

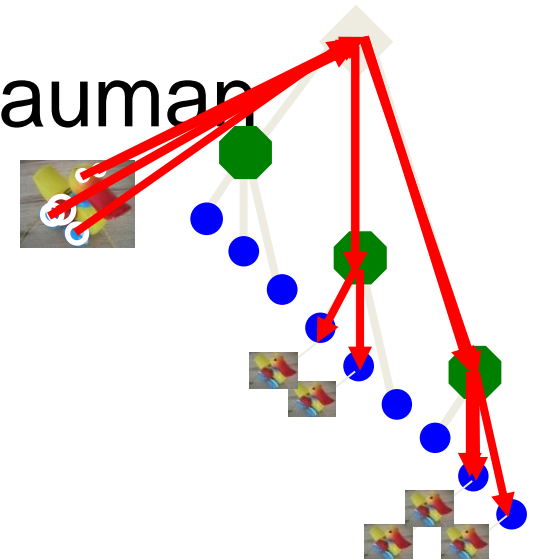
TP13 - Indexing local features

Computer Vision, FCUP, 2019/20

Miguel Coimbra

Slides by Prof. Kristen Grauman

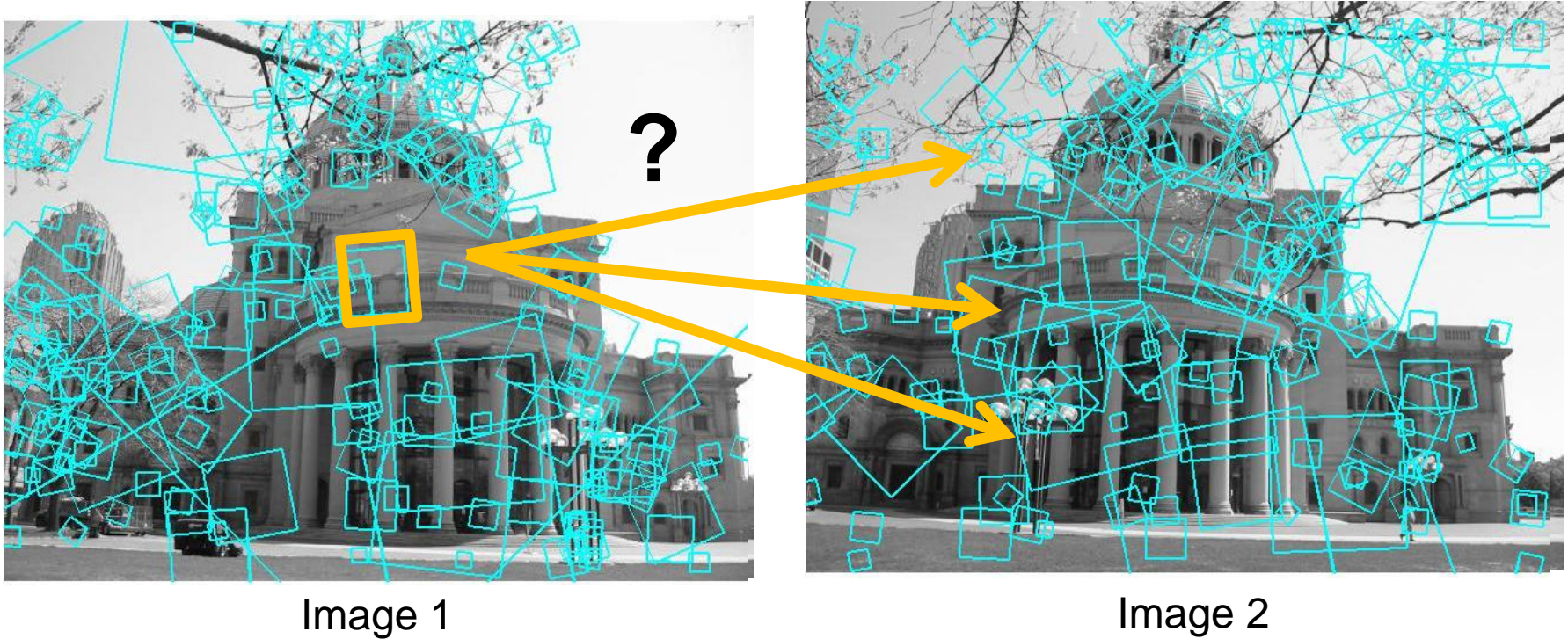
Index	
"Along I-75," From Detroit to Florida; <i>inside back cover</i>	Butterfly Center, McGuire; 134
"Drive I-95," From Boston to Florida; <i>inside back cover</i>	CAA (see AAA)
1929 Spanish Trail Roadway; 101-102,104	CCC, The; 111,113,115,135,142
511 Traffic Information; 83	Ca d'Zan; 147
A1A (Barrier Isl) - I-95 Access; 86	Caloosahatchee River; 152
AAA (and CAA); 83	Name; 150
AAA National Office; 88	Canaveral Natnl Seashore; 173
Abbreviations,	Cannon Creek Airpark; 130
Colored 25 mile Maps; cover	Canopy Road; 106,169
Exit Services; 196	Cape Canaveral; 174
Travelogue; 85	Castillo San Marcos; 169
Africa; 177	Cave Diving; 131
Agricultural Inspection Stns; 126	Cayo Costa, Name; 150
Ah-Tah-Thi-Ki Museum; 160	Celebration; 93
Air Conditioning, First; 112	Charlotte County; 149
	Charlotte Harbor; 150
	Chautauqua; 116
	Chipley; 114



Matching local features



Matching local features



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)

Matching local features



Image 1

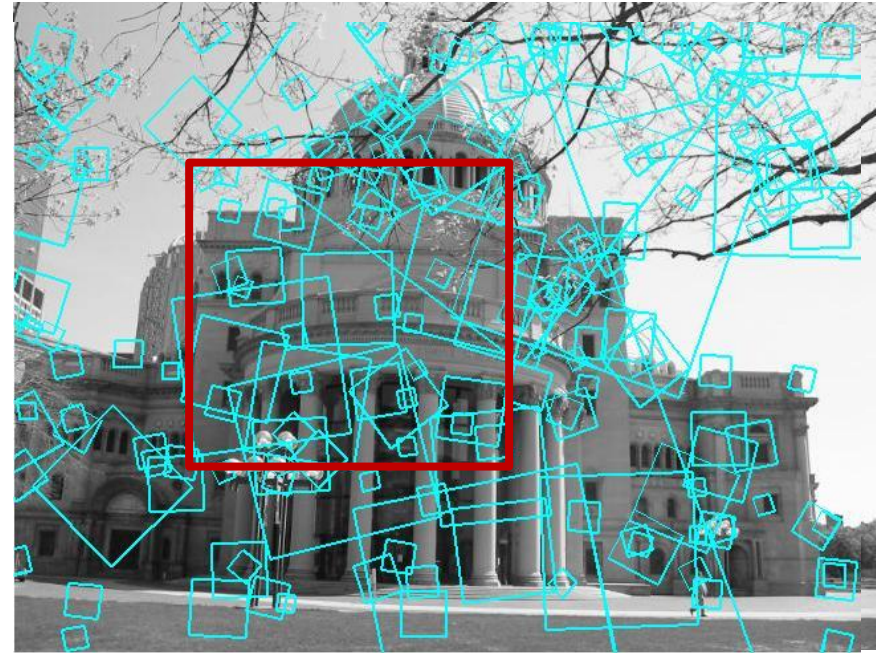
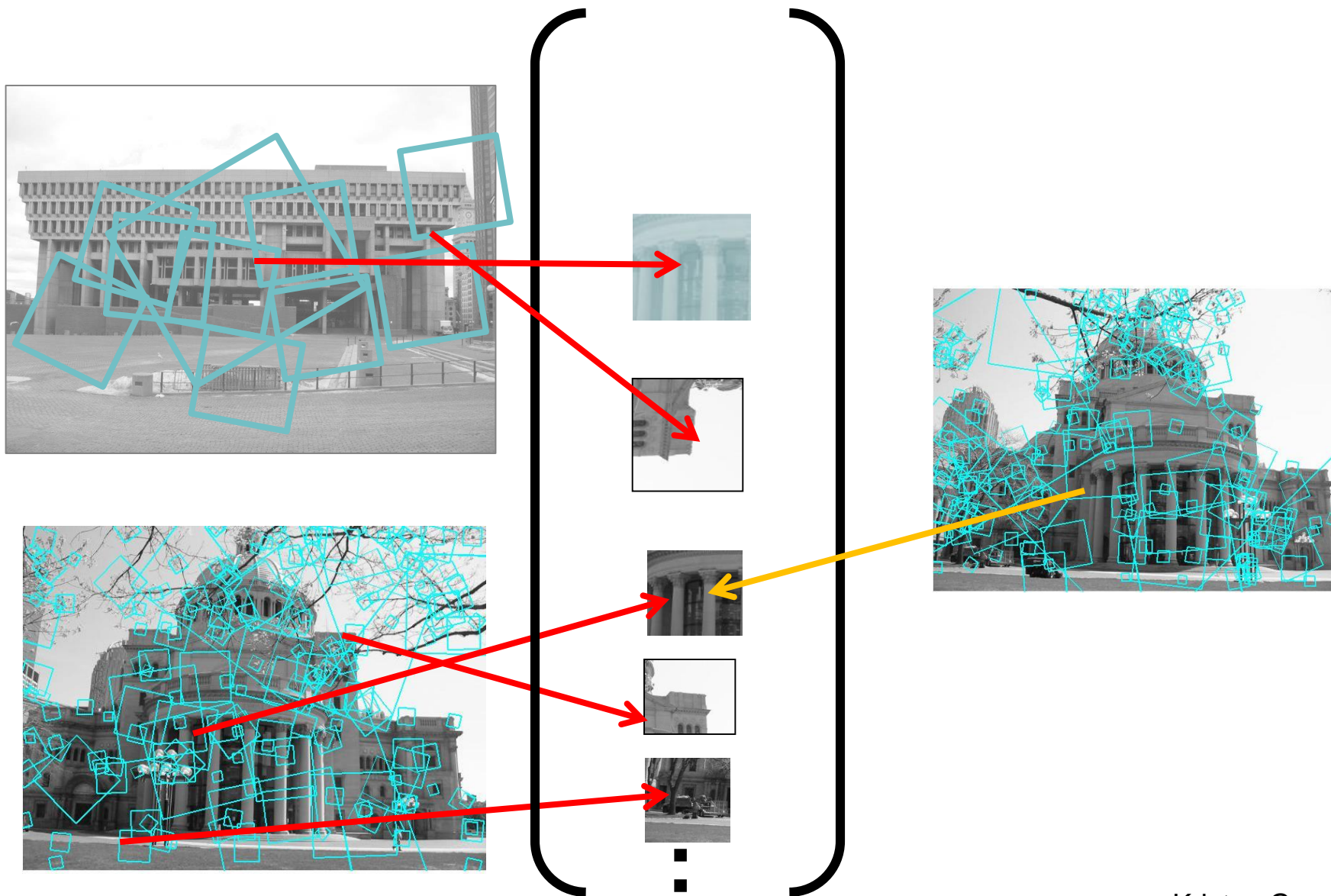


Image 2

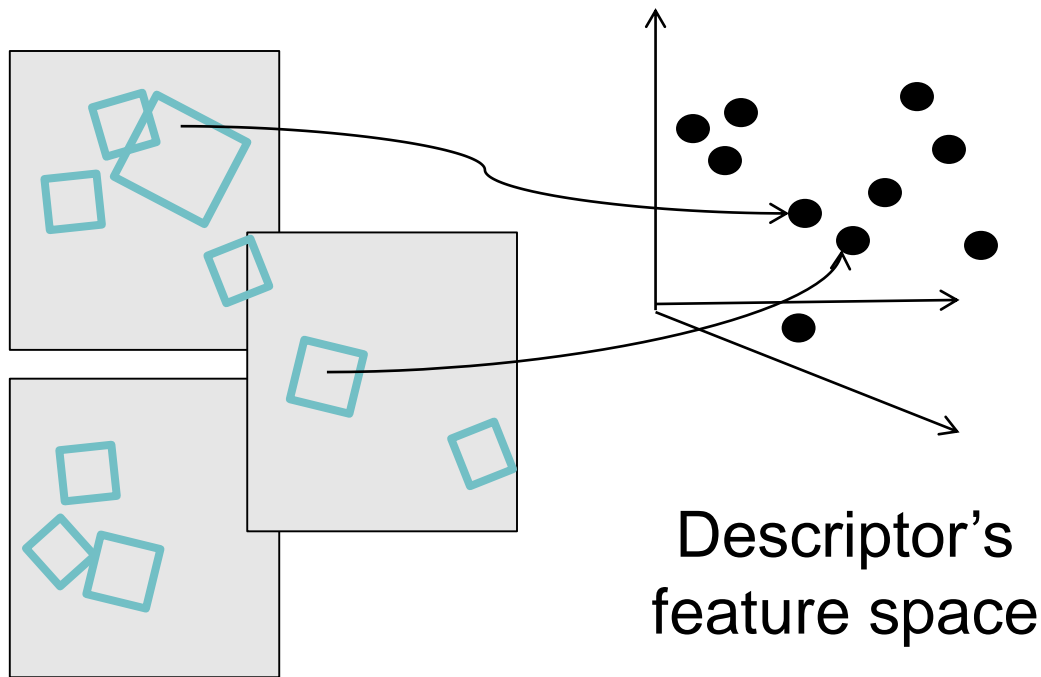
In stereo case, may constrain by proximity if we make assumptions on max disparities.

Indexing local features



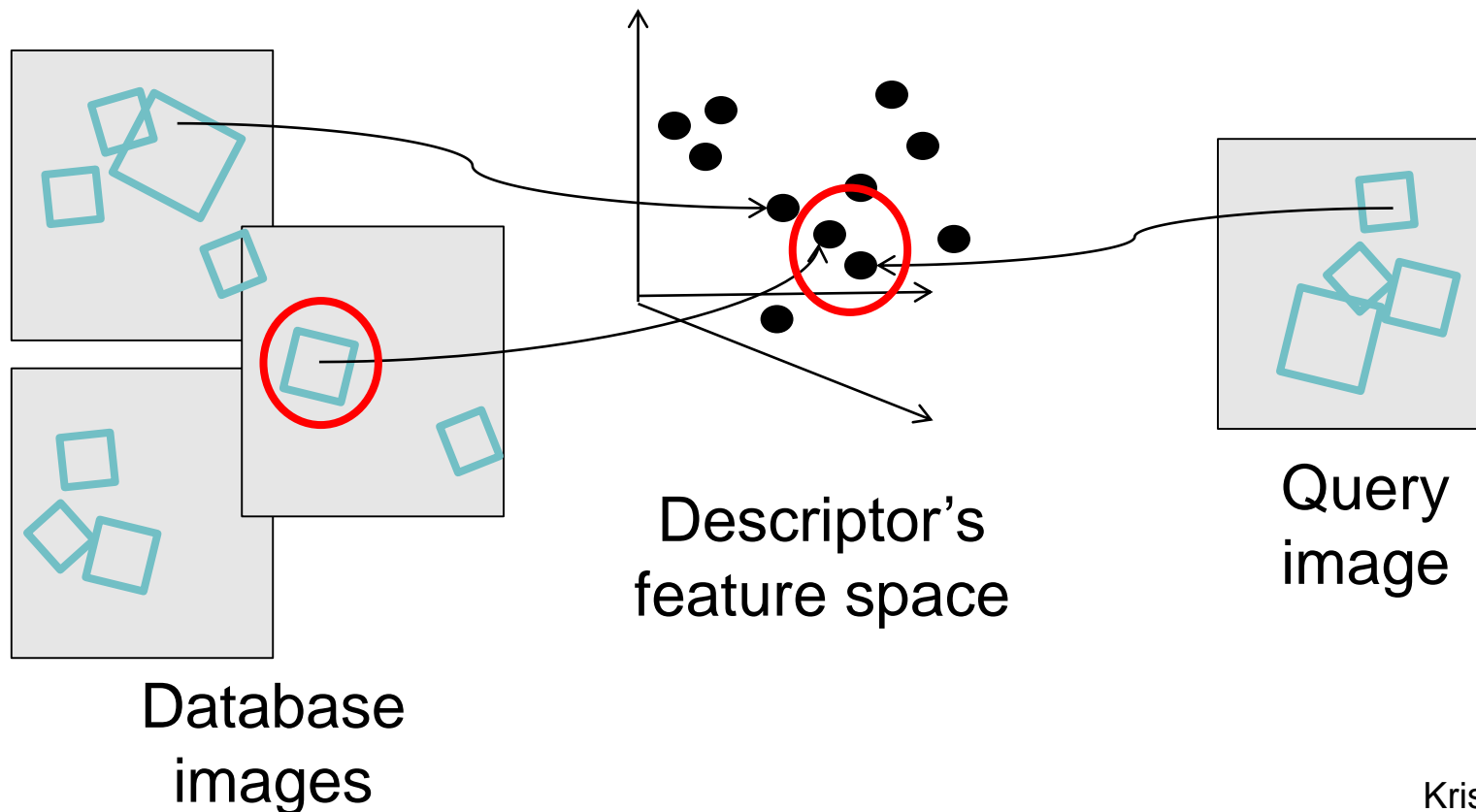
Indexing local features

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



Indexing local features

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



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?

Indexing local features: inverted file index

Index	
"Along I-75," From Detroit to Florida; <i>inside back cover</i>	Butterfly Center, McGuire; 134
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Agricultural Inspection Stns; 126	Cayo Costa, Name; 150
Ah-Tah-Thi-Ki Museum; 160	Celebration; 93
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Alachua; 132	Chautauqua; 116
County; 131	ChIPLEY; 114
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Bernard Castro; 136	Crab Trap II; 144
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	Eight Reale; 176
	Ellenton; 144-145
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	Supreme Court; 107
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	Coin System; 190
	Exit Services; 189
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	History; 189
	Names; 189
	Service Plazas; 190
	Spur SR91; 76
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	Toll Plazas; 190
	Ford, Henry; 152

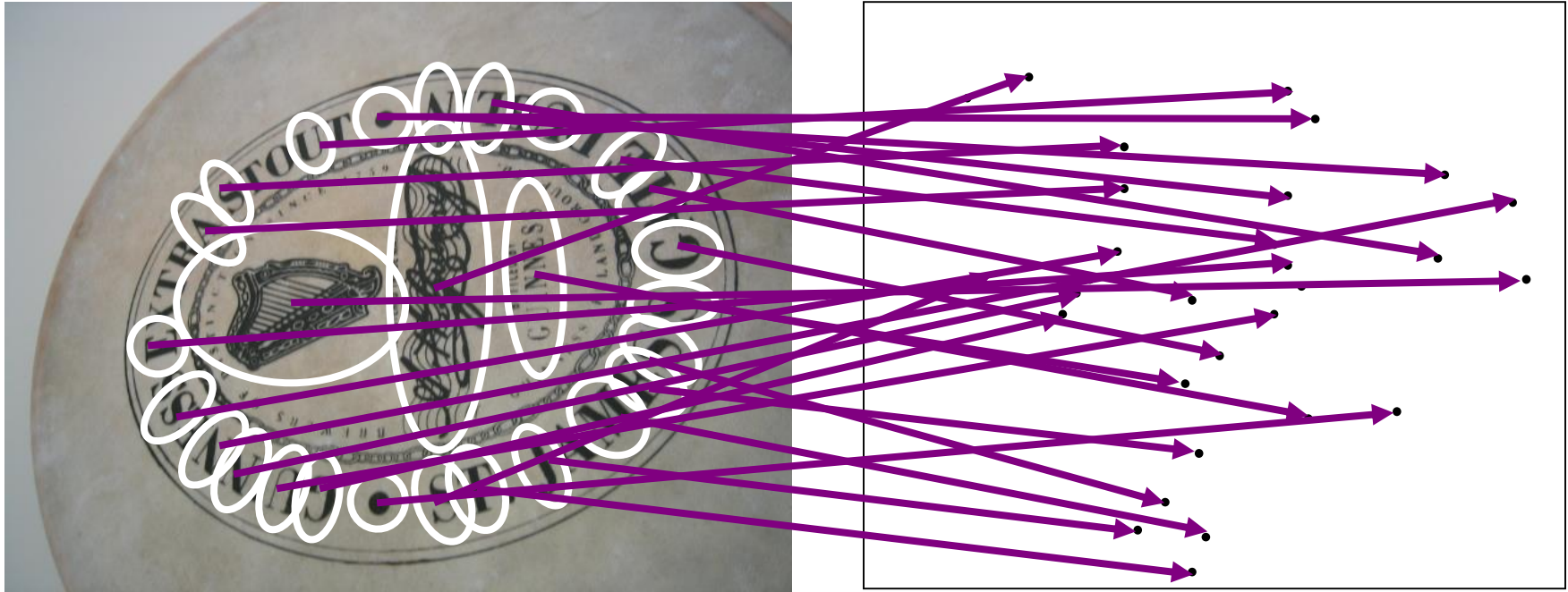
- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index...
- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words".

Text retrieval vs. image search

- What makes the problems similar, different?

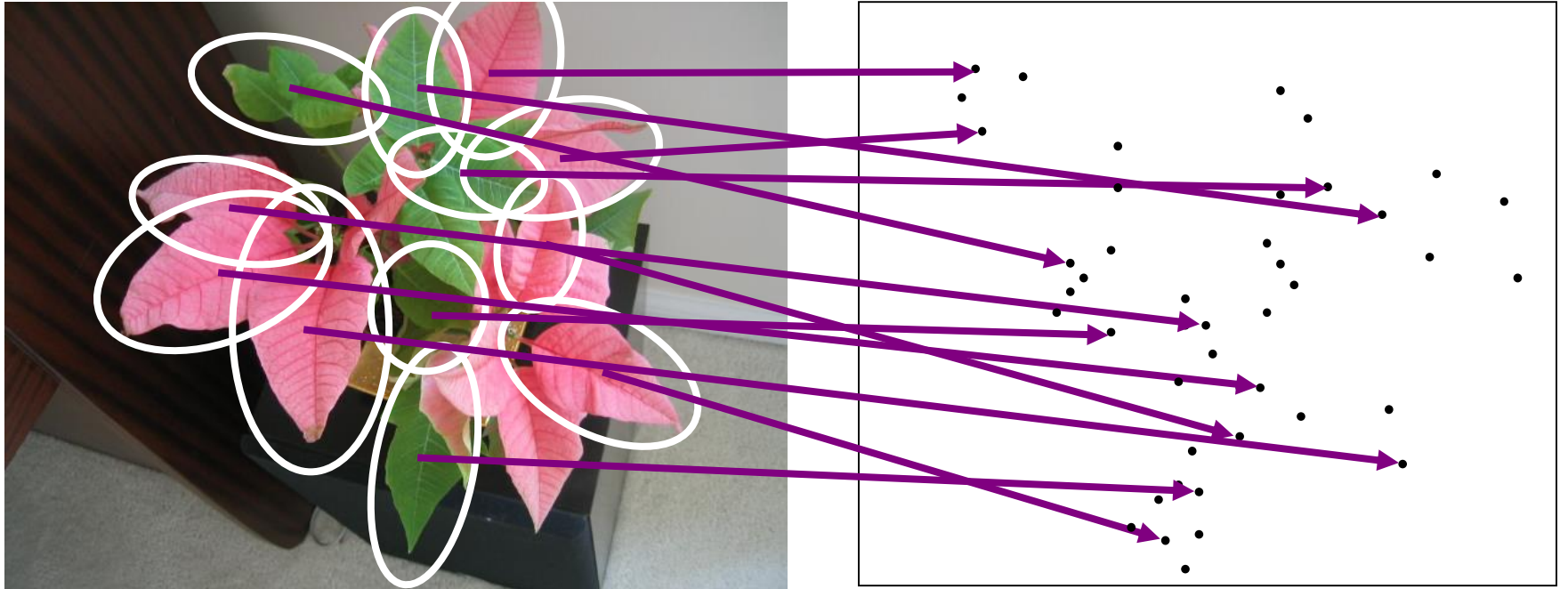
Visual words: main idea

- Extract some local features from a number of images ...

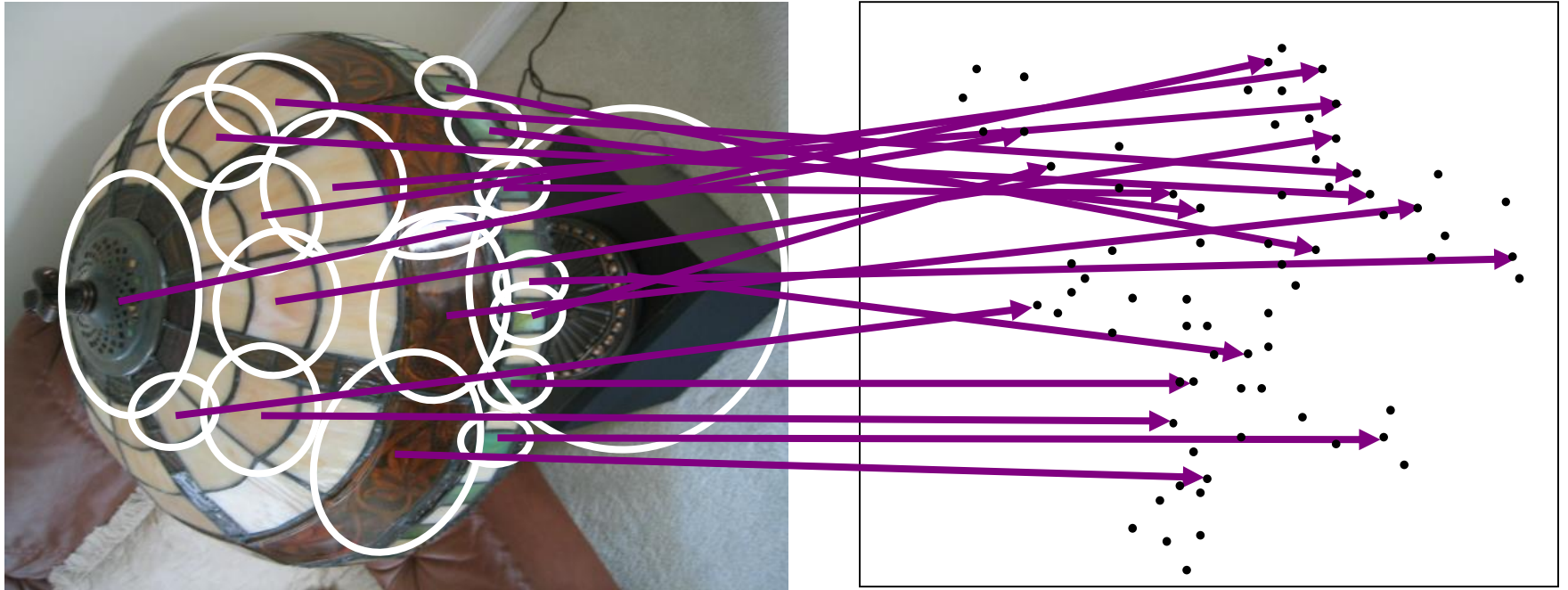


e.g., SIFT descriptor space: each point is 128-dimensional

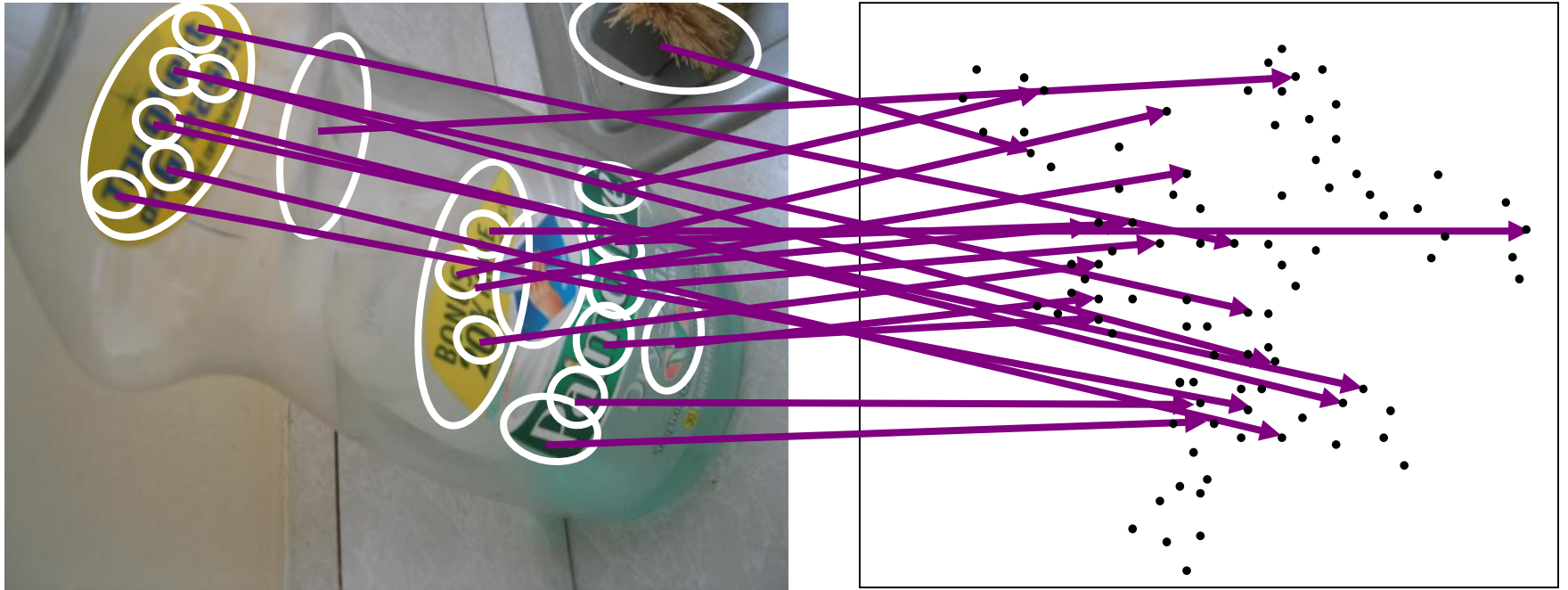
Visual words: main idea

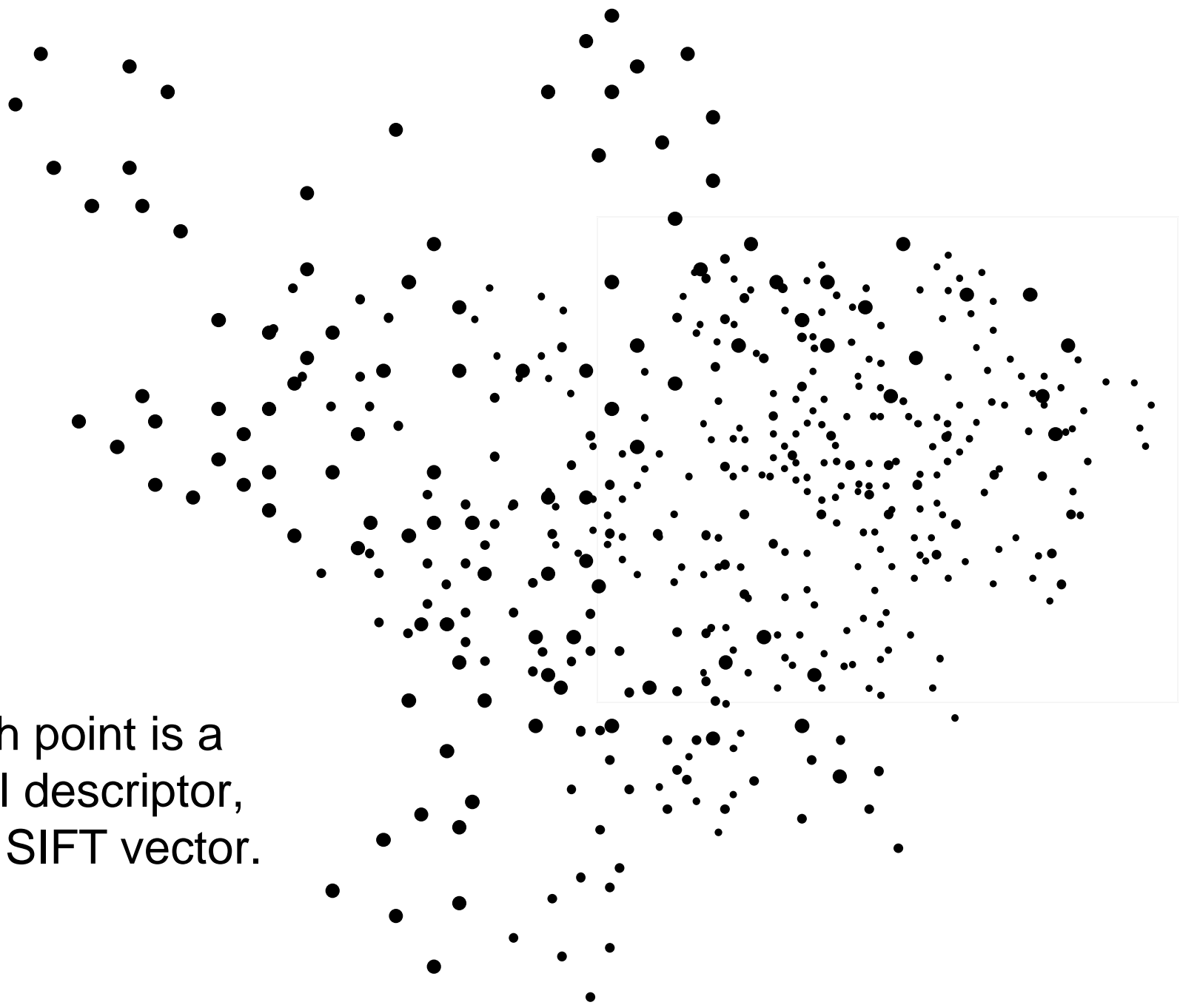


Visual words: main idea

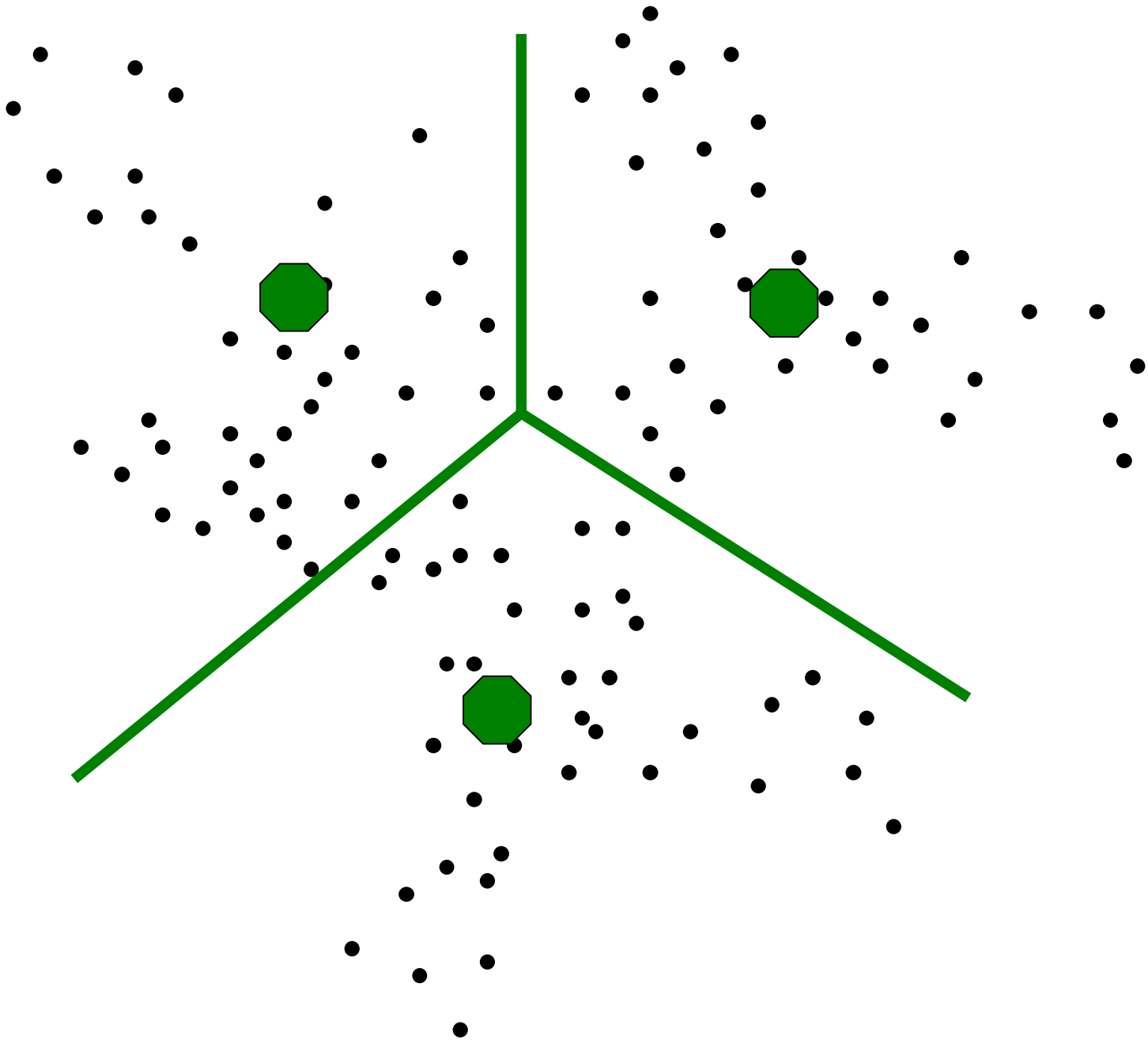


Visual words: main idea



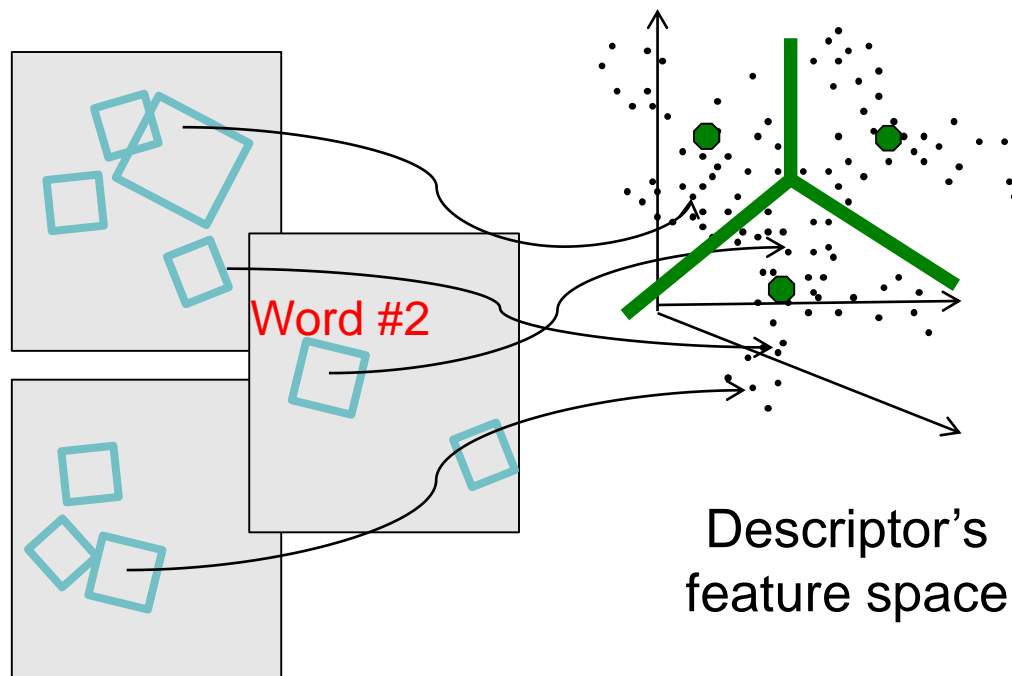


Each point is a
local descriptor,
e.g. SIFT vector.



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.

Visual words

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

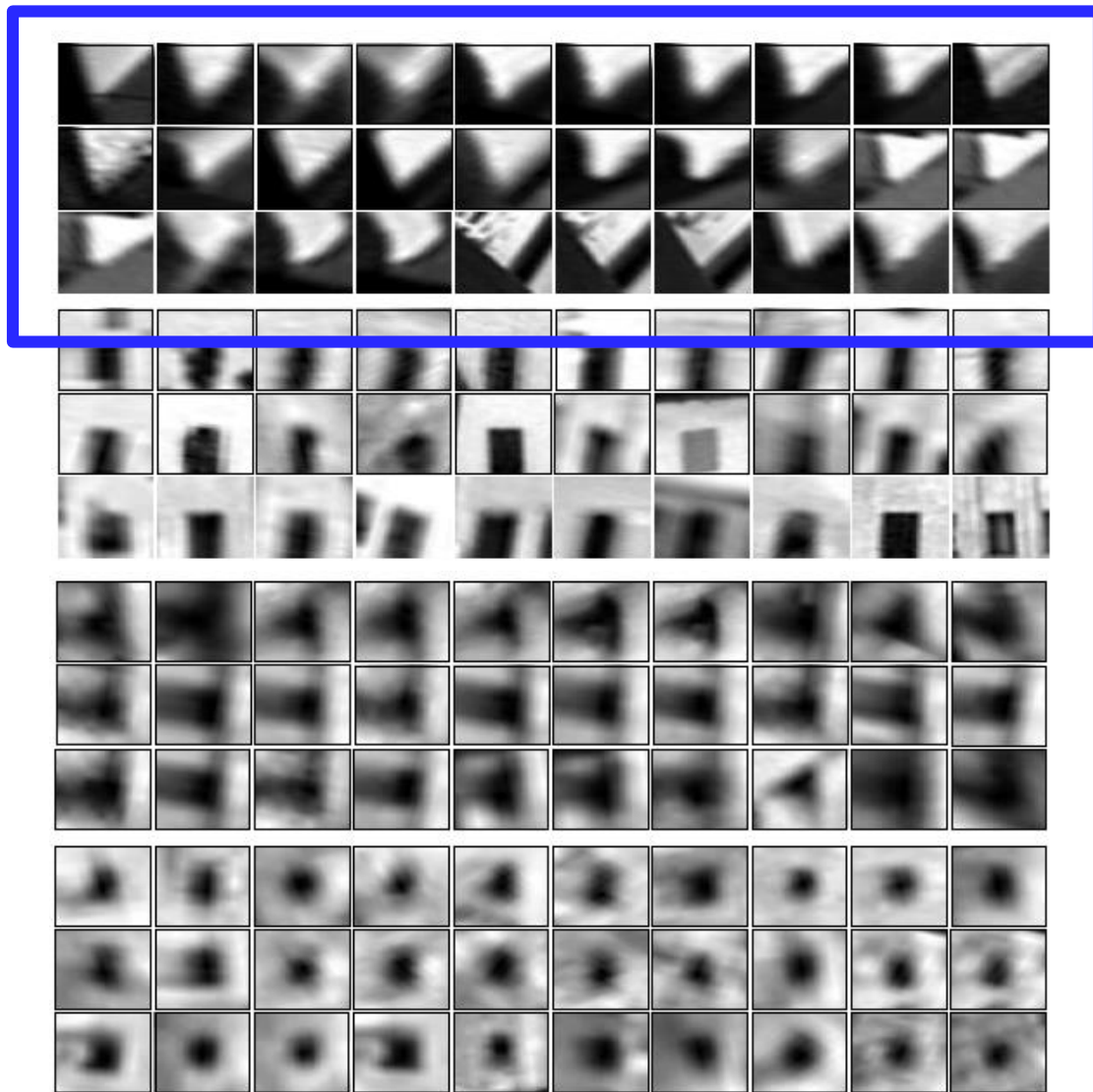
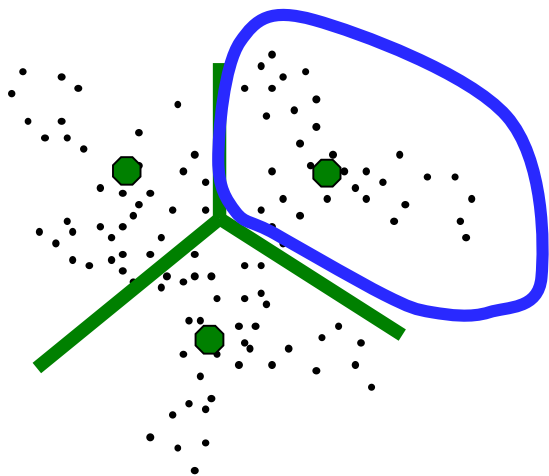
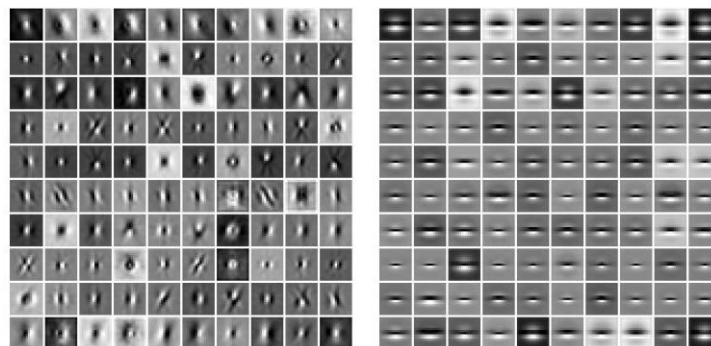
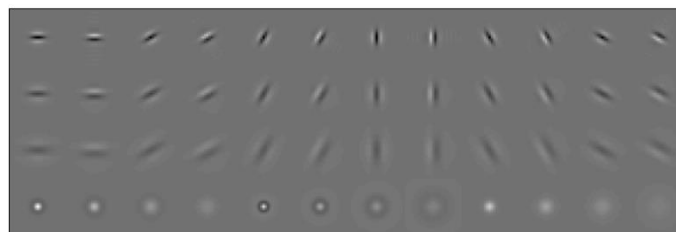
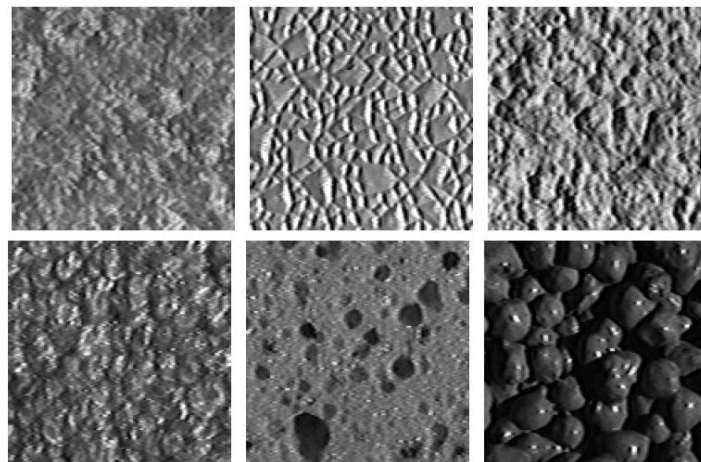


Figure from Sivic & Zisserman, ICCV 2003

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.



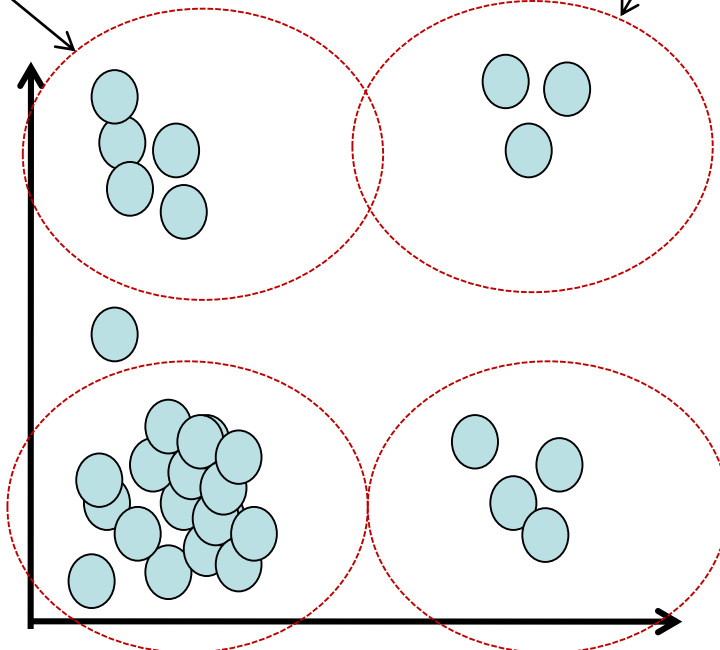
Leung & Malik 1999; Varma & Zisserman, 2002

Recall: Texture representation example

Windows with primarily horizontal edges

Both

Dimension 2 (mean d/dy value)



Dimension 1 (mean d/dx value)

Windows with small gradient in both directions

Windows with primarily vertical edges

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

⋮

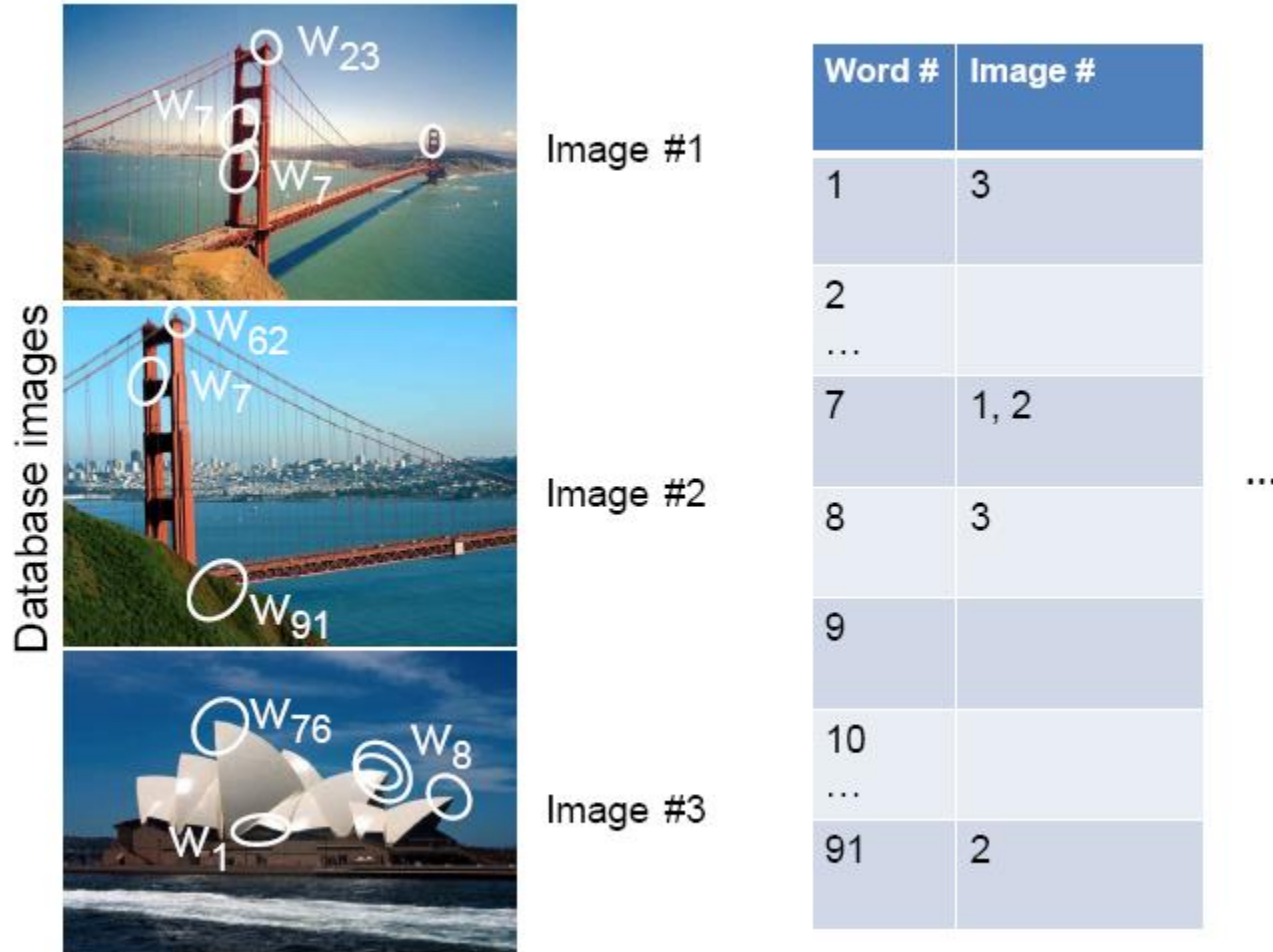
statistics to summarize patterns in small windows

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

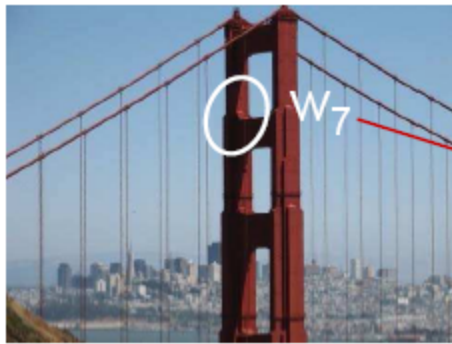
Inverted file index



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

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.

- 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 messages that reach our eyes.

For a long time, the retinal image was considered as a movie screen. It is now known that the image is processed in a more complex manner following the path to the various centers of the cortex, Hubel and Wiesel have demonstrated that the *message about the image falling on the retina undergoes a*

wise analysis in a system of nerve cells stored in columns. In this system each cell has its specific function and is responsible for a specific detail in the pattern of the retinal image.

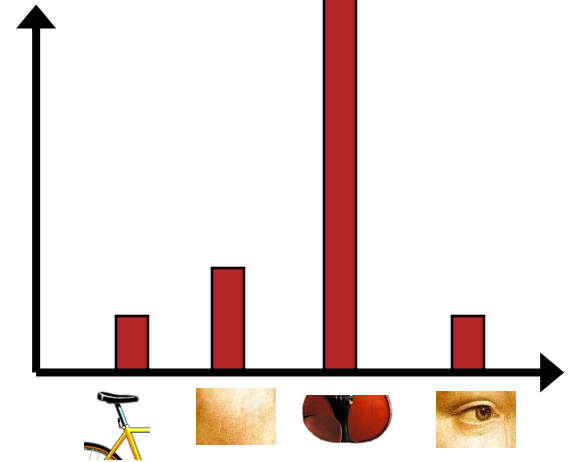
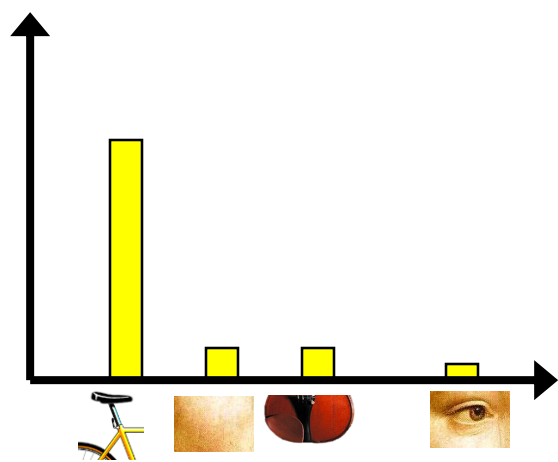
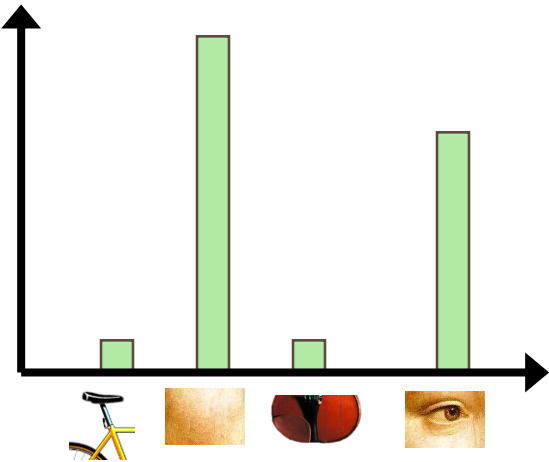
**sensory, brain,
visual, perception,
retinal, cerebral cortex,
eye, cell, optical
nerve, image
Hubel, Wiesel**

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 predicted 30% increase in exports to \$750bn, compared with \$575bn in 2004.

The surplus is expected to annoy the US, which has long complained about China's trade policies. China's government has agreed to a deal with the US that the yuan is to be allowed to rise in value.

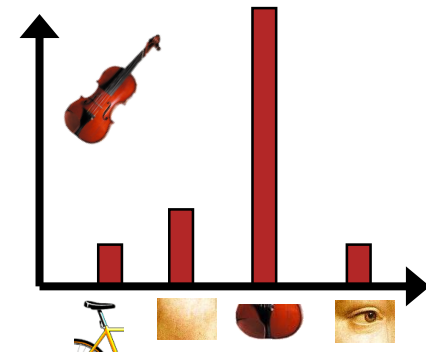
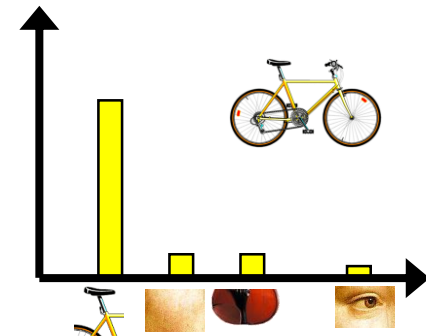
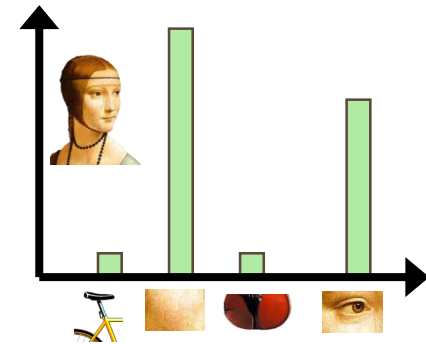
The US government also needs to increase its demand for yuan to meet the country's needs. China's government has permitted it to trade within a narrow band but the US wants the yuan to be allowed to trade freely. However, Beijing has made it clear that it will take its time and tread carefully before allowing the yuan to rise further in value.

**China, trade,
surplus, commerce,
exports, imports, US,
yuan, bank, domestic,
foreign, increase,
trade, value**



Bags of visual words

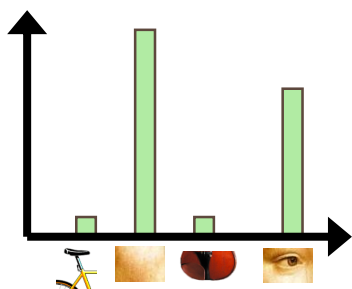
- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.



Comparing bags of words

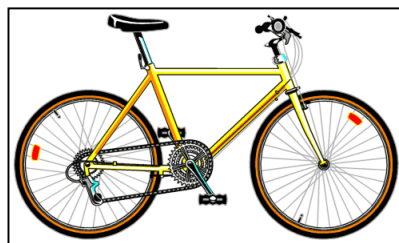
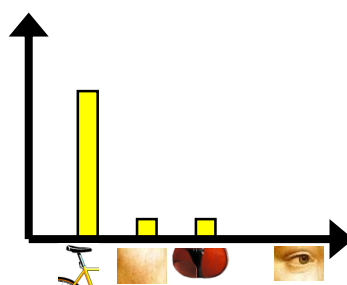
- Rank frames by normalized scalar product between their (possibly weighted) occurrence counts---*nearest neighbor* search for similar images.

[1 8 1 4]



\vec{d}_j

[5 1 1 0]



\vec{q}

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

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

for vocabulary of V words

tf-idf weighting

- Term frequency – inverse document frequency
- 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

Bags of words for content-based image retrieval

Visually defined query

“Groundhog Day” [Rammis, 1993]

“Find this clock”



“Find this place”



Example



retrieved shots



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

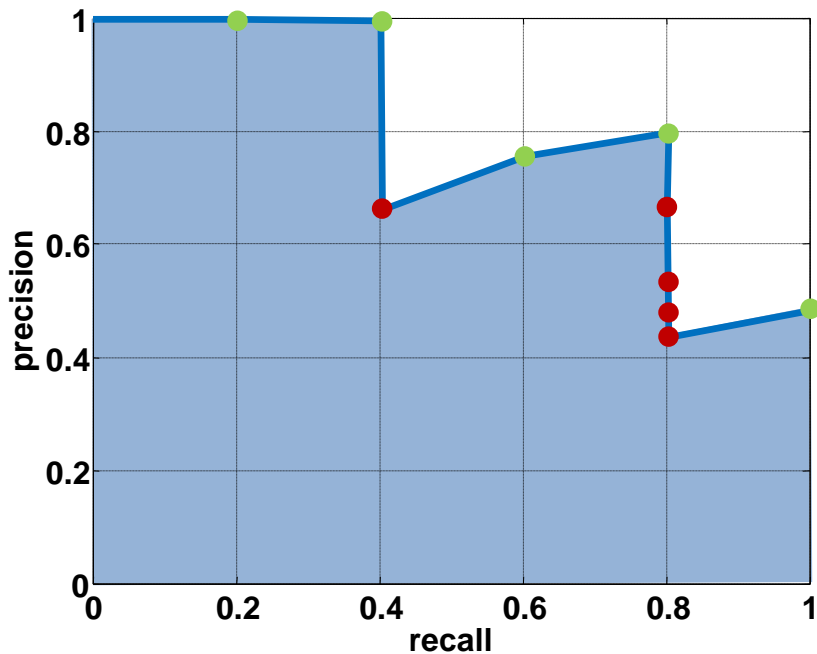
Scoring retrieval quality



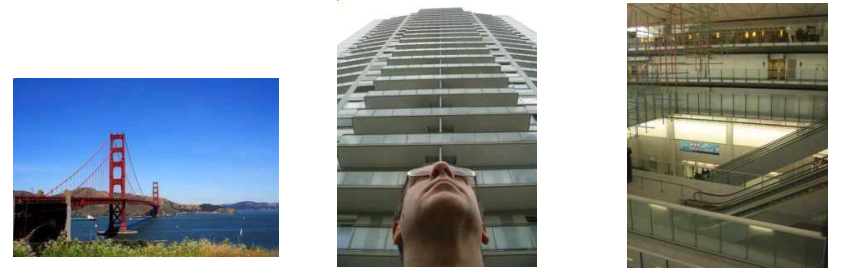
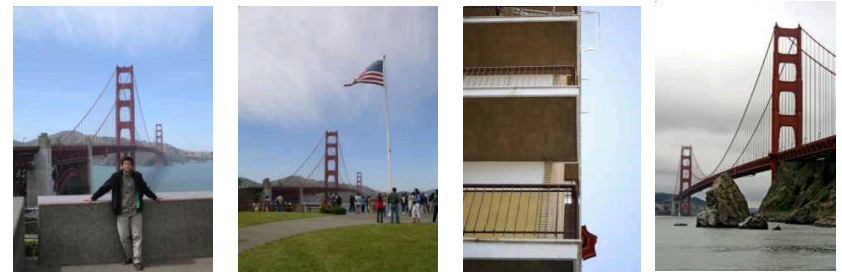
Query

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

precision = $\frac{\text{\#relevant}}{\text{\#returned}}$
recall = $\frac{\text{\#relevant}}{\text{\#total relevant}}$

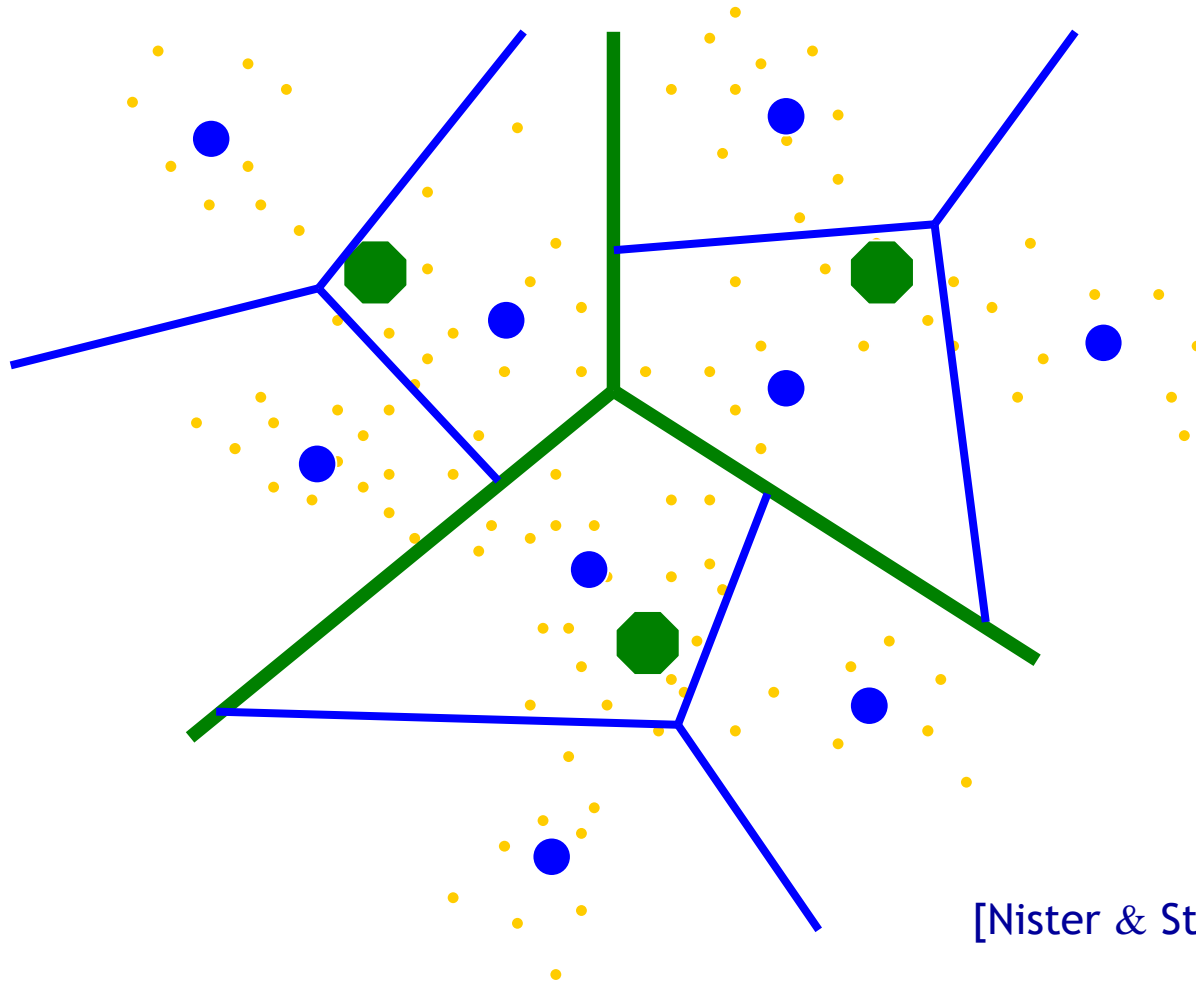


Results (ordered):



Vocabulary Trees: hierarchical clustering for large vocabularies

- Tree construction:

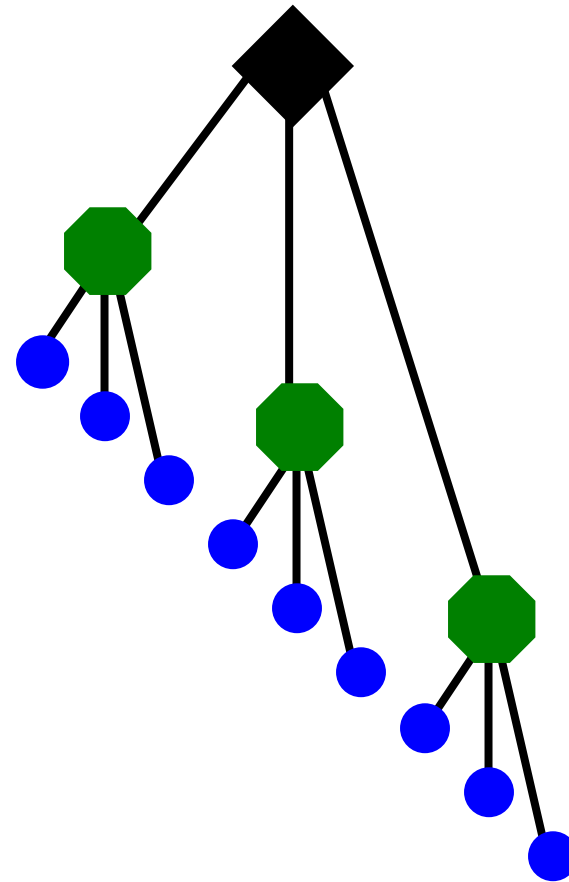


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

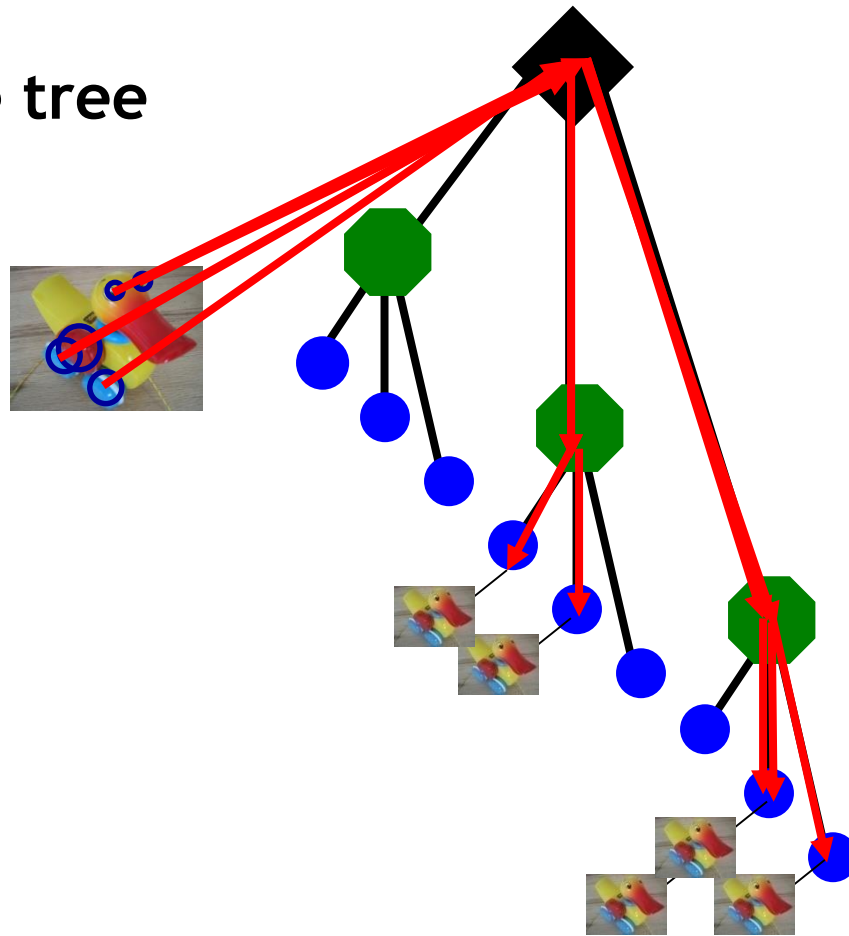
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

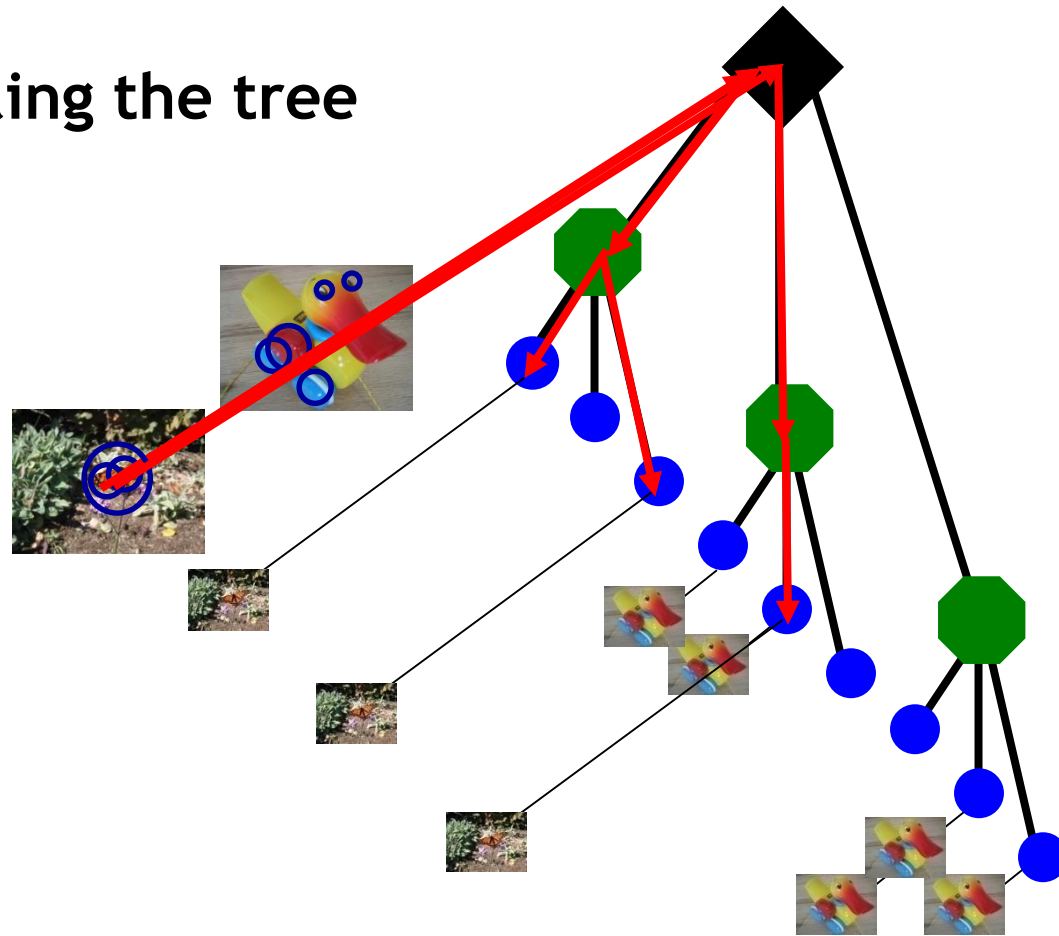
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

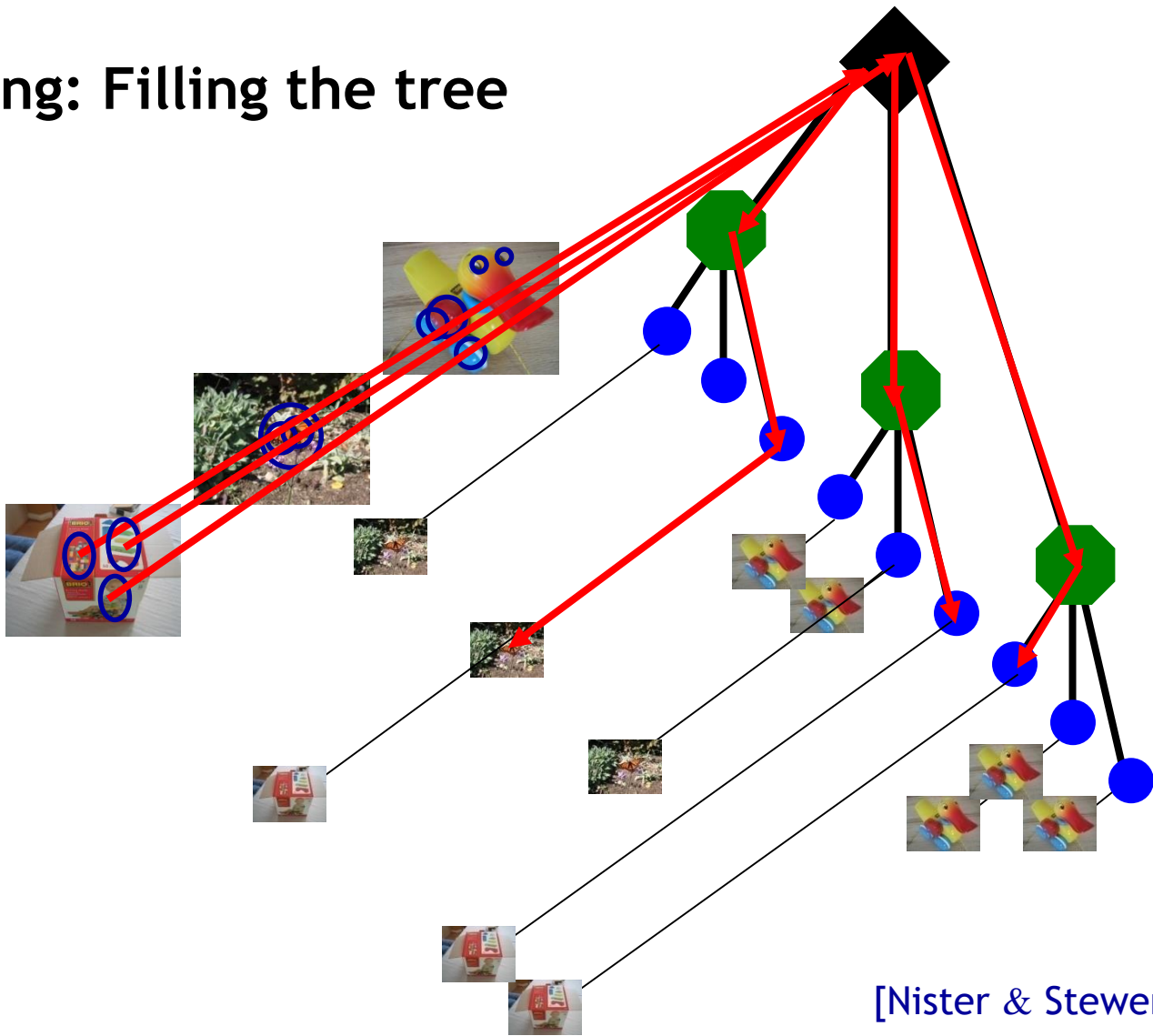
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

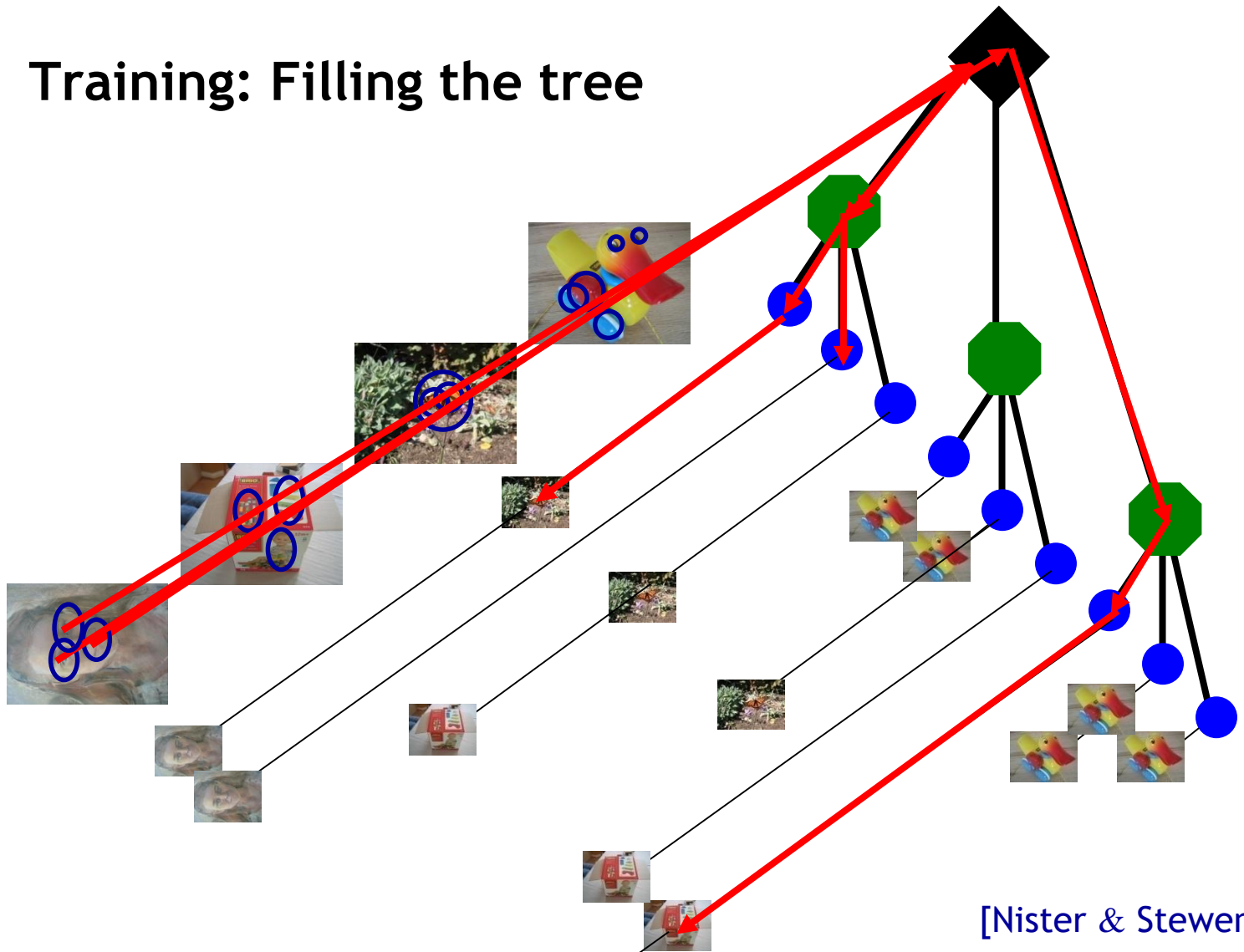
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

- Training: Filling the tree



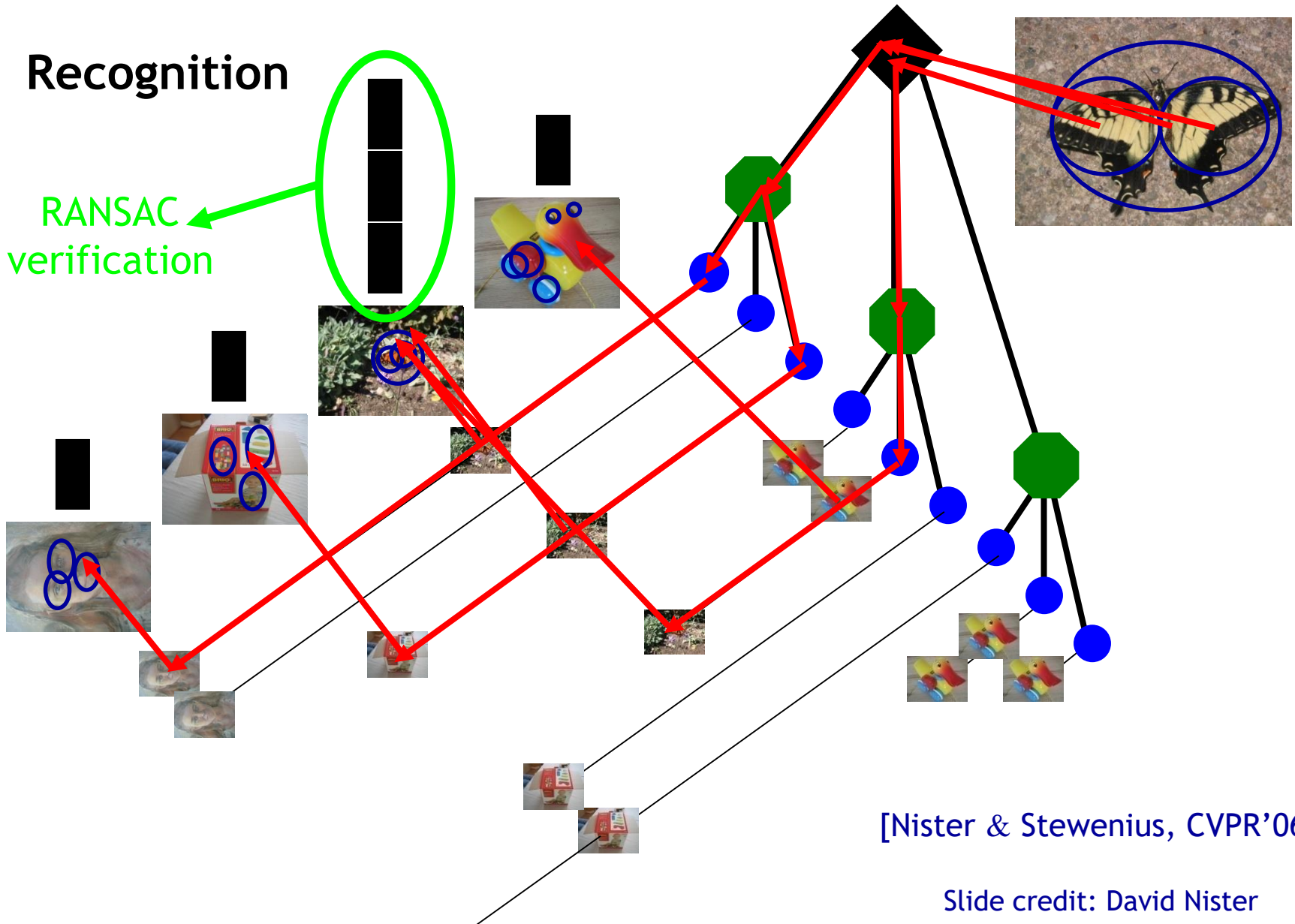
[Nister & Stewenius, CVPR'06]

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

Vocabulary Tree

- Recognition

RANSAC
verification



[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