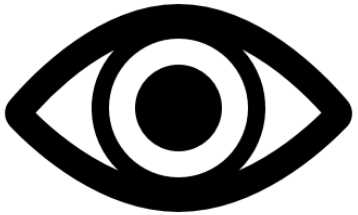


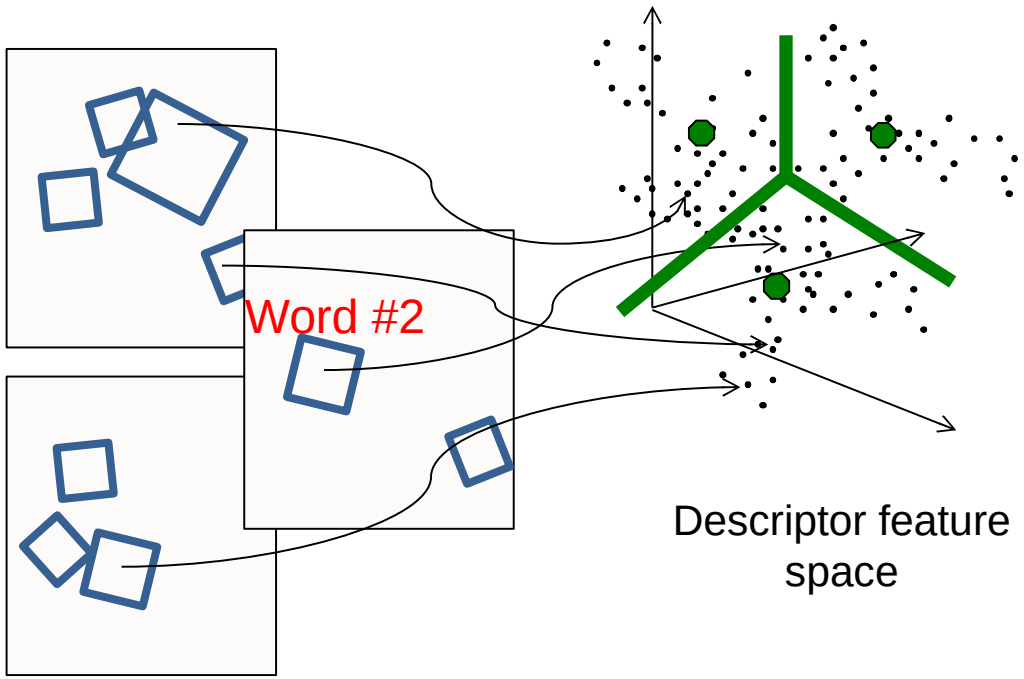
Advanced Image Processing

Large scale scene recognition
and
advanced feature encoding

SYDE 671

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.

Scene Categorization

Oliva and Torralba, 2001


Coast


Forest


Highway


Inside City


Mountain


Open Country


Street


Tall Building

Fei Fei and Perona, 2005

\+


Bedroom


Kitchen


Living Room


Office


Suburb

Lazebnik, Schmid, and Ponce, 2006

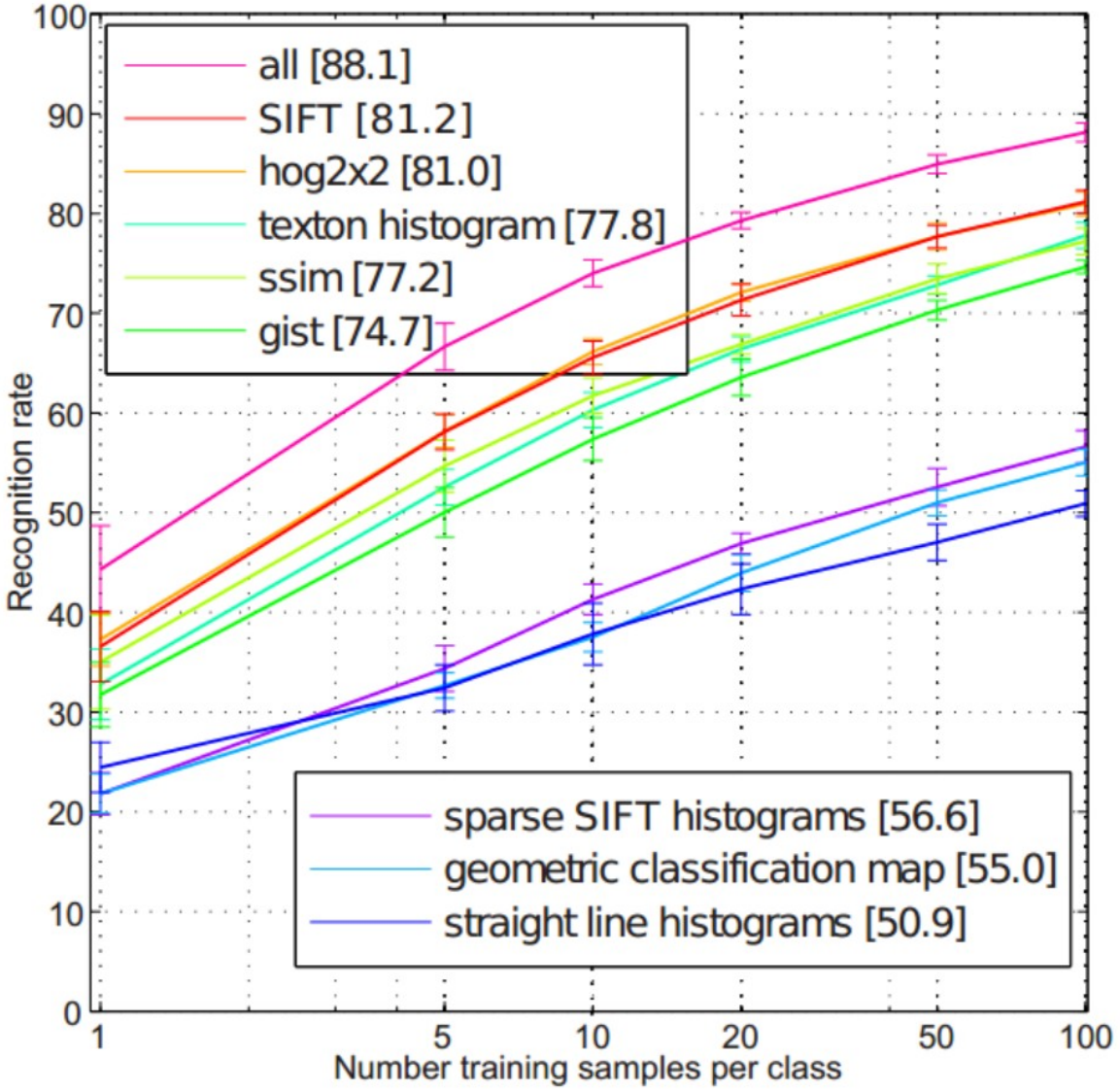
\+


Industrial

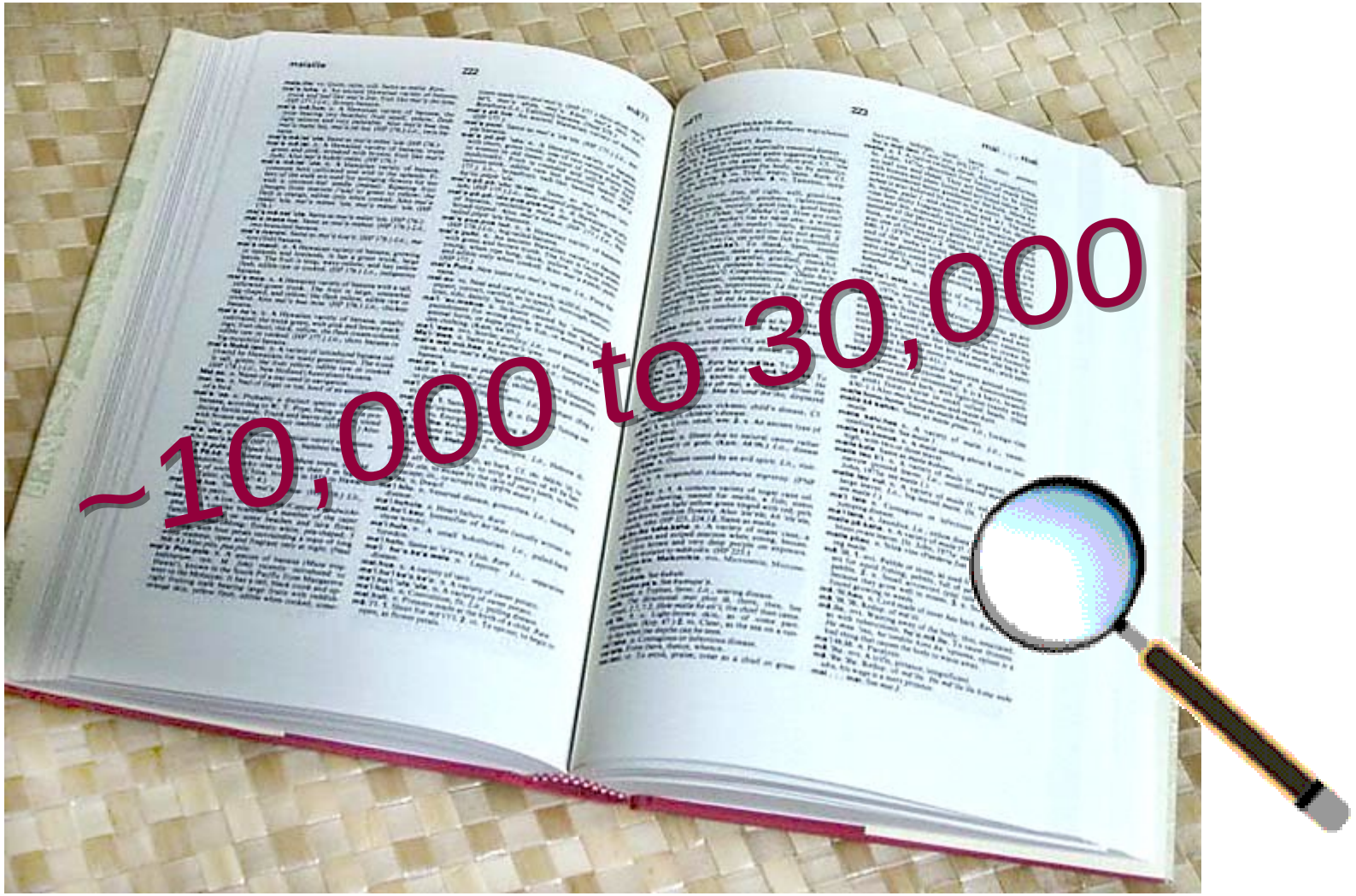

Store

15 Scene Database

15 Scene Recognition Rate



How many object categories are there?



OK, but how many places?

Biederman 1987


abbey


airplane cabin


airport terminal
Abfall


apple orchard


assembly hall


bakery
Garlic
Garlic


car factory

cockpit


construction site


food court


interior car


lounge

stadium

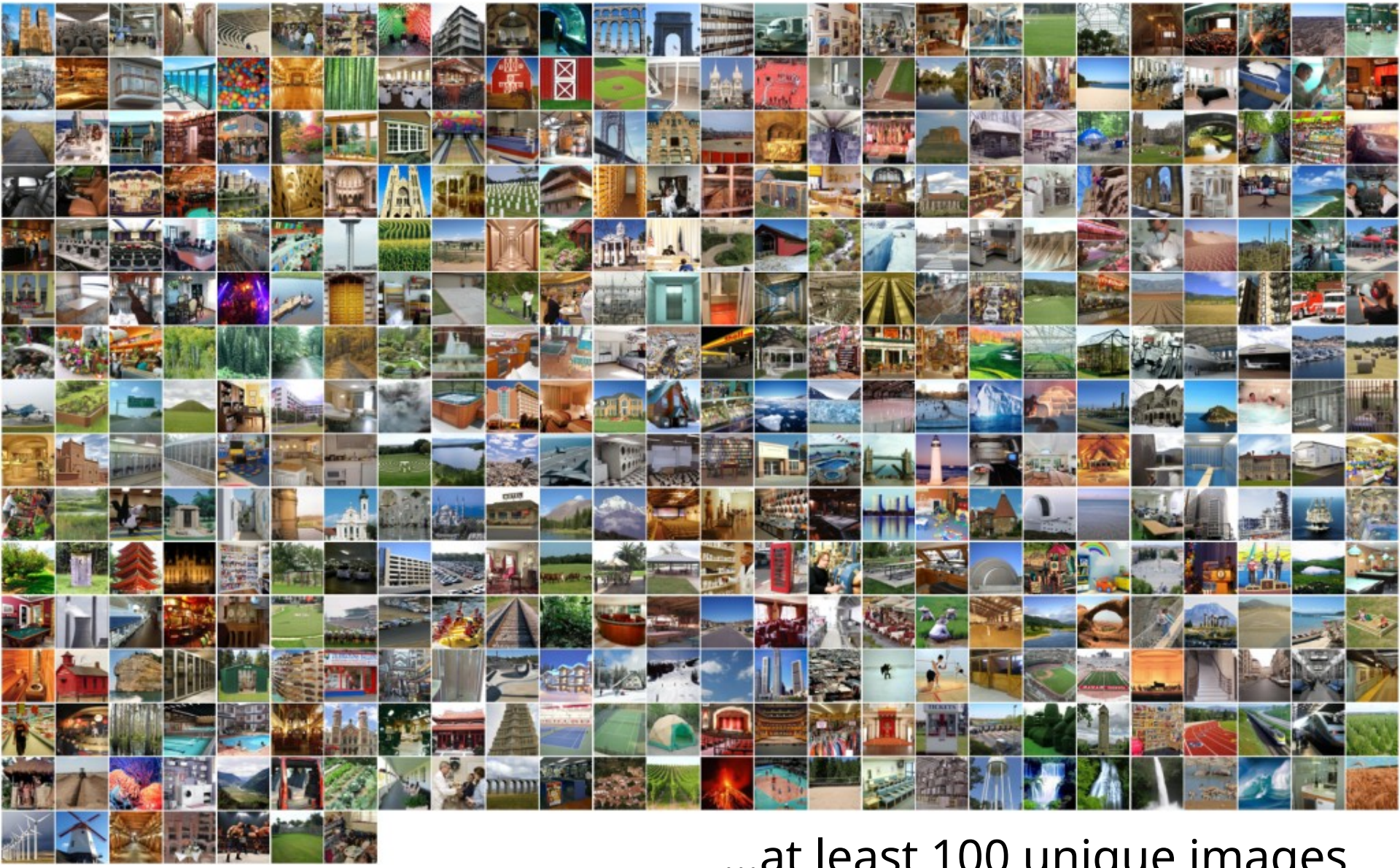

BLUE SQUARE
BET NOW AT BLUESQUARE.COM
WEMBLEY STADIUM
npower


stream


train station
O'Hare

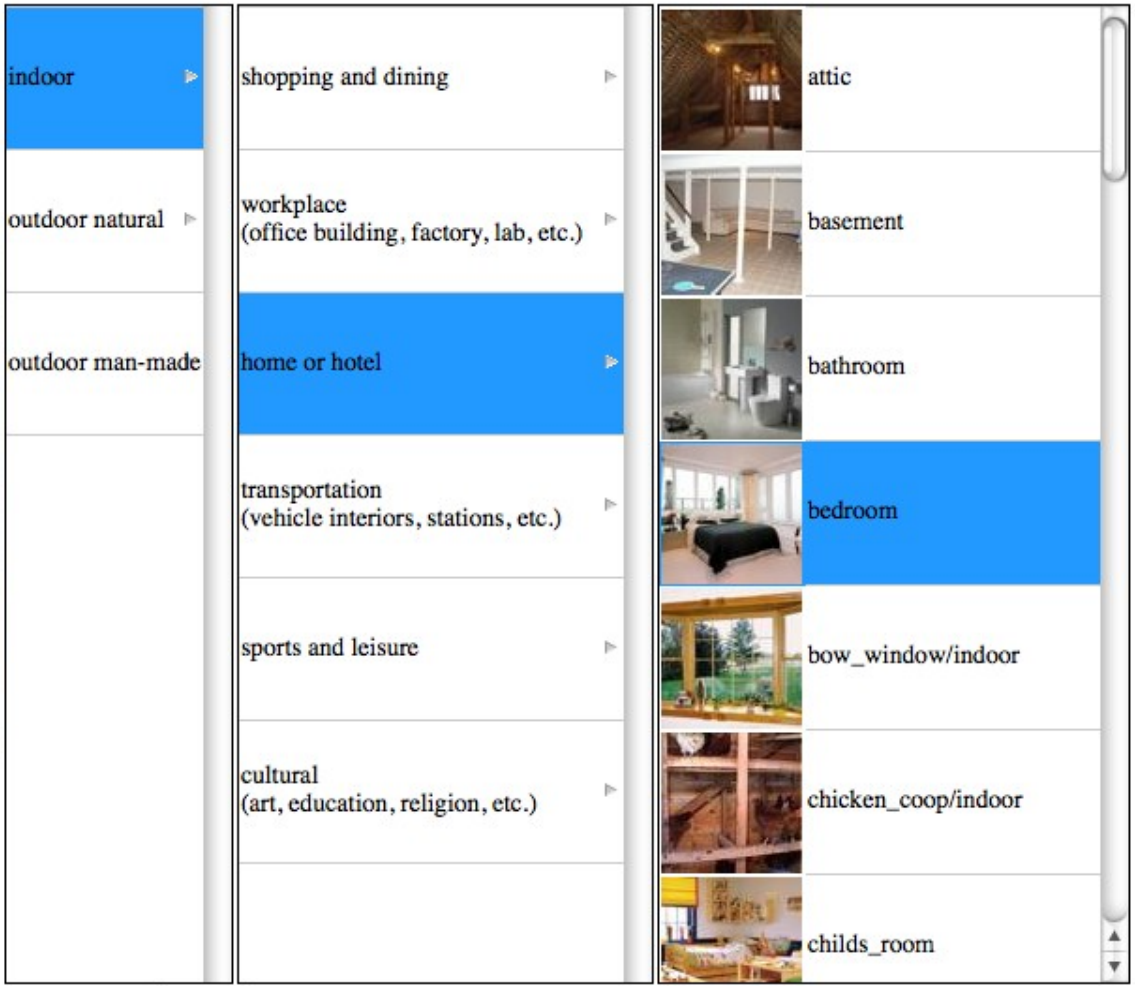

SUN Database – Xiao et al. CVPR 2010
130k images
899 categories
7 APR 2007

397 Well-sampled Categories



...at least 100 unique images

Evaluating Human Scene Classification



Accuracy	98%	90%	68%


1
2


TELEPHONE

bathroom(100%)

beauty salon(100%)

bedroom(100%)

bullring(100%)

playground(100%)

greenhouse outdoor(100%)

podium outdoor(100%)

phone booth(100%)

tennis court outdoor(100%)

wind farm(100%)

veterinarians office(100%)

riding arena(100%)

Scene category

Most confusing categories

Inn (0%)

Restaurant patio (44%)

Chalet (19%)

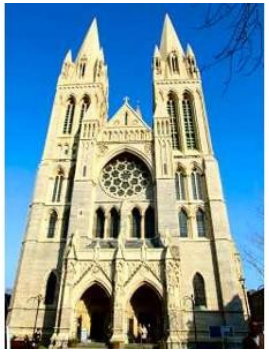
Bayou (0%)

River (67%)

Coast (8%)

Basilica (0%)

Cathedral(29%)



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

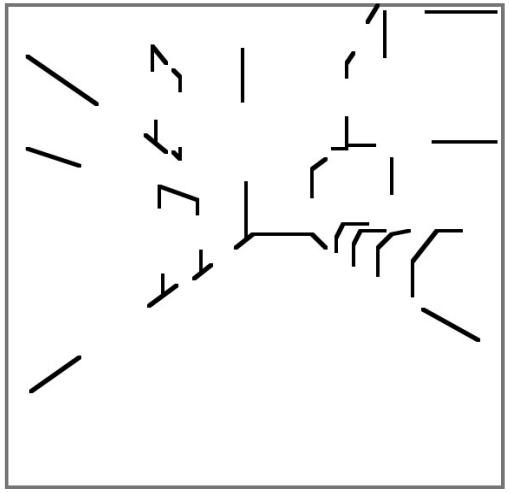
ceiling wall column screen seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat seat

Similar objects, and similar spatial layout

Different lighting, different materials, different “stuff”

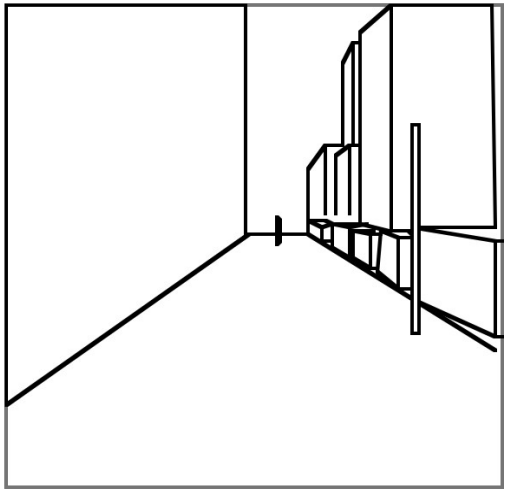
Scene emergent features

“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

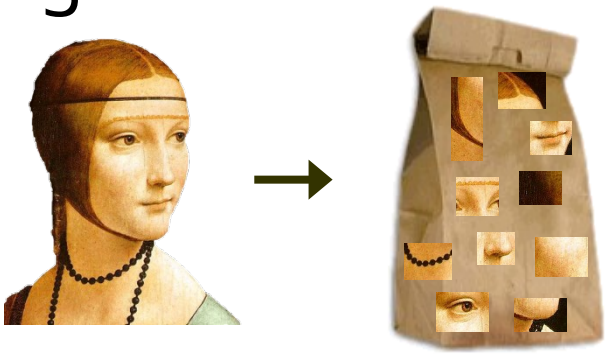
Textures

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)

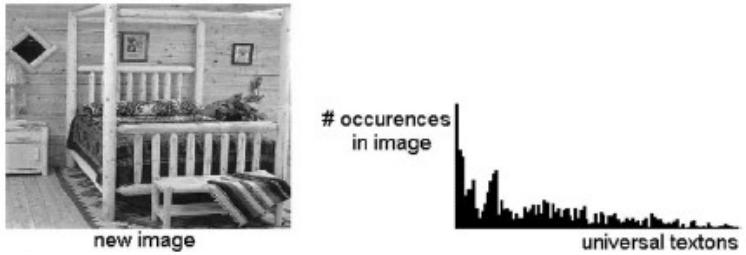
Global Texture Descriptors

Bag of words



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

Non-localized textons

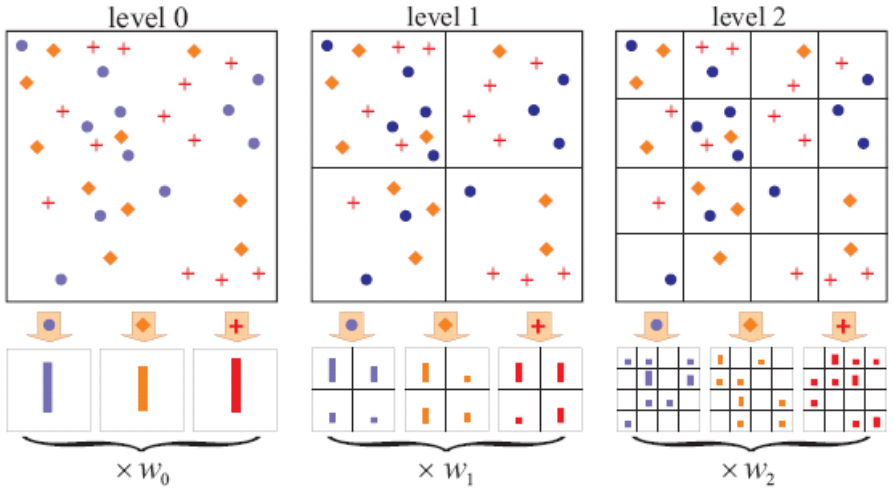


Walker, Malik. Vision Research 2004

...

Spatially organized textures

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



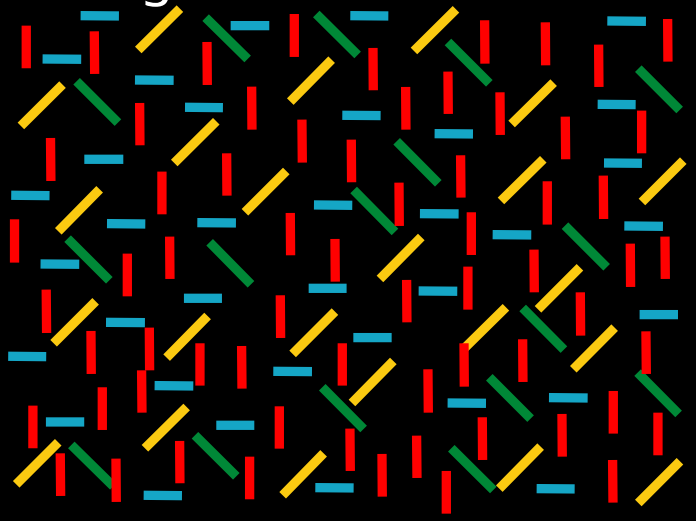
S. Lazebnik, et al, CVPR 2006

...

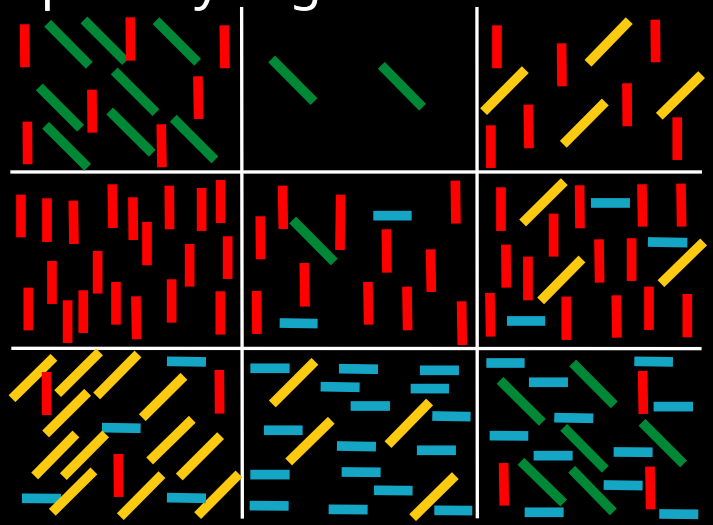
R. Datta, D. Joshi, J. Li, and J. Z. Wang, **Image Retrieval: Ideas, Influences, and Trends of the New Age**, *ACM Computing Surveys*, vol. 40, no. 2, pp. 5:1-60, 2008.

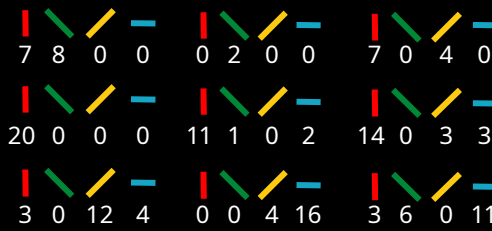
Bag of words

Bag of words model

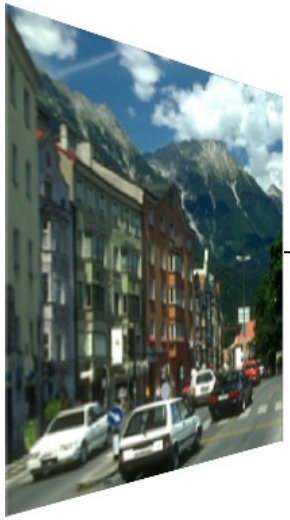


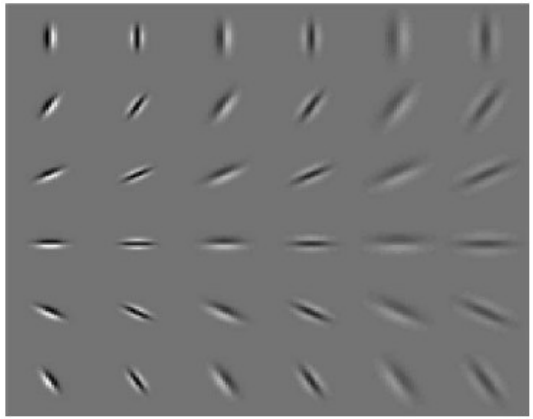
Spatially organized textures





Textons





Filter bank

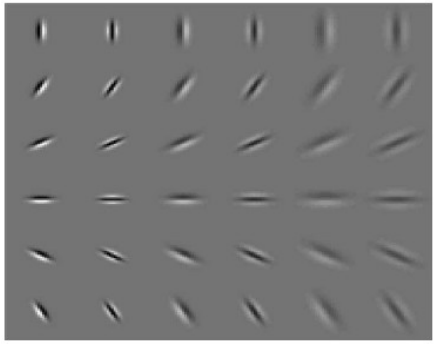
Vector of filter responses
at each pixel

Kmeans over a set of
vectors on a
collection
of images

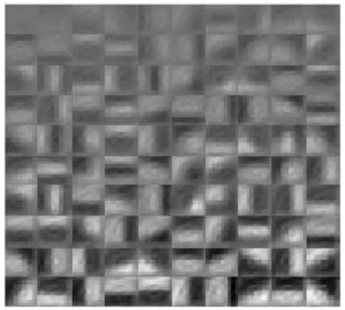
Malik, Belongie, Shi, Leung, 1999

Textons

Filter bank

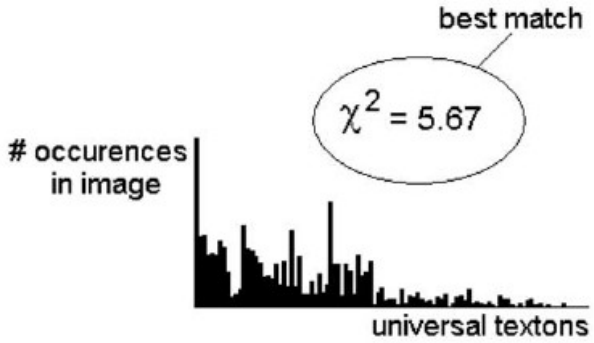


K-means (100 clusters)

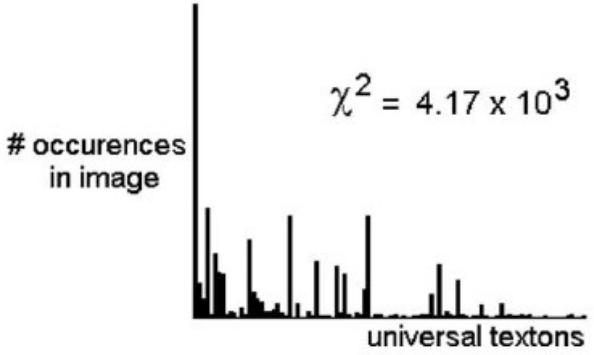


Malik, Belongie, Shi, Leung, 1999

label = bedroom



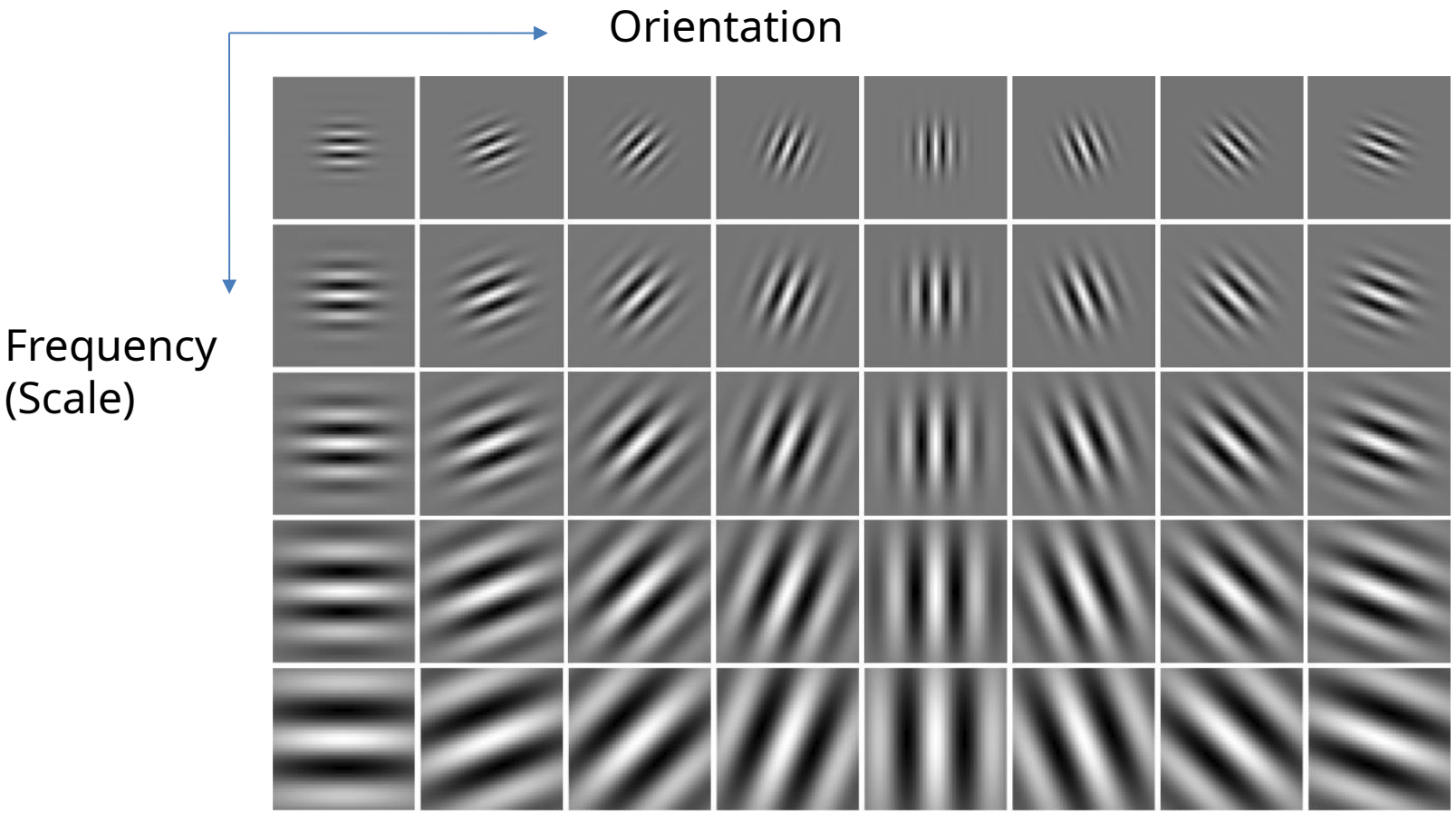
label = beach



Walker, Malik, 2004

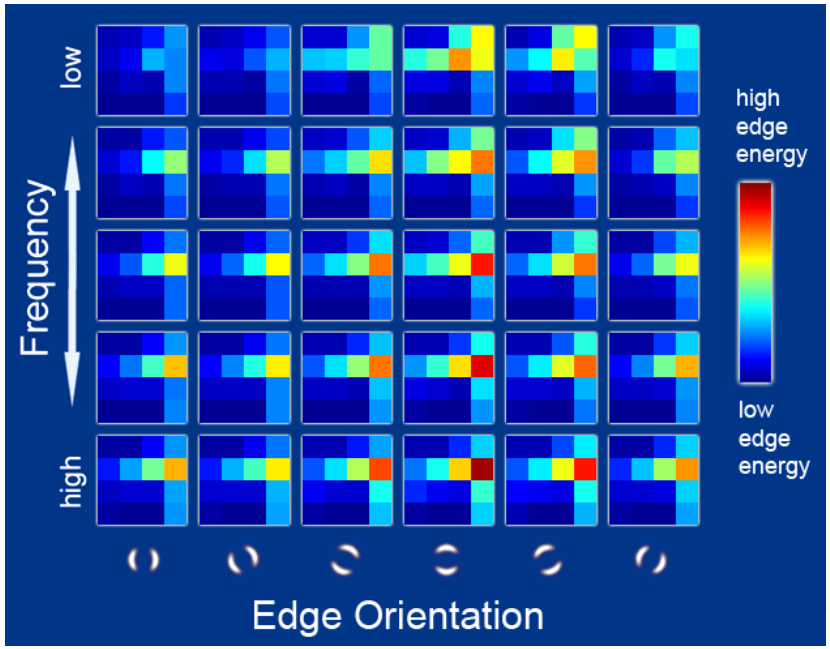
Gabor filter

- Sinusoid modulated by a Gaussian kernel
- analyze whether there is a specific frequency content in a specific direction at a pixel.



Global scene descriptors: GIST

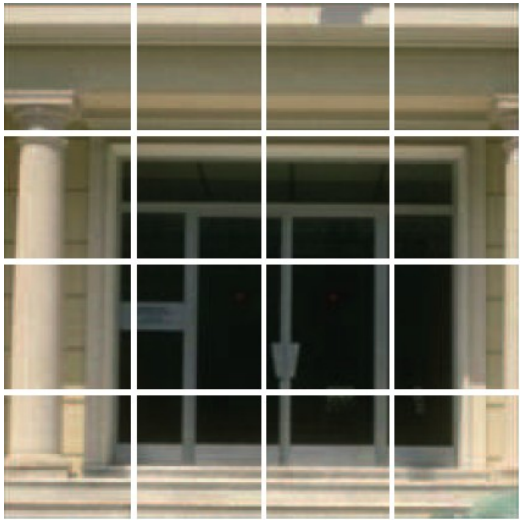
- The “gist” of a scene: Oliva & Torralba (2001)

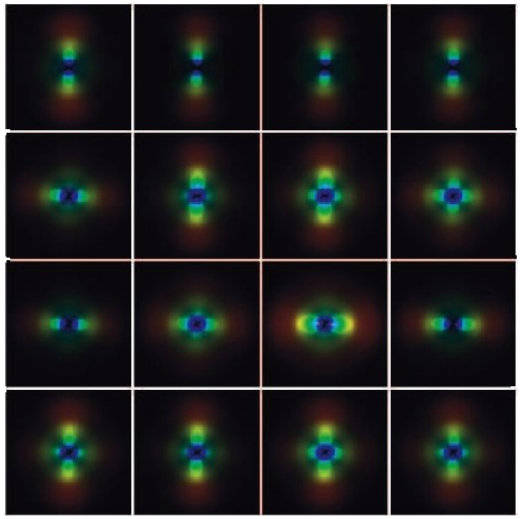


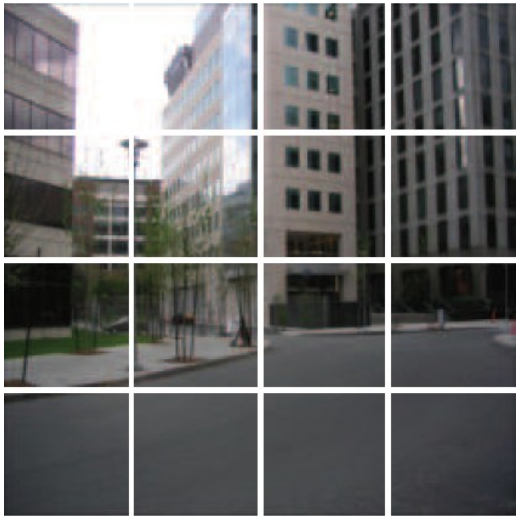
http://people.csail.mit.edu/torralba/code/spatialenvelope/

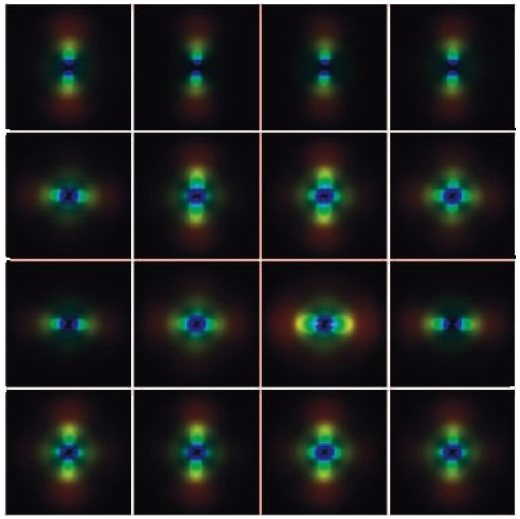
Gist descriptor

Oliva and Torralba, 2001









Apply oriented Gabor filters over different scales.

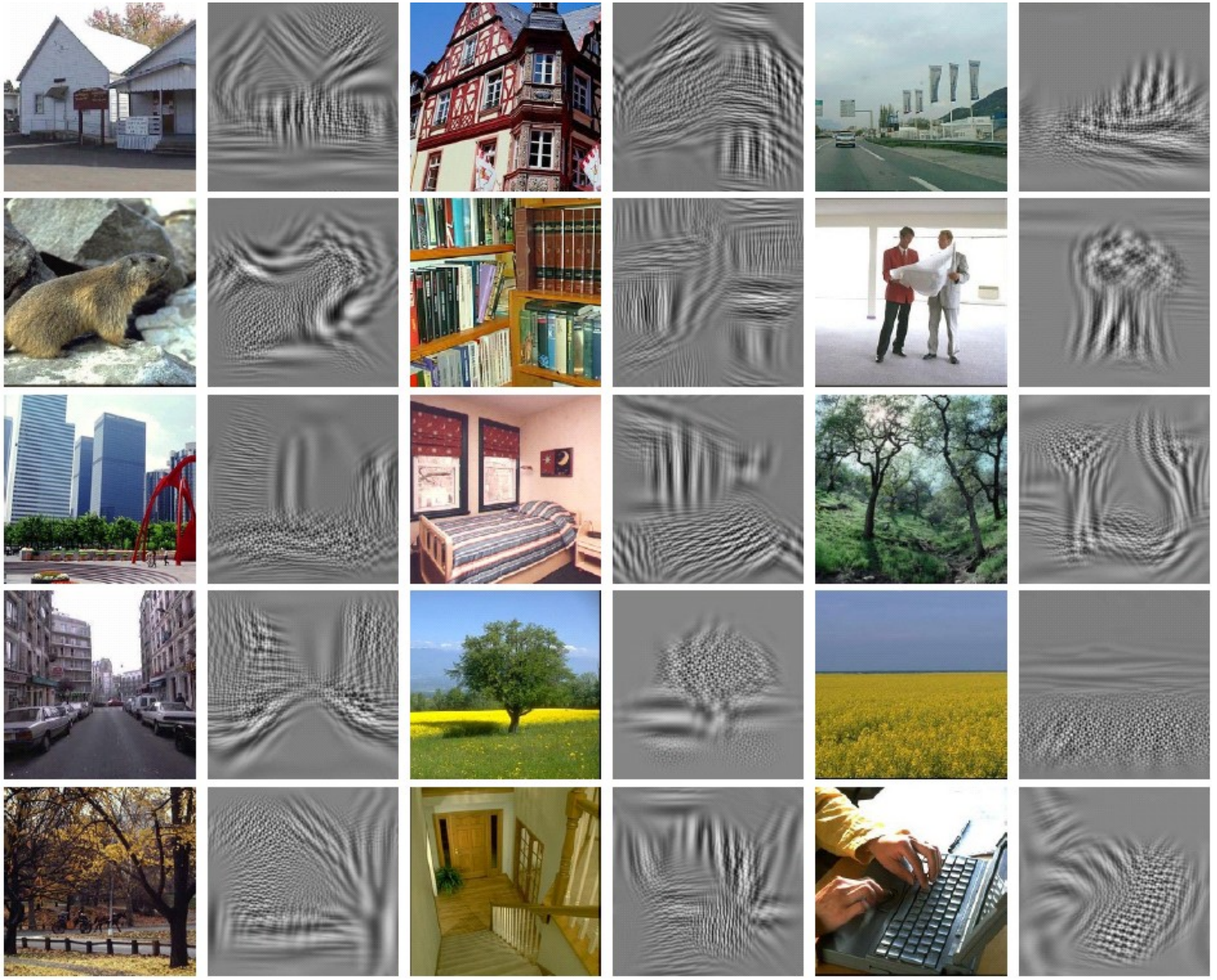
Average filter energy per bin.

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

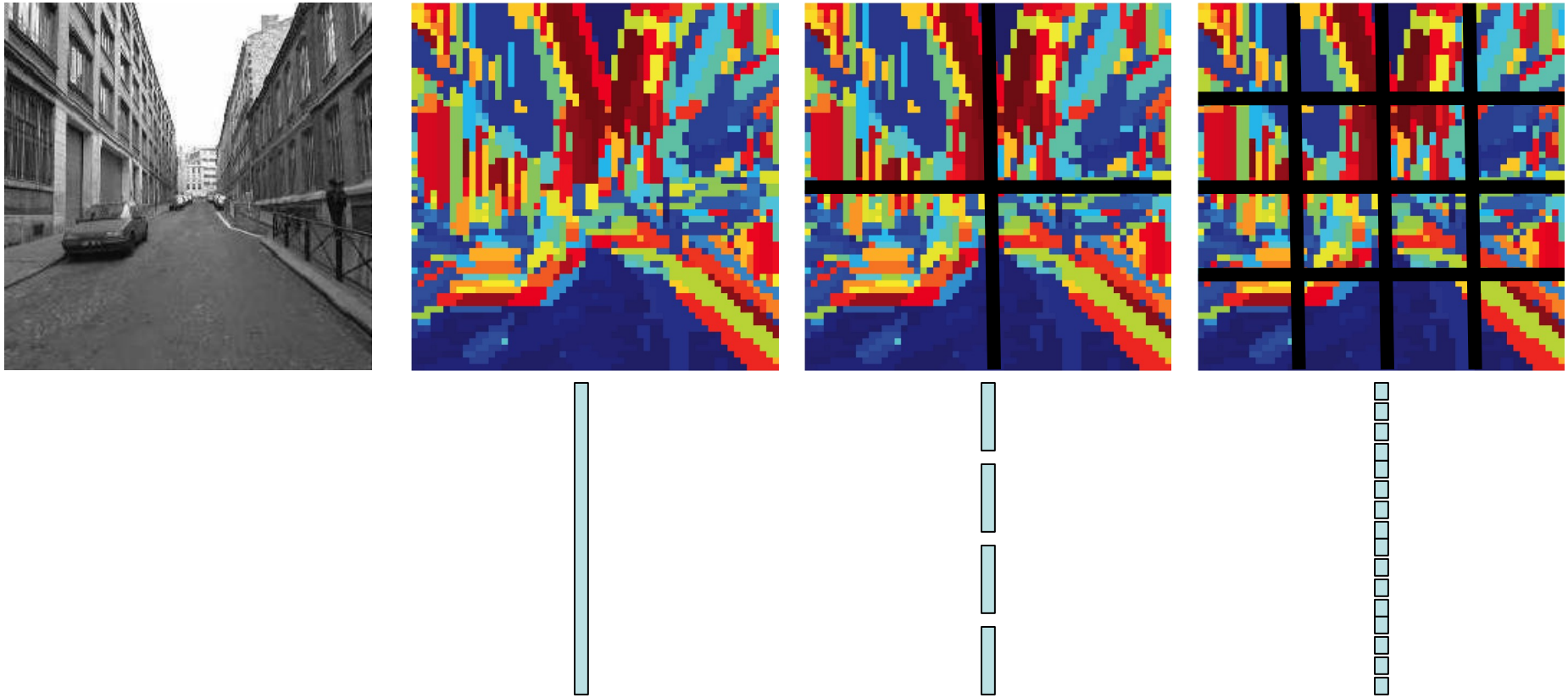


Global features (I) ~ global features (I’)

Oliva & Torralba (2001)

Bag of words & spatial pyramid matching

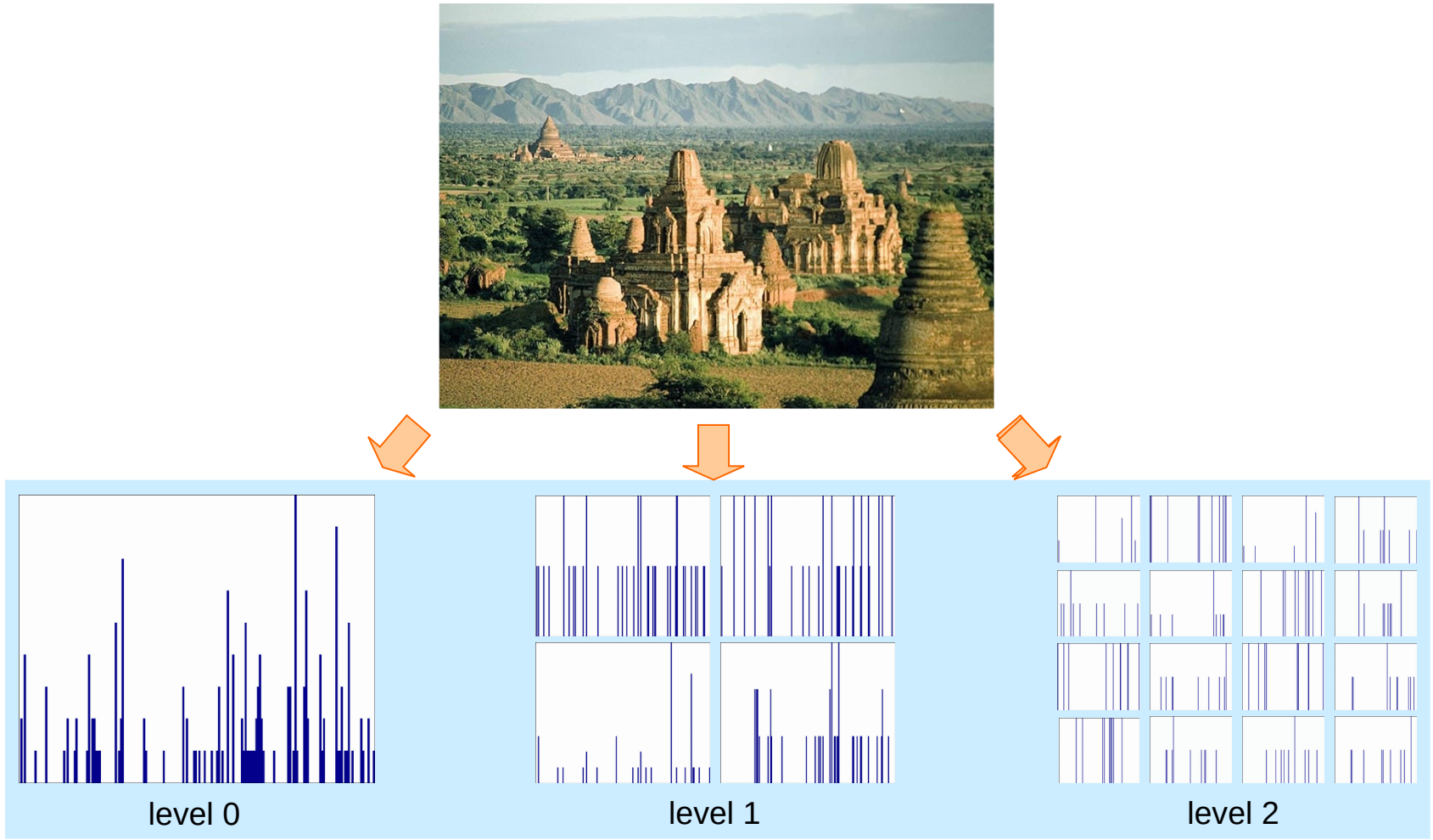
Sivic, Zisserman, 2003. Visual words = Kmeans of SIFT descriptors



But any way to improve the quantization approach itself?

S. Lazebnik, et al, CVPR 2006

We already looked at the Spatial Pyramid

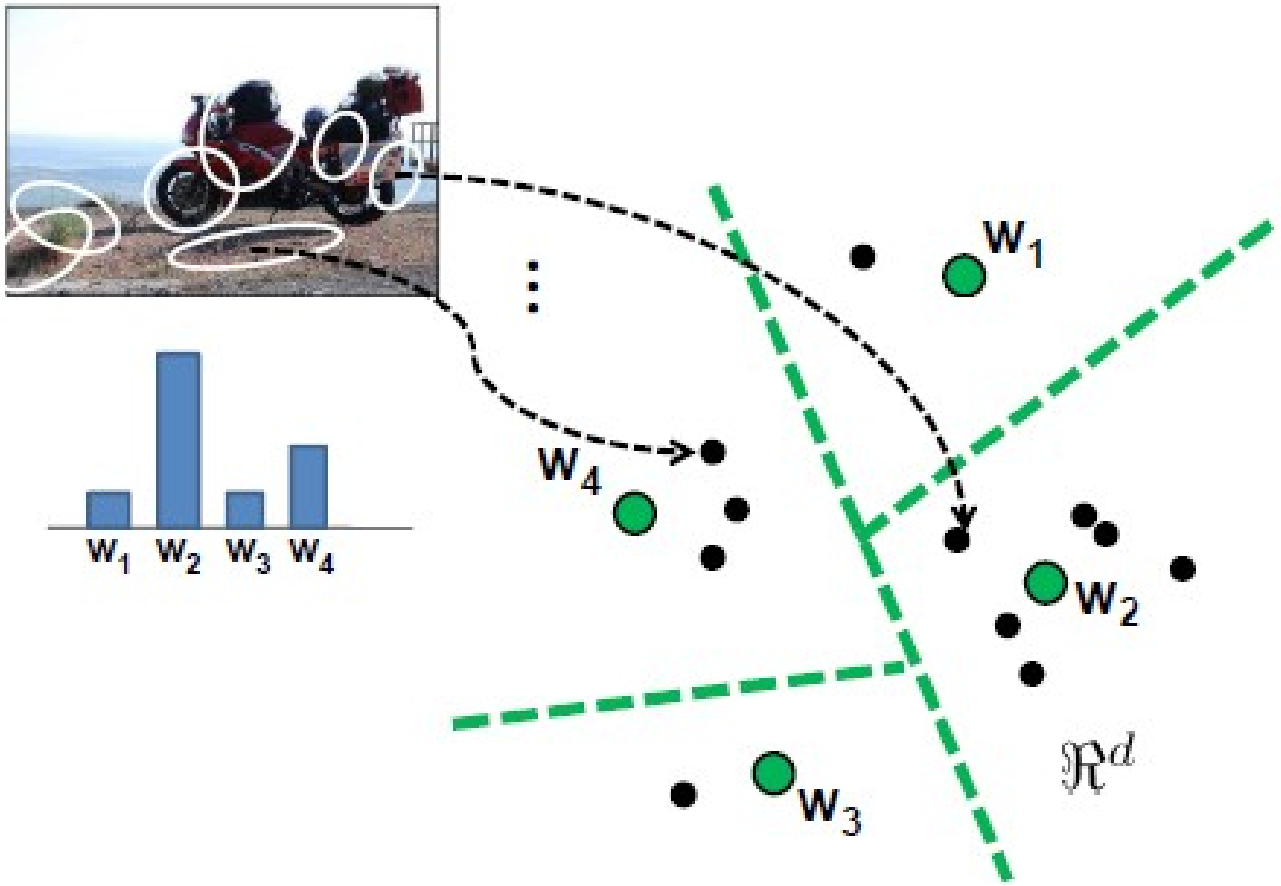


But today we're not talking about ways to preserve *spatial* information…about quantization itself.

Better Bags of Visual Features

- More advanced quantization / encoding methods that were/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 K-means Bag of Words

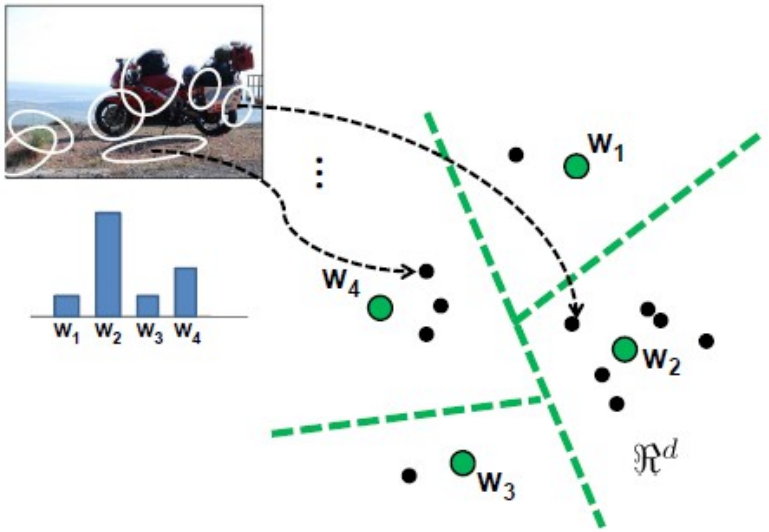


http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

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

Why not including **other statistics**?

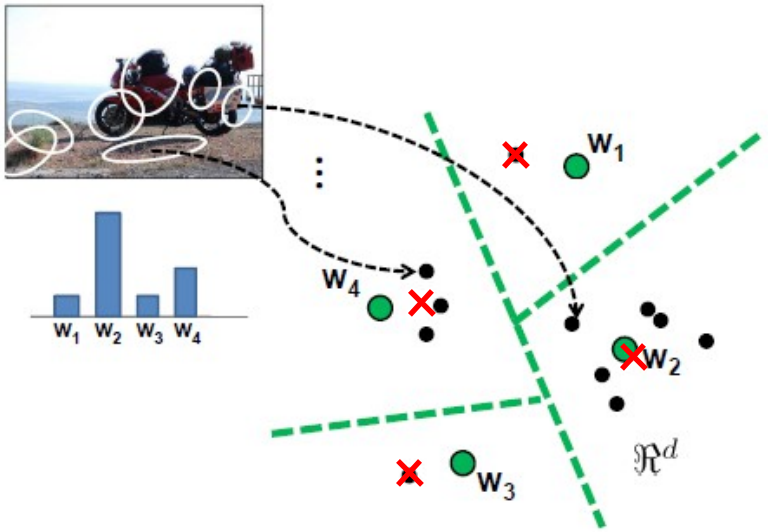


Motivation

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

Why not including **other statistics**? For instance:

- mean of local descriptors



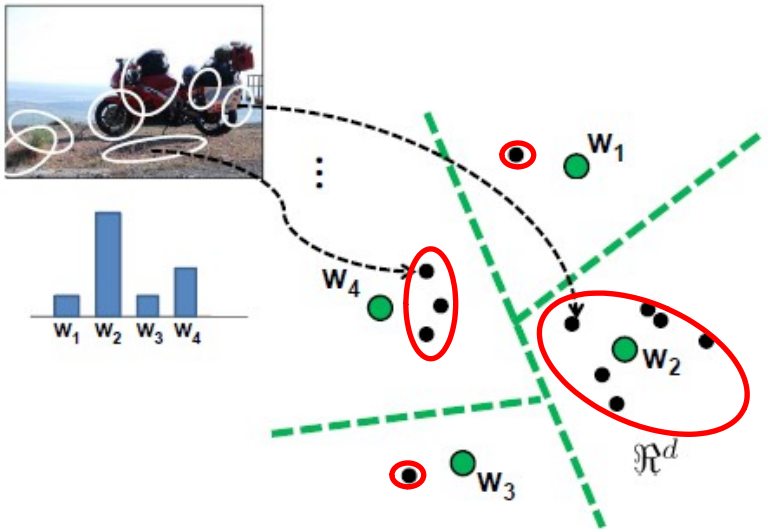
http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

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

Why not including **other statistics**? For instance:

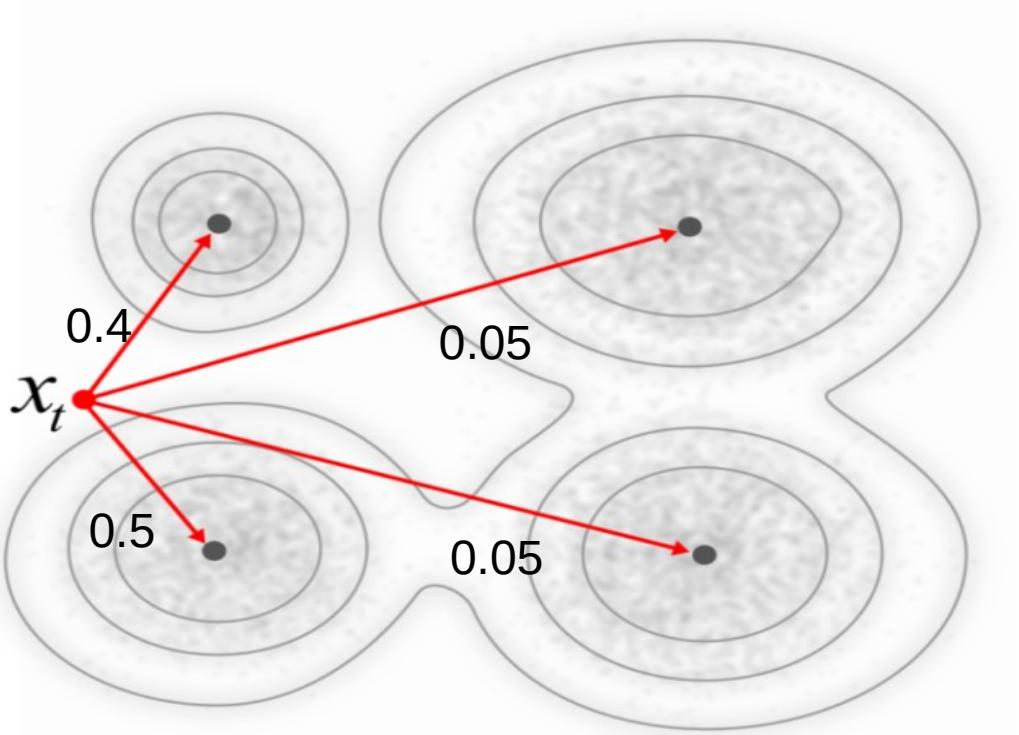
- mean of local descriptors
- (co)variance of local descriptors



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

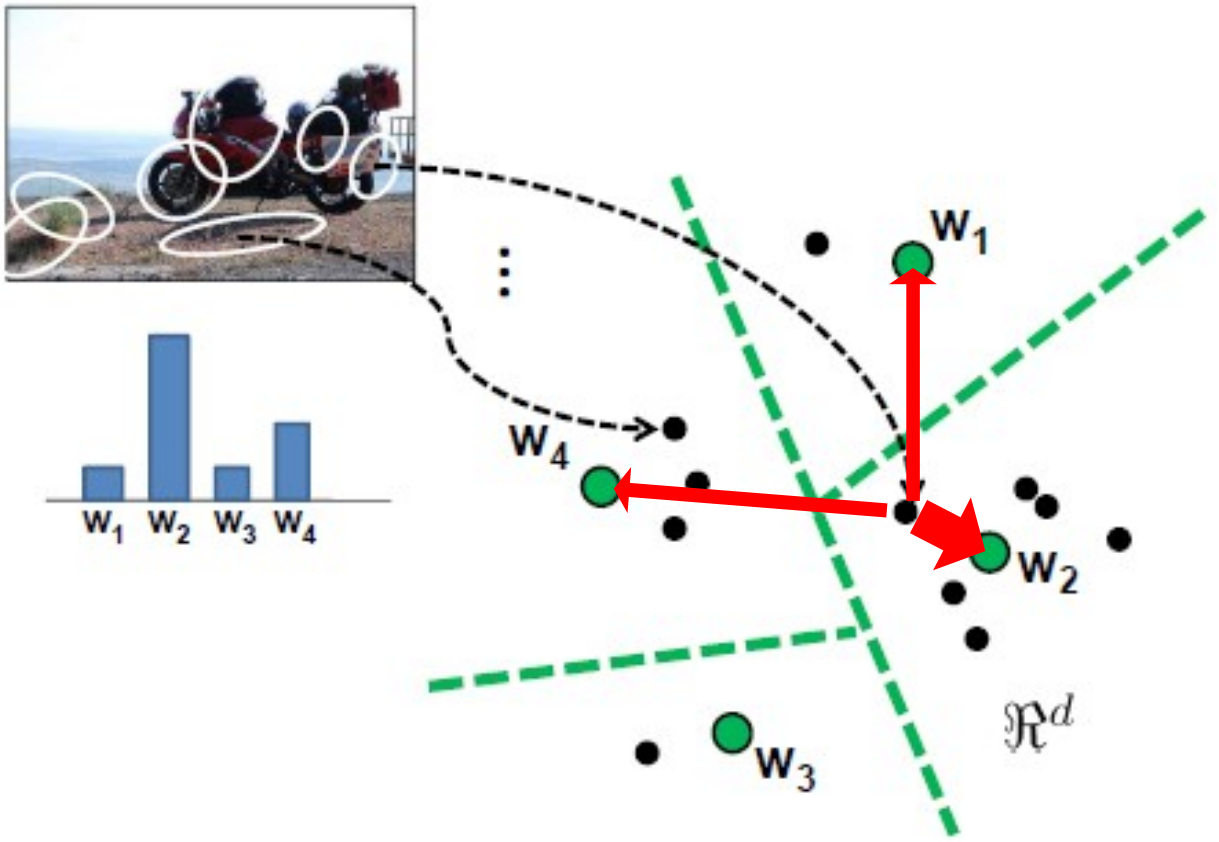
Gaussian Mixture Model (GMM)

- GMM can be thought of as “soft” k-means.
- Each component has a mean and a standard deviation along each direction (or full covariance)
- Can easily represent non-circular distributions



Simple case: Soft Assignment

- “Kernel codebook encoding” by Chatfield et al. 2011.
- Cast a set of proportional votes (weights) to *n* mo gle ‘hai



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 implement, but it makes an inverted file i

New query image

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

VLAD – Vectors of Locally-Aggregated Descriptors

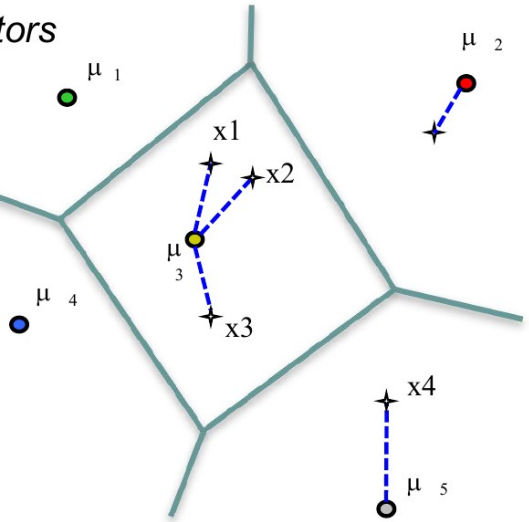
Given a codebook $\{\mu_i, i = 1 \dots N\}$, e.g. learned with K-means, and a set of local descriptors

$$X = \{x_t, t = 1 \dots T\}$$

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

① *assign descriptors*

:



VLAD – Vectors of Locally-Aggregated Descriptors

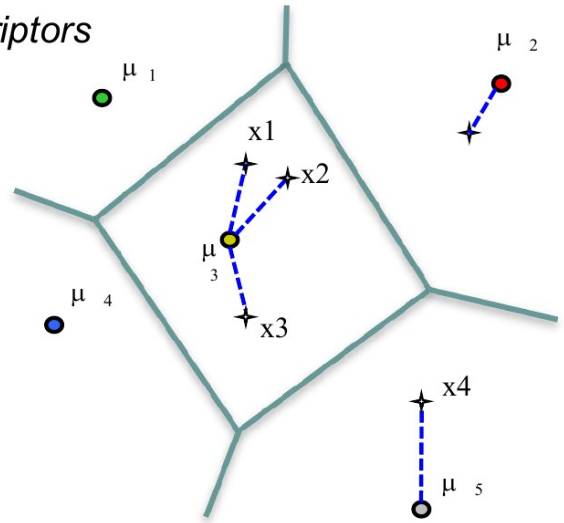
Given a codebook $\{\mu_i, i = 1 \dots N\}$, e.g. learned with K-means, and a set of local descriptors

$$X = \{x_t, t = 1 \dots T\}$$

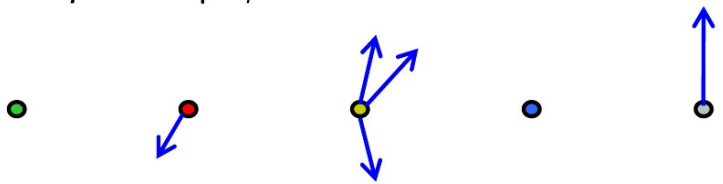
assign: $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$

- compute $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$

① *assign descriptors*



② *compute x-μ i*



VLAD – Vectors of Locally-Aggregated Descriptors

Given a codebook $\{\mu_i, i = 1 \dots N\}$, e.g. learned with K-means, and a set of local descriptors

$$X = \{x_t, t = 1 \dots T\}$$

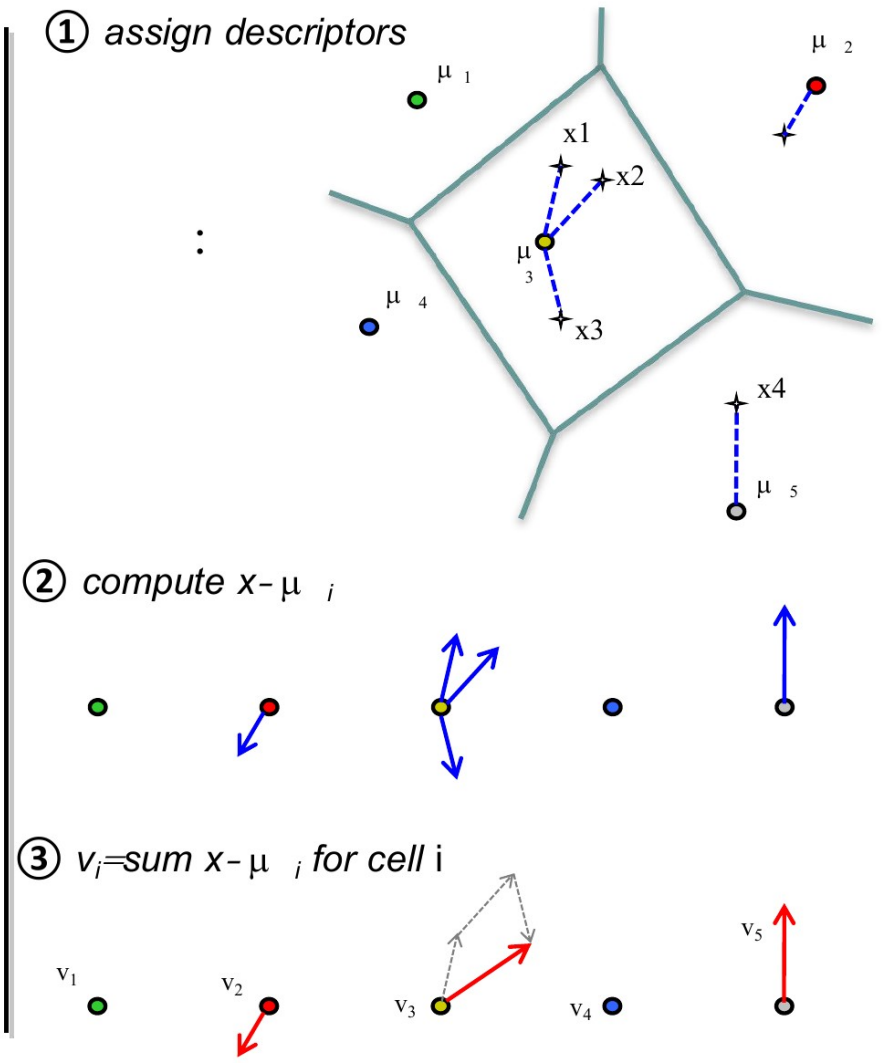
assign: $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$

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

VLAD descriptor dimension: k x d

k = number of cluser centers

d = dimensionality of the descriptors used.

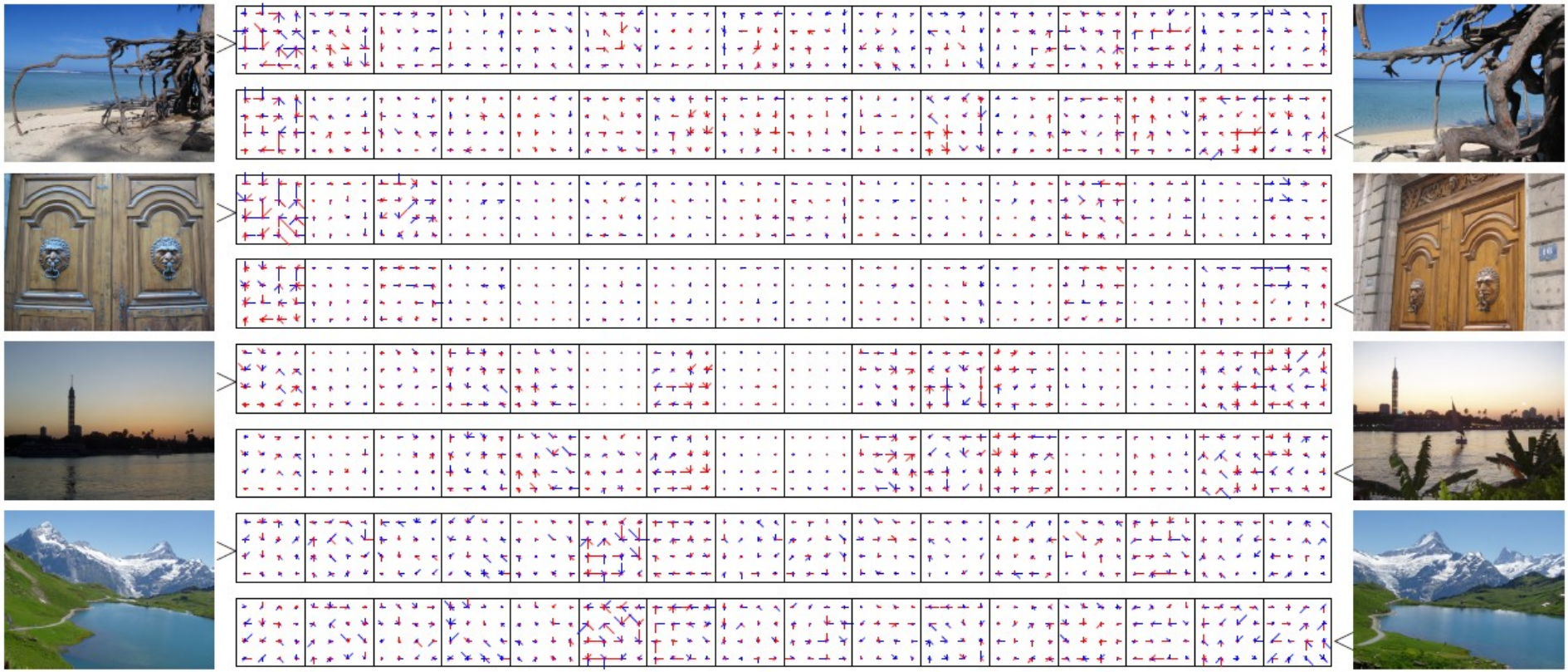


Jégou, Douze, Schmid and Pérez,
"Aggregating local descriptors into a compact image representation",
CVPR'10.

A first example: the VLAD

A graphical representation of

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



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

Why can’t we train good recognition systems?

- Training Data
  - Huge issue, but not always a variable we control.
- Representation
  - Are the local features themselves lossy?
  - What about feature quantization?

What about skipping quantization completely?

In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani (2008)

Quantization inherently averages the parts which are *most discriminative* !!!

Quantization error of densely computed image descriptors (SIFT) using a large codebook (size 6,000) of Caltech- 101. Red = high error; Blue = low error. The most informative descriptors (eye, nose, etc.) have the highest quantization error

What about skipping quantization completely?

In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani

Claims:

1. Quantization damages non-parametric classifiers
2. Image-to-Image vs. Image-to-Class Distance

What about NN image-to-image matching?

In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani

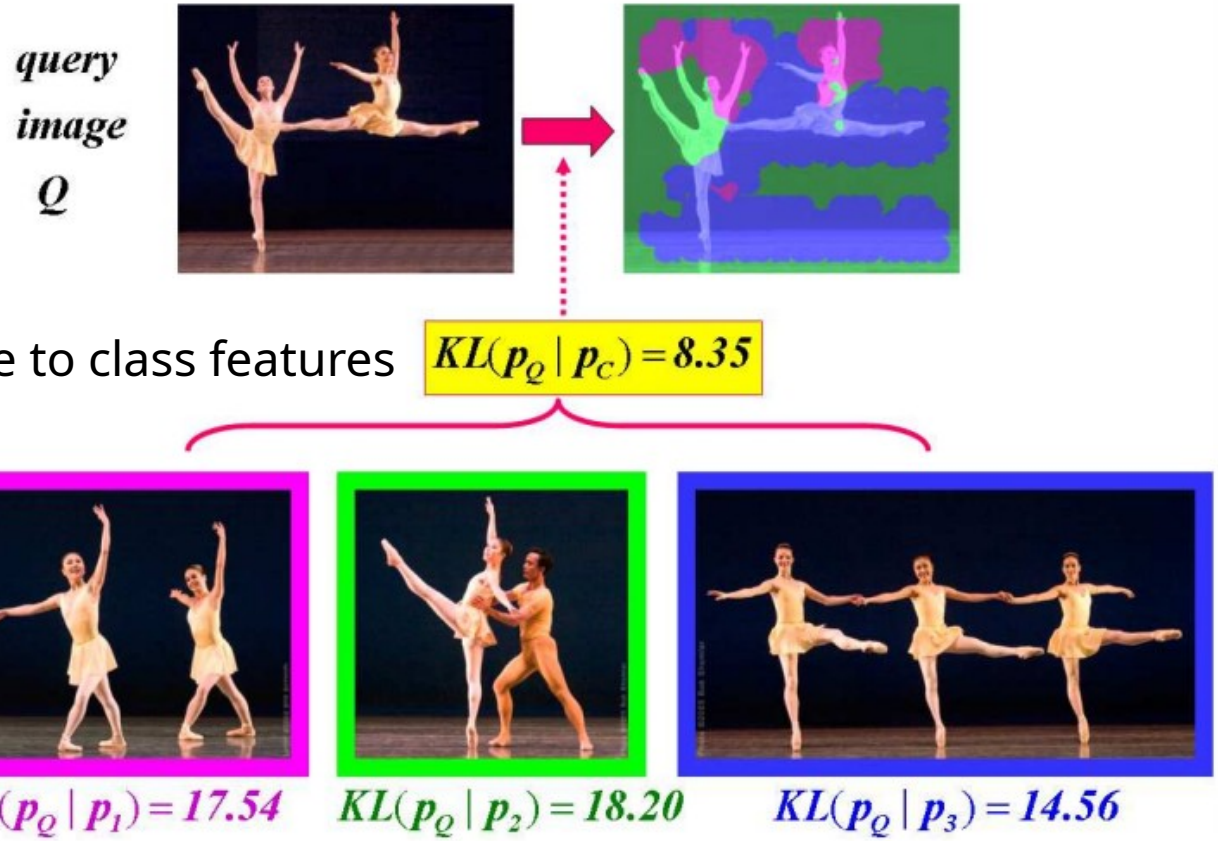
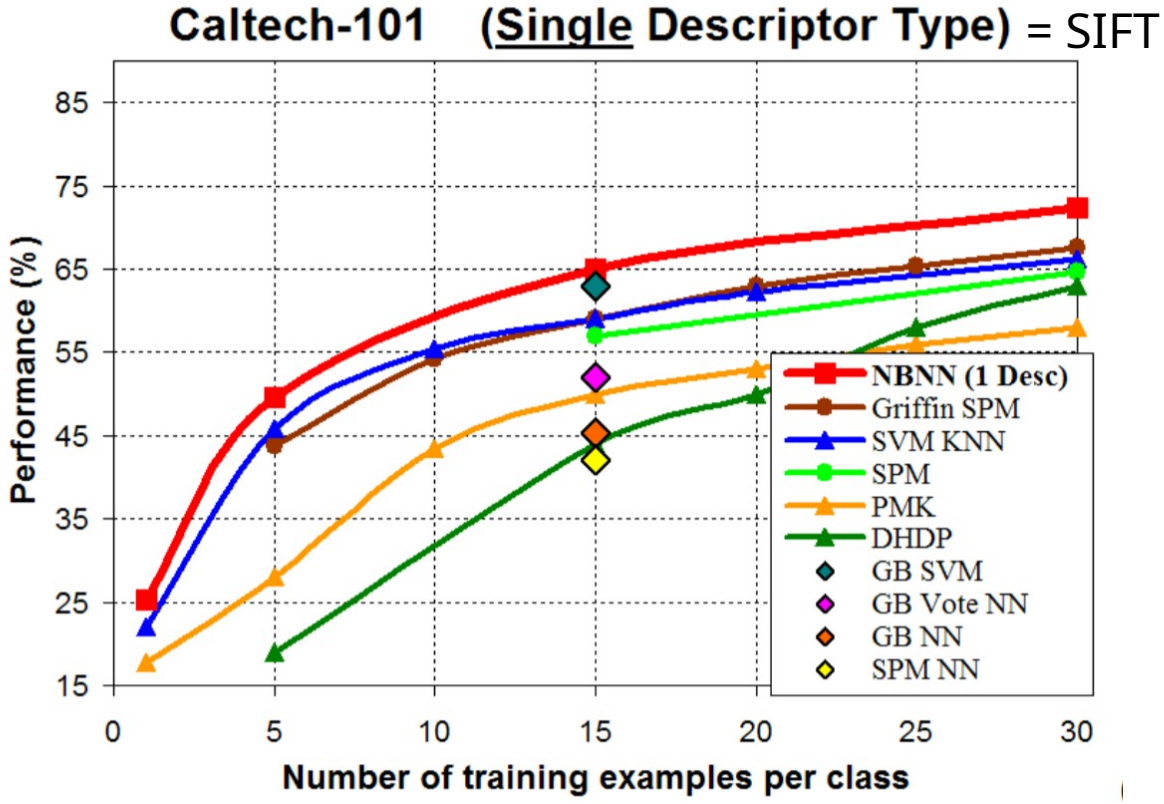


Image to image features NN

If I do both of these, NN can be a pretty good classifier!

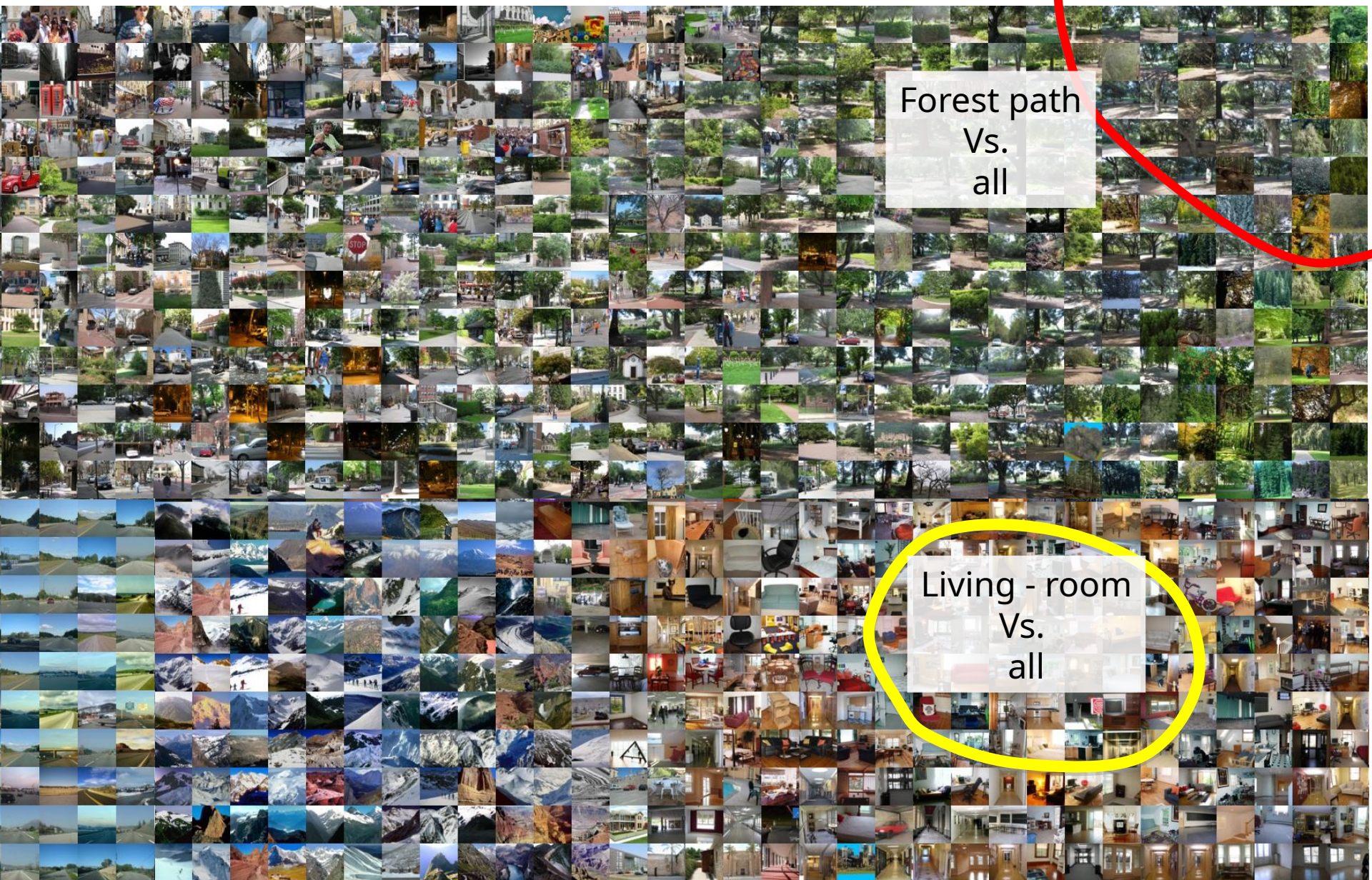


In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani

Summary

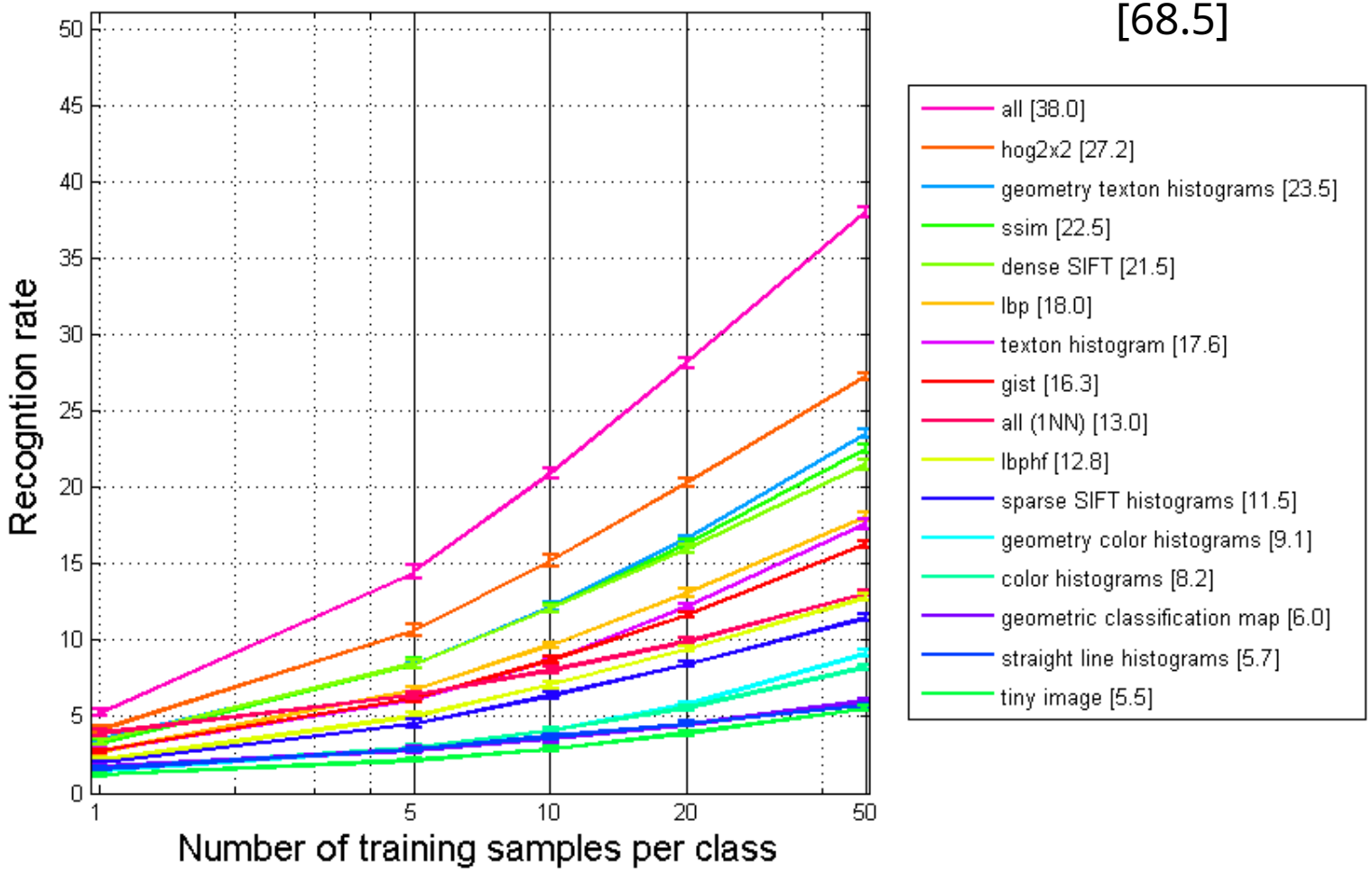
- Methods to better characterize the distribution of visual words in an image:
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD
  - No quantization

Learning Scene Categorization



Feature Accuracy

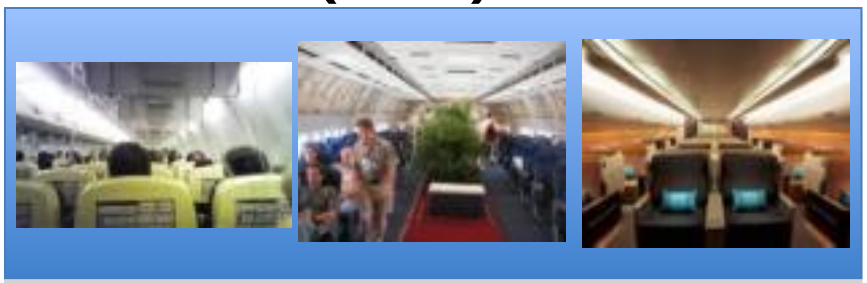
Humans [68.5]



Classifier: 1-vs-all SVM with histogram intersection, chi squared, or RBF kernel.

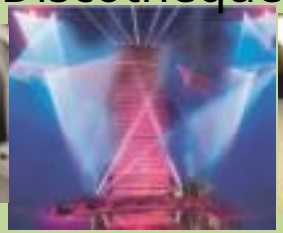
A look into the results

Airplane cabin (64%)



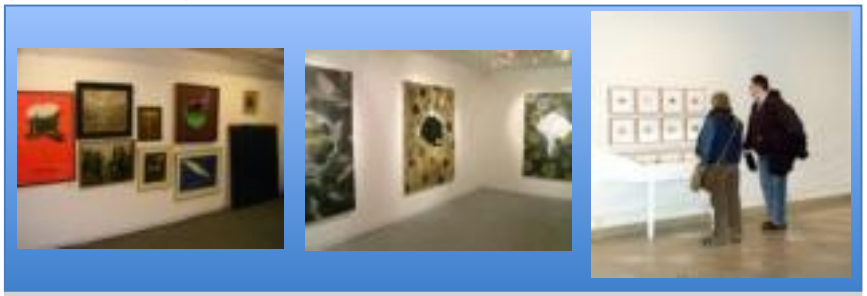
Van interior

Discotheque

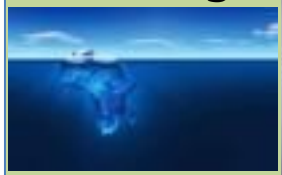


Toyshop

Art gallery (38%)



Iceberg



Hotel room

Kitchenette

All the results available on the web

...

Humans good Comp. good

limousine interior (95% vs 80%)

riding arena (100% vs 90%)

sauna (96% vs 95%)

skatepark (96% vs 90%)

subway interior (96% vs 80%)

Humans bad Comp. bad

Human good Comp. bad

Human bad Comp. good