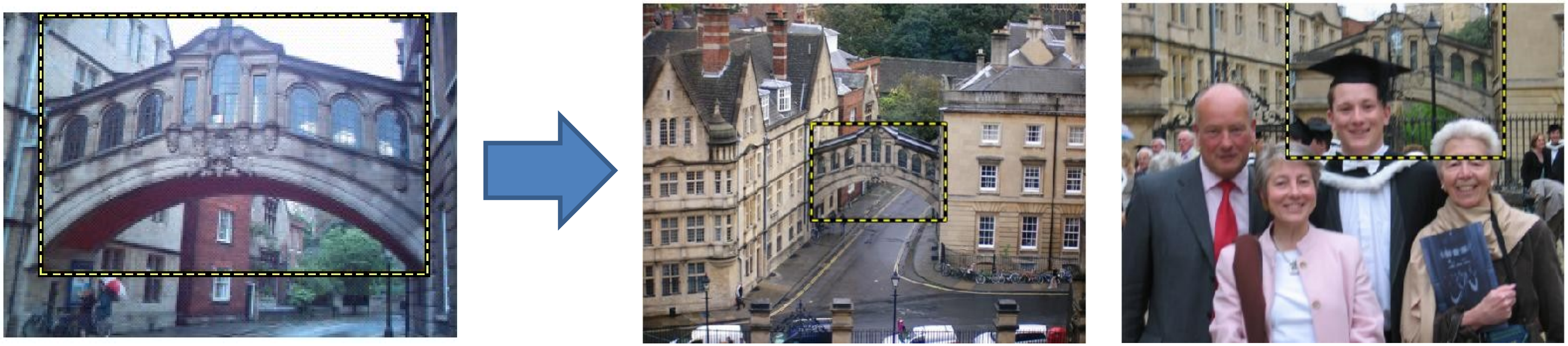
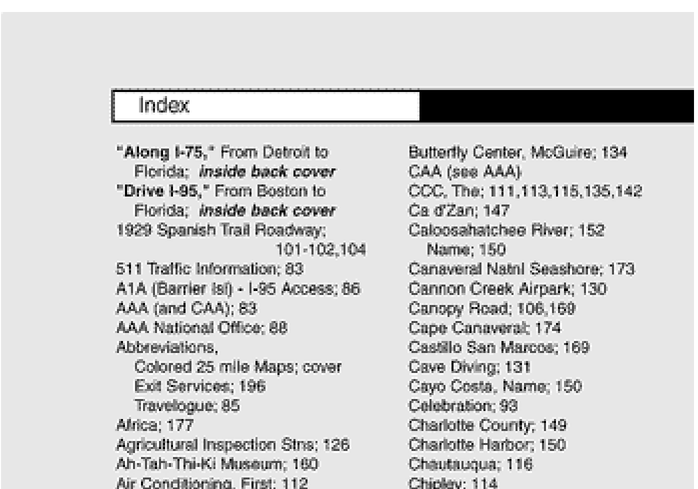


Indexing local features

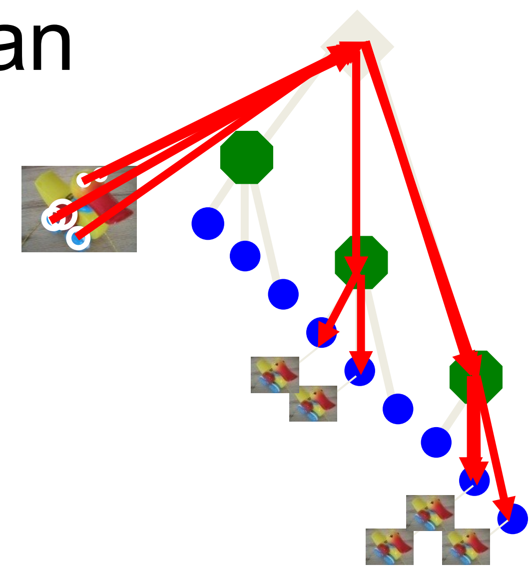
Wed March 30

Prof. Kristen Grauman

UT-Austin



Index



Matching local features

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Matching local features

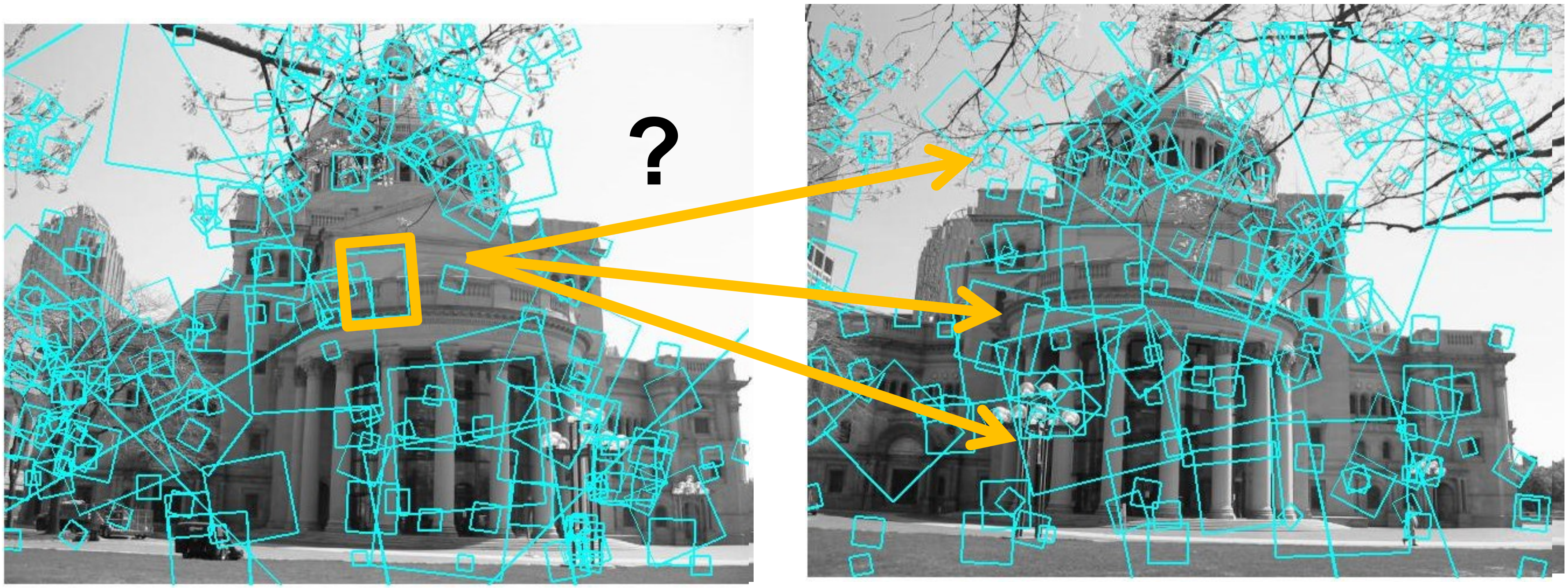

Image 1 Image 2

To generate **candidate matches**, find patches that have the most similar appearance (e.g., lowest SSD)

Simplest approach: compare them all, take the closest (or closest k, or within a thresholded distance)

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Matching local features

Image 1

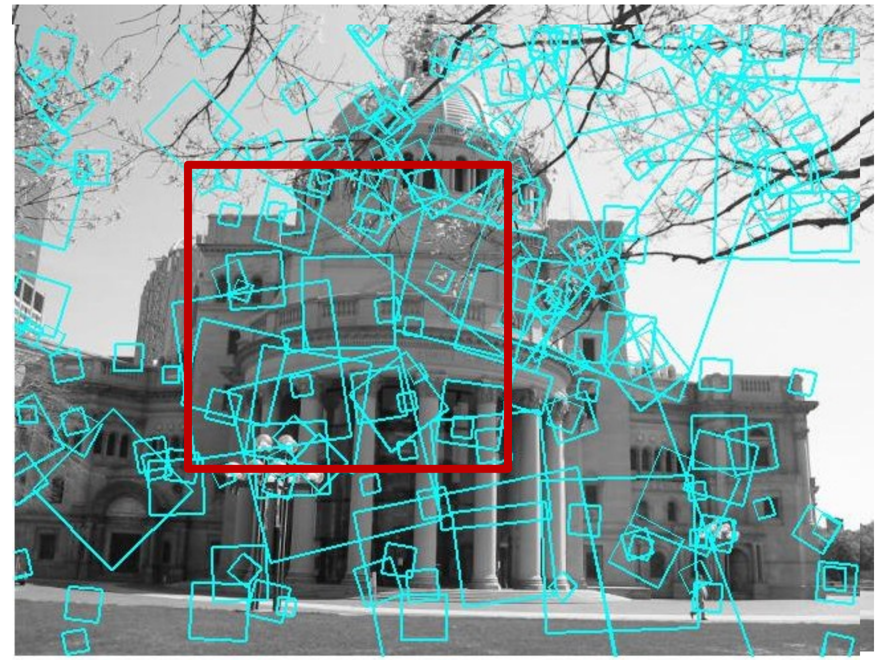

Image 2

In stereo case, may constrain by proximity if we make assumptions on max disparities.

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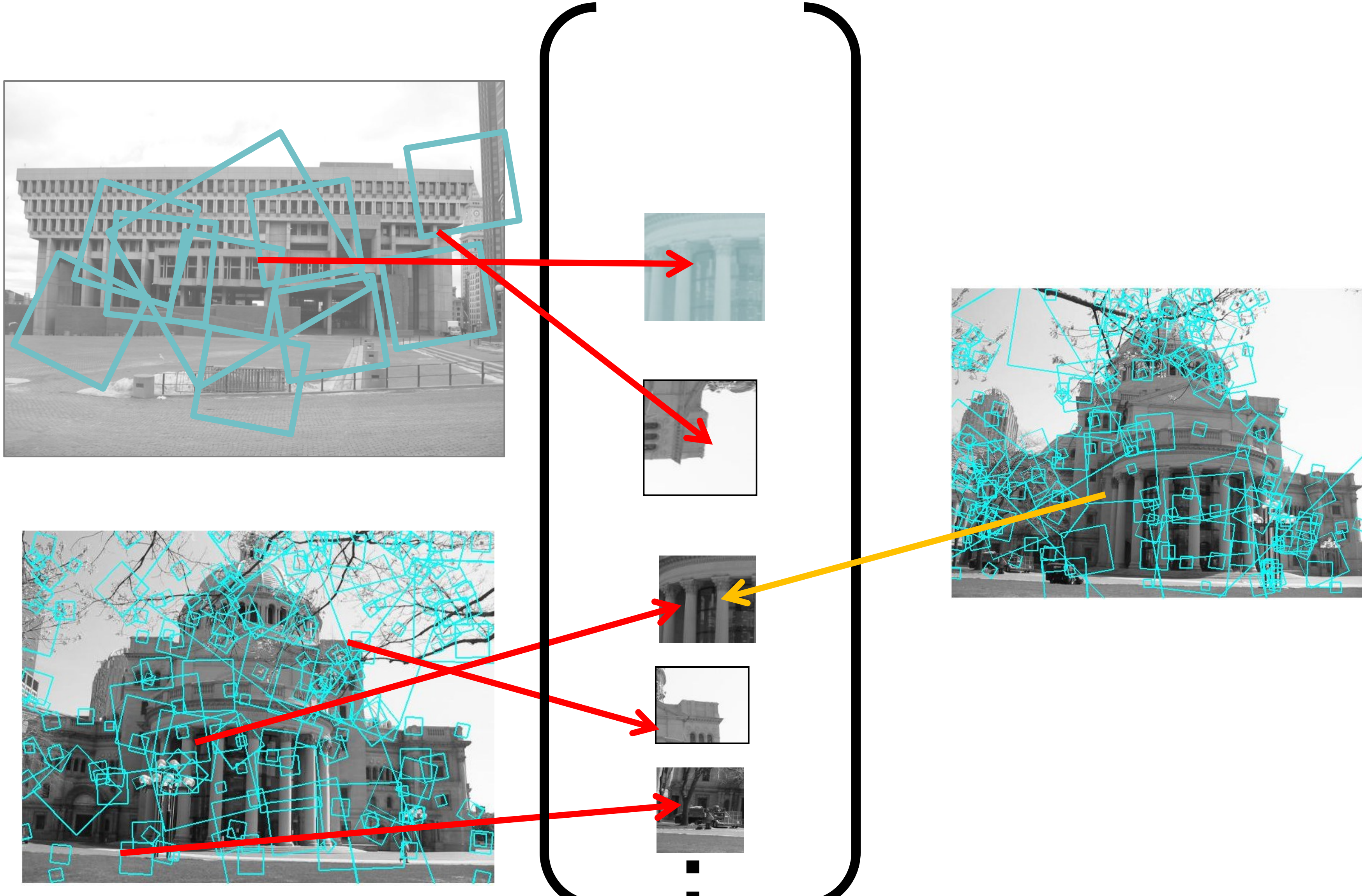
Indexing local features



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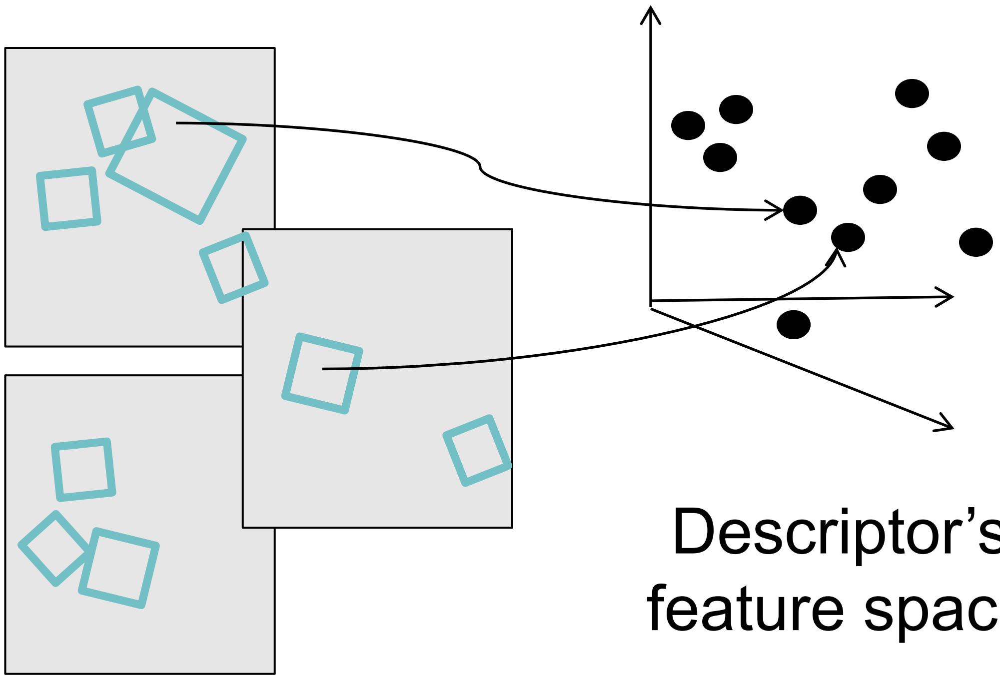
Indexing local features

- Each patch / region has a descriptor, which is a point in some high-dimensional feature space (e.g., SIFT)



Descriptor's feature space

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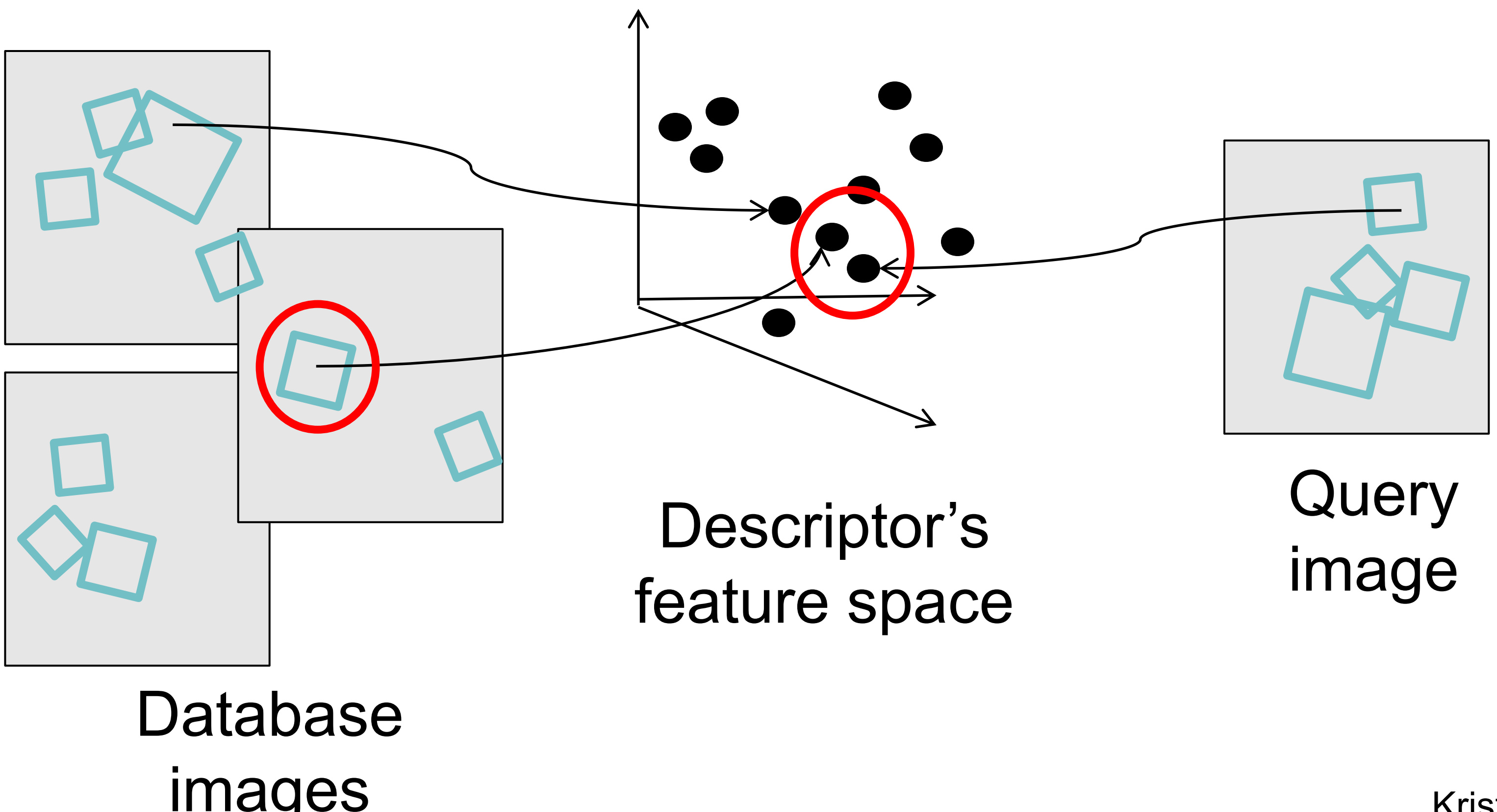
Indexing local features

- When we see close points in feature space, we have similar descriptors, which indicates similar local content.



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Indexing local features

- With potentially thousands of features per image, and hundreds to millions of images to search, how to efficiently find those that are relevant to a new image?

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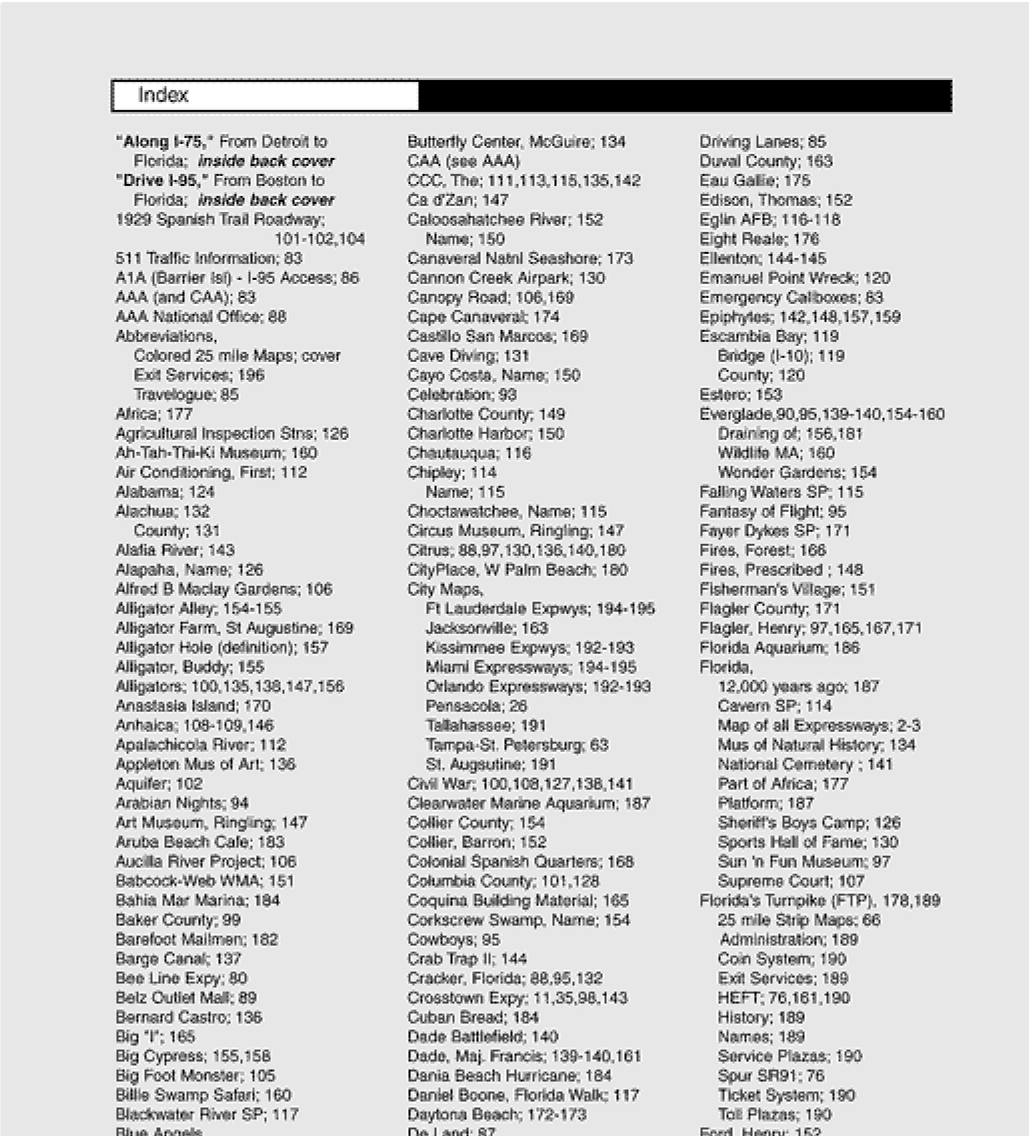
Indexing local features: inverted file index


Index

- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index…
- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words".

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Text retrieval vs. image search

- What makes the problems similar, different?

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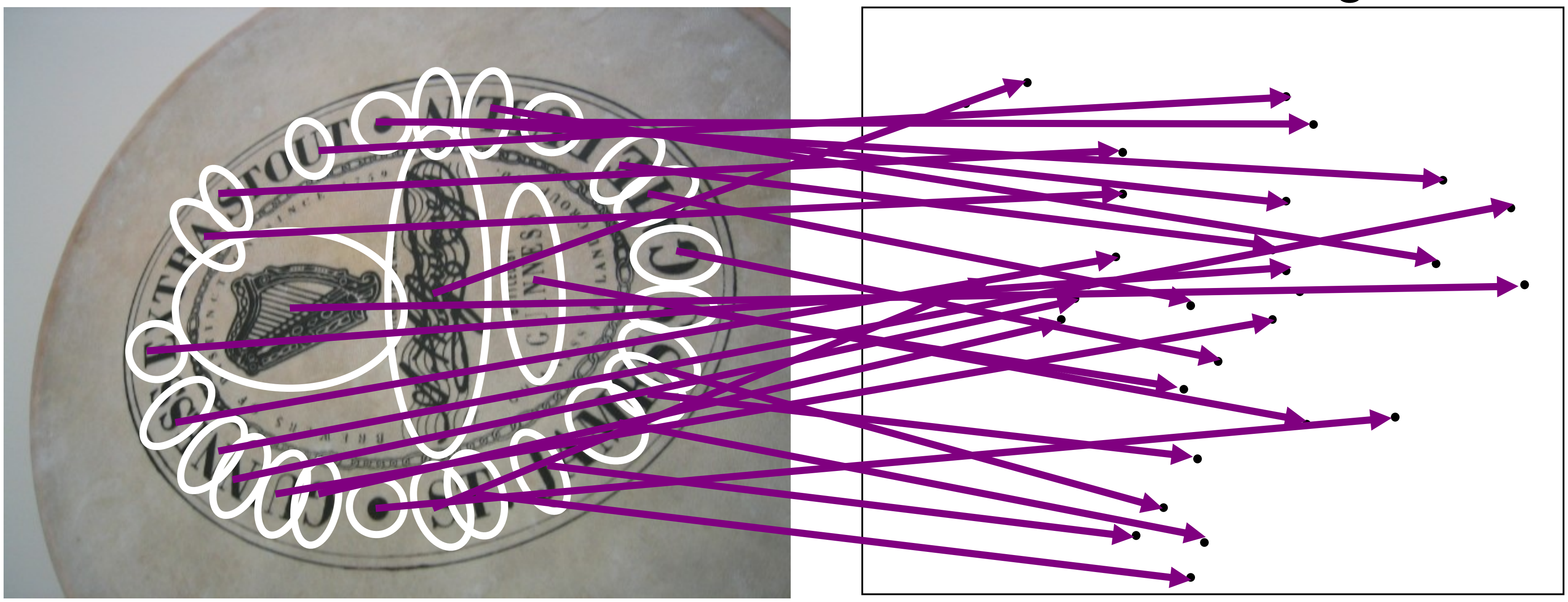
Visual words: main idea

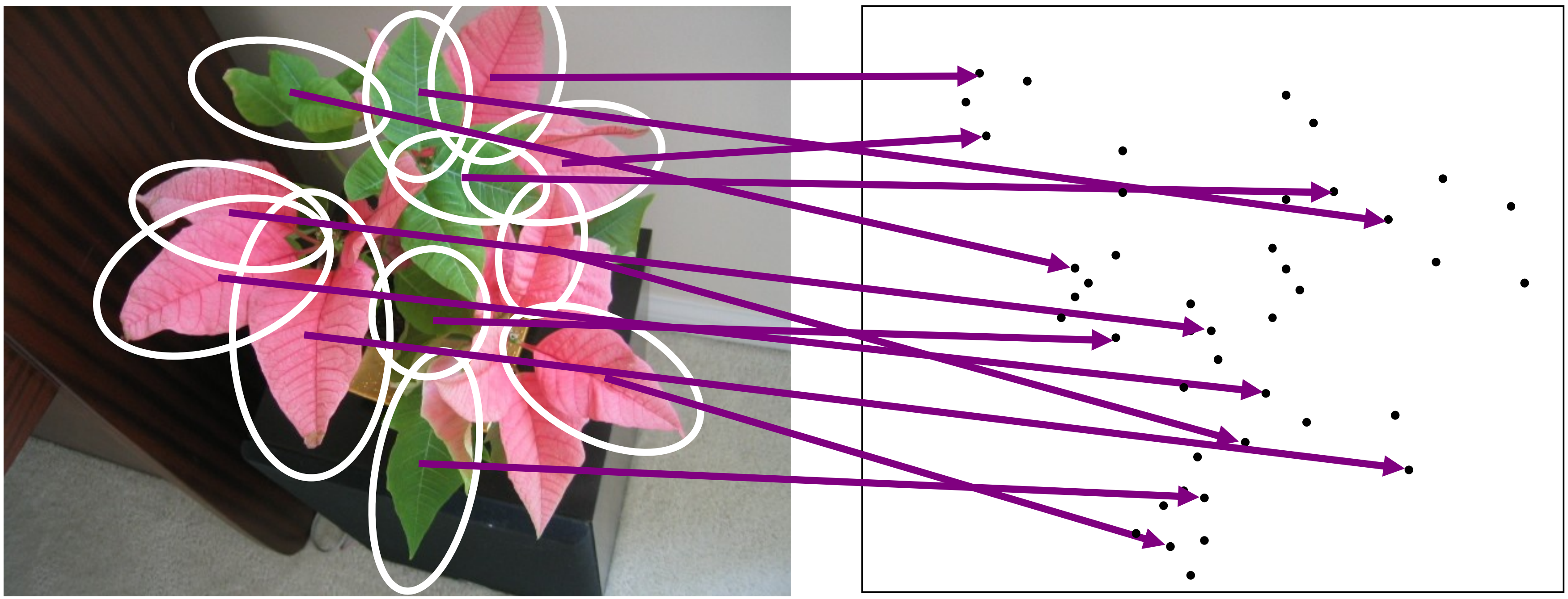
- Extract some local features from a number of images …



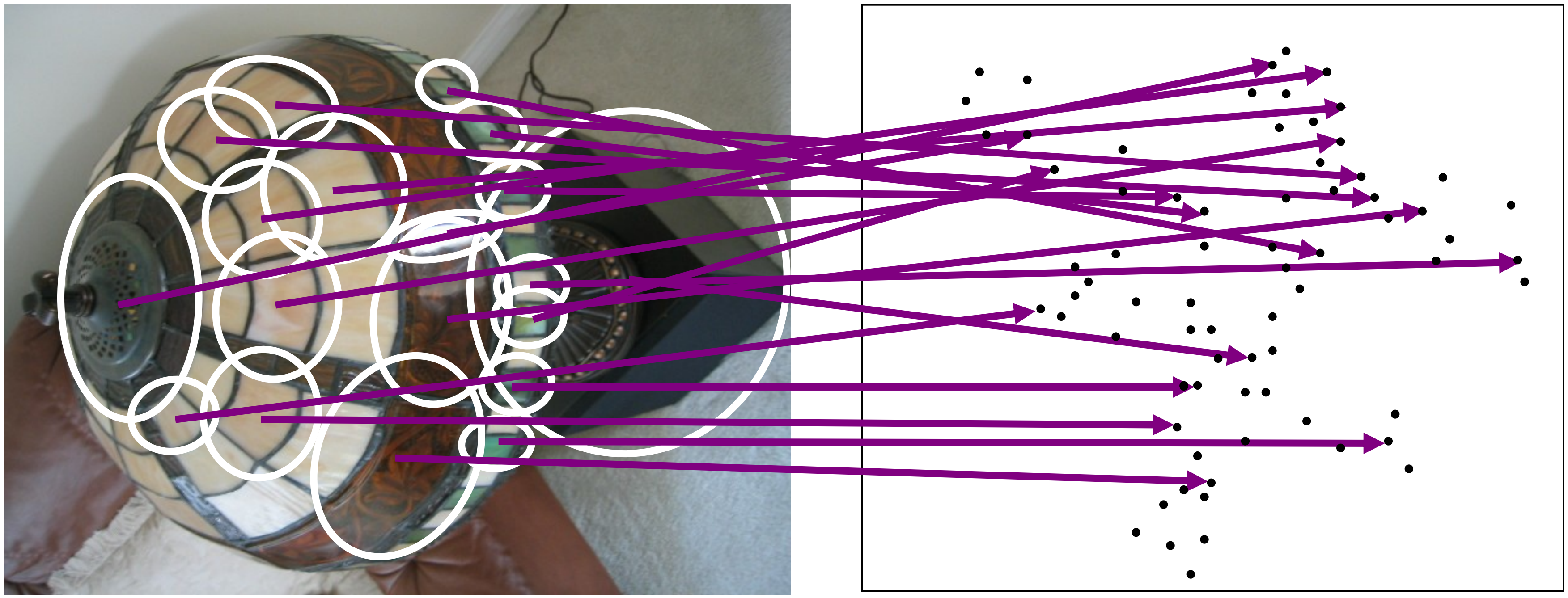
e.g., SIFT descriptor space: each point is 128-dimensional

Slide credit: D. Nister, CVPR 2006

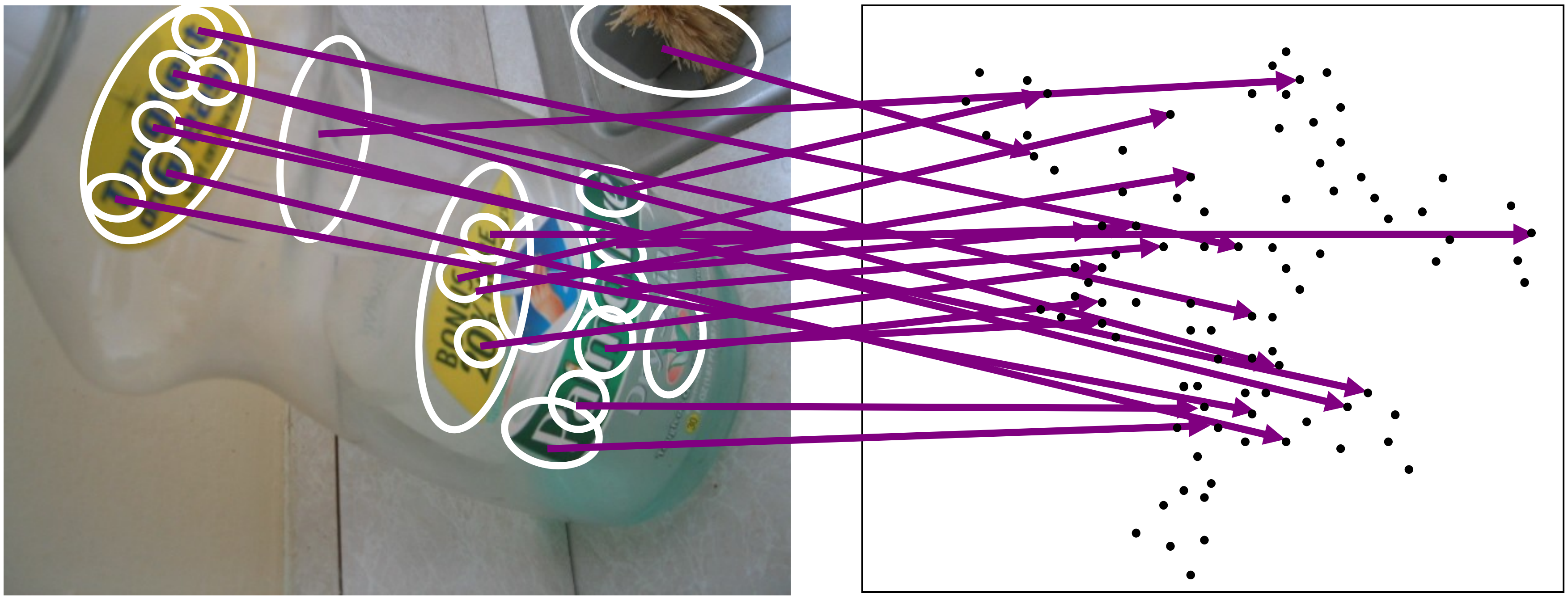
Visual words: main idea

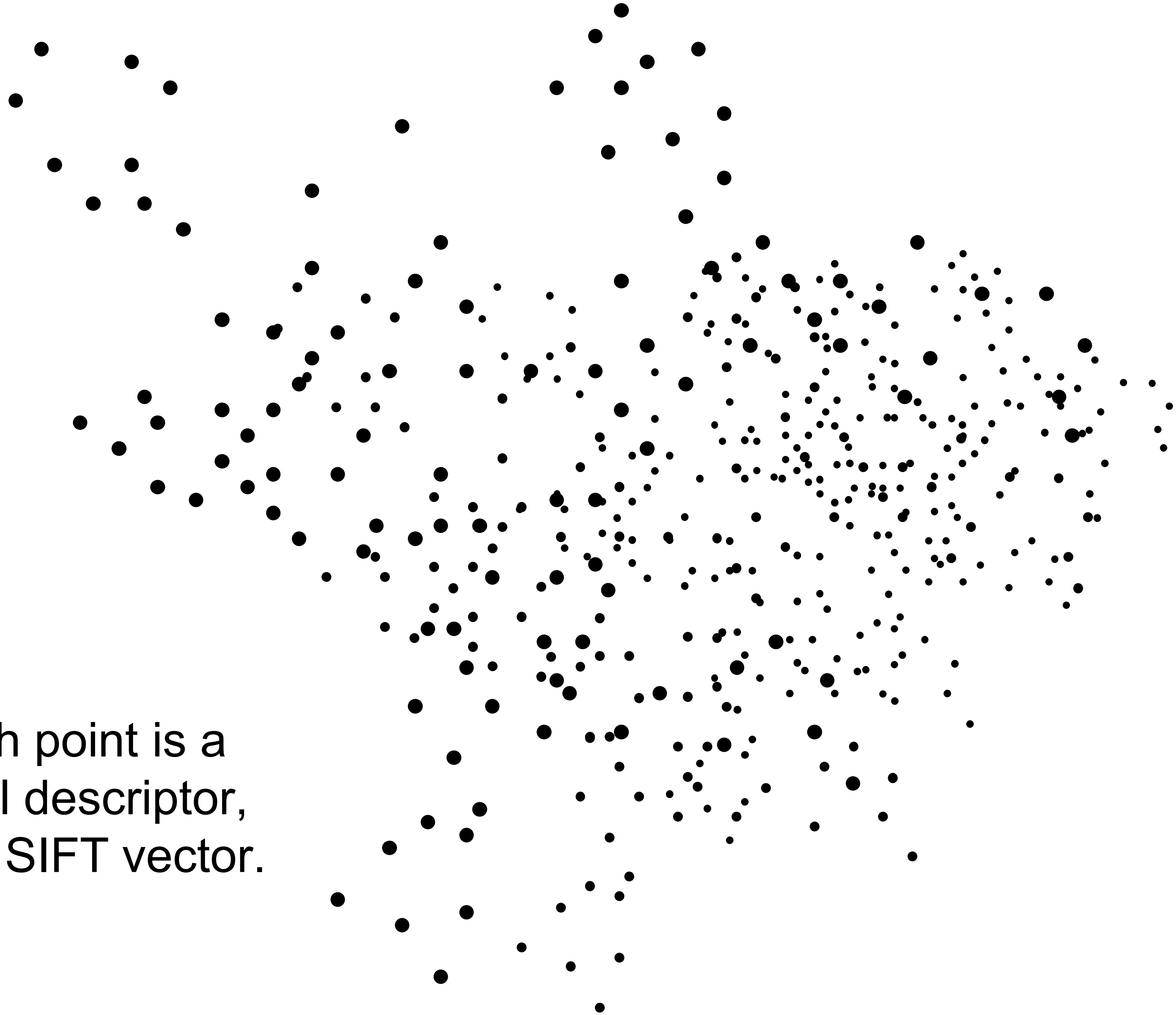


Visual words: main idea

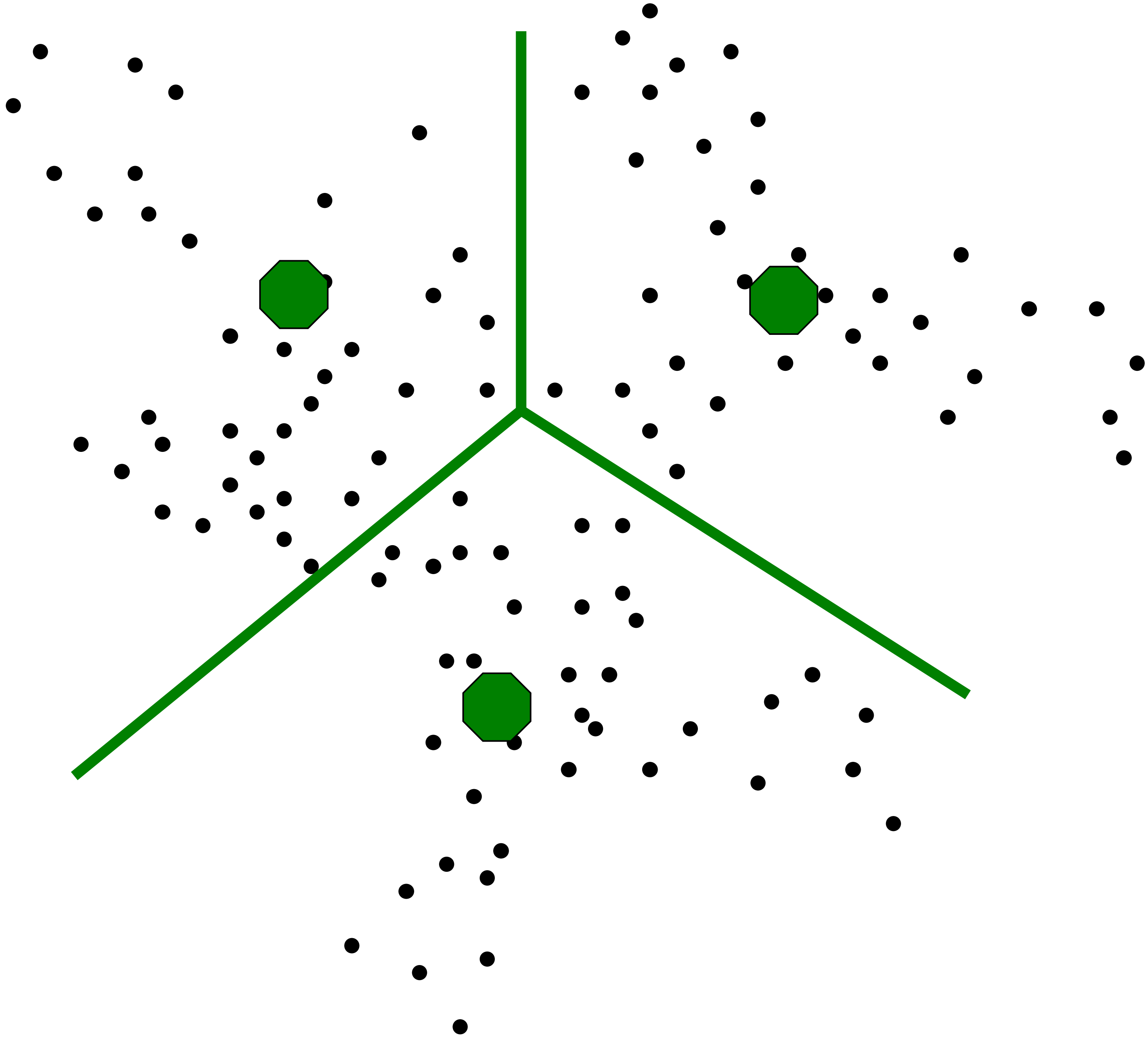


Visual words: main idea



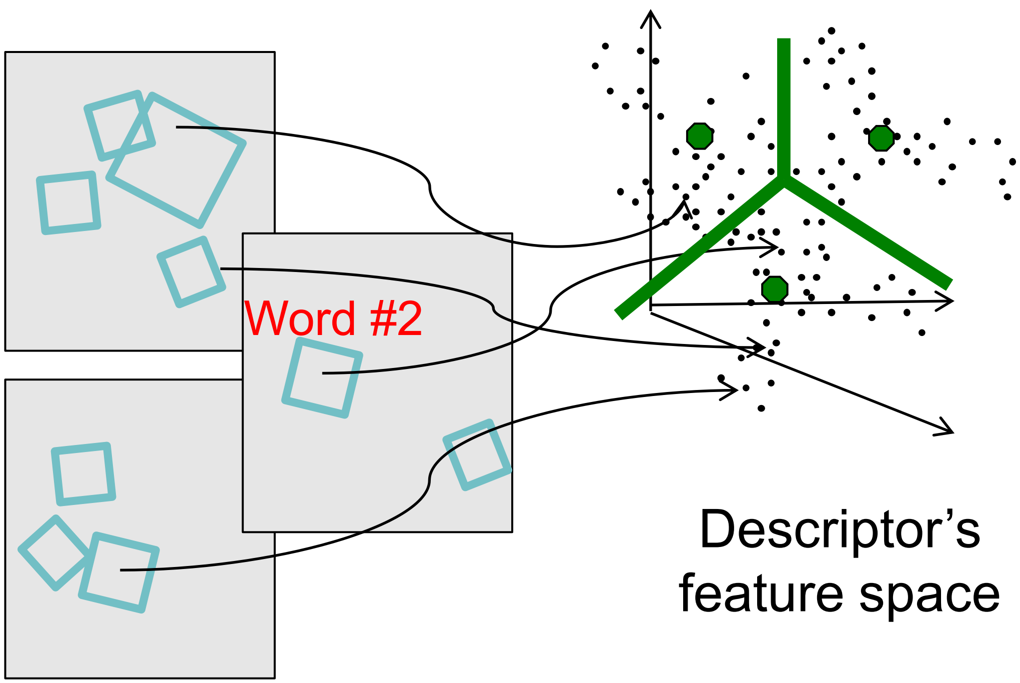


Each point is a
local descriptor,
e.g. SIFT vector.



Visual words

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



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

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

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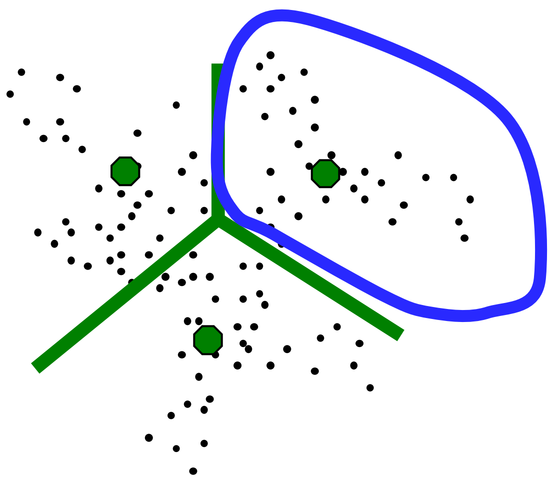
Visual words

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



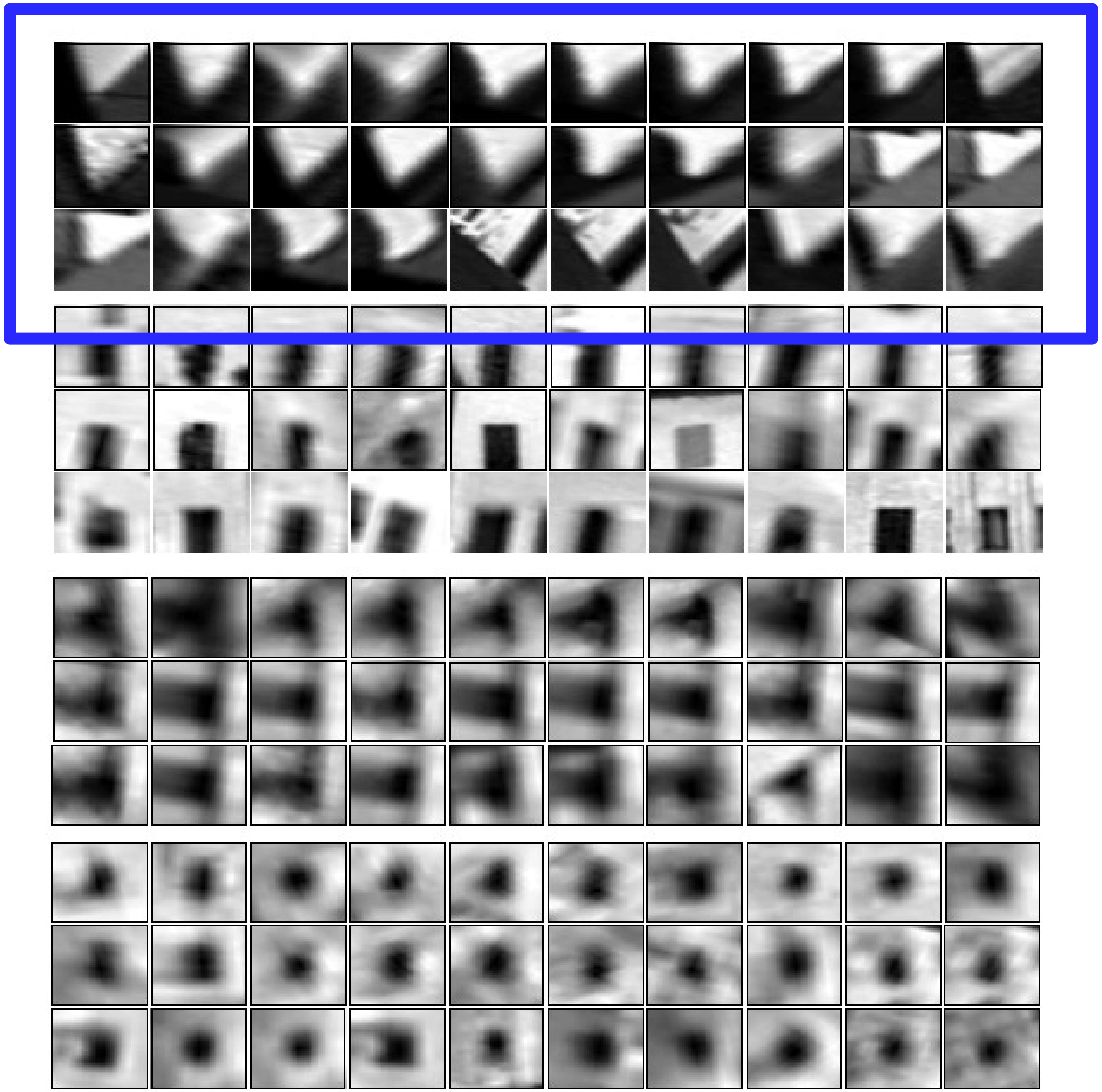


Figure from Sivic & Zisserman, ICCV 2003

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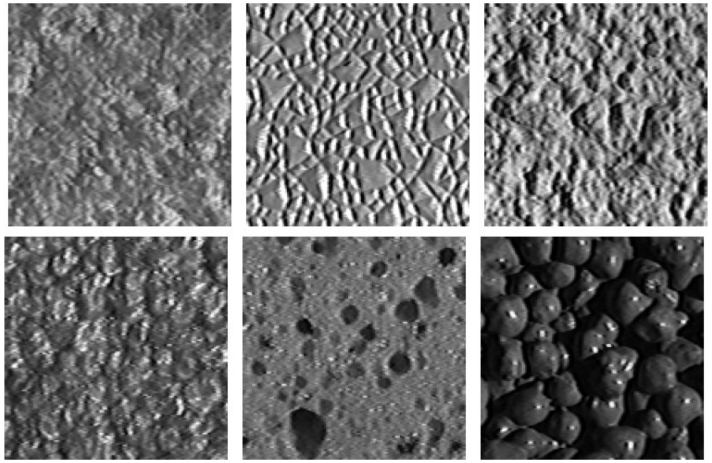
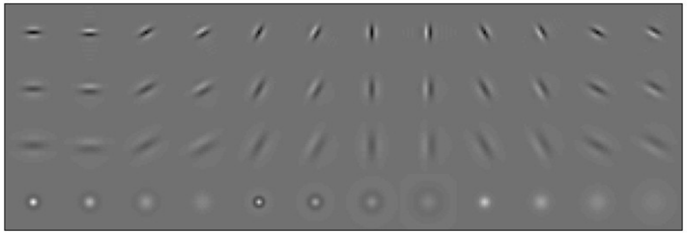
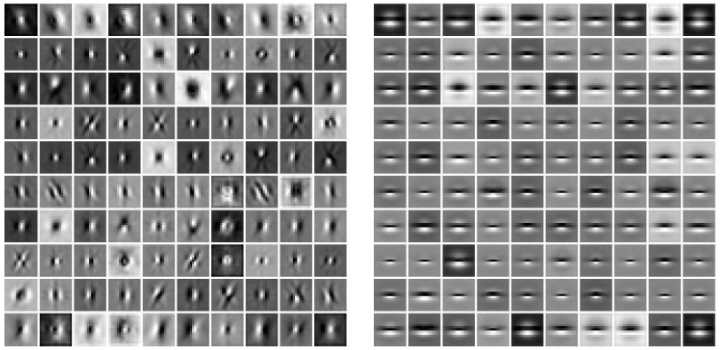
Visual words and textons

- 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

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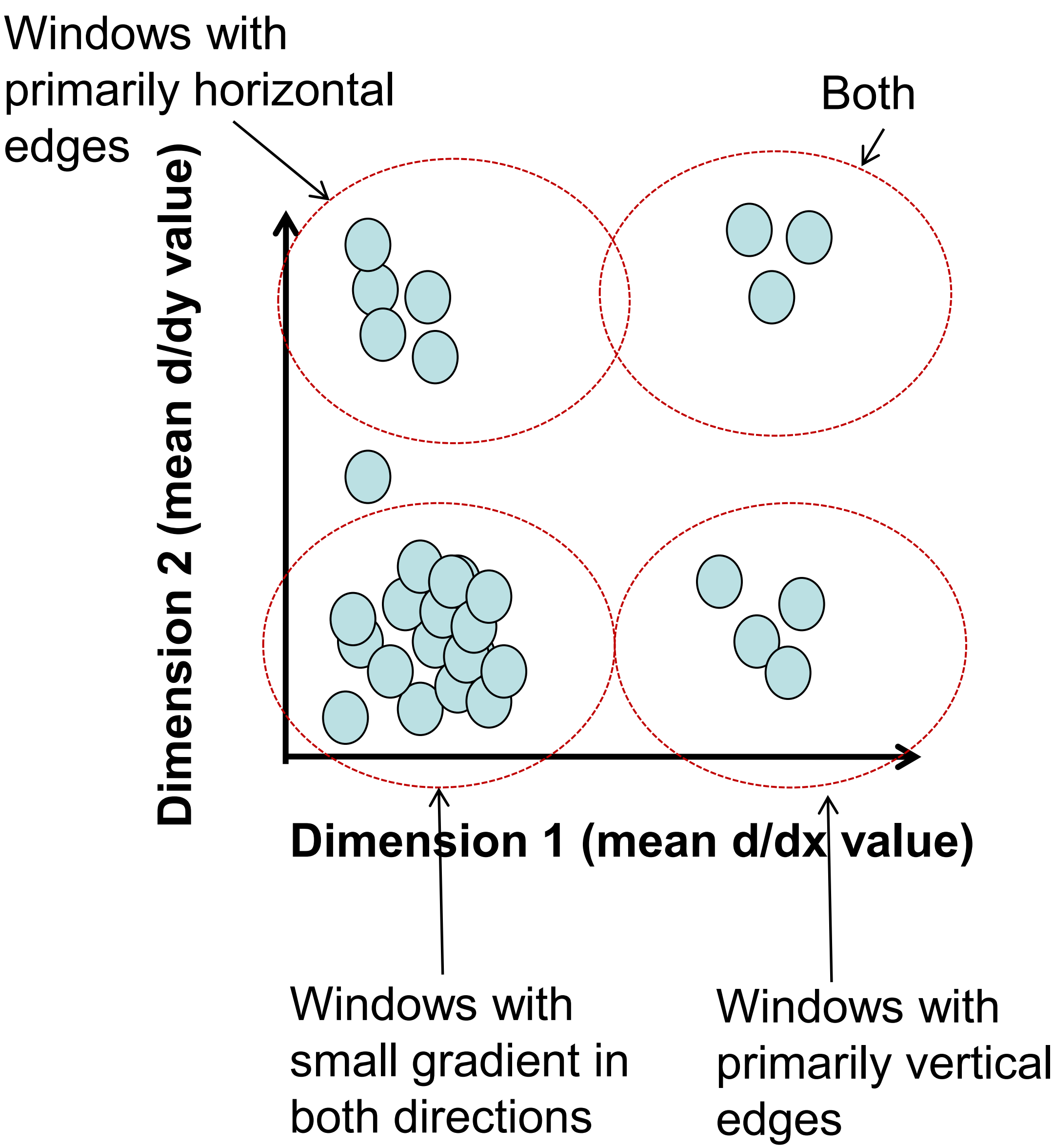
Recall: Texture representation example



	mean d/dx value	**mean d/dy value**
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

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Visual vocabulary formation

Issues:

- Sampling strategy: where to extract features?
- Clustering / quantization algorithm
- Unsupervised vs. supervised
- What corpus provides features (universal vocabulary?)
- Vocabulary size, number of words

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Inverted file index

Database images

Image #1

Image #2

Image #3

Word #	Image #
1	3
2 …	
7	1, 2
8	3
9	
10 …	
91	2

…

- Database images are loaded into the index mapping words to image numbers

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Inverted file index

When will this give us a significant gain in efficiency?

New query image

Word #	Image #
1	3
2 …	
7	1, 2
8	3
9	
10 …	
91	2

…

- New query image is mapped to indices of database images that share a word.

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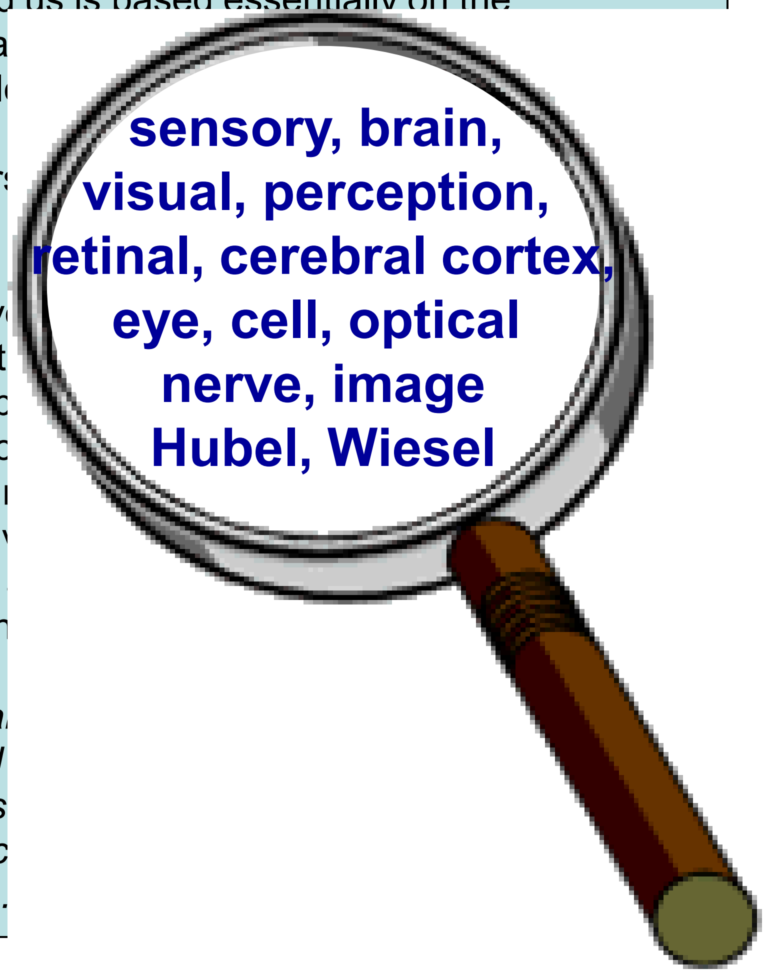
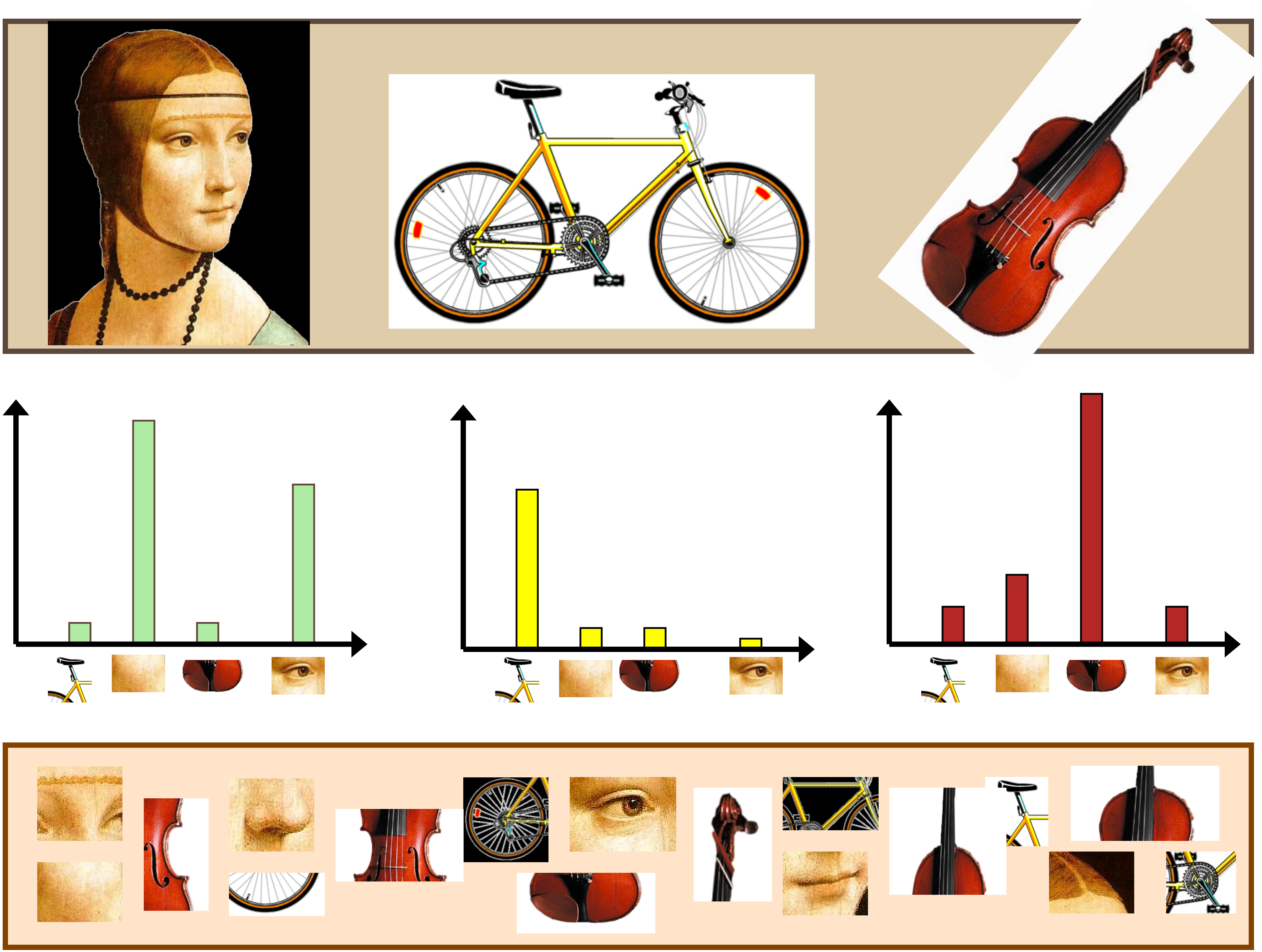
- If a local image region is a visual word, how can we summarize an image (the document)?

Analogy to documents

Of all the sensory impressions proceeding to
the brain, the visual experiences are the
dominant ones. Our perception of the world
around us is based essentially on the
messa
For a l
image
centers
movie
image
discov
know t
percep
more c
followi
to the v
Hubel
demon
image
wise a
stored
has its
a spec
image.

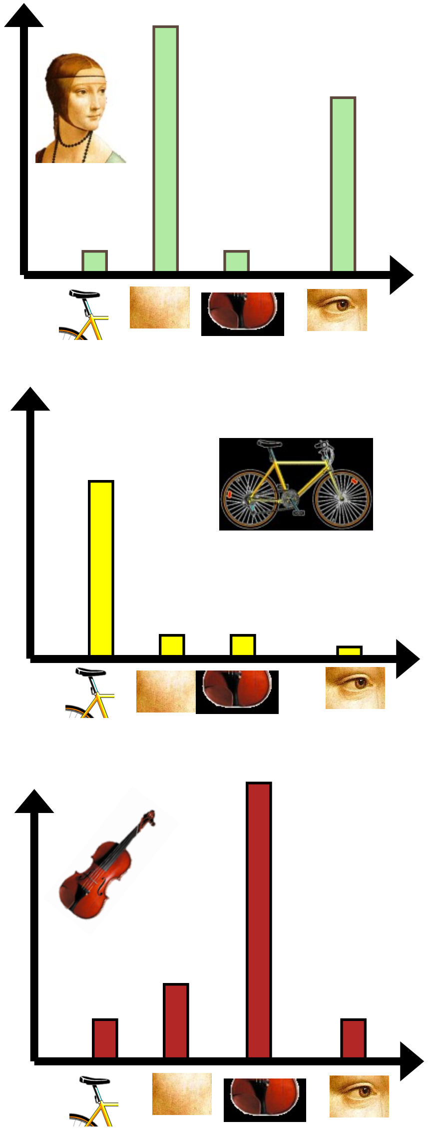


China is forecasting a trade surplus of $90bn
(£51bn) to $100bn this year, a threefold
increase on 2004's $32bn. The Commerce
Ministry said the surplus would be created by
a pred
compa
$660b
annoy
China'
delibe
agree
yuan i
gover
also n
demar
countr
yuan a
permit
the US
freely.
it will t
allowir



Bags of visual words

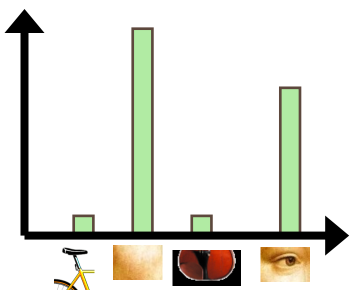
- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.



Comparing bags of words

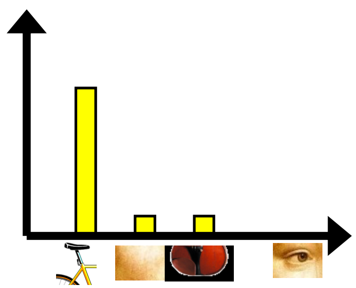
- Rank frames by normalized scalar product between their (possibly weighted) occurrence counts---*nearest neighbor* search for similar images.

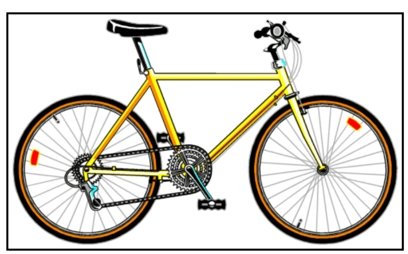
[1 8 1 4]



$\vec{d}_j$

[5 1 1 0]





$\vec{q}$

$$sim(d_j, q) = \frac{\langle d_j, q \rangle}{\|d_j\| \|q\|}$$

$$= \frac{\sum_{i=1}^{V} d_j(i) * q(i)}{\sqrt{\sum_{i=1}^{V} d_j(i)^2} * \sqrt{\sum_{i=1}^{V} q(i)^2}}$$

for vocabulary of *V* words

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tf-idf weighting

- **T**erm **f**requency – **i**nverse **d**ocument **f**requency
- Describe frame by frequency of each word within it, downweight words that appear often in the database
- (Standard weighting for text retrieval)

Number of occurrences of word i in document d

Number of words in document d

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

Total number of documents in database

Number of documents word i occurs in, in whole database

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Bags of words for content-based image retrieval

Visually defined query

"Groundhog Day" [Rammis, 1993]

"Find this clock"

"Find this place"

Slide from Andrew Zisserman
Sivic & Zisserman, ICCV 2003

Example

retrieved shots

Slide from Andrew Zisserman
Sivic & Zisserman, ICCV 2003

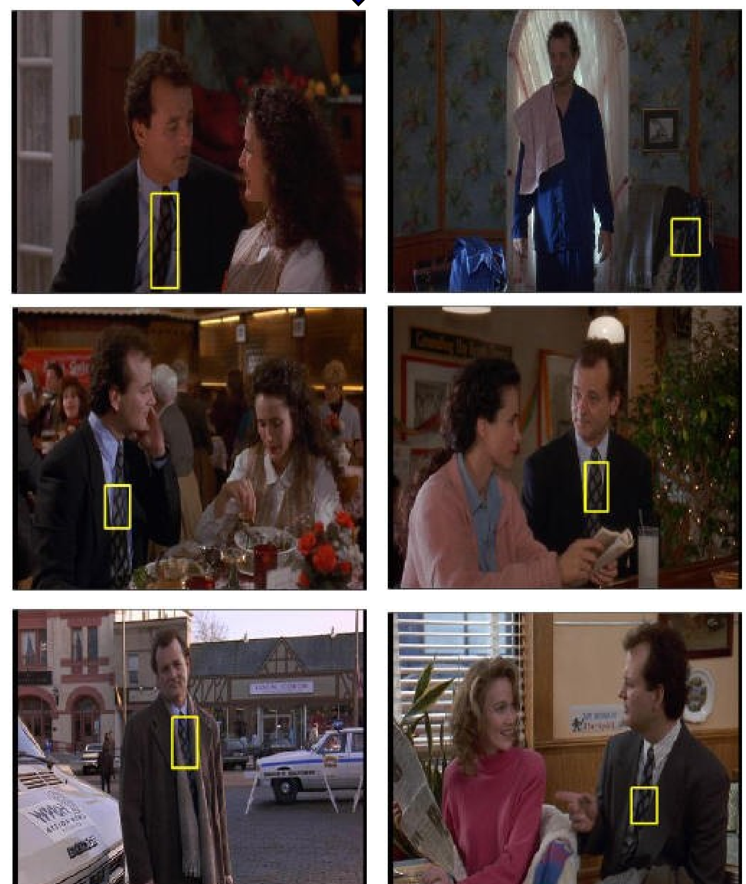
Video Google System

1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

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

Query region



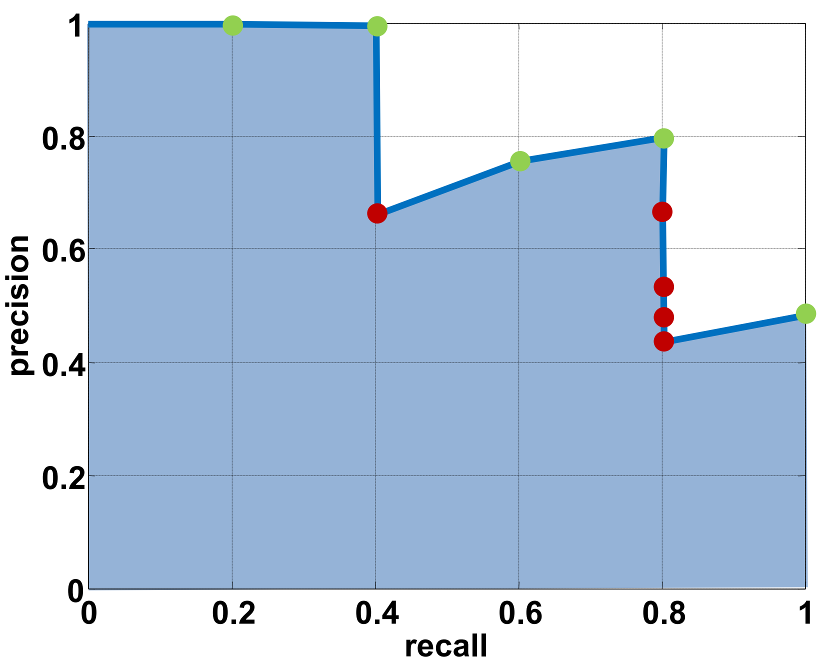
Retrieved frames

Scoring retrieval quality

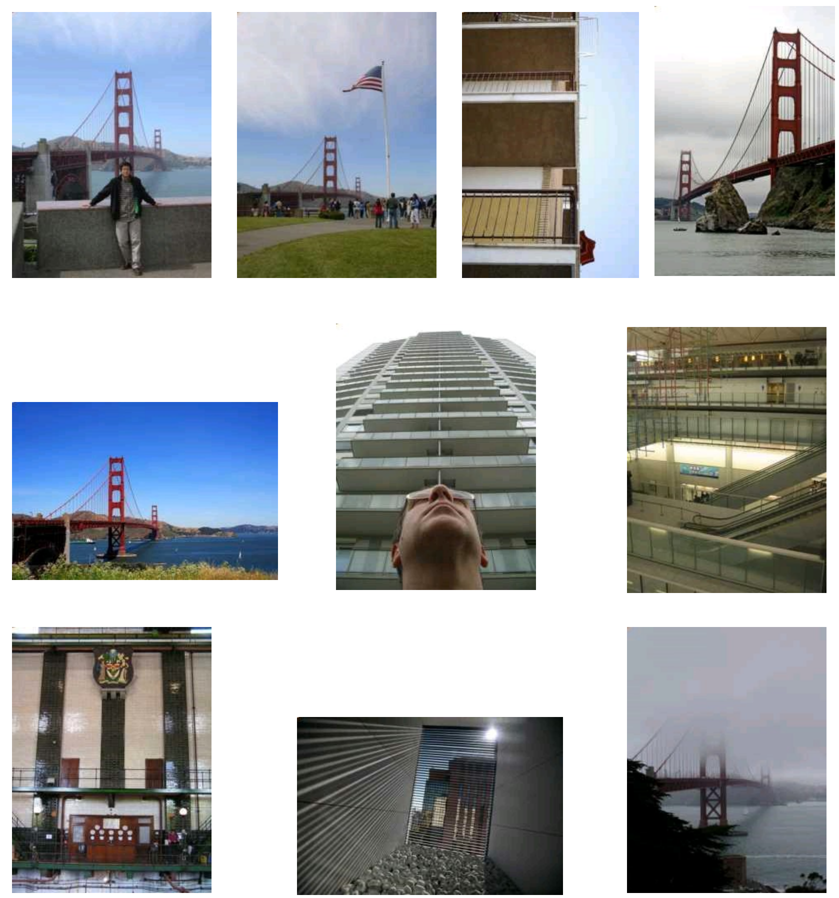
Query

Database size: 10 images
Relevant (total): 5 images

precision = #relevant / #returned
recall = #relevant / #total relevant



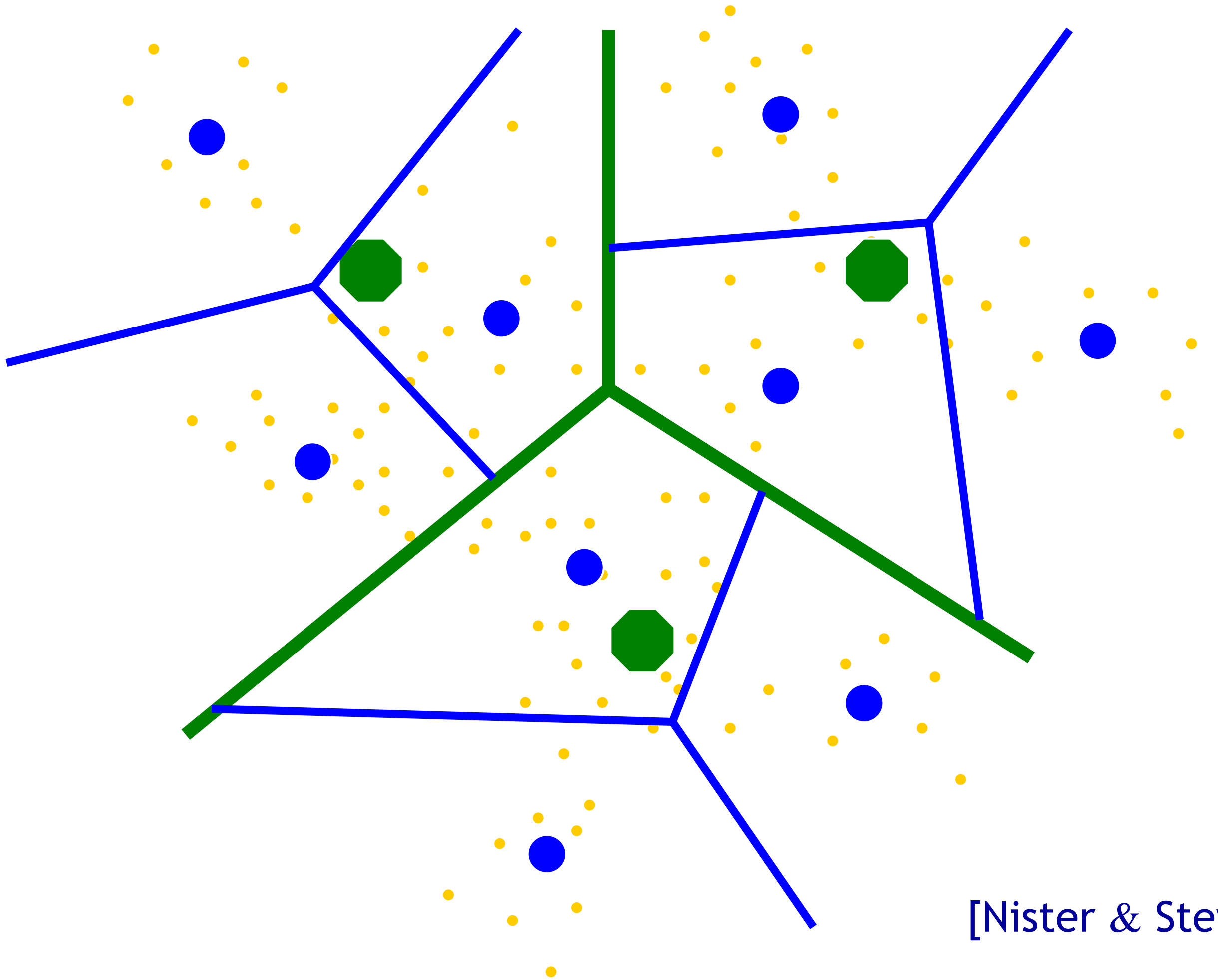
Results (ordered):



Slide credit: Ondrej Chum

Vocabulary Trees: hierarchical clustering for large vocabularies

- **Tree construction:**

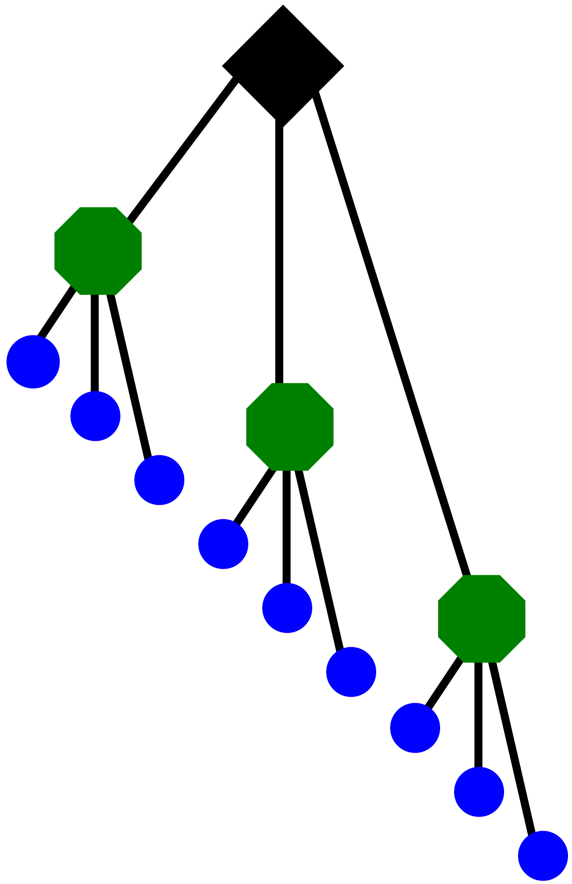


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- **Training: Filling the tree**

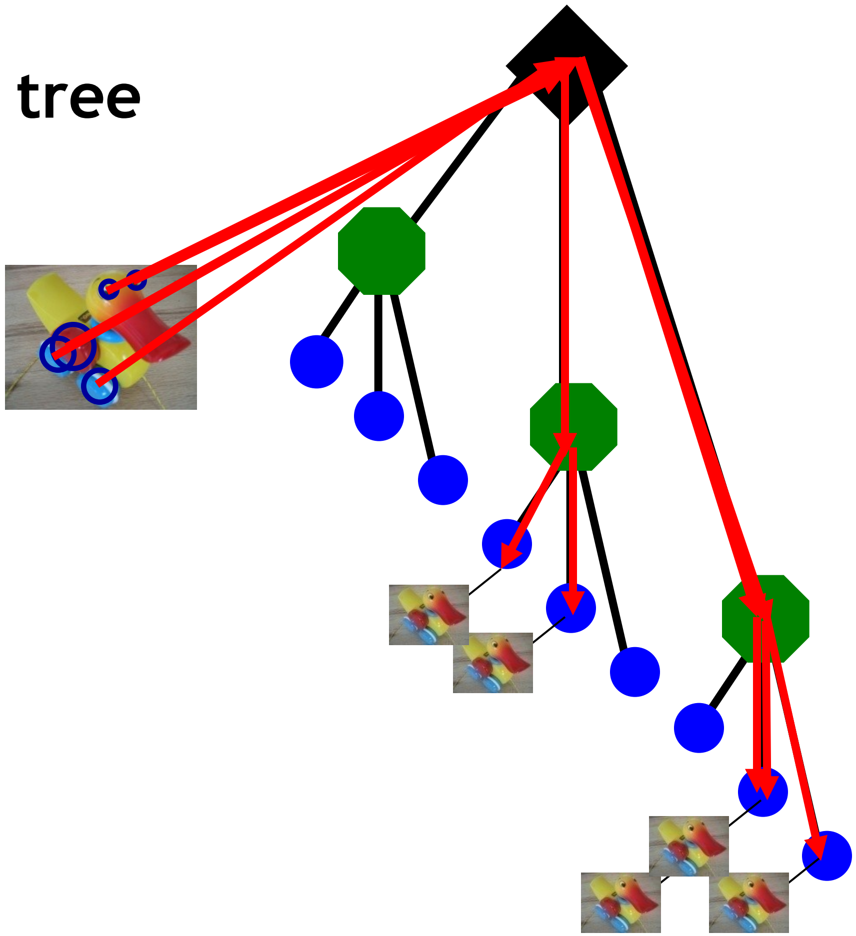


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- **Training: Filling the tree**

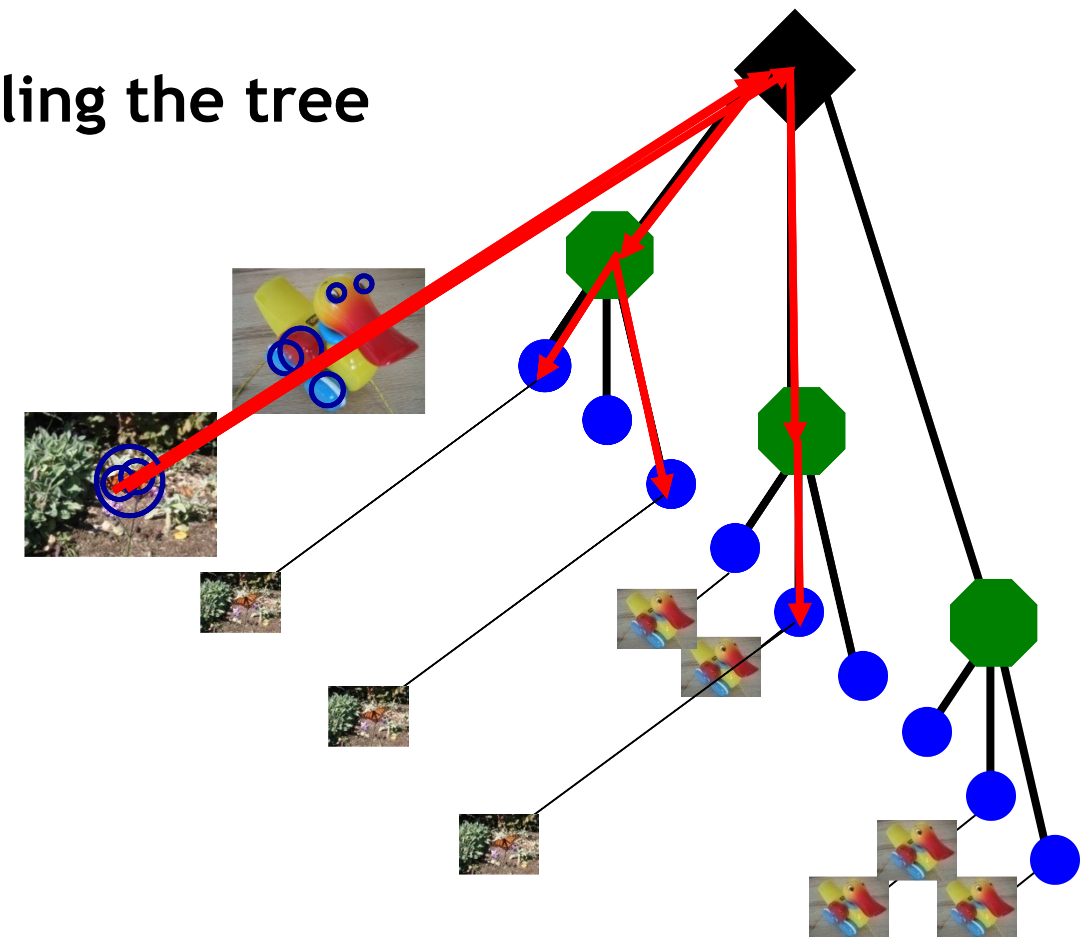


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- **Training: Filling the tree**

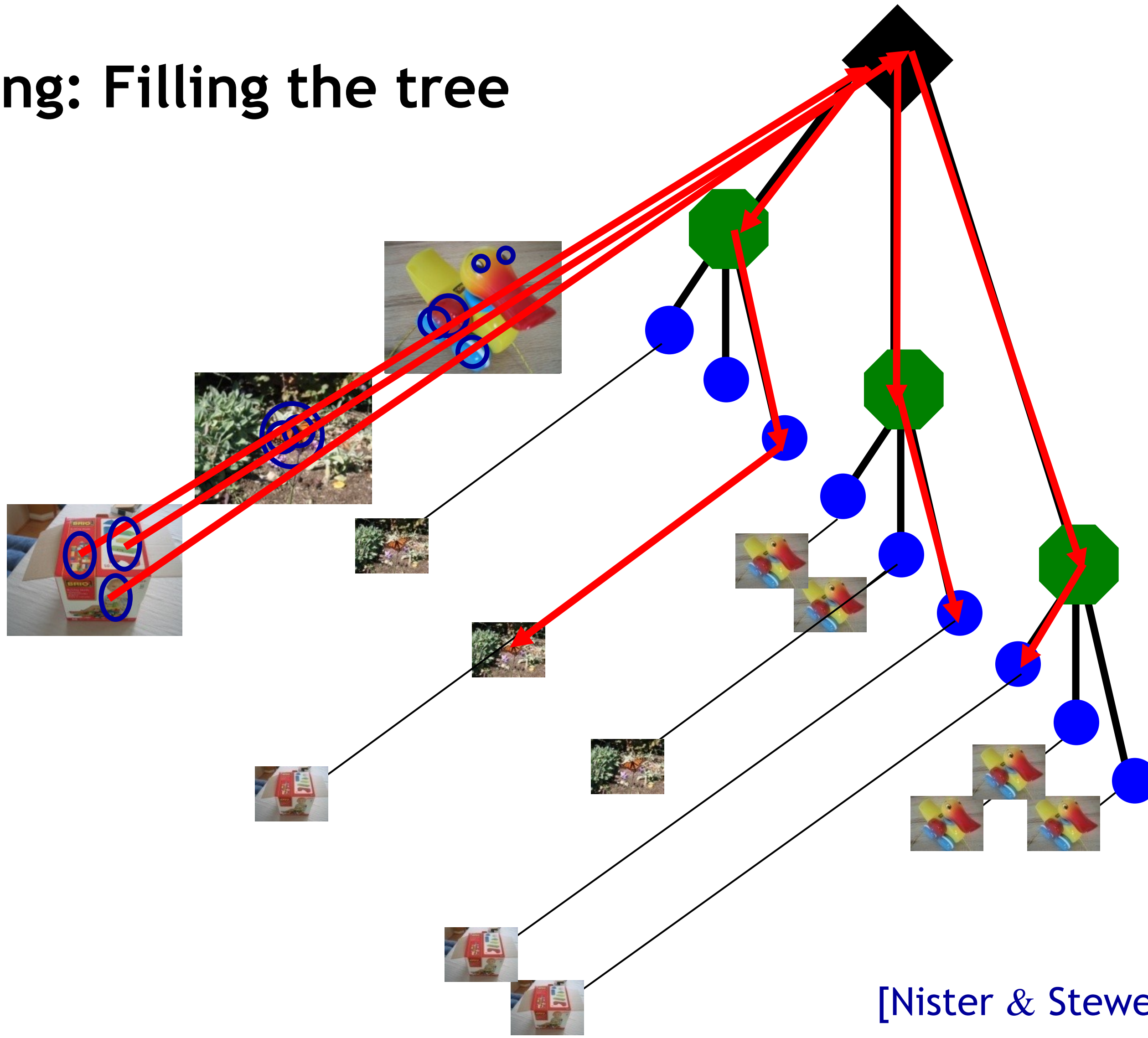


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- **Training: Filling the tree**

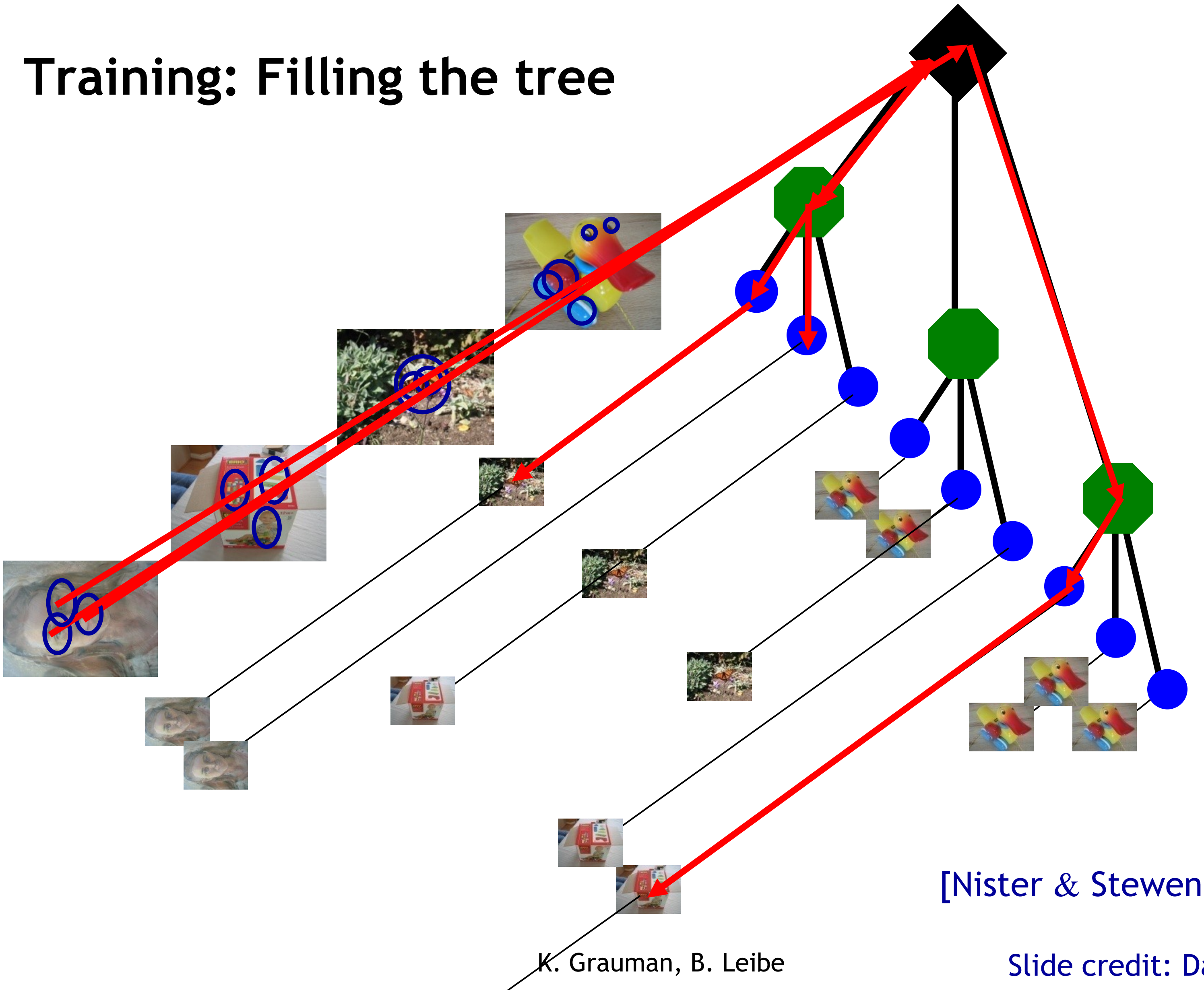


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- **Training: Filling the tree**



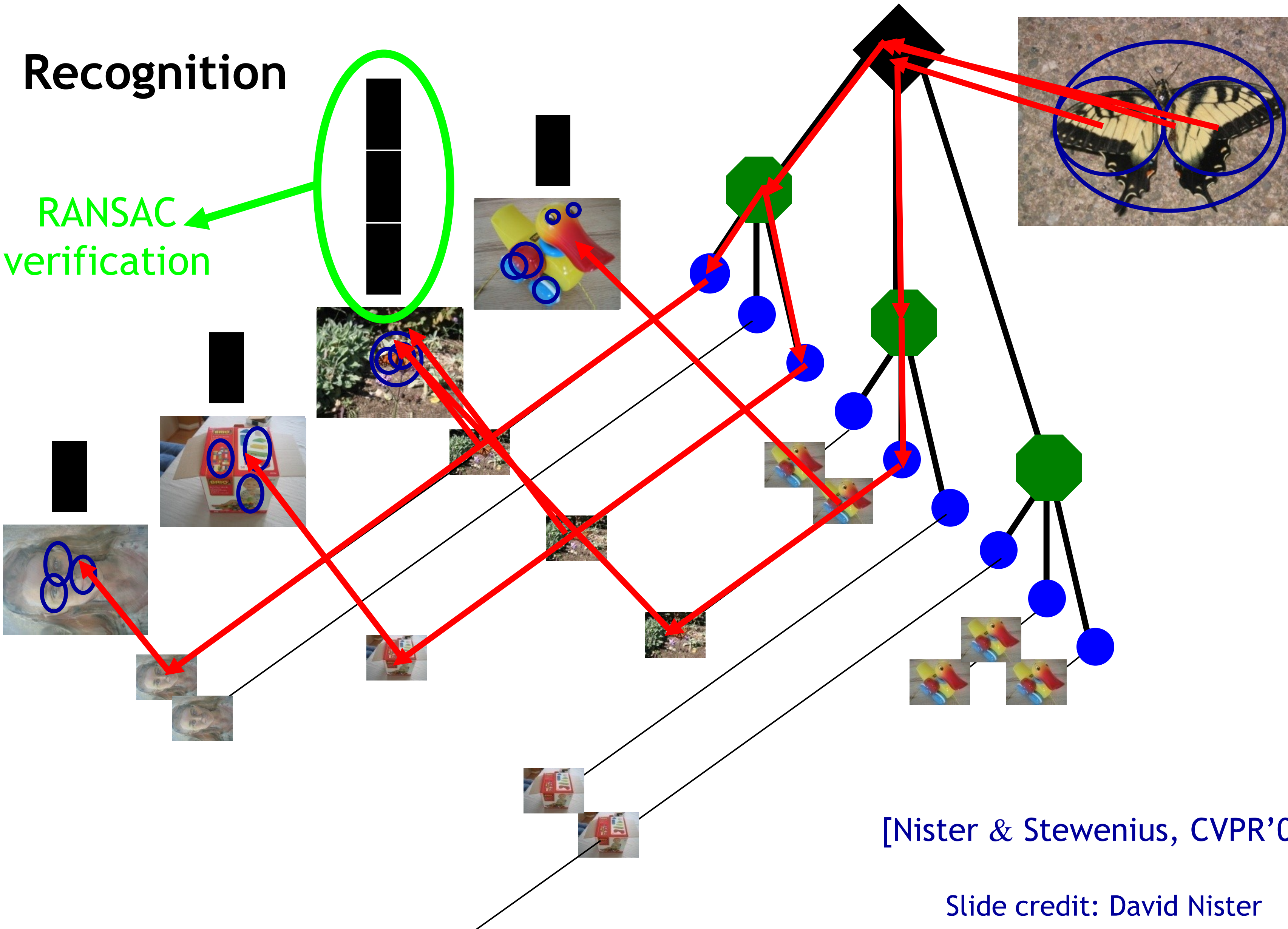
[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

What is the computational advantage of the hierarchical representation bag of words, vs. a flat vocabulary?

Vocabulary Tree

- **Recognition**



[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Bags of words: pros and cons

+ flexible to geometry / deformations / viewpoint
+ compact summary of image content
+ provides vector representation for sets
+ very good results in practice

- basic model ignores geometry – must verify afterwards, or encode via features
- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear

Summary

- **Matching local invariant features**: useful not only to provide matches for multi-view geometry, but also to find objects and scenes.
- **Bag of words** representation: quantize feature space to make discrete set of visual words
  - Summarize image by distribution of words
  - Index individual words
- **Inverted index**: pre-compute index to enable faster search at query time