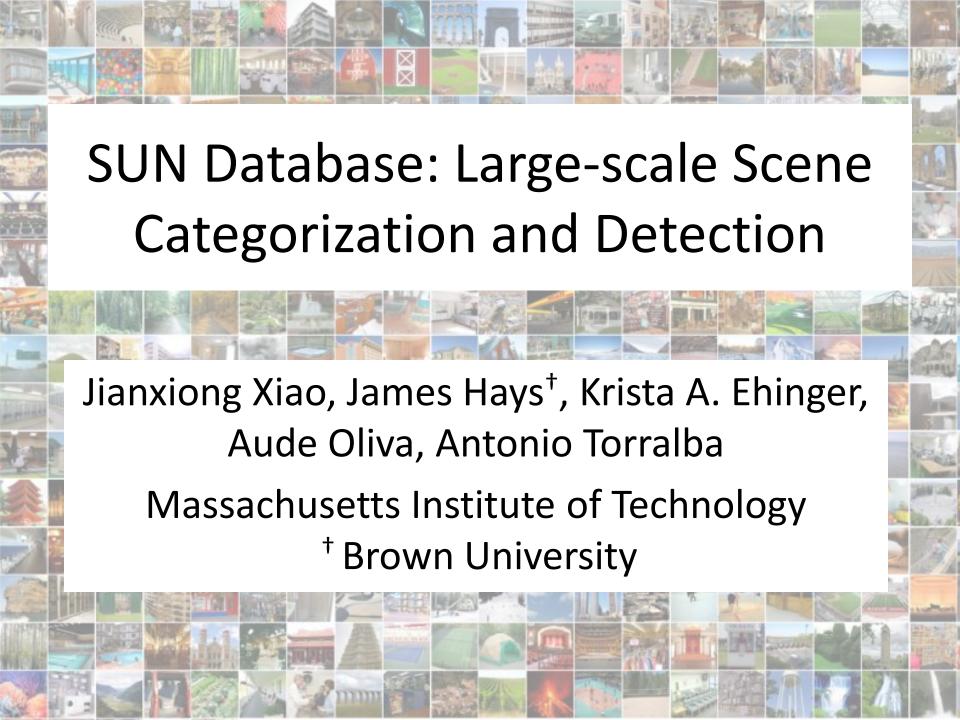
Recap: Viola/Jones detector

- Rectangle features
- Integral images for fast computation
- Boosting for feature selection
- Attentional cascade for fast rejection of negative windows

Project 3

- I have office hours today
- Let's talk more about scene recognition



Scene Categorization

Oliva and Torralba, 2001

















Coast

Forest

Highway

Inside City

Mountain

Open Country

Street

Tall Building

Fei Fei and Perona, 2005









Kitchen



Living Room



Office



Suburb

Lazebnik, Schmid, and Ponce, 2006





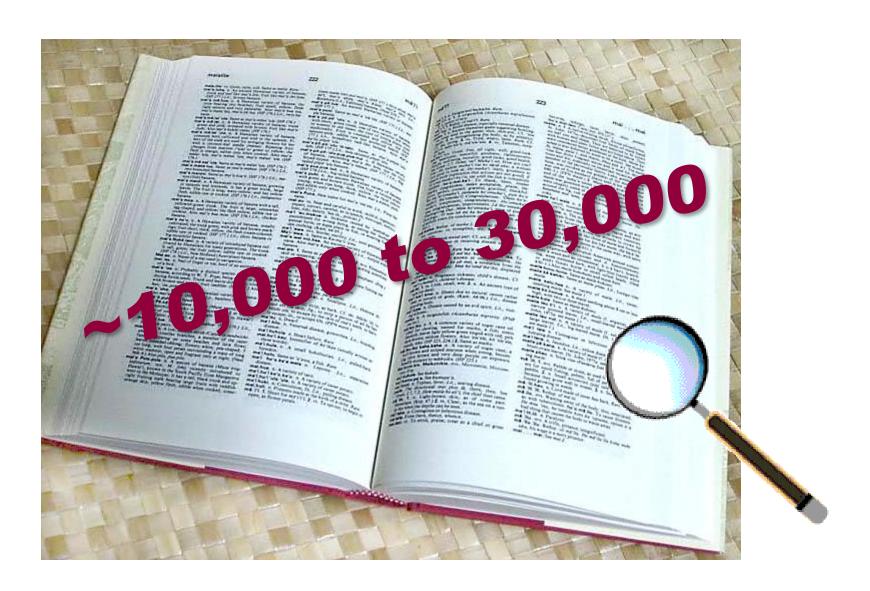
Industrial



Store

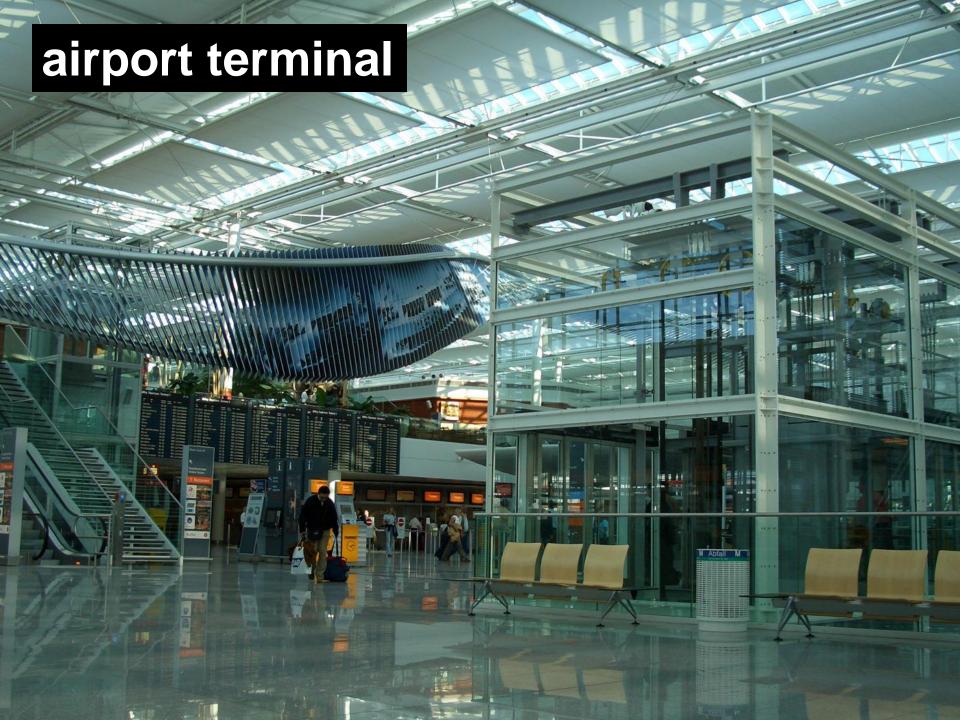
15 Scene Database

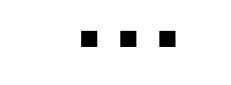
How many object categories are there?







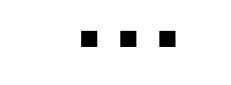








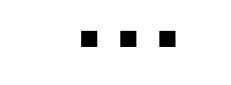








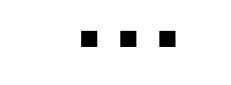






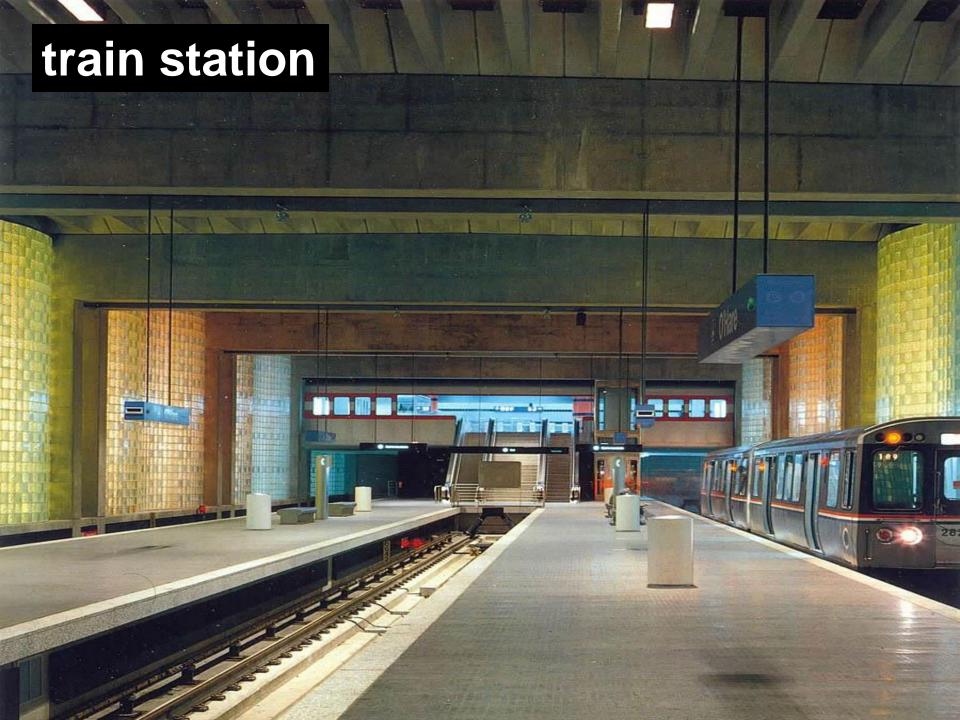


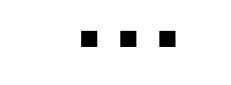


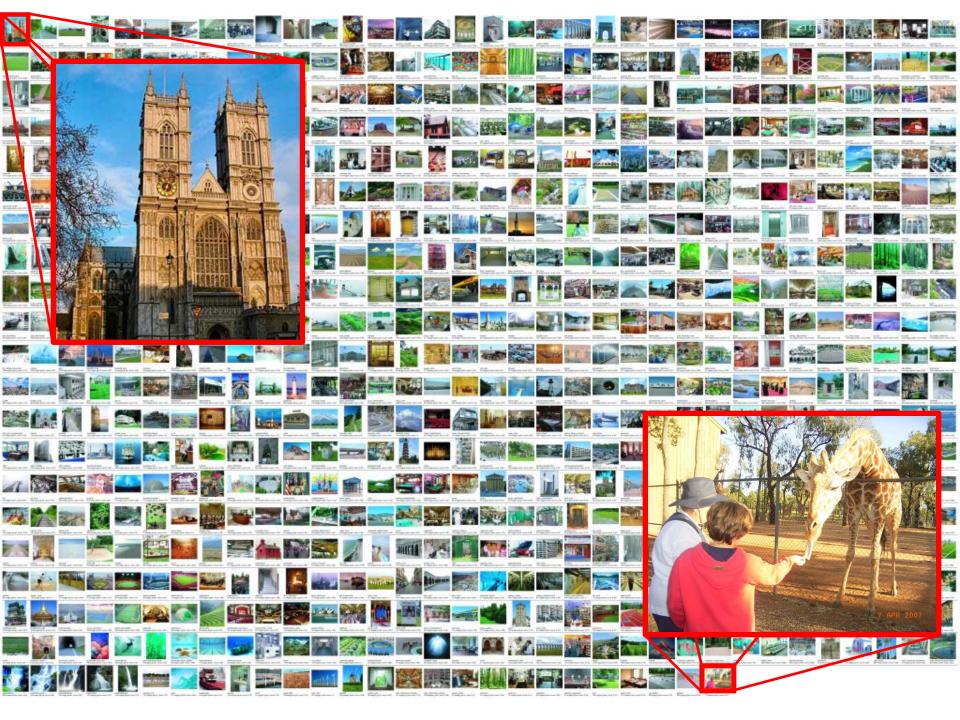




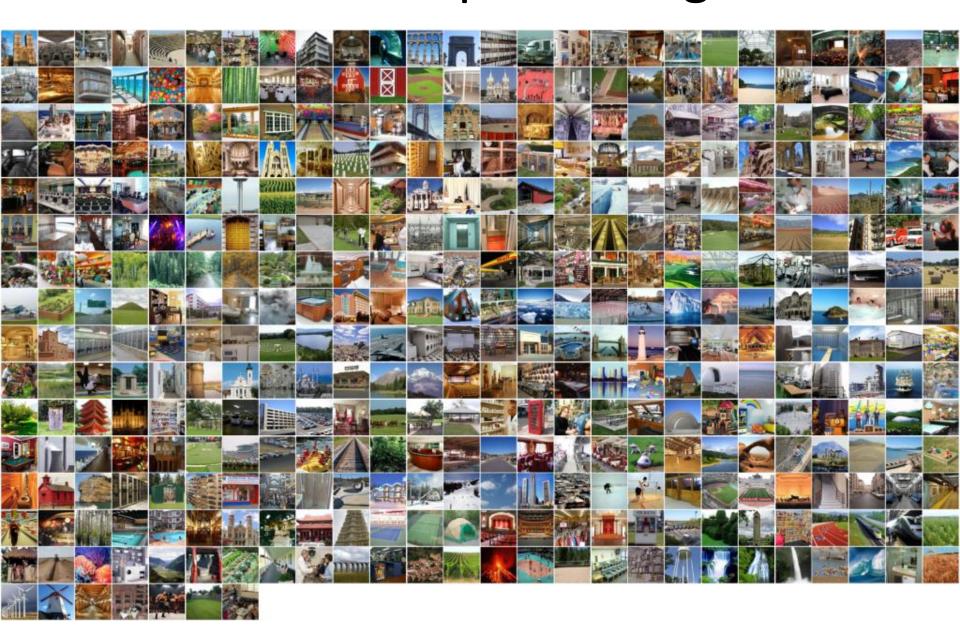








397 Well-sampled Categories



Evaluating Human Scene Classification

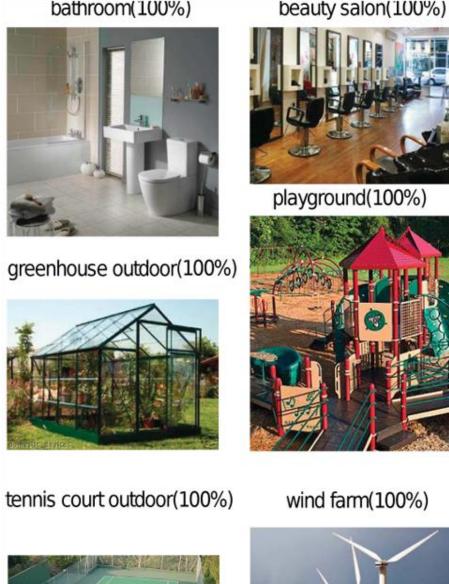


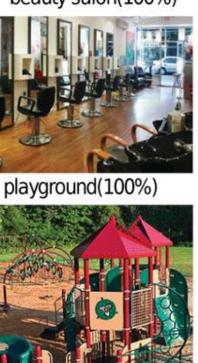


"Good worker" Accuracy 98%

90%

68%







bedroom(100%)



bullnng(100%)









Scene category

Most confusing categories

Inn (0%)



Bayou (0%)



Basilica (0%)



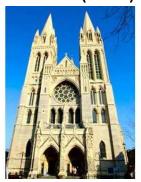
Restaurant patio (44%)



River (67%)



Cathedral(29%)



Chalet (19%)



Coast (8%)



Courthouse (21%)



Conclusion: humans can do it

- The SUN database is reasonably consistent and 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?



Different objects, different spatial layout

Fireplace

Coffee table

armchair

armchair

Floor

alarm

Side-table

carpet

Bed

Which are the important elements?





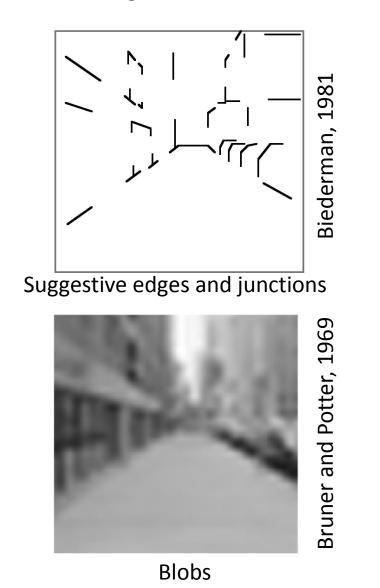


Similar objects, and similar spatial layout

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



Simple geometric forms



Textures

Oliva and Torralba, 2001

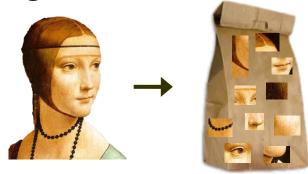
Global Image Descriptors

- 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

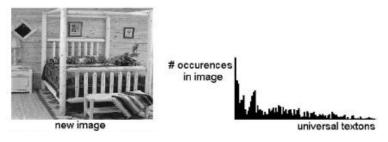
Global Texture Descriptors

Bag of words



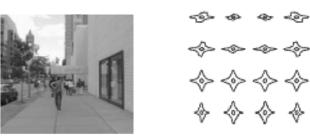
Sivic et. al., ICCV 2005 Fei-Fei and Perona, CVPR 2005

Non localized textons

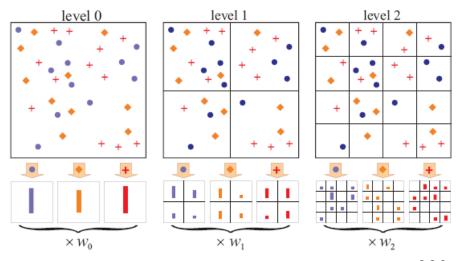


Walker, Malik. Vision Research 2004

Spatially organized textures



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

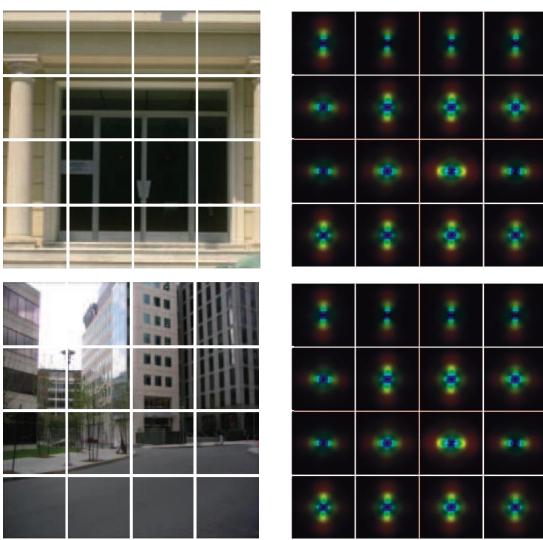


S. Lazebnik, et al, CVPR 2006

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



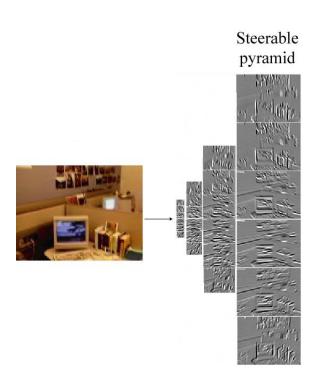
- Apply oriented Gabor filters over different scales
- Average filter energy in each bin

- 8 orientations
- 4 scales
- x 16 bins
- 512 dimensions

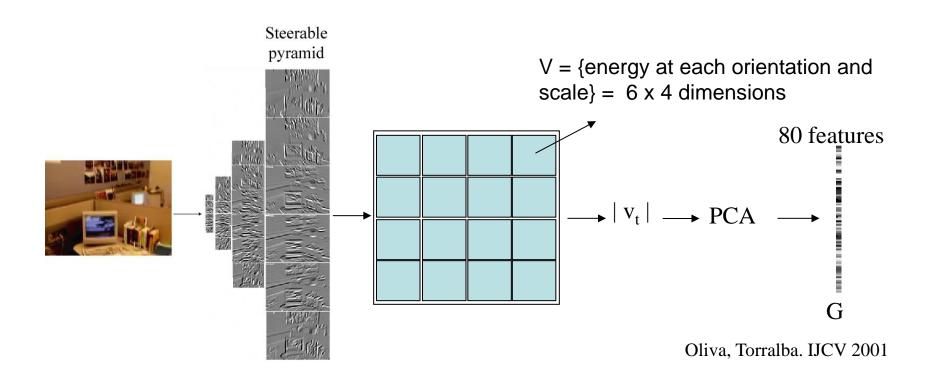
Similar to SIFT (Lowe 1999) applied to the entire image

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; ...

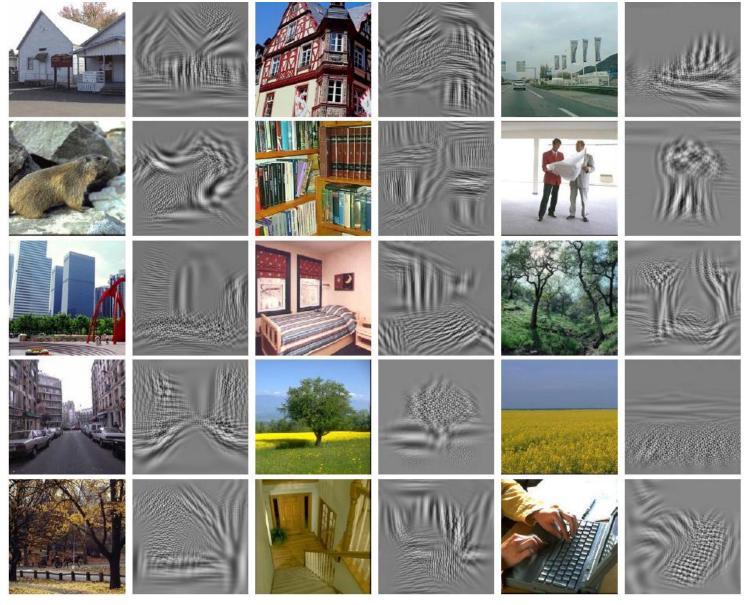
Gist descriptor



Gist descriptor

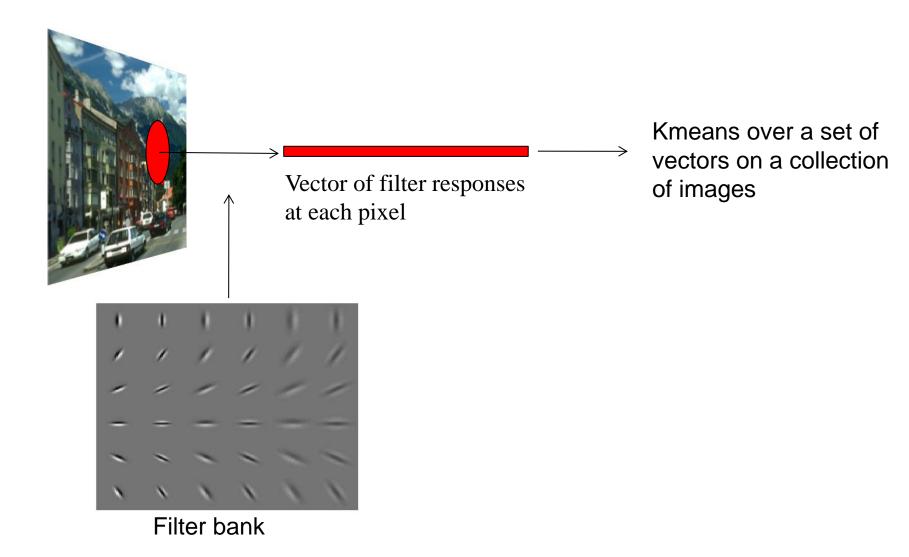


Example visual gists



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

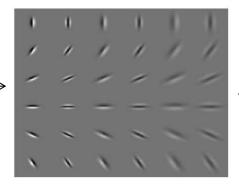
Textons



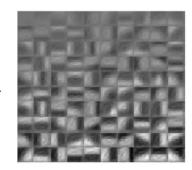
Textons



Filter bank



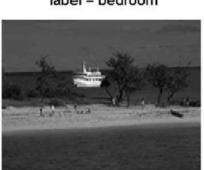
K-means (100 clusters)



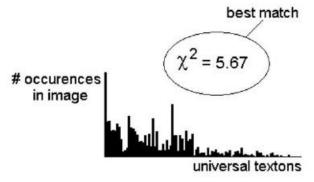
Malik, Belongie, Shi, Leung, 1999



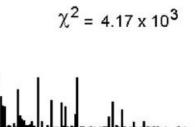
label = bedroom



label = beach



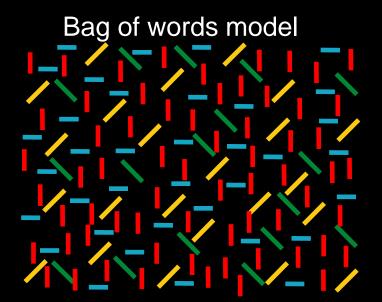
occurences in image



universal textons

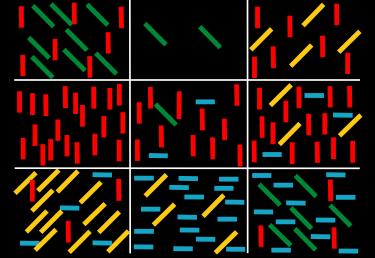
Walker, Malik, 2004

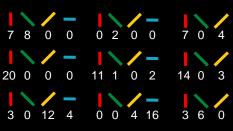
Bag of words





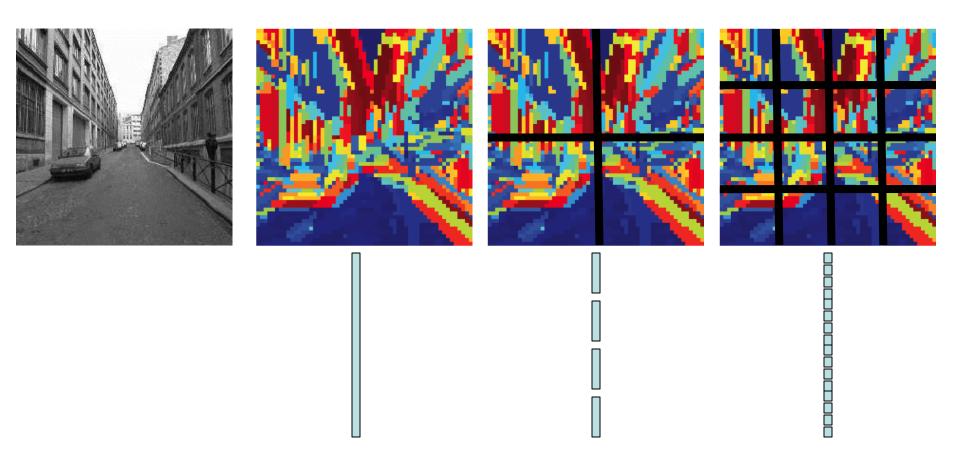
Spatially organized textures





Bag of words & spatial pyramid matching

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

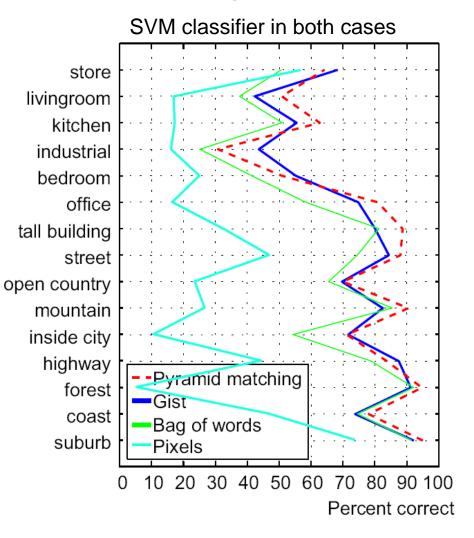


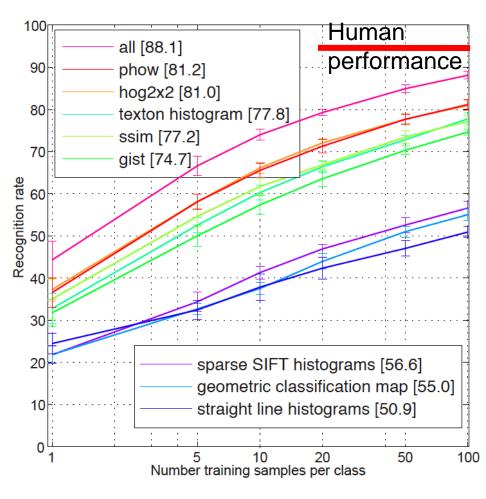
Learning Scene Categorization



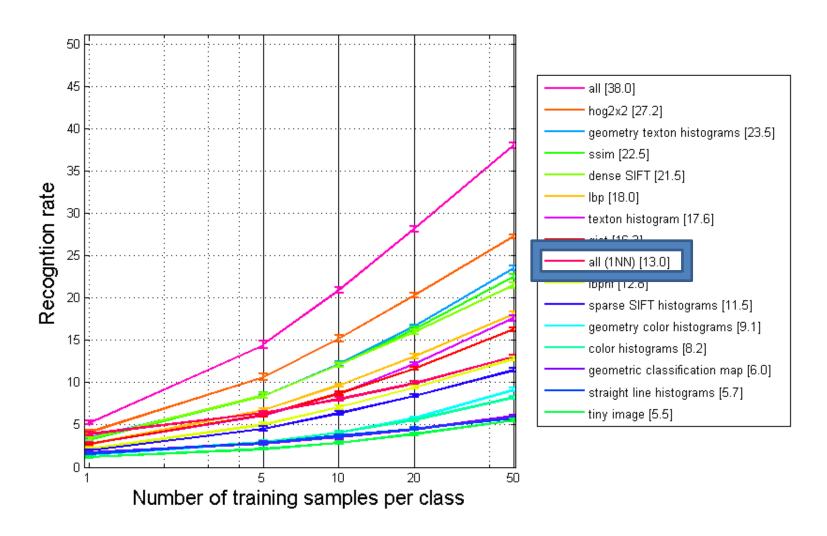
Scene recognition

100 training samples per class

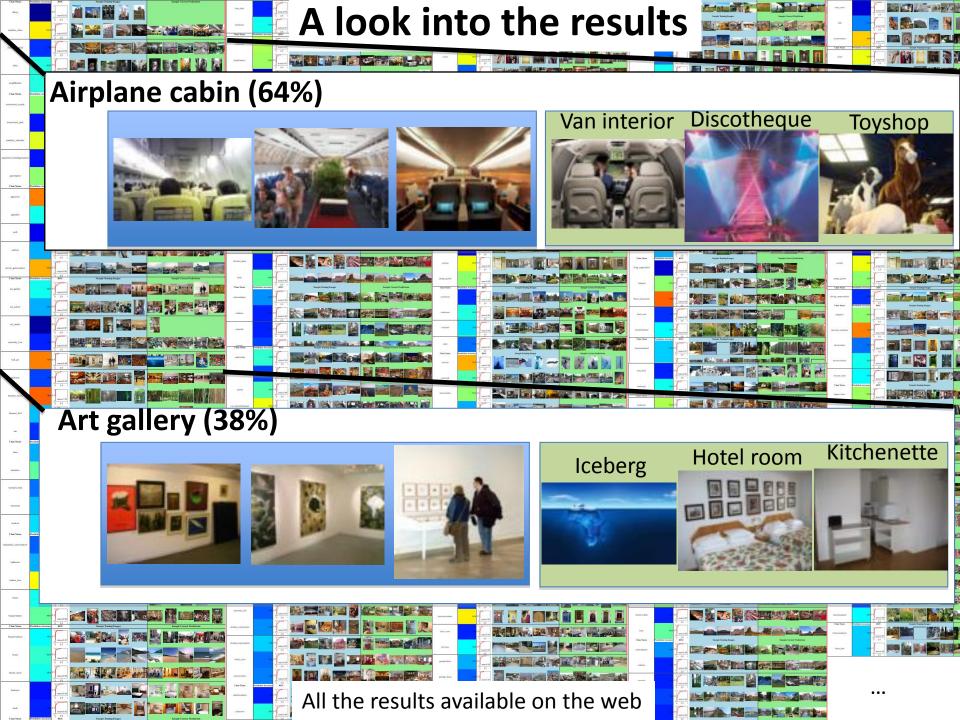


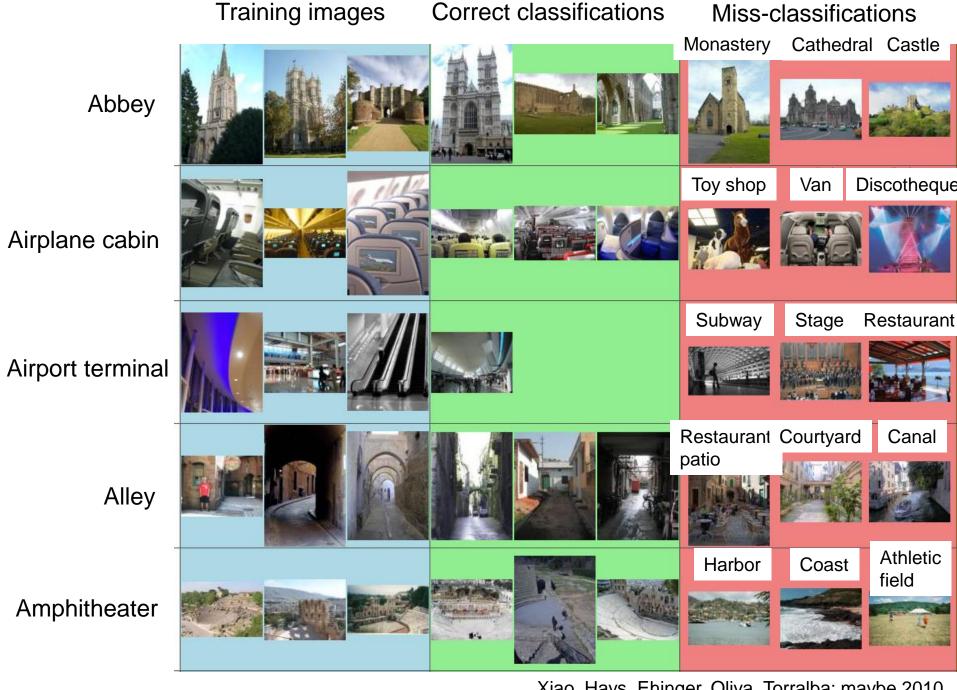


Feature Accuracy



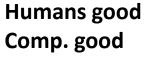
Classifier: 1-vs-all SVM with histogram intersection, chi squared, or RBF kernel.





Xiao, Hays, Ehinger, Oliva, Torralba; maybe 2010

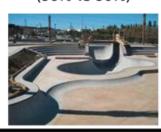
limousine interior (95% vs 80%) riding arena (100% vs 90%) sauna (96% vs 95%) skatepark (96% vs 90%) subway interior (96% vs 80%)













Humans bad Comp. bad

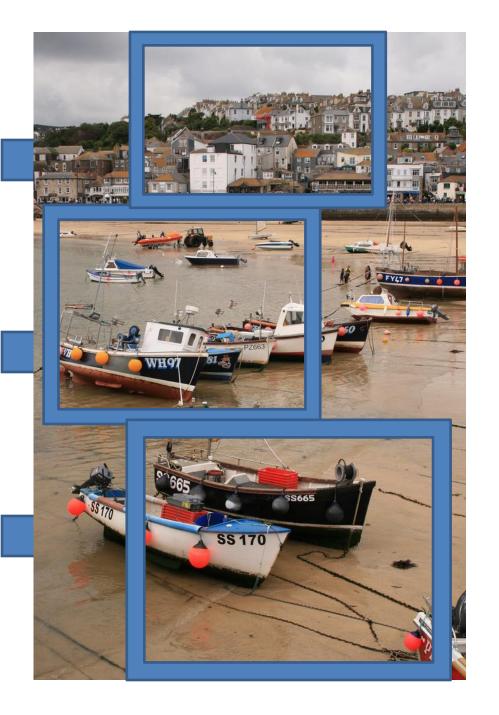
Human good Comp. bad

Human bad Comp. good







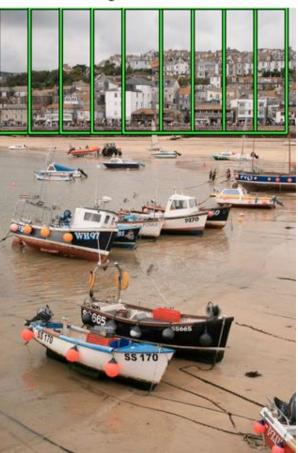


Local Scene Detection

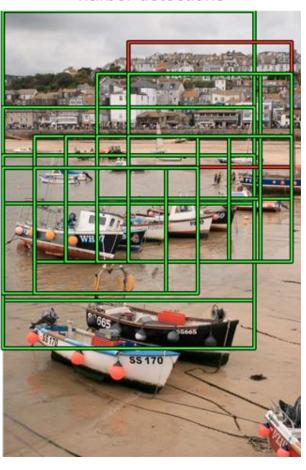
beach detections



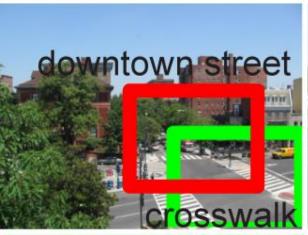
village detections

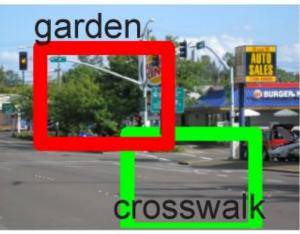


harbor detections



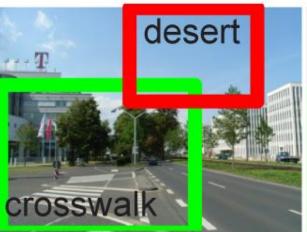
Confident Subscene Detections















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%?

- Deep learning gets about the same performance
- Fisher vector encoding gets up to 47.2%