Computer Vision and Machine Learning Winter School

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Large-scale visual search – part 1

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With slides from: O. Chum, K. Grauman, S. Lazebnik, B. Leibe, D. Lowe, J. Philbin, J. Ponce, D. Nister, C. Schmid, N. Snavely, A. Zisserman

Outline

Part 1. Going large-scale

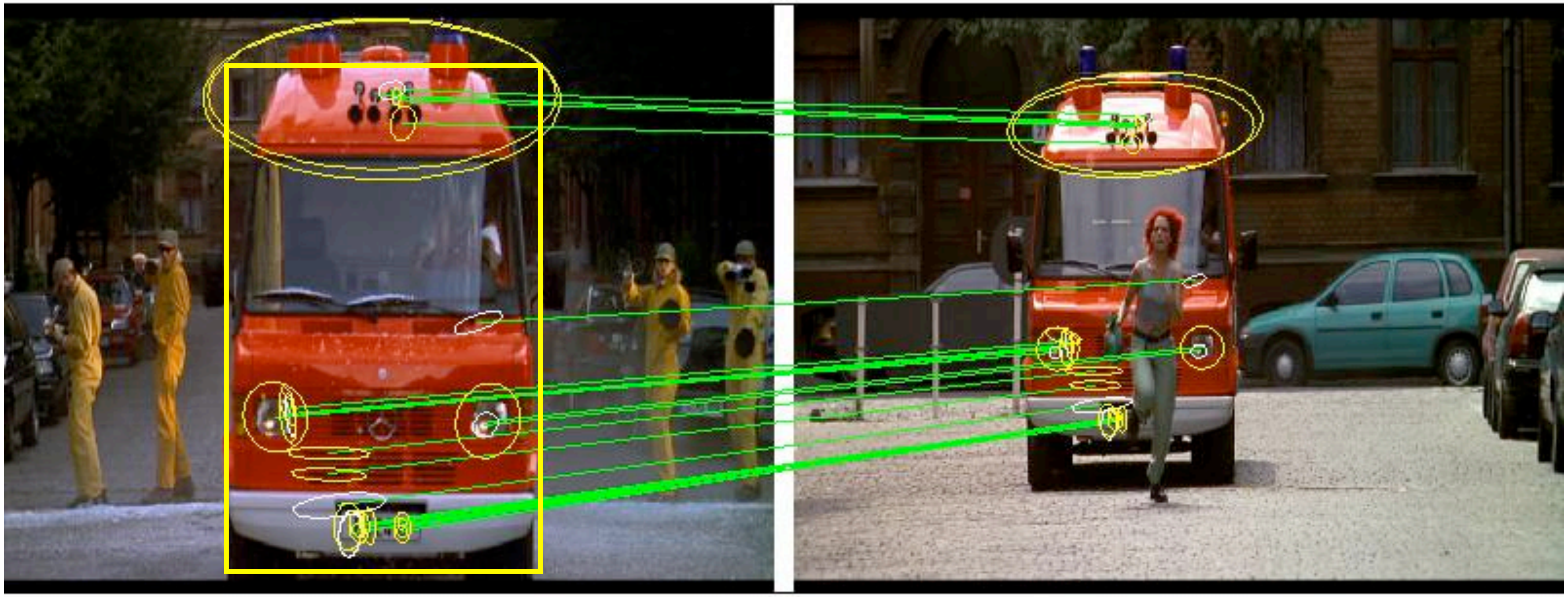
- Approximate nearest neighbour matching
- Bag-of-visual-words representation
- Efficient visual search and extensions
- Applications

Part 2. Very large scale visual indexing – recent work (C. Schmid)

Example II: Two images again

1000+ descriptors per image

Match regions between frames using SIFT descriptors and spatial consistency



Multiple regions overcome problem of partial occlusion

Approach - review

1. Establish tentative (or putative) correspondence based on local appearance of individual features (now)

2. Verify matches based on semi-local / global geometric relations (You have just seen this).

What about multiple images?

• So far, we have seen successful matching of a query image to a single target image using local features.

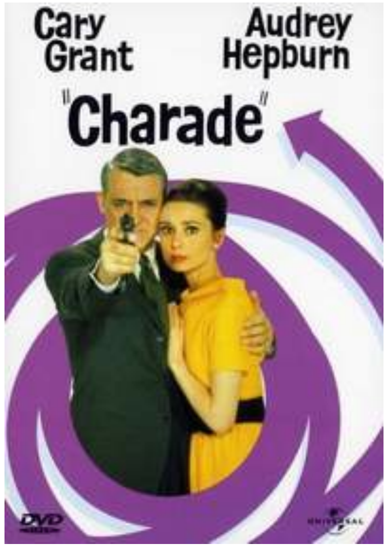
• How to generalize this strategy to multiple target images with reasonable complexity?

- 10, 10^2, 10^3, …, $\mathbf{10^7}$, … 10^{10} images?

Example: Visual search in an entire feature length movie

Visually defined query

"Find this bag"



"Charade" [Donen, 1963]

Demo:
http://www.robots.ox.ac.uk/~vgg/research/vgoogle/index.html

History of “large scale” visual search with local regions

Schmid and Mohr ’97	– 1k images
Sivic and Zisserman’03	– 5k images
Nister and Stewenius’06	– 50k images (1M)
Philbin et al.’07	– 100k images
Chum et al.’07 + Jegou et al.’07	– 1M images
Chum et al.’08	– 5M images
Jegou et al. ’09	– 10M images

All on a single machine in ~ 1 second!

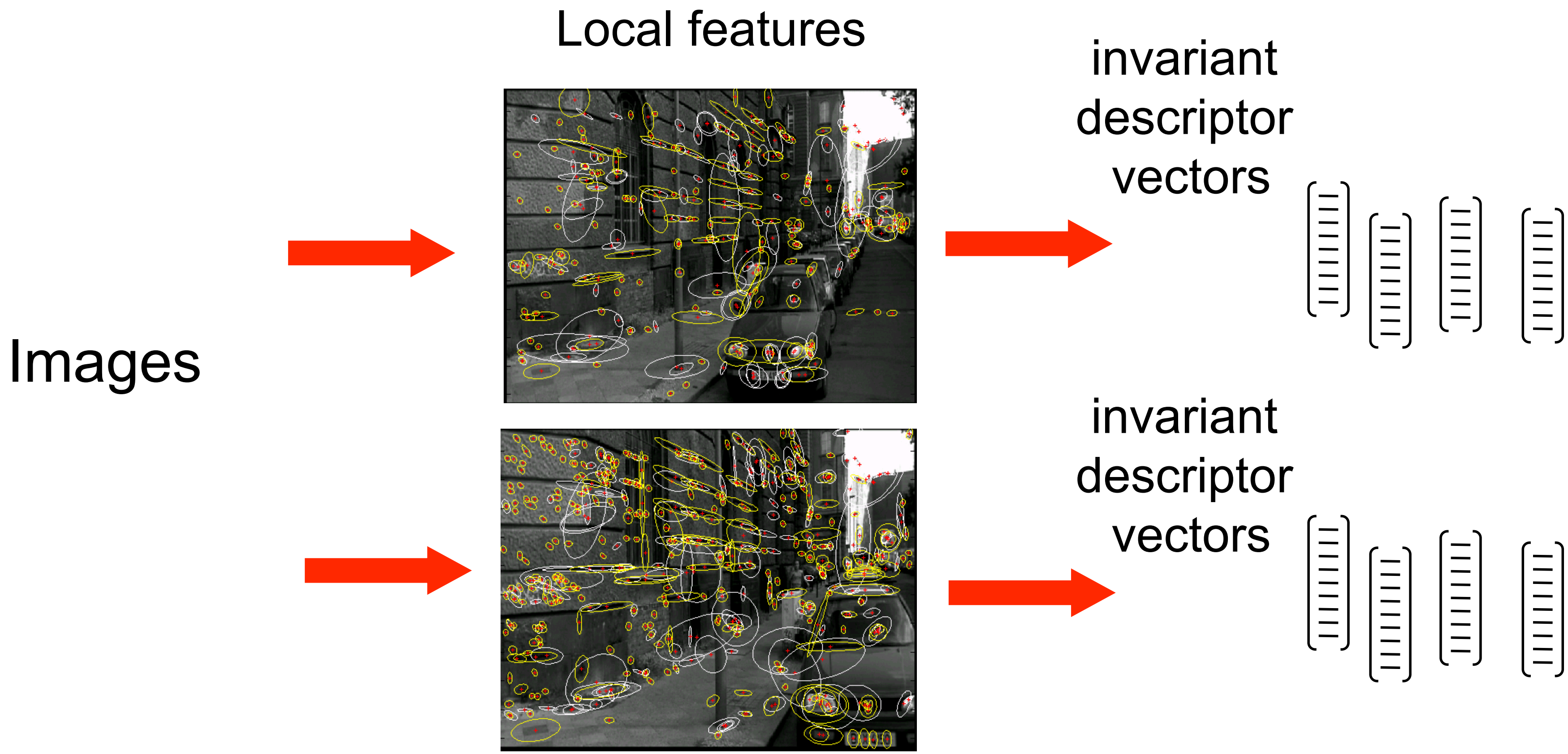
Two strategies

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)

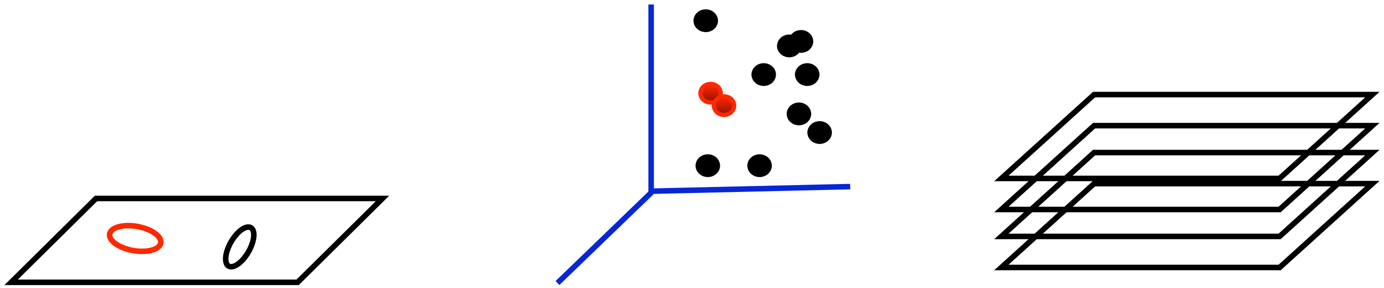
Strategy I: Efficient approximate NN search



1. Compute local features in each image independently (Part 1)
2. “Label” each feature by a descriptor vector based on its intensity (Part 1)
3. Finding corresponding features is transformed to finding nearest neighbour vectors
4. Rank matched images by number of (tentatively) corresponding regions
5. Verify top ranked images based on spatial consistency (Part 2)

Finding nearest neighbour vectors

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



Model image

128D descriptor space

Image database

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:

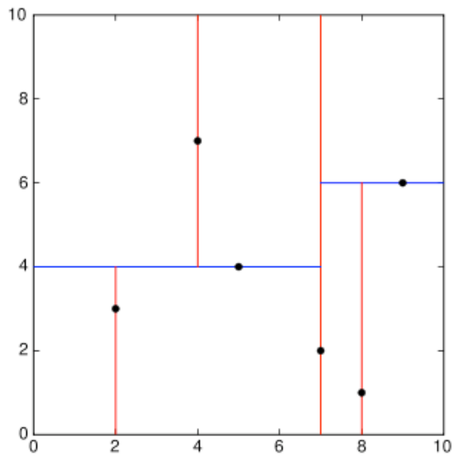
$$\forall j \; NN(j) = \arg\min_i ||\mathbf{x}_i - \mathbf{x}_j||$$

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

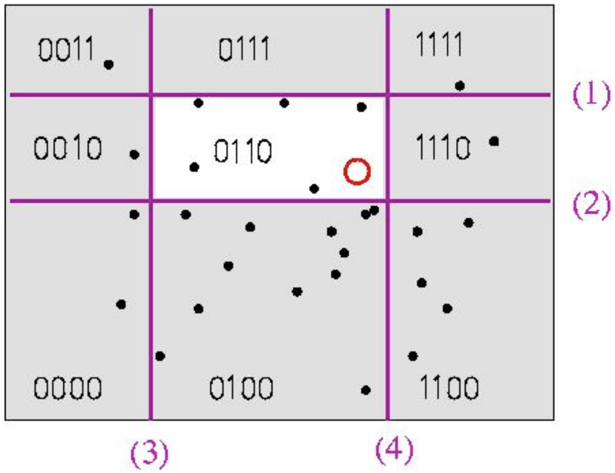
Nearest-neighbour matching is the major computational bottleneck

- 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.

Indexing local features: approximate nearest neighbor search



Best-Bin First (BBF), a variant of k-d trees that uses priority queue to examine most promising branches first [Beis & Lowe, CVPR 1997]



Locality-Sensitive Hashing (LSH), a randomized hashing technique using hash functions that map similar points to the same bin, with high probability [Indyk & Motwani, 1998]

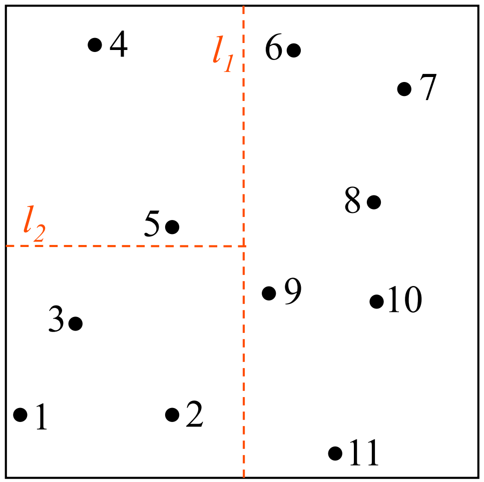
K-d tree

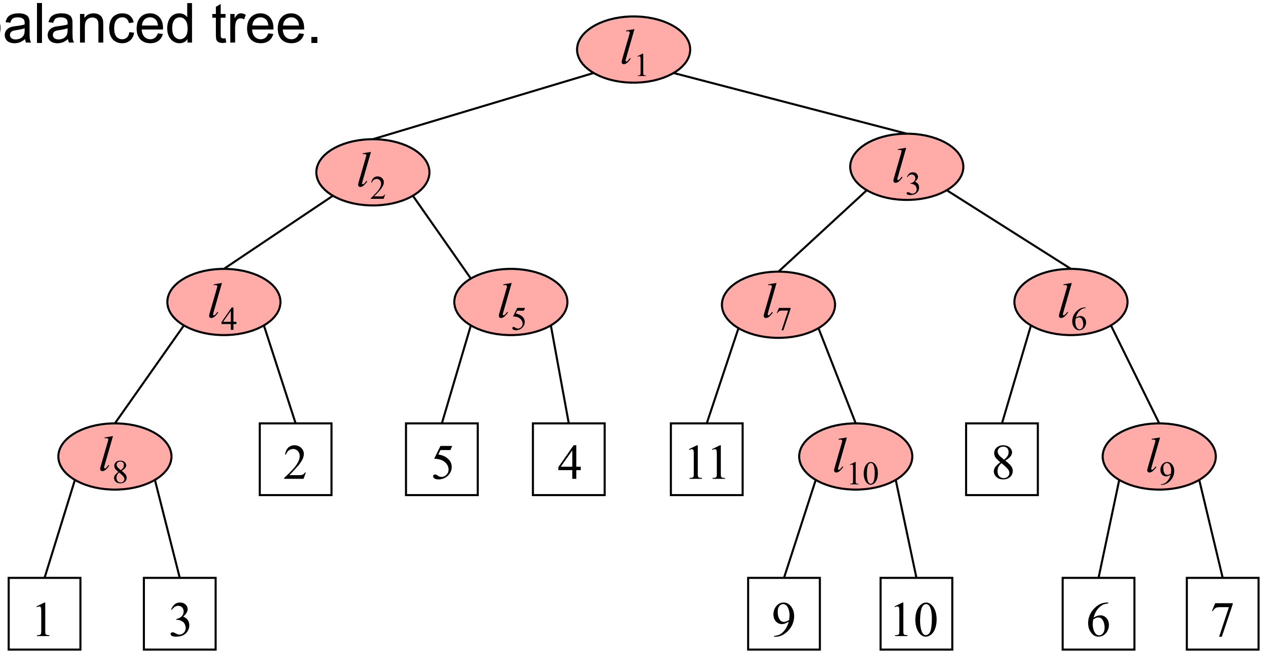
• K-d tree is a binary tree data structure for organizing a set of points in a K-dimensional space.

• 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.

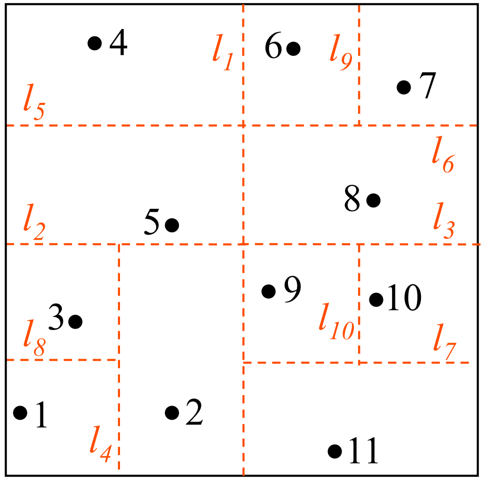


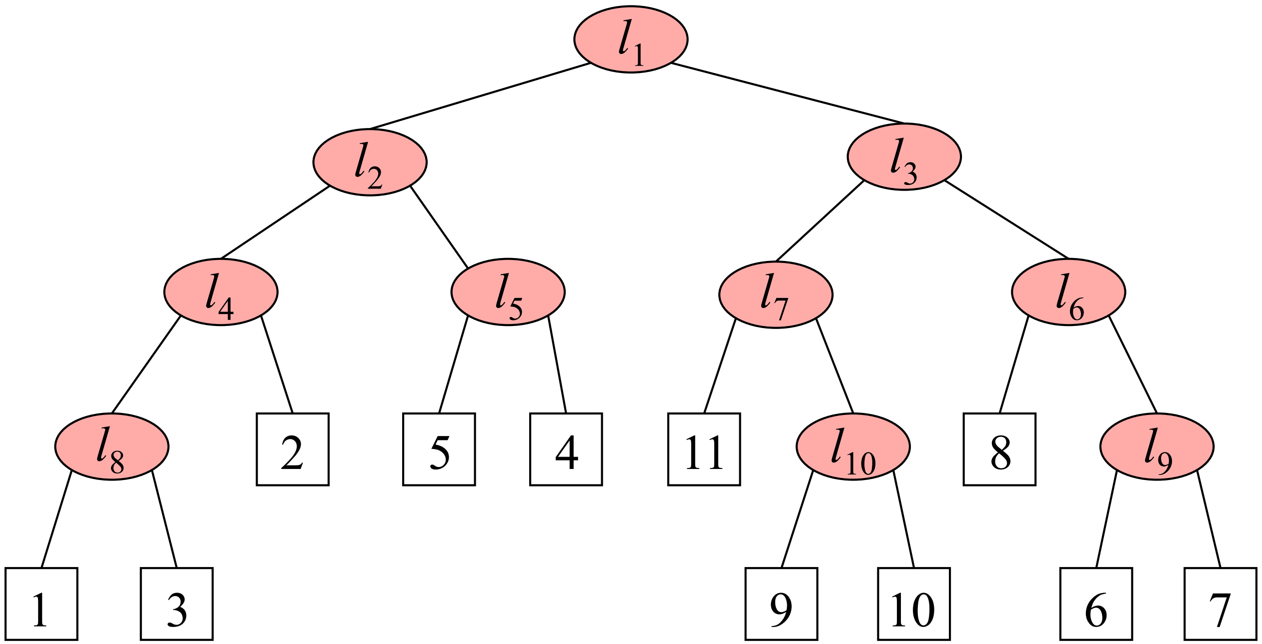


Images: Anna Atramentov

K-d tree construction

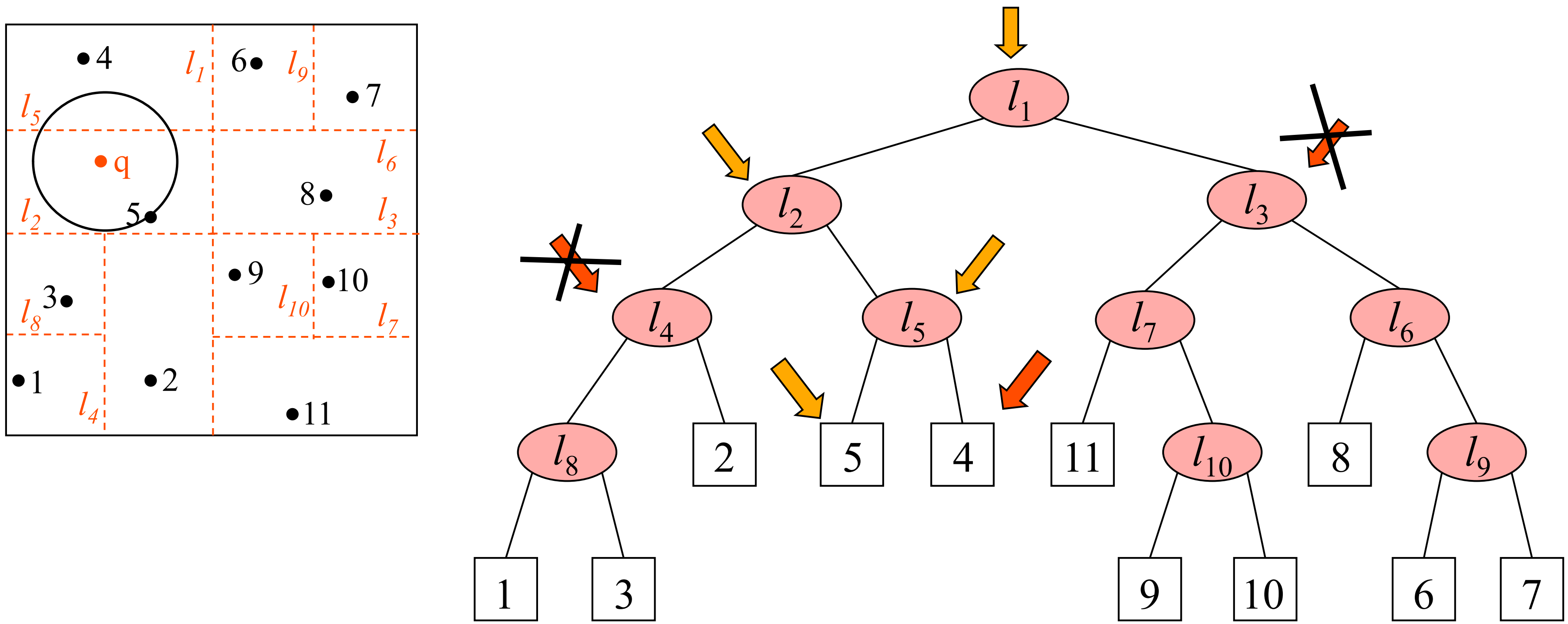
Simple 2D example





Slide credit: Anna Atramentov

K-d tree query



Slide credit: Anna Atramentov

K-d tree: Backtracking

Backtracking is necessary as the true nearest neighbor may not lie in the query cell.

But in some cases, almost all cells need to be inspected.

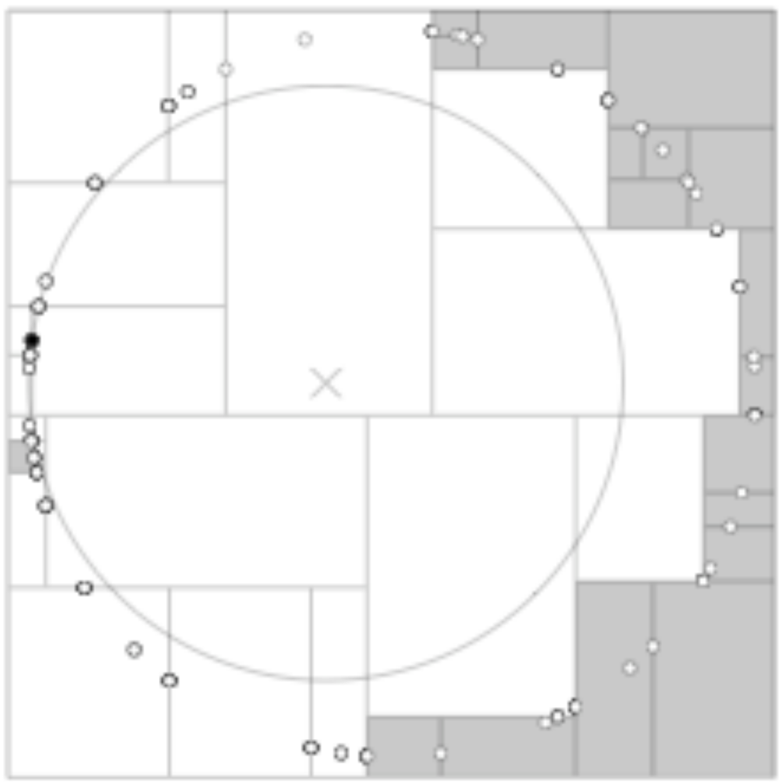


Figure 6.6

A bad distribution which forces almost all nodes to be inspected.

Figure: A. Moore

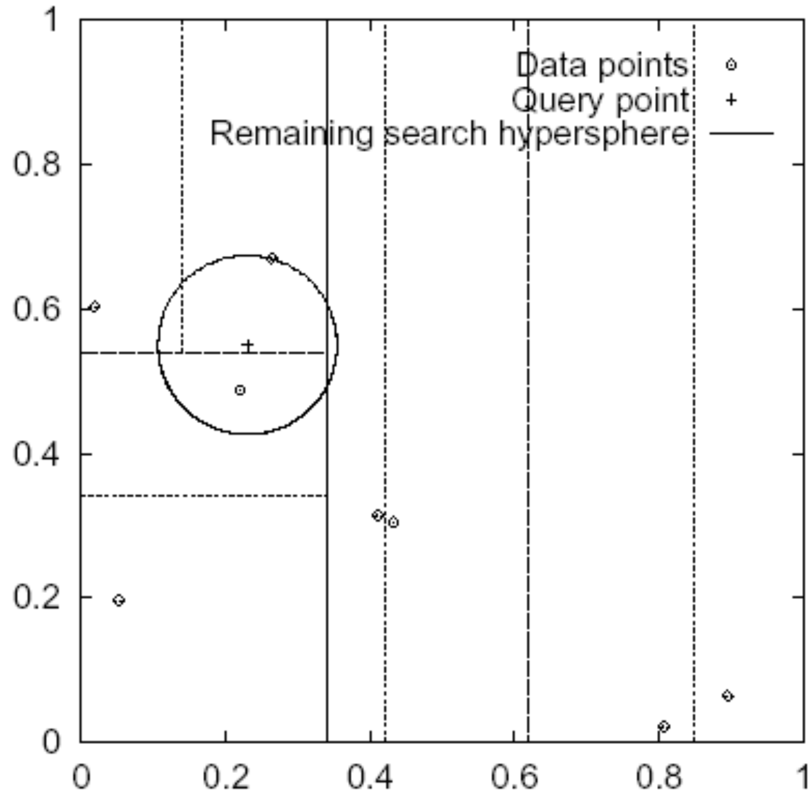
Solution: Approximate nearest neighbor K-d tree

Key ideas:

• Search k-d tree bins in order of distance from query

• Requires use of a priority queue

• Limit the number of neighbouring k-d tree bins to explore: only approximate NN is found

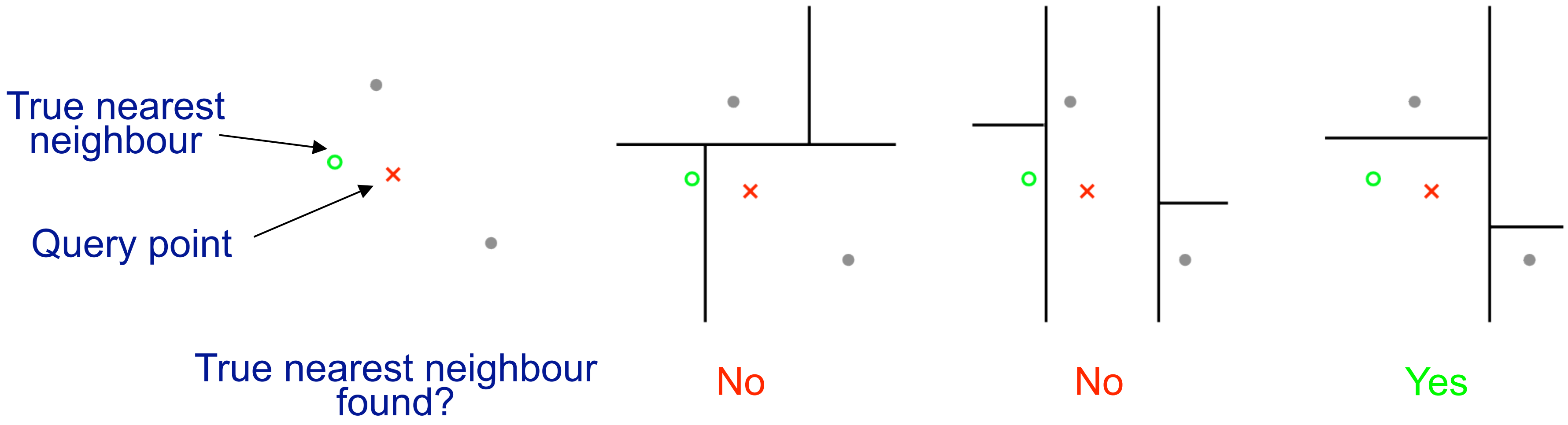


• Reduce the boundary effects by randomization

Randomized K-d trees

- How to choose the dimension to split and the splitting point?
  - Pick dimension with the highest variance
  - Split at the mean/median

- Multiple randomized trees increase the chances of finding nearby points



Approximate NN search using a randomized forest of K-d trees: Algorithm summary

1. Descent all (typically 8) trees to the leaf node

2. Search k-d tree bins in order of distance from query
   - Distance between the query and the bin is defined as the minimum distance between the query and any point on the bin boundary
   - Requires the use of a priority queue:
     - During lookup an entry is added to the priority queue about the option not taken
     - For multiple trees, the queue is shared among the trees
   - Limit the number of neighbouring K-d tree bins to explore (parameter of the algorithm, typically set to 512)

Experimental evaluation for SIFT matching

http://www.cs.ubc.ca/~lowe/papers/09muja.pdf

FAST APPROXIMATE NEAREST NEIGHBORS WITH AUTOMATIC ALGORITHM CONFIGURATION

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Keywords: nearest-neighbors search, randomized kd-trees, hierarchical k-means tree, clustering.

Abstract: For many computer vision problems, the most time consuming component consists of nearest neighbor matching in high-dimensional spaces. There are no known exact algorithms for solving these high-dimensional problems that are faster than linear search. Approximate algorithms are known to provide large speedups with only minor loss in accuracy, but many such algorithms have been published with only minimal guidance on selecting an algorithm and its parameters for any given problem. In this paper, we describe a system that answers the question, "What is the fastest approximate nearest-neighbor algorithm for my data?" Our system will take any given dataset and desired degree of precision and use these to automatically determine the best algorithm and parameter values. We also describe a new algorithm that applies priority search on hierarchical k-means trees, which we have found to provide the best known performance on many datasets. After testing a range of alternatives, we have found that multiple randomized k-d trees provide the best performance for other datasets. We are releasing public domain code that implements these approaches. This library provides about

Randomized K-d trees

Performance w.r.t. the number of trees

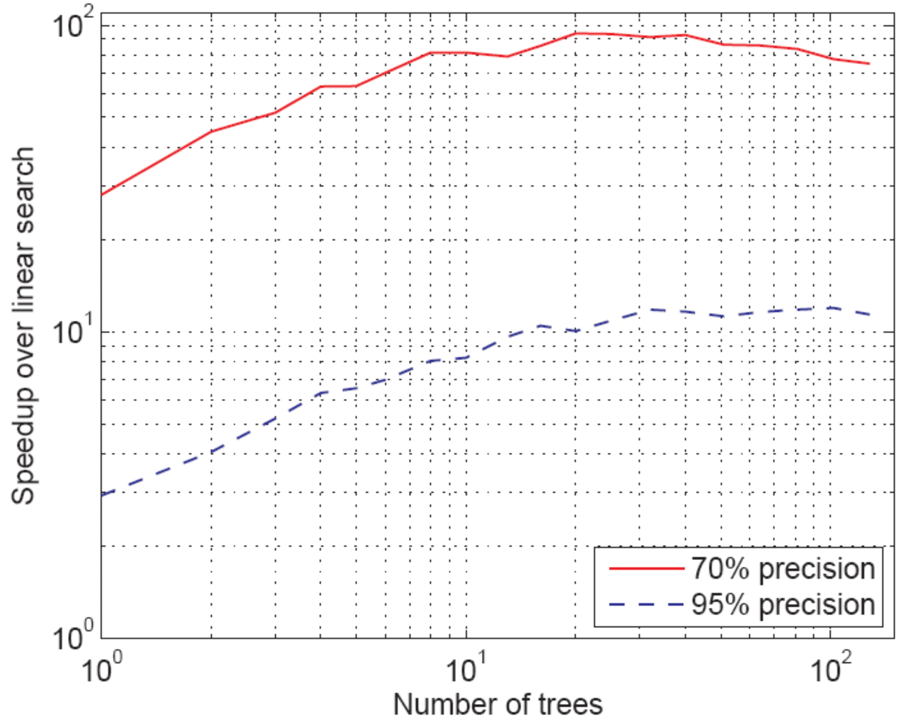


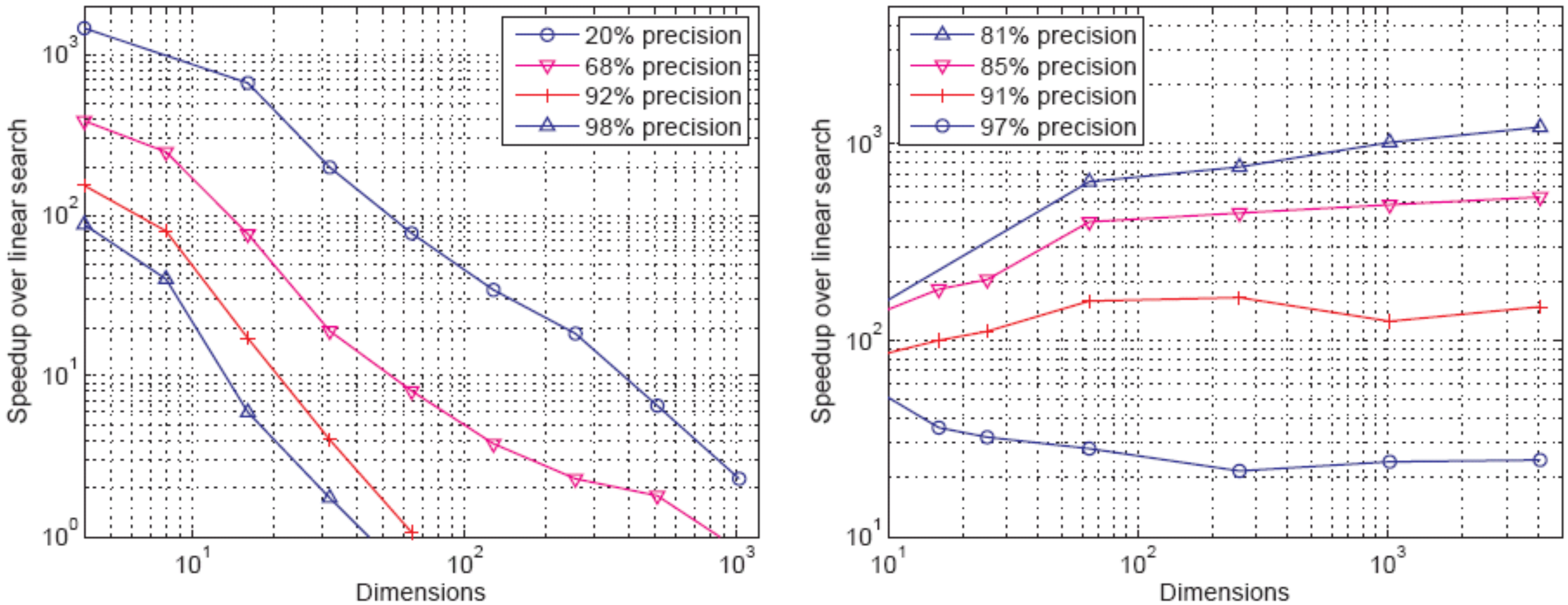
Figure 2: Speedup obtained by using multiple random kd-trees (100K SIFT features dataset)

d=128, n=100K

Precision: percentage of true nearest neighbours found

Randomized K-d trees

Performance w.r.t. the number of dimensions



(a) Random vectors

(b) Image patches

Figure 4: Search efficiency for data of varying dimensionality. The random vectors (a) represent the hardest case in which dimensions have no correlations, while most real-world problems behave more like the image patches (b)

Randomized K-d trees: discussion

- Find approximate nearest neighbor in O(logN) time, where N is the number of data points.
- Increased memory requirements: needs to store multiple (~8) trees
- Good performance in practice for recognition problems (NN-search for SIFT descriptors and image patches).
- Code available online:
  http://people.cs.ubc.ca/~mariusm/index.php/FLANN/FLANN

Variation: K-means tree [Muja&Lowe, 2009]

- Partition of the space is determined by recursive application of k-means clustering.
- Cell boundaries are not axis aligned, but given by the set of cluster centers.
- Also called “tree structured vector quantization”.
- Finding nearest neighbor to a query point involves recursively finding nearest cluster center.
- Look-up complexity O(logN)
- Also used for vocabulary quantization (see later) [Nister&Stewenius’06]

Example

3-nary tree construction:

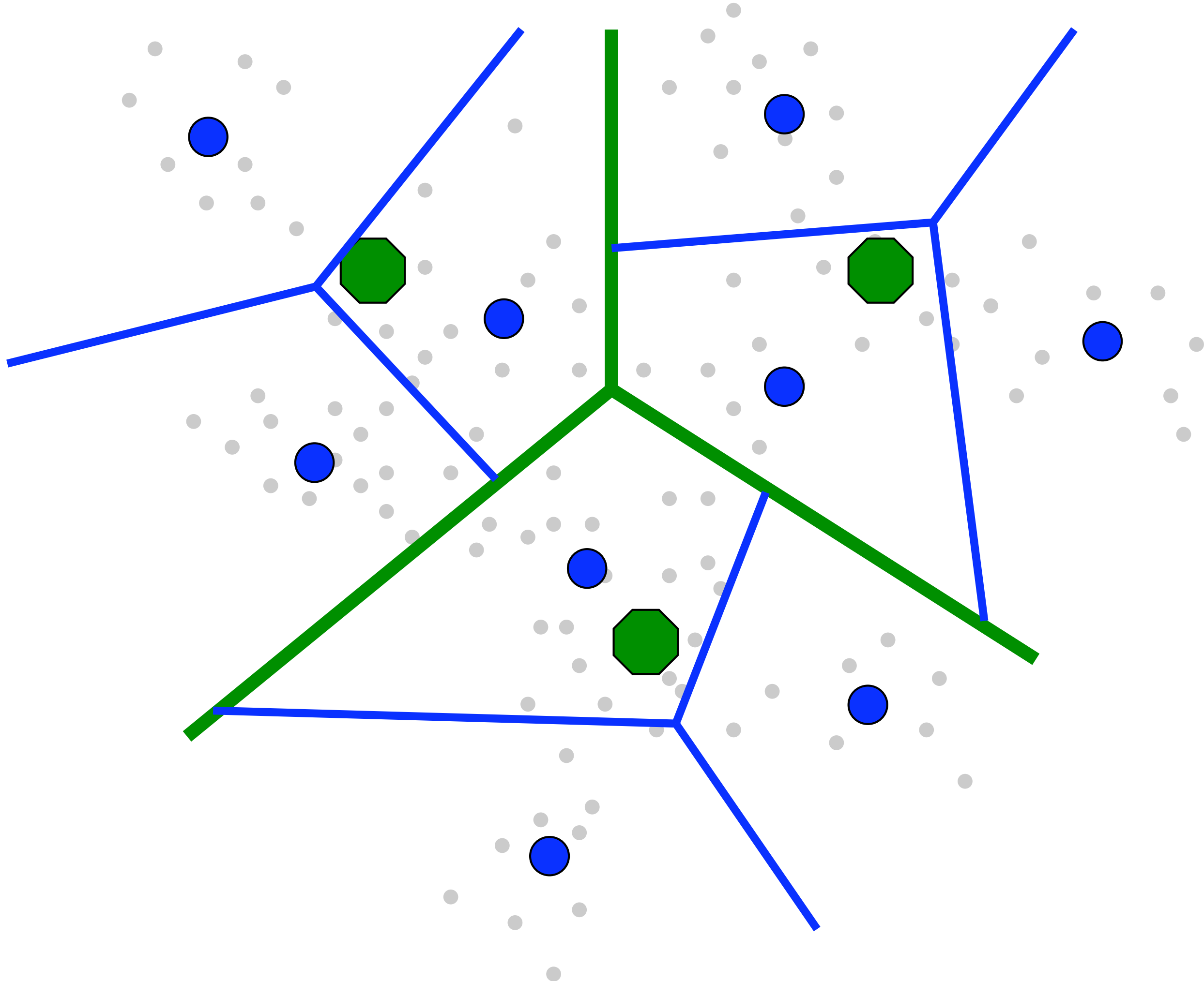


Figure credit: David Nister

Example

Query look-up:

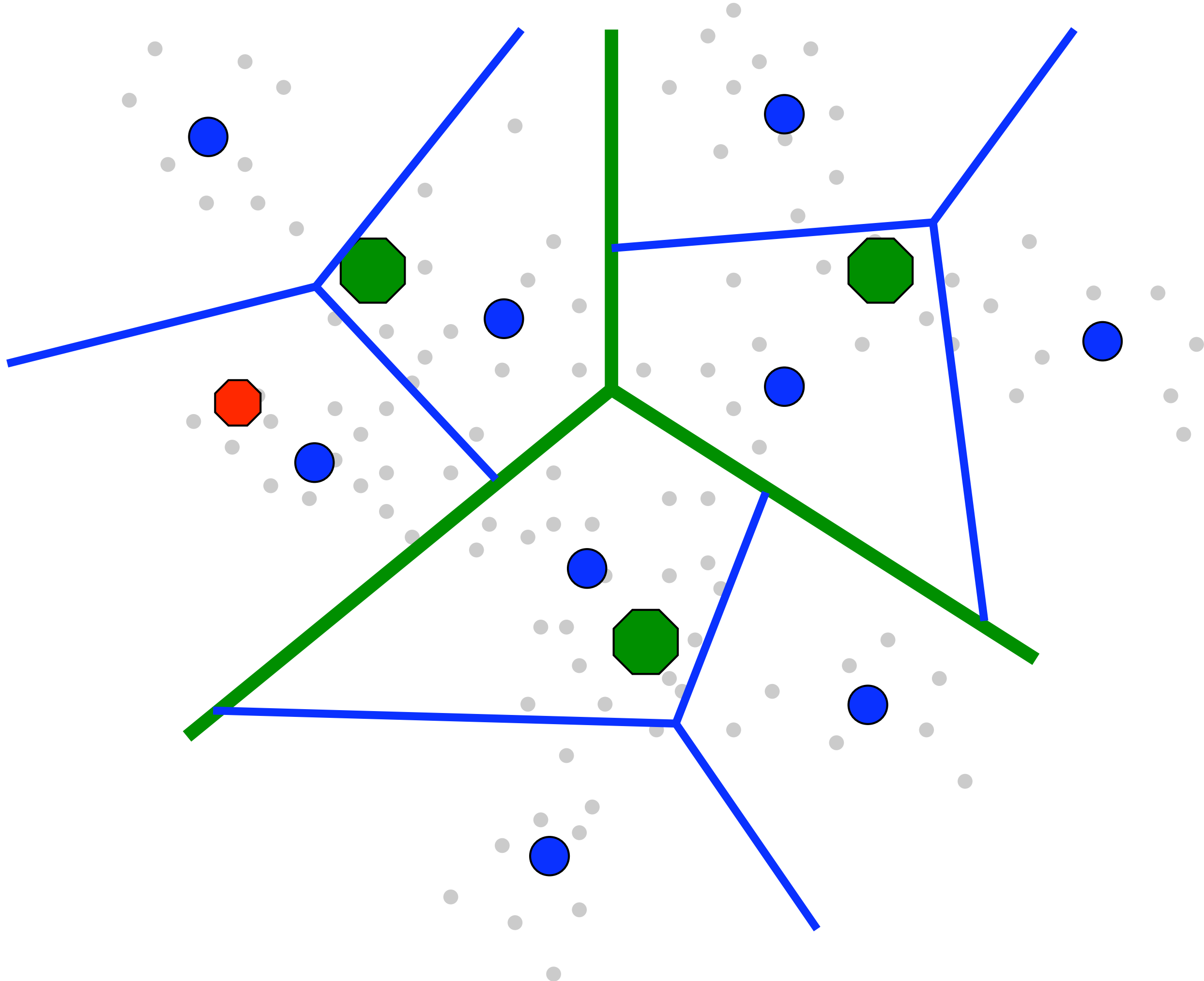
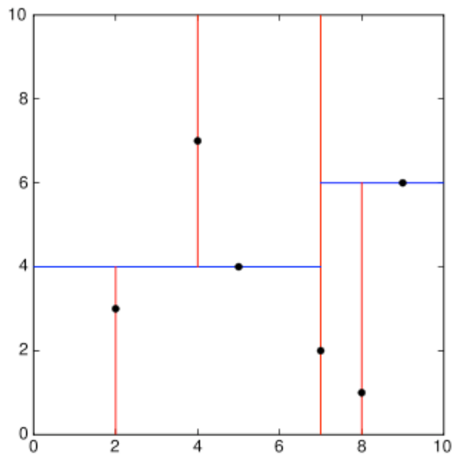


Figure credit: David Nister

Indexing local features: approximate nearest neighbor search



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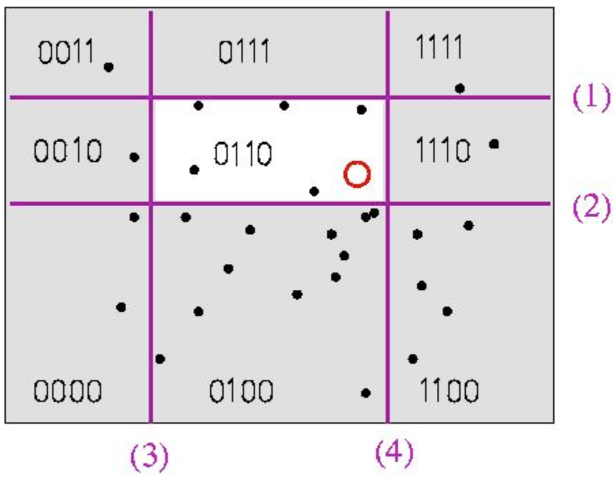


Locality-Sensitive Hashing (LSH), a randomized hashing technique using hash functions that map similar points to the same bin, with high probability [Indyk & Motwani, 1998]

Locality Sensitive Hashing (LSH)

Idea: construct hash functions $g: R^d \rightarrow Z^k$ such that

for any points p,q:

If $||p-q|| \leq r$, then $Pr[g(p)=g(q)]$ is "high" or "not-so-small"
If $||p-q|| > cr$, then $Pr[g(p)=g(q)]$ is "small"

Example of g: linear projections

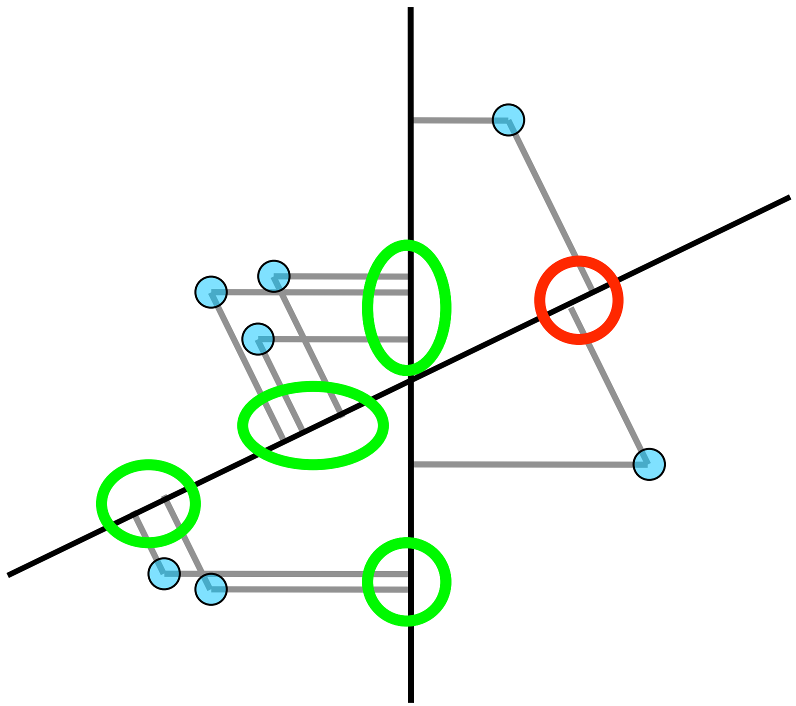
$g(p)=<h_1(p),h_2(p),\ldots,h_k(p)>$, where $h_{X,b}(p)=\lfloor (p*X+b)/w \rfloor$

$\lfloor . \rfloor$ is the "floor" operator.
X_i are sampled from a Gaussian.
w is the width of each quantization bin.
b is sampled from uniform distr. $[0,w]$.

[Datar-Immorlica-Indyk-Mirrokni'04]

Locality Sensitive Hashing (LSH)

- Choose a random projection
- Project points
- Points close in the original space remain close under the projection
- Unfortunately, converse not true



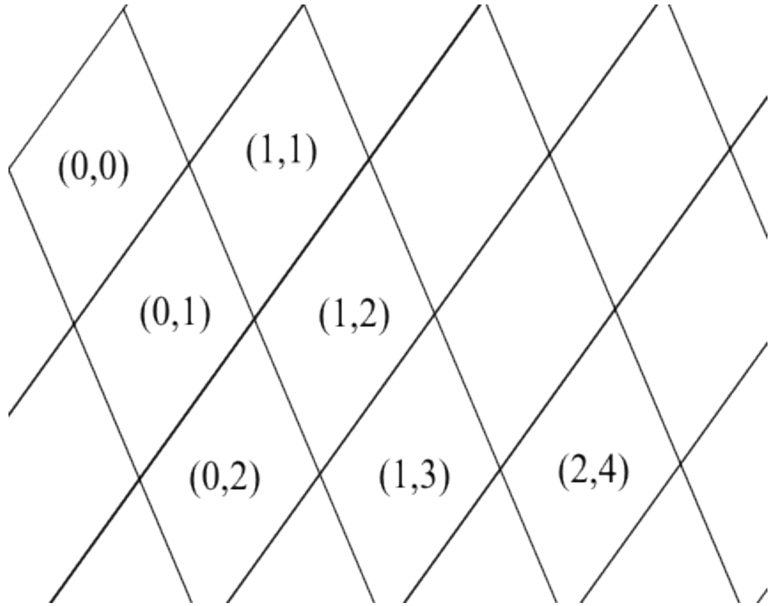
- Answer: use multiple quantized projections which define a high-dimensional "grid"

Slide: Philbin, Chum, Isard, Zissrman

Locality Sensitive Hashing (LSH)

- Cell contents can be efficiently indexed using a hash table

- Repeat to avoid quantization errors near the cell boundaries



- Point that shares at least one cell = potential candidate

- Compute distance to all candidates

Slide: Philbin, Chum, Isard, Zissrman

LSH: discussion

In theory, query time is O(kL), where k is the number of projections and L is the number of hash tables, i.e. independent of the number of points, N.

In practice, LSH has high memory requirements as large number of projections/ hash tables are needed.

Code and more materials available online:

http://www.mit.edu/~andoni/LSH/

Hashing functions could be also data-dependent (PCA) or learnt from labeled point pairs (close/far).

Y. Weiss, A. Torralba, and R. Fergus, "Spectral hashing," in *NIPS, 2008.*

R. Salakhutdinov and G. Hinton, "Semantic Hashing," ACM SIGIR, 2007.

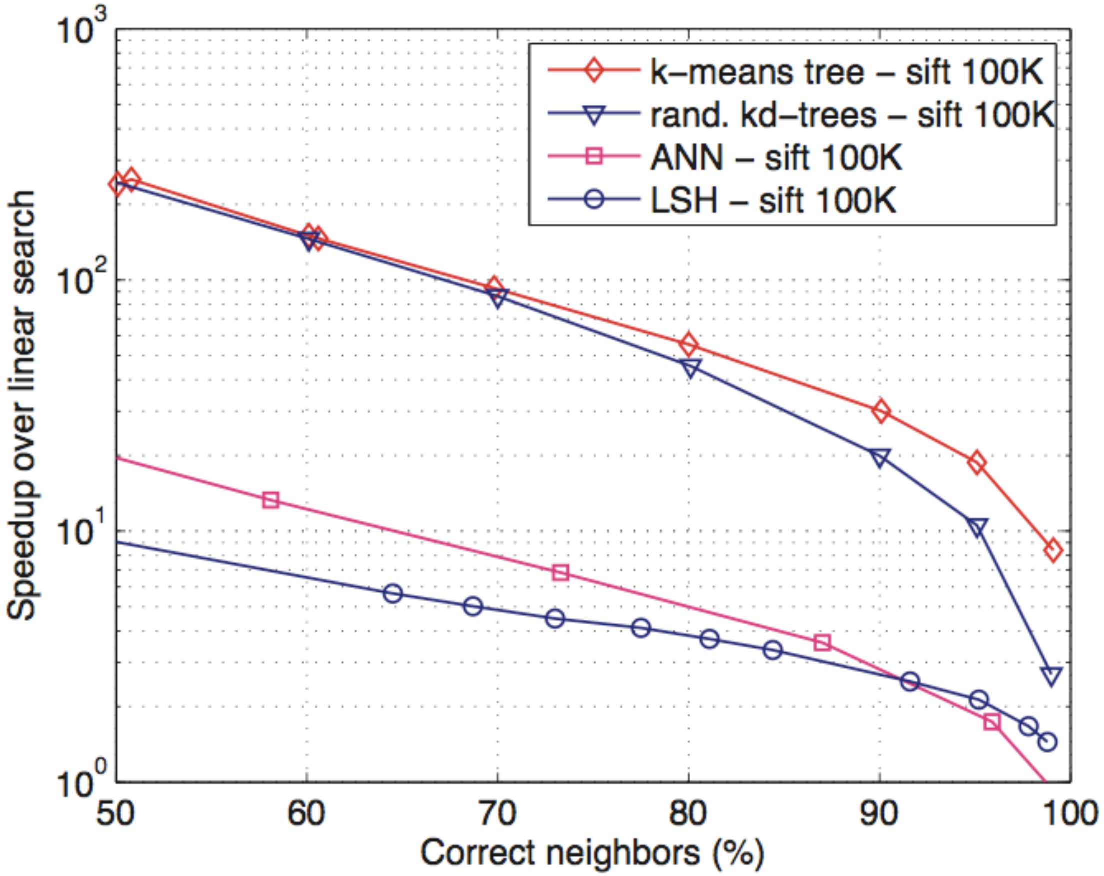
See also:

http://cobweb.ecn.purdue.edu/~malcolm/yahoo Slaney2008(LSHTutorialDraft).pdf

http://www.sanjivk.com/EECS6898/ApproxNearestNeighbors_2.pdf

Comparison of approximate NN-search methods

Dataset: 100K SIFT descriptors



Code for all methods available online, see Muja&Lowe'09

Figure: Muja&Lowe'09

Approximate nearest neighbour search (references)

J. L. Bentley. Multidimensional binary search trees used for associative searching. Comm. ACM, 18(9), 1975.

Freidman, J. H., Bentley, J. L., and Finkel, R. A. An algorithm for finding best matches in logarithmic expected time. *ACM Trans. Math. Softw., 3:209–226, 1977.*

Arya, S., Mount, D. M., Netanyahu, N. S., Silverman, R., and Wu, A. Y. An optimal algorithm for approximate nearest neighbor searching in fixed dimensions. *Journal of the ACM, 45:891–923, 1998.*

C. Silpa-Anan and R. Hartley. Optimised KD-trees for fast image descriptor matching. In CVPR, 2008.

M. Muja and D. G. Lowe. Fast approximate nearest neighbors with automatic algorithm configuration. In VISAPP, 2009.

P. Indyk and R. Motwani, "Approximate nearest neighbors: towards removing the curse of dimensionality," in *Proc. of 30th ACM Symposium on Theory of Computing, 1998*

G. Shakhnarovich, P. Viola, and T. Darrell, "Fast pose estimation with parameter-sensitive hashing," in *Proc. of the IEEE International Conference on Computer Vision, 2003.*

R. Salakhutdinov and G. Hinton, "Semantic Hashing," ACM SIGIR, 2007.

Y. Weiss, A. Torralba, and R. Fergus, "Spectral hashing," in *NIPS, 2008.*

ANN - search (references continued)

O. Chum, J. Philbin, and A. Zisserman. Near duplicate image detection: min-hash and tf-idf weighting. BMVC., 2008.

M. Raginsky and S. Lazebnik, “Locality-Sensitive Binary Codes from Shift-Invariant Kernels,” in *Proc. of Advances in neural information processing systems, 2009.*

B. Kulis and K. Grauman, “Kernelized locality-sensitive hashing for scalable image search,” Proc. of the IEEE International Conference on Computer Vision, 2009.

J. Wang, S. Kumar, and S.-F. Chang, “Semi-supervised hashing for scalable image retrieval,” in IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2010.

J. Wang, S. Kumar, and S.-F. Chang, “Sequential projection learning for hashing with compact codes,” in Proceedings of the 27th International Conference on Machine Learning, 2010.

So far …

- Linear exhaustive search can be prohibitively expensive for large image collections

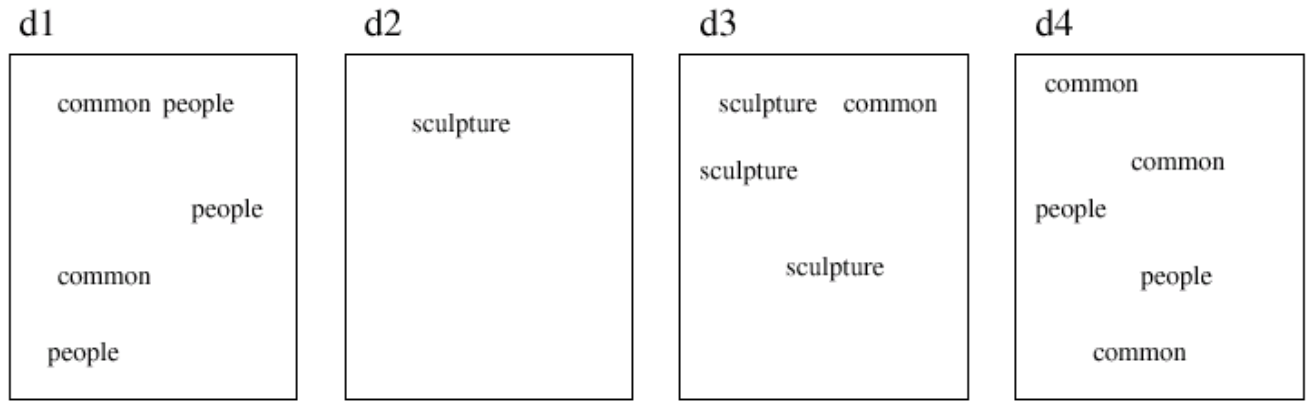
- Answer (so far): approximate NN search methods
  - Randomized KD-trees
  - Locality sensitive hashing

- However, memory footprint can be still high.
  Example: N = 10^7 images, 10^{10} SIFT features with 128B per feature ⇒ 1TB of memory

Look how text-based search engines (Google) index documents – **inverted files**.

Indexing text with inverted files

Document collection:



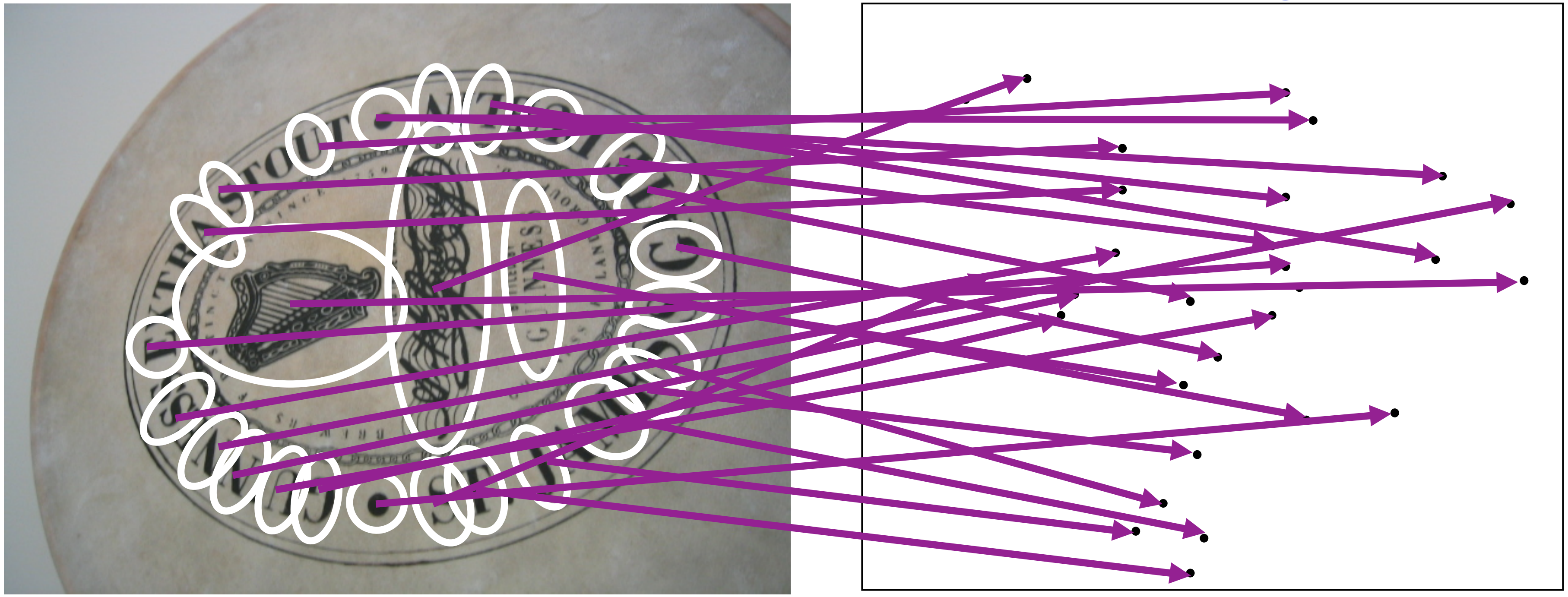
Inverted file:

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

Extract some local features from a number of images …

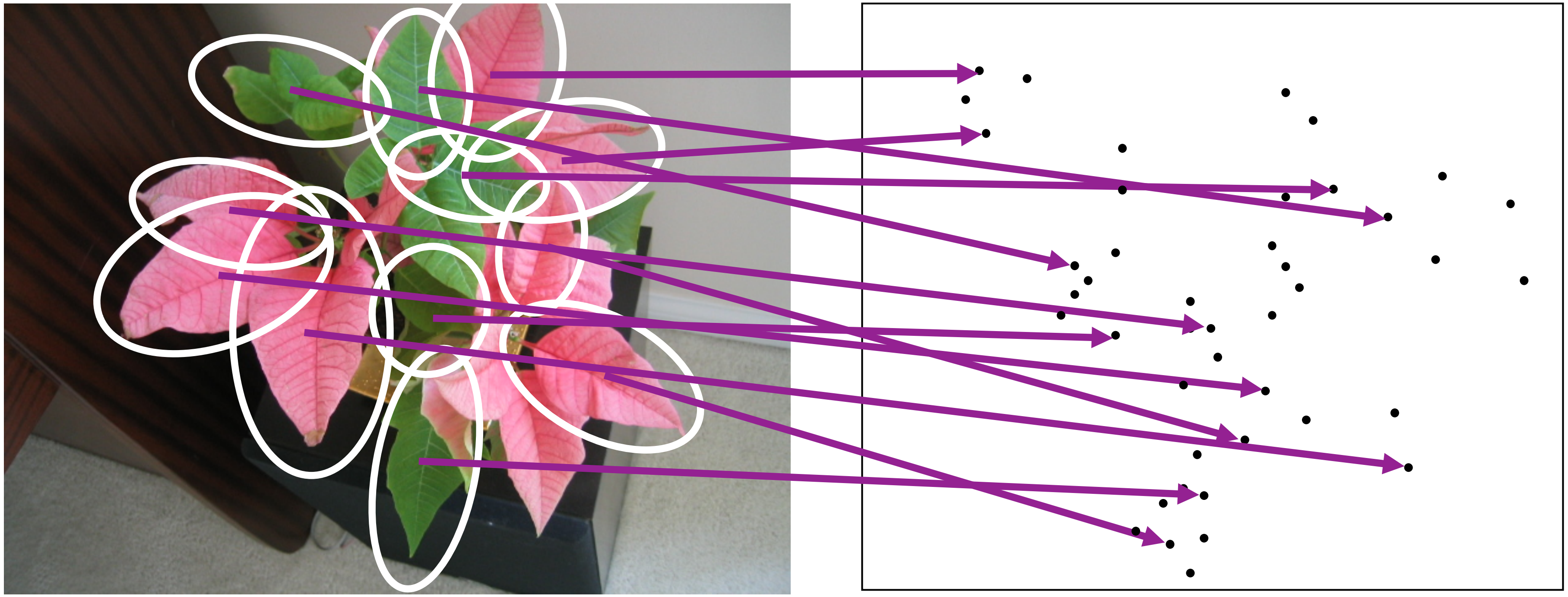


e.g., SIFT descriptor space: each point is 128-dimensional

Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

Visual words: main idea



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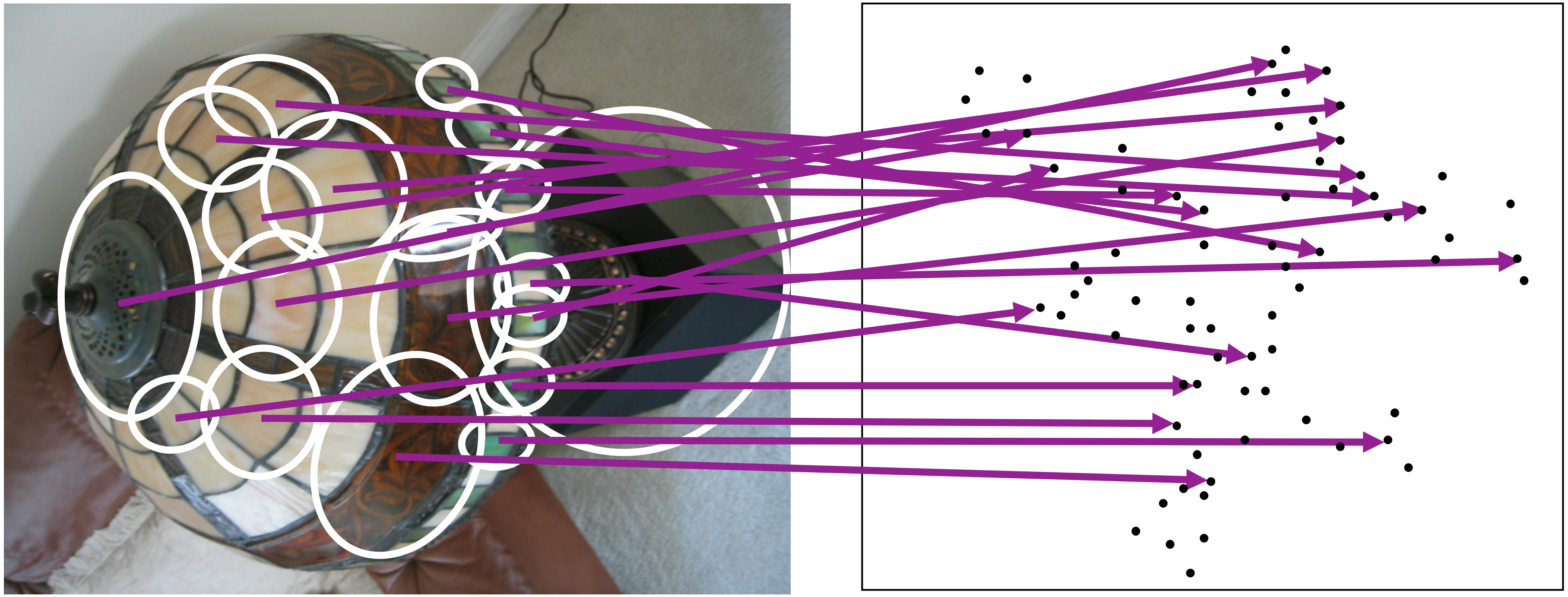

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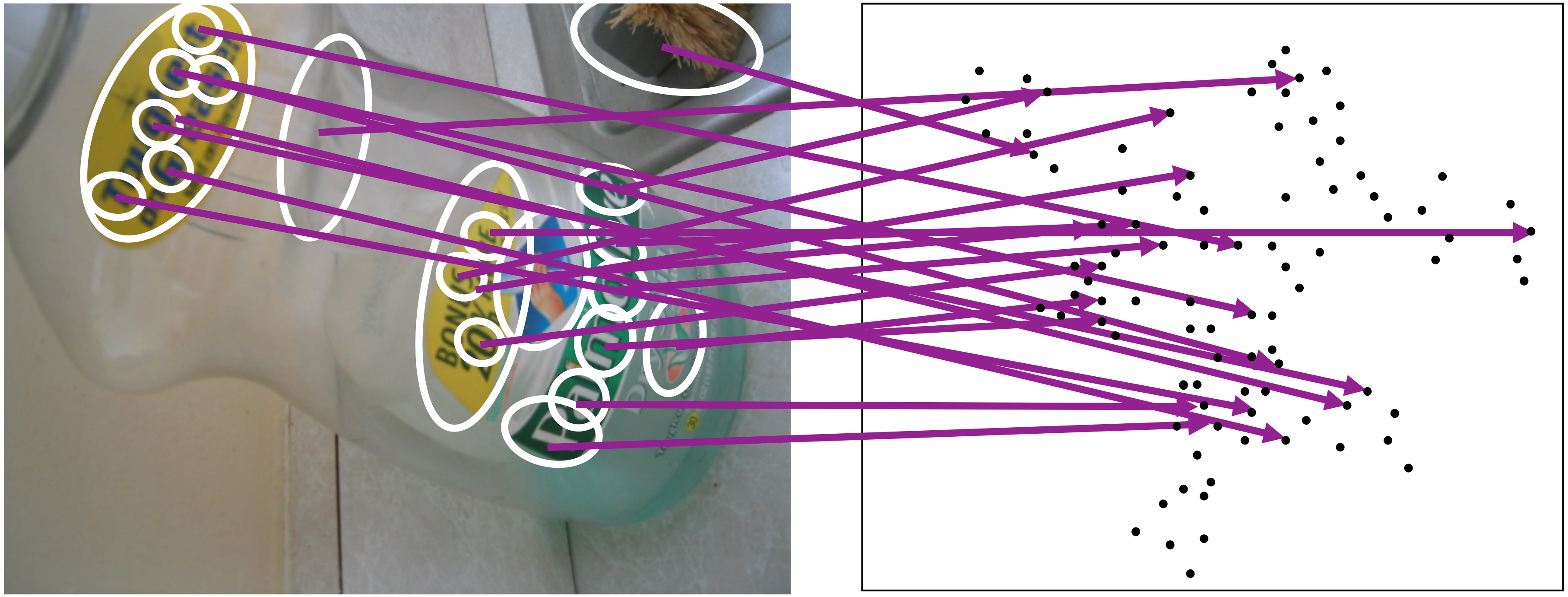

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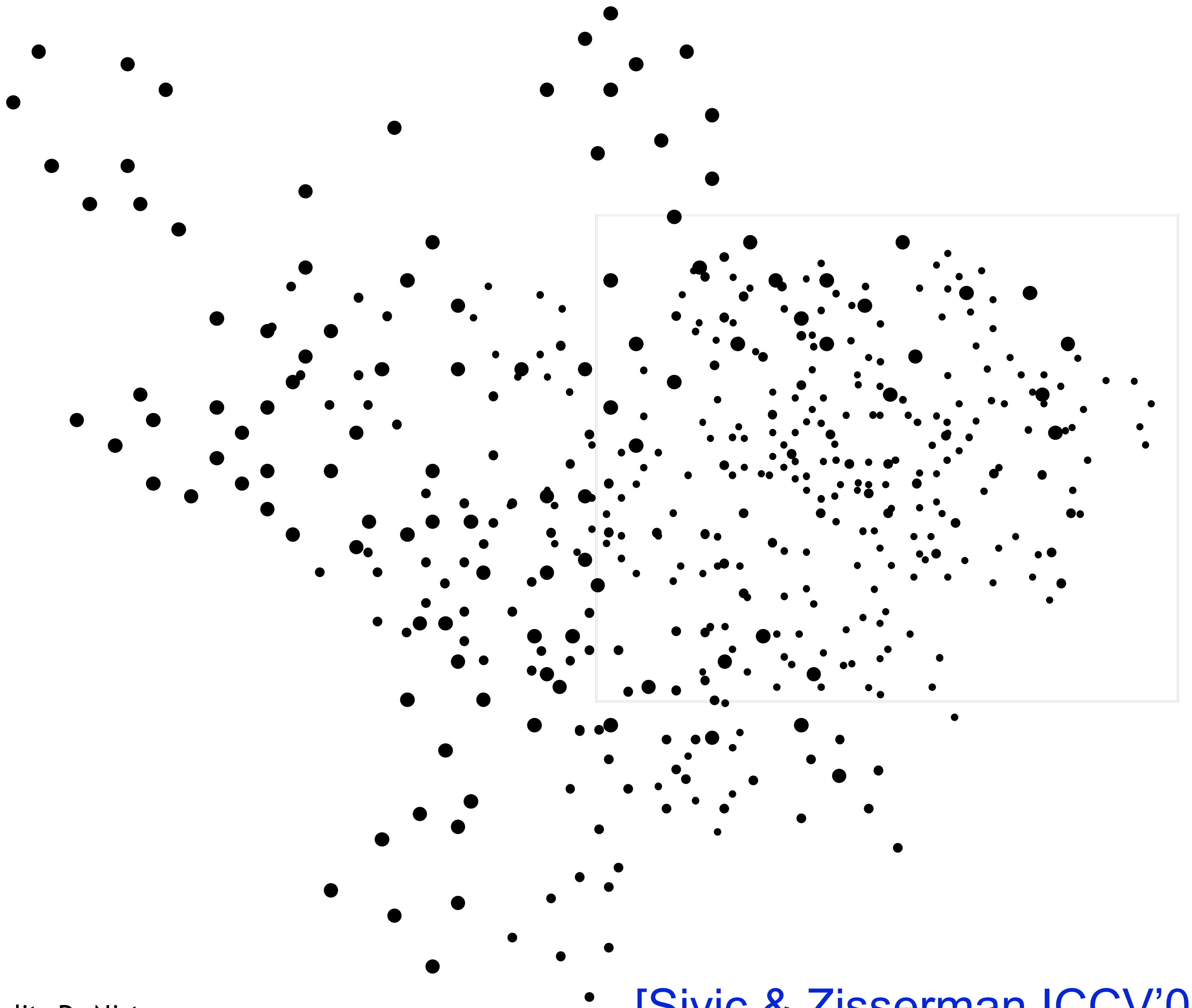

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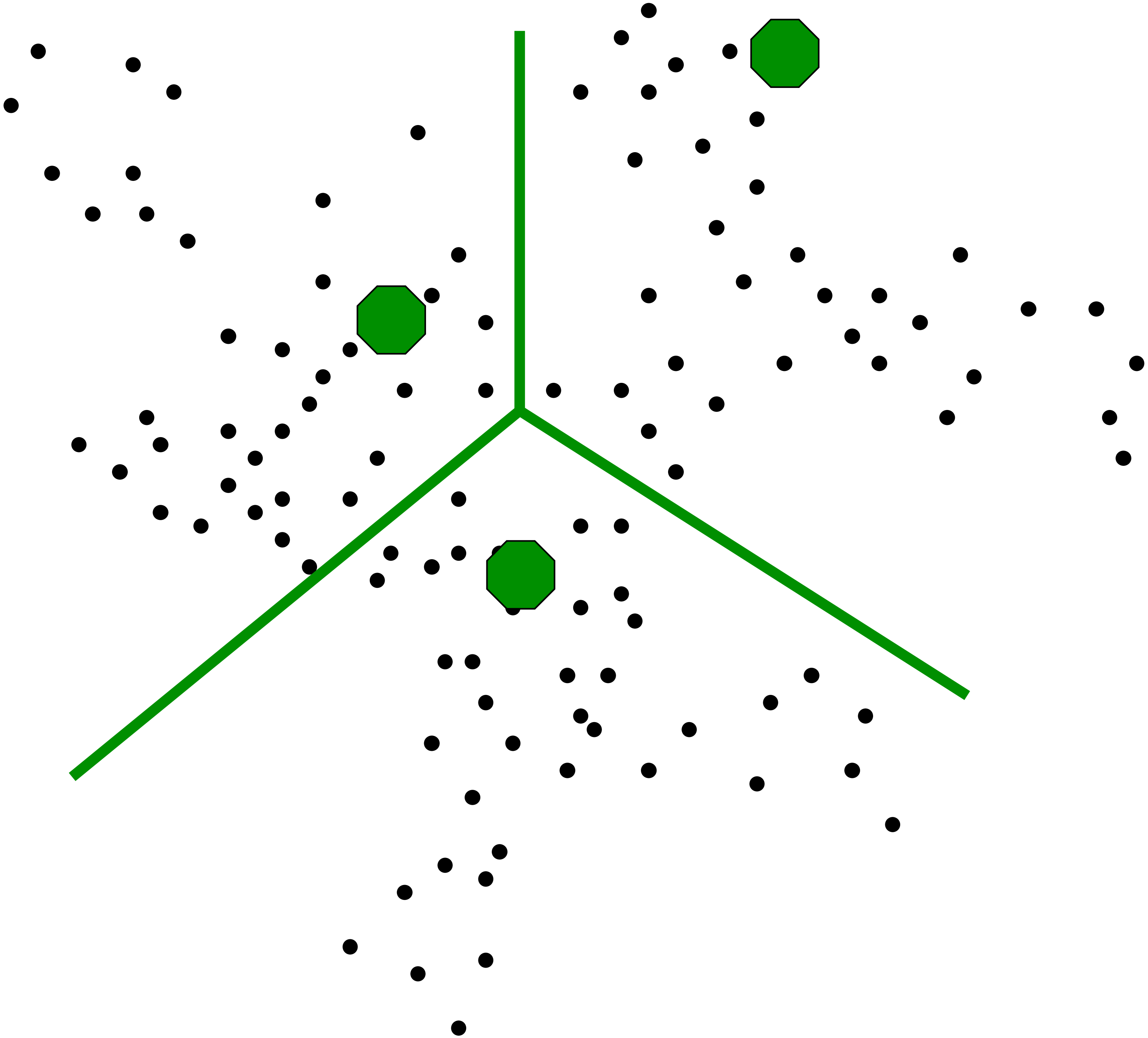
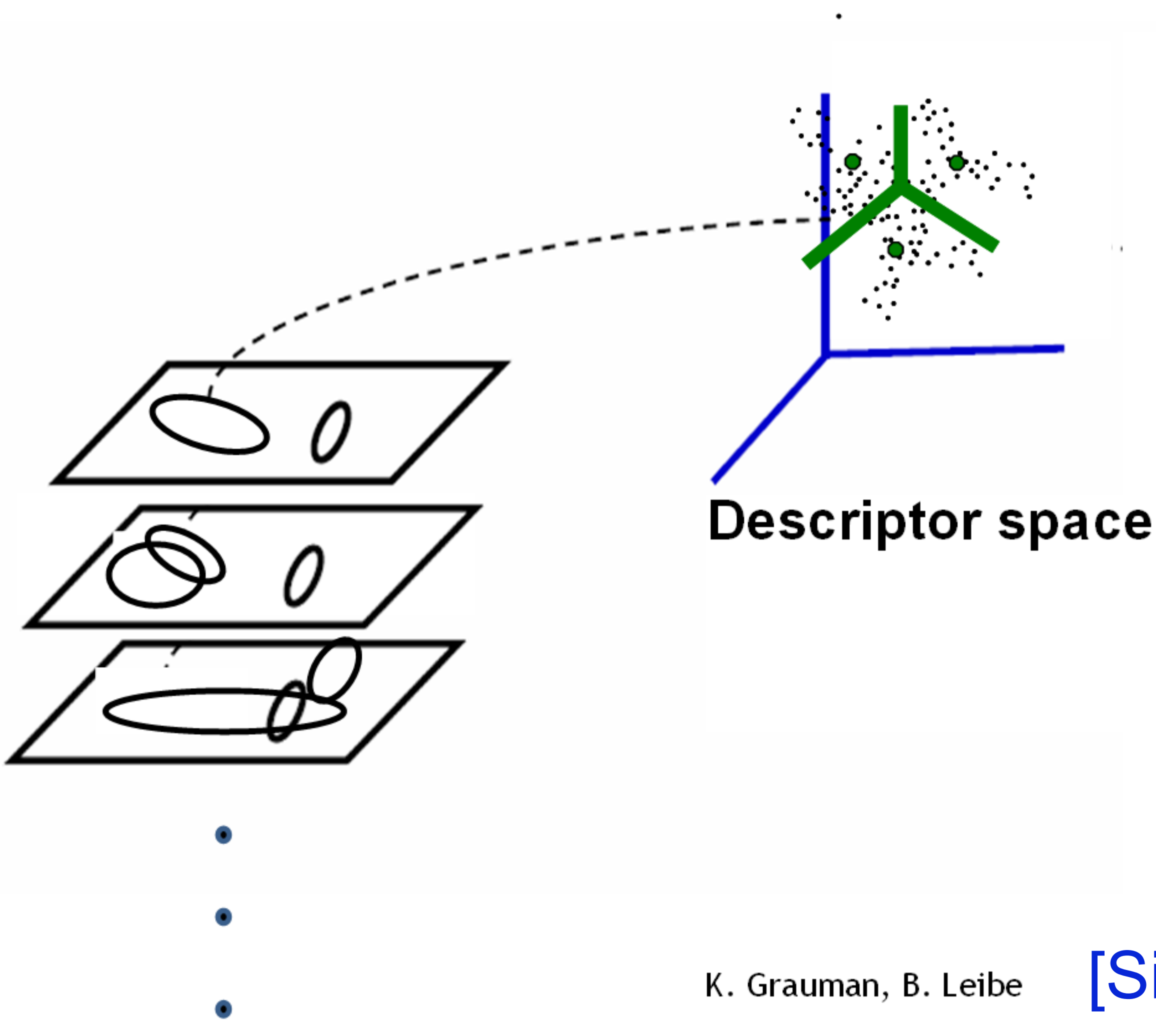


Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

Visual words: main idea

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



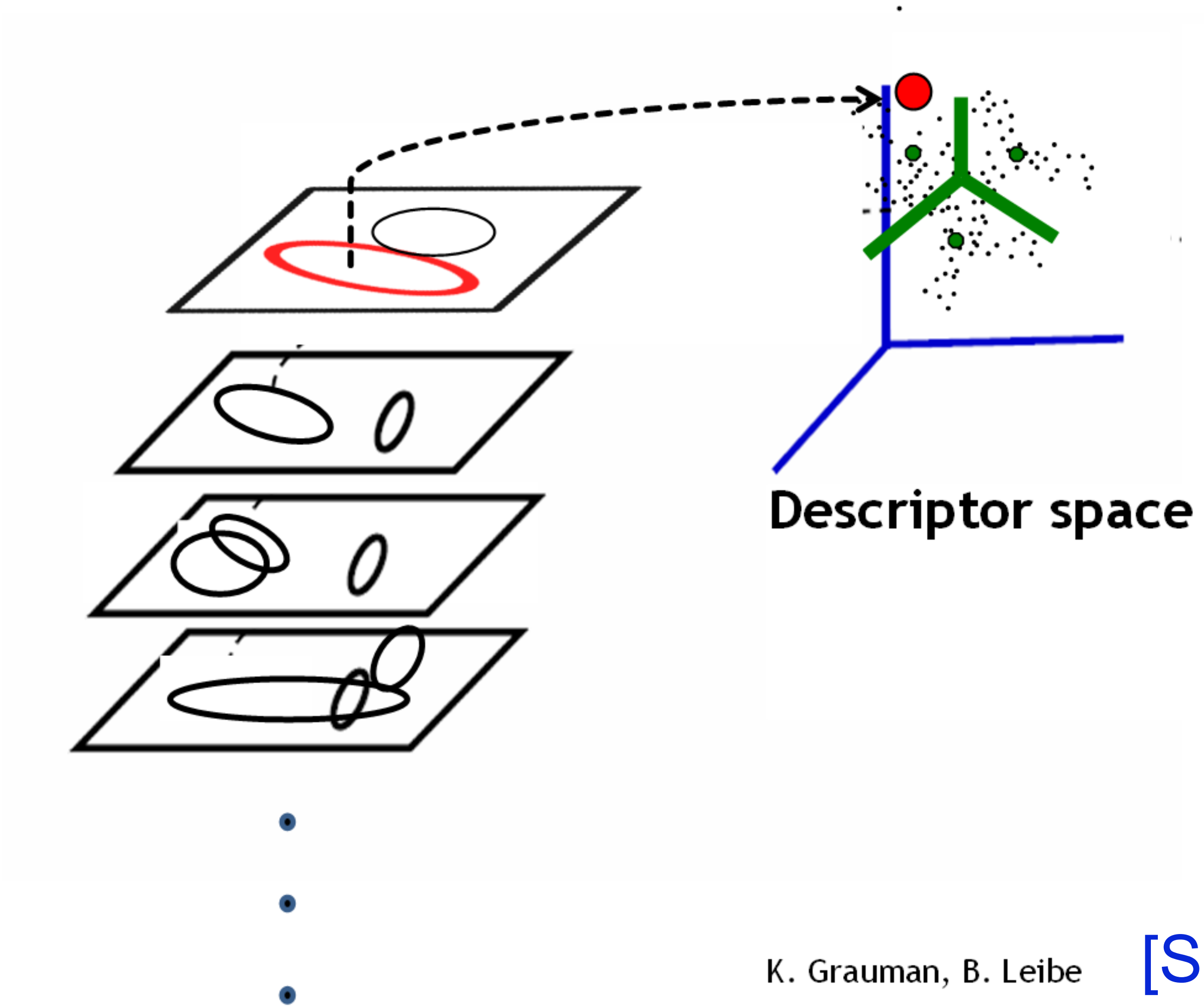
- Quantize via clustering, let cluster centers be the prototype "words"

K. Grauman, B. Leibe

[Sivic & Zisserman,ICCV'03]

Visual words: main idea

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



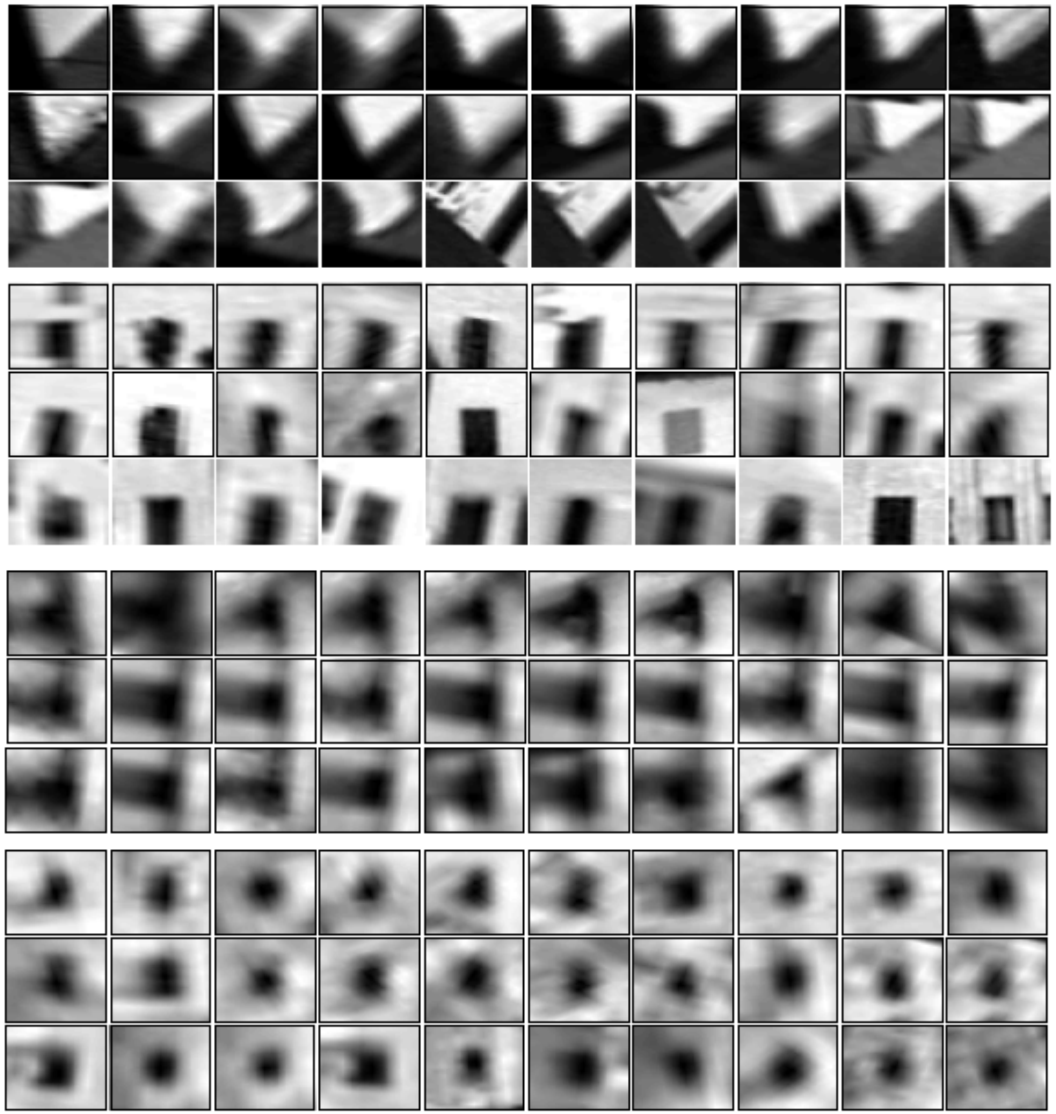
- Determine which word to assign to each new image region by finding the closest cluster center.

K. Grauman, B. Leibe

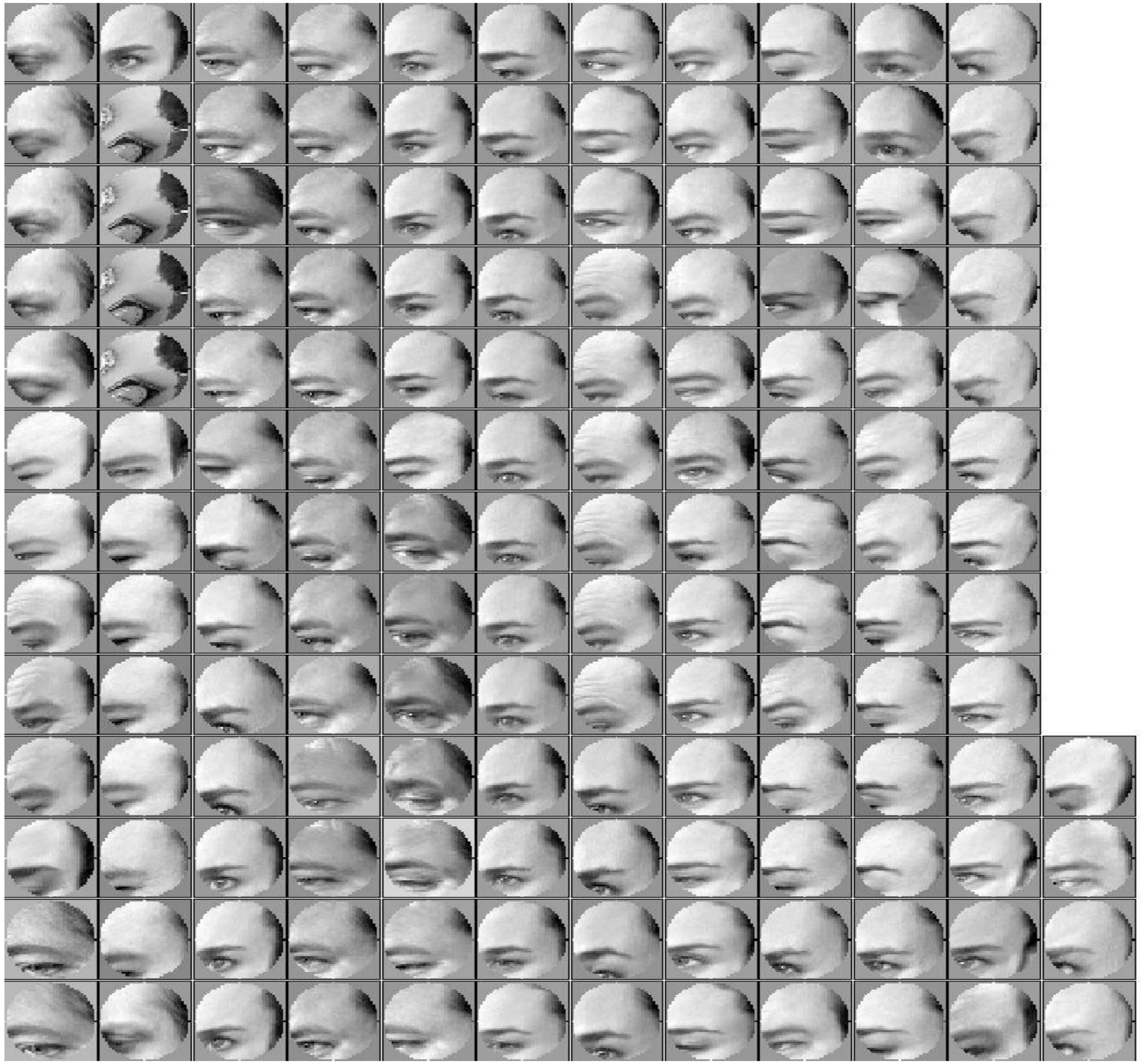
[Sivic & Zisserman,ICCV'03]

Visual words

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

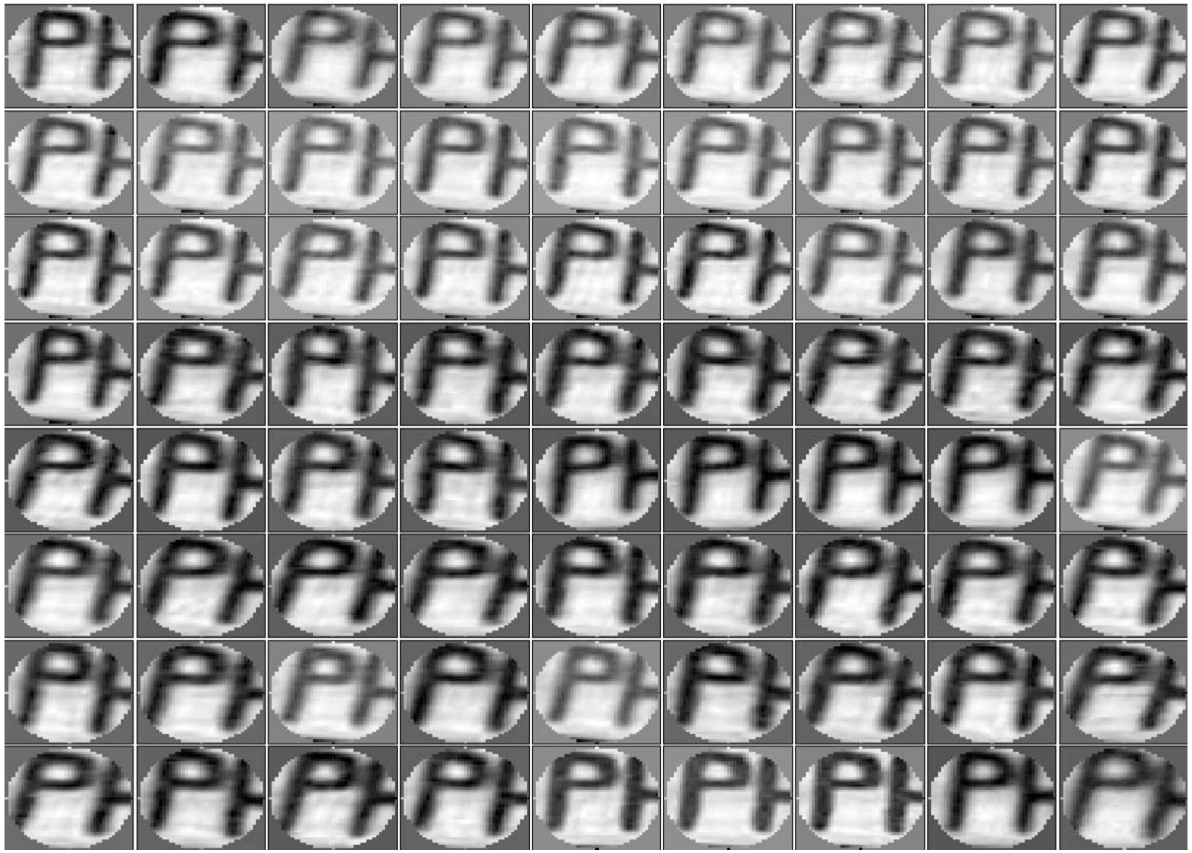


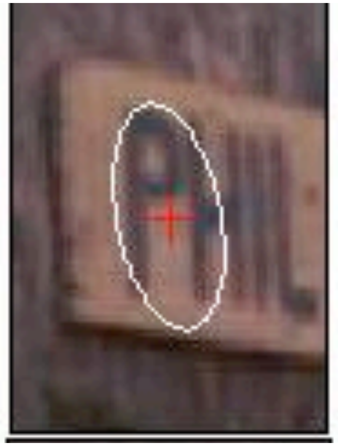
Samples of visual words (clusters on SIFT descriptors):



More specific example

Samples of visual words (clusters on SIFT descriptors):

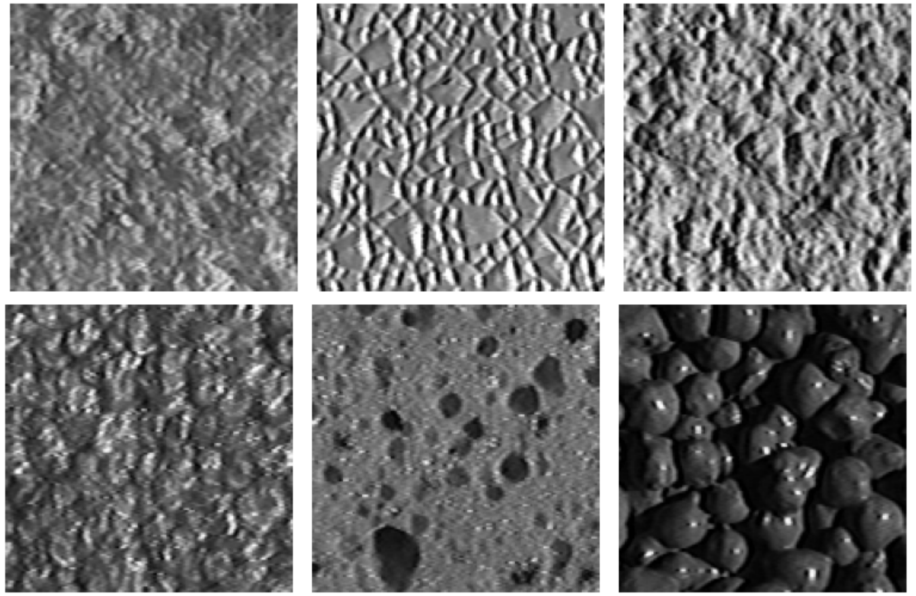




More specific example

Visual words

- First explored for texture and material representations
- *Texton* = cluster center of filter responses over collection of images
- Describe textures and materials based on distribution of prototypical texture elements.



Leung & Malik 1999; Varma & Zisserman, 2002; Lazebnik, Schmid & Ponce, 2003;

Inverted file index for images comprised of visual words

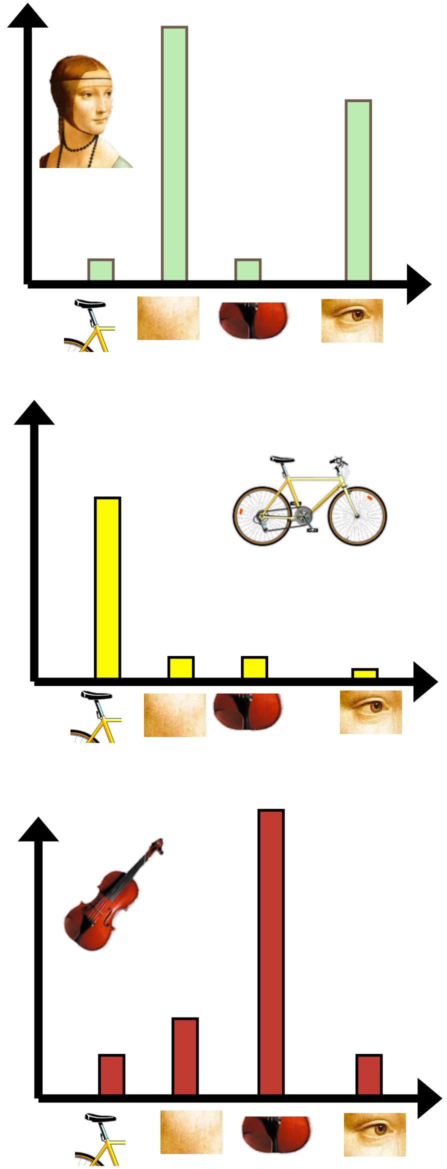
frame #5

frame #10

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

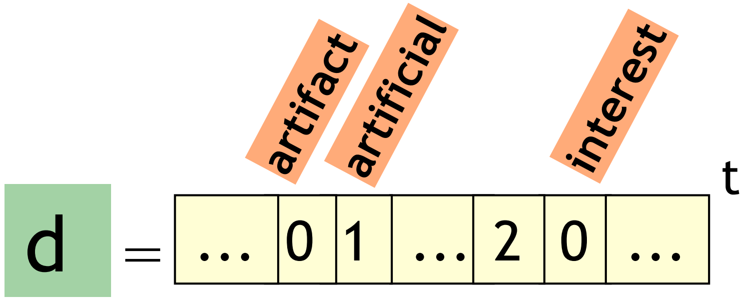
- Score each image by the number of common visual words (tentative correspondences)
- Worst case complexity is linear in the number of images N
- In practice, it is linear in the length of the lists (<< N)

Another interpretation: Bags of visual words



Summarize entire image based on its distribution (histogram) of visual word occurrences.

Analogous to bag of words representation commonly used for documents.



Hofmann 2001

Slide: Grauman&Leibe, Image: L. Fei-Fei

Another interpretation: the bag-of-words model

For a vocabulary of size K, each image is represented by a K-vector

$$\mathbf{v}_d = (t_1, \ldots, t_i, \ldots, t_K)^\top$$

where t_i is the number of occurrences of visual word i.

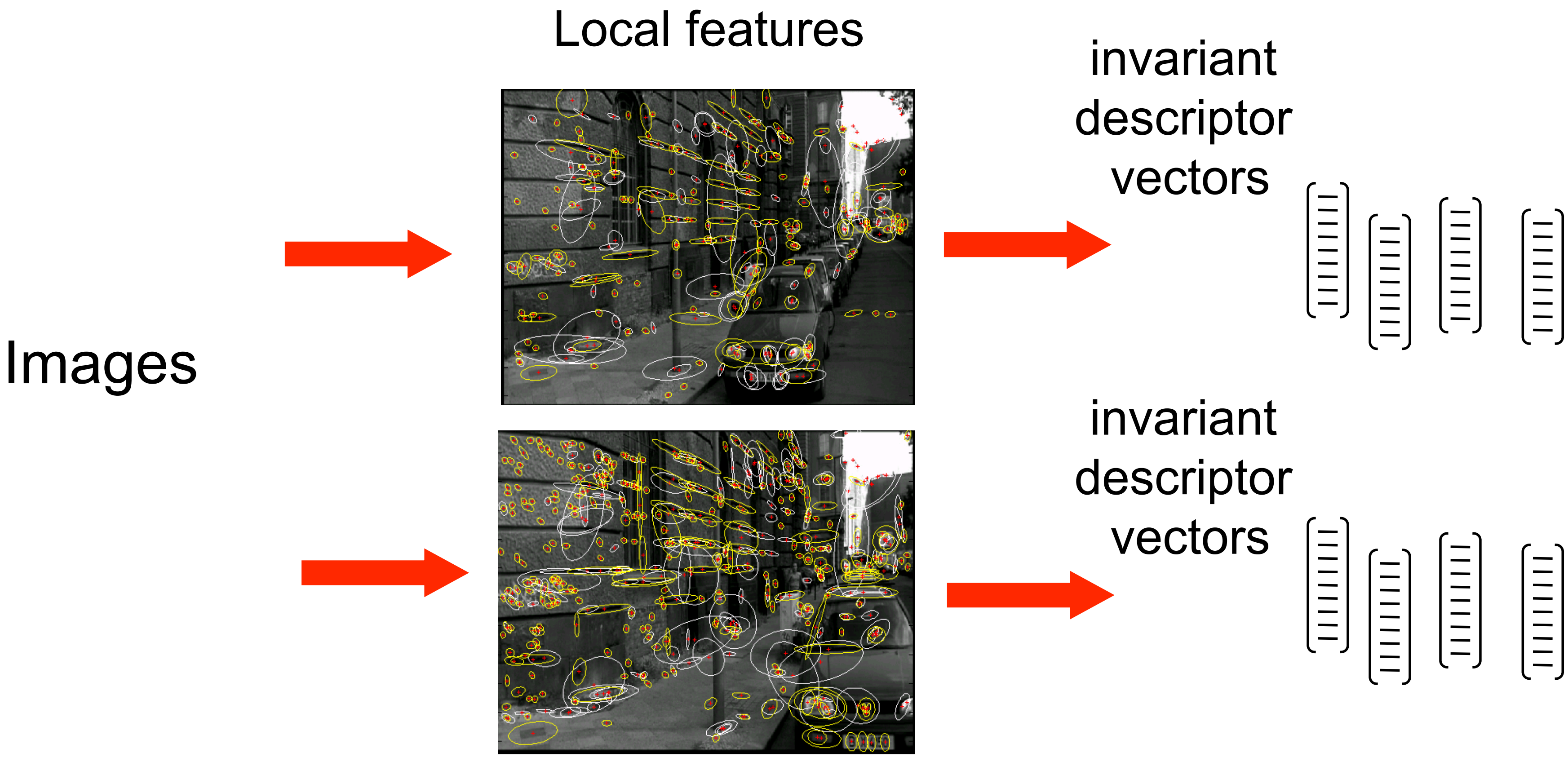
Images are ranked by the normalized scalar product between the query vector v_q and all vectors in the database v_d:

$$f_d = \frac{\mathbf{v}_q{}^\top \mathbf{v}_d}{\|\mathbf{v}_q\|_2 \; \|\mathbf{v}_d\|_2}$$

Scalar product can be computed efficiently using inverted file.

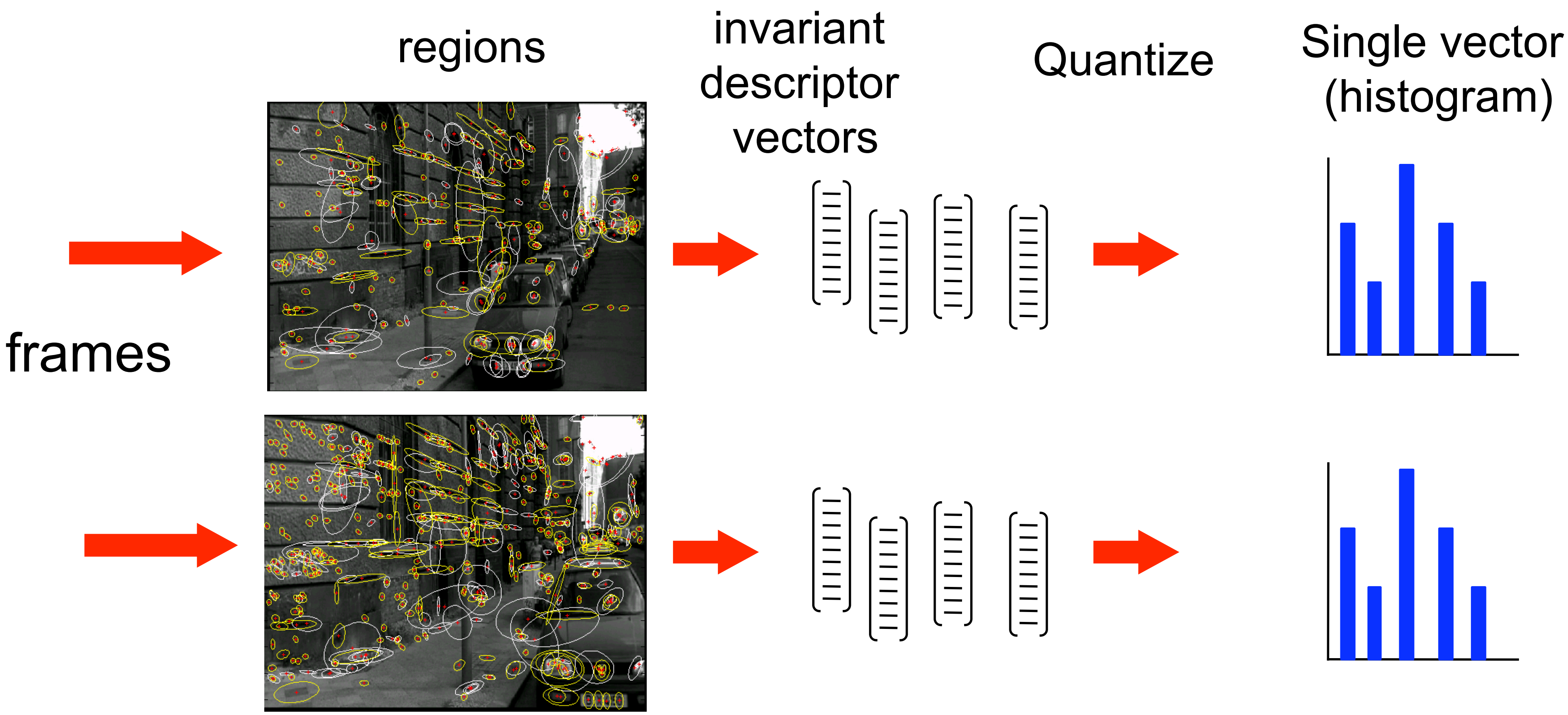
What if vectors are binary? What is the meaning of $\mathbf{v}_q{}^\top \mathbf{v}_d$?

Strategy I: Efficient approximate NN search



1. Compute local features in each image independently (offline)
2. "Label" each feature by a descriptor vector based on its intensity (offline)
3. Finding corresponding features is transformed to finding nearest neighbour vectors
4. Rank matched images by number of (tentatively) corresponding regions
5. Verify top ranked images based on spatial consistency (The first part of this lecture)

Strategy II: Match histograms of visual words



1. Compute affine covariant regions in each frame independently (offline)
2. “Label” each region by a vector of descriptors based on its intensity (offline)
3. **Build histograms of visual words by descriptor quantization (offline)**
4. **Rank retrieved frames by matching vis. word histograms using inverted files.**
5. Verify retrieved frame based on spatial consistency (The first part of the lecture)

Visual words: discussion I.

Efficiency – cost of quantization

• Need to still assign each local descriptor to one of the cluster centers. Could be prohibitive for large vocabularies (K=1M)

• Approximate NN-search still needed

• True also for building the vocabulary

Visual words: discussion II.

Generalization

• Is vocabulary/quantization learned on one dataset good for searching another dataset?

• Experimentally observe a loss in performance.

But, see recent work by Jegou et al.:

Hamming Embedding and Weak Geometry Consistency for Large Scale Image Search, ECCV'2008

http://lear.inrialpes.fr/pubs/2008/JDS08a/

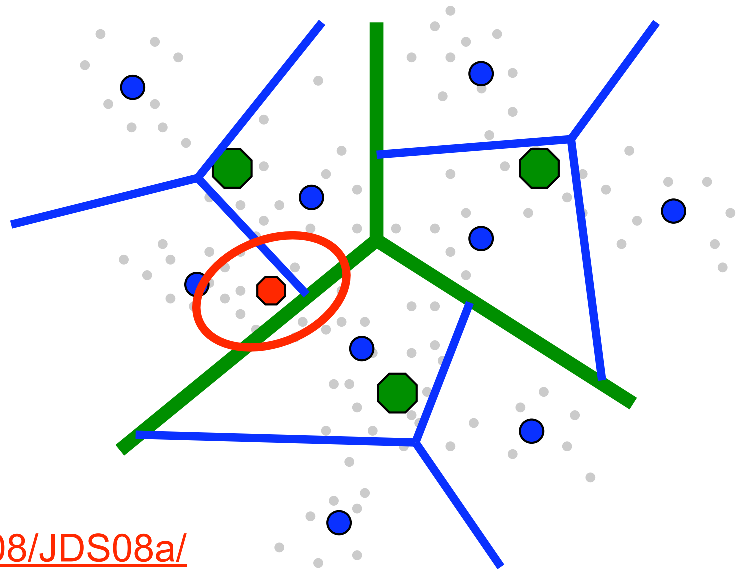
Visual words: discussion III.

- What about quantization effects?
- Visual word assignment can change due to e.g.

  noise in region detection,

  descriptor computation or

  non-modeled image variation (3D effects, lighting)



See also:

Jegou et al., ECCV'2008, http://lear.inrialpes.fr/pubs/2008/JDS08a/

Philbin et al. CVPR'08, http://www.robots.ox.ac.uk/~vgg/publications/html/philbin08-bibtex.html

Mikulik et al., ECCV'10, http://cmp.felk.cvut.cz/~chum/papers/mikulik_eccv10.pdf

Philbin et al., ECCV'10, http://www.di.ens.fr/~josef/publications/philbin10b.pdf

Visual words: discussion IV.

- Need to determine the size of the vocabulary, K.

- Other algorithms for building vocabularies, e.g.

agglomerative clustering / mean-shift, but typically more expensive.

- Supervised quantization?

Also give examples of images / descriptors which should and should not match.

E.g.:
Philbin et al. ECCV’10, http://www.robots.ox.ac.uk/~vgg/publications/html/philbin10b-bibtex.html

Visual search using local regions (references)

C. Schmid, R. Mohr, Local Greyvalue Invariants for Image Retrieval, PAMI, 1997

J. Sivic, A. Zisserman, Text retrieval approach to object matching in videos, ICCV, 2003

D. Nister, H. Stewenius, Scalable Recognition with a Vocabulary Tree, CVPR, 2006.

J. Philbin, O. Chum, M. Isard, J. Sivic, A. Zisserman, Object retrieval with large vocabularies and fast spatial matching, CVPR, 2007

O. Chum, J. Philbin, M. Isard, J. Sivic, A. Zisserman, Total Recall: Automatic Query Expansion with a Generative Feature Model for Object Retrieval, ICCV, 2007

H. Jegou, M. Douze, C. Schmid, Hamming embedding and weak geometric consistency for large scale image search, ECCV'2008

O. Chum, M. Perdoch, J. Matas: Geometric min-Hashing: Finding a (Thick) Needle in a Haystack, CVPR 2009

H. Jégou, M. Douze and C. Schmid, On the burstiness of visual elements, CVPR, 2009

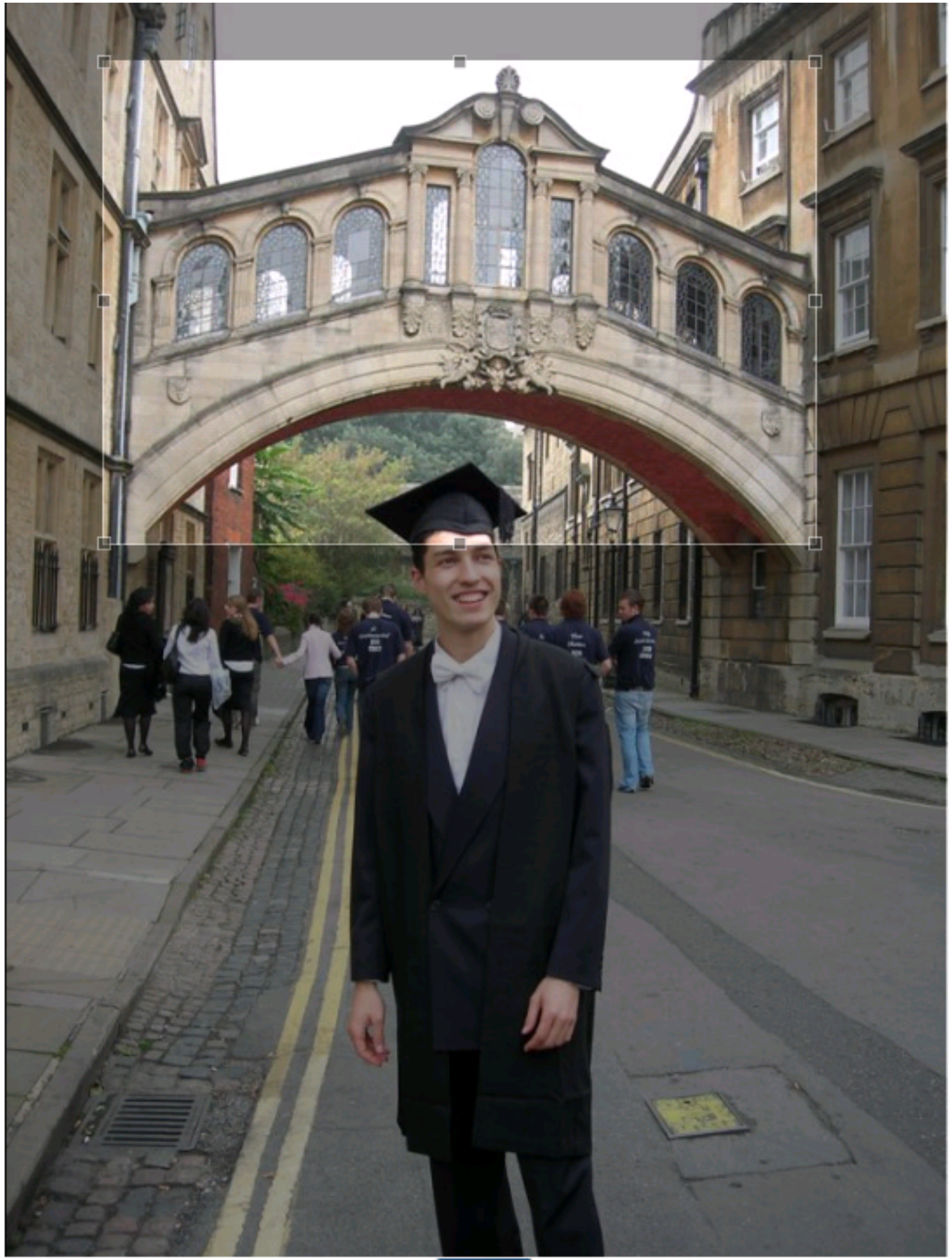
H. Jégou, M. Douze, C. Schmid and P. Pérez, Aggregating local descriptors into a compact image representation, CVPR'2010

Efficient visual search for objects and places

Oxford Buildings Search - demo

http://www.robots.ox.ac.uk/~vgg/research/oxbuildings/index.html

Example



Search

Search results 1 to 20 of 104844

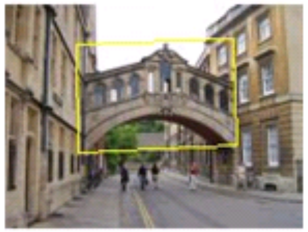
1

ID: oxc1_hertford_000011
Score: 1816.000000
Putative: 2325
Inliers: 1816
Hypothesis: 1.000000 0.000000 0.000015 0.000000 1.000000 0.000031
Detail

2

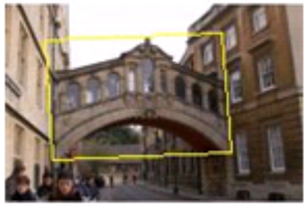
ID: oxc1_all_souls_000075
Score: 352.000000
Putative: 645
Inliers: 352
Hypothesis: 1.162245 0.041211 -70.414459 -0.012913 1.146417 91.276093
Detail

3



ID: oxc1_hertford_000064
Score: 278.000000
Putative: 527
Inliers: 278
Hypothesis: 0.928686 0.026134 169.954620 -0.041703 0.937558 97.962112
Detail

4

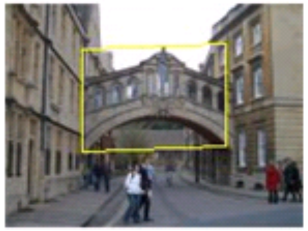


ID: oxc1_oxford_001612
Score: 252.000000
Putative: 451
Inliers: 252
Hypothesis: 1.046026 0.069416 51.576881 -0.044949 1.046938 76.264442
Detail

5

ID: oxc1_hertford_000123
Score: 225.000000
Putative: 446
Inliers: 225
Hypothesis: 1.361741 0.090413 -34.673317 -0.084659 1.301689 -32.281090
Detail

6



ID: oxc1_oxford_001085
Score: 224.000000
Putative: 389
Inliers: 224
Hypothesis: 0.848997 0.000000 195.707611 -0.031077 0.895546 114.583961
Detail

7

ID: oxc1_hertford_000077
Score: 195.000000
Putative: 386
Inliers: 195
Hypothesis: 1.465144 0.069286 -108.473091 -0.097598 1.461877 -30.205191
Detail

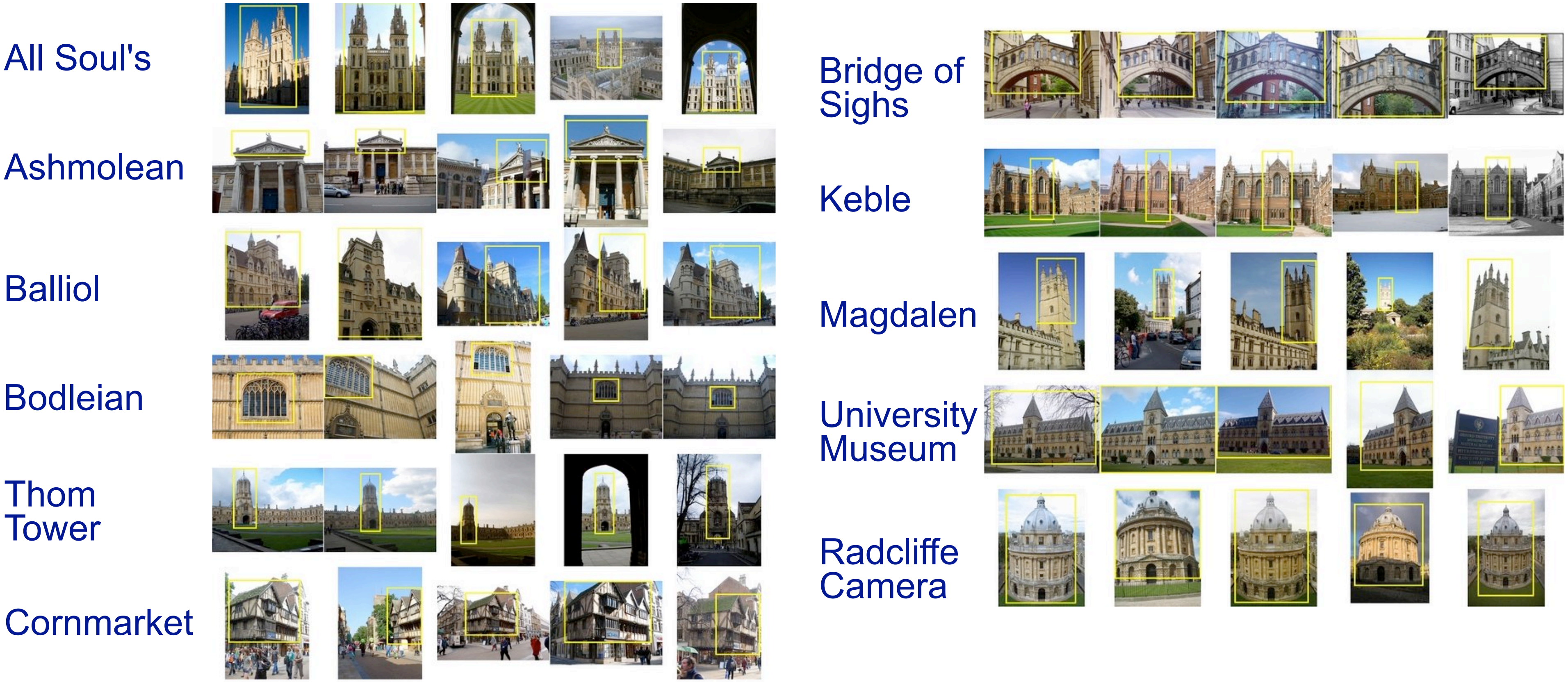
Oxford buildings dataset

- Automatically crawled from flickr
- Consists of:

Dataset	Resolution	# images	# features	Descriptor size
i	1024×768	5,062	16,334,970	1.9 GB
ii	1024×768	99,782	277,770,833	33.1 GB
iii	500×333	1,040,801	1,186,469,709	141.4 GB
Total		1,145,645	1,480,575,512	176.4 GB

Oxford buildings dataset

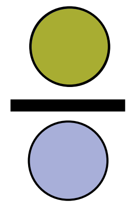
- Landmarks plus queries used for evaluation



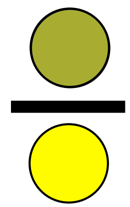
- Ground truth obtained for 11 landmarks
- Evaluate performance by mean Average Precision

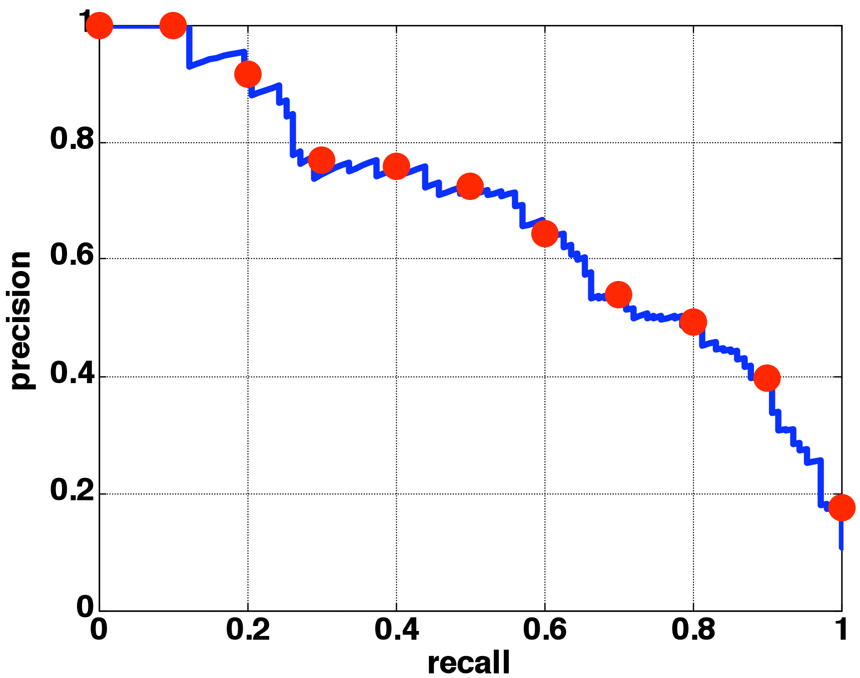
Measuring retrieval performance: Precision - Recall

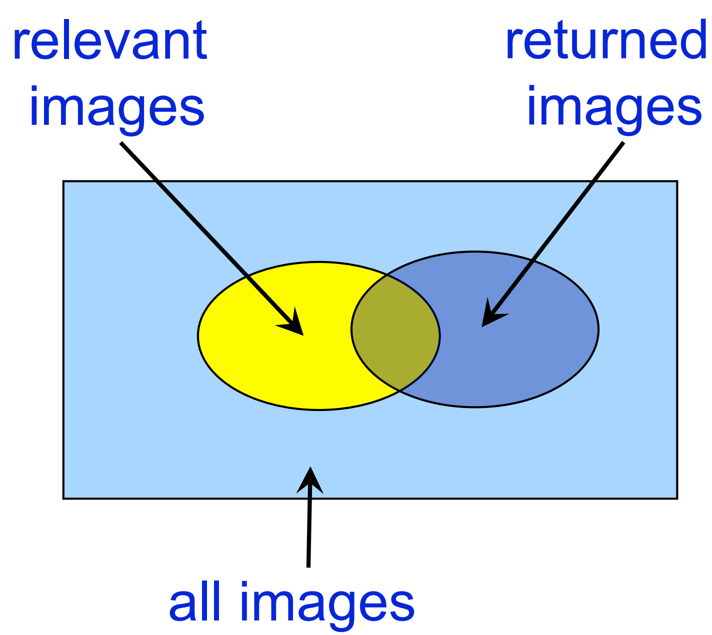
- Precision: % of returned images that are relevant



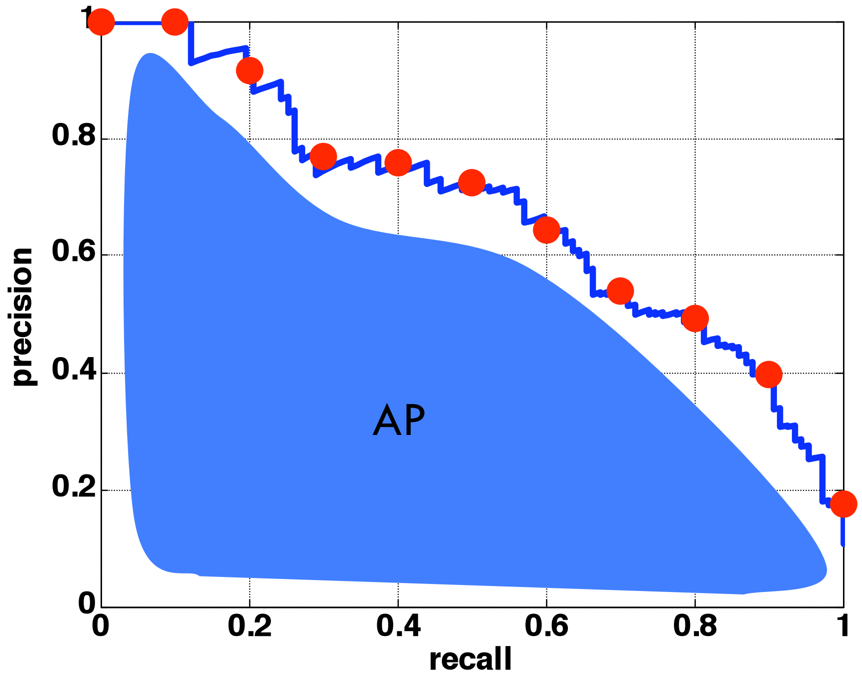
- Recall: % of relevant images that are returned





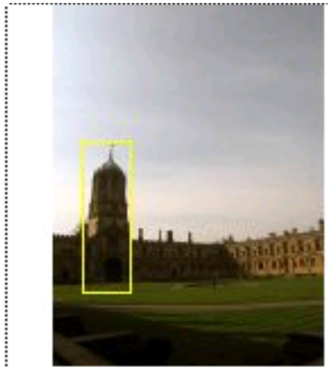


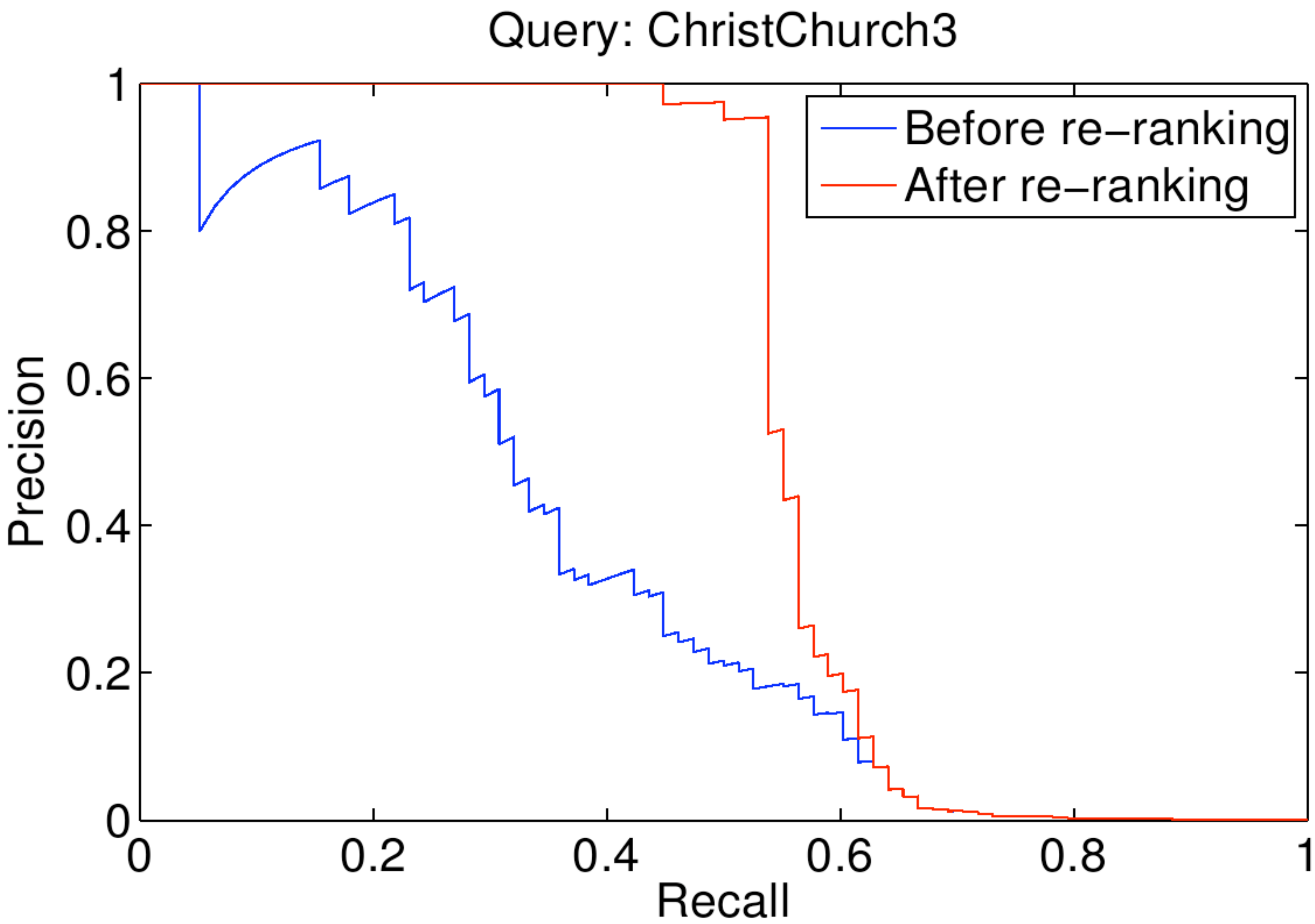
Average Precision



- A good AP score requires both high recall and high precision
- Application-independent

Performance measured by mean Average Precision (mAP) over 55 queries on 100K or 1.1M image datasets

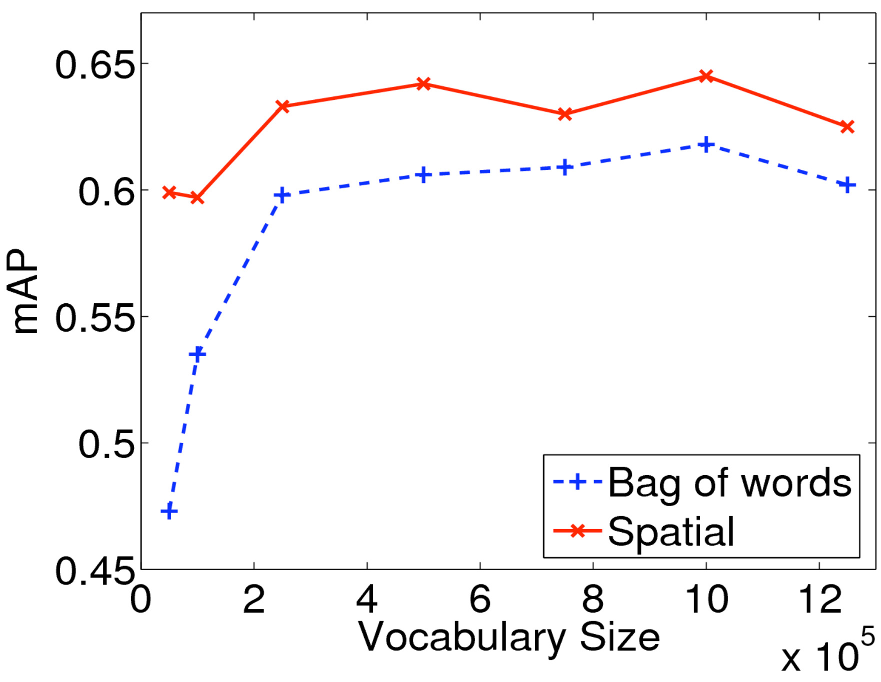




Query: ChristChurch3
Before re−ranking
After re−ranking
Precision
Recall
0
0.2
0.4
0.6
0.8
1

Mean Average Precision variation with vocabulary size

vocab size	bag of words	spatial
50K	0.473	0.599
100K	0.535	0.597
250K	0.598	0.633
500K	0.606	0.642
750K	0.609	0.630
1M	0.618	0.645
1.25M	0.602	0.625



What objects/scenes local regions do not work on?

What objects/scenes local regions do not work on?

E.g. texture-less objects, objects defined by shape, deformable objects, wiry objects.

Example applications of large scale visual search and matching

Sony Aibo (Evolution Robotics)

SIFT usage

- Recognize docking station
- Communicate with visual cards

Other uses

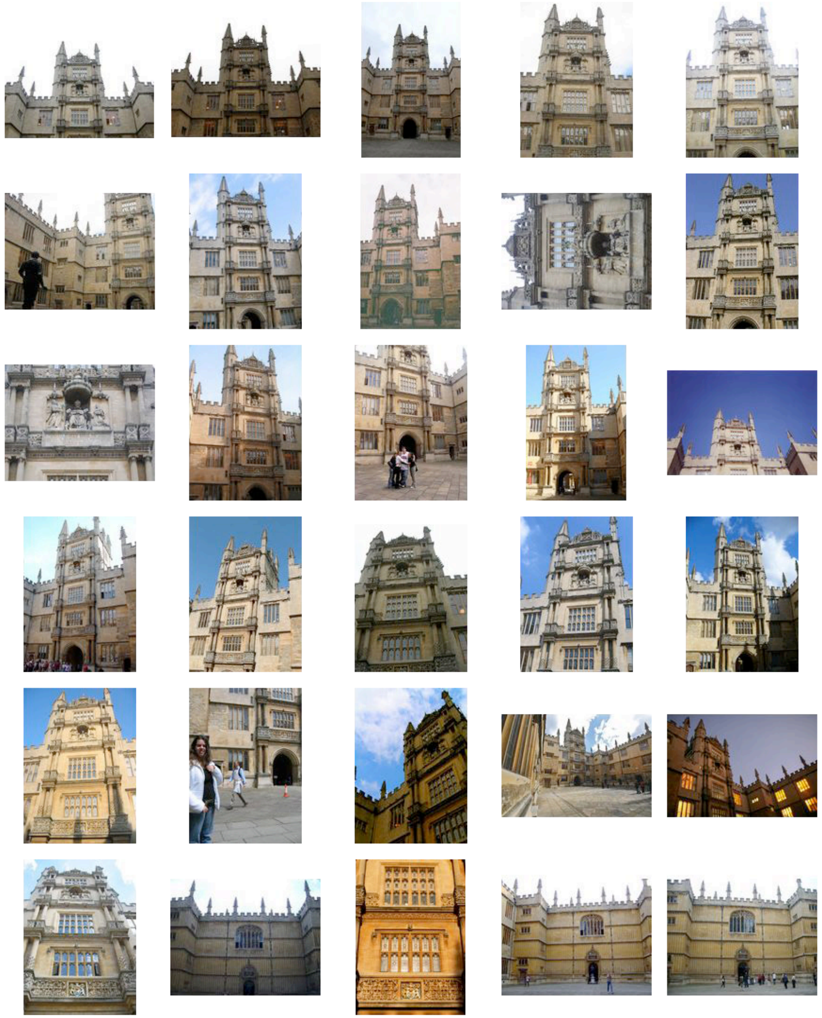
- Place recognition
- Loop closure in SLAM

Slide credit: David Lowe

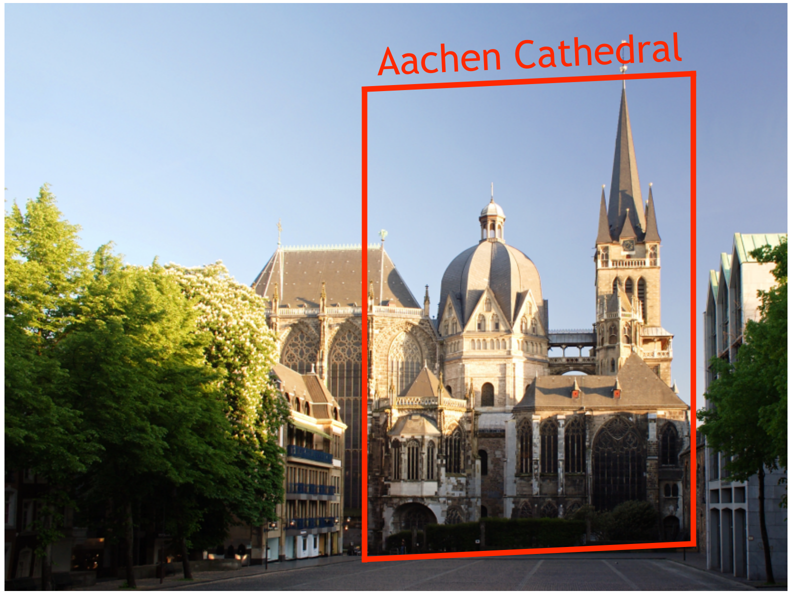
Application: Internet-based inpainting

Photo-editing using images of the same place

[Whyte, Sivic and Zisserman, 2009]



Mobile tourist guide

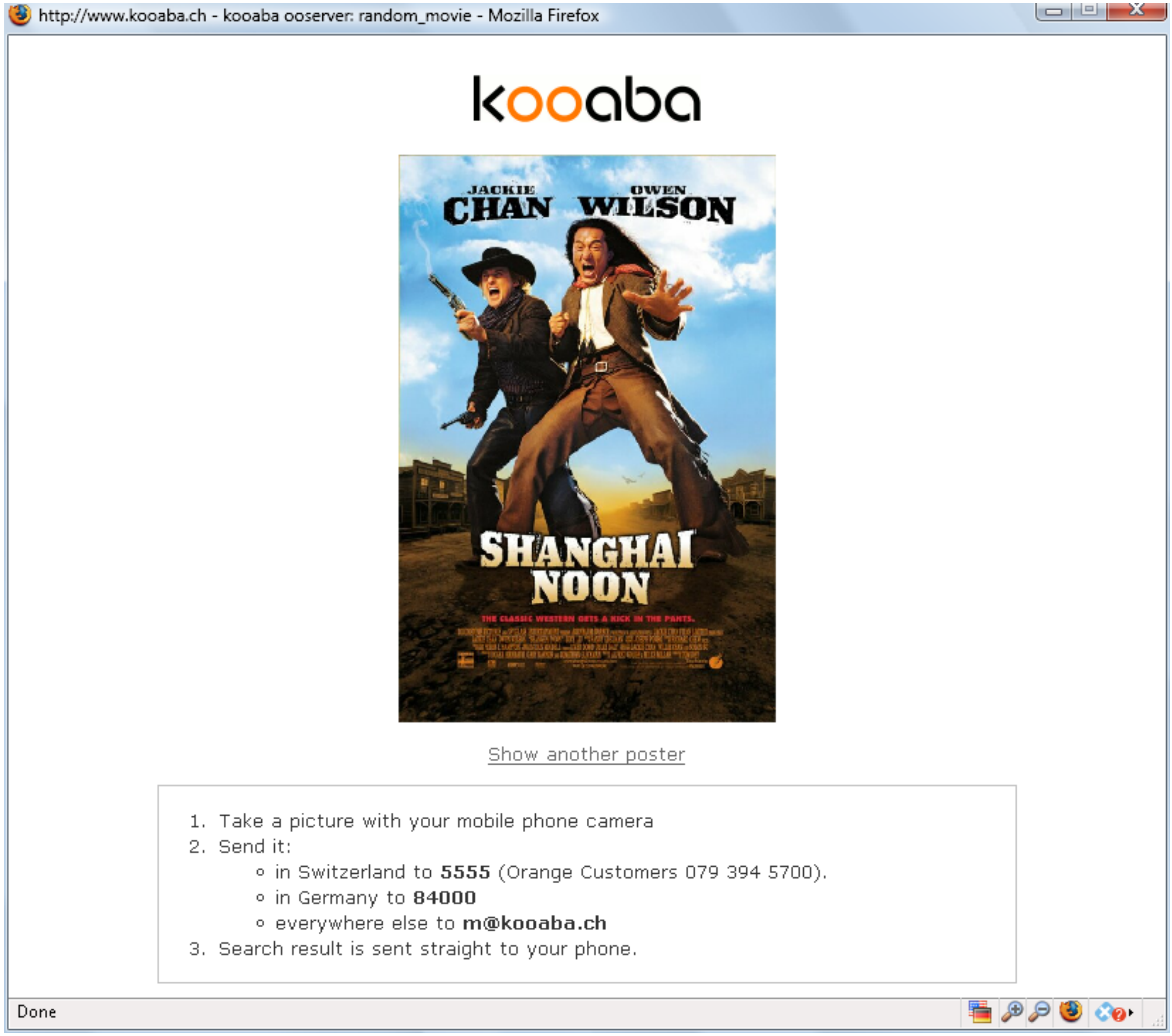


Mobile tourist guide

- **Self-localization**
- **Object/building recognition**
- **Photo/video augmentation**

[Quack, Leibe, Van Gool, CIVR'08]

Web Demo: Movie Poster Recognition



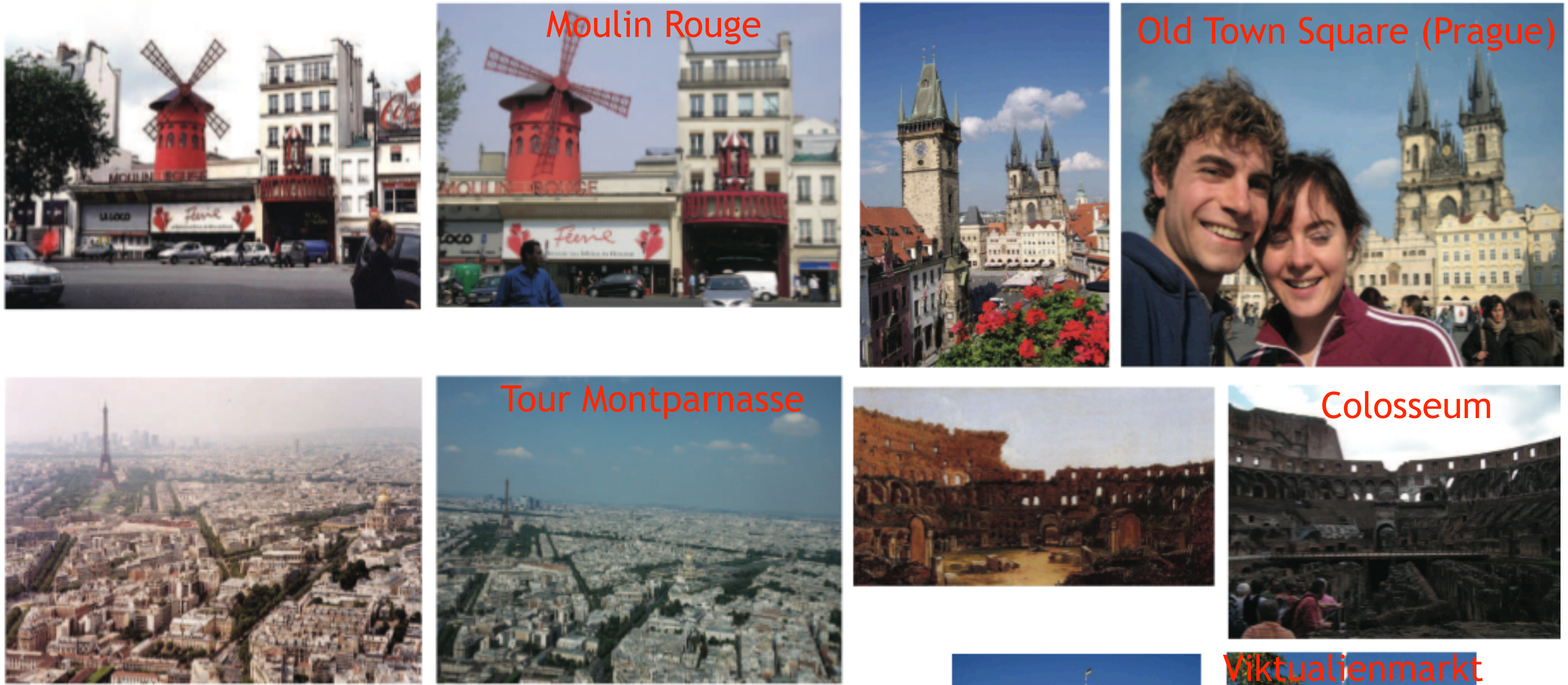
50’000 movie posters indexed

Query-by-image from mobile phone available in Switzer-land

http://www.kooaba.com/en/products_engine.html#

K. Grauman, B. Leibe

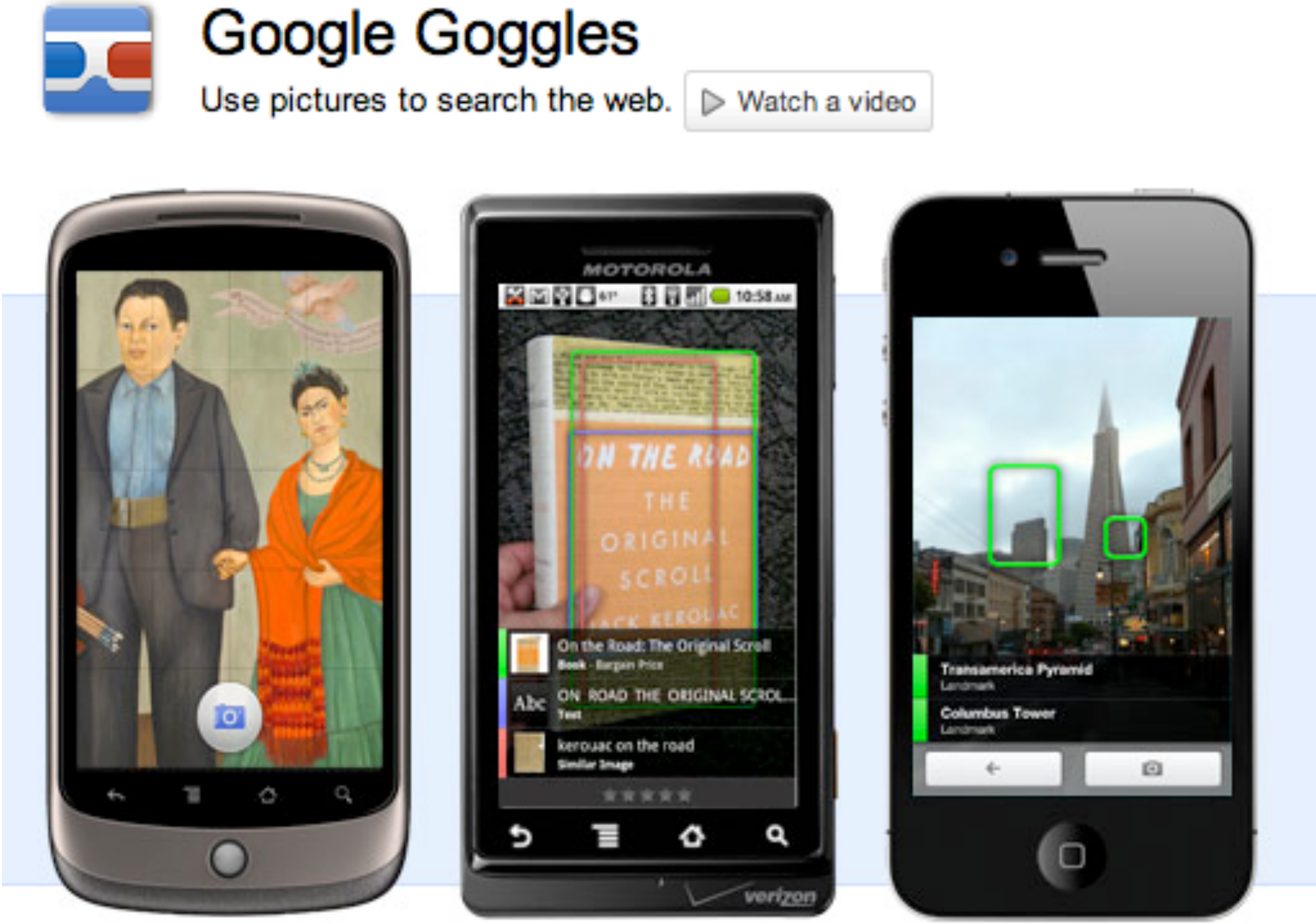
Image Auto-Annotation



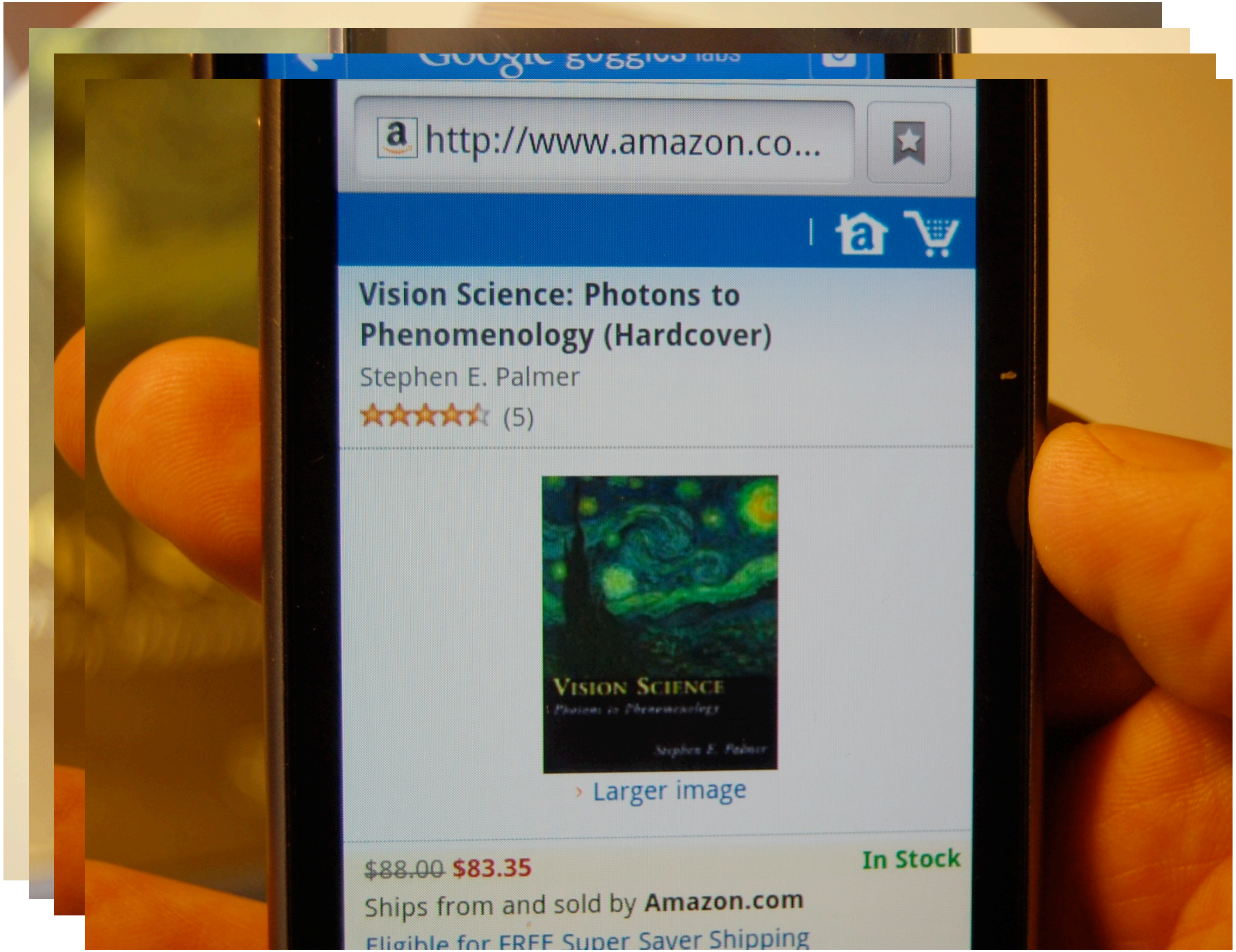
Left: Wikipedia image
Right: closest match from Flickr

[Quack CIVR'08]

Visual search in your pocket



Example



Slide credit: I. Laptev

Google Goggles

Use pictures to search the web. ▷ Watch a video

but it doesn't work well yet on things like food, cars, plants, or animals.

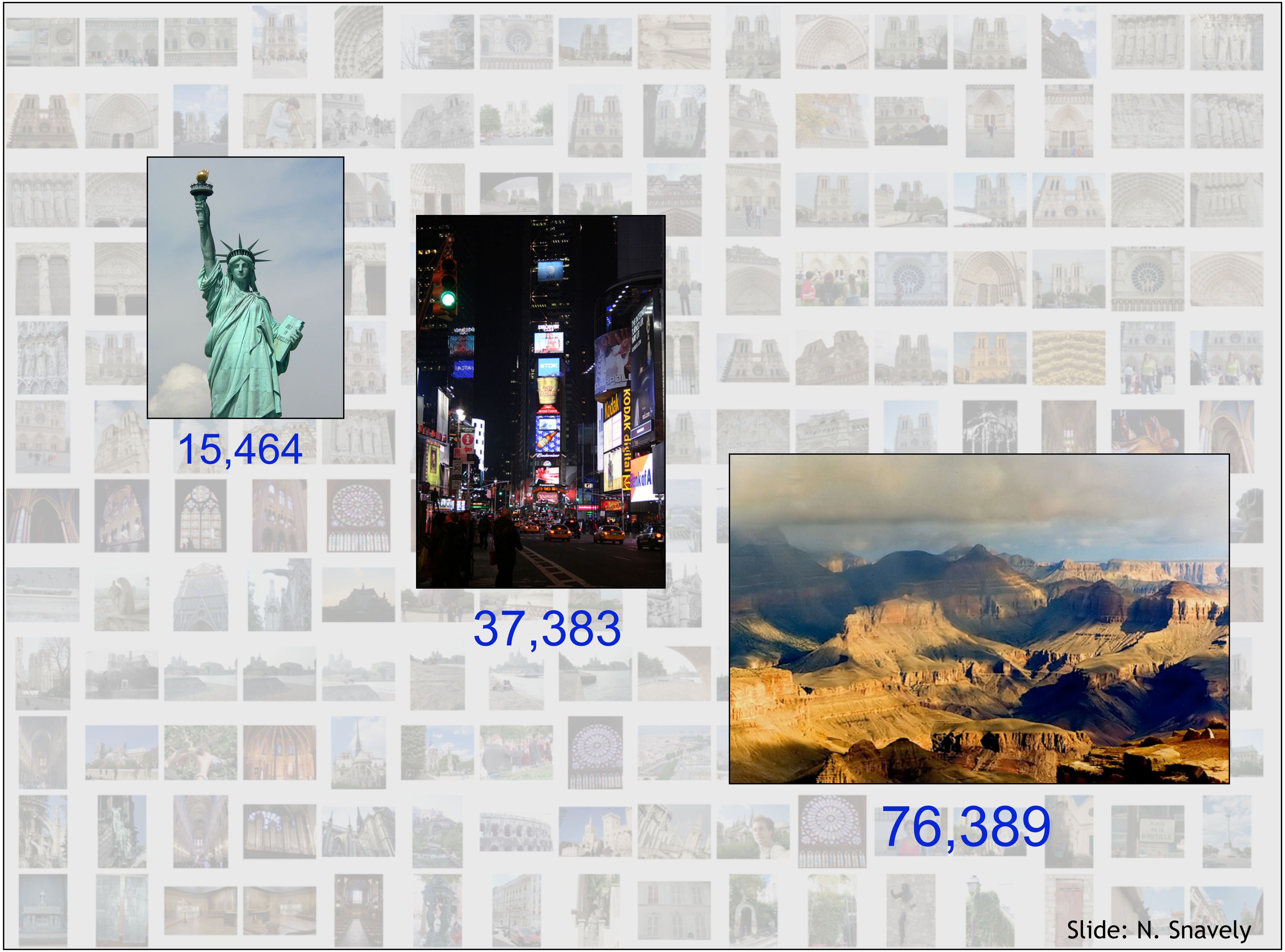
Building Rome in a Day – or –

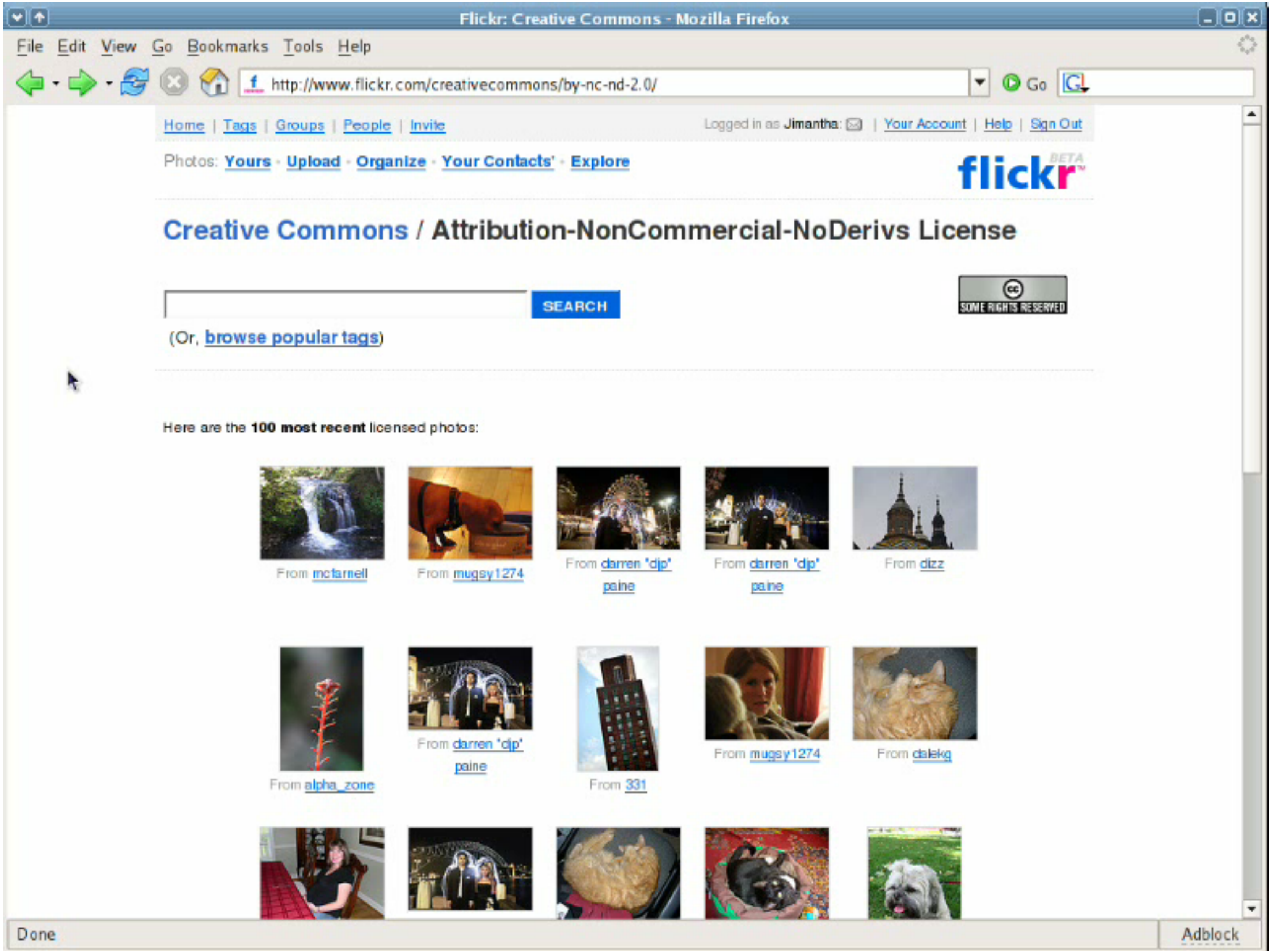
matching and 3D reconstruction in large unstructured datasets.

Goal: Build a 3D model of a city from
a large collection of images downloaded from the Internet

Use a cluster with 500 CPU cores.

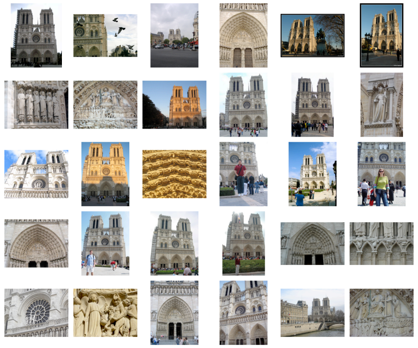
Building Rome in a Day, Sameer Agarwal, Noah Snavely, Ian Simon, Steven M. Seitz and Richard Szeliski,
International Conference on Computer Vision, 2009
http://grail.cs.washington.edu/rome/


15,464
37,383
76,389
Slide: N. Snavely



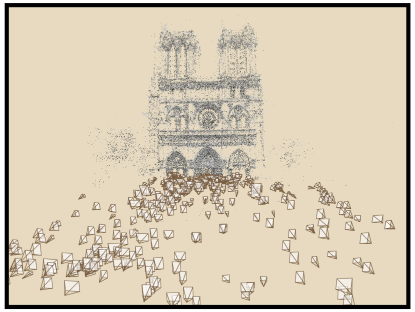
Slide: N. Snavely

Photo Tourism overview



Input photographs

Scene reconstruction



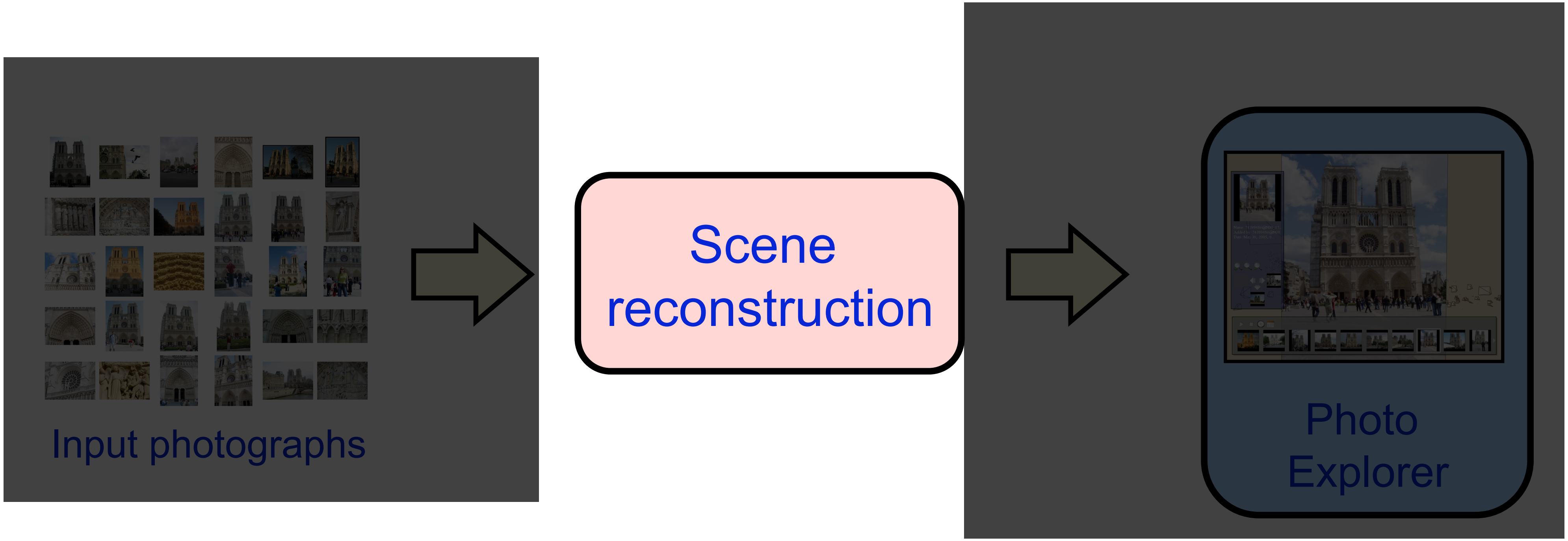
Relative camera positions and orientations

Point cloud

Sparse correspondence

Photo Explorer

Photo Tourism overview

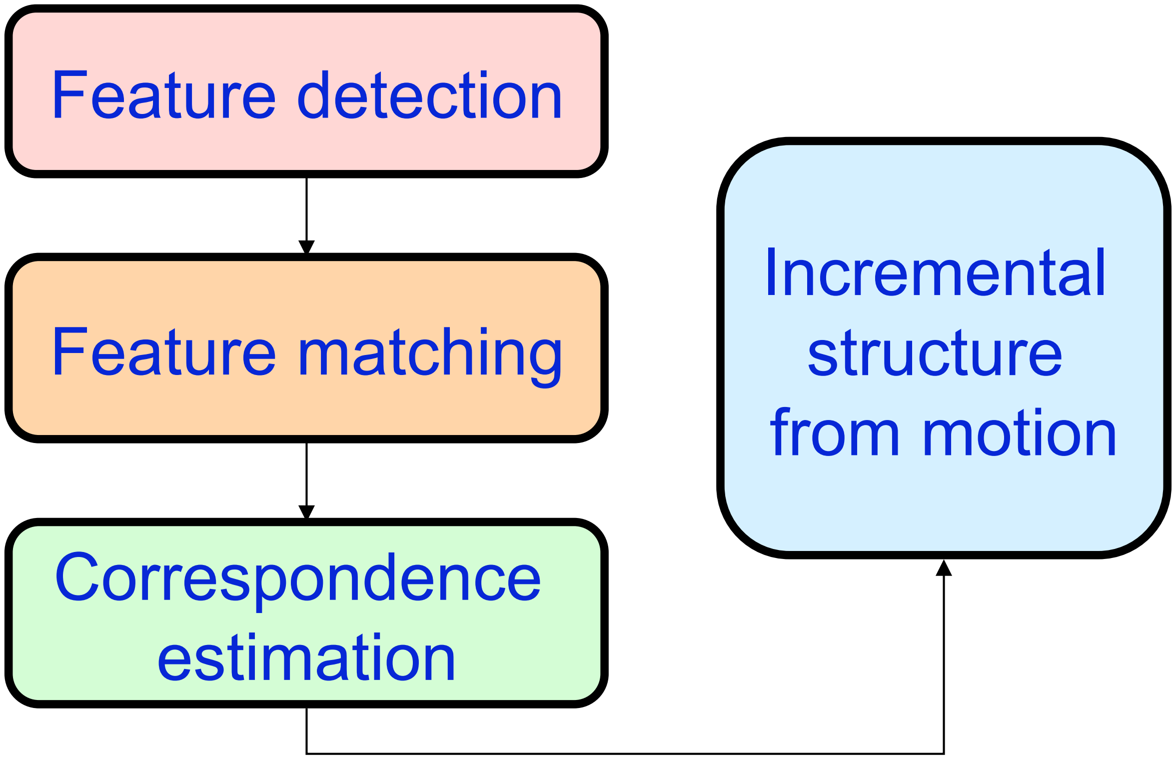


Slide: N. Snavely

Scene reconstruction

Automatically estimate

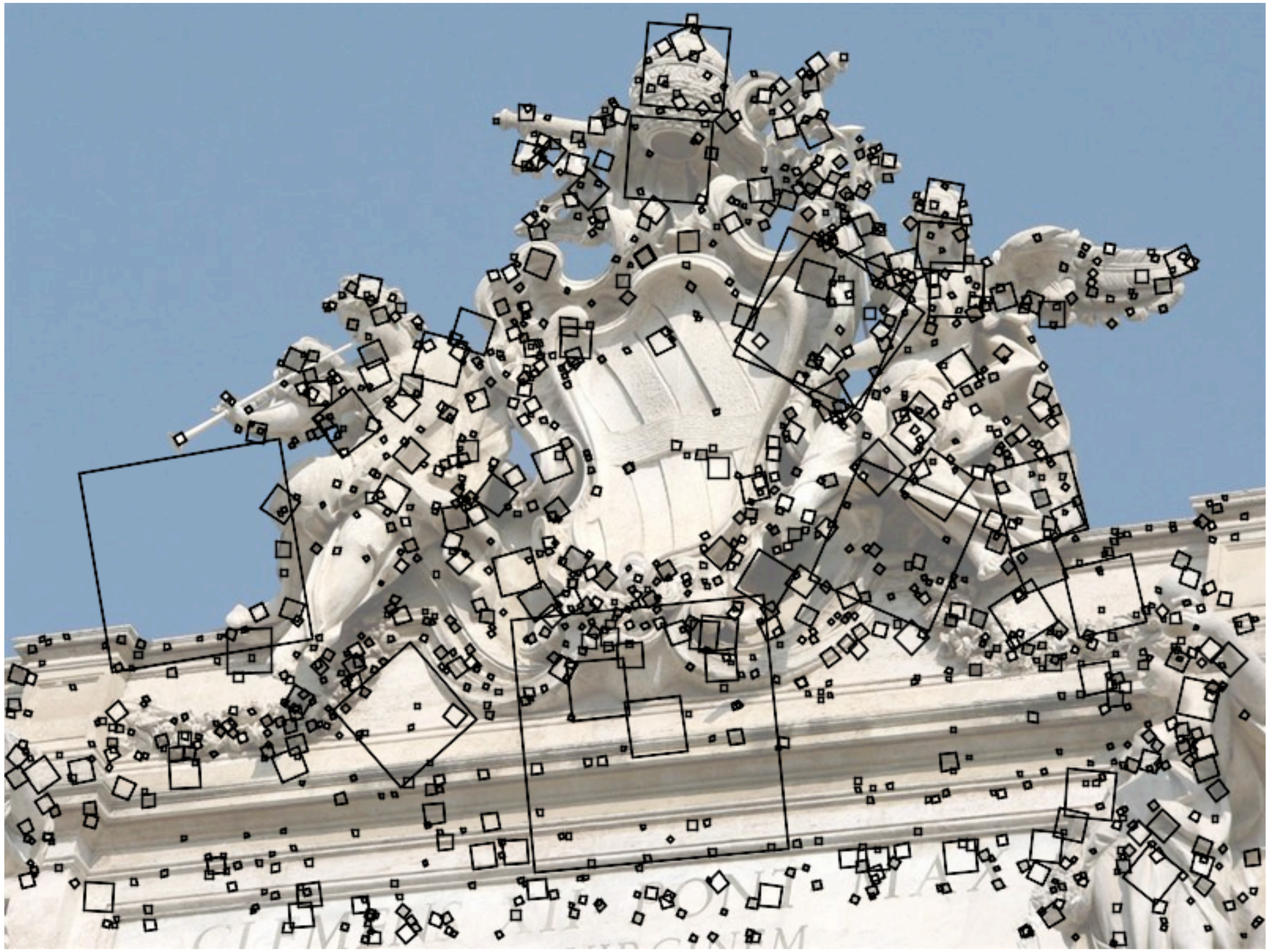
- position, orientation, and focal length of cameras
- 3D positions of feature points



Slide: N. Snavely

Feature detection

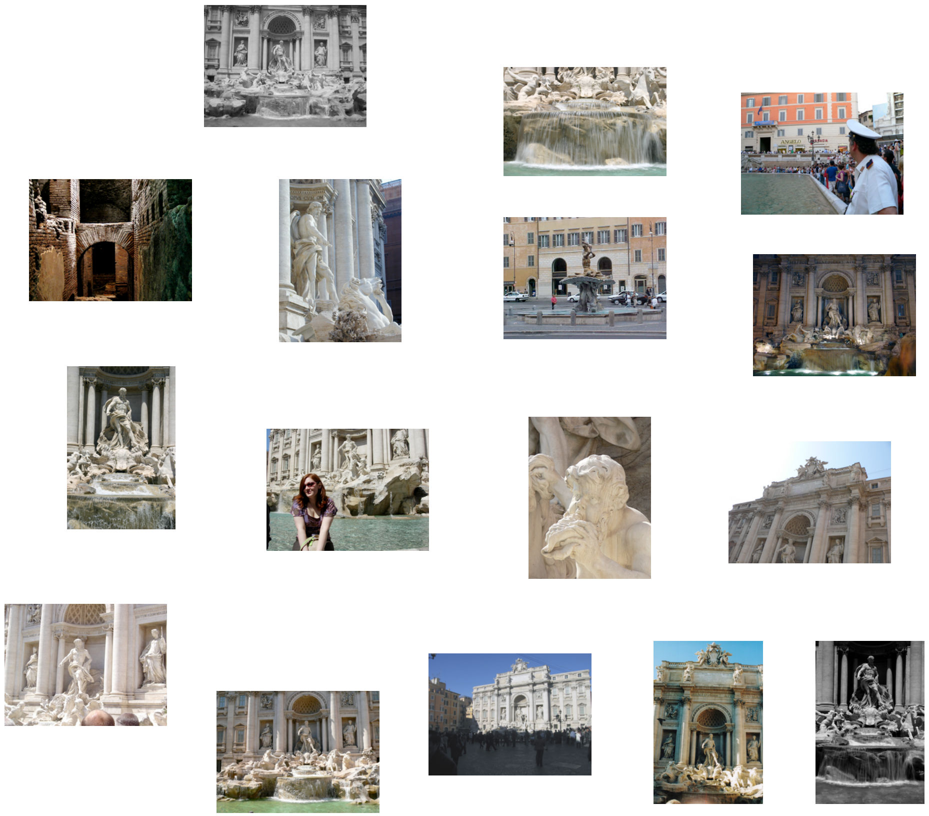
Detect features using SIFT [Lowe, IJCV 2004]



Slide: N. Snavely

Feature detection

Detect features using SIFT [Lowe, IJCV 2004]



Slide: N. Snavely

Feature detection

Detect features using SIFT [Lowe, IJCV 2004]

Slide: N. Snavely

Feature matching

Complexity of matching:

Unfortunately, even with a well optimized implementation of the matching procedure described above, it is not practical to match all pairs of images in our corpus. For a corpus of 100,000 images, this translates into 5,000,000,000 pairwise comparisons, which with 500 cores operating at 10 image pairs per second per core would require about 11.5 days to match. Furthermore, this does not even take into account the network transfers required for all cores to have access to all the SIFT feature data for all images.

From Agarwal et al. “Building Rome in a Day”, ICCV’09

Feature matching

Obtain candidate pairs of images to match using
visual vocabulary matching based on k-means tree

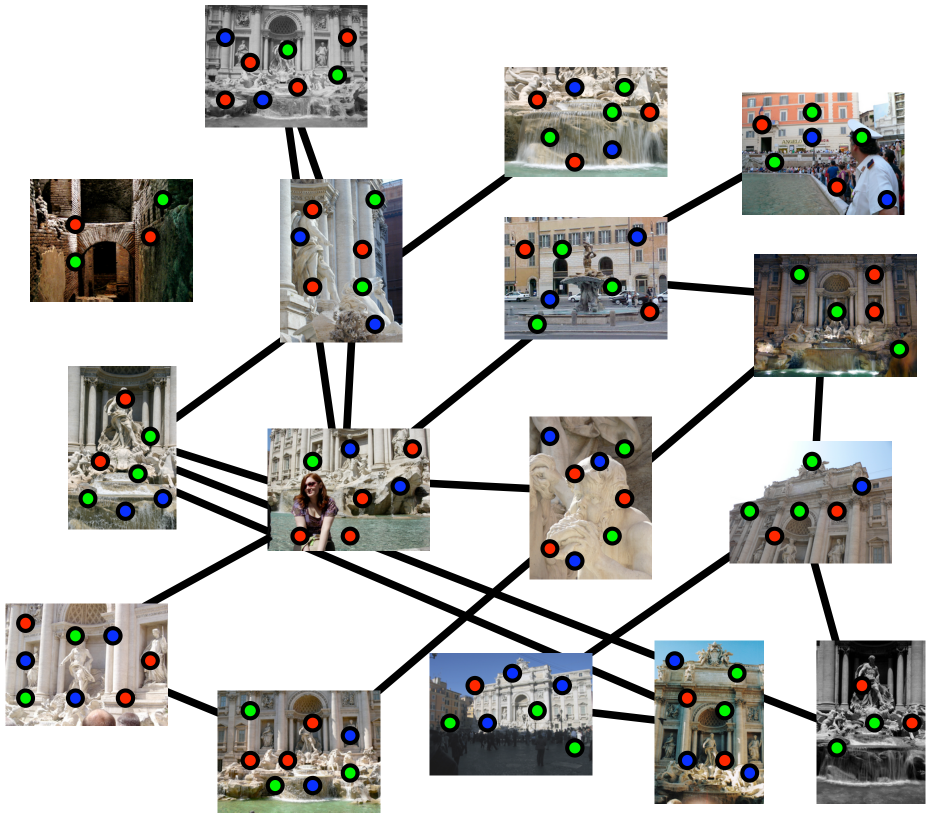


Figure: N. Snavely

Feature matching

Match features between candidate pairs using
K-d trees built on SIFT descriptors.

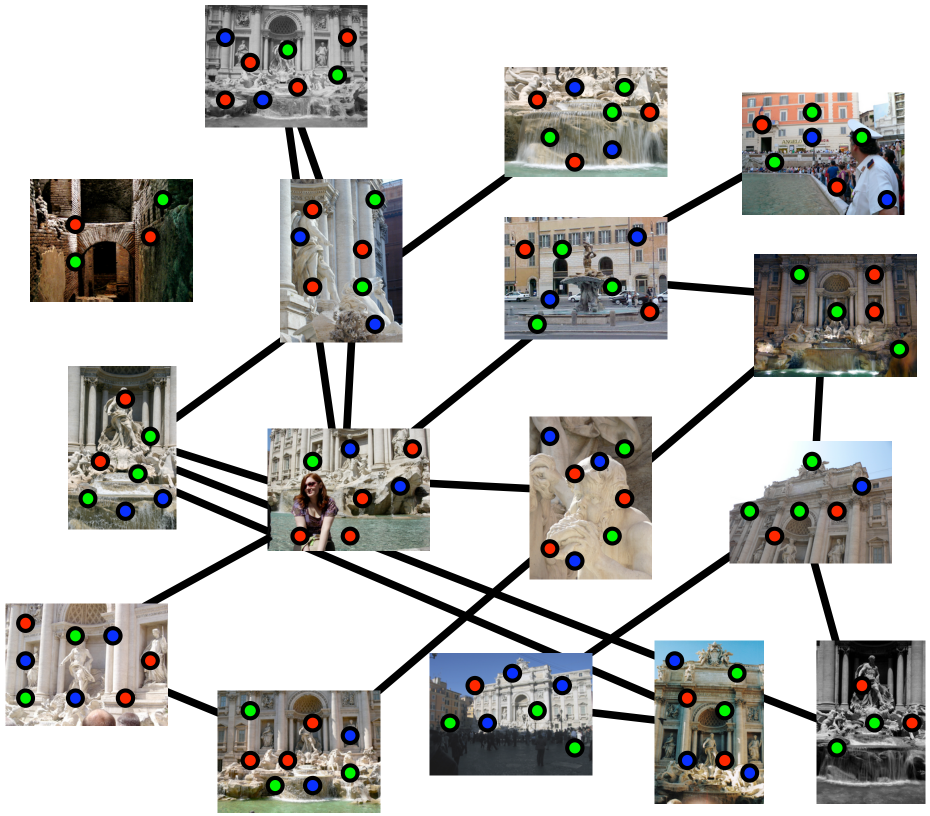
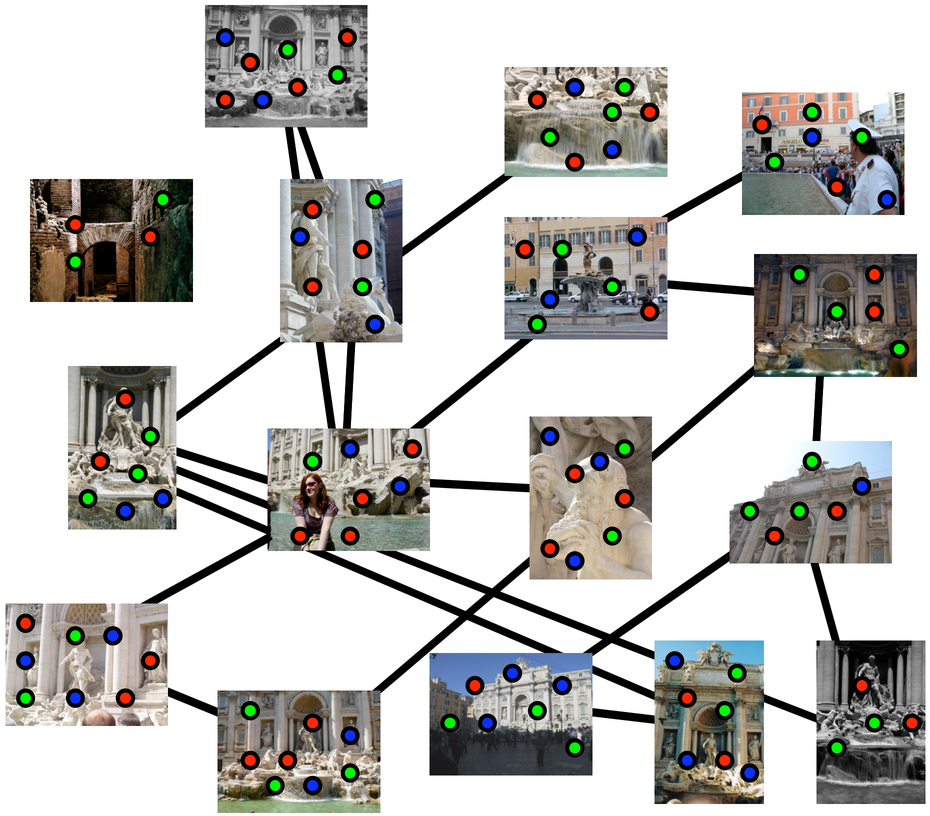


Figure: N. Snavely

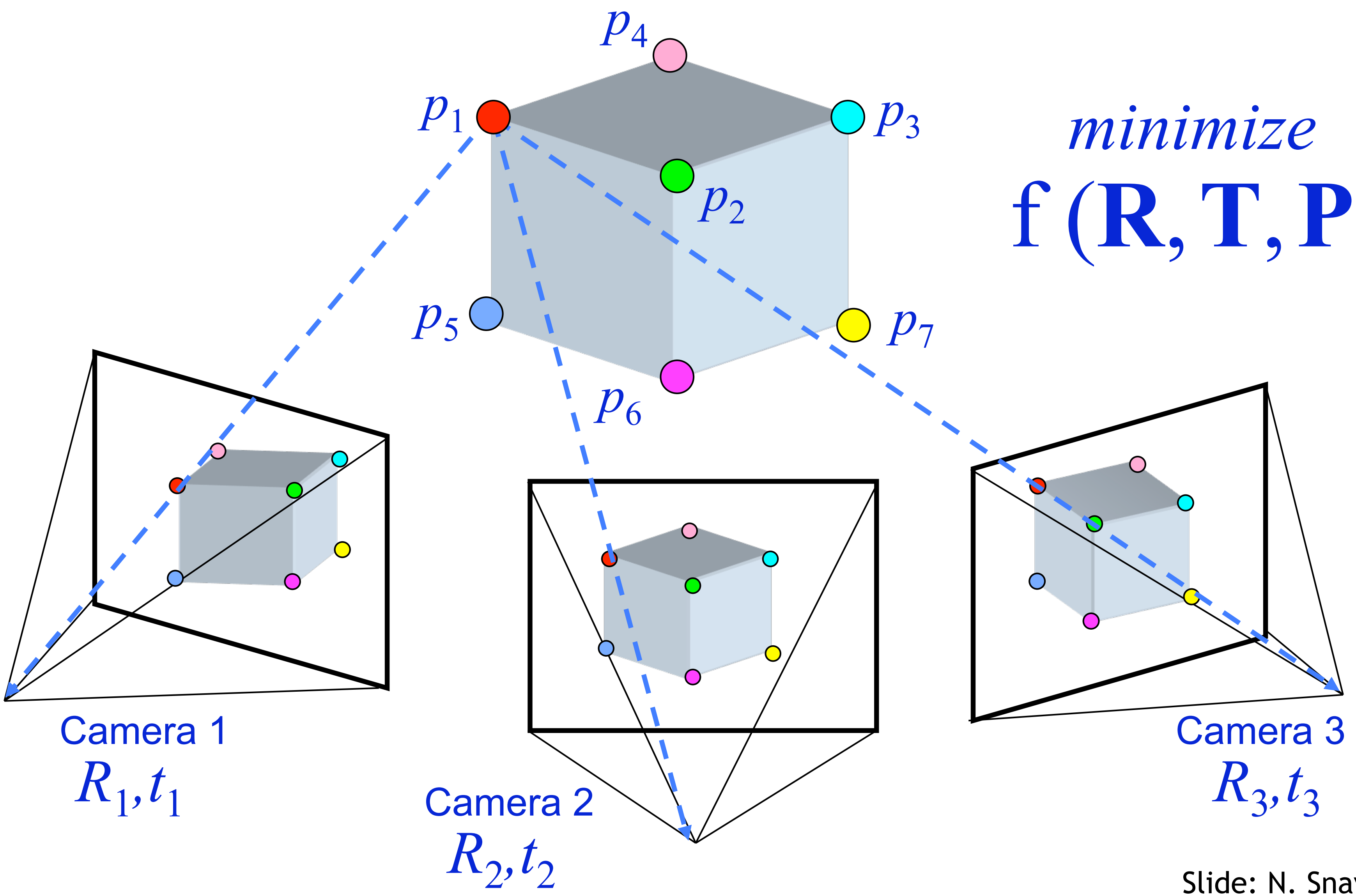
Feature matching

Refine matching using RANSAC [Fischler & Bolles 1987] to estimate fundamental matrices between pairs



Slide: N. Snavely

Structure from motion (R. Keriven's class)

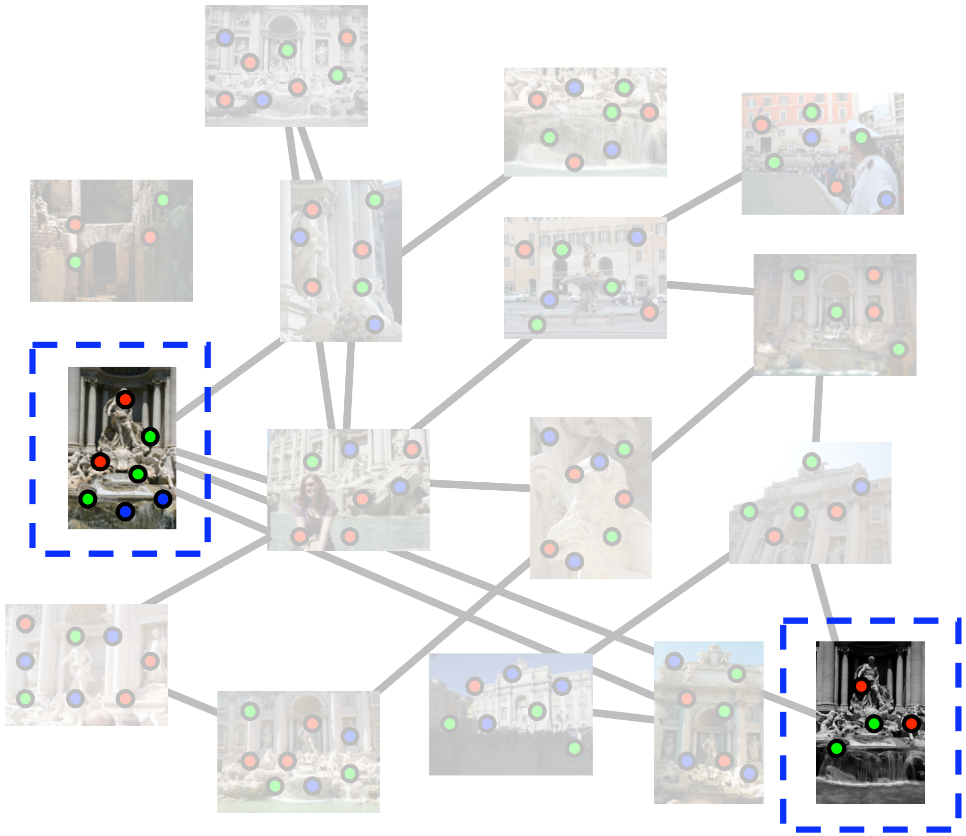


minimize

$$f\,(\mathbf{R},\mathbf{T},\mathbf{P})$$

Slide: N. Snavely

Incremental structure from motion

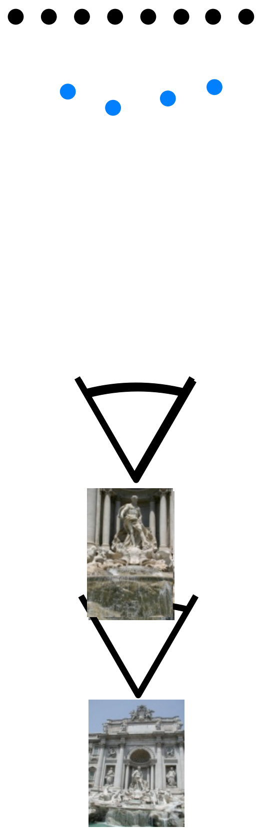


Slide: N. Snavely

Incremental structure from motion

Slide: N. Snavely

Incremental structure from motion



Slide: N. Snavely

Reconstruction and photo explorer

[Agarwal, Snavely, Simon, Seitz and Szeliski ’09]

•150,000 images from Flickr.com associated with the tags "Rome" or "Roma"

• Matching and reconstruction: 21 hours on a cluster with 496 compute cores

Slide: N. Snavely

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Slide: N. Snavely

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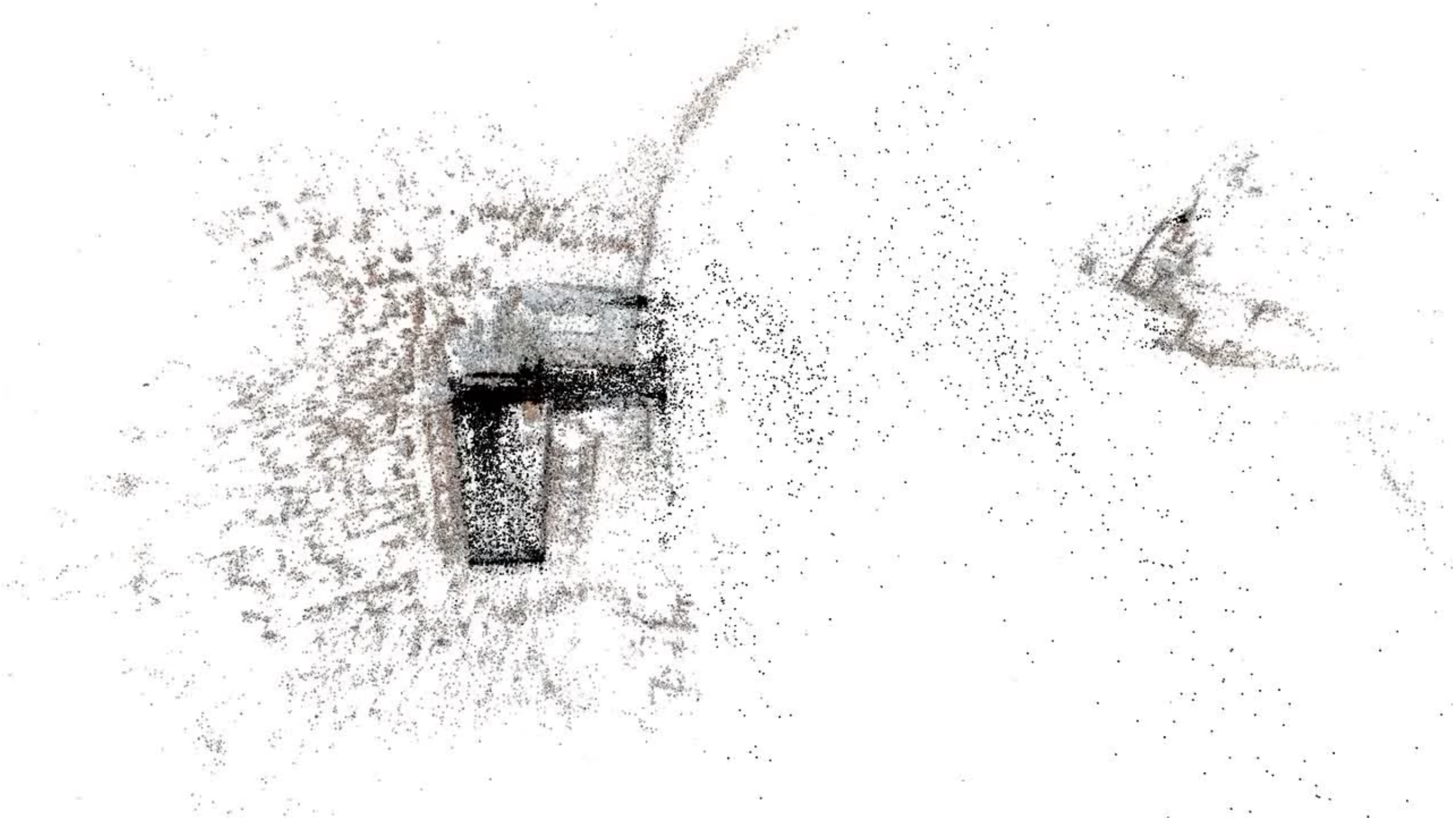

- 250,000 Venice images from Flickr.com
- Matching and reconstruction: 27 hours on a cluster with 496 compute cores

Slide: N. Snavely

Reconstruction and photo explorer

[Agarwal, Snavely, Simon, Seitz and Szeliski ’09]

- 250,000 Venice images from Flickr.com
- Matching and reconstruction: 27 hours on a cluster with 496 compute cores

Slide: N. Snavely

Example of the final 3D point cloud and cameras

57,845 downloaded images, 11,868 registered images. This video: 4,619 images.

The end