

Indexing local features

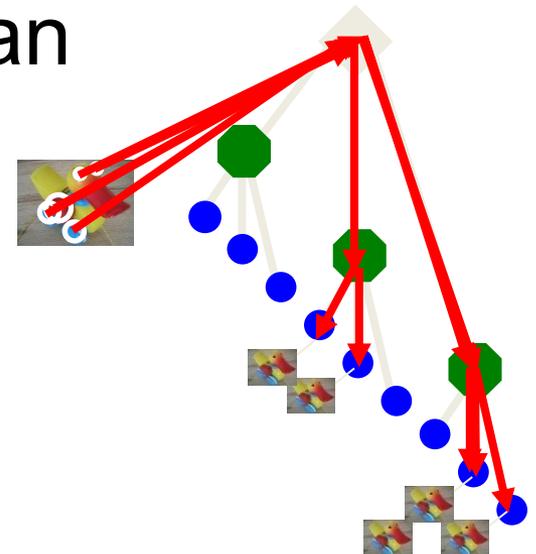
Wed March 30

Prof. Kristen Grauman

UT-Austin

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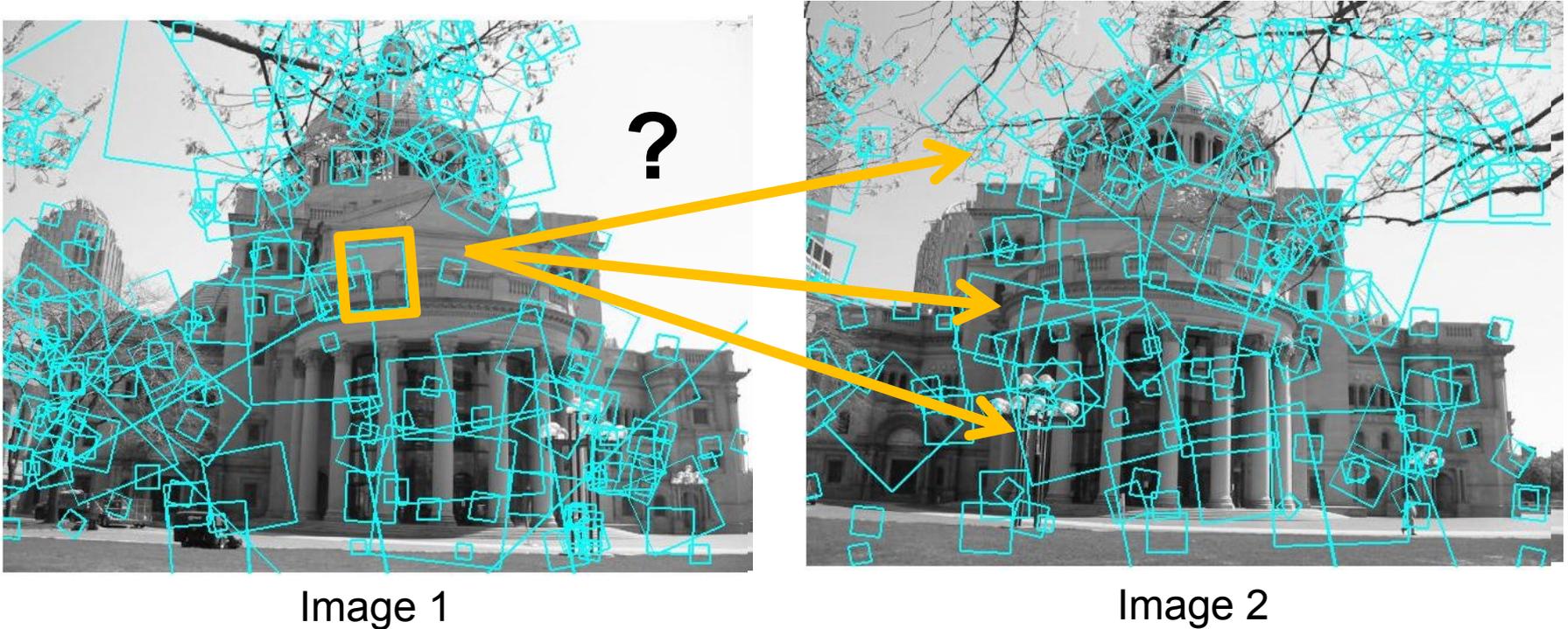
<p>"Along I-75," From Detroit to Florida; <i>inside back cover</i></p> <p>"Drive I-95," From Boston to Florida; <i>inside back cover</i></p> <p>1929 Spanish Trail Roadway; 101-102,104</p> <p>511 Traffic Information; 83</p> <p>A1A (Barrier Isl) - I-95 Access; 86</p> <p>AAA (and CAA); 83</p> <p>AAA National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



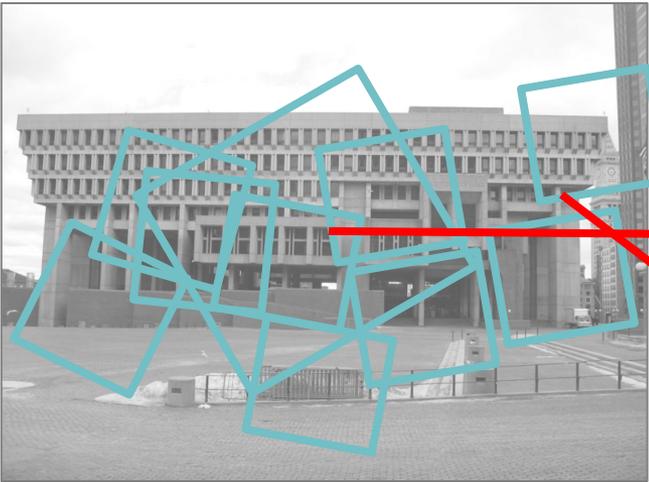
Image 1



Image 2

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

Indexing local features

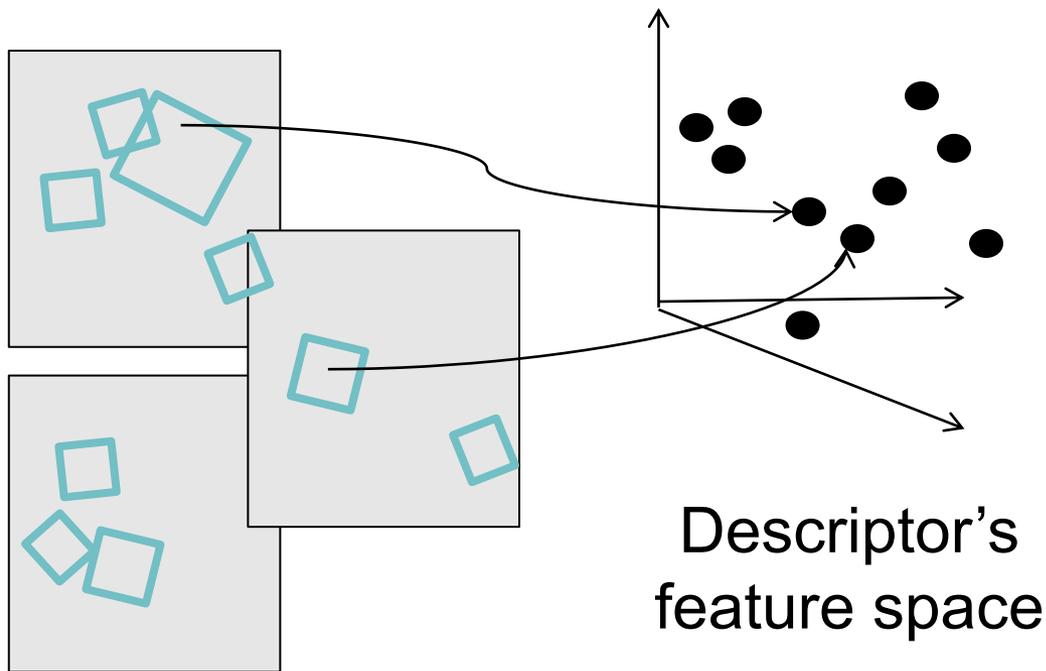


⋮



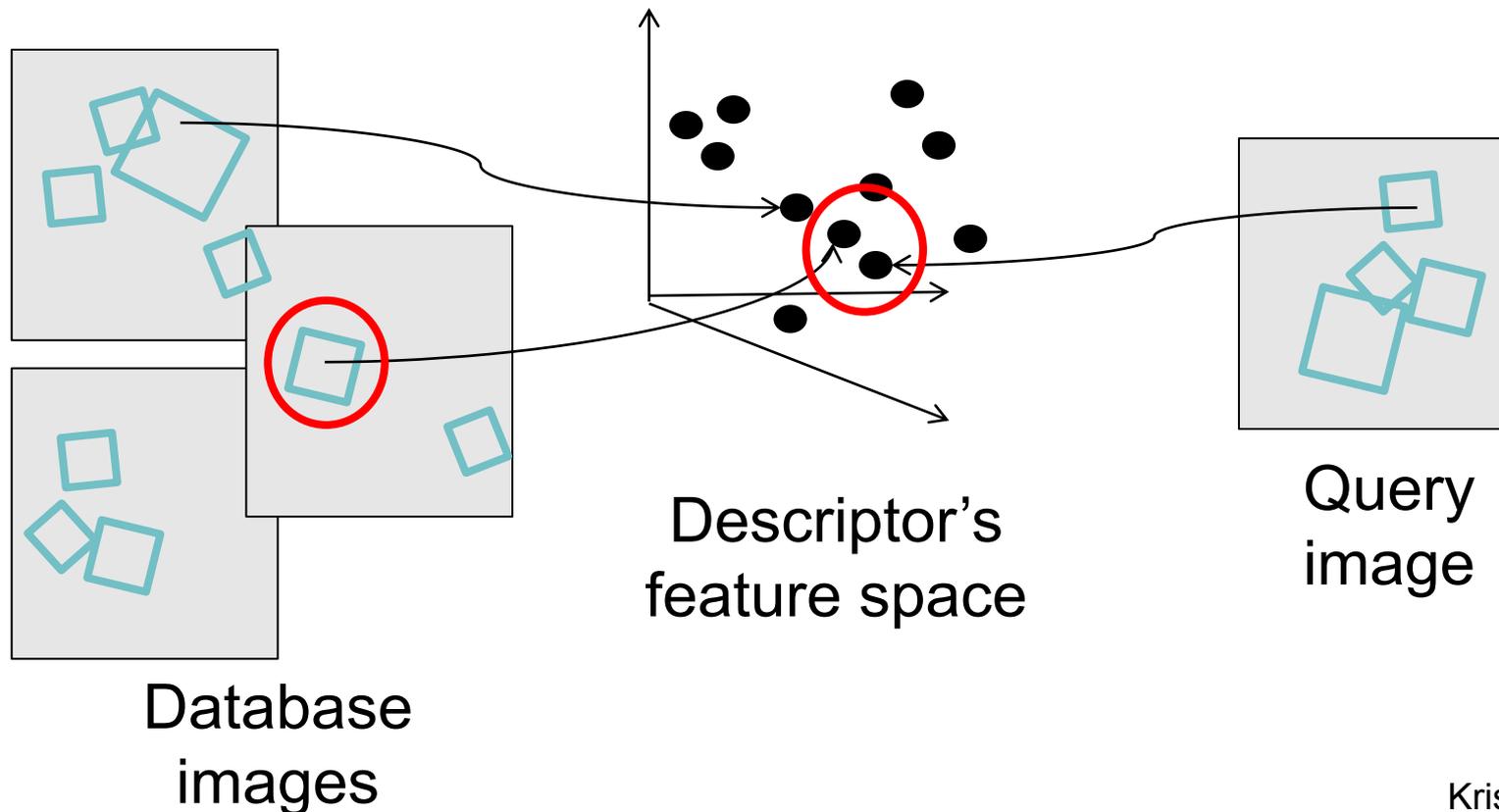
Indexing local features

- 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

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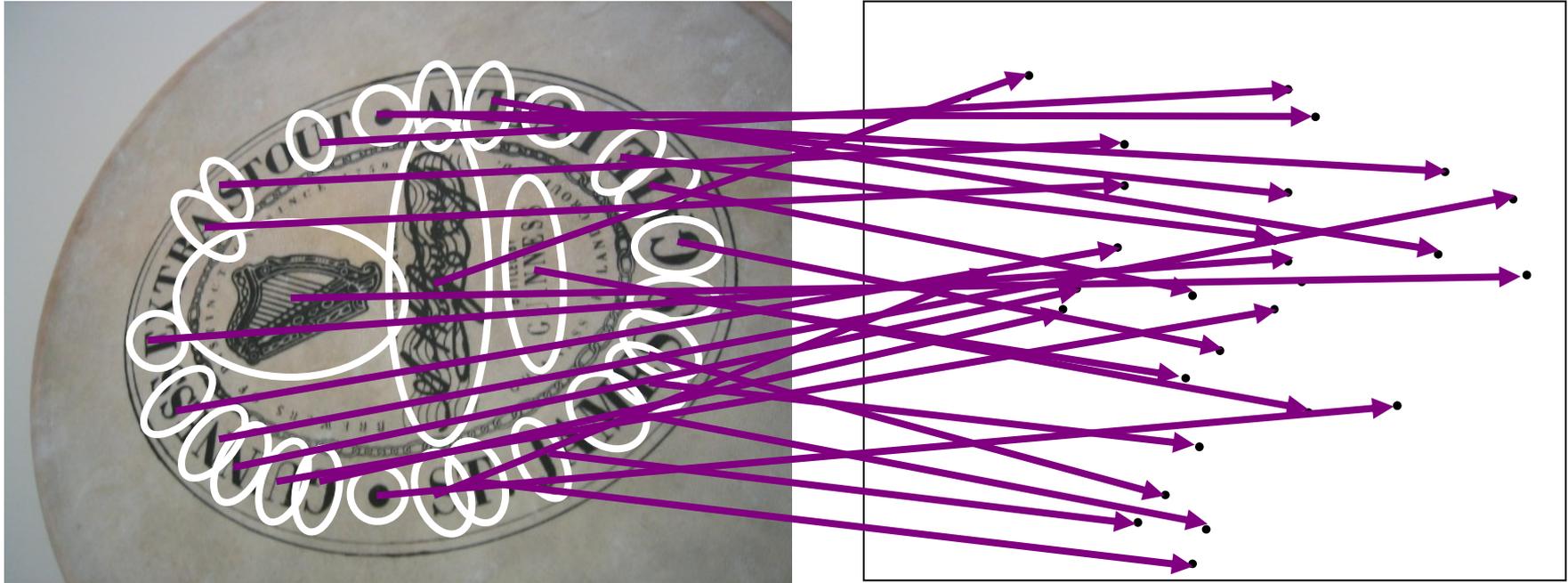
- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index...
- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words".

Text retrieval vs. image search

- What makes the problems similar, different?

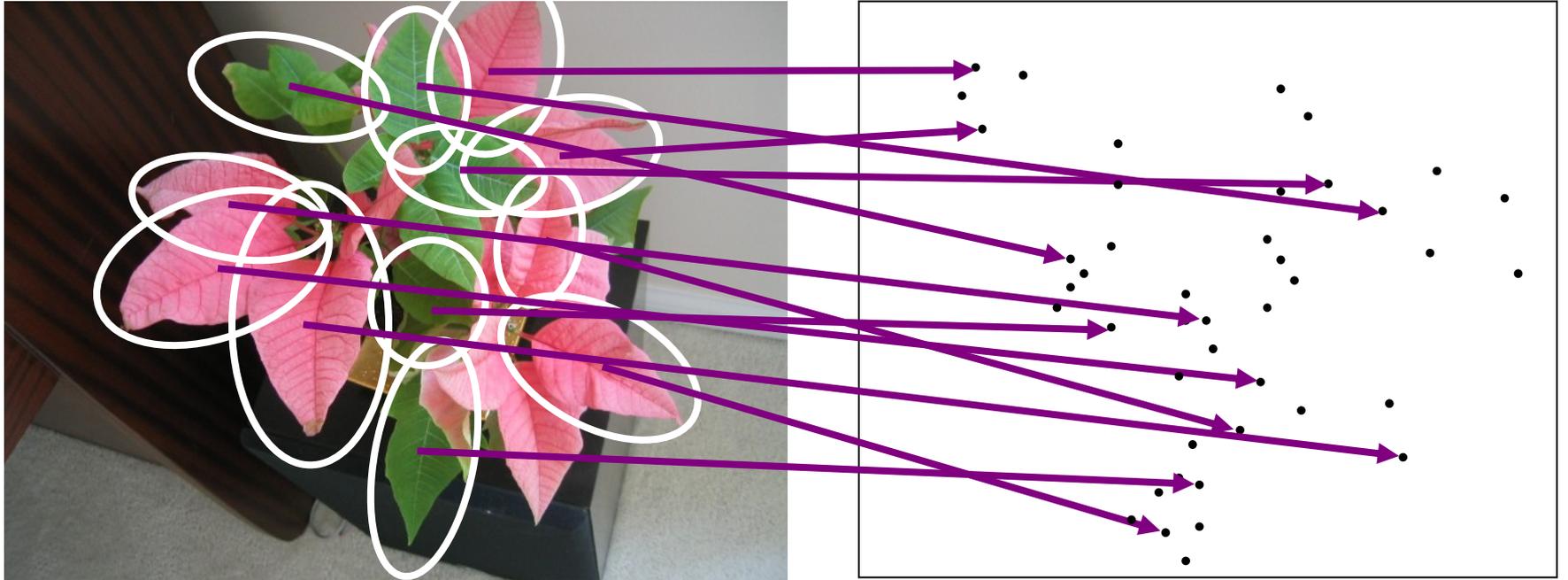
Visual words: main idea

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

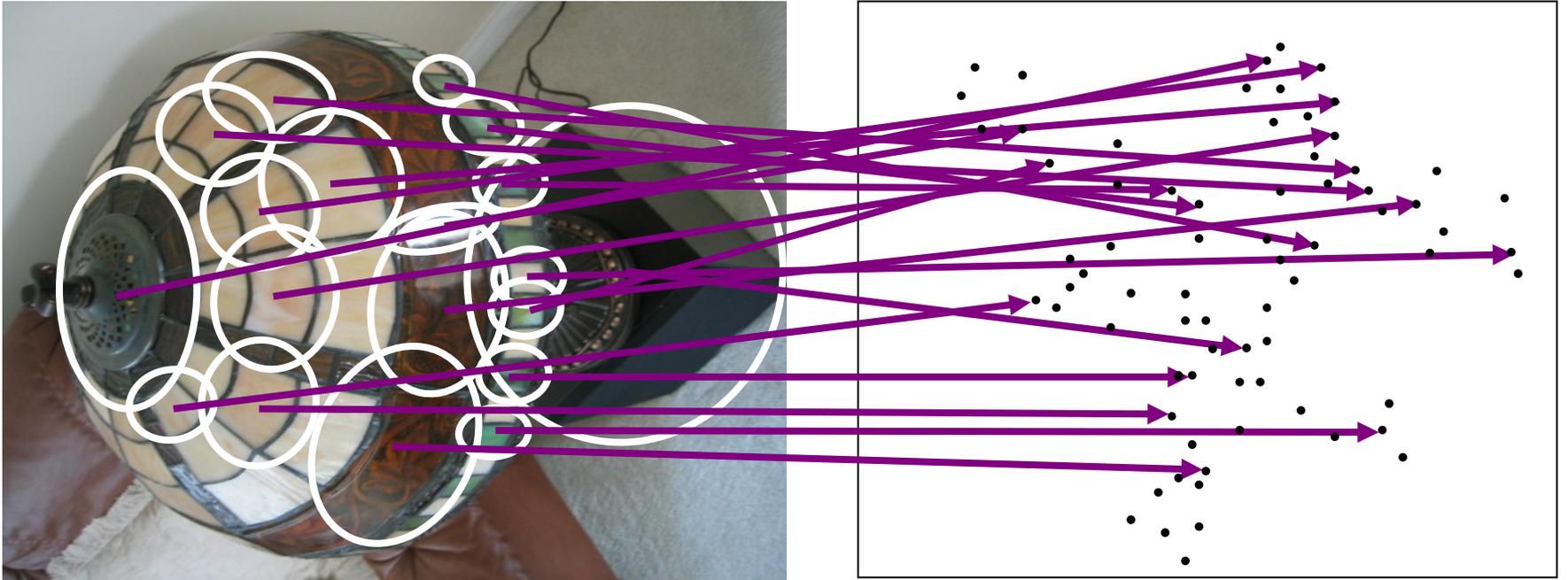


e.g., SIFT descriptor space: each point is 128-dimensional

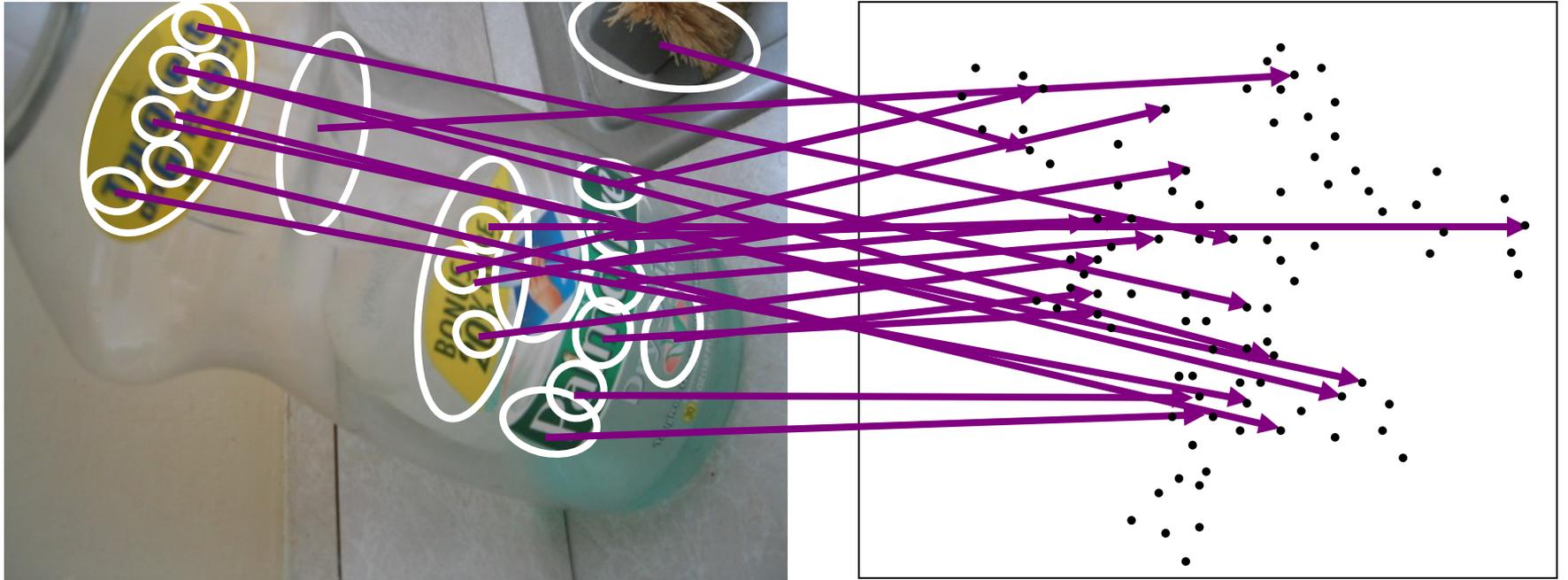
Visual words: main idea



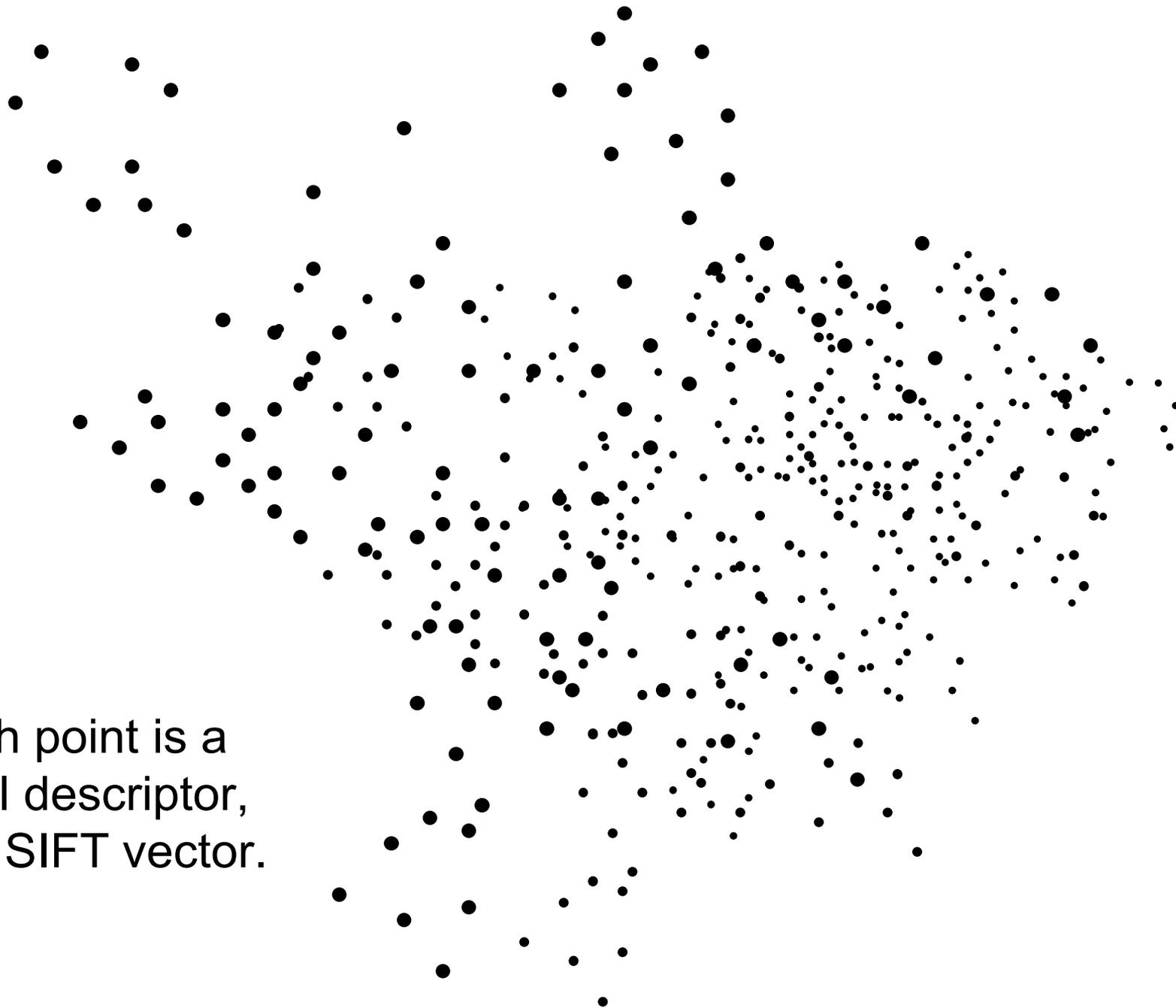
Visual words: main idea

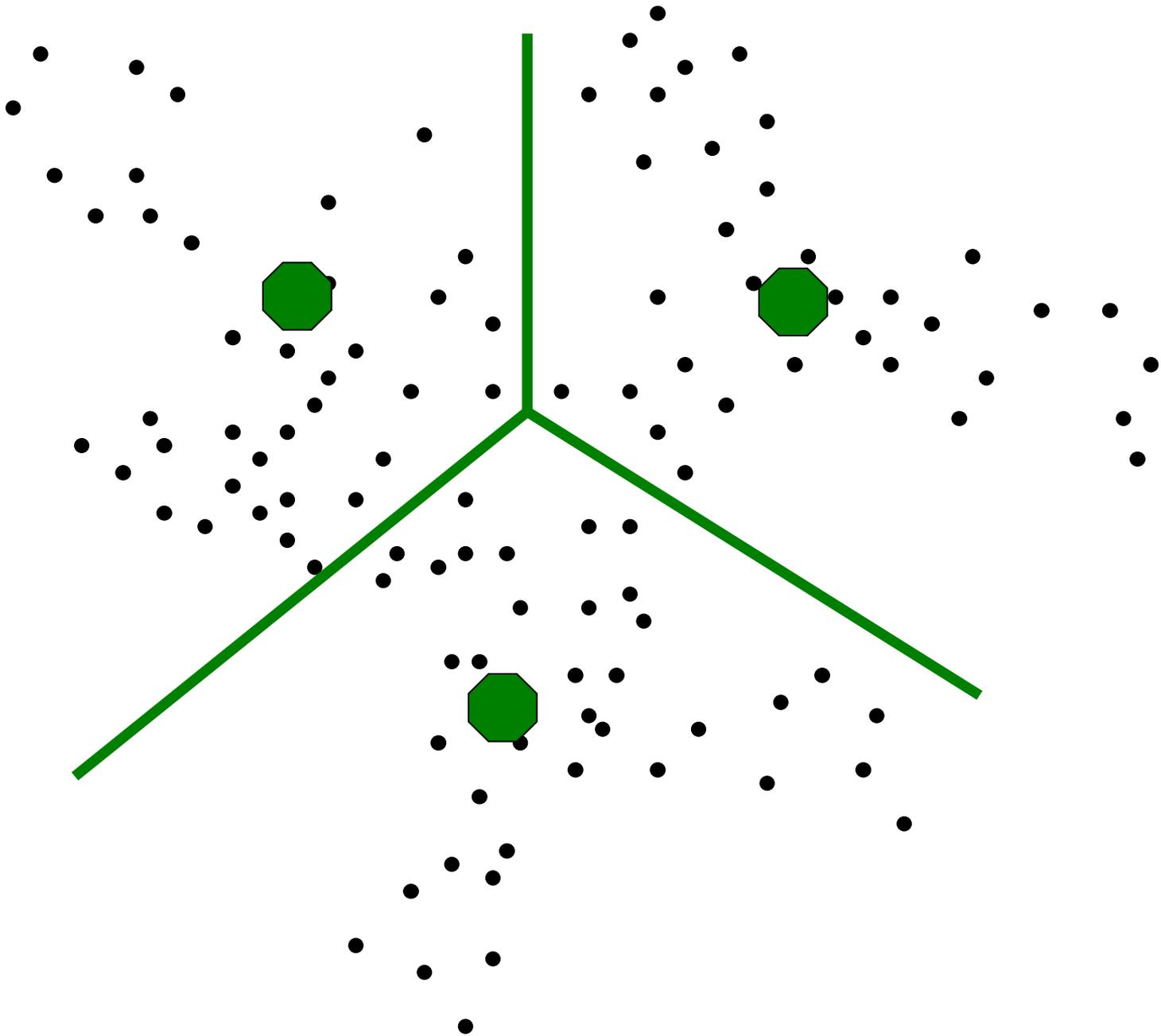


Visual words: main idea



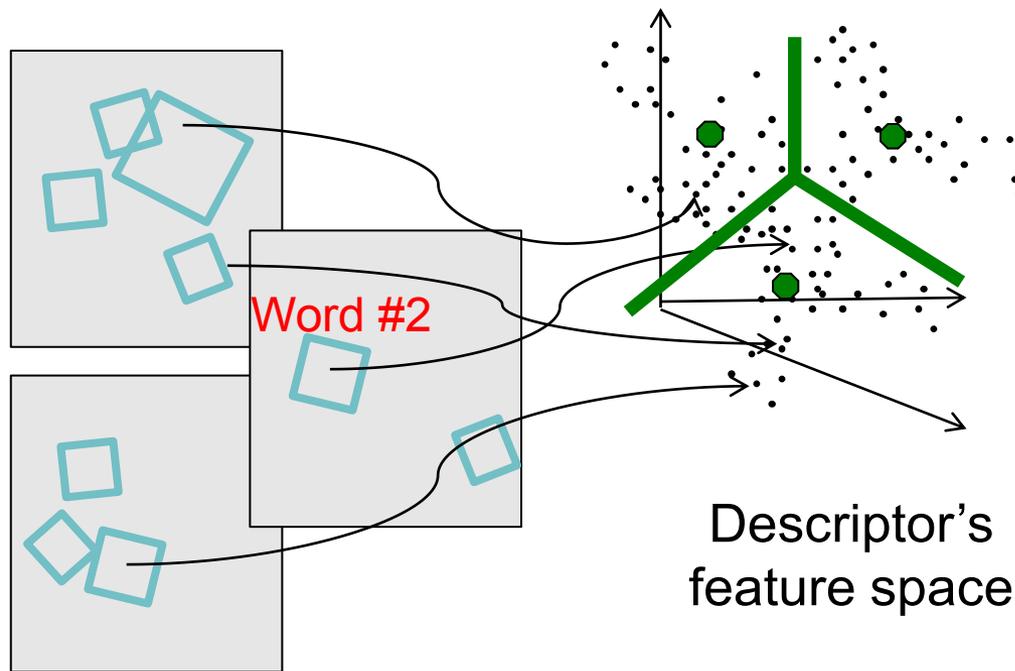
Each point is a
local descriptor,
e.g. SIFT vector.





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

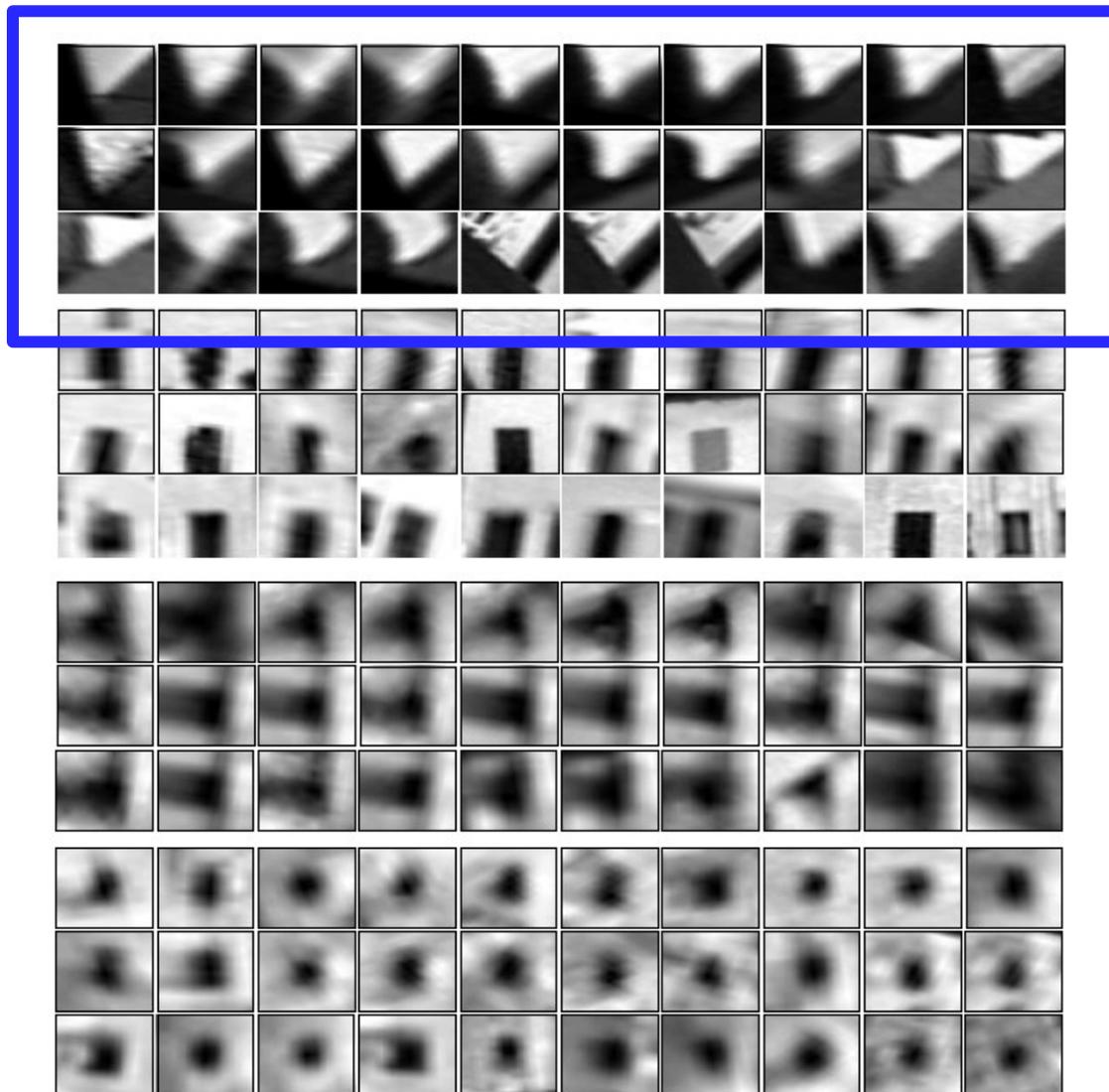
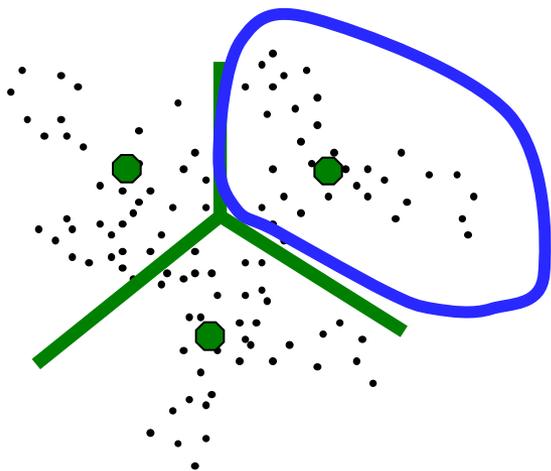
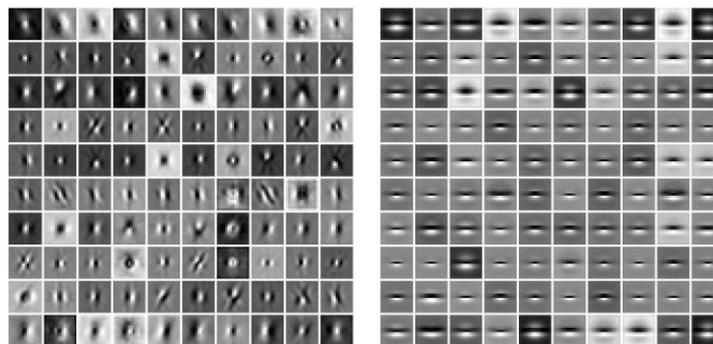
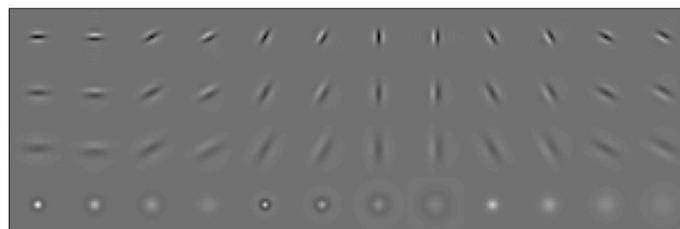
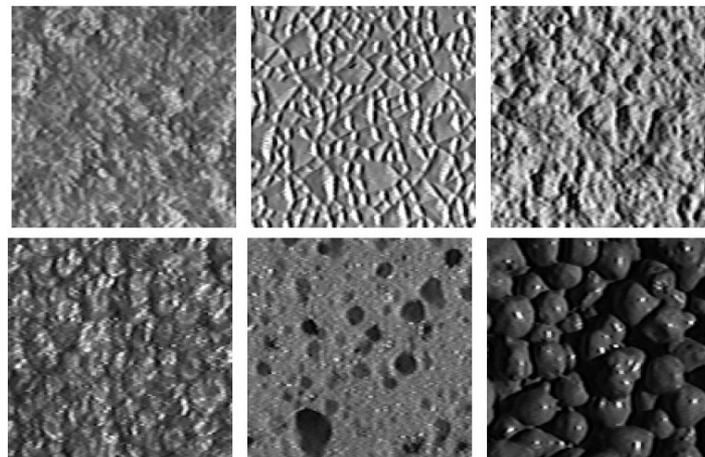


Figure from Sivic & Zisserman, ICCV 2003

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.



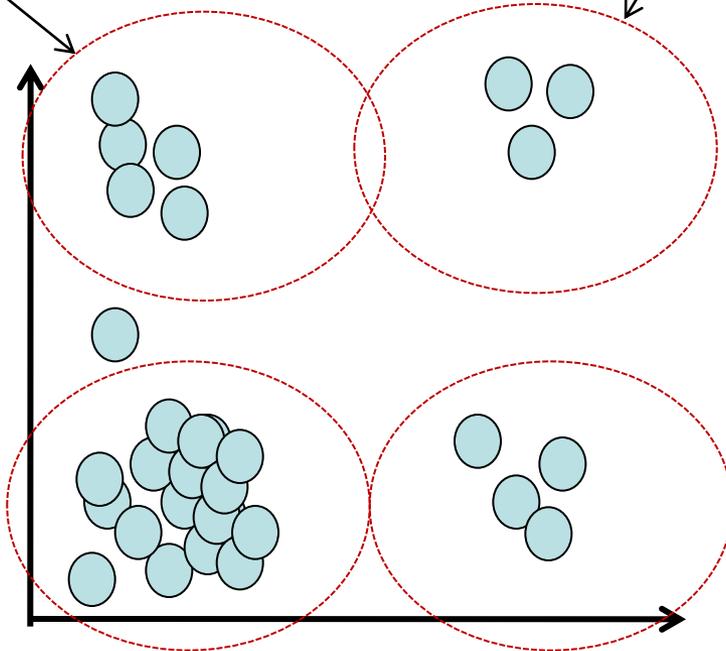
Leung & Malik 1999; Varma & Zisserman, 2002

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

⋮

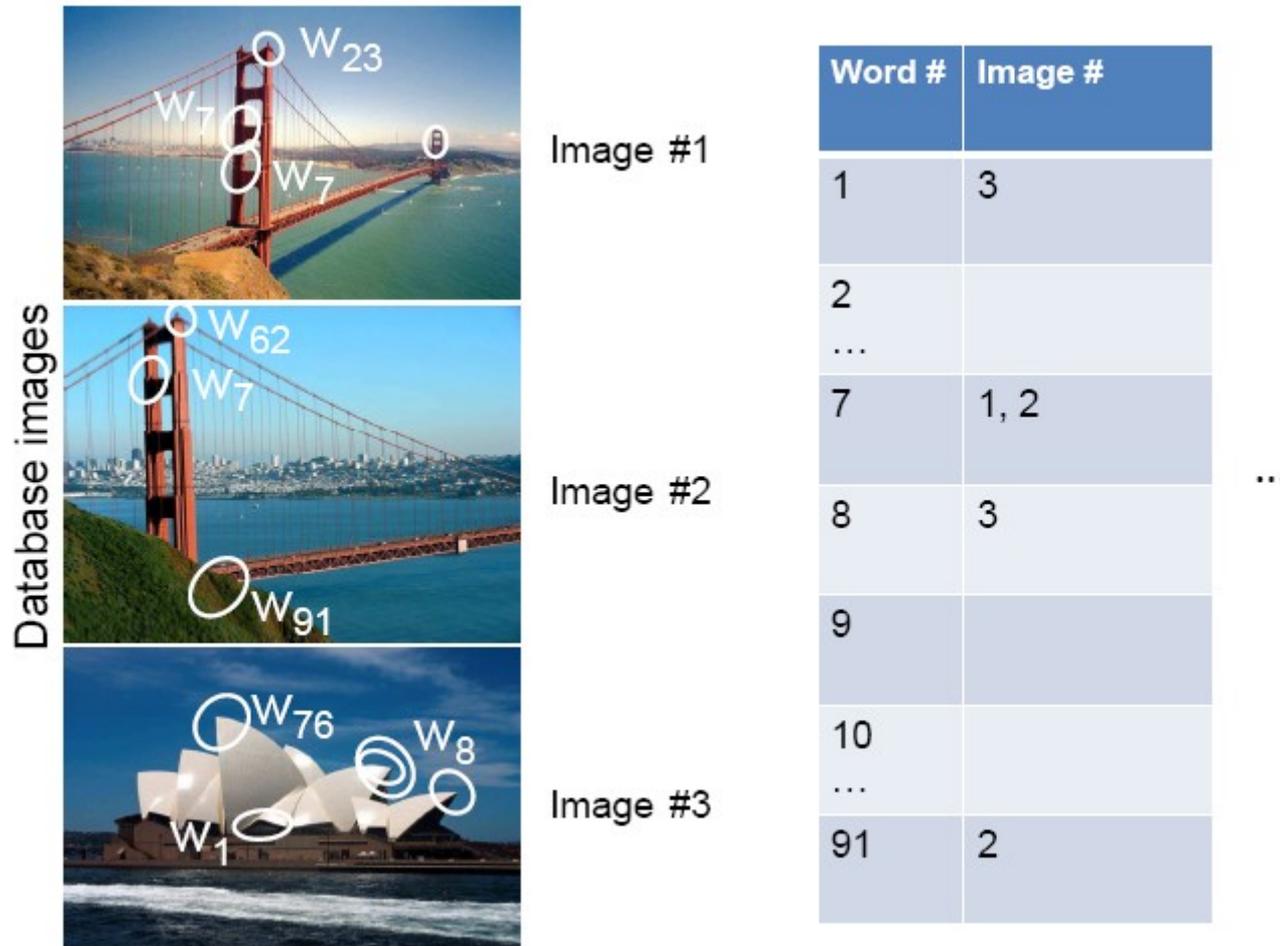
**statistics to
summarize patterns
in small windows**

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

message.
For a long time, the image centers in the brain were thought to be the only centers for visual perception. However, the discovery of the Hubel and Wiesel image processing model has shown that the visual cortex is not only a storage area for visual information, but also a processing area. The visual cortex has its own image processing system.



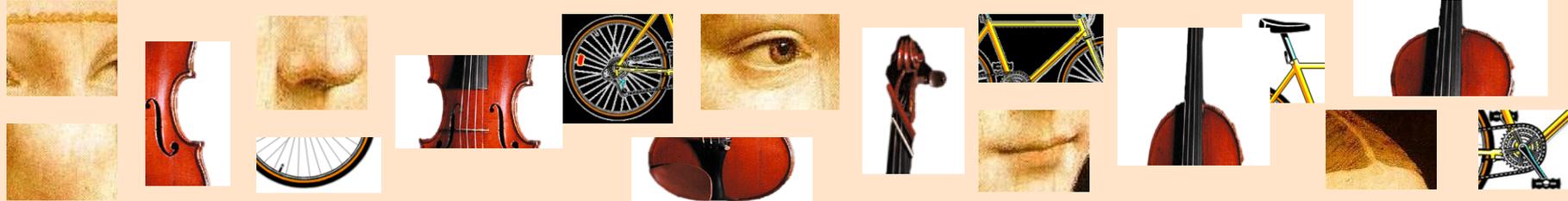
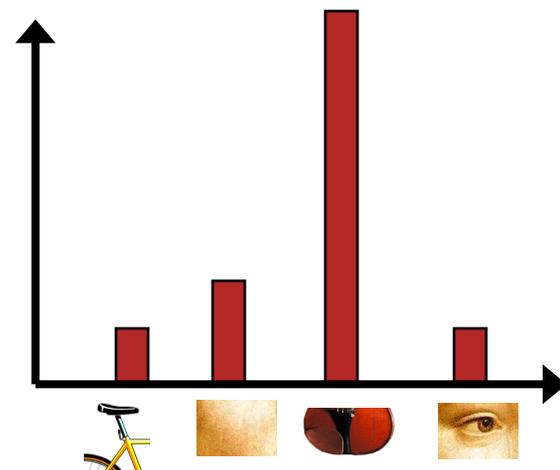
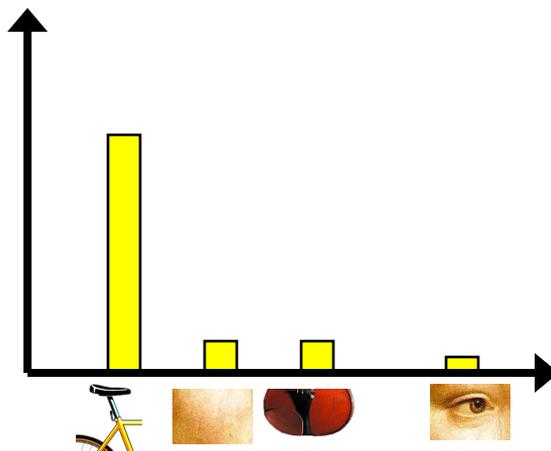
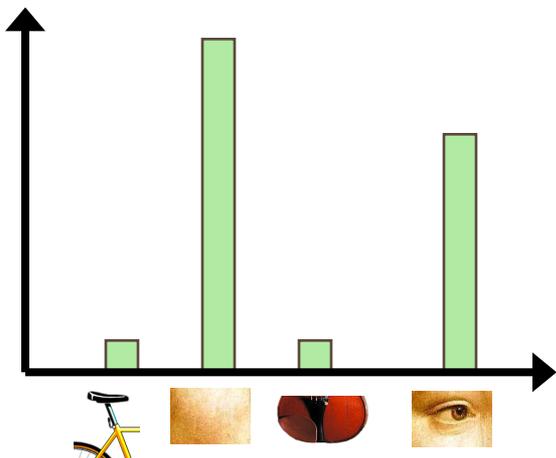
**sensory, brain,
visual, perception,
retinal, cerebral cortex,
eye, cell, optical
nerve, image
Hubel, Wiesel**

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
company
\$660b
annoy
China's
deliberate
agrees
yuan is
govern
also n
deman
countr
yuan a
permit
the US
freely.
it will t
allowin

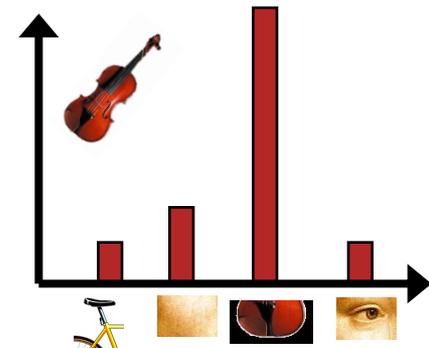
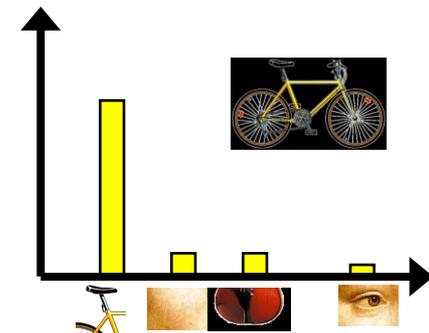
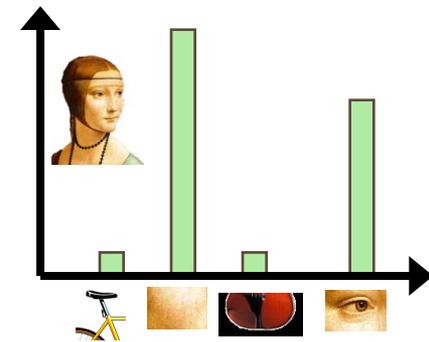


**China, trade,
surplus, commerce,
exports, imports, US,
yuan, bank, domestic,
foreign, increase,
trade, value**



Bags of visual words

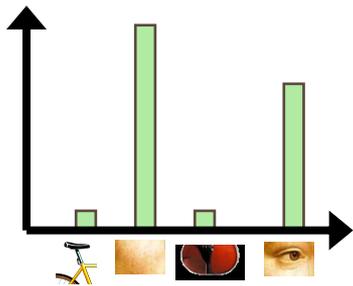
- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.



Comparing bags of words

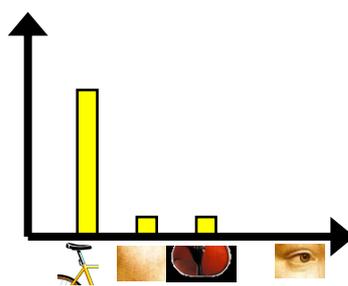
- Rank frames by normalized scalar product between their (possibly weighted) occurrence counts---*nearest neighbor* search for similar images.

[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



Start frame 52907



Key frame 53026



End frame 53028



Start frame 54342



Key frame 54376



End frame 54644



Start frame 51770



Key frame 52251



End frame 52348



Start frame 54079



Key frame 54201



End frame 54201



Start frame 38909



Key frame 39126



End frame 39300



Start frame 40760



Key frame 40826



End frame 41049



Start frame 39301



Key frame 39676



End frame 39730

Video Google System

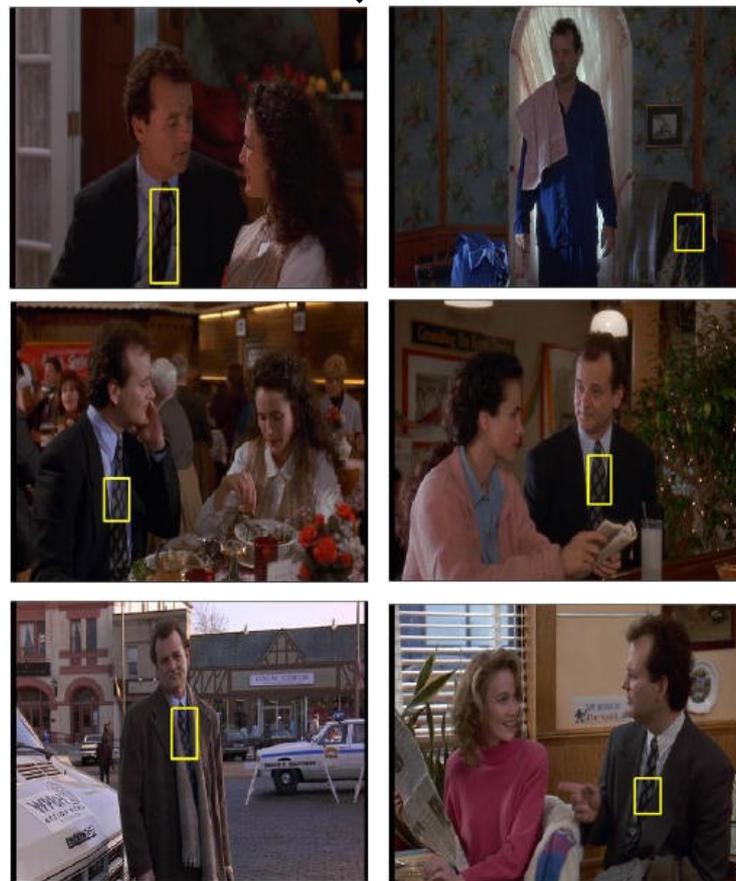
1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

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



Query region



Retrieved frames

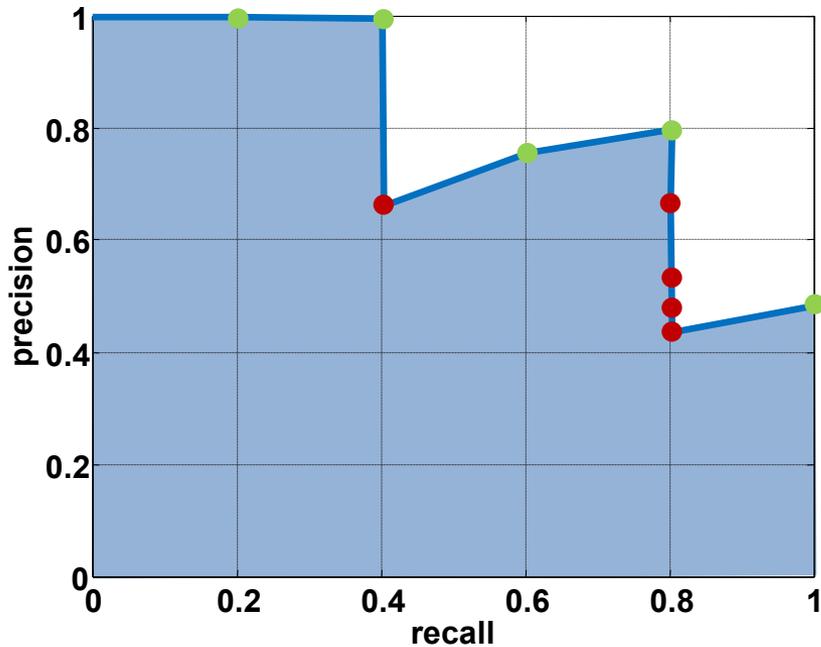
Scoring retrieval quality



Query

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

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

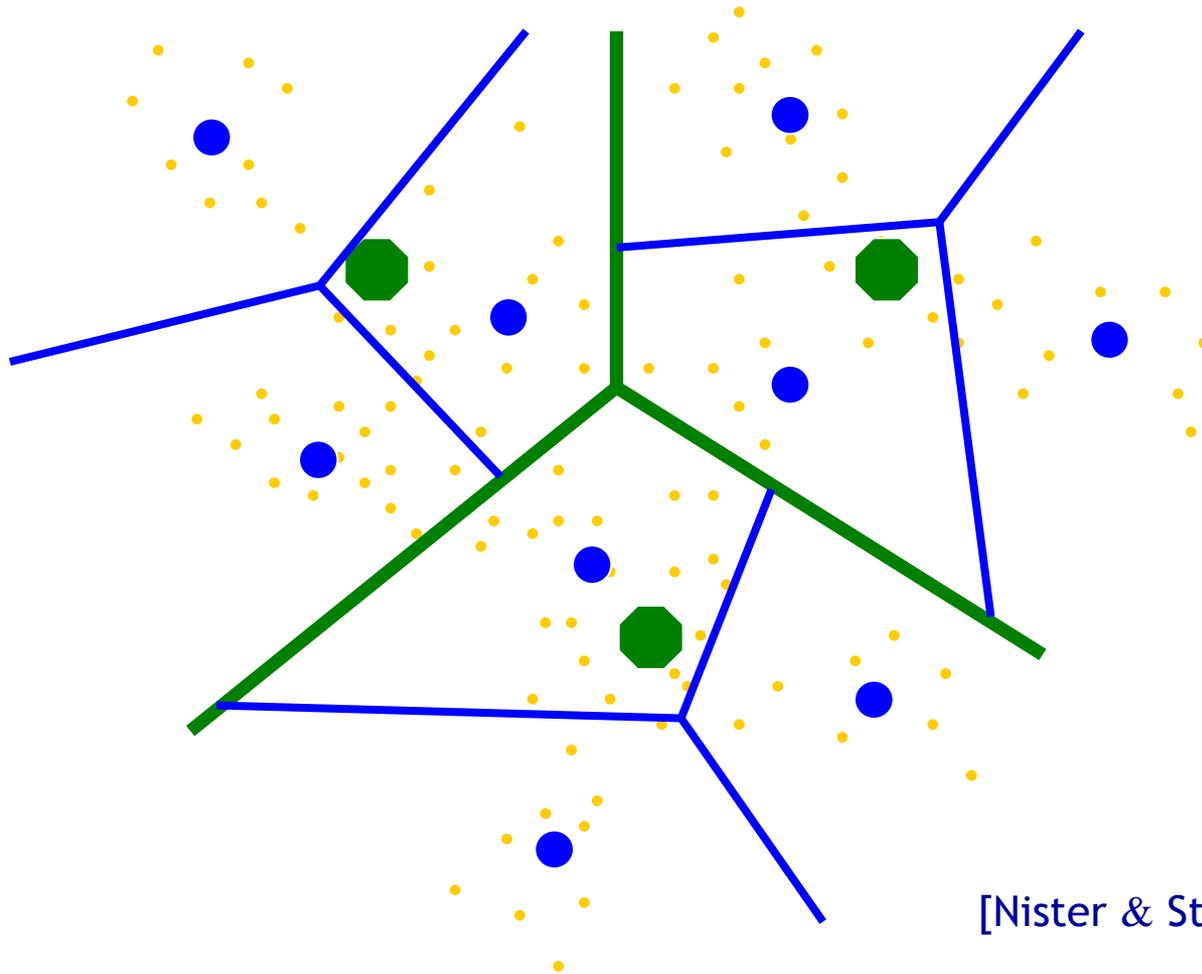


Results (ordered):



Vocabulary Trees: hierarchical clustering for large vocabularies

- Tree construction:

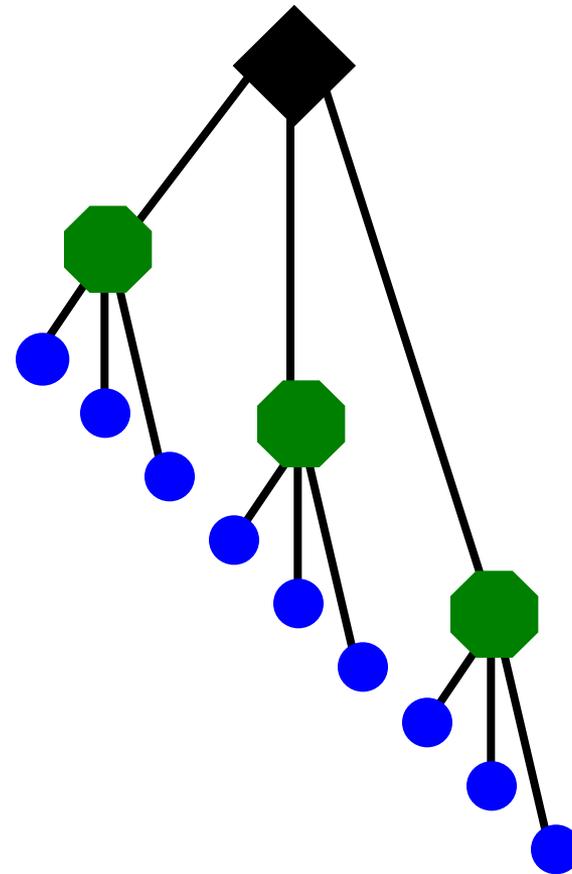


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

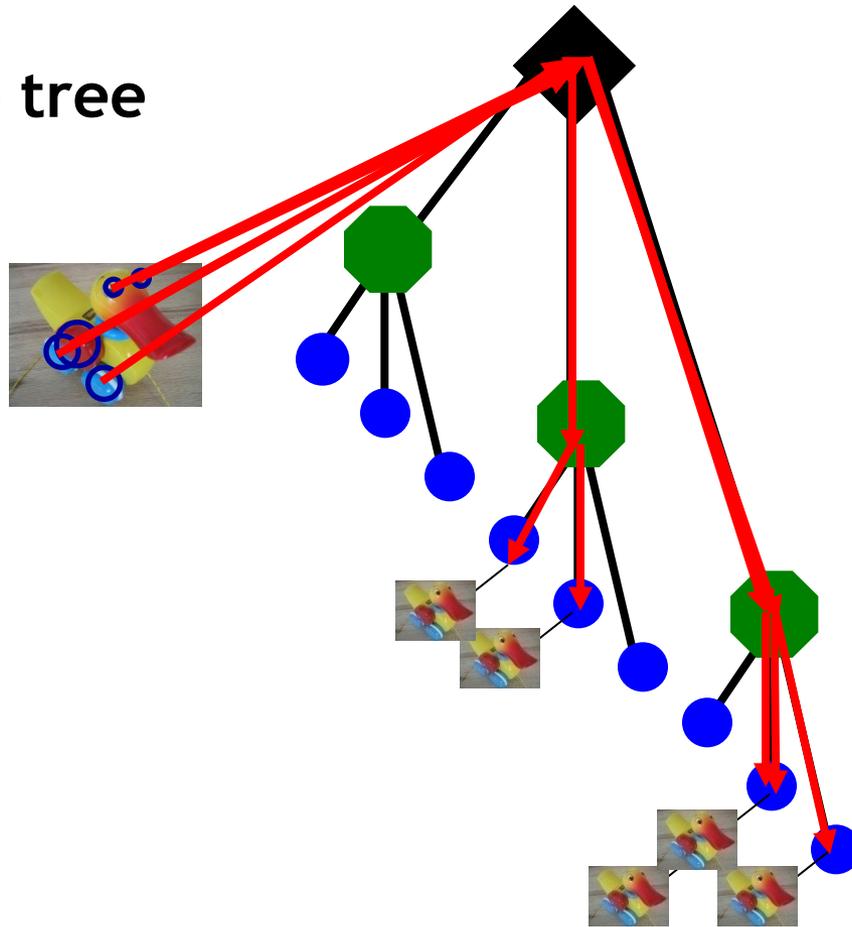
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

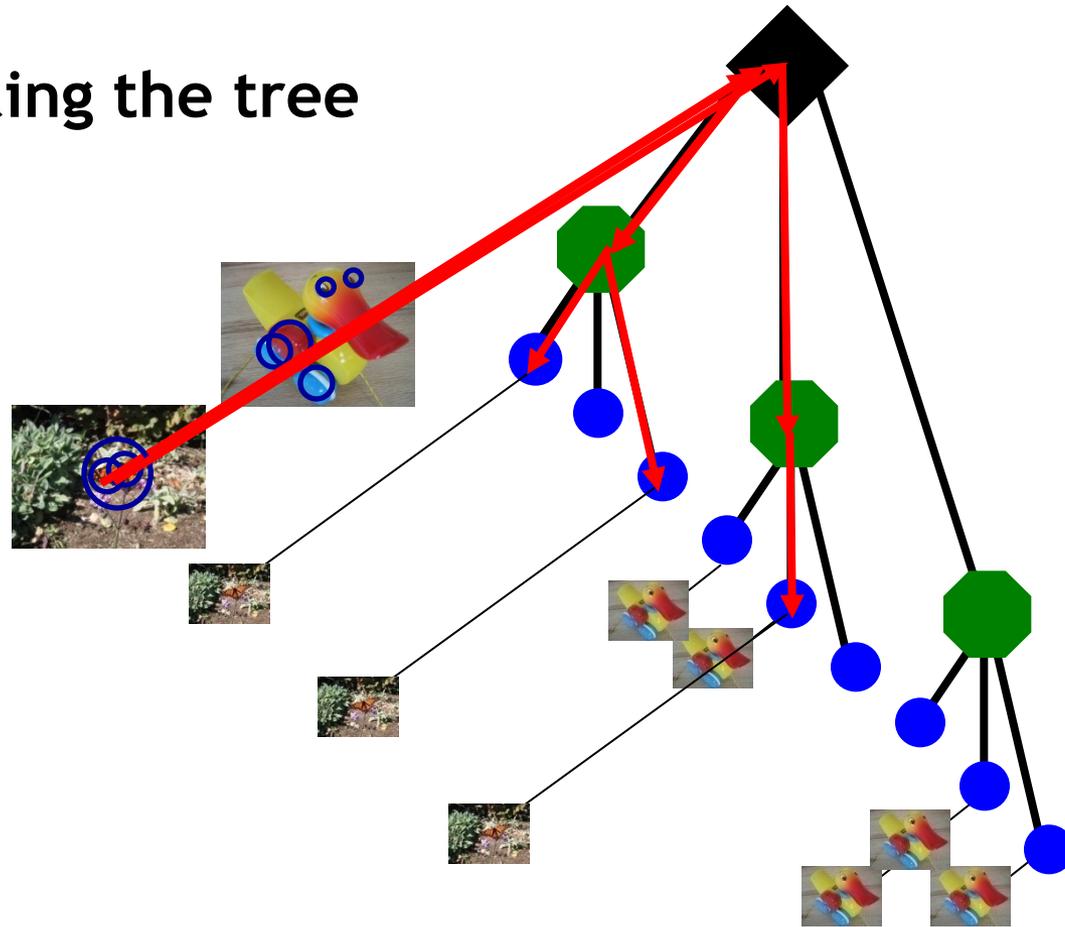
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

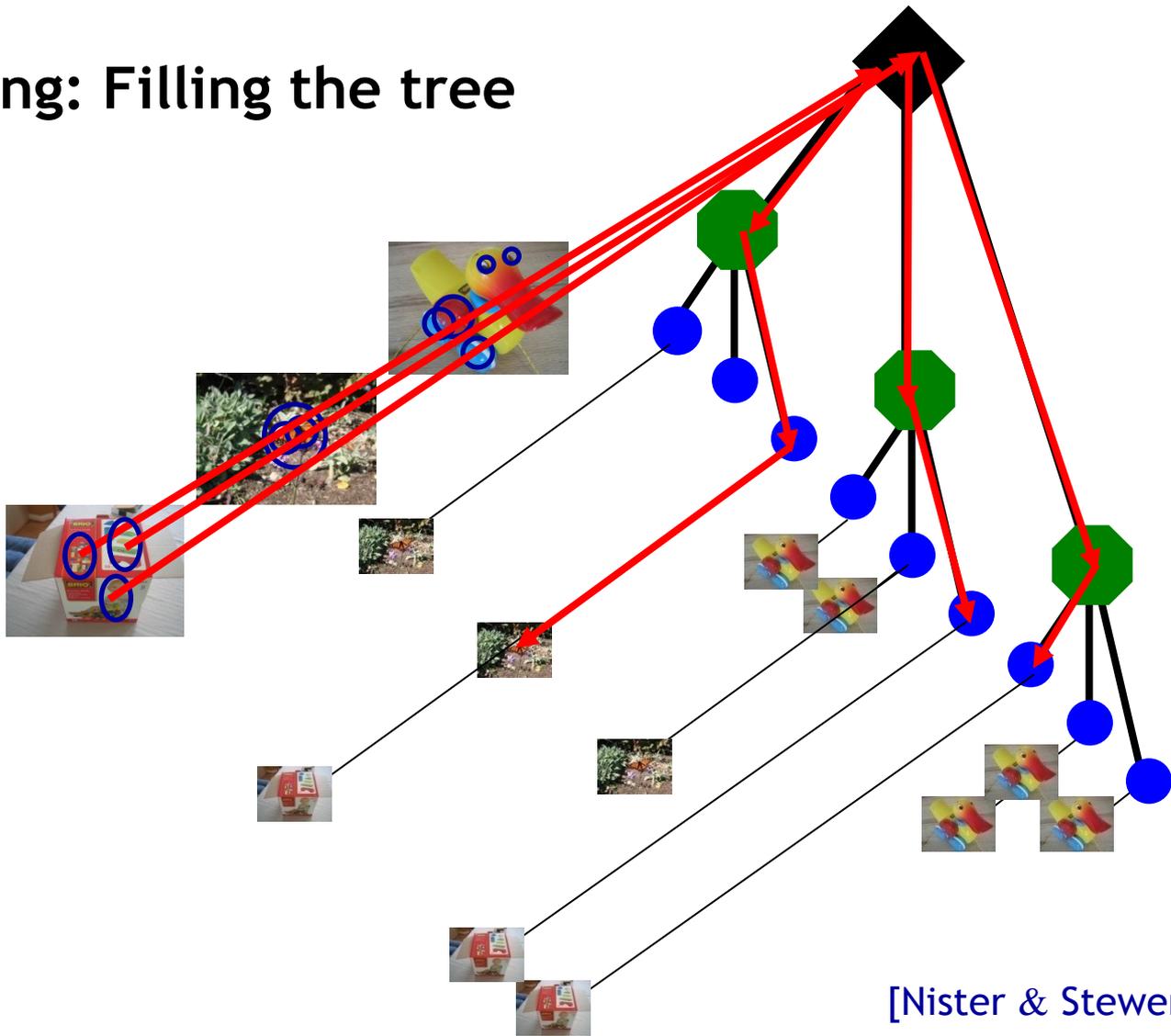
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

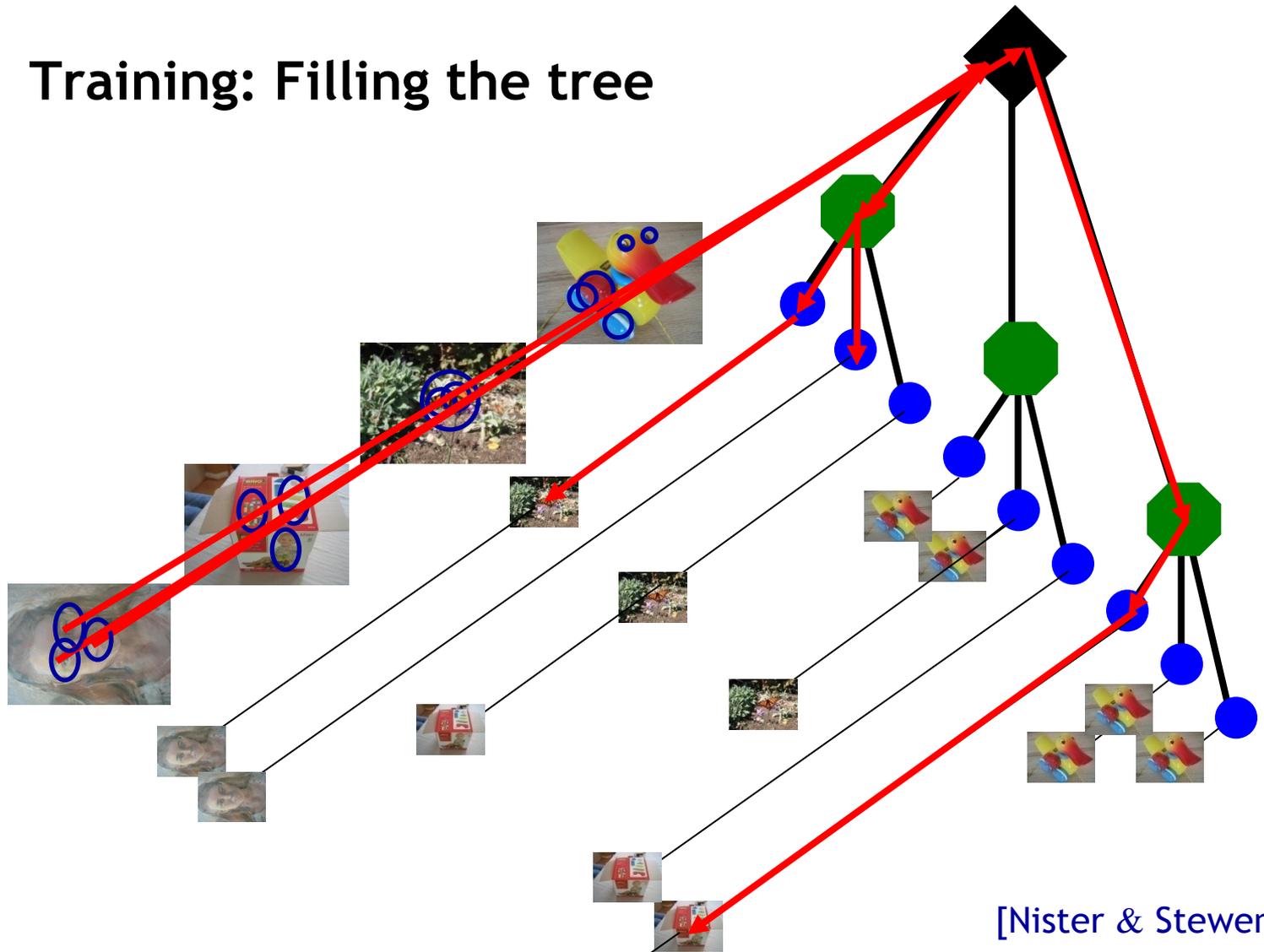
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[Nister & Stewenius, CVPR'06]

Vocabulary Tree

- Training: Filling the tree



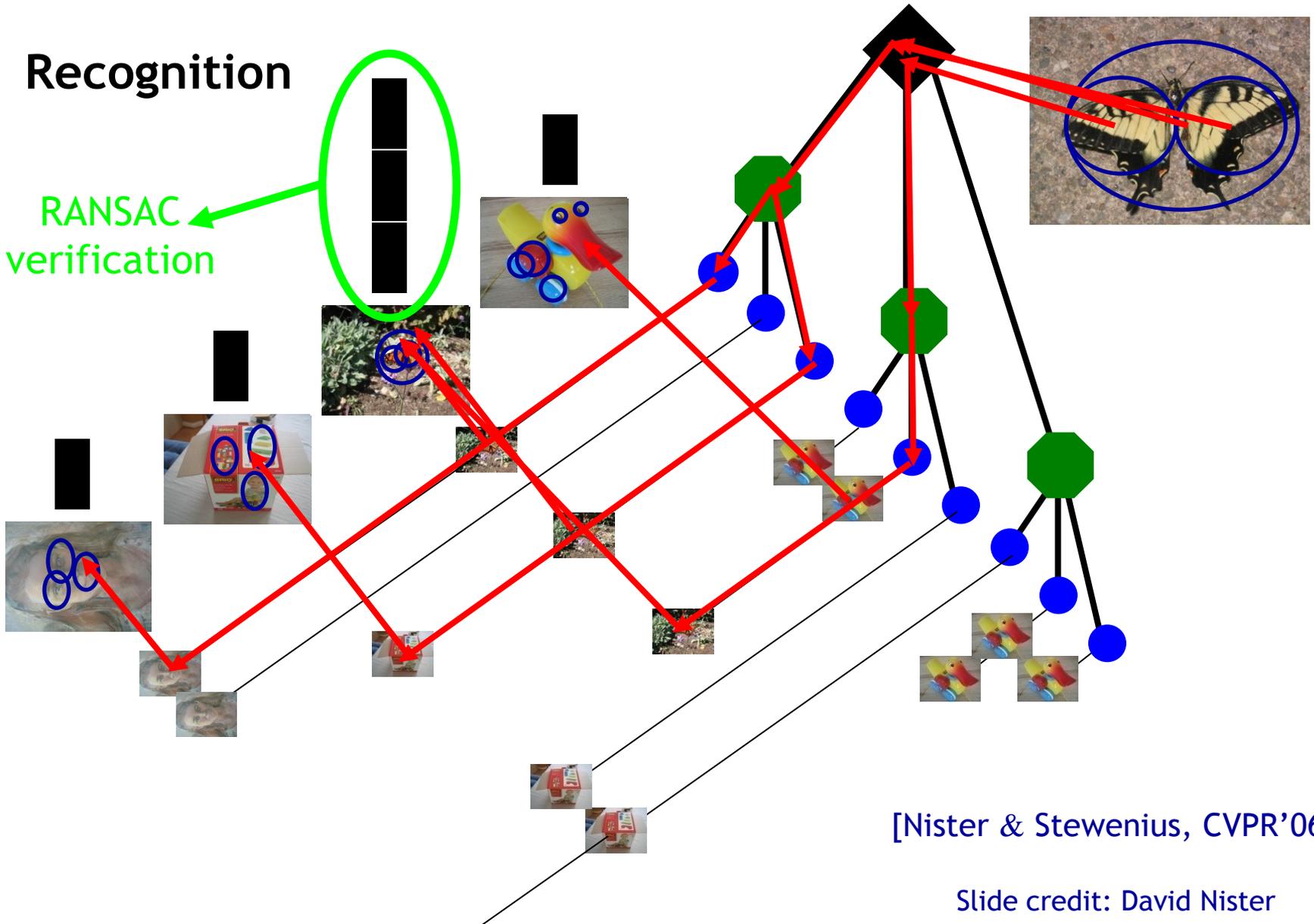
[Nister & Stewenius, CVPR'06]

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