CS 558: Computer Vision
10th Set of Notes

Instructor: Philippos Mordohai
Webpage: www.cs.stevens.edu/~mordohai
E-mail: Philippos.Mordohai@stevens.edu
Office: Lieb 215

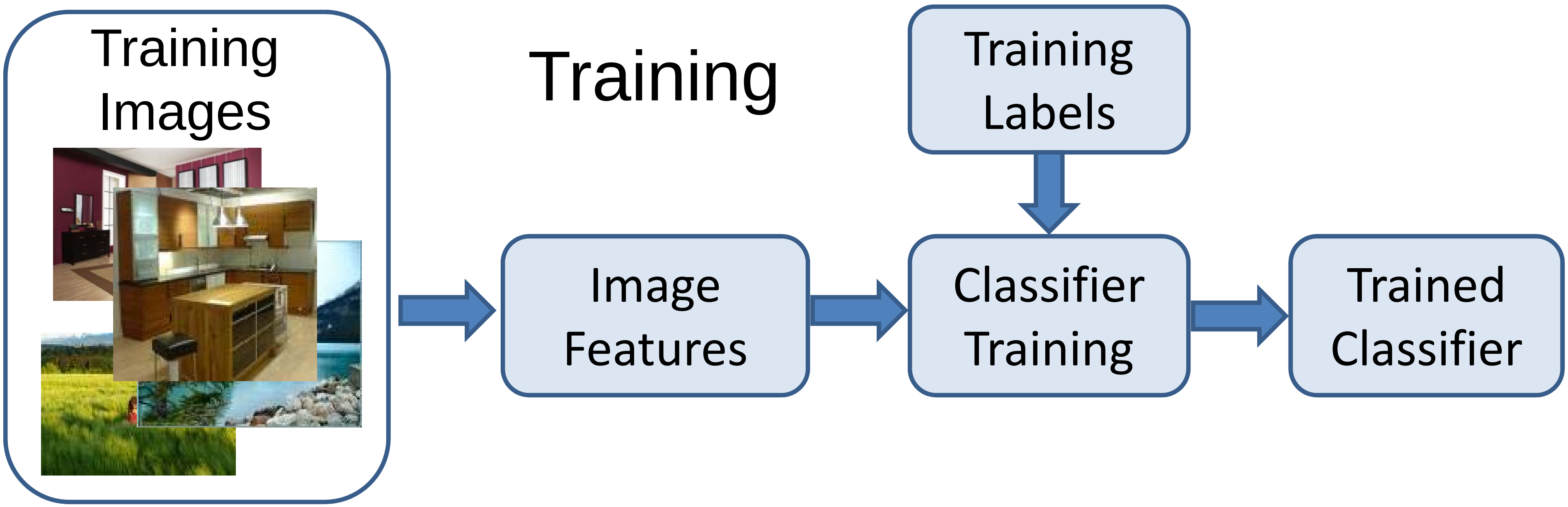
Overview

- Image Features and Categorization
  - Histograms
  - Bags of features/visual words
  - Vocabulary trees
  - Spatial layout and context (preview)

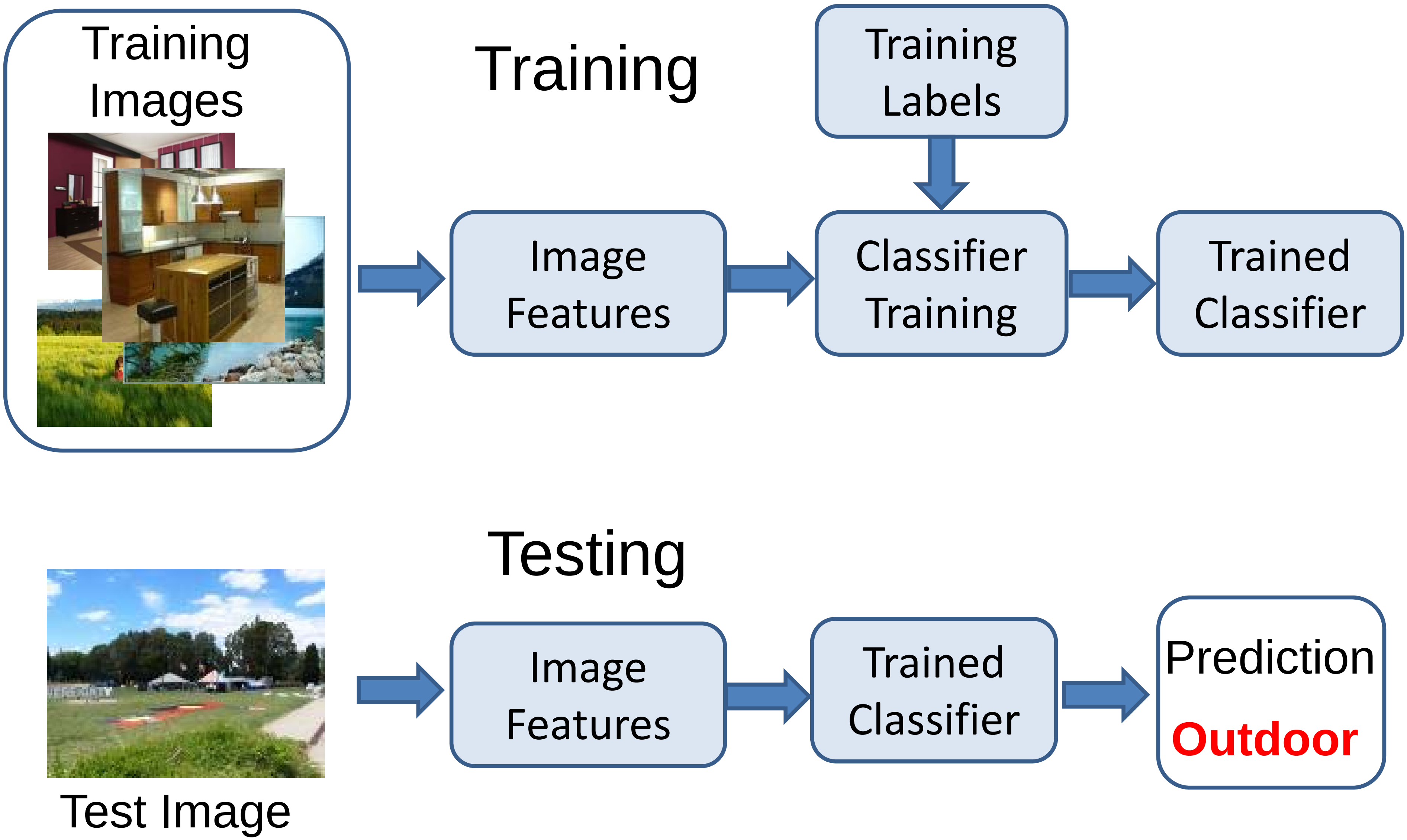
  - Based on slides by K. Grauman, D. Hoiem and S. Lazebnik

Image Features and Categorization

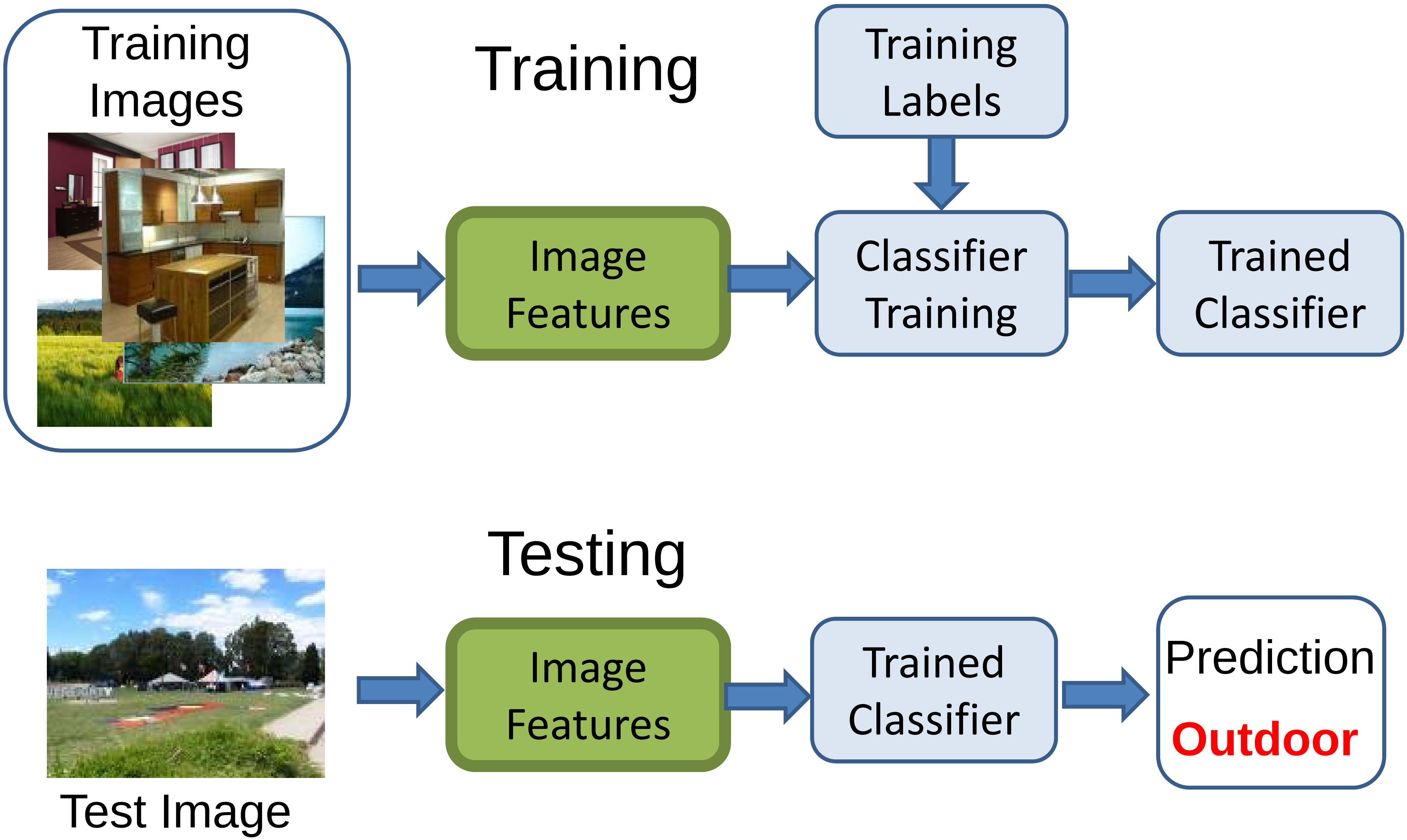
Training phase



Testing phase



Testing phase



Q: What are good features for…

- recognizing a beach?






Q: What are good features for…

- recognizing fabrics?






Q: What are good features for…

- recognizing a mug?






What are the right features?

Depends on what we want to know!

- Object: shape
  - Local shape info, shading, shadows, texture
- Scene : geometric layout
  - linear perspective, gradients, line segments
- Material properties: albedo, feel, hardness
  - Color, texture
- Action: motion
  - Optical flow, tracked points

General Principles of Representation

- Coverage
  - Ensure that all relevant information is captured
- Conciseness
  - Minimize number of features without sacrificing coverage
- Directness
  - Ideal features are independently useful for prediction

Image Representations

- Templates
  - Intensity, gradients, etc.
- Histograms
  - Color, texture, SIFT descriptors, etc.
- Average of features

Image Intensity

Gradient template

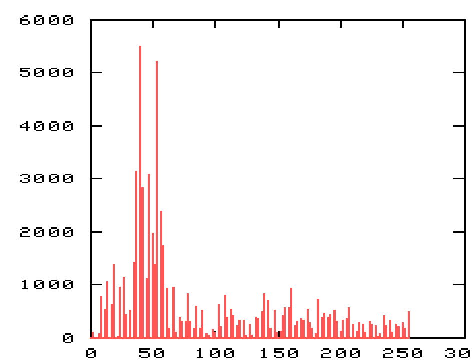
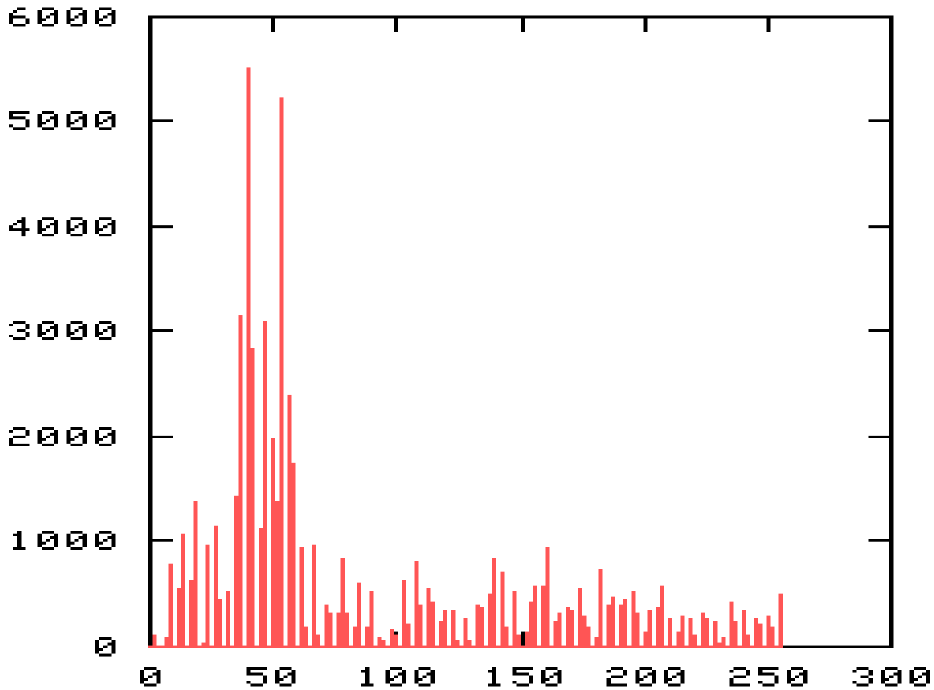
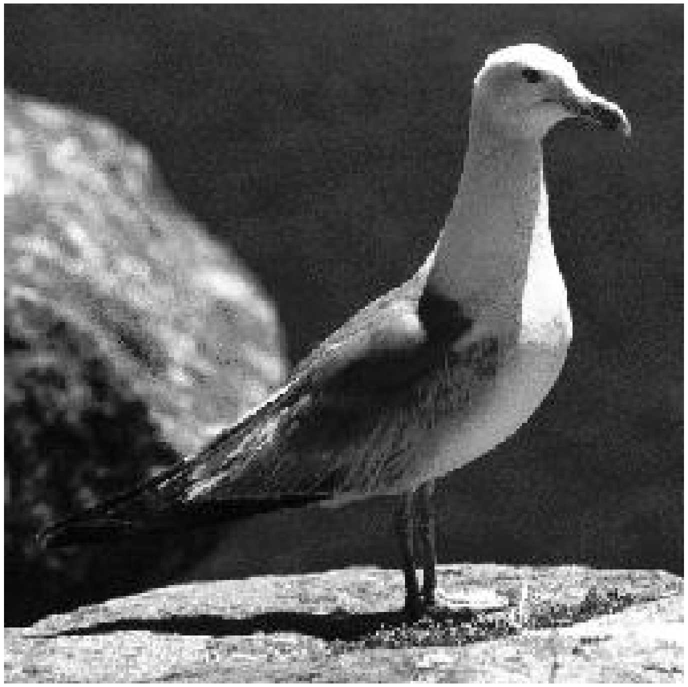


Image representations: histograms





Global histogram

- Represent distribution of features
  – Color, texture, depth, …

Images from Dave Kauchak

Image representations: histograms

- Data samples in 2D

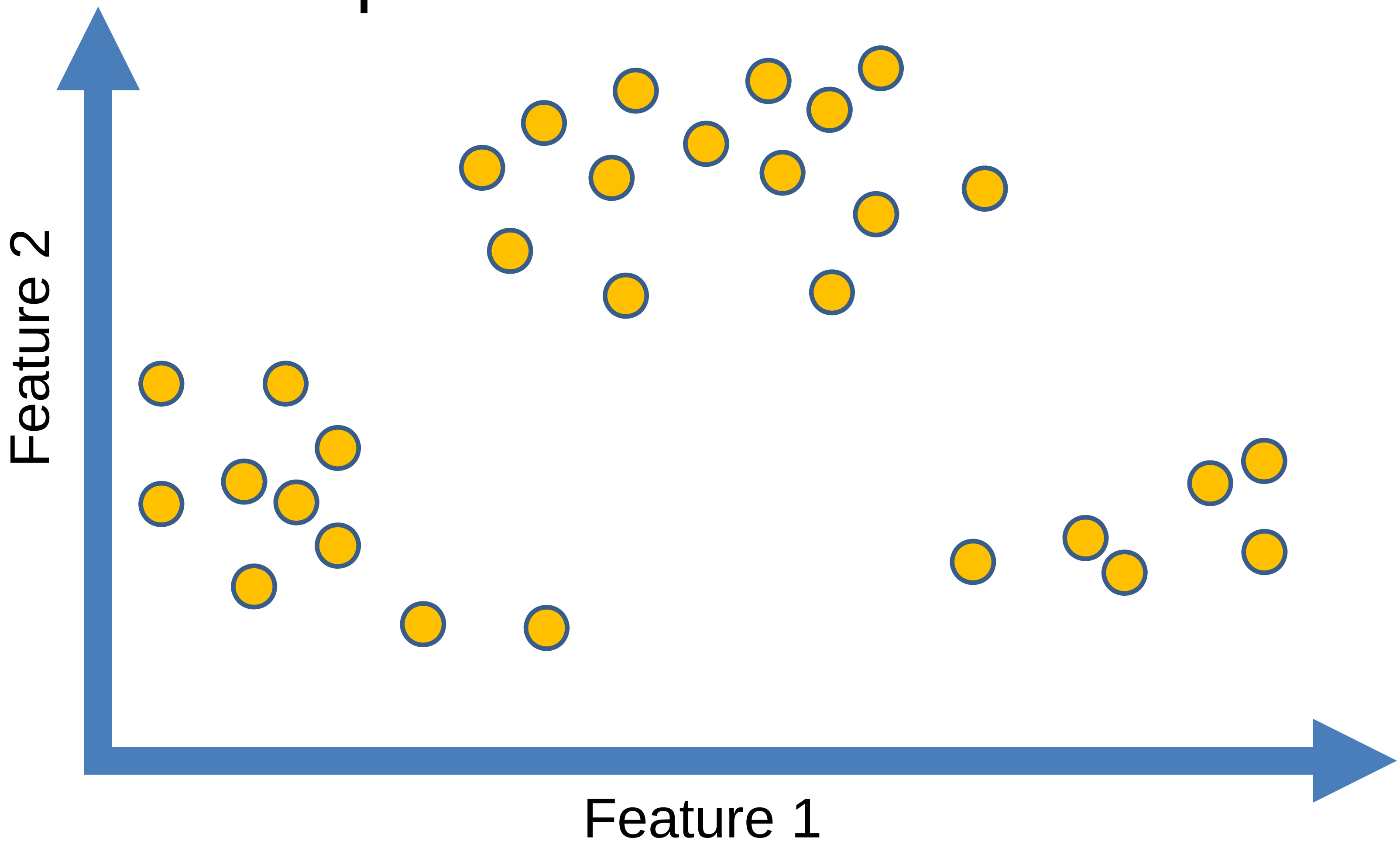


Image representations: histograms

- Probability or count of data in each bin
- Marginal histogram on feature 1

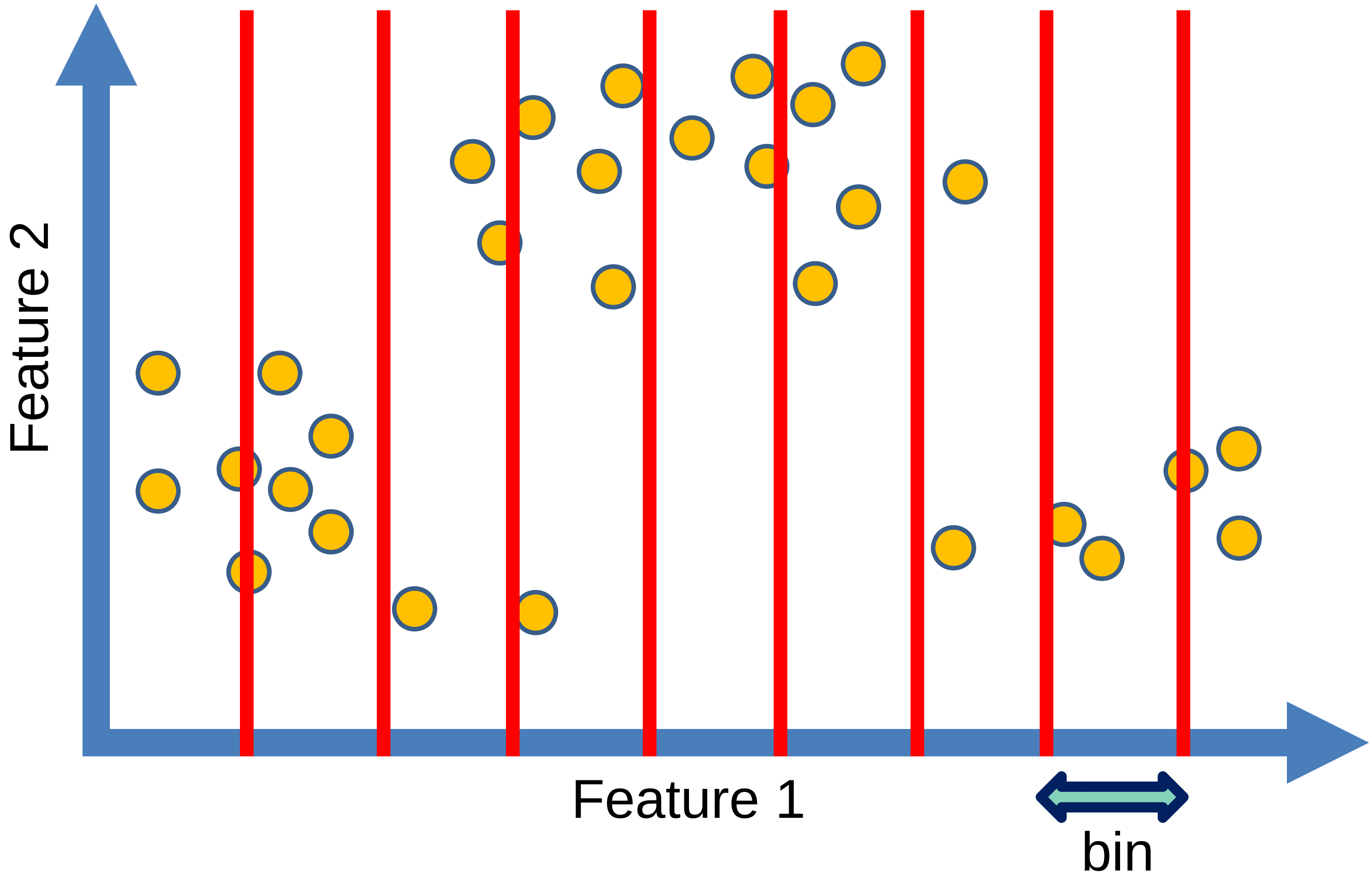


Image representations: histograms

- Marginal histogram on feature 2

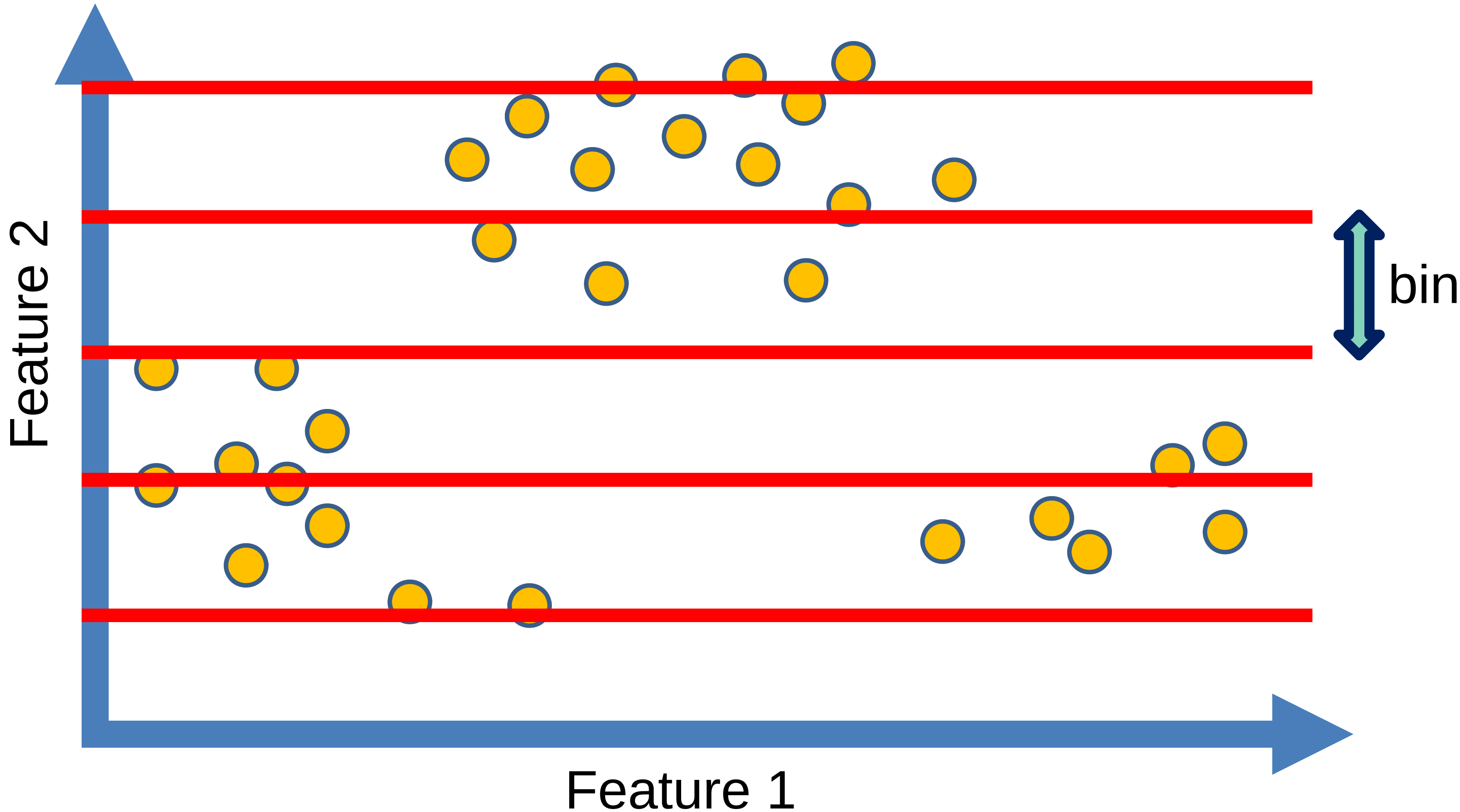
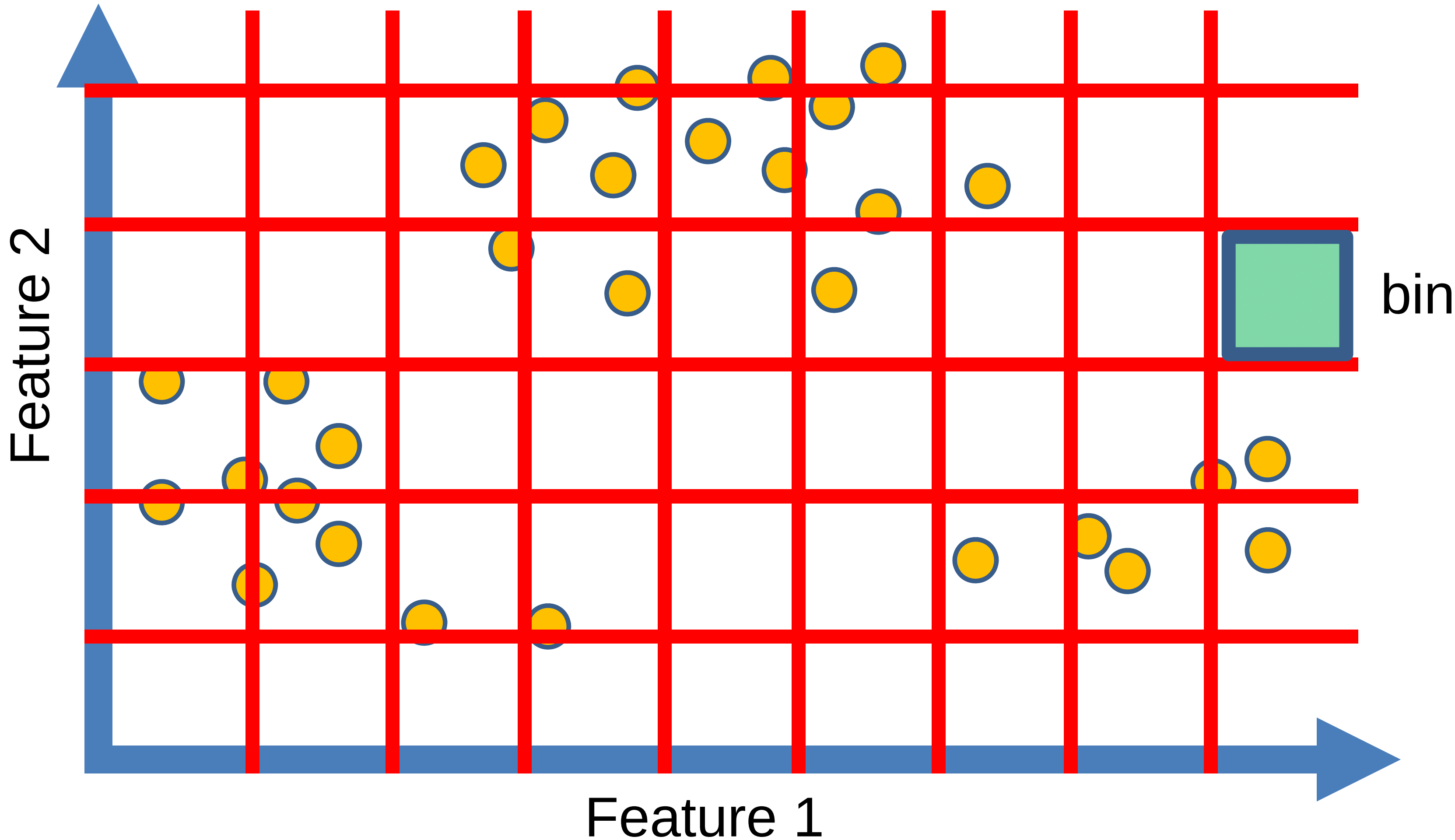
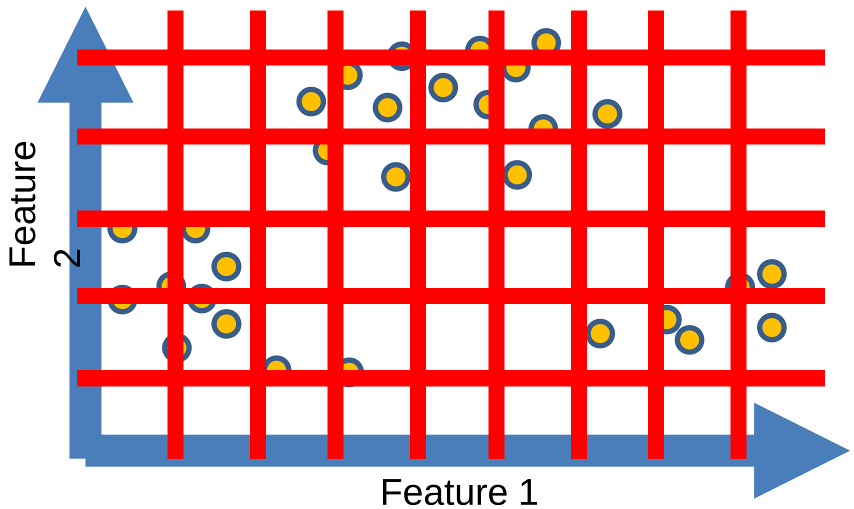


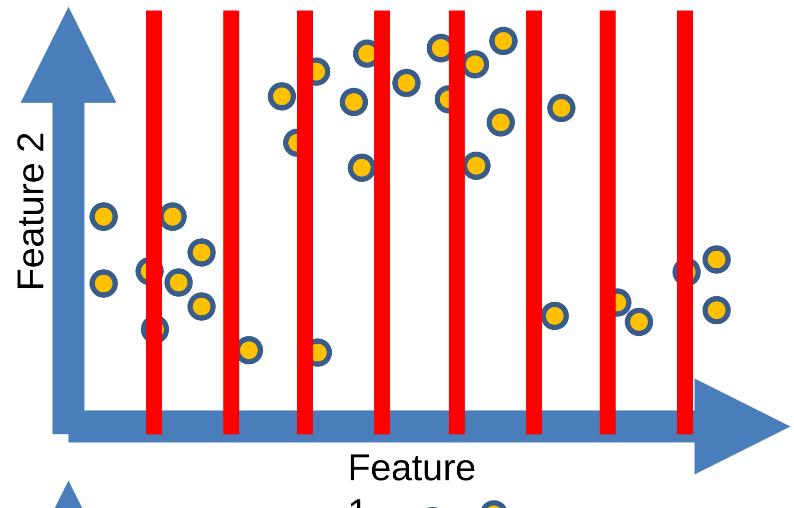
Image representations: histograms

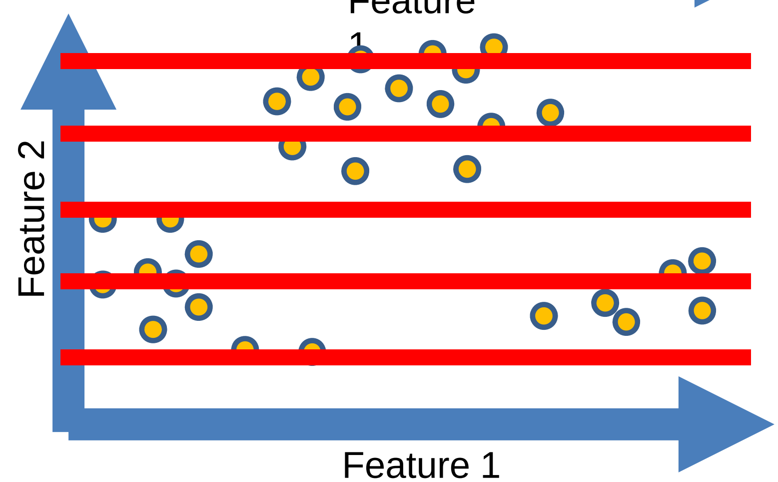
- Joint histogram



Modeling multi-dimensional data







Joint histogram

- Requires lots of data
- Loss of resolution to avoid empty bins

Marginal histogram

- Requires independent features
- More data/bin than joint histogram

Computing histogram distance

- Histogram intersection

$$\text{histint}(h_i, h_j) = 1 - \sum_{m=1}^{K} \min\left(h_i(m), h_j(m)\right)$$

- Chi-squared Histogram matching distance

$$\chi^2(h_i, h_j) = \frac{1}{2} \sum_{m=1}^{K} \frac{[h_i(m) - h_j(m)]^2}{h_i(m) + h_j(m)}$$

- Earth mover's distance
  (Cross-bin similarity measure)
  - minimal cost paid to transform one distribution into the other

[Rubner et al. The Earth Mover's Distance as a Metric for Image Retrieval, IJCV 2000]

Histograms: implementation issues

- Quantization
  - Grids: fast but applicable only with few dimensions
  - Clustering: slower but can quantize data in higher dimensions (see next slides)

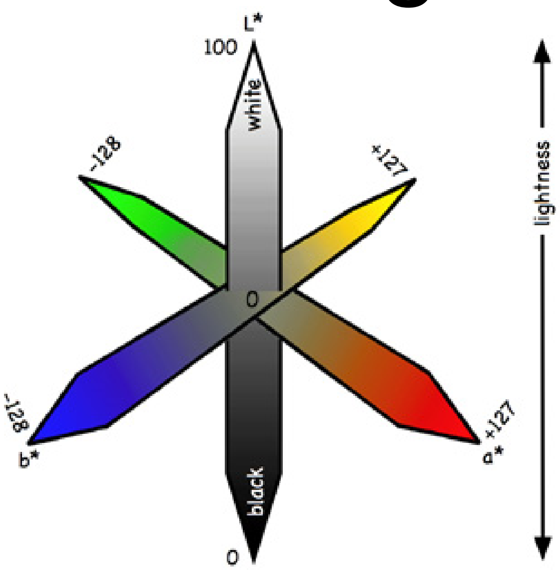
Few Bins
Need less data
Coarser representation

Many Bins
Need more data
Finer representation

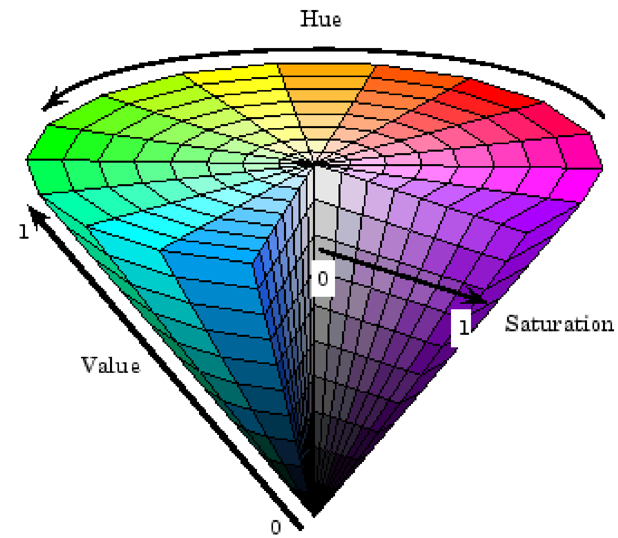
- Matching
  - Histogram intersection or Euclidean distance may be faster
  - Chi-squared distance often works better
  - Earth mover’s distance is good when nearby bins represent similar values

What kind of things do we compute histograms of?

- Color

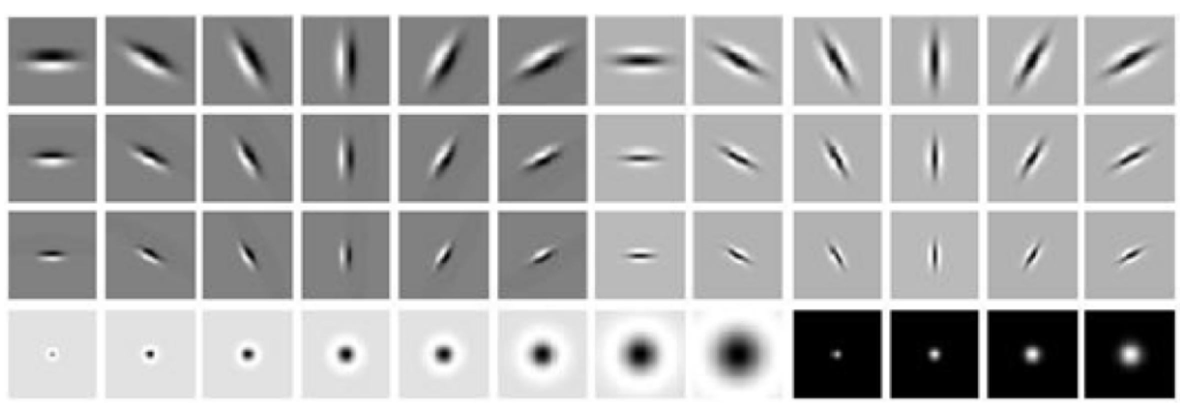


L*a*b* color space



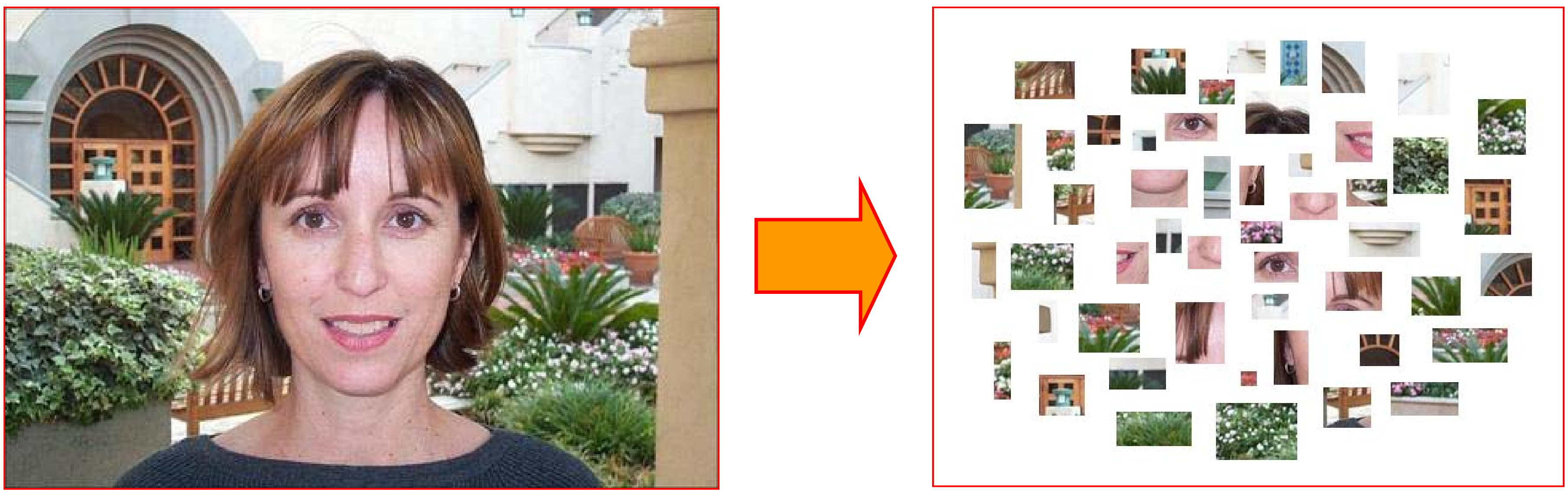
HSV color space

- Texture (filter banks or descriptors)



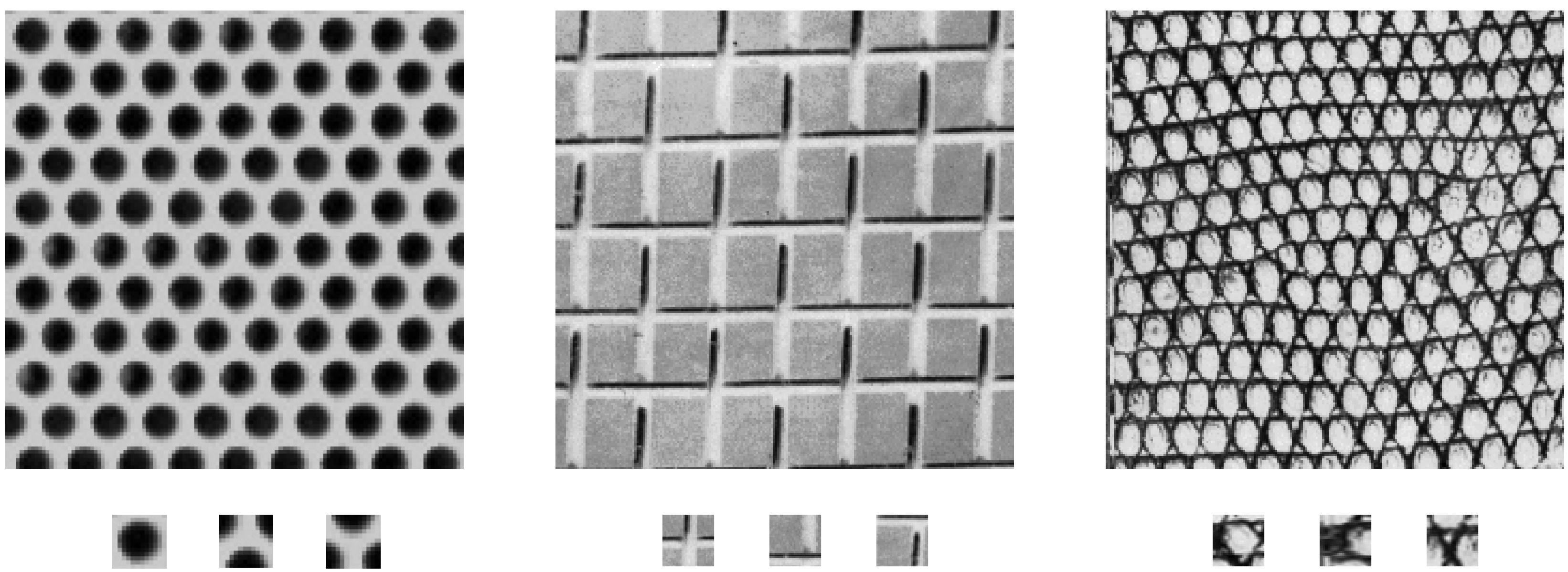
Bags of Features/Visual Words

Bags of features

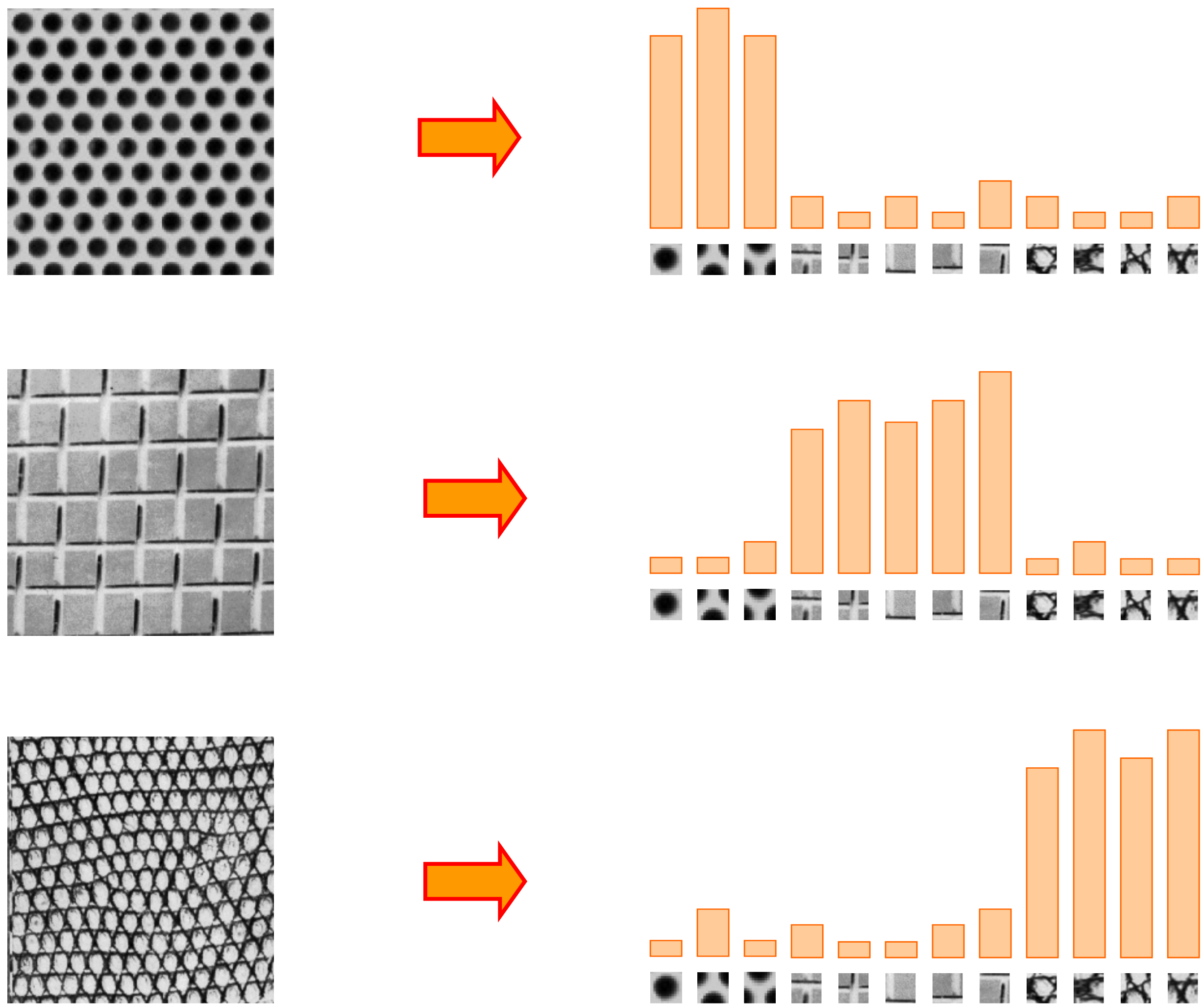


Origin 1: Texture recognition

- Texture is characterized by the repetition of basic elements or *textons*
- For stochastic textures, it is the identity of the textons, not their spatial arrangement, that matters



Origin 1: Texture recognition



Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

Origin 2: Bag-of-words models

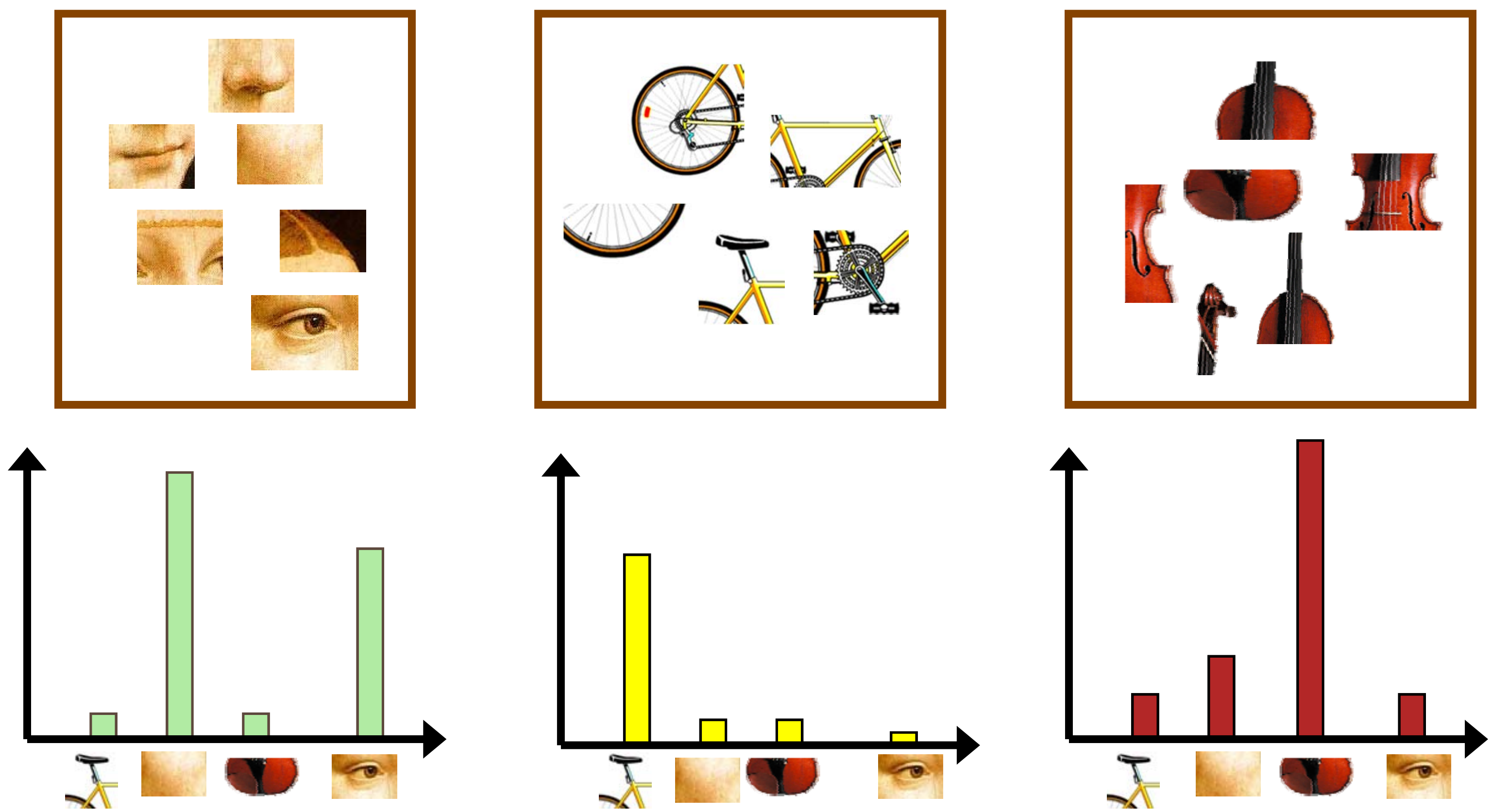
- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

Bag-of-features steps

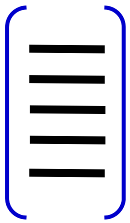
1. Extract local features
2. Learn “visual vocabulary”
3. Quantize local features using visual vocabulary
4. Represent images by frequencies of “visual words”



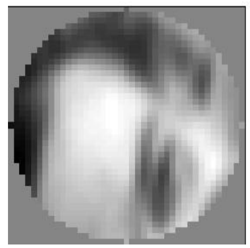
Local feature extraction

- Regular grid or interest regions

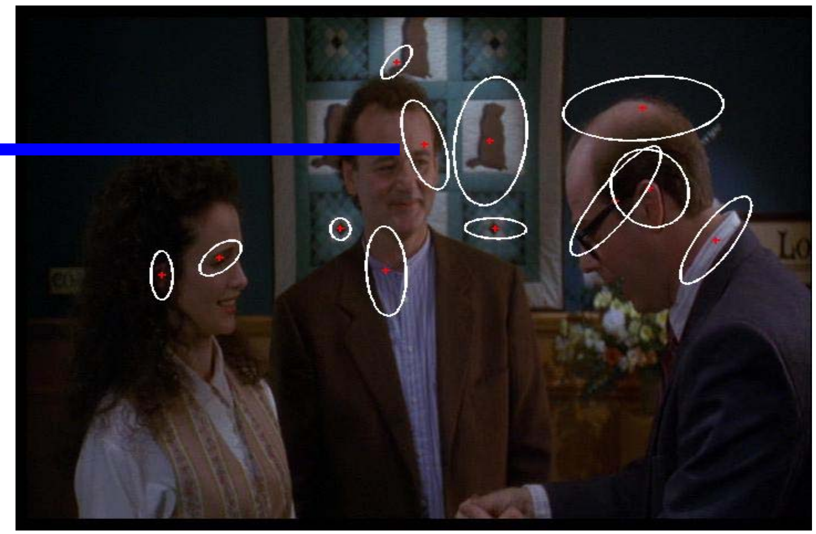
Local feature extraction



Compute descriptor



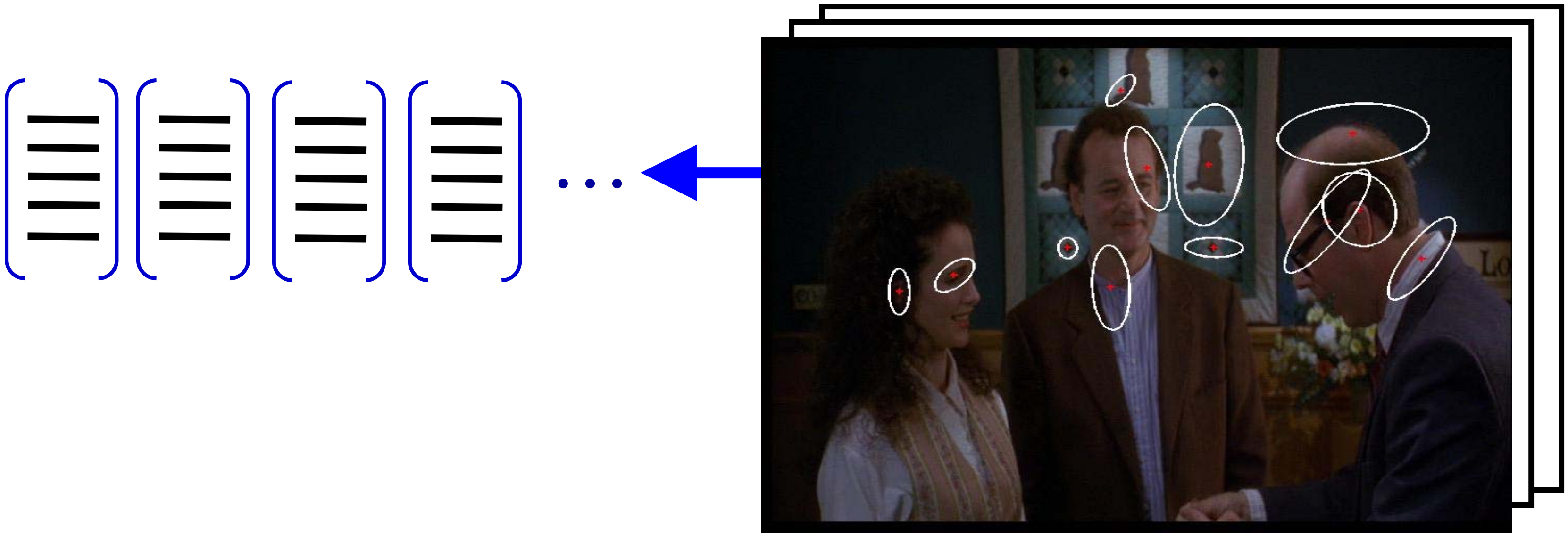
Normalize patch



Detect patches

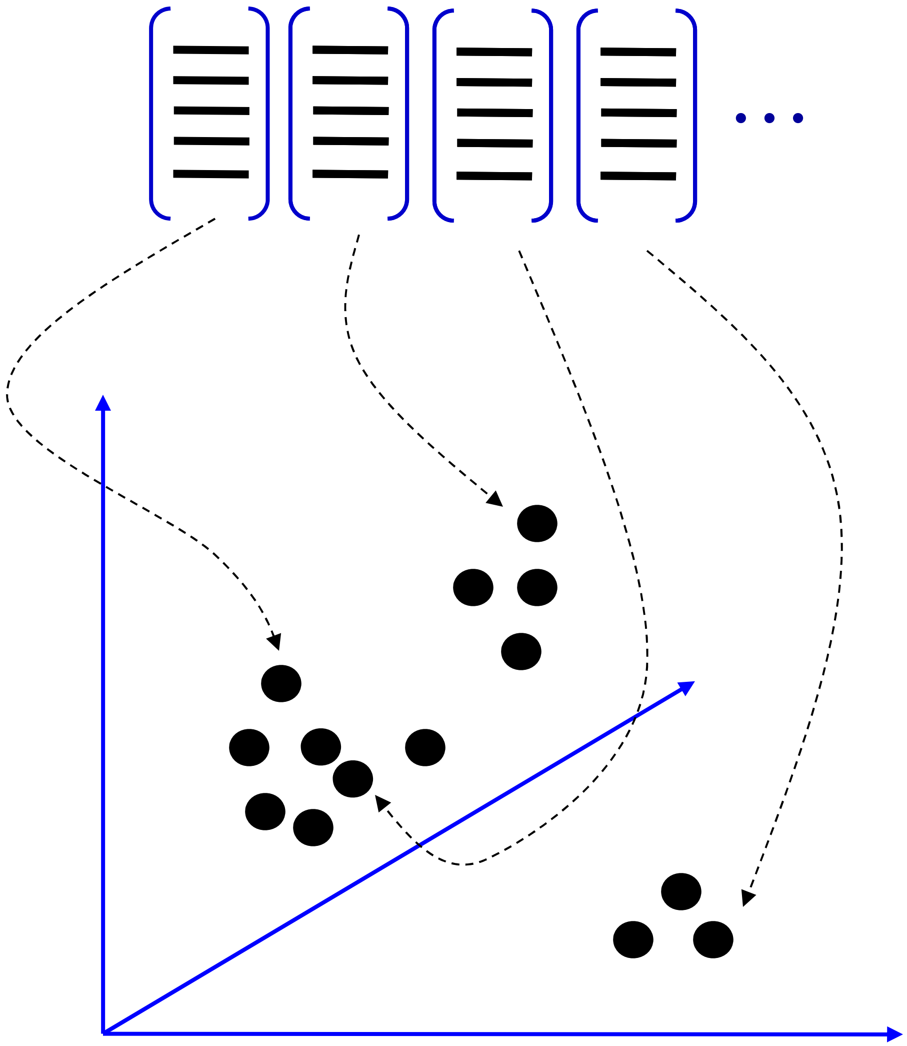
Slide credit: Josef Sivic

Local feature extraction



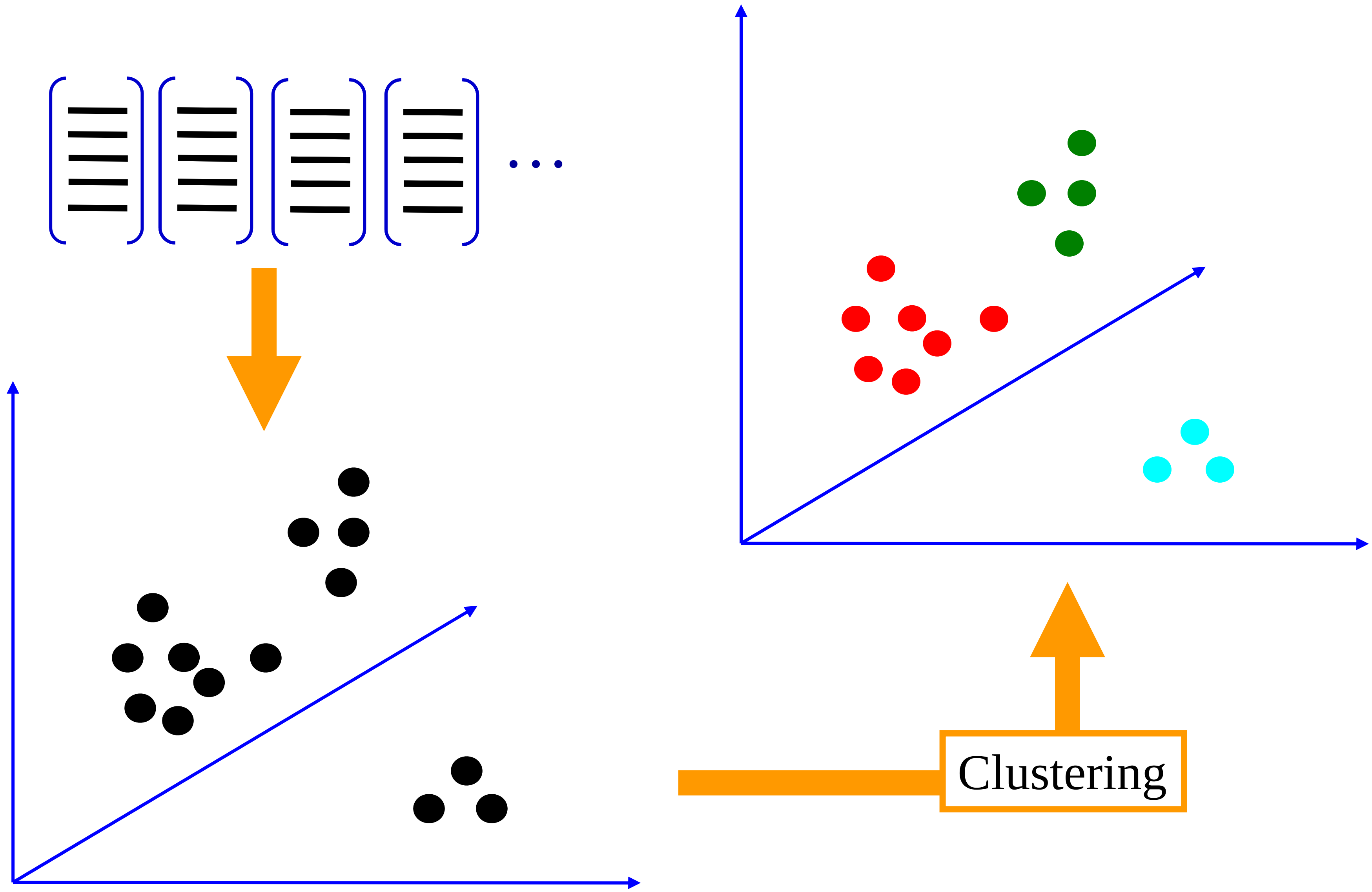
Slide credit: Josef Sivic

Learning the visual vocabulary



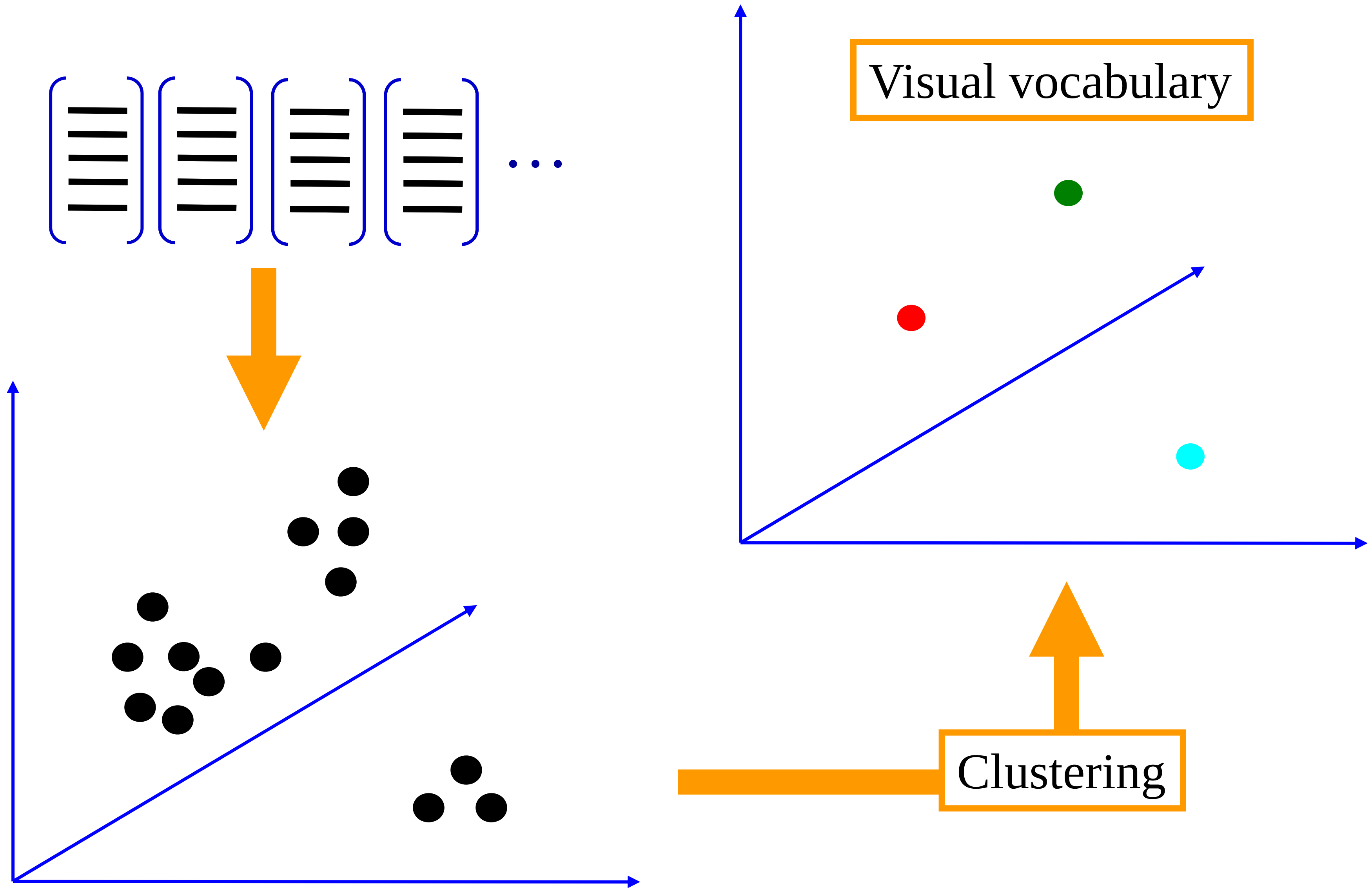
Slide credit: Josef Sivic

Learning the visual vocabulary



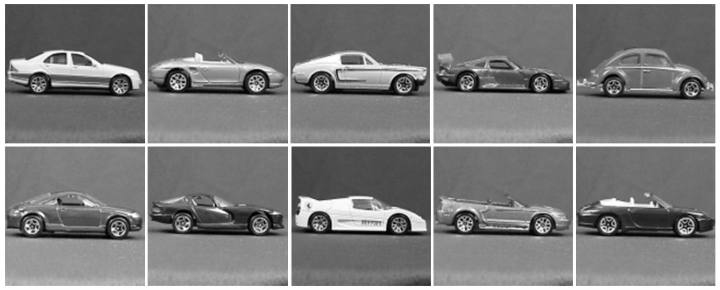
Slide credit: Josef Sivic

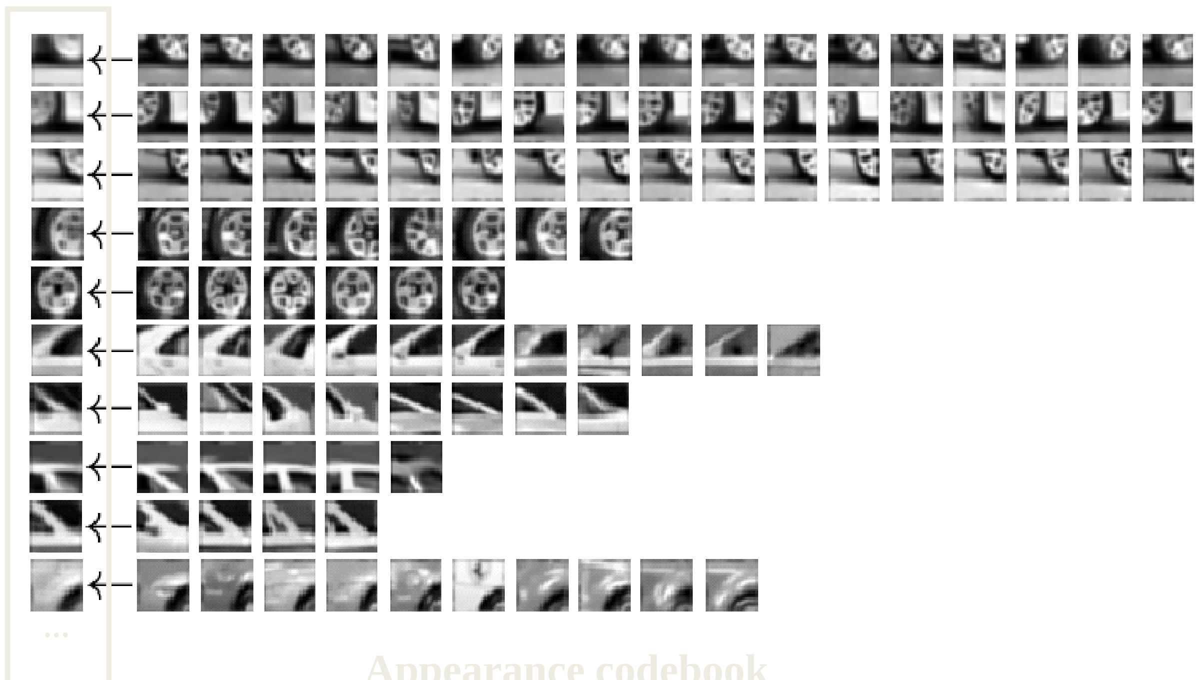
Learning the visual vocabulary



Slide credit: Josef Sivic

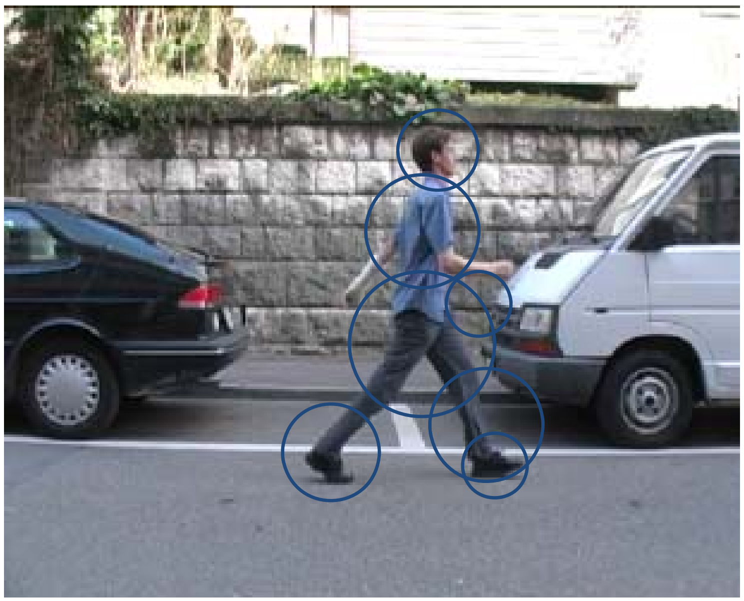
Example codebook





Source: B. Leibe

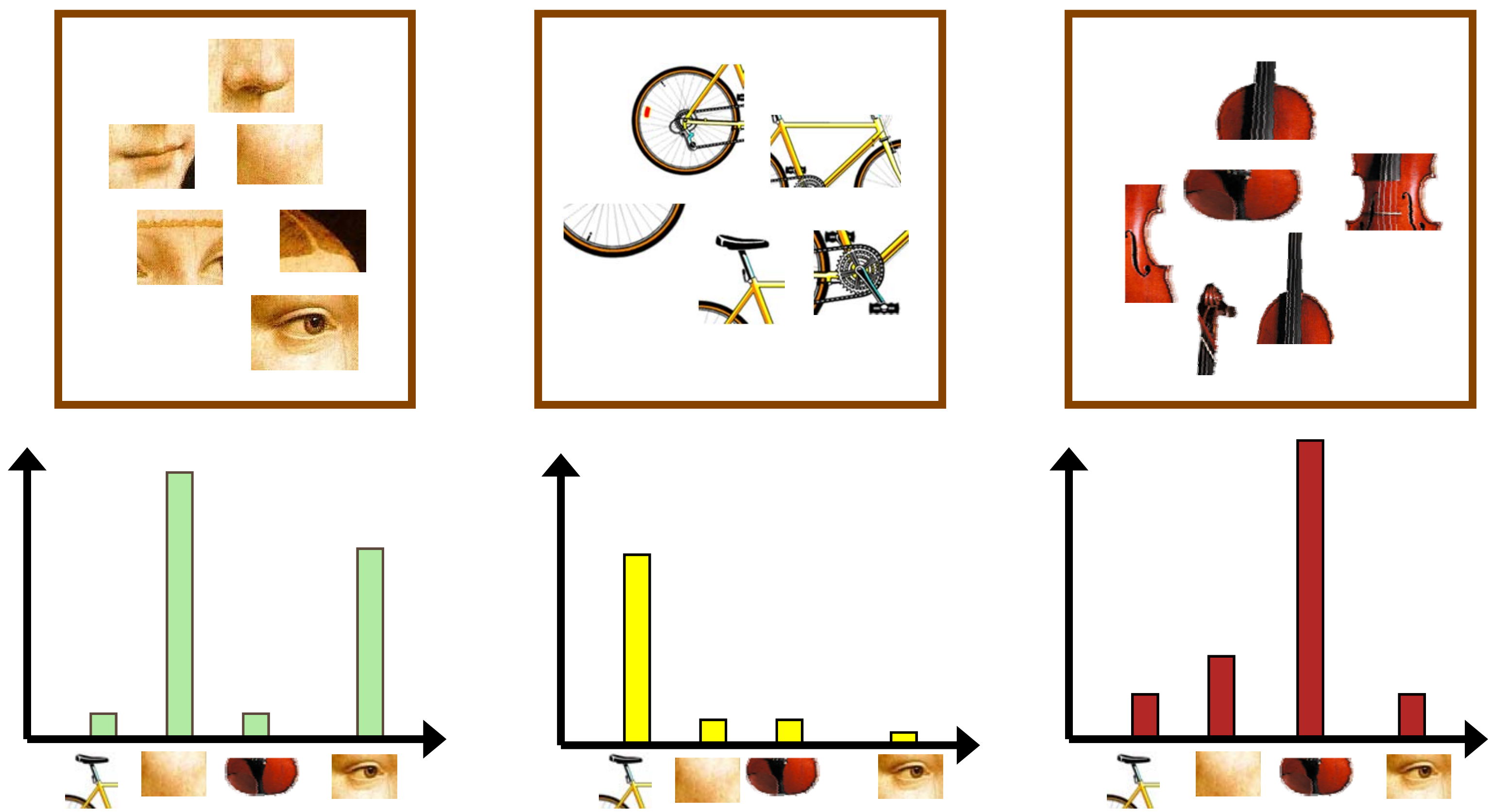
Another codebook



Source: B. Leibe

Bag-of-features steps

1. Extract local features
2. Learn "visual vocabulary"
3. Quantize local features using visual vocabulary
4. Represent images by frequencies of "visual words"

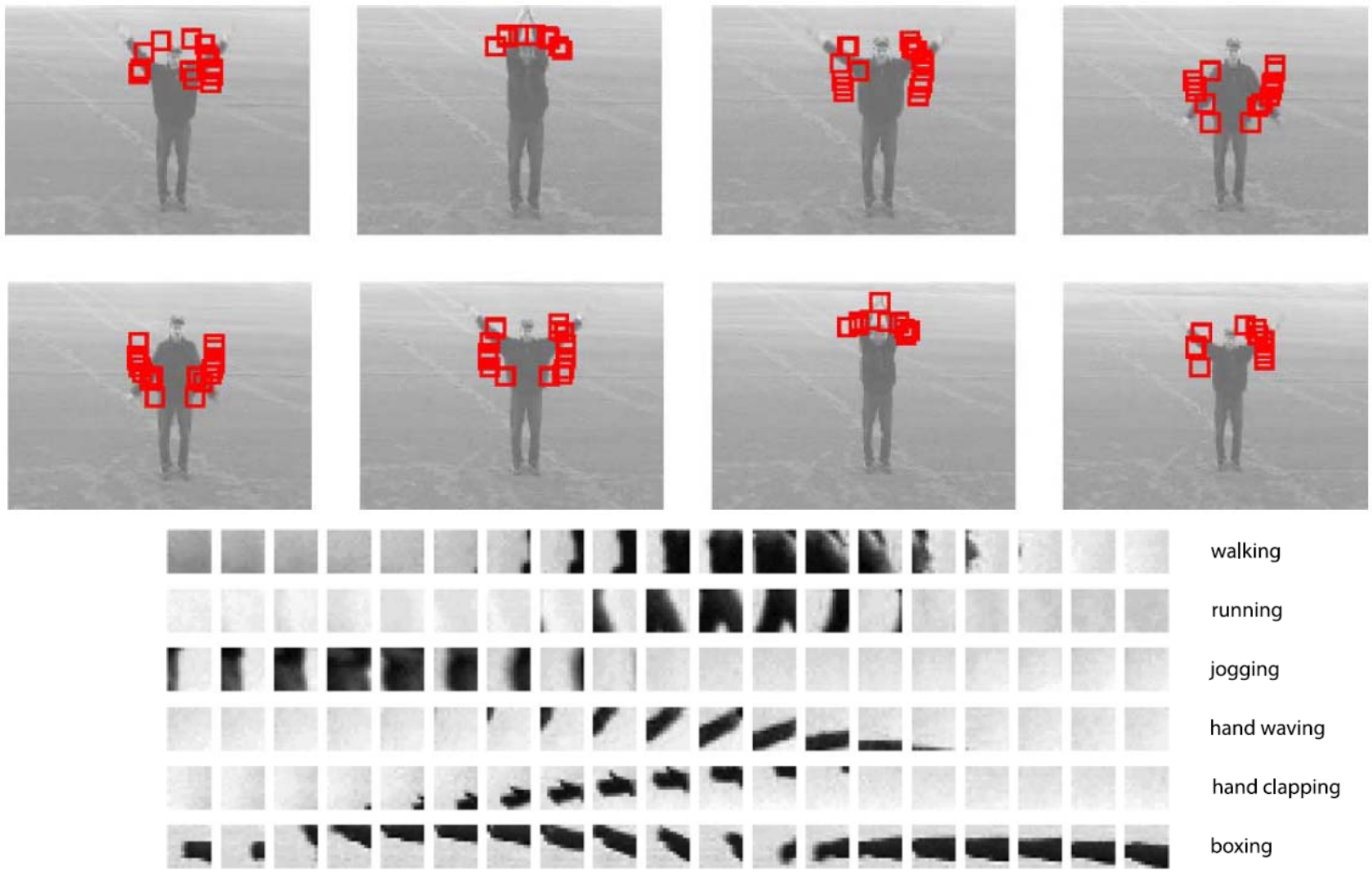


Visual vocabularies: Details

- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
  - Right size is application-dependent
- Improving efficiency of quantization
  - Vocabulary trees (Nister and Stewenius, 2006)
- Improving vocabulary quality
  - Discriminative/supervised training of codebooks
  - Sparse coding, non-exclusive assignment to codewords
- More discriminative bag-of-words representations
  - Fisher Vectors (Perronnin et al., 2007), VLAD (Jegou et al., 2010)
- Incorporating spatial information

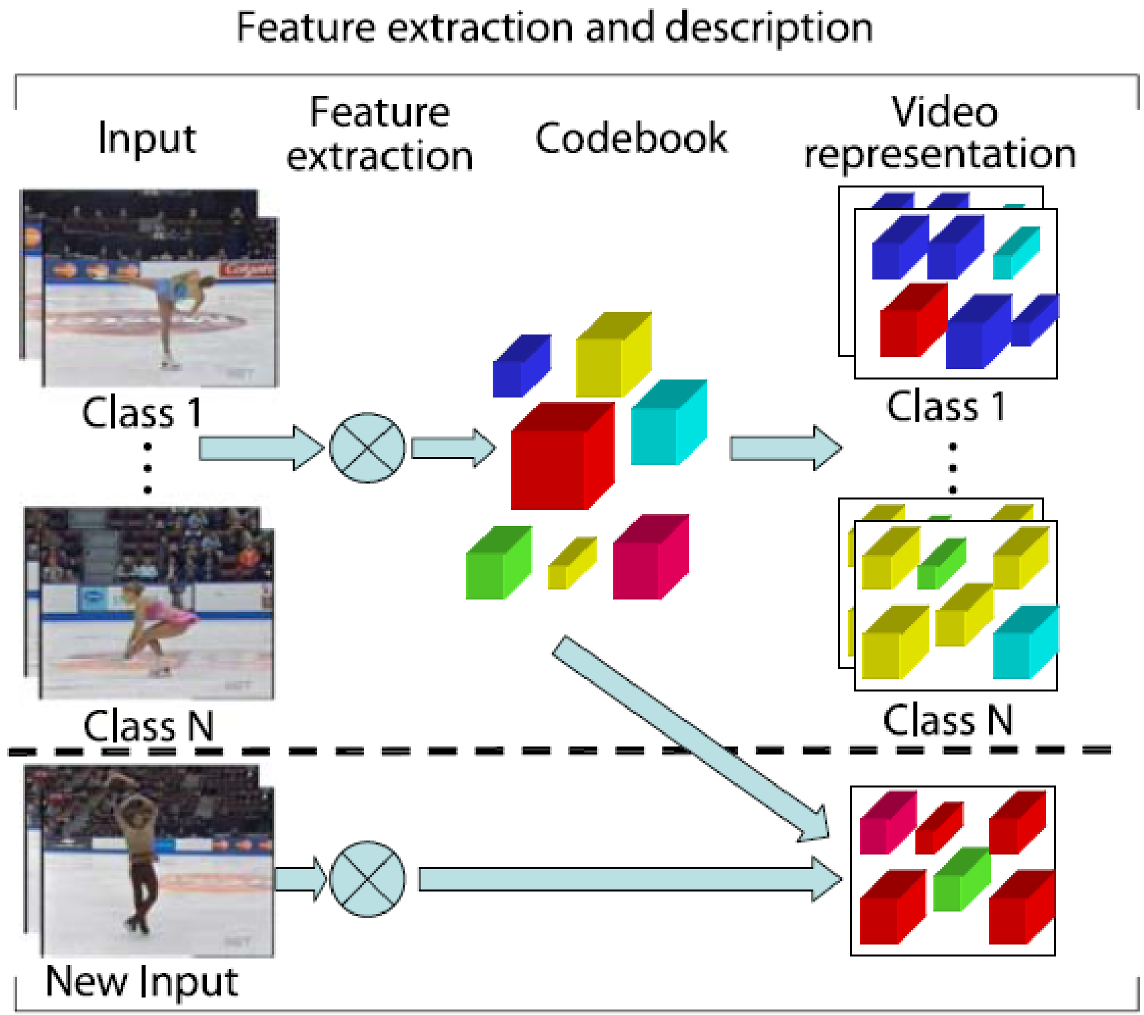
Bags of features for action recognition

Space-time interest points



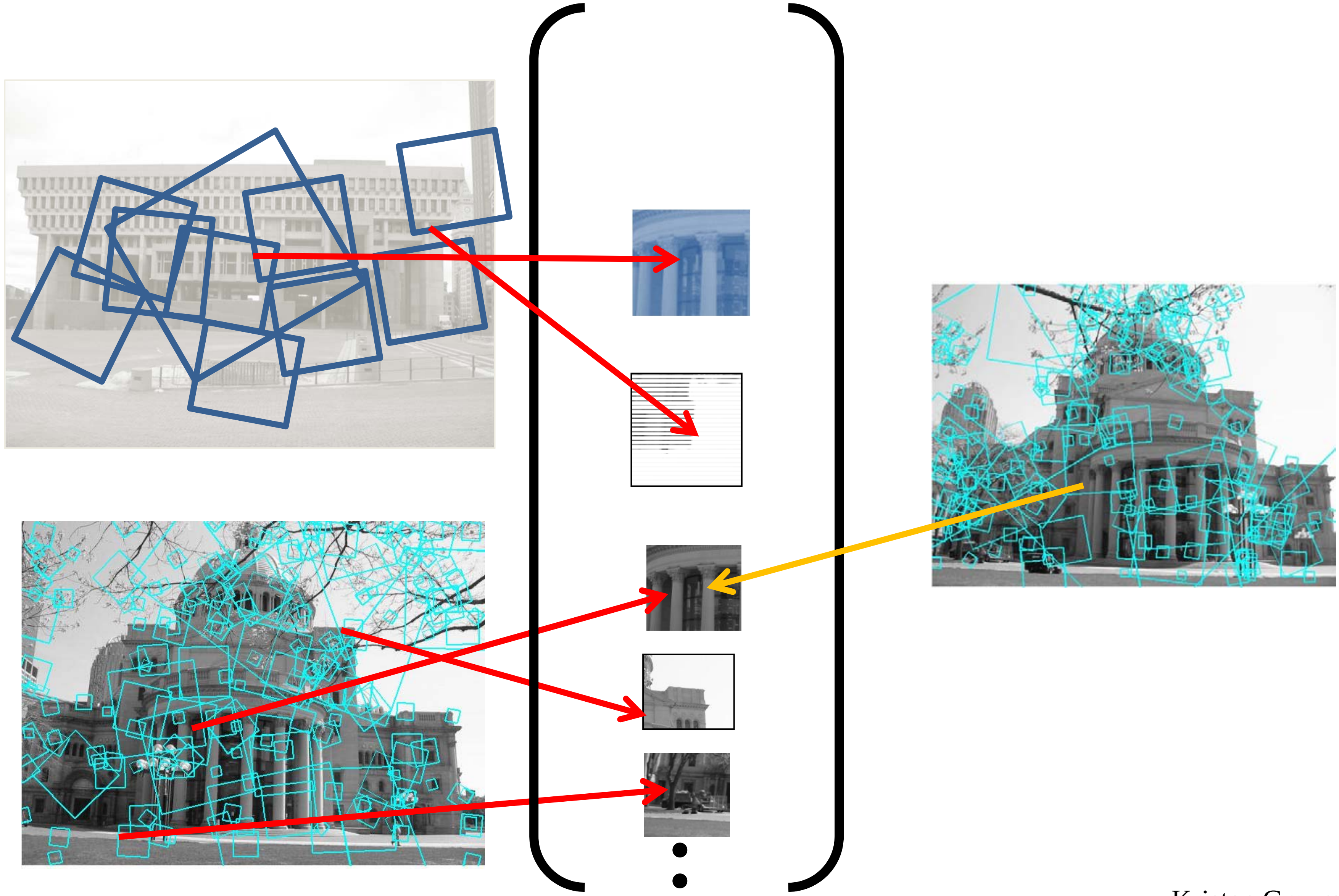
Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, **Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words**, IJCV 2008.

Bags of features for action recognition



Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, **Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words**, IJCV 2008.

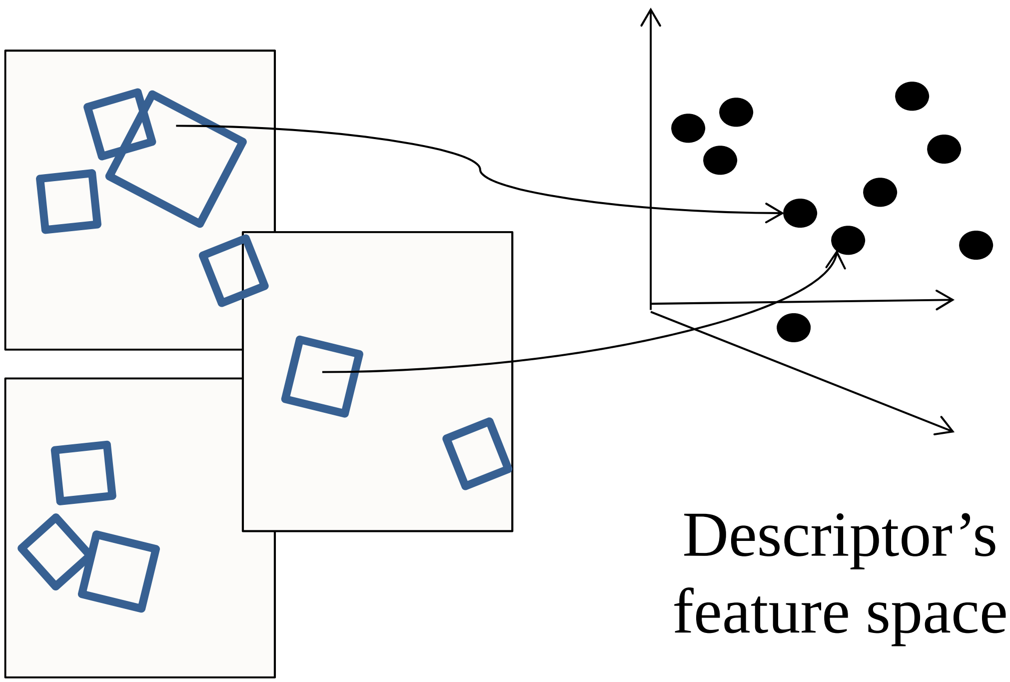
Indexing local features



Kristen Grauman

Indexing local features

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

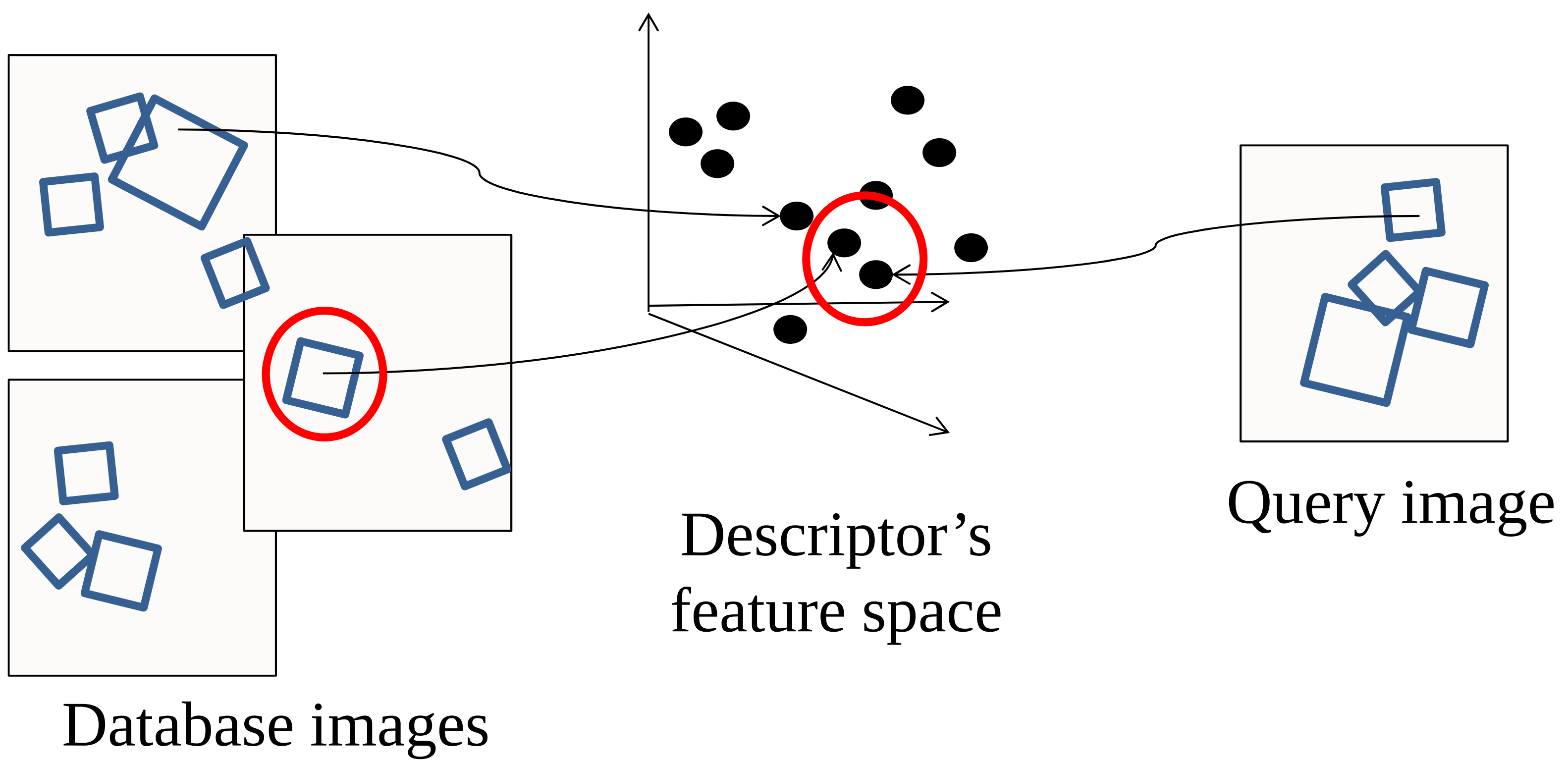


Descriptor's feature space

Kristen Grauman

Indexing local features

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



Kristen Grauman

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?

Kristen Grauman

Indexing local features: inverted file index

Index

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

Kristen Grauman

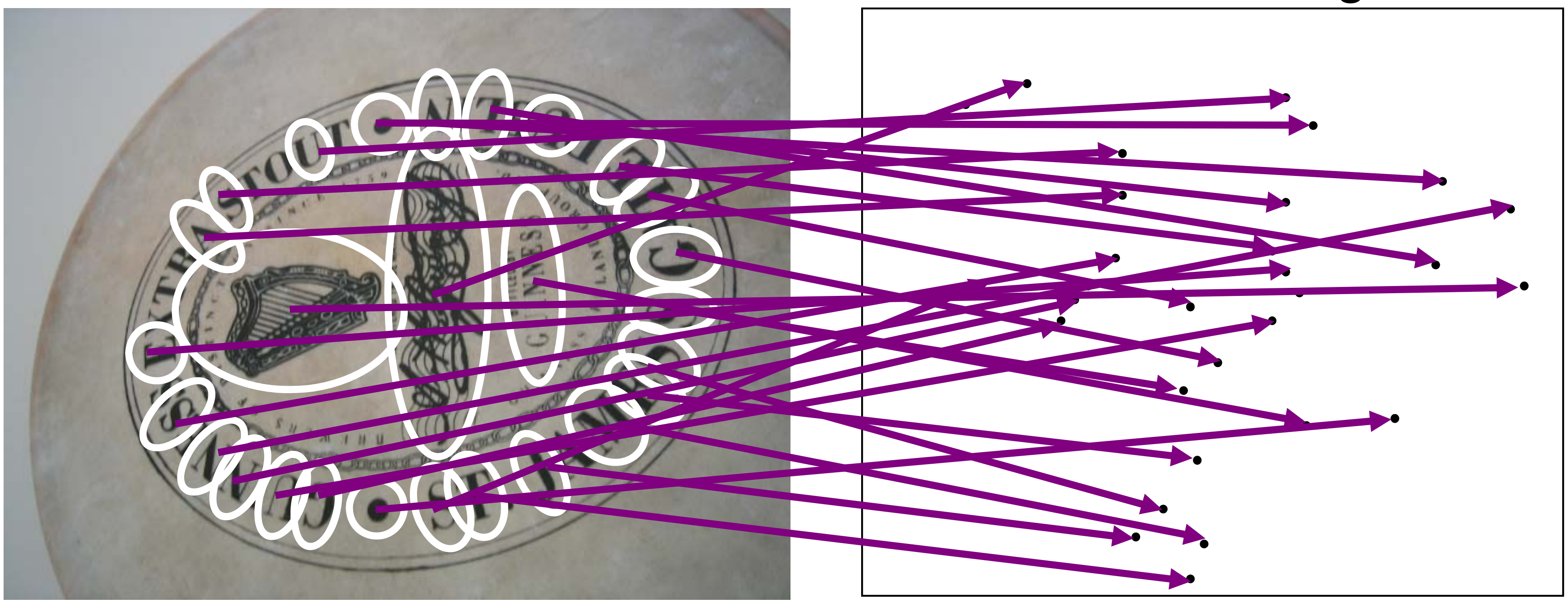
Text retrieval vs. image search

- What makes the problems similar, different?

Kristen Grauman

Visual words: main idea

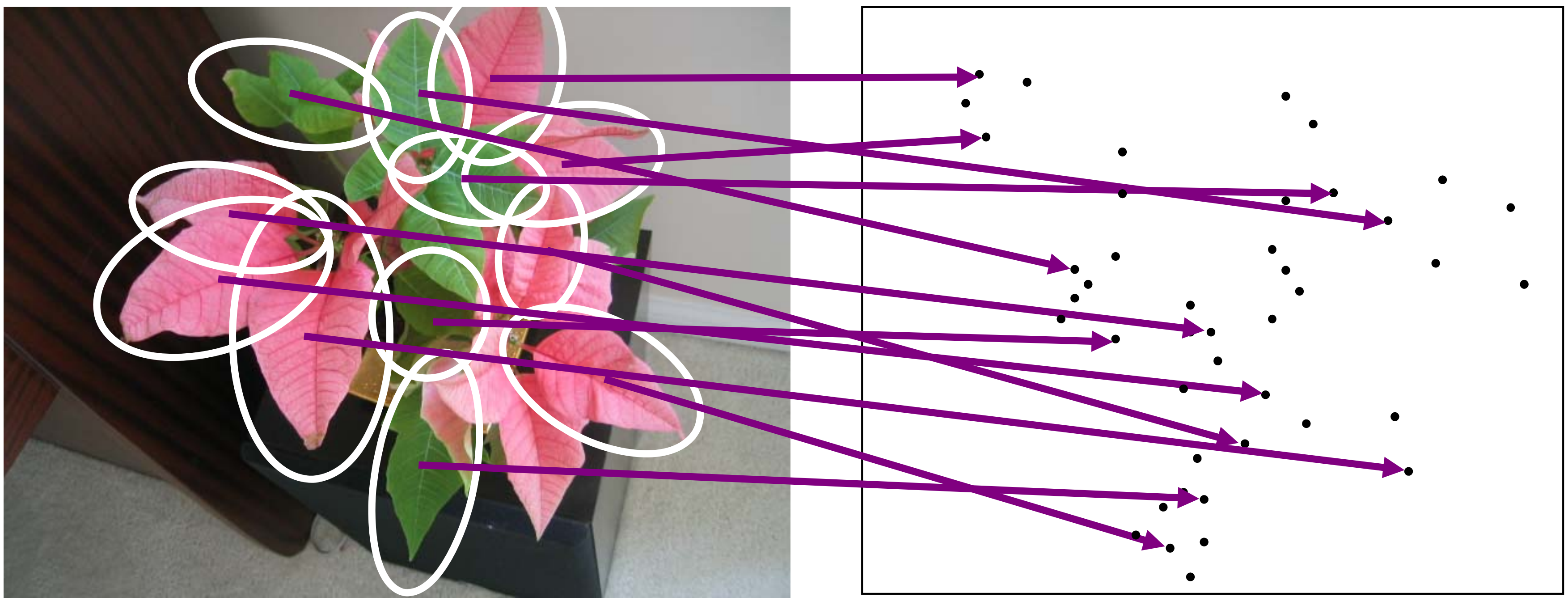
- Extract some local features from a number of images …

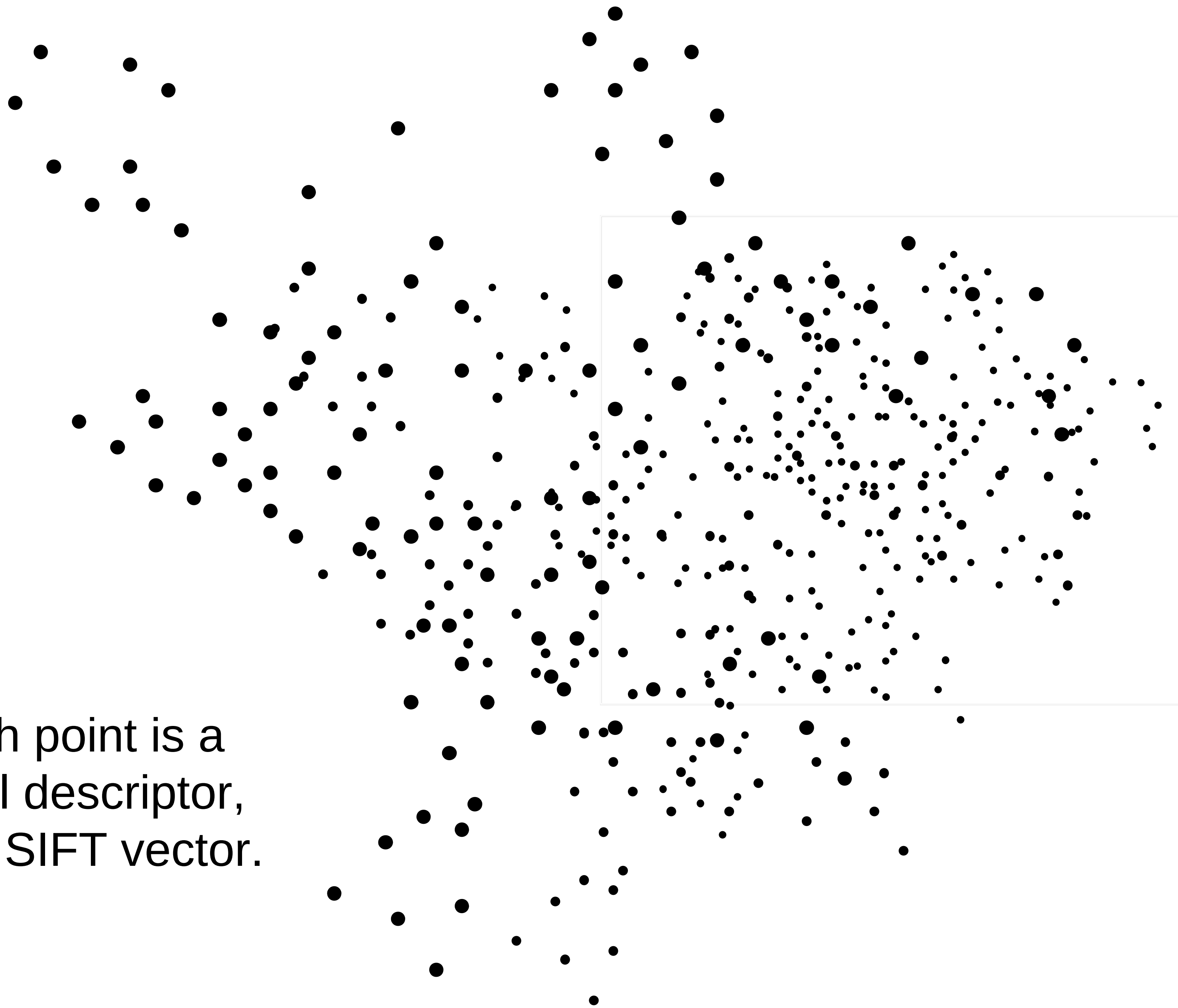


e.g., SIFT descriptor space: each point is 128-dimensional

Slide credit: D. Nister, CVPR 2006

Visual words: main idea

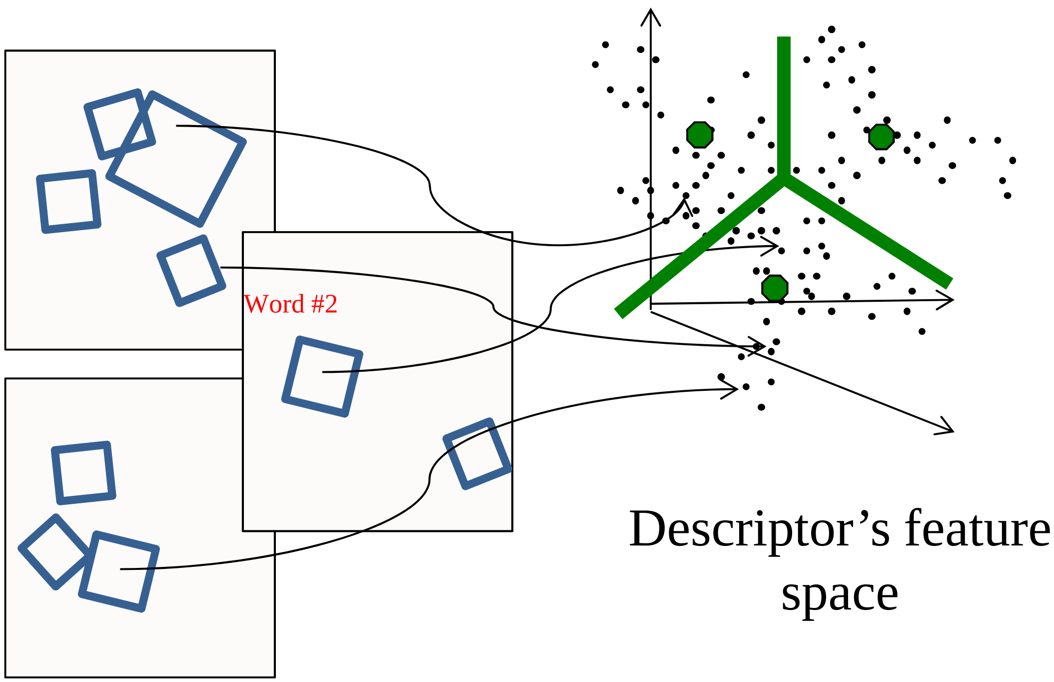




Each point is a
local descriptor,
e.g. SIFT vector.

Visual words

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

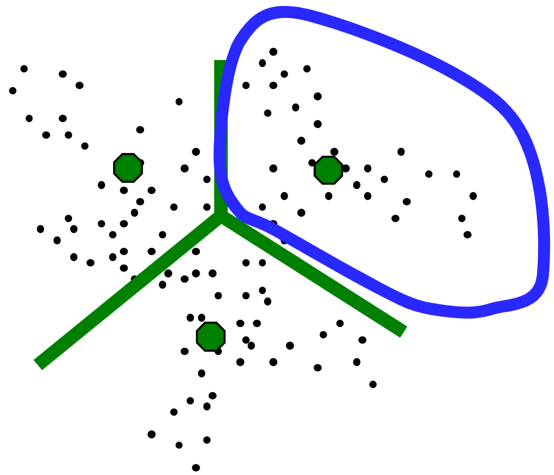


- Quantize via clustering, let cluster centers be the prototype "words"
- Determine which word to assign to each new image region by finding the closest cluster center.

Kristen Grauman

Visual words

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



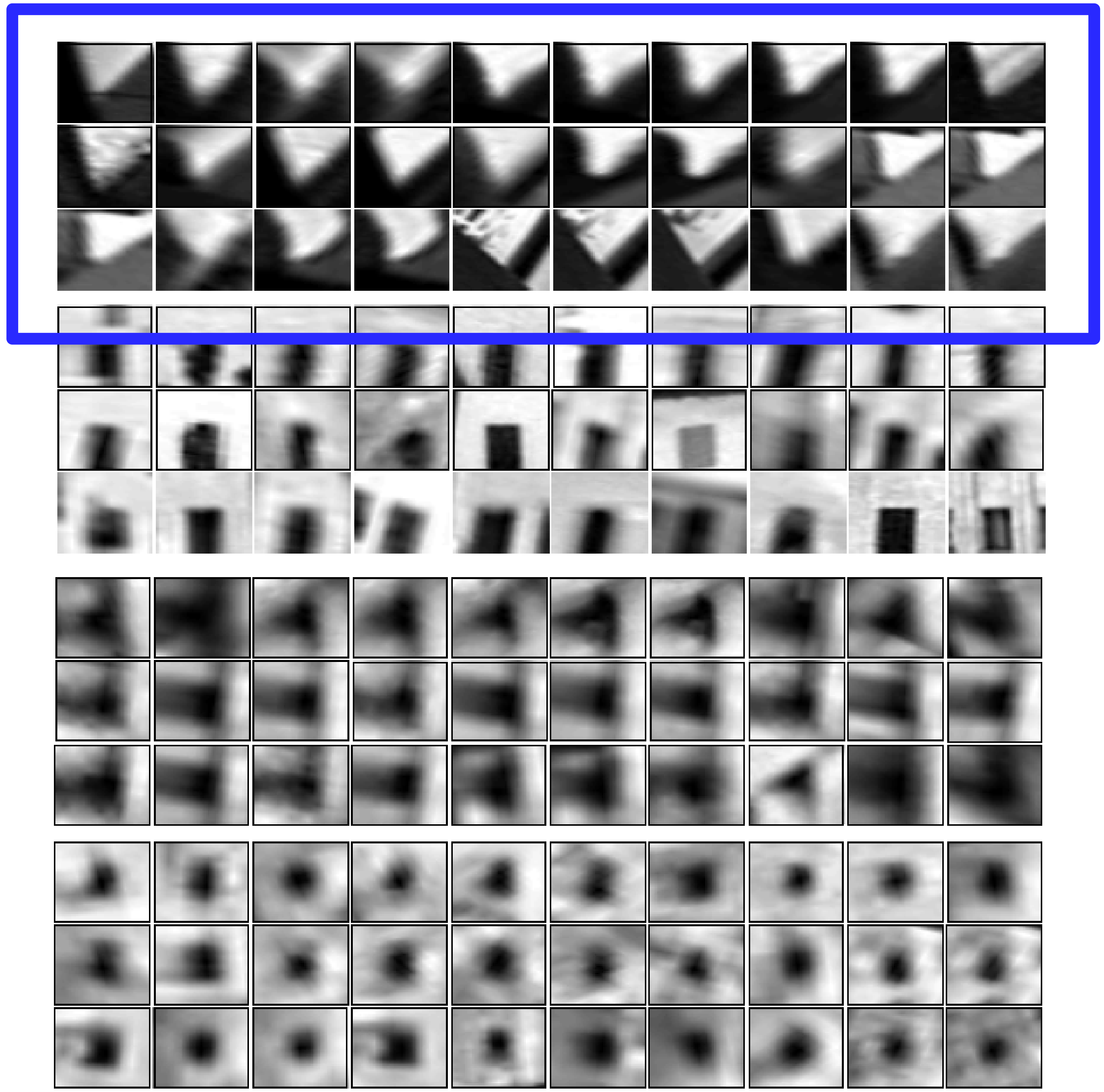


Figure from Sivic & Zisserman, ICCV 2003

Kristen Grauman

Inverted file index

Database images

Image #1

Image #2

Image #3

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

…

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

Kristen Grauman

Inverted file index

When will this give us a significant gain in efficiency?

New query image

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

…

⋮ ⋮

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

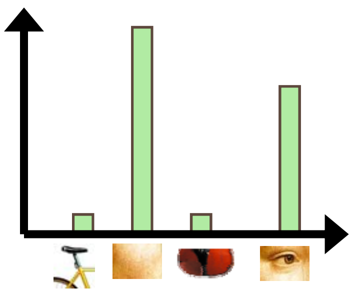
Kristen Grauman

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

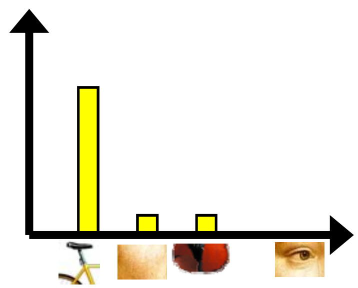
Comparing bags of words

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

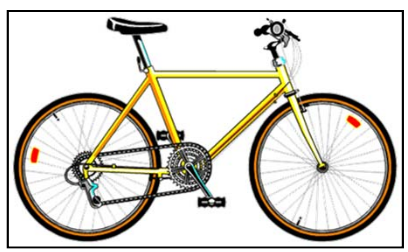
[1 8 1 4]



[5 1 1 0]



$\vec{d}_j$



$\vec{q}$

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

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

for vocabulary of V words

Kristen Grauman

tf-idf weighting

- Term frequency – inverse document frequency
- Describe frame by frequency of each word within it, downweight words that appear often in the database
- (Standard weighting for text retrieval)

Number of occurrences of word i in document d

Total number of documents in database

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

Number of words in document d

Number of documents word i occurs in, in whole database

Kristen Grauman

Query Expansion

Query: ***golf green***

Results:

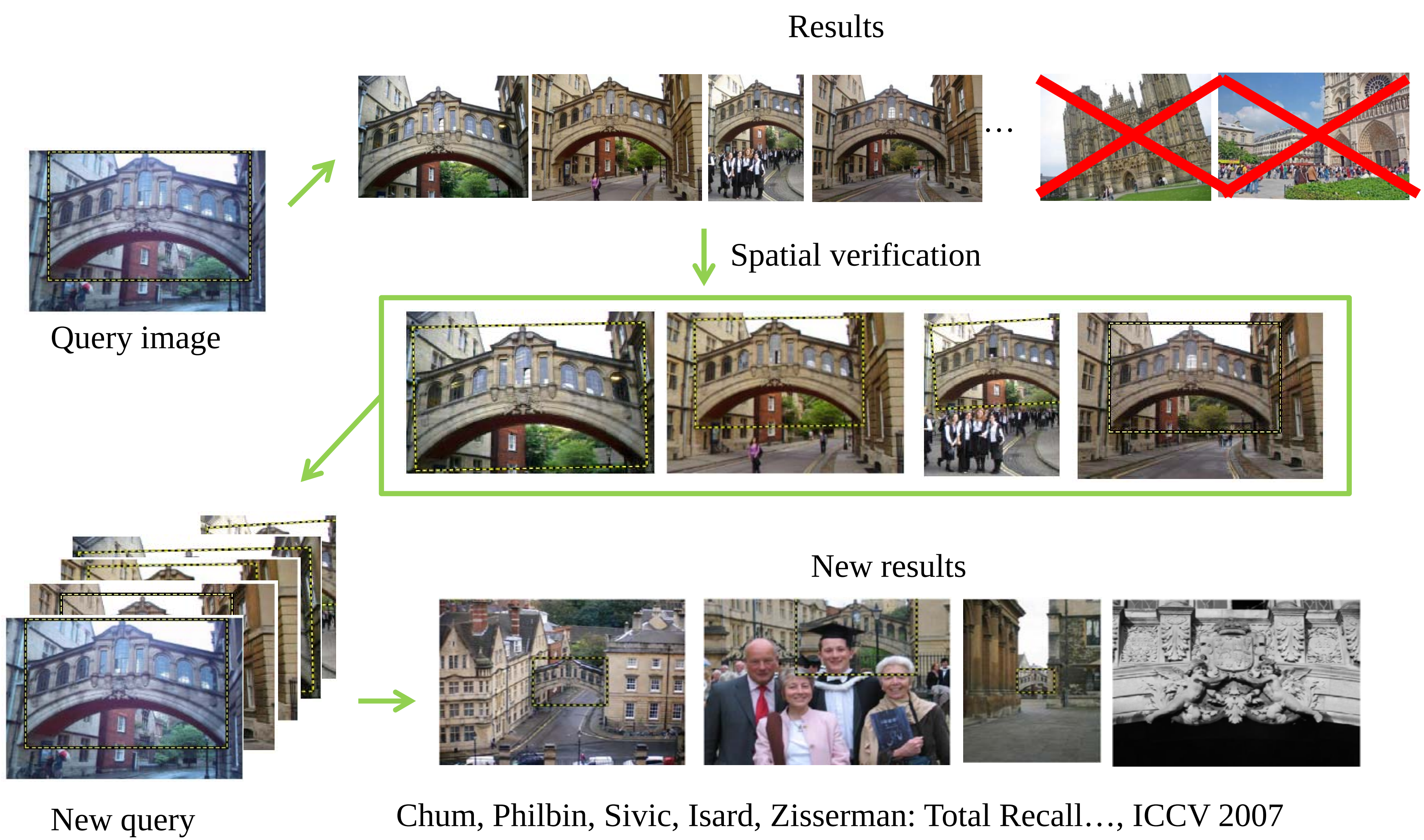
- How can the grass on the ***greens*** at a ***golf*** course be so perfect?
- For example, a skilled ***golf***er expects to reach the ***green*** on a par-four hole in **...**
- Manufactures and sells synthetic ***golf*** putting ***green****s* and mats.

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



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

Slide credit: Ondrej Chum

Bags of words for content-based image retrieval

Visually defined query

"Groundhog Day" [Rammis, 1993]

"Find this clock"

"Find this place"

Slide from Andrew Zisserman
Sivic & Zisserman, ICCV 2003

Example

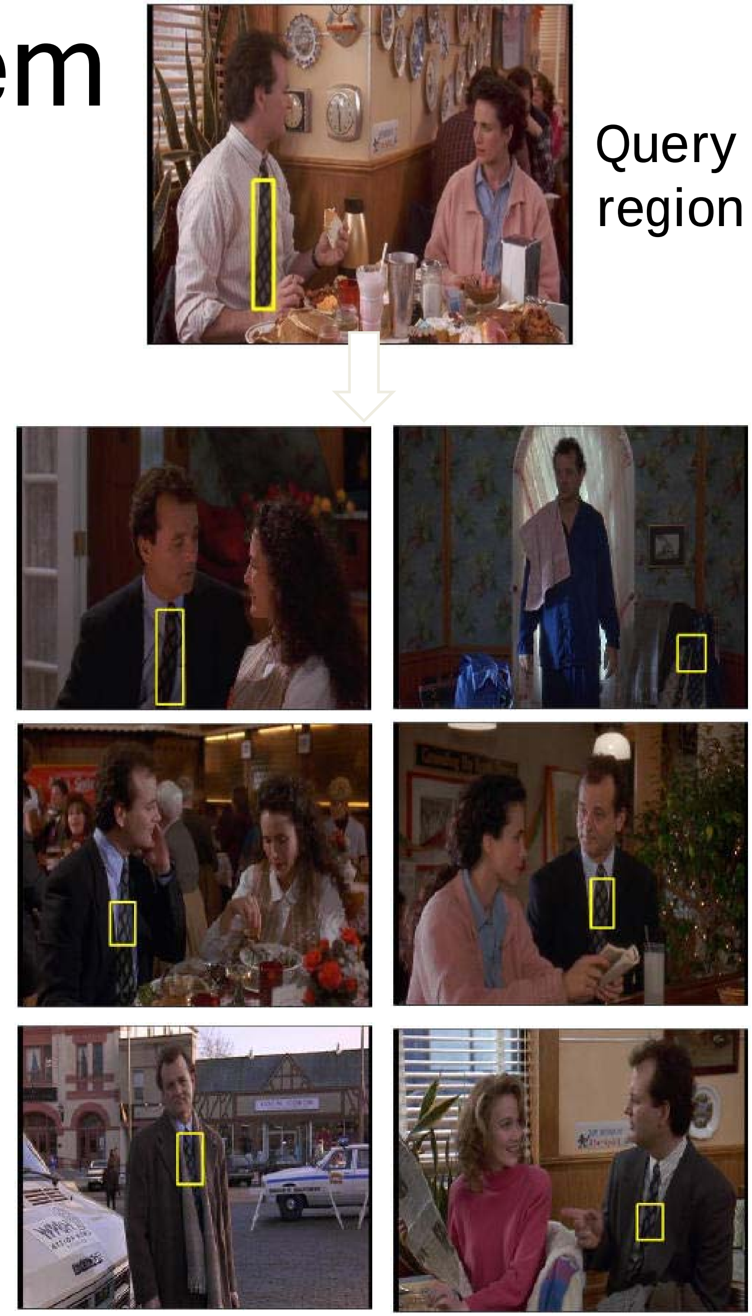
retrieved shots

Slide from Andrew Zisserman
Sivic & Zisserman, ICCV 2003

Video Google System

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

Sivic & Zisserman, ICCV 2003



Query region

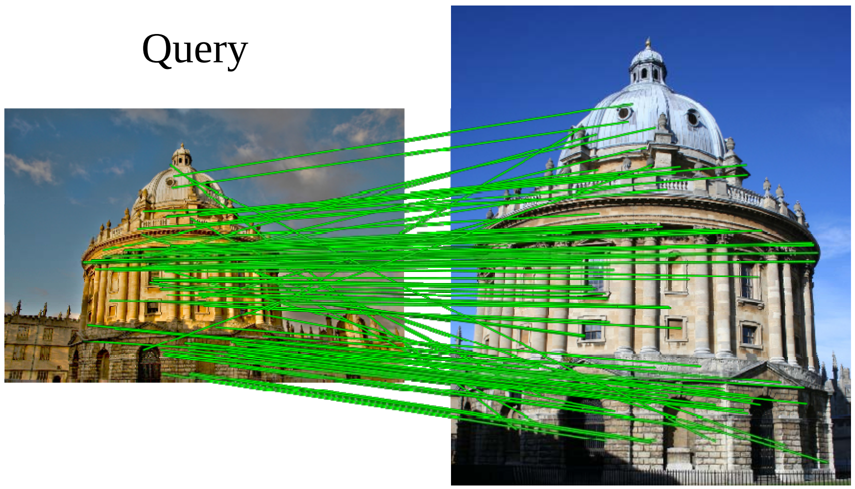
Retrieved frames

Is having the same set of visual words enough to identify the object or scene?

How to verify spatial agreement?

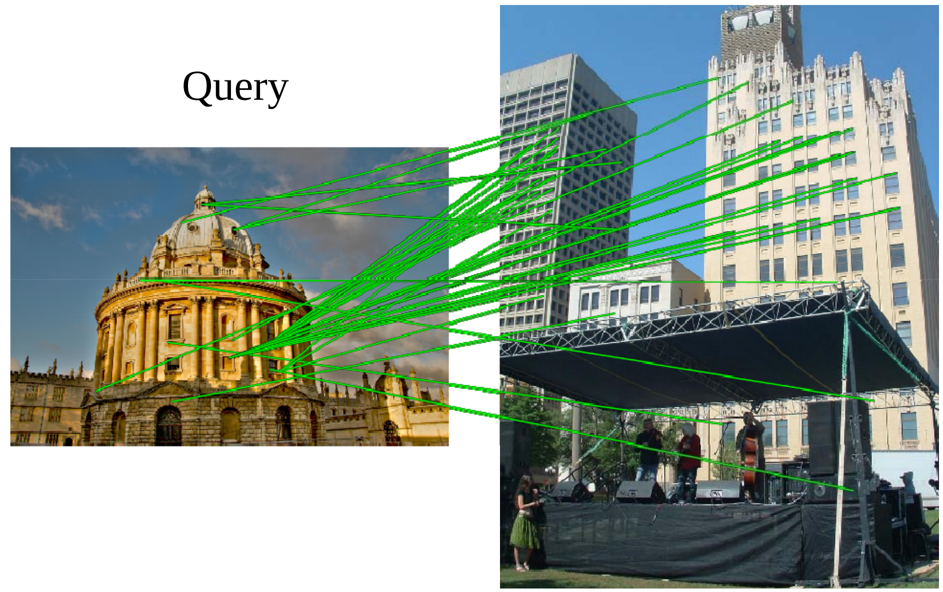
Spatial Verification

Query



DB image with high BoW similarity

Query



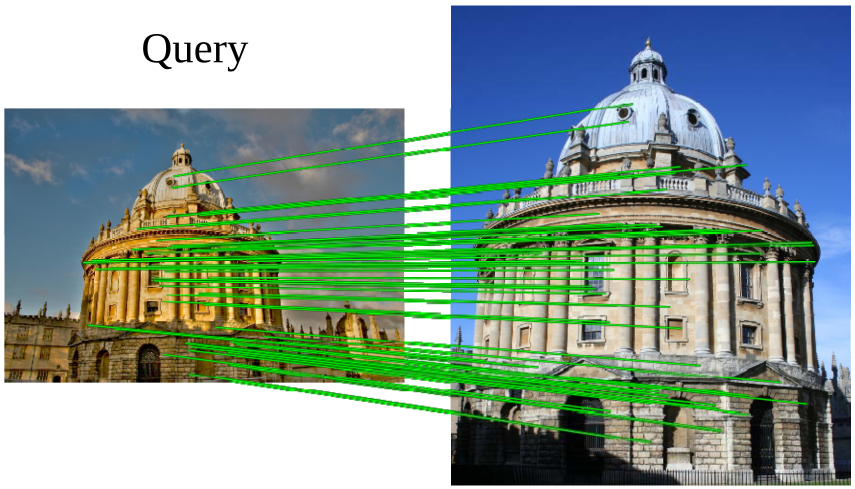
DB image with high BoW similarity

Both image pairs have many visual words in common.

Slide credit: Ondrej Chum

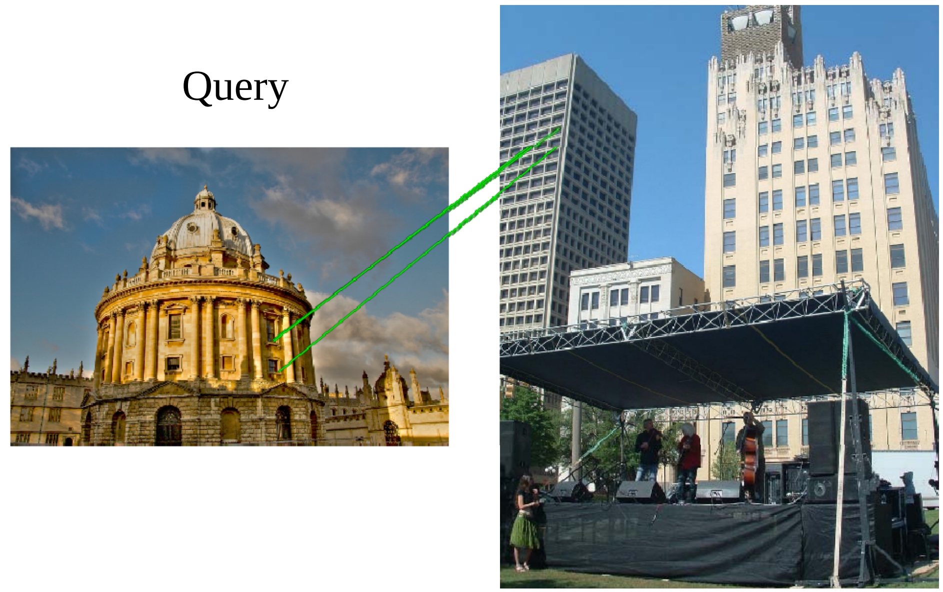
Spatial Verification

Query



DB image with high BoW similarity

Query



DB image with high BoW similarity

Only some of the matches are mutually consistent

Slide credit: Ondrej Chum

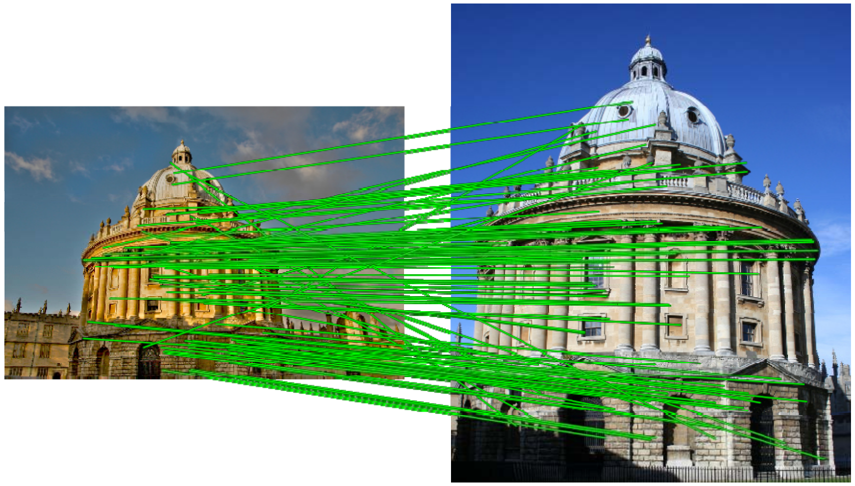
Spatial Verification: two basic strategies

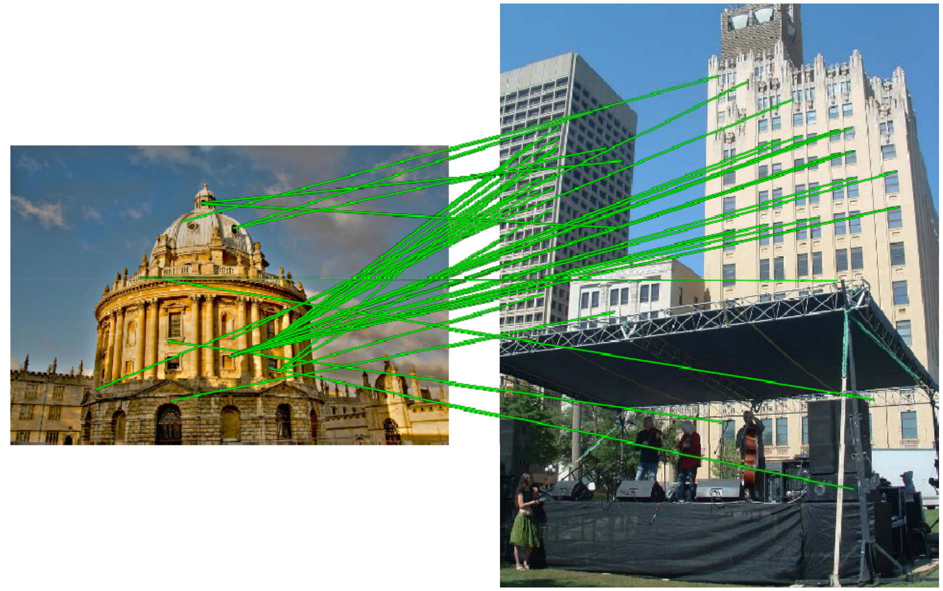
- RANSAC
  - Typically sort by BoW similarity as initial filter
  - Verify by checking support (inliers) for possible transformations
    - e.g., "success" if a transformation with > N inlier correspondences can be found

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

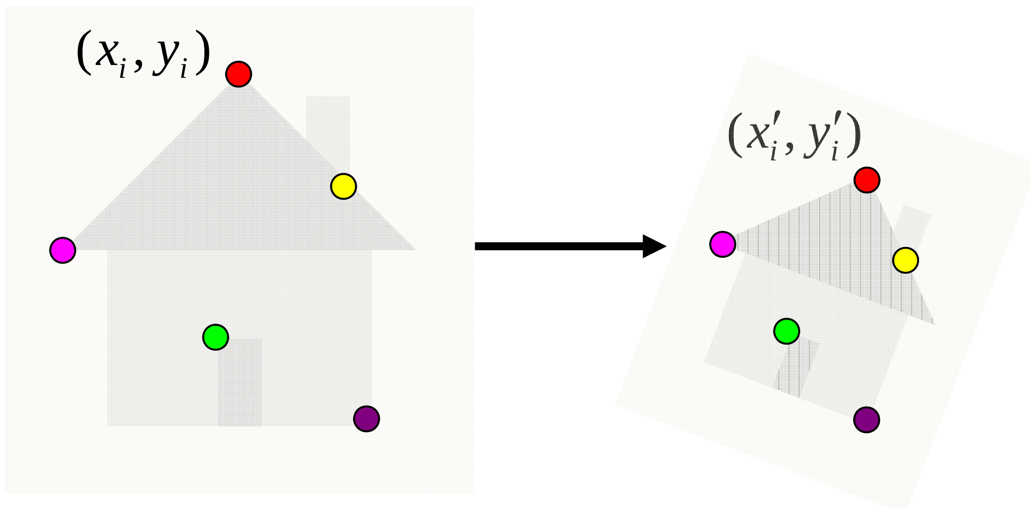
Kristen Grauman

RANSAC verification





Recall: Fitting an affine transformation

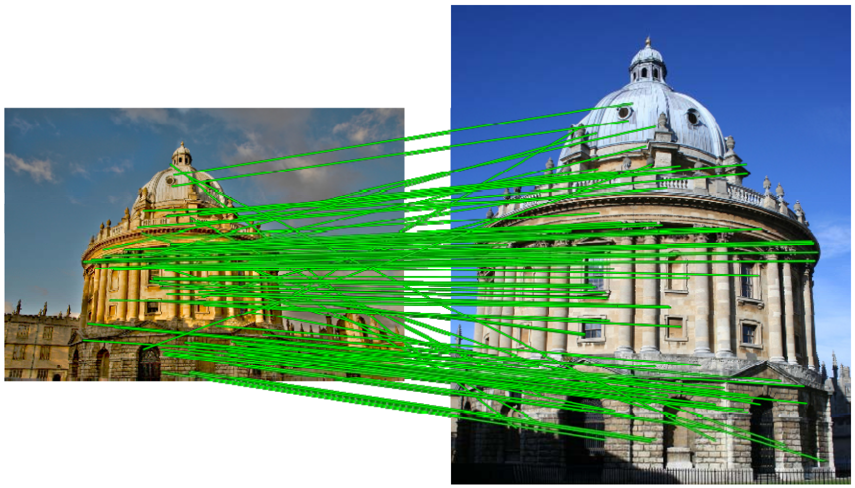


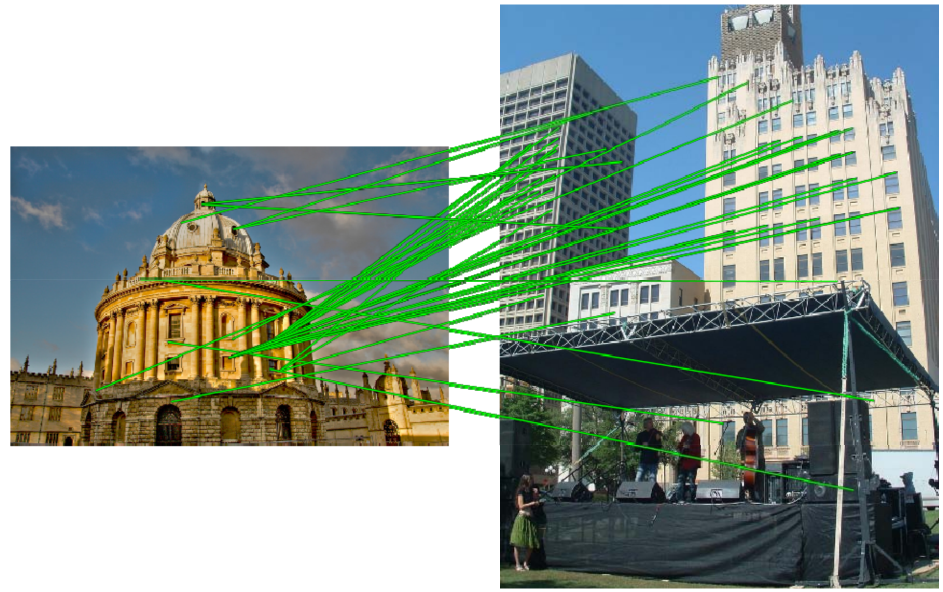
Approximates viewpoint changes for roughly planar objects and roughly orthographic cameras.

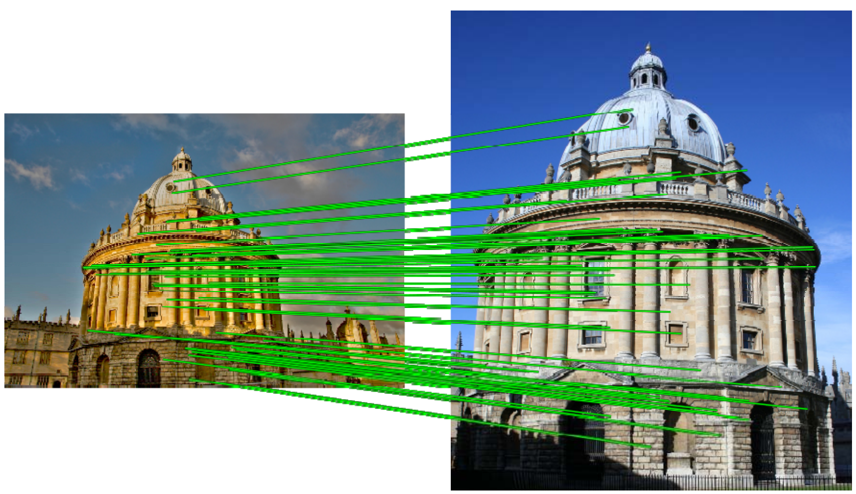
$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

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

RANSAC verification







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).

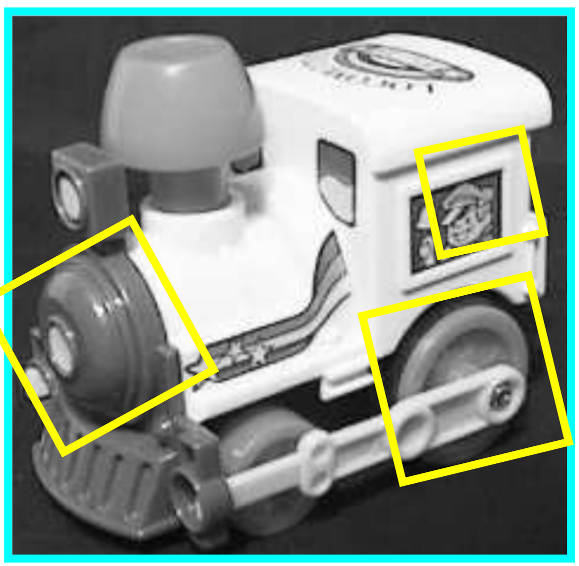
Model

Novel image

Adapted from Lana Lazebnik

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

Generalized Hough Transform details

- **Training phase:** For each model feature, record 2D location, scale, and orientation of model (relative to normalized feature frame)
- **Test phase:** Let each match between 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

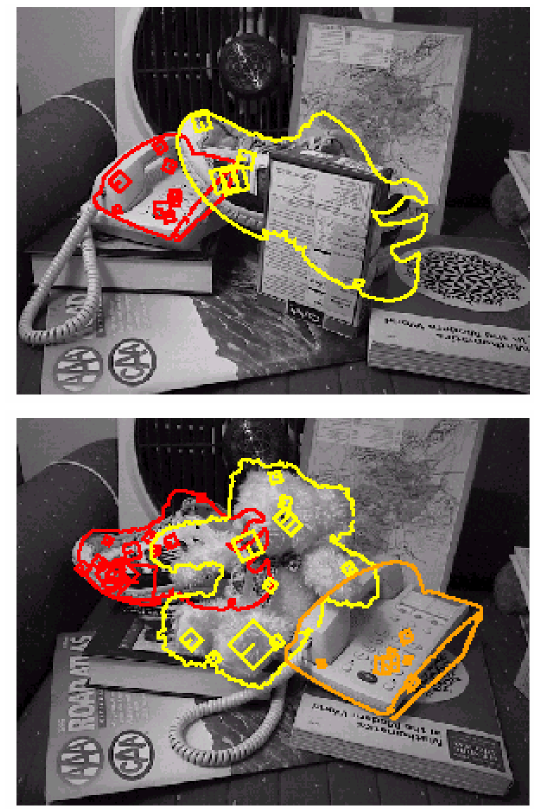
David G. Lowe. **"Distinctive image features from scale-invariant keypoints."** *IJCV* 60 (2), pp. 91-110, 2004.

Slide credit: Lana Lazebnik

Results

Background subtraction
for model boundaries

Objects recognized,



Recognition in spite
of occlusion

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

Generalized 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

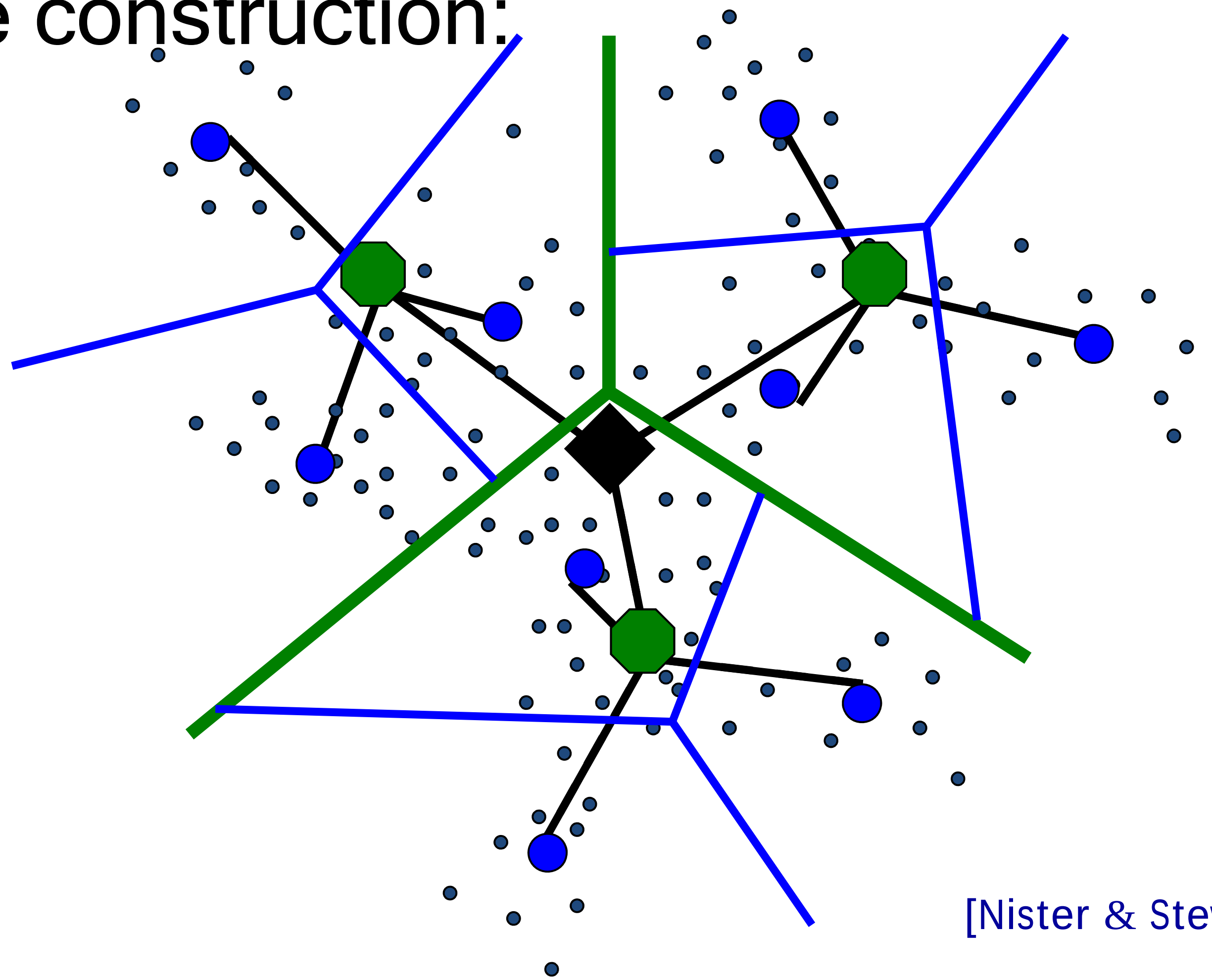
RANSAC

- 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

Kristen Grauman

Vocabulary Trees: hierarchical clustering for large vocabularies

- Tree construction:

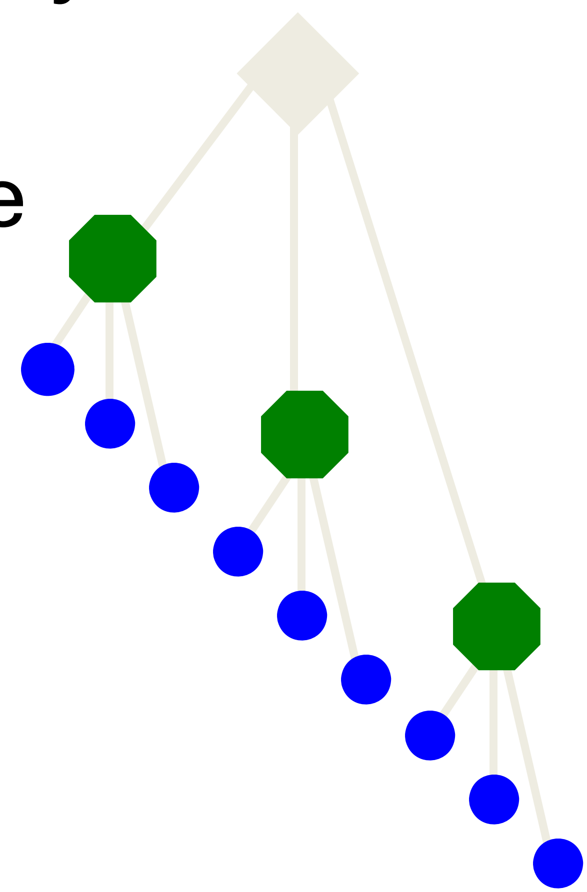


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- Training: Filling the tree

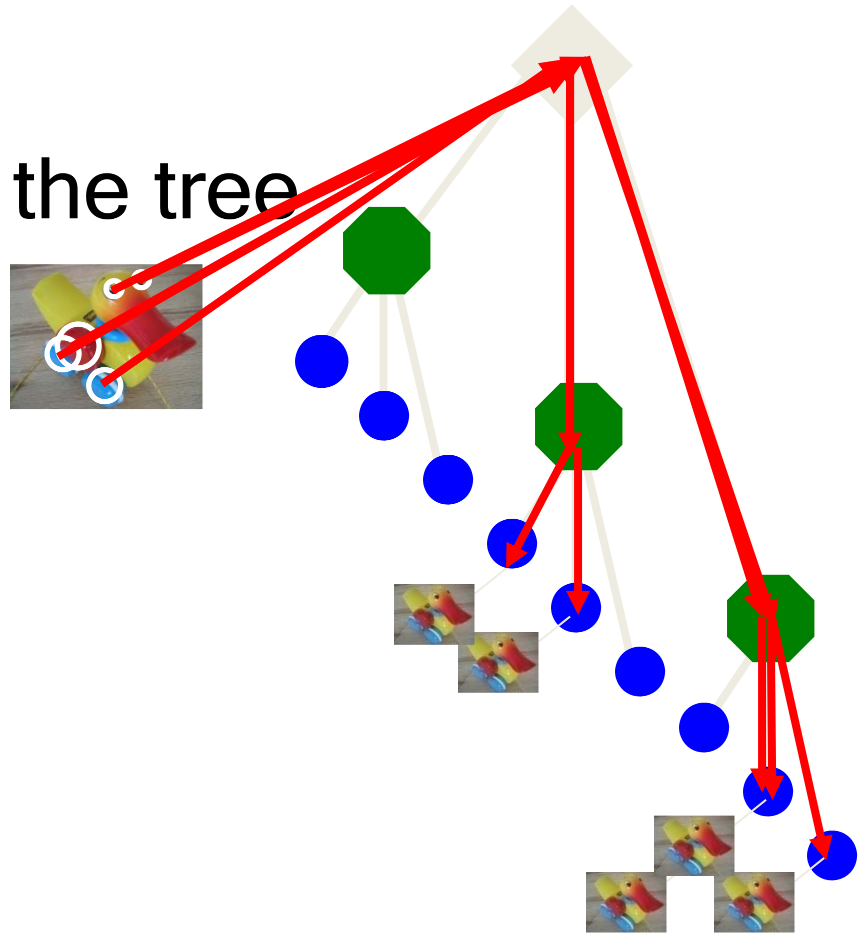


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- Training: Filling the tree

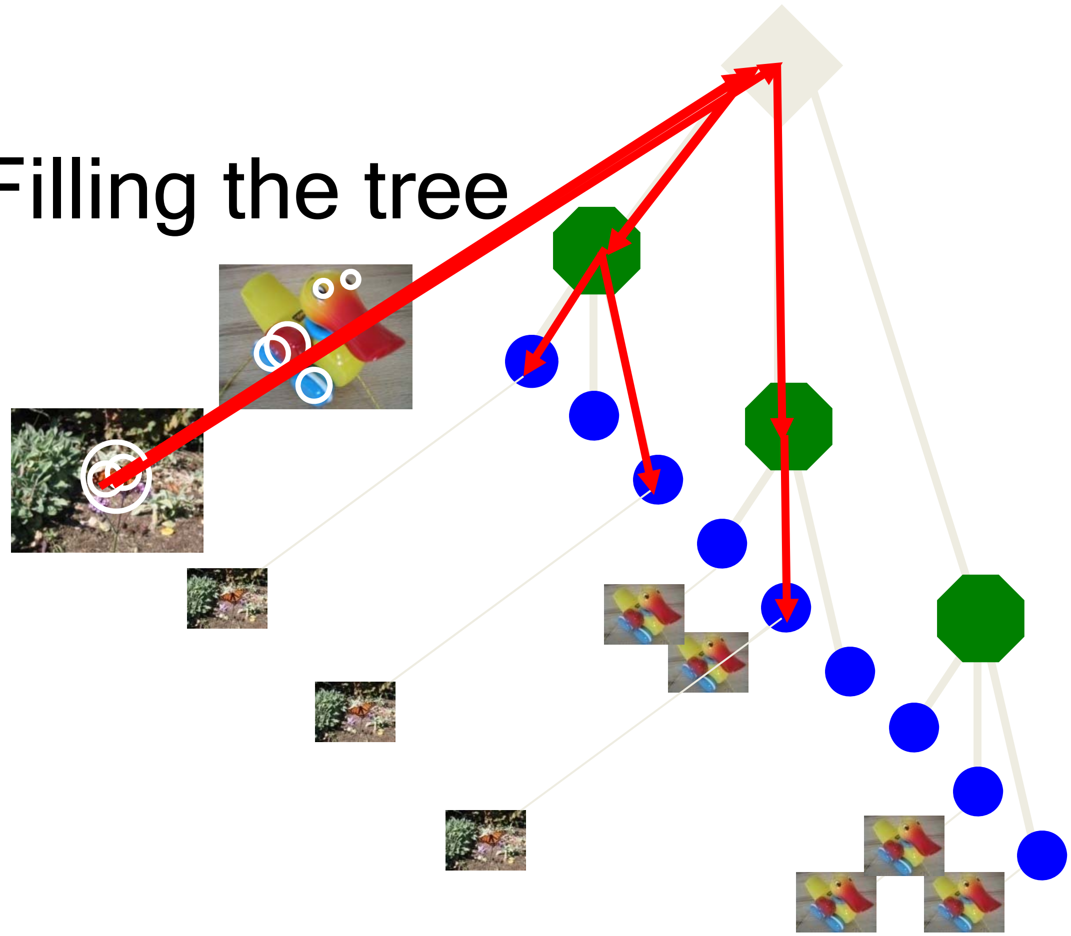


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- Training: Filling the tree

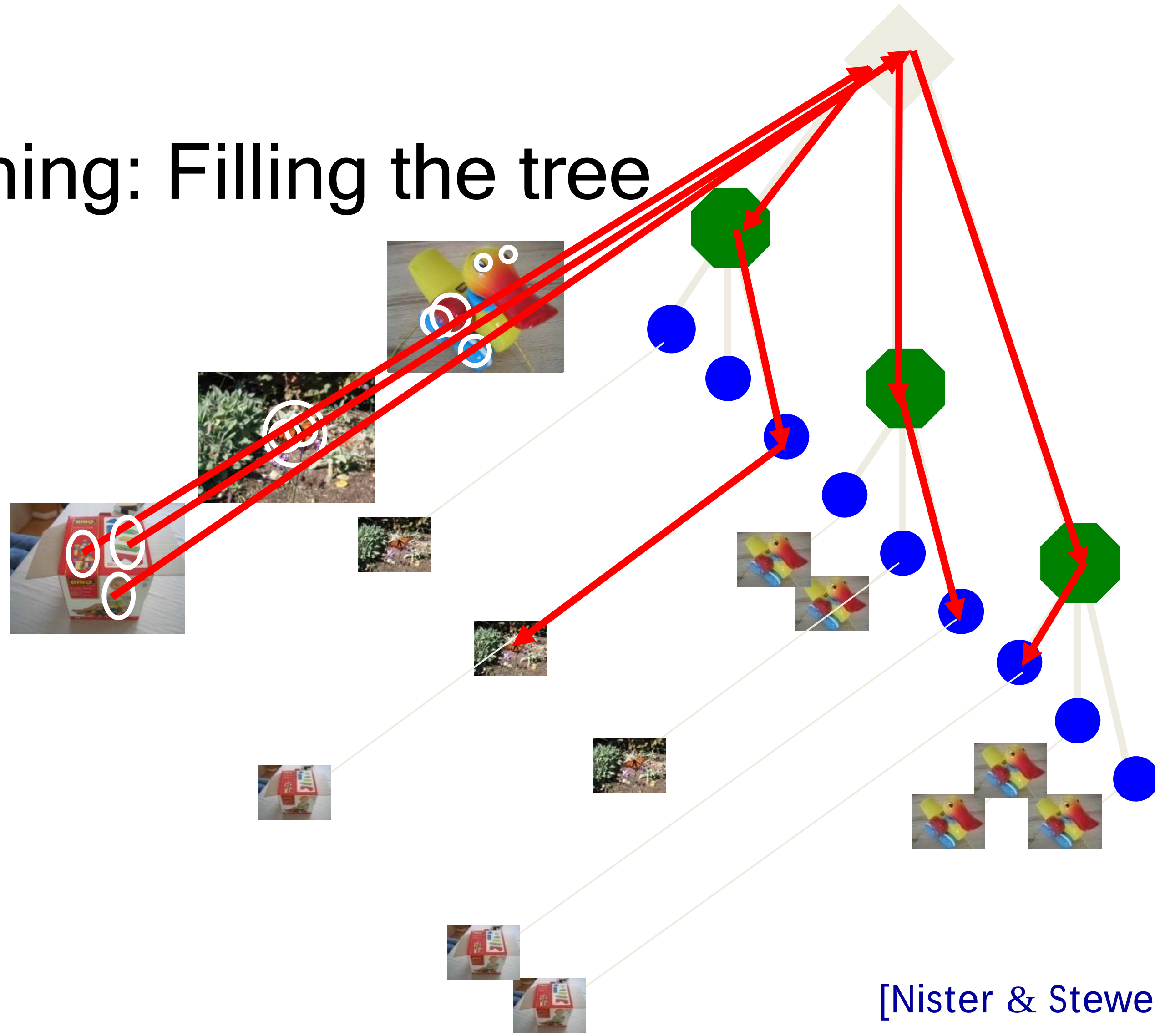


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- Training: Filling the tree

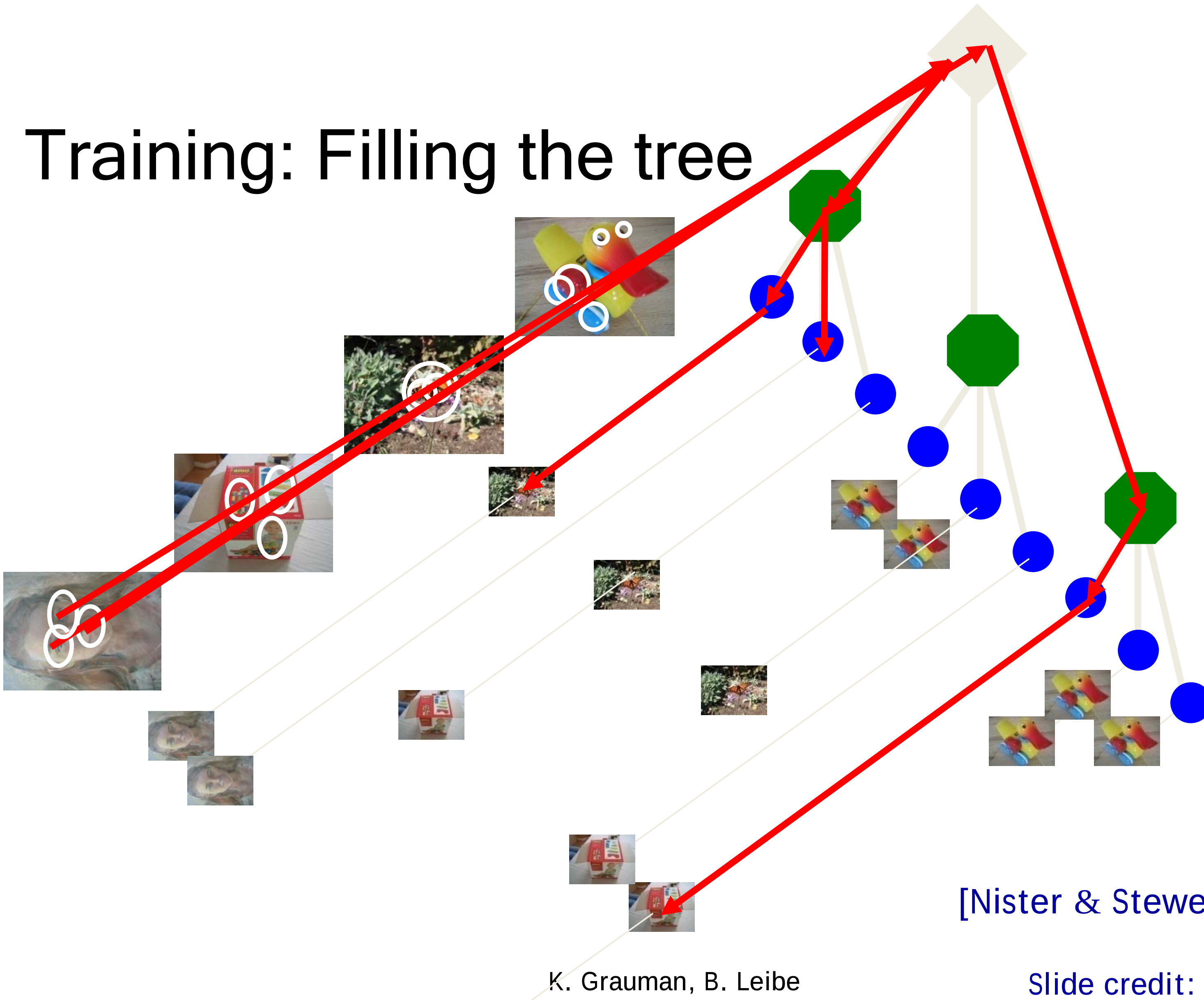


[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

Vocabulary Tree

- Training: Filling the tree



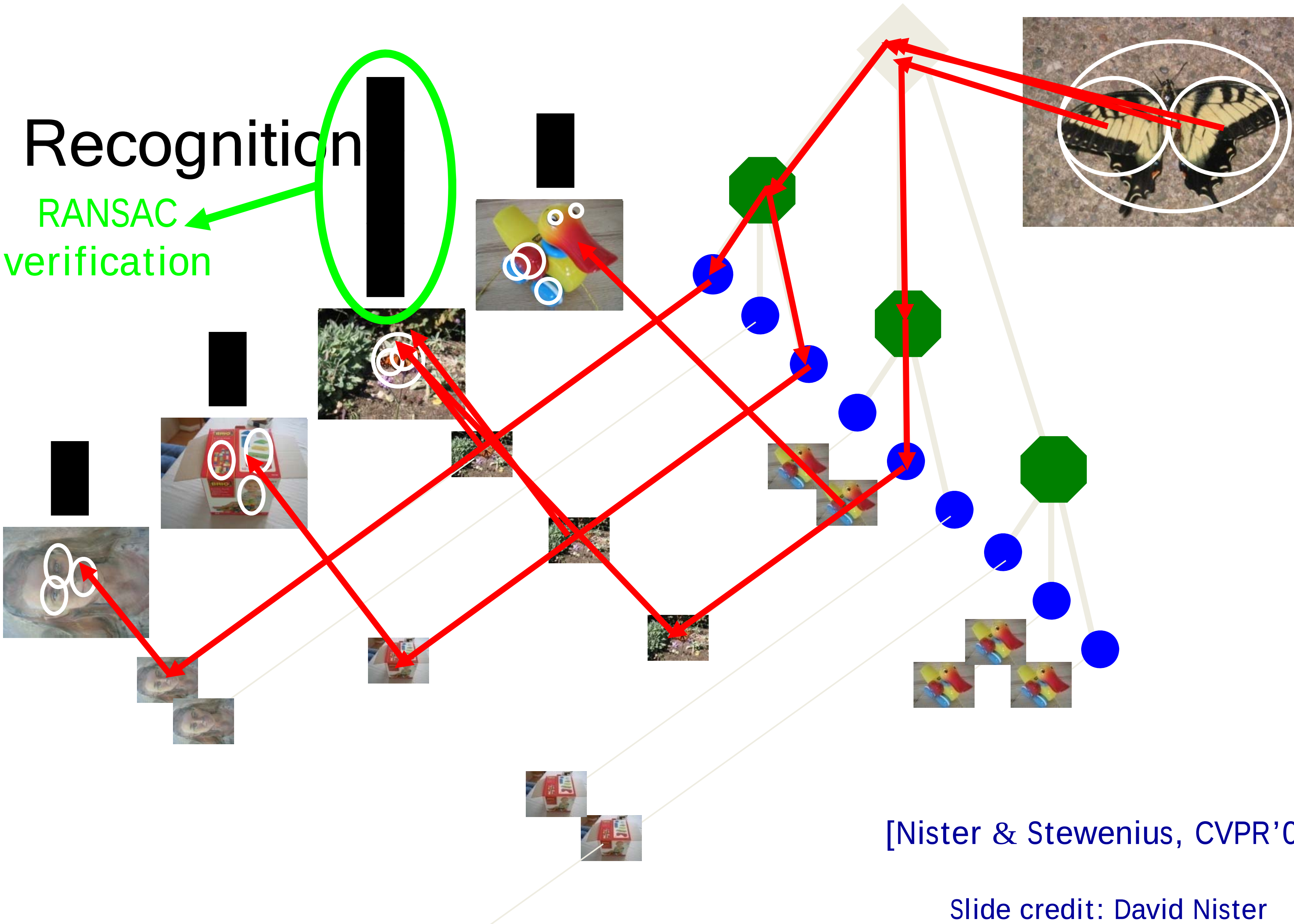
[Nister & Stewenius, CVPR'06]

Slide credit: David Nister

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

Vocabulary Tree

- Recognition



[Nister & Stewenius, CVPR'06]

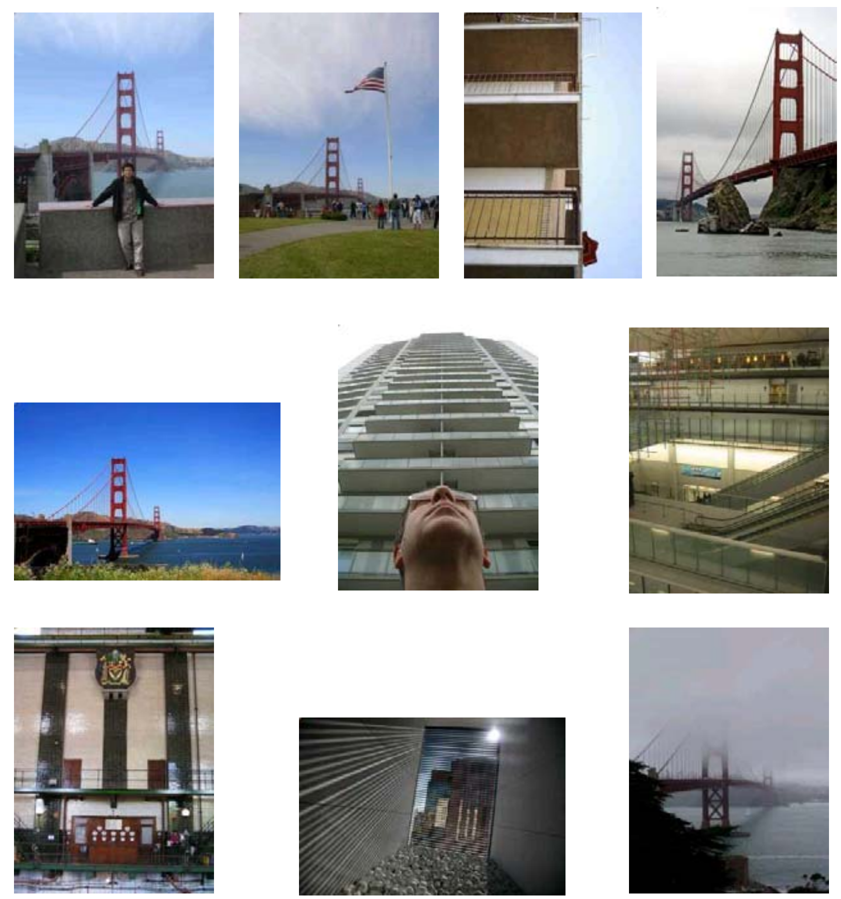
Slide credit: David Nister

Scoring retrieval quality

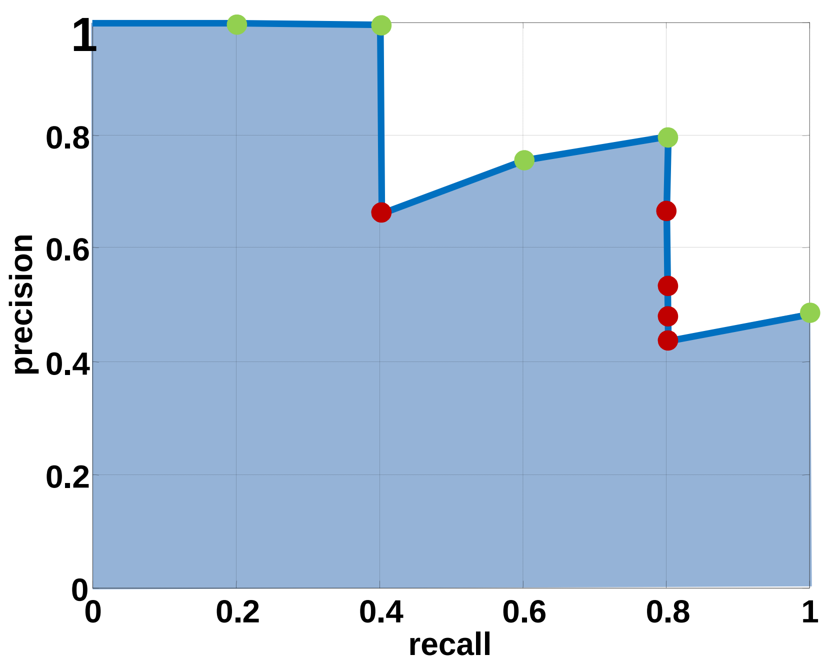
Query

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

Results (ordered):



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



Slide credit: Ondrej Chum

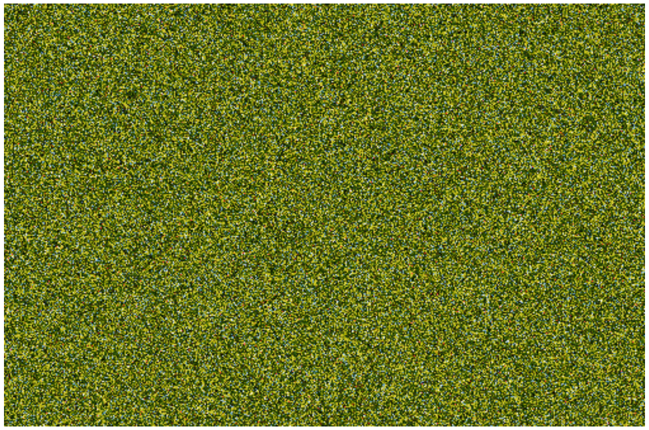
Bags of words: pros and cons

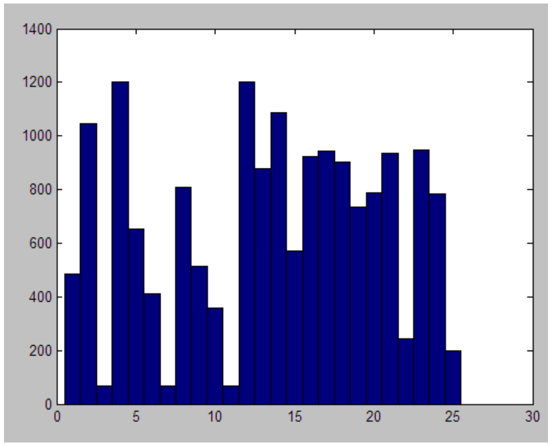
+ flexible to geometry / deformations / viewpoint
+ compact summary of image content
+ provides vector representation for sets
+ very good results in practice

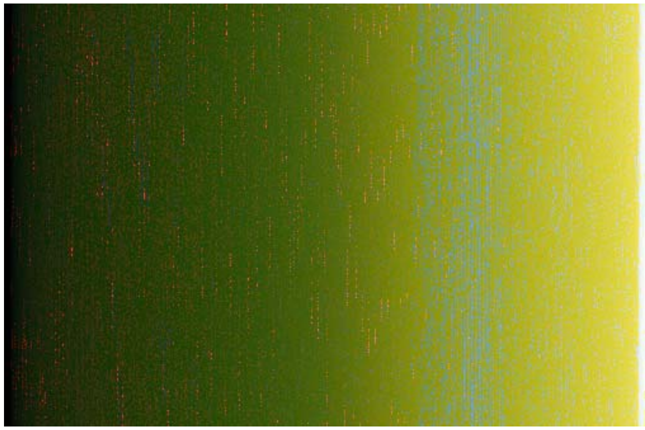
- basic model ignores geometry – must verify afterwards, or encode via features
- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear

Spatial Layout and Context

But what about spatial layout?

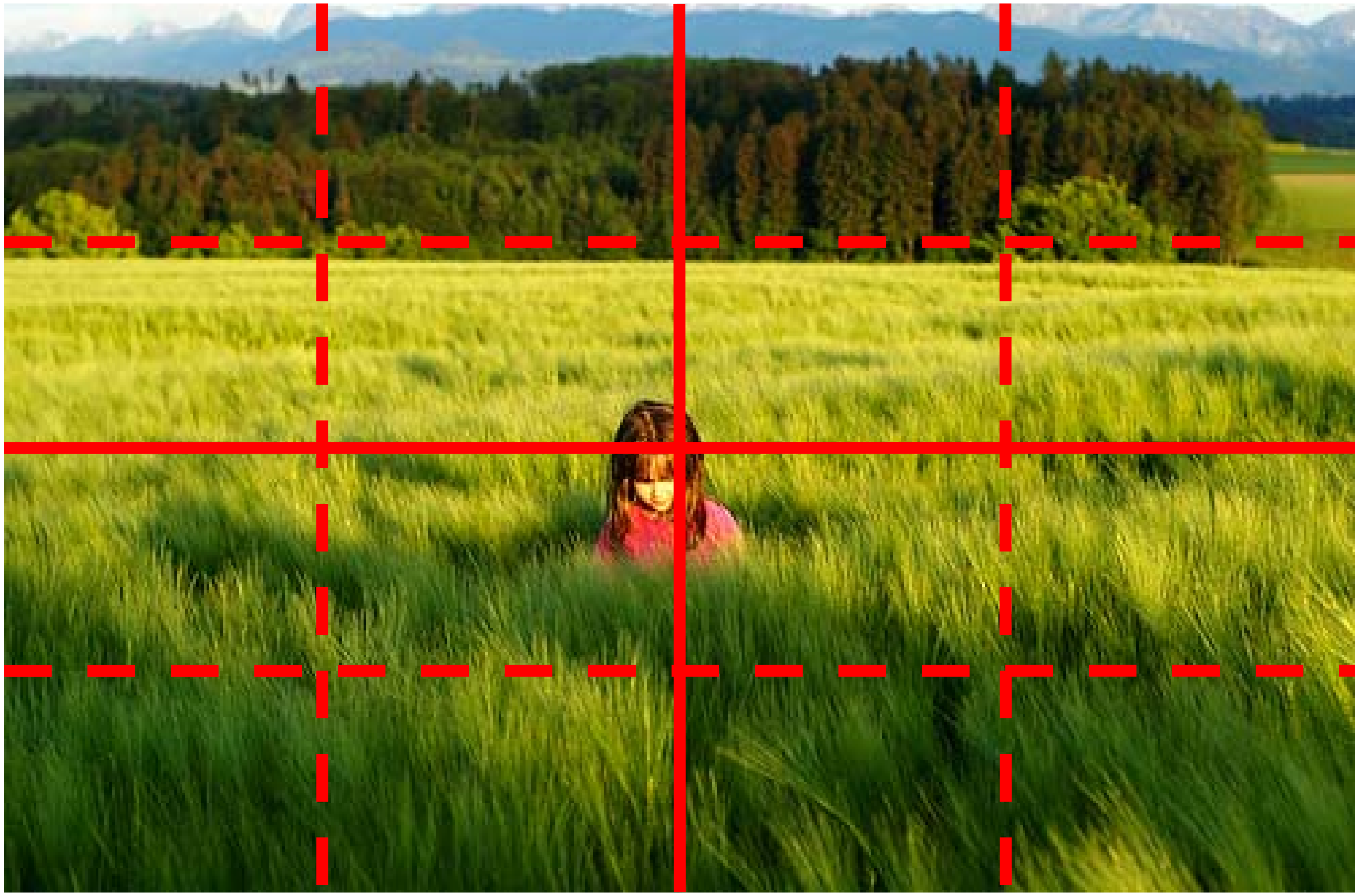






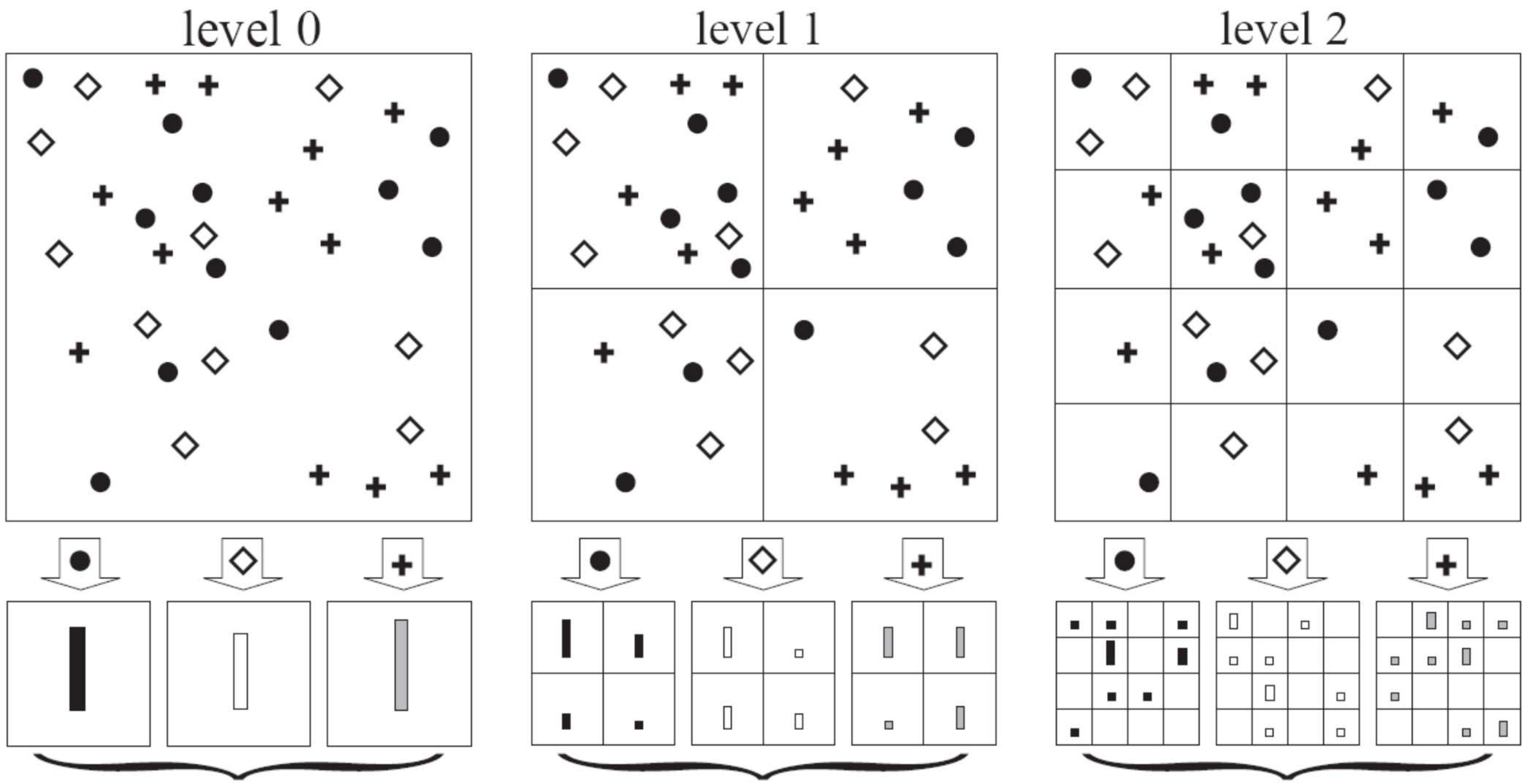
All of these images have the same color histogram

Spatial pyramid



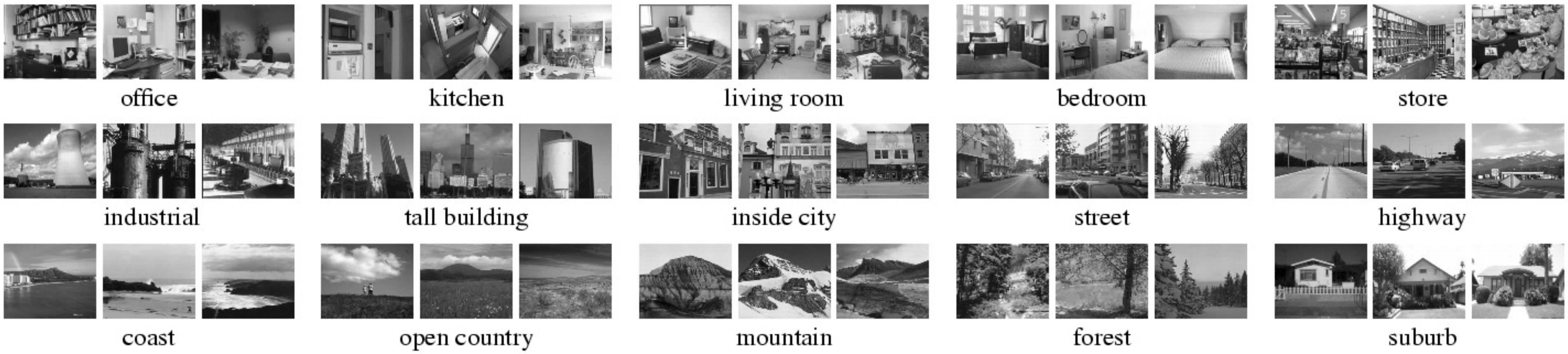
Compute histogram in each spatial bin

Spatial pyramid



[Lazebnik et al. CVPR 2006]

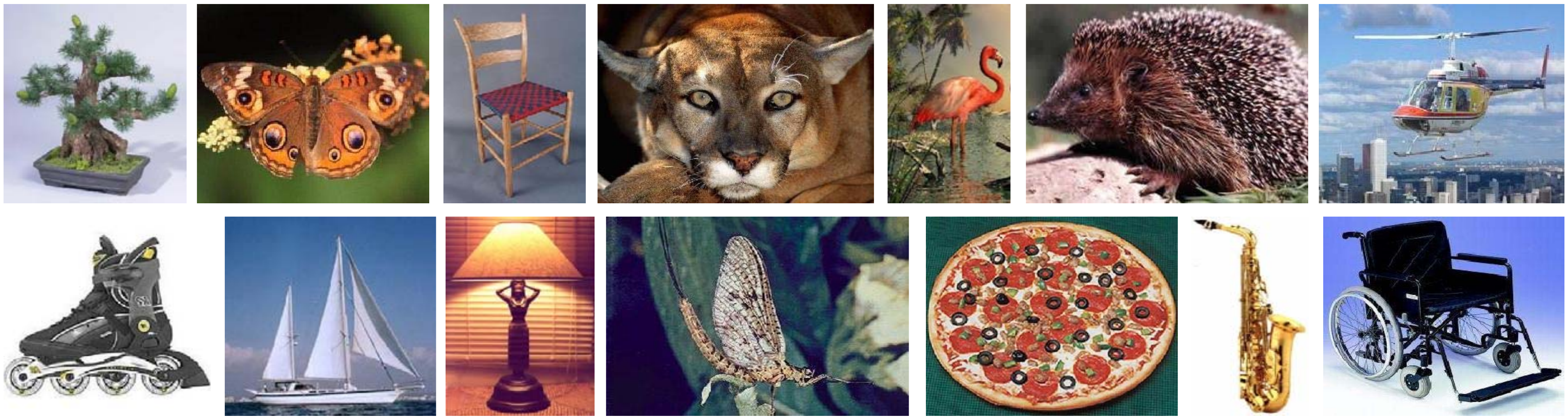
Results: Scene category dataset



Multi-class classification results
(100 training images per class)

	Weak features (vocabulary size: 16)		Strong features (vocabulary size: 200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0 (1×1)	45.3 $\pm$0.5		72.2 $\pm$0.6	
1 (2×2)	53.6 $\pm$0.3	56.2 $\pm$0.6	77.9 $\pm$0.6	79.0 $\pm$0.5
2 (4×4)	61.7 $\pm$0.6	64.7 $\pm$0.7	79.4 $\pm$0.3	**81.1** $\pm$0.3
3 (8×8)	63.3 $\pm$0.8	**66.8** $\pm$0.6	77.2 $\pm$0.4	80.7 $\pm$0.3

Results: Caltech101 dataset

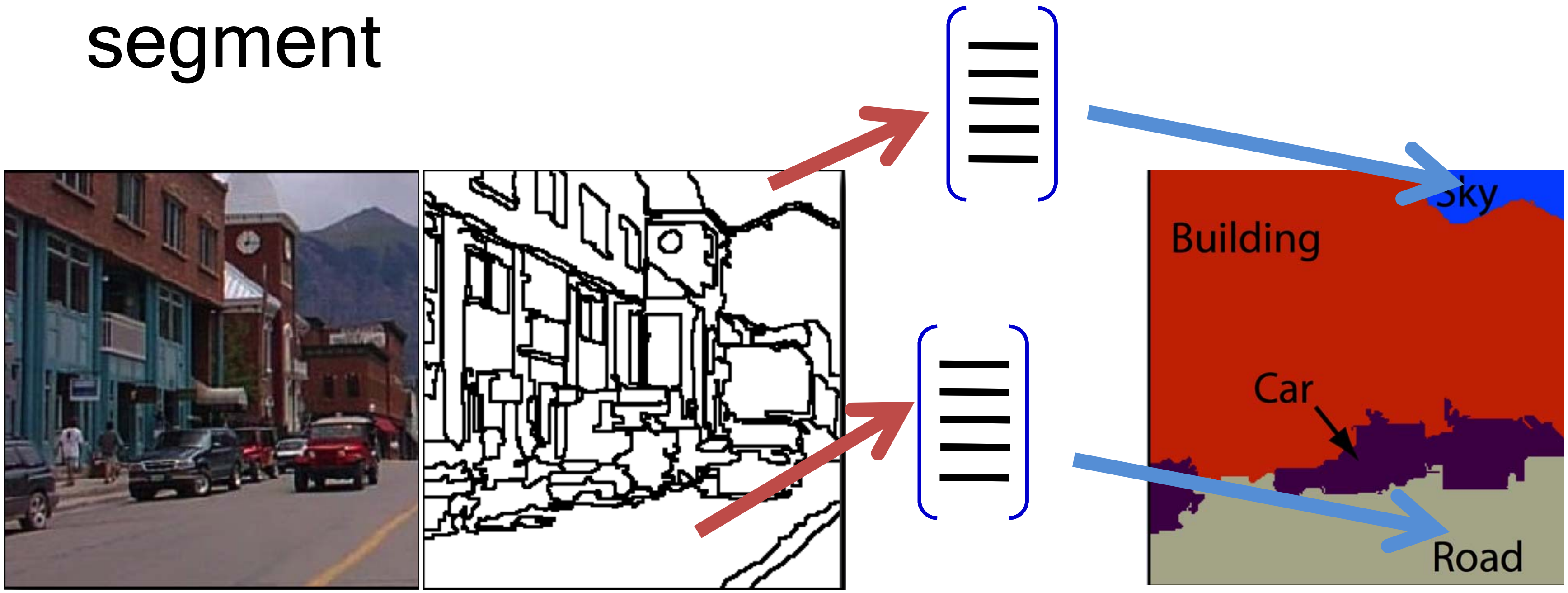


Multi-class classification results (30 training images per class)

	Weak features (16)		Strong features (200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0	15.5 ±0.9		41.2 ±1.2	
1	31.4 ±1.2	32.8 ±1.3	55.9 ±0.9	57.0 ±0.8
2	47.2 ±1.1	49.3 ±1.4	63.6 ±0.9	**64.6** ±0.8
3	52.2 ±0.8	**54.0** ±1.1	60.3 ±0.9	64.6 ±0.7

Region representation

- Segment the image into superpixels
- Use features to represent each image segment



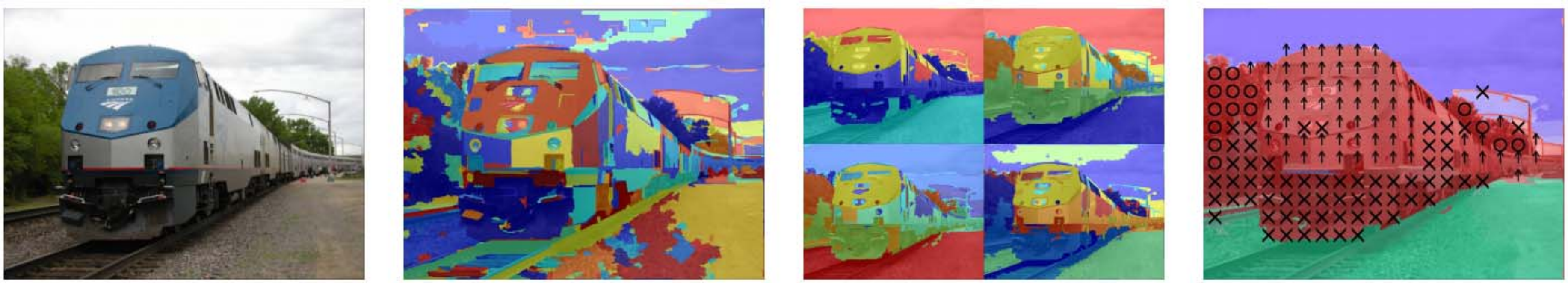
Joseph Tighe and Svetlana Lazebnik

Region representation

- Color, texture, BoW
  - Only computed within the local region
- Shape of regions
- Position in the image

Working with regions

- Spatial support is important – multiple segmentations



(a) Input (b) Superpixels (c) Multiple Hypotheses (d) Geometric Labels

Geometric context [Hoiem et al. ICCV 2005]