Visual Recognition and Machine Learning Summer School

Grenoble 2010

Instance-level recognition – part 3

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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

1. Local invariant features (45 mins, C. Schmid)

2. Matching and recognition with local features (45 mins, J. Sivic)

3. **Efficient visual search (45 mins, J. Sivic)**

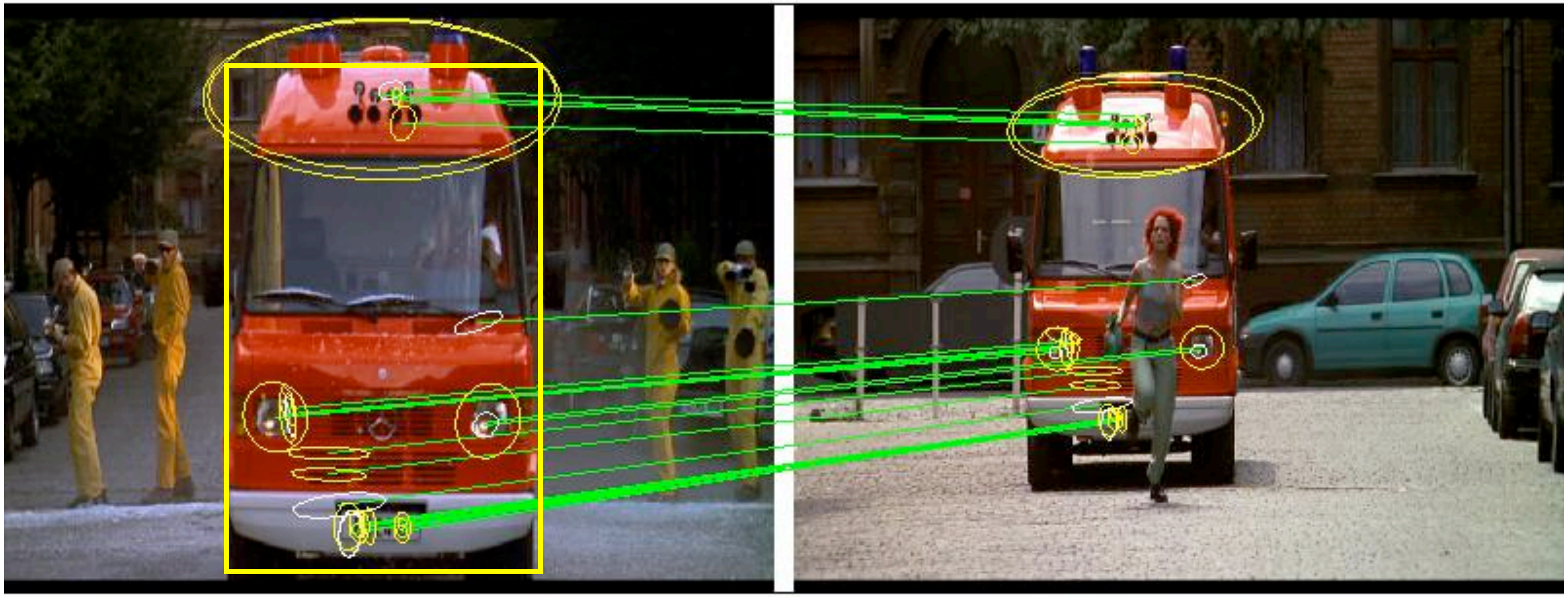
4. Very large scale visual indexing – recent work (45 mins, C. Schmid)

Practical session (60 mins)

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 (Part 2).

What about multiple images?

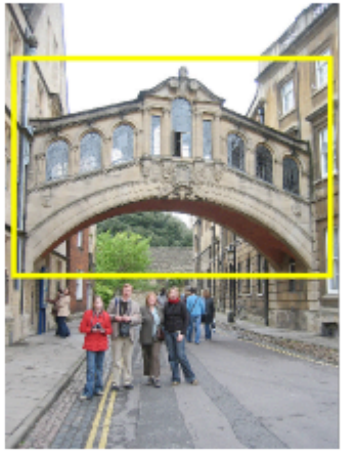
- So far, we have seen successful matching of a query image to a single target image using local features.

- 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 a large photo-collection

Given a query image, find images depicting the same place / object in a large unordered image collection.

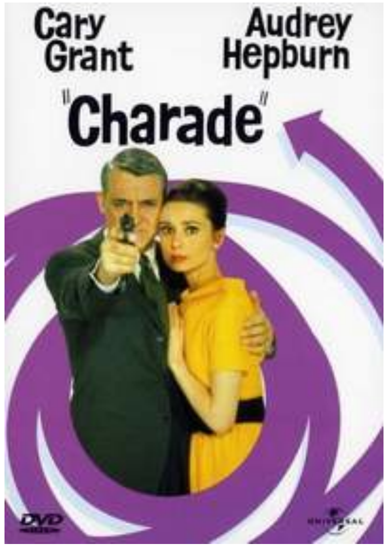


Find these landmarks ...in these images and 1M more

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!

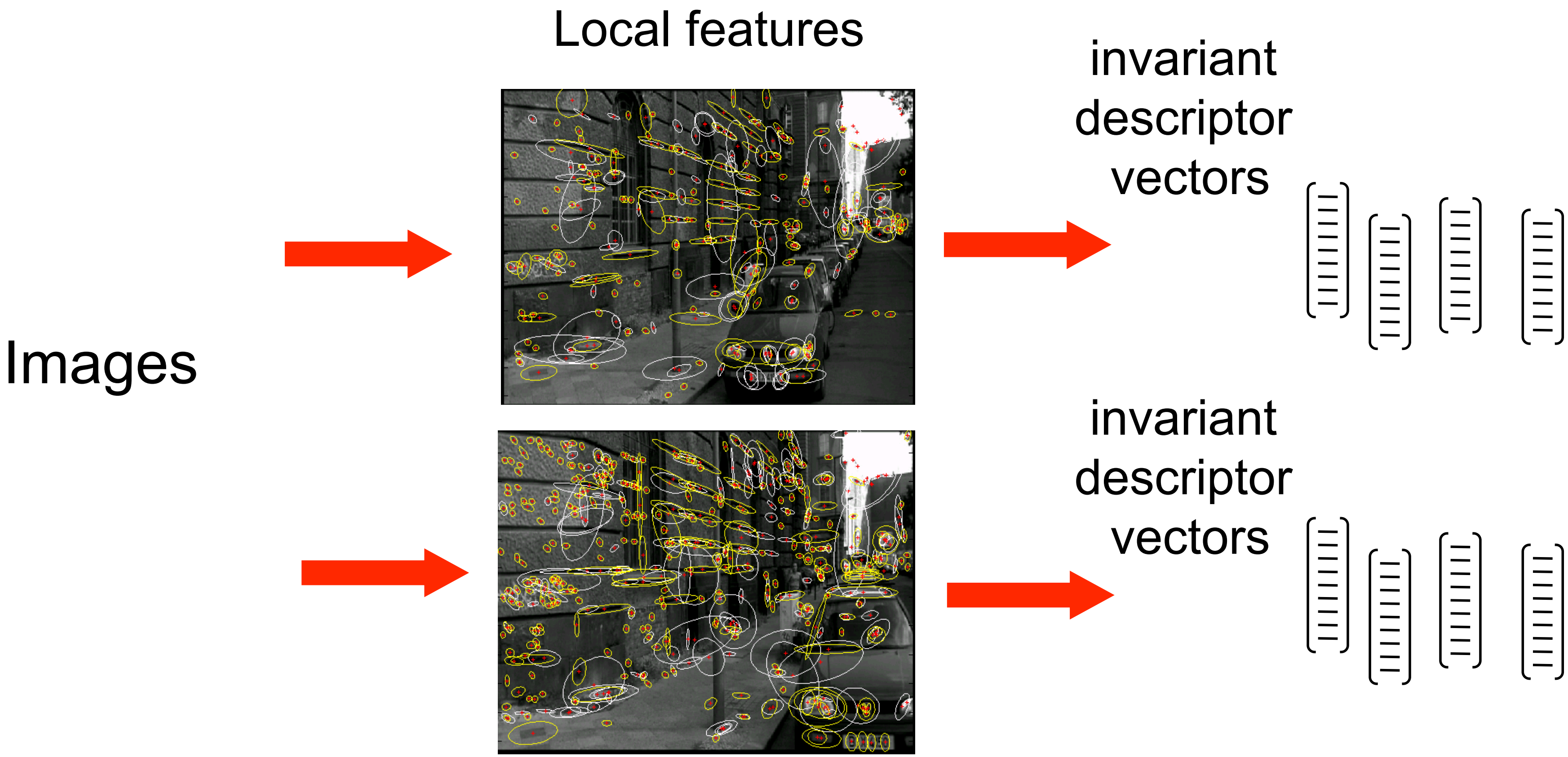
Two strategies

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)

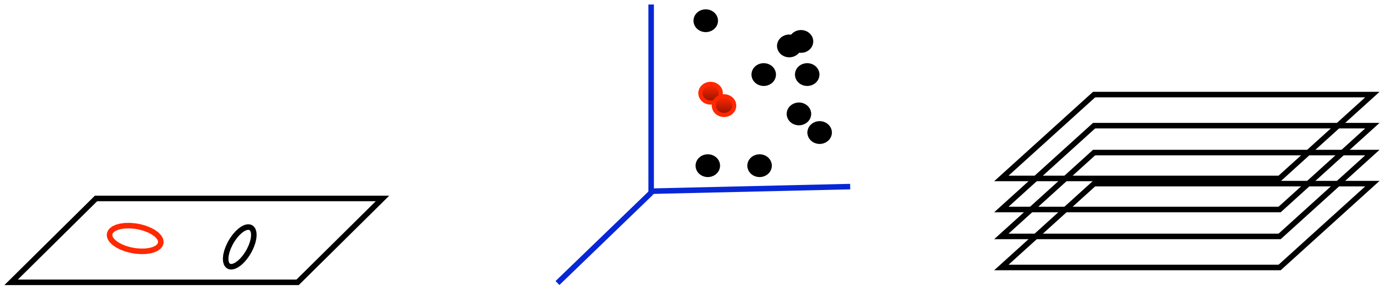
Strategy I: Efficient approximate NN search



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:

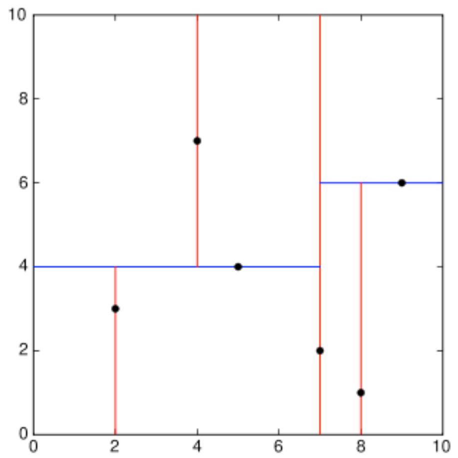
$$\forall j \; NN(j) = \arg\min_i ||\mathbf{x}_i - \mathbf{x}_j||$$

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

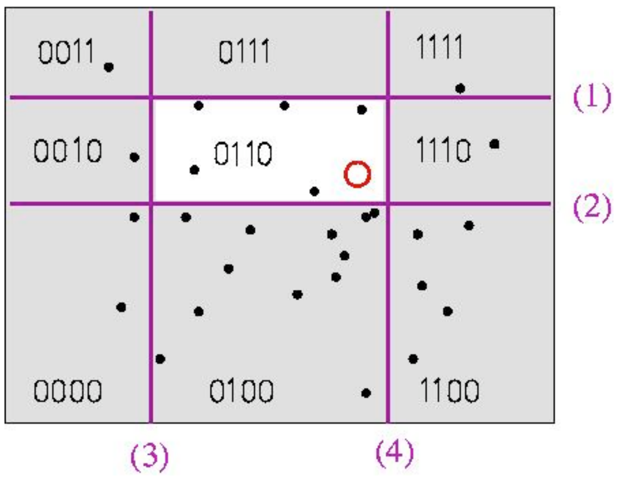
Nearest-neighbour matching is the major computational bottleneck

- 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



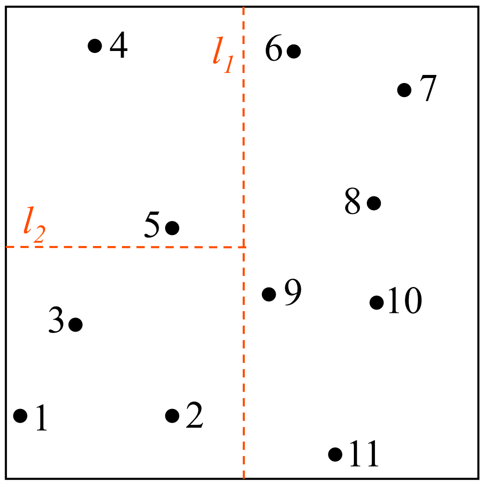
Best-Bin First (BBF), a variant of k-d trees that uses priority queue to examine most promising branches first [Beis & Lowe, CVPR 1997]

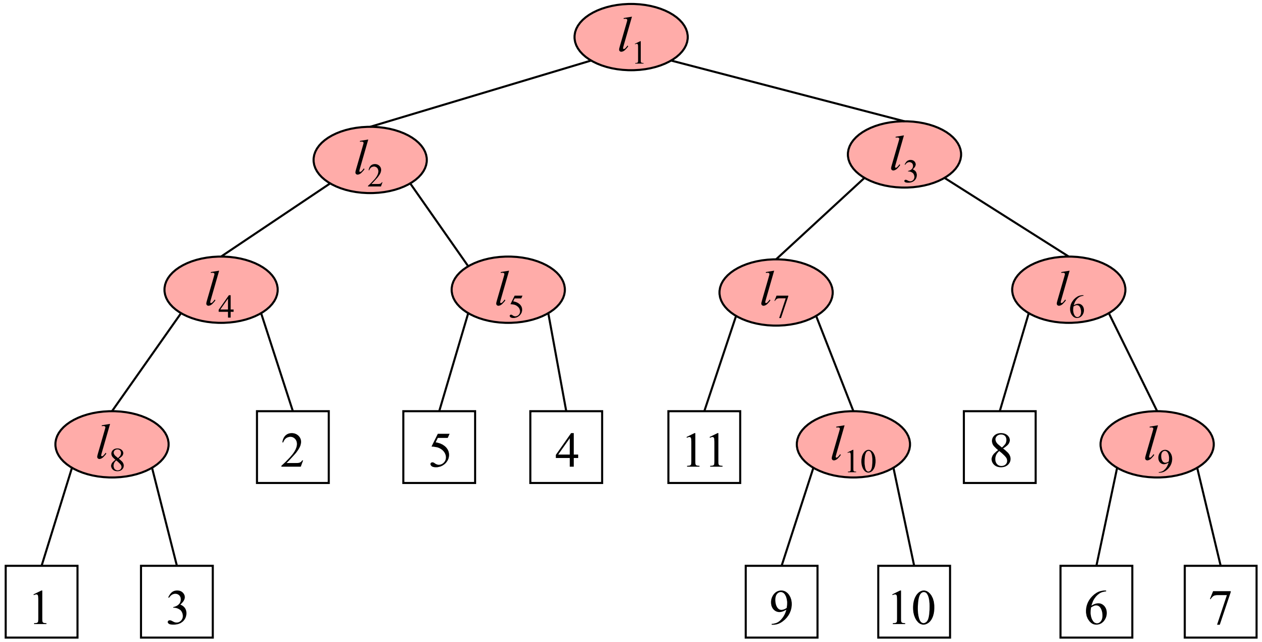


Locality-Sensitive Hashing (LSH), a randomized hashing technique using hash functions that map similar points to the same bin, with high probability [Indyk & Motwani, 1998]

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.

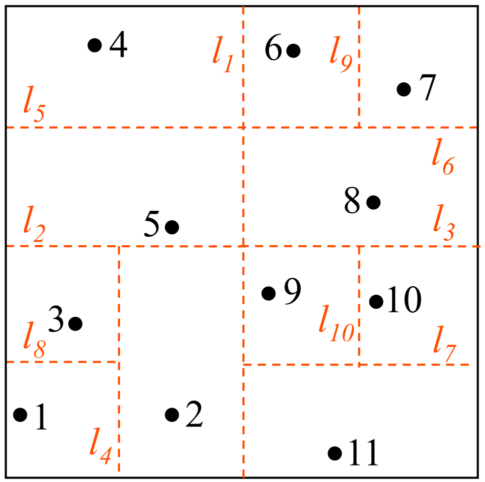


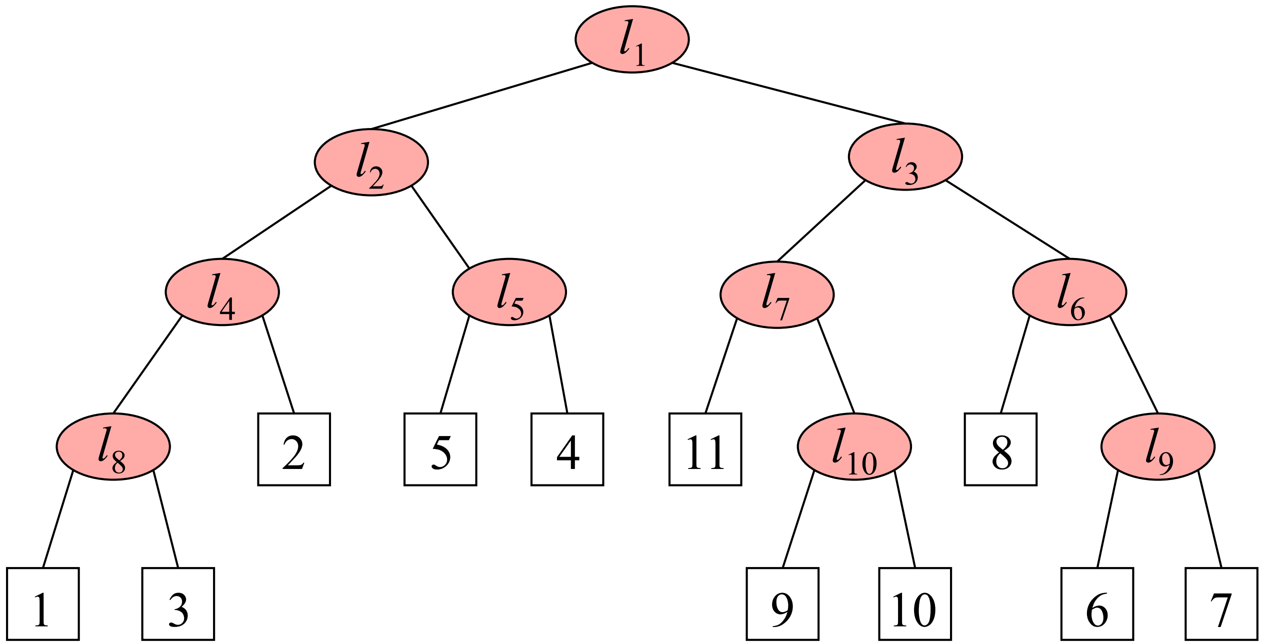


Images: Anna Atramentov

K-d tree construction

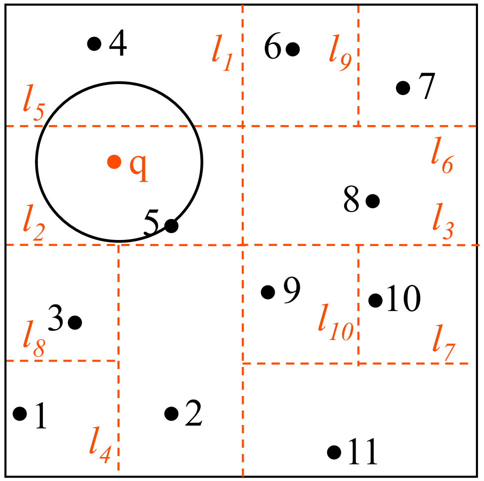
Simple 2D example

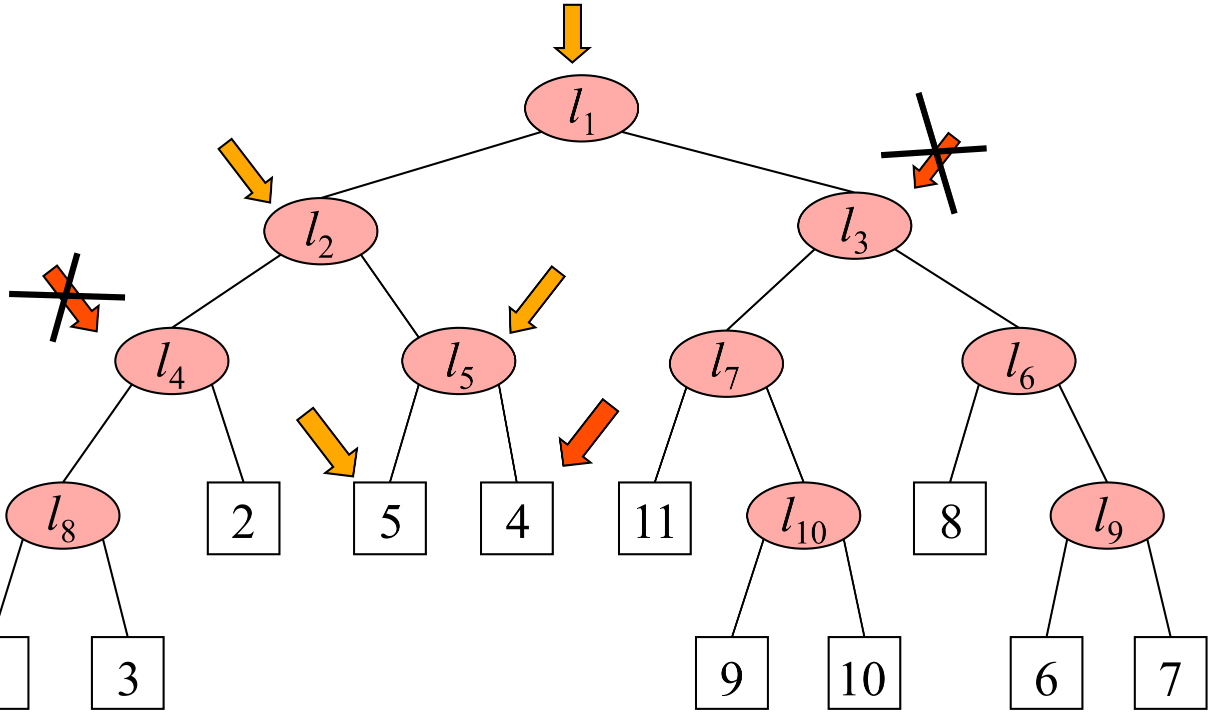




Slide credit: Anna Atramentov

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.

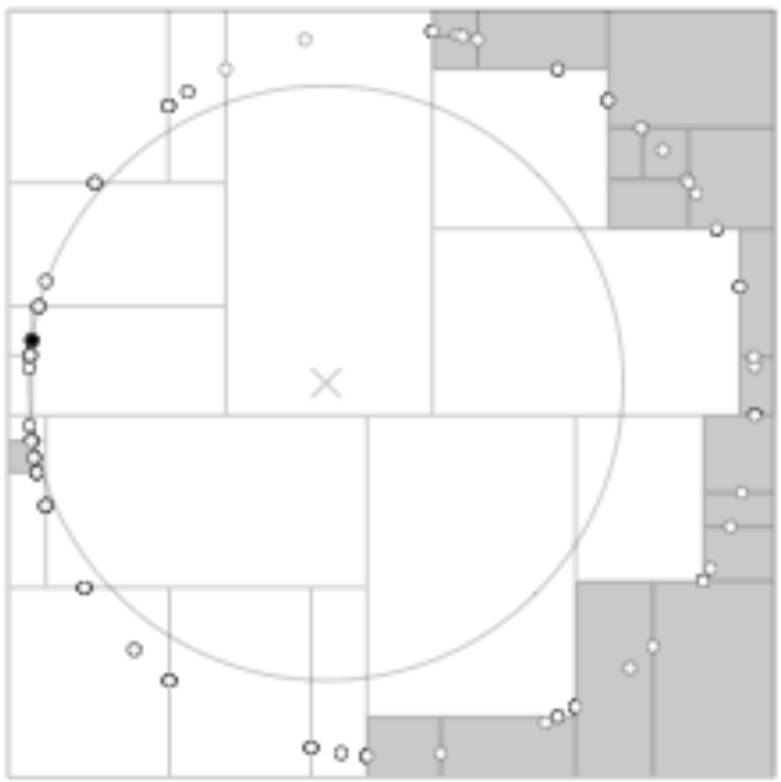


Figure 6.6

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

Figure: A. Moore

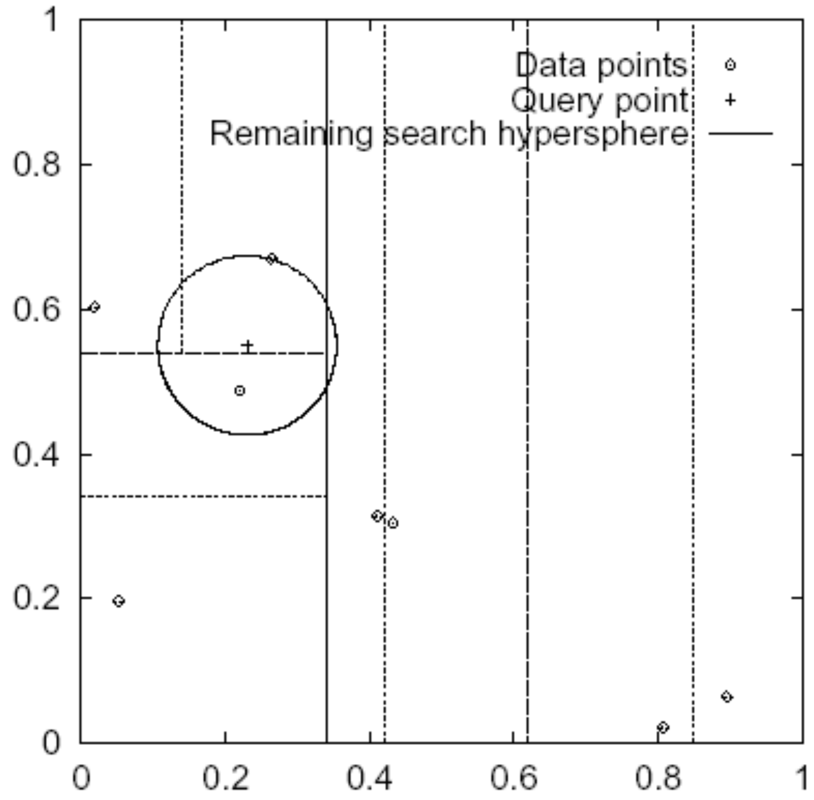
Solution: Approximate nearest neighbor K-d tree

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

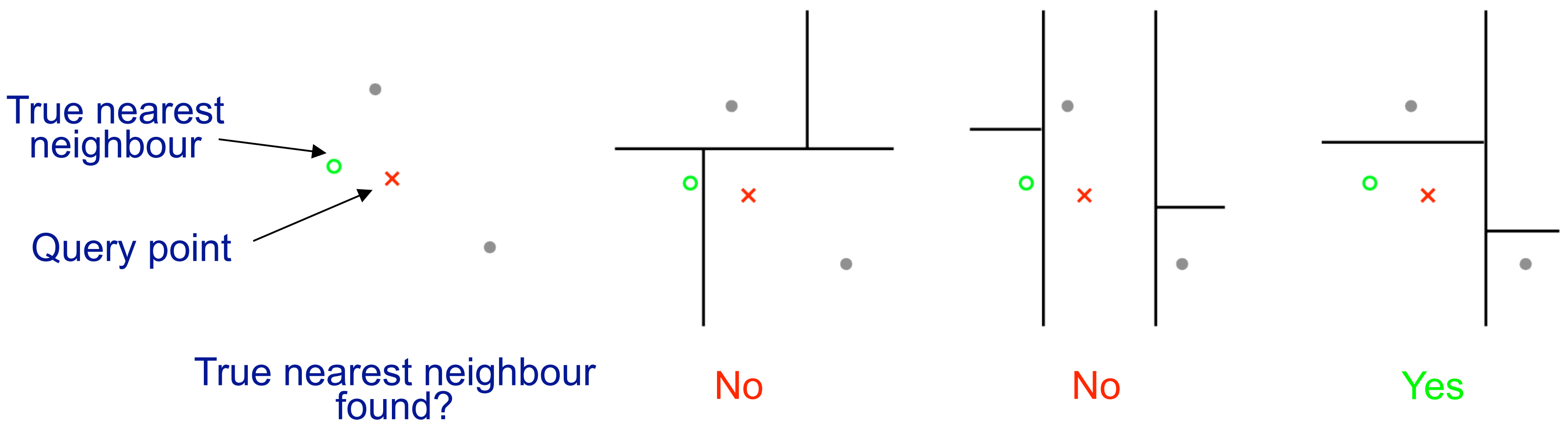


• Reduce the boundary effects by randomization

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

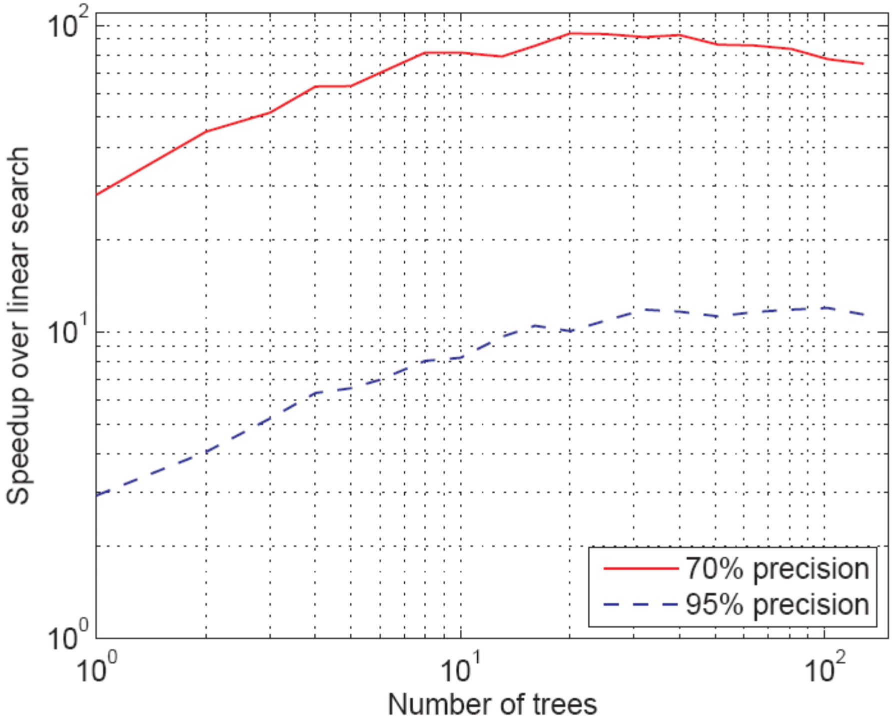
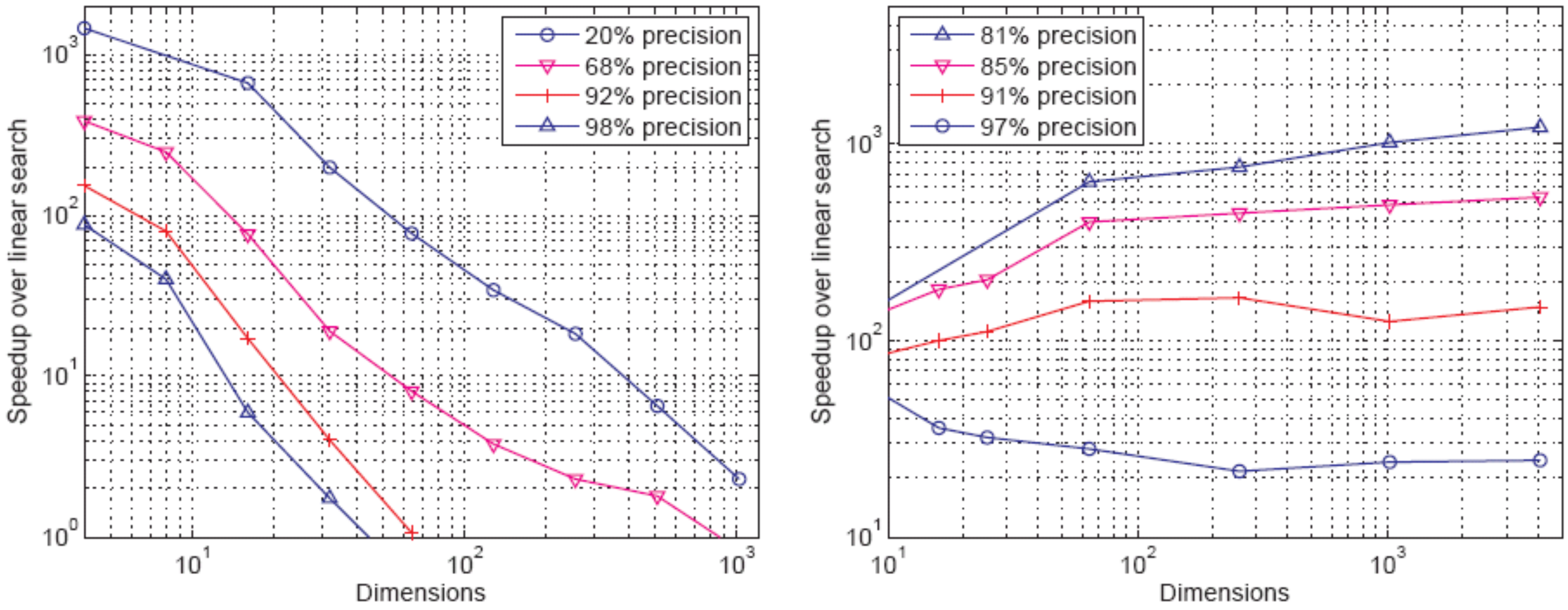


Figure 2: Speedup obtained by using multiple random kd-trees (100K SIFT features dataset)

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:

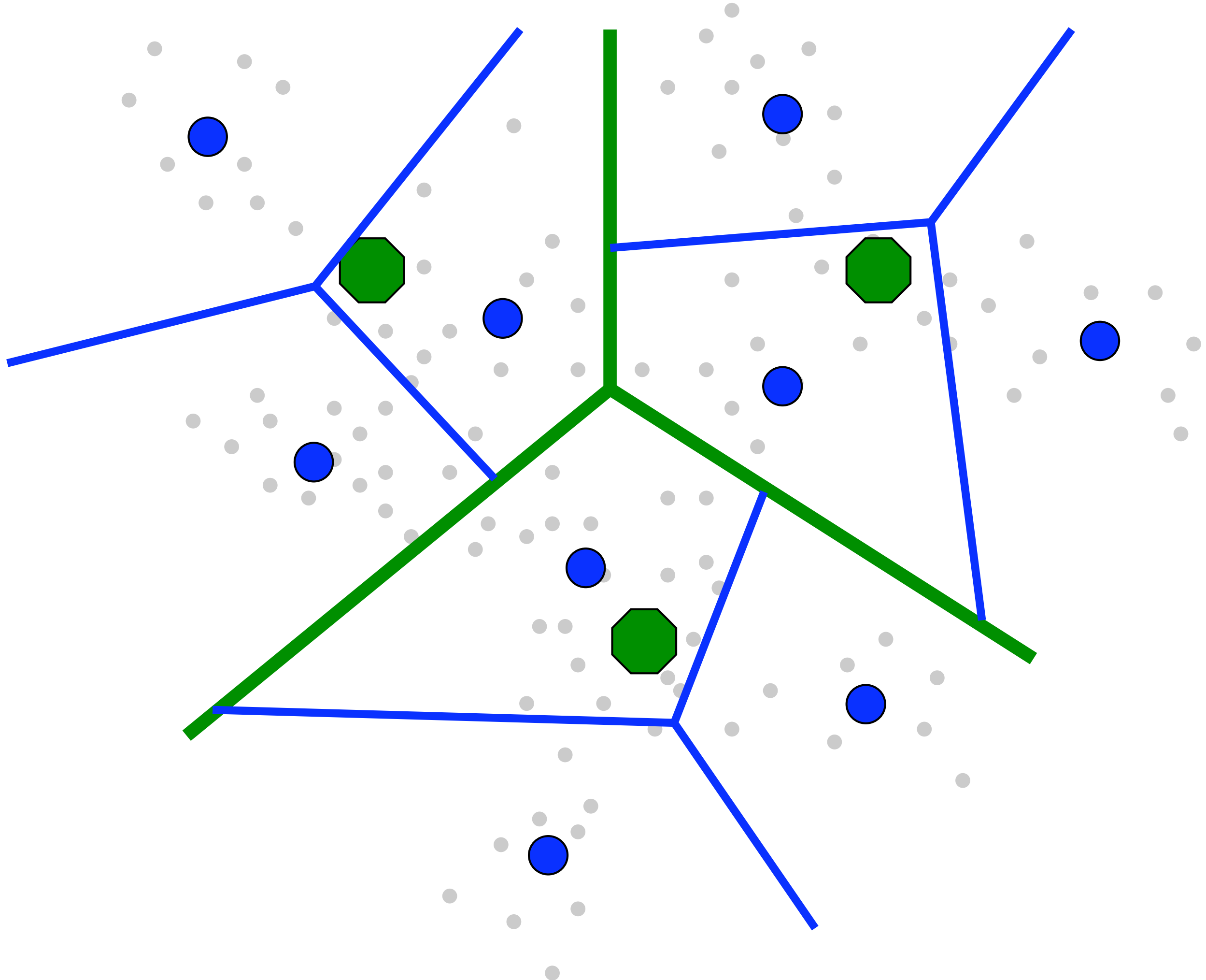


Figure credit: David Nister

Example

Query look-up:

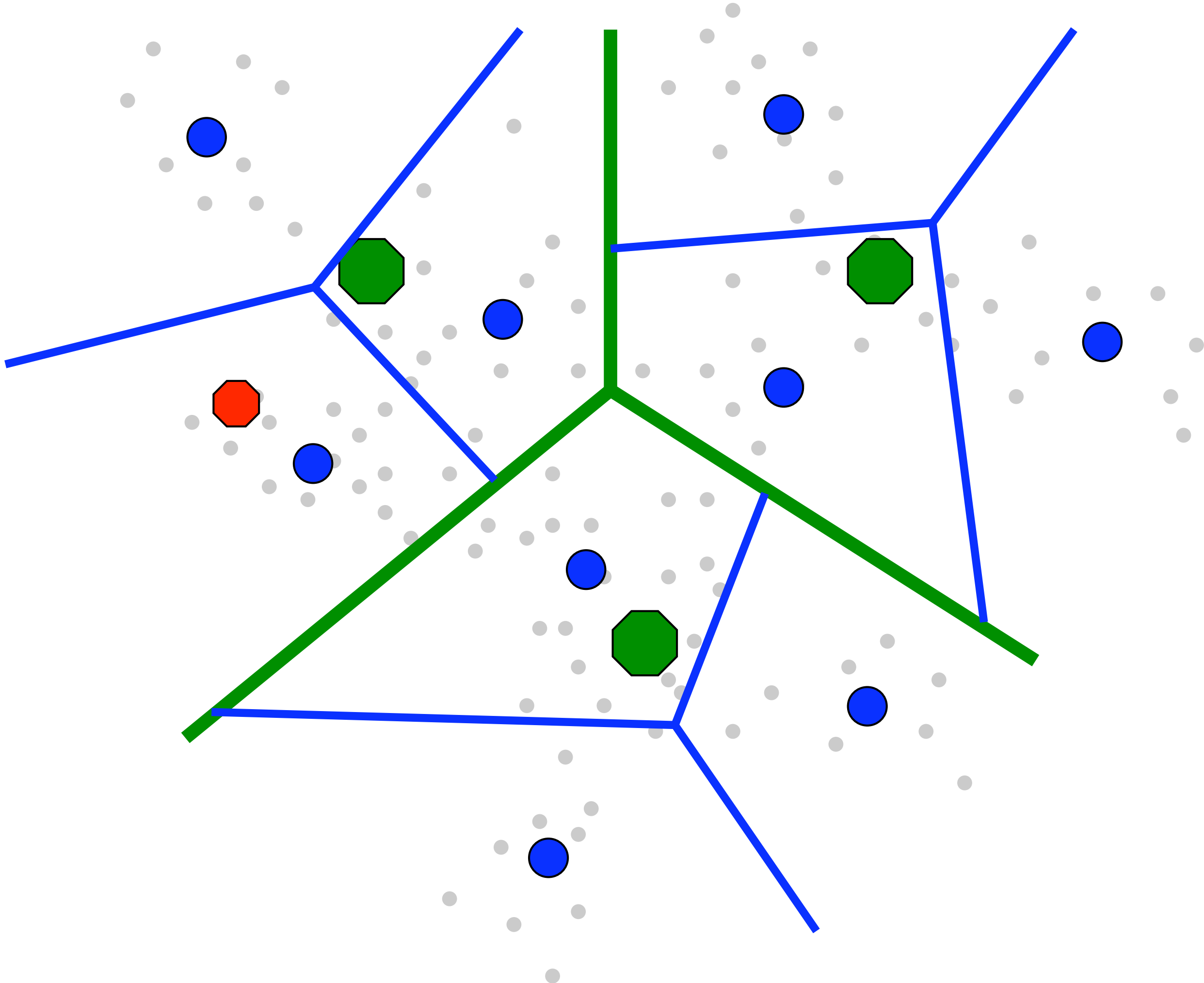
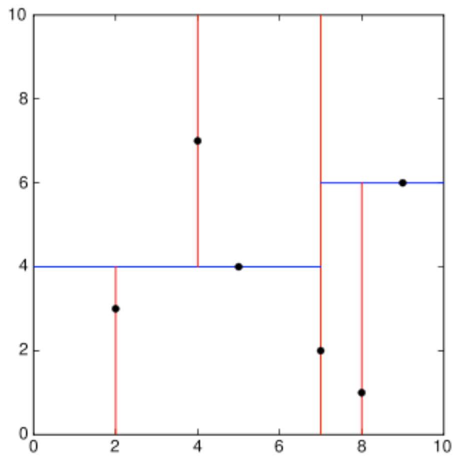


Figure credit: David Nister

Indexing local features: approximate nearest neighbor search



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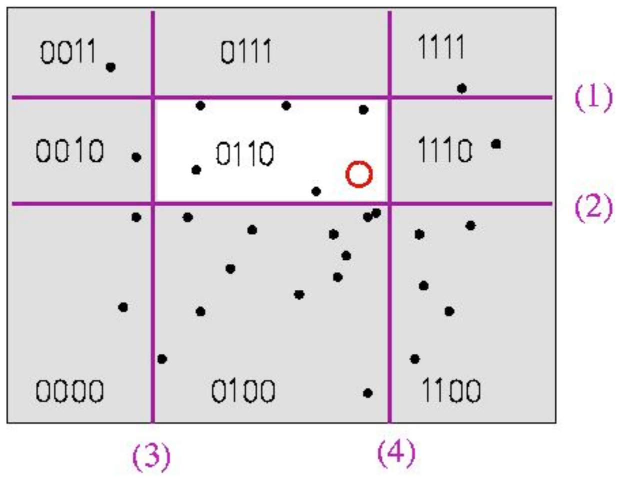


Locality-Sensitive Hashing (LSH), a randomized hashing technique using hash functions that map similar points to the same bin, with high probability [Indyk & Motwani, 1998]

Locality Sensitive Hashing (LSH)

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

for any points p,q:

If $||p-q|| \le r$, 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

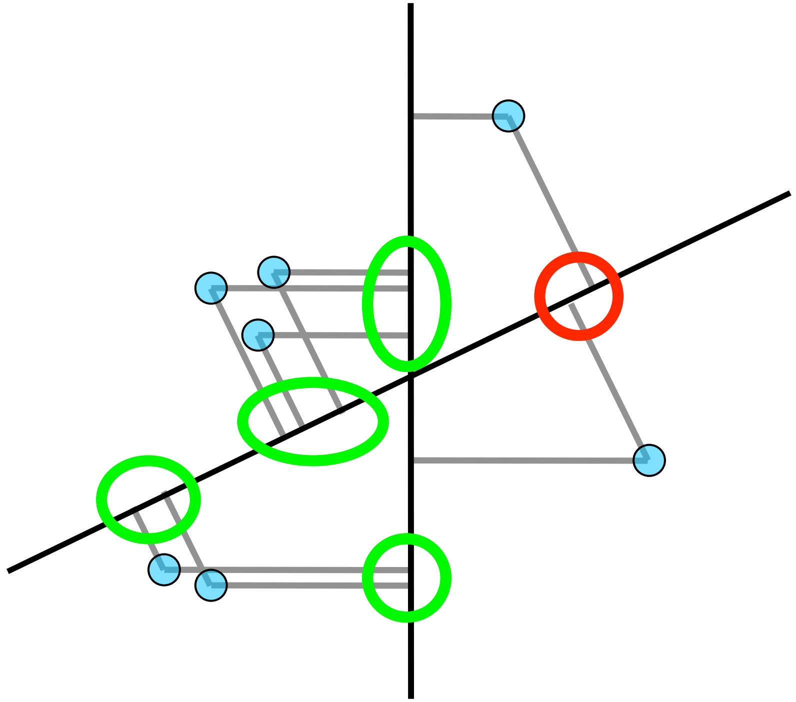
$g(p)=<h_1(p),h_2(p),\ldots,h_k(p)>$, where $h_{X,b}(p)=\lfloor (p*X+b)/w \rfloor$

$\lfloor . \rfloor$ 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



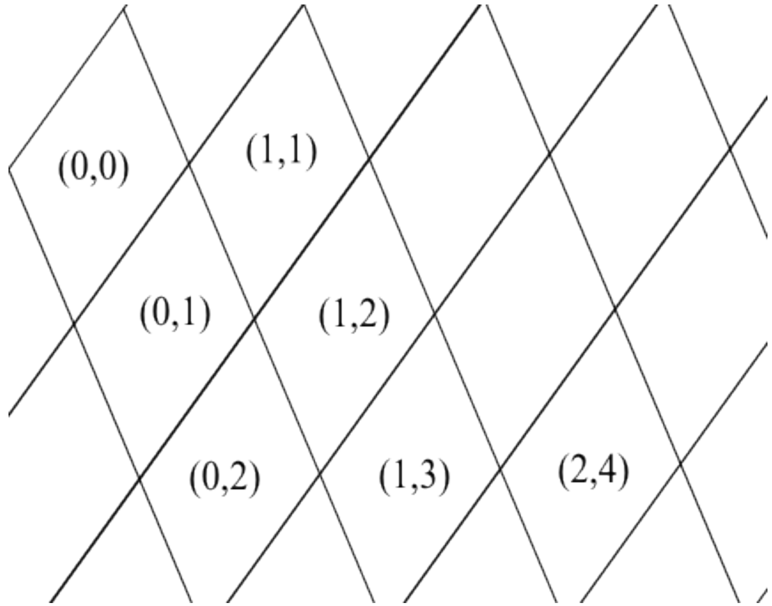
- Answer: use multiple quantized projections which define a high-dimensional “grid”

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.

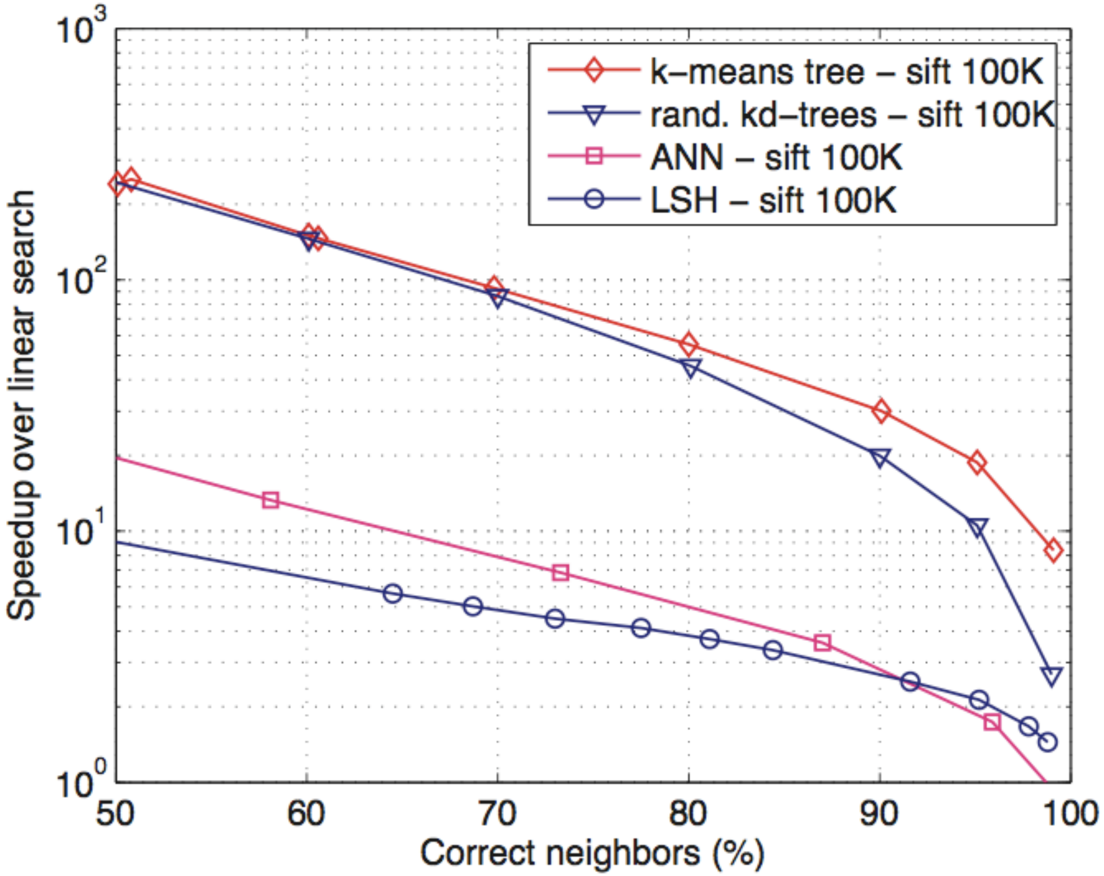
In practice, LSH has high memory requirements as large number of projections/hash tables are needed.

Code and more materials available online:
http://www.mit.edu/~andoni/LSH/

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

So far …

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

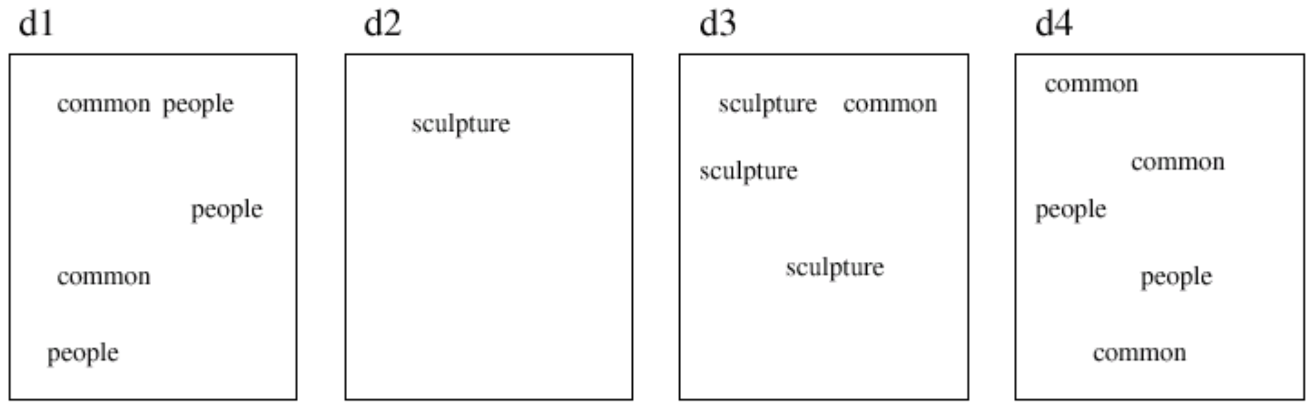
- Answer (so far): approximate NN search methods
  - Randomized KD-trees
  - Locality sensitive hashing

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

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

Indexing text with inverted files

Document collection:



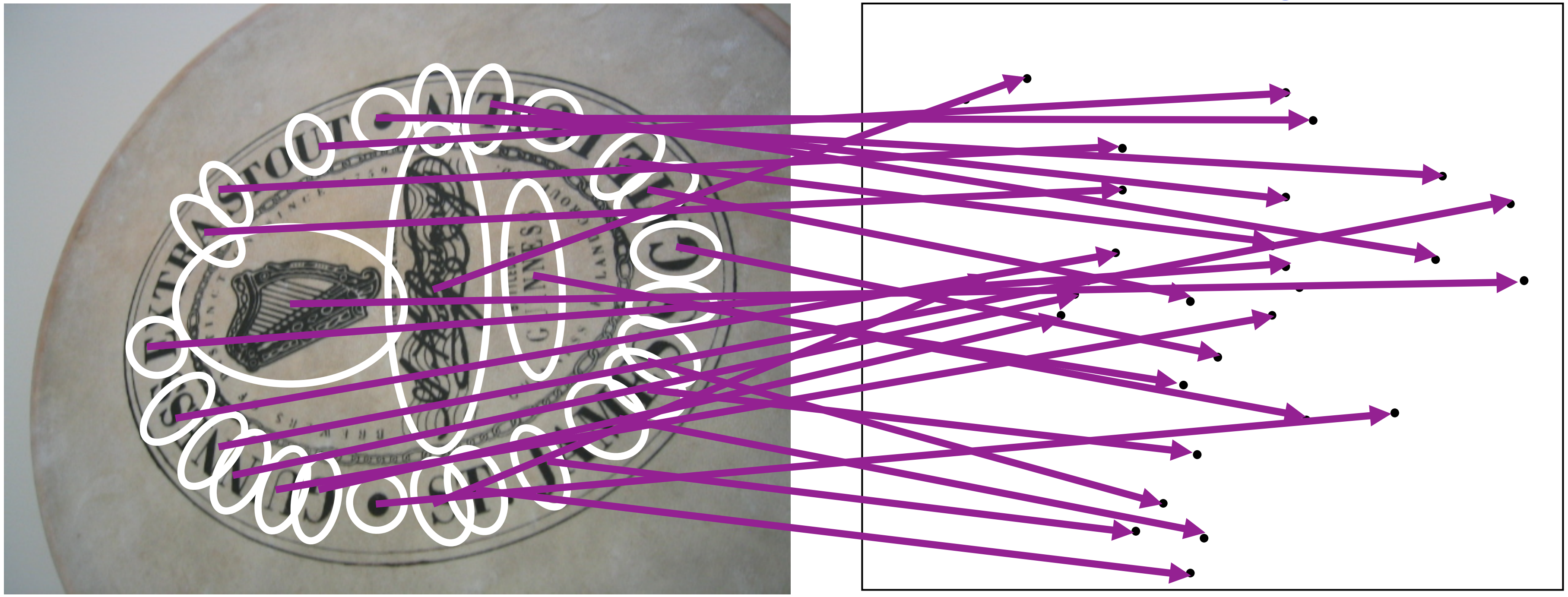
Inverted file:

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 …

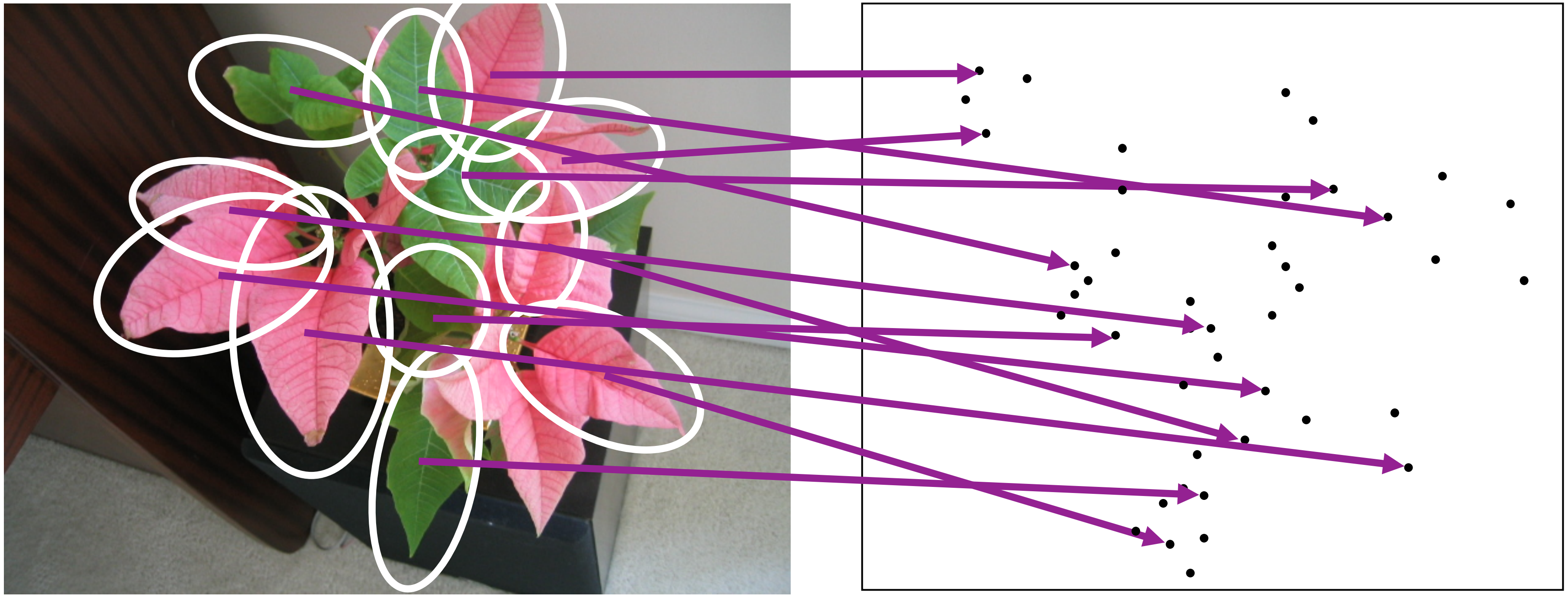


e.g., SIFT descriptor space: each point is 128-dimensional

Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

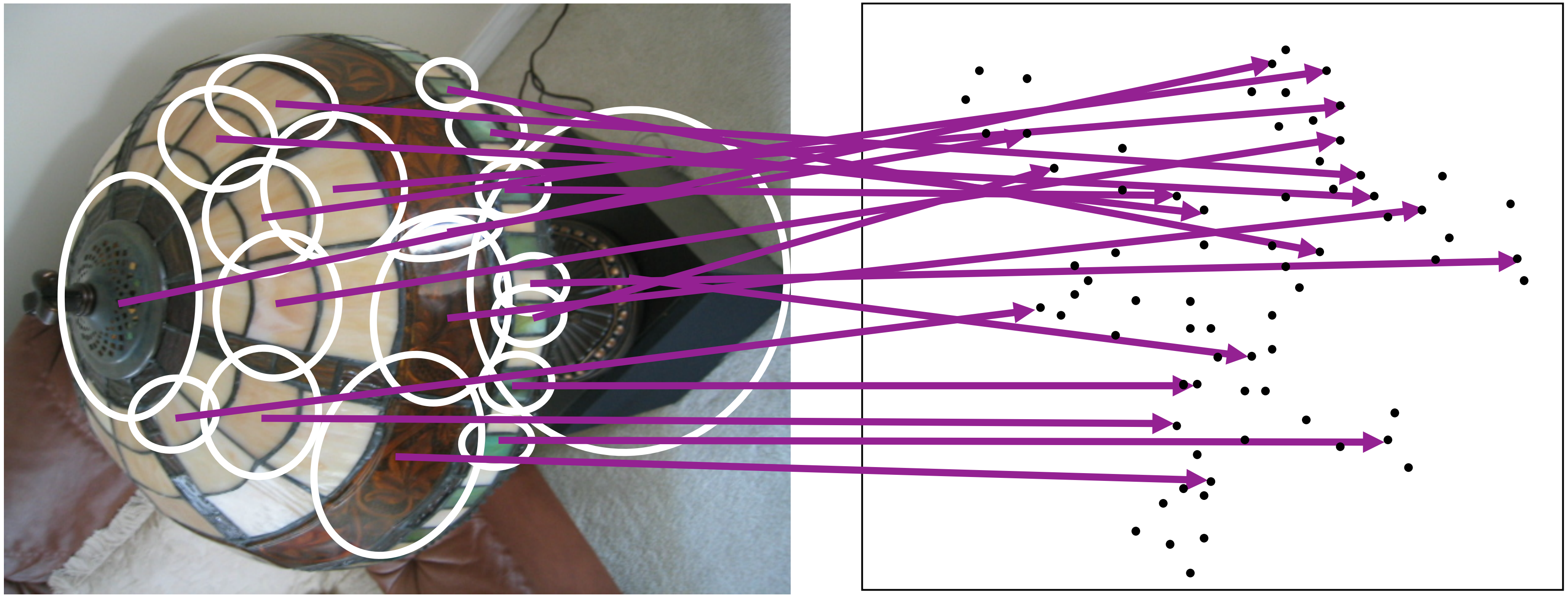
Visual words: main idea



Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

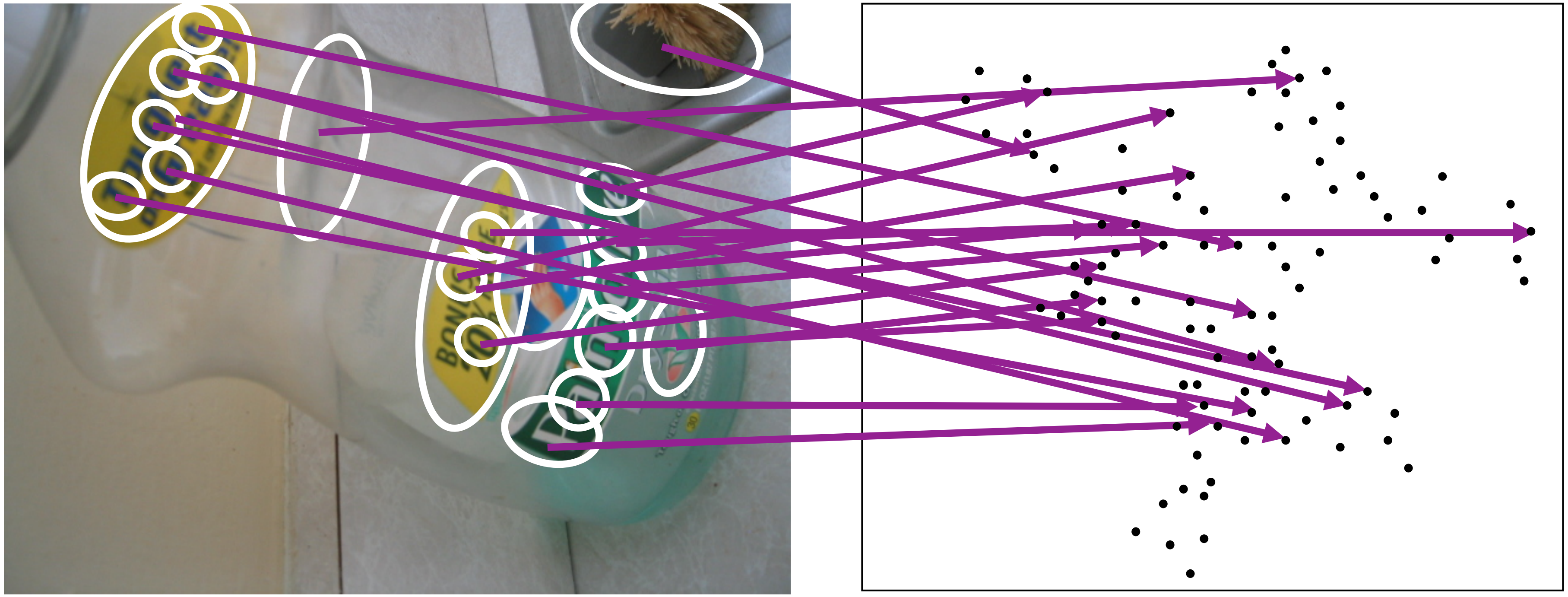
Visual words: main idea



Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

Visual words: main idea



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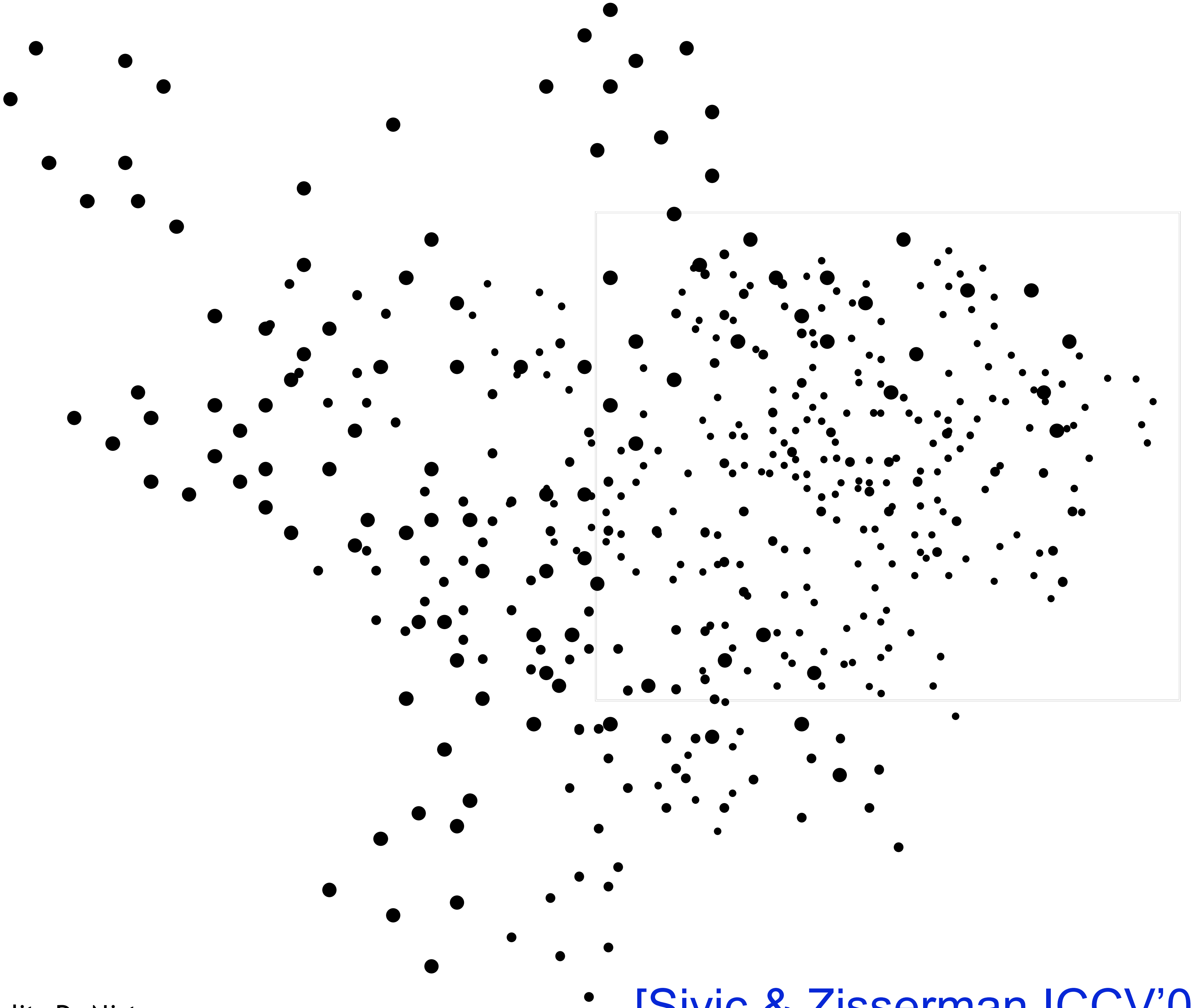
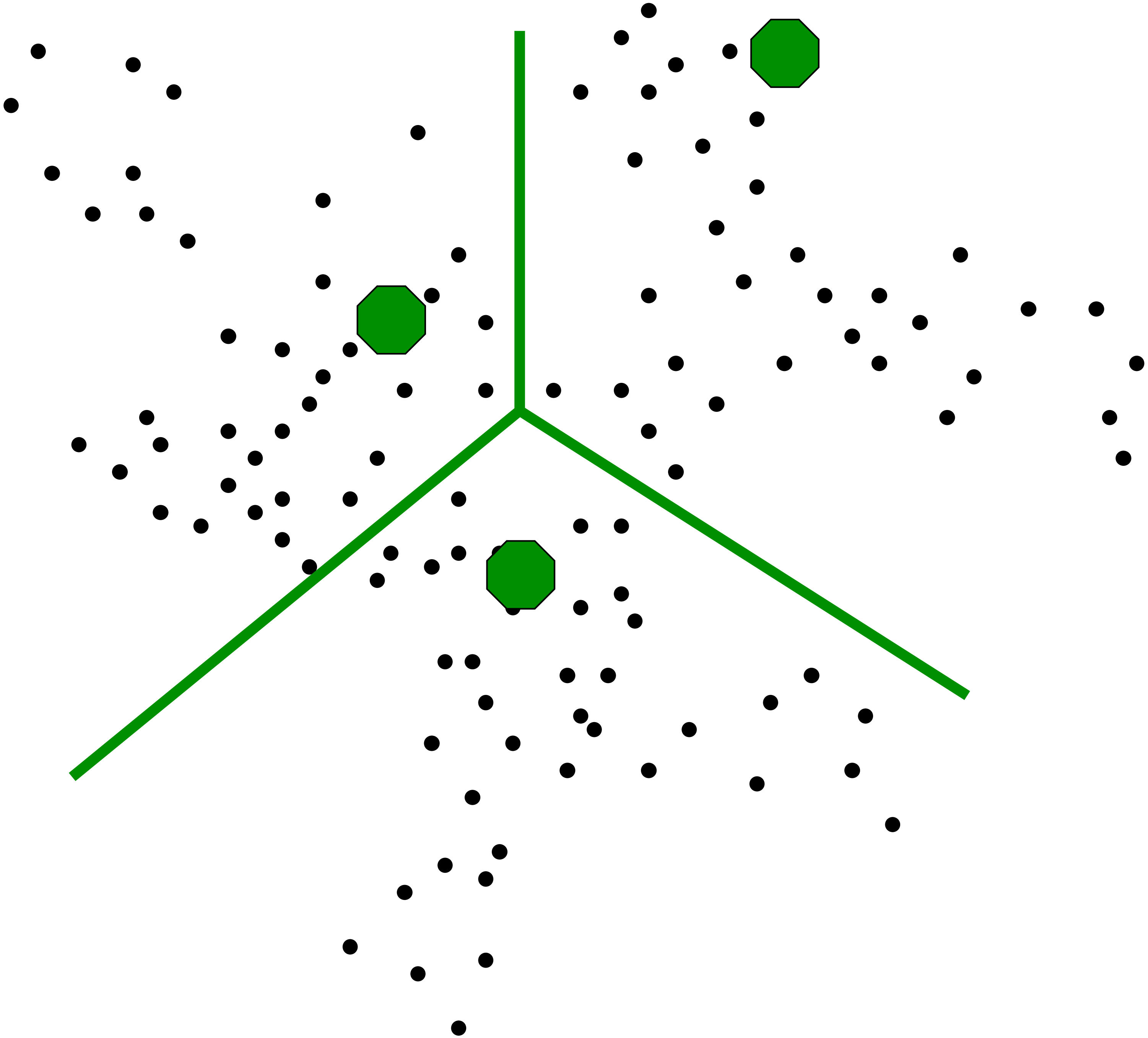
[Sivic & Zisserman,ICCV'03]



Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

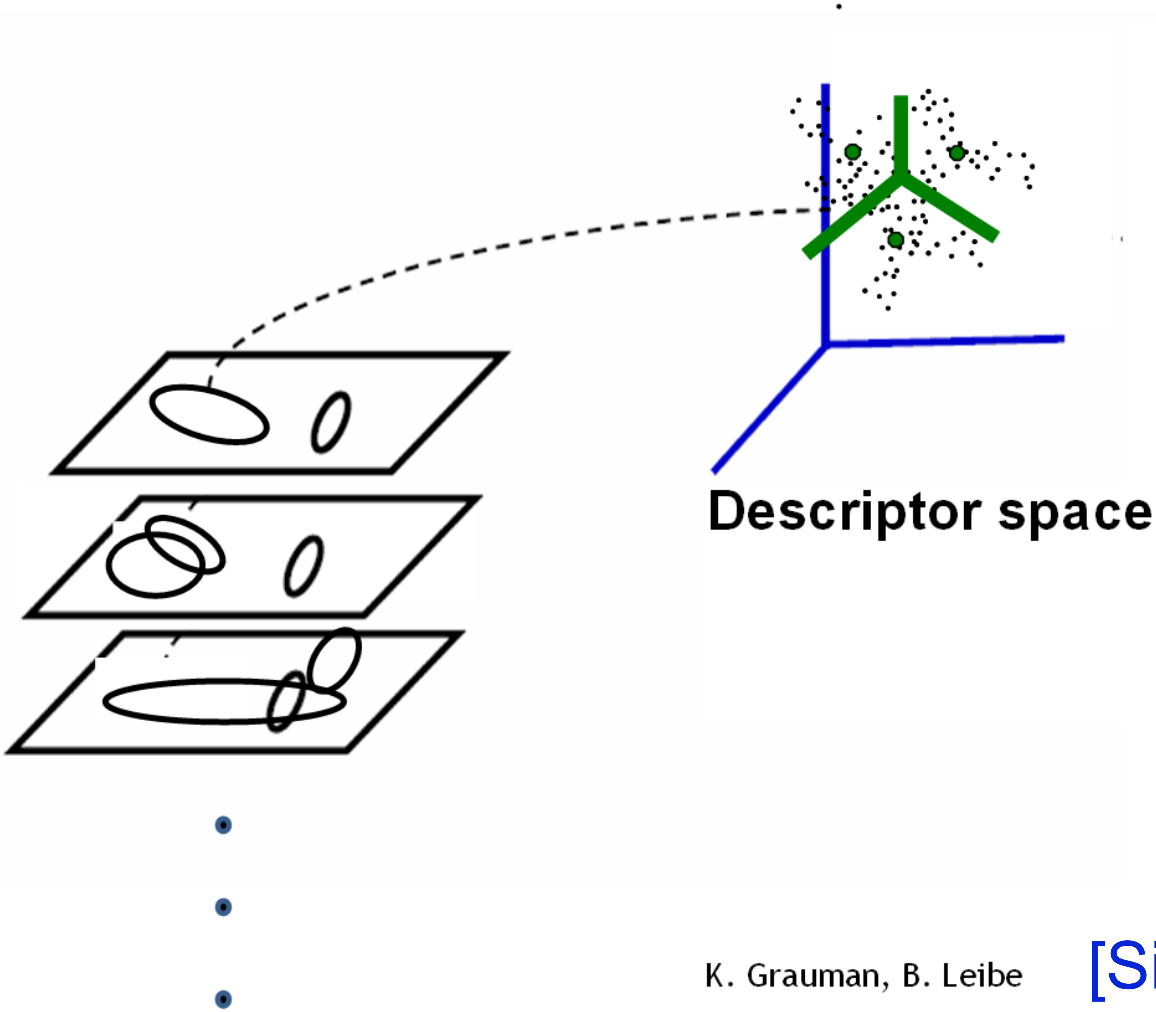


Slide credit: D. Nister

[Sivic & Zisserman,ICCV'03]

Visual words: main idea

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



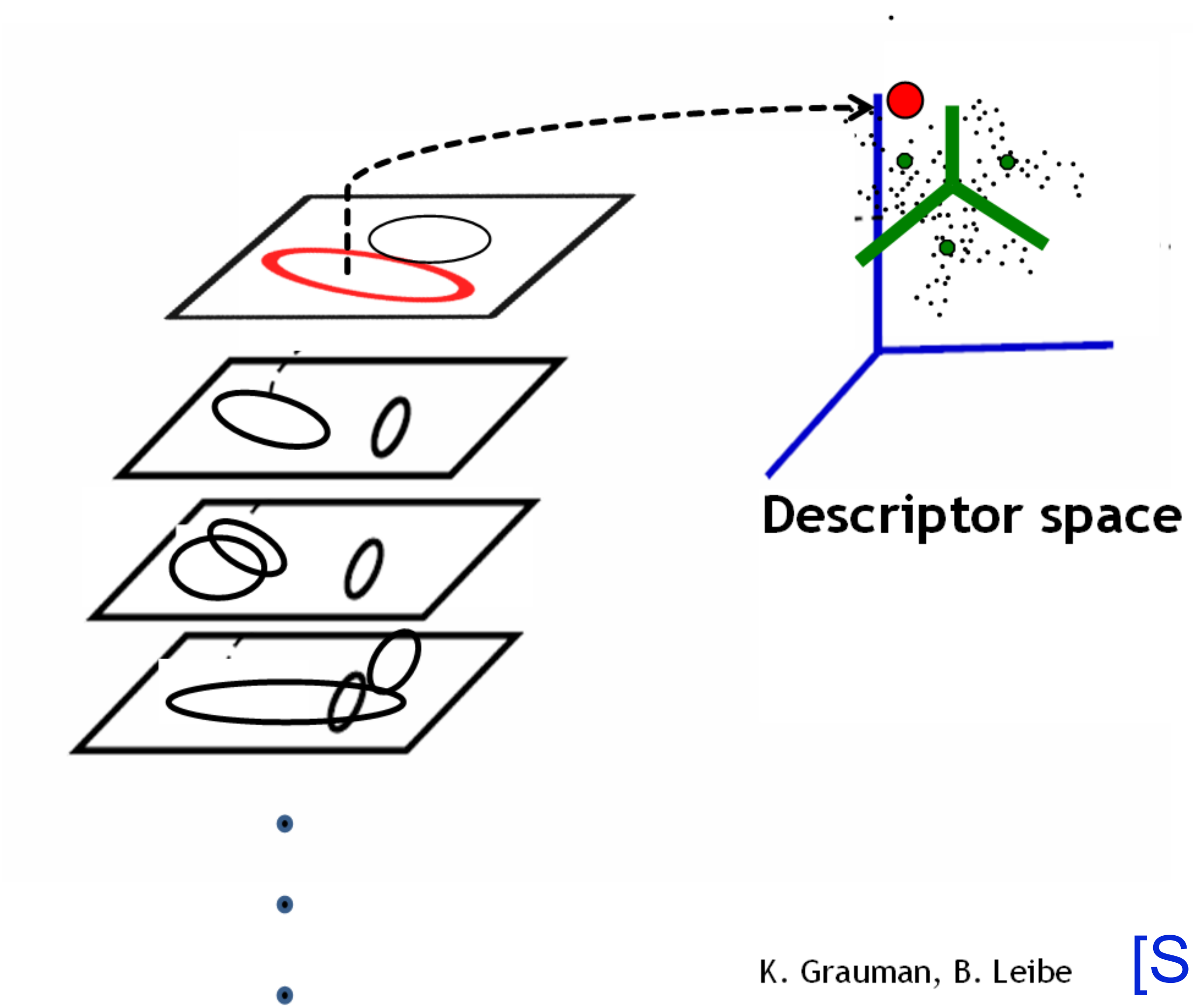
- Quantize via clustering, let cluster centers be the prototype "words"

K. Grauman, B. Leibe

[Sivic & Zisserman,ICCV'03]

Visual words: main idea

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



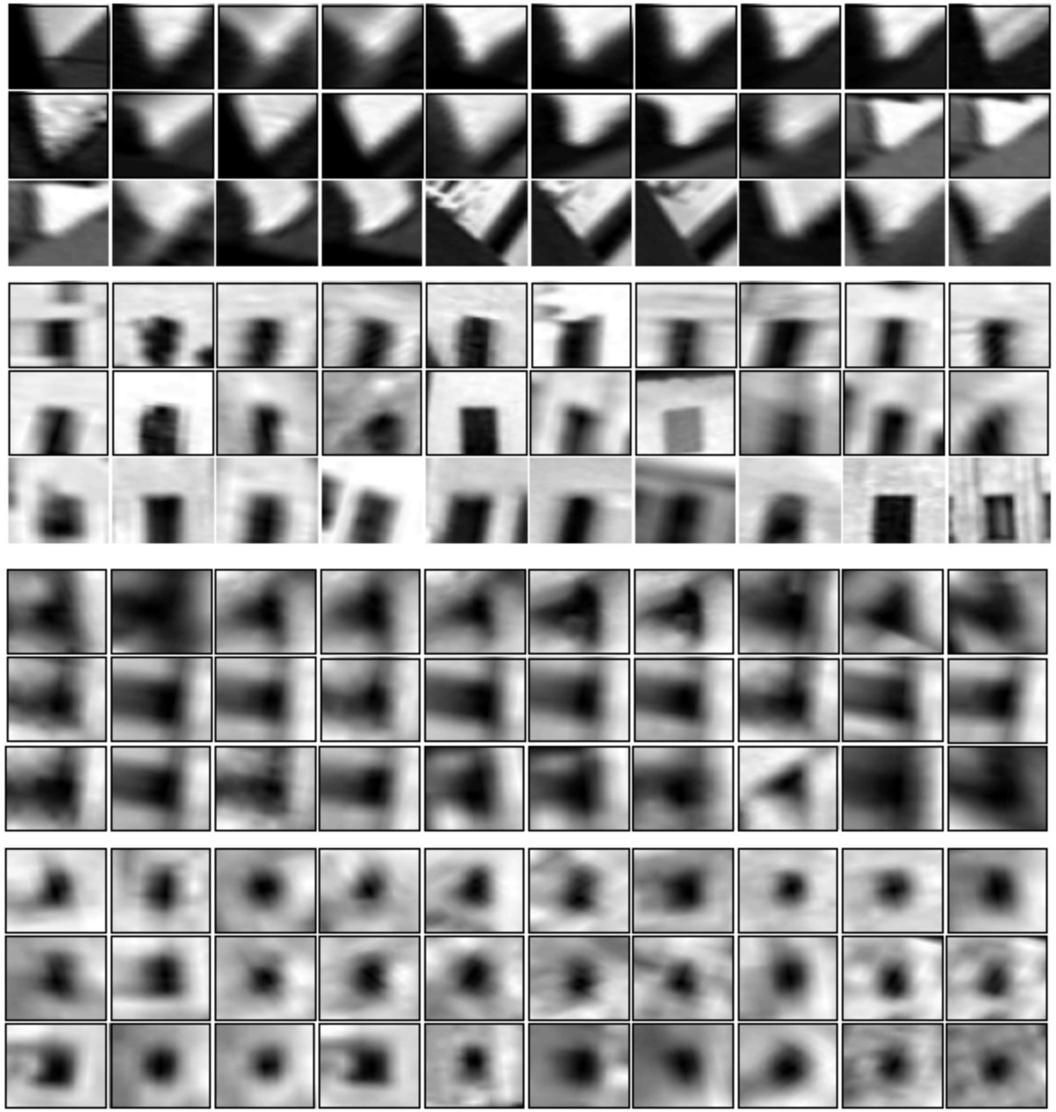
- Determine which word to assign to each new image region by finding the closest cluster center.

K. Grauman, B. Leibe

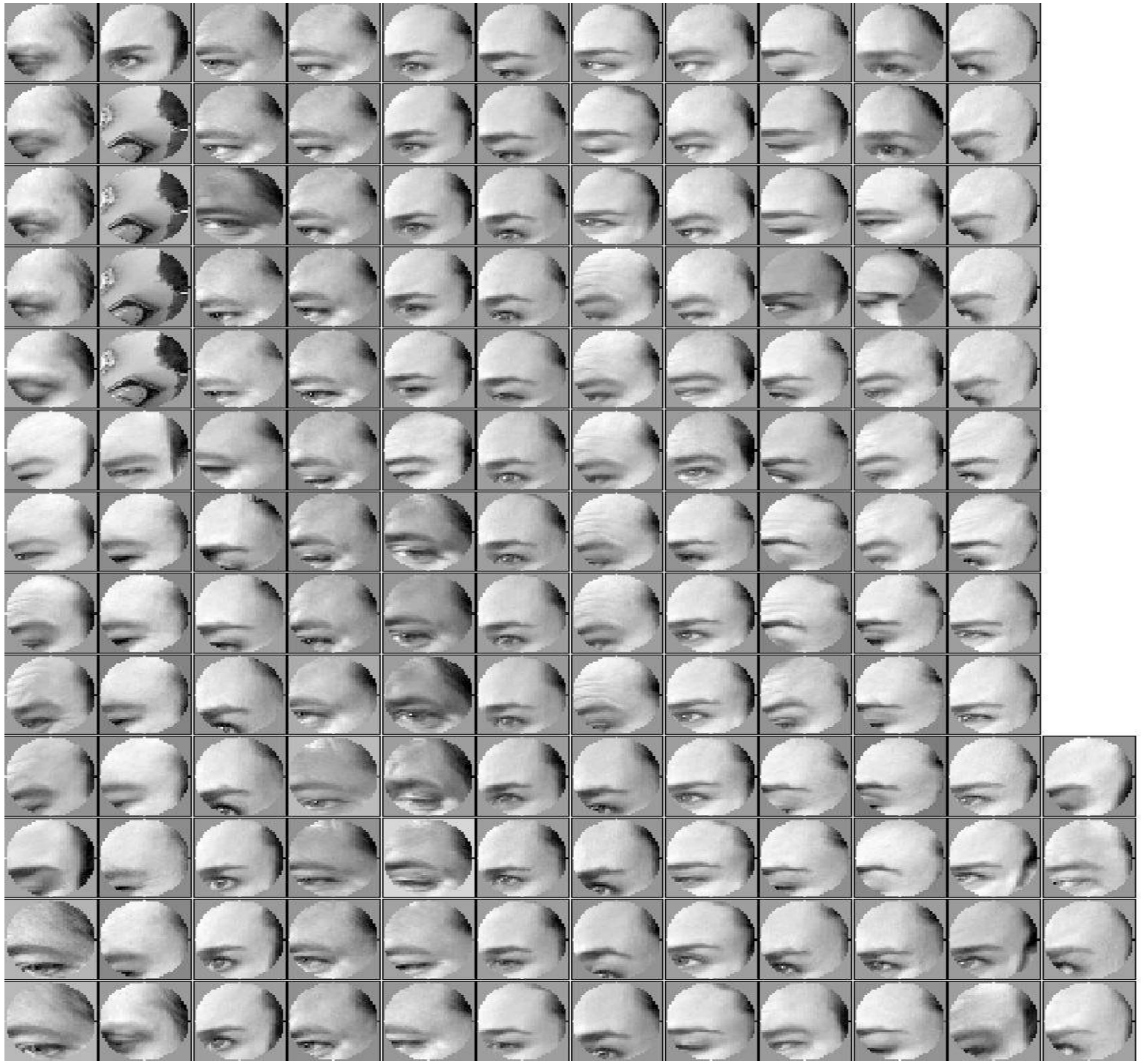
[Sivic & Zisserman,ICCV'03]

Visual words

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

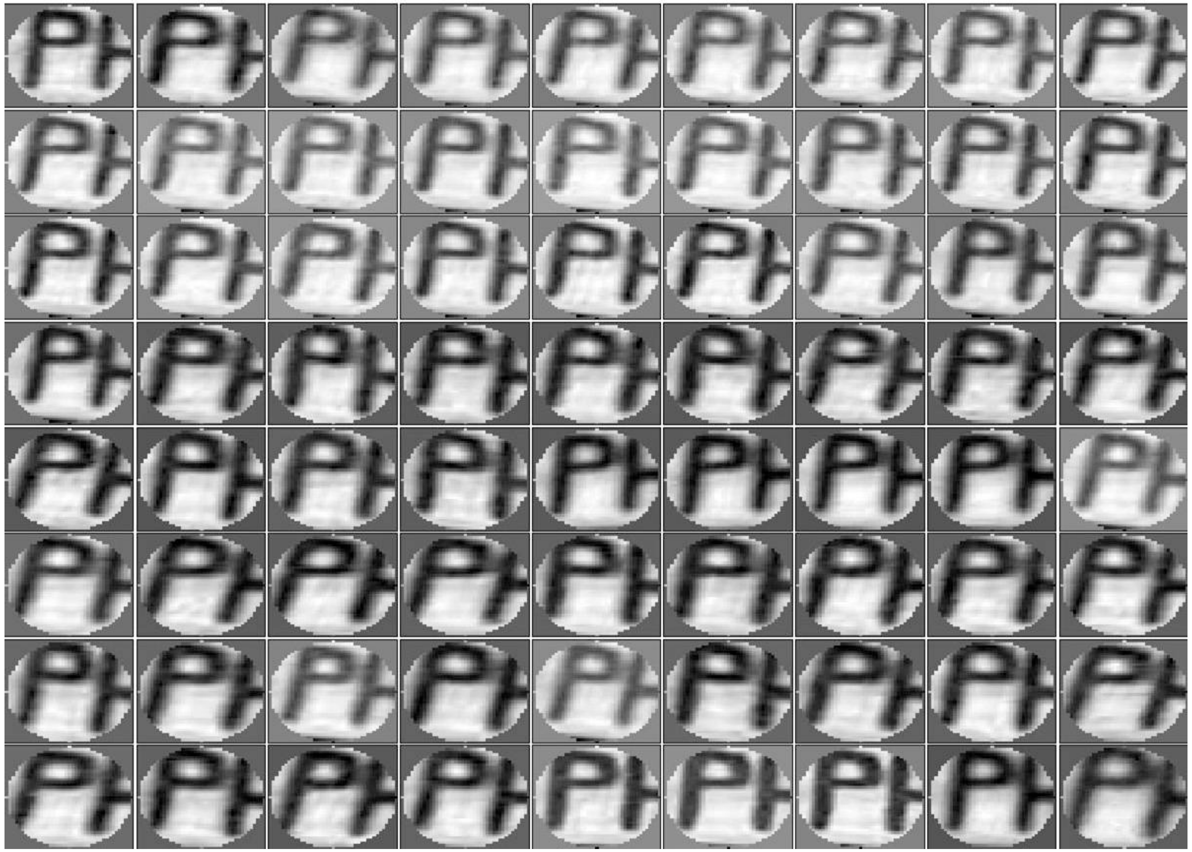


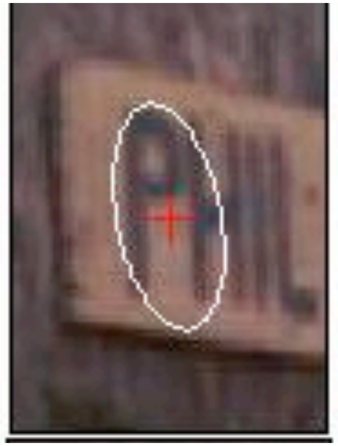
Samples of visual words (clusters on SIFT descriptors):



More specific example

Samples of visual words (clusters on SIFT descriptors):

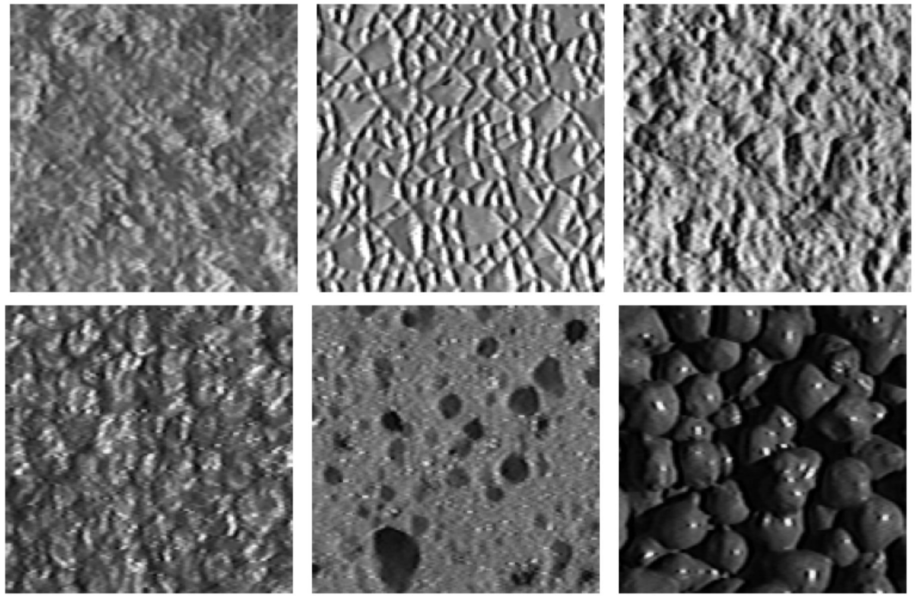




More specific example

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;

Slide: Grauman&Leibe

Inverted file index for images comprised of visual words

frame #5

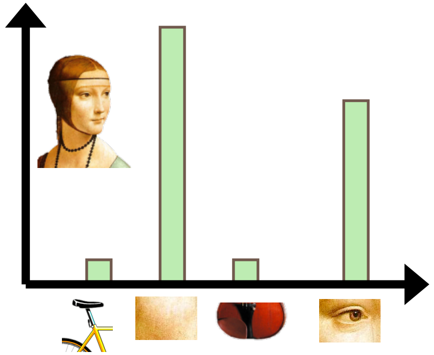
frame #10

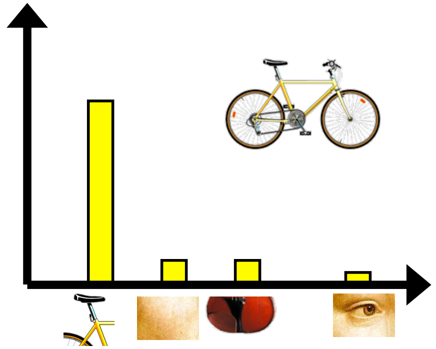
Word number		List of image numbers
1	→	5,10, ...
2	→	10,...
...		...

- 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.



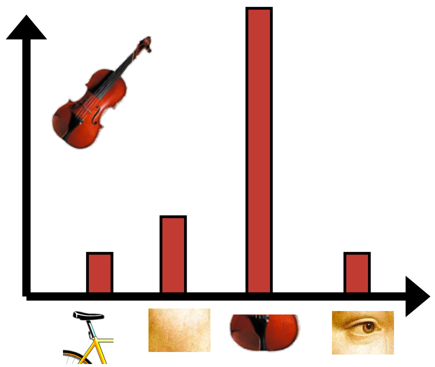


Analogous to bag of words representation commonly used for documents.

artifact artificial interest

d = | … | 0 | 1 | … | 2 | 0 | … | t

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.

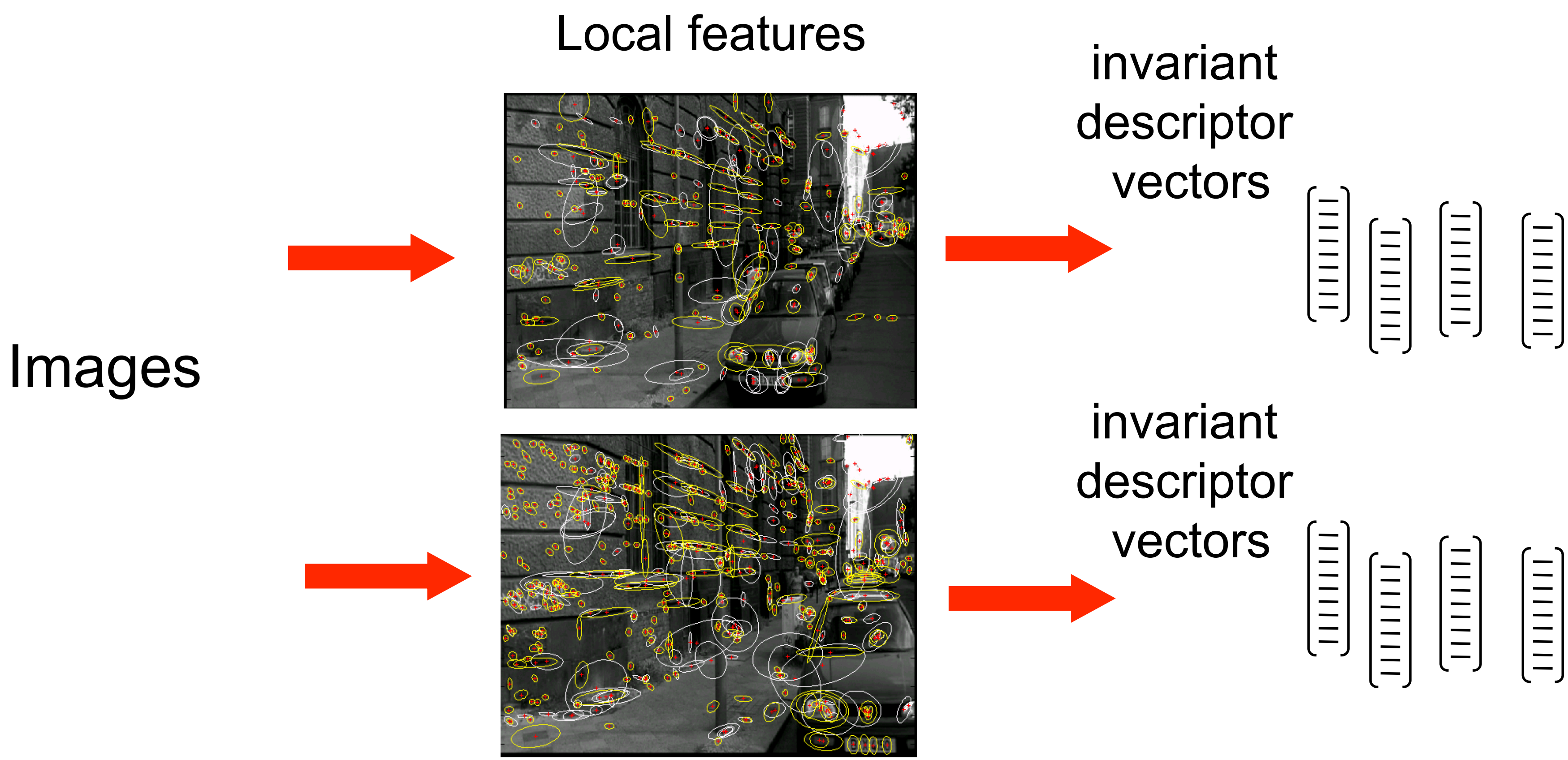
Images are ranked by the normalized scalar product between the query vector v_q and all vectors in the database v_d:

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

Scalar product can be computed efficiently using inverted file.

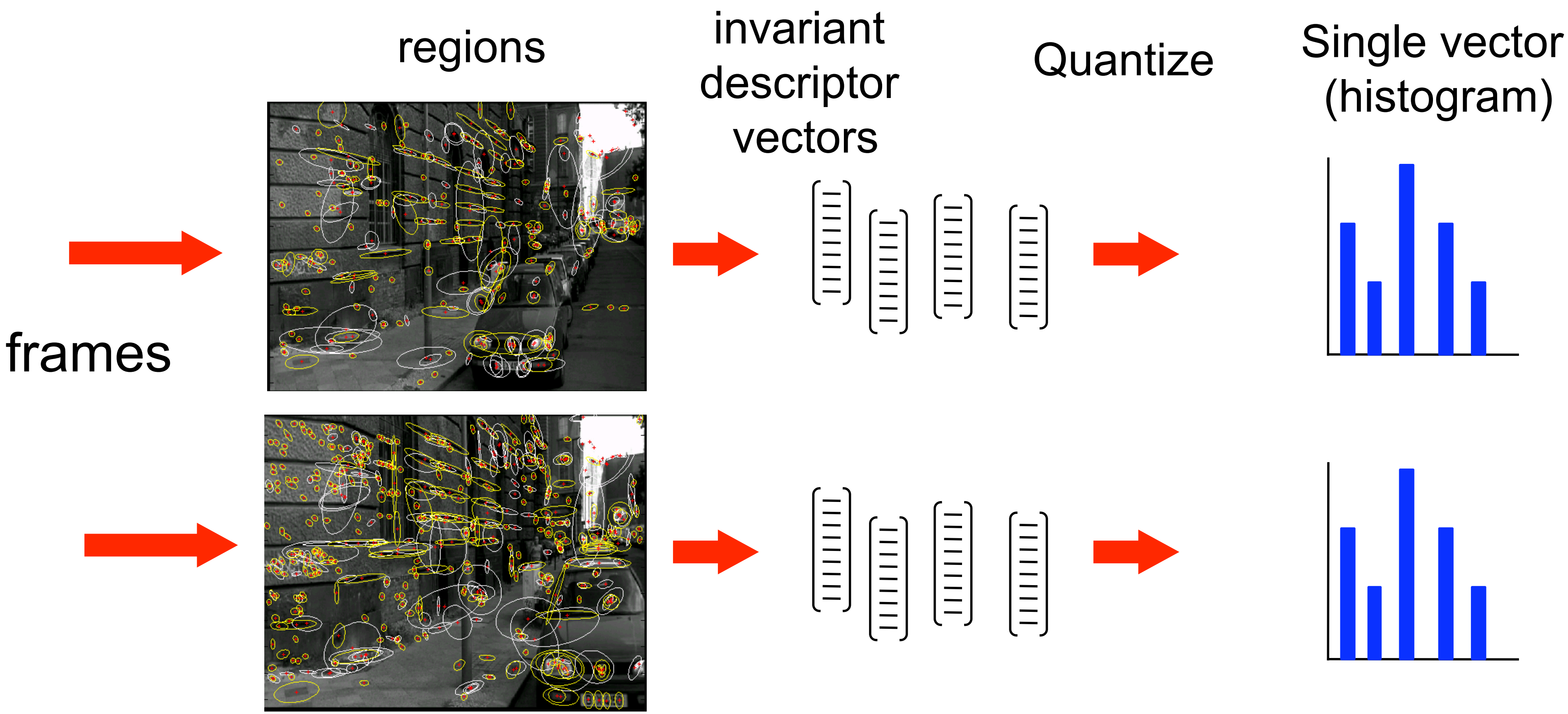
What if vectors are binary? What is the meaning of $\mathbf{v}_q{}^\top \mathbf{v}_d$?

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 (Part 2)

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 (Part 2)

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.

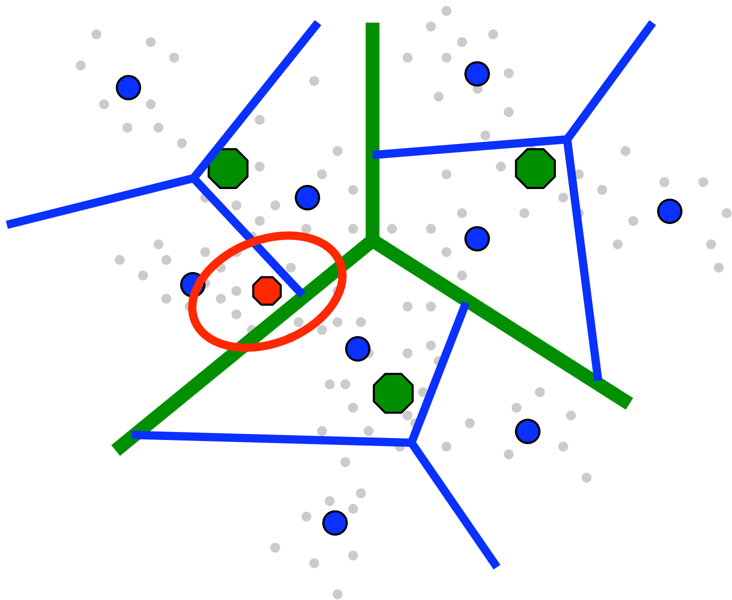
But, see recent work by Jegou et al.:

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

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

Demo

Oxford Buildings Search

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

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

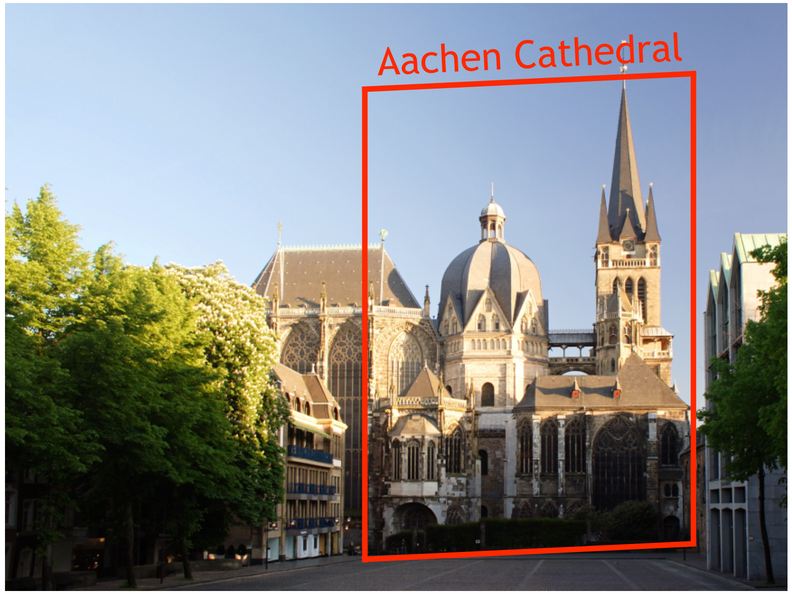
- Recognize docking station
- Communicate with visual cards

Other uses

- Place recognition
- Loop closure in SLAM

Slide credit: David Lowe

Mobile tourist guide



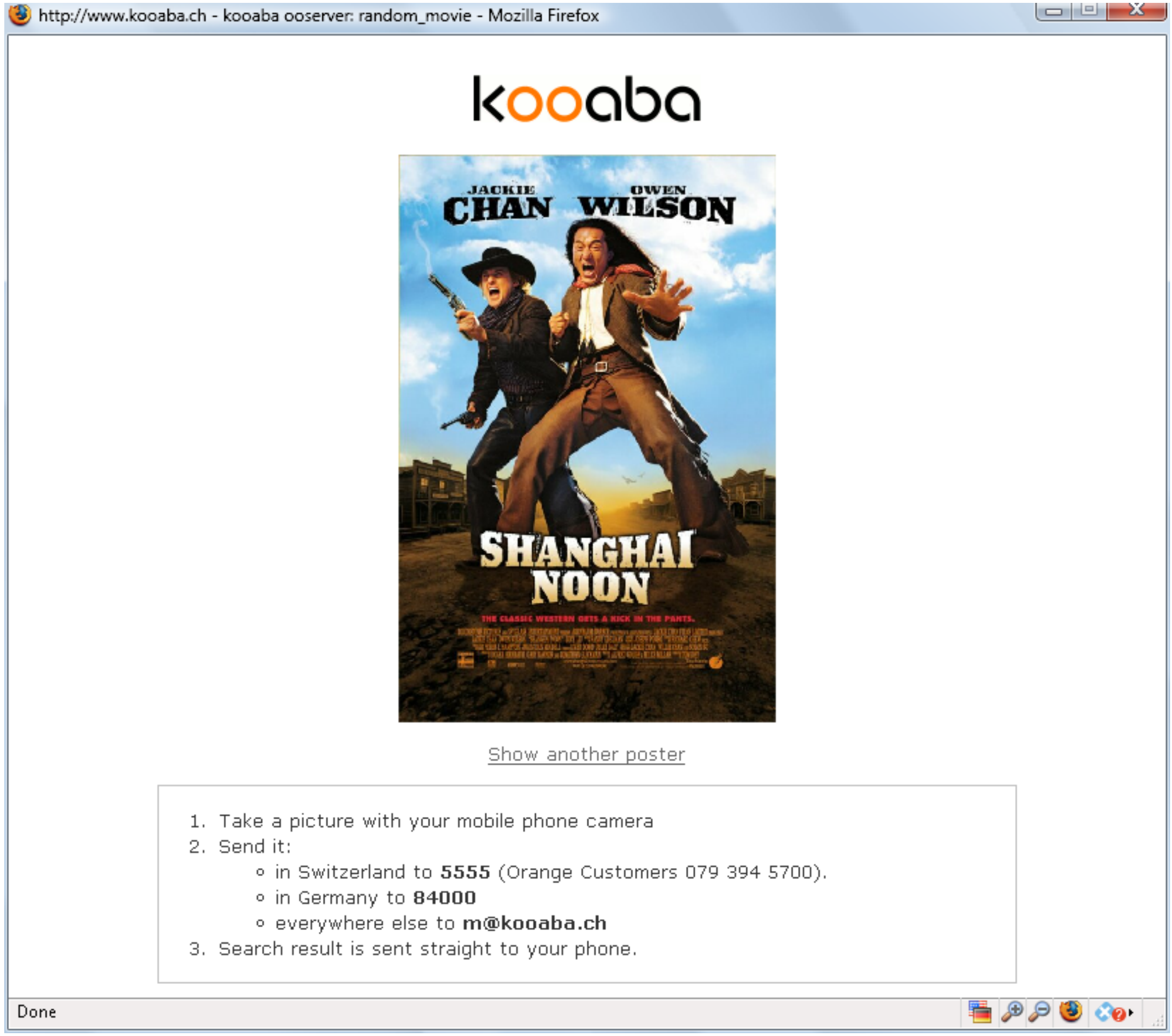
Mobile tourist guide
- **Self-localization**
- **Object/building recognition**
- **Photo/video augmentation**

[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#

Image Auto-Annotation

Left: Wikipedia image
Right: closest match from Flickr

[Quack CIVR'08]

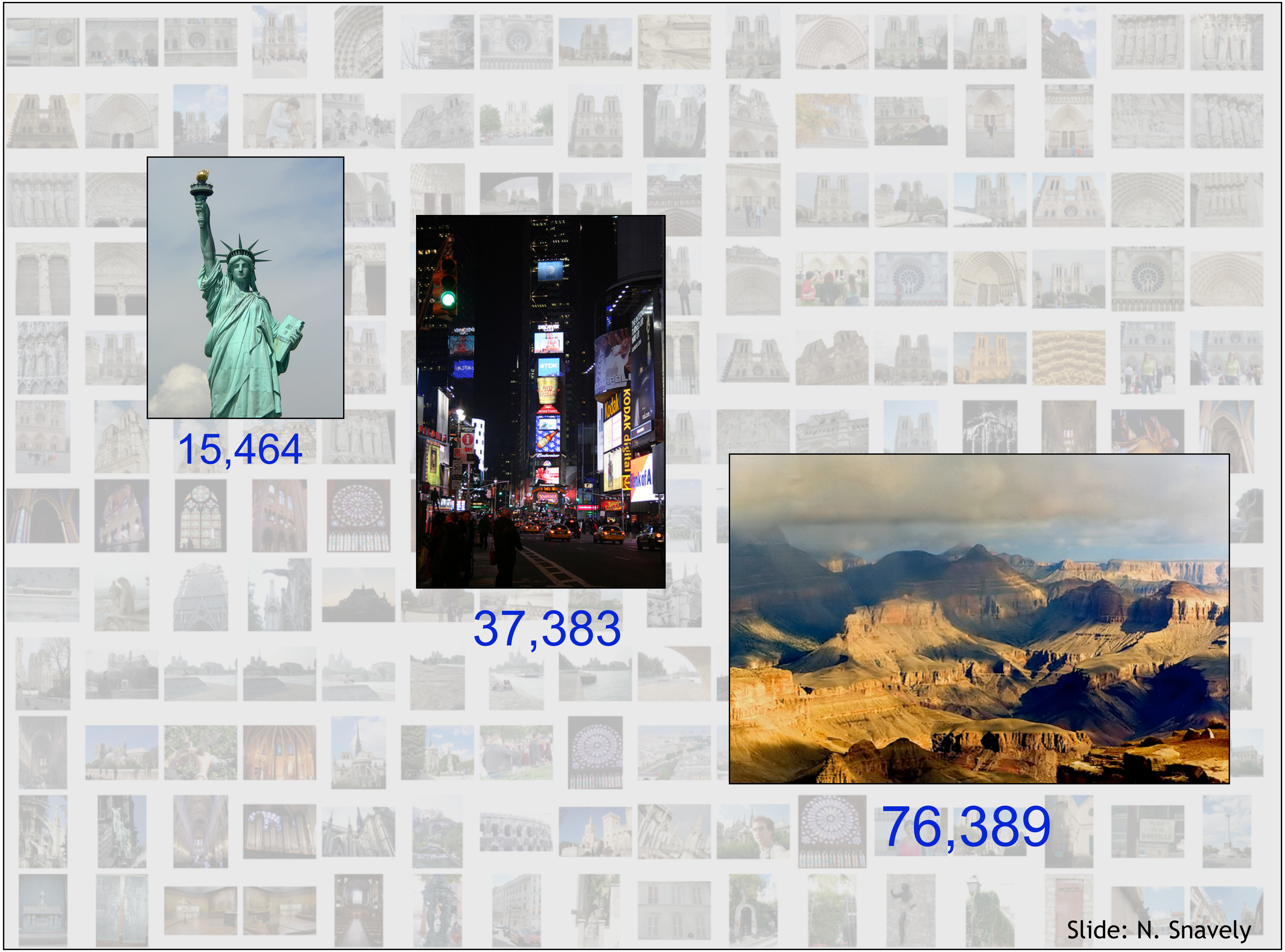
Building Rome in a Day – or –

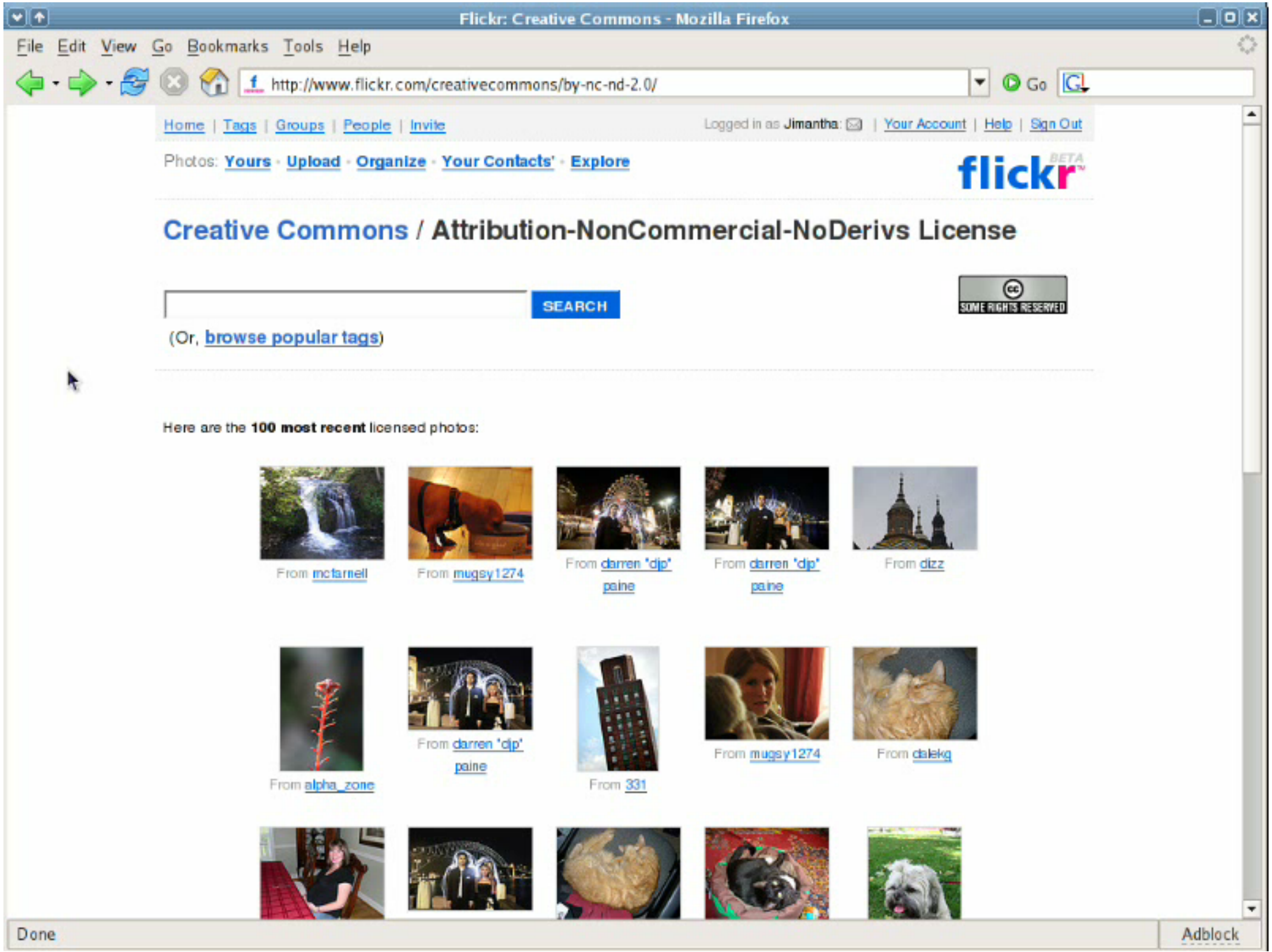
matching and 3D reconstruction in large unstructured datasets.

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

Example of the final 3D point cloud and cameras

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

Outline

1. Local invariant features (45 mins, C. Schmid)

2. Matching and recognition with local features (45 mins, J. Sivic)

3. Efficient visual search (45 mins, J. Sivic)

4. **Very large scale visual indexing – recent work (45 mins, C. Schmid)**

Practical session (60 mins)