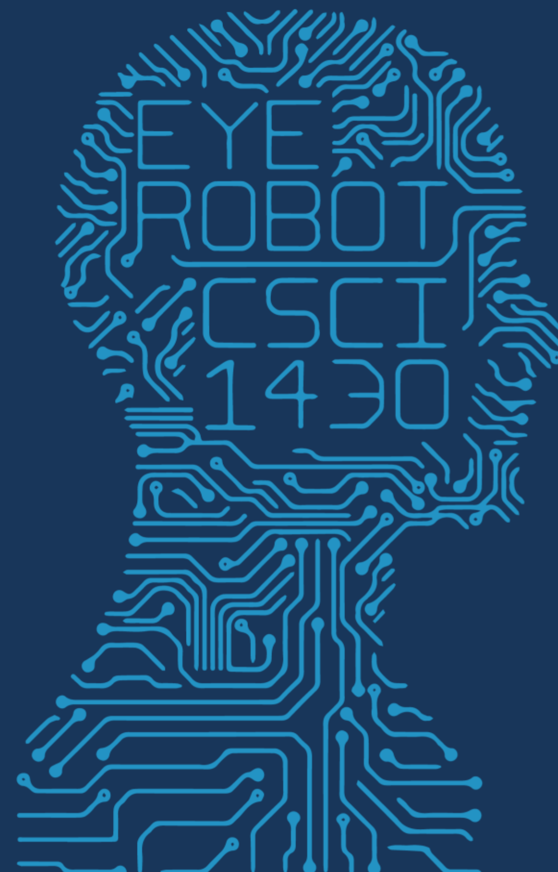

1950

Future Vision

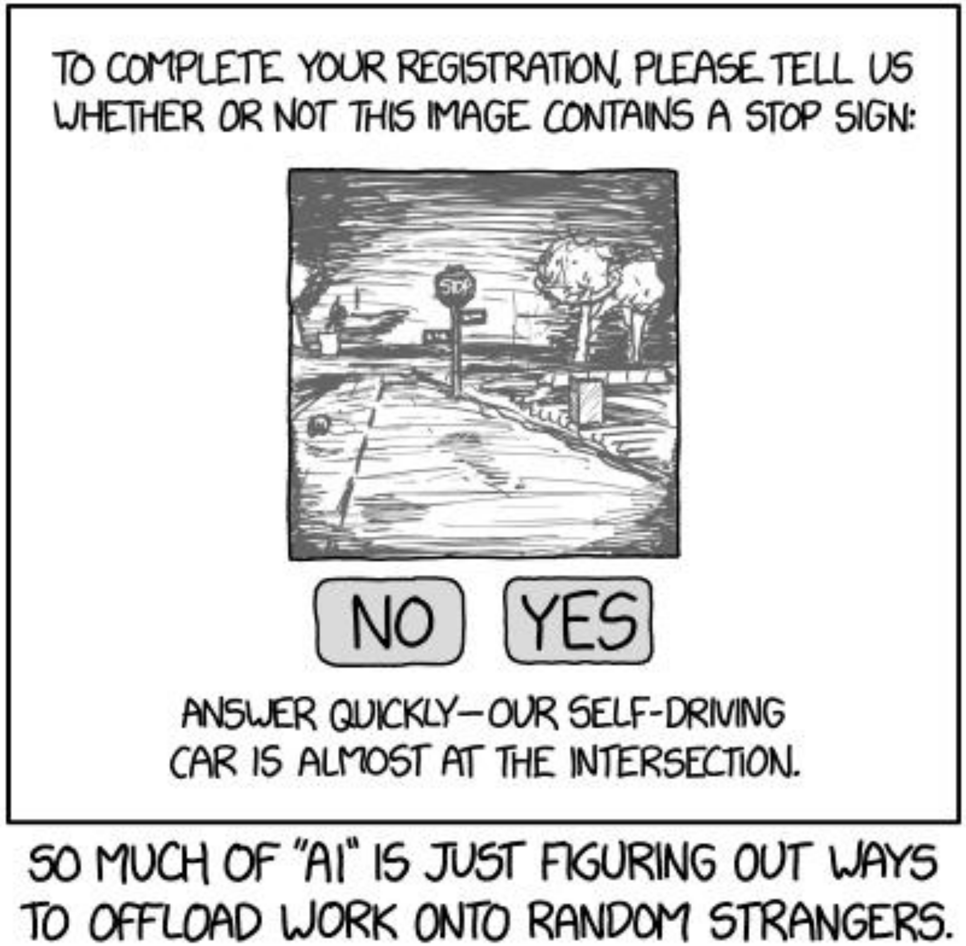



24 February 2020

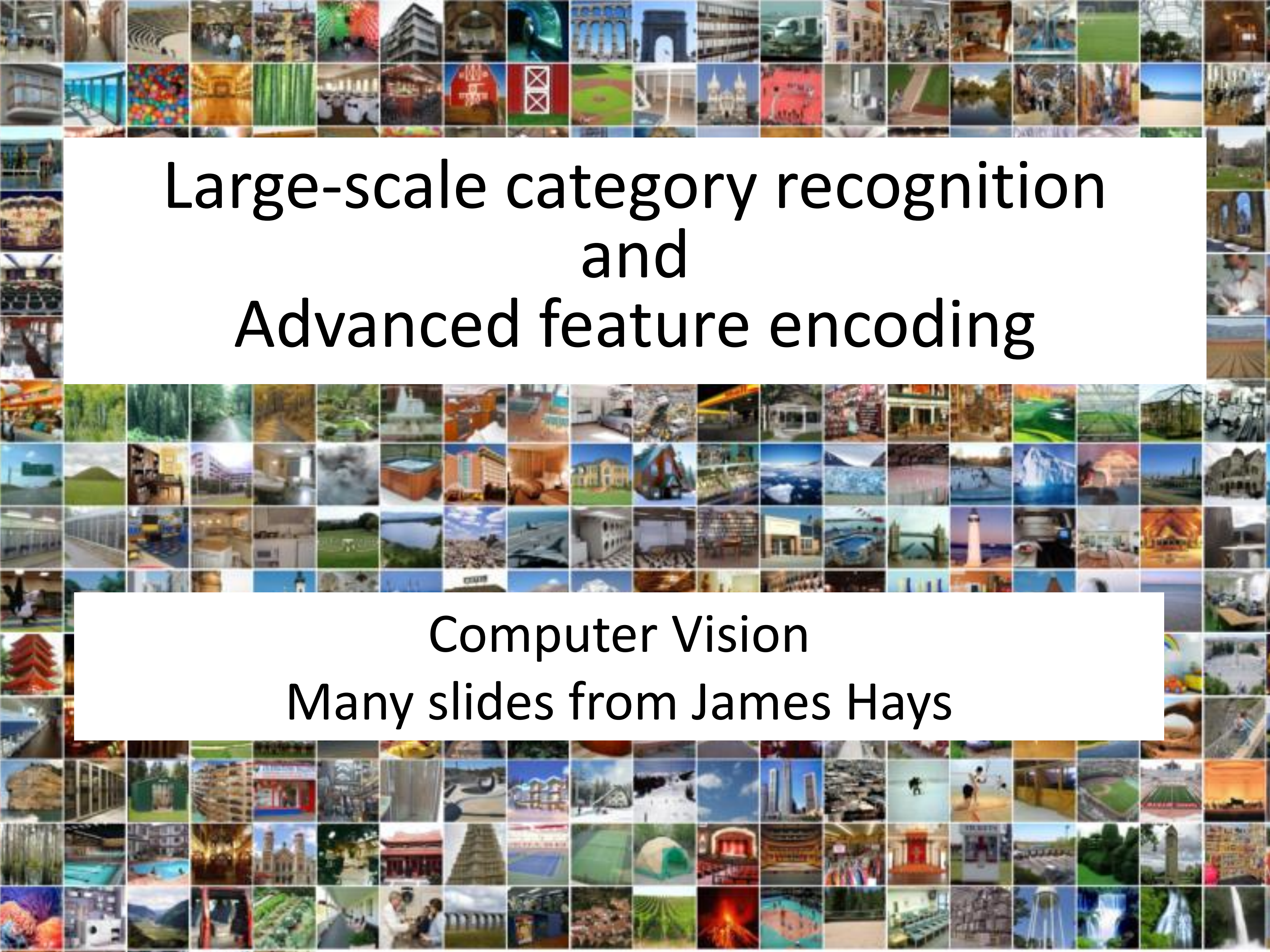
Computer Vision


SO MUCH OF "AI" IS JUST FIGURING OUT WAYS TO OFFLOAD WORK ONTO RANDOM STRANGERS.

Thanks to **Iuliu Balibanu**




*Alt-text: "Crowdsourced steering" doesn't sound quite as appealing as "self driving".*



# Large-scale category recognition and Advanced feature encoding

Computer Vision

Many slides from James Hays

# 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

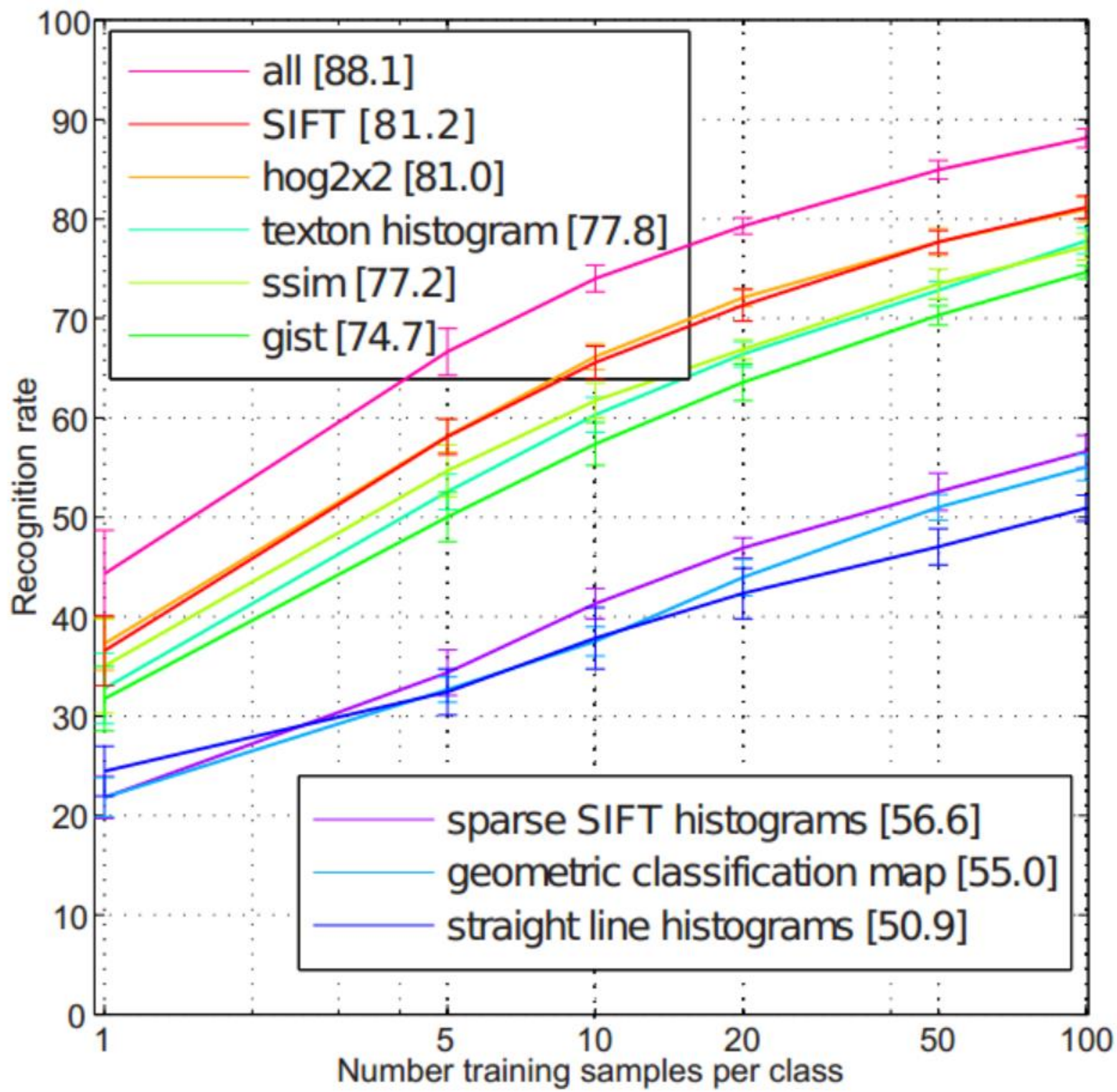
+


Industrial

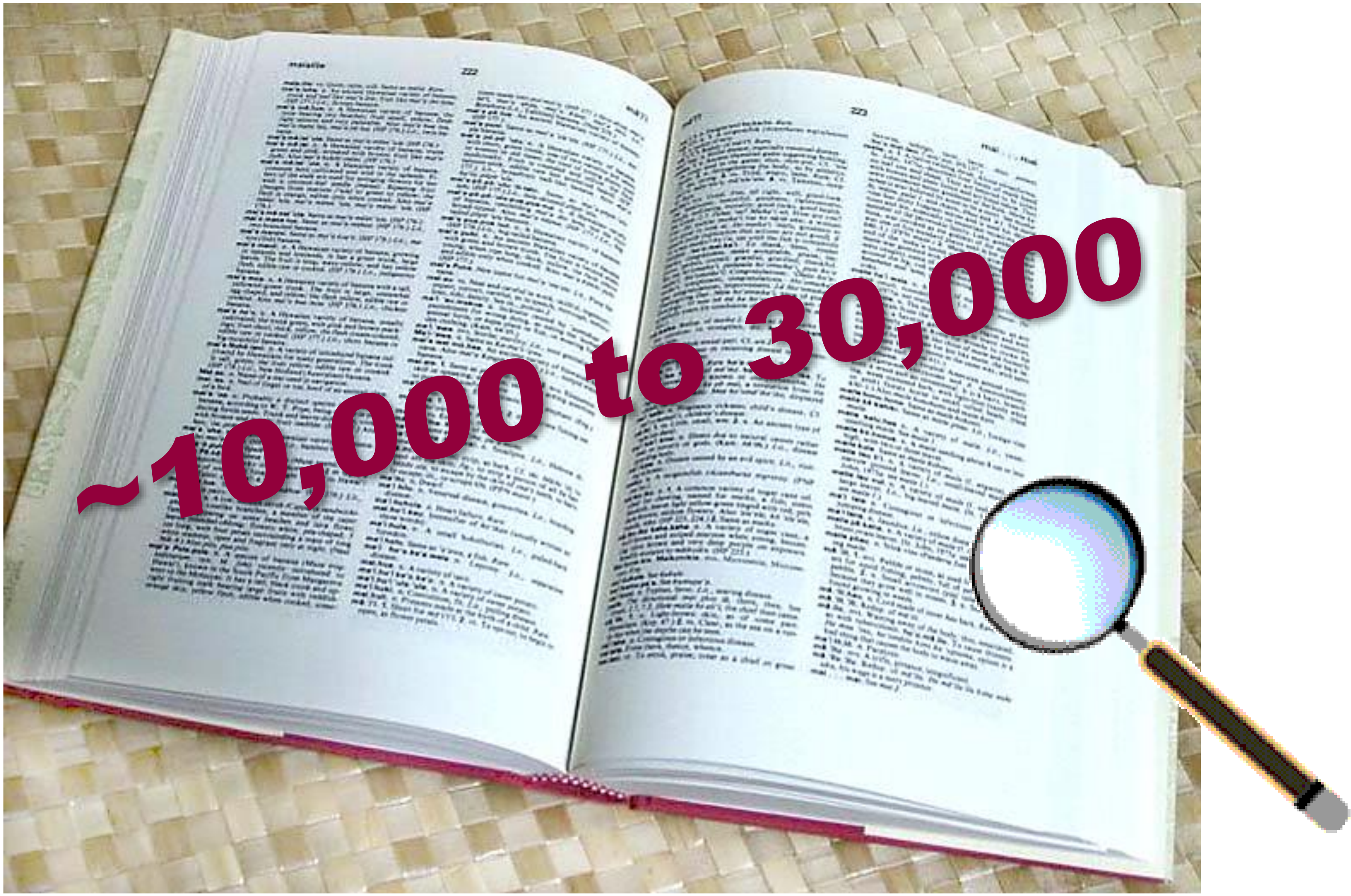

Store

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

■ ■ ■


apple orchard


assembly hall

# bakery

■ ■ ■

# car factory

# cockpit


construction site

■ ■ ■


food court


interior car

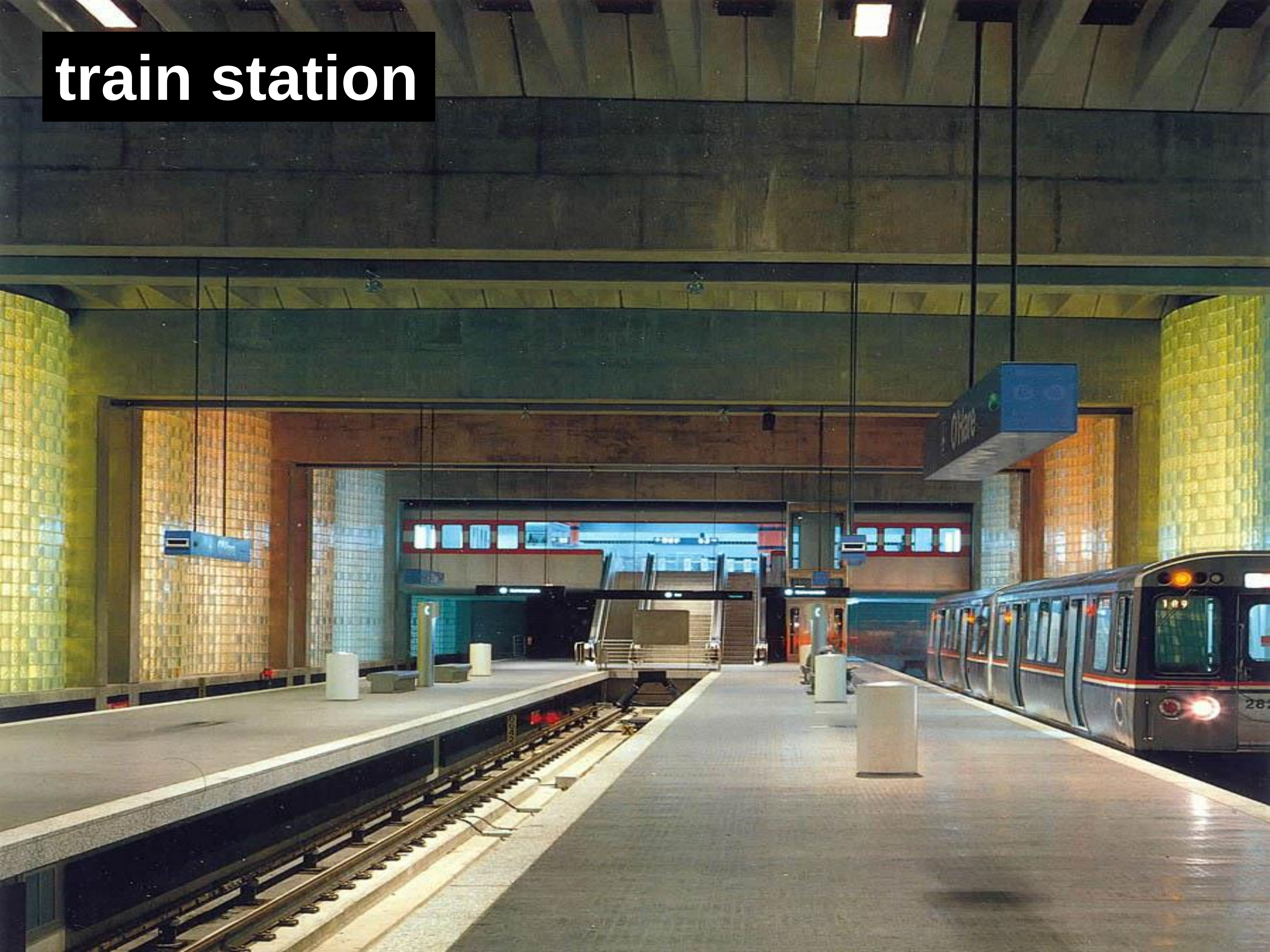

lounge

■ ■ ■

stadium


stream

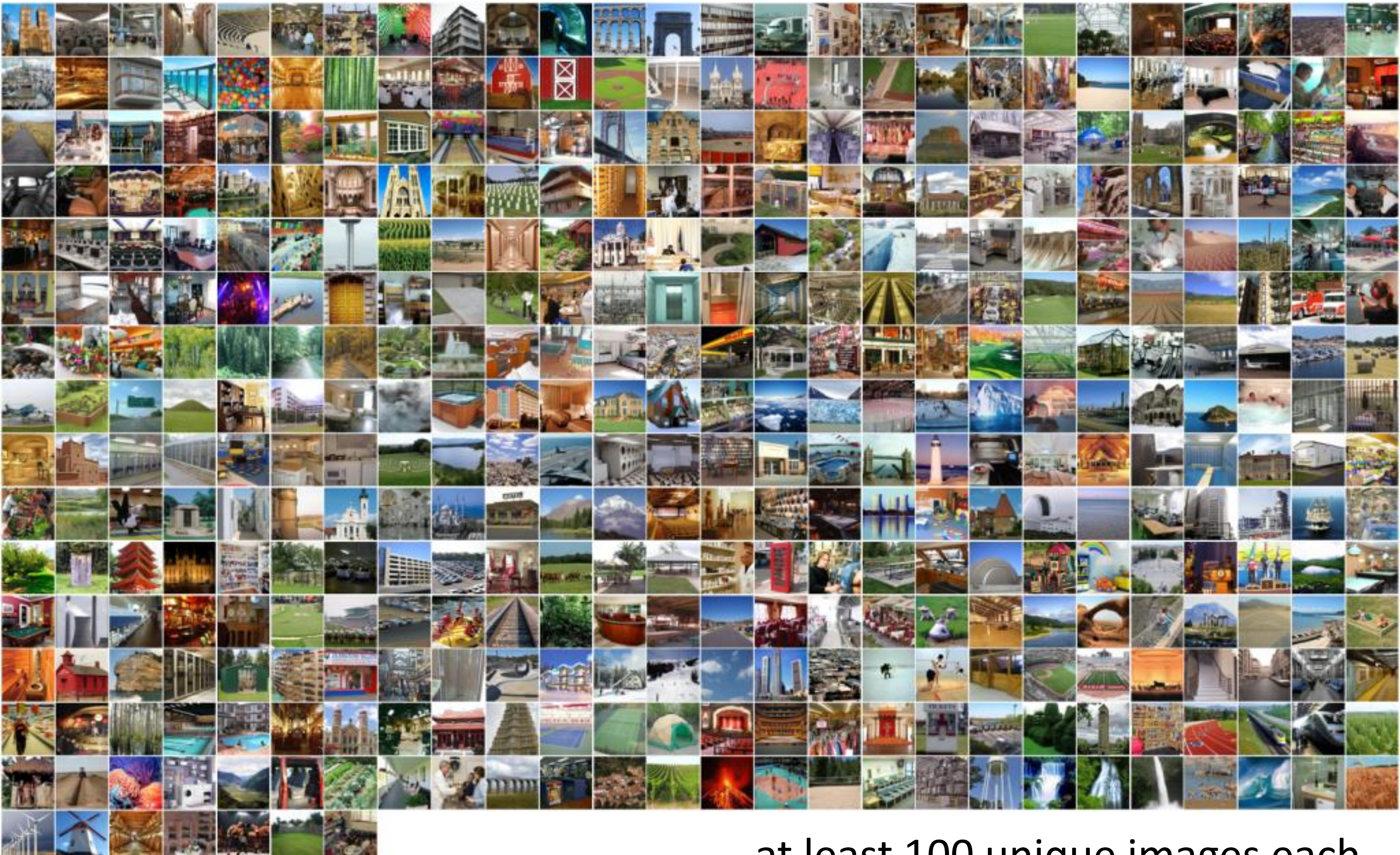
# train station



■ ■ ■


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

# 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%)

Restaurant patio (44%)

Chalet (19%)

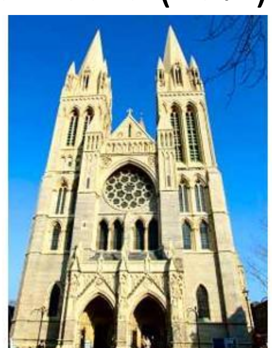
Bayou (0%)

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?



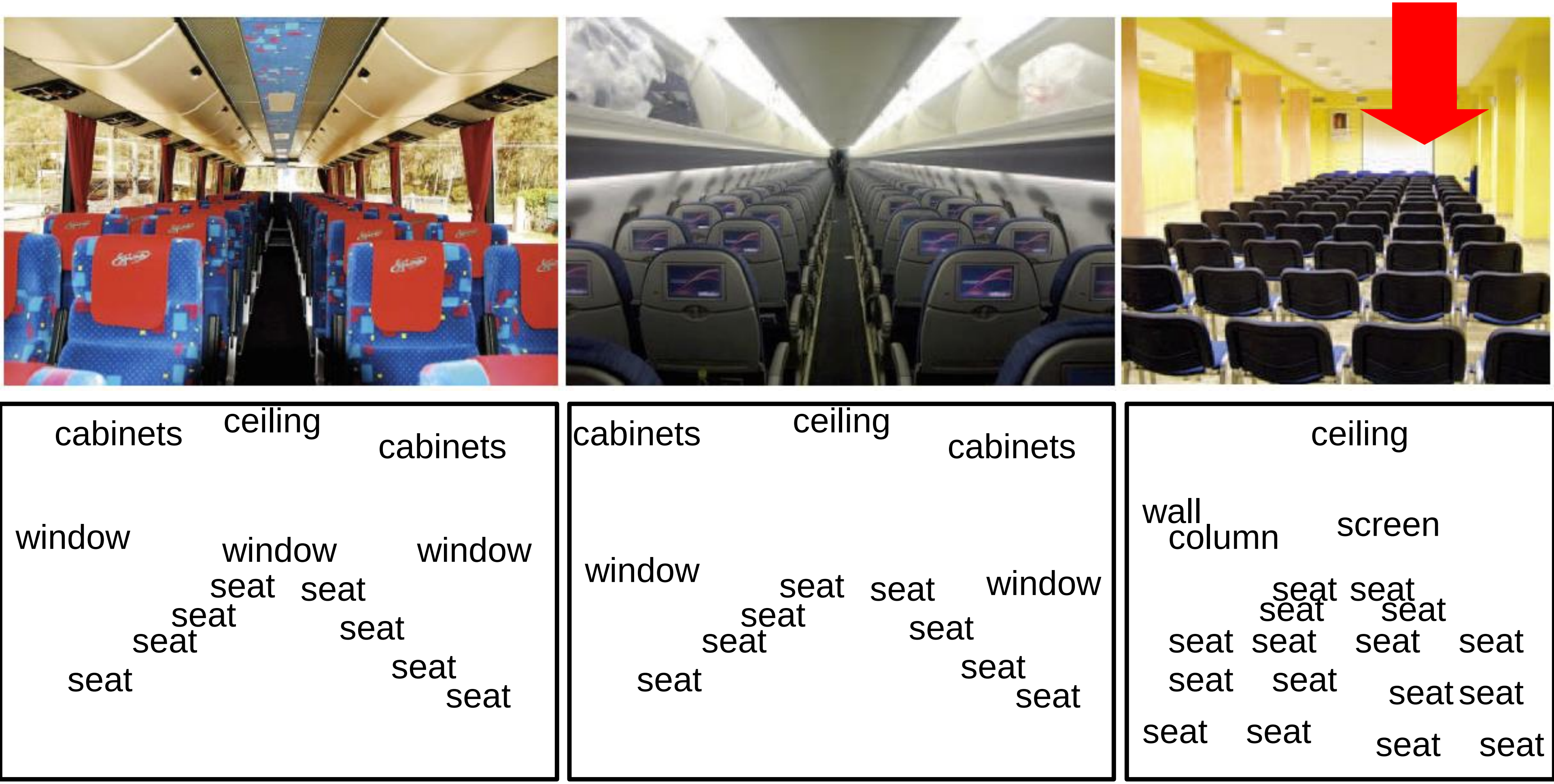
Ceiling
Light
Door Door
Door
Wall Door Wall Door
Floor

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?

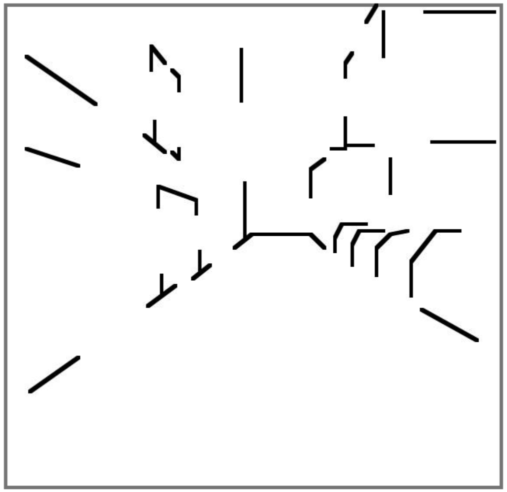



Similar objects, and similar spatial layout

Different lighting, different materials, different "stuff"

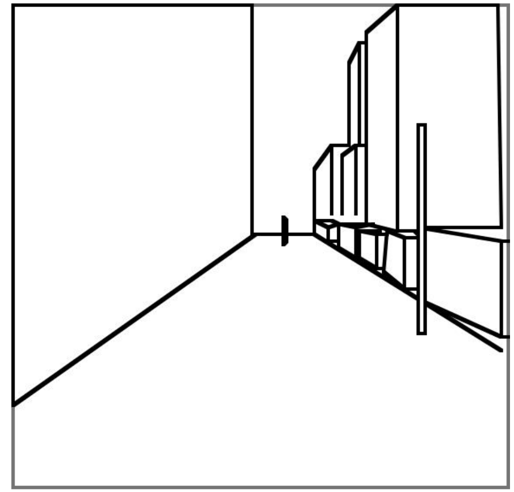
# Scene emergent features

"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

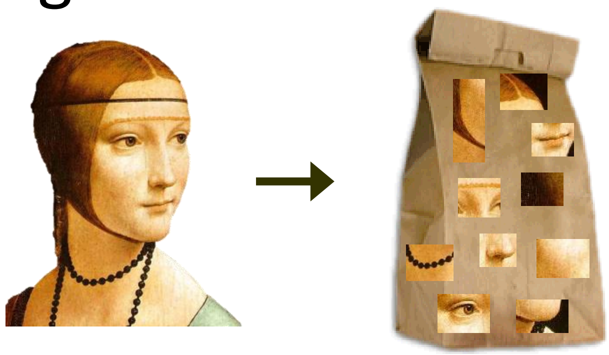
# Global Image Descriptors

- 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

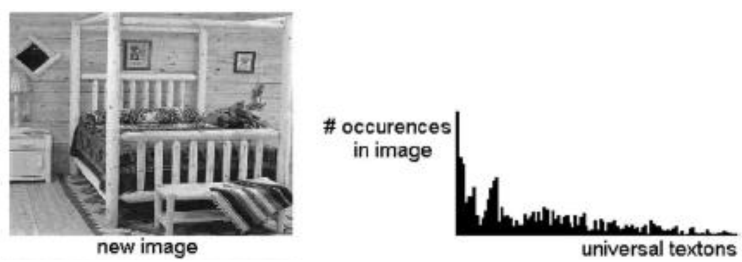
# Global Texture Descriptors

## Bag of words



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

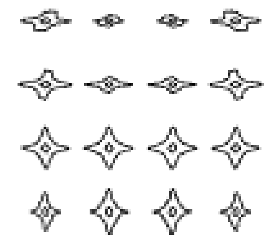
## Non-localized textons



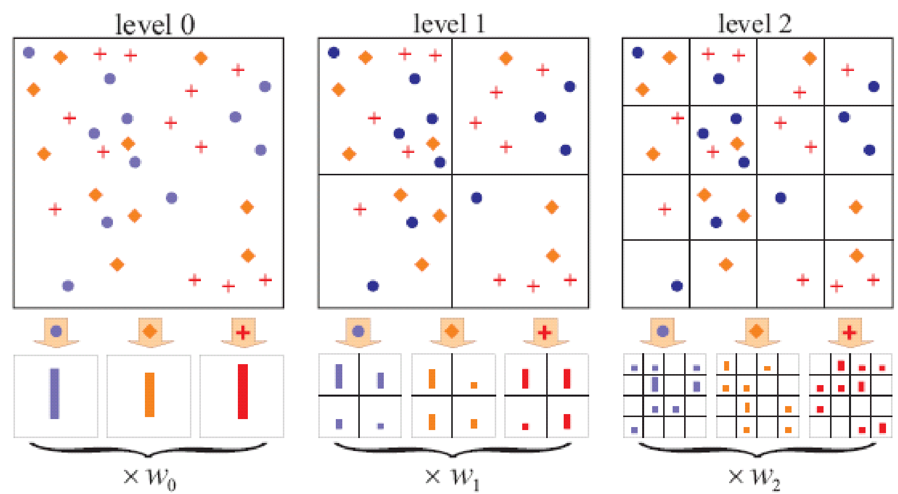

Walker, Malik. Vision Research 2004

…

## Spatially organized textures



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




S. Lazebnik, et al, CVPR 2006

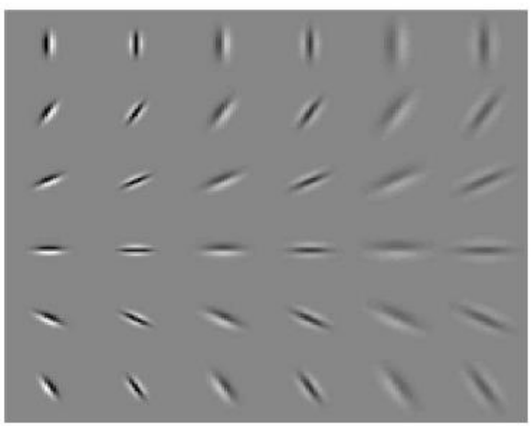
…

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

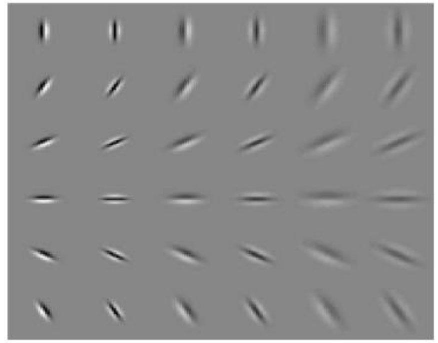


Filter bank

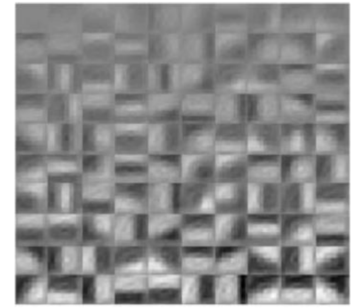
Malik, Belongie, Shi, Leung, 1999

# Textons

Filter bank

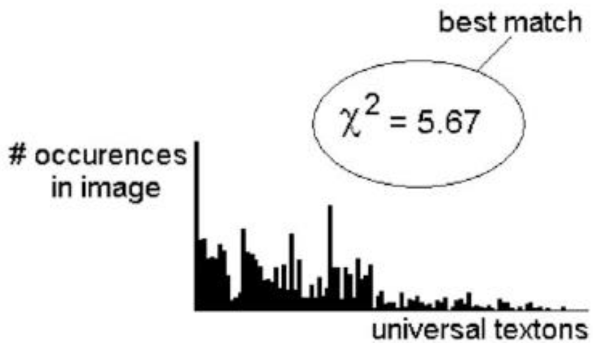


K-means (100 clusters)

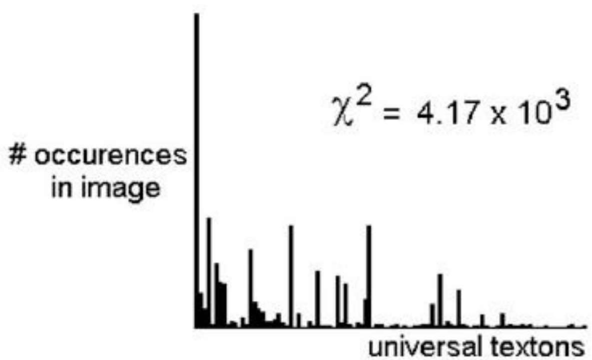


Malik, Belongie, Shi, Leung, 1999

label = bedroom



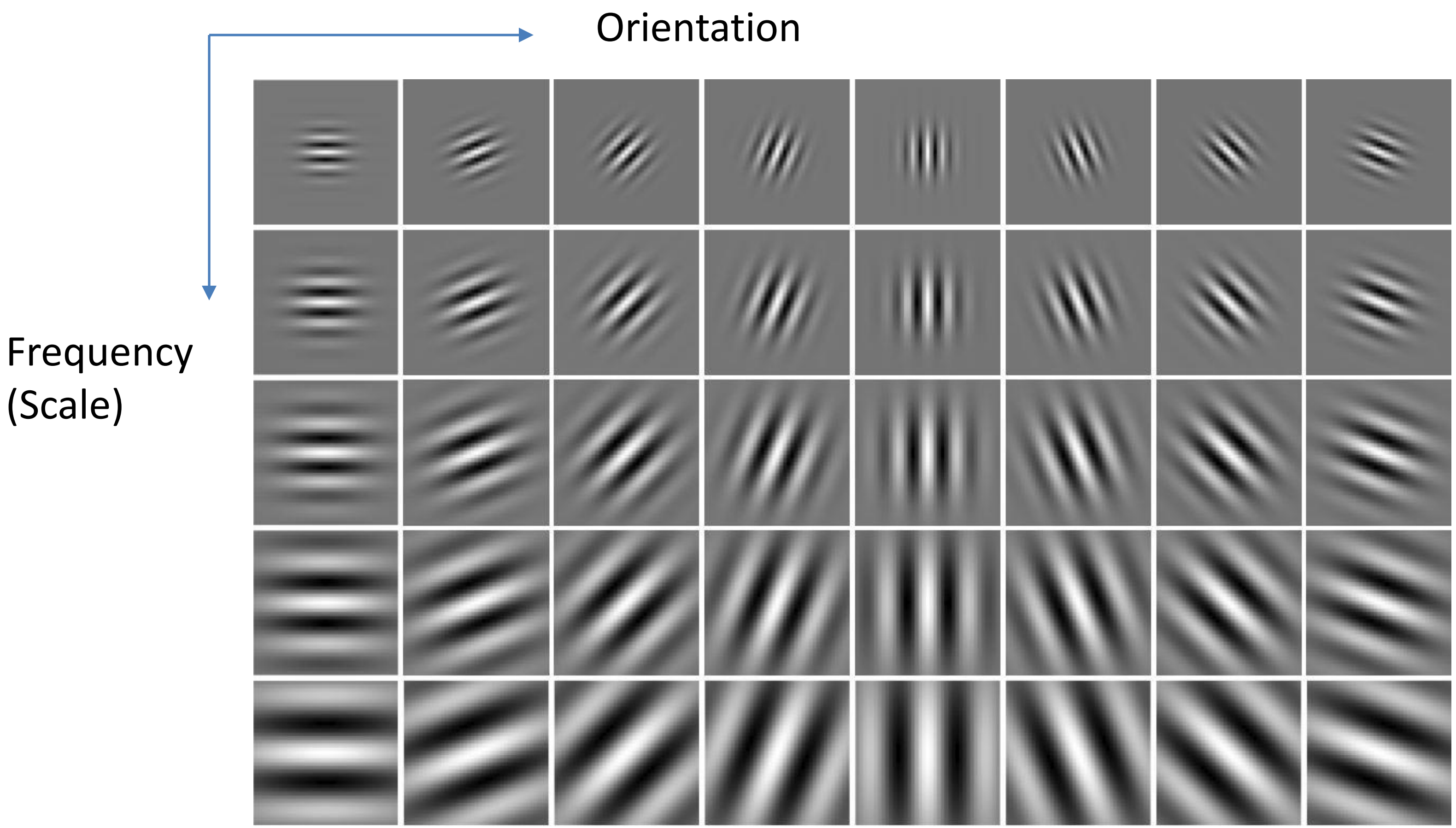

label = beach




Walker, Malik, 2004

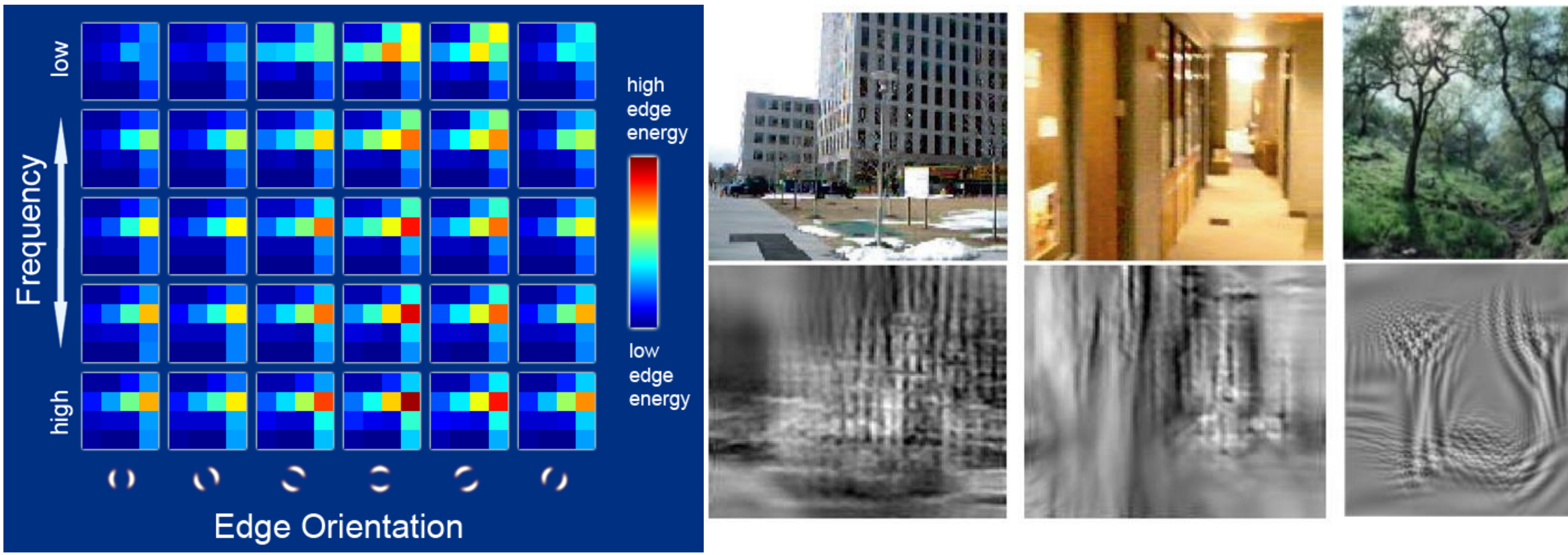
# Gabor filter

- Sinusoid modulated by a Gaussian kernel



# Global scene descriptors: GIST

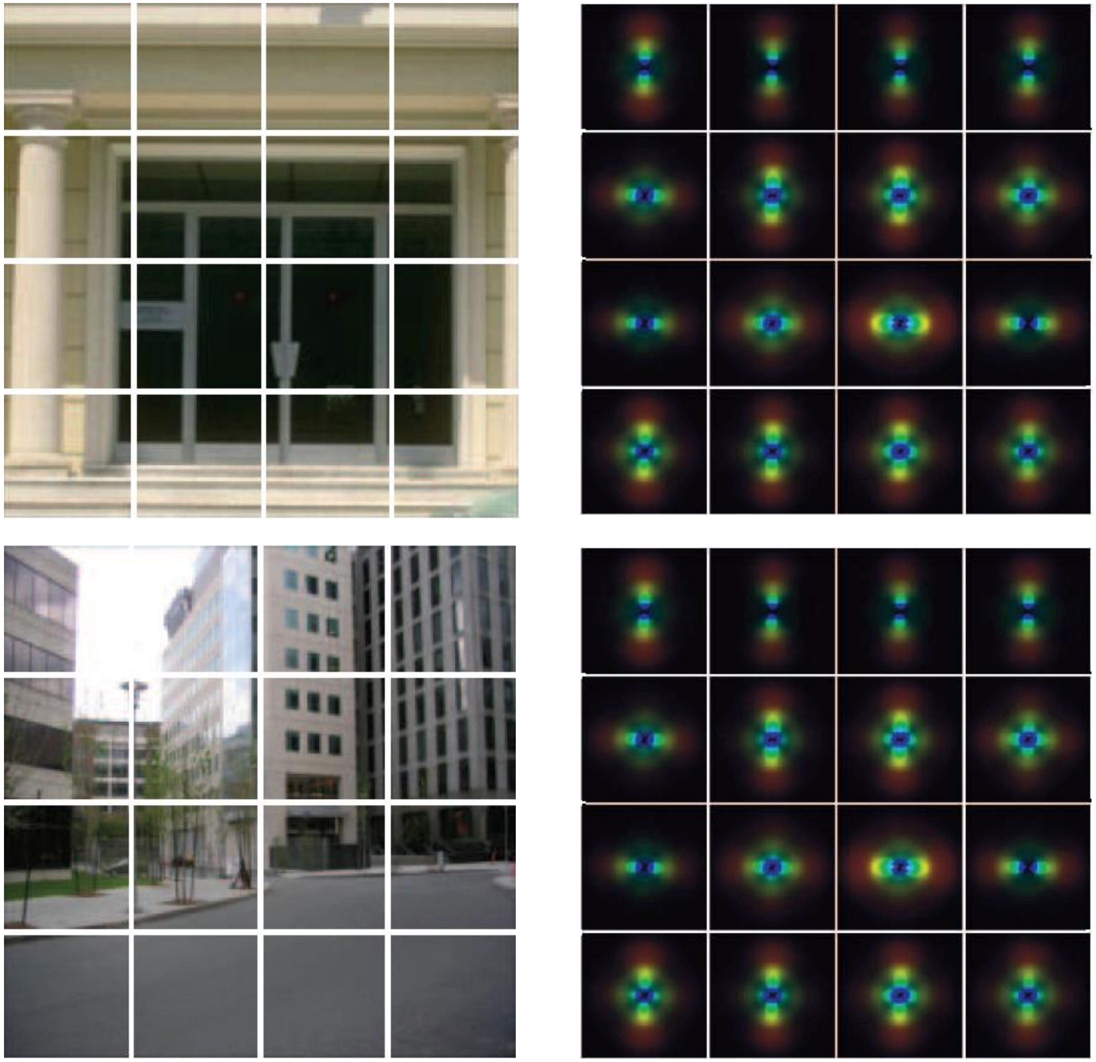
- The "gist" of a scene: Oliva & Torralba (2001)




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

# Gist descriptor

Oliva and Torralba, 2001



Apply oriented Gabor filters over different scales.

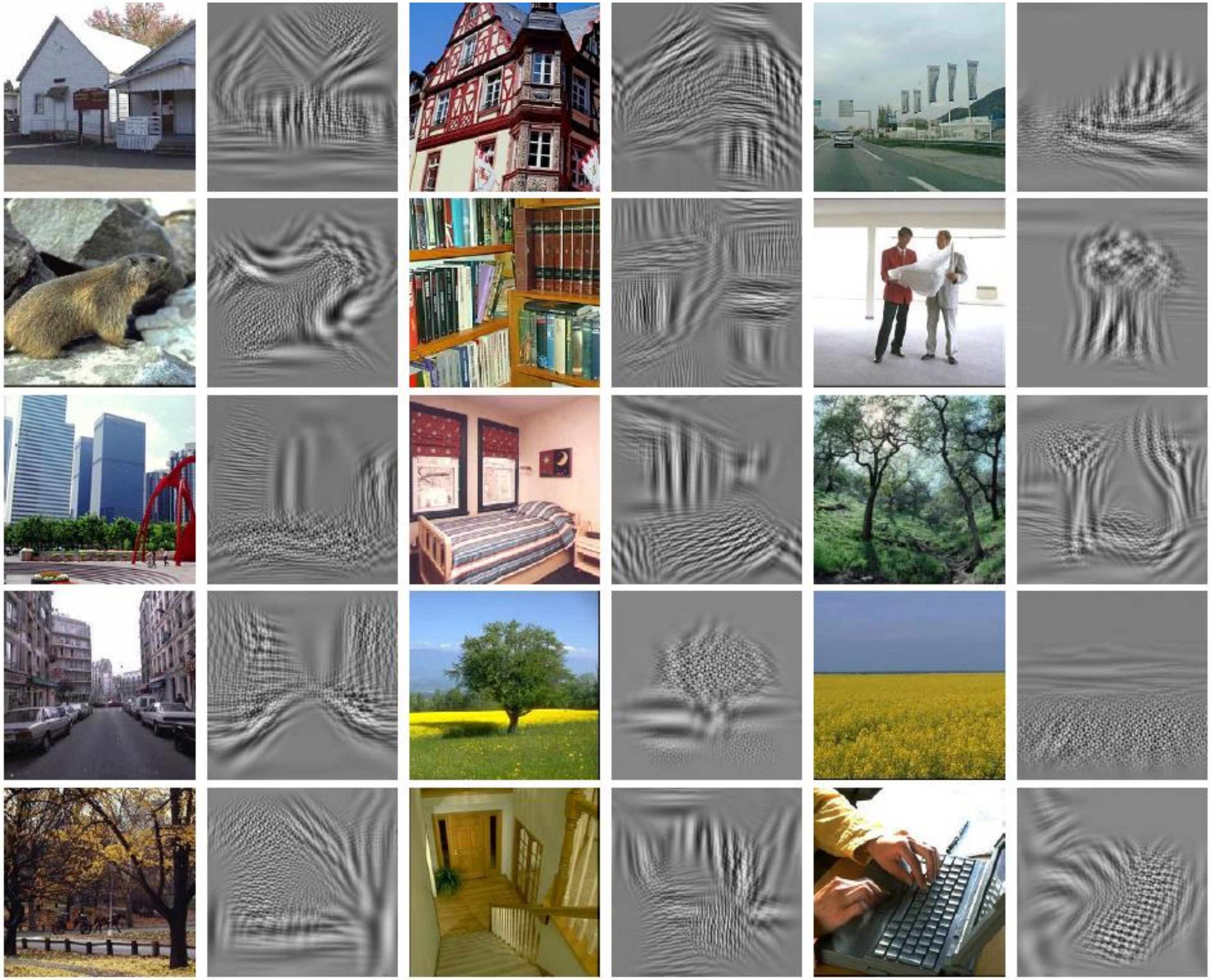
Average filter energy per bin.

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

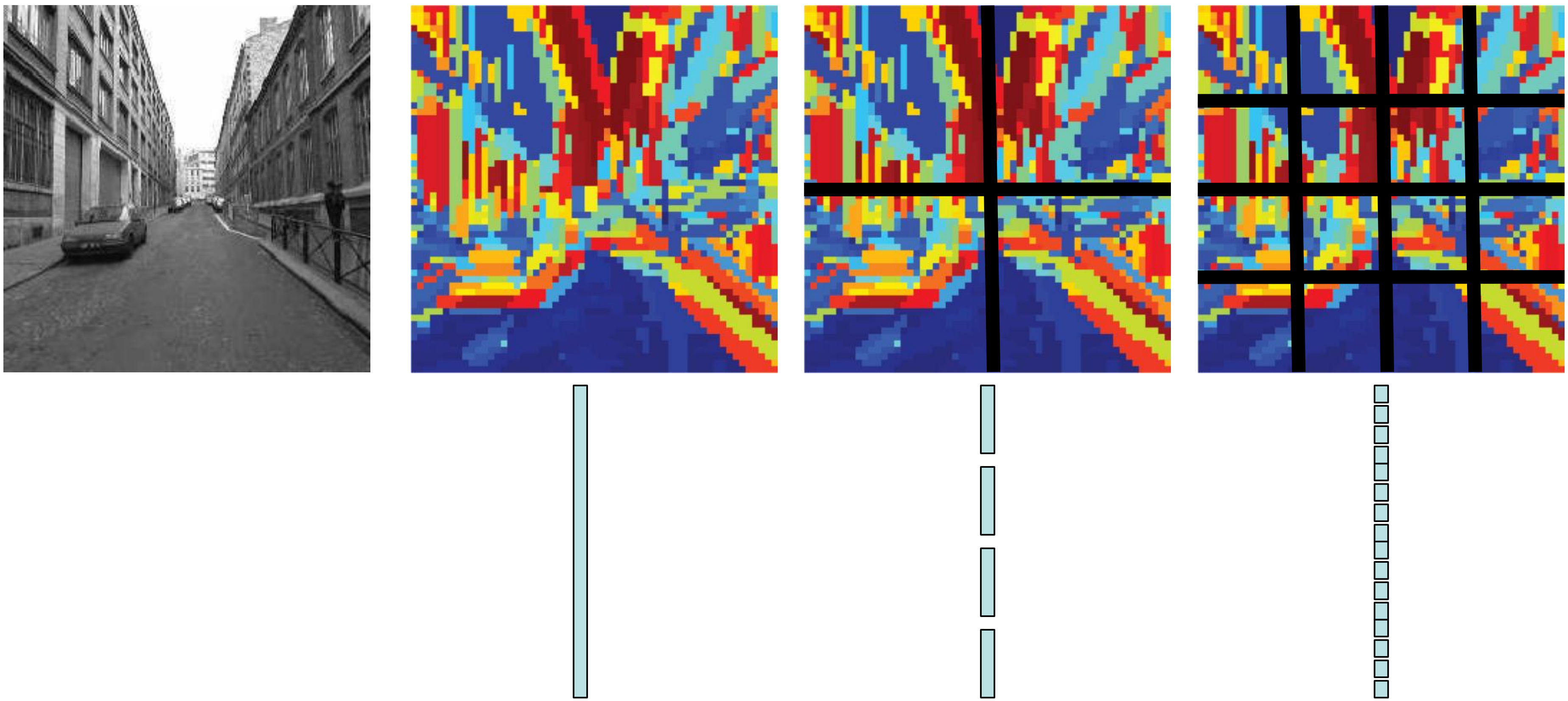


Global features (I) ~ global features (I')

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?

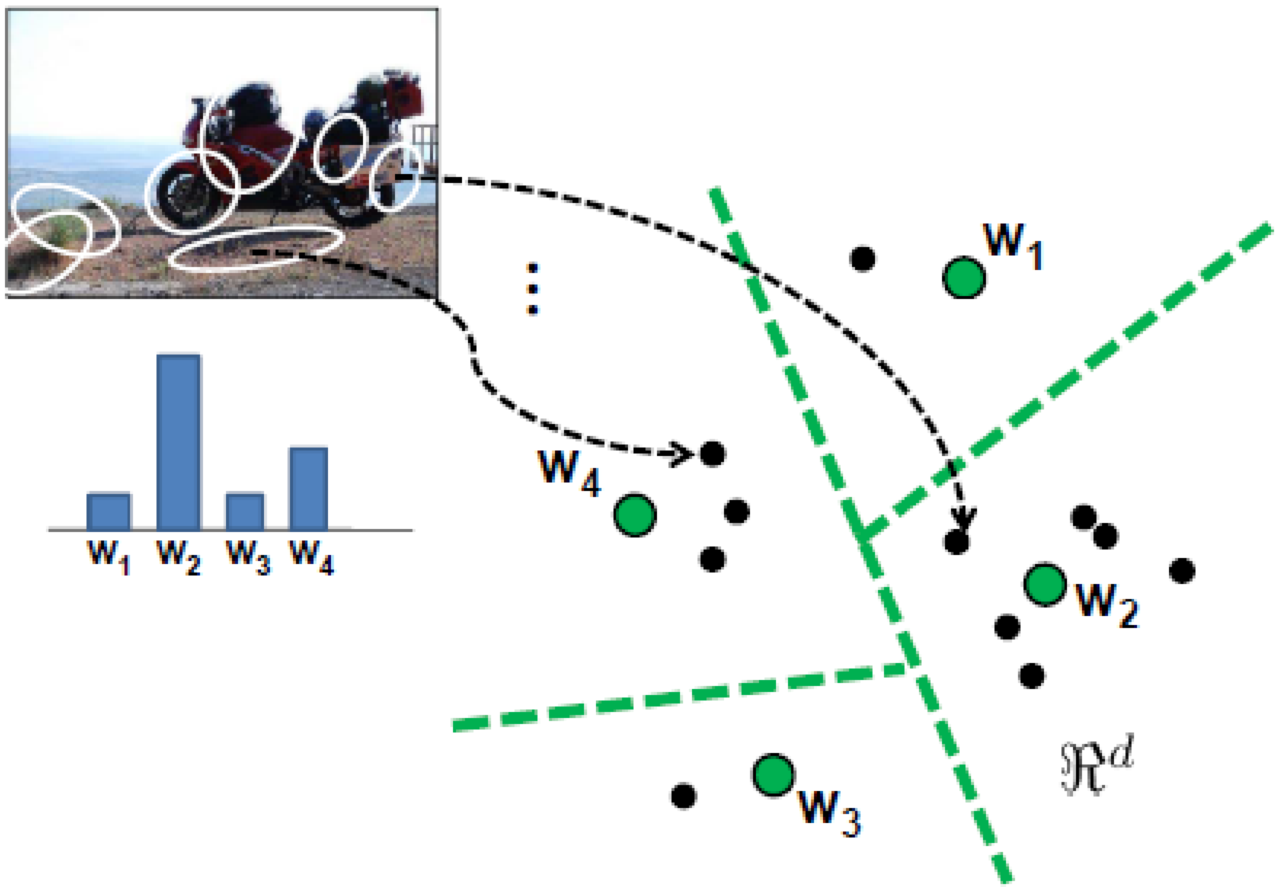
S. Lazebnik, et al, CVPR 2006

# 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 K-means Bag of Words

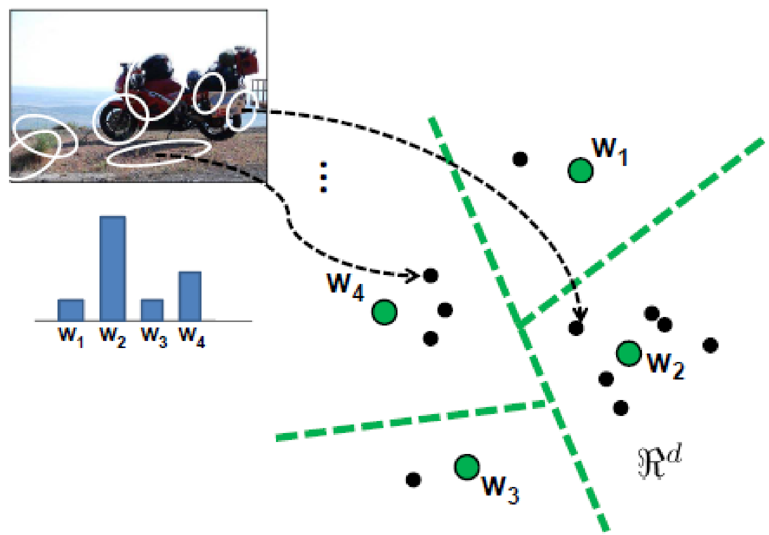



http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

# Motivation

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

Why not including **other statistics**?



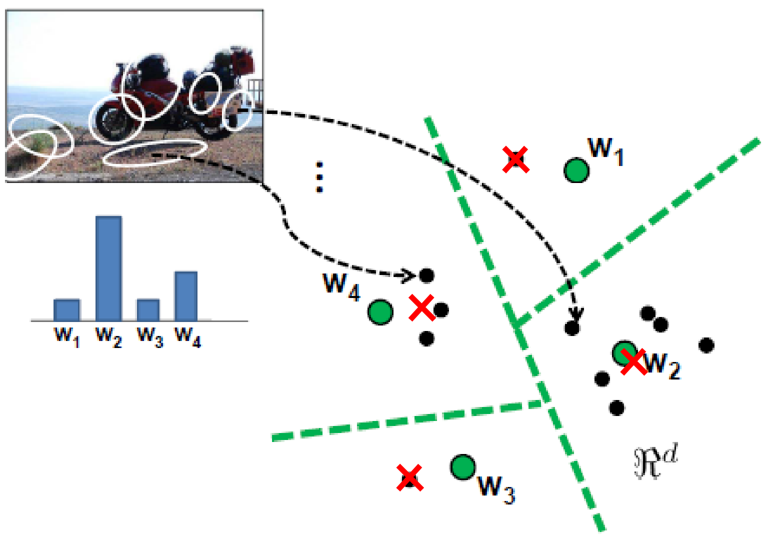

http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

# 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 ×



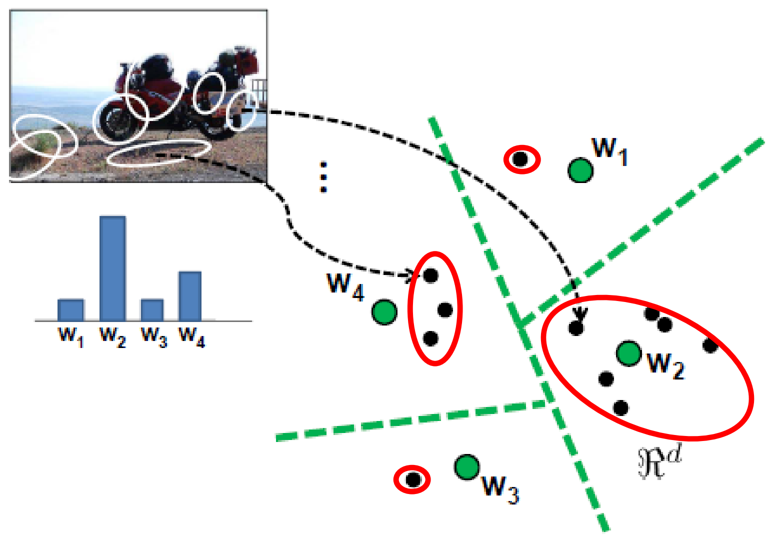

http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

# 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:

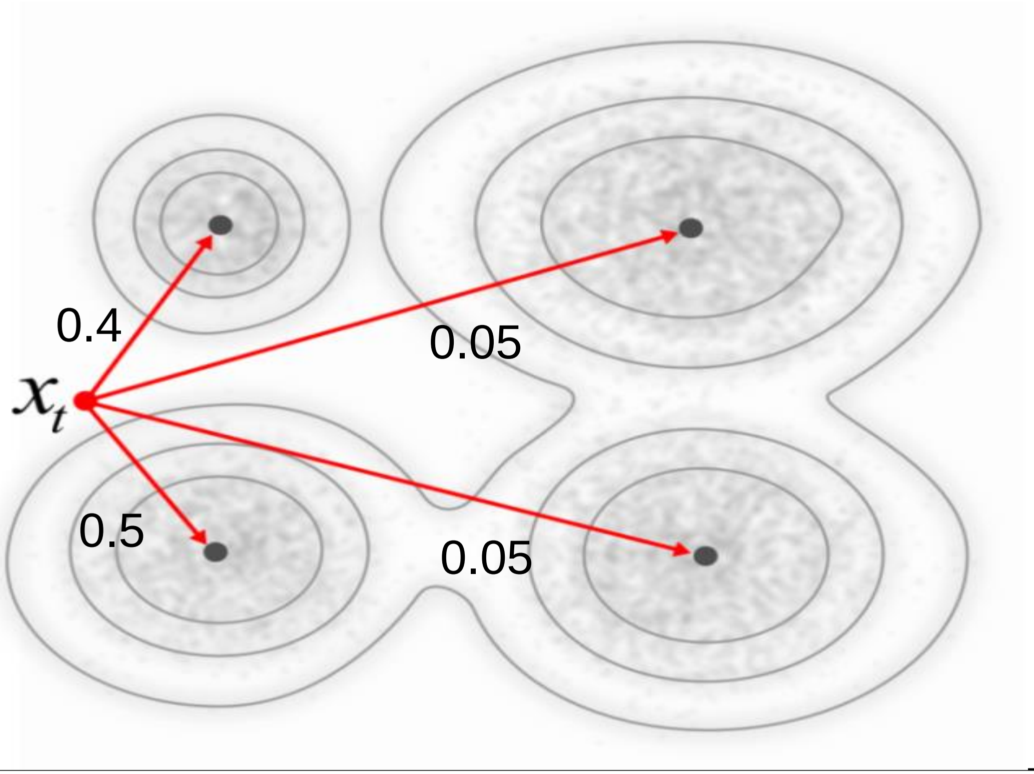
- mean of local descriptors
- (co)variance of local descriptors




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

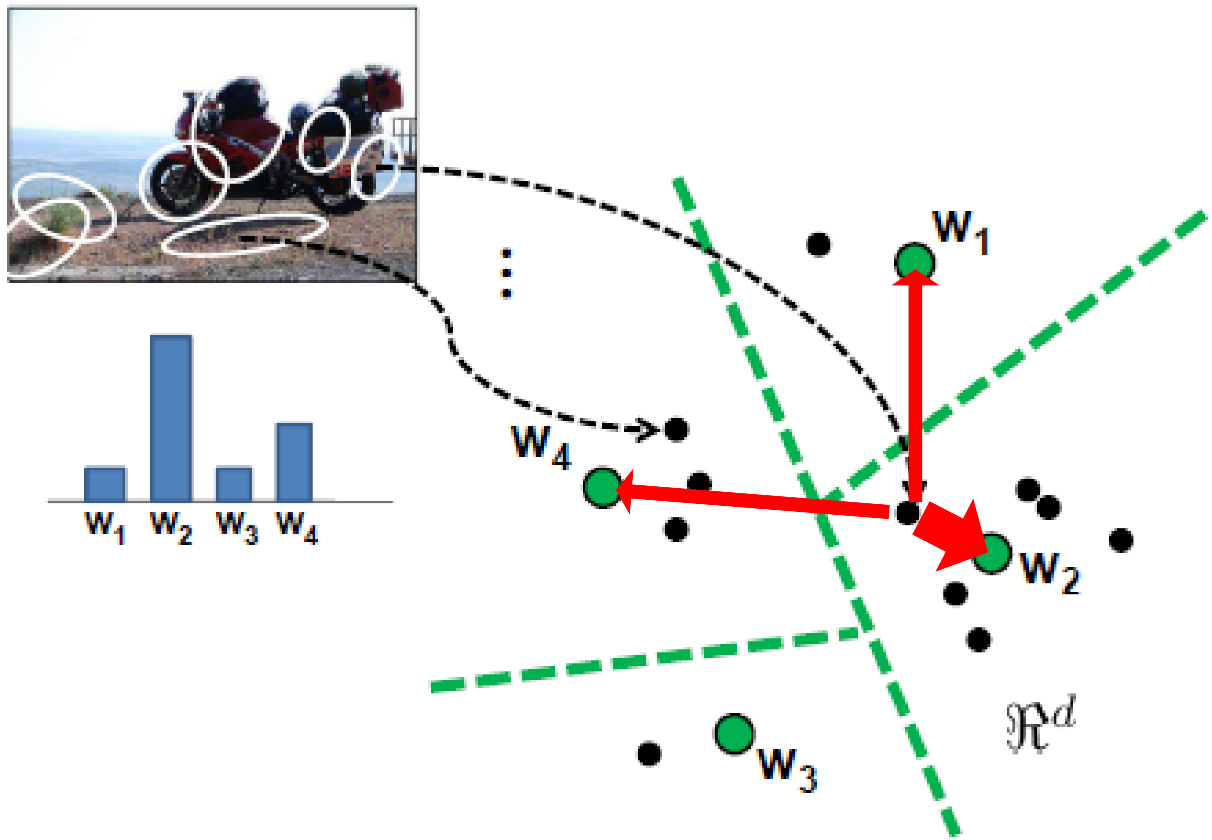
# Gaussian Mixture Model (GMM)

- 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

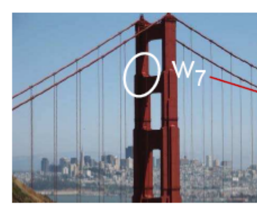
- "Kernel codebook encoding" by Chatfield et al. 2011.
- Cast a set of proportional votes (weights) to *n* most similar clusters, rather than a single 'hard' vote.



# 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 implement, but it makes an inverted file index *less sparse*.



New query image

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

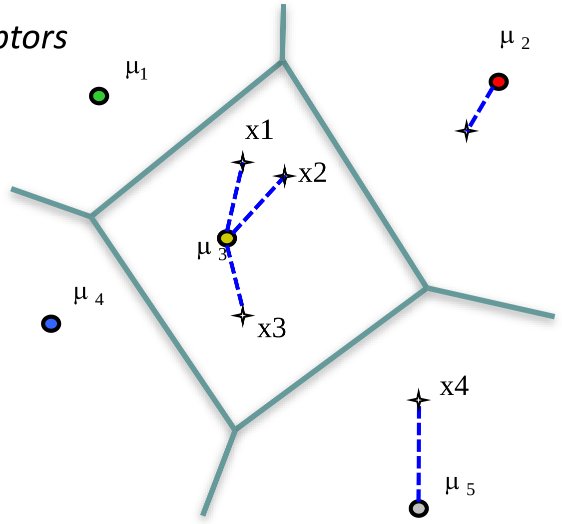
…

# 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 descriptors $X = \{x_t, t = 1 \ldots T\}$

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

① *assign descriptors*




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

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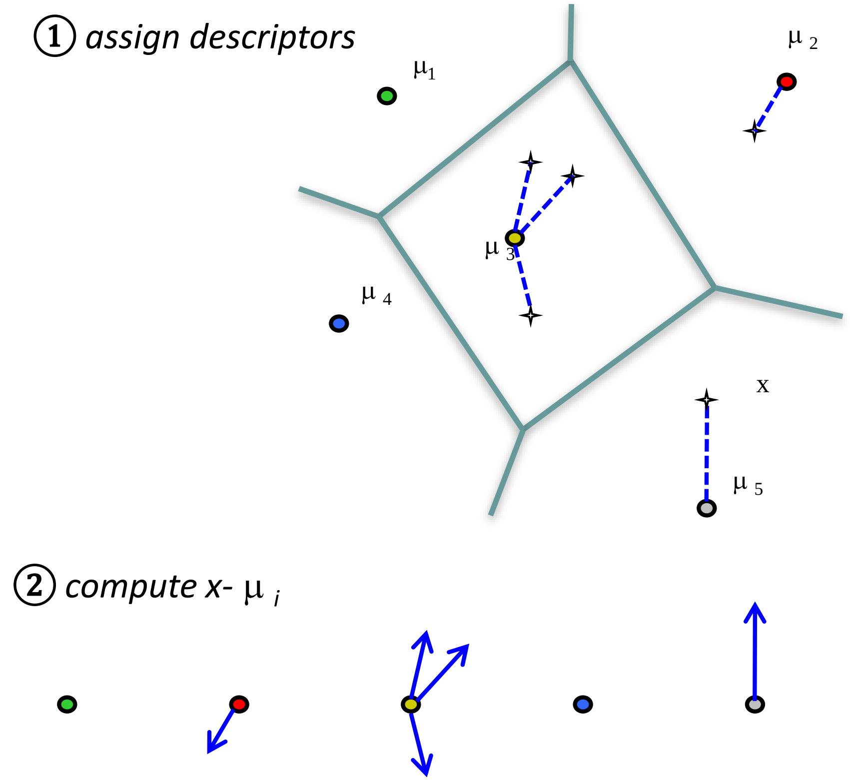
① assign: $$\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$$

②③ compute: $$v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$$

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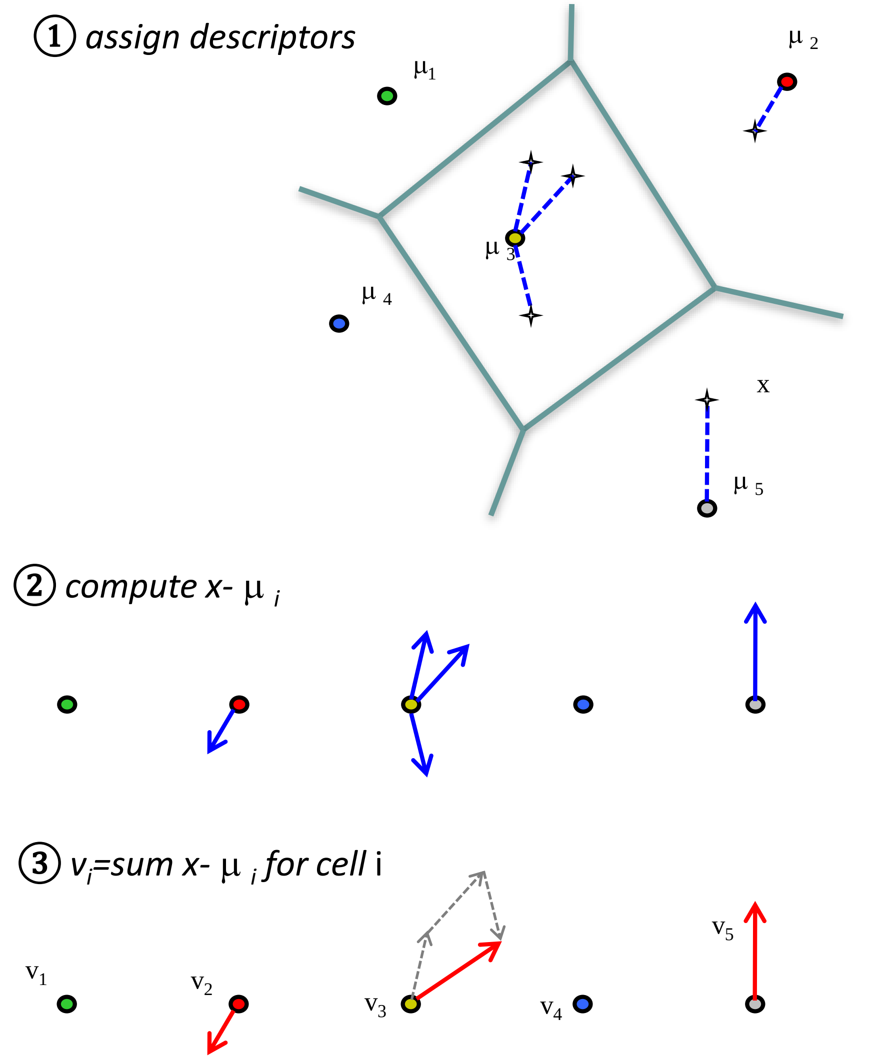
②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$

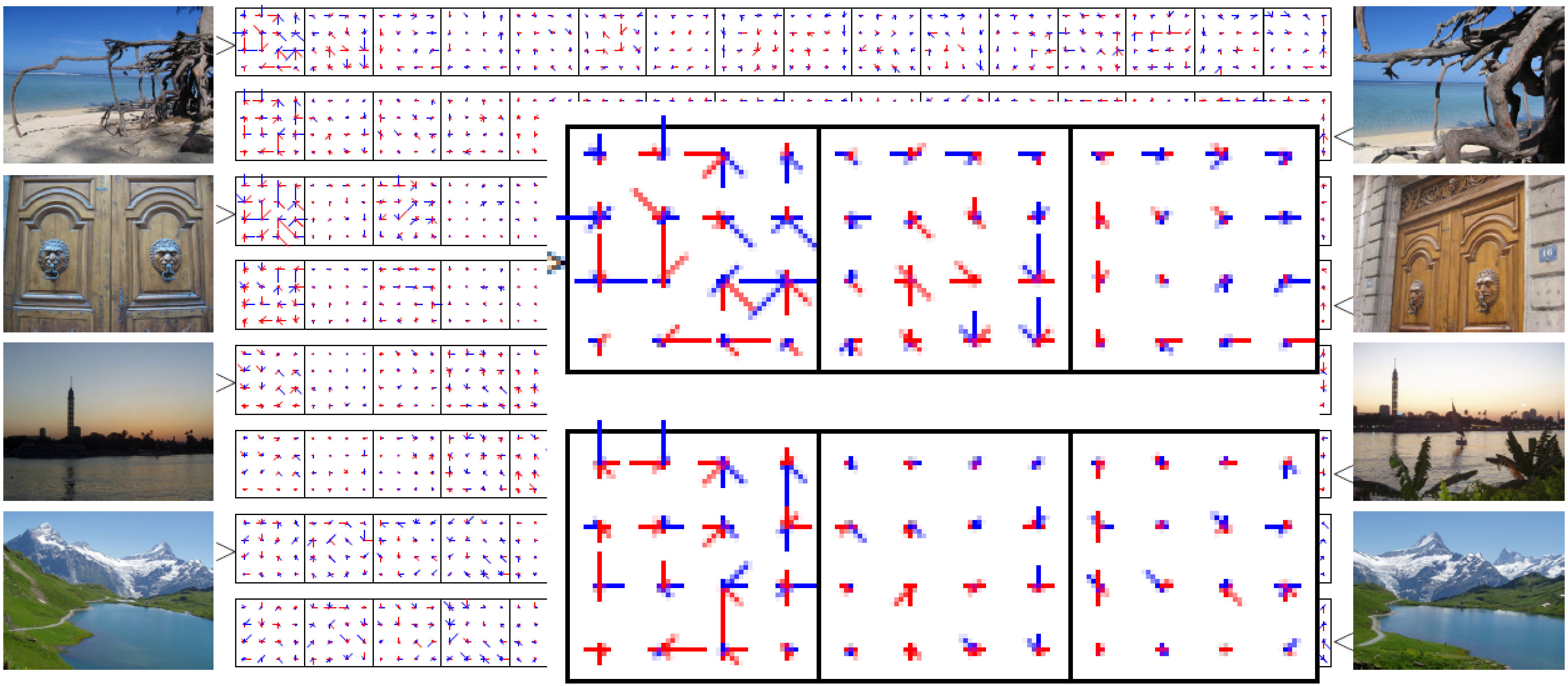
- concatenate $v_i$'s + $\ell_2$ normalize




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.

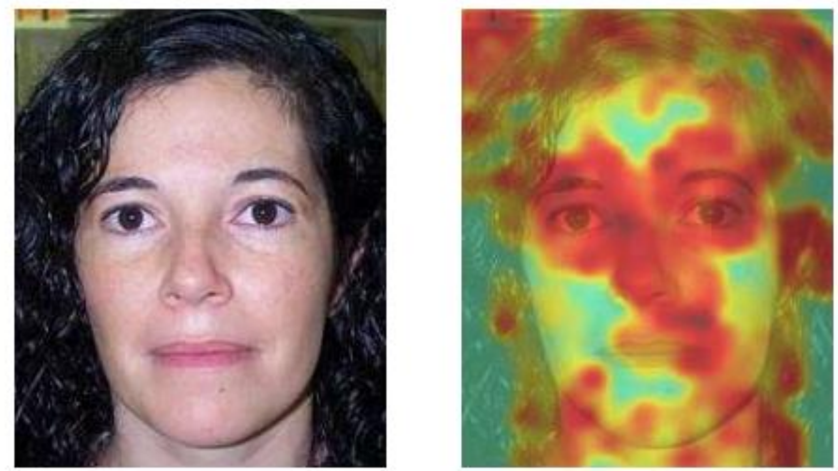
# Why can’t we train good recognition systems?

- 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

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 NN image-to-image matching?

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

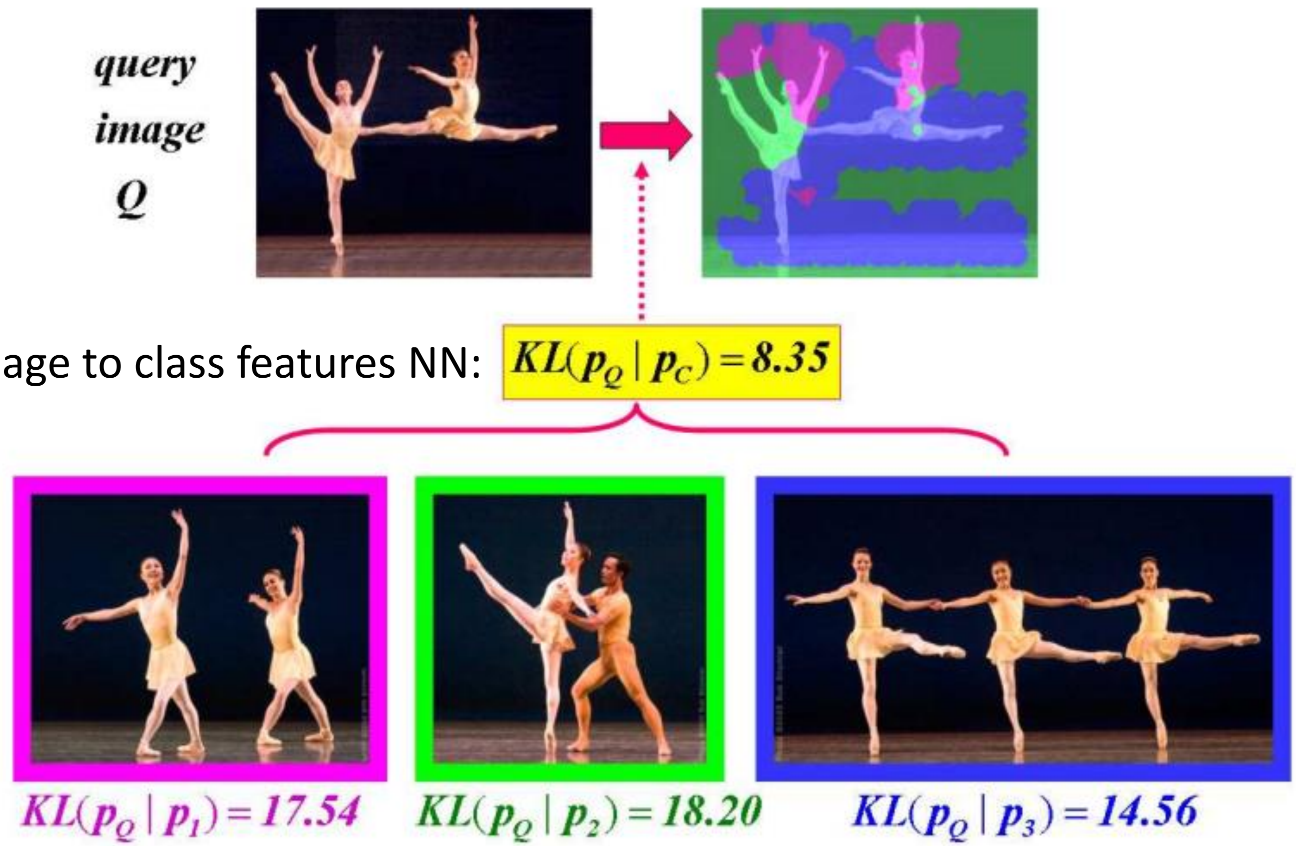
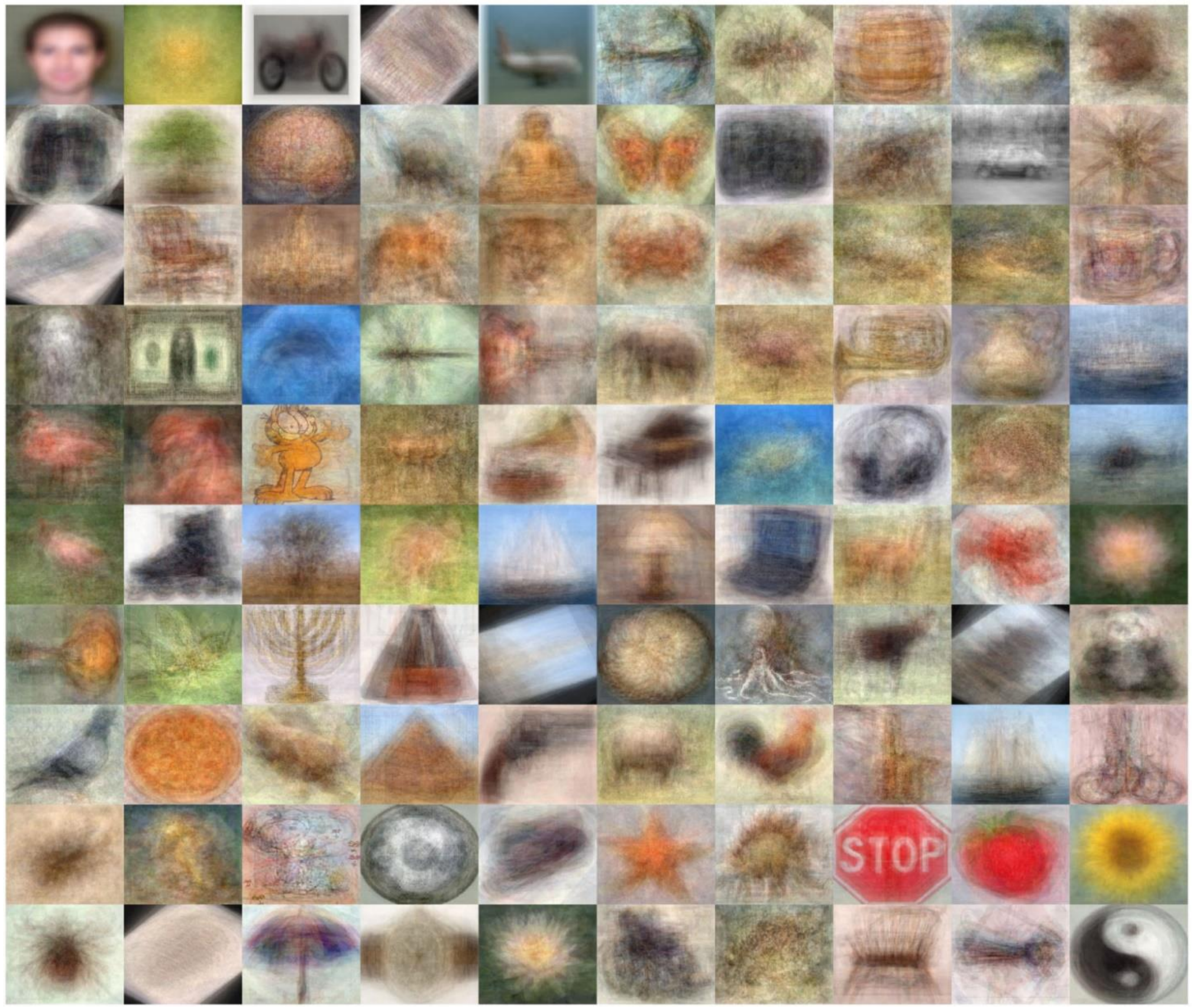


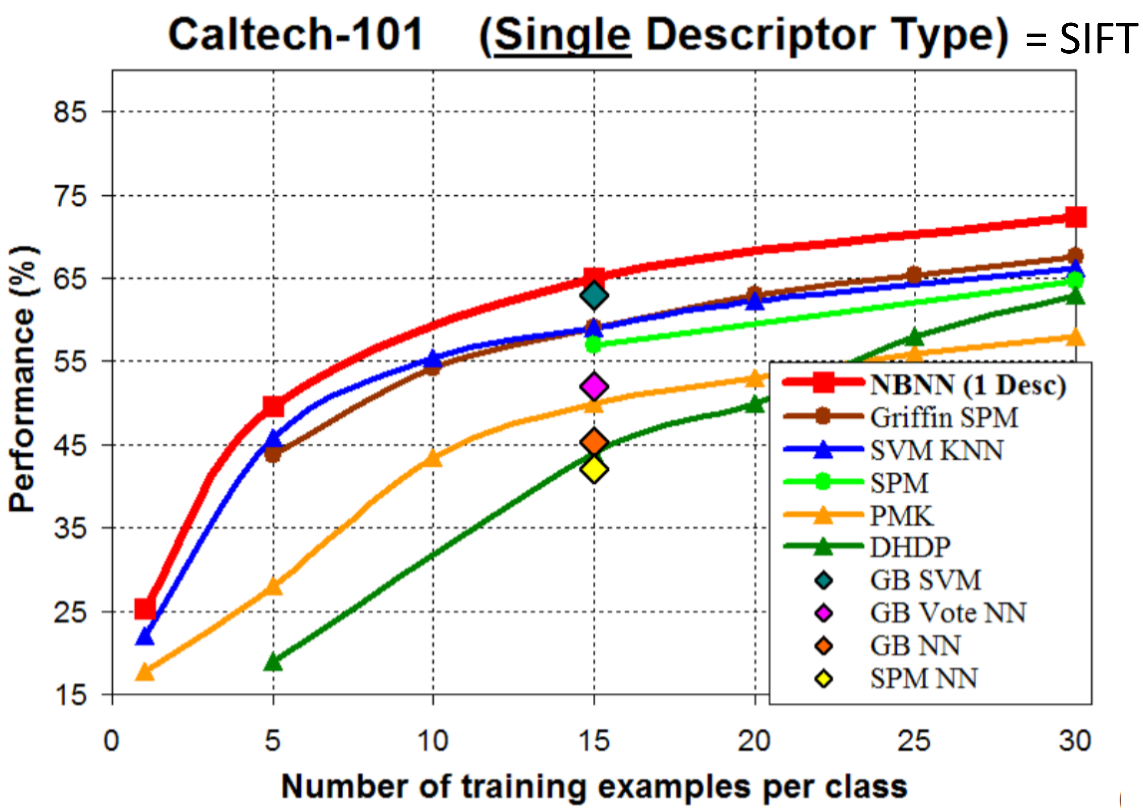

Image to class features NN:

Image to image features NN

# CalTech 101 (2004) –100 object classes; mean images



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

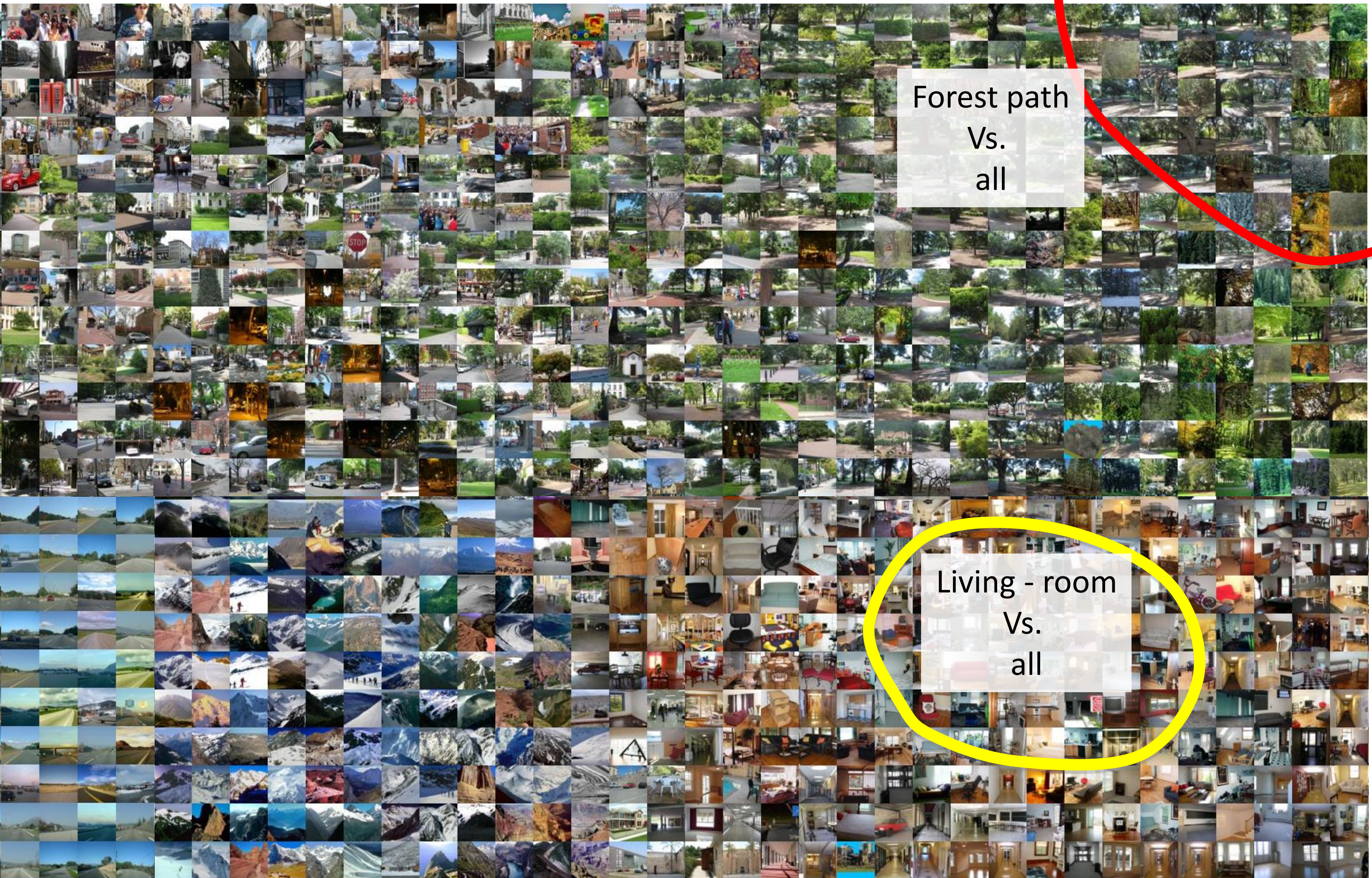



In Defense of Nearest-Neighbor Based Image Classification
Boiman, Shechtman, Irani

# Summary

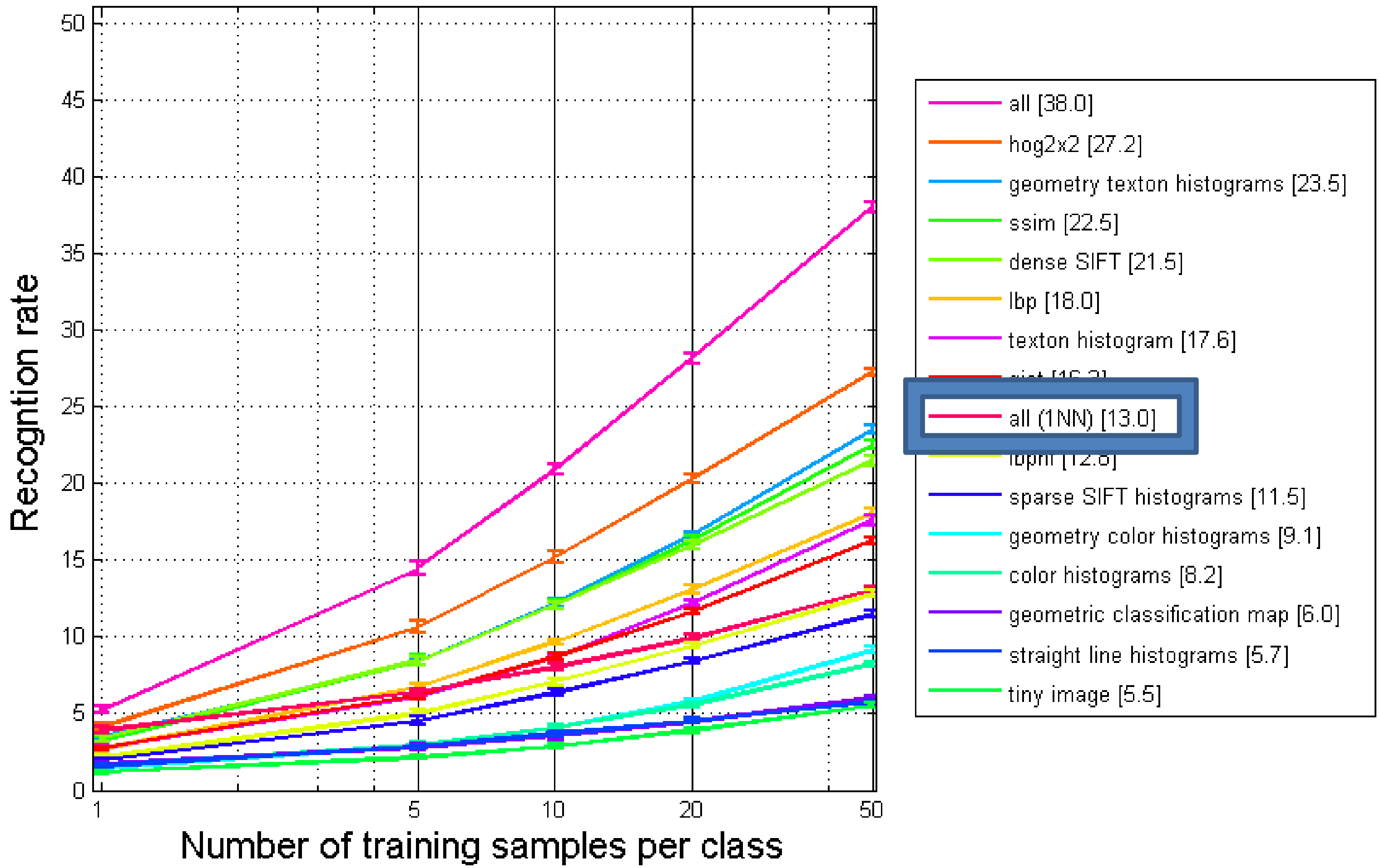
- Methods to better characterize the distribution of visual words in an image:
  - Soft assignment (a.k.a. Kernel Codebook)
  - VLAD
  - No quantization

# Learning Scene Categorization

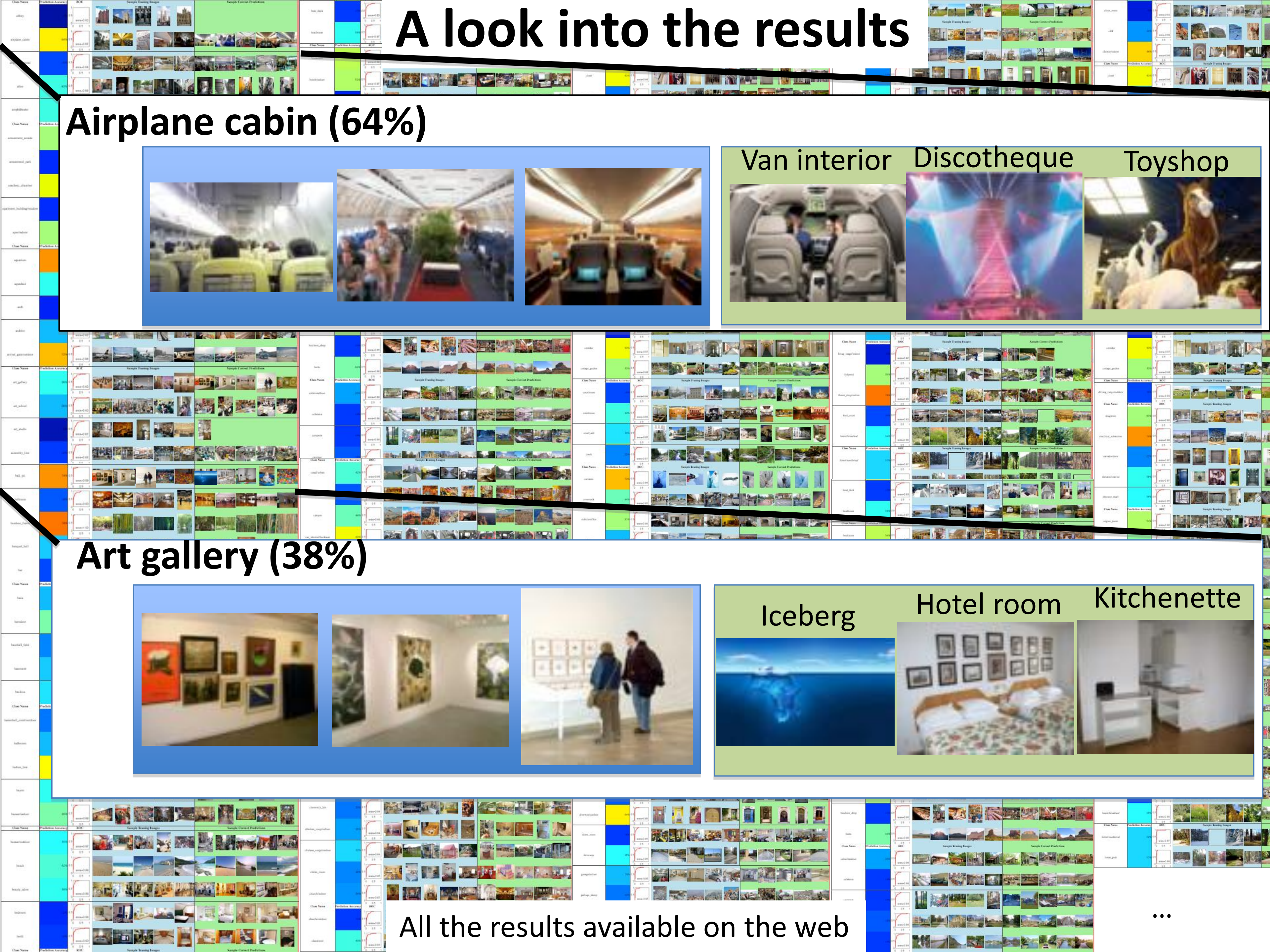


# Feature Accuracy

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**

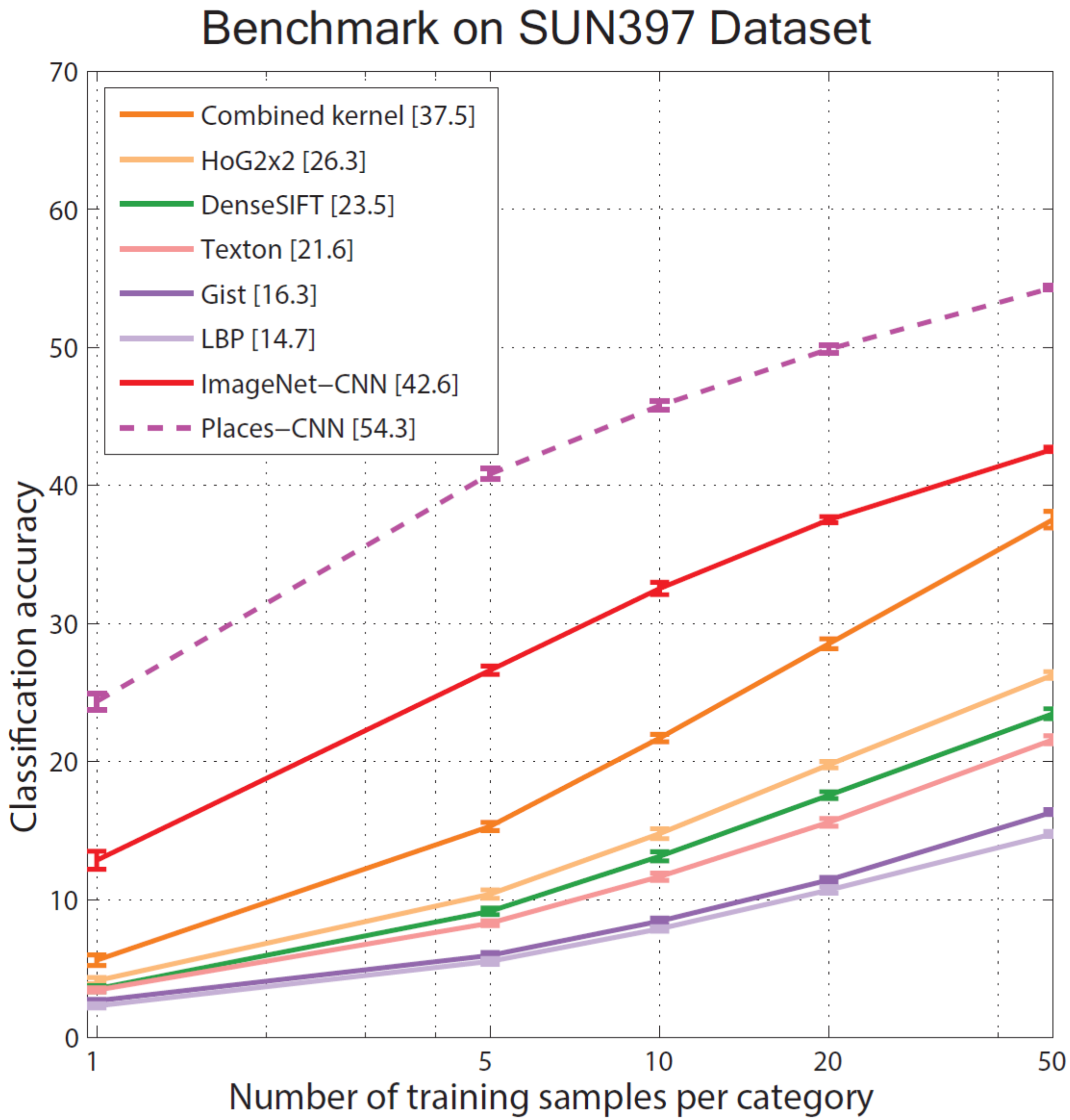
**Human good**
**Comp. bad**

**Human bad**
**Comp. good**

# How do we do better than 40%?

- Features from deep learning based on ImageNet allow us to reach 42%...

  Not much better…




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