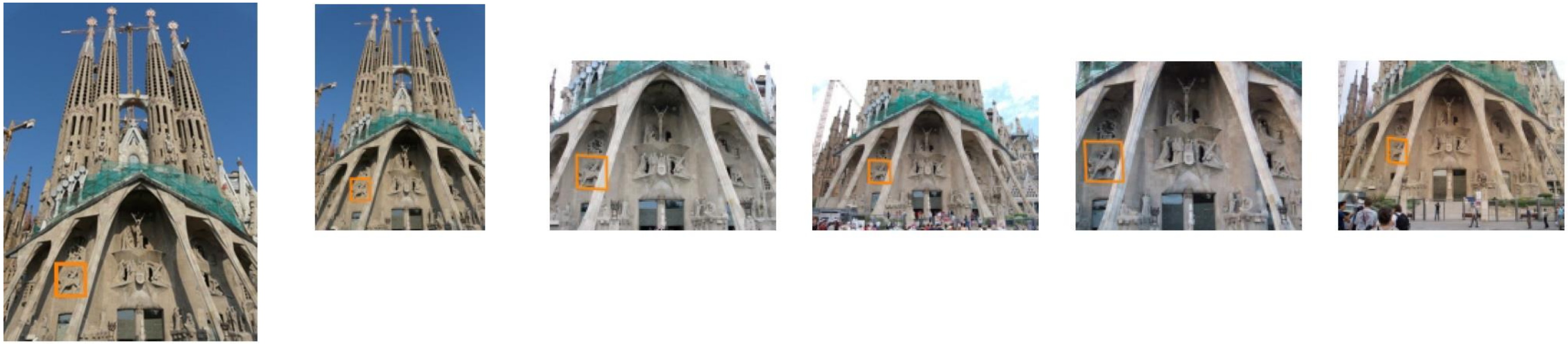
What is this?

... and what is that?

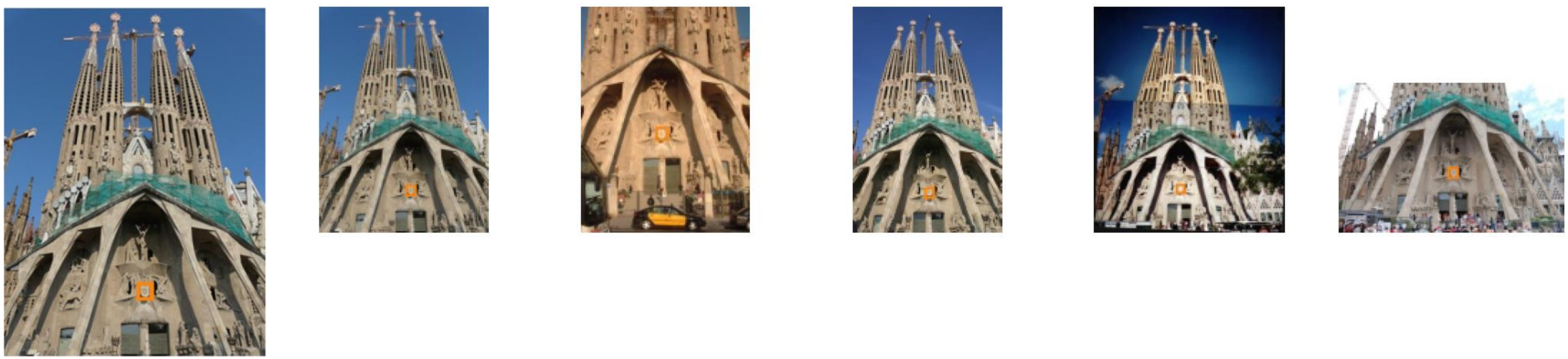


Let's query!

Retrieval for Browsing



Query 1

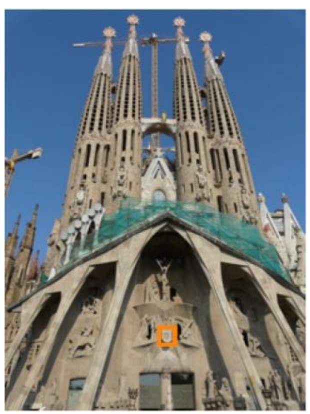


Query 2

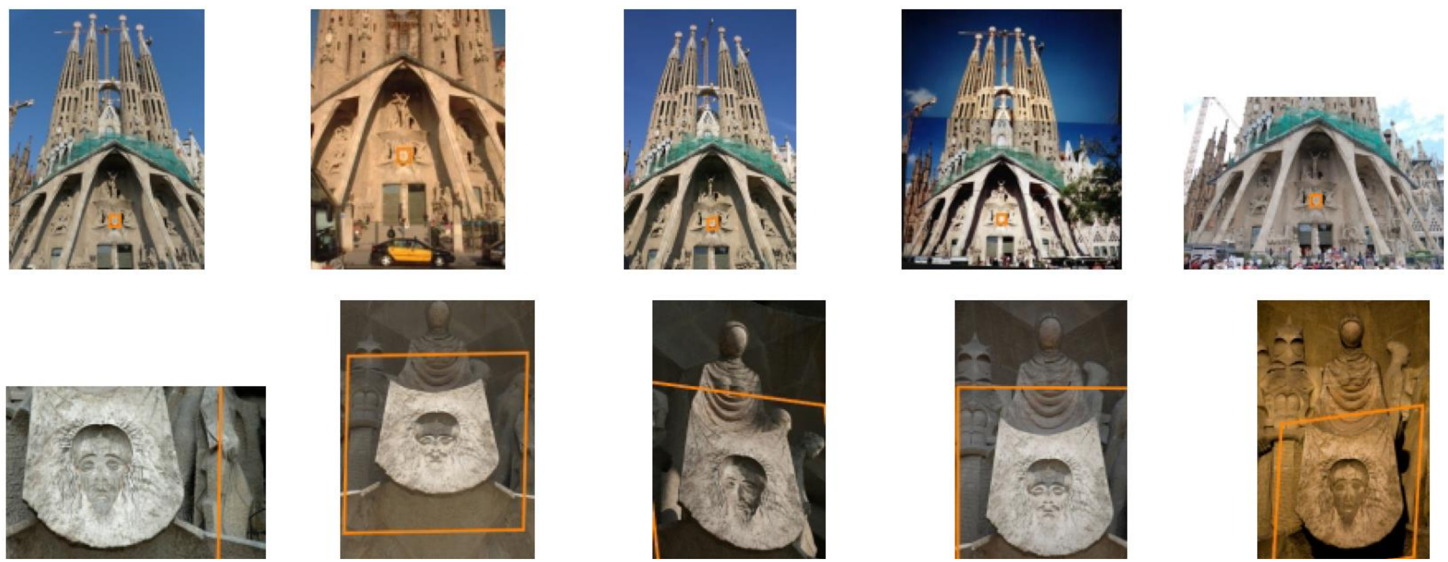
GOOD! ... to maximize mAP

Retrieval for Browsing

Query 1



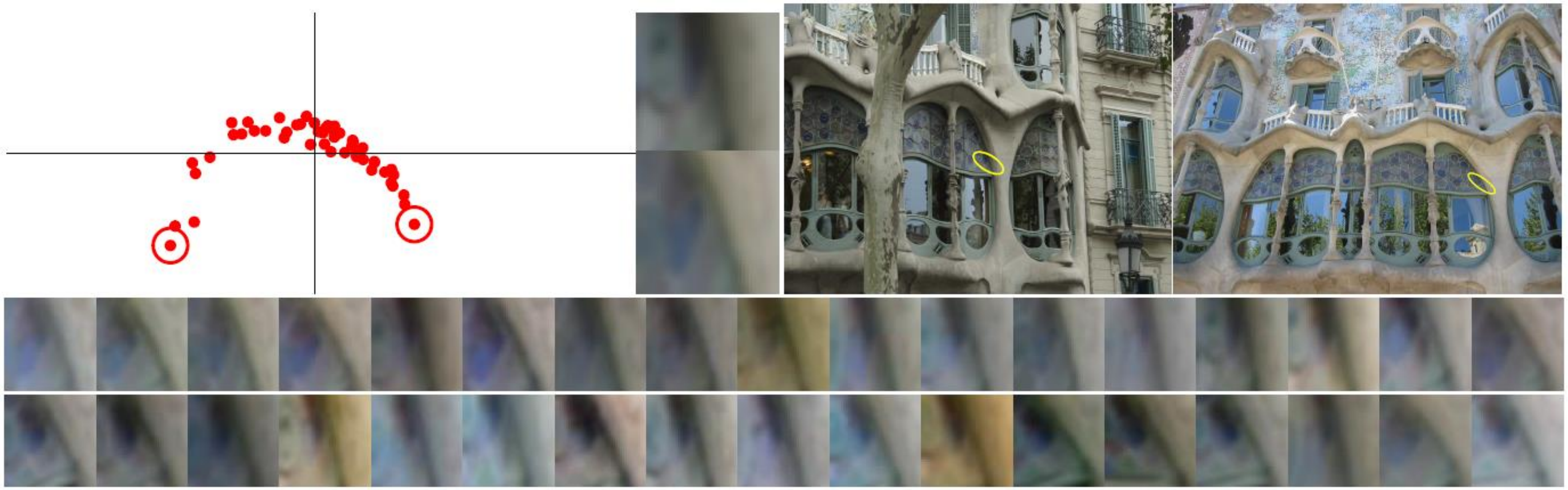
Query 2



Mikulik, Chum, Matas

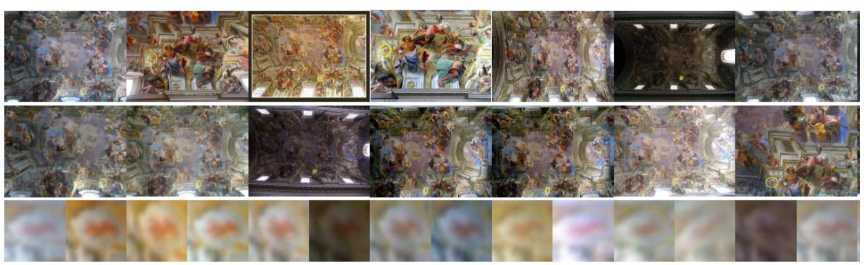
Application
Surface Patch Appearance Mining

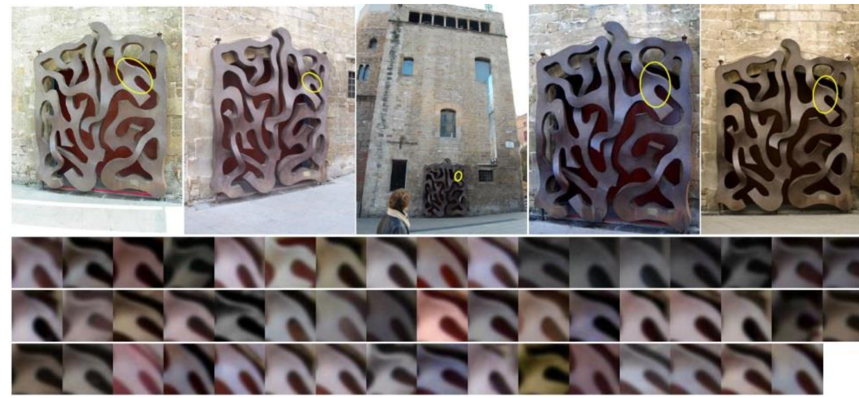
Appearance Variance of a Single Feature



Mikulik, Perdoch, Chum, Matas: Learning Vocabularies over a Fine Quantization, IJCV 2012

- over 5 million images
- almost 20k clusters of 750k images (visual word based)
- 733k successfully matched in WBS matching (raw descriptor based)
- over 111 M feature tracks established (12.3 M with 6+ features)
- 564 M features in the tracks (319.5 M in tracks of 6+ features)





http://cmp.felk.cvut.cz/~qqmikula/publications/ijcv2012/index.html

Storing Geometry

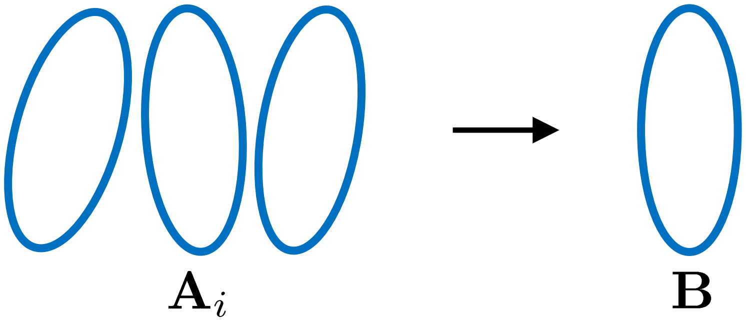
(ellipse compression)

Geometry compression

- Ellipses + gravity vector used to hypothesize affine transformations
- Ellipses represented as an affine trasform

$$\mathbf{A} = \begin{pmatrix} a & 0 \\ b & c \end{pmatrix},$$

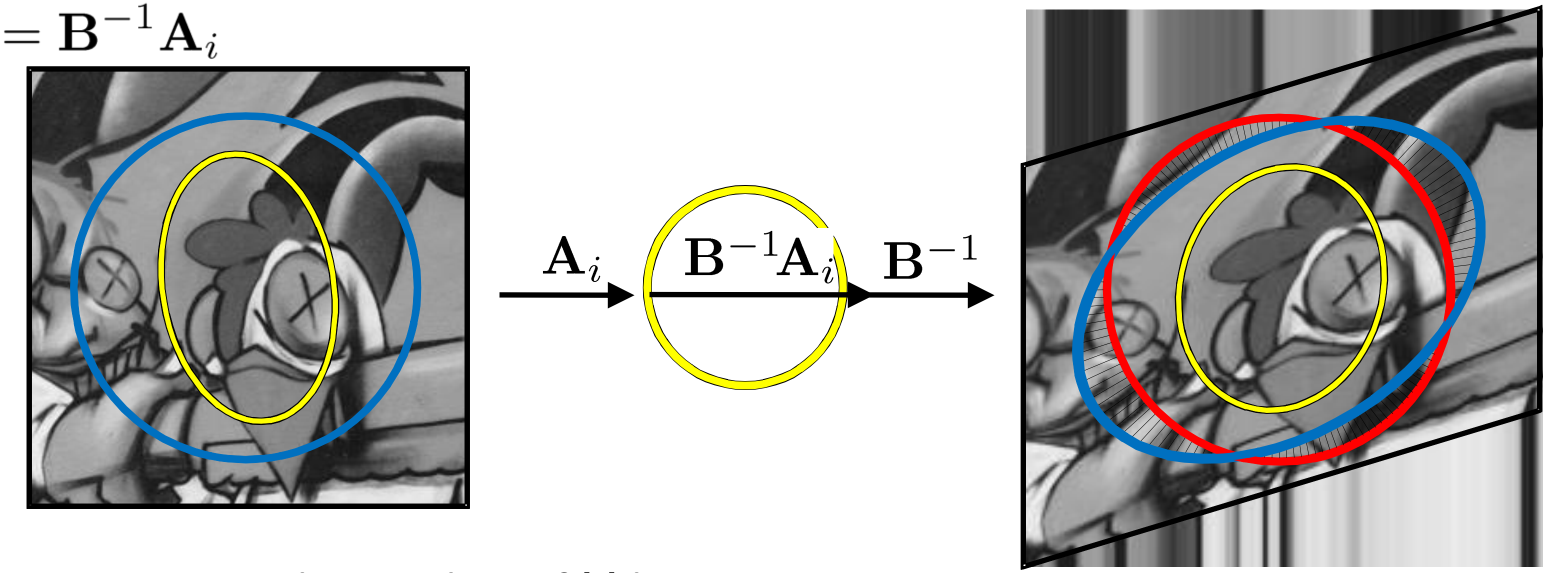
- Vector quantization, minimizing error of the generated model



$$\mathbf{H} = \mathbf{B}^{-1}\mathbf{A}_i = \mathbf{I} + \mathcal{E}.$$

Minimizing Geometric Error of H

- $\mathbf{H} = \mathbf{B}^{-1}\mathbf{A}_i$



  - We capture the quality of H by integrating reprojection error over unit circle

$$e = \int\limits_{\|\mathbf{x}\|^2=1} \|\mathbf{I}\mathbf{x} - (\mathbf{I} + \mathcal{E})\mathbf{x}\|^2 = \int\limits_{\|\mathbf{x}\|^2=1} \|\mathcal{E}\mathbf{x}\|^2,$$

using simple manipulations

$$e = \int\limits_{\alpha=0}^{2\pi} \left\| \mathcal{E} \begin{pmatrix} \cos\alpha \\ \sin\alpha \end{pmatrix} \right\|^2 = \pi \cdot \|\mathcal{E}\|_F^2, \quad \mathcal{E} = \mathbf{B}^{-1}\mathbf{A}_i - \mathbf{I}.$$

  - Frobenius norm can be used in space of transformations as a similarity.

K-means-like Clustering

- For a set of transformations **A**, we are looking for a best set **B** of K representative candidates B_j

$$\mathcal{A} = \{\mathbf{A}_1, \ldots, \mathbf{A}_N\}, \quad \mathcal{B} = \{\mathbf{B}_1, \ldots, \mathbf{B}_K\}, \quad N \ll K$$

- assignment step

$$f(i) = \operatorname*{argmin}_j \|\mathbf{B}_j^{-1}\mathbf{A}_i - \mathbf{I}\|_F^2 \quad \mathcal{A}_j = \{\mathbf{A}_i, f(i) = j\}$$

- refinement step

$$\mathbf{B}_j = \operatorname*{argmin}_{\mathbf{B}} \sum_{\mathbf{A}_i \in \mathcal{A}_j} \|\mathbf{B}^{-1}\mathbf{A}_i - \mathbf{I}\|_F^2$$

- which leads to a closed form solution

$$\mathbf{B}_j = \begin{pmatrix} -\frac{\sum_{k=1}^n a_k \sum_{k=1}^n c_k^2}{D} & 0 \\ \frac{\sum_{k=1}^n c_k b_k \sum_{k=1}^n a_k}{D} & \sum_{k=1}^n c_k / \sum_{k=1}^n c_k^2 \end{pmatrix}$$

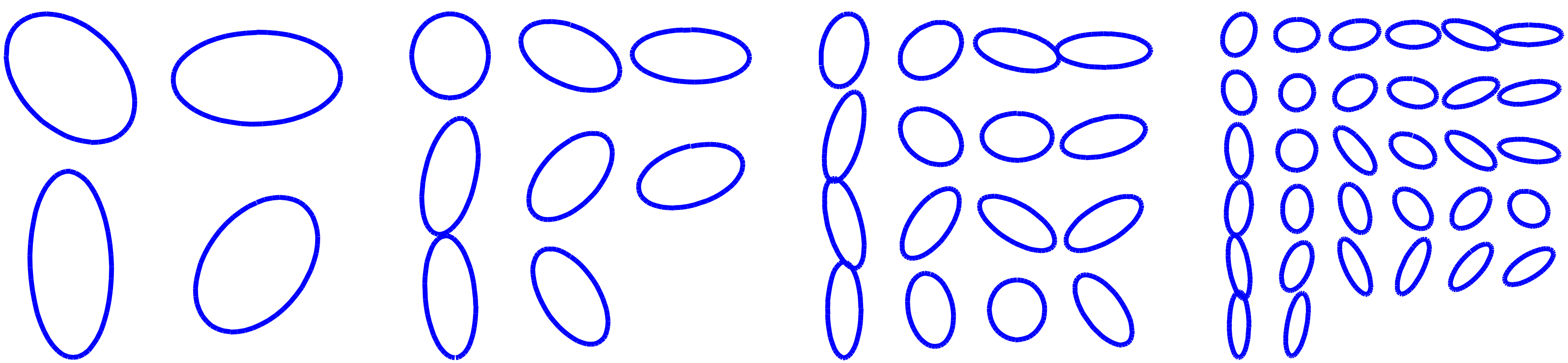
$$D = \sum_{k=1}^n c_k b_k - \sum_{k=1}^n c_k^2 \sum_{k=1}^n a_k^2 - \sum_{k=1}^n c_k^2 \sum_{k=1}^n b_k^2$$

Geometric "vocabularies"

- Assuming that the scale and shape of the ellipse are independent, scale can be extracted and quantized separately.
- Each geometric vocabulary is characterized by two numbers (x, y) and denoted SxEy

  x – number of bits for encoding scale.

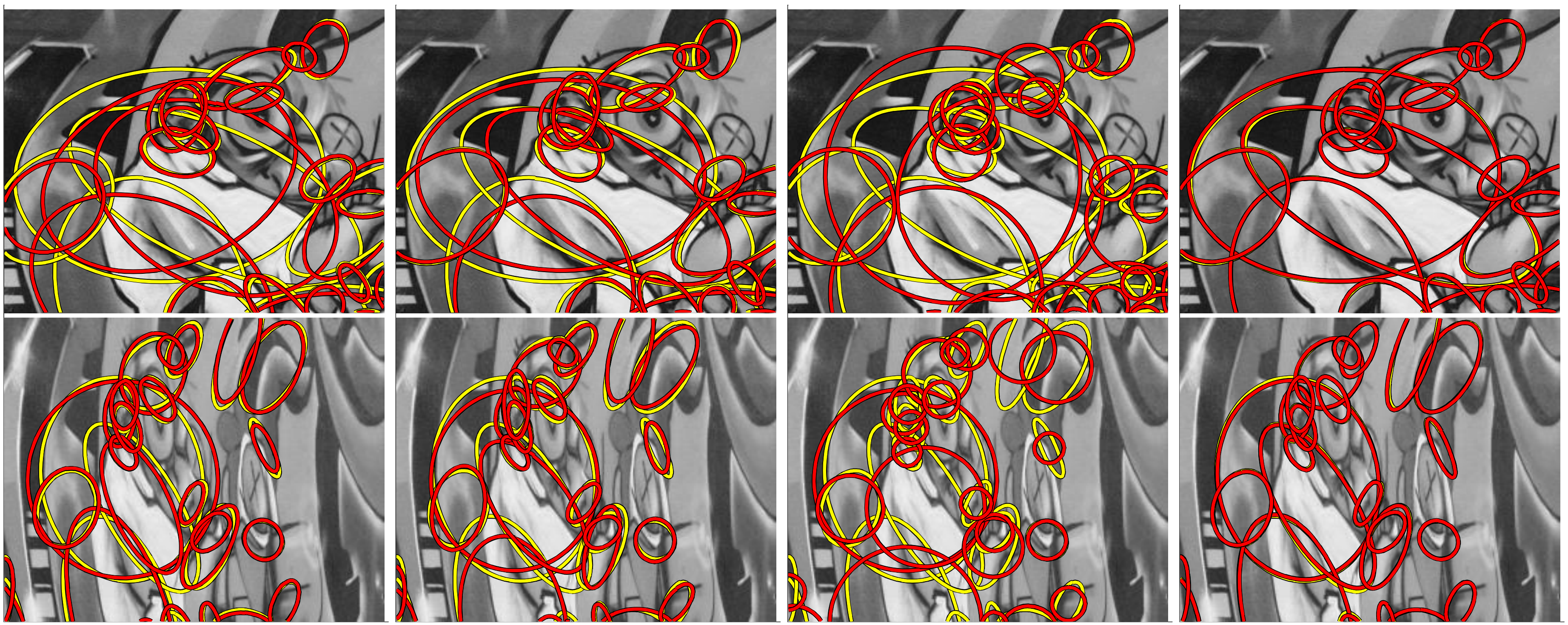
  y – number of bits for encoding ellipse shape.
- Geometric vocabularies learnt on a set of local geometries of 10M affine covariant points (for visualisation scale was quantized separately).



y = 2, K = 2^2 y = 3, K = 2^3 y = 4, K = 2^4 y = 5, K = 2^5

Geometric “vocabularies”

S0E8	S4E4	S8E0	S4E12
256 ellipses	16 scales, 16 ellipses	256 scales	16 scales, 4k ellipses



Summary

Geometric constraints

- semi-loacal
- global

are useful for

- filtering out false positives
- object localization by robust model estimation
- number of other applications

Advertisement

PhD and **post-doc** positions available
on large scale object and category retrieval

chum@cmp.felk.cvut.cz
http://cmp.felk.cvut.cz/~chum