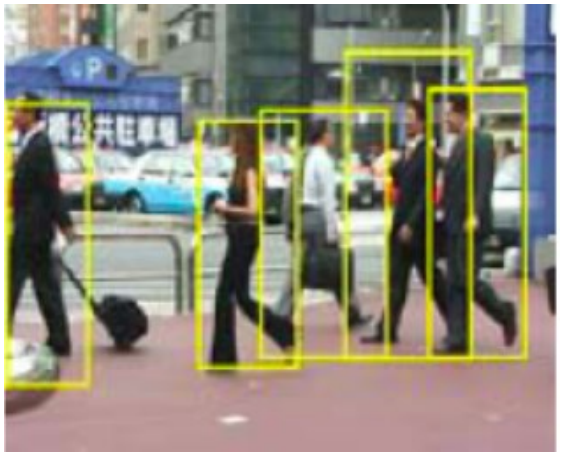
Advanced Computer Vision

Large-scale Instance Recognition

Category vs. instance recognition

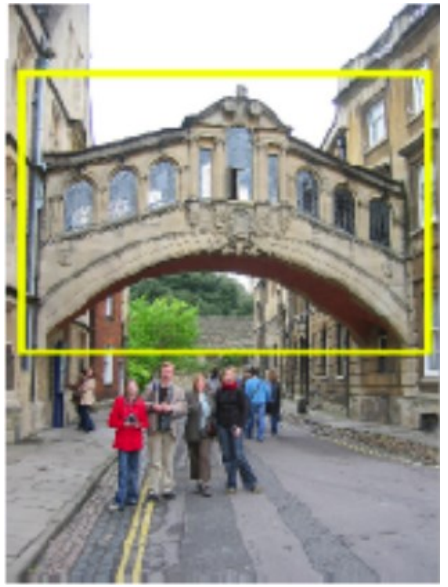
Category:

- Find all the people
- Find all the buildings
- Often within a single image
- Often ‘sliding window’

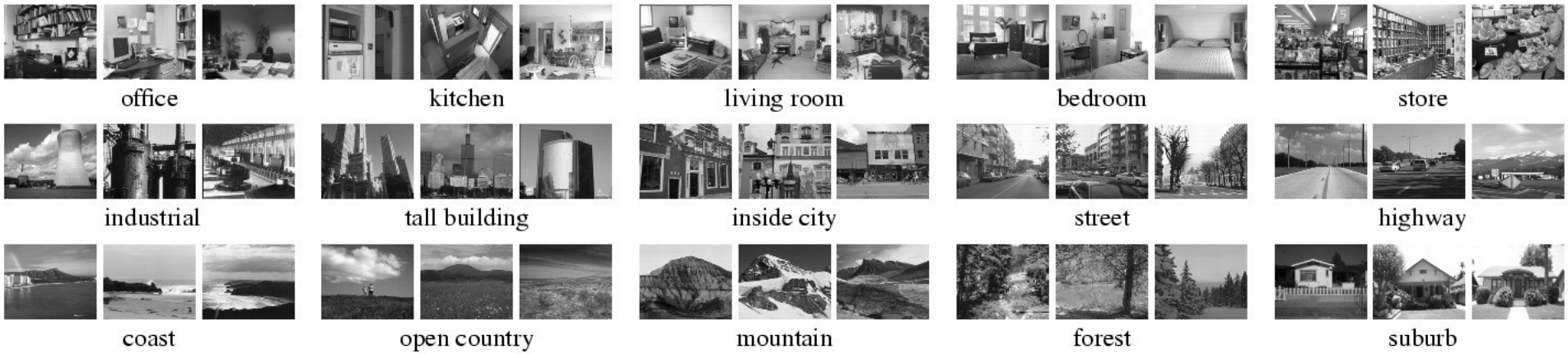


Instance:

- Is this face James?
- Find this specific famous building
- Often within a database of images

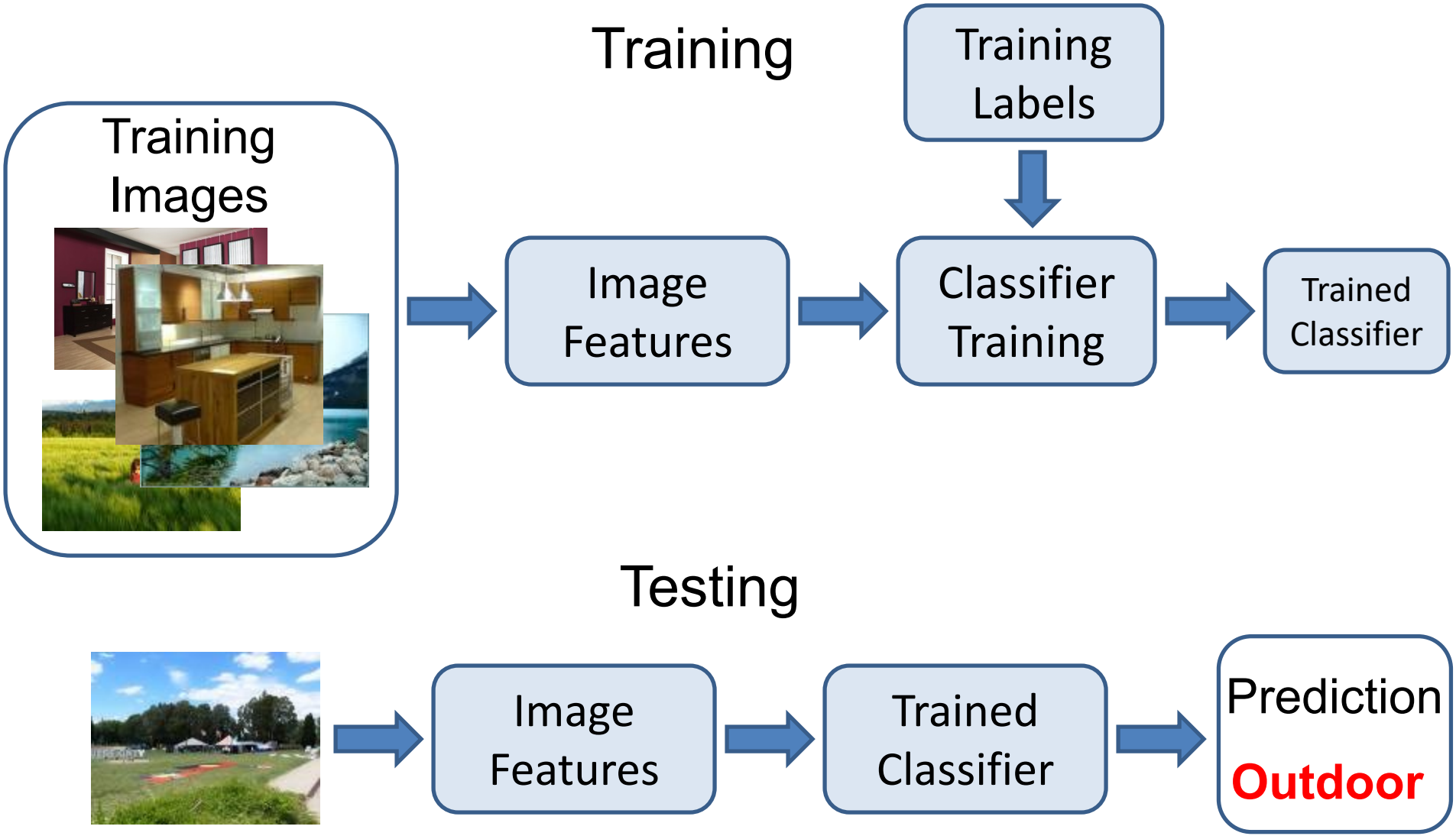


Scene recognition dataset



Instance or category?

Recognition



Recognition Issues

How to summarize the content of an entire image?
How to gauge overall similarity?

How large should the vocabulary be?
How to perform quantization efficiently?

How to score the retrieval results?

How might we add more spatial verification?

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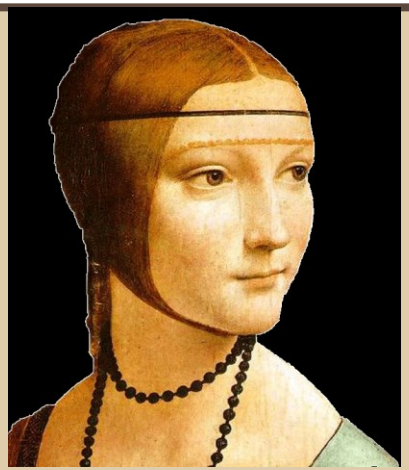
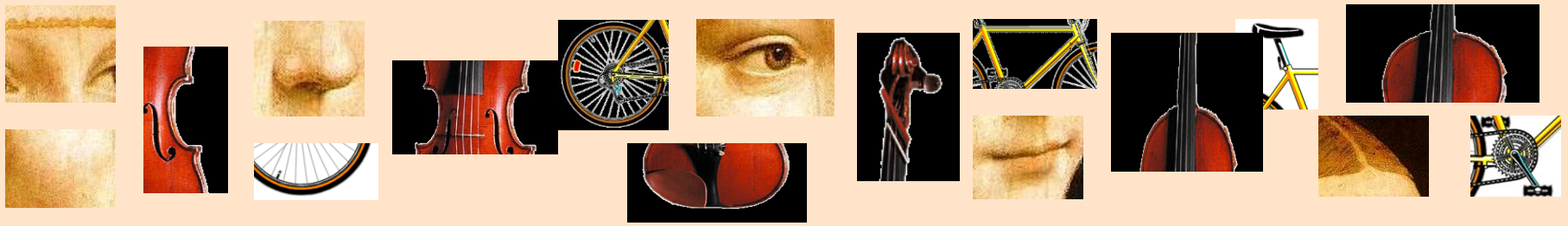
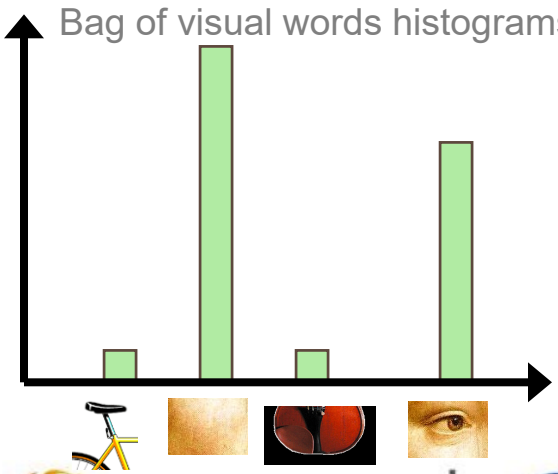
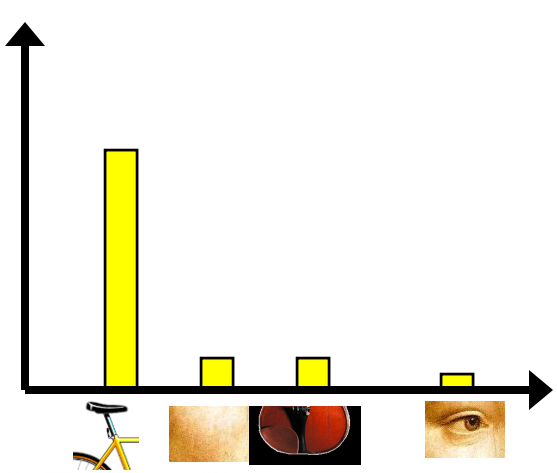


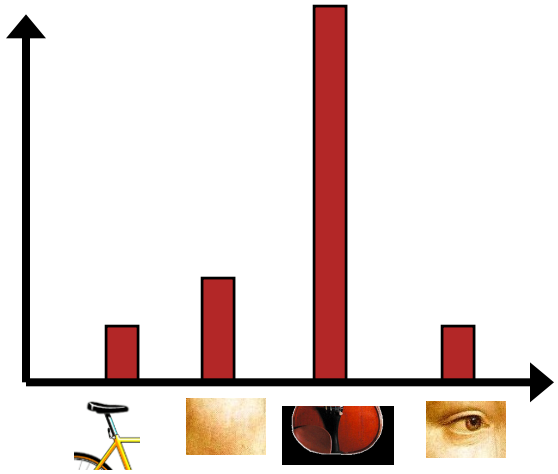
Visual words



Bag of visual words histograms





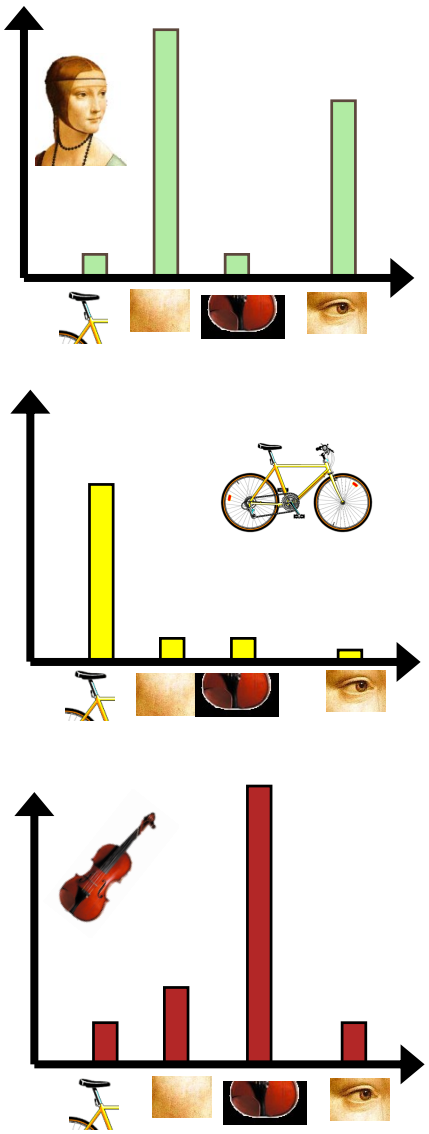


Bags of visual words

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

Visual words

Bag of visual words histograms

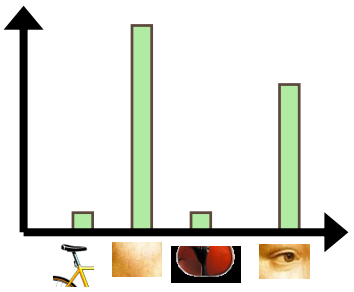


Comparing bags of words

Compute cosine similarity (normalized scalar (dot) product) between their occurrence counts, then rank and pick smallest. *Nearest neighbor* search for similar images.

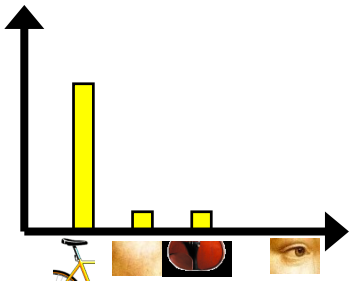
Database image

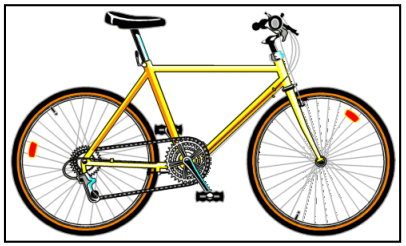
$\vec{d}_j = [1 \quad 8 \quad 1 \quad 4]$



Query

$\vec{q} = [5 \quad 1 \quad 1 \quad 0]$





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

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

for vocabulary of *V* words

Comparing bags of words

Why might we use cosine similarity here?

What 'intuitive' effect does this provide?

Database image

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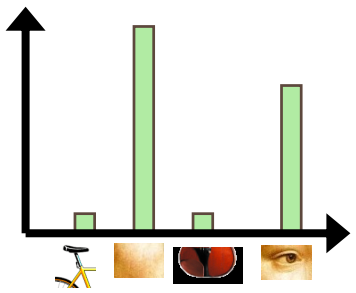

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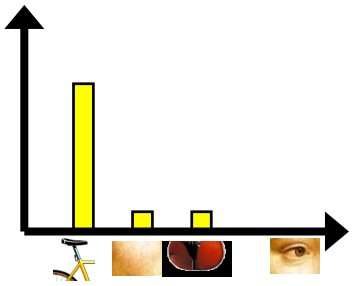

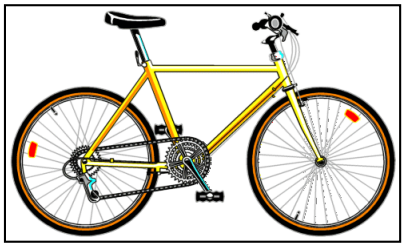

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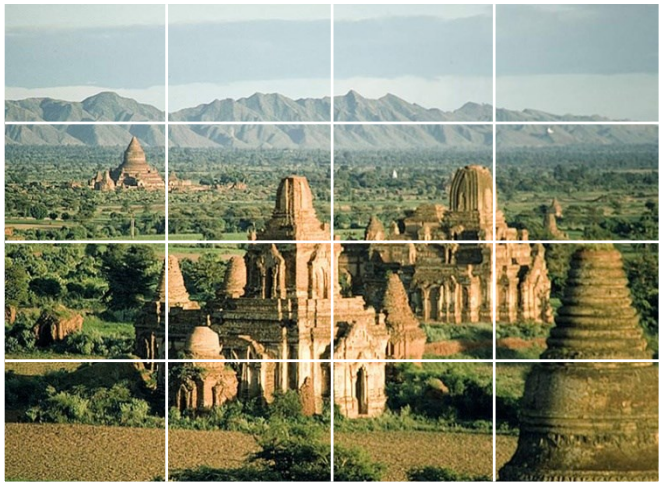
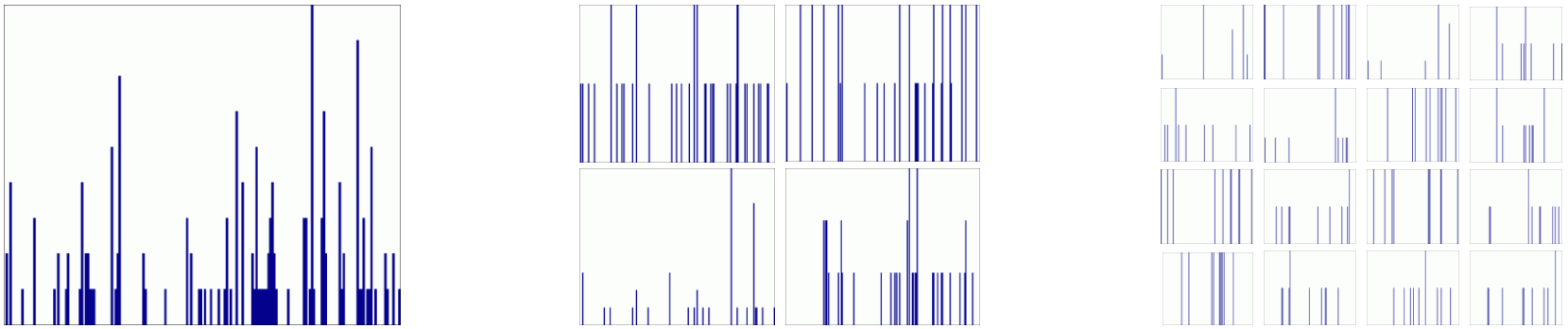
for vocabulary of *V* words

Spatial pyramid representation

- Extension of a bag of features
- Locally orderless representation at several levels of resolution

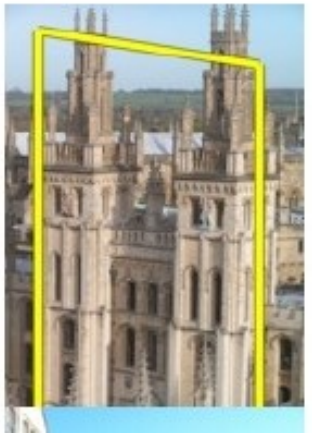




level 0 level 1 level 2

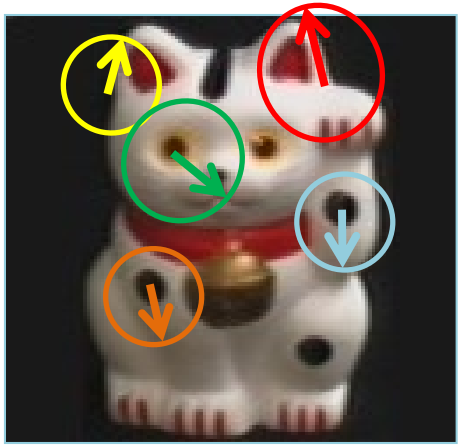
Lazebnik, Schmid & Ponce (CVPR 2006)

How can we quickly find images in a large database that match a given image region?

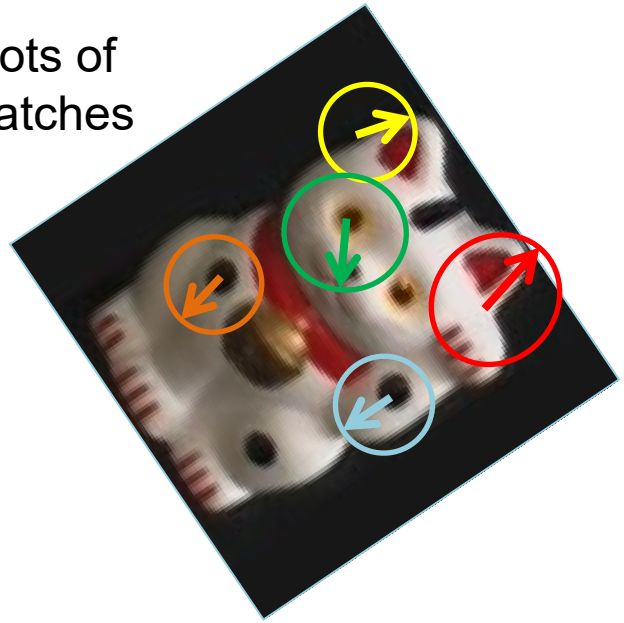


Simple idea

See how many keypoints are close to keypoints in each other image



Lots of Matches

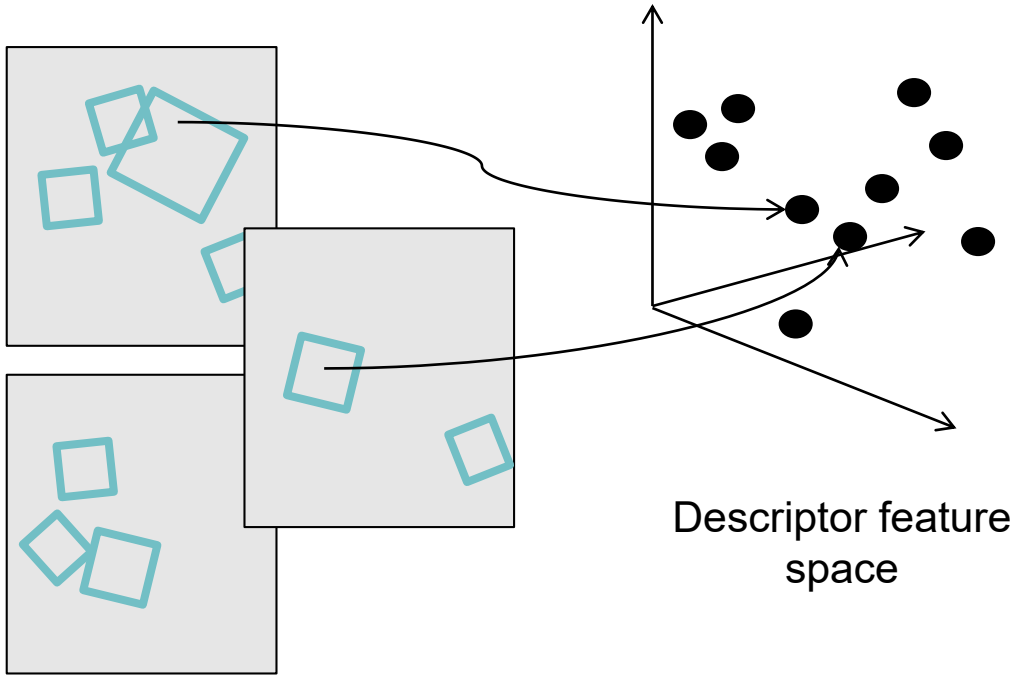


Few or No Matches

But this will be really, really slow!

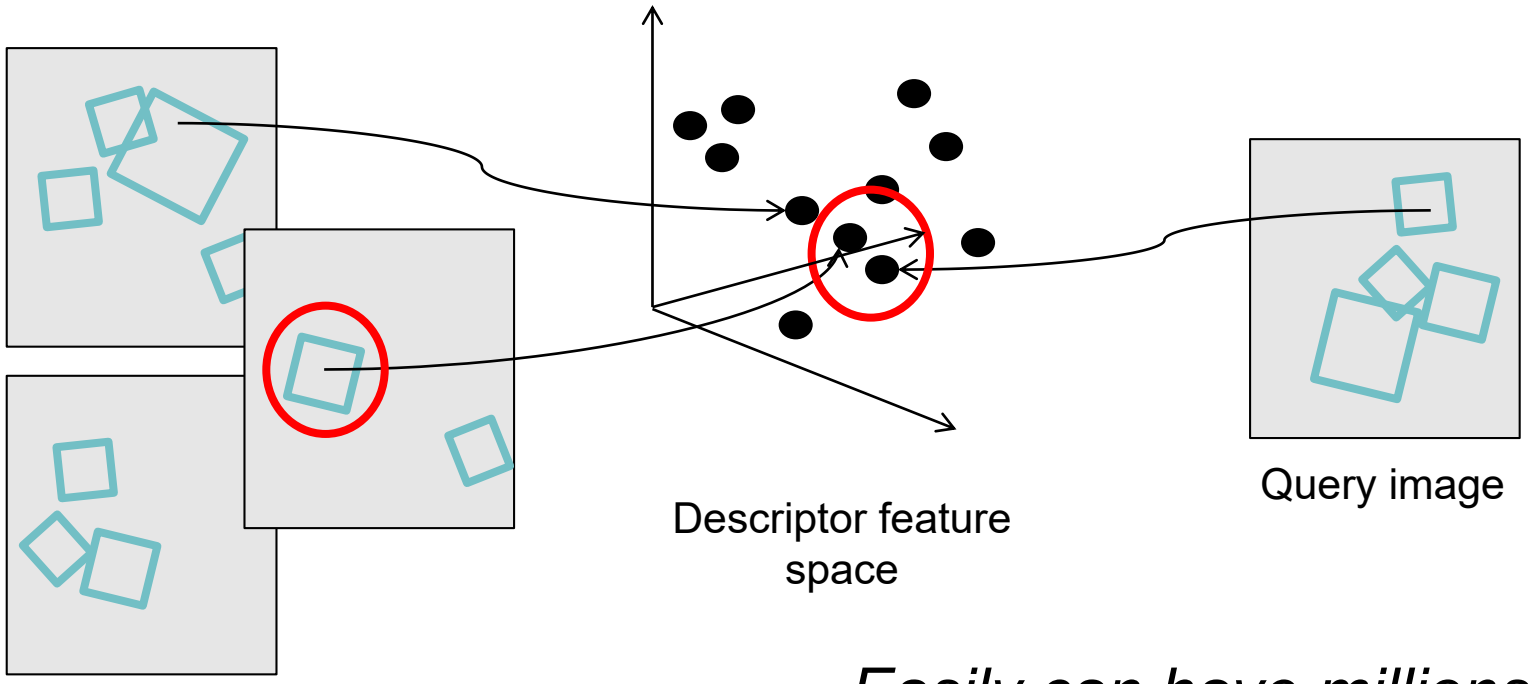
Indexing local features

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



Indexing local features

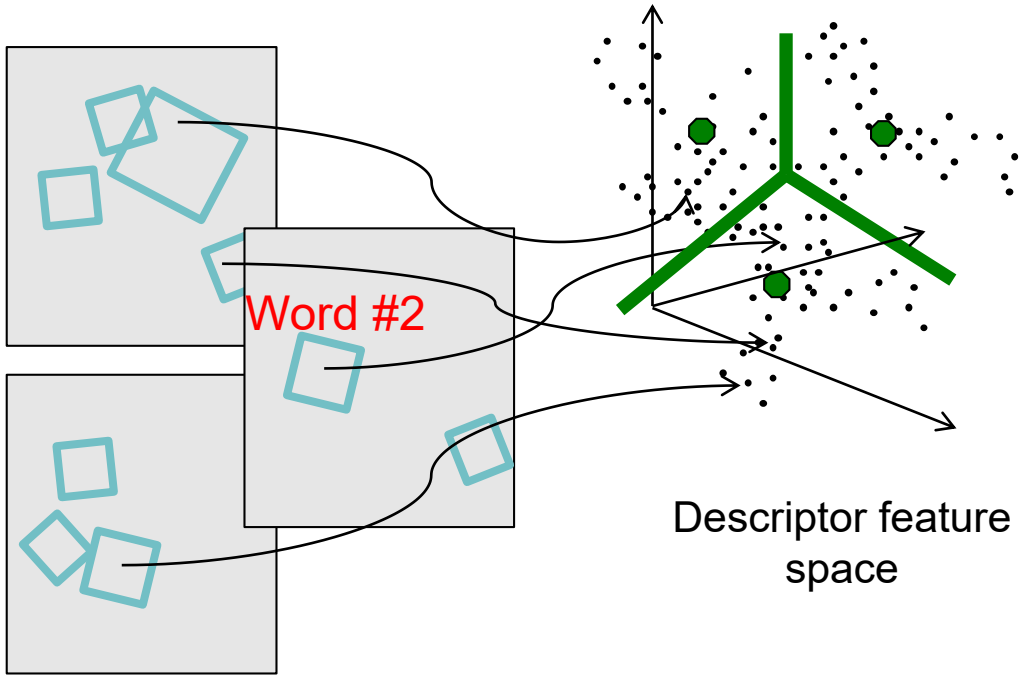
- When we see close points in feature space, we have similar descriptors, which indicates similar local content.



Easily can have millions of features to search!

Visual words

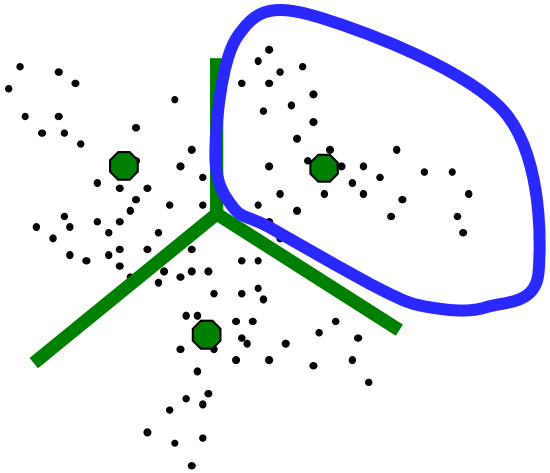
Map high-dimensional descriptors to tokens/words by quantizing the feature space.



- Quantize via clustering; cluster centers are the visual “words”
- Assign word to each image region by finding the closest cluster center.

Visual words

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



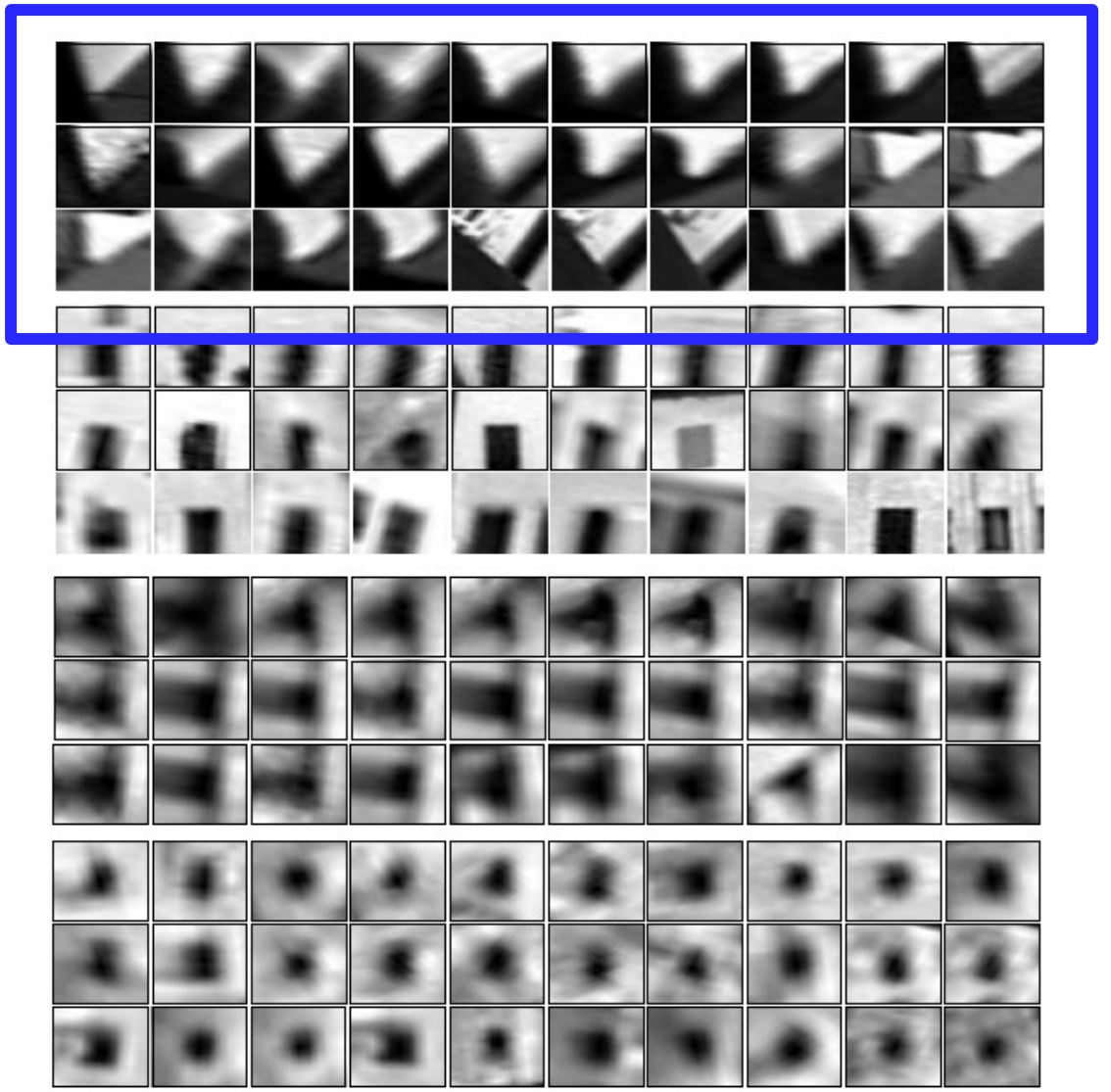
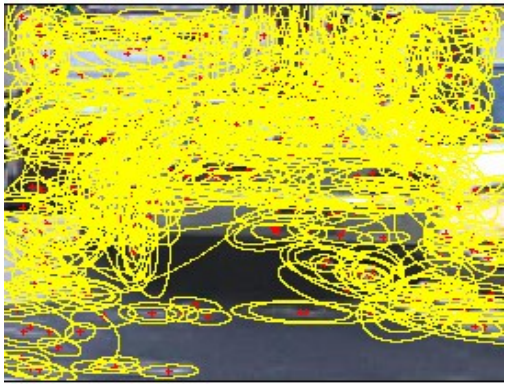


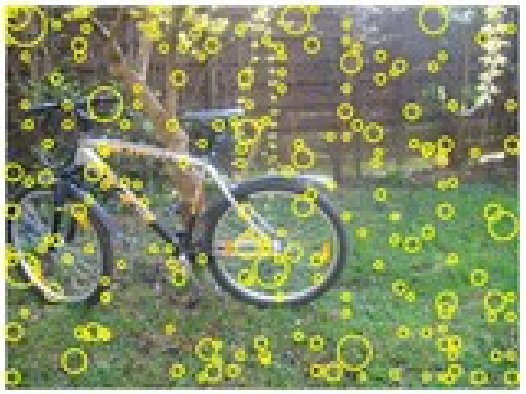
Figure from Sivic & Zisserman, ICCV 2003

Sampling strategies

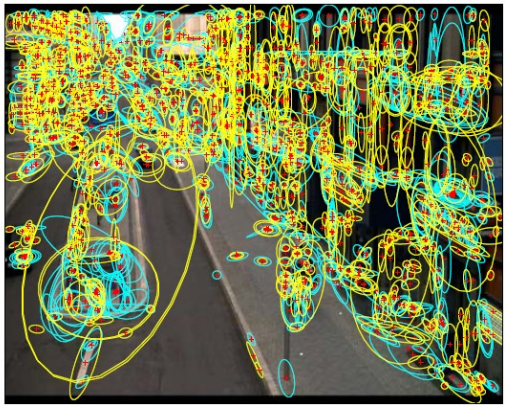


Sparse, at interest points

Dense, uniformly



Randomly



Multiple interest operators

- To find specific textured objects, sparse sampling from interest points often more reliable.
- Multiple complementary interest operators offer more image coverage.
- For object categorization, dense sampling offers better coverage.

[See Nowak, Jurie & Triggs, ECCV 2006]

Image credits: F-F. Li, E. Nowak, J. Sivic
K. Grauman, B. Leibe

Fast lookup: inverted 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.

Build Inverted Index from Database

Image #1

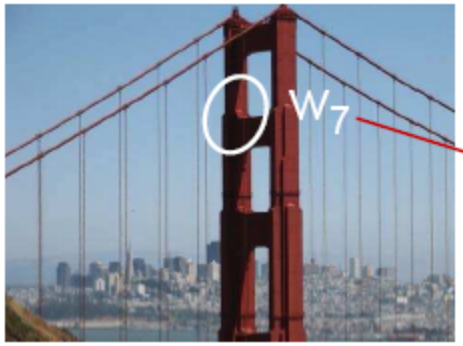
Image #2

Image #3

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

…

Query Inverted Index



New query image

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

Candidate matches

Image #1

Image #2

Query Inverted Index

New query image

Word #	Image #
1	3
2	
…	
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Candidate matches

Image #1

Image #2

1. Extract words in query
2. Inverted file index to find relevant frames
3. Compare/sort word counts

Inverted index

Key requirement: *sparsity*.

If most images contain most words, then we're not better off than exhaustive search.

- Exhaustive search would mean comparing the visual word distribution of a query versus every page.

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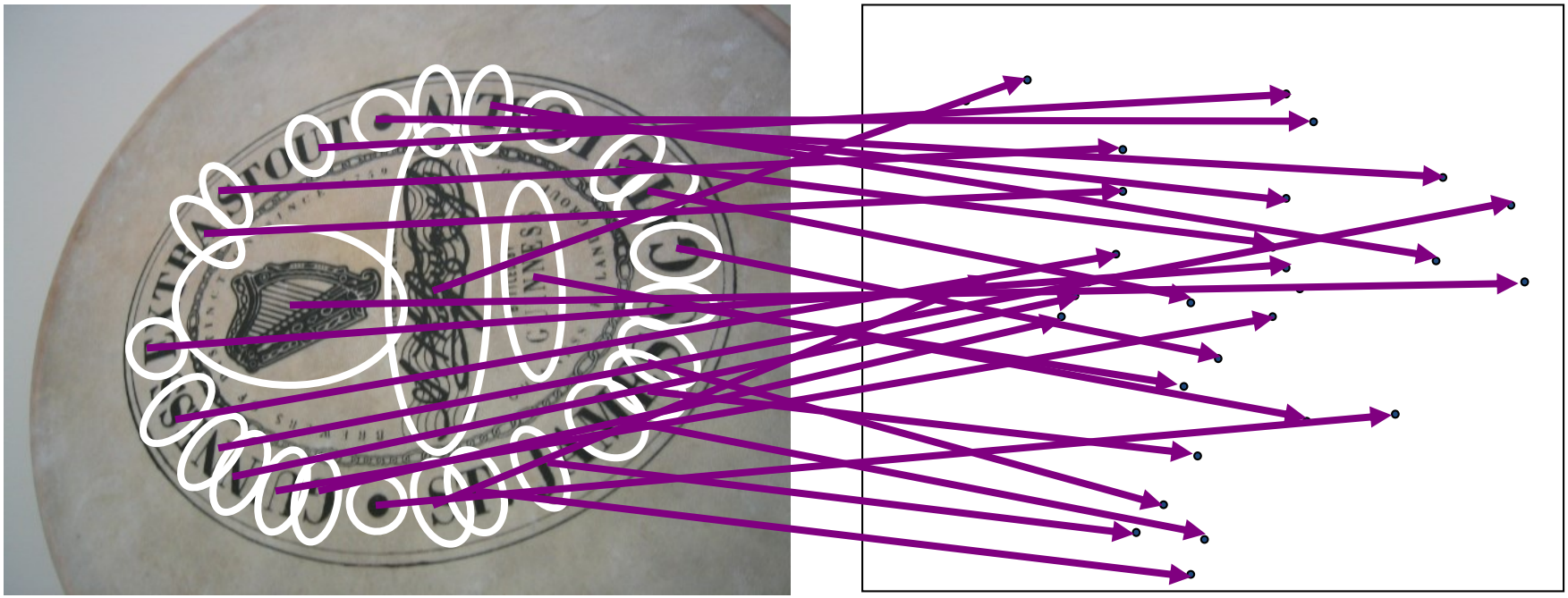
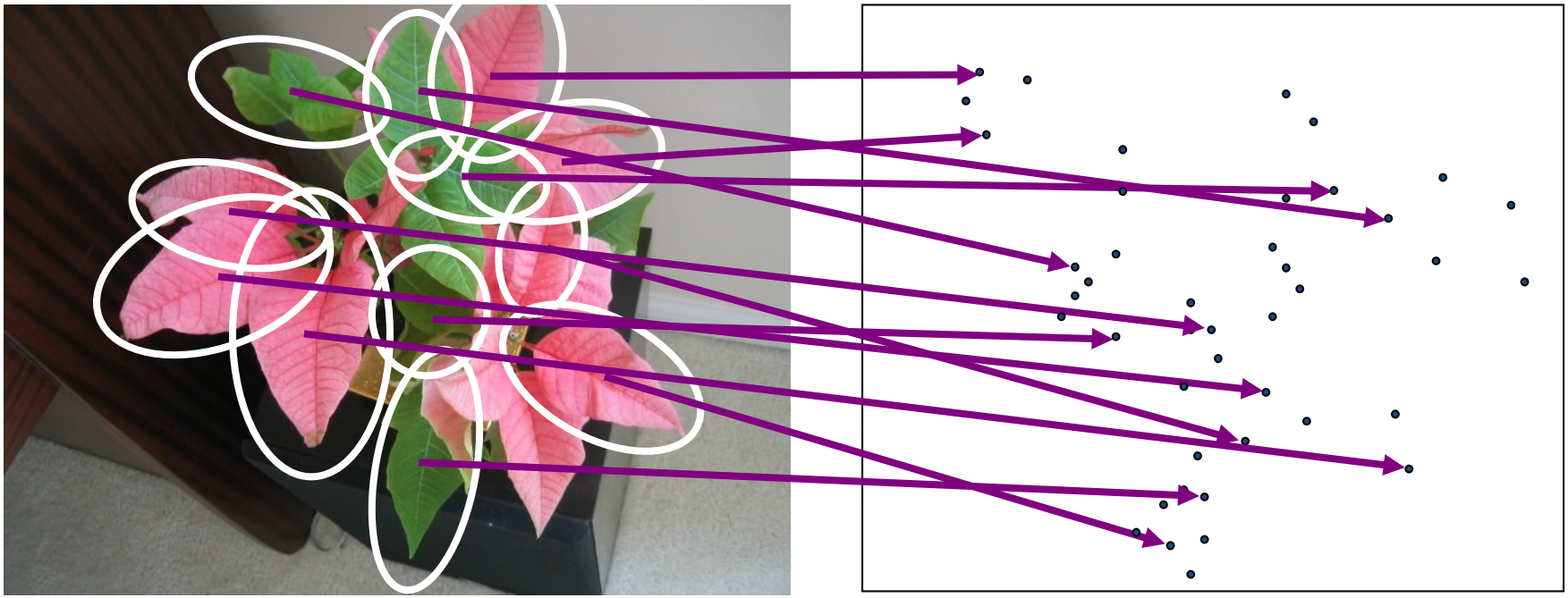
Training the vocabulary tree



Training the vocabulary tree



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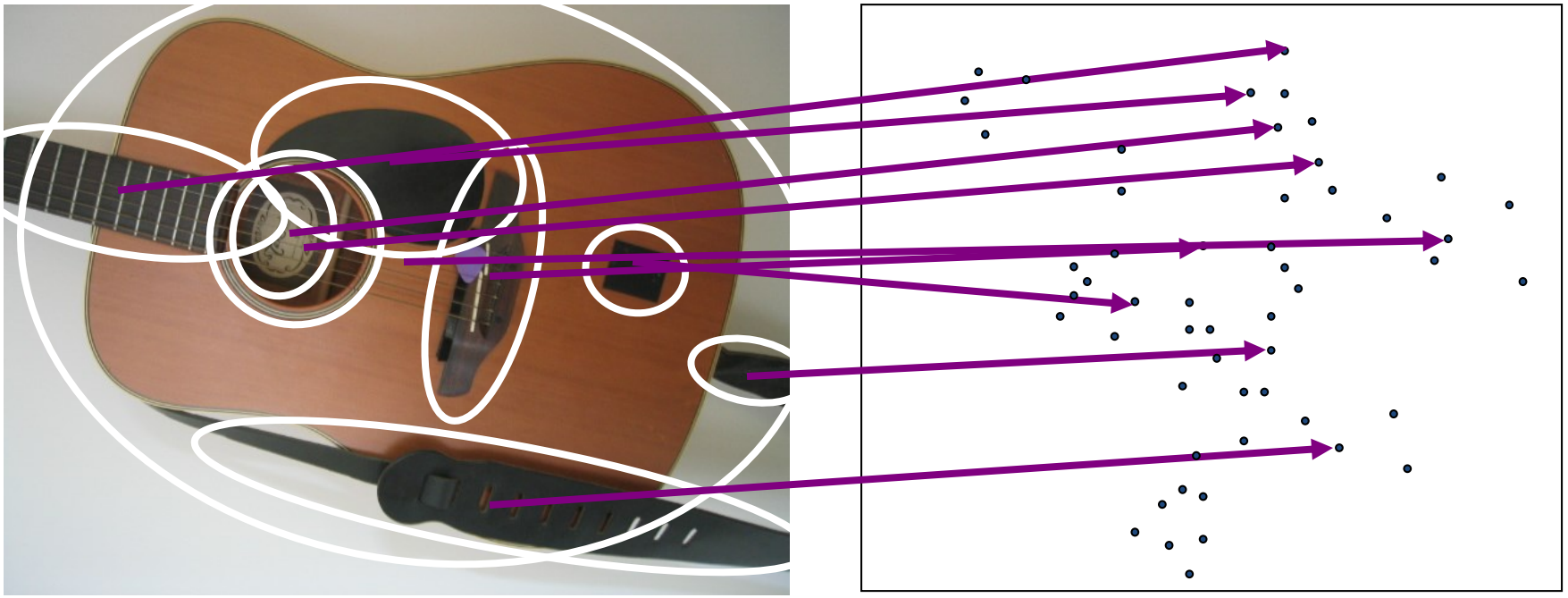

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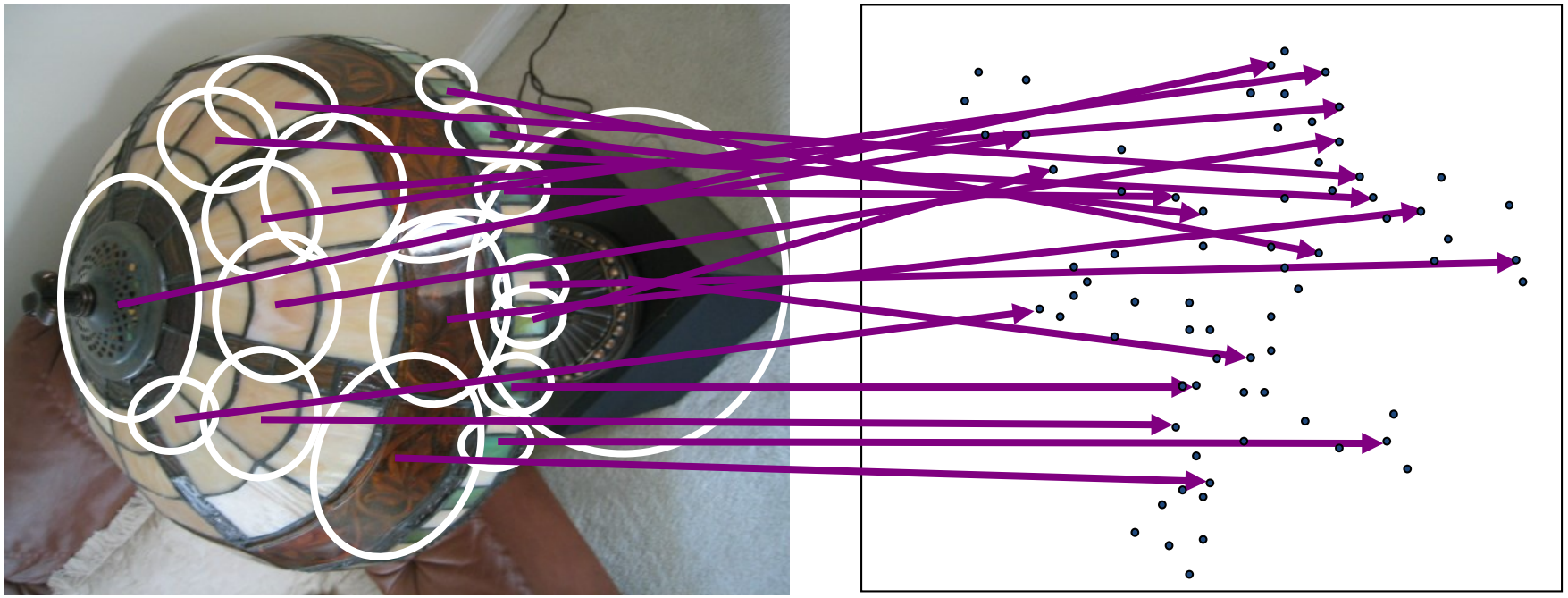

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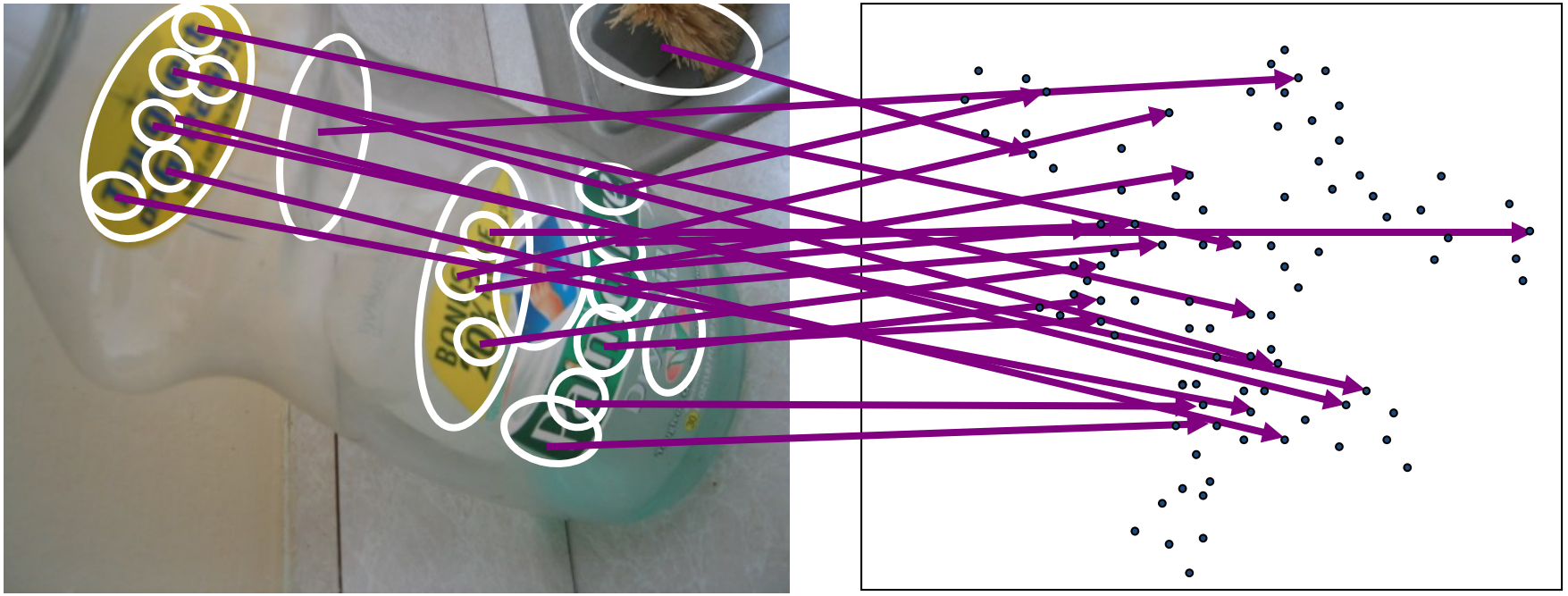

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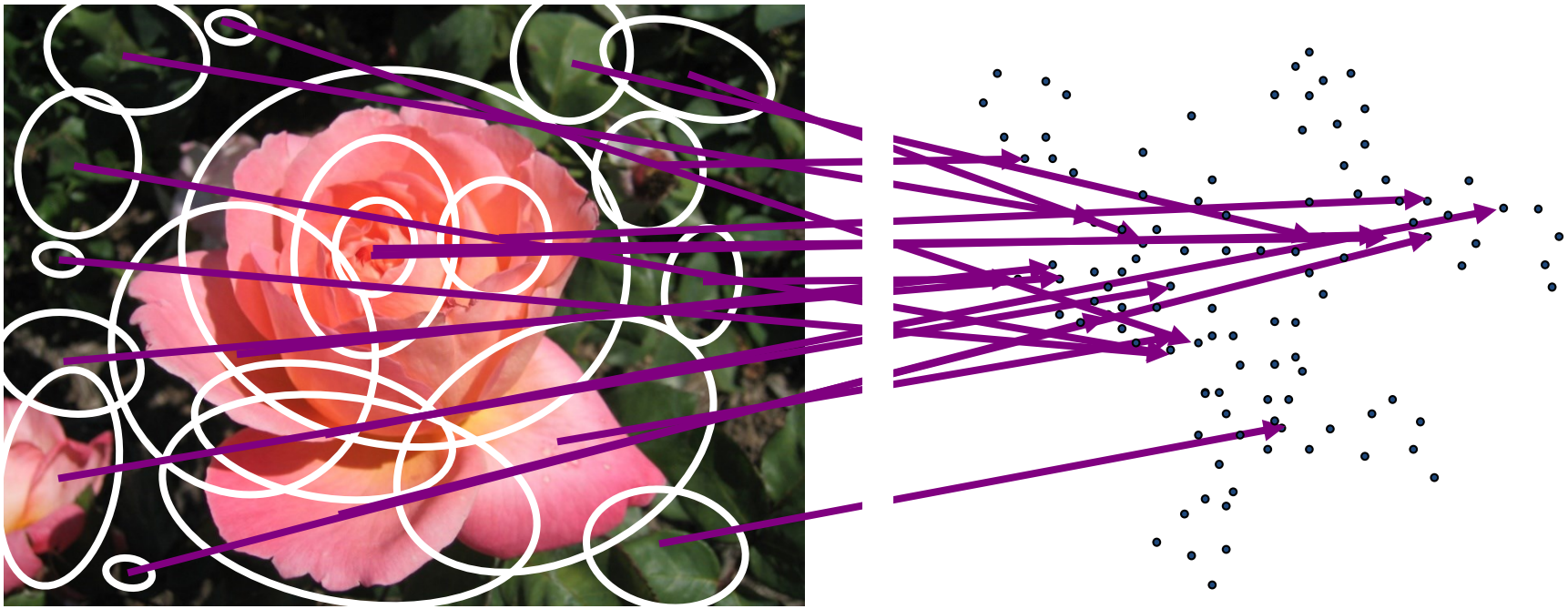
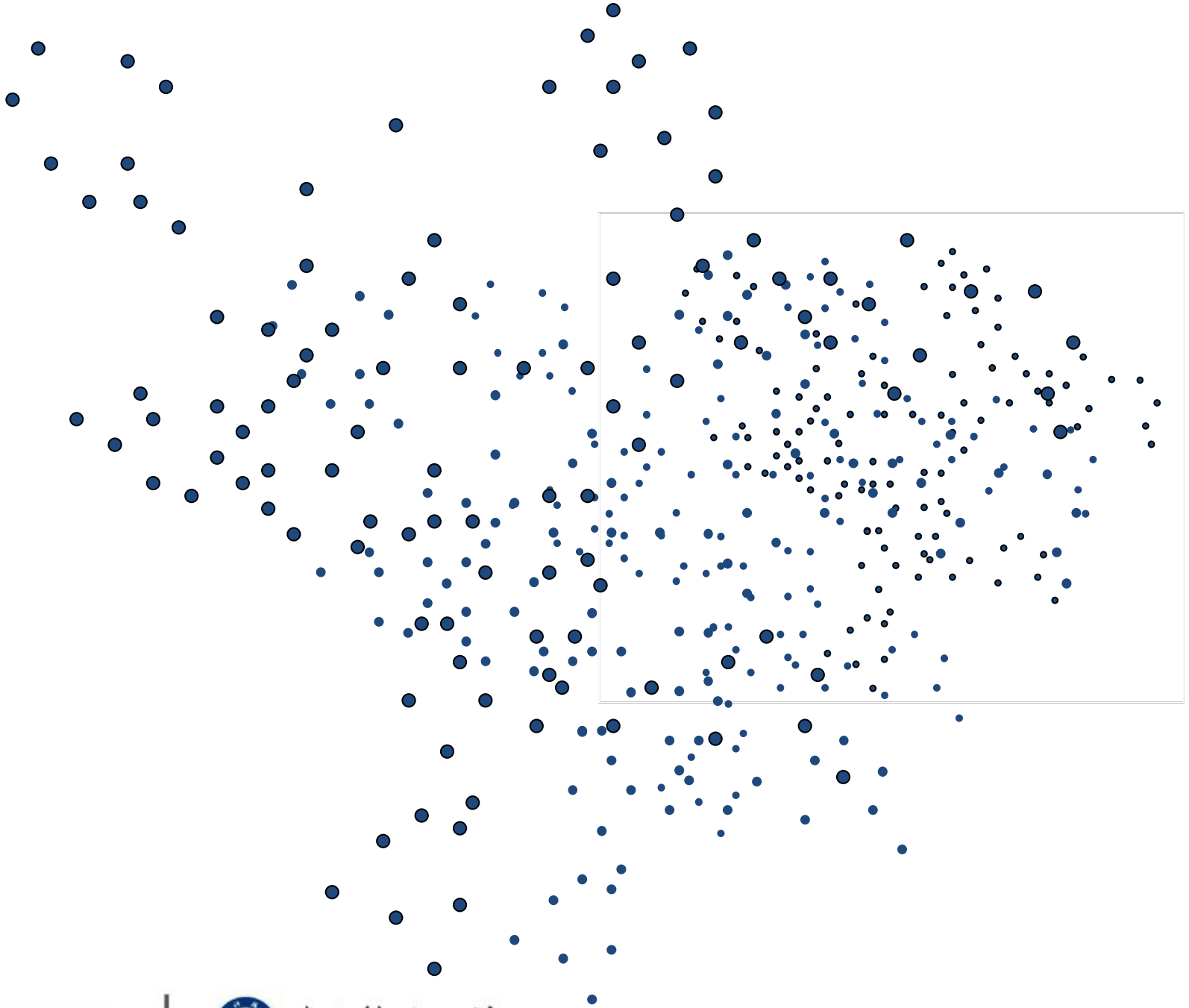
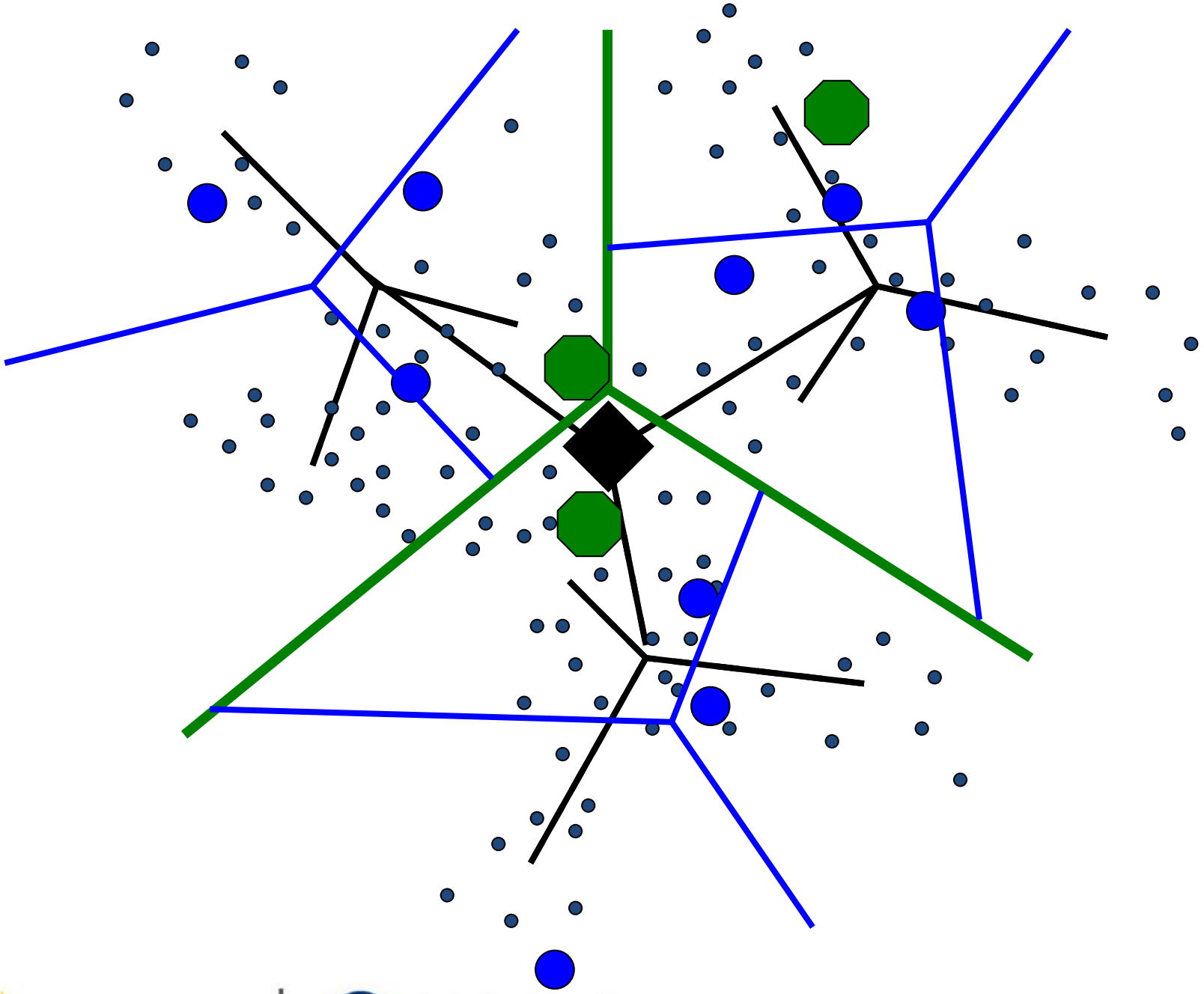
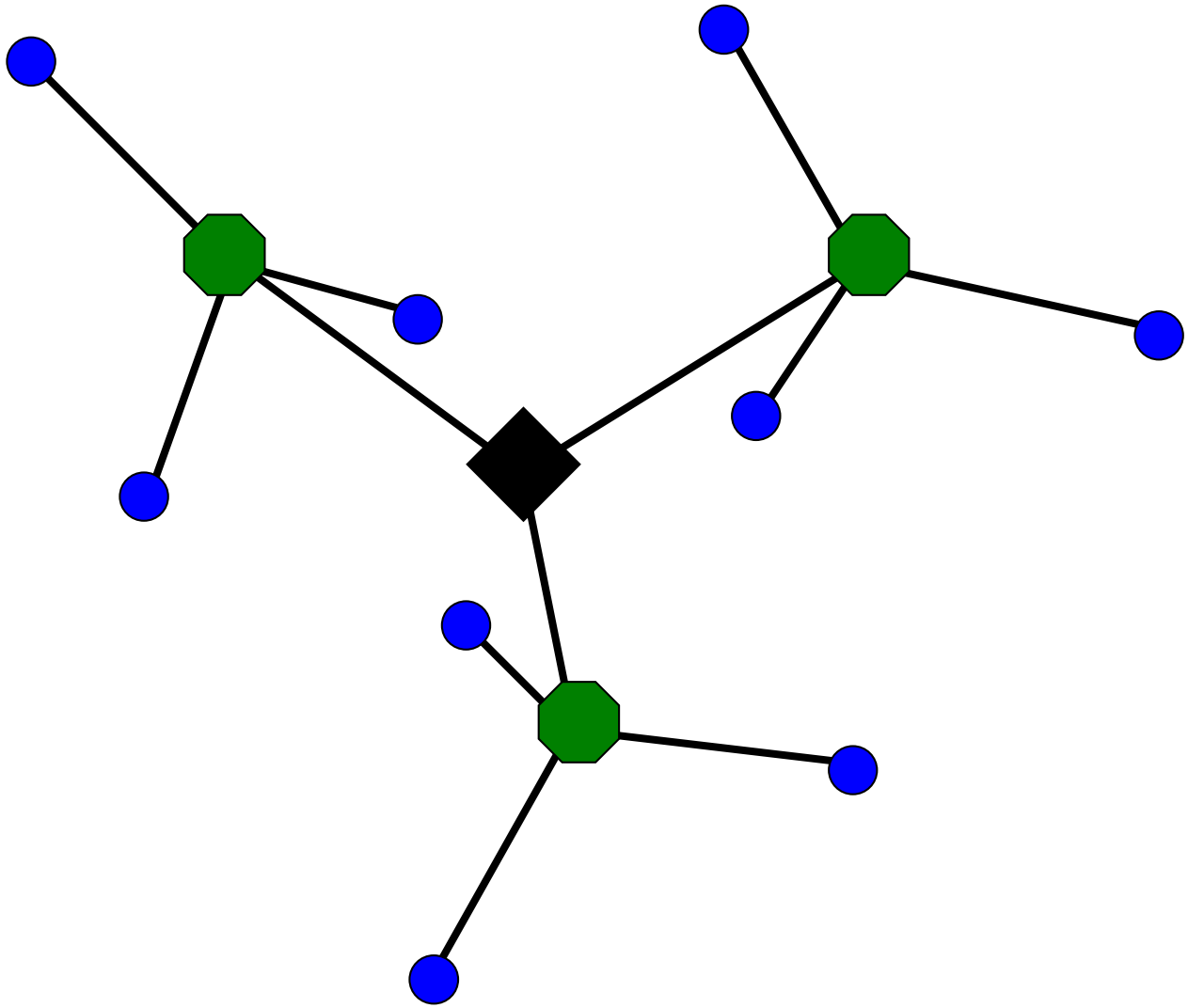
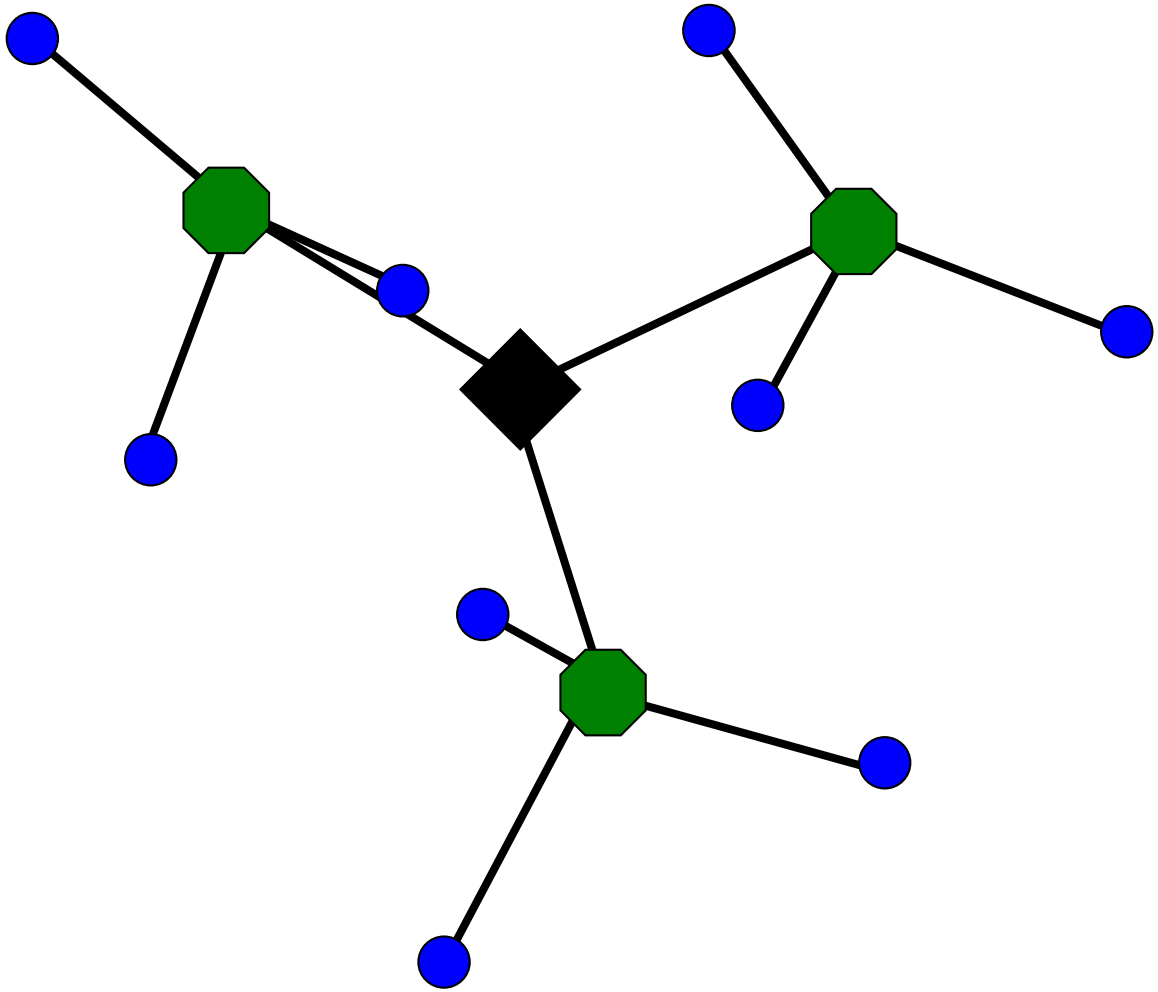
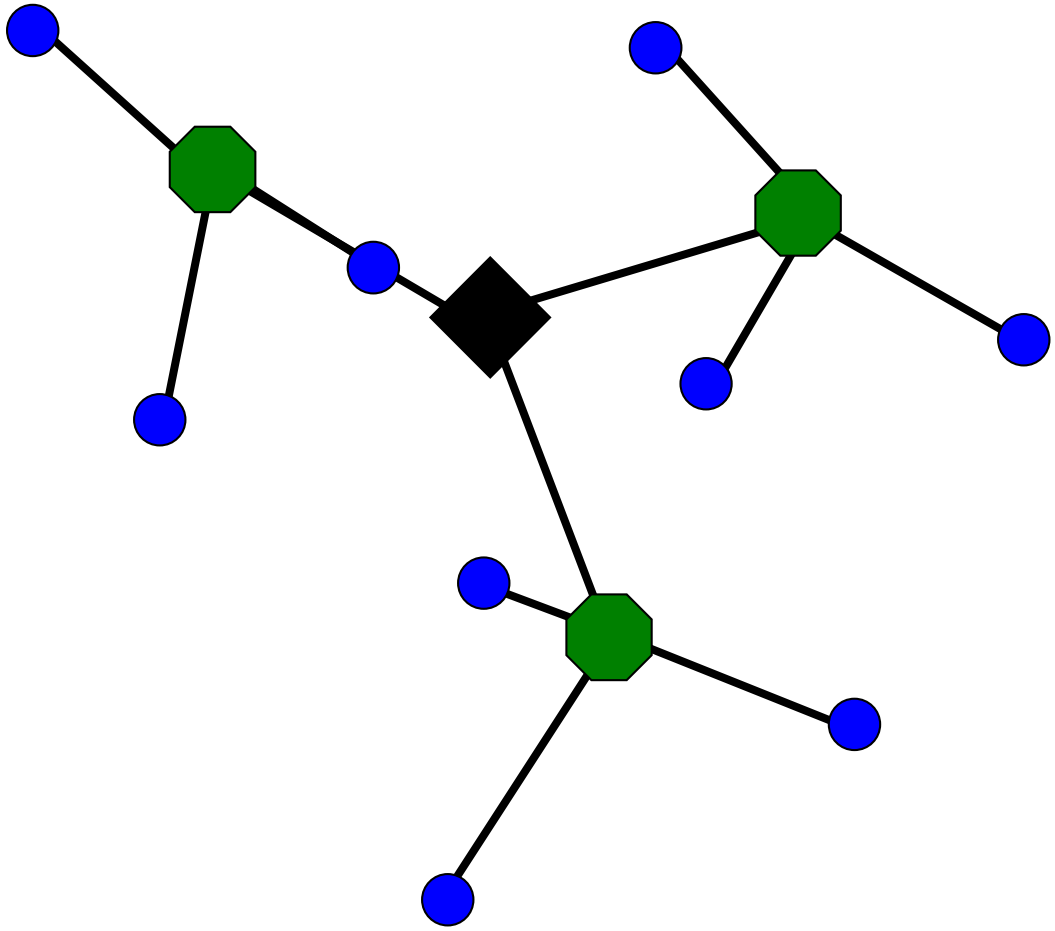


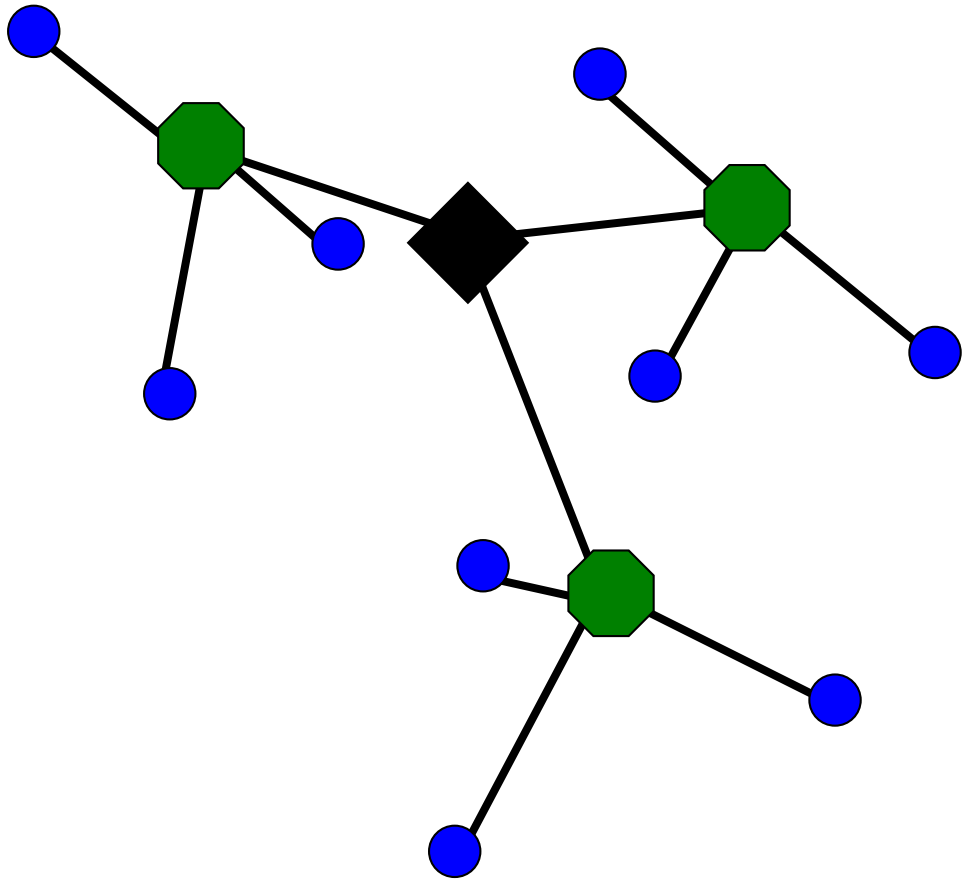


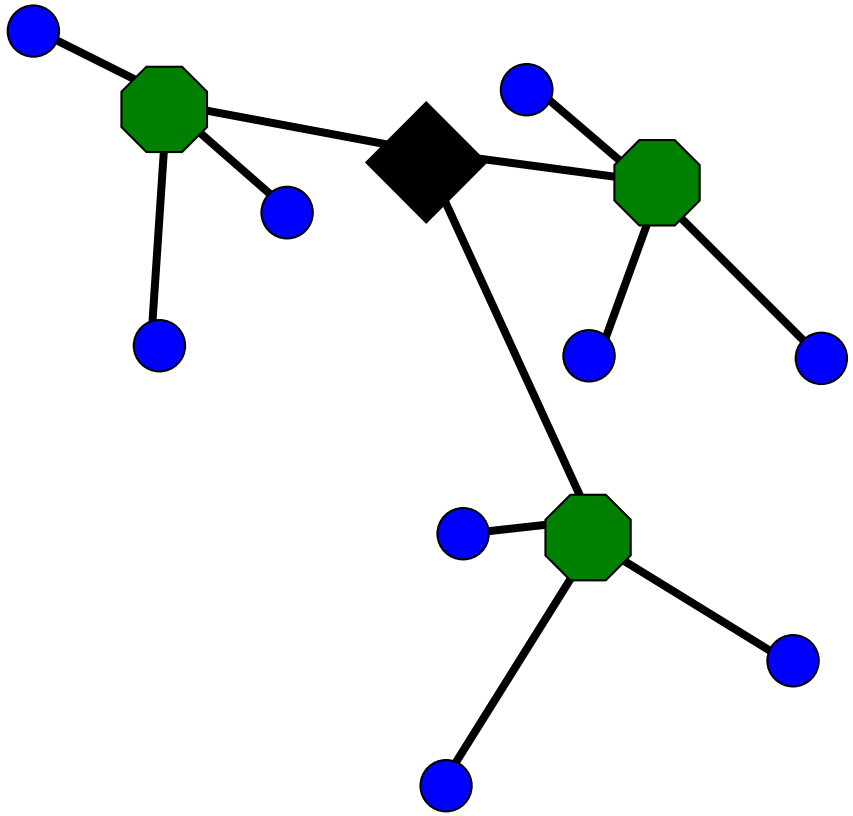


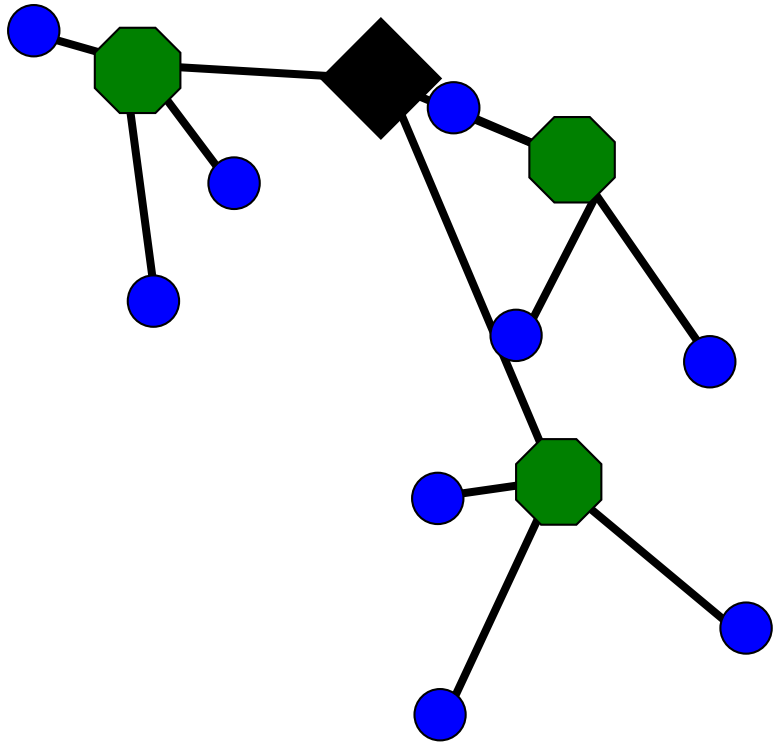


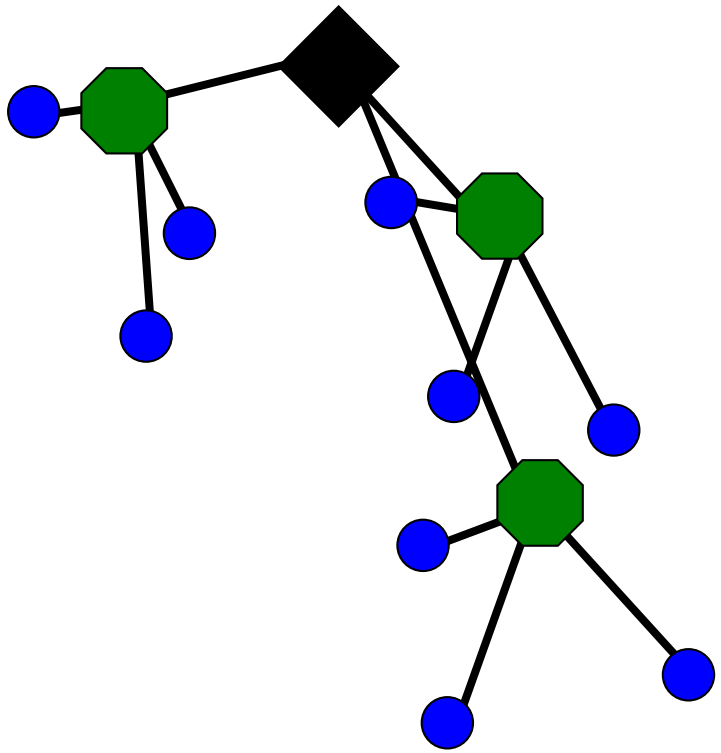


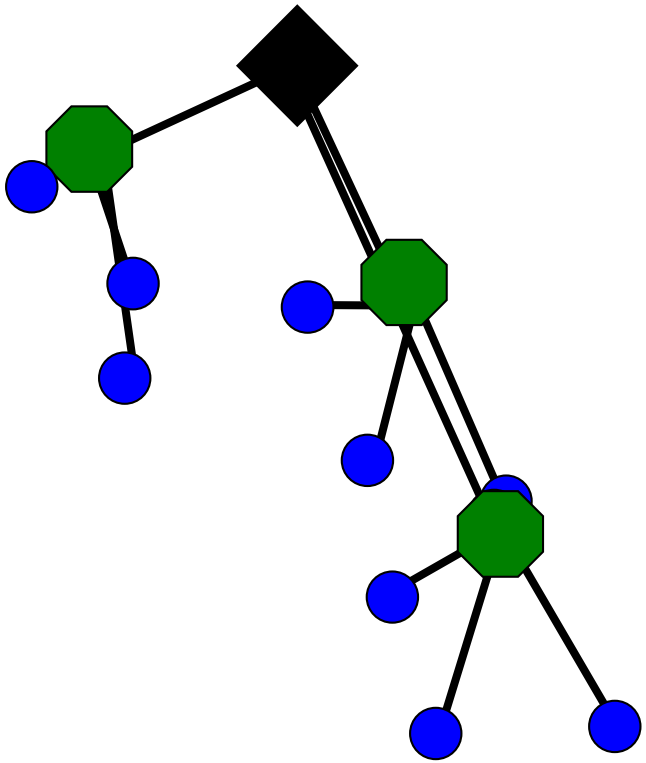


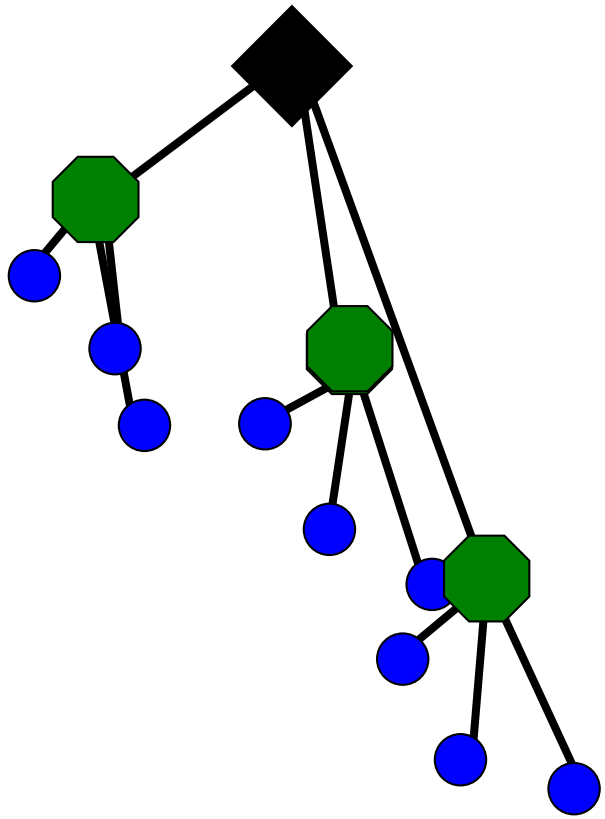




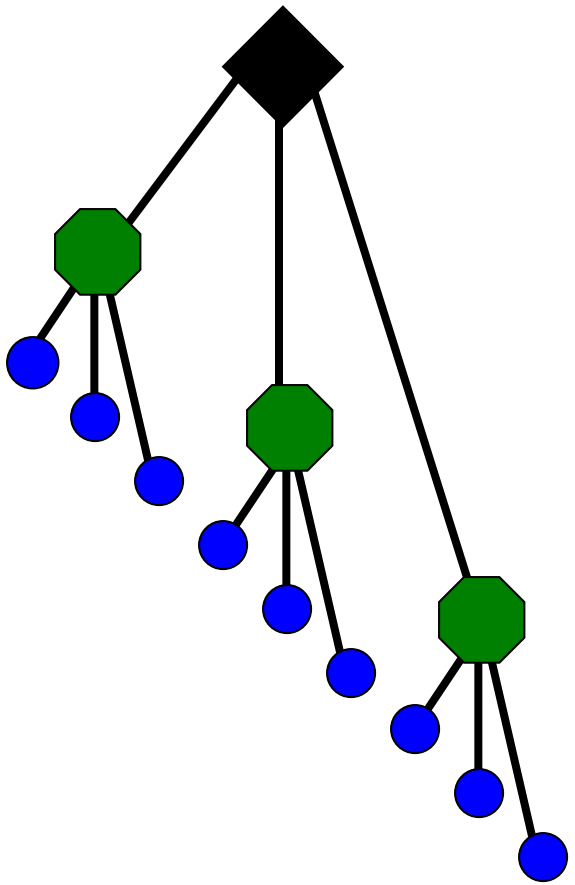




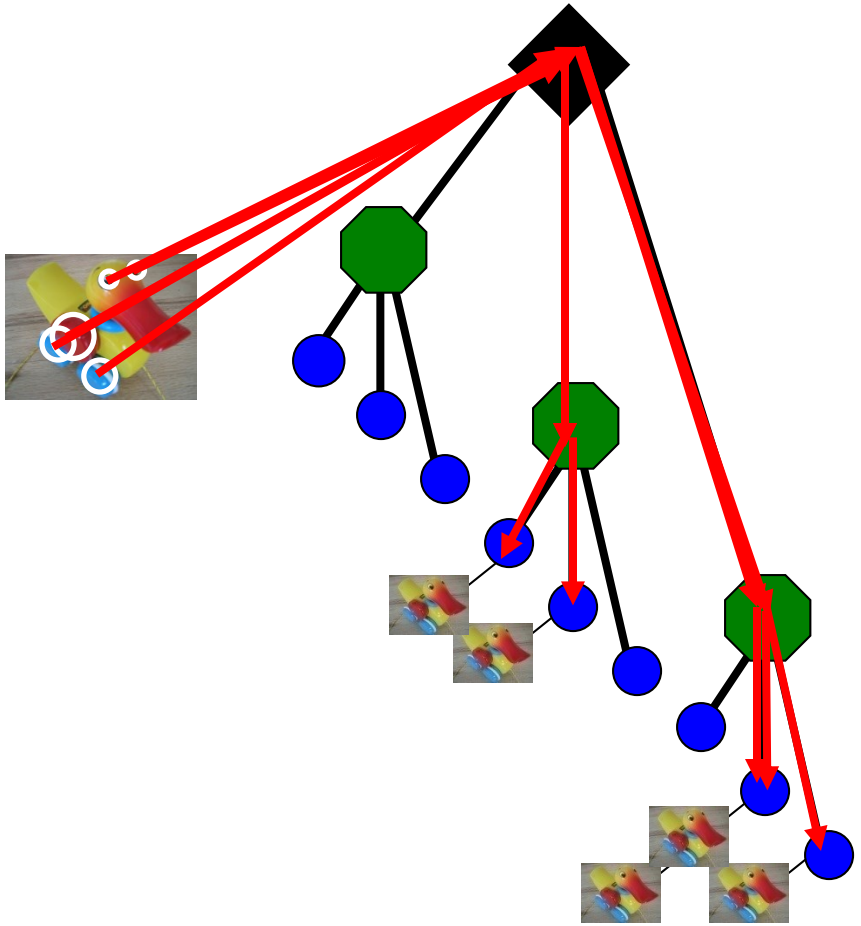


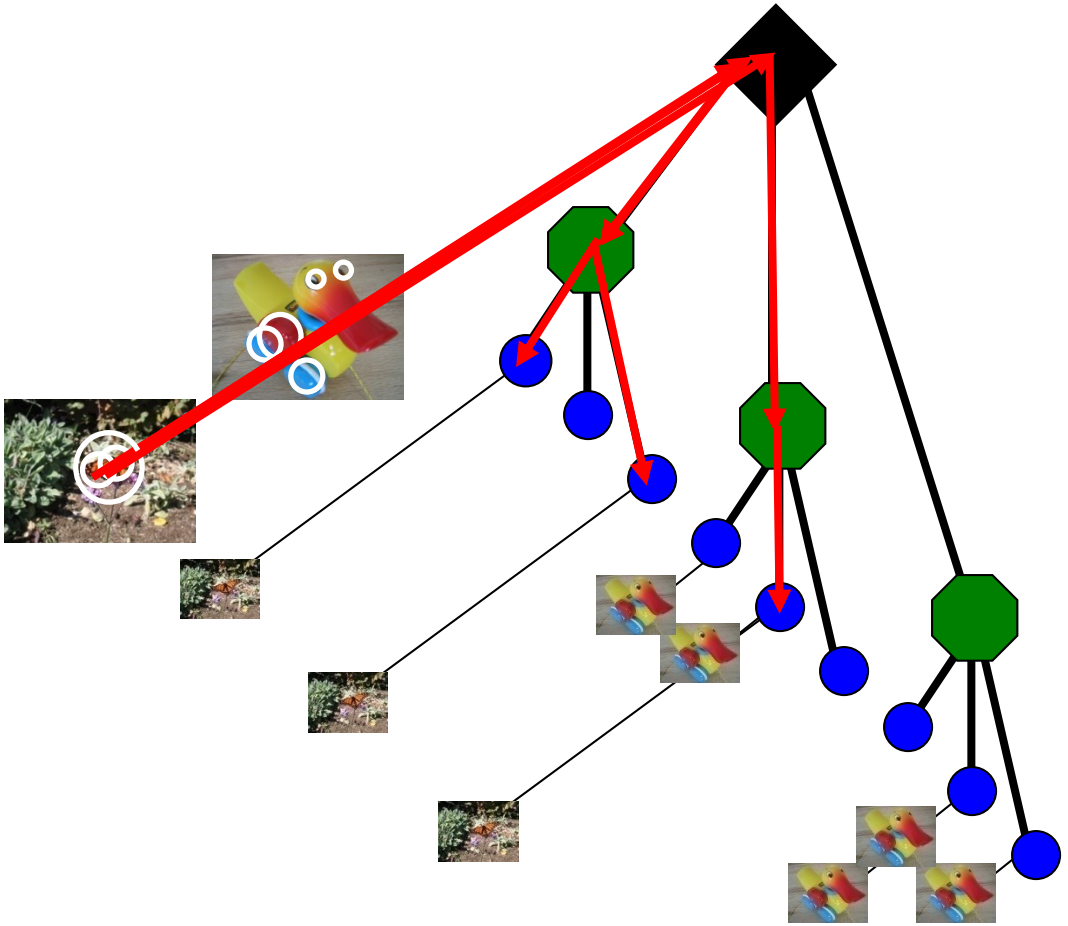


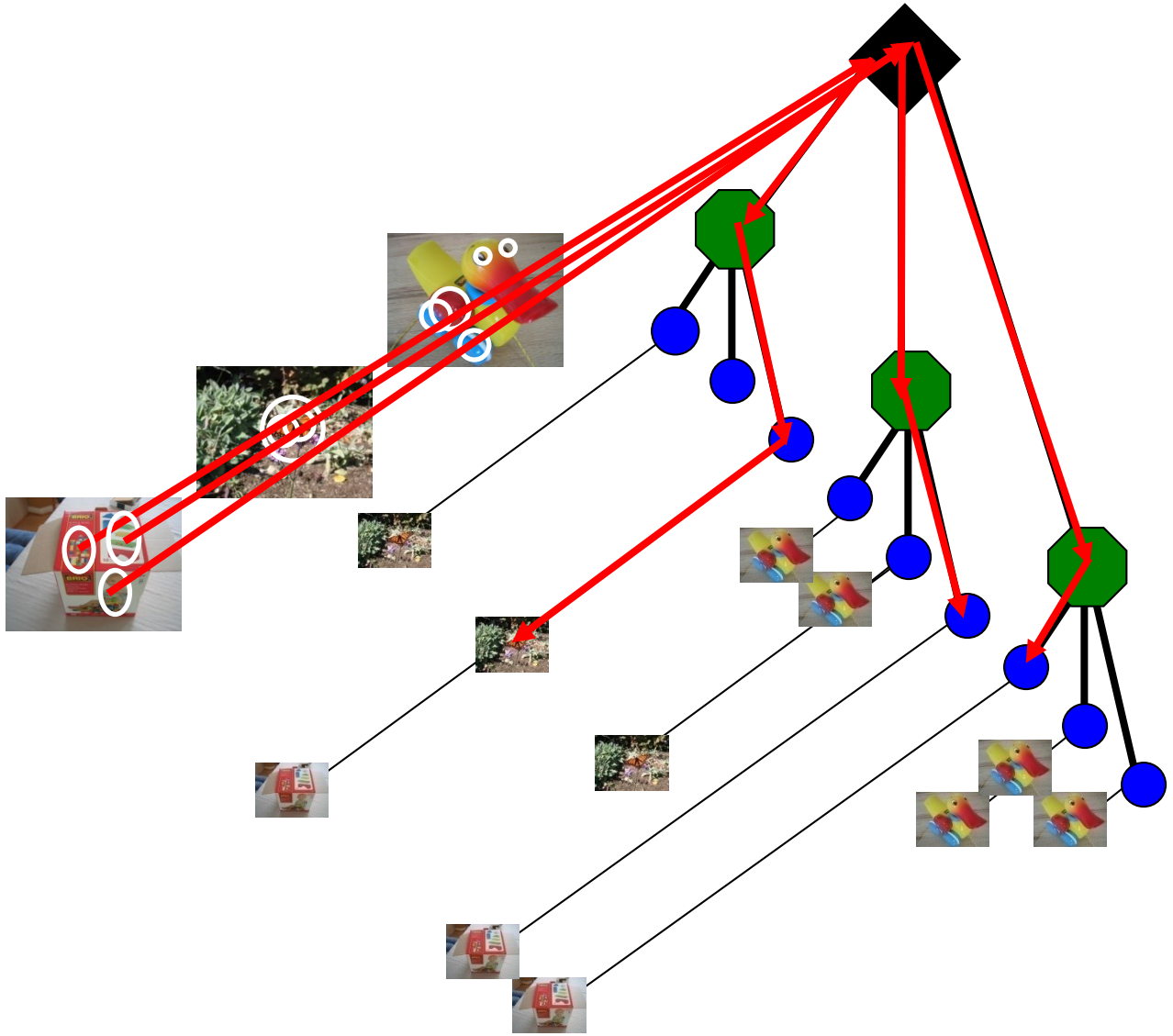
Vocabulary tree built recursively



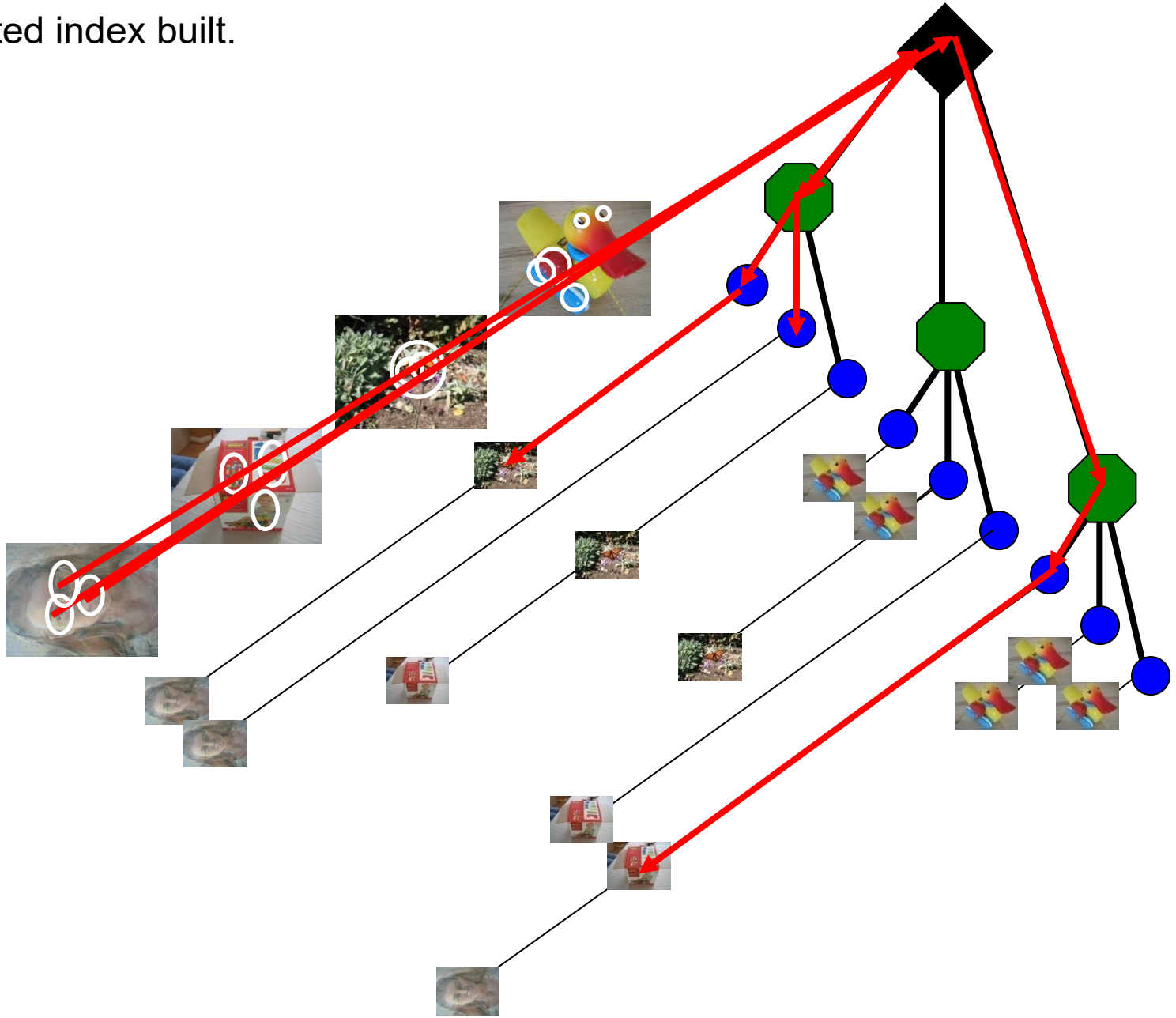
Each leaf has inverted index

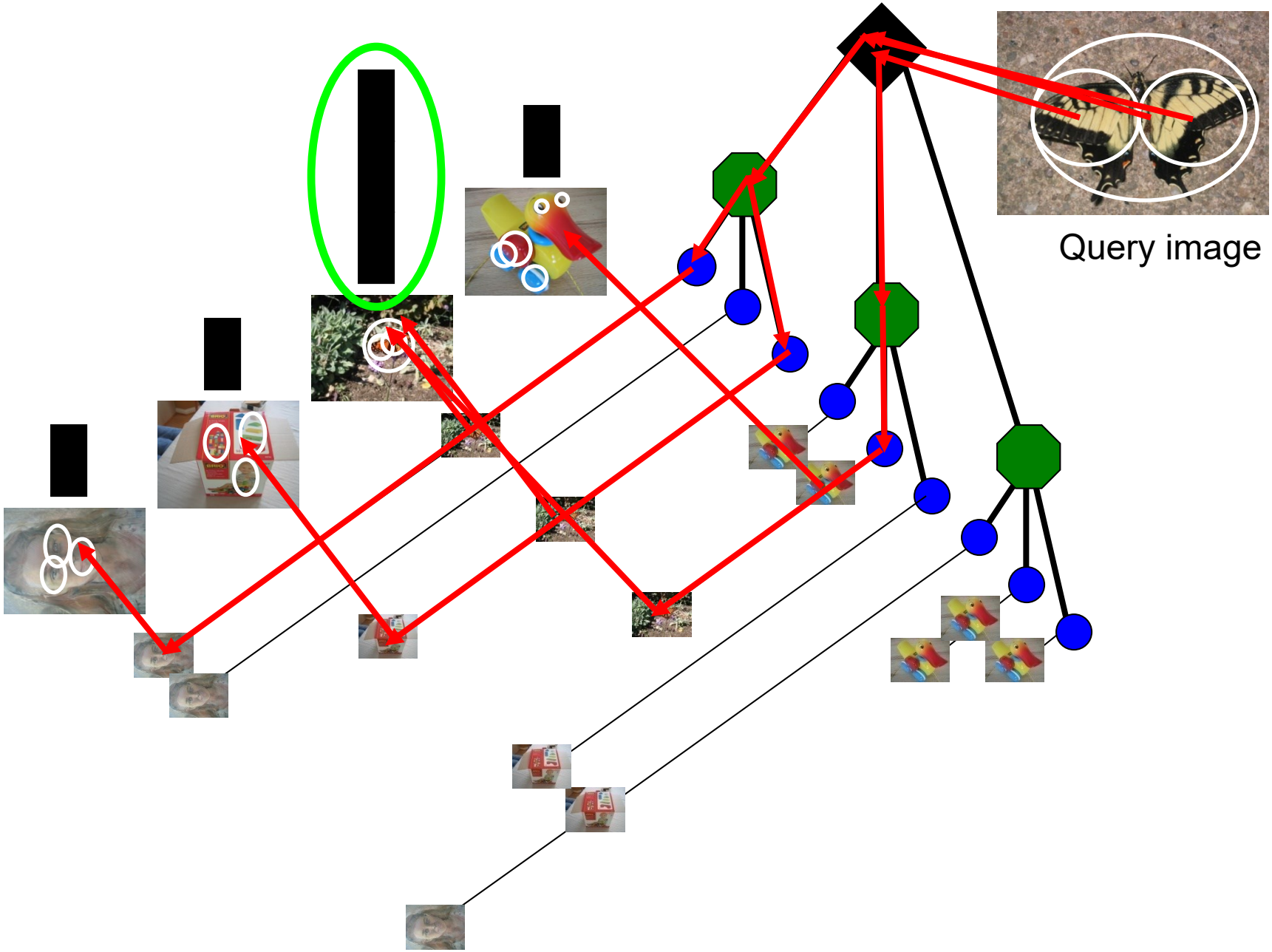




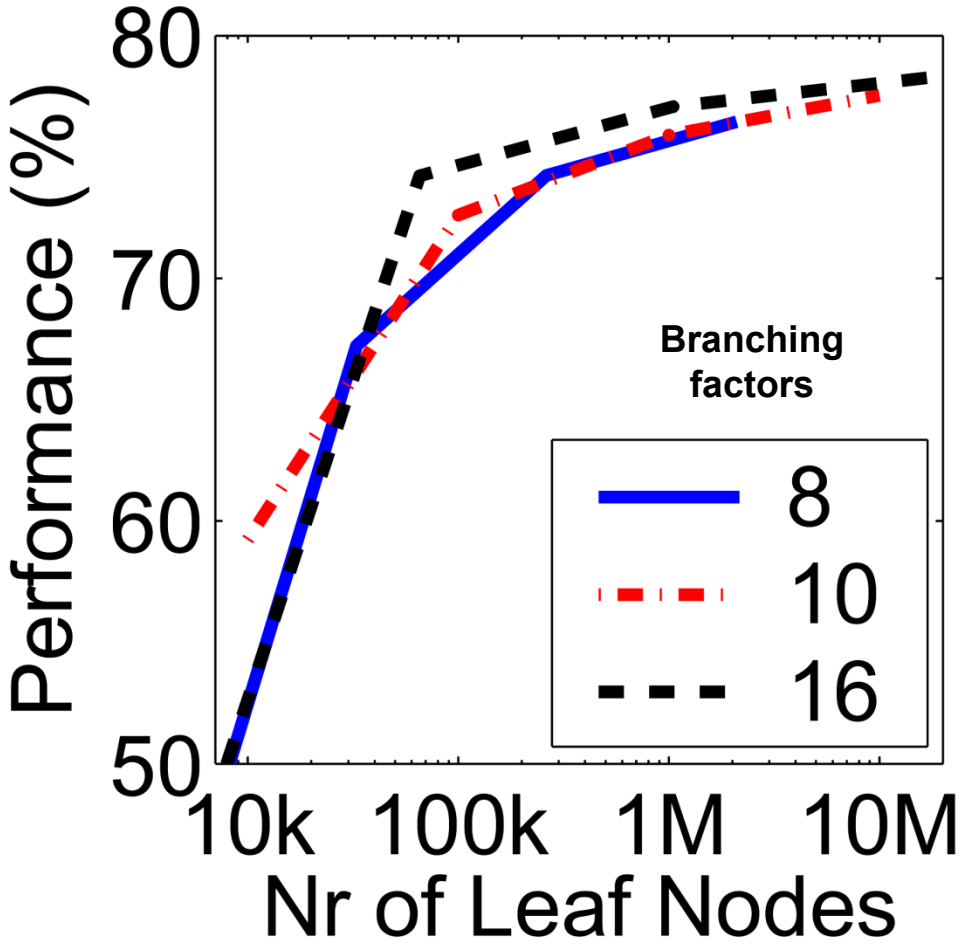


Inverted index built.

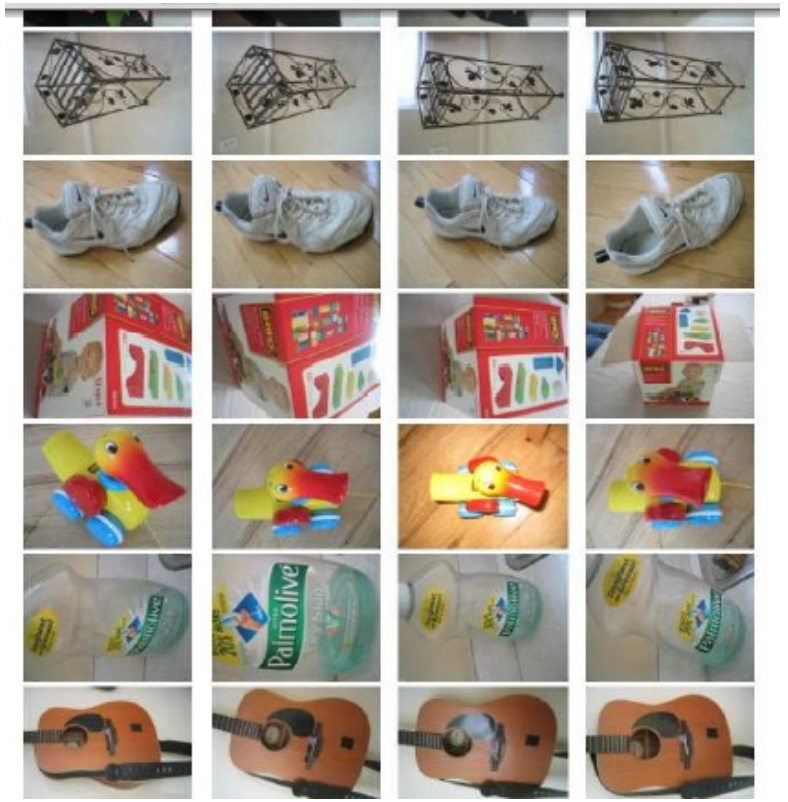



Query image

Vocabulary size



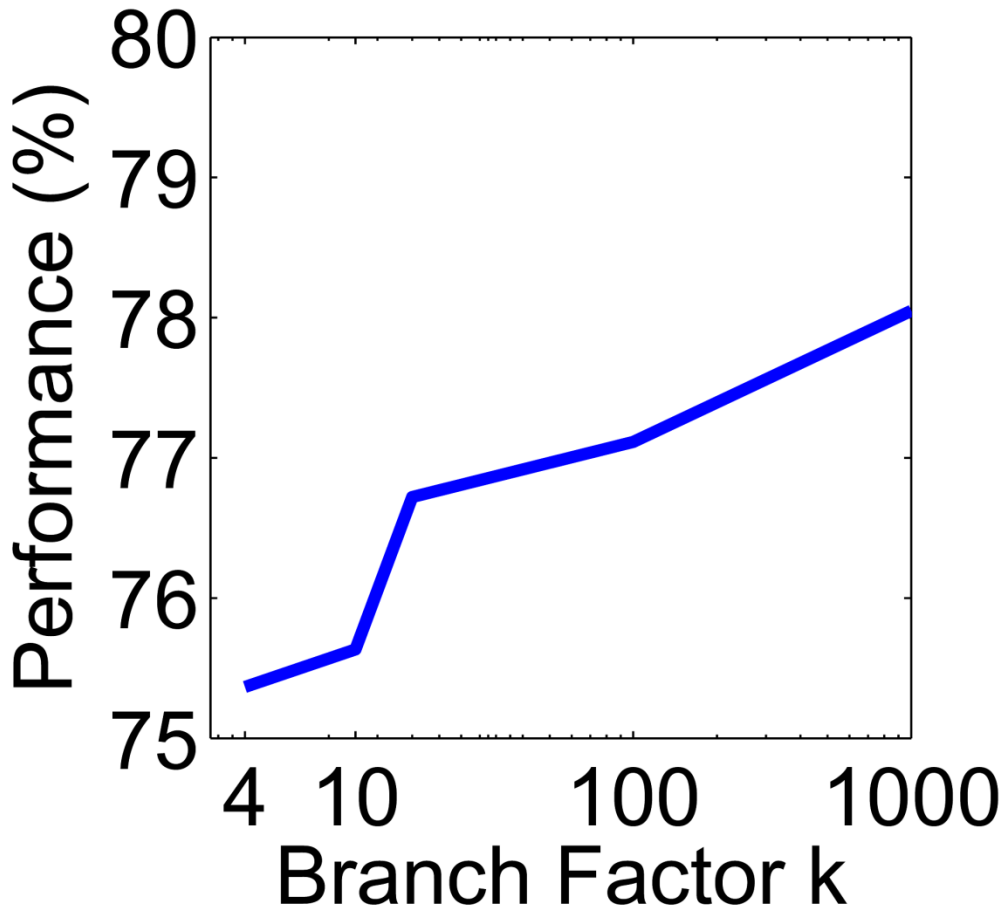
Recognition with 6347 images



Nister & Stewenius, CVPR 2006

Influence on performance, sparsity

Higher branch factor works better (but slower)



Visual words/bags of words

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

- background and foreground mixed when bag covers whole image *-> is it really instance recognition?*
- optimal vocabulary formation remains unclear
- basic model ignores geometry – must verify afterwards, or encode via features

Recognition 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?

How to score the retrieval results?

How might we add more spatial verification?

Precision and Recall

True positive (tp) – correct attribution
True negative (tn) – correct rejection

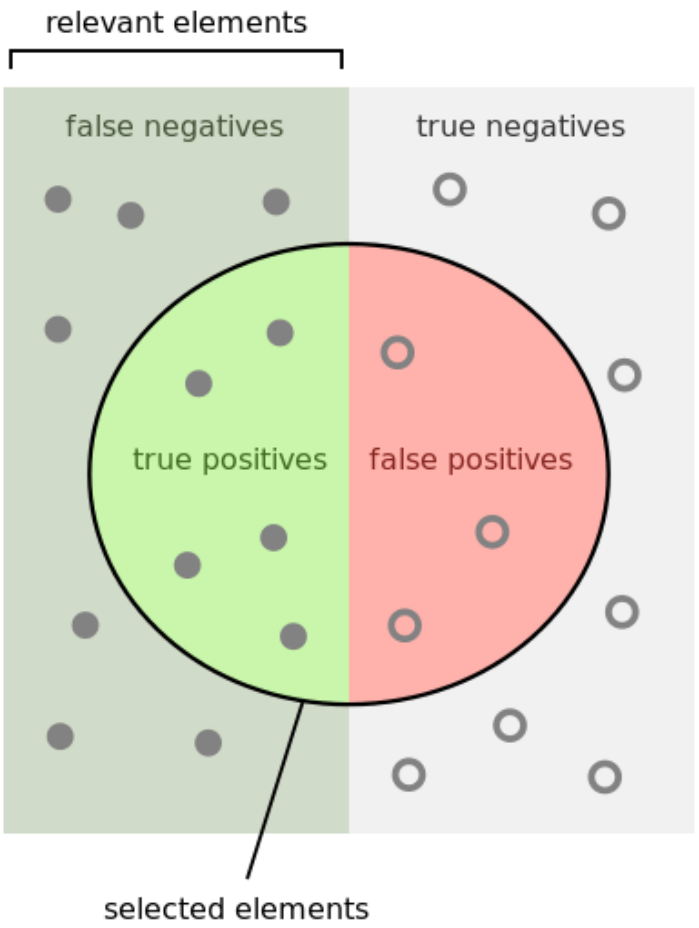
False positive (fp) – incorrect attribution
False negative (fn) – incorrect rejection

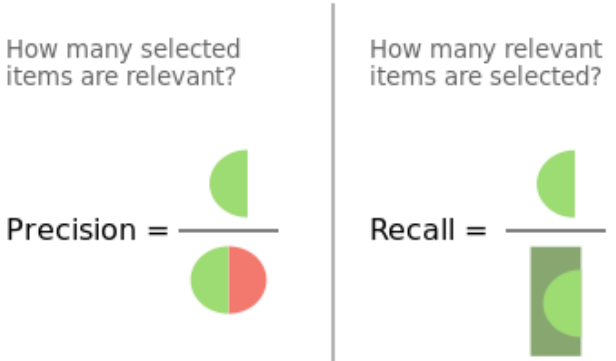
$$\text{Precision} = \frac{tp}{tp + fp}$$

Precision = #relevant / #returned

$$\text{Recall} = \frac{tp}{tp + fn}$$

Recall = #relevant / #total relevant



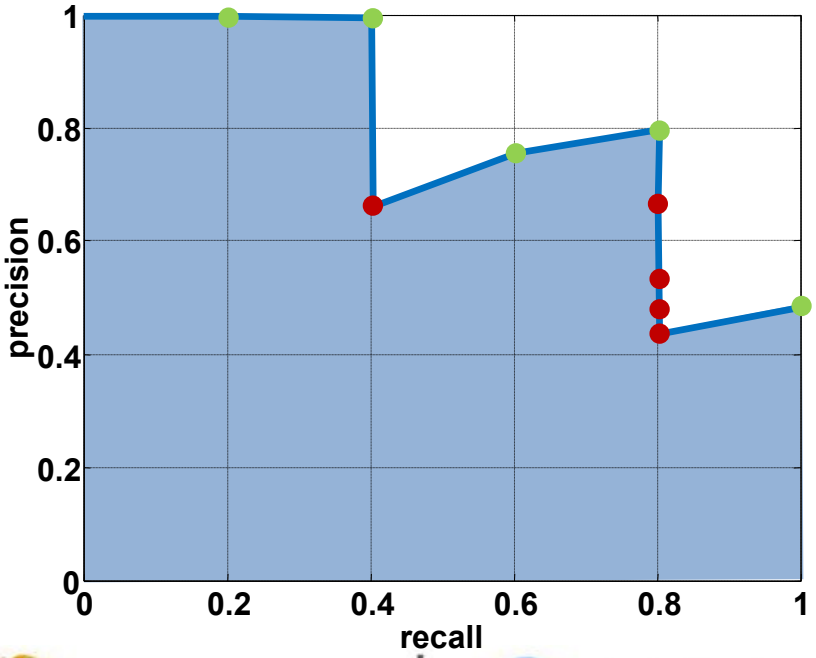


Scoring retrieval quality

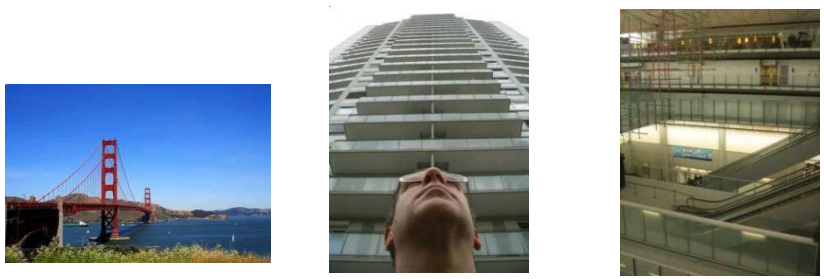
Query

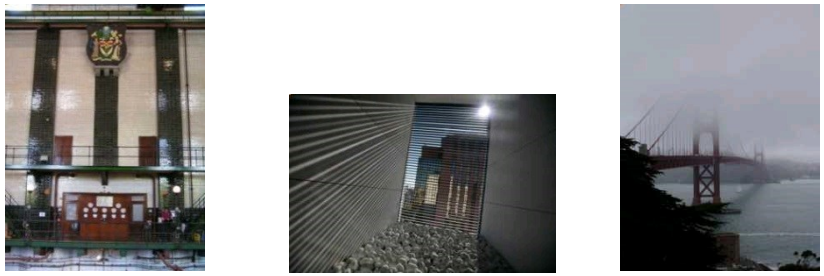
Database size: 10 images
Relevant (total): 5 images

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



Results (ordered):





Slide credit: Ondrej Chum

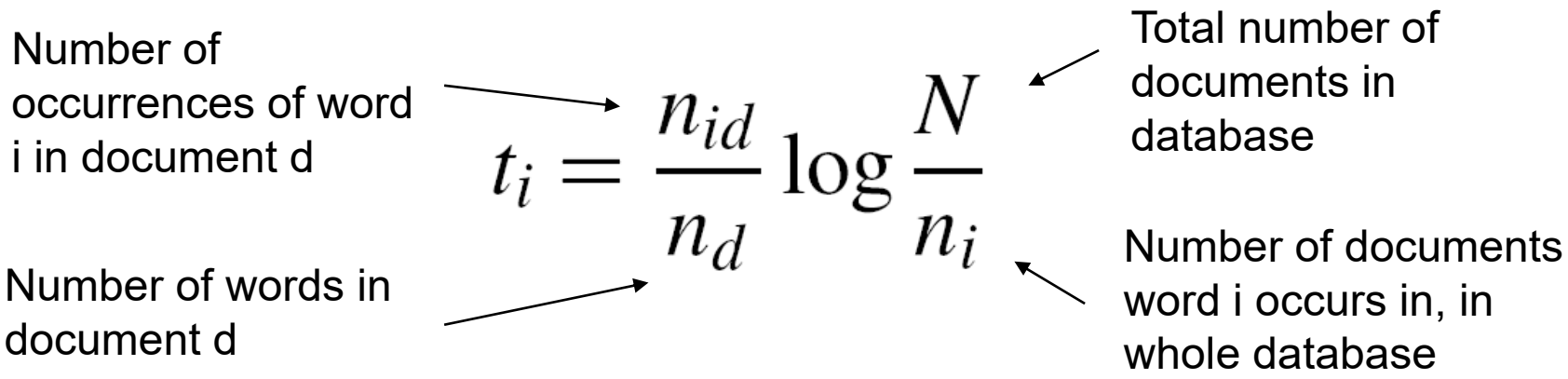
What else can we borrow from text retrieval?

Index

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
agrees
yuan i
goverr
also n
demar
countr
yuan a
permit
the US
freely.
it will t
allowir

tf-idf weighting

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



Query expansion

Query: ***golf green***

Results:

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

Slide credit: Ondrej Chum

Query expansion

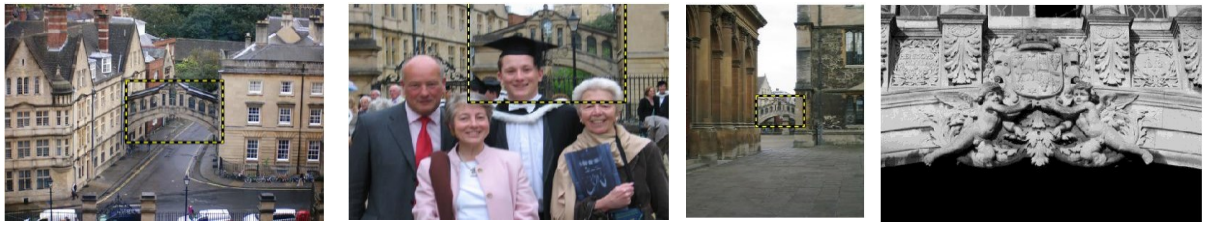
Results

Query image

Spatial verification

New query

New results



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

Recognition Issues

How to summarize the content of an entire image? And gauge overall similarity?

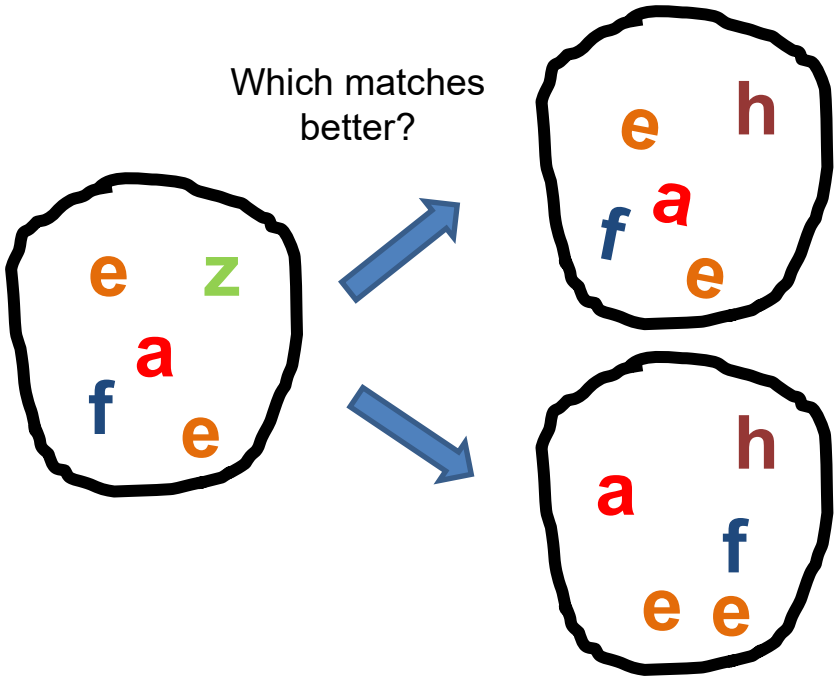
How large should the vocabulary be? How to perform quantization efficiently?

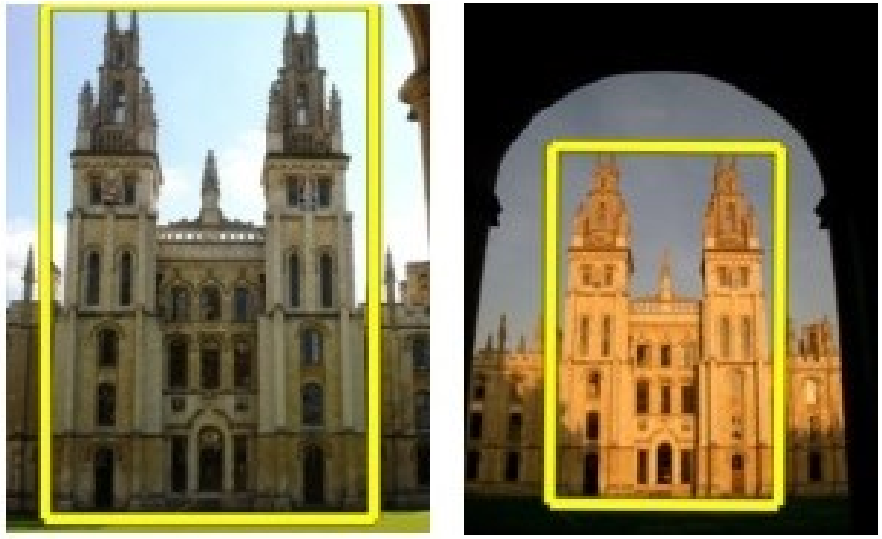
How to score the retrieval results?

How might we add more spatial verification?

Can we be more accurate?

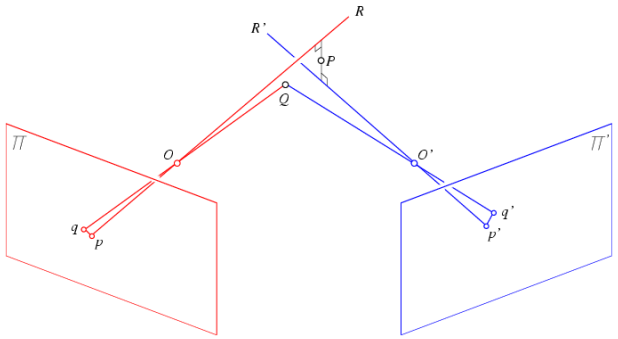
So far, we treat each image as containing a "bag of words", with no spatial information

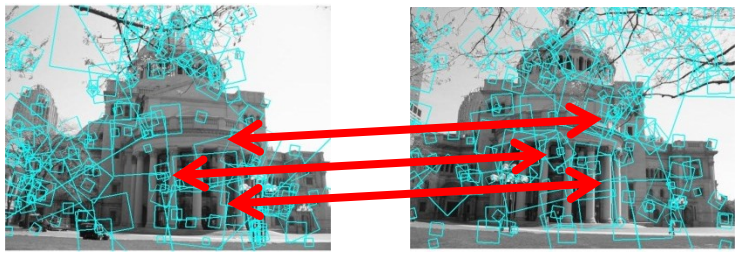




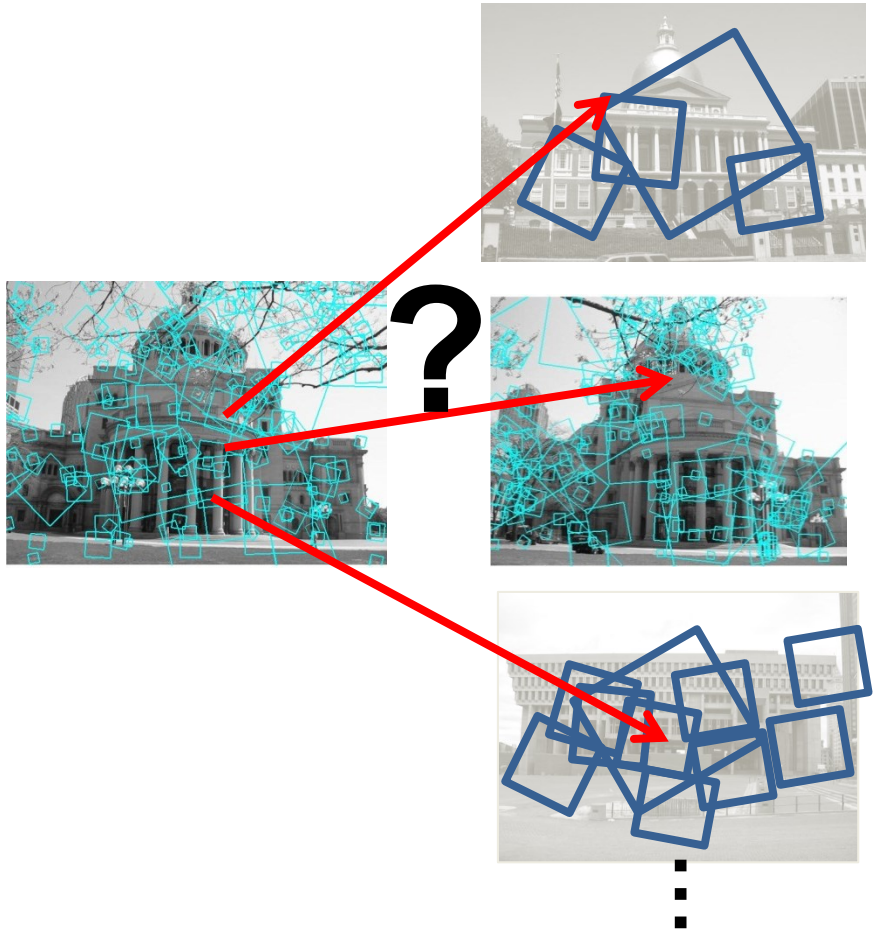
Real objects have consistent geometry

Multi-view matching





vs



Matching two given views for depth

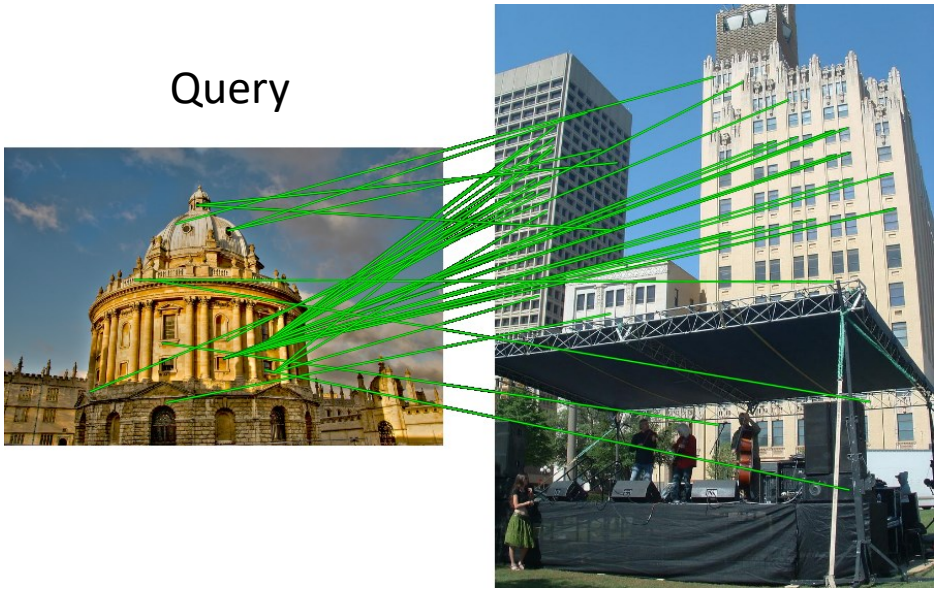
Search for a matching view for recognition

Spatial Verification

Query

DB image with high BoW similarity

Query



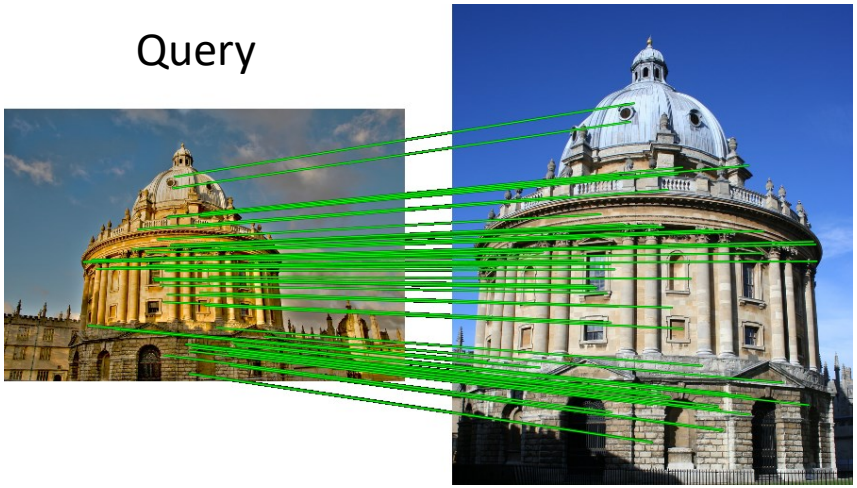
DB image with high BoW similarity

Both image pairs have many visual words in common.

Slide credit: Ondrej Chum

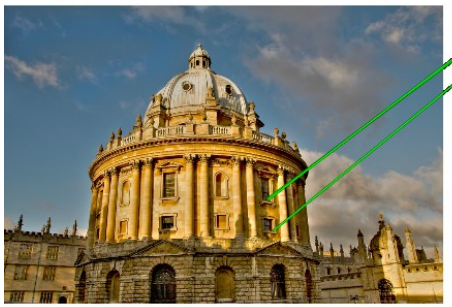
Spatial Verification

Query



DB image with high BoW similarity

Query



DB image with high BoW similarity

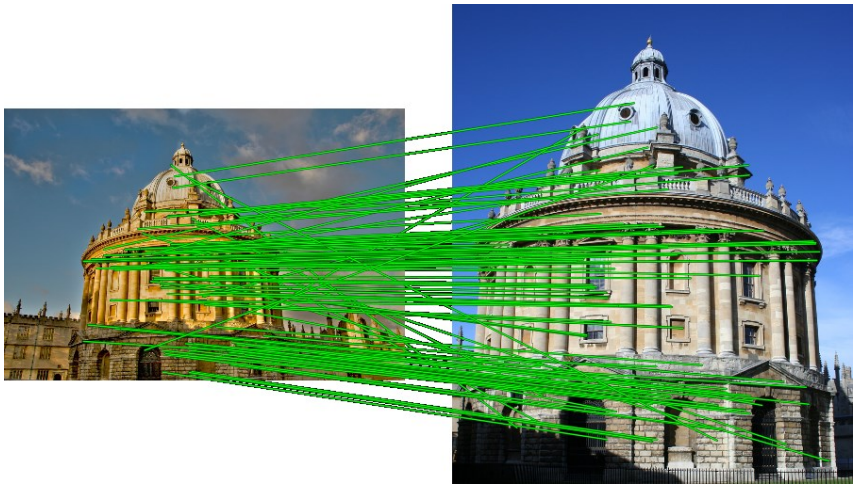
Only some of the matches are mutually consistent with real-world geometry imaged by a camera.

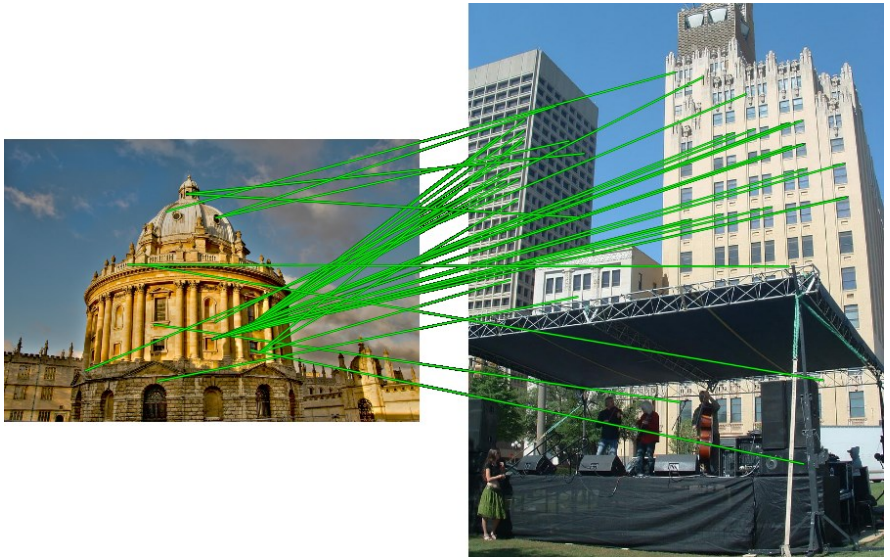
Spatial Verification: two basic strategies

- 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

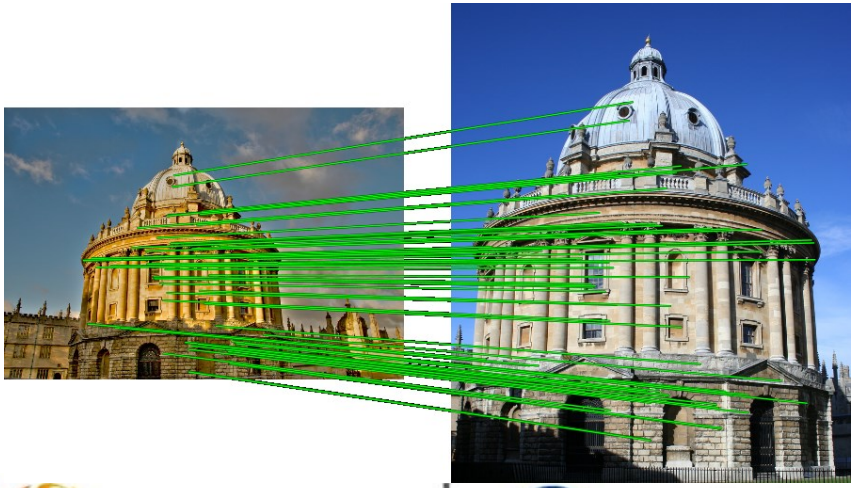
- Generalized Hough Transform
  - Let each matched feature cast a vote on location, scale, orientation of the model object
  - Verify parameters with enough votes

No verification

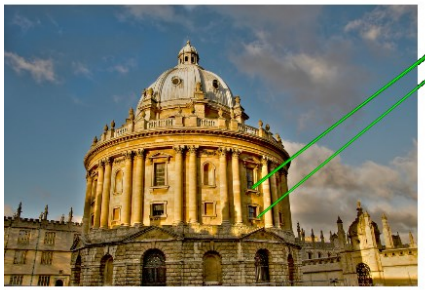




RANSAC verification



Fails to meet threshold on # inliers! Good!



Recognition via alignment

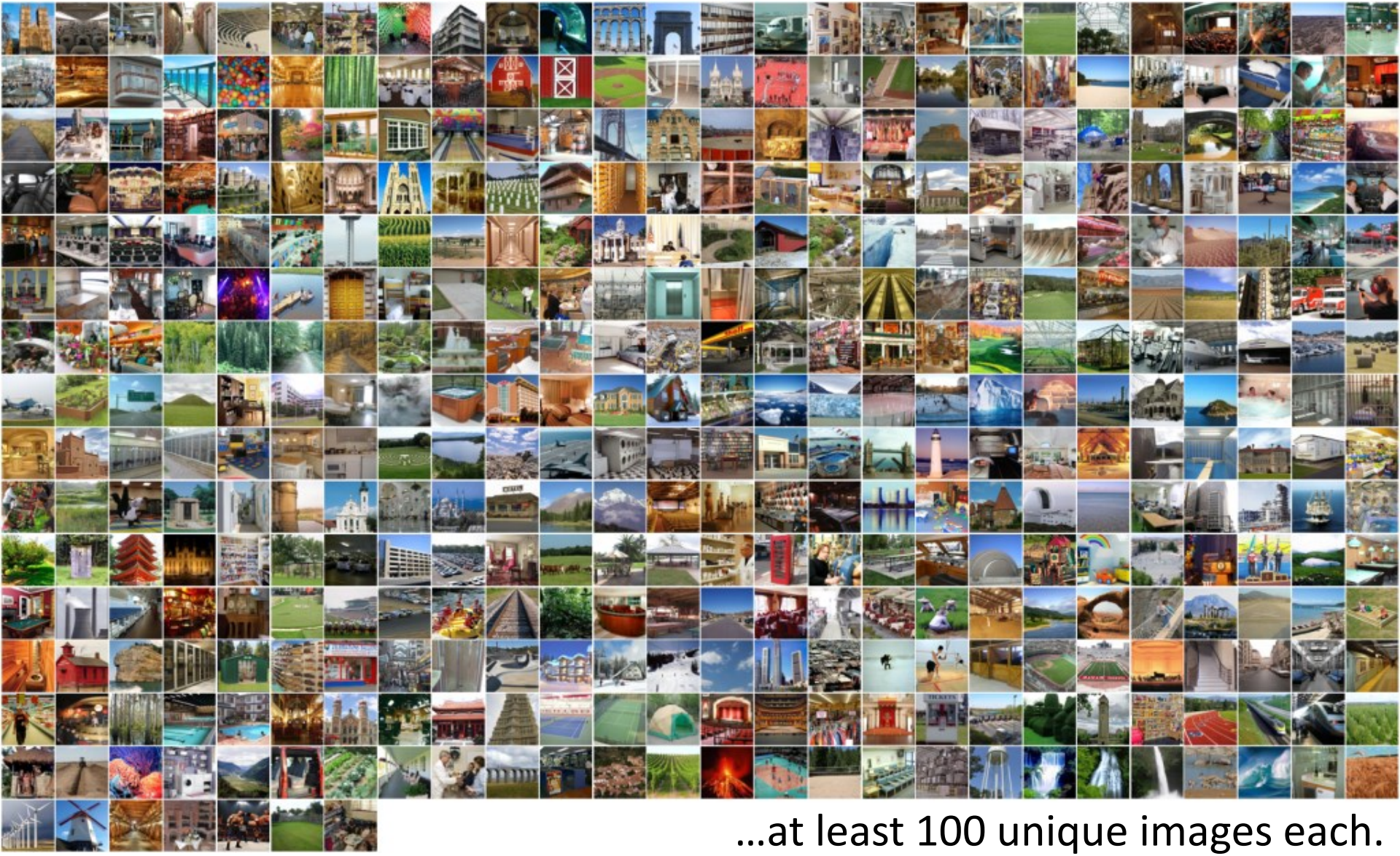
Pros:

– Effective for reliable features within clutter
– Great for matching specific instances

Cons:

– Expensive post-process (how long for proj3?!)
– Not suited for category recognition

397 Well-sampled Categories



…at least 100 unique images each.

Evaluating Human Scene Classification

?

Accuracy	98%	90%	68%

bathroom(100%)

beauty salon(100%)

bedroom(100%)

bullring(100%)

playground(100%)

phone booth(100%)

greenhouse outdoor(100%)

podium outdoor(100%)

tennis court outdoor(100%)

wind farm(100%)

veterinarians office(100%)

riding arena(100%)

Scene category

Most confusing categories

Inn (0%)

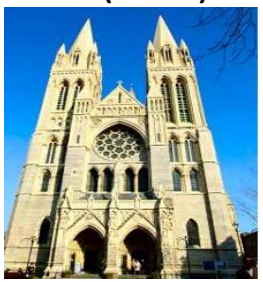
Bayou (0%)

Basilica (0%)

Restaurant patio (44%)

River (67%)

Cathedral(29%)



Chalet (19%)

Coast (8%)

Courthouse (21%)

Conclusion: humans can do it

- The SUN database is reasonably consistent and categories can be told apart by humans.

- With many very specific categories, humans get it right 2/3rds of the time *from experience and from exploring the label space.*

So, how do humans classify scenes?

How do we classify scenes?

Ceiling
Light
Door
Door
Door
Wall
Door
Wall
Door
Floor

Ceiling
Lamp
Painting
mirror
mirror
wall
Fireplace
armchair
armchair
Coffee table

wall
painting
wall
Lamp
phone
alarm
Bed
Side-table
carpet

Different objects, different spatial layout

Which are the important elements?

cabinets ceiling cabinets window window window seat seat seat seat seat seat seat seat

cabinets ceiling cabinets window seat seat window seat seat seat seat seat seat

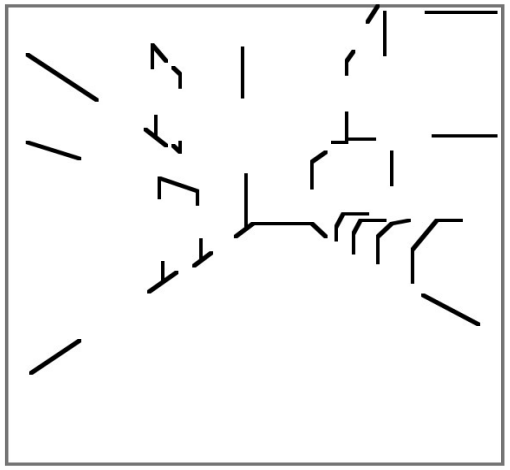
ceiling wall column screen seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat

Similar objects, and similar spatial layout

Different lighting, different materials, different “stuff”

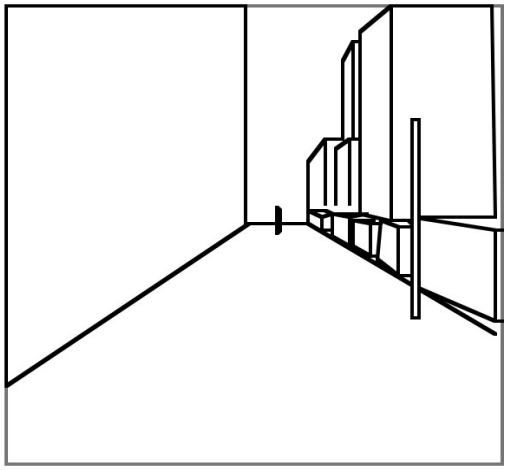
Scene emergent features

"Recognition via features that are not those of individual objects but "emerge" as objects are brought into relation to each other to form a scene." – Biederman 81



Biederman, 1981

Suggestive edges and junctions



Biederman, 1981

Simple geometric forms

Bruner and Potter, 1969

Blobs

Oliva and Torralba, 2001

Textures

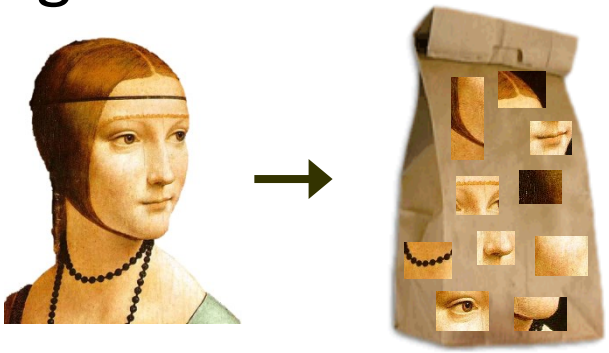
Global Image Descriptors

- Tiny images (Torralba et al, 2008)
- Color histograms
- Self-similarity (Shechtman and Irani, 2007)
- Geometric class layout (Hoiem et al, 2005)
- Geometry-specific histograms (Lalonde et al, 2007)
- Dense and Sparse SIFT histograms
- Berkeley texton histograms (Martin et al, 2001)
- HoG 2x2 spatial pyramids
- Gist scene descriptor (Oliva and Torralba, 2008)

Texture Features

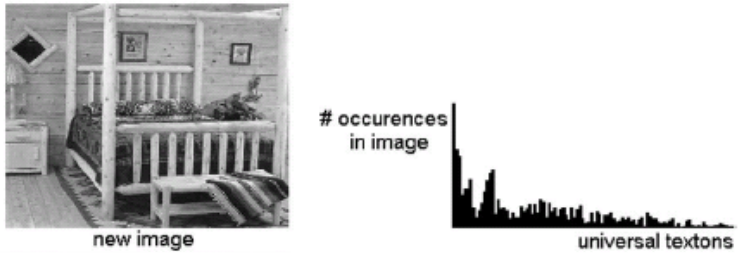
Global Texture Descriptors

Bag of words



Sivic et. al., ICCV 2005
Fei-Fei and Perona, CVPR 2005

Non-localized textons

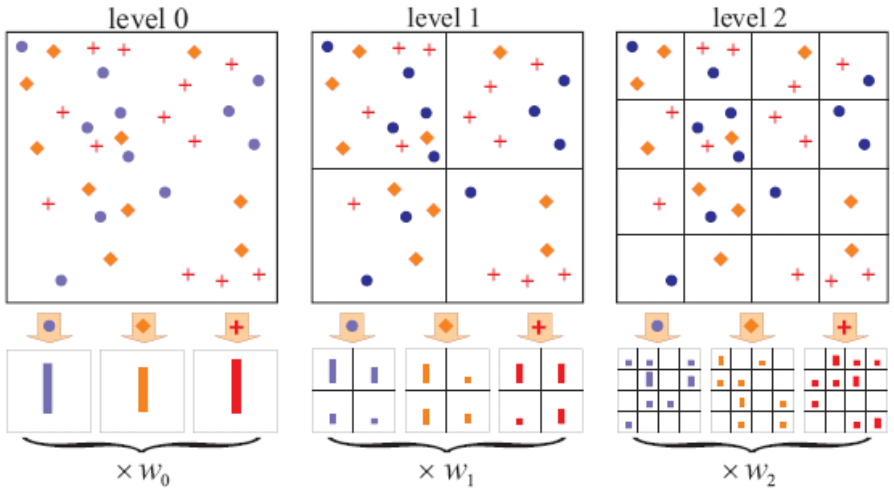


Walker, Malik. Vision Research 2004

...

Spatially organized textures

M. Gorkani, R. Picard, ICPR 1994
A. Oliva, A. Torralba, IJCV 2001



S. Lazebnik, et al, CVPR 2006

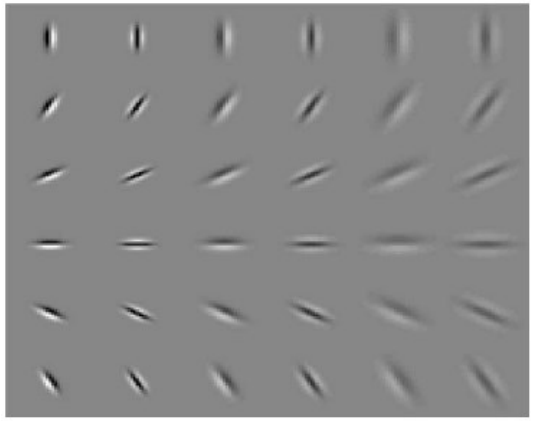
...

R. Datta, D. Joshi, J. Li, and J. Z. Wang, **Image Retrieval: Ideas, Influences, and Trends of the New Age**, *ACM Computing Surveys*, vol. 40, no. 2, pp. 5:1-60, 2008.

Textons

Vector of filter responses at each pixel

Kmeans over a set of vectors on a collection of images

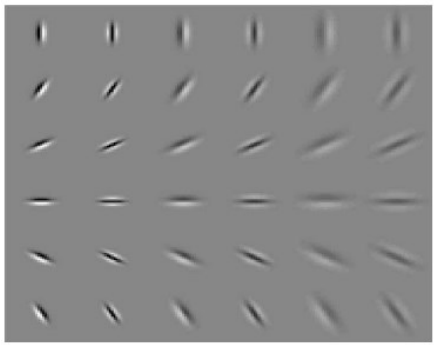


Filter bank

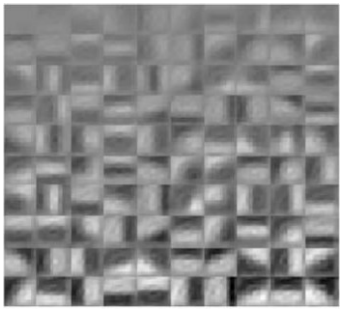
Malik, Belongie, Shi, Leung, 1999

Textons

Filter bank

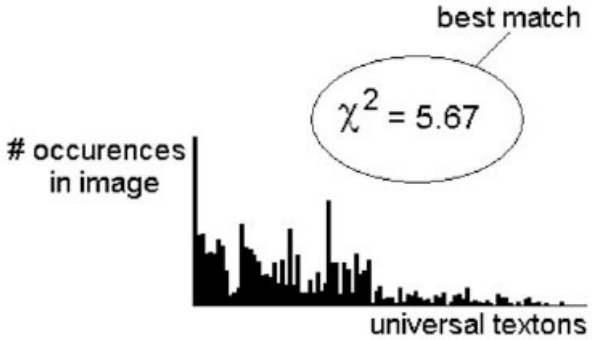


K-means (100 clusters)

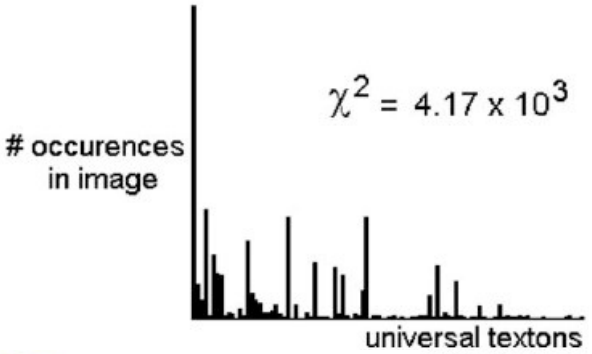


Malik, Belongie, Shi, Leung, 1999

label = bedroom



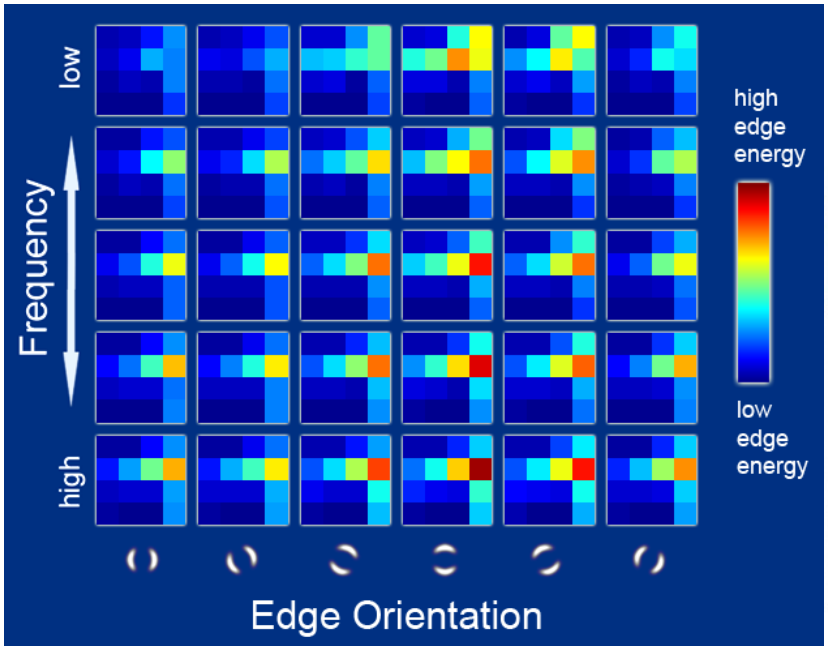
label = beach



Walker, Malik, 2004

Global scene descriptors: GIST

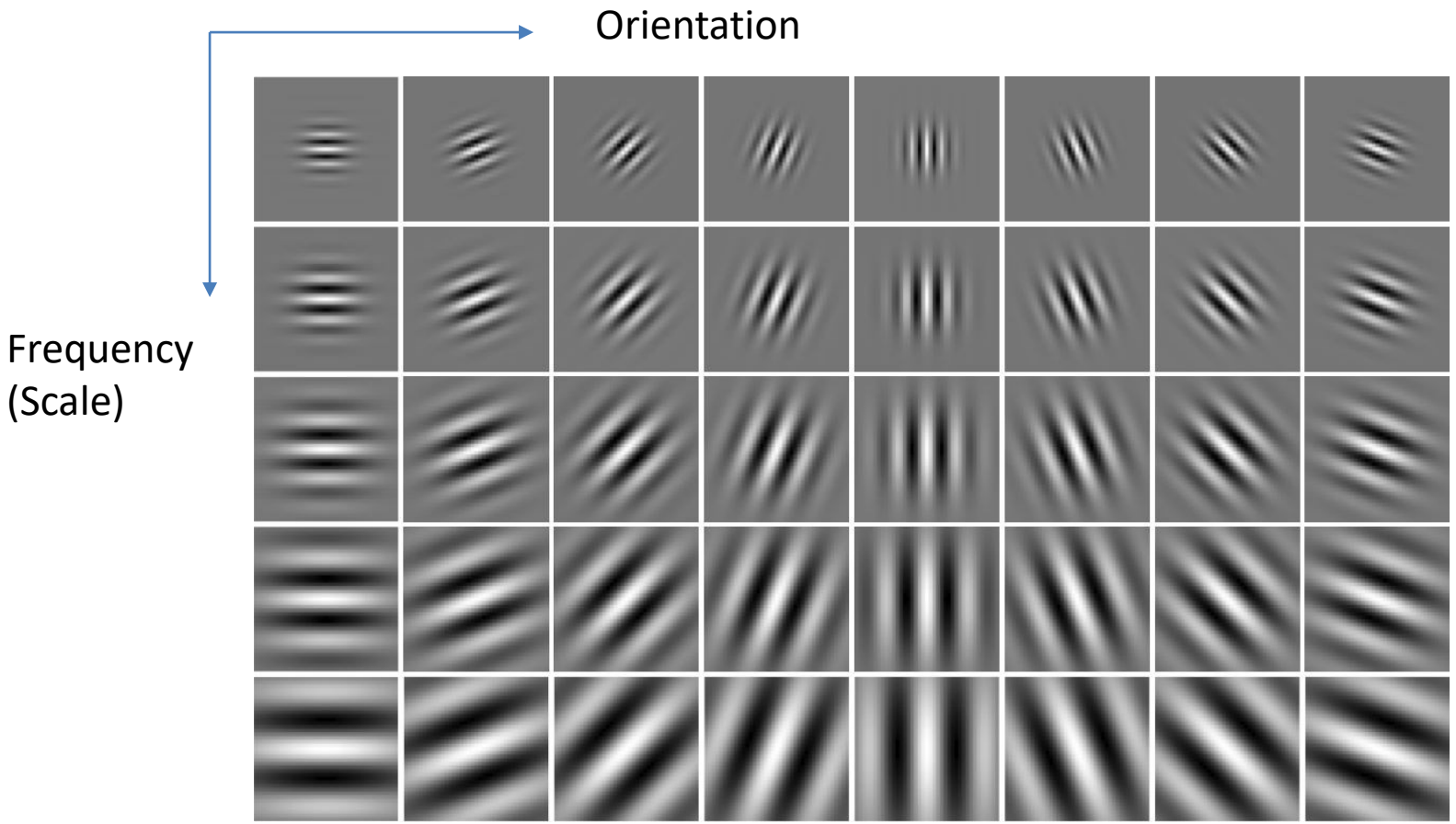
- The “gist” of a scene: Oliva & Torralba (2001)



http://people.csail.mit.edu/torralba/code/spatialenvelope/

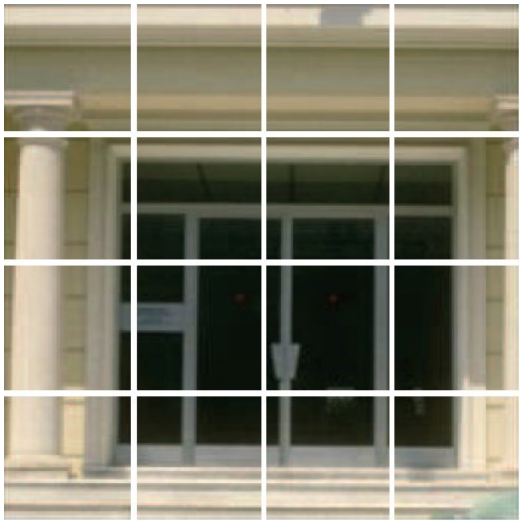
Gabor filter

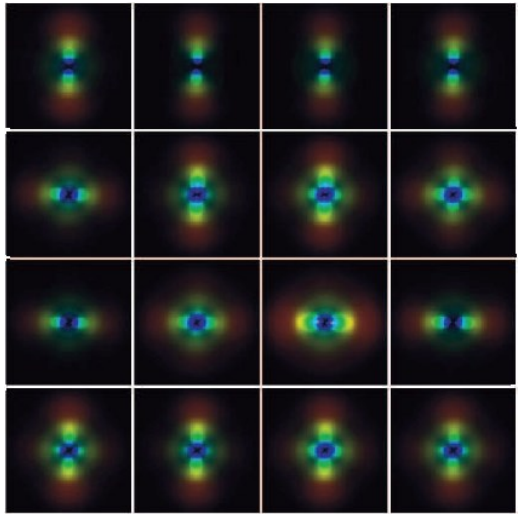
- Sinusoid modulated by a Gaussian kernel

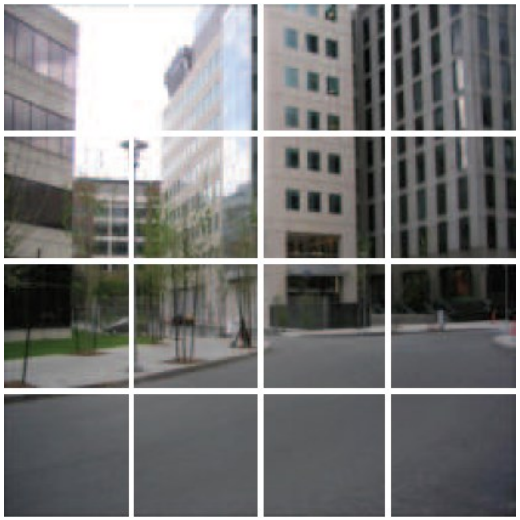


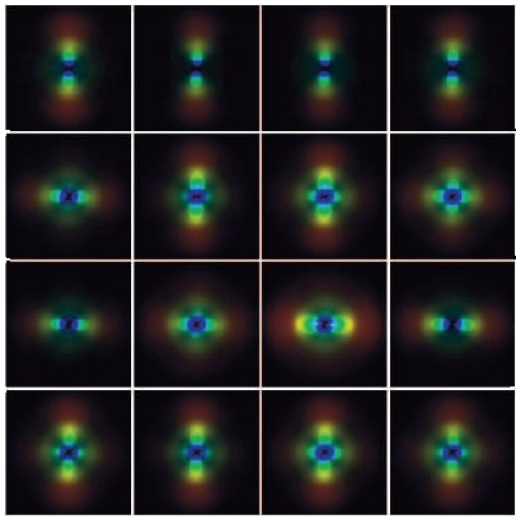
Gist descriptor

Oliva and Torralba, 2001









Apply oriented Gabor filters over different scales.

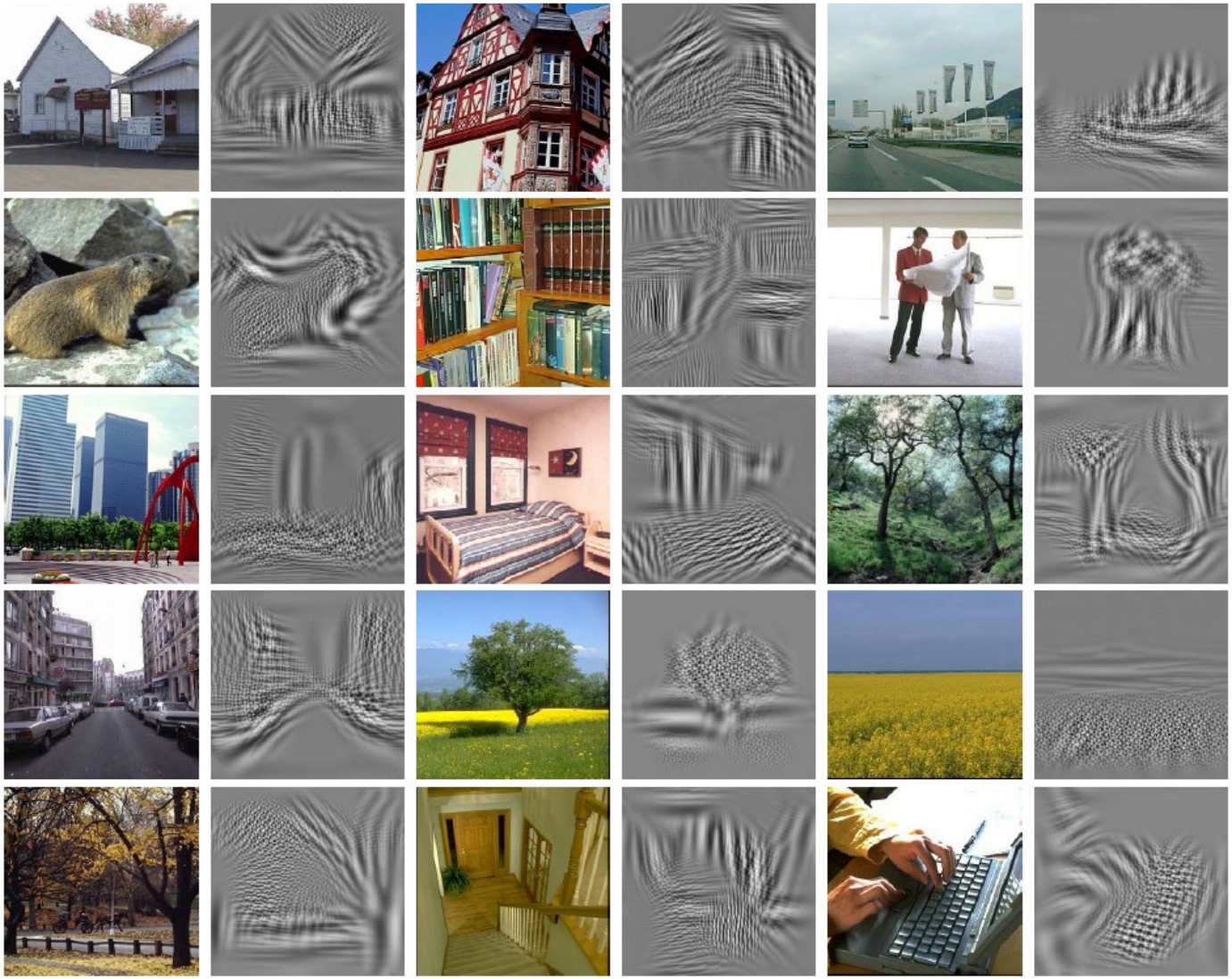
Average filter energy per bin.

Similar to SIFT (Lowe 1999) applied to the entire image.

8	orientations
4	scales
x 16	bins
512	dimensions

M. Gorkani, R. Picard, ICPR 1994; Walker, Malik. Vision Research 2004; Vogel et al. 2004; Fei-Fei and Perona, CVPR 2005; S. Lazebnik, et al, CVPR 2006; …

Example visual gists



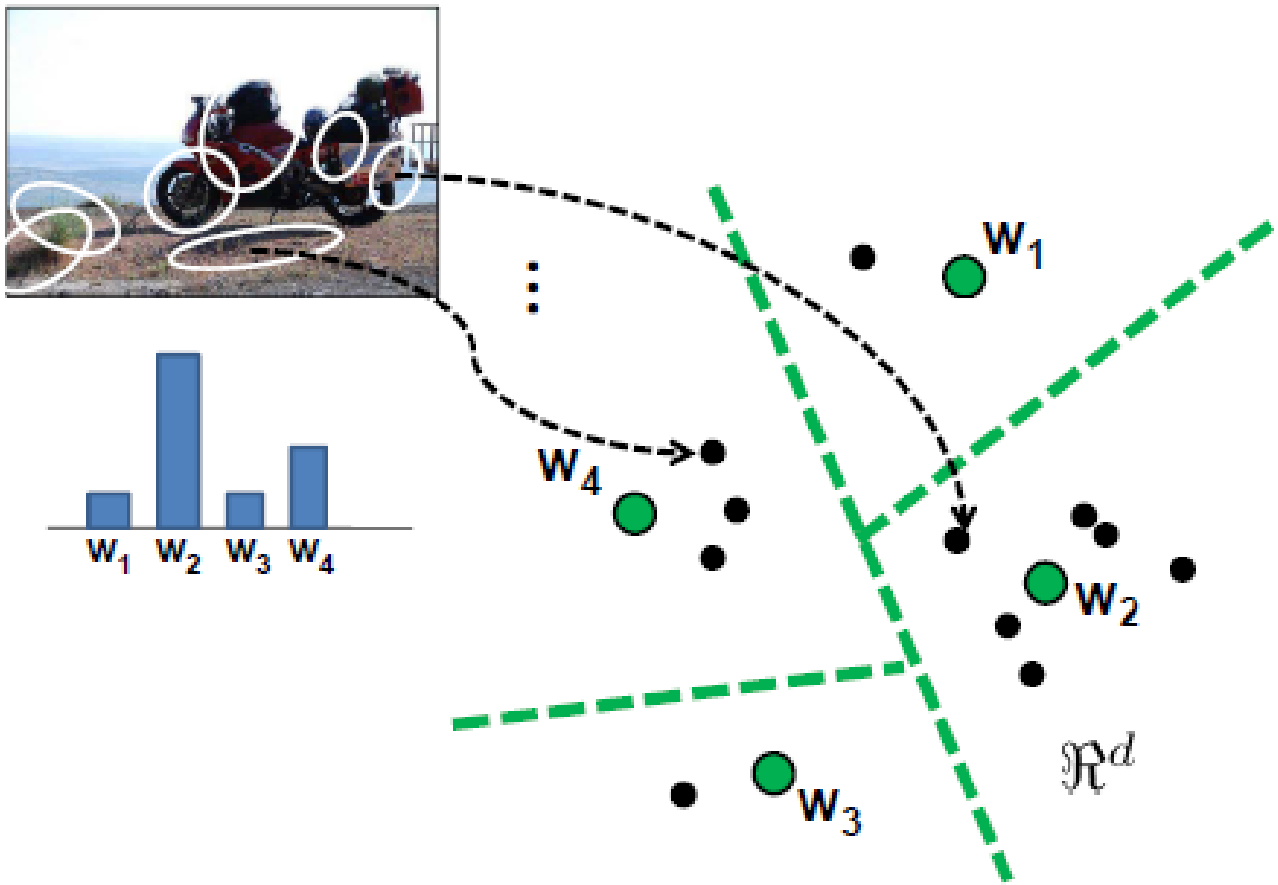
Global features (I) ~ global features (I’)

Oliva & Torralba (2001)

Better Bags of Visual Features

- More advanced quantization / encoding methods that are near the state-of-the-art in image classification and image retrieval.
  - Mixtures of Gaussians
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD – Vectors of Locally-Aggregated Descriptors
- Deep learning has taken attention away from these methods…

Standard Kmeans Bag of Words

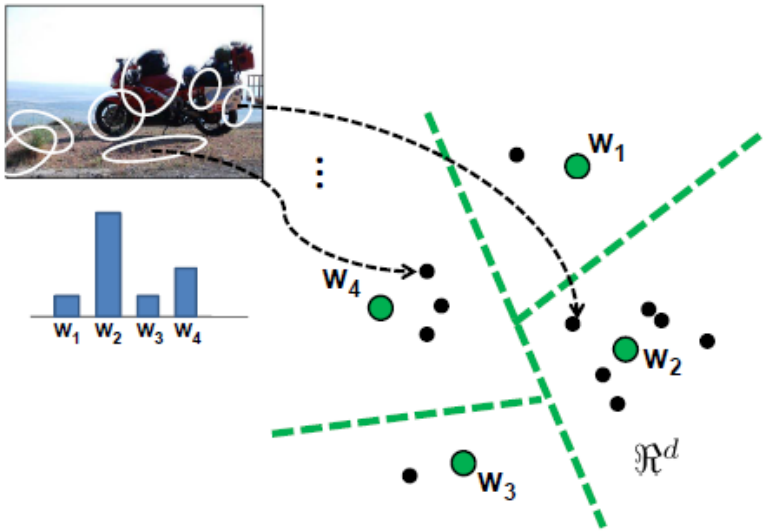


http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

•*Bag of Visual Words* is only about **counting** the number of local descriptors assigned to each Voronoi region

- Why not in**stics**?



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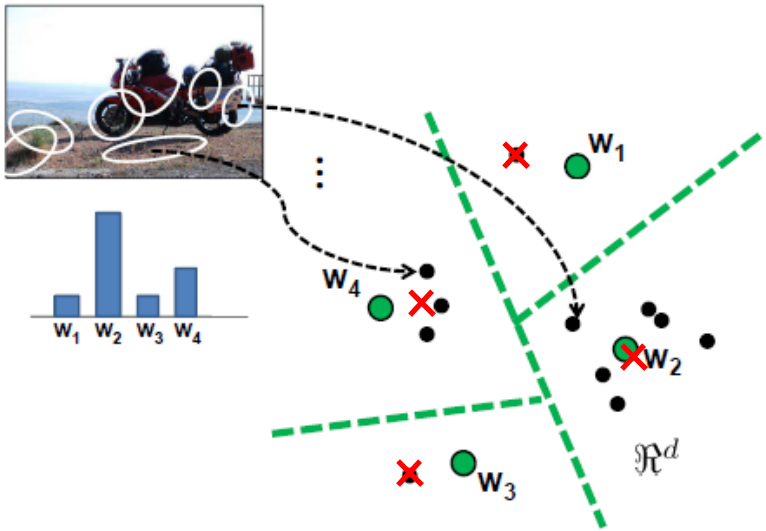
  - mean c



http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

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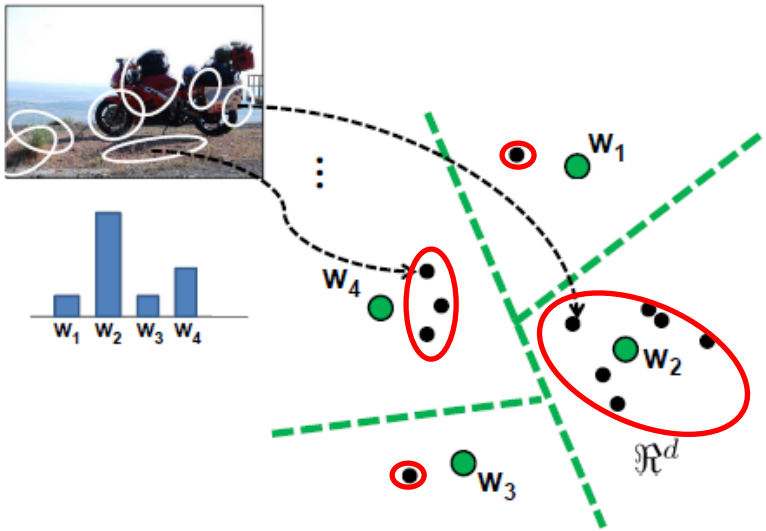
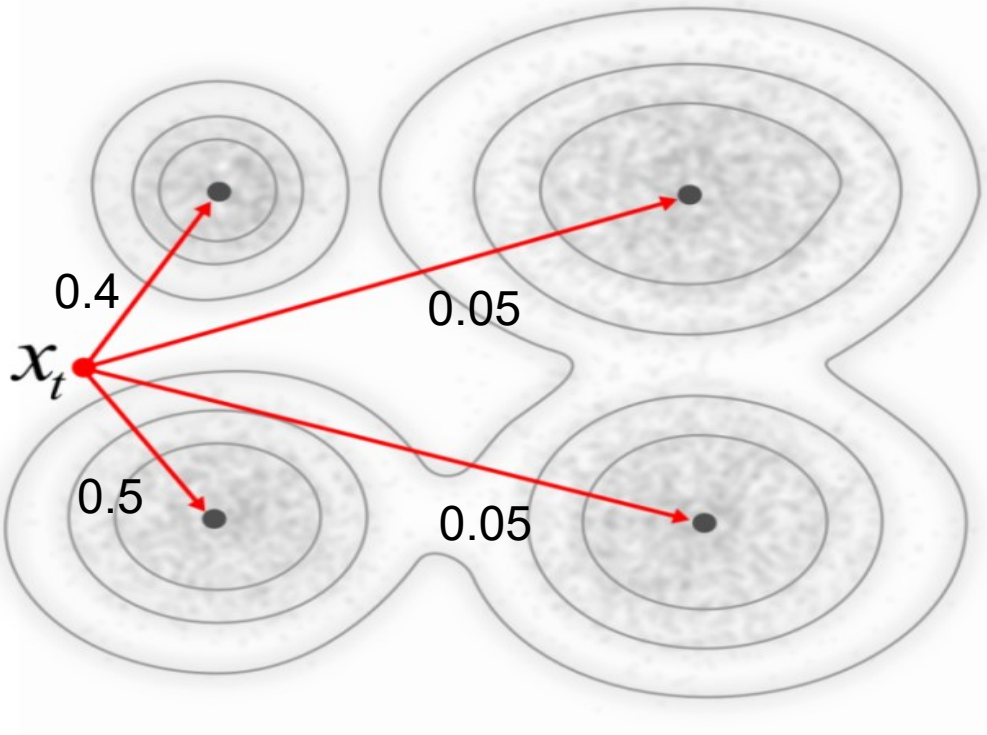
  - mean c
  - (co)var



http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

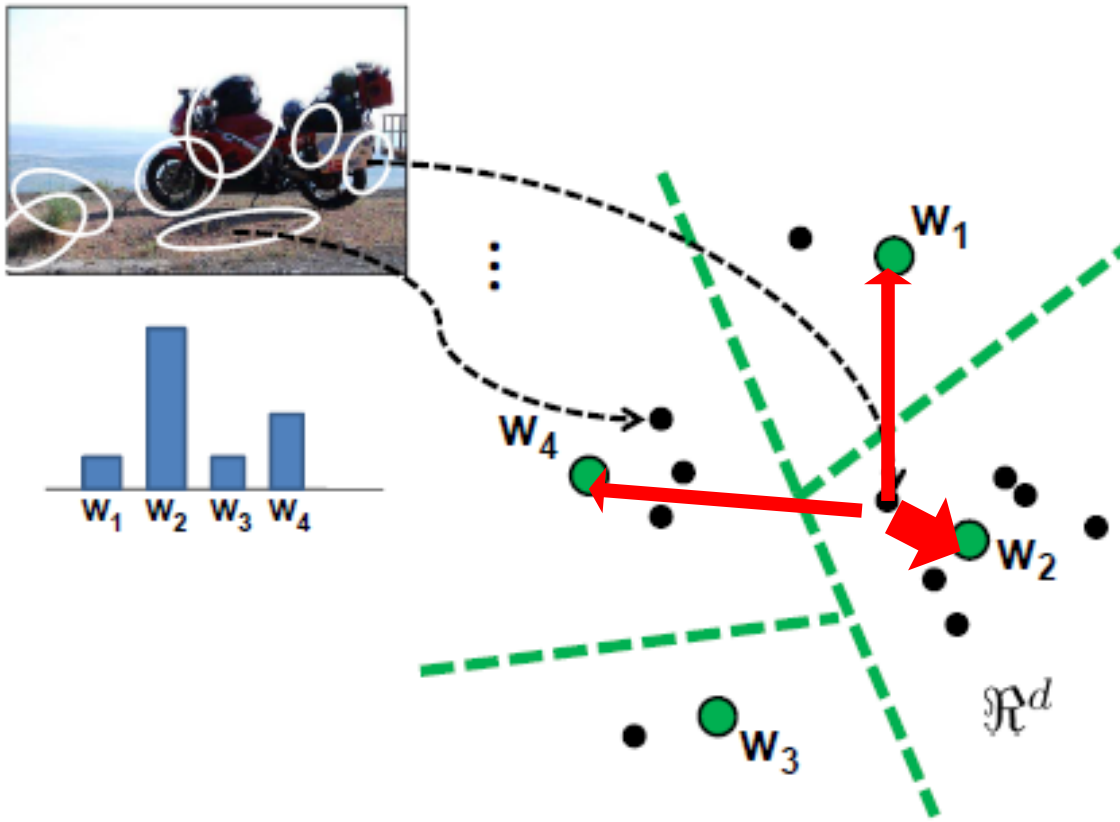
Mixture of Gaussians (GMM)

- GMM can be thought of as “soft” kmeans.
- Each component has a mean and a standard deviation along each direction (or full cov
- Can ea distribu



Simple case: Soft Assignment

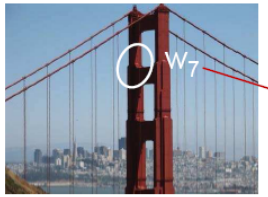
- “Kernel codebook encoding” by Chatfield et al. 2011.
- Cast) to *n* mos e ‘hard’ vote



Simple case: Soft Assignment

- “Kernel codebook encoding” by Chatfield et al. 2011.
- Cast a set of proportional votes (weights) to *n* most similar clusters, rather than a single ‘hard’ vote.

- This is fast and easy to ir ‹es an inverted file index *less*



New query image

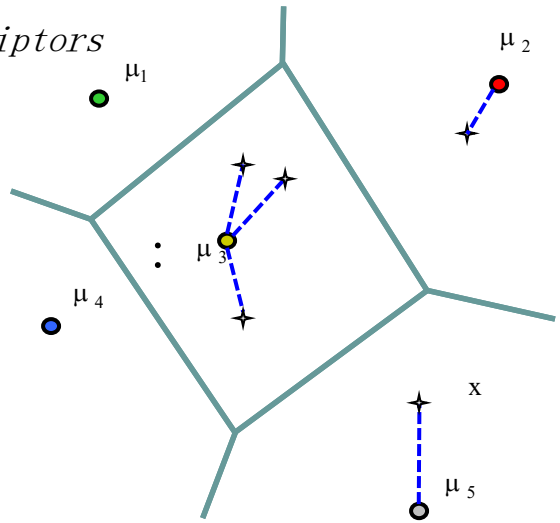
Word #	Image #
1	3
2	
7	1, 2
8	3
9	
10	
91	2

VLAD – Vectors of Locally-Aggregated Descriptors

Given a codebook $\{\mu_i, i = 1 \ldots N\}$, e.g. learned with K-means, and a set of local descriptor $X = \{x_t, t = 1 \ldots T\}$

- ① assign $NN(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$

① *assign descriptors*



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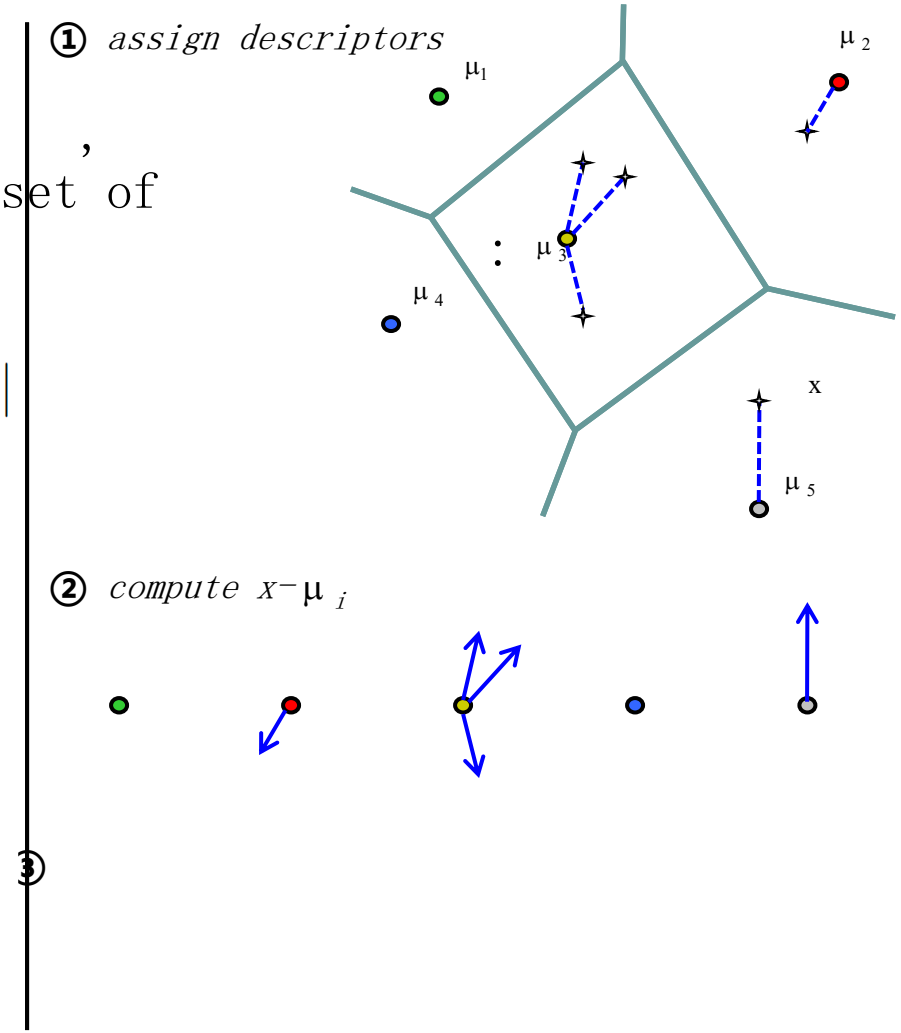
- ① assign $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$
- ②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$



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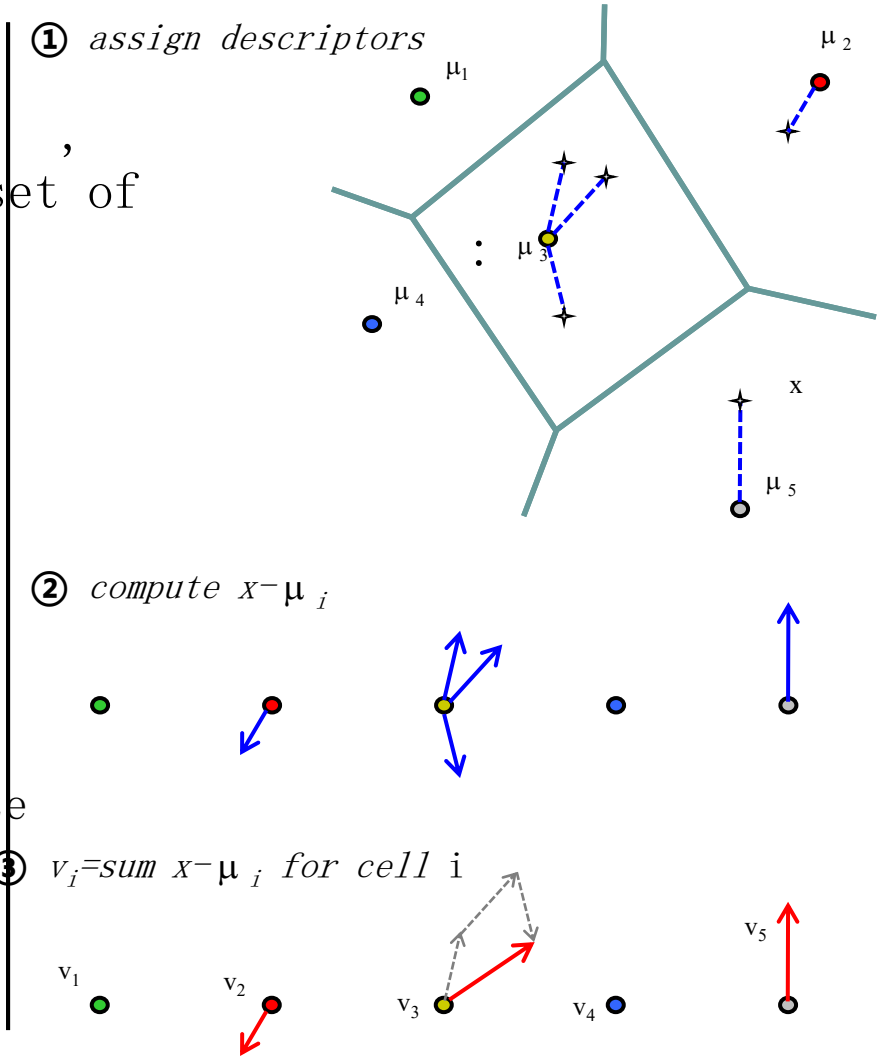
- ②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$
- concatenate v_i's, ℓ_2 normalize



Jégou, Douze, Schmid and Pérez, "Aggregating local descriptors into a compact image representation" CVPR'10.

A first example: the VLAD

A graphical representation $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$

Jégou, Douze, Schmid and Pérez, "Aggregating local descriptors into a compact image representation" CVPR' 10.

Summary

- **Bag of words**: quantize feature space into discrete visual words
  - Summarize image by distribution of words
- **Inverted index**: visual word index for faster query time
- **Evaluation:**
- **Additional spatial verification alignment:**
  - Robust fitting : RANSAC, Generalized Hough Transform
  - We will do this in detail later on in the course

Lessons from a decade later

For *Category* recognition (project 3)

- Bag of Feature models remained the state of the art until Deep Learning.
- Spatial layout either isn't that important or its too difficult to encode.
- Quantization error is, in fact, the bigger problem.
  Advanced feature encoding methods address this.
- Bag of feature models are nearly obsolete.
  At best they seem to be inspiring tweaks to deep models e.g., NetVLAD.

Lessons from a decade later

For *instance* retrieval (this lecture):

- deep learning is taking over.
- learn better local features (replace SIFT)
  e.g., MatchNet 2015
- learn better image embeddings (replace visual word histograms)
  e.g., Vo and Hays 2016.
- learn spatial verification
  e.g., DeTone, Malisiewicz, and Rabinovich 2016.
- learn a monolithic deep network to recognition all locations
  e.g., Google's PlaNet 2016.