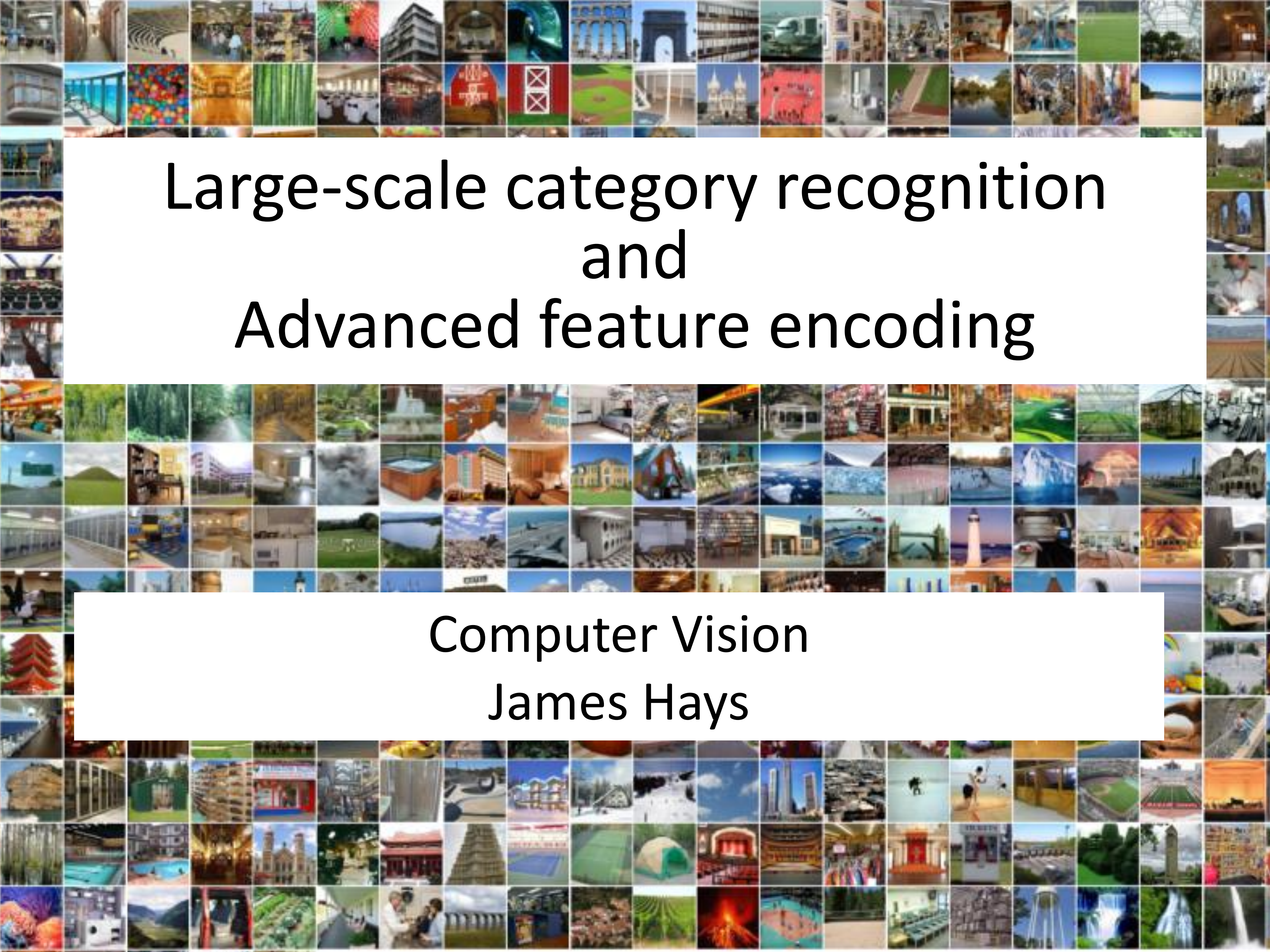


Large-scale category recognition and Advanced feature encoding

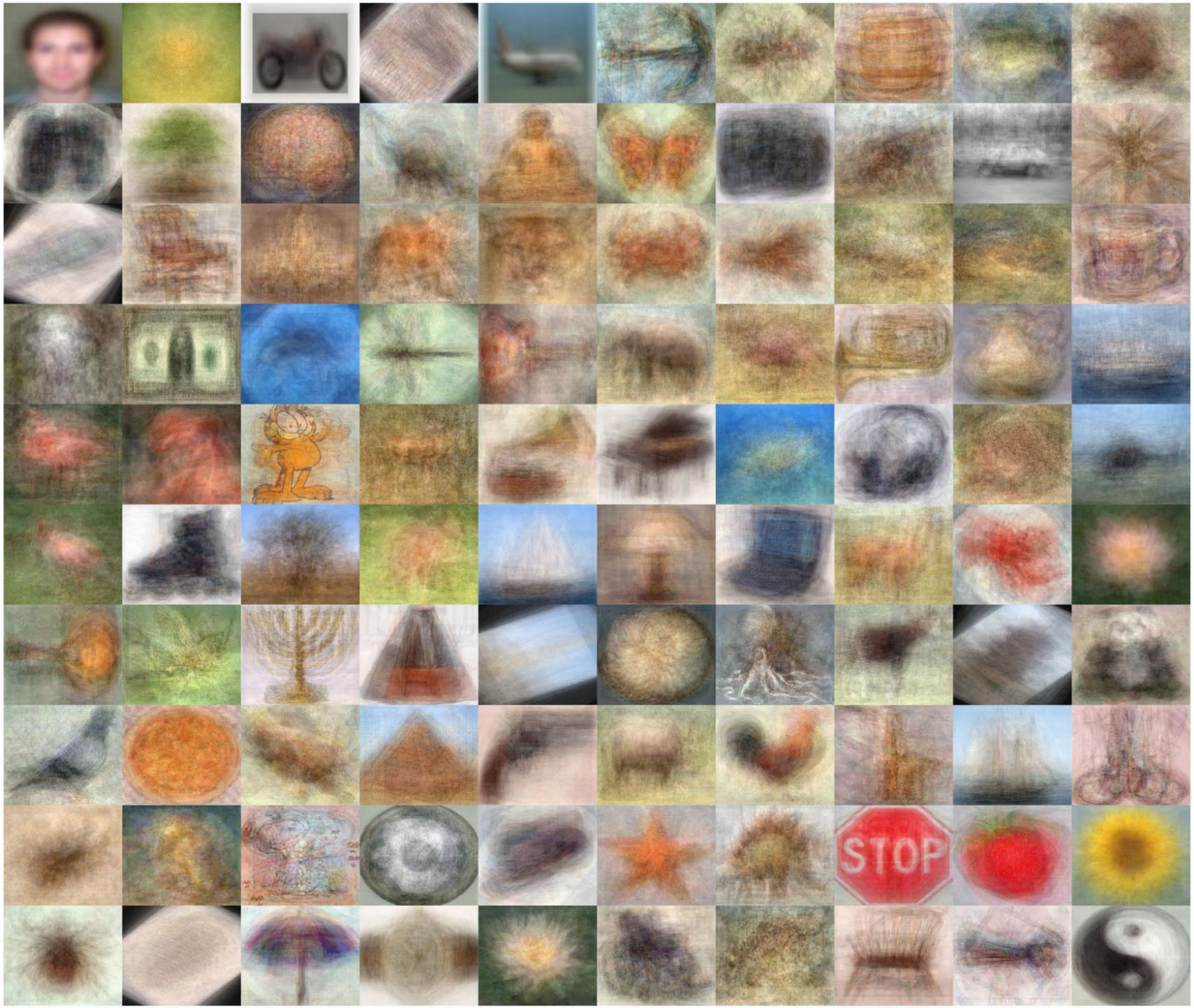
Computer Vision

James Hays

Why do good recognition systems go bad?

- E.g. Why isn't our Bag of Words classifier at 90% instead of 70%?
- Training Data
  - Huge issue, but not necessarily a variable you can manipulate.
- Representation
  - Are the local features themselves lossy?
  - What about feature quantization? That's VERY lossy.
- Learning method
  - Probably not such a big issue, unless you're learning the representation (e.g. deep learning).

CalTech 101 - 2004



SUN Database: Large-scale Scene Categorization and Detection

Jianxiong Xiao, James Hays[†], Krista A. Ehinger, Aude Oliva, Antonio Torralba

Massachusetts Institute of Technology

[†] Brown University

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

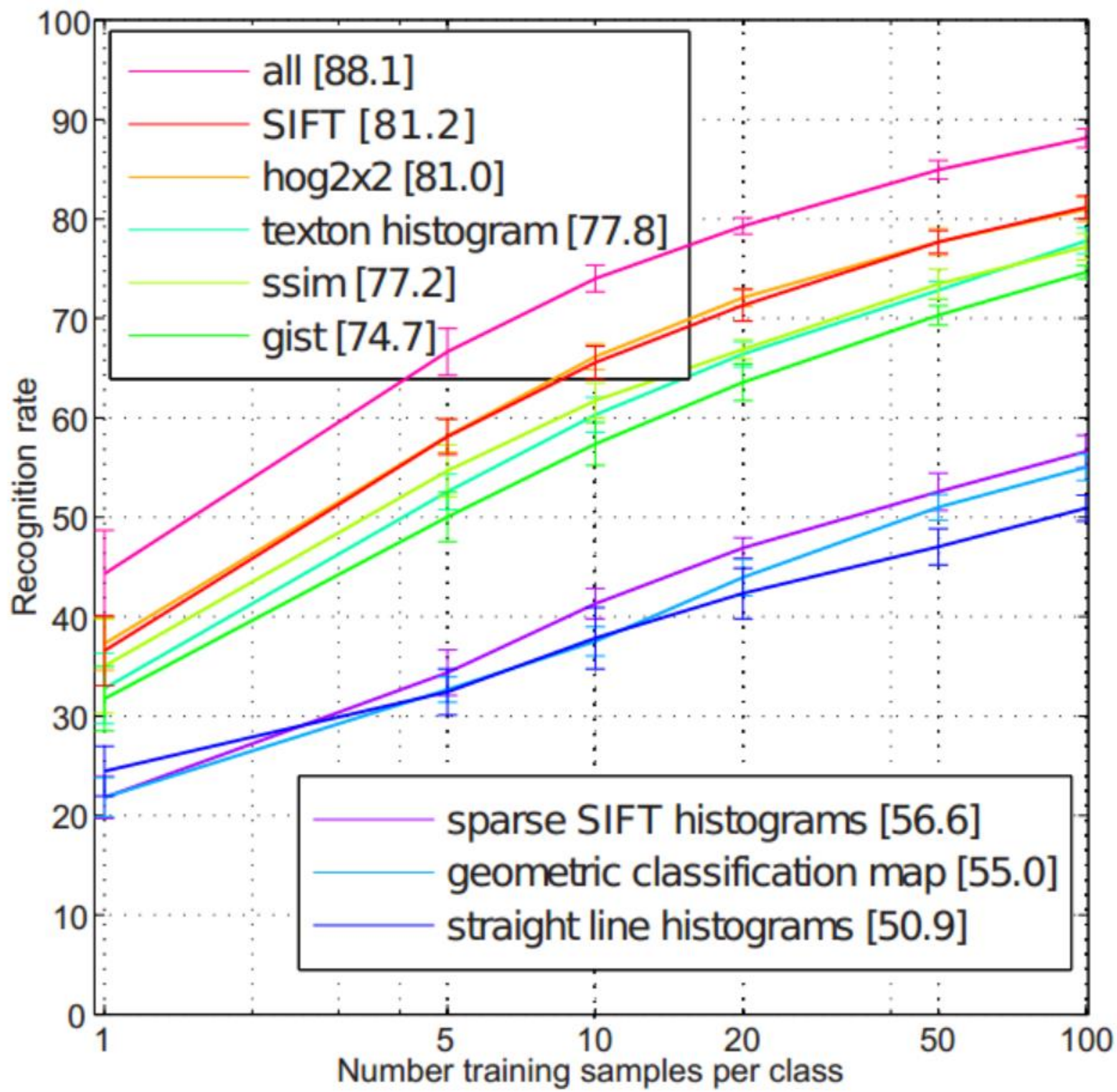
+


Industrial

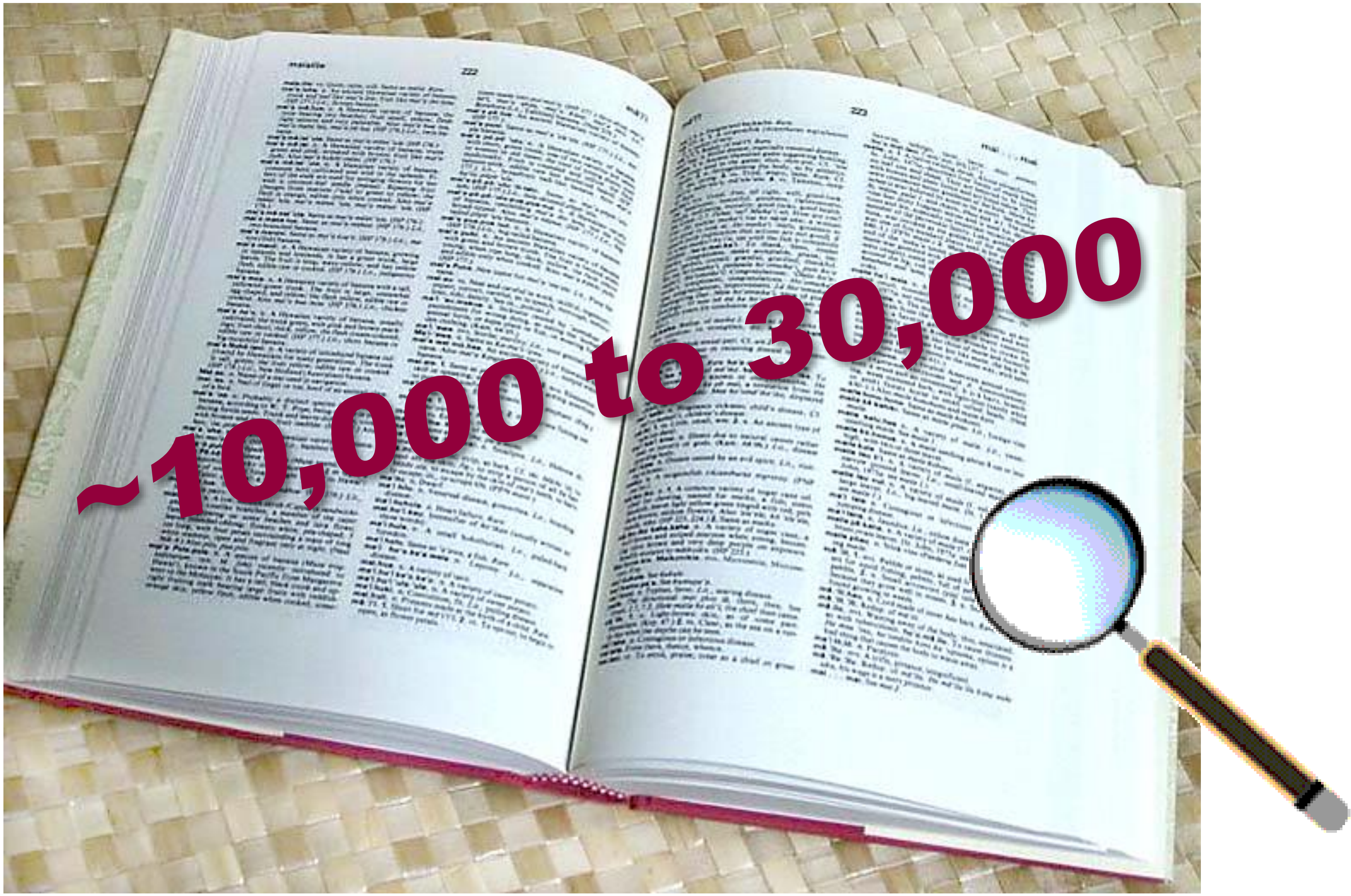

Store

15 Scene Database

15 Scene Recognition Rate



How many object categories are there?



Biederman 1987


abbey


airplane cabin

airport terminal

■ ■ ■


apple orchard


assembly hall

bakery

...


car factory


cockpit


construction site

...


food court


interior car

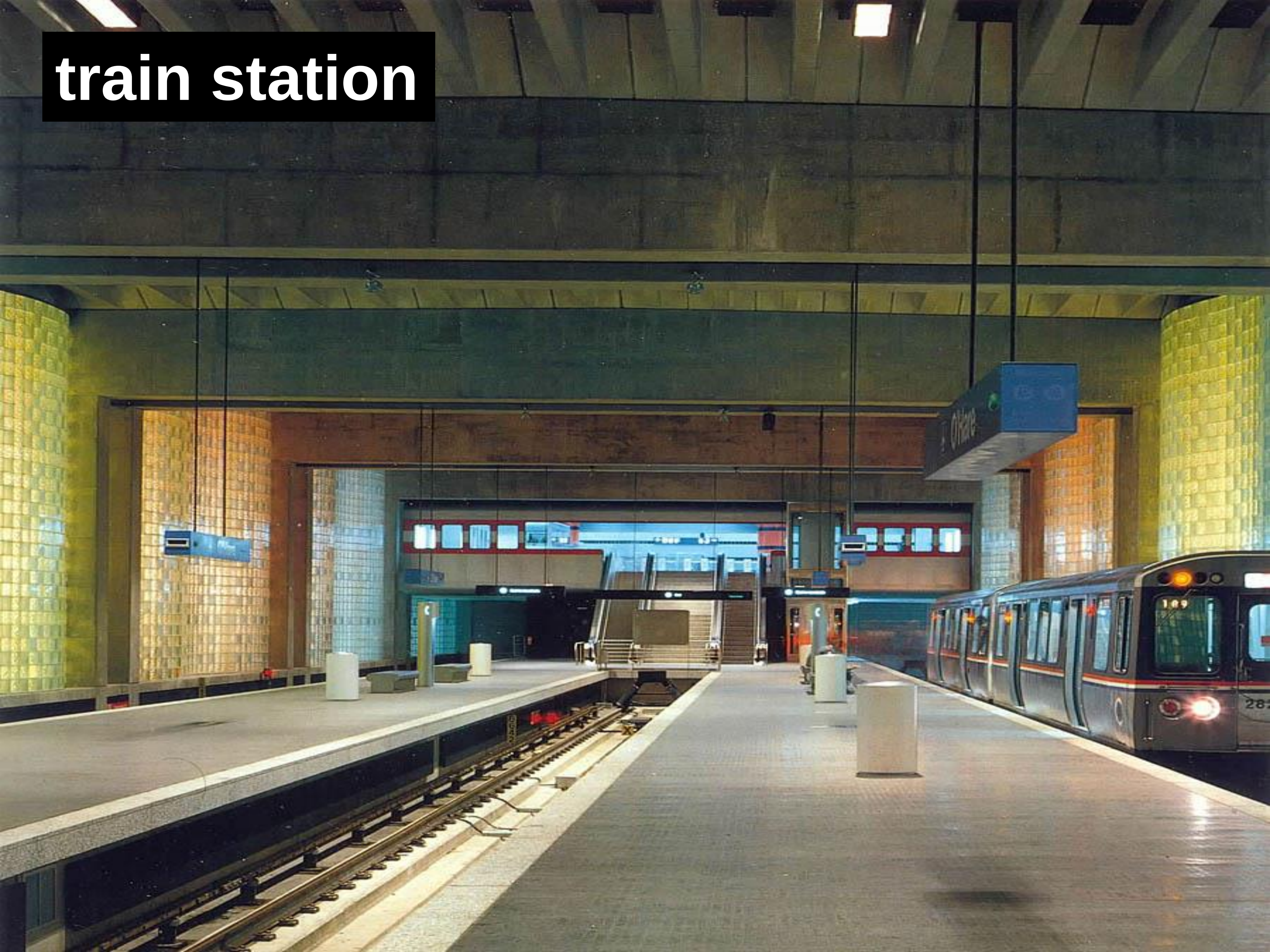

lounge

■ ■ ■

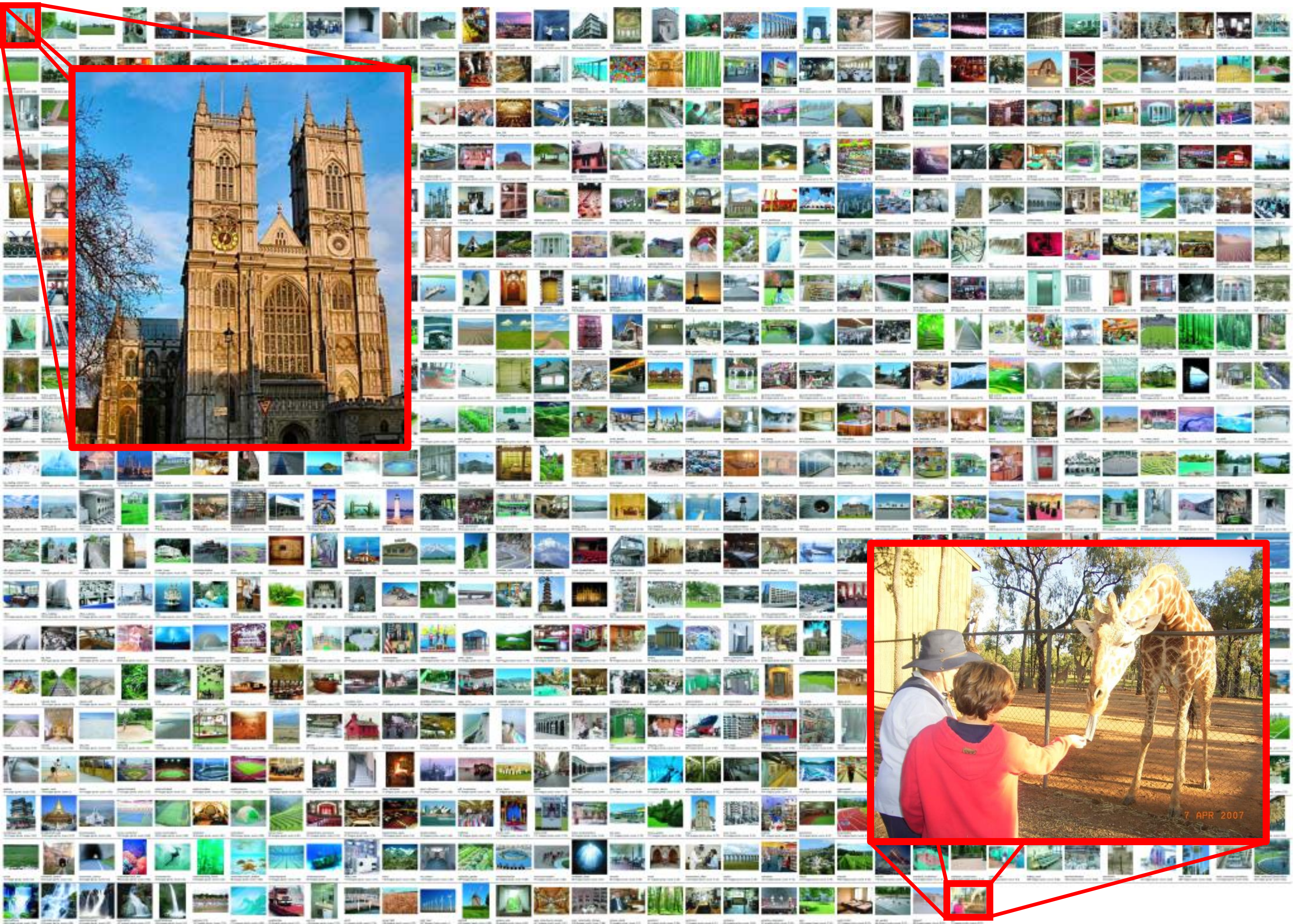
stadium


stream

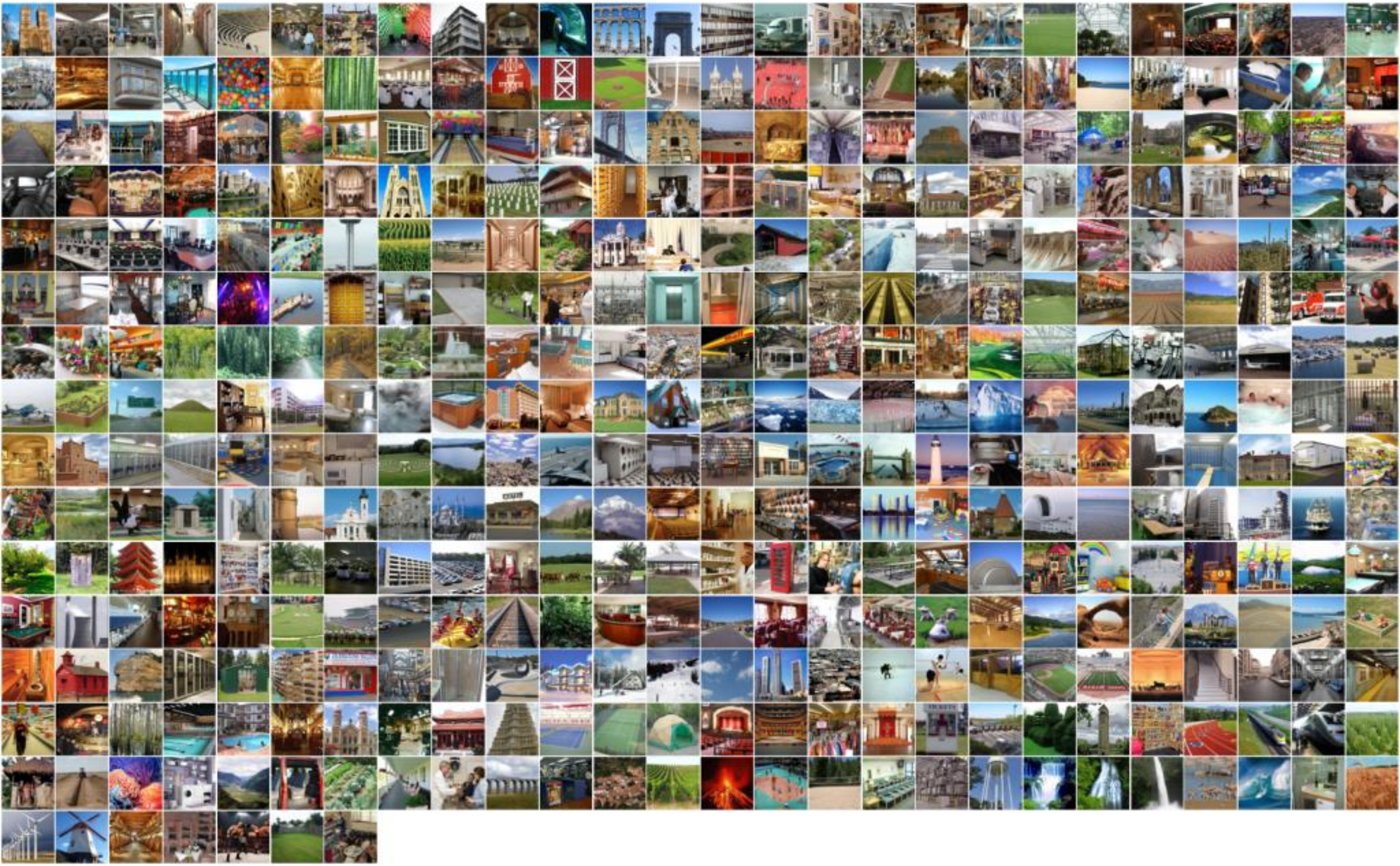
train station



■ ■ ■


7 APR 2007

397 Well-sampled Categories



Evaluating Human Scene Classification

?

"Good worker" 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%)

Restaurant patio (44%)

Chalet (19%)

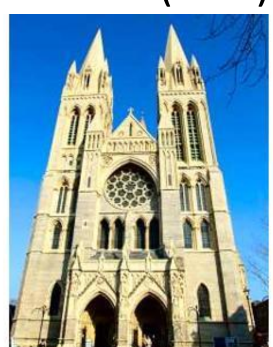
Bayou (0%)

River (67%)

Coast (8%)

Basilica (0%)

Cathedral(29%)



Courthouse (21%)

Conclusion: humans can do it

- The SUN database is reasonably consistent and differentiable -- even with a huge number of very specific categories, humans get it right 2/3rds of the time *with no training.*
- We also have a good benchmark for computational methods.

How do we 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

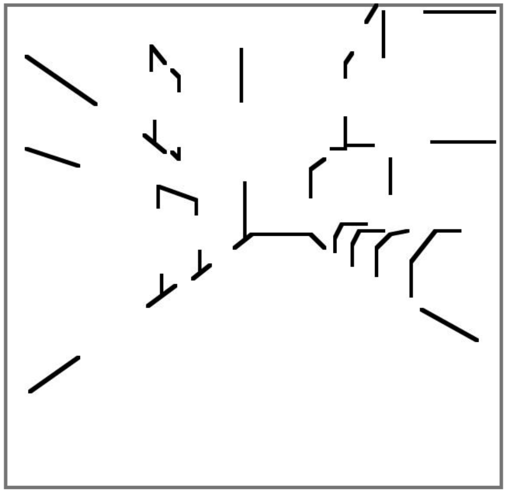
ceiling
wall screen
column
seat seat
seat seat
seat seat seat seat
seat seat seat seat
seat seat seat seat

Similar objects, and similar spatial layout

Different lighting, different materials, different “stuff”

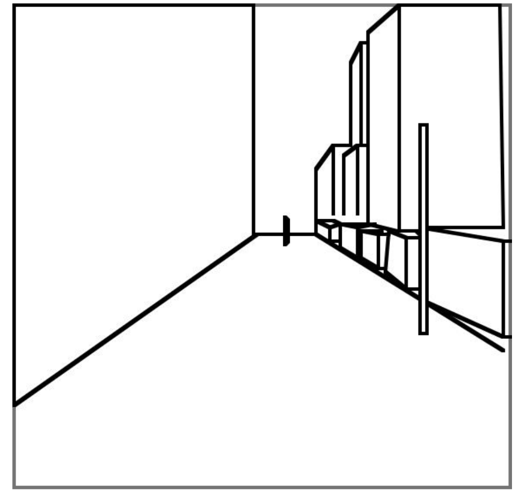
Scene emergent features

“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

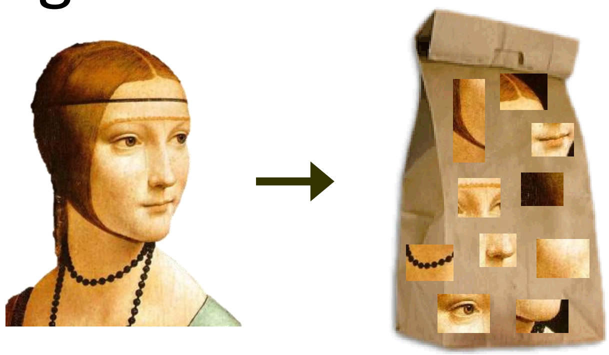
Global Image Descriptors

- 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

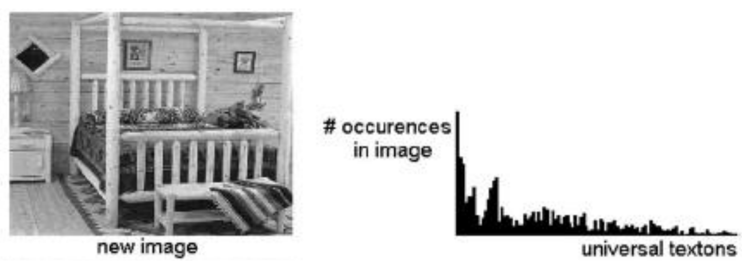
Global Texture Descriptors

Bag of words



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

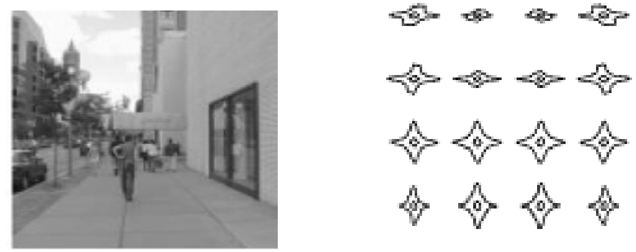
Non localized textons



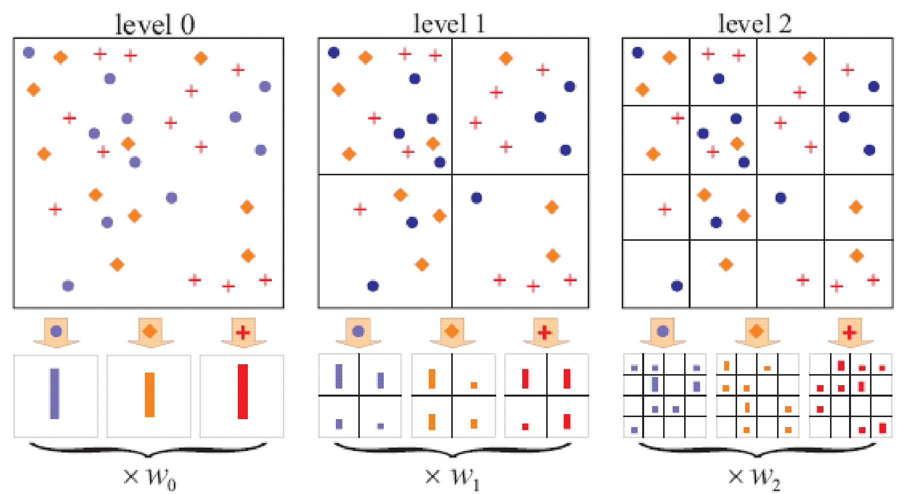
Walker, Malik. Vision Research 2004

…

Spatially organized textures



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



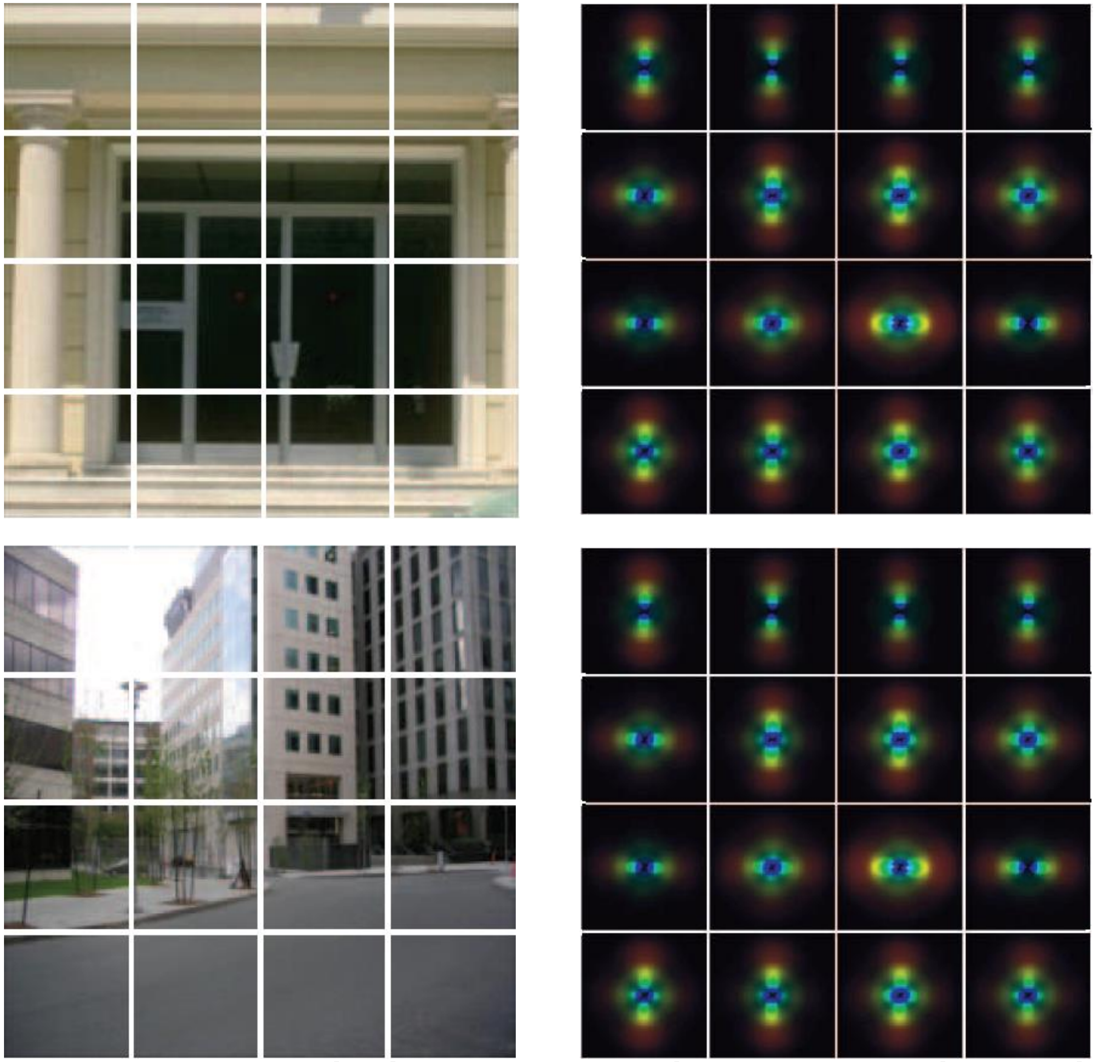
S. Lazebnik, et al, CVPR 2006

…

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.

Gist descriptor

Oliva and Torralba, 2001



- Apply oriented Gabor filters over different scales
- Average filter energy in each bin

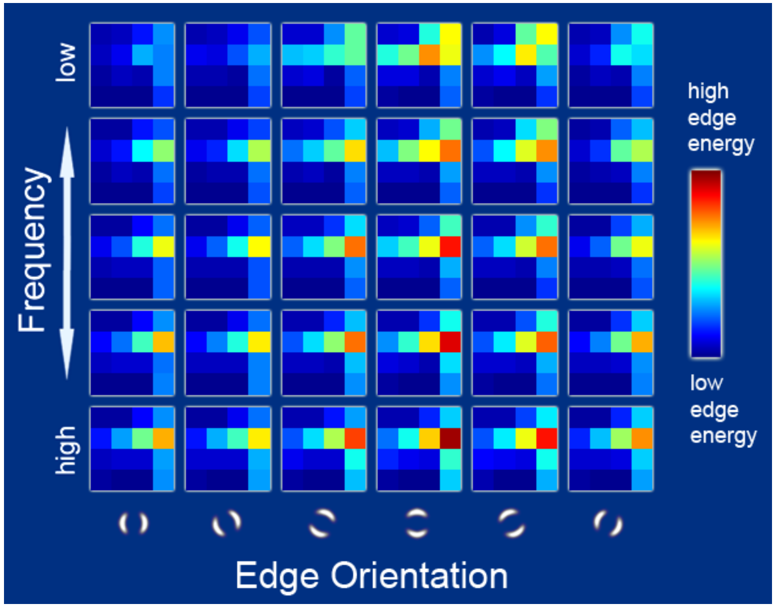
8 orientations
4 scales
x 16 bins
512 dimensions

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

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; …

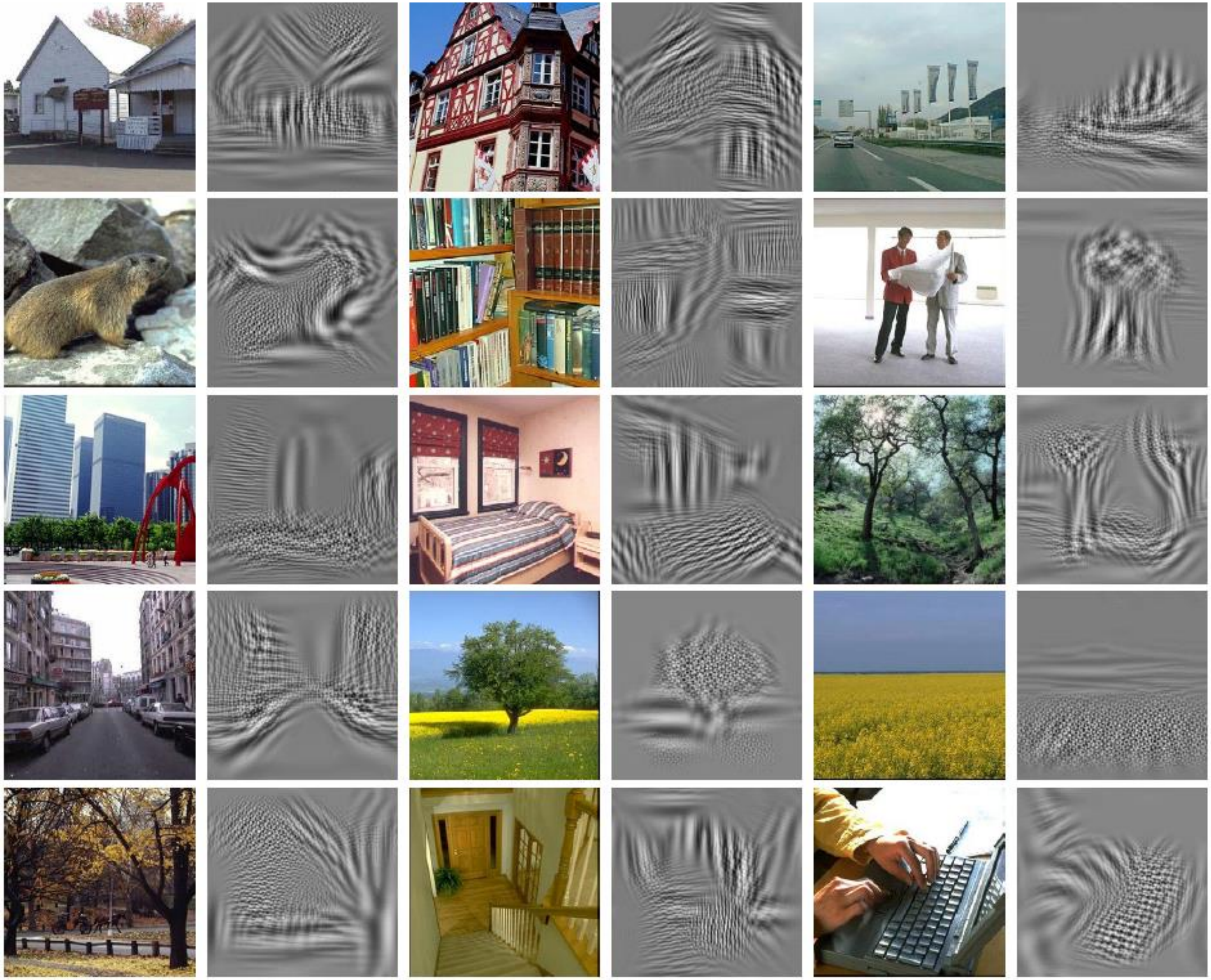
Global scene descriptors

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



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

Example visual gists



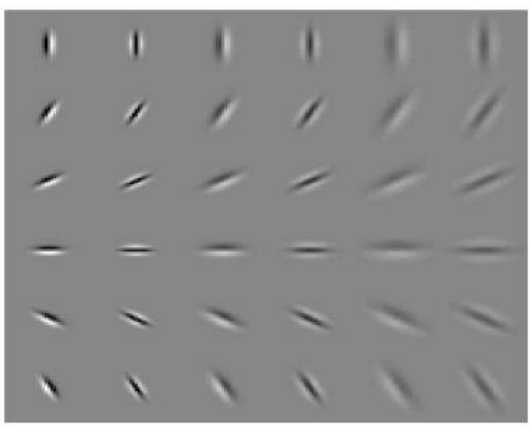
Global features (I) ~ global features (I')

Oliva & Torralba (2001)

Textons

Vector of filter responses at each pixel

Kmeans over a set of vectors on a collection of images

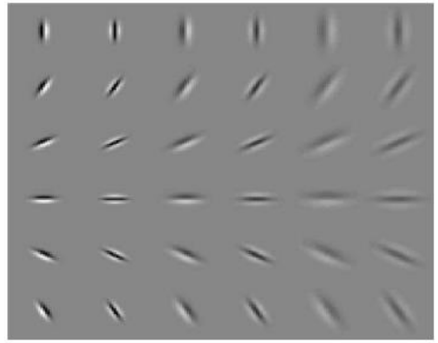


Filter bank

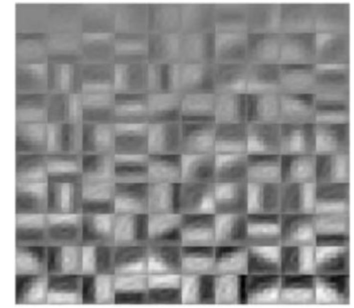
Malik, Belongie, Shi, Leung, 1999

Textons

Filter bank

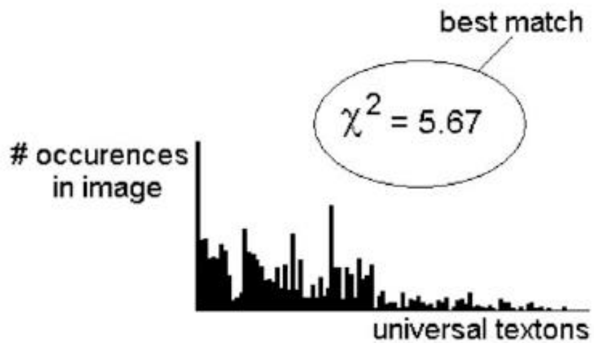


K-means (100 clusters)

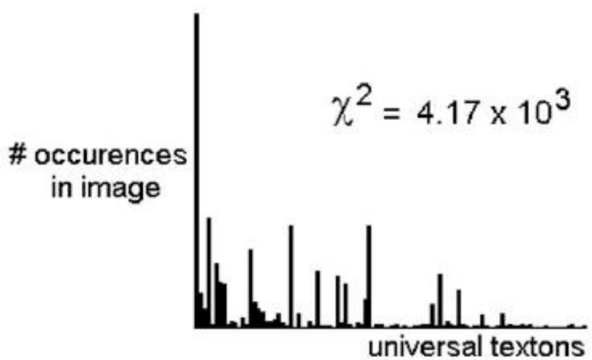


Malik, Belongie, Shi, Leung, 1999

label = bedroom



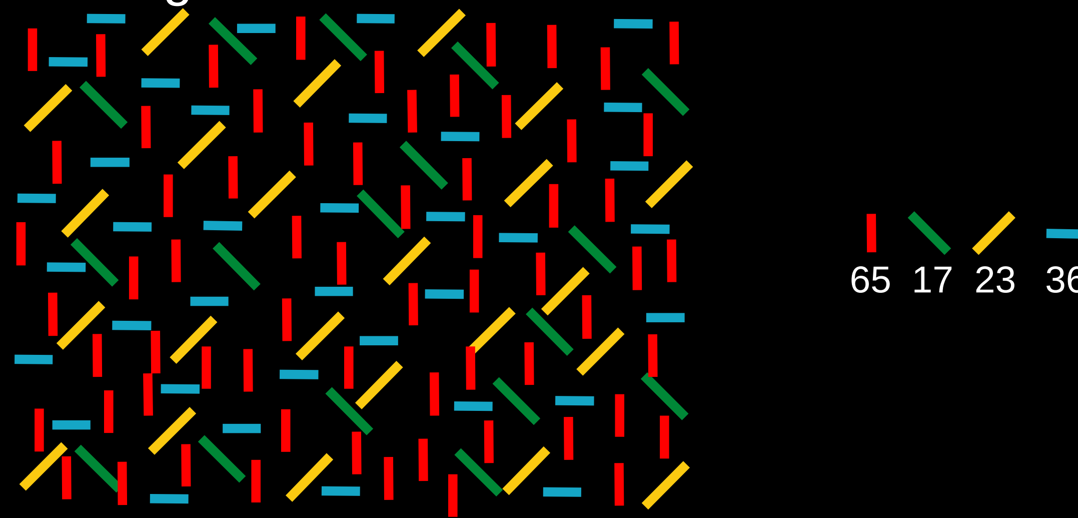
label = beach



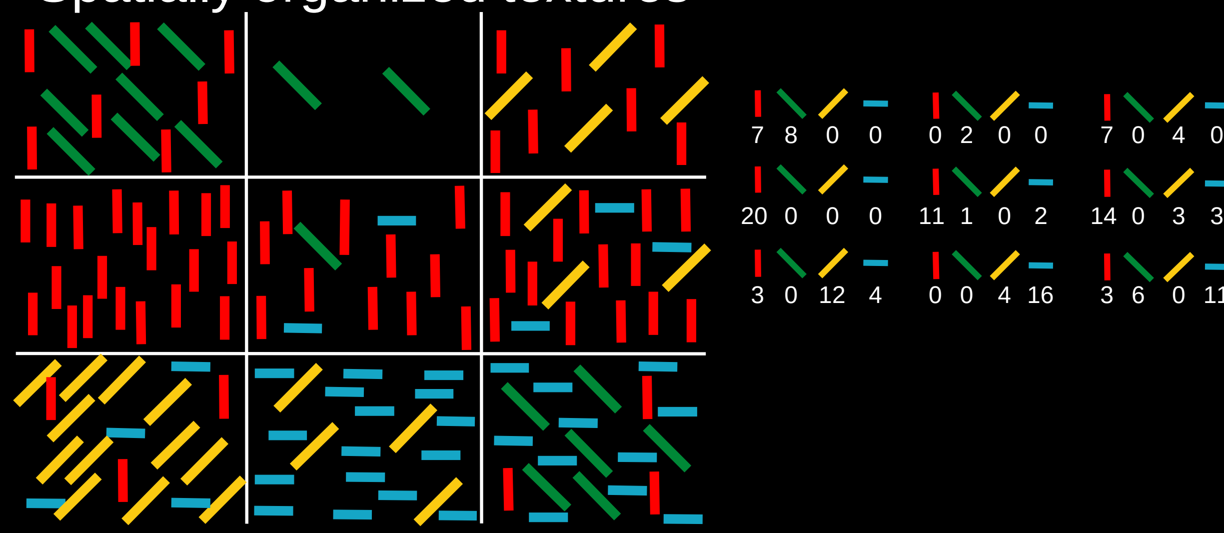
Walker, Malik, 2004

Bag of words

Bag of words model

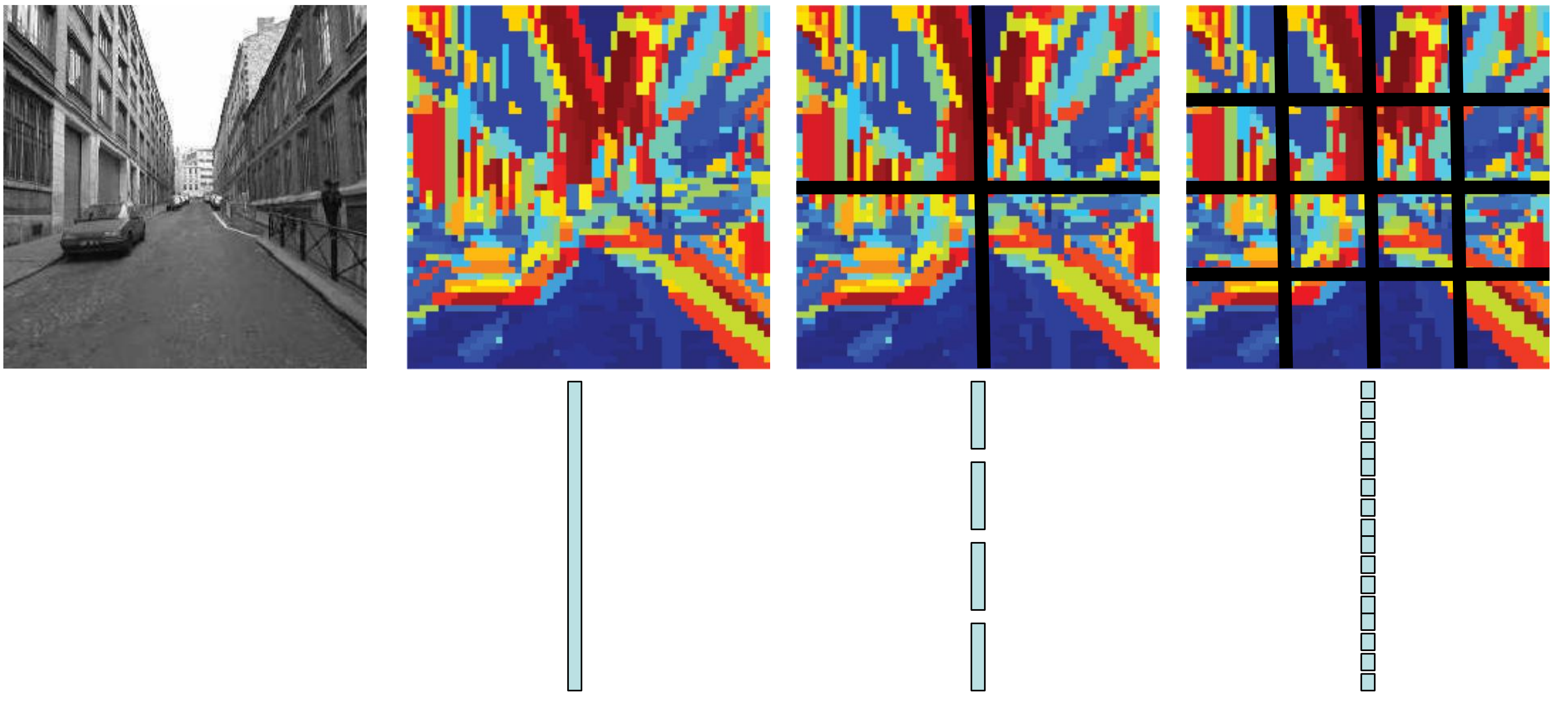


Spatially organized textures



Bag of words & spatial pyramid matching

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

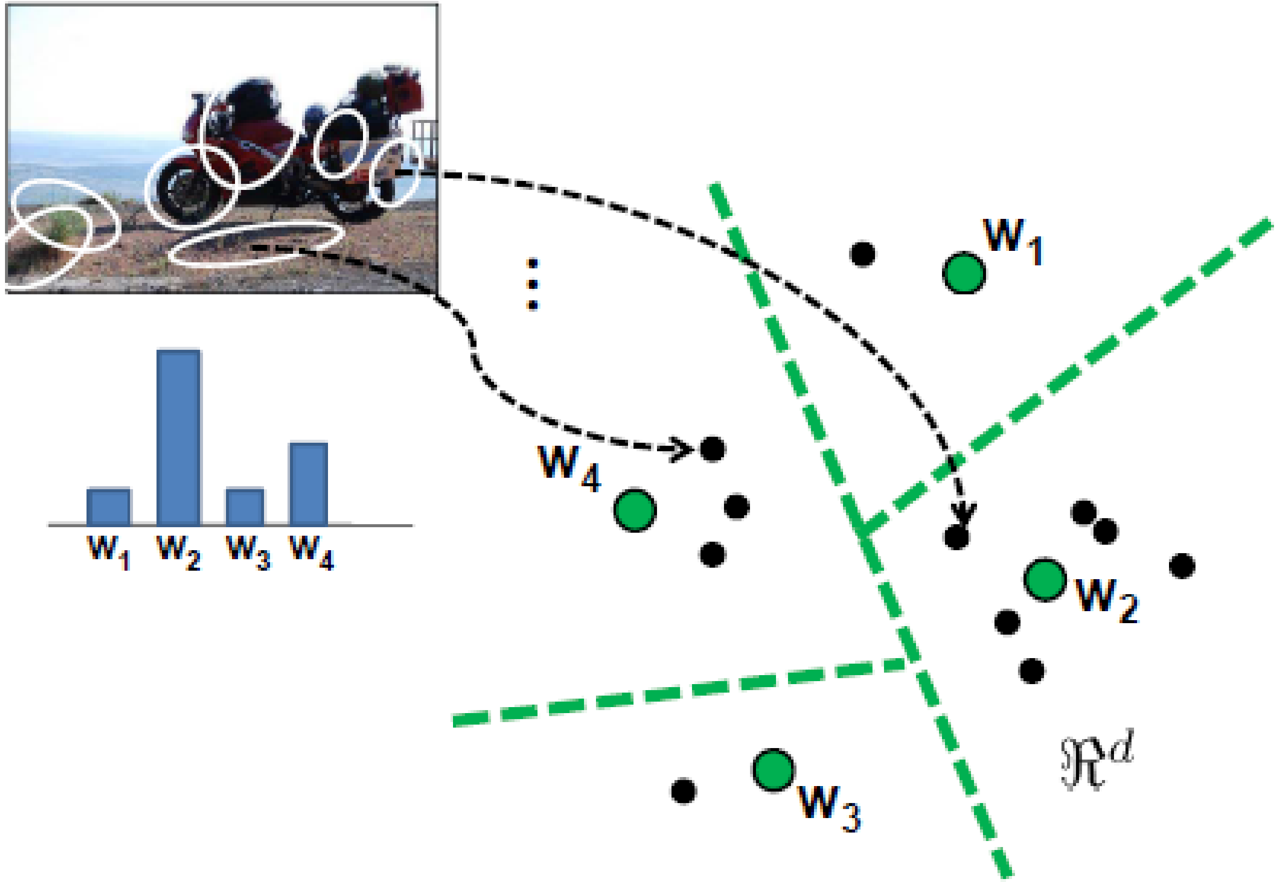


S. Lazebnik, et al, CVPR 2006

Better Bags of Visual Features

- More advanced quantization / encoding methods that are near the state-of-the-art in image classification and image retrieval.
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD
  - Fisher Vector
- Deep learning has taken attention away from these methods.

Standard Kmeans Bag of Words

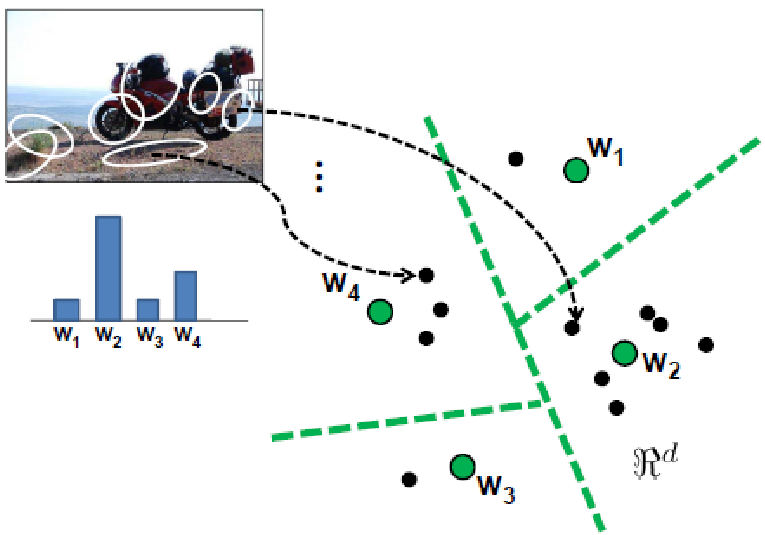


http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

Motivation

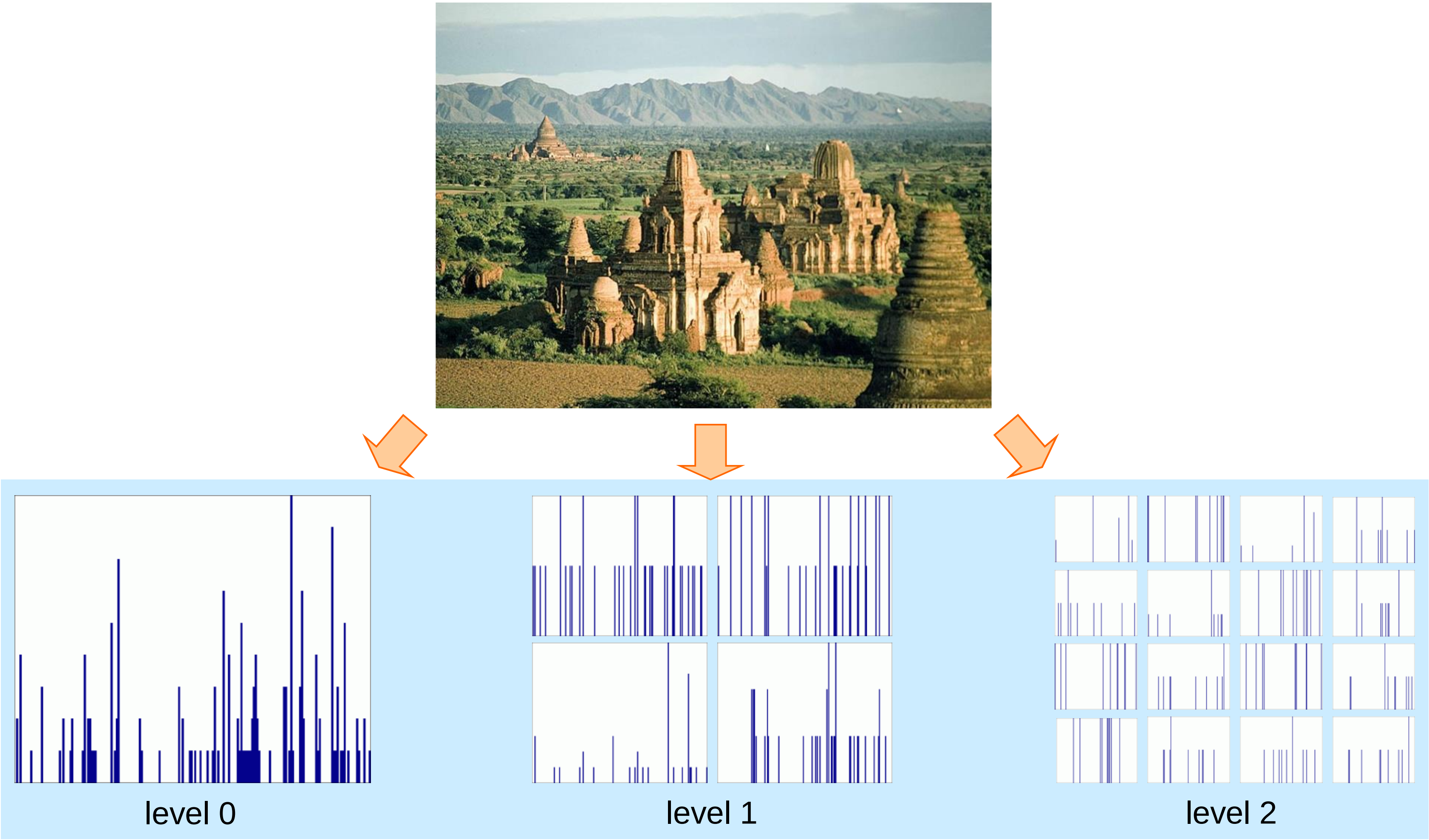
Bag of Visual Words is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**?



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

We already looked at the Spatial Pyramid



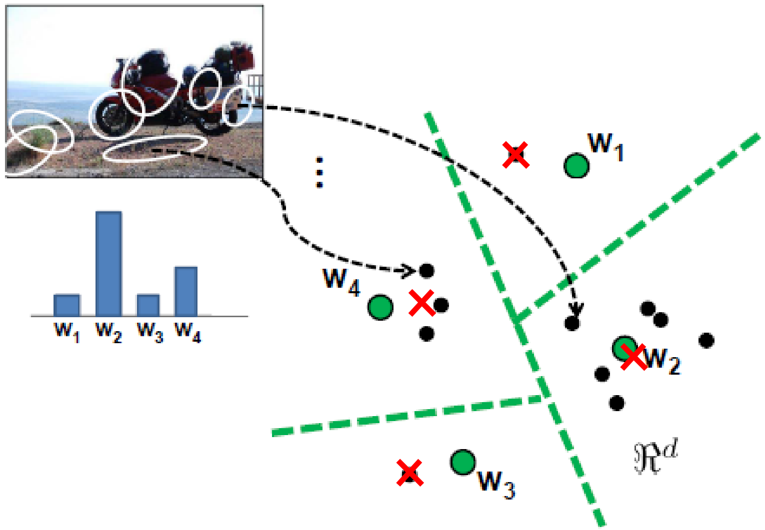
But today we're not talking about ways to preserve *spatial* information.

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 ×



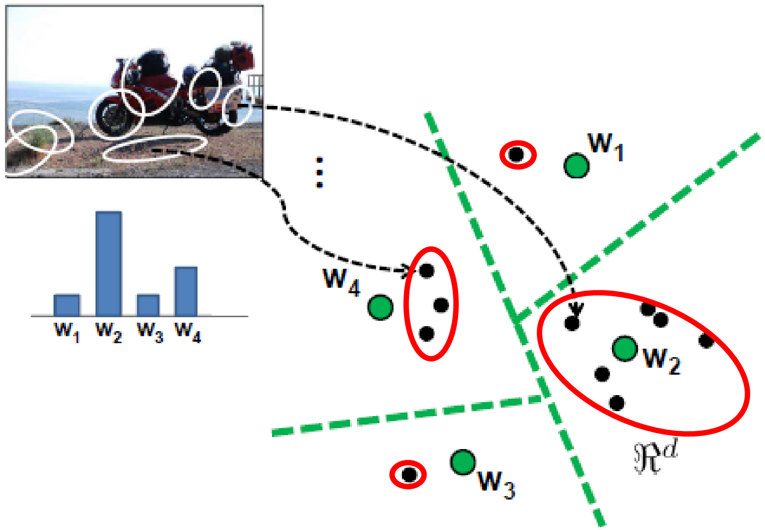
http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

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:

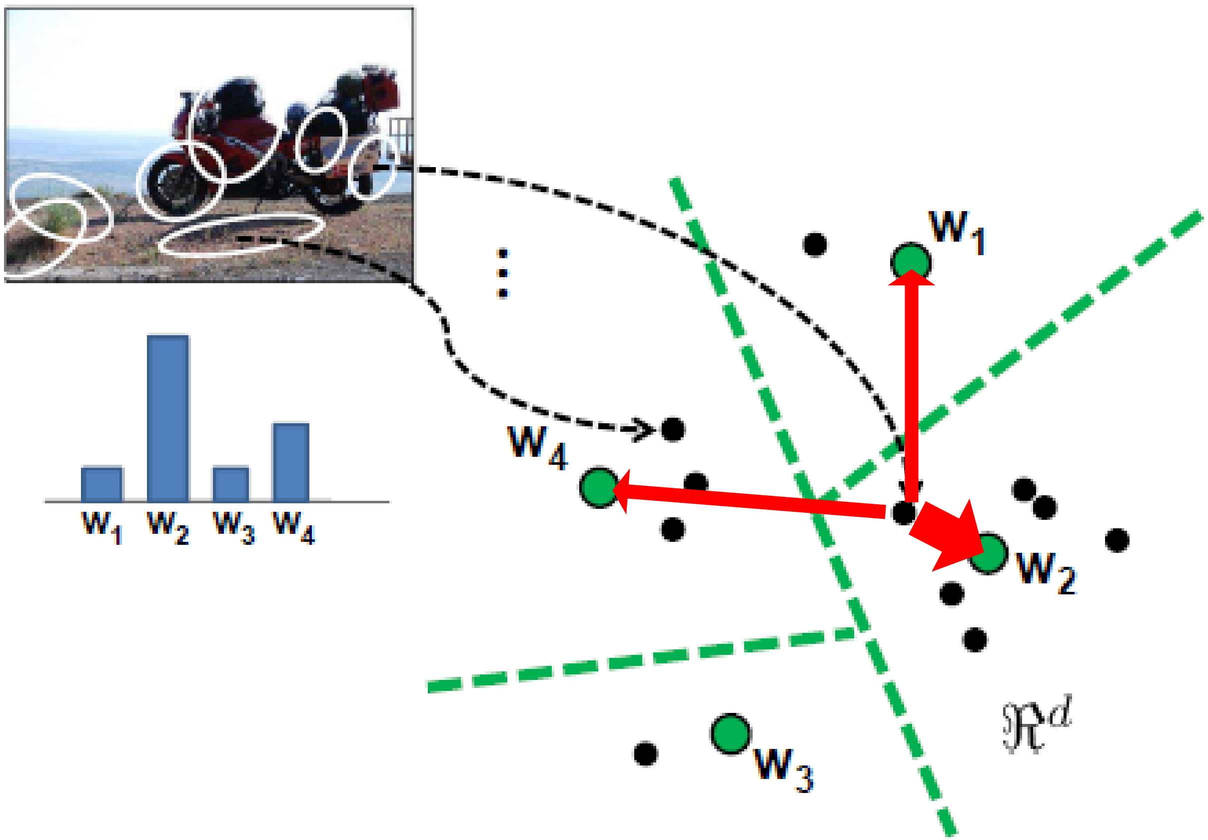
- mean of local descriptors
- (co)variance of local descriptors



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

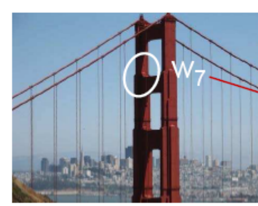
Simple case: Soft Assignment

- Called "Kernel codebook encoding" by Chatfield et al. 2011. Cast a weighted vote into the most similar clusters.



Simple case: Soft Assignment

- Called “Kernel codebook encoding” by Chatfield et al. 2011. Cast a weighted vote into the most similar clusters.
- This is fast and easy to implement (try it for Project 4!) but it does have some downsides for image retrieval – the inverted file index becomes less sparse.



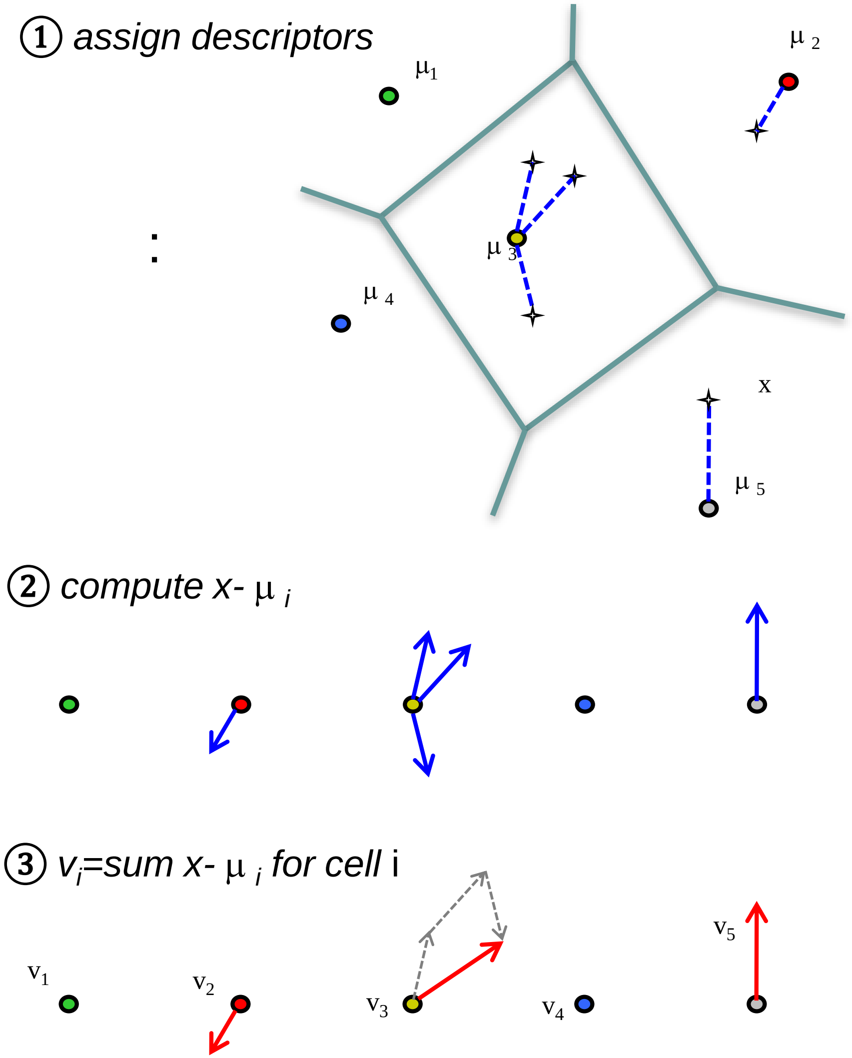
New query image

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

VLAD

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

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

The Fisher vector
Score function

Given a likelihood function u_λ with parameters λ, the **score function** of a given sample X is given by:

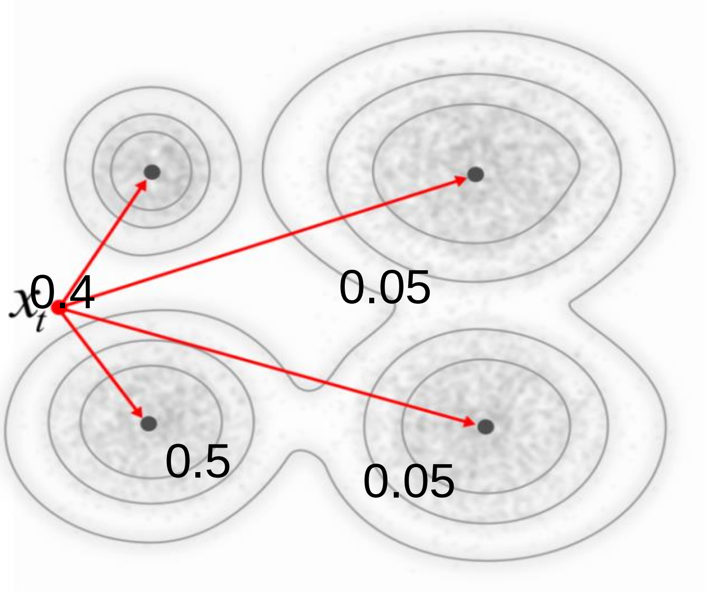
$$\boxed{G_\lambda^X = \nabla_\lambda \log u_\lambda(X)}$$

$\rightarrow$ Fixed-length vector whose **dimensionality depends only on # parameters**.

Intuition: direction in which the parameters λ of the model should we modified to better fit the data.

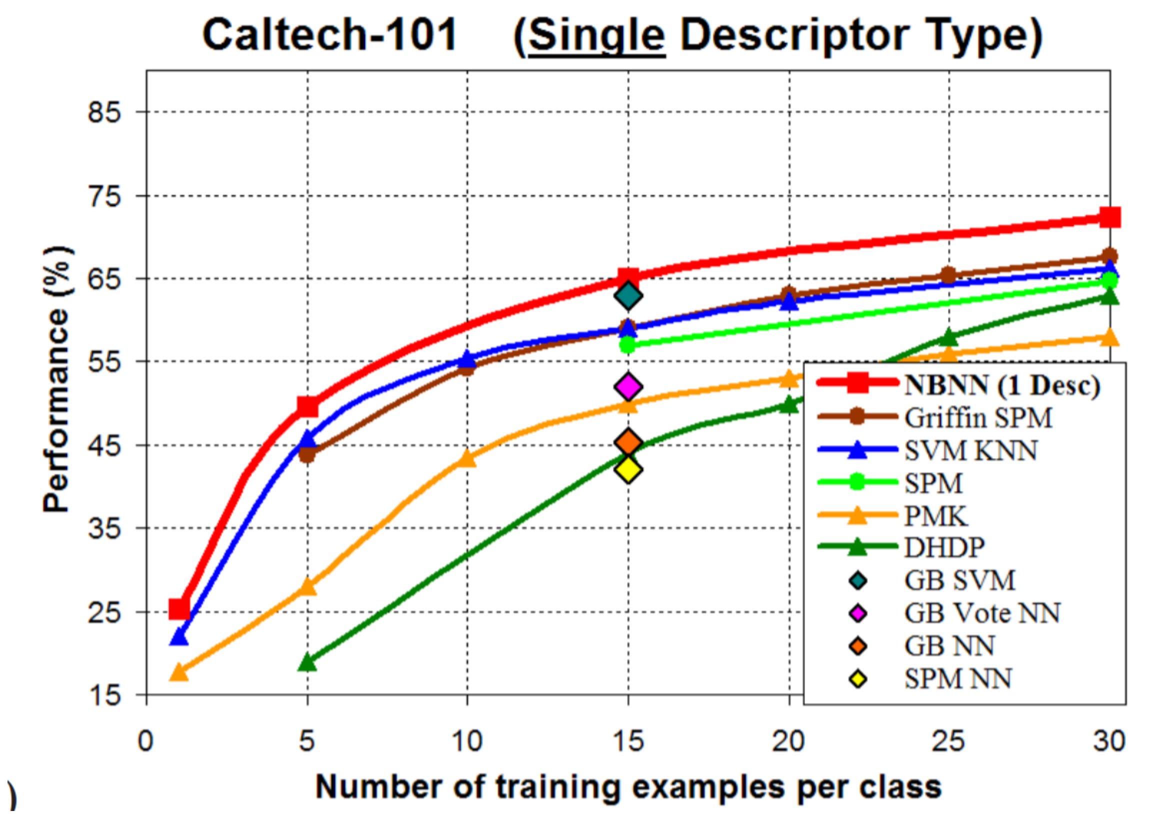
Aside: Mixture of Gaussians (GMM)

- For Fisher Vector image representations, u_λ is a GMM.
- GMM can be thought of as “soft” kmeans.



- Each component has a mean and a standard deviation along each direction (or full covariance)

What about skipping quantization / summarization completely?

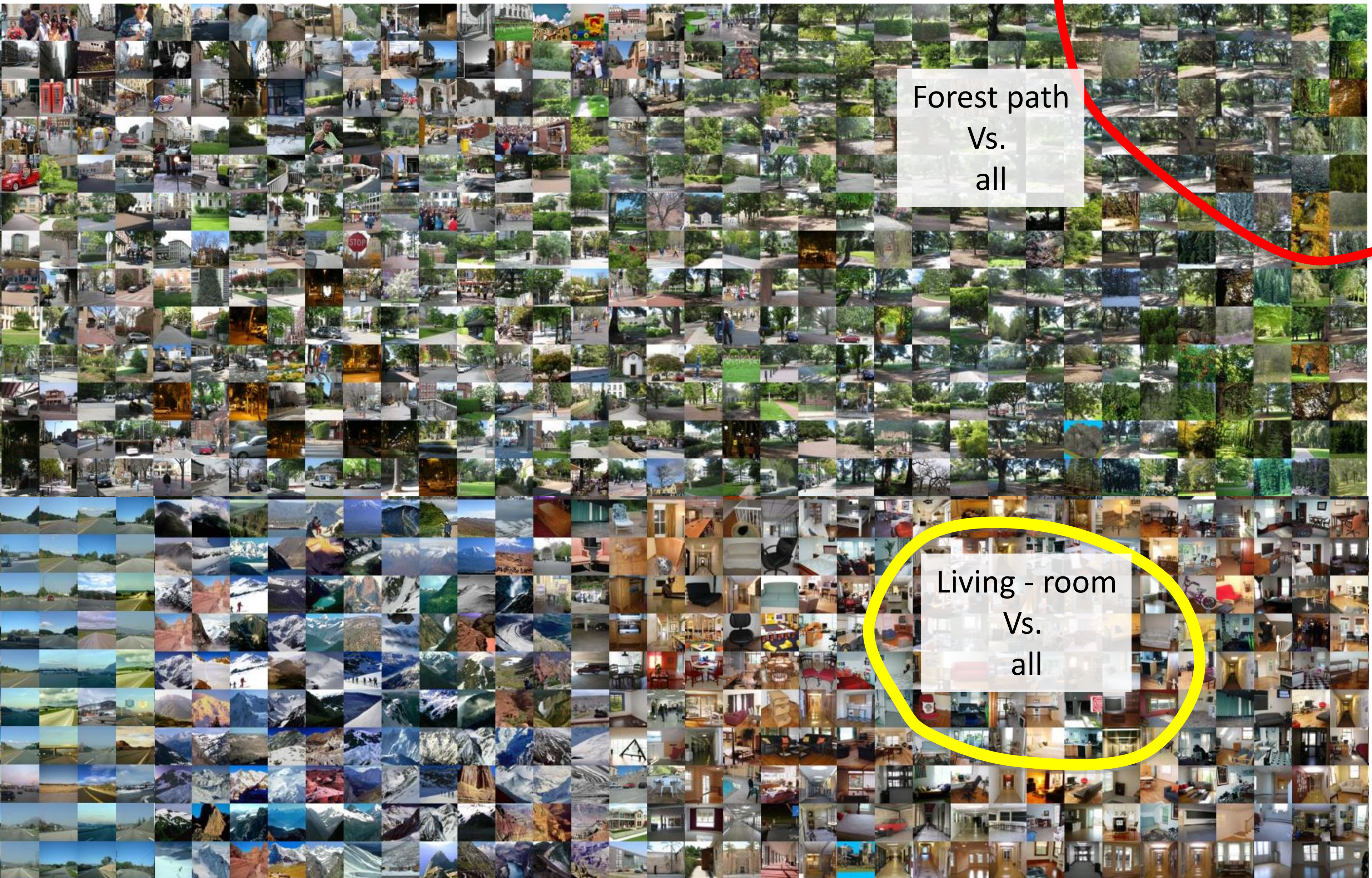


In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani

Summary

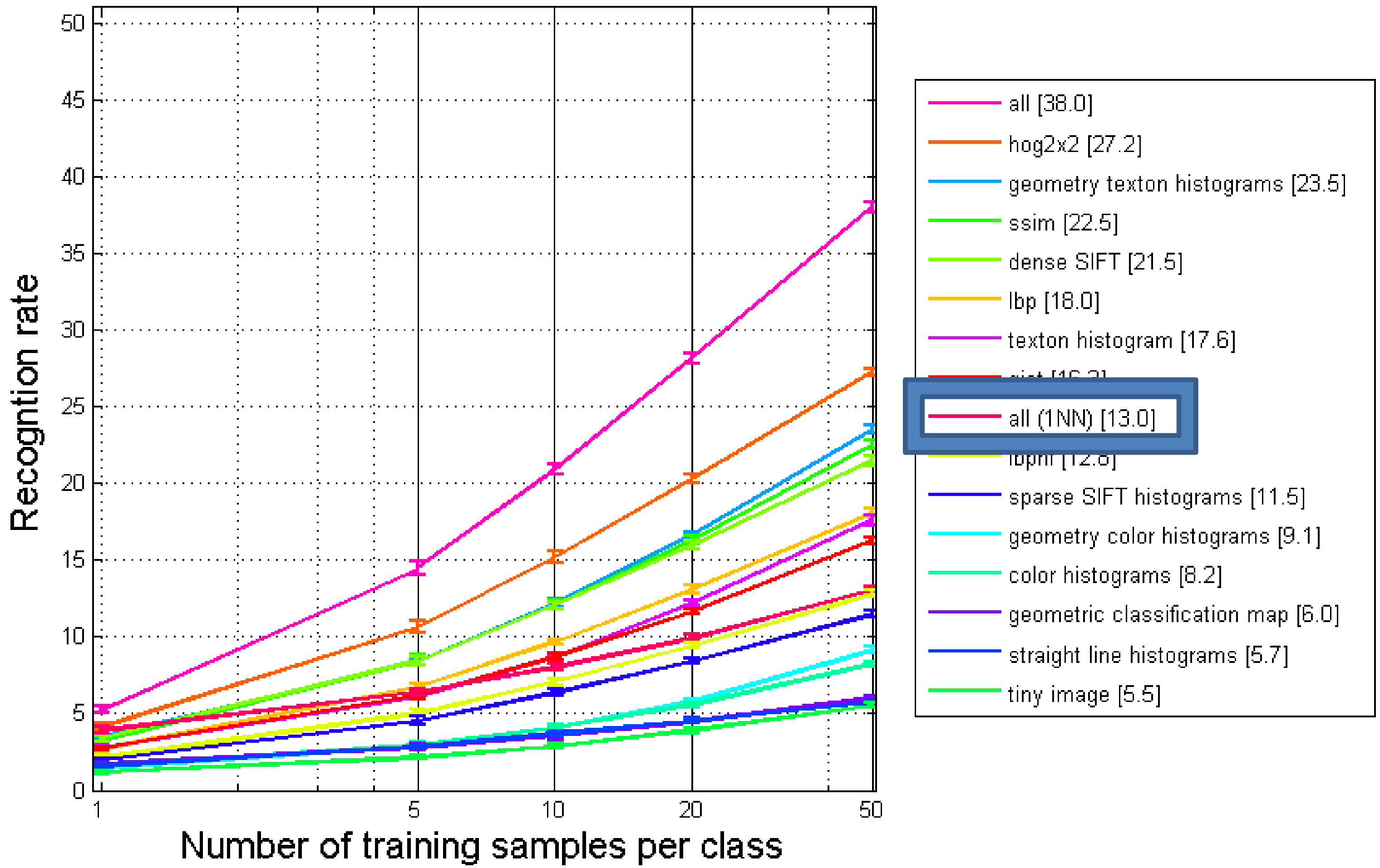
- We’ve looked at methods to better characterize the distribution of visual words in an image:
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD
  - Fisher Vector
  - No quantization

Learning Scene Categorization

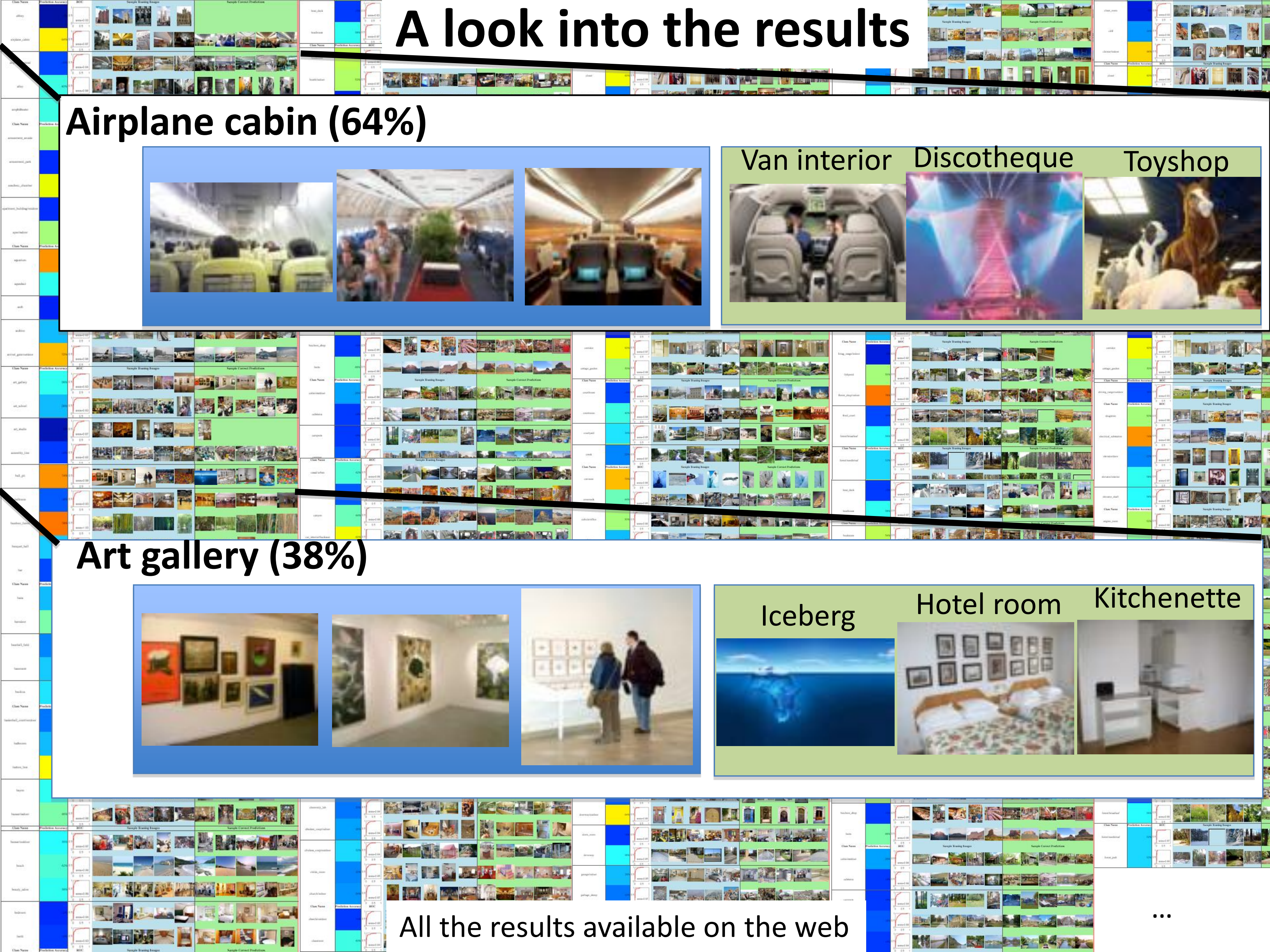


Feature Accuracy

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

Humans bad
Comp. bad

Human good
Comp. bad

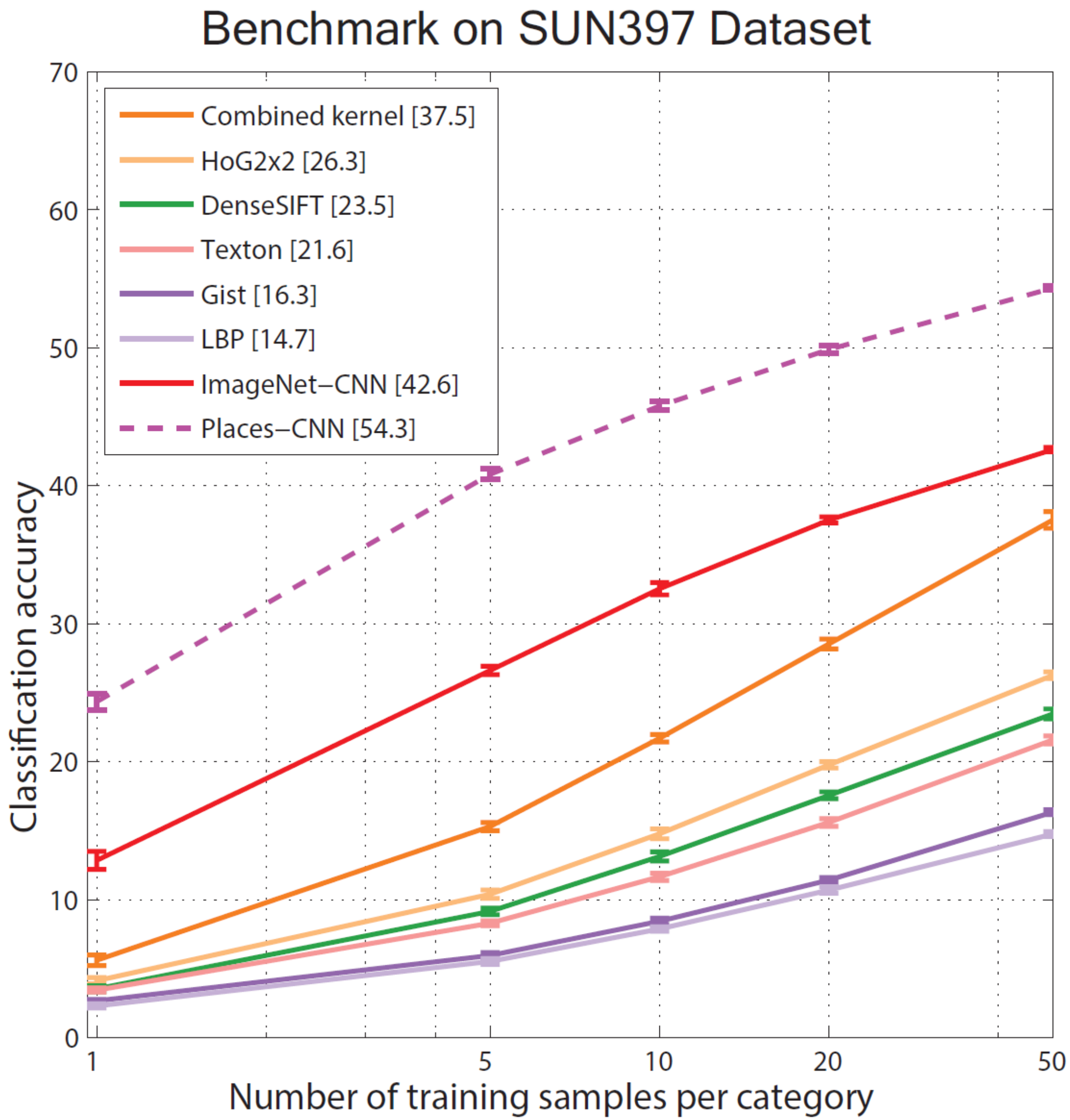
Human bad
Comp. good

Database and source code available at
http://groups.csail.mit.edu/vision/SUN/

Additional details available:
SUN Database: Large-scale Scene Recognition from Abbey to Zoo. Jianxiong Xiao, James Hays, Krista A. Ehinger, Aude Oliva, Antonio Torralba. *CVPR 2010.*

How do we do better than 40%?

- Features from deep learning on ImageNet get 42%
- Fisher vector encoding gets up to 47.2%



B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, and A. Oliva. "Learning Deep Features for Scene Recognition using Places Database." Advances in Neural Information Processing Systems 27 (NIPS), 2014