

Instance Recognition



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ECE 6554 Advanced Computer Vision

Administrative stuffs

- Paper review submitted?
- Topic presentation
- Experiment presentation
- “For”/ “Against” discussion lead
- Questions?

Today's class

- Review keypoint detection and descriptors
- Review SIFT features
- Indexing features
- Fast image search

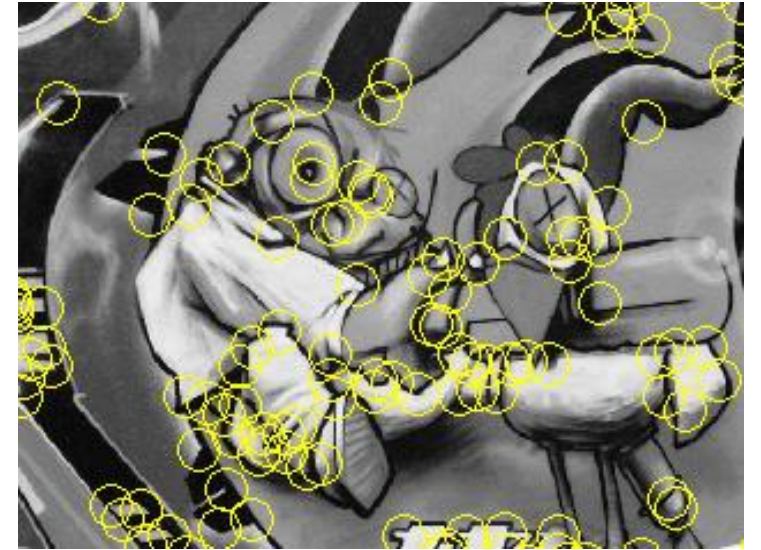
Discussion – Think-pair-share

- Find a person you don't know
- Discuss
 - strength,
 - weakness, and
 - potential extension
- Share with class

Keypoint detection and descriptors

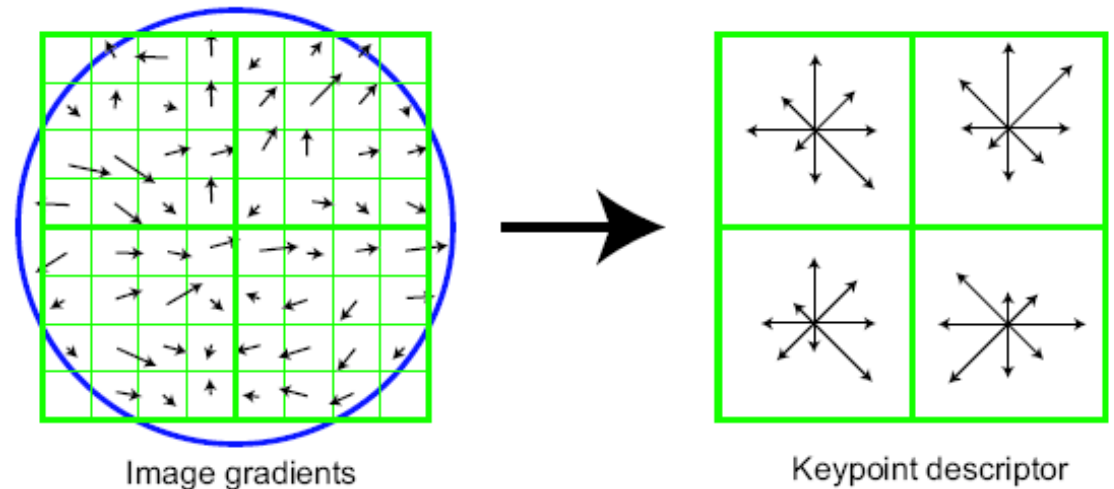
- **Keypoint detection:** repeatable and distinctive

- Corners, blobs, stable regions
- Harris, DoG



- **Descriptors:** robust and selective

- spatial histograms of orientation
- SIFT



Local Descriptors

- The ideal descriptor should be
 - Robust
 - Distinctive
 - Compact
 - Efficient
- Most available descriptors focus on edge/gradient information
 - Capture texture information
 - Color rarely used

Scale Invariant Feature Transform

Basic idea:

- Take 16x16 square window around detected feature
- Compute edge orientation (angle of the gradient - 90°) for each pixel
- Throw out weak edges (threshold gradient magnitude)
- Create histogram of surviving edge orientations

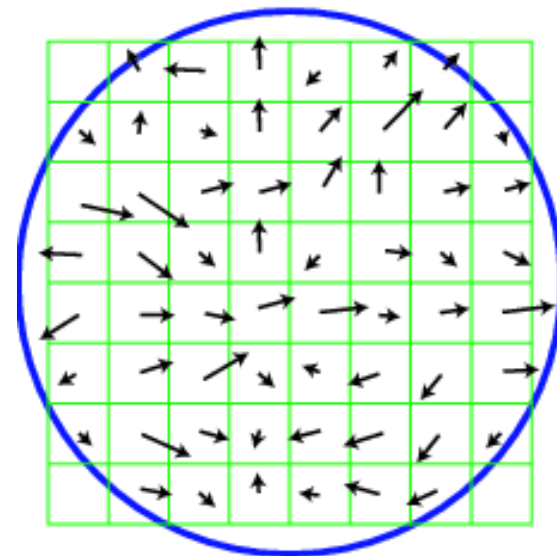
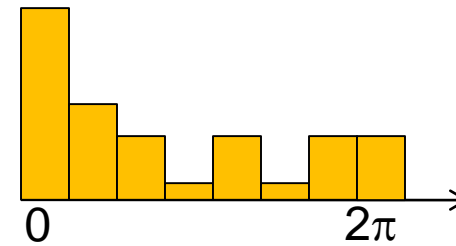
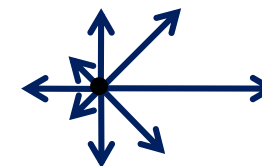


Image gradients



angle histogram



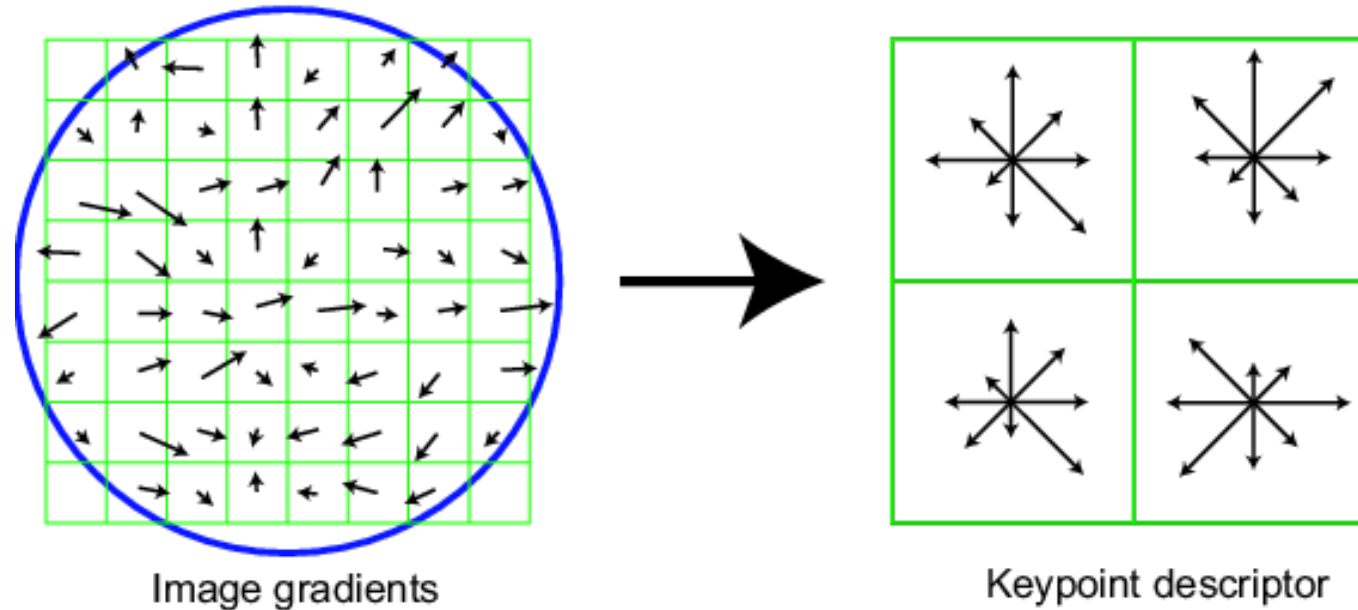
Keypoint descriptor

Adapted from slide by David Lowe

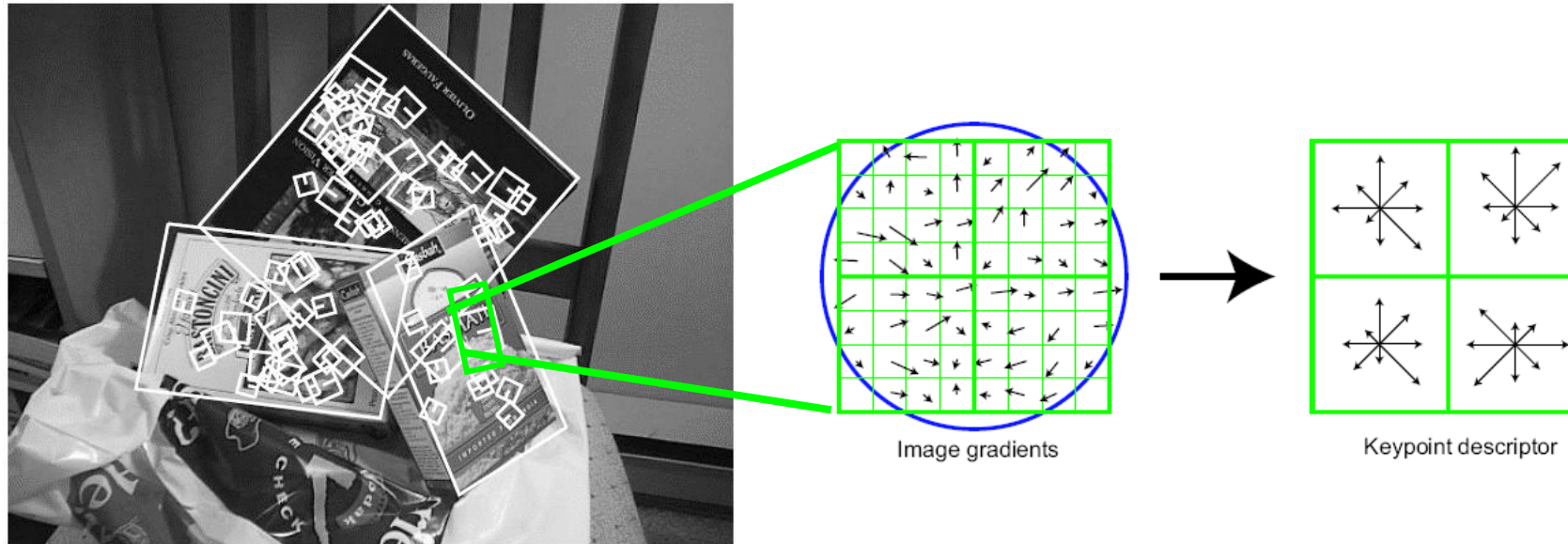
SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor



Local Descriptors: SIFT Descriptor



Histogram of oriented gradients

- Captures important texture information
- Robust to small translations / affine deformations

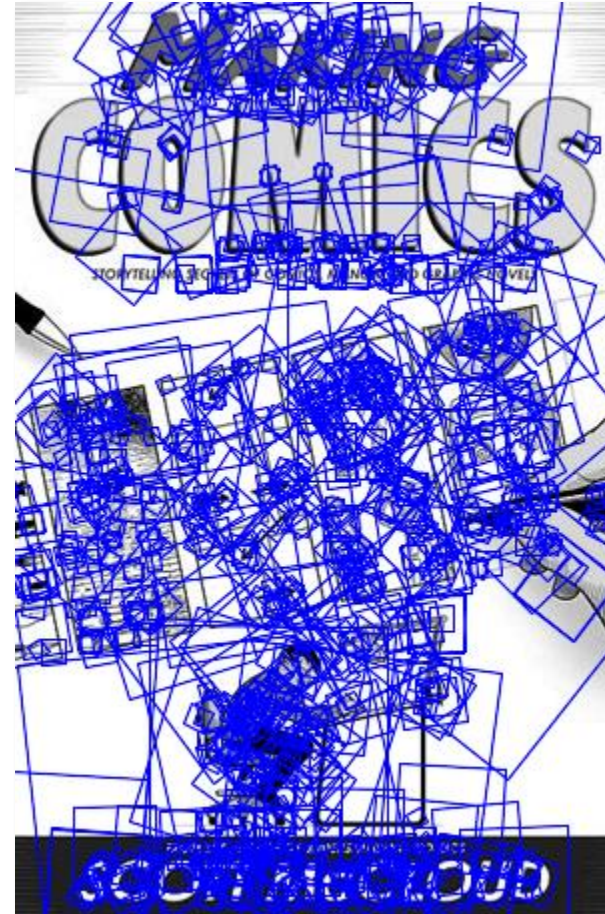
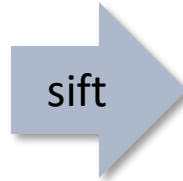
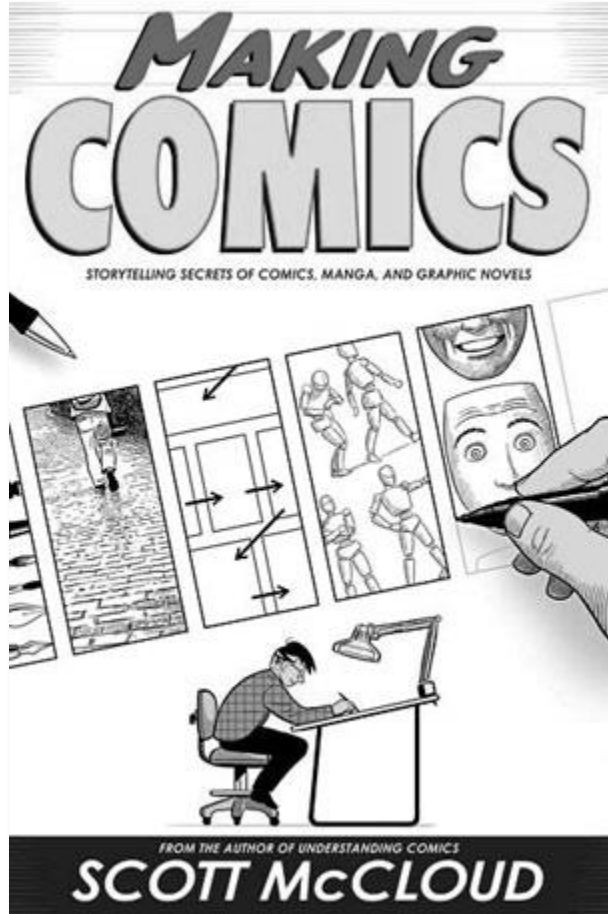
Details of Lowe's SIFT algorithm

- Run DoG detector
 - Find maxima in location/scale space
 - Remove edge points
- Find all major orientations
 - Bin orientations into 36 bin histogram
 - Weight by gradient magnitude
 - Weight by distance to center (Gaussian-weighted mean)
 - Return orientations within 0.8 of peak
 - Use parabola for better orientation fit
- For each (x,y,scale,orientation), create descriptor:
 - Sample 16x16 gradient mag. and rel. orientation
 - Bin 4x4 samples into 4x4 histograms
 - Threshold values to max of 0.2, divide by L2 norm
 - Final descriptor: 4x4x8 normalized histograms

$$\mathbf{H} = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$$\frac{\text{Tr}(\mathbf{H})^2}{\text{Det}(\mathbf{H})} < \frac{(r+1)^2}{r}$$

SIFT Example



868 SIFT features

Feature matching

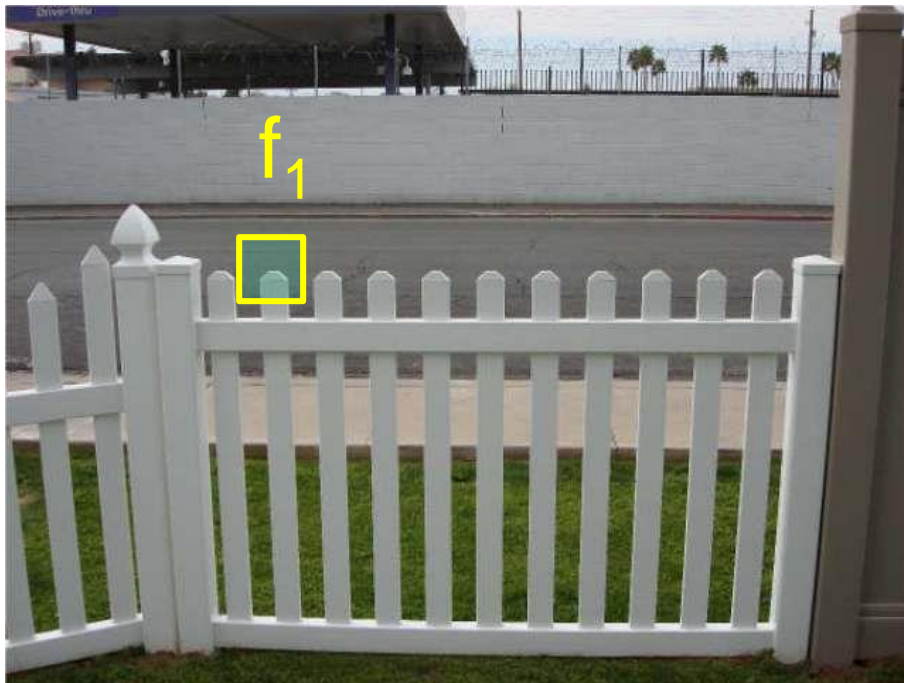
Given a feature in I_1 , how to find the best match in I_2 ?

1. Define distance function that compares two descriptors
2. Test all the features in I_2 , find the one with min distance

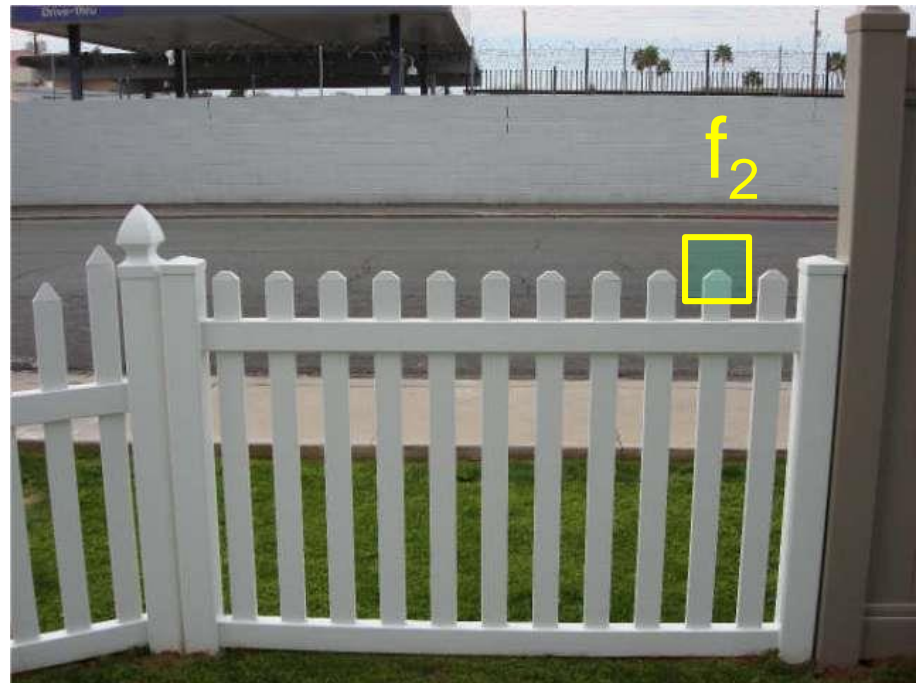
Feature distance

How to define the difference between two features f_1, f_2 ?

- Simple approach: L_2 distance, $\|f_1 - f_2\|$
- can give good scores to ambiguous (incorrect) matches



I_1

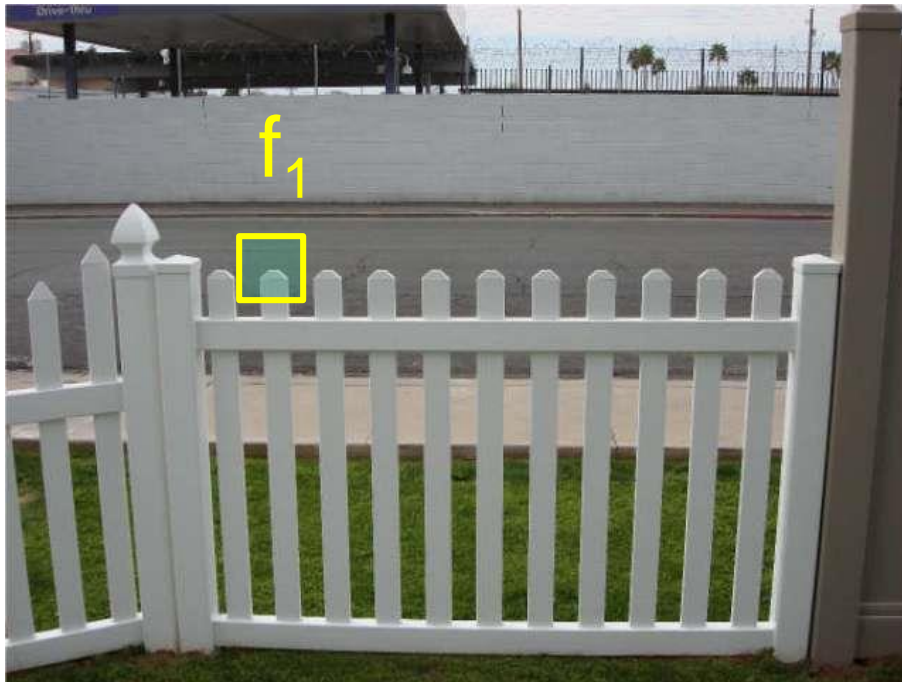


I_2

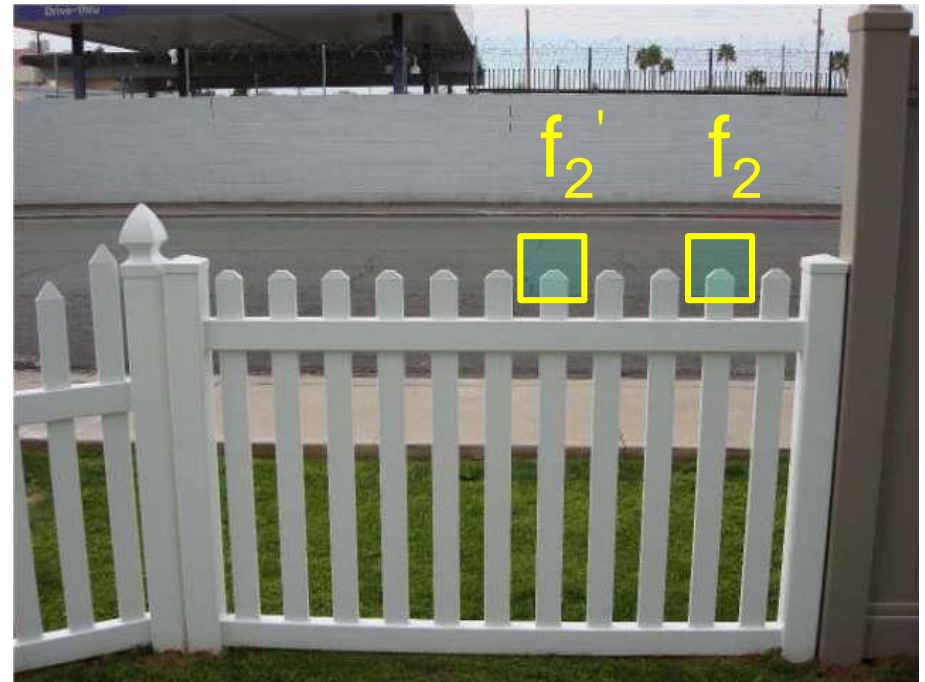
Feature distance

How to define the difference between two features f_1, f_2 ?

- Better approach: ratio distance = $\|f_1 - f_2\| / \|f_1 - f_2'\|$
 - f_2 is best SSD match to f_1 in I_2
 - f_2' is 2nd best SSD match to f_1 in I_2
 - gives large values for ambiguous matches

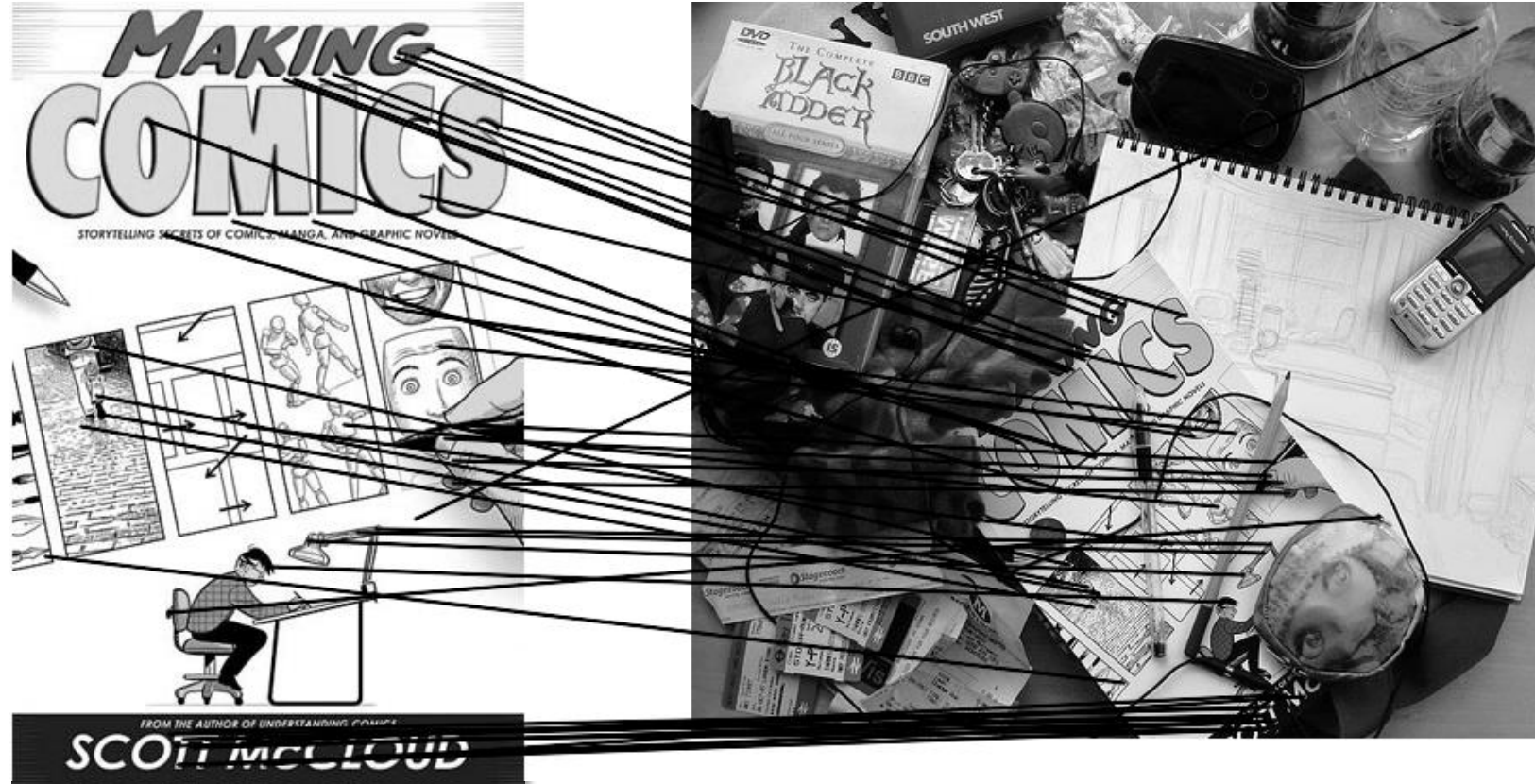


I_1



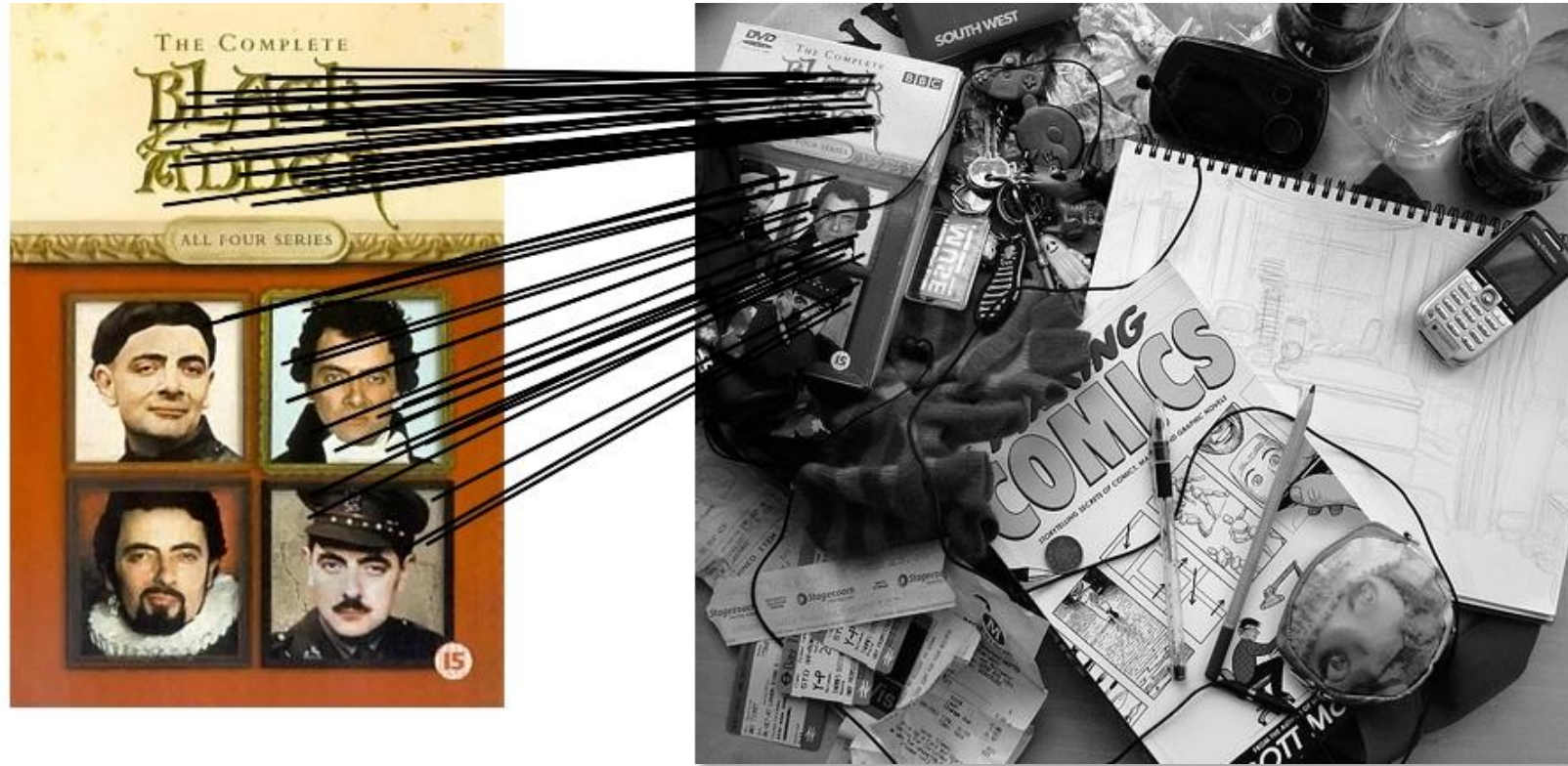
I_2

Feature matching example



51 matches

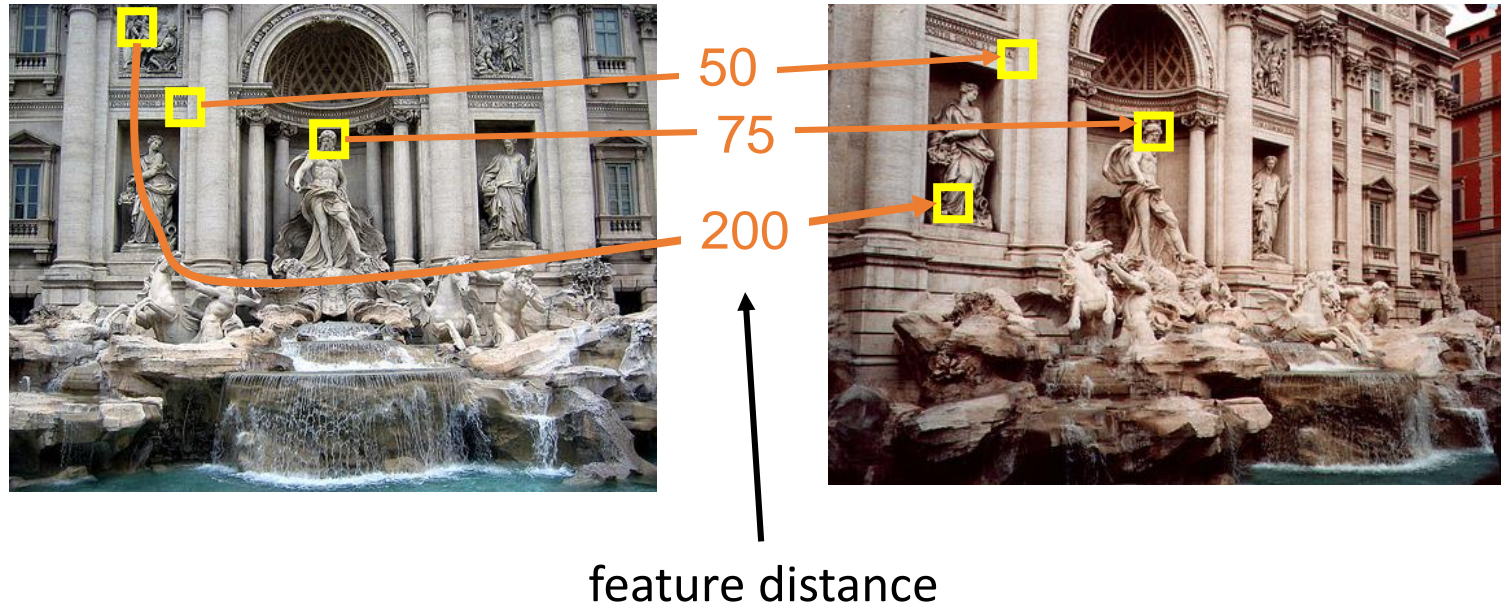
Feature matching example



58 matches

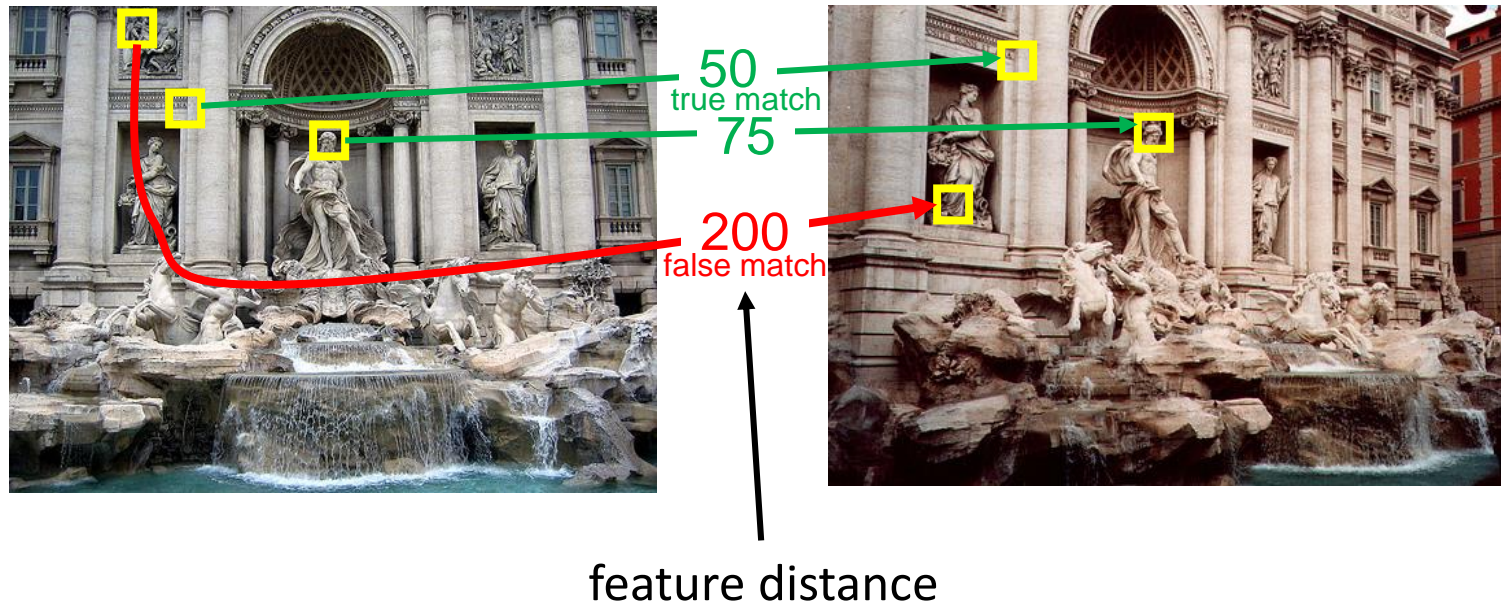
Evaluating the results

How can we measure the performance of a feature matcher?



True/false positives

How can we measure the performance of a feature matcher?



The distance threshold affects performance

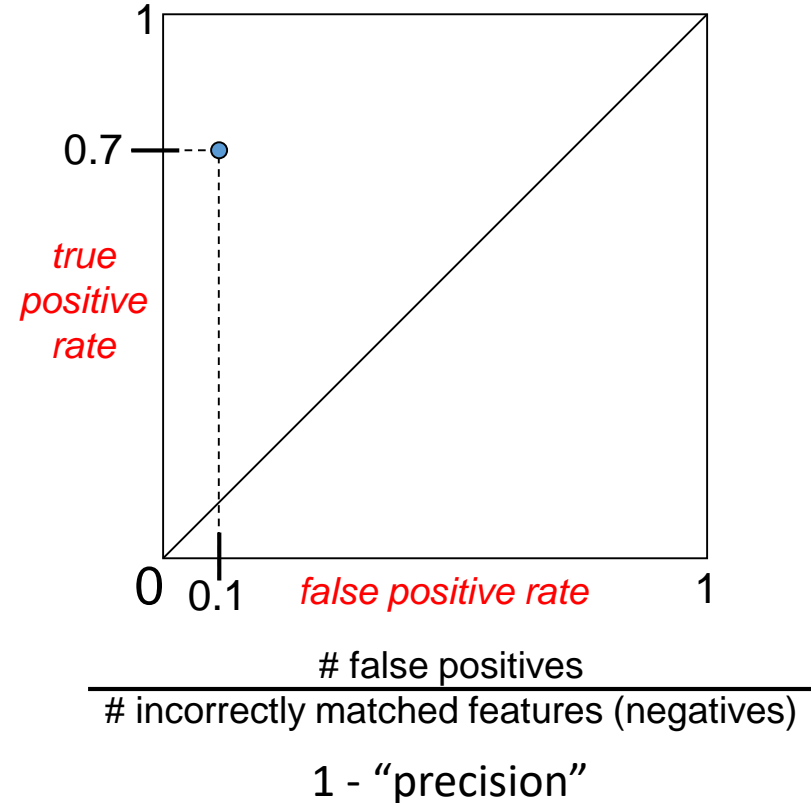
- True positives = # of detected matches that are correct
 - Suppose we want to maximize these—how to choose threshold?
- False positives = # of detected matches that are incorrect
 - Suppose we want to minimize these—how to choose threshold?

Evaluating the results

How can we measure the performance of a feature matcher?

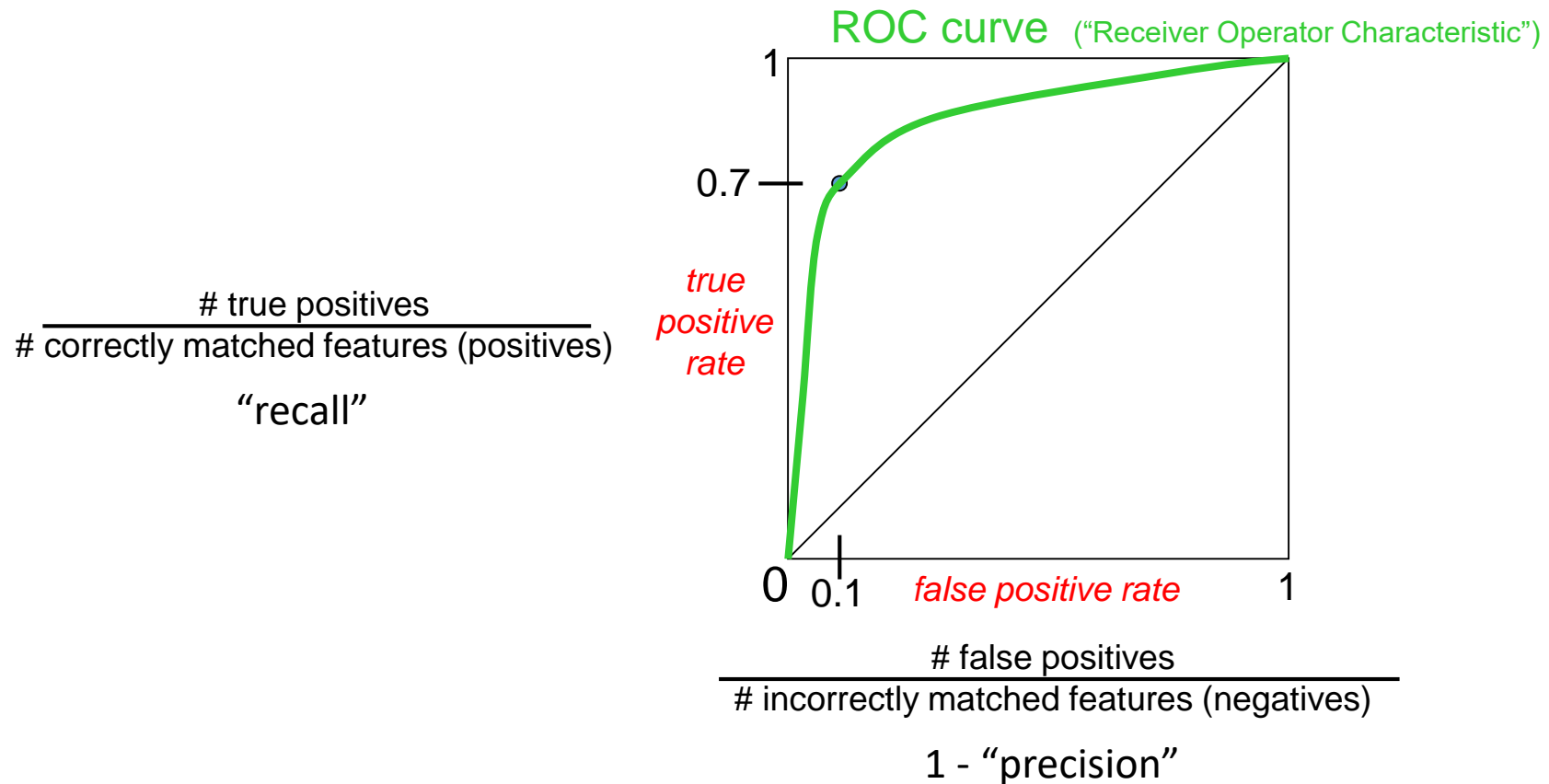
$$\frac{\text{\# true positives}}{\text{\# correctly matched features (positives)}}$$

“recall”



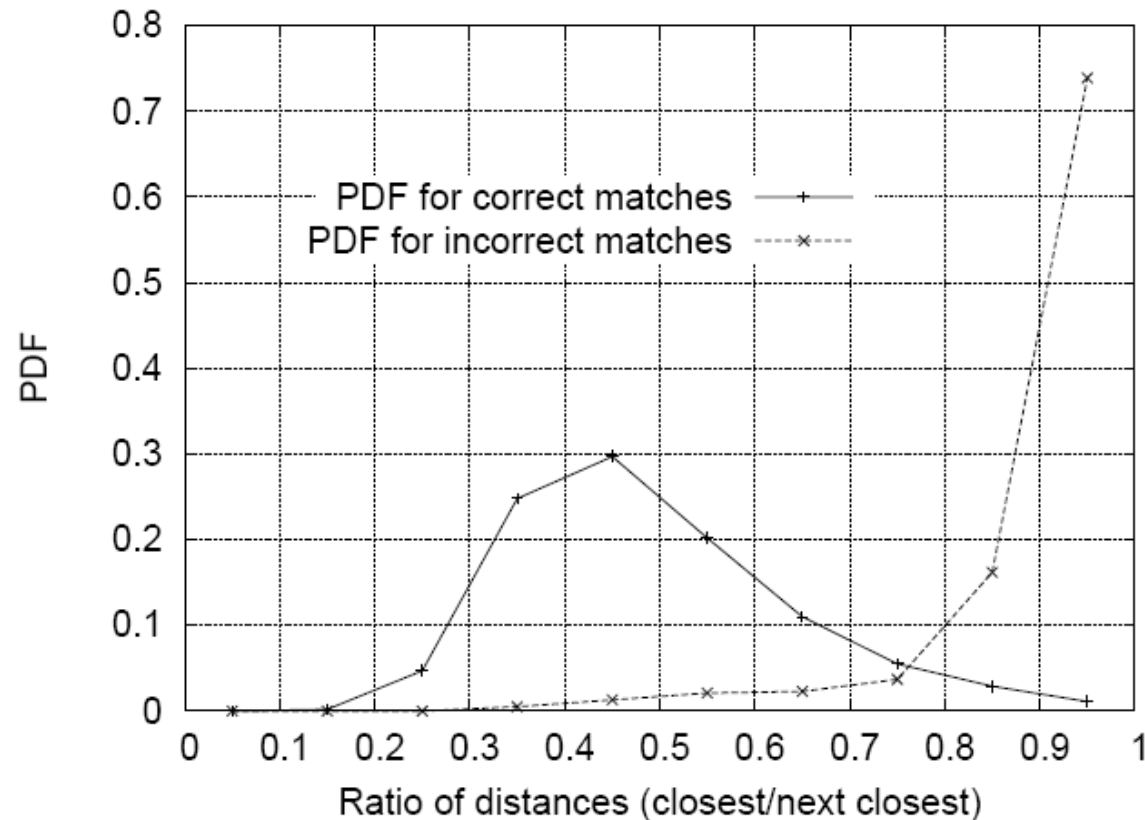
Evaluating the results

How can we measure the performance of a feature matcher?

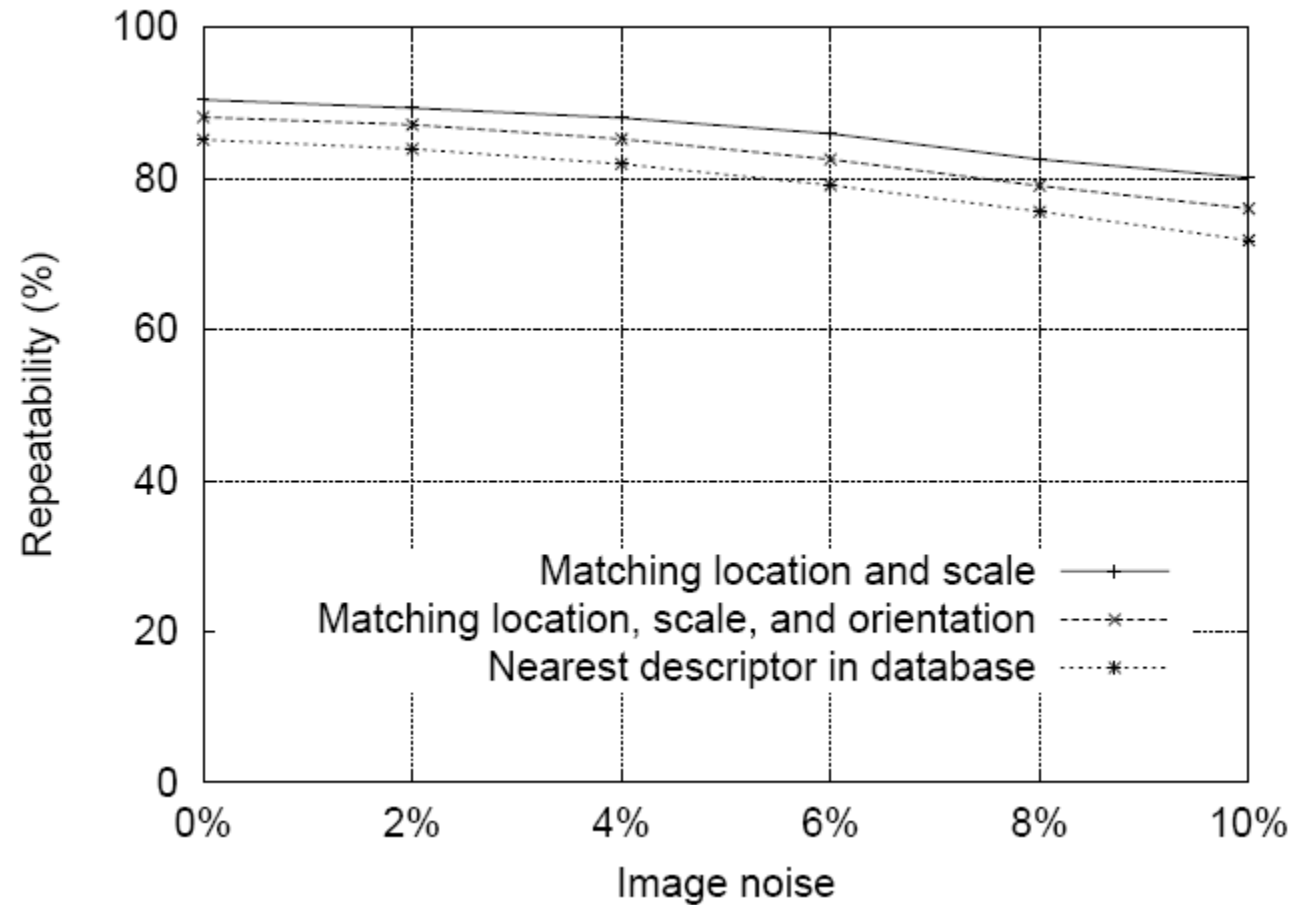


Matching SIFT Descriptors

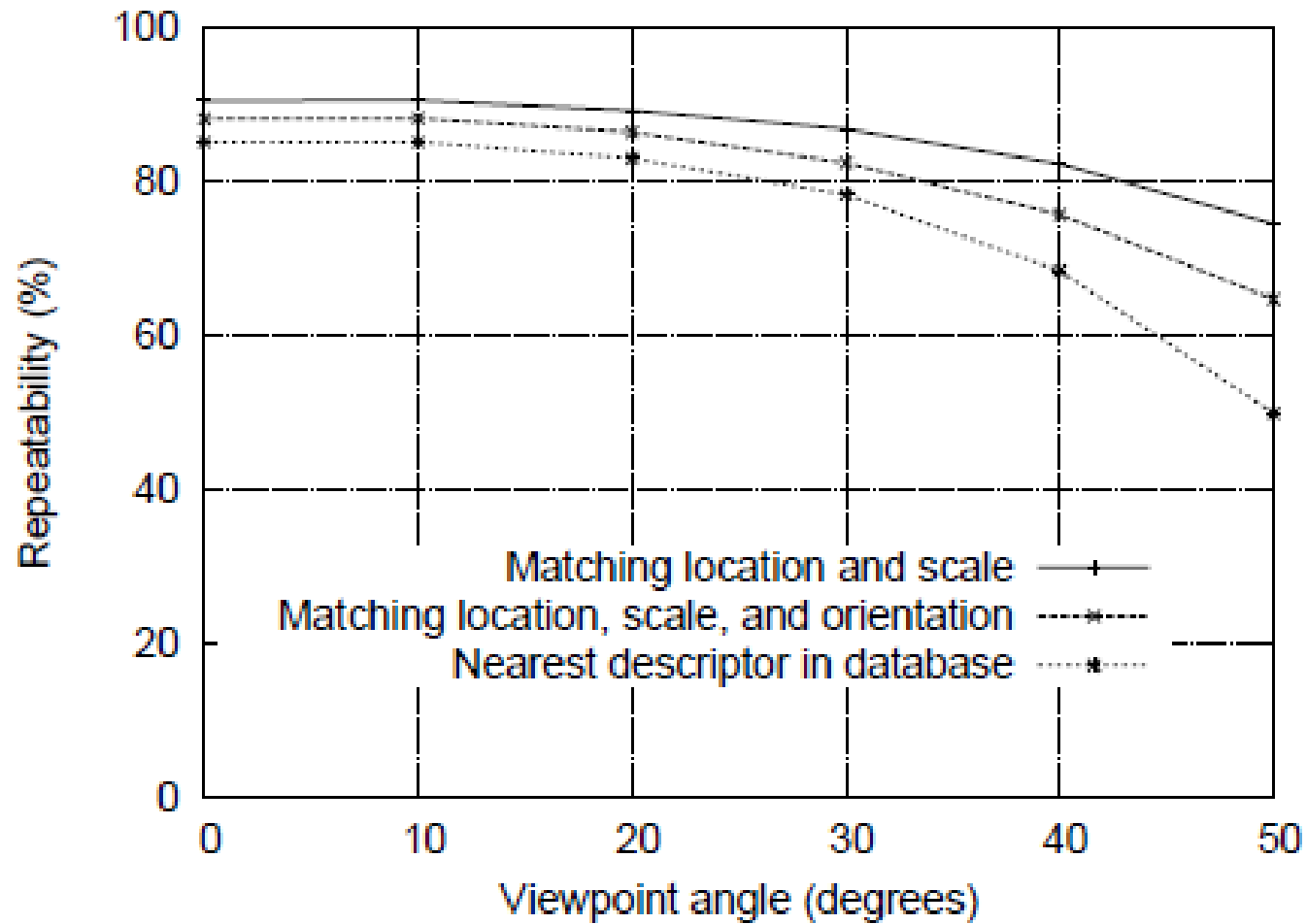
- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



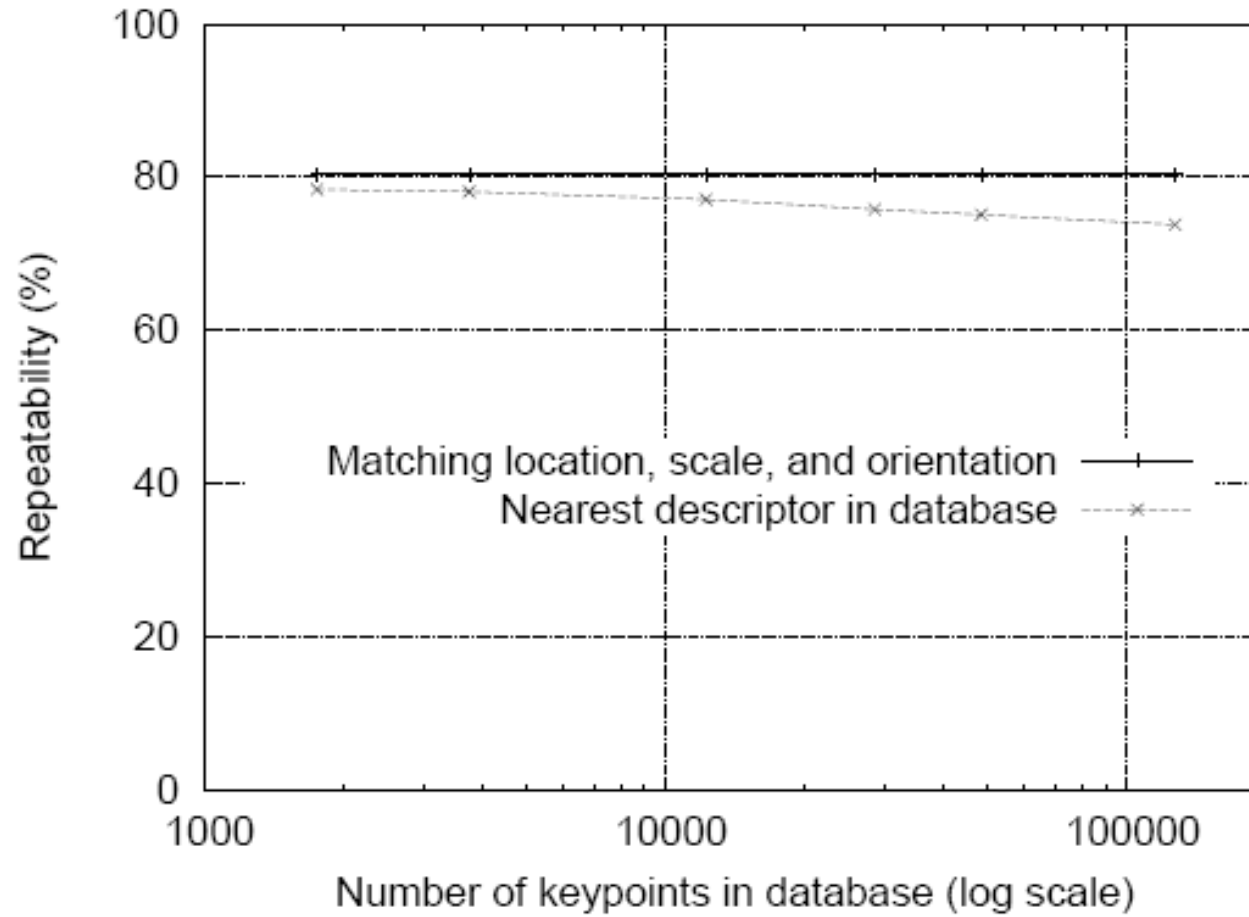
SIFT Repeatability



SIFT Repeatability



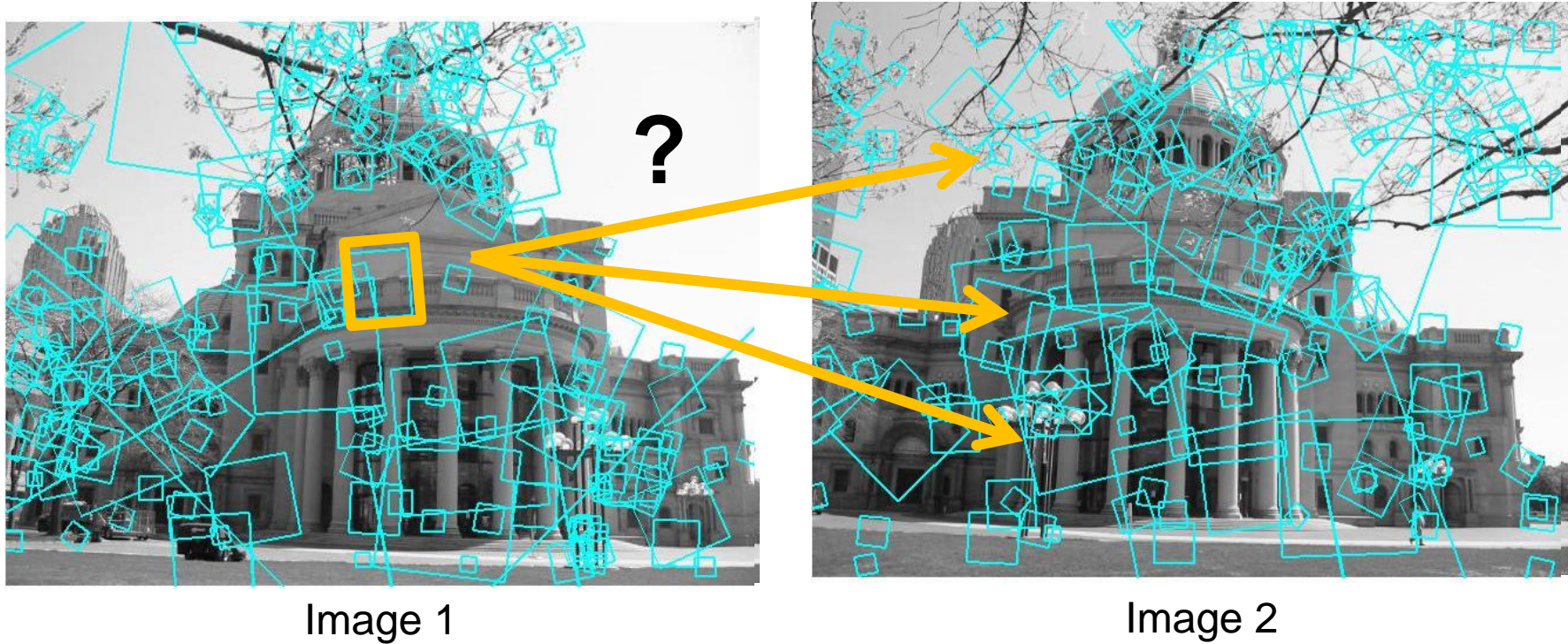
SIFT Repeatability



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

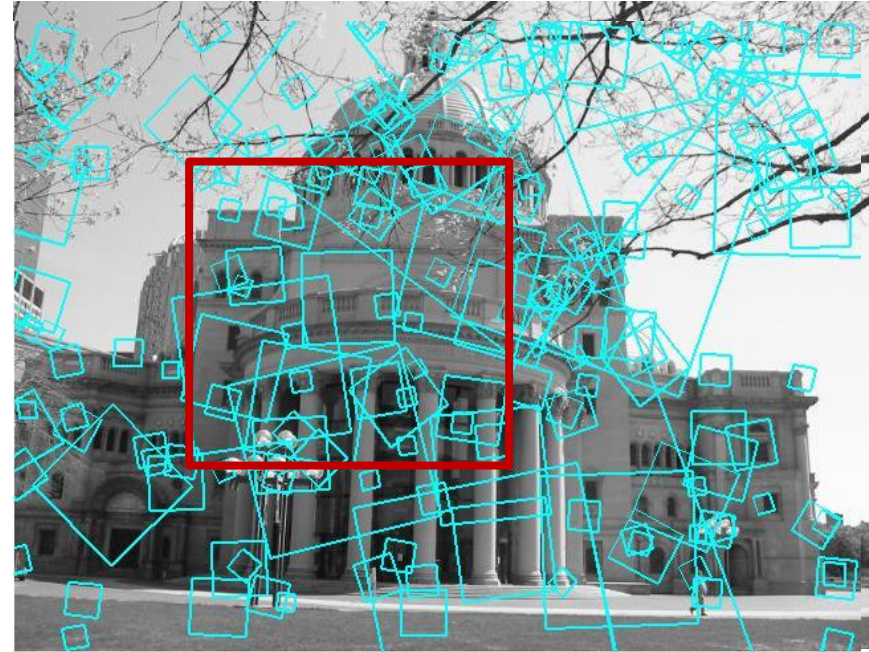
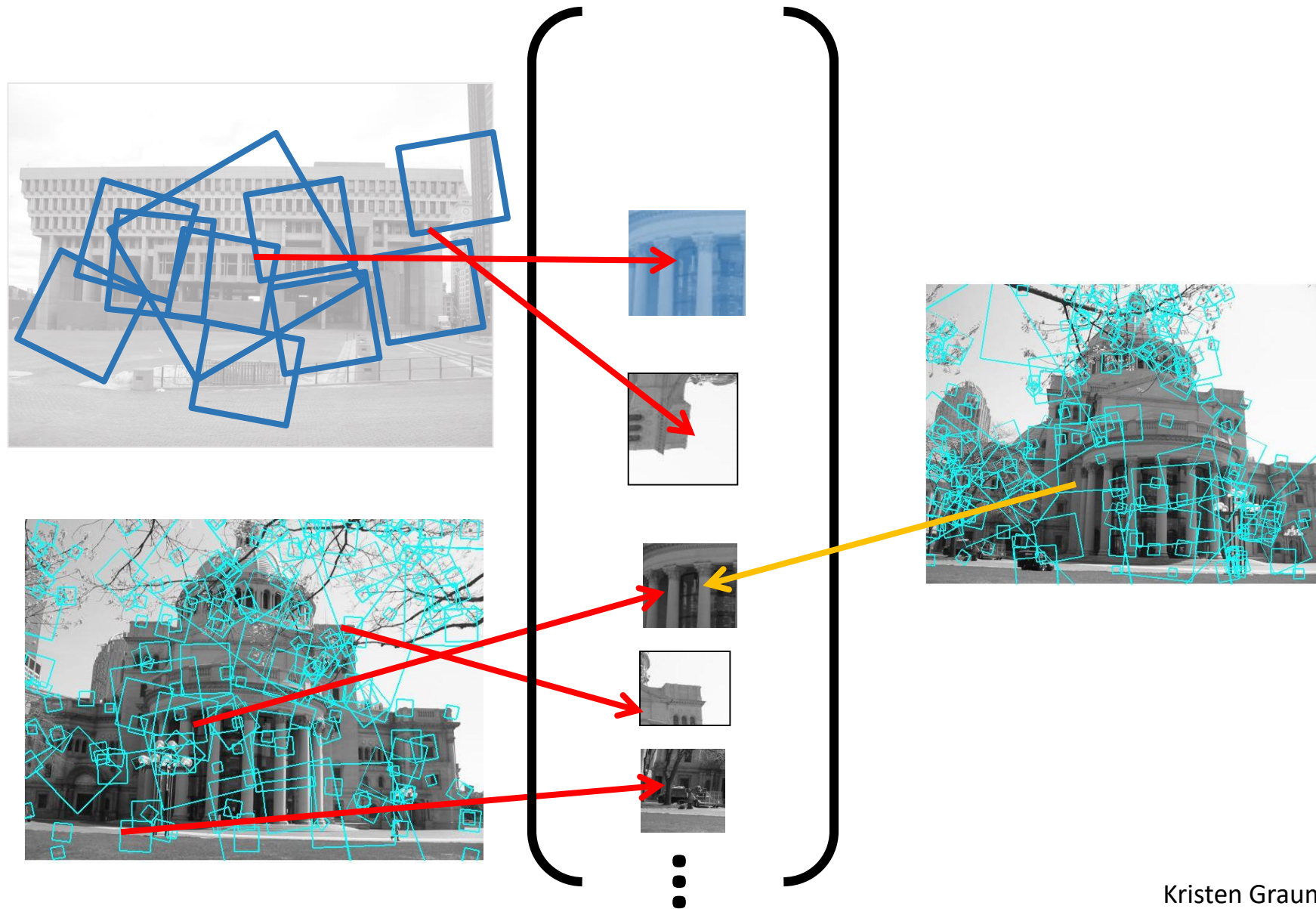


Image 2

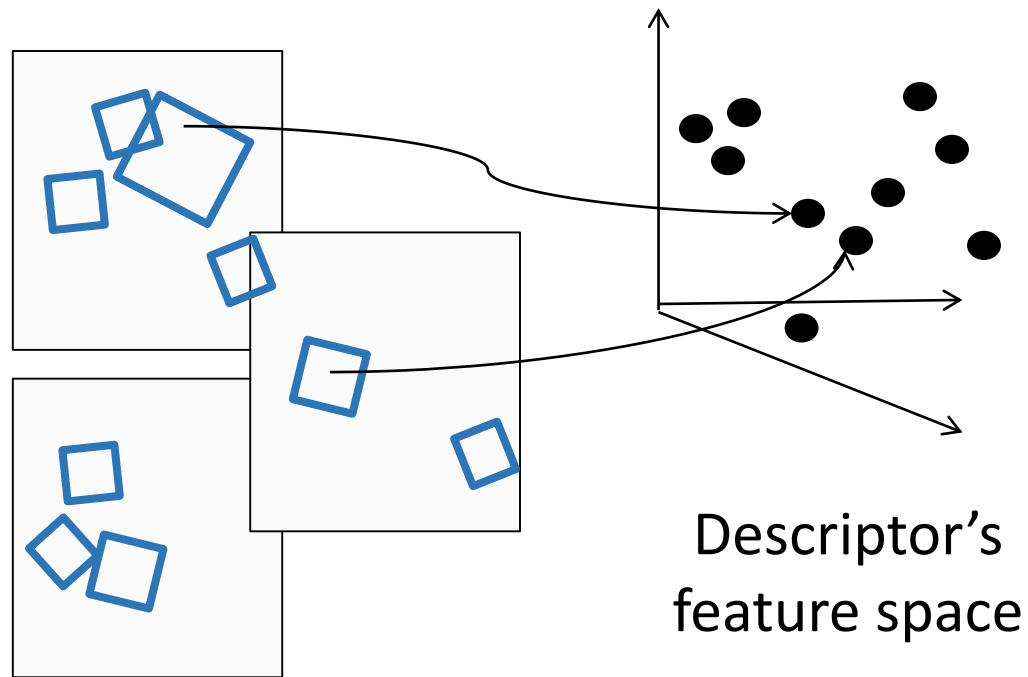
In stereo case, may constrain by proximity if we make assumptions on max disparities.

Indexing local features



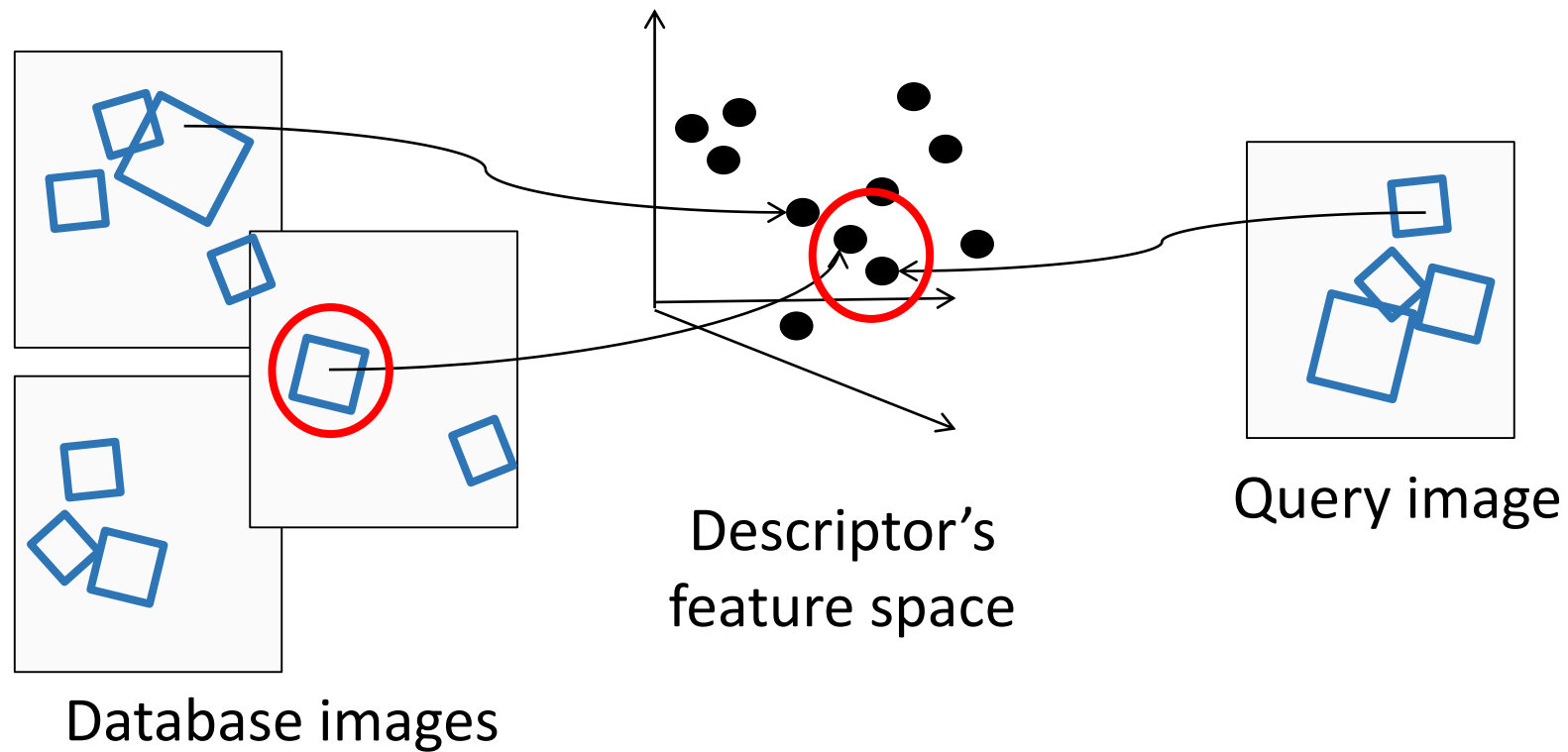
Indexing local features

- 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	Driving Lanes; 85
"Drive I-95," From Boston to Florida; <i>inside back cover</i>	CAA (see AAA)	Duval County; 163
1929 Spanish Trail Roadway; 101-102,104	CCC, The; 111,113,115,135,142	Eau Gallie; 175
511 Traffic Information; 83	Ca d'Zan; 147	Edison, Thomas; 152
A1A (Barrier Is) - I-95 Access; 86	Caloosahatchee River; 152	Eglin AFB; 116-118
AAA (and CAA); 83	Name; 150	Eight Reale; 176
AAA National Office; 88	Canaveral Natrl Seashore; 173	Ellenton; 144-145
Abbreviations,	Cannon Creek Airpark; 130	Emanuel Point Wreck; 120
Colored 25 mile Maps; cover	Canopy Road; 106,169	Emergency Callboxes; 83
Exit Services; 196	Cape Canaveral; 174	Epiphytes; 142,148,157,159
Travelogue; 85	Castillo San Marcos; 169	Escambia Bay; 119
Africa; 177	Cave Diving; 131	Bridge (I-10); 119
Agricultural Inspection Strs; 126	Cayo Costa, Name; 150	County; 120
Ah-Tah-Thi-Ki Museum; 160	Celebration; 93	Esterio; 153
Air Conditioning, First; 112	Charlotte County; 149	Everglade,90,95,139-140,154-160
Alabama; 124	Charlotte Harbor; 150	Draining of; 156,181
Alachua; 132	Chautauqua; 116	Wildlife MA; 160
County; 131	ChIPLEY; 114	Wonder Gardens; 154
Alafia River; 143	Name; 115	Falling Waters SP; 115
Alapaha, Name; 126	Choctawatchee, Name; 115	Fantasy of Flight; 95
Alfred B Maclay Gardens; 106	Circus Museum, Ringling; 147	Fayer Dykes SP; 171
Alligator Alley; 154-155	Citrus; 88,97,130,136,140,180	Fires, Forest; 166
Alligator Farm, St Augustine; 169	CityPlace, W Palm Beach; 180	Fires, Prescribed ; 148
Alligator Hole (definition); 157	City Maps,	Fisherman's Village; 151
Alligator, Buddy; 155	Fl Lauderdale Expwys; 194-195	Flagler County; 171
Alligators; 100,135,138,147,156	Jacksonville; 163	Flagler, Henry; 97,165,167,171
Anastasia Island; 170	Kissimmee Expwys; 192-193	Florida Aquarium; 186
Anhaica; 108-109,146	Miami Expressways; 194-195	Florida,
Apalachicola River; 112	Orlando Expressways; 192-193	12,000 years ago; 187
Appleton Mus of Art; 136	Pensacola; 26	Cavern SP; 114
Aquifer; 102	Tallahassee; 191	Map of all Expressways; 2-3
Arabian Nights; 94	Tampa-St. Petersburg; 63	Mus of Natural History; 134
Art Museum, Ringling; 147	St. Augustine; 191	National Cemetery ; 141
Aruba Beach Cafe; 183	Civil War; 100,108,127,138,141	Part of Africa; 177
Aucilla River Project; 106	Clearwater Marine Aquarium; 187	Platform; 187
Babcock-Web WMA; 151	Collier County; 154	Sheriff's Boys Camp; 126
Bahia Mar Marina; 184	Collier, Barron; 152	Sports Hall of Fame; 130
Baker County; 99	Colonial Spanish Quarters; 168	Sun 'n Fun Museum; 97
Barefoot Mailmen; 182	Columbia County; 101,128	Supreme Court; 107
Barge Canal; 137	Coquina Building Material; 165	Florida's Turnpike (FTP), 178,189
Bee Line Expy; 80	Corkscrew Swamp, Name; 154	25 mile Strip Maps; 66
Belz Outlet Mall; 89	Cowboys; 95	Administration; 189
Bernard Castro; 136	Crab Trap II; 144	Coin System; 190
Big "I"; 165	Cracker, Florida; 88,95,132	Exit Services; 189
Big Cypress; 155,158	Crosstown Expy; 11,35,98,143	HEFT; 76,161,190
Big Foot Monster; 105	Cuban Bread; 184	History; 189
Billie Swamp Safari; 160	Dade Battlefield; 140	Names; 189
Blackwater River SP; 117	Dade, Maj. Francis; 139-140,161	Service Plazas; 190
Blue Angels	Dania Beach Hurricane; 184	Spur SR91; 76
	Daniel Boone, Florida Walk; 117	Ticket System; 190
	Daytona Beach; 172-173	Toll Plazas; 190
	De Land; 87	Ford, Henry; 152

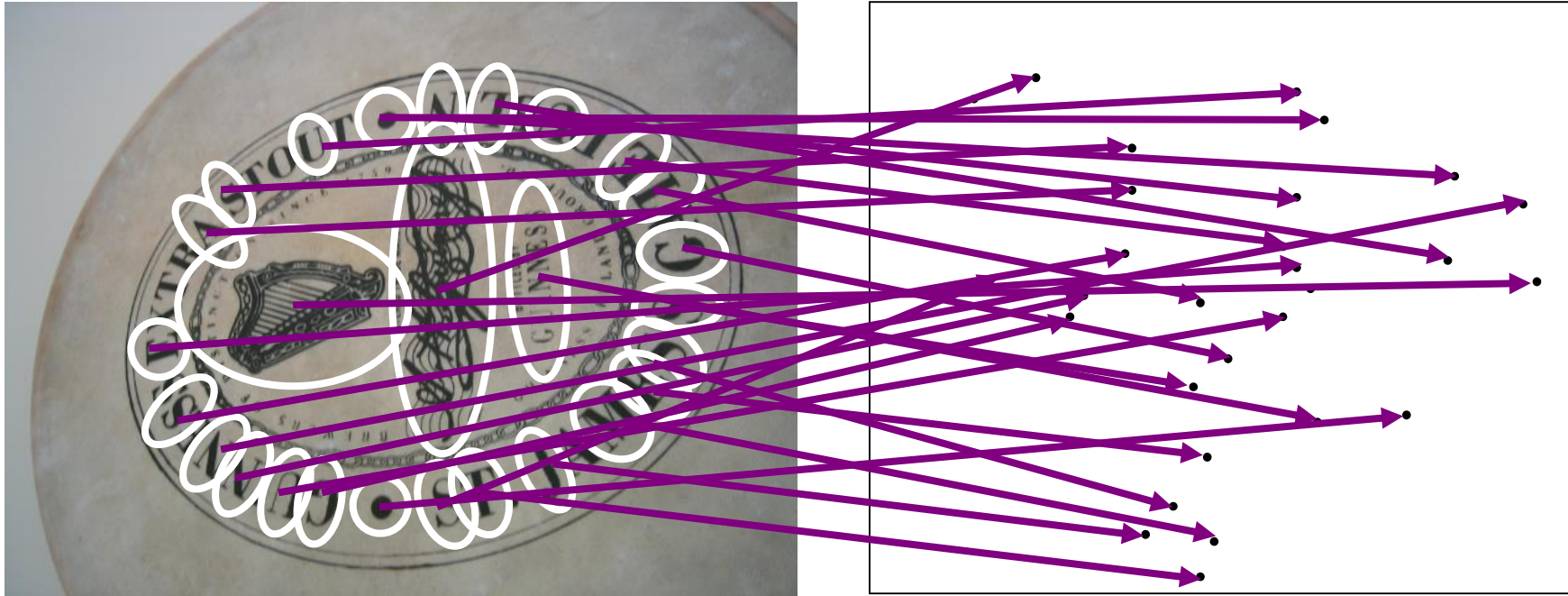
- For text documents, an efficient way to find all *pages* on which a *word* occurs is to use an index...
- We want to find all *images* in which a *feature* occurs.
- To use this idea, we'll need to map our features to "visual words".

Text retrieval vs. image search

- What makes the problems similar, different?

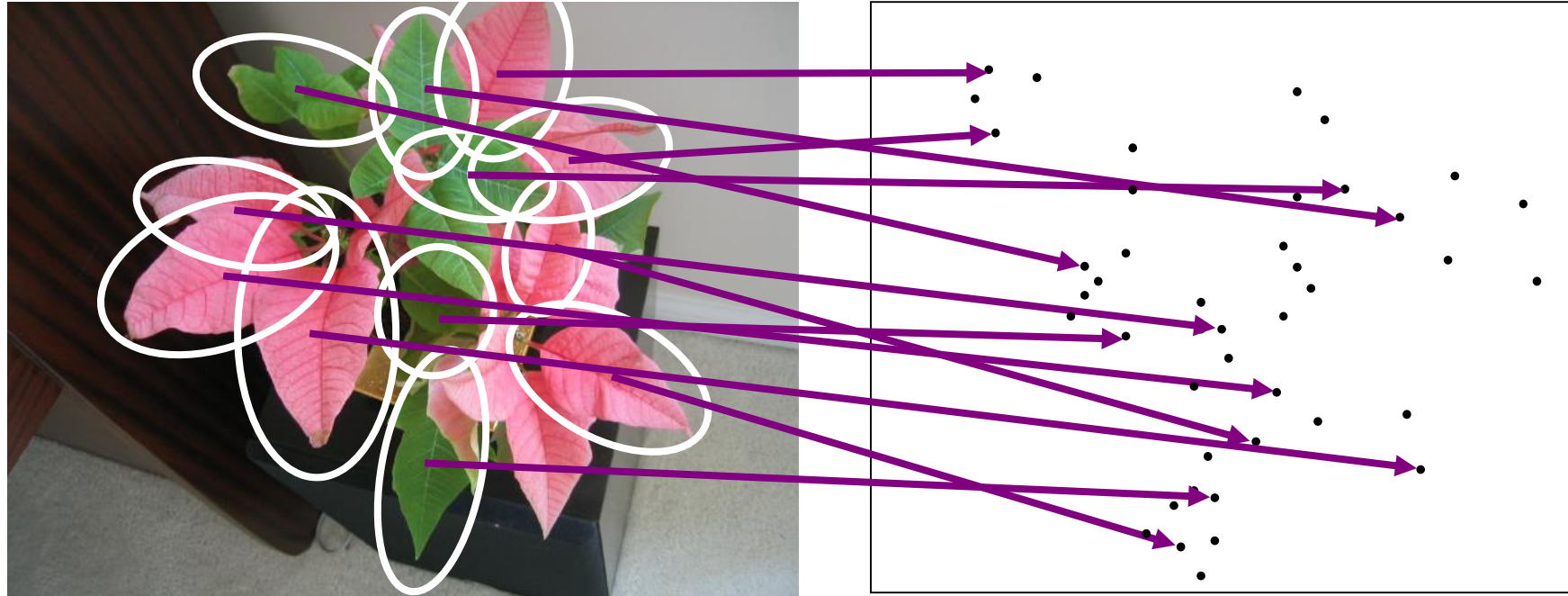
Visual words: main idea

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

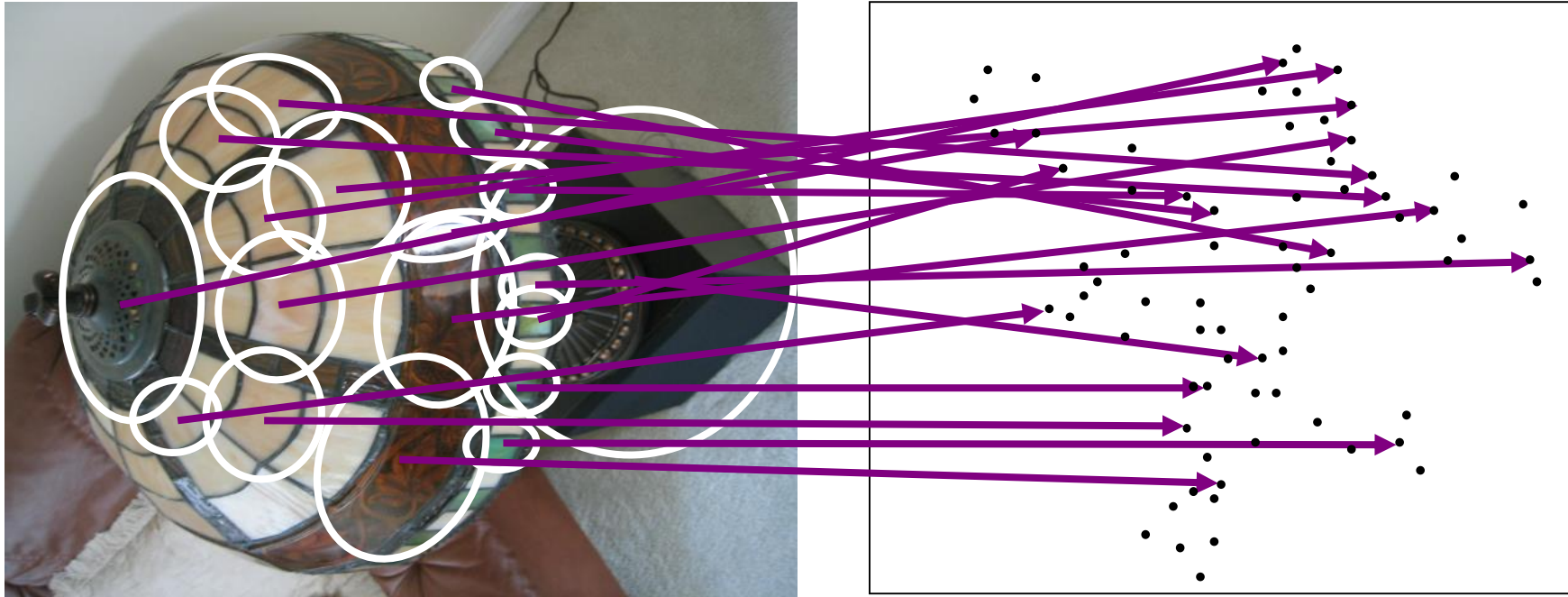


e.g., SIFT descriptor space: each point is 128-dimensional

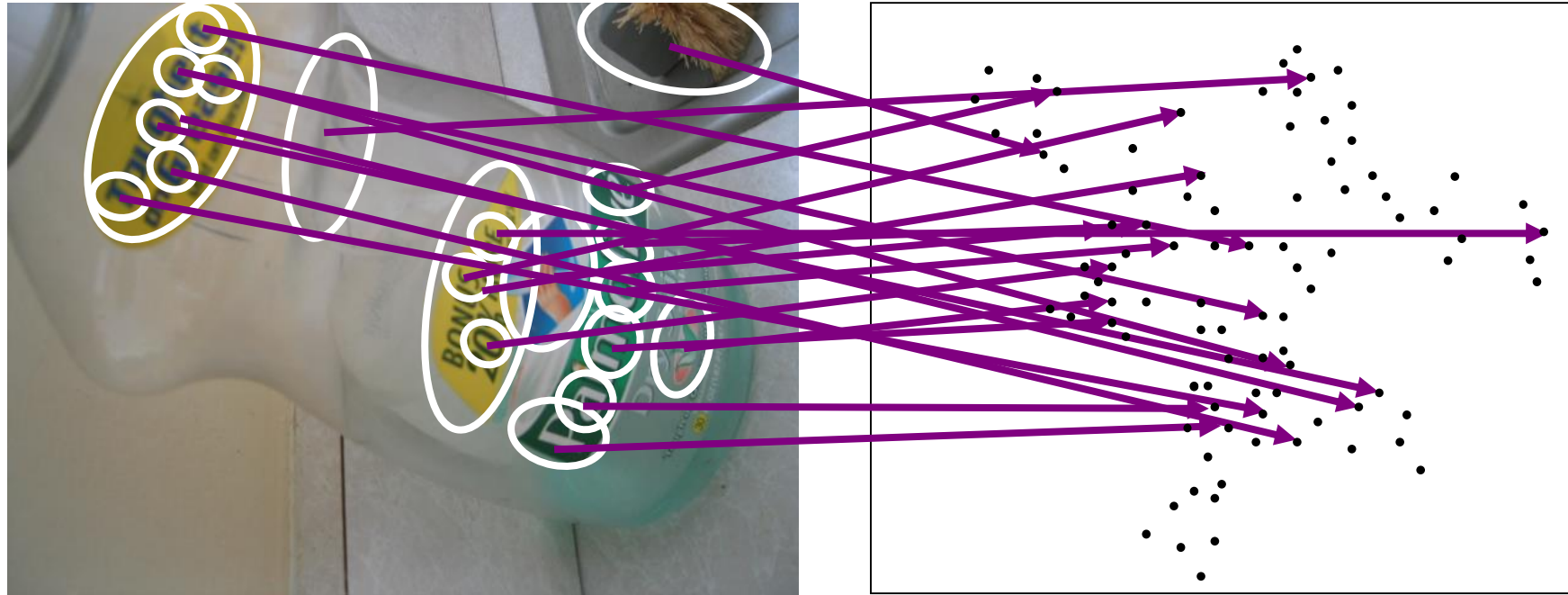
Visual words: main idea



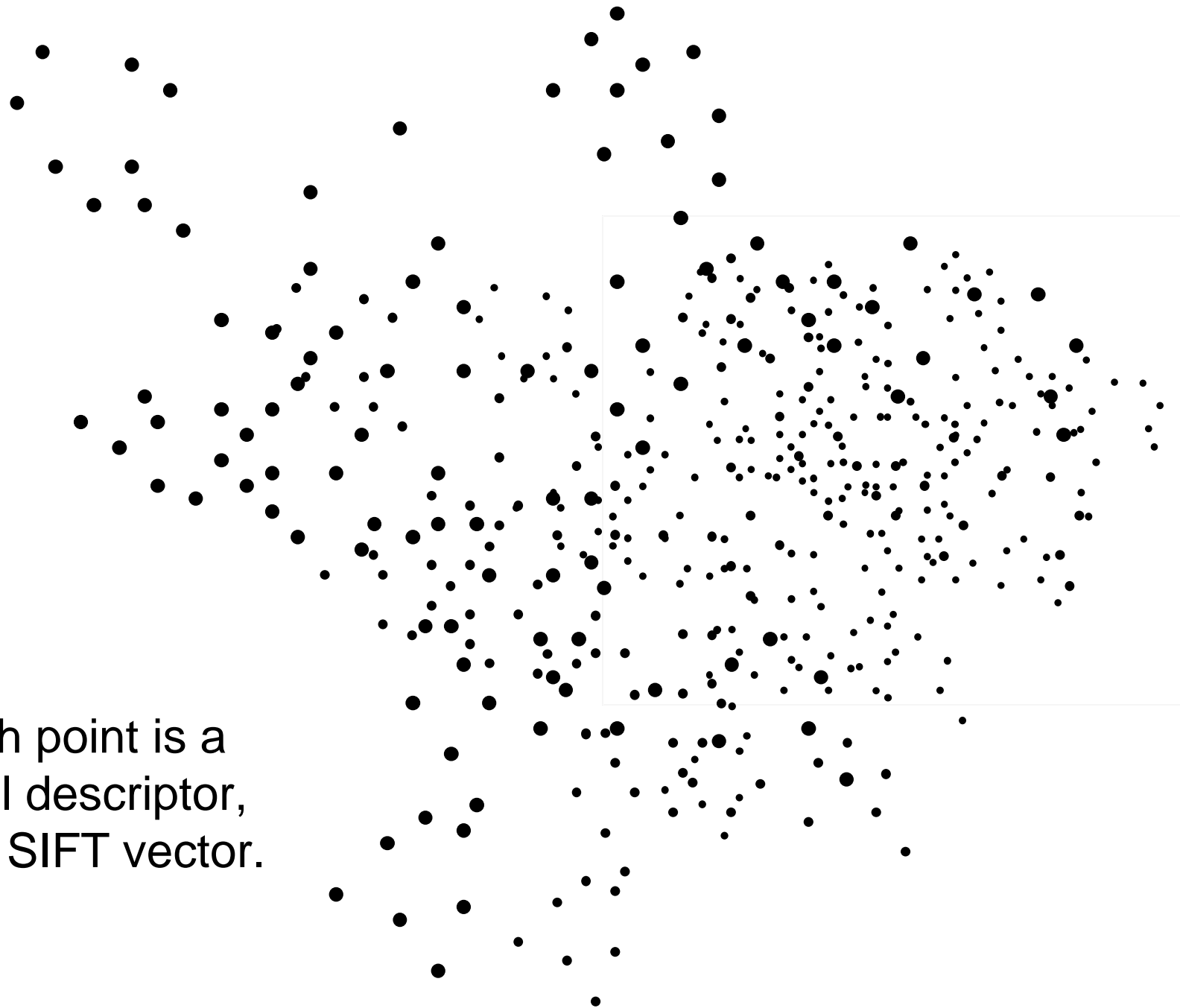
Visual words: main idea

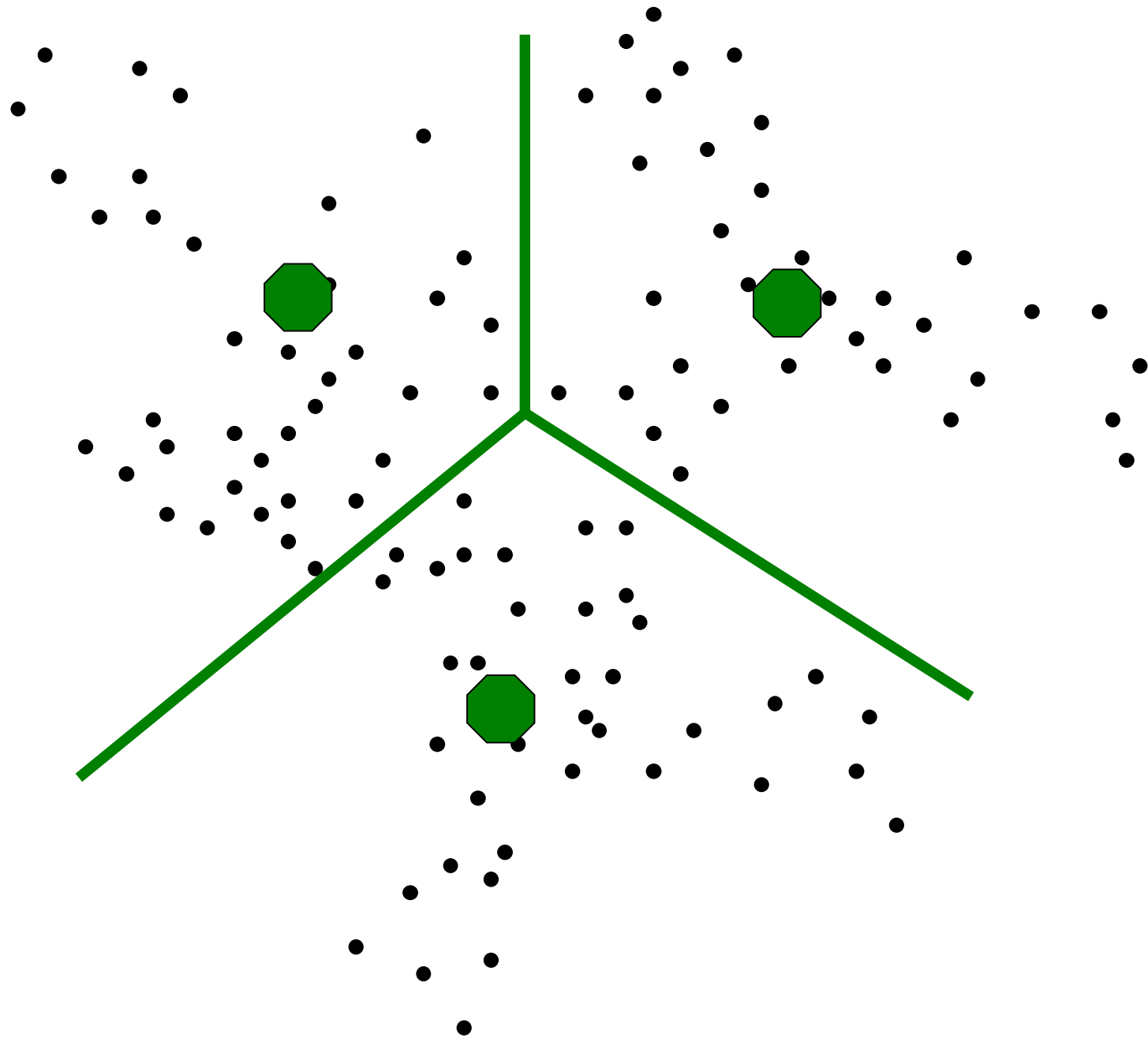


Visual words: main idea



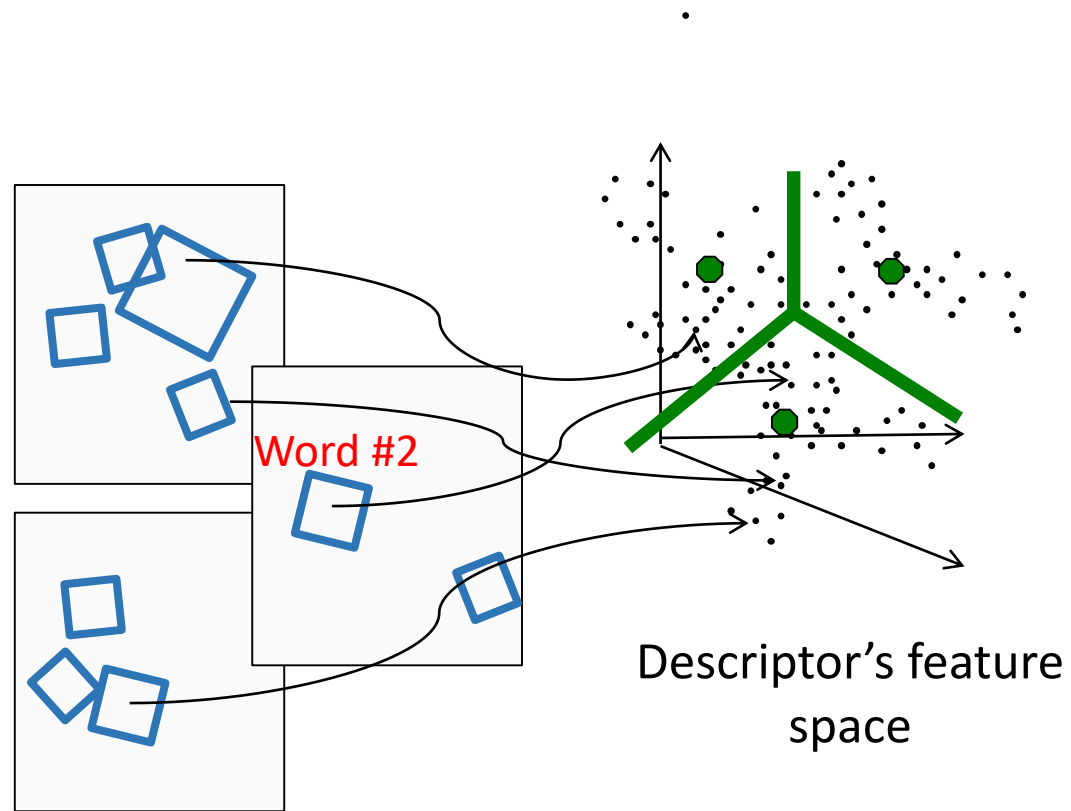
Each point is a
local descriptor,
e.g. SIFT vector.





Visual words

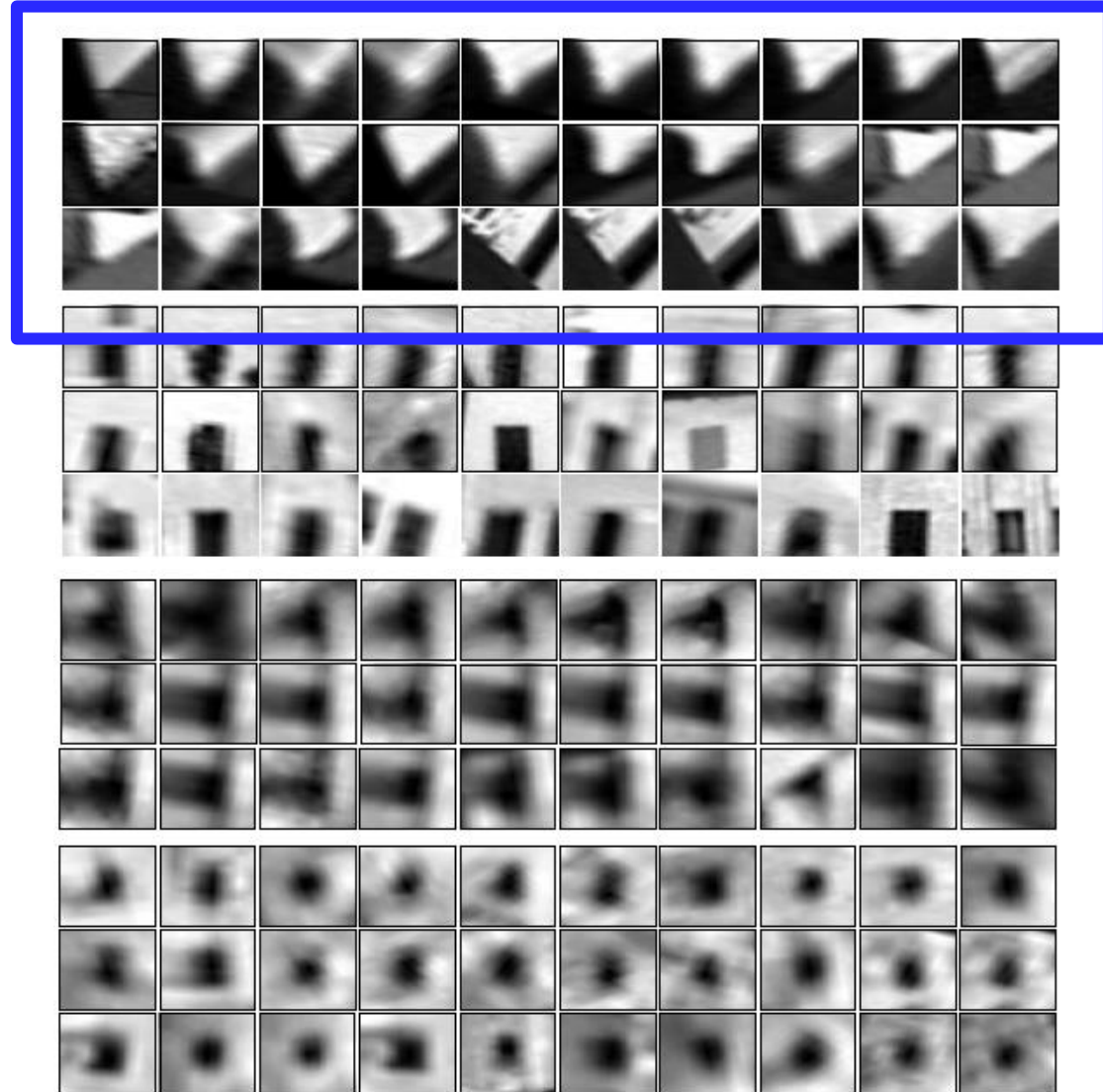
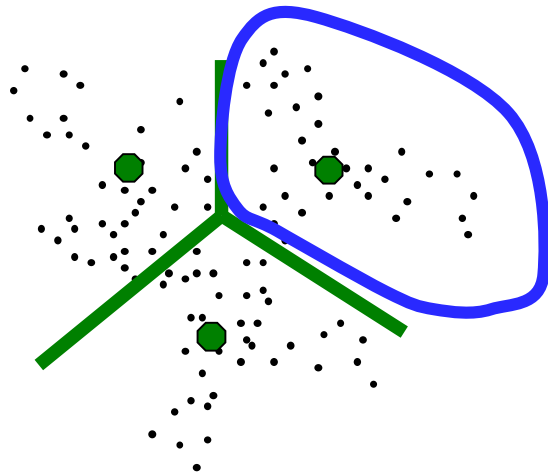
- Map high-dimensional descriptors to tokens/words by quantizing the feature space



- 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.

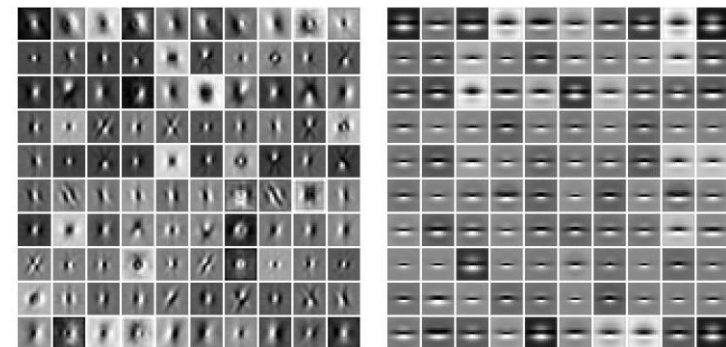
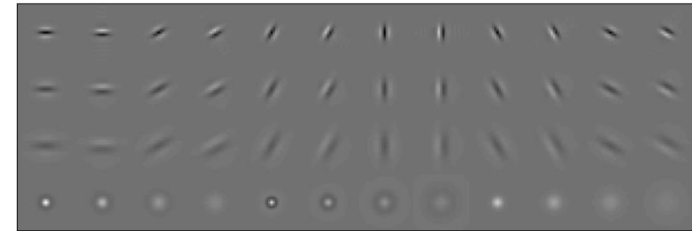
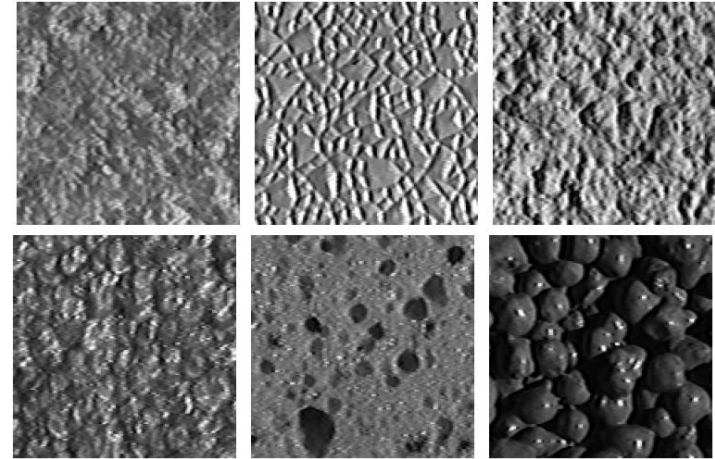
Visual words

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



Visual words and textons

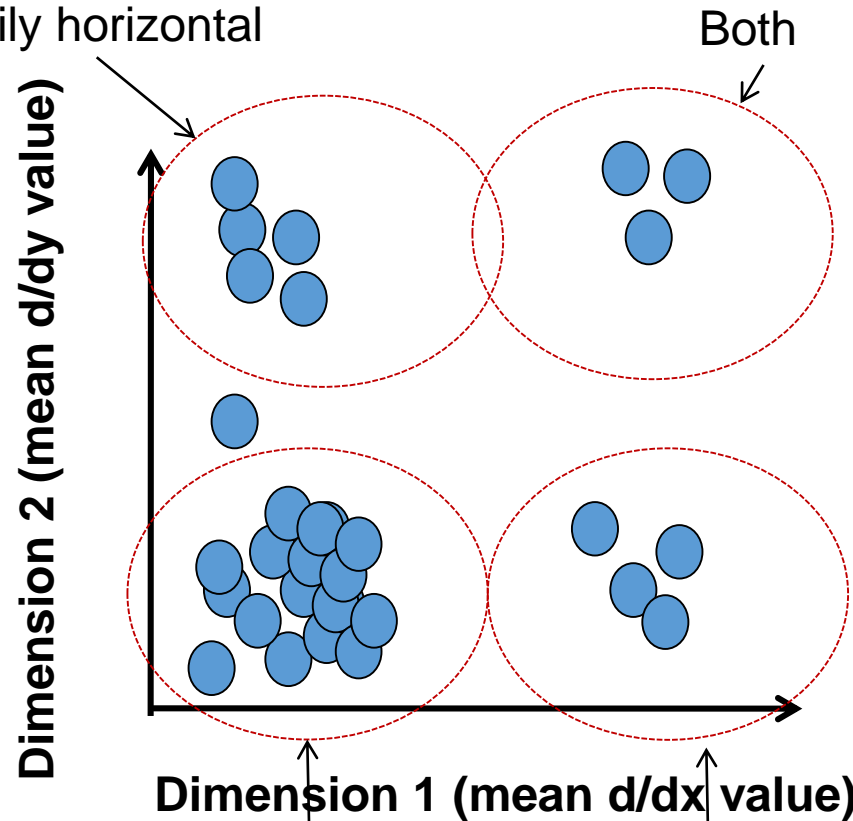
- First explored for texture and material representations
- *Texton* = cluster center of filter responses over collection of images
- Describe textures and materials based on distribution of prototypical texture elements.



Leung & Malik 1999; Varma & Zisserman, 2002

Recall: Texture representation example

Windows with primarily horizontal edges



Windows with small gradient in both directions

Windows with primarily vertical edges

	<u>mean d/dx value</u>	<u>mean d/dy 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:

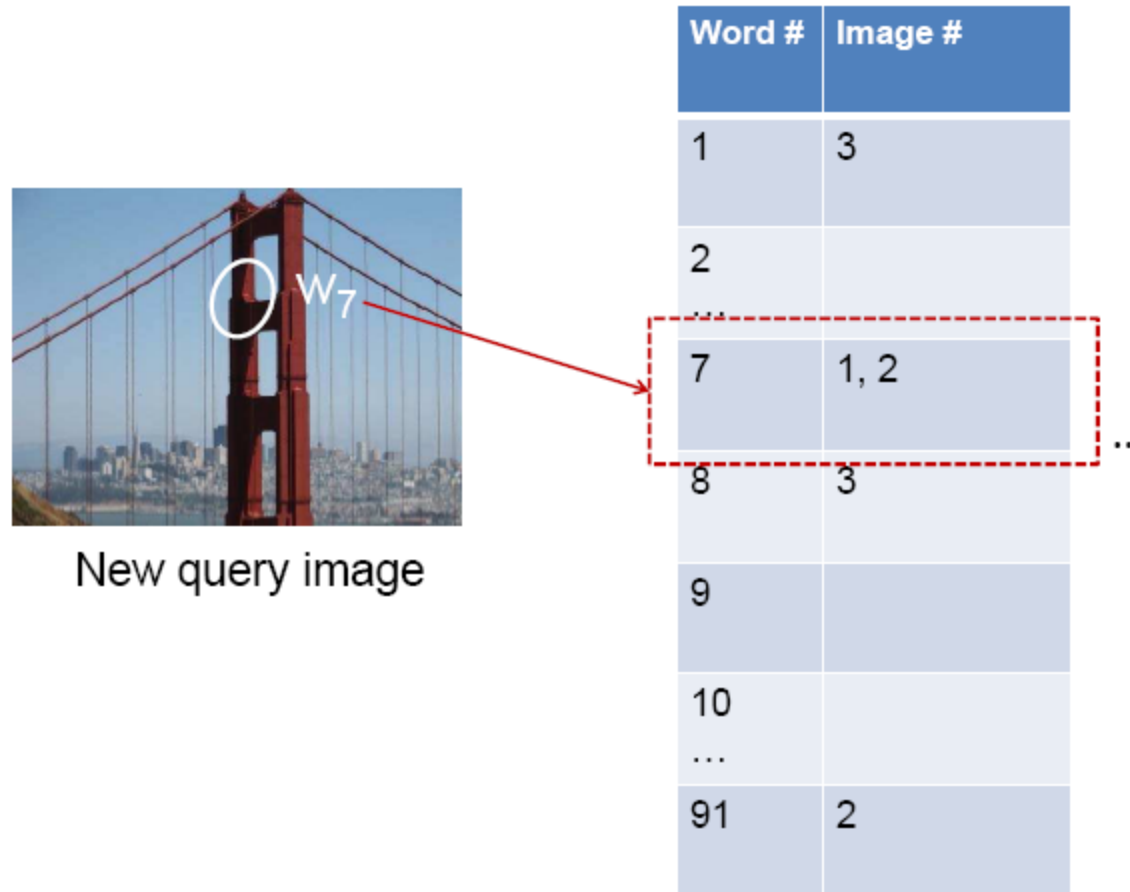
- Sampling strategy: where to extract features?
- Clustering / quantization algorithm
- Unsupervised vs. supervised
- What corpus provides features (universal vocabulary?)
- Vocabulary size, number of words

Inverted file index



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

Inverted file index



- 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)?

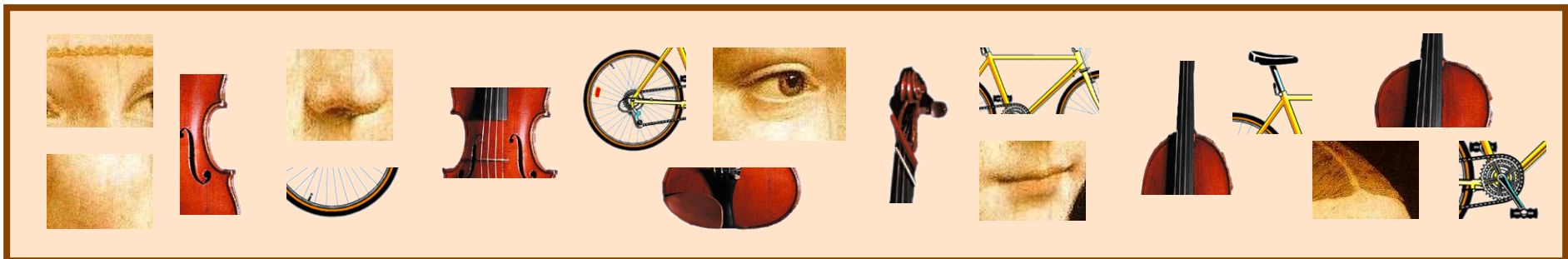
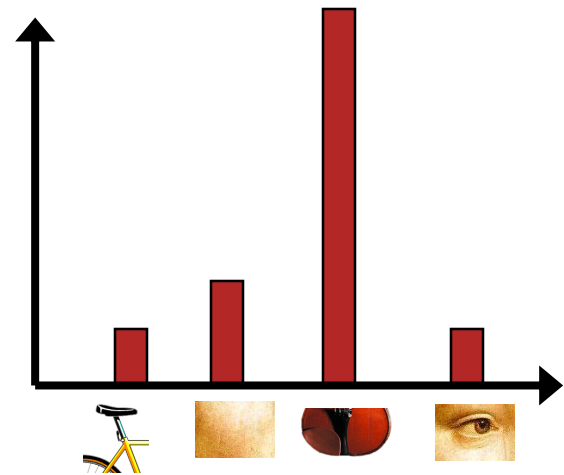
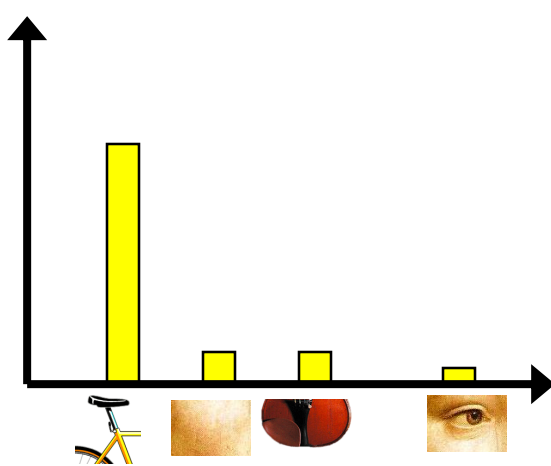
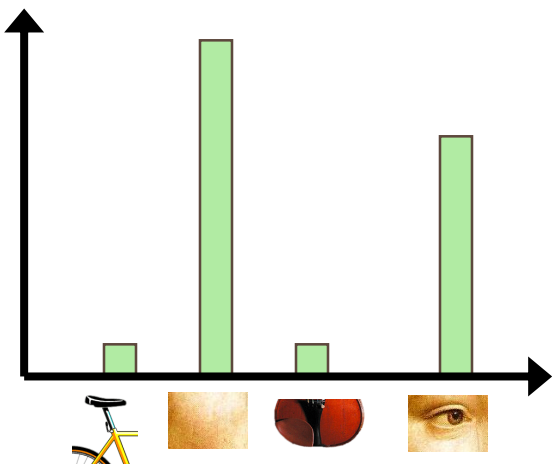
Analogy to documents

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 these impressions. It takes about 1/10th of a second for light to reach the brain from our eyes. The brain then processes the information. It is thought that the brain processes information at a point by point basis. The brain is a complex system of cerebral cells. It is upon which the visual information is processed. Through the visual system, the brain now knows the world around it. The perception of the world is more complex than the visual information. The visual information is processed through various cell layers. The visual information is processed by Hubel and Wiesel. They have been able to show that the visual system receives a message about the image falling on the retina. The image undergoes a step-wise analysis in a system of nerve cells stored in columns. In this system, each cell has its specific function and is responsible for detecting a specific detail in the pattern of the retinal image.

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

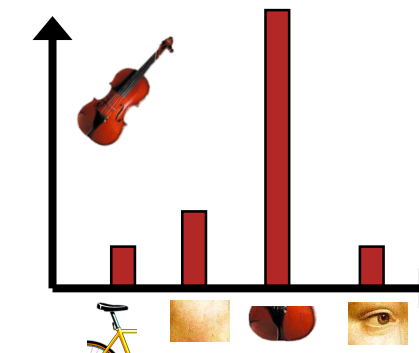
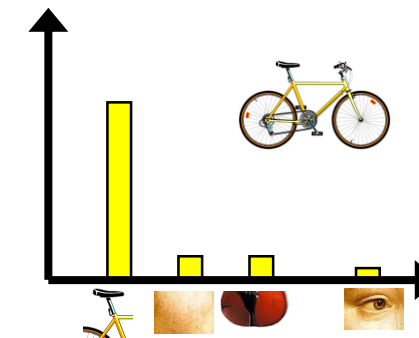
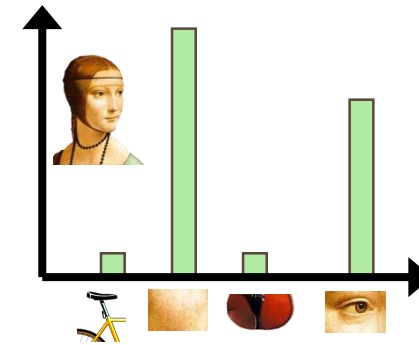
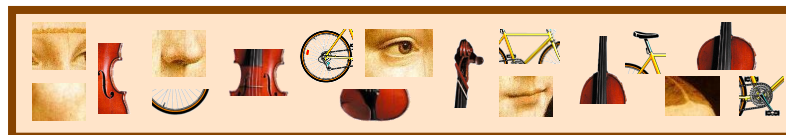
China is forecasting a trade surplus of \$90bn (£51bn) to \$100bn this year, a threefold increase on 2004's \$32bn. The Commerce Ministry said the surplus would be \$100bn, a predicted 30% jump in exports and a 18% rise in imports. The ministry said it would further analyze the situation. China's government has decided to raise the surplus to \$100bn. One factor is the rise in exports. Xiaochua said the surplus is more to be expected. The surplus stayed within the range of \$100bn. The value of the yuan rose 10% in July and permitted it to be used to trade freely. However, Beijing has made it clear that it will take its time and tread carefully in allowing the yuan to rise further in value.

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



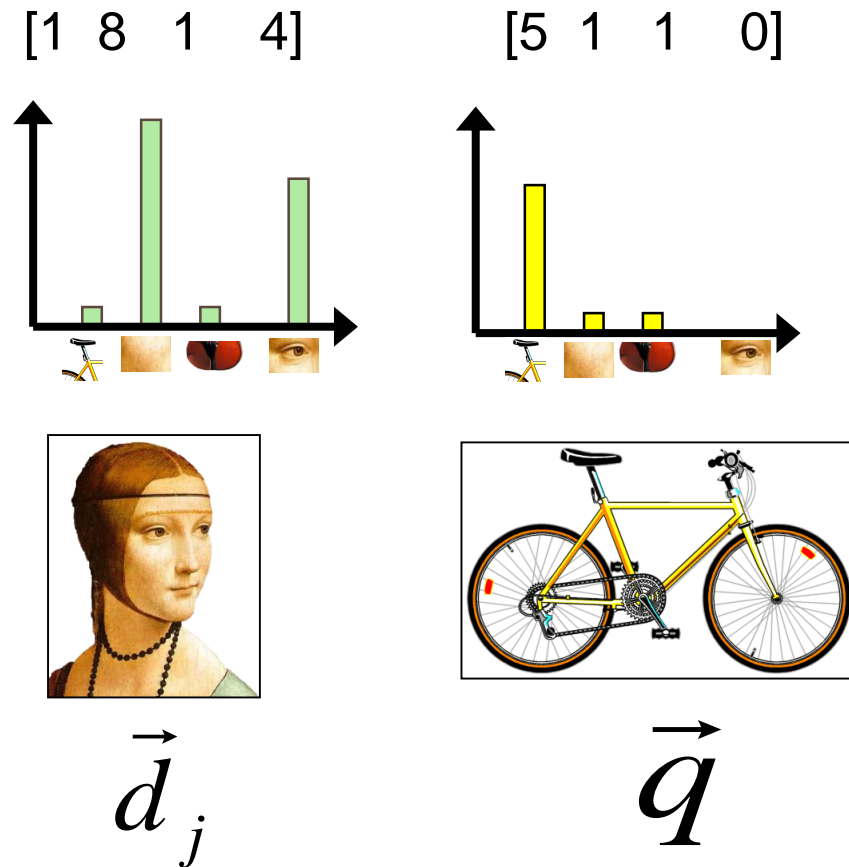
Bags of visual words

- 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.



Bags of words for content-based image retrieval

Visually defined query

“Find this clock”



“Find this place”



“Groundhog Day” [Rammis, 1993]



Example



retrieved shots



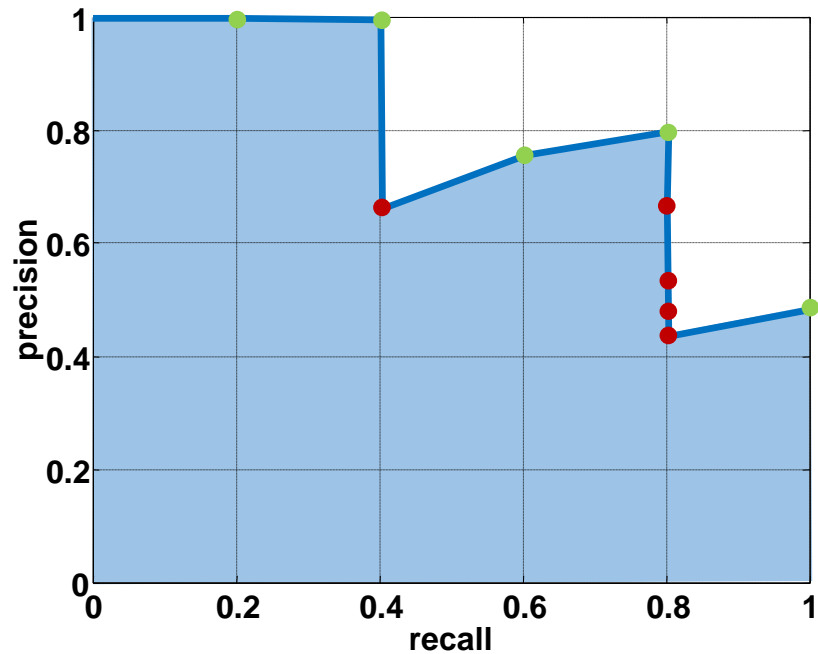
Scoring retrieval quality



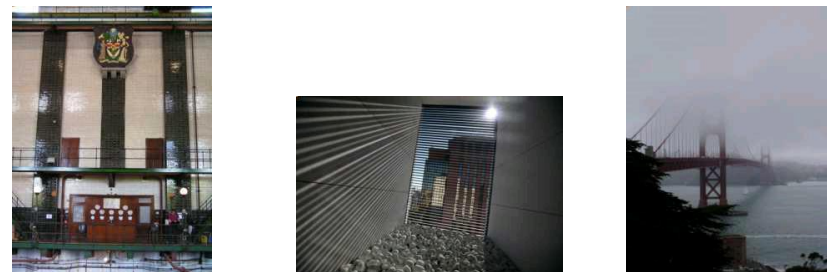
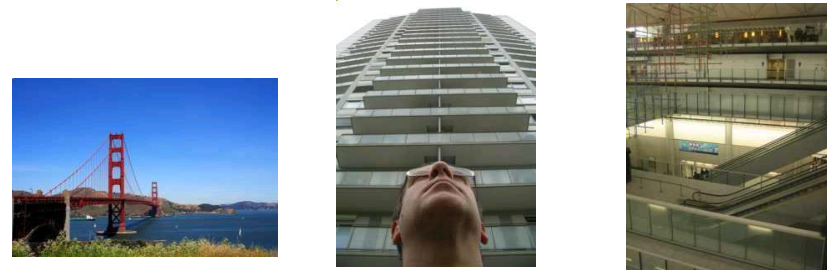
Query

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

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

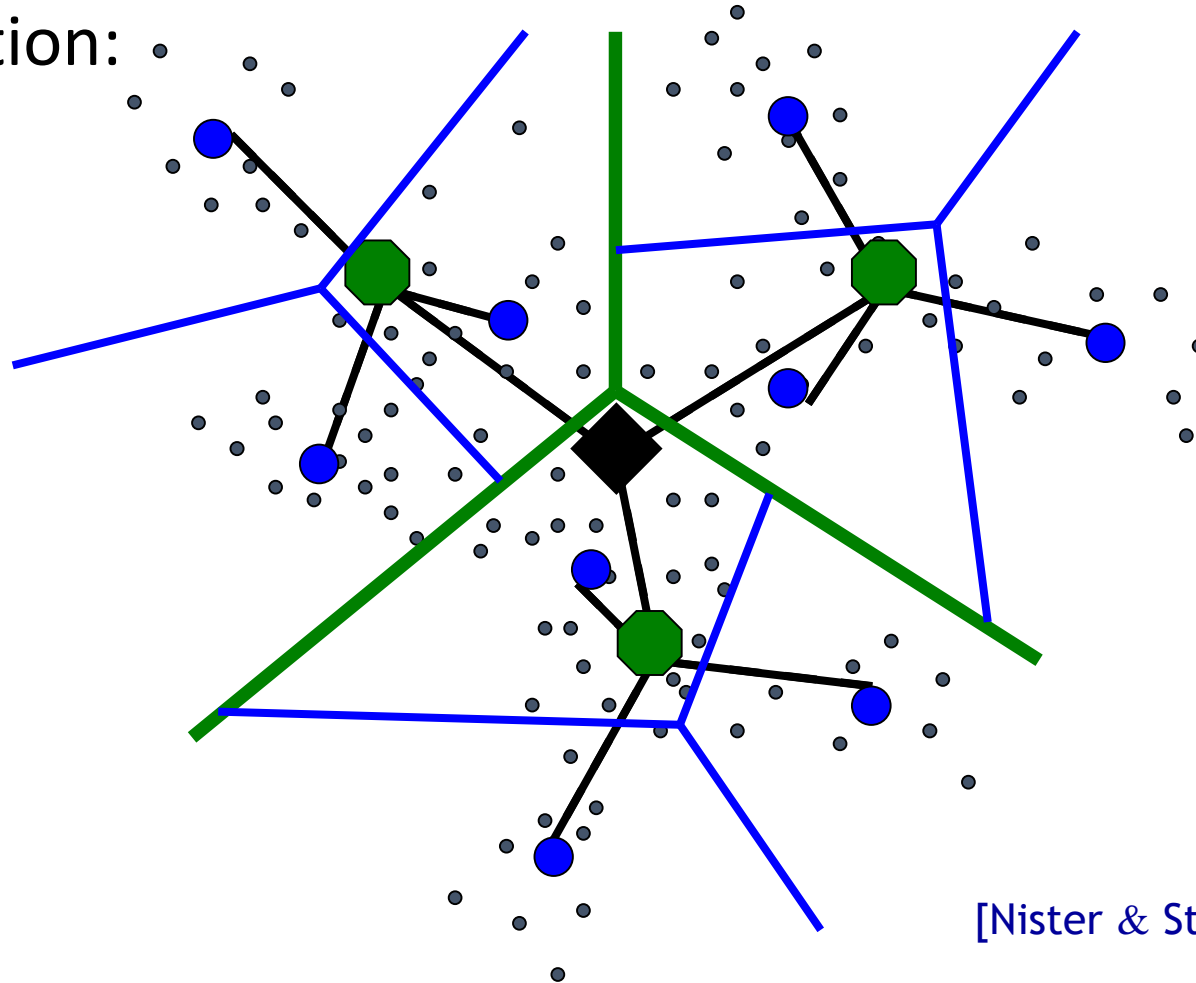


Results (ordered):



Vocabulary Trees: hierarchical clustering for large vocabularies

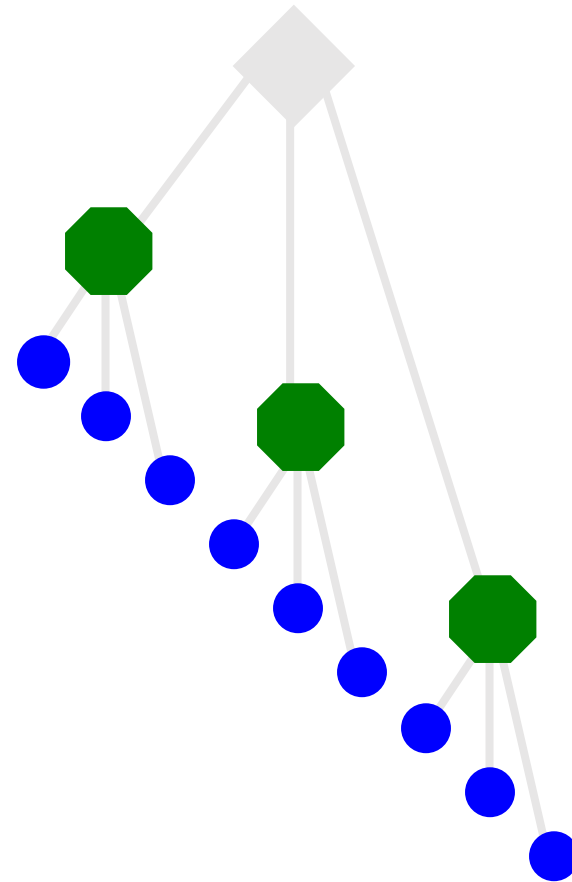
- Tree construction:



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

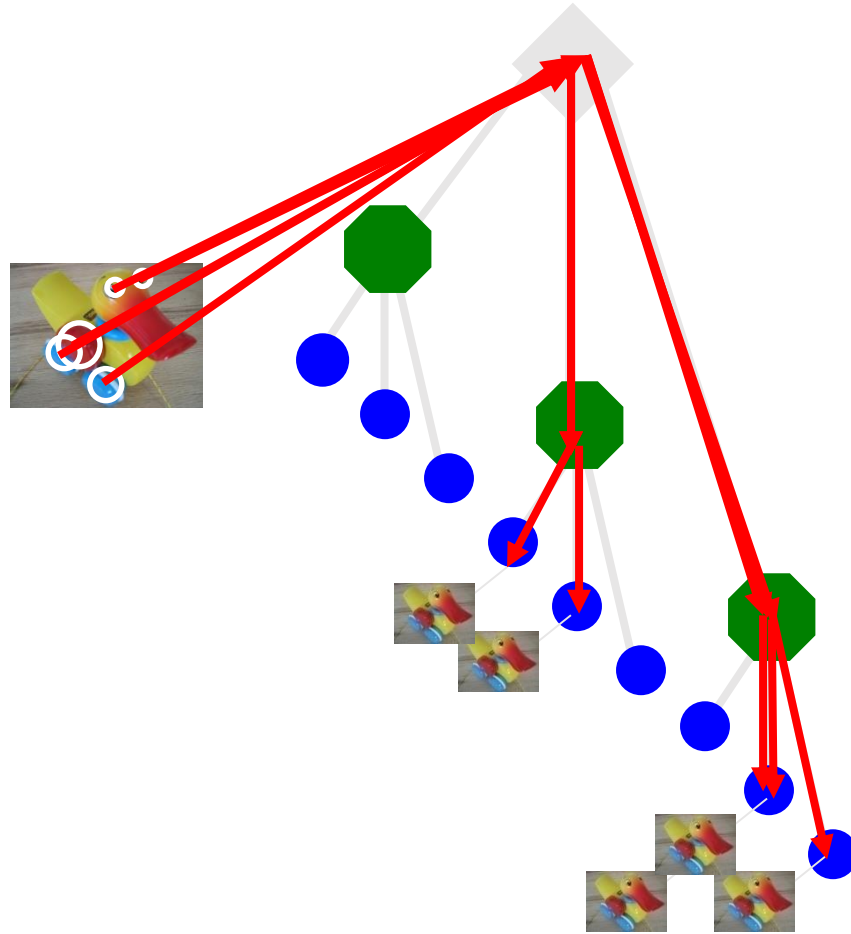
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

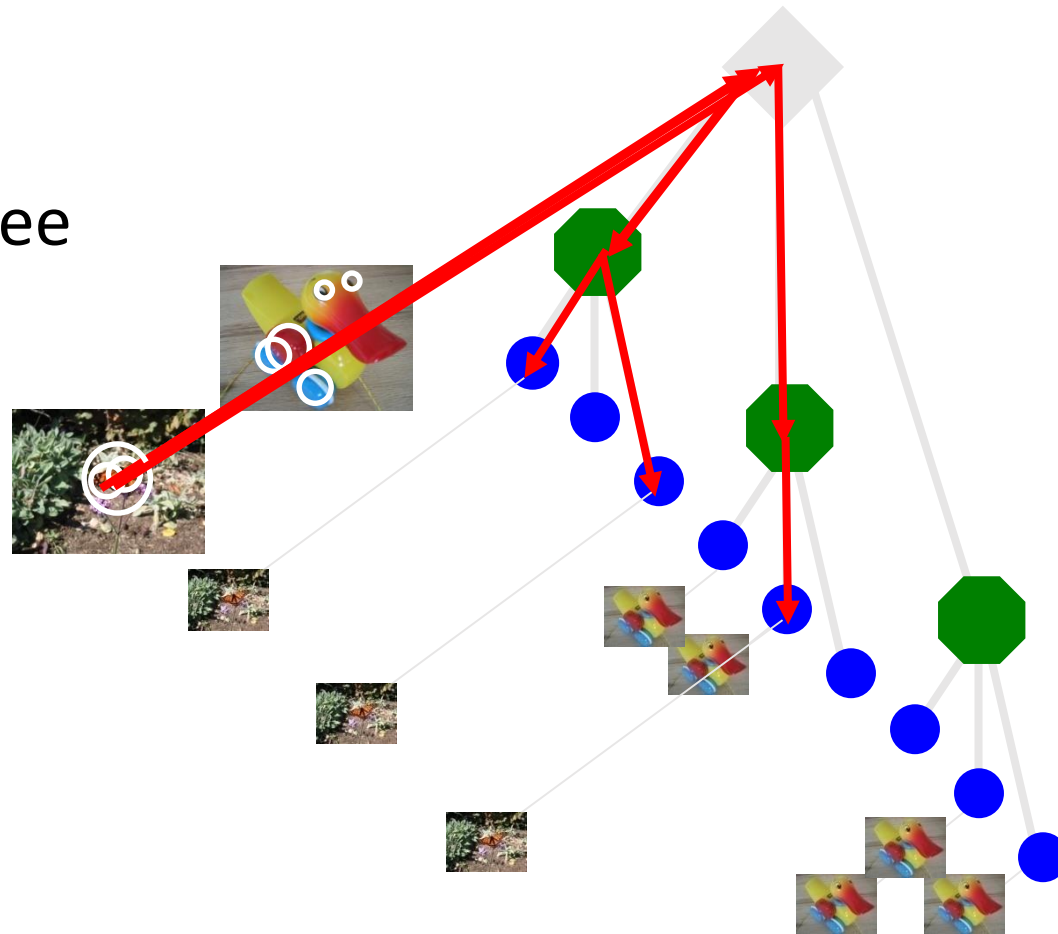
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

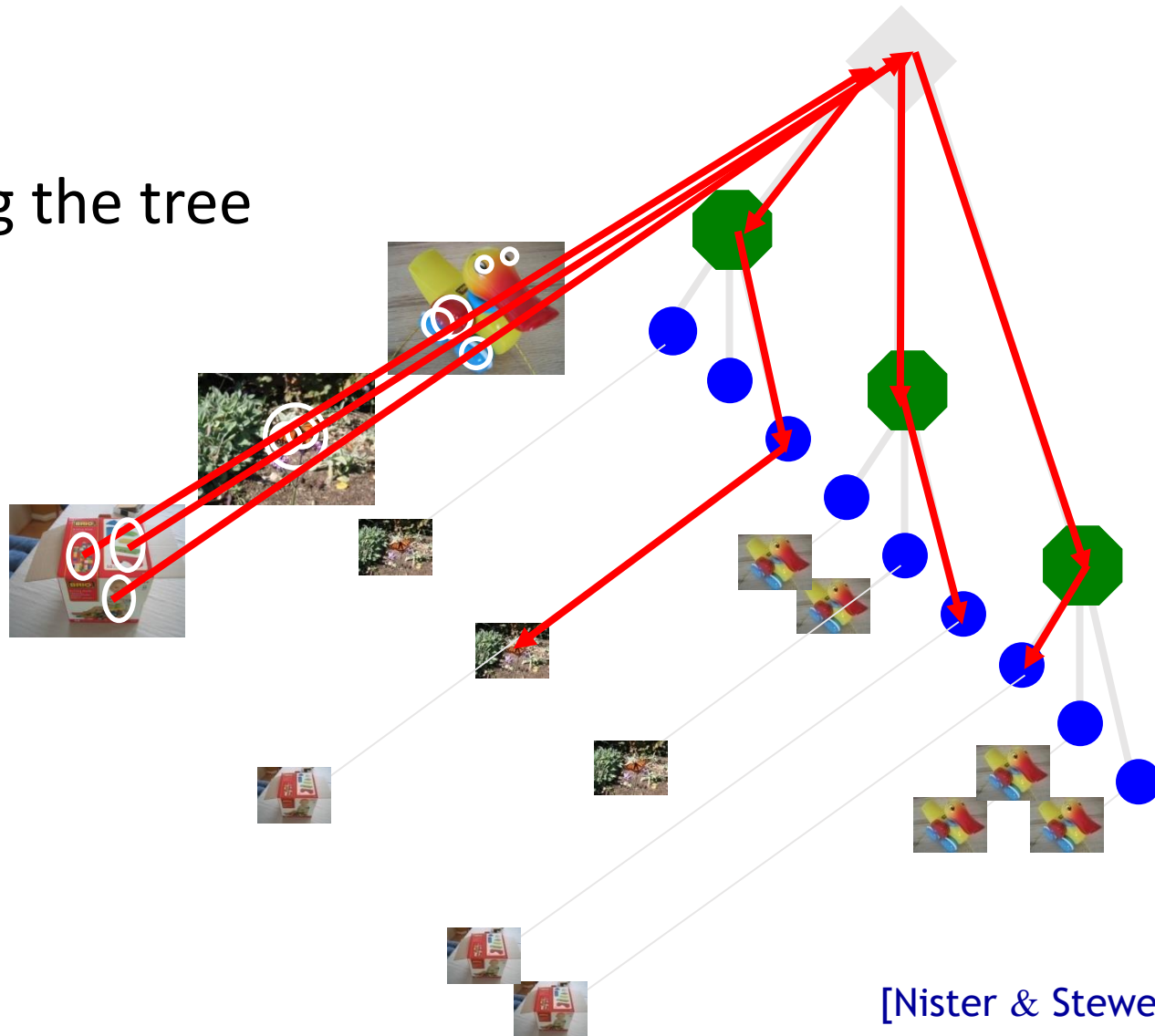
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

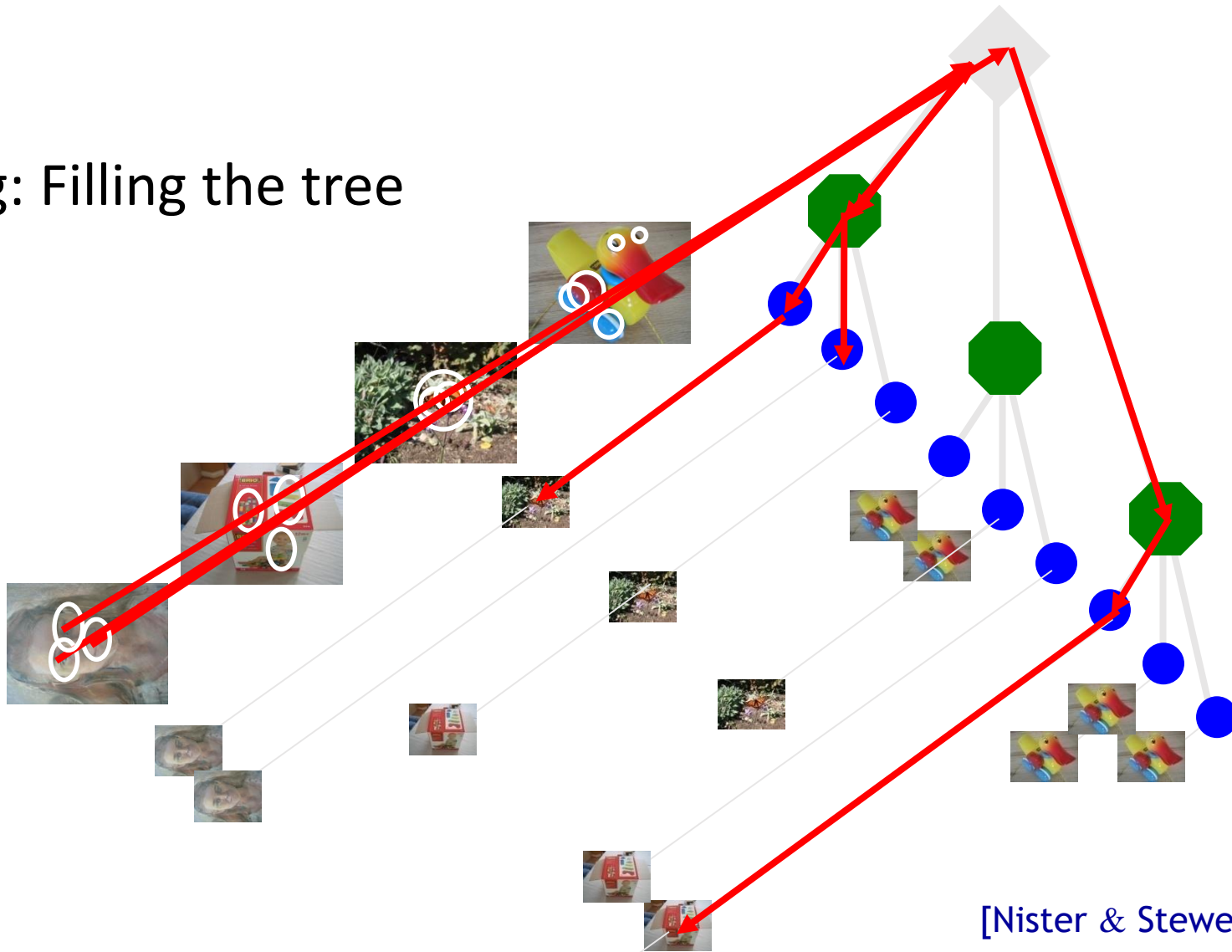
- Training: Filling the tree



[Nister & Stewenius, CVPR'06]

Vocabulary Tree

- Training: Filling the tree



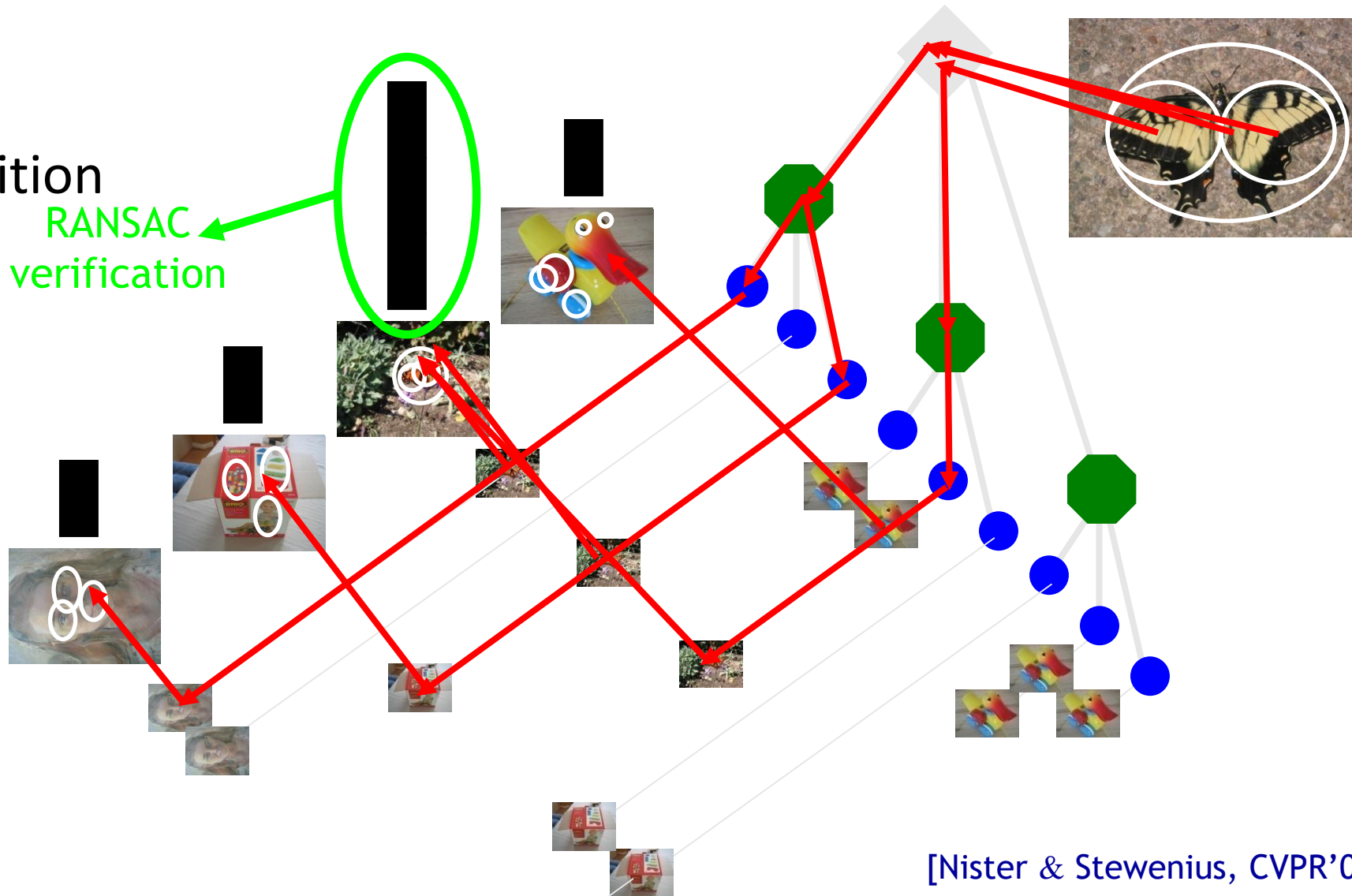
[Nister & Stewenius, CVPR'06]

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

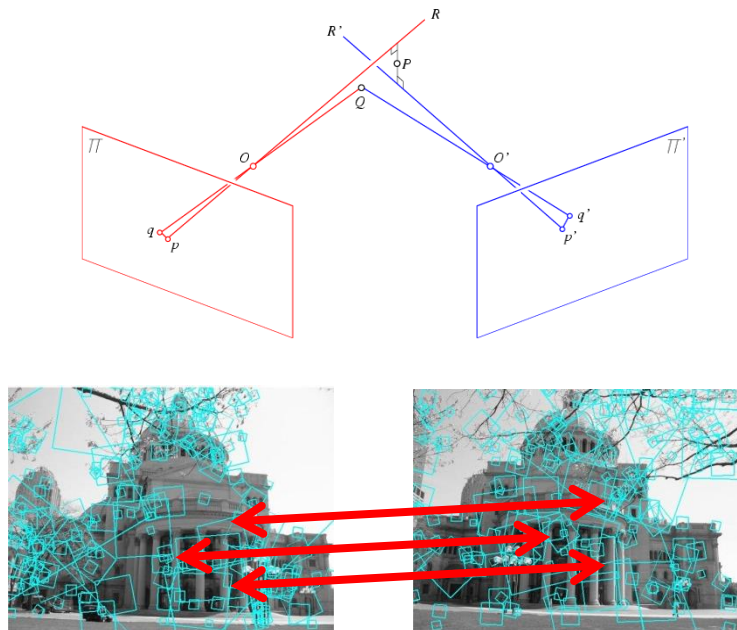
- + flexible to geometry / deformations / viewpoint
- + compact summary of image content
- + provides vector representation for sets
- + very good results in practice

- 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 So Far

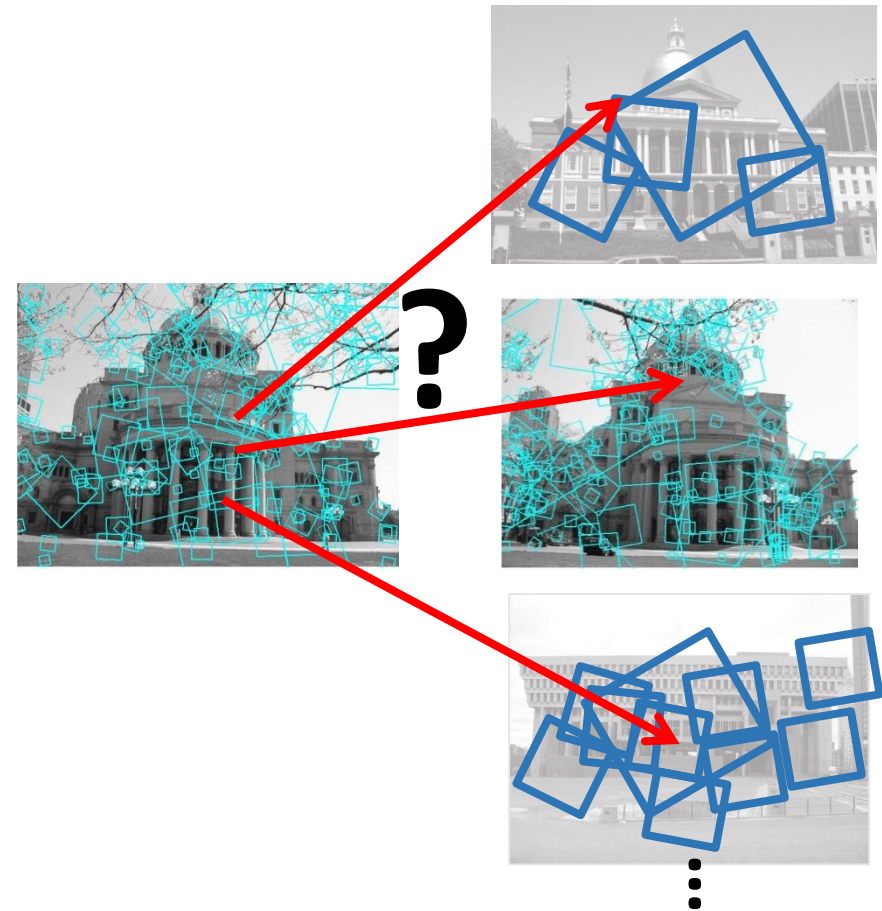
- **Matching local invariant features:** useful not only to provide matches for multi-view geometry, but also to find objects and scenes.
- **Bag of words** representation: quantize feature space to make discrete set of visual words
 - Summarize image by distribution of words
 - Index individual words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

Multi-view matching



Matching two given views for depth

VS



Search for a matching view for recognition

Instance recognition

- Motivation – visual search
- Visual words
 - quantization, index, bags of words
- Spatial verification
 - affine; RANSAC, Hough
- Other text retrieval tools
 - tf-idf, query expansion
- Example applications

Instance recognition: remaining issues

- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
- Is having the same set of visual words enough to identify the object/scene? How to verify spatial agreement?
- How to score the retrieval results?

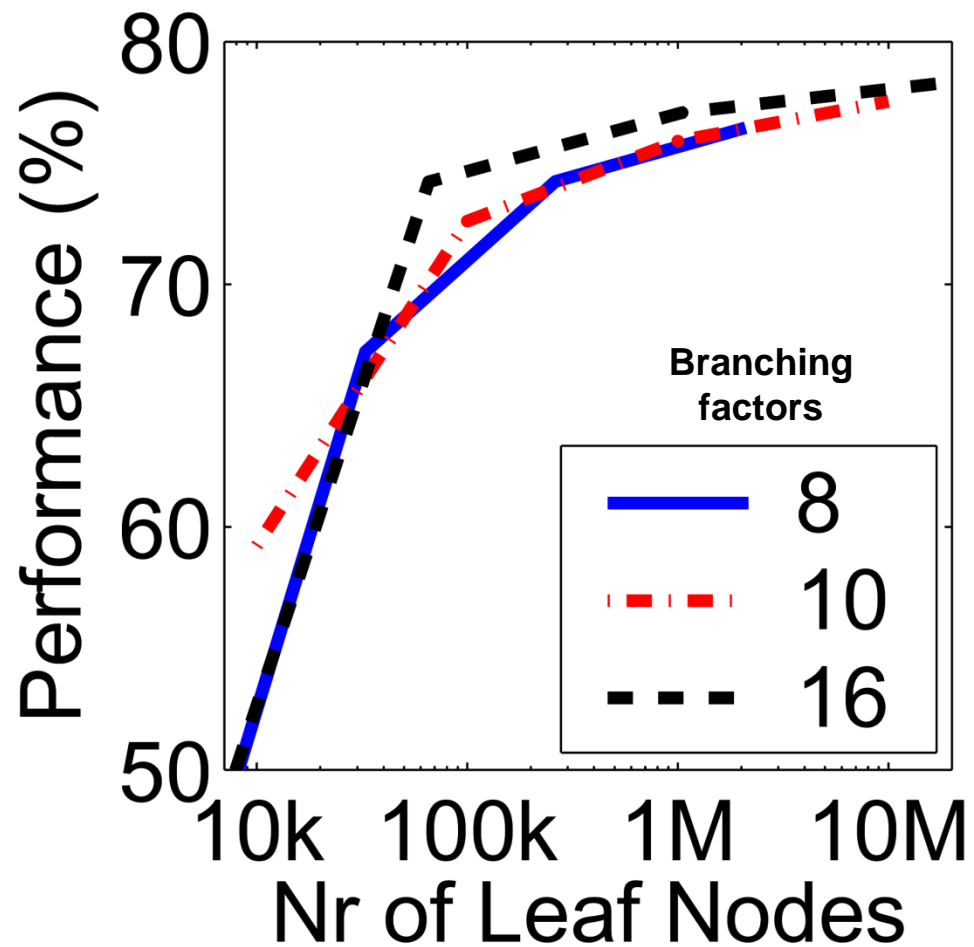
Instance recognition: remaining issues

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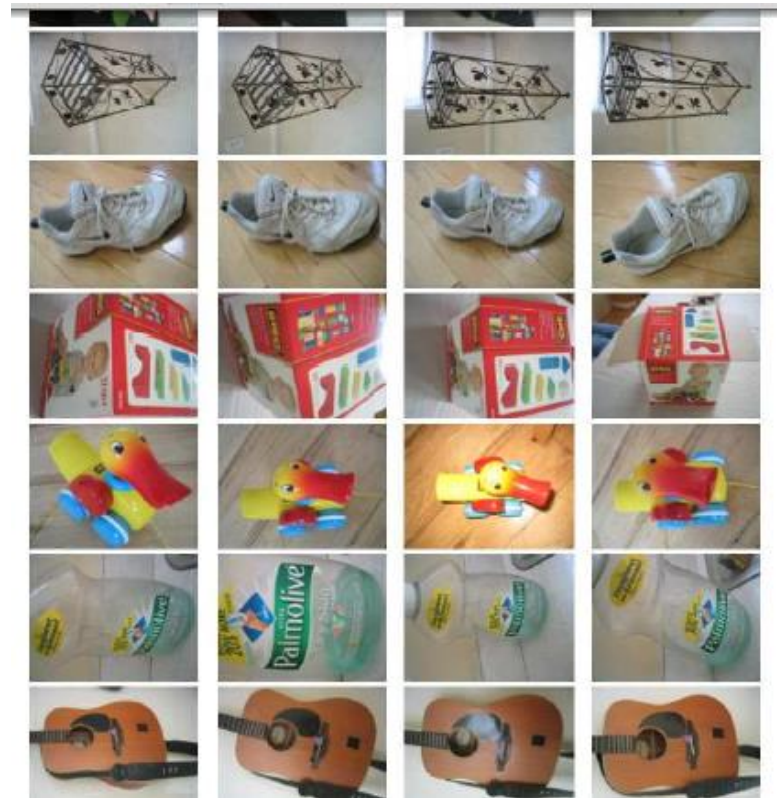
Instance recognition: remaining issues

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- How to score the retrieval results?

Vocabulary size



Results for recognition task with 6347 images

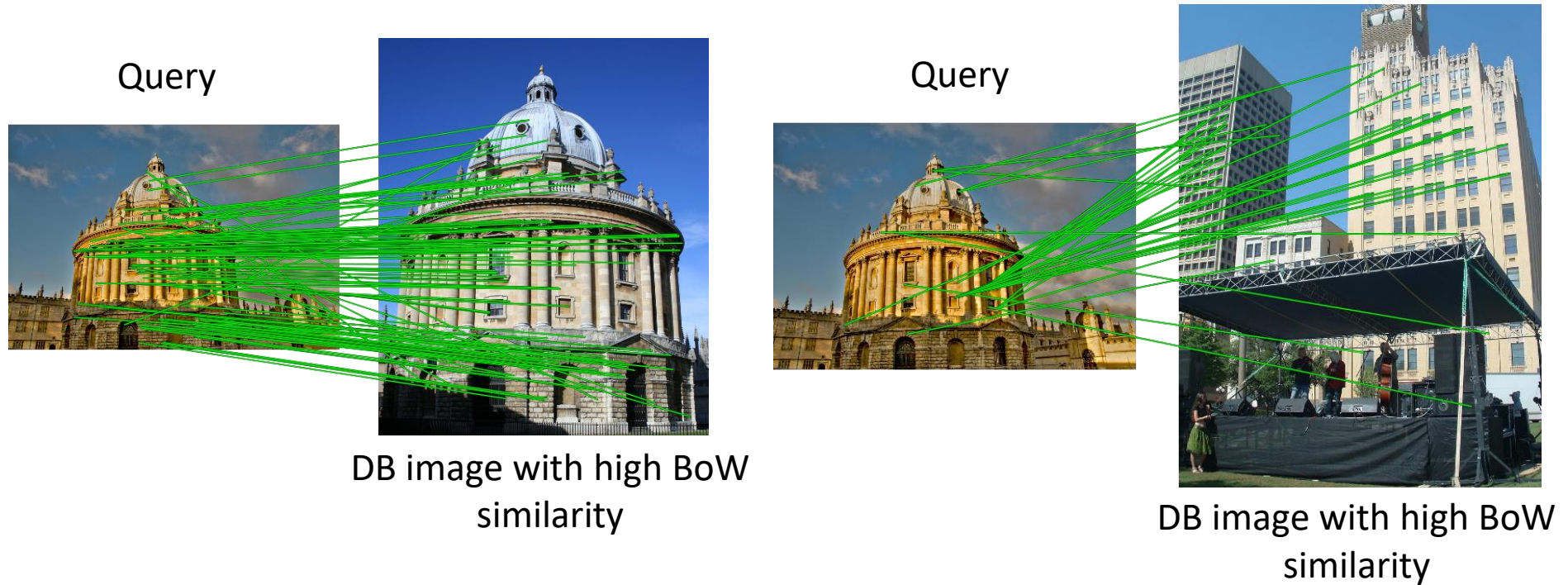


Influence on performance, sparsity

Instance recognition: remaining issues

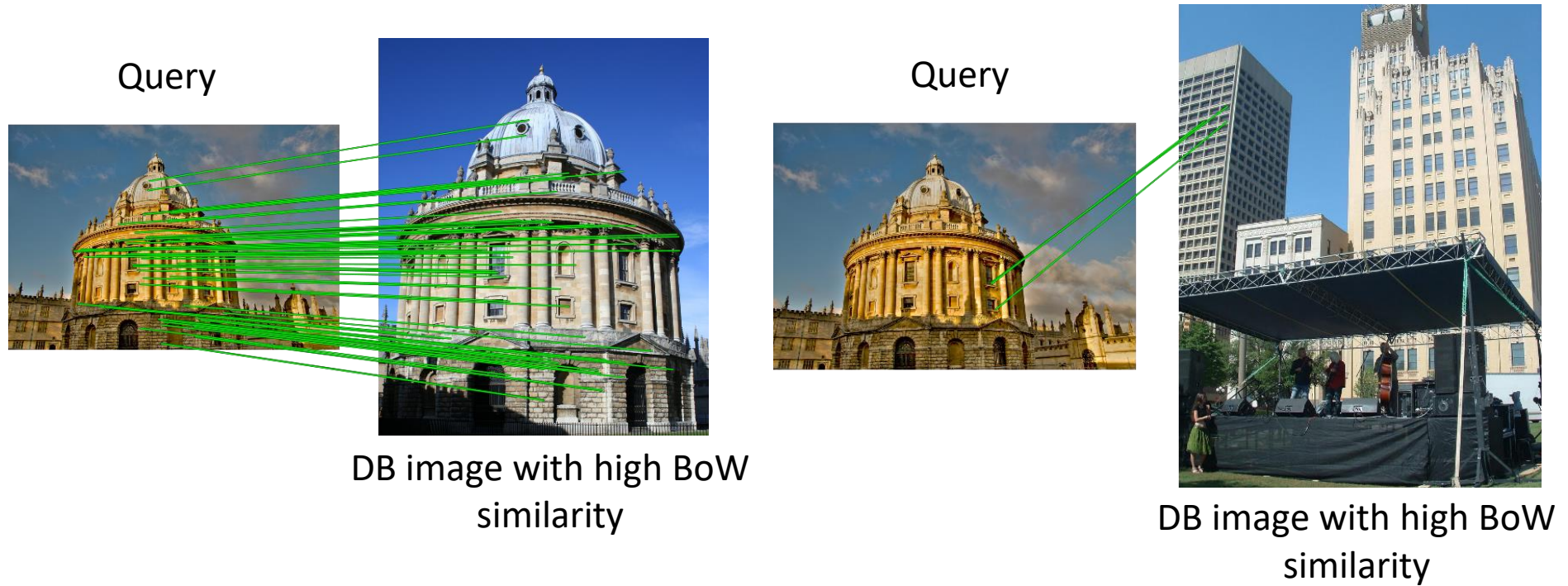
- How to summarize the content of an entire image? And gauge overall similarity?
- How large should the vocabulary be? How to perform quantization efficiently?
- Is having the same set of visual words enough to identify the object/scene? How to verify spatial agreement?
- How to score the retrieval results?

Spatial Verification



Both image pairs have many visual words in common.

Spatial Verification



Only some of the matches are mutually consistent

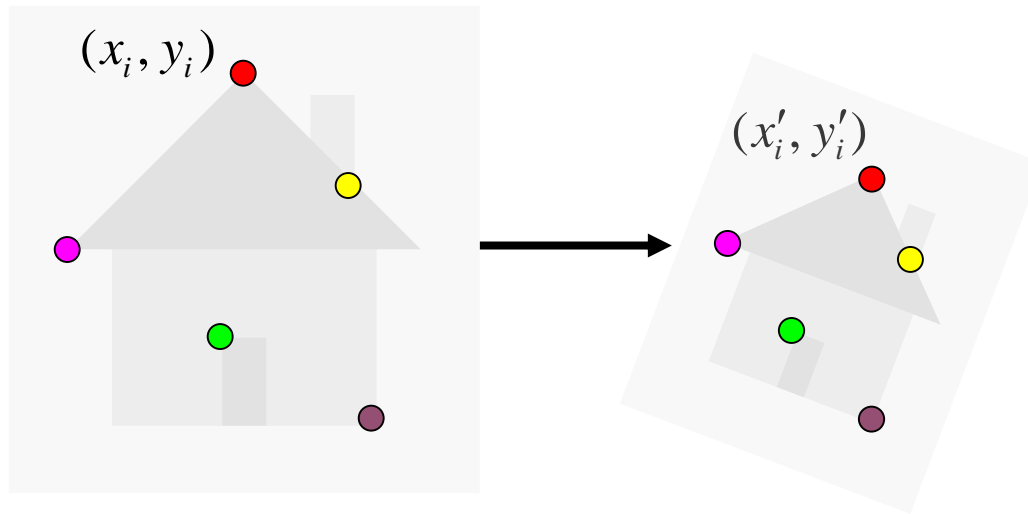
Spatial Verification: two basic strategies

- RANSAC
 - Typically sort by BoW similarity as initial filter
 - Verify by checking support (inliers) for possible transformations
 - e.g., “success” if find a transformation with $> N$ inlier correspondences
- Generalized Hough Transform
 - Let each matched feature cast a vote on location, scale, orientation of the model object
 - Verify parameters with enough votes

RANSAC verification



Recall: Fitting an affine transformation

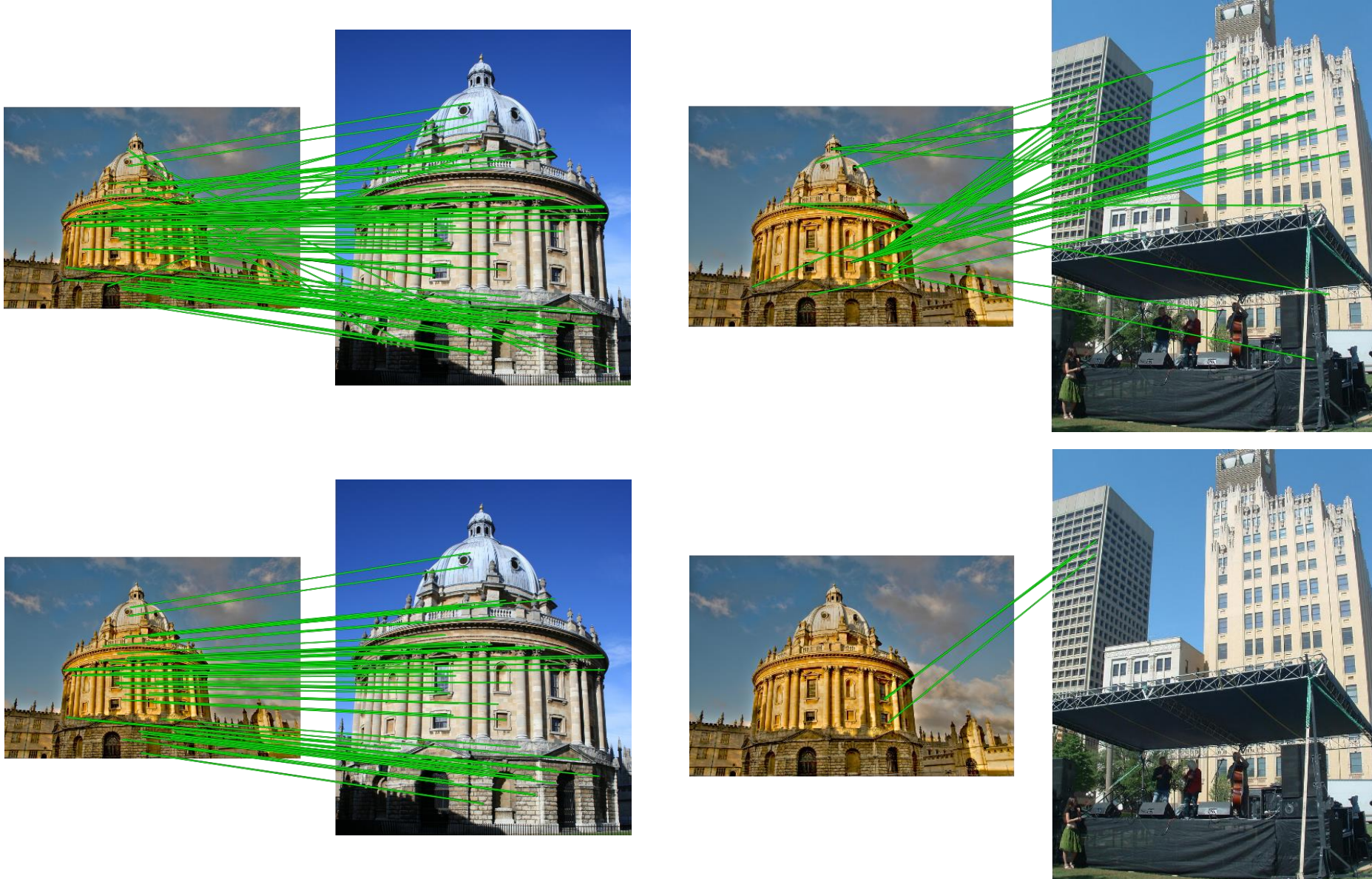


Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras.

$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} x_i & y_i & \dots & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \dots \\ x'_i \\ y'_i \\ \dots \end{bmatrix}$$

RANSAC verification



Video Google System

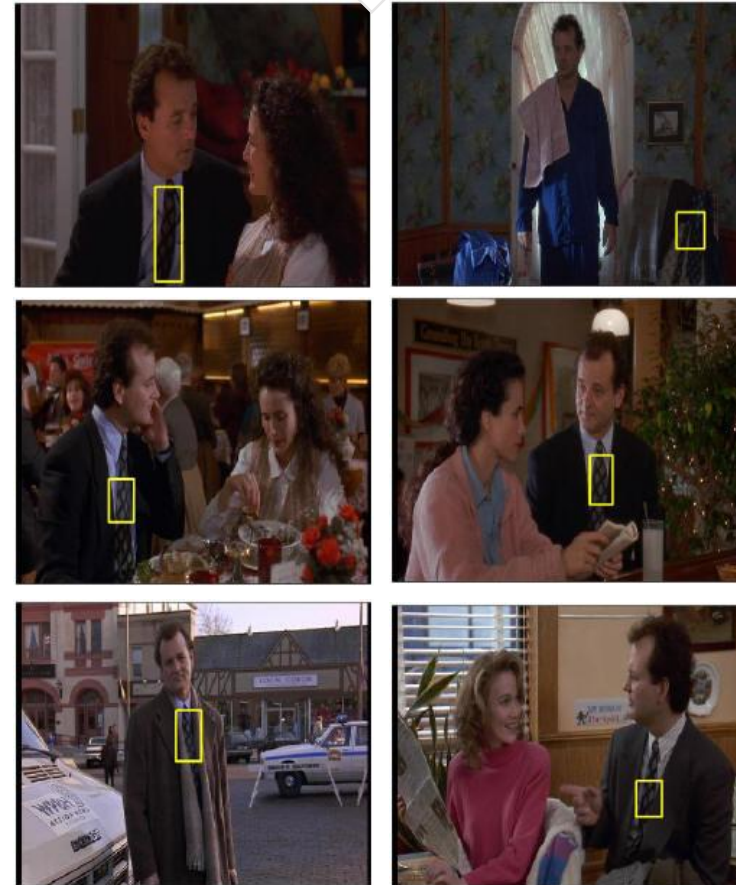
1. Collect all words within query region
2. Inverted file index to find relevant frames
3. Compare word counts
4. Spatial verification

Sivic & Zisserman, ICCV 2003

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



Query region



Retrieved frames

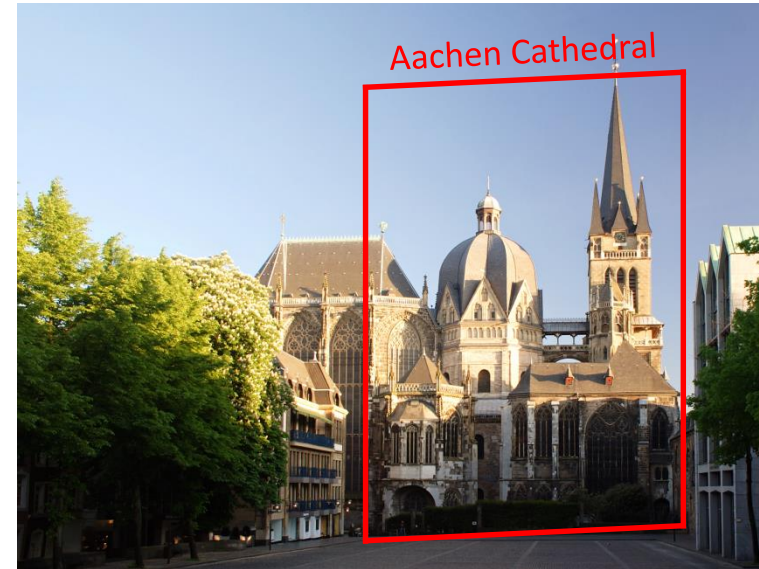
Kristen Grauman

Example Applications

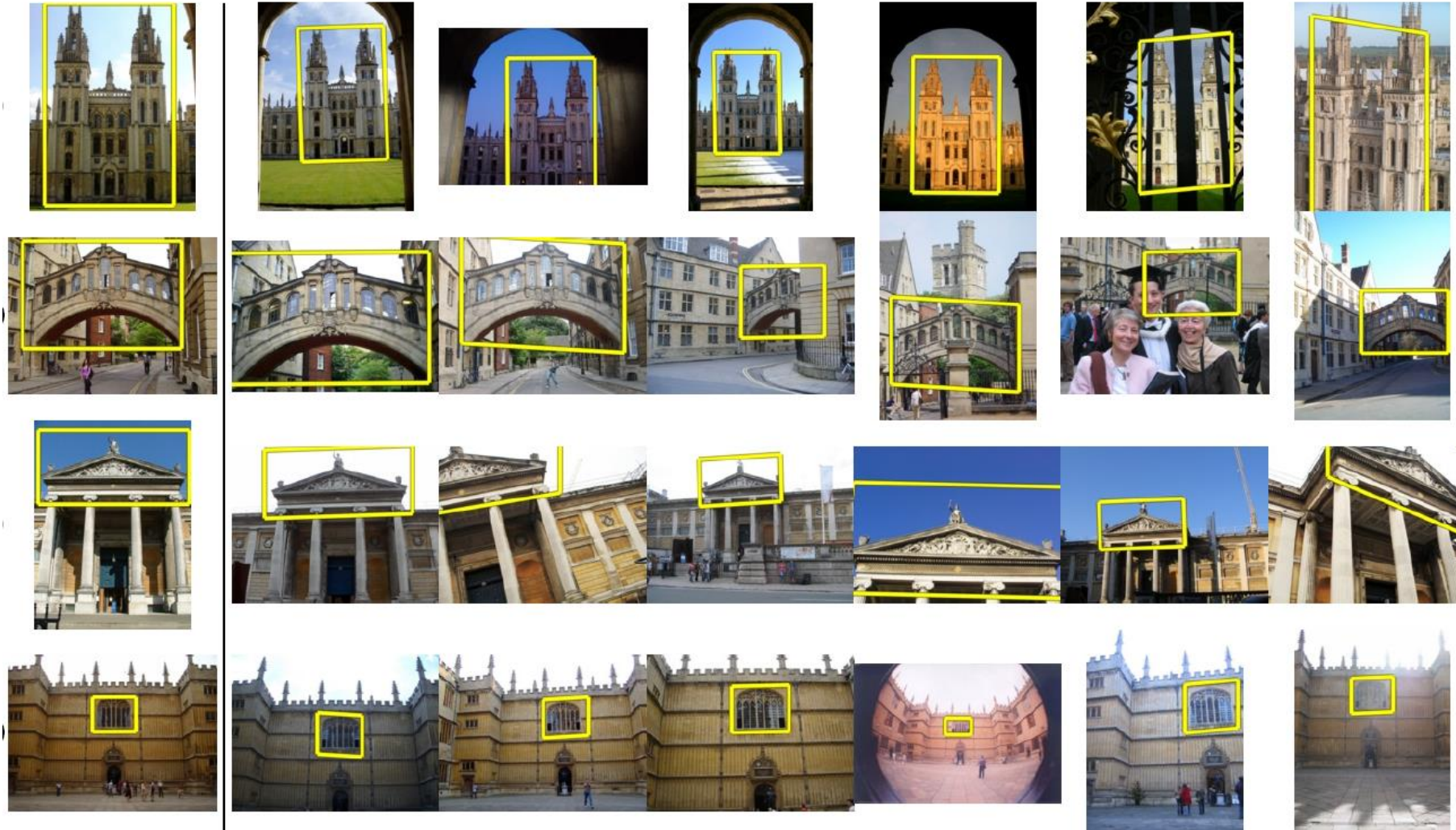


Mobile tourist guide

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



Application: Large-Scale Retrieval



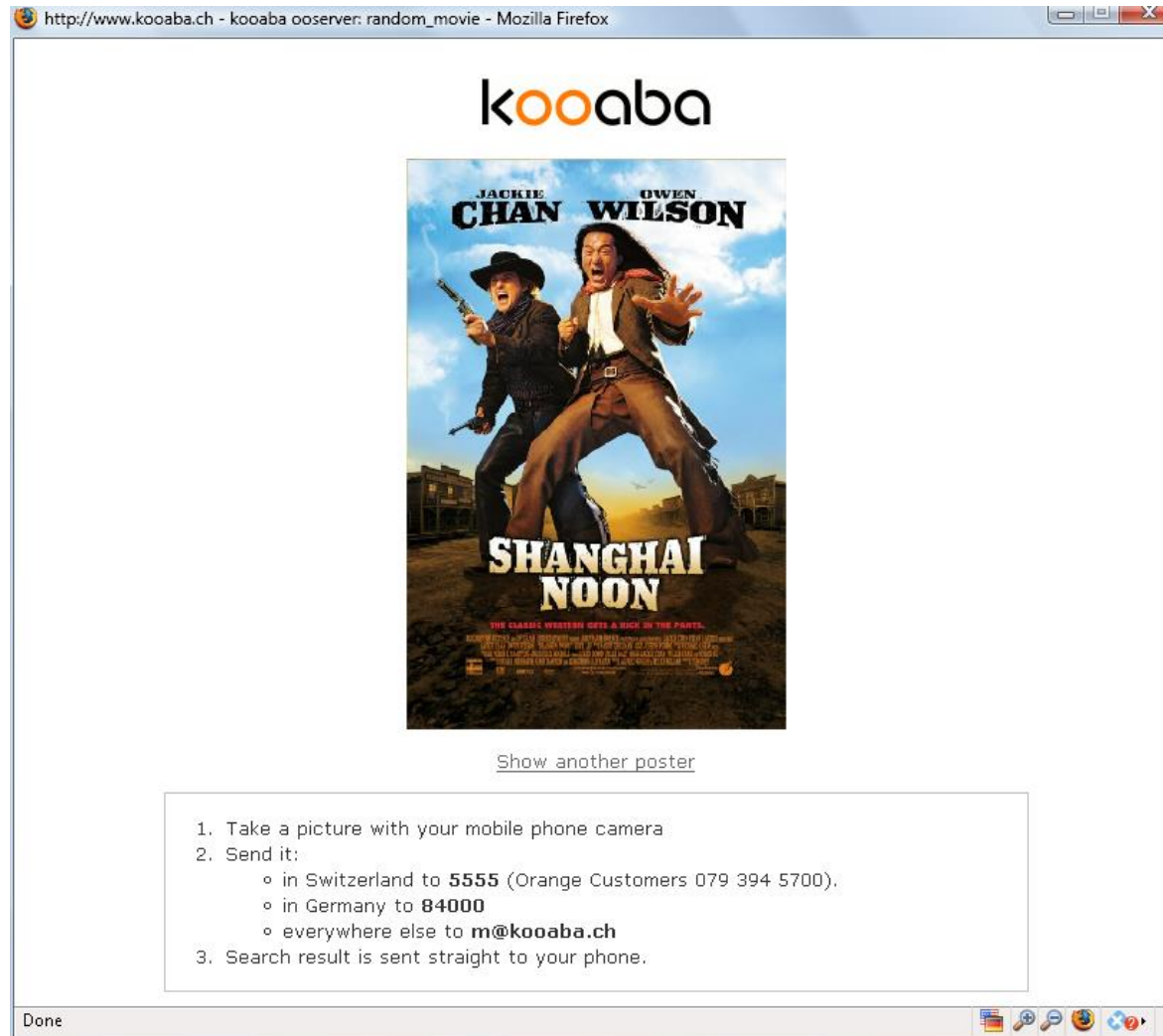
Query

Results from 5k Flickr images (demo available for 100k set)

Web Demo: Movie Poster Recognition

50'000 movie posters indexed

Query-by-image from mobile phone available in Switzerland



The screenshot shows a web browser window with the address bar displaying "http://www.kooaba.ch - kooaba ooserver: random_movie - Mozilla Firefox". The main content area features the "kooaba" logo at the top, followed by a movie poster for "Shanghai Noon" starring Jackie Chan and Owen Wilson. Below the poster is a link that says "Show another poster". At the bottom of the page, there is a box containing the following instructions:

1. Take a picture with your mobile phone camera
2. Send it:
 - in Switzerland to **5555** (Orange Customers 079 394 5700).
 - in Germany to **84000**
 - everywhere else to **m@kooaba.ch**
3. Search result is sent straight to your phone.

The browser's status bar at the bottom shows "Done" and various system icons.

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



Google Goggles

Use pictures to search the web. [▶ Watch a video](#)



Get Google Goggles

Android (1.6+ required)

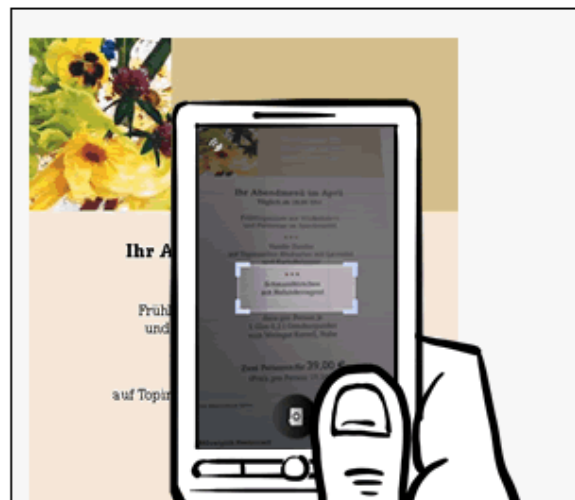
Download from [Android Market](#).

[Send Goggles to Android phone](#)

New! iPhone (iOS 4.0 required)

Download [from the App Store](#).

[Send Goggles to iPhone](#)

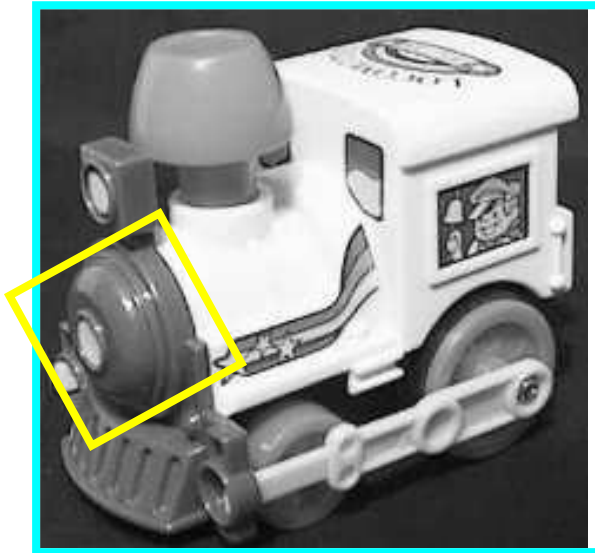


Spatial Verification: two basic strategies

- RANSAC
 - Typically sort by BoW similarity as initial filter
 - Verify by checking support (inliers) for possible transformations
 - e.g., “success” if find a transformation with $> N$ inlier correspondences
- Generalized Hough Transform
 - Let each matched feature cast a vote on location, scale, orientation of the model object
 - Verify parameters with enough votes

Voting: Generalized Hough Transform

- If we use scale, rotation, and translation invariant local features, then each feature match gives an alignment hypothesis (for scale, translation, and orientation of model in image).



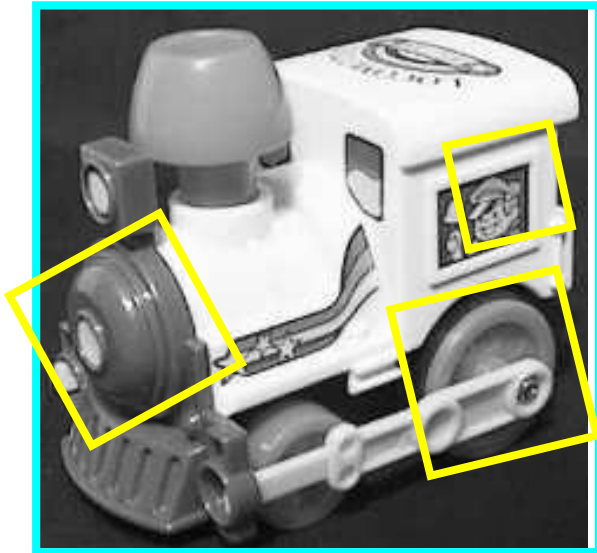
Model



Novel image

Voting: Generalized Hough Transform

- A hypothesis generated by a single match may be unreliable,
- So let each match **vote** for a hypothesis in Hough space



Model



Novel image

Gen Hough Transform details (Lowe's system)

- **Training phase:** For each model feature, record 2D location, scale, and orientation of model (relative to normalized feature frame)
- **Test phase:** Let each match btwn a test SIFT feature and a model feature vote in a 4D Hough space
 - Use broad bin sizes of 30 degrees for orientation, a factor of 2 for scale, and 0.25 times image size for location
 - Vote for two closest bins in each dimension
- Find all bins with at least three votes and perform geometric verification
 - Estimate least squares *affine* transformation
 - Search for additional features that agree with the alignment

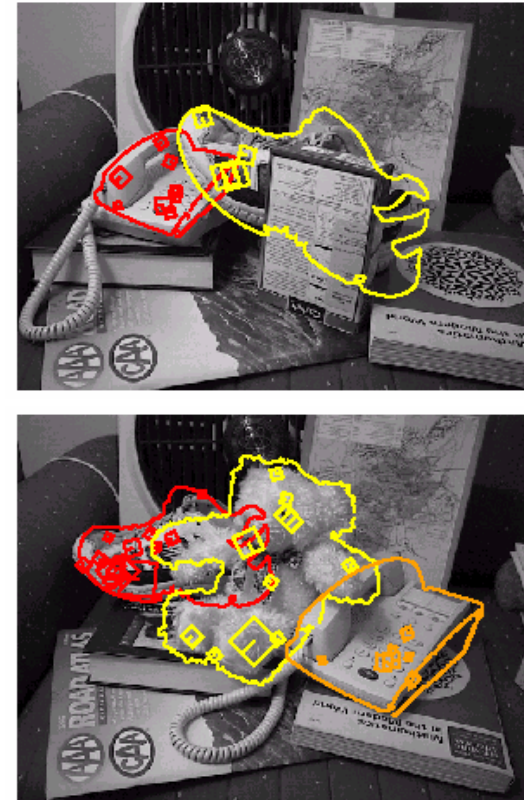
Example result



Background subtract for
model boundaries



Objects recognized,



Recognition in spite
of occlusion

Recall: difficulties of voting

- Noise/clutter can lead to as many votes as true target
- Bin size for the accumulator array must be chosen carefully
- In practice, good idea to make broad bins and spread votes to nearby bins, since verification stage can prune bad vote peaks.

Gen Hough vs RANSAC

GHT

- Single correspondence -> vote for all consistent parameters
- Represents uncertainty in the model parameter space
- Linear complexity in number of correspondences and number of voting cells; beyond 4D vote space impractical
- Can handle high outlier ratio

RANSAC

- Minimal subset of correspondences to estimate model -> count inliers
- Represents uncertainty in image space
- Must search all data points to check for inliers each iteration
- Scales better to high-d parameter spaces

What else can we borrow from text retrieval?

Index

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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 predicted 30% jump in exports with a 18% rise in imports. The ministry said further a 18% rise in exports. China's deliberate policy to the surplus is one factor. Xiaochua more to be stayed within the value of the yuan. July and permitted it to trade freely. However, Beijing has made that it will take its time and tread carefully allowing the yuan to rise further in value.

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

tf-idf weighting

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

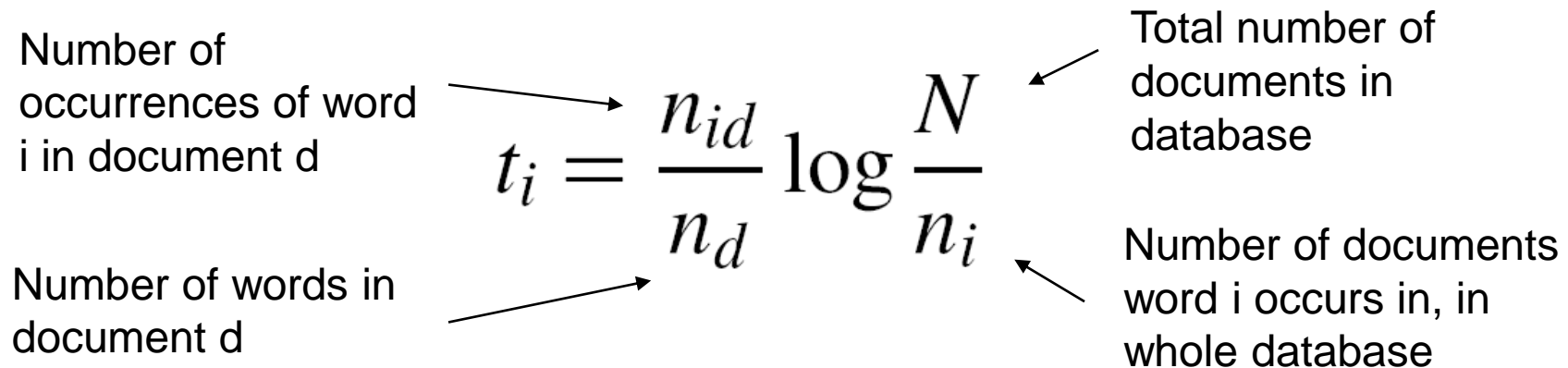
Number of occurrences of word i in document d

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

The diagram illustrates the components of the tf-idf formula. On the left, two lines of text describe the variables: 'Number of occurrences of word i in document d' and 'Number of words in document d'. Arrows from these lines point to the numerator n_{id} and denominator n_d of the fraction in the formula, respectively. On the right, two more lines of text describe the variables: 'Total number of documents in database' and 'Number of documents word i occurs in, in whole database'. Arrows from these lines point to the N and n_i in the logarithmic term of the formula, respectively.

Query expansion

Query: *golf green*

Results:

- How can the grass on the *greens* at a *golf* course be so perfect?
- For example, a skilled *golfer* expects to reach the *green* on a par-four hole in ...
- Manufactures and sells synthetic *golf* putting *greens* and mats.

Irrelevant result can cause a `topic drift`:

- Volkswagen **Golf**, 1999, **Green**, 2000cc, petrol, manual, , hatchback, 94000miles, 2.0 GTi, 2 Registered Keepers, HPI Checked, Air-Conditioning, Front and Rear Parking Sensors, ABS, Alarm, Alloy

Query Expansion



Chum, Philbin, Sivic, Isard, Zisserman: Total Recall..., ICCV 2007

Slide credit: Ondrej Chum

Recognition via alignment

Pros:

- Effective when we are able to find reliable features within clutter
- Great results for matching specific instances

Cons:

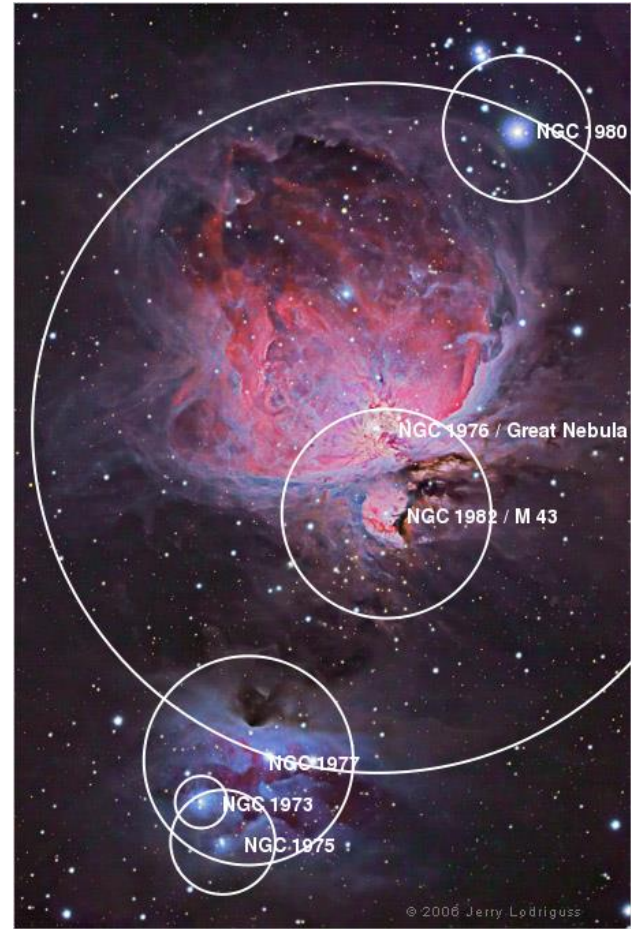
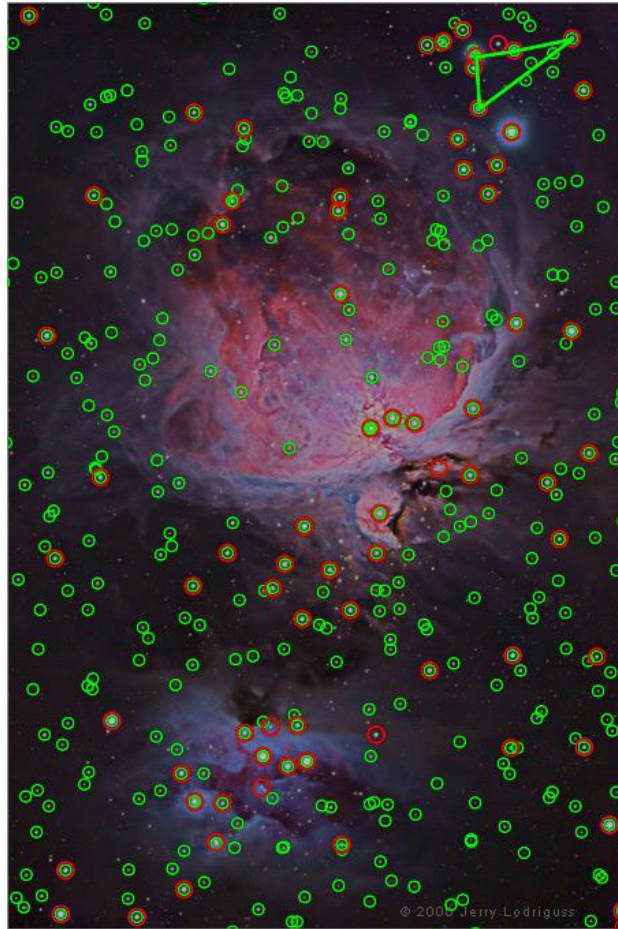
- Scaling with number of models
- Spatial verification as post-processing – not seamless, expensive for large-scale problems
- Not suited for category recognition.

Making the Sky Searchable: Fast Geometric Hashing for Automated Astrometry

Sam Roweis, Dustin Lang & Keir Mierle
University of Toronto

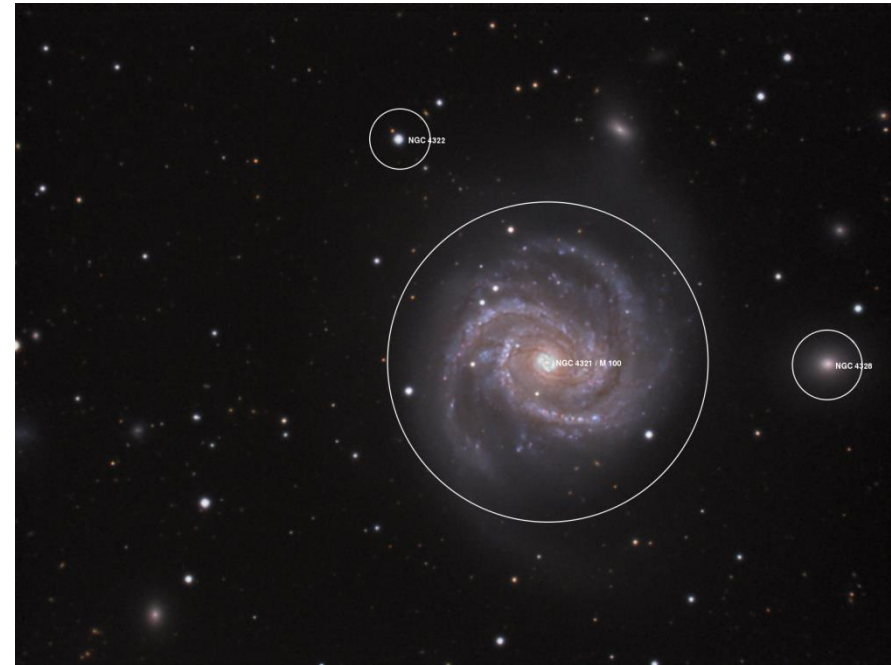
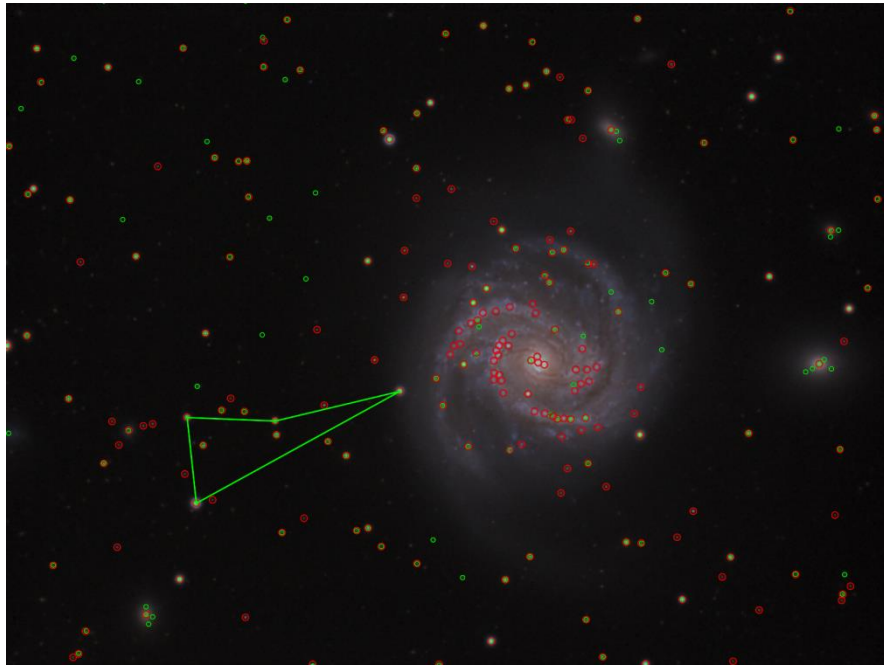
David Hogg & Michael Blanton
New York University

Example



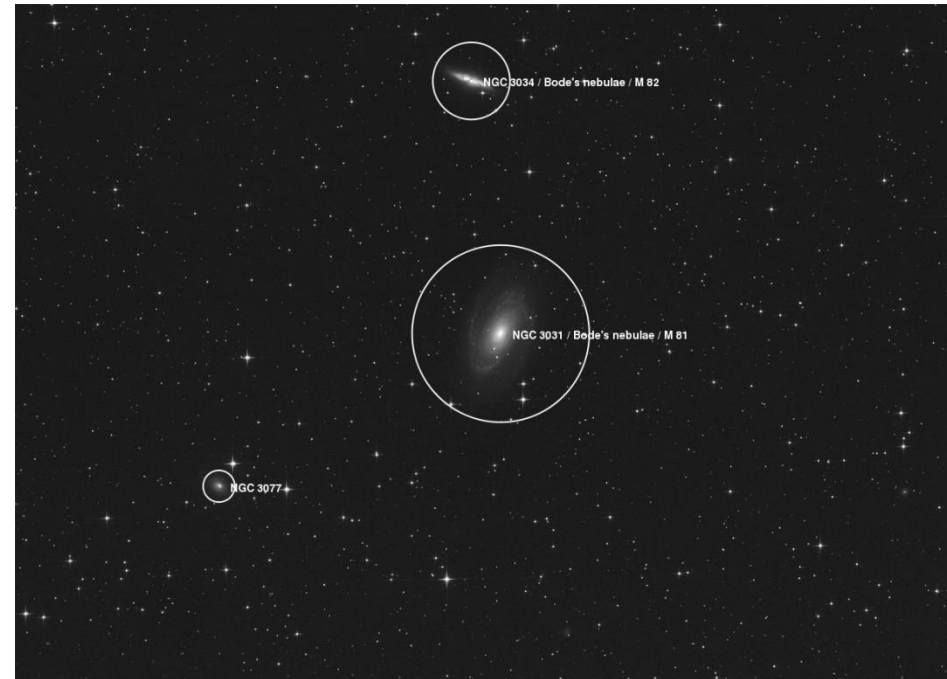
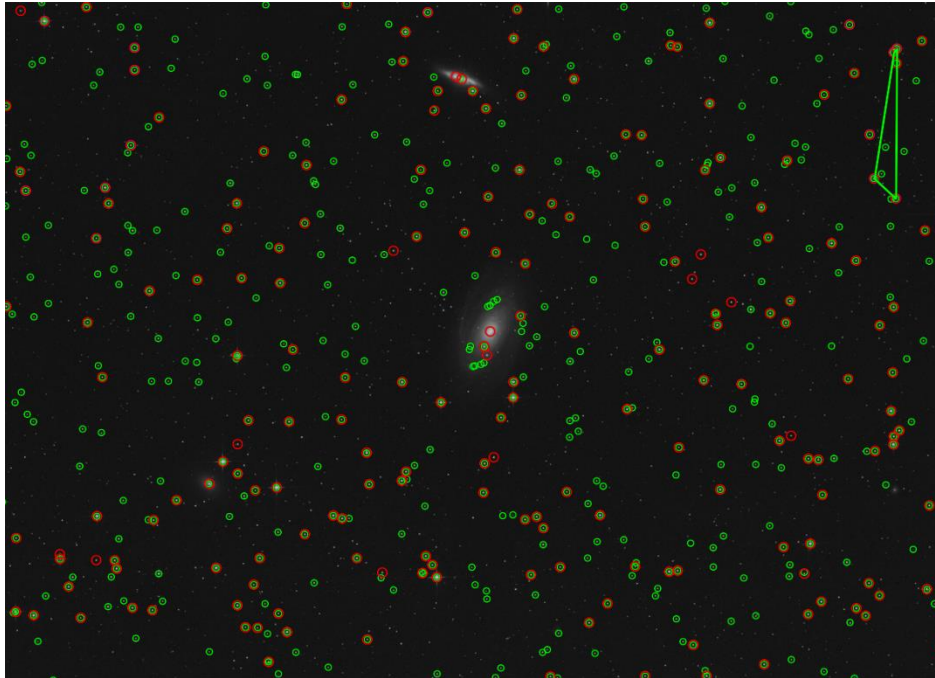
A shot of the Great Nebula, by Jerry Lodriguss (c.2006), from astropix.com
<http://astrometry.net/gallery.html>

Example



An amateur shot of M100, by Filippo Ciferri (c.2007) from flickr.com
<http://astrometry.net/gallery.html>

Example



A beautiful image of Bode's nebula (c.2007) by Peter Bressler, from starlightfriend.de
<http://astrometry.net/gallery.html>

Things to remember

- **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
- **Recognition of instances via alignment**: matching local features followed by spatial verification
 - Robust fitting : RANSAC, GHT