Visual Data on the Internet

http://www.boingboing.net/2009/07/30/bb-video-send-me-a-l.html

With slides from James Hays,
Antonio Torralba, and Frederic Heger

15-463: Computational Photography
Alexei Efros, CMU, Spring 2010

Big issues

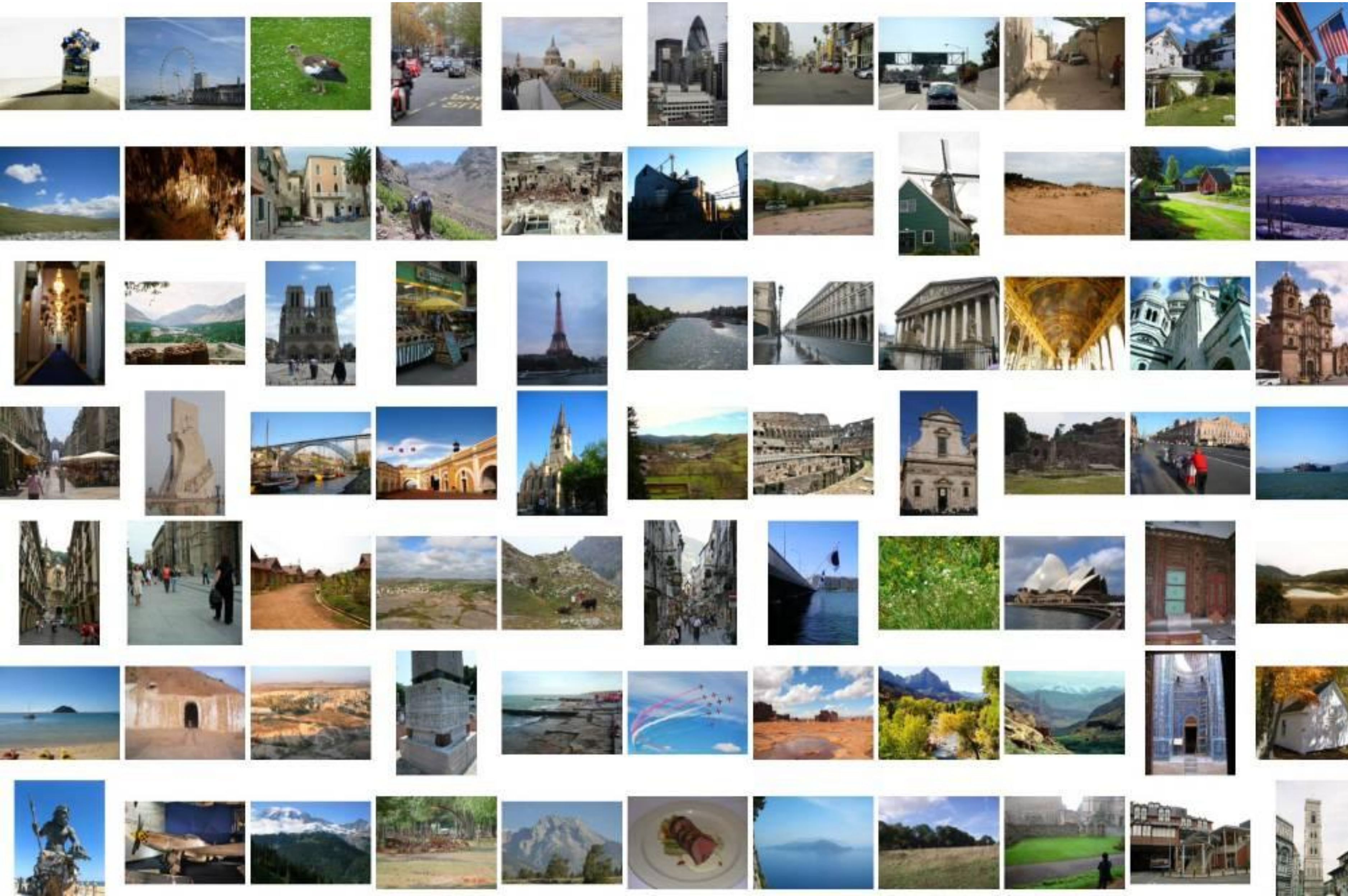
- What is out there on the Internet? How do we get it? What can we do with it?
- How do we compute distances between images?

Subject-specific Data

Photos of Coliseum

Portraits of Bill Clinton

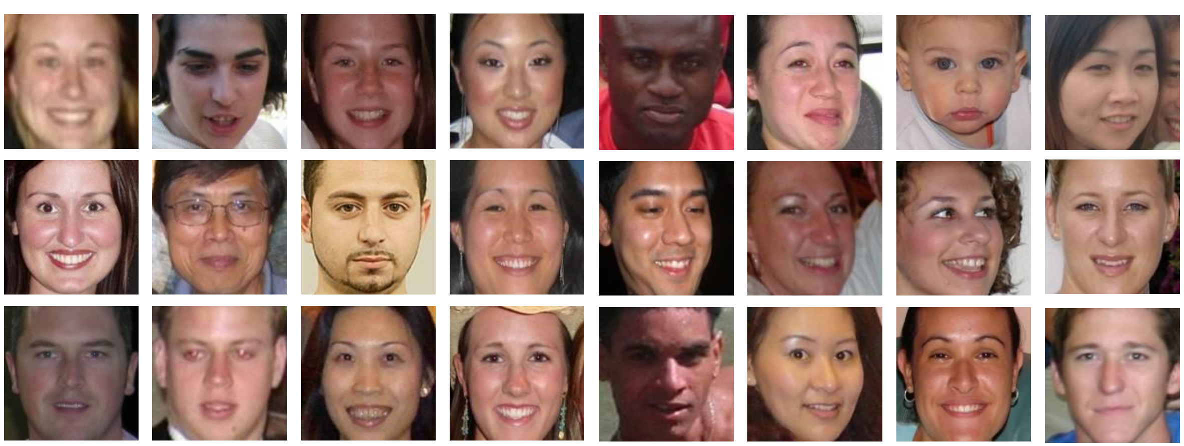
Much of Captured World is "generic"



Generic Data

street scenes

Food plates



faces

pedestrians

The Internet as a Data Source

- Social Networking Sites (e.g. Facebook, MySpace)
- Image Search Engines (e.g. Google, Bing)
- Photo Sharing Sites (e.g. $\boxed{\text{Flickr,}}$ Picasa, Panoramio, photo.net, dpchallenge.com)
- Computer Vision Databases (e.g. CalTech 256, PASCAL VOC, LabelMe, Tiny Images, image-net.org, ESP game, Squigl, Matchin)

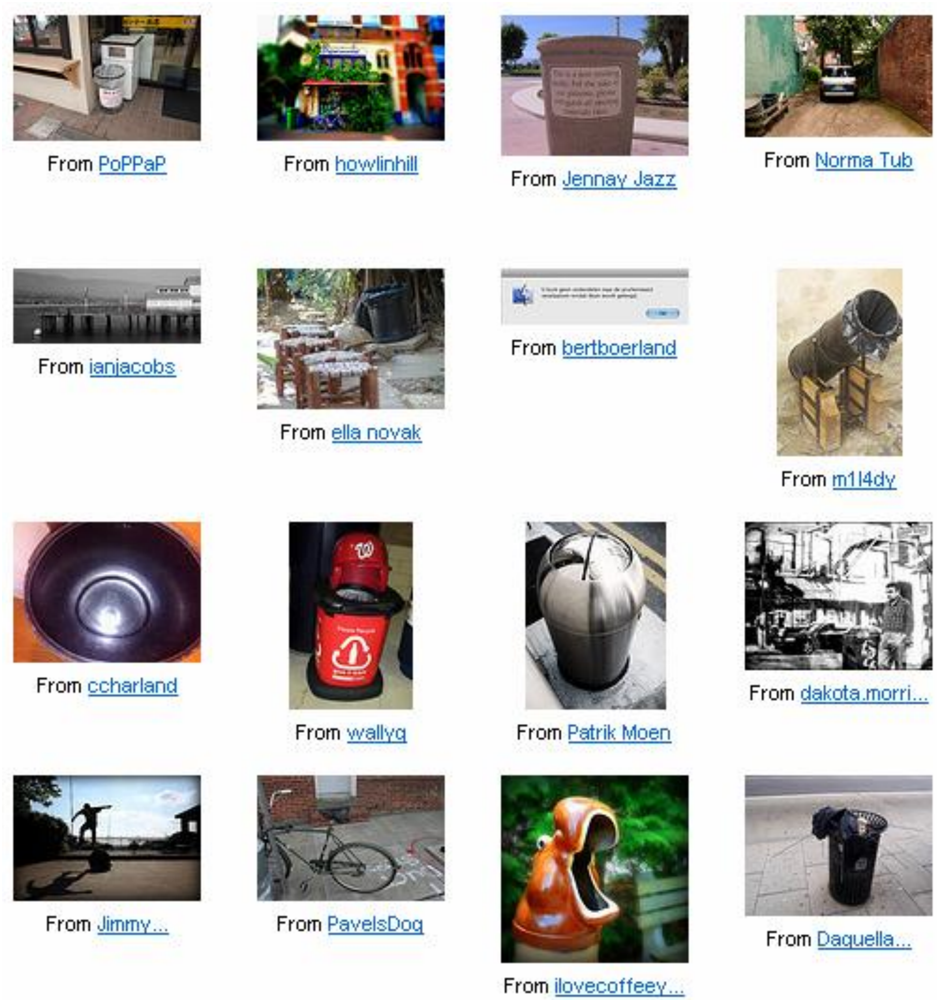
How Big is Flickr?

- As of June 19th, 2009
- Total content:
  - 3.6 billion photographs
  - 100+ million geotagged images
- *Public* content:
  - 1.3 billion photographs
  - 74 million geotagged images

How Annotated is Flickr? (tag search)

- Party – 7,355,998
- Paris – 4,139,927
- Chair – 232,885
- Violin – 55,015
- Trashcan – 9,818

Trashcan Results



- http://www.flickr.com/search/?q=trashcan+NOT+party&m=tags&z=t&page=5

Is Generic Data useful?

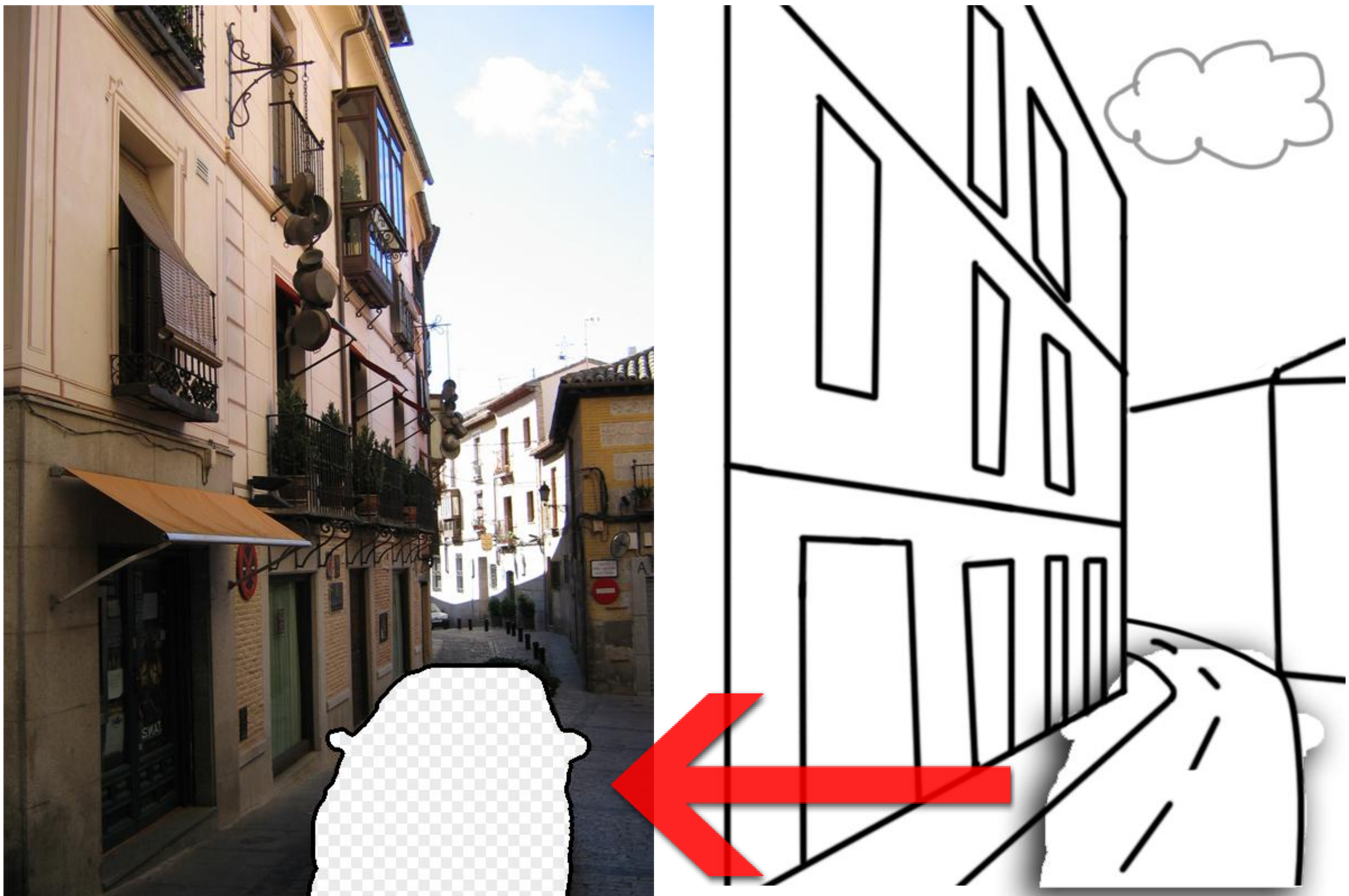
A motivating example…

[Hays and Efros. Scene Completion Using Millions of Photographs. SIGGRAPH 2007 and CACM October 2008.]

Diffusion Result

Efros and Leung result

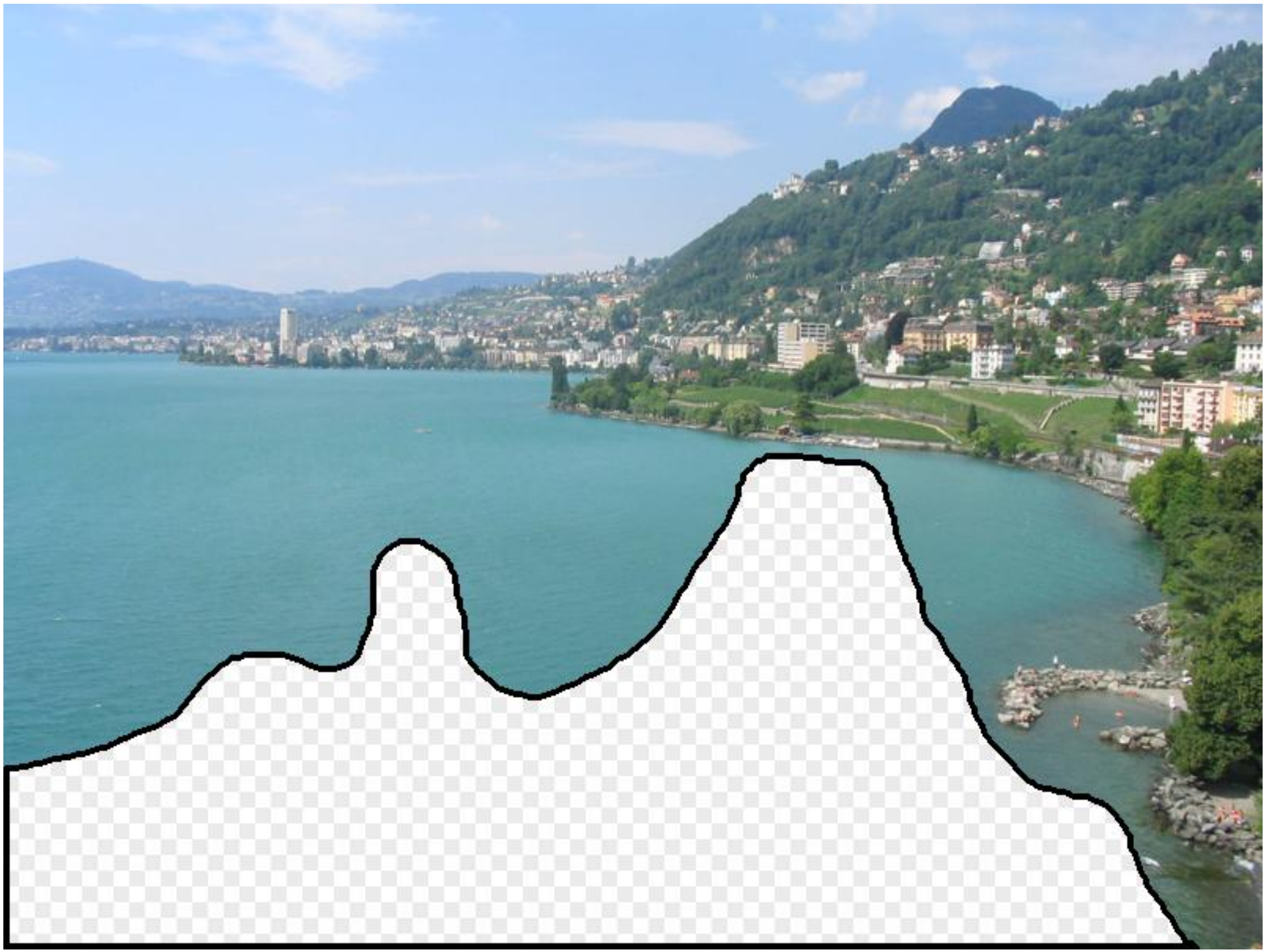
Scene Matching for Image Completion



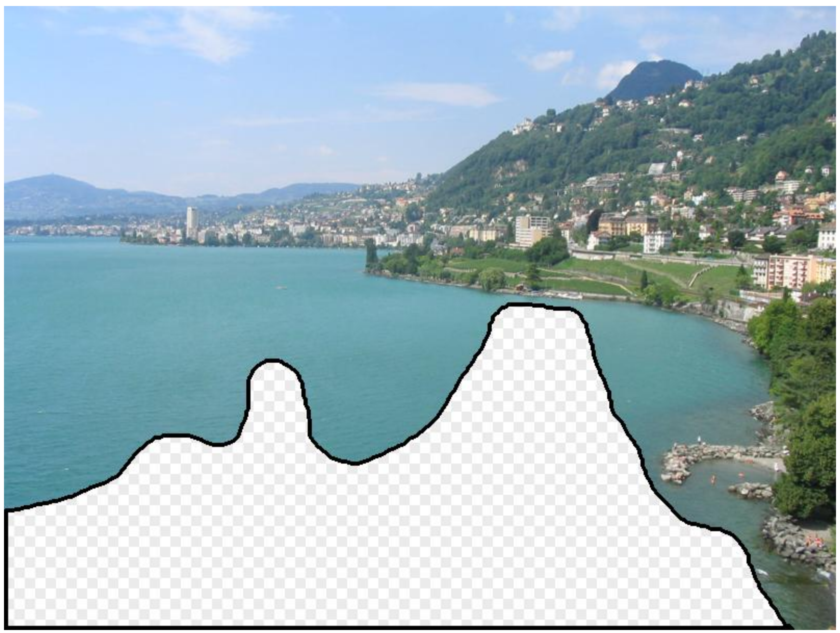
Scene Completion Result

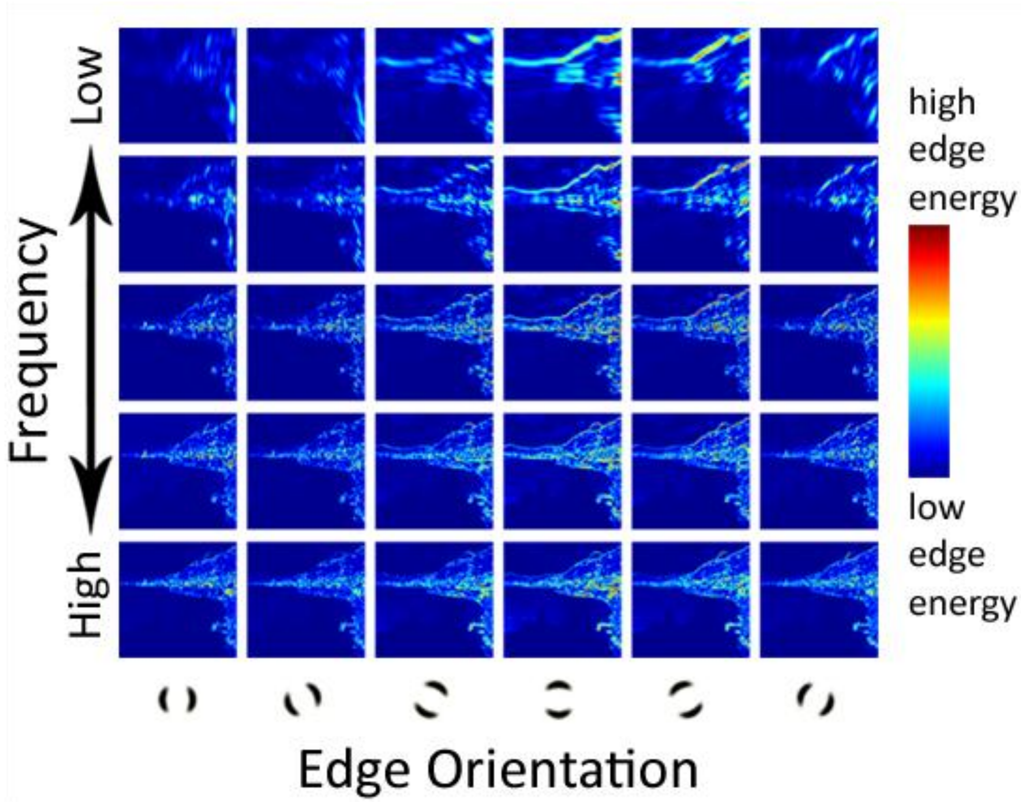
The Algorithm

Scene Matching

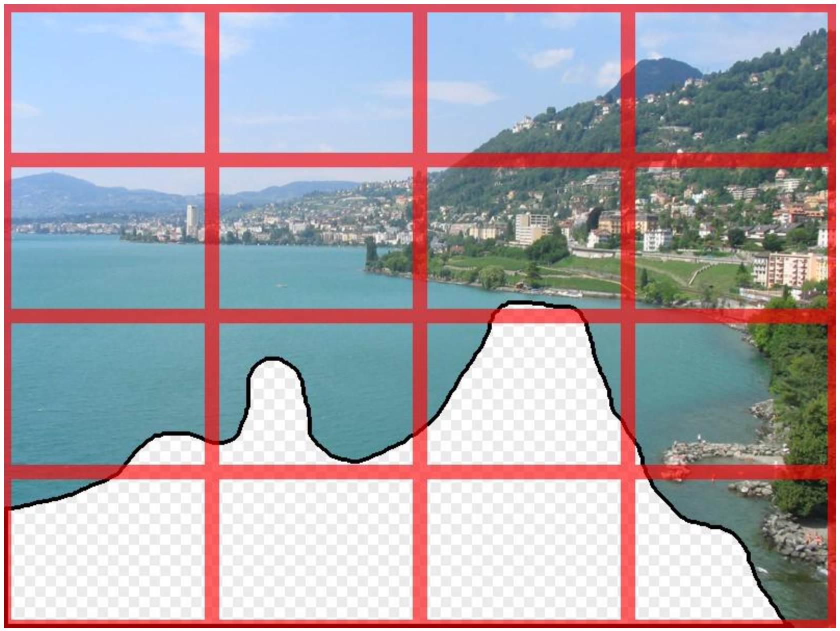


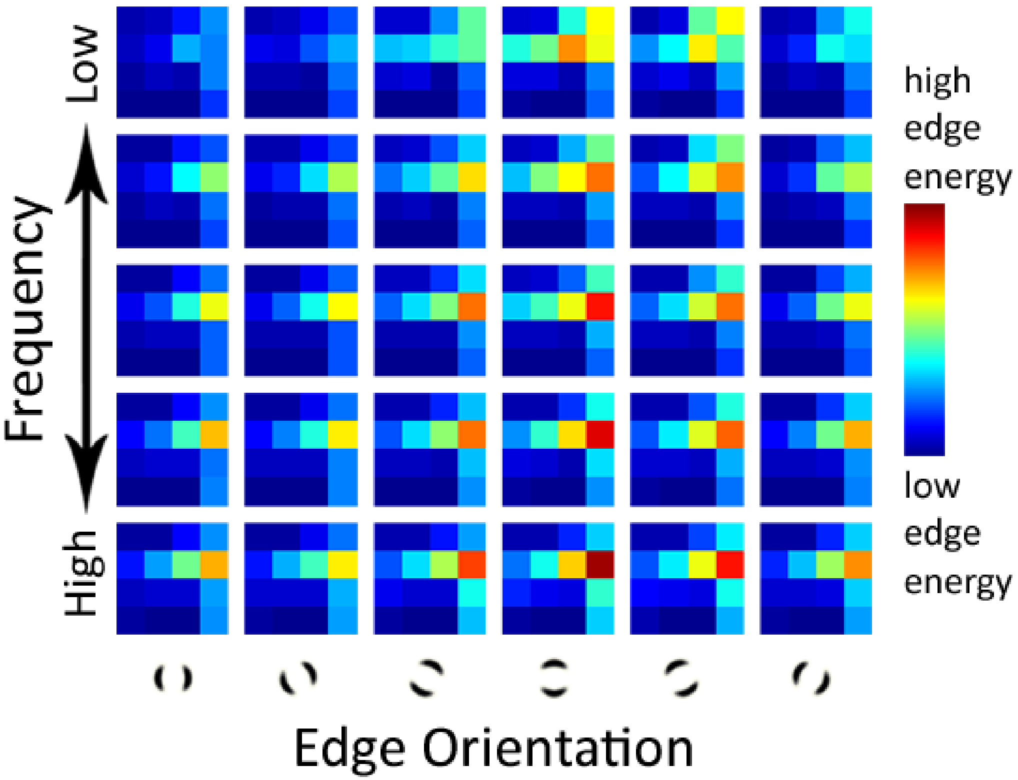
Scene Descriptor





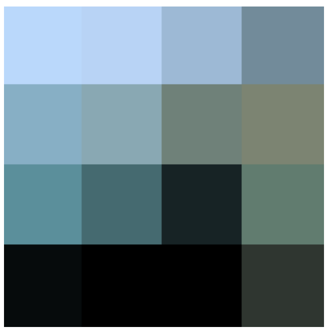
Scene Descriptor

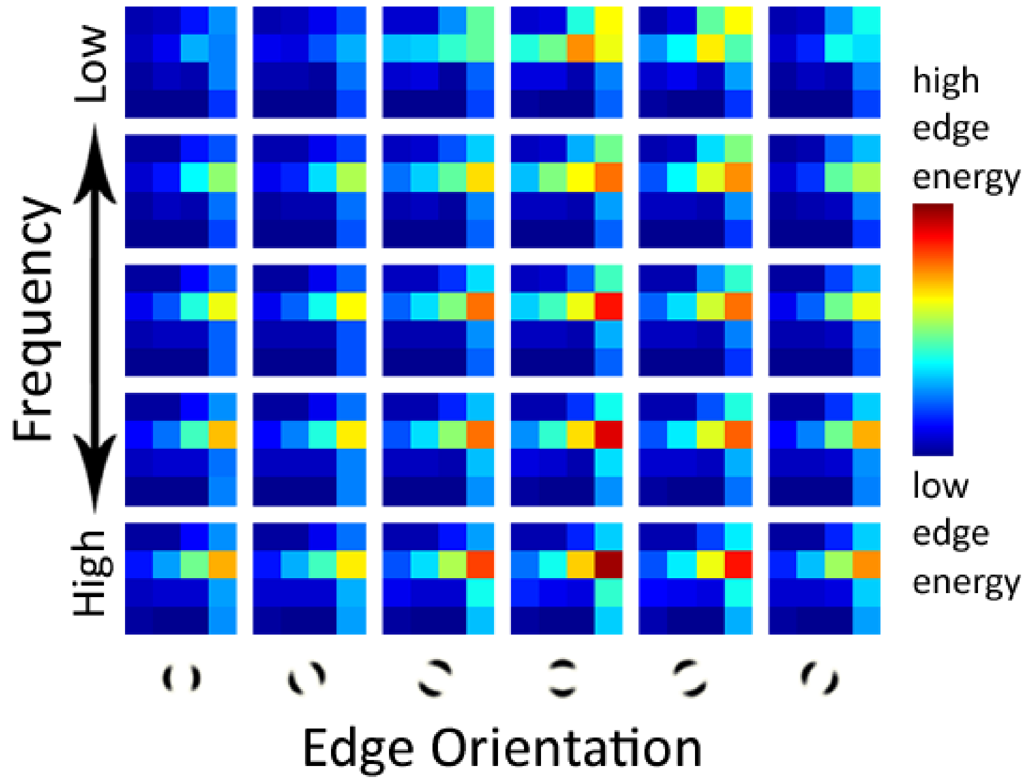




Scene Gist Descriptor
(Oliva and Torralba 2001)

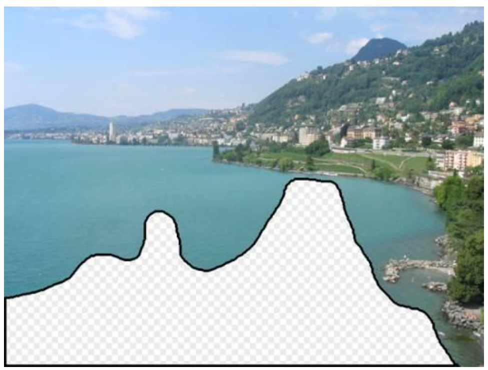
Scene Descriptor

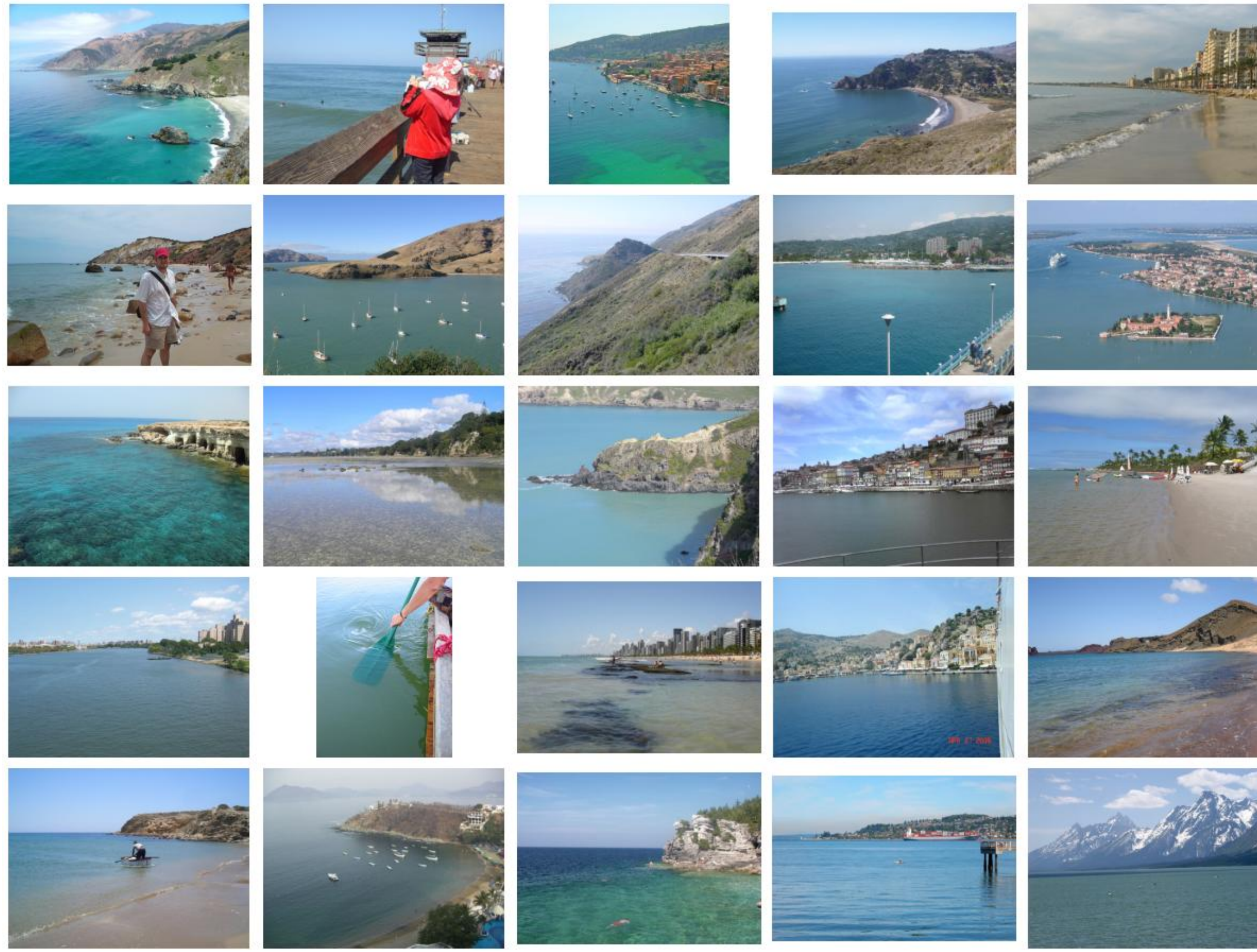




Scene Gist Descriptor
(Oliva and Torralba 2001)

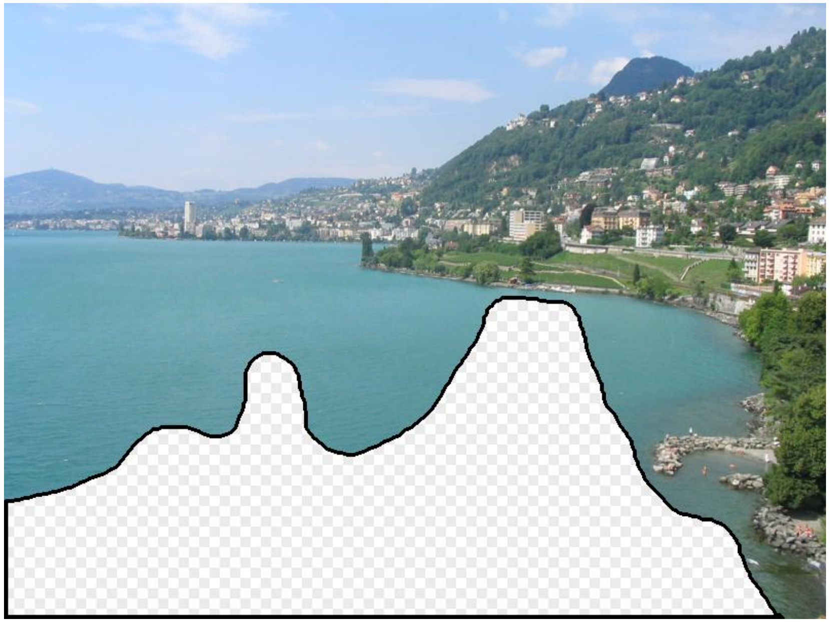
2 Million Flickr Images





… 200 total

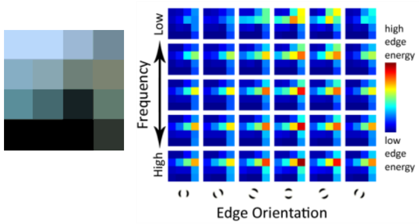
Context Matching



Graph cut + Poisson blending

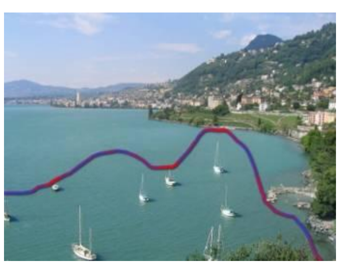
Result Ranking

We assign each of the 200 results a score which is the sum of:

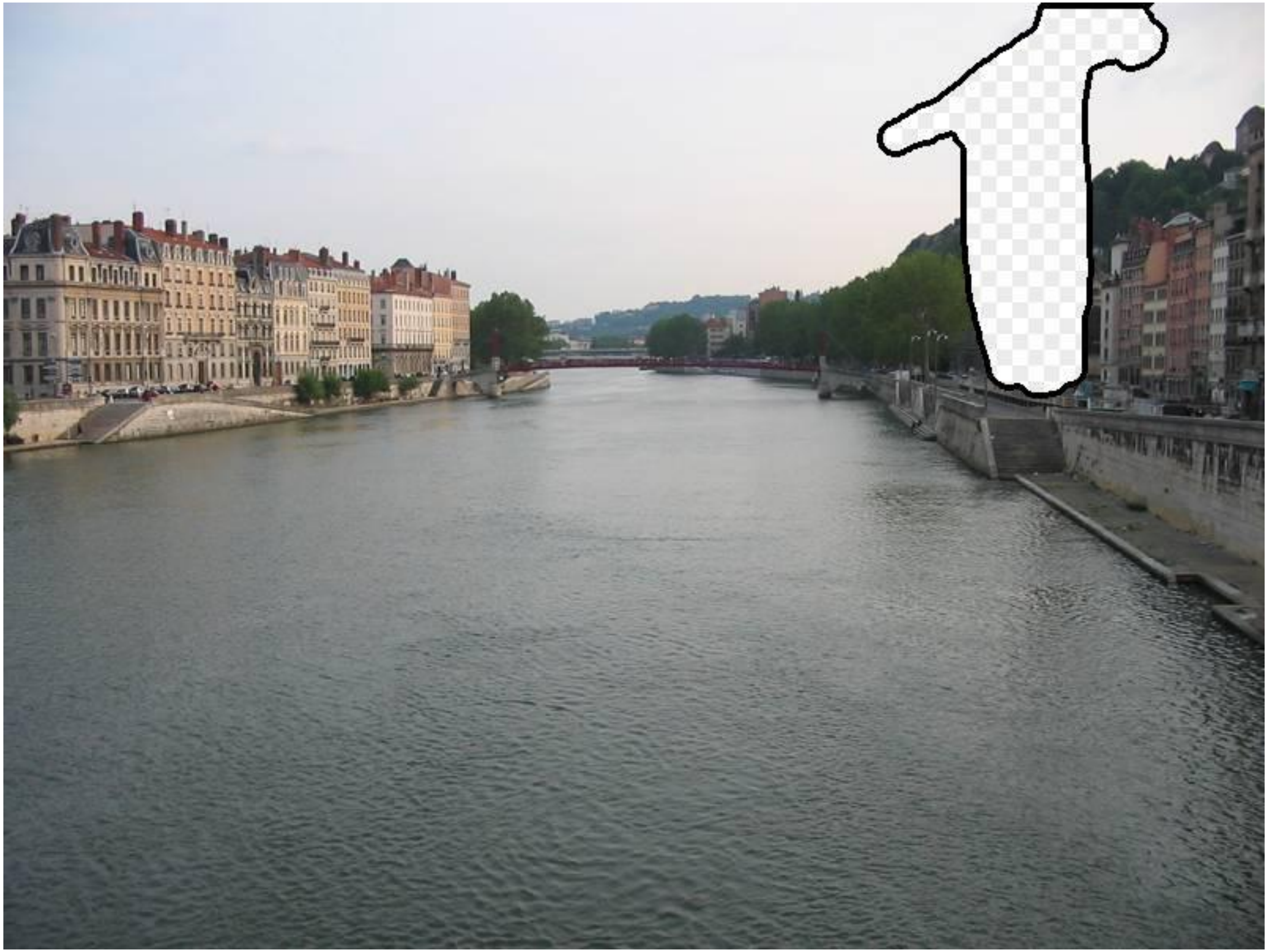


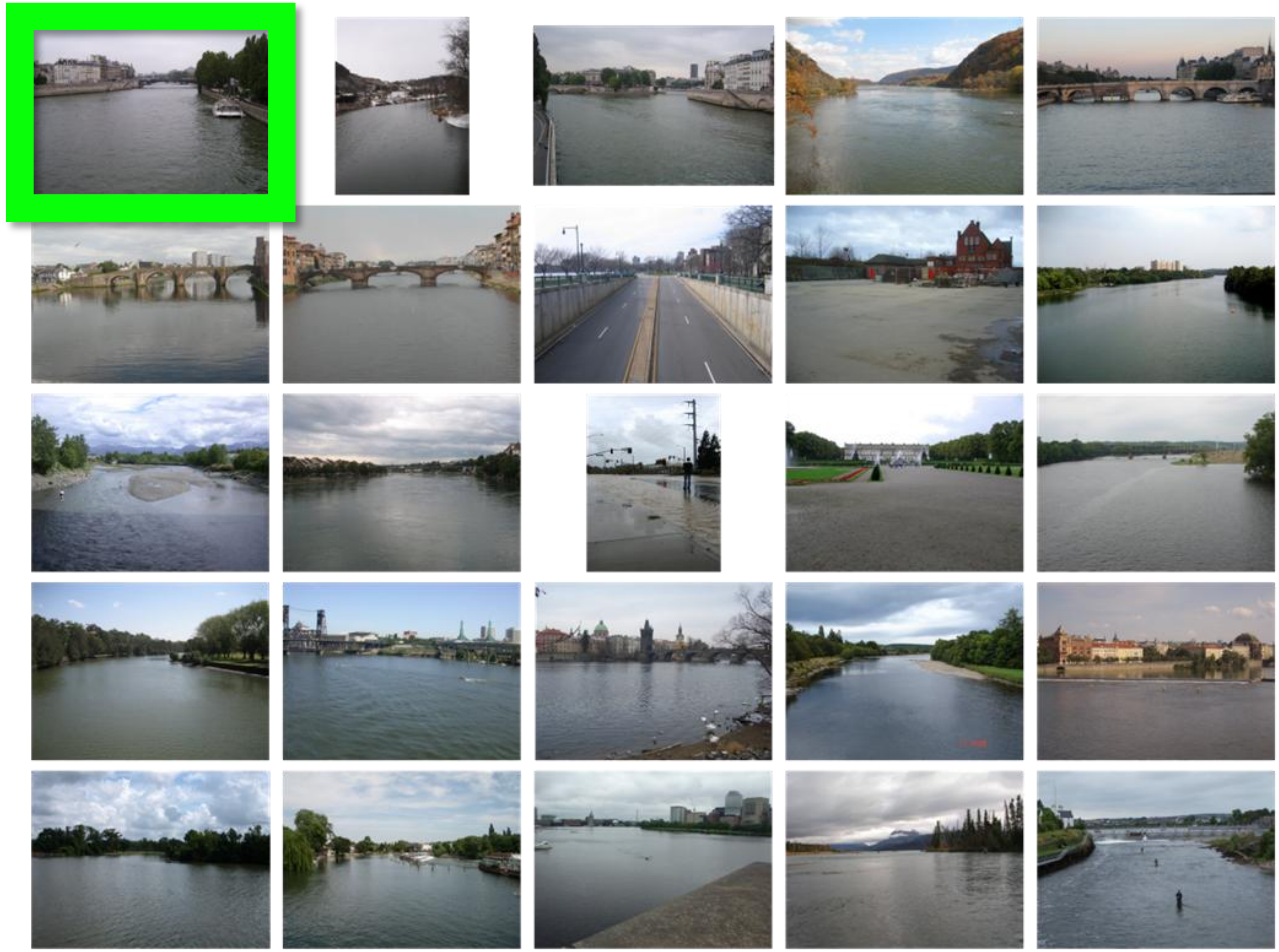
The scene matching distance

The context matching distance
(color + texture)

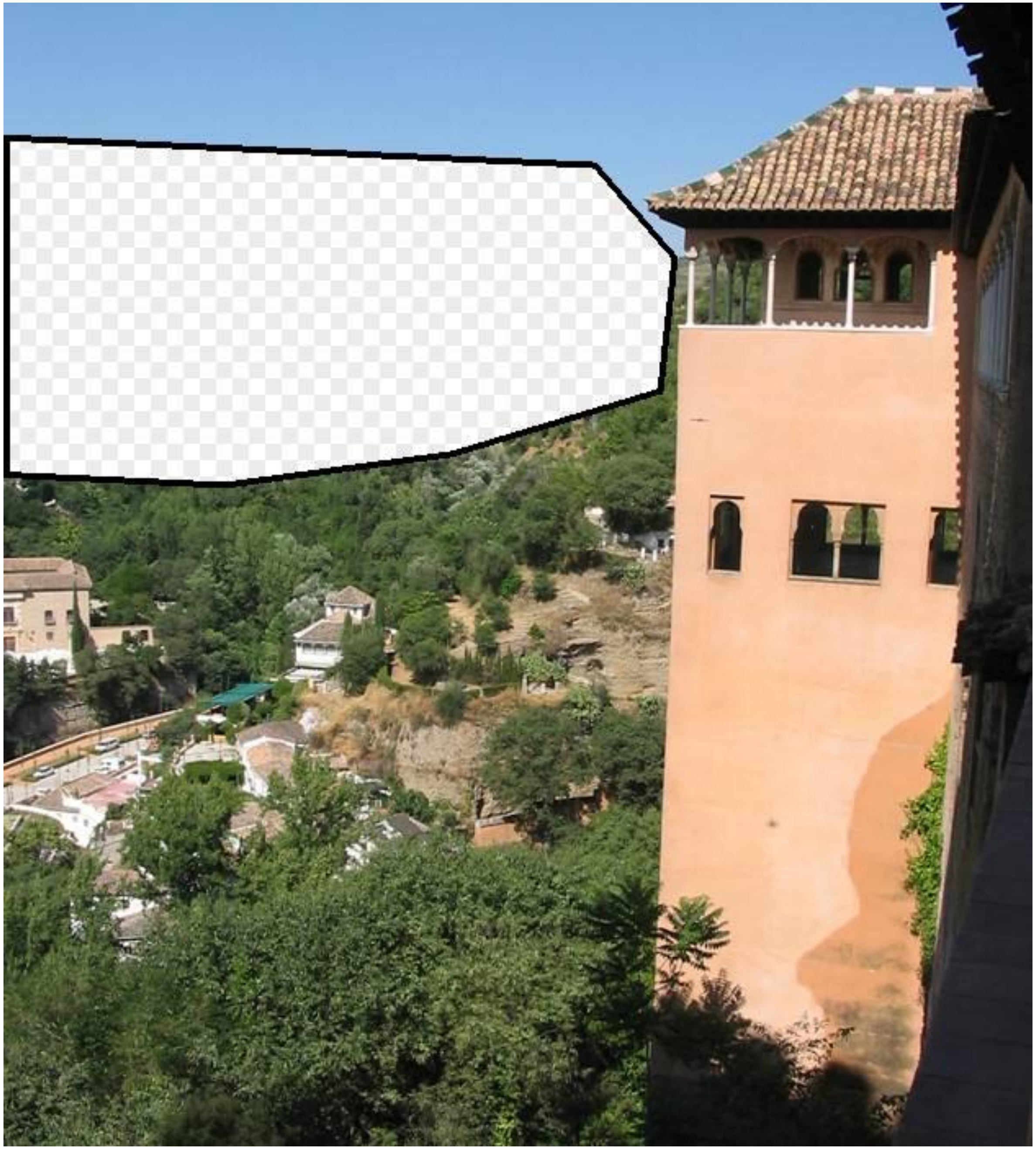


The graph cut cost

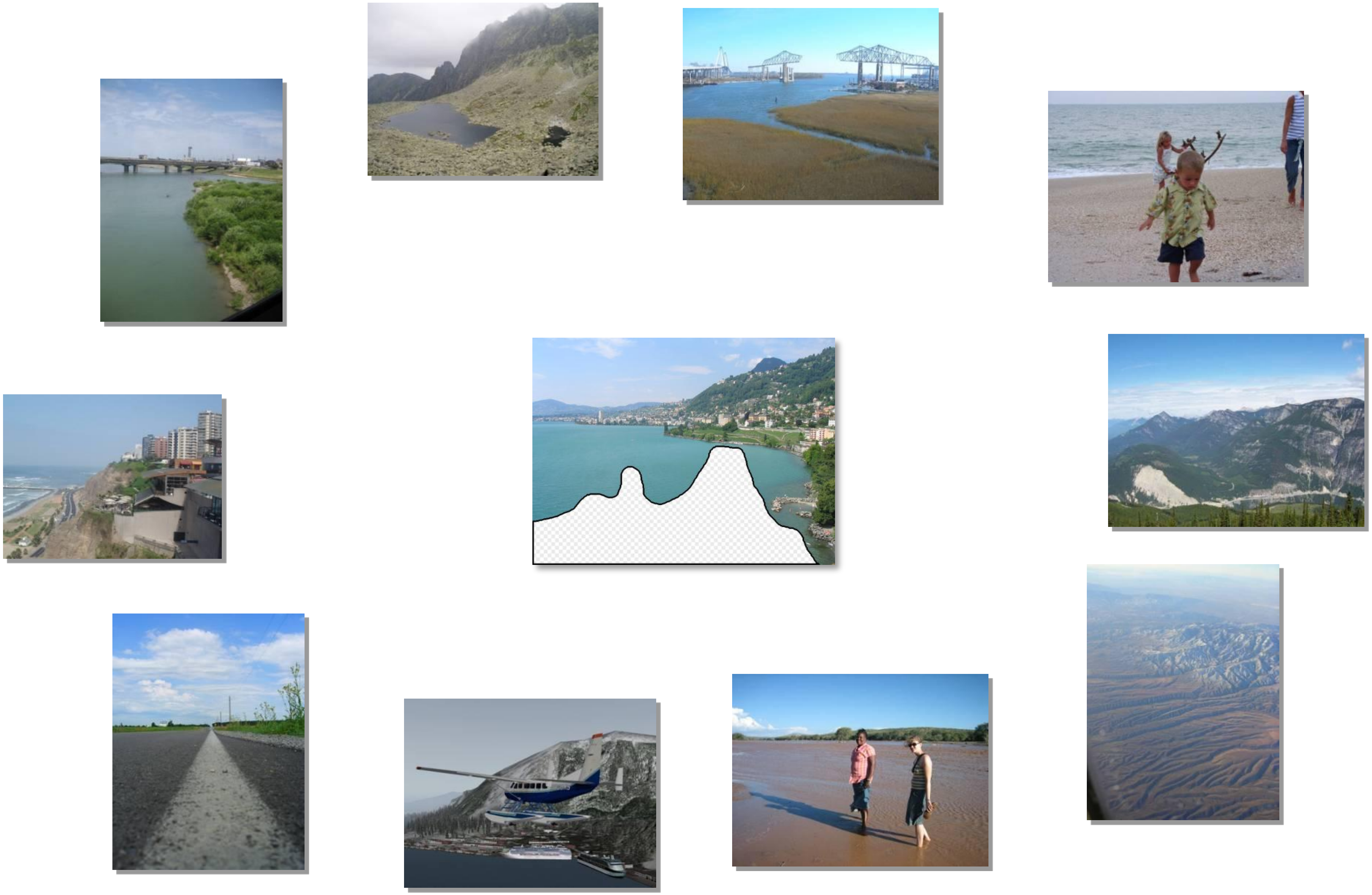




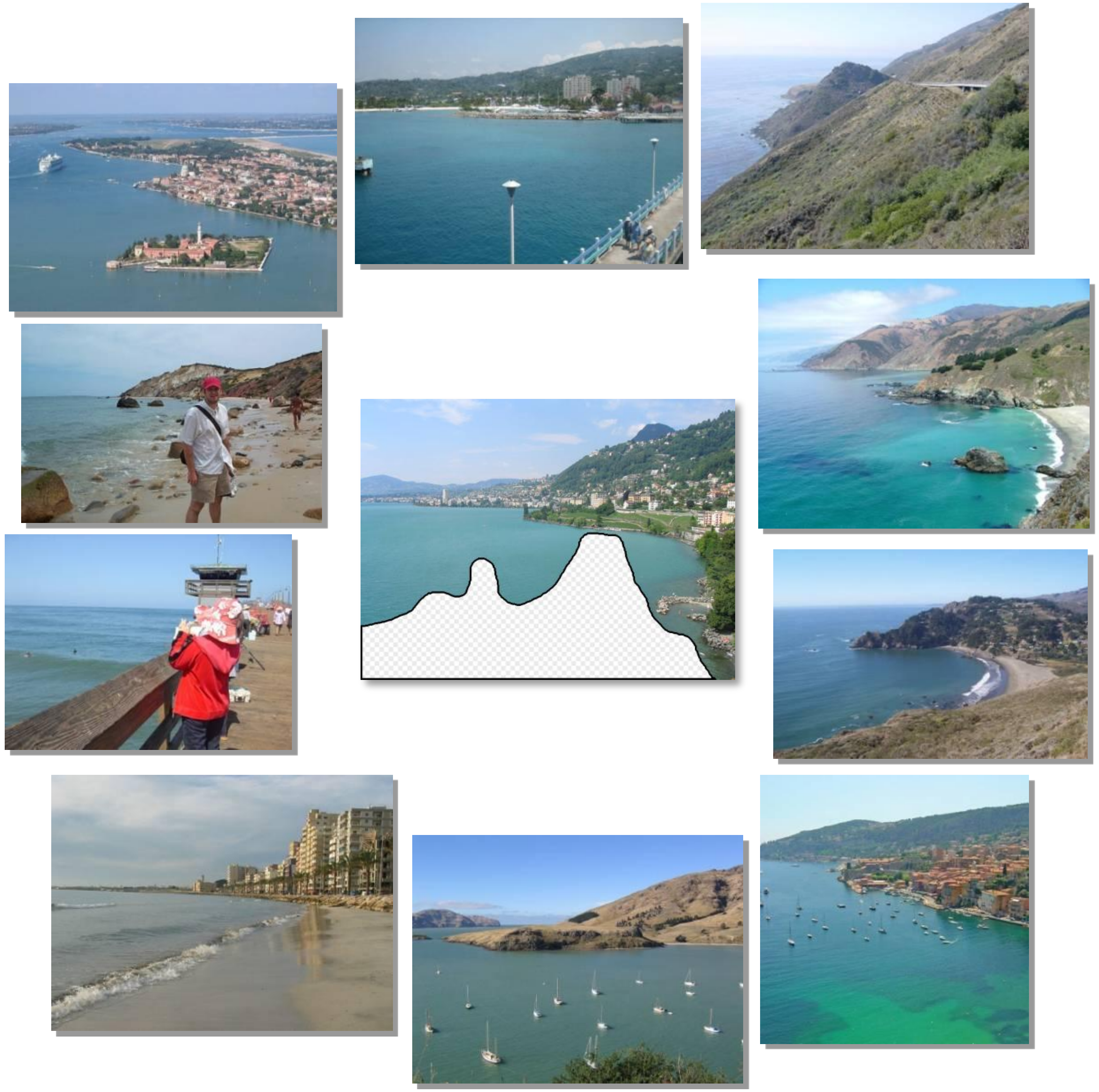
… 200 scene matches



Why does it work?



Nearest neighbors from a collection of 20 thousand images



Nearest neighbors from a collection of 2 million images

“Unreasonable Effectiveness of Data”

[Halevy, Norvig, Pereira 2009]

- Parts of our world can be explained by elegant mathematics
  - physics, chemistry, astronomy, etc.
- But much cannot
  - psychology, economics, genetics, etc.
- Enter <u>The Data!</u>
  - Great advances in several fields:
    - e.g. speech recognition, machine translation
    - Case study: Google

- A.I. for the postmodern world:
  - all questions have already been answered…many times, in many ways
  - Google is dumb, the "intelligence" is <u>in the data</u>

How about <u>visual</u> data?

- text is simple:
  - clean, segmented, compact, 1D
- Visual data is much harder:
  - Noisy, unsegmented, high entropy, 2D/3D

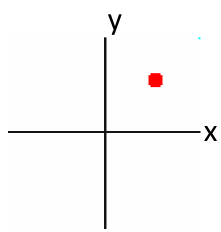
Quick Overview

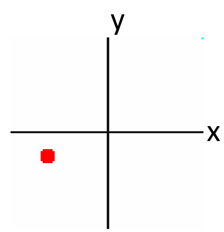
Comparing Images

Uses of Visual Data

The Dangers of Data

Distance Metrics

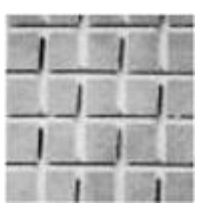


-


= Euclidian distance of 5 units


-

= Grayvalue distance of 50 values


-

= ?

SSD says these are not similar

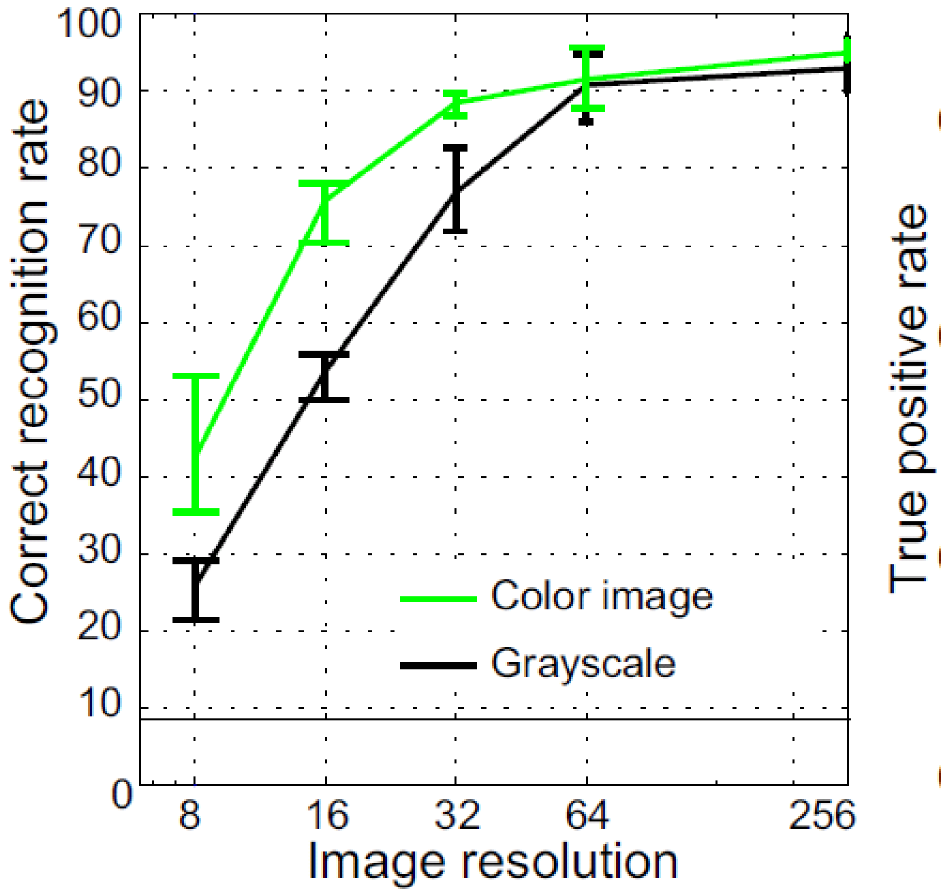
?

Tiny Images

- 80 million tiny images: a large dataset for non-parametric object and scene recognition Antonio Torralba, Rob Fergus and William T. Freeman. PAMI 2008.

c) Segmentation of 32x32 images

Human Scene Recognition



a) Scene recognition

Tiny Images Project Page

http://groups.csail.mit.edu/vision/TinyImages/

Powers of 10

Number of images on my hard drive: 10^4

Number of images seen during my first 10 years: 10^8

(3 images/second * 60 * 60 * 16 * 365 * 10 = 630720000)

Number of images seen by all humanity: 10^{20}

106,456,367,669 humans[1] * 60 years * 3 images/second * 60 * 60 * 16 * 365 =

1 from http://www.prb.org/Articles/2002/HowManyPeopleHaveEverLivedonEarth.aspx

Number of photons in the universe: 10^{88}

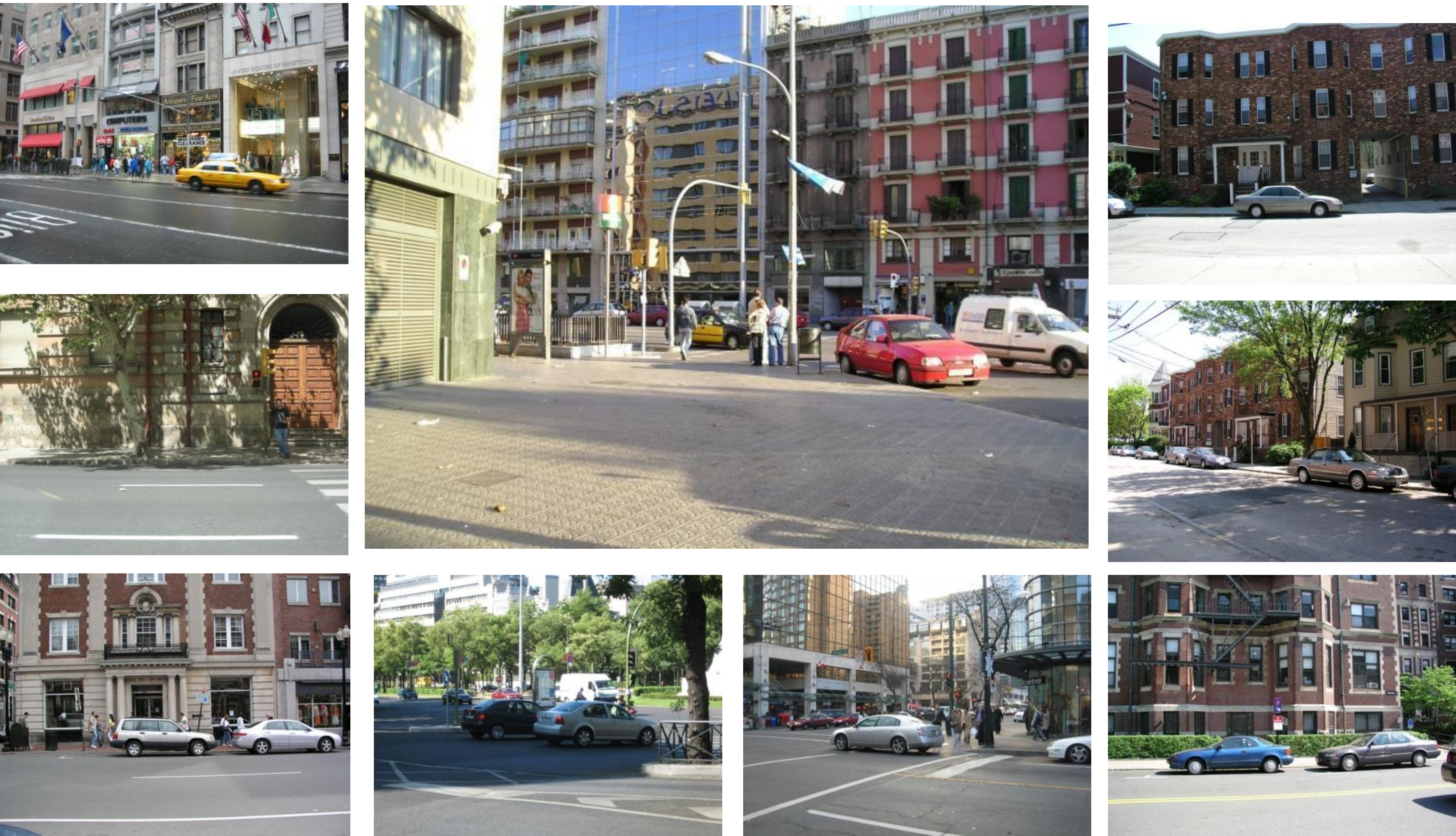
Number of all 32x32 images: 10^{7373}

$256^{32*32*3} \sim 10^{7373}$

Scenes are unique

But not all scenes are so original

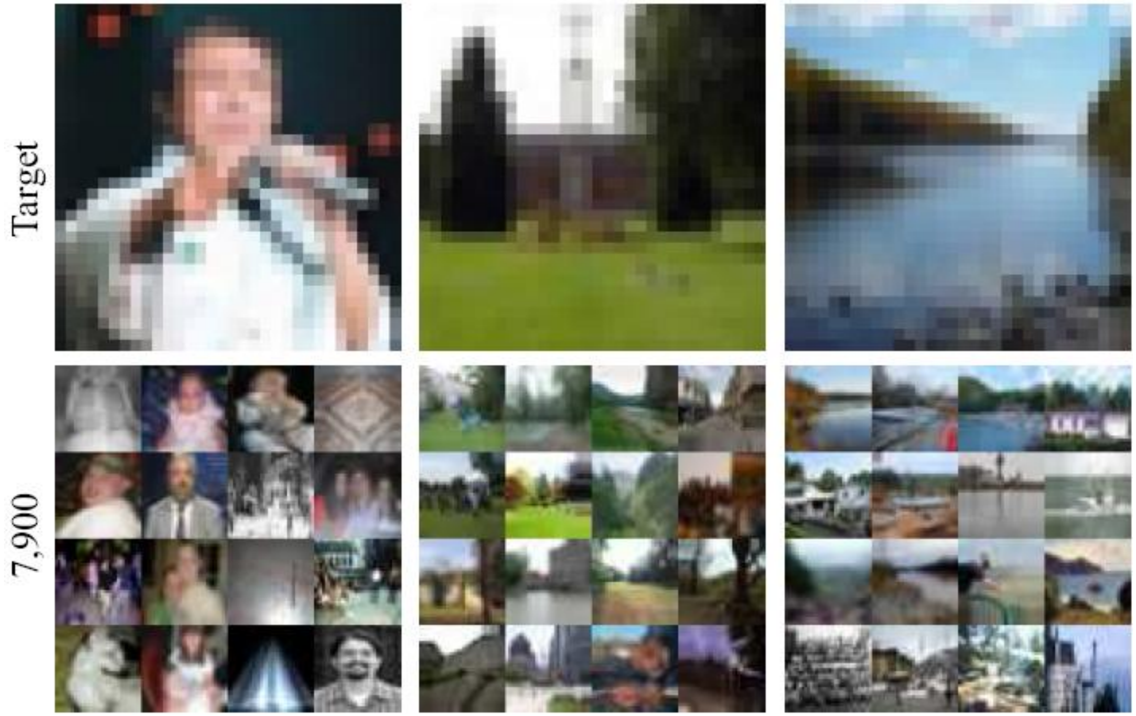
But not all scenes are so original



Lots

Of

Images

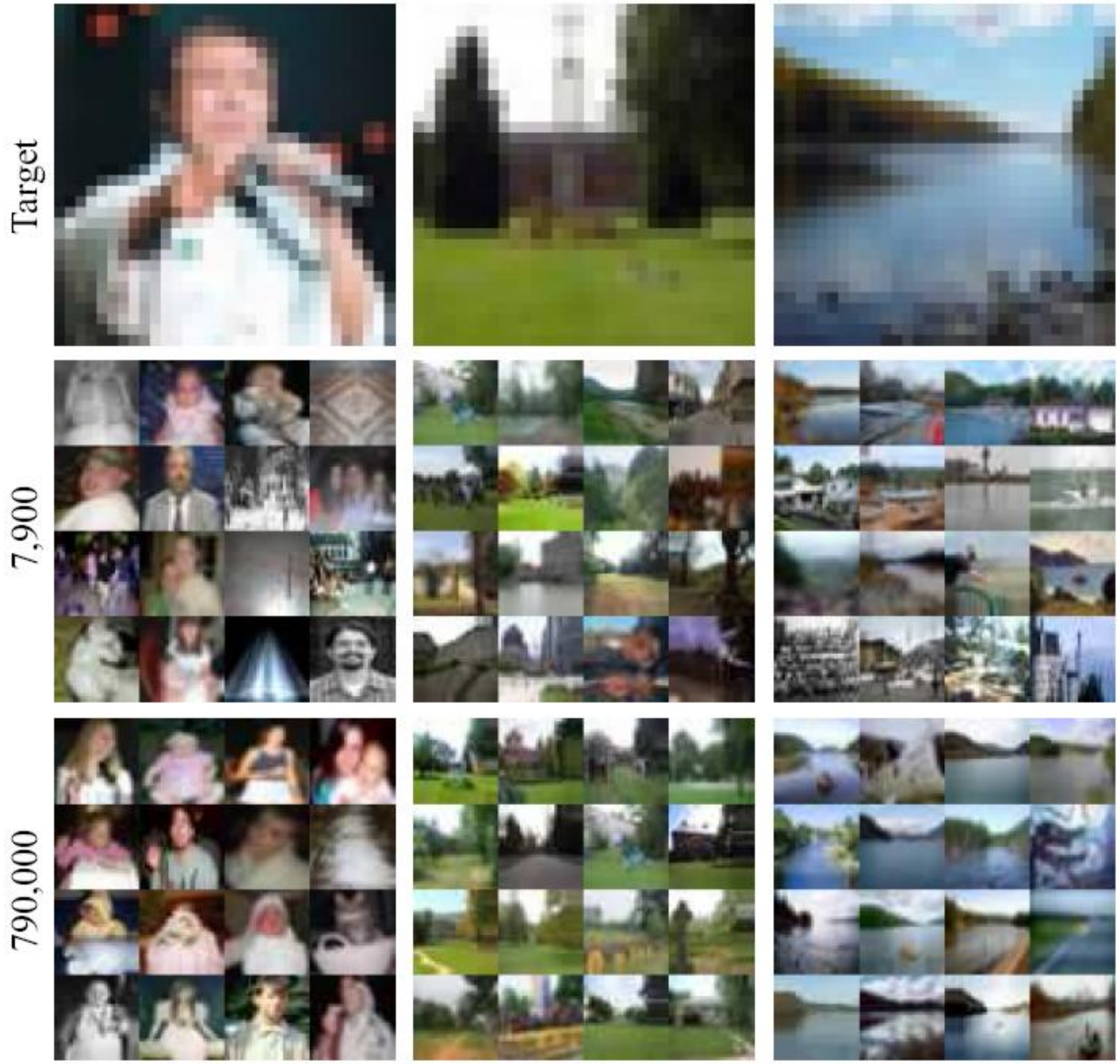


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images

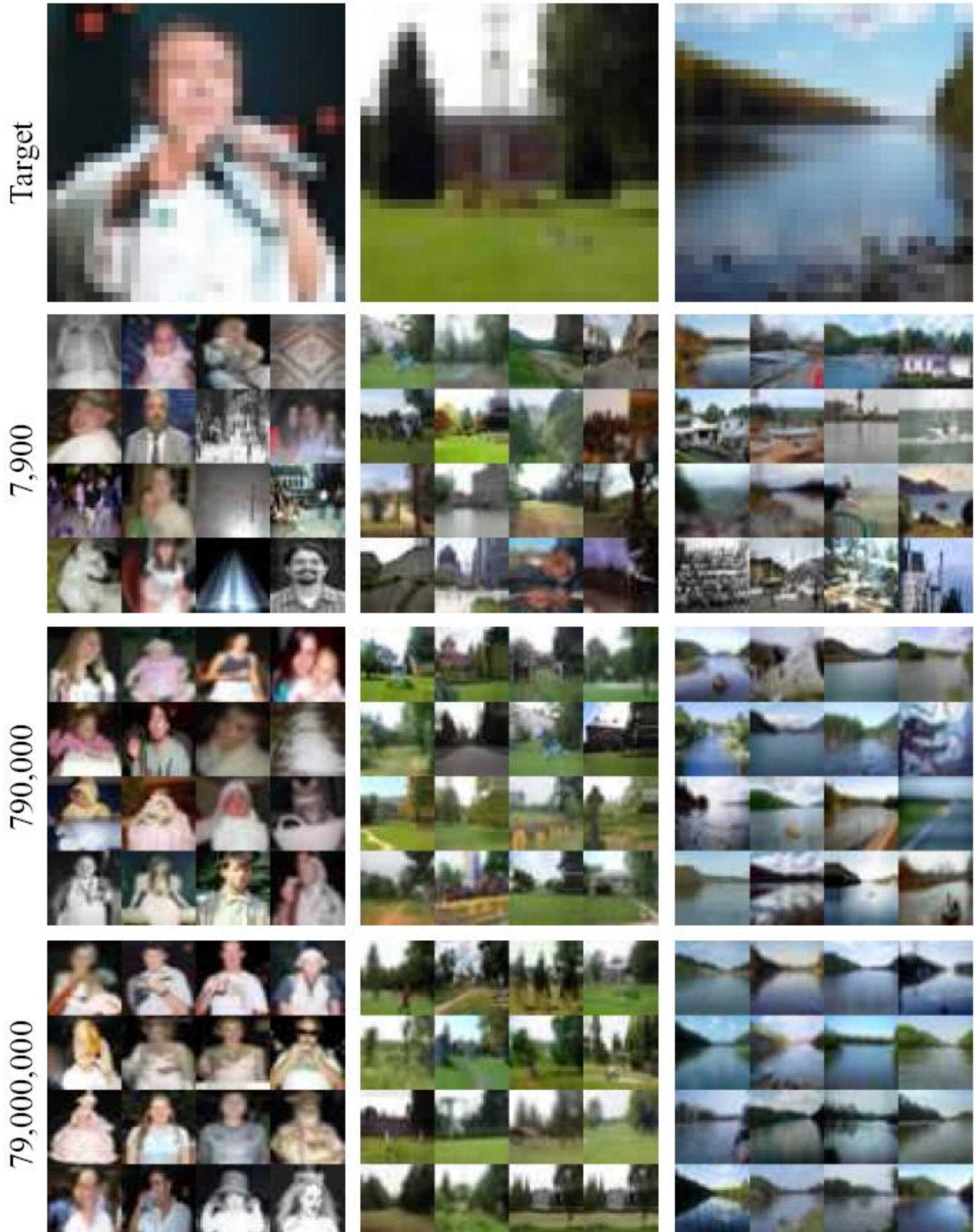


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images



Automatic Colorization Result

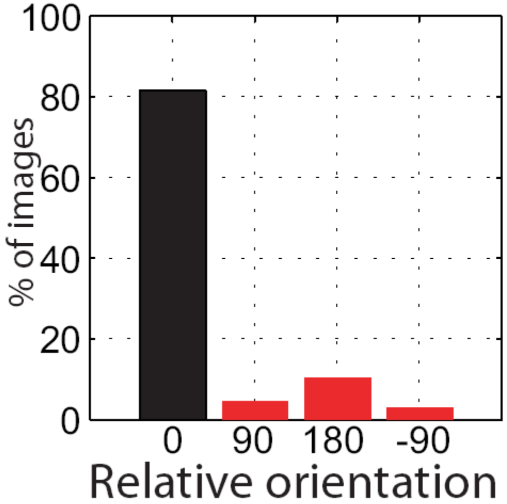
Grayscale input High resolution

Colorization of input using average

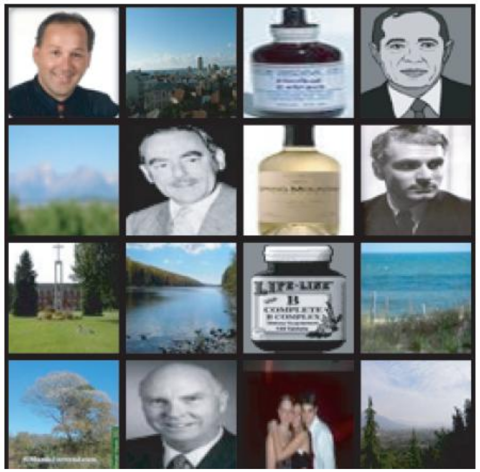
A. Torralba, R. Fergus, W.T.Freeman. 2008

Automatic Orientation

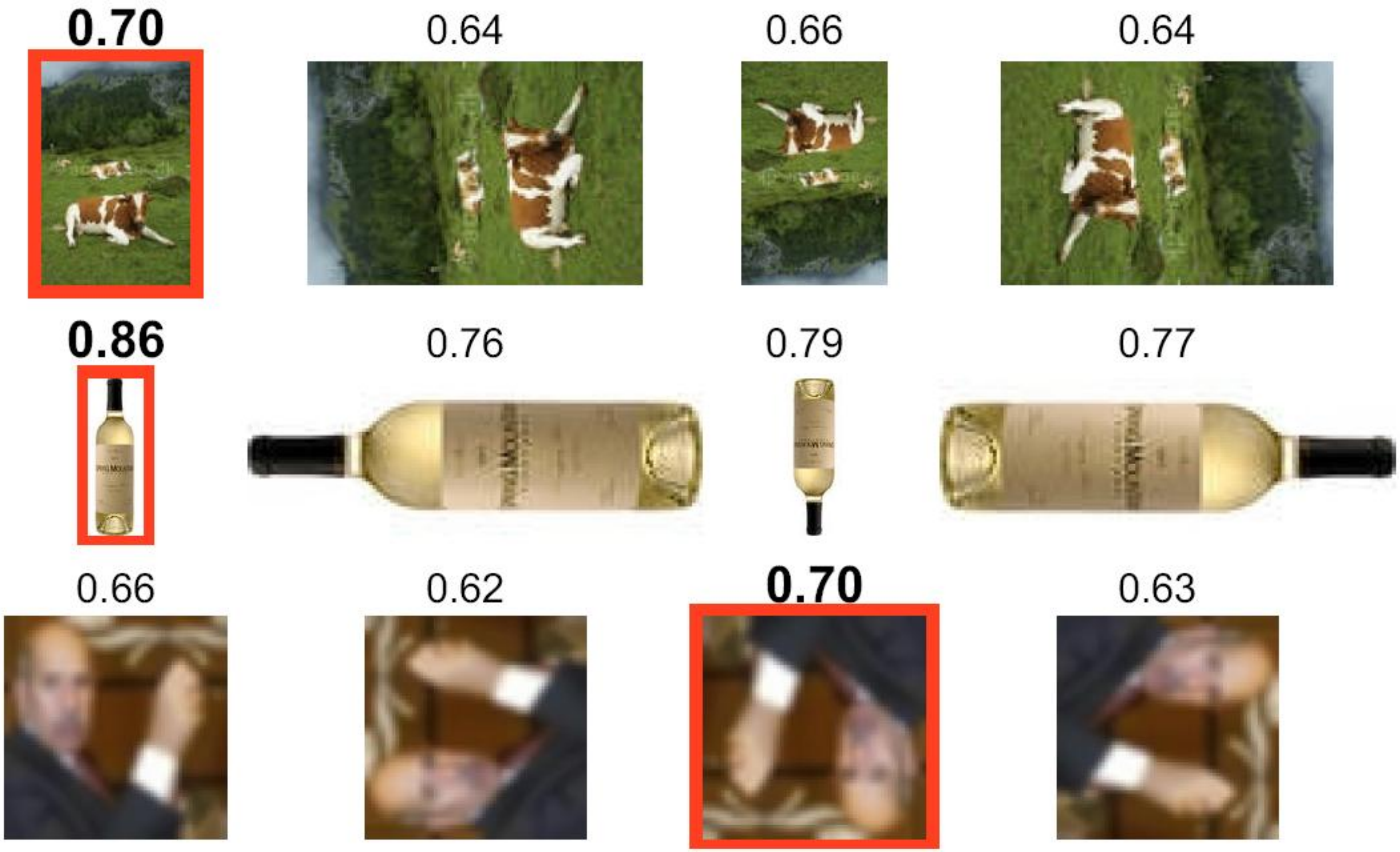
- Many images have ambiguous orientation
- Look at top 25% by confidence:



- Examples of high and low confidence images:



Automatic Orientation Examples



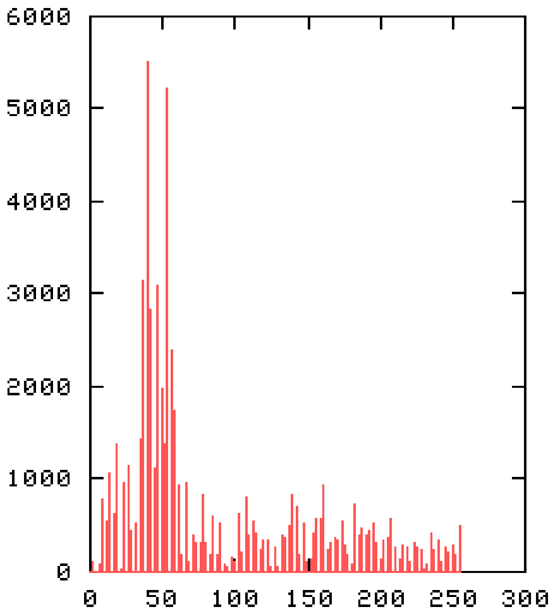
A. Torralba, R. Fergus, W.T.Freeman. 2008

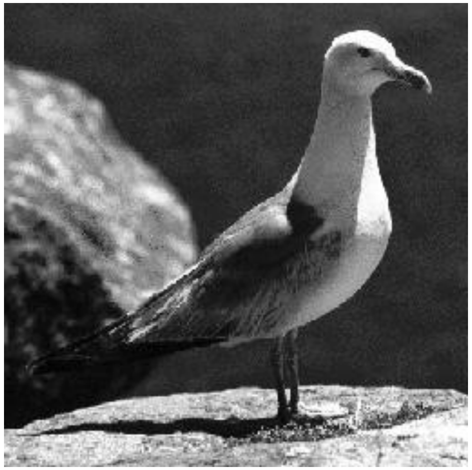
Tiny Images Discussion

- Why SSD?
- Can we build a better image descriptor?

Image Representations: Histograms

Images from Dave Kauchak



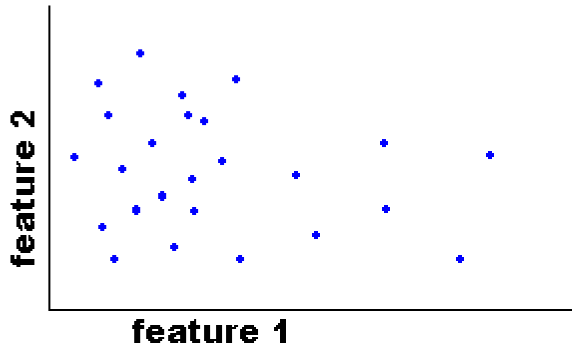


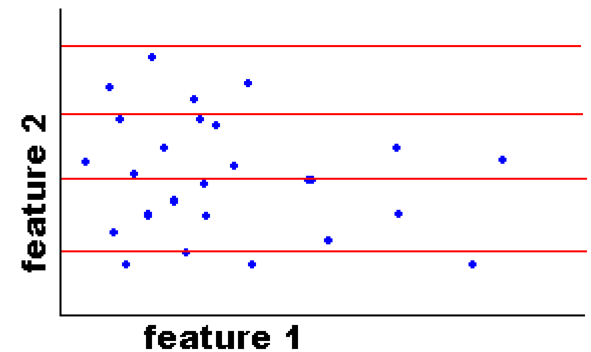
global histogram

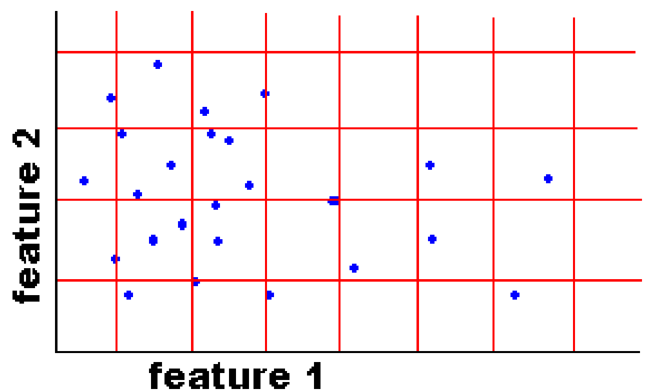
- Represent distribution of features
  - Color, texture, depth, …

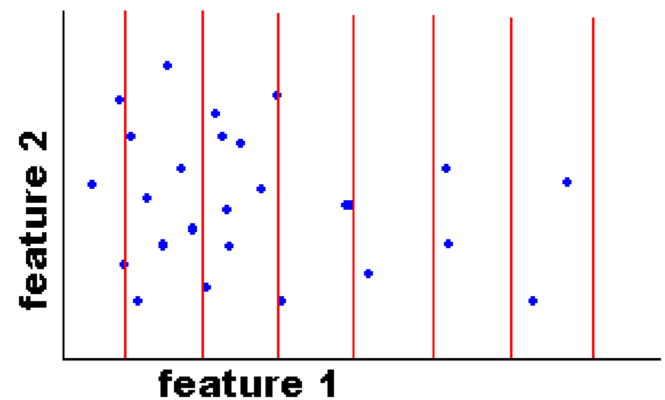
Image Representations: Histograms

Images from Dave Kauchak









Joint histogram

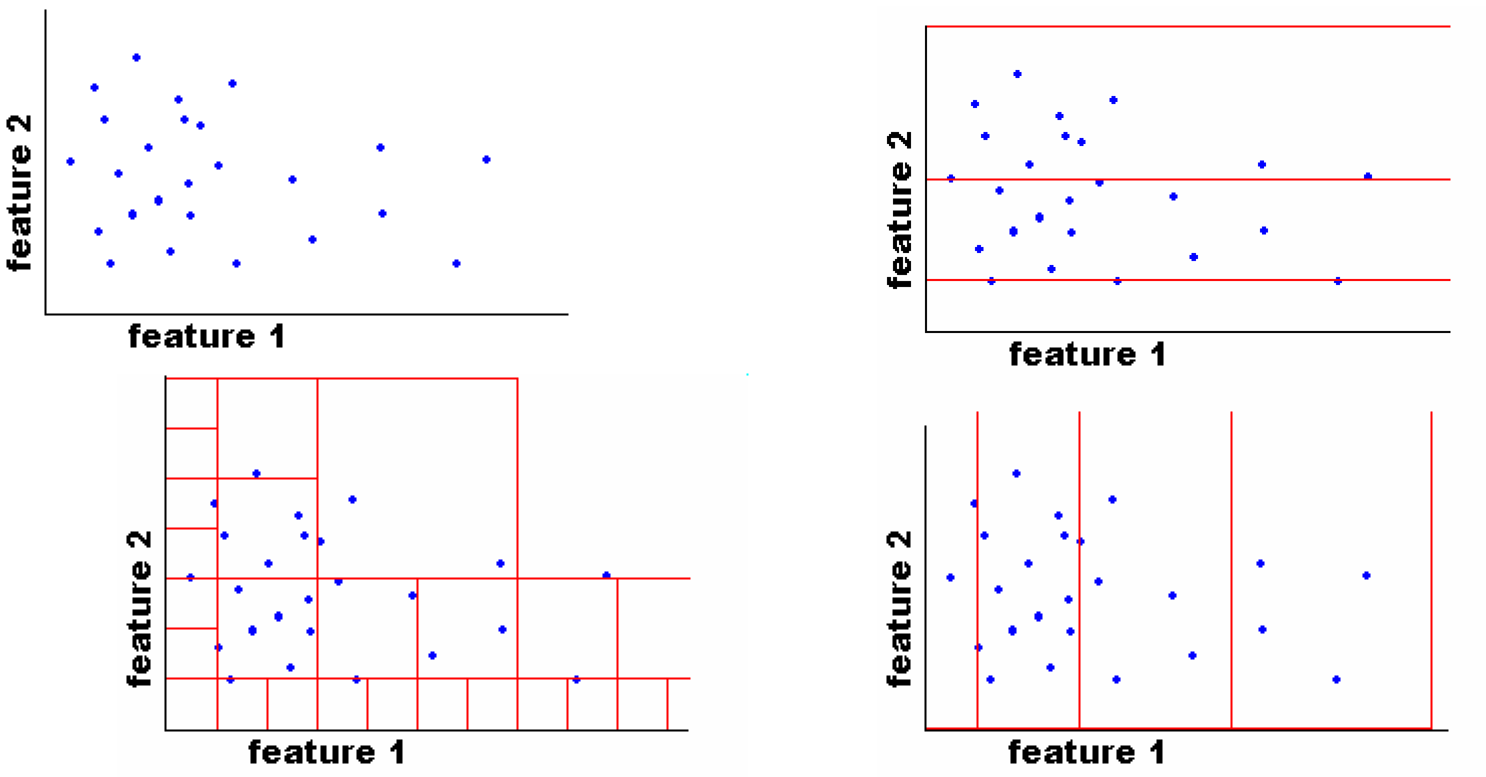
- Requires lots of data
- Loss of resolution to avoid empty bins

Marginal histogram

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

Image Representations: Histograms

Images from Dave Kauchak

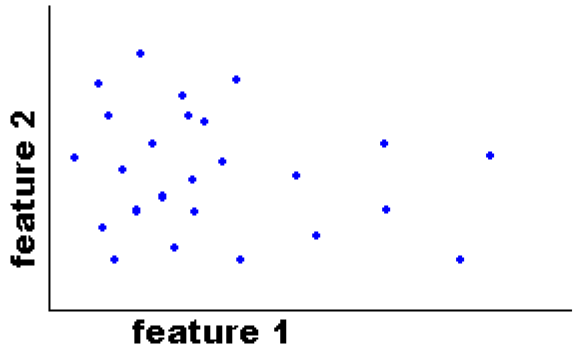


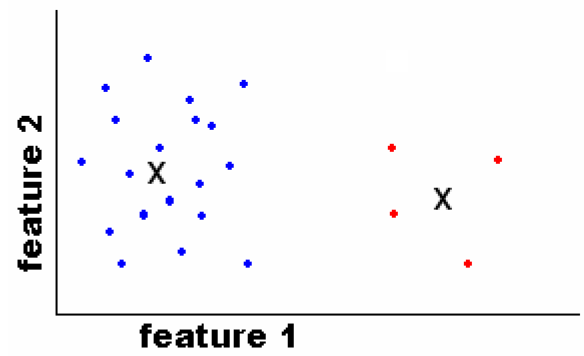
Adaptive binning

- Better data/bin distribution, fewer empty bins
- Can adapt available resolution to relative feature importance

Image Representations: Histograms

Images from Dave Kauchak

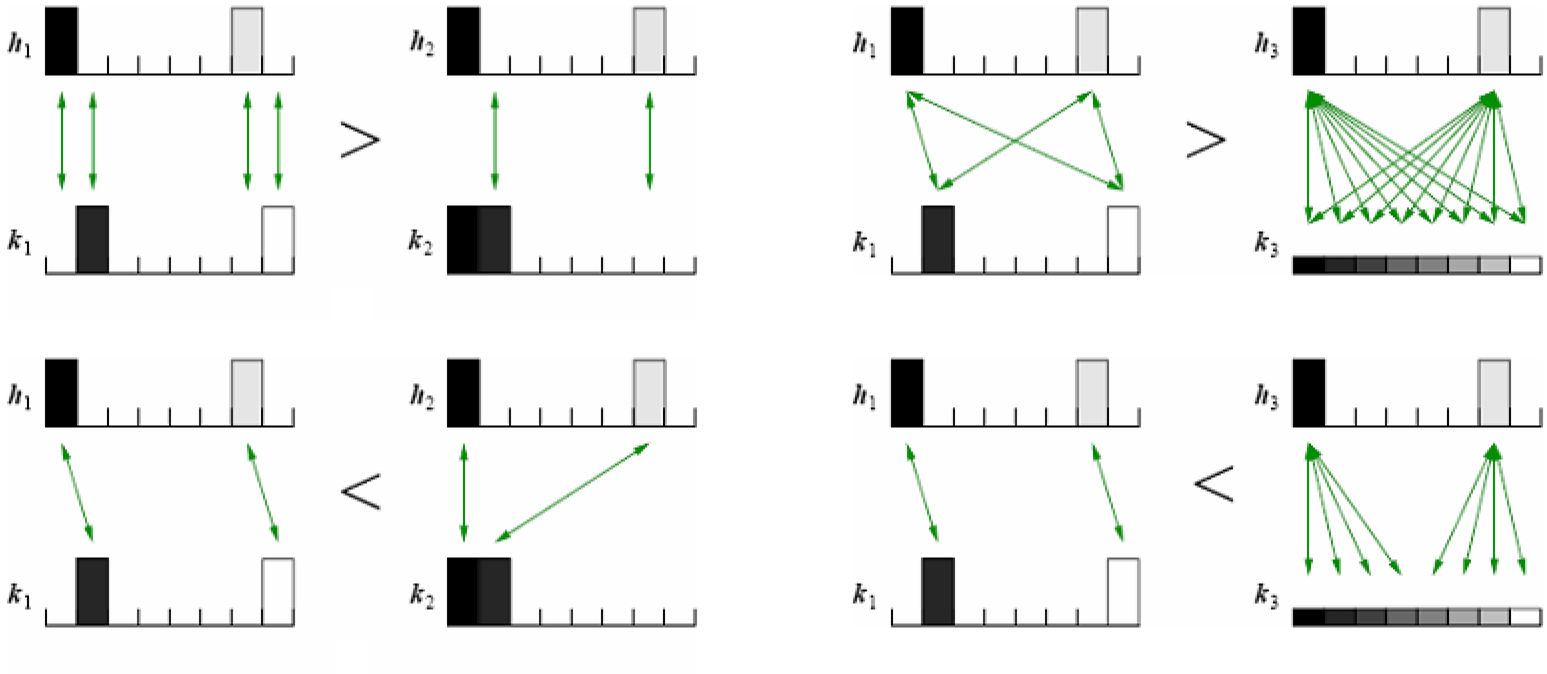




Clusters / Signatures

- "super-adaptive" binning
- Does not require discretization along any fixed axis

Issue: How to Compare Histograms?



Bin-by-bin comparison

Sensitive to bin size.

Could use wider bins …
… but at a loss of resolution

Cross-bin comparison

How much cross-bin influence is necessary/sufficient?

Red Car Retrievals (Color histograms)

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

Histogram matching distance

Capturing the “essence” of texture

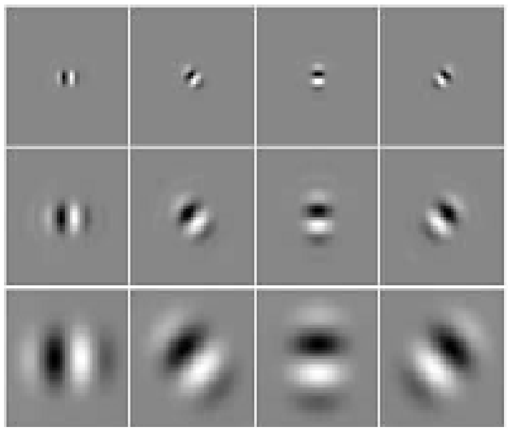
…for real images

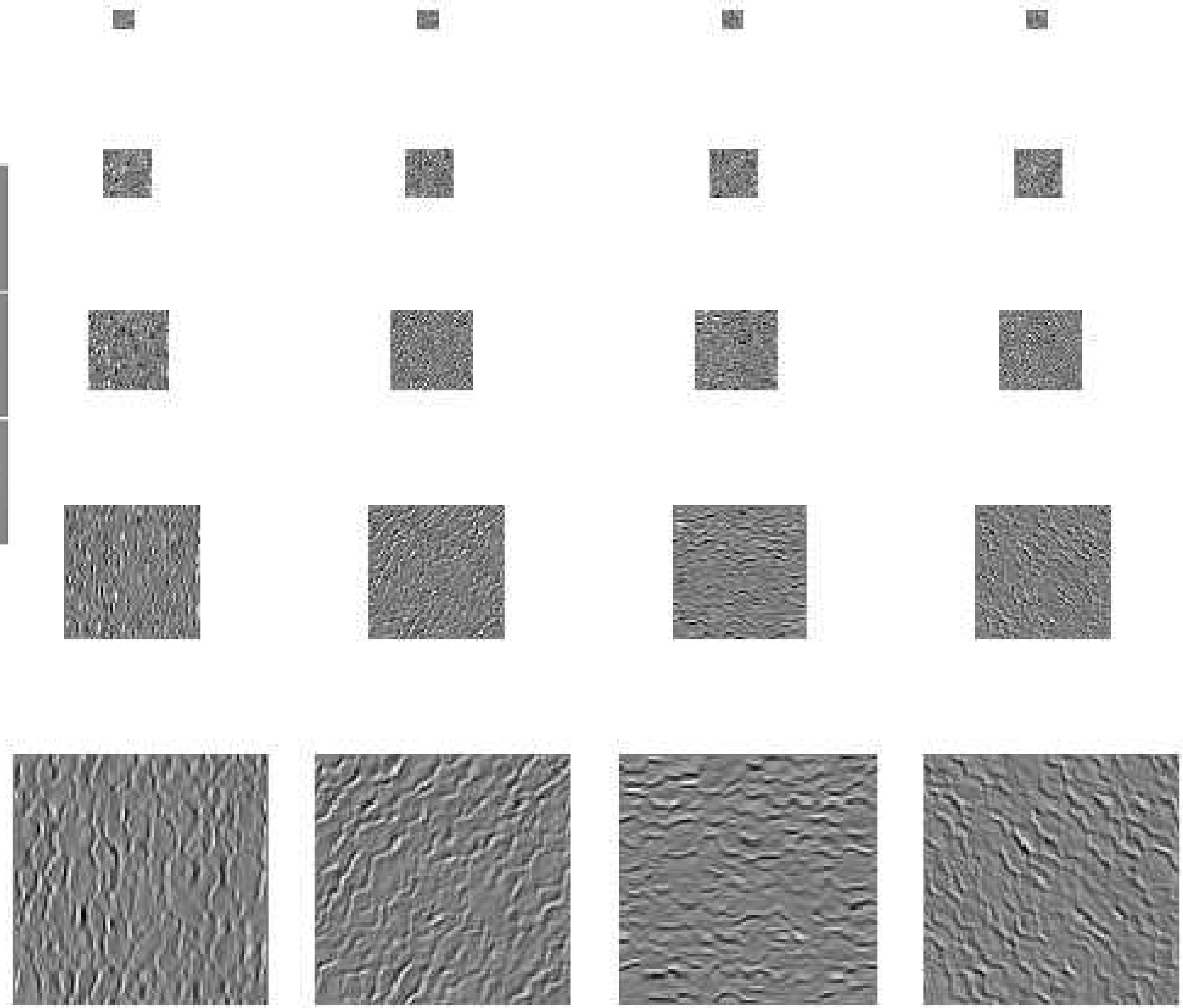

We don’t want an actual texture realization, we want a texture invariant

What are the tools for capturing <u>statistical</u> properties of some signal?

Multi-scale filter decomposition

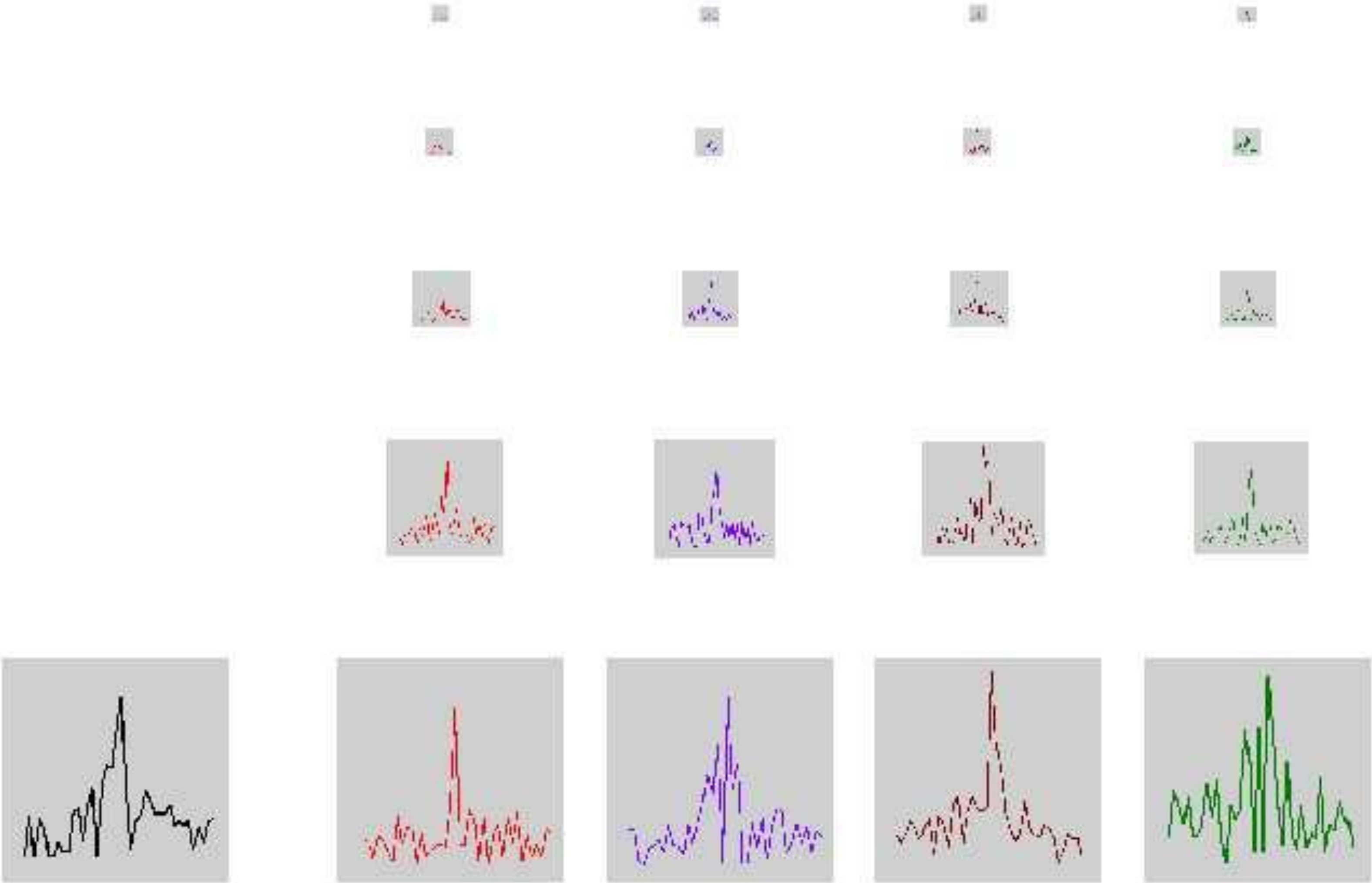
Filter bank





Input image

Filter response histograms



Heeger & Bergen ‘95

Start with a noise image as output

Main loop:

- Match pixel histogram of output image to input
- Decompose input and output images using multi-scale filter bank (Steerable Pyramid)
- Match subband histograms of input and output pyramids
- Reconstruct input and output images (collapse the pyramids)

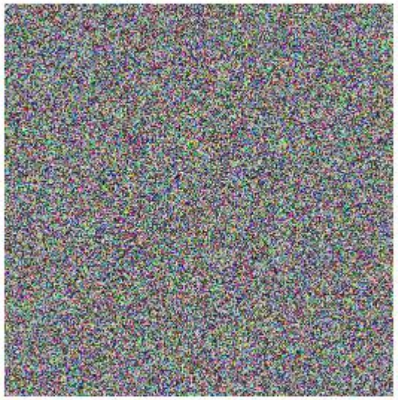
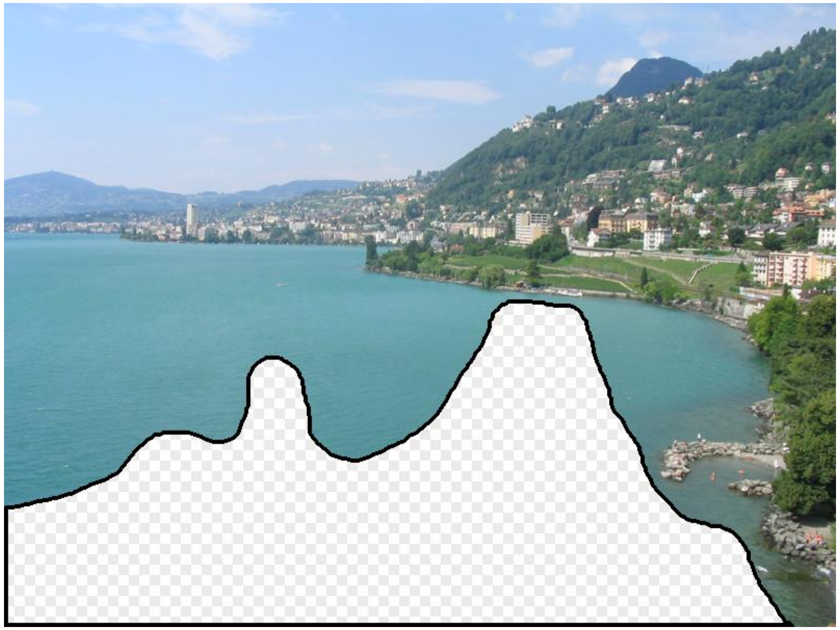
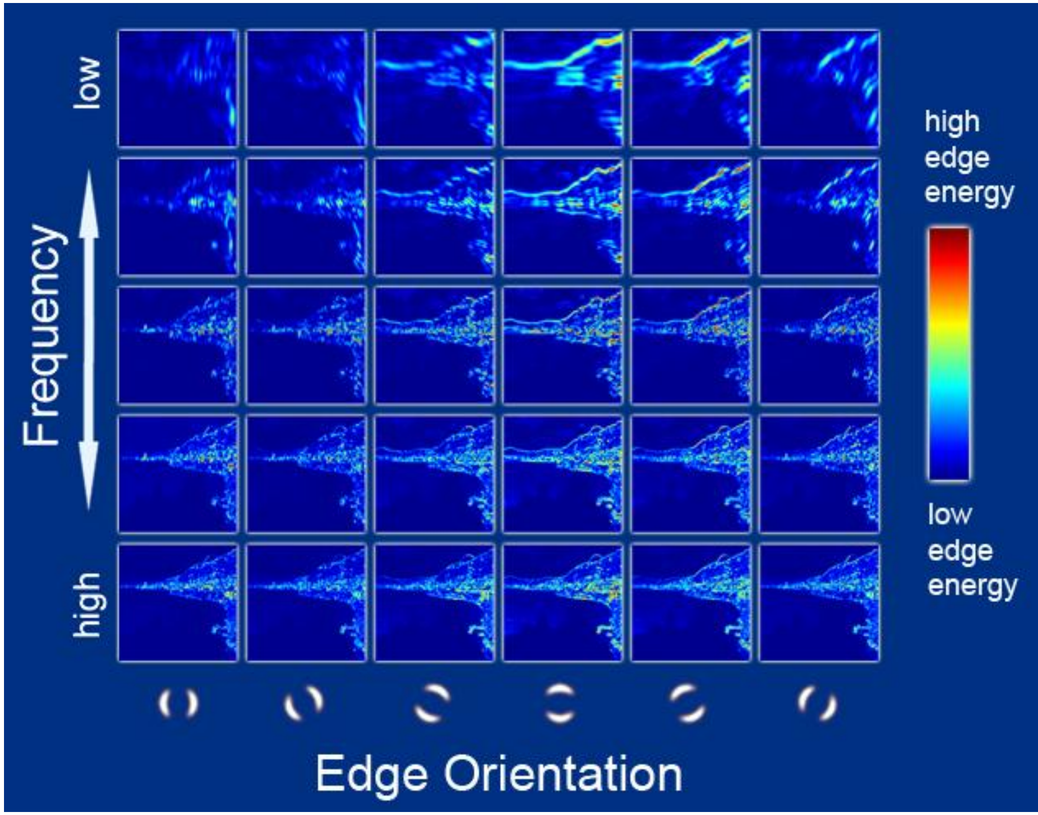


Image Descriptors

- Blur + SSD
- Color / Texture histograms
- Gradients + Histogram (GIST, SIFT, HOG, etc)
- "Bag of Visual Words"

Gist Scene Descriptor





Hays and Efros, SIGGRAPH 2007

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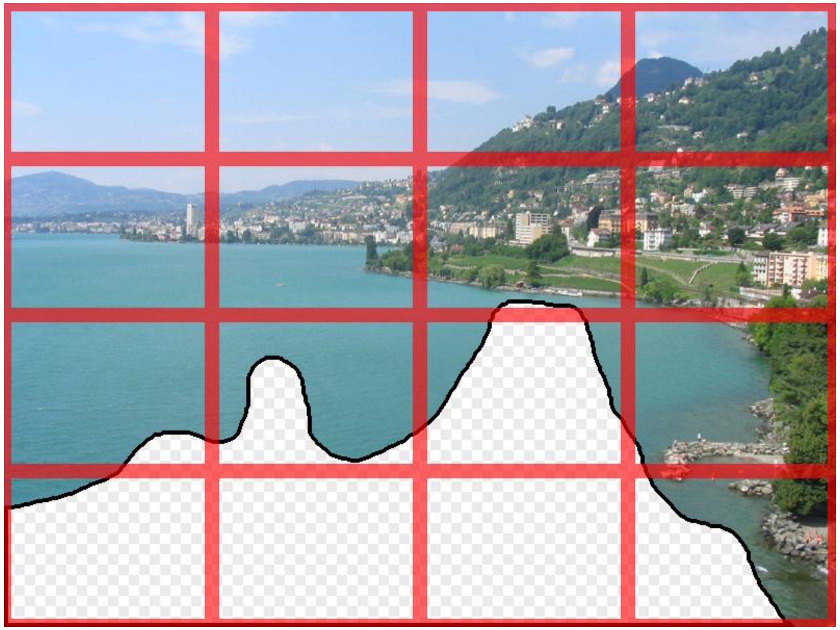

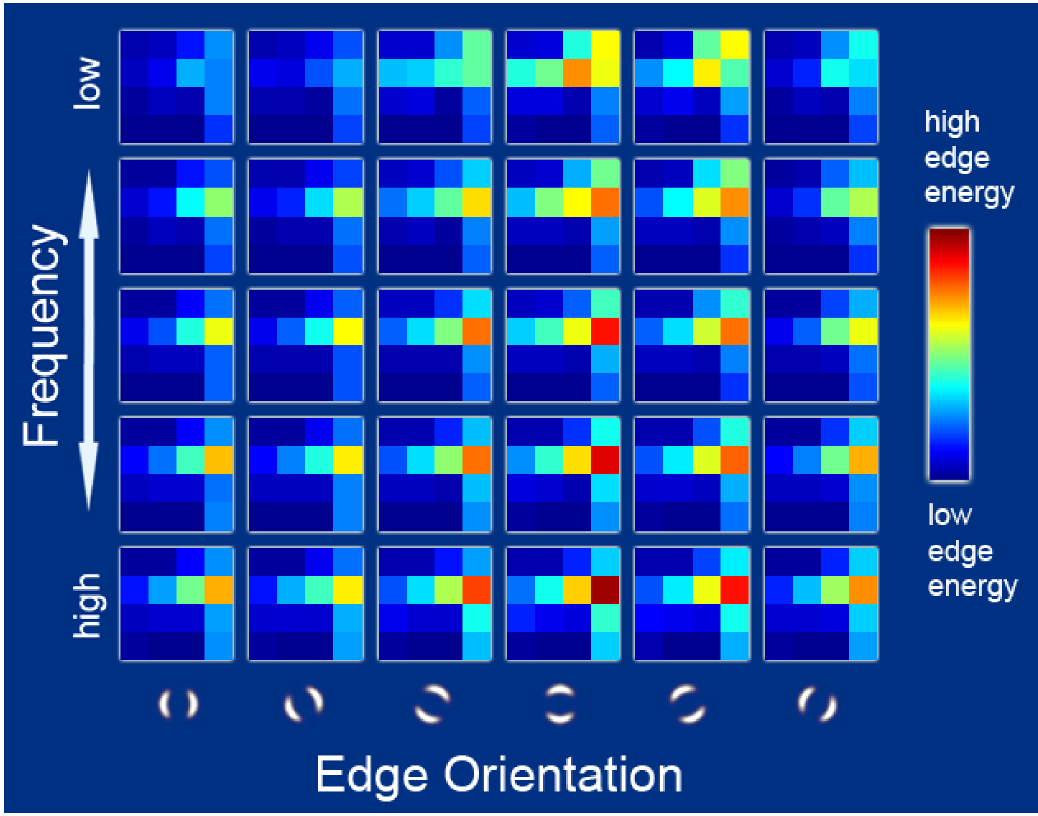

Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

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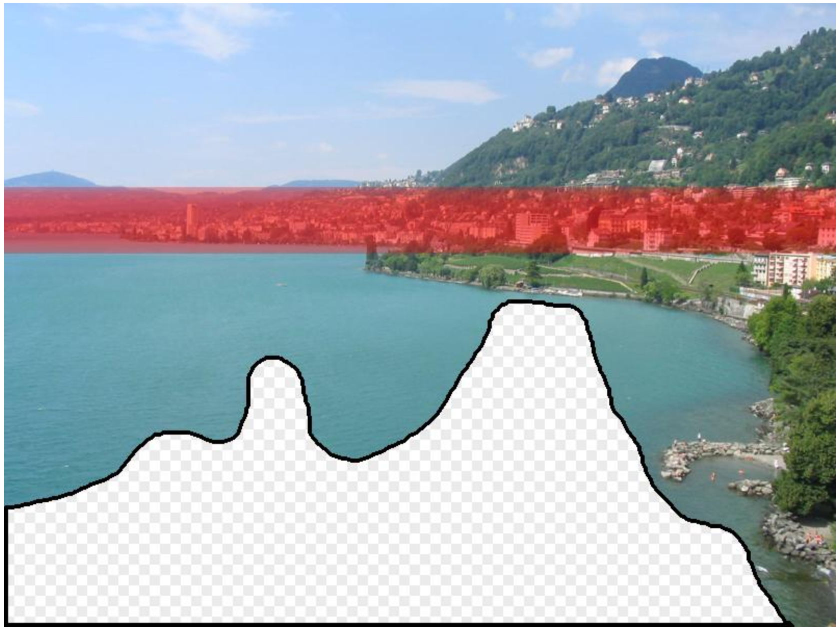

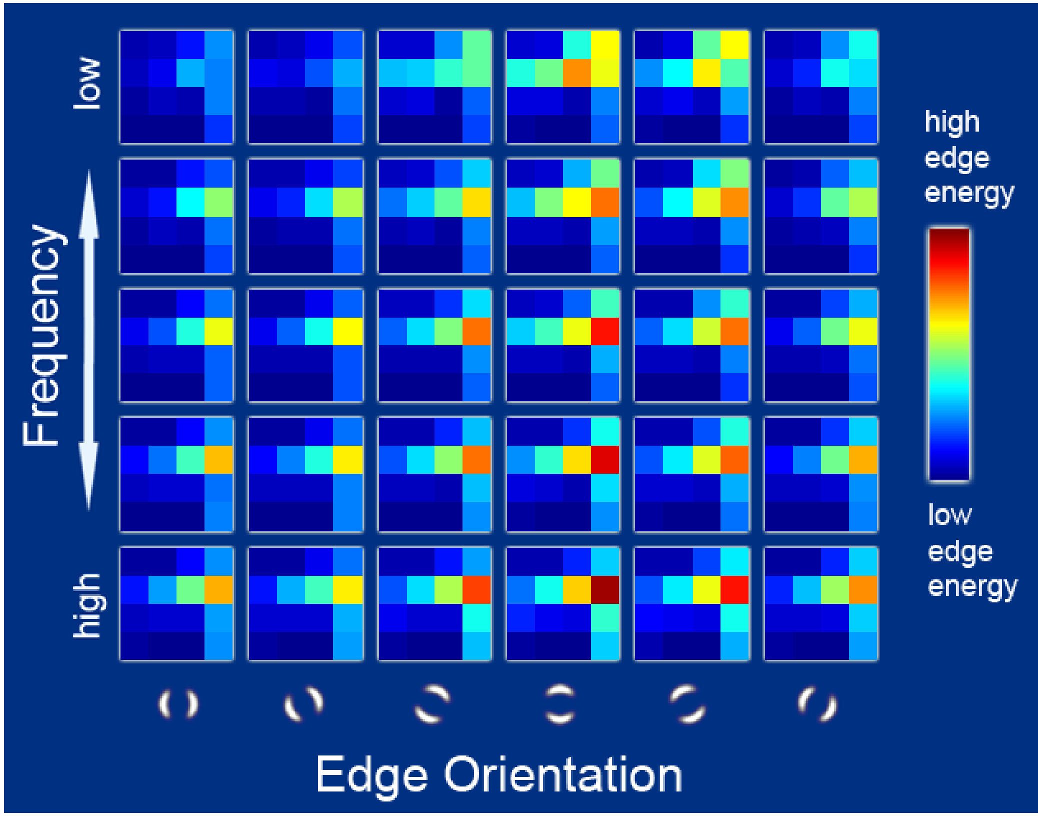

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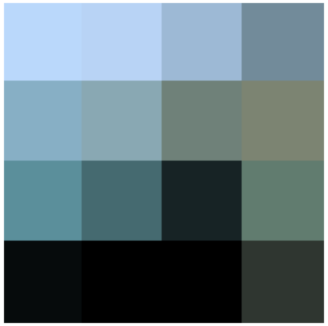
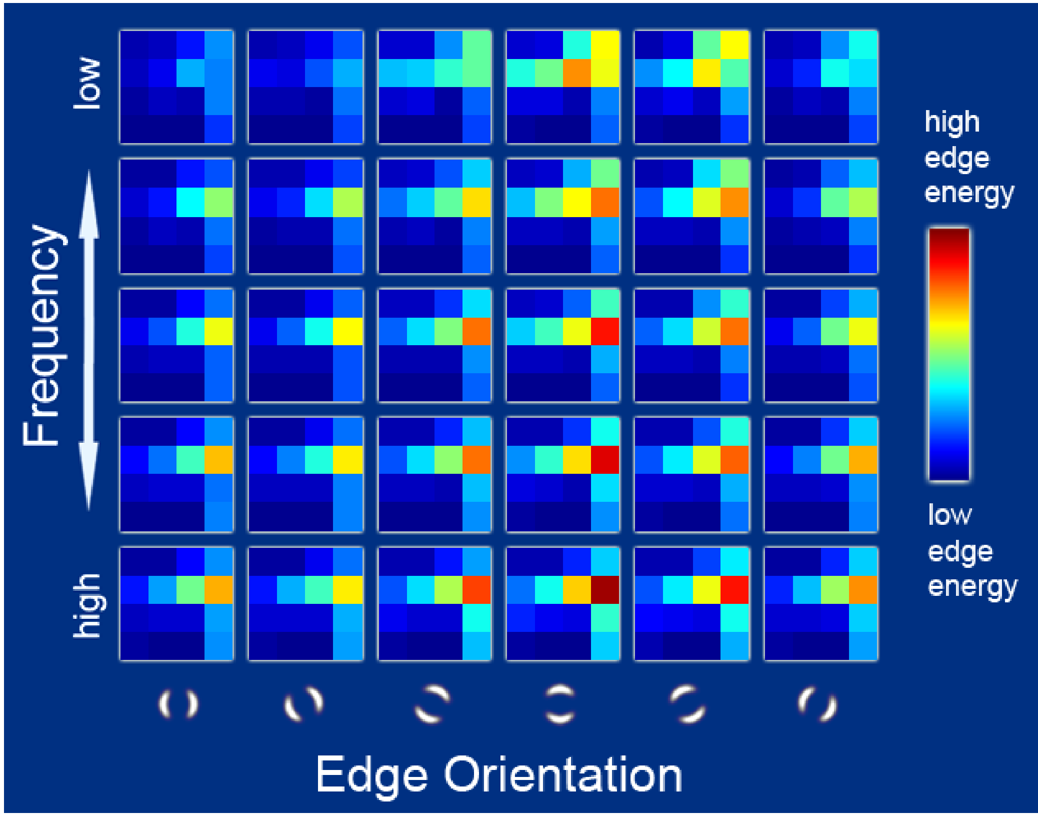


+



Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

Scene matching with camera transformations

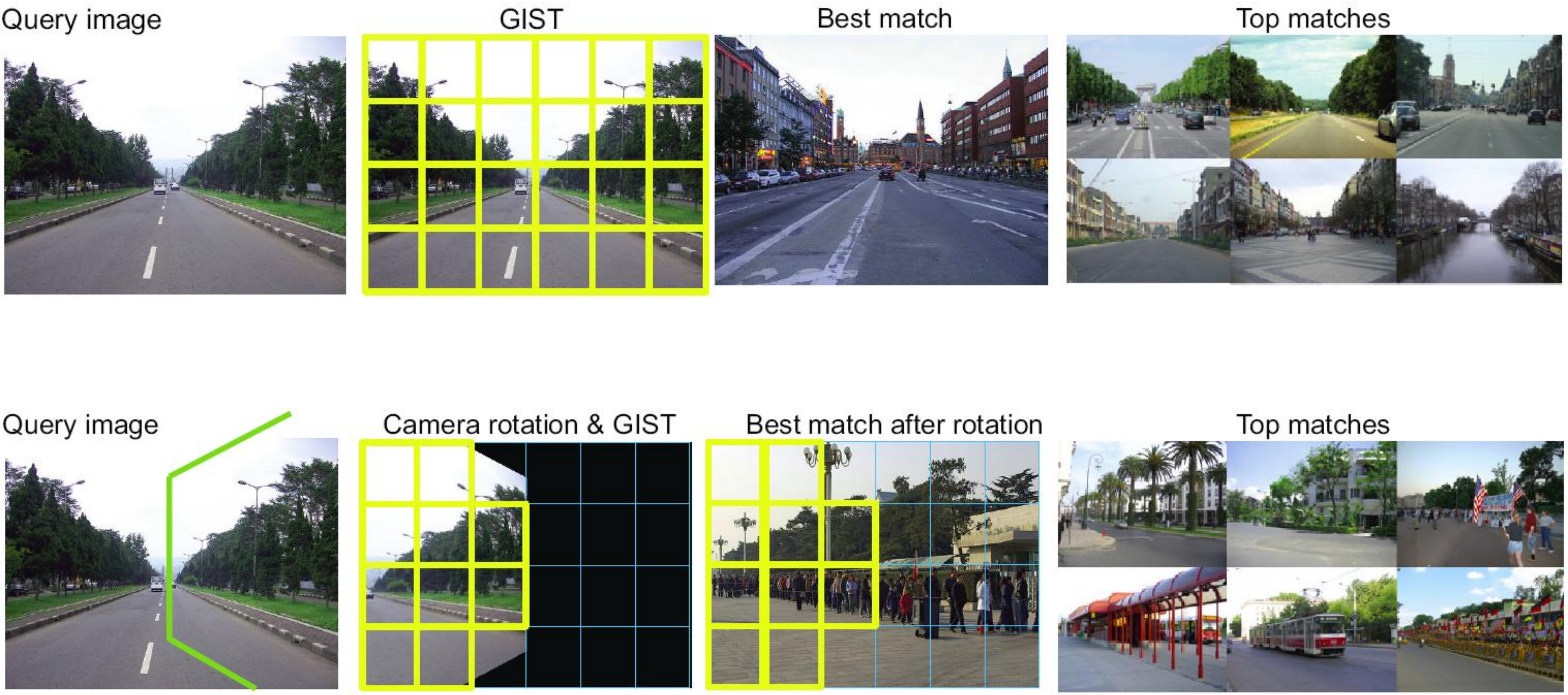
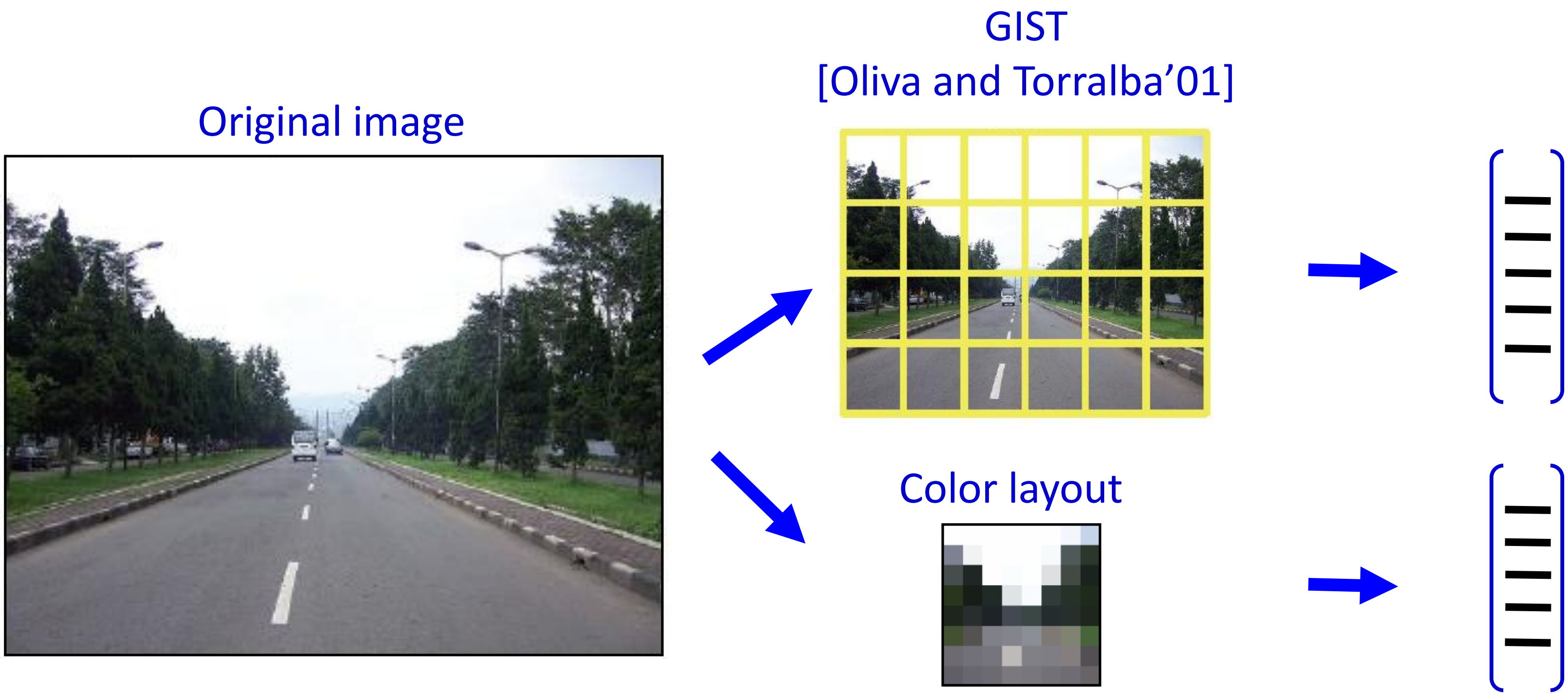
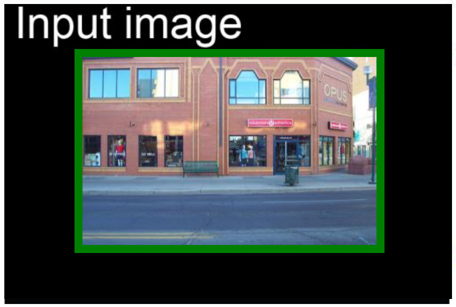


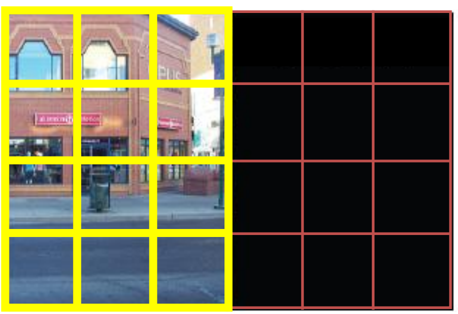
Image representation



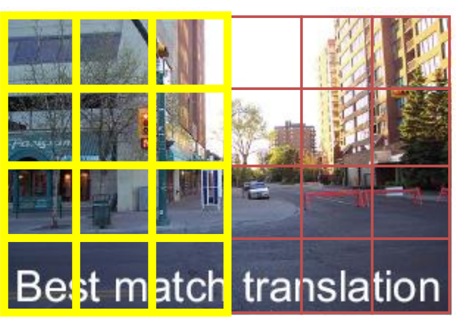
Scene matching with camera view transformations: Translation



1. Move camera



2. View from the virtual camera



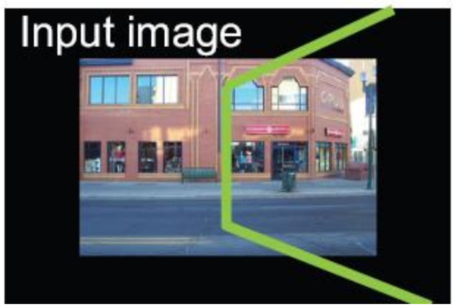
3. Find a match to fill the missing pixels

4. Locally align images

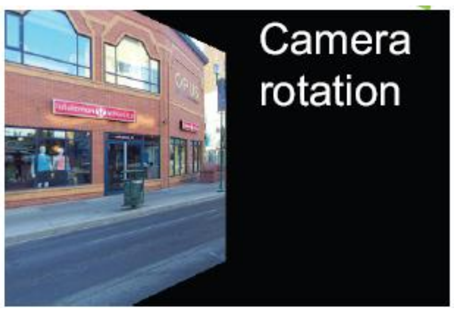
5. Find a seam

6. Blend in the gradient domain

Scene matching with camera view transformations: Camera rotation



1. Rotate camera



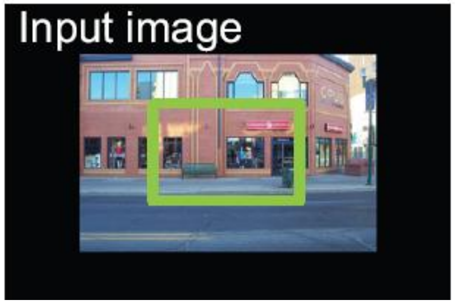
2. View from the virtual camera

3. Find a match to fill-in the missing pixels

4. Stitched rotation

5. Display on a cylinder

Scene matching with camera view transformations: Forward motion



1. Move camera

2. View from the virtual camera

3. Find a match to replace pixels

Tour from a single image

Navigate the virtual space using intuitive motion controls

Video

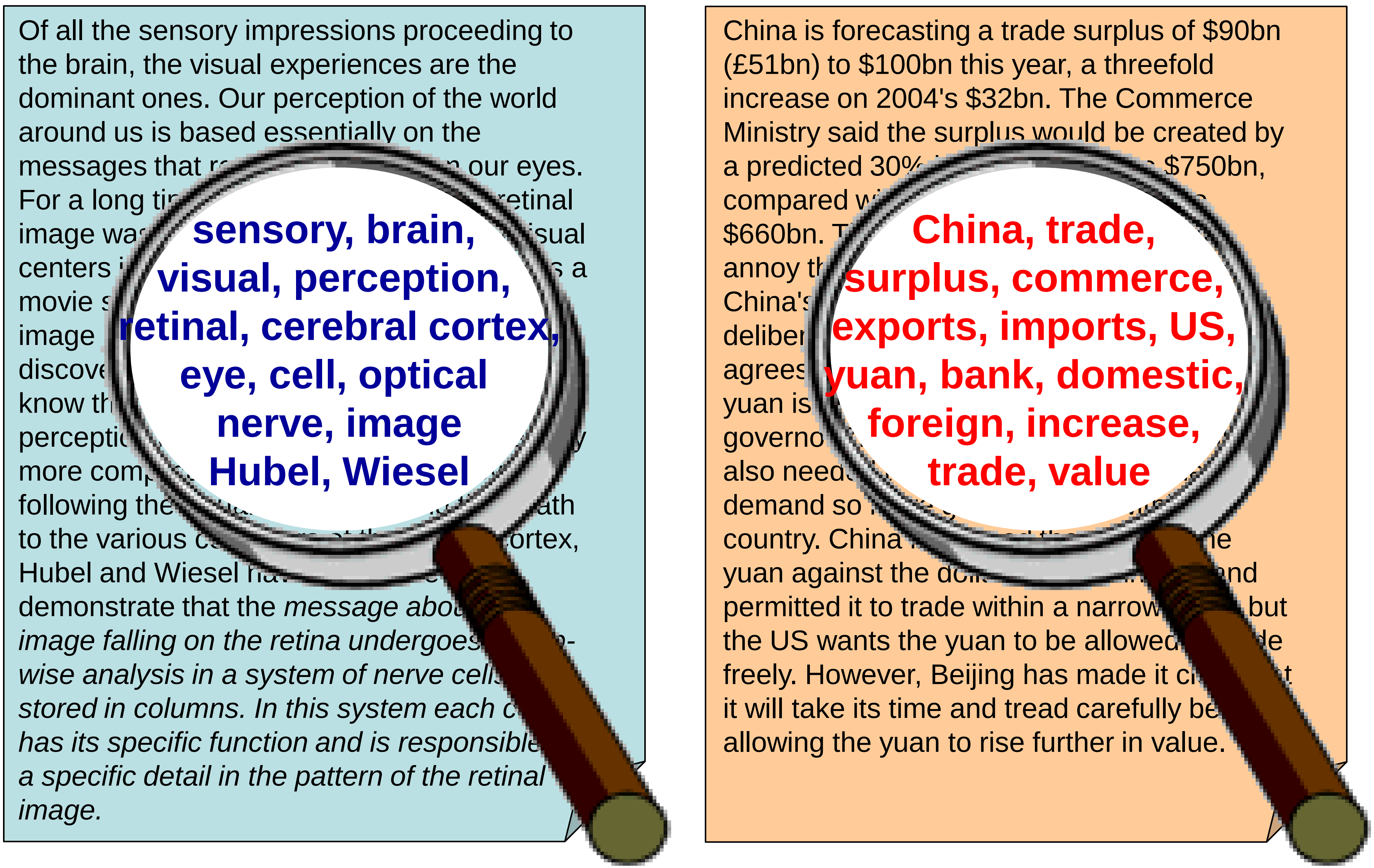
http://www.youtube.com/watch?v=E0rboU10rPo

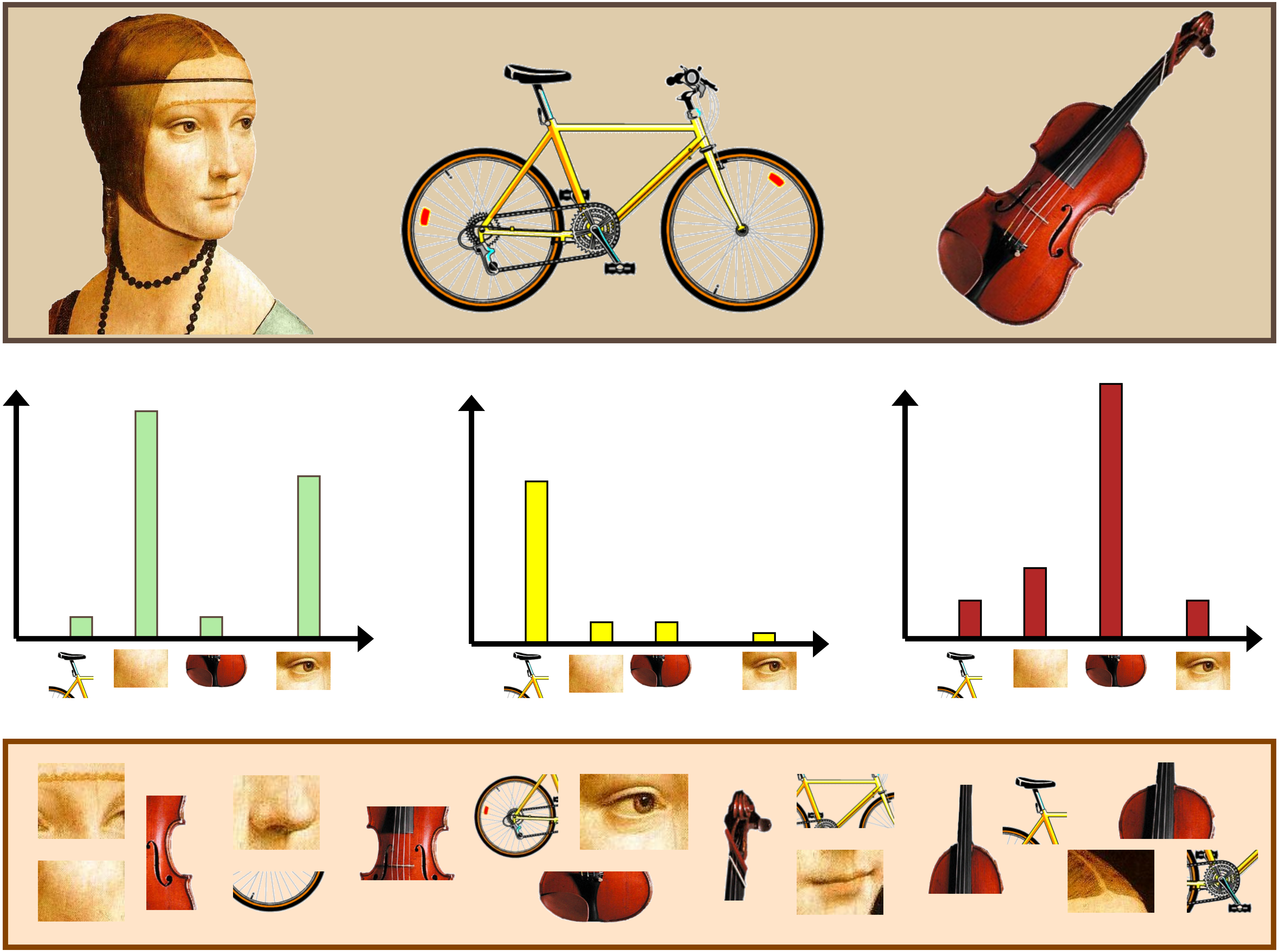
Comparing Images

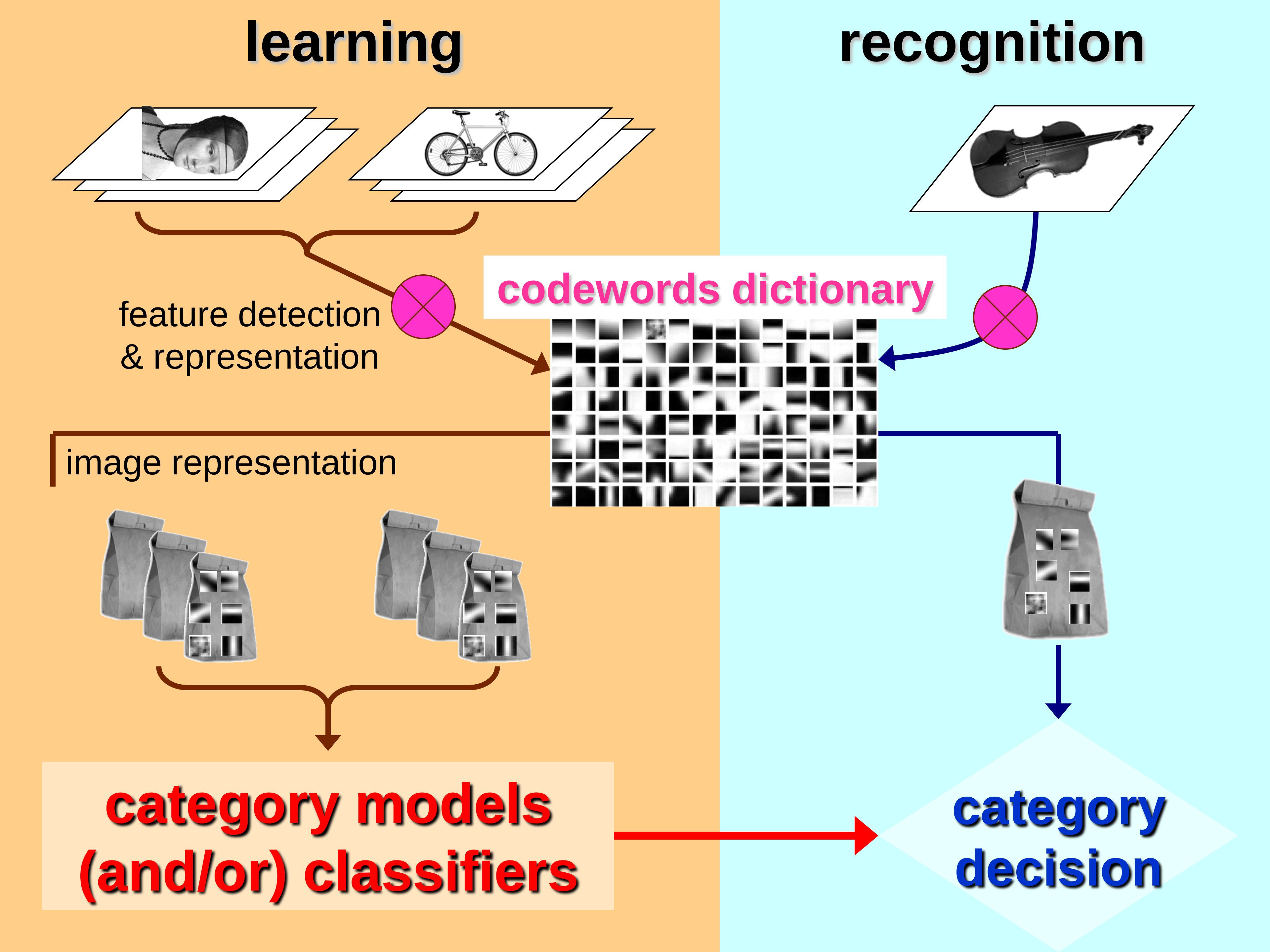
- (Blurred) SSD
- Color / Texture Histograms
- Spatial Histograms (GIST, etc)
- Bag of “Visual Words”

Object → **Bag of ‘words’**

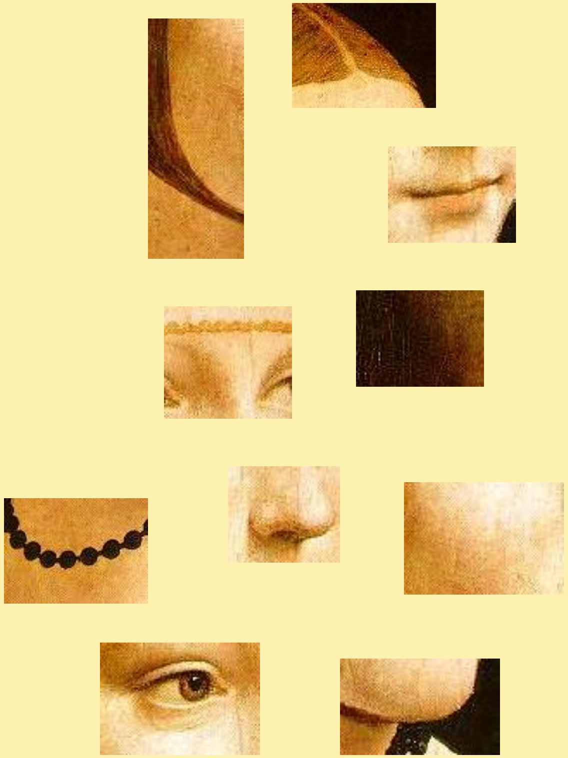
Analogy to documents






learning
recognition
feature detection
& representation
codewords dictionary
image representation
category models
(and/or) classifiers
category
decision

1.Feature detection and representation

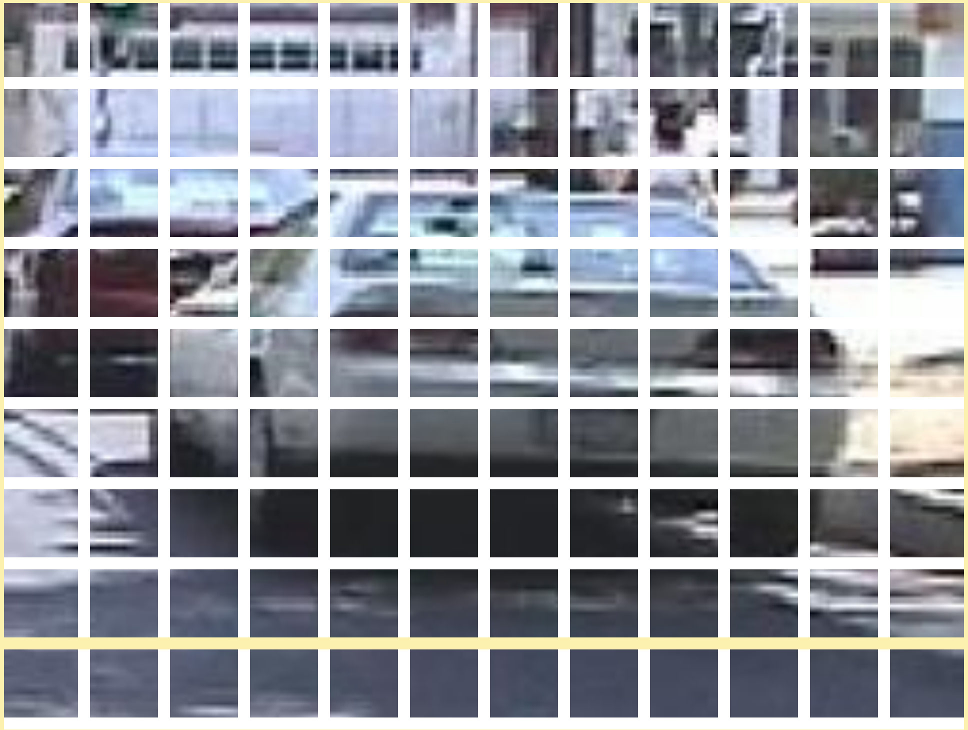


Feature detection

- Sliding Window
  - Leung et al, 1999
  - Viola et al, 1999
  - Renninger et al 2002

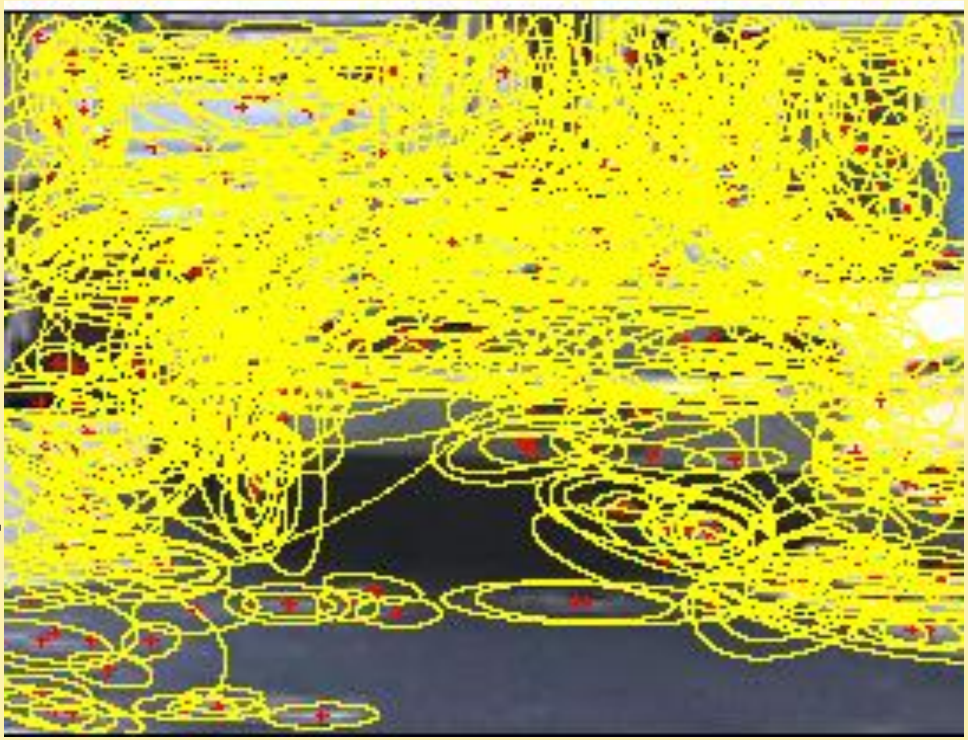
Feature detection

- Sliding Window
  - Leung et al, 1999
  - Viola et al, 1999
  - Renninger et al 2002
- Regular grid
  - Vogel et al. 2003
  - Fei-Fei et al. 2005



Feature detection

- Sliding Window
  - Leung et al, 1999
  - Viola et al, 1999
  - Renninger et al 2002
- Regular grid
  - Vogel et al. 2003
  - Fei-Fei et al. 2005
- Interest point detector
  - Csurka et al. 2004
  - Fei-Fei et al. 2005
  - Sivic et al. 2005



Feature detection

- Sliding Window
  - Leung et al, 1999
  - Viola et al, 1999
  - Renninger et al 2002
- Regular grid
  - Vogel et al. 2003
  - Fei-Fei et al. 2005
- Interest point detector
  - Csurka et al. 2004
  - Fei-Fei et al. 2005
  - Sivic et al. 2005
- Other methods
  - Random sampling (Ullman et al. 2002)
  - Segmentation based patches
    - Barnard et al. 2003, Russell et al 2006, etc.)

Feature Representation

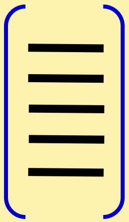
Visual words, aka textons, aka keypoints:

K-means clustered pieces of the image

- Various Representations:
  - Filter bank responses
  - Image Patches
  - SIFT descriptors

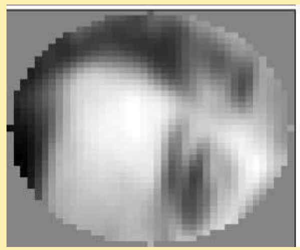
All encode more-or-less the same thing…

Interest Point Features

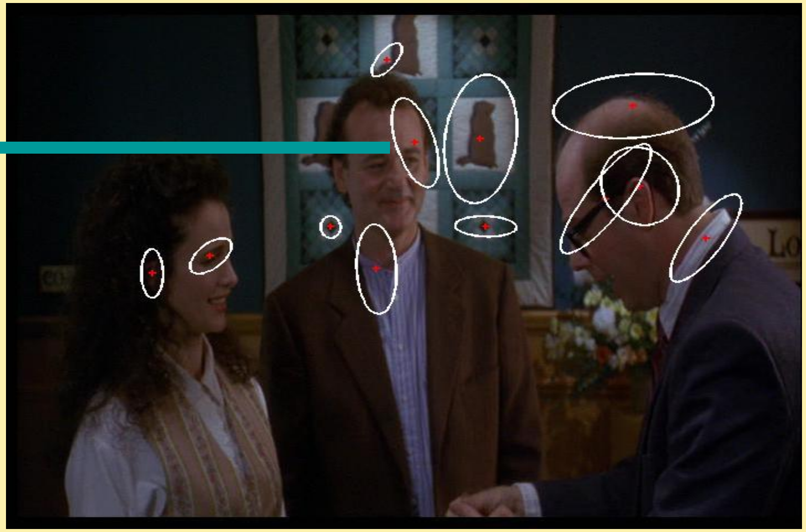


Compute SIFT descriptor

[Lowe'99]



Normalize patch



Detect patches

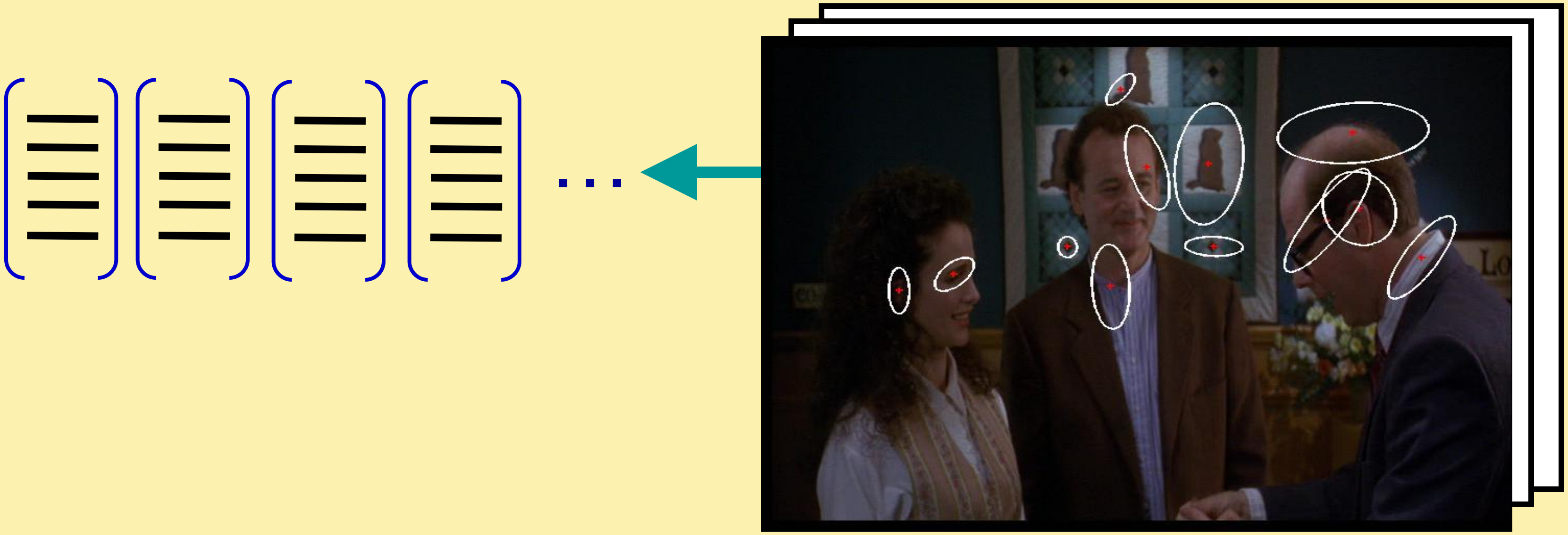
[Mikojaczyk and Schmid '02]

[Matas et al. '02]

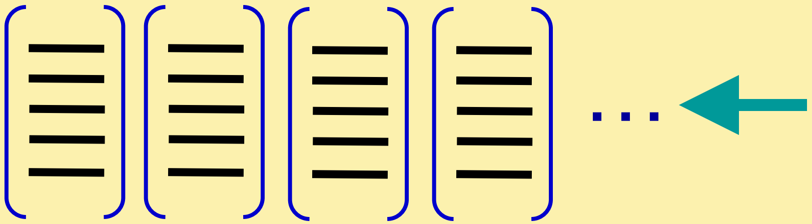
[Sivic et al. '03]

Slide credit: Josef Sivic

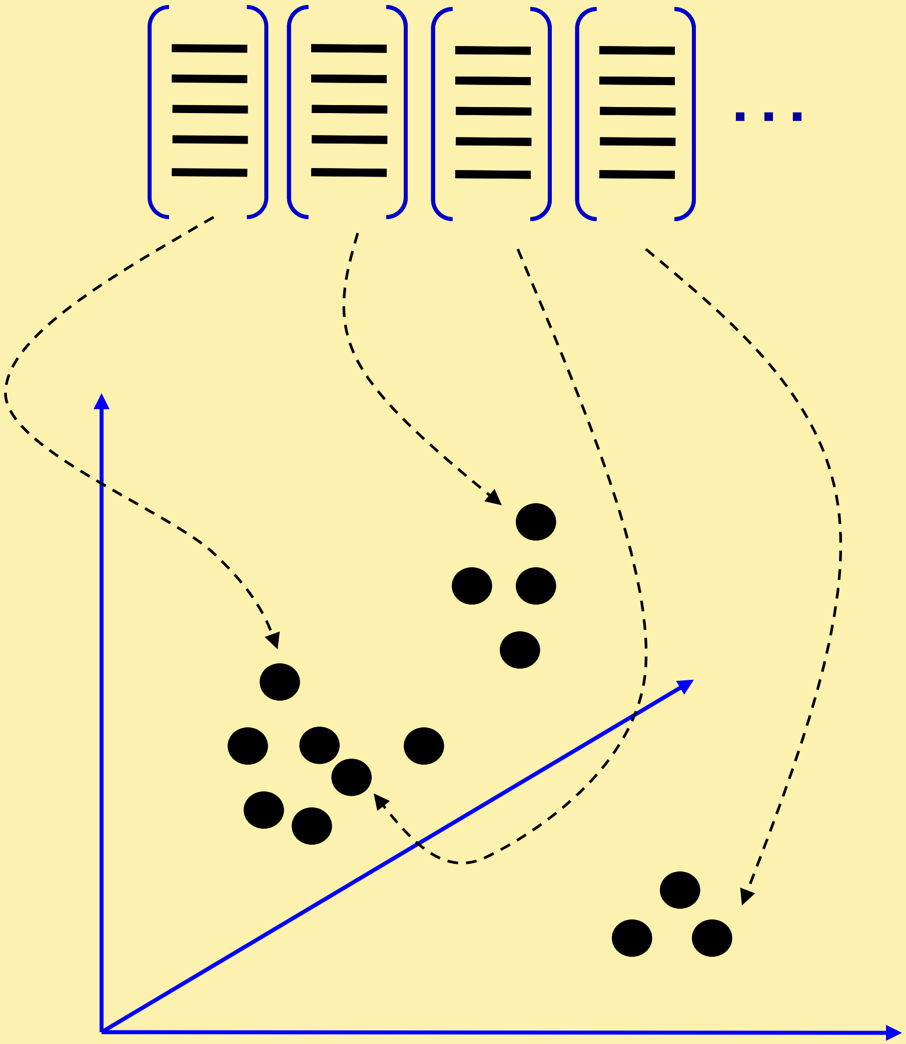
Interest Point Features



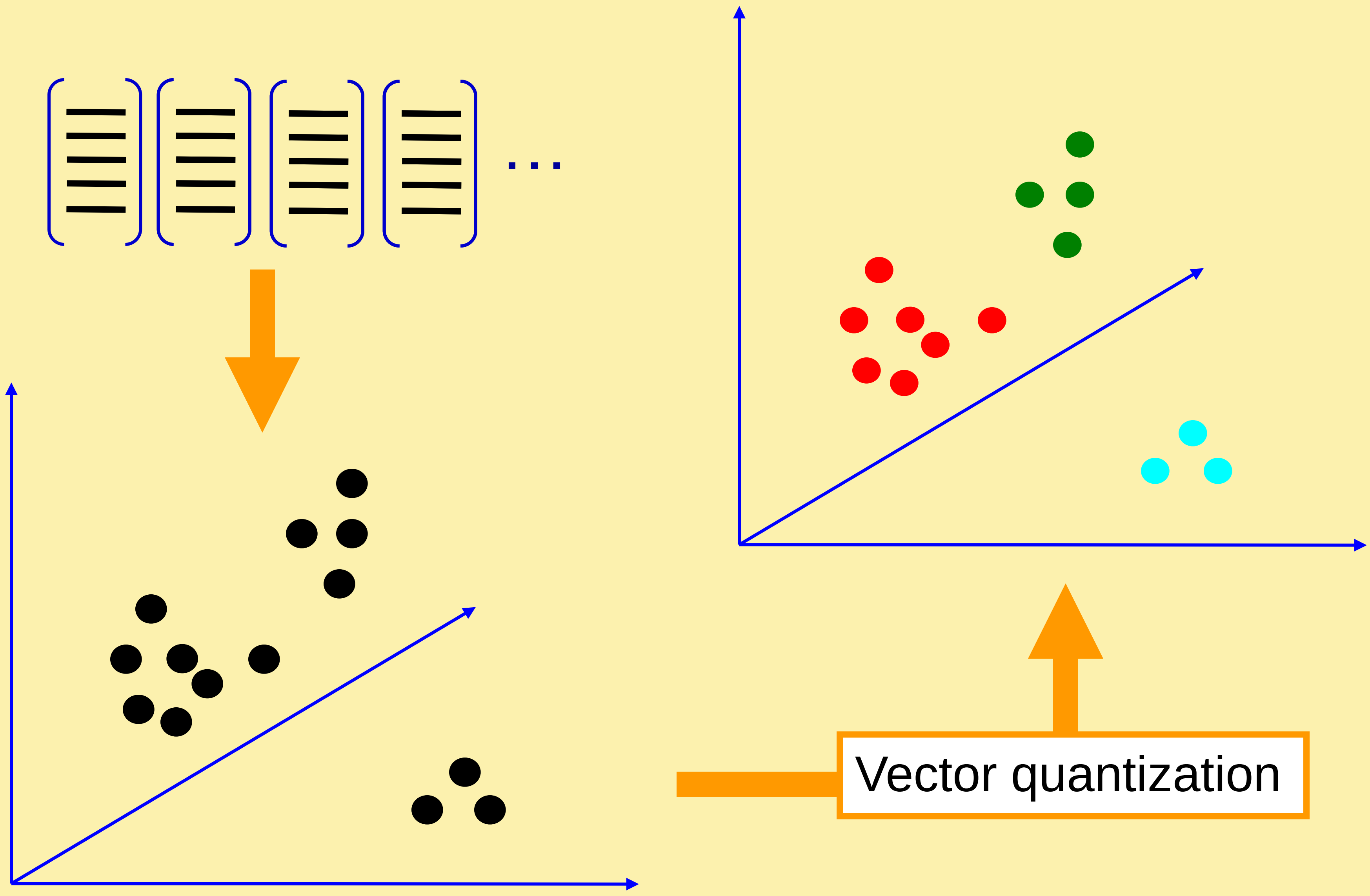
Patch Features



dictionary formation

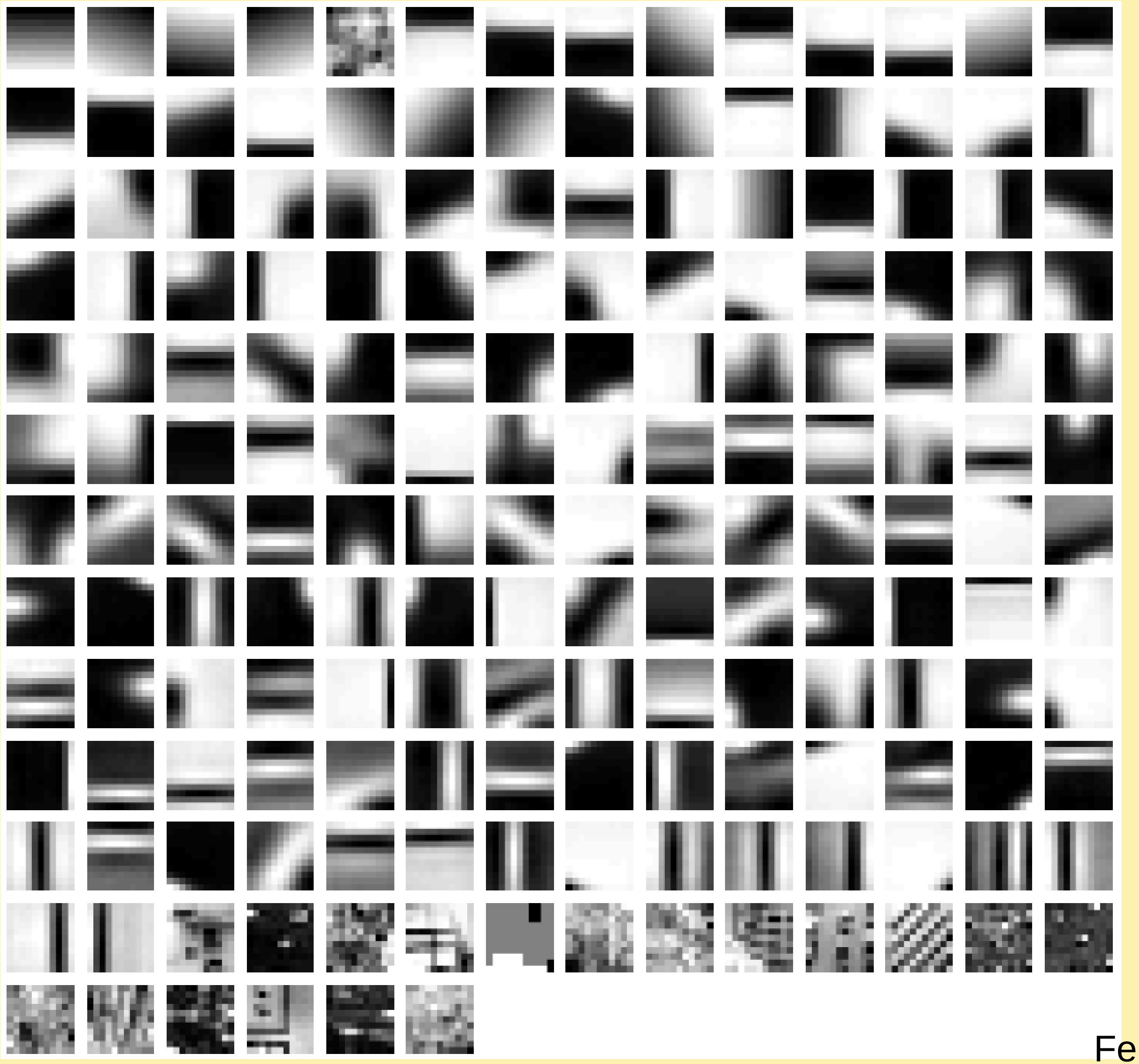


Clustering (usually k-means)



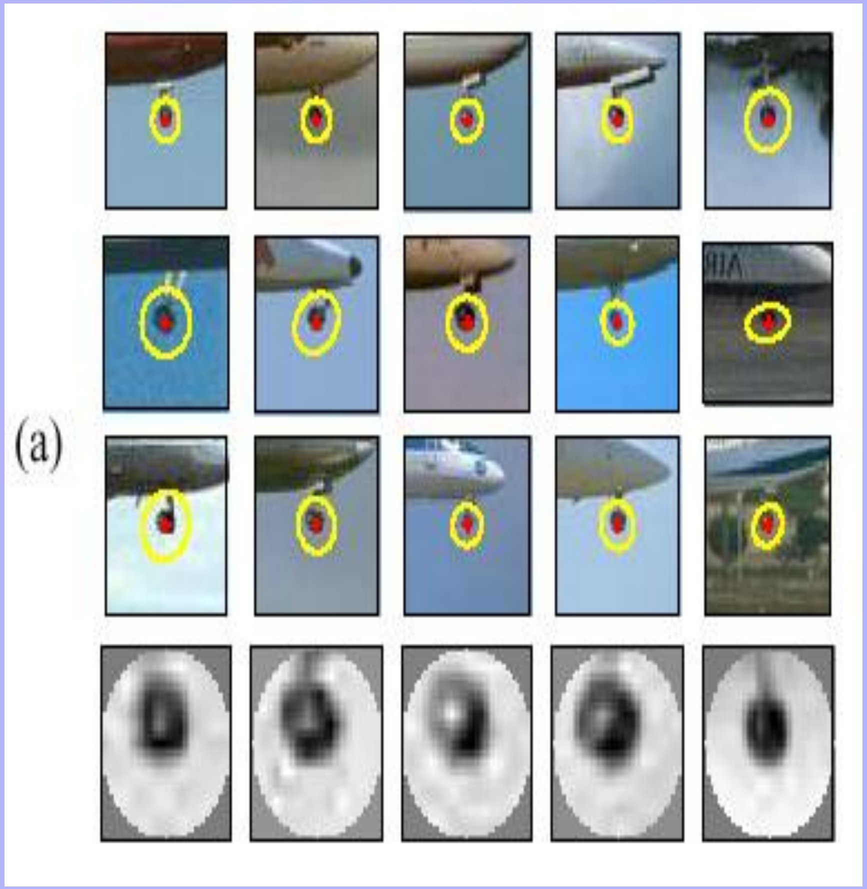
Slide credit: Josef Sivic

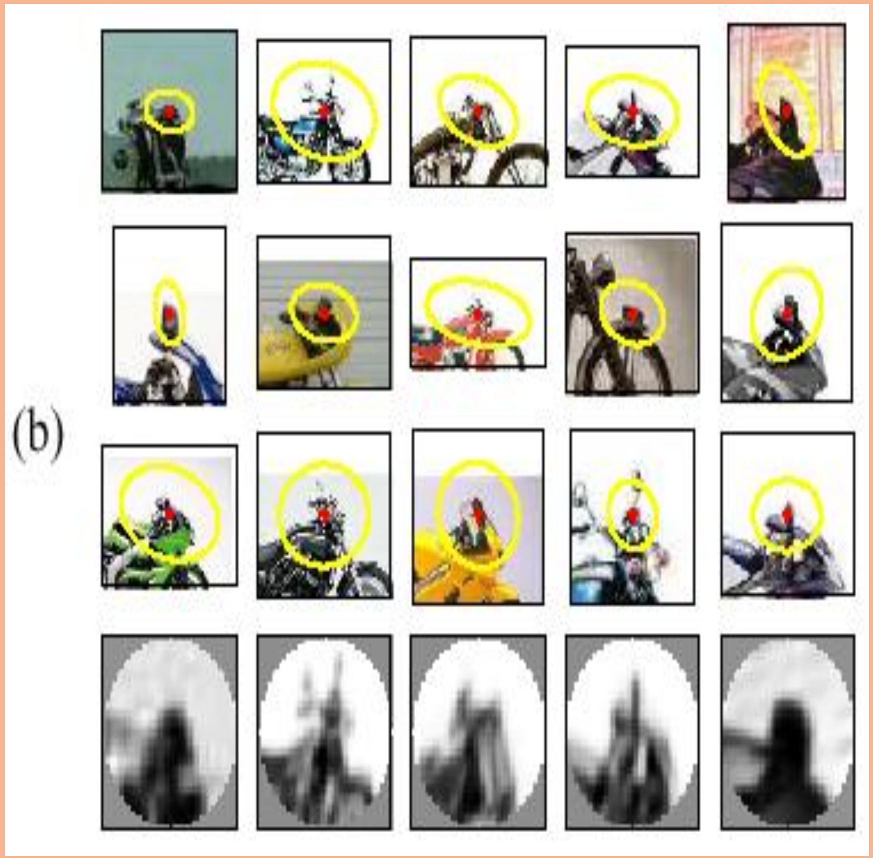
Clustered Image Patches



Fei-Fei et al. 2005

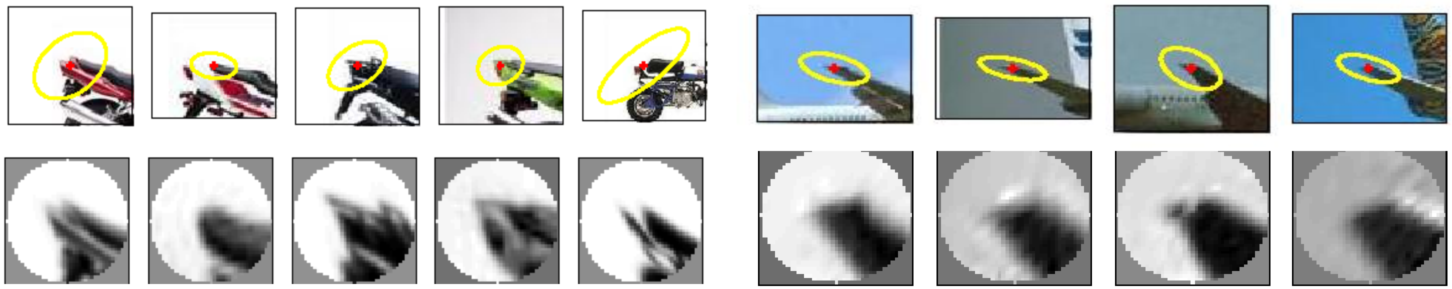
Image patch examples of codewords



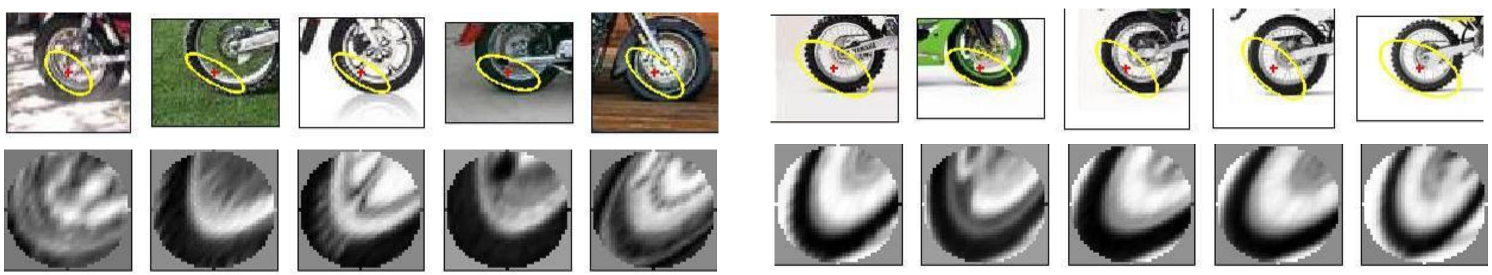


Sivic et al. 2005

Visual synonyms and polysemy

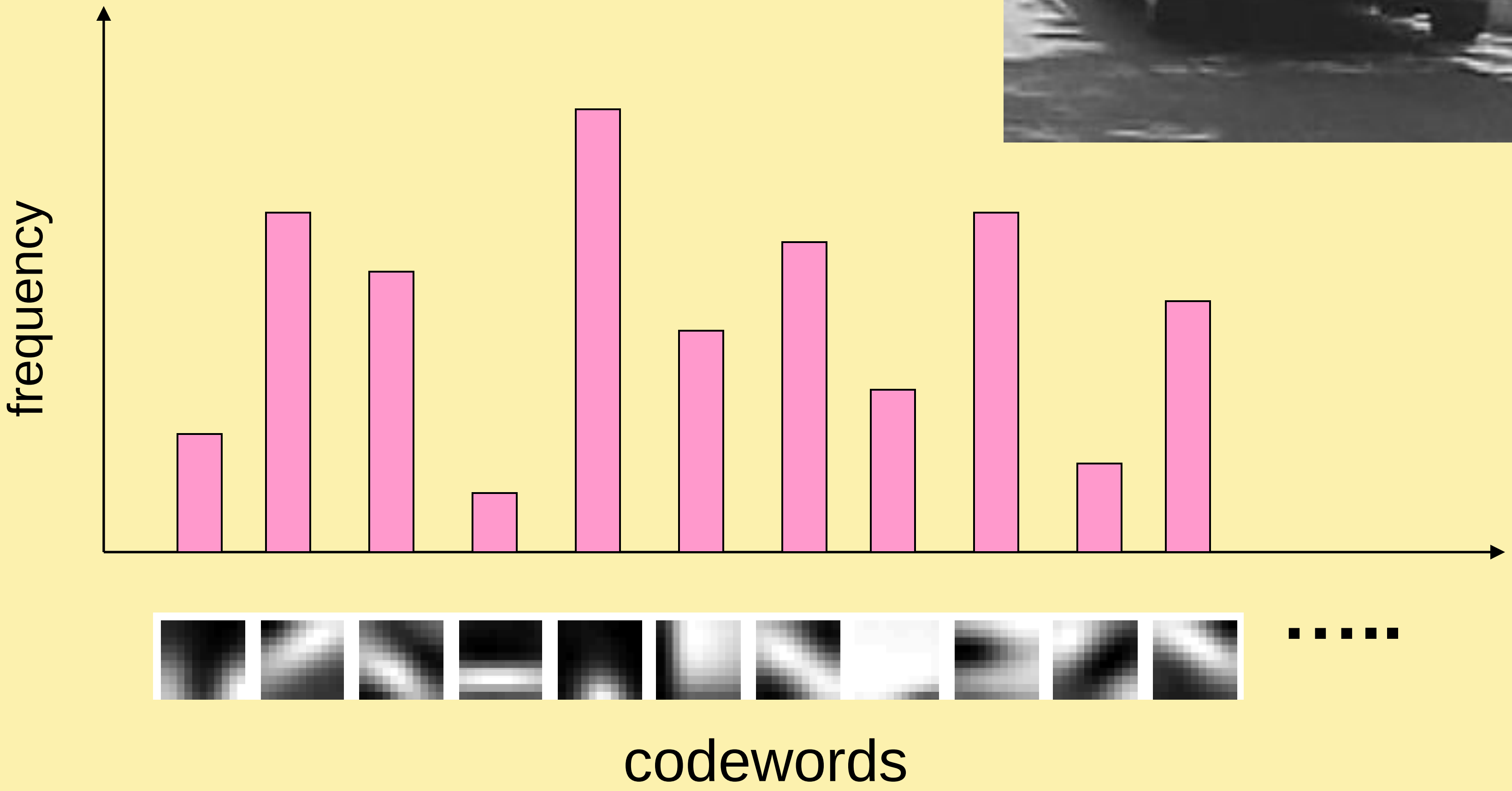


Visual Polysemy. Single visual word occurring on different (but locally similar) parts on different object categories.



Visual Synonyms. Two different visual words representing a similar part of an object (wheel of a motorbike).

Image representation



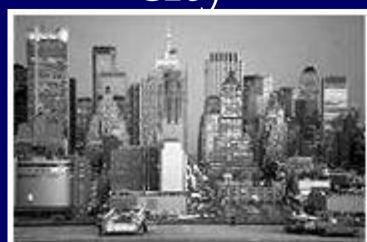
Scene Classification (Renninger & Malik)

beach

mountain

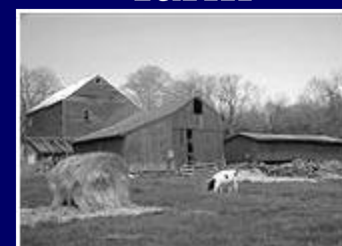
forest

city



street

farm



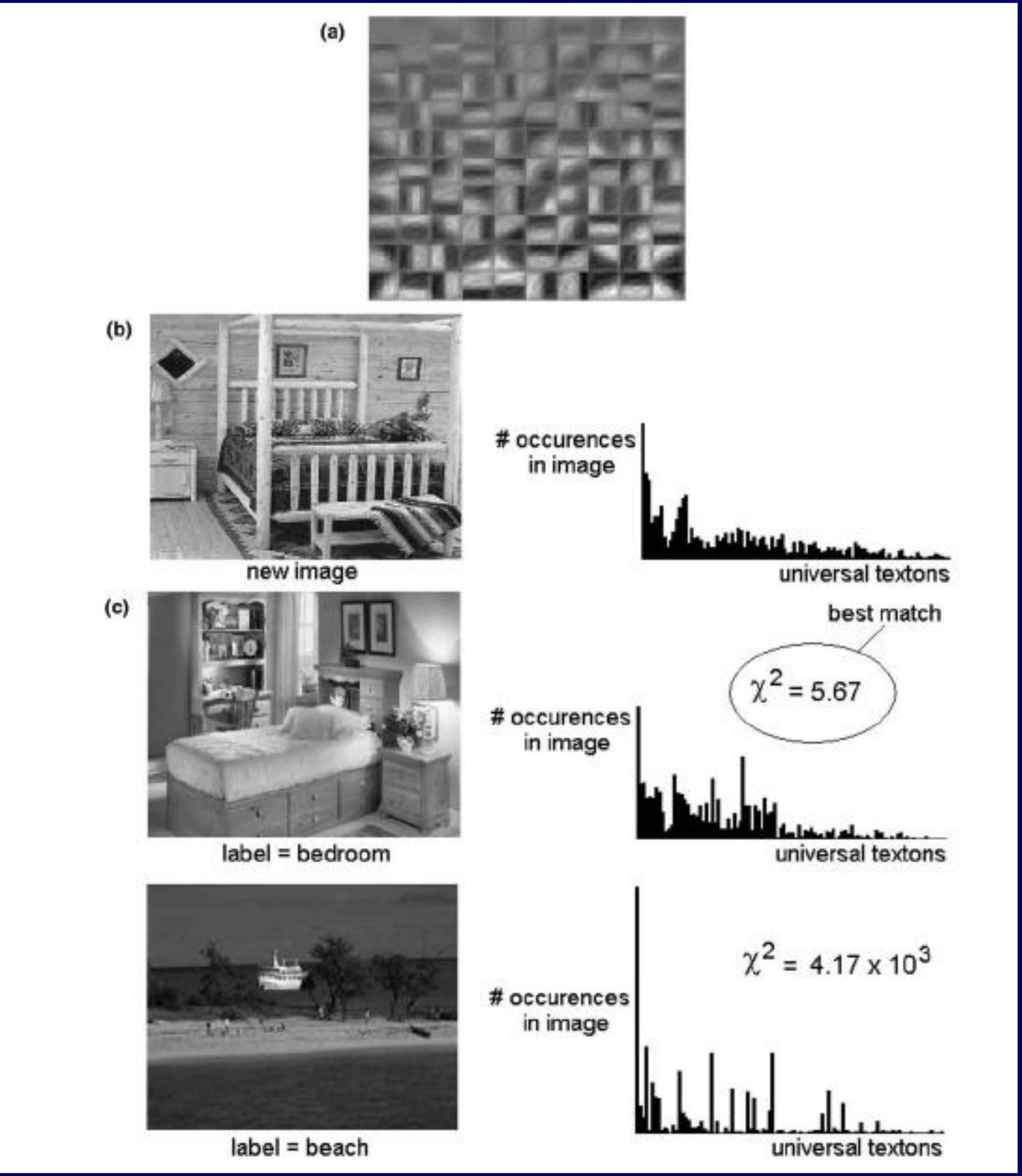
kitchen

livingroom

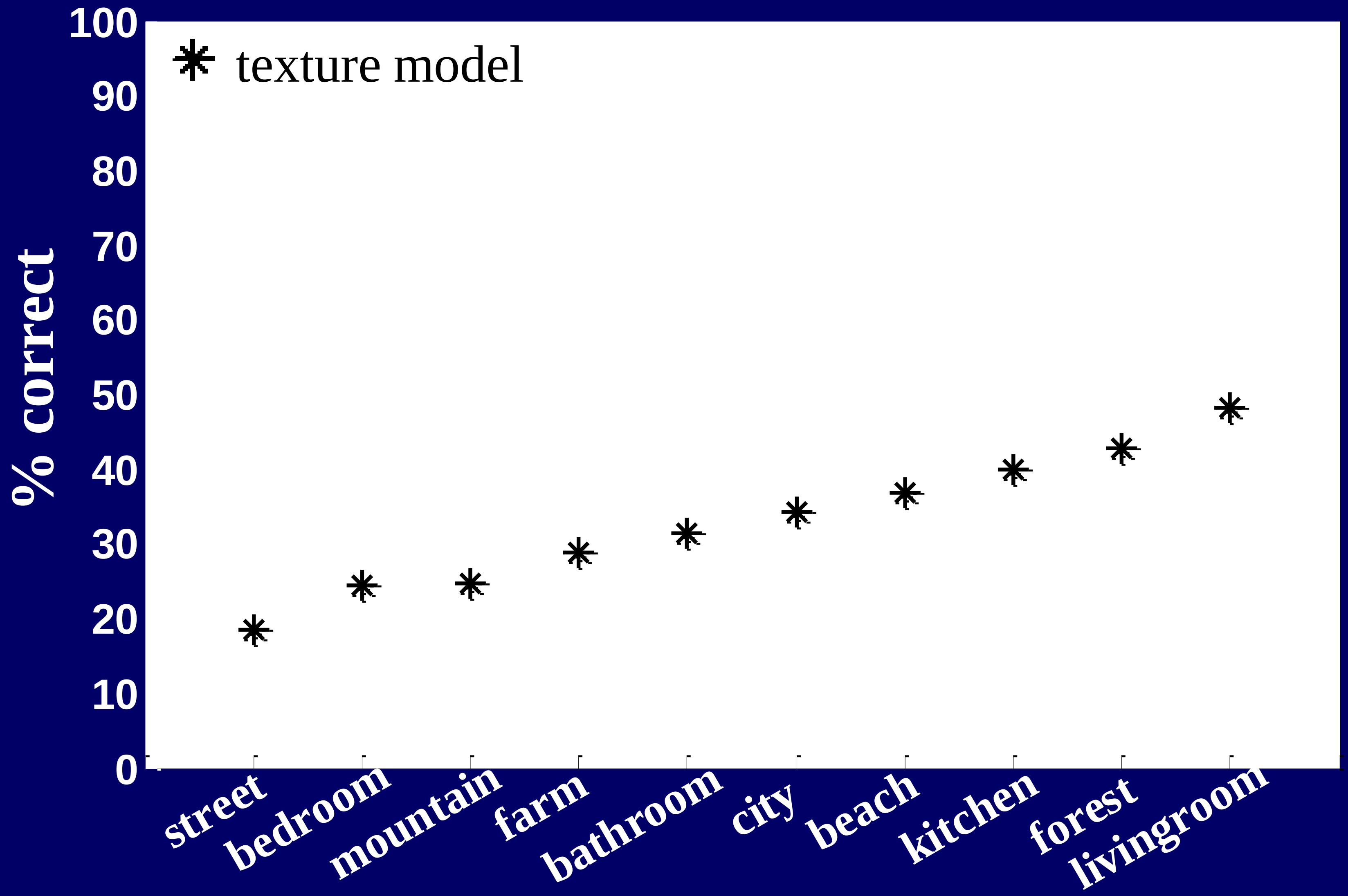
bedroom

bathroom

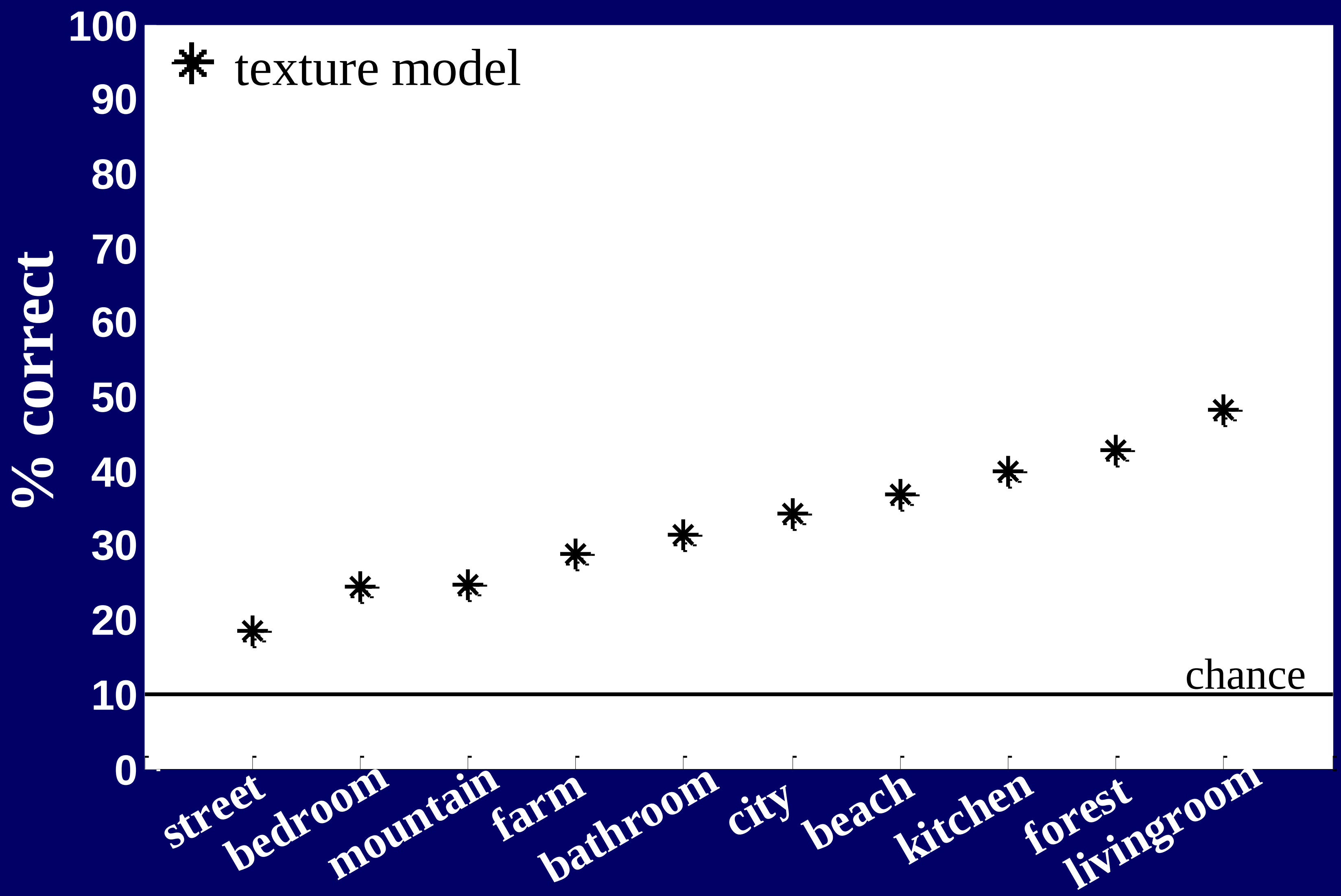
kNN Texton Matching



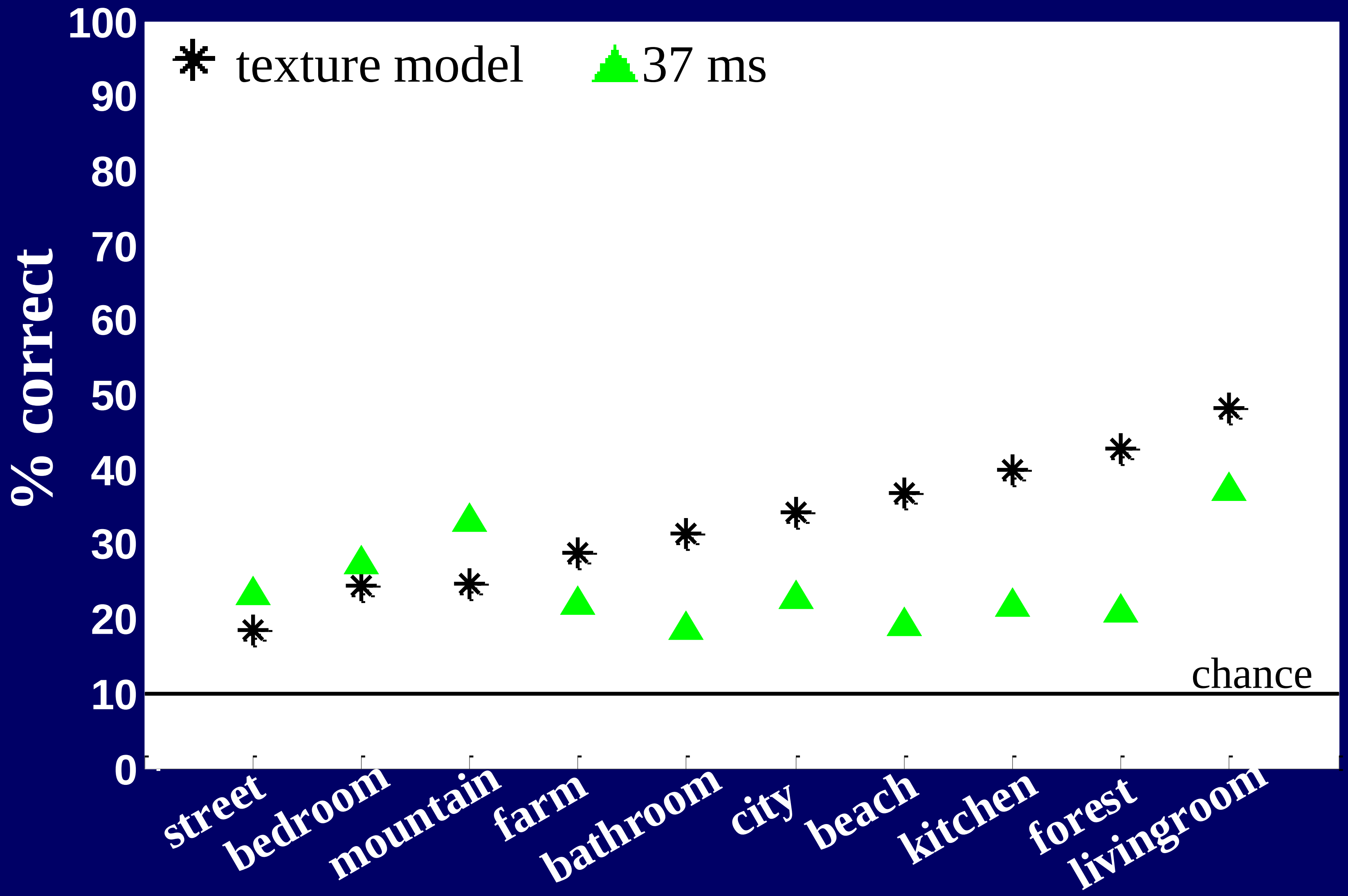
Discrimination of Basic Categories



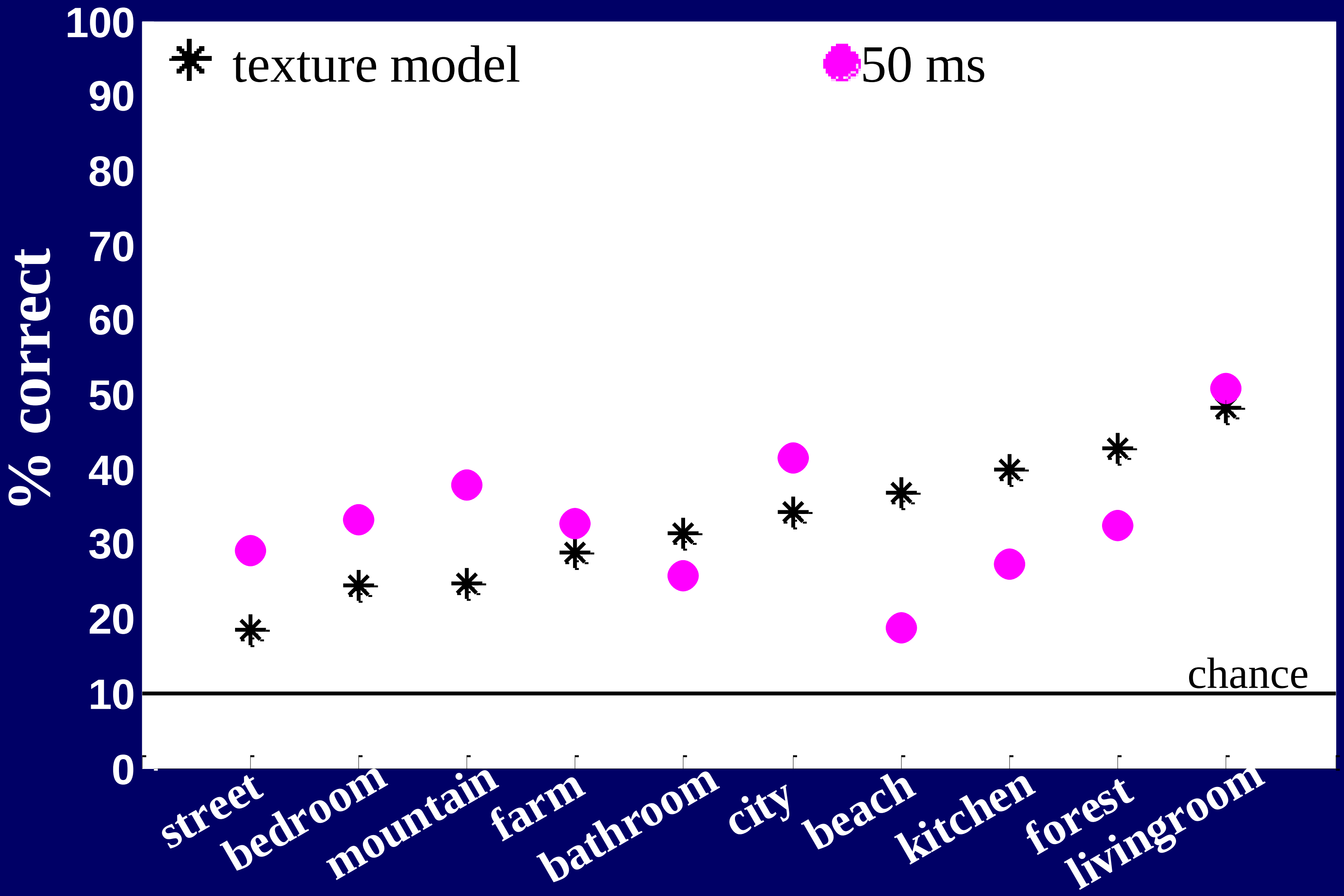
Discrimination of Basic Categories



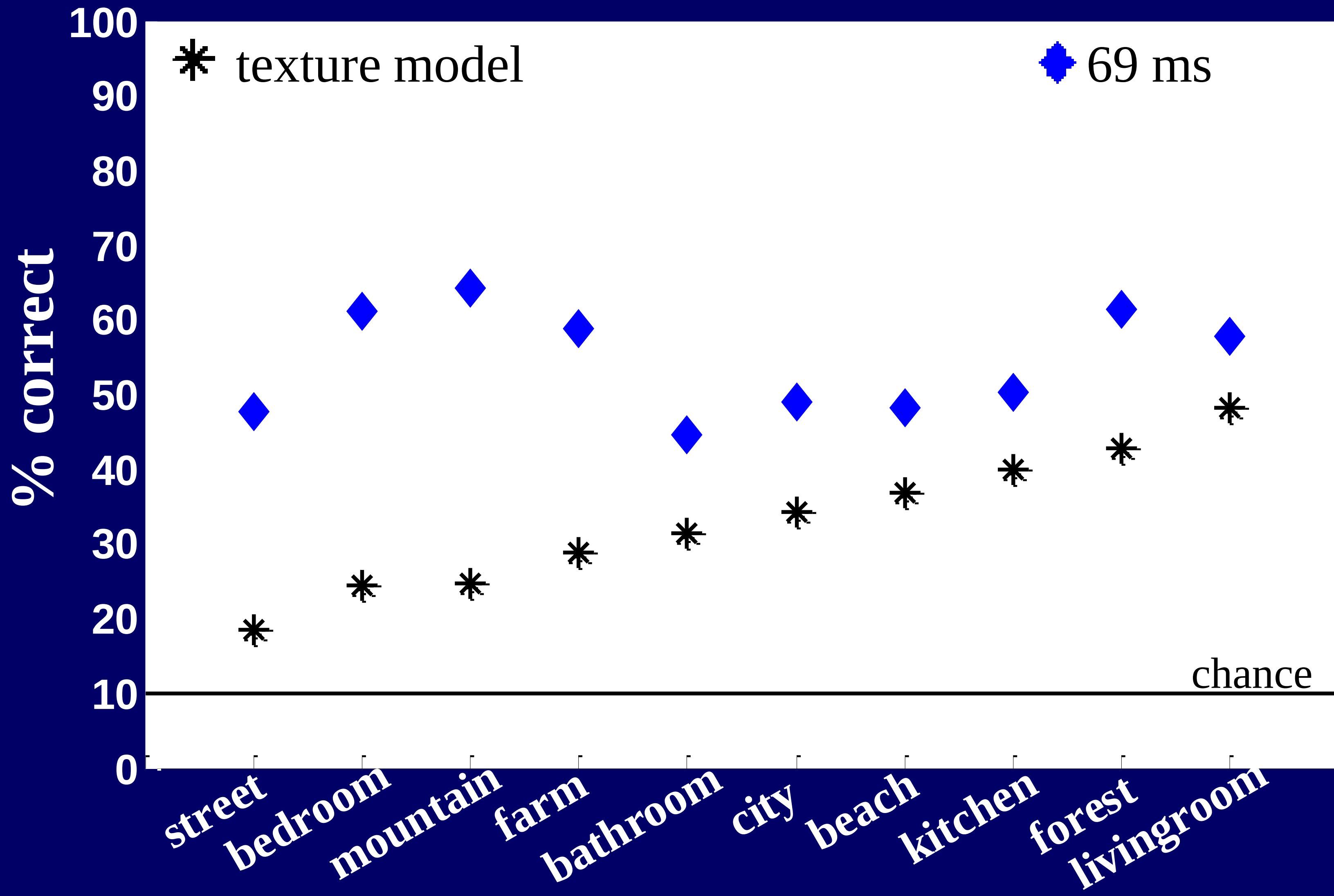
Discrimination of Basic Categories



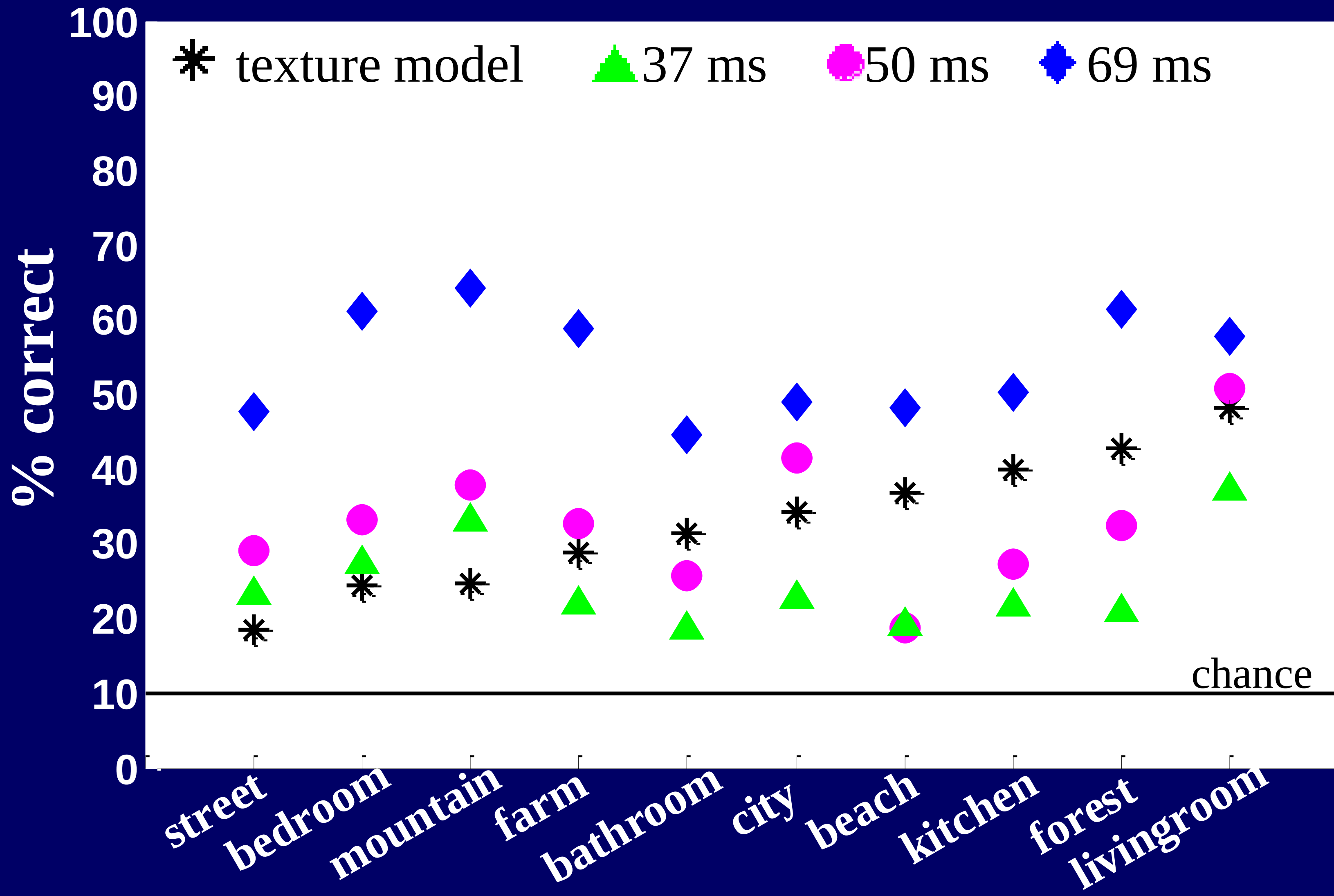
Discrimination of Basic Categories



Discrimination of Basic Categories



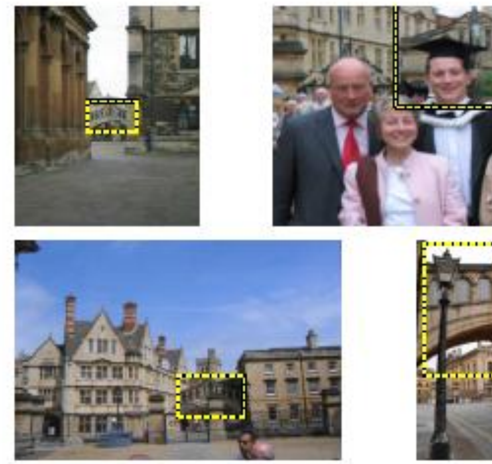
Discrimination of Basic Categories



Video Google / Total Recall

query

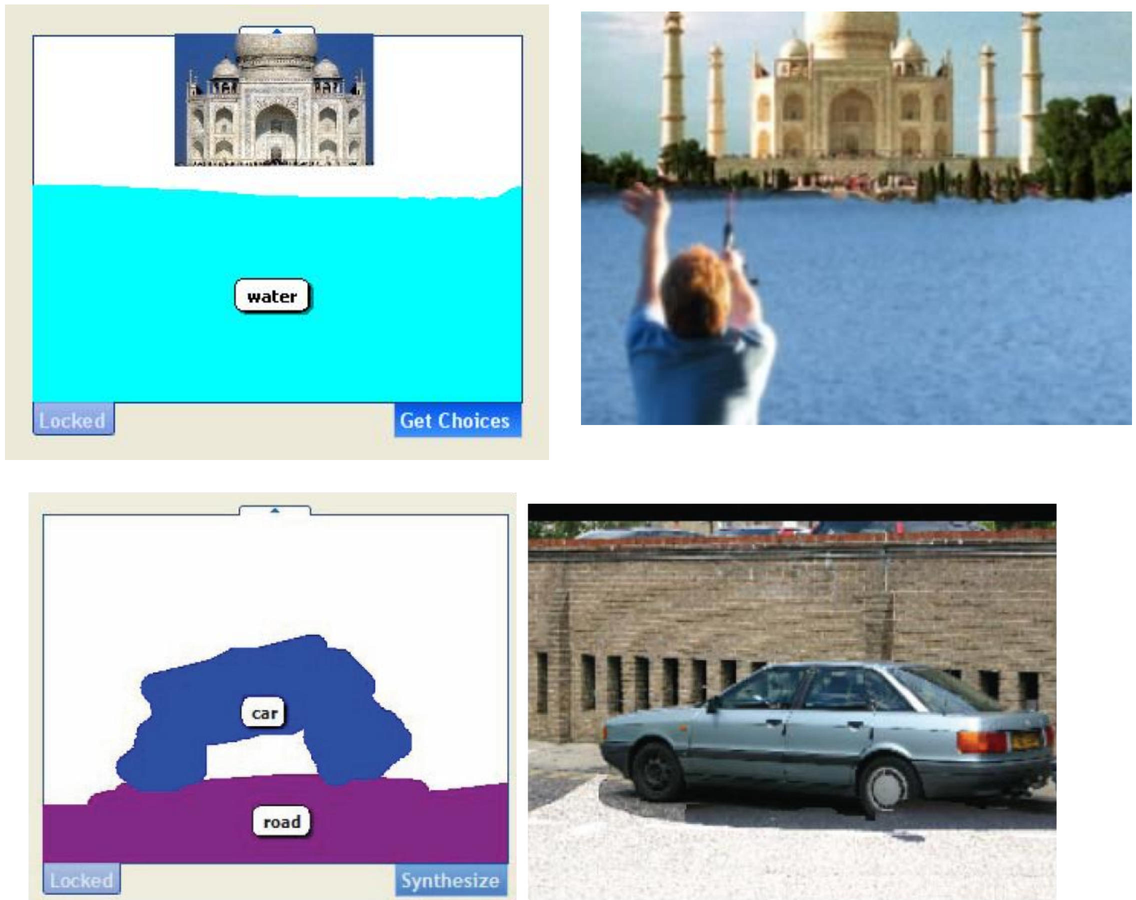
Video Google
[Sivic et al]



Total Recall
[Philbin et al]

Using Data for Graphics…

Semantic Photo Synthesis [EG'06]



Johnson, Brostow, Shotton, Arandjelovic, Kwatra, and Cipolla. Eurographics 2006.

Photo Clip Art [SG'07]

Inserting a single object -- still very hard!

- object size, orientation
- scene illumination

Lalonde et al, SIGGRAPH 2007

Photo Clip Art [SG'07]

Use database to find well-fitting object

Lalonde et al, SIGGRAPH 2007

Face Swapping [SG'08]

Original photographs

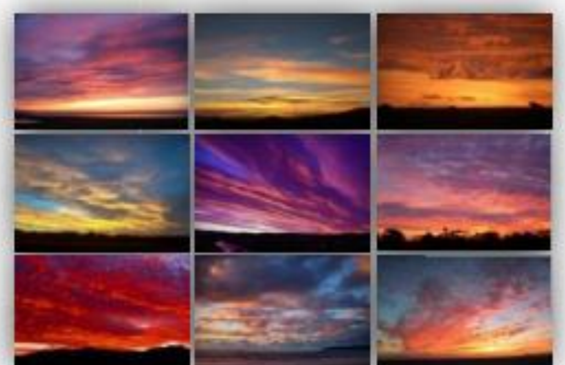
D. Bitouk, N. Kumar, S. Dhillon, P. N. Belhumeur, and S. K. Nayar, SIGGRAPH'08

SkyFinder [SG'09]

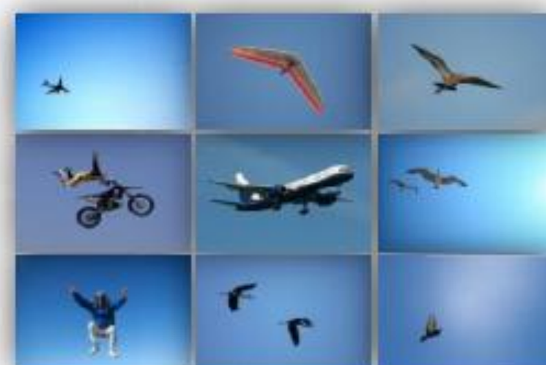
(a) *blue + normal-sky + horizon + R3*

(b) *cloudy + normal-sky + horizon + R5*

(c) *sunset + landscape + horizon + sun*



(e) *sunset + landscape + horizon + R5*



(f) *blue + object-in-sky + R1*

(g) *cloudy + full-sky + R5*

Tao, Yuan, Sun, SIGGRAPH 2009

Webcam Clip Art [SG Asia'09]

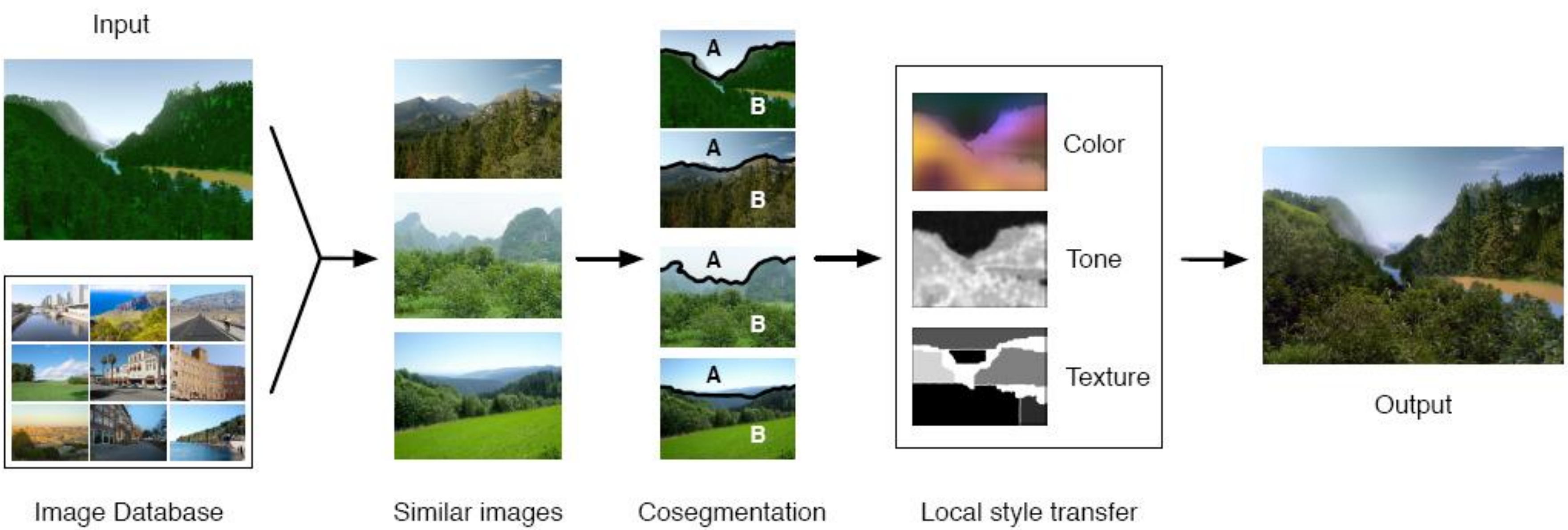
(a) source webcam (b) target webcam (c) transfer results

Object transfer

illuminant transfer

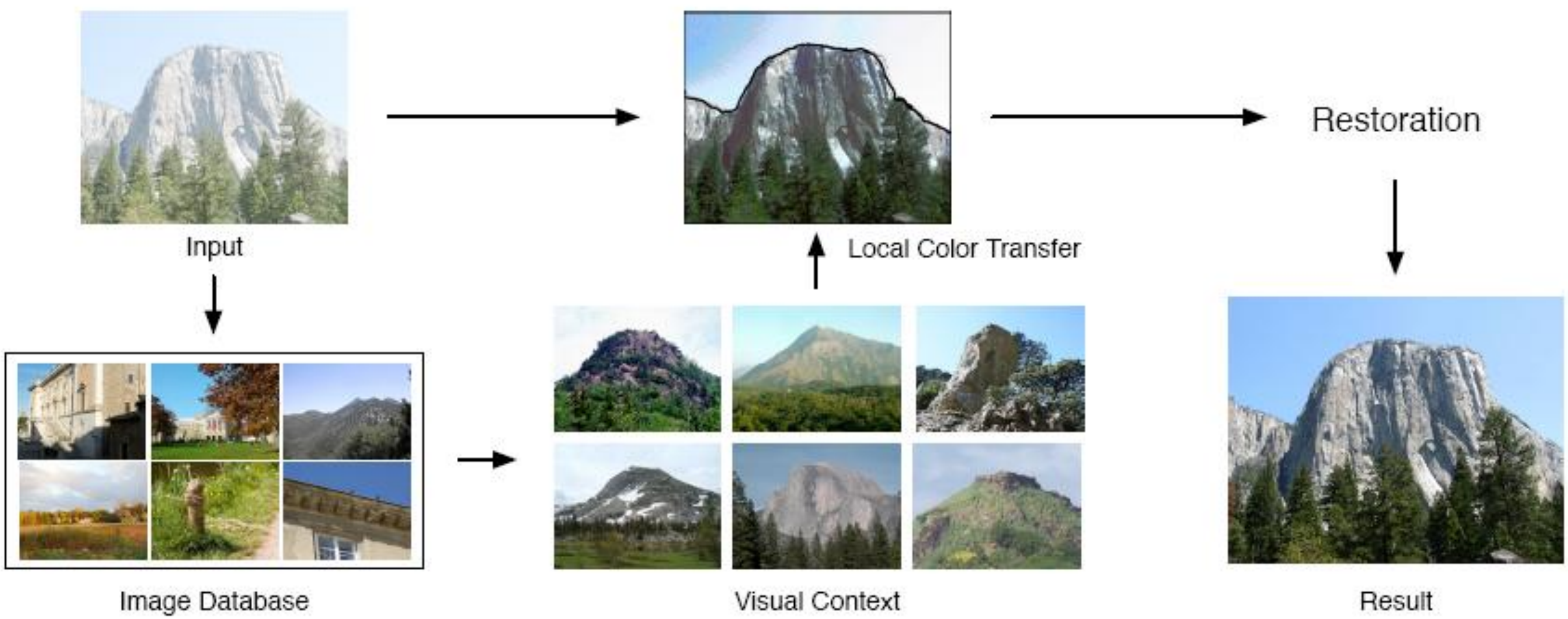
Lalonde et al, SIGGRAPH Asia 2009

CG2Real



CG2Real: Improving the Realism of Computer Generated Images using a Large Collection of Photographs, Johnson, Dale, Avidan, Pfister, Freeman, Matusik, Tech. Rep. MIT-CSAIL-TR-2009-034

Image Restoration using Online Photo Collections [ICCV'09]



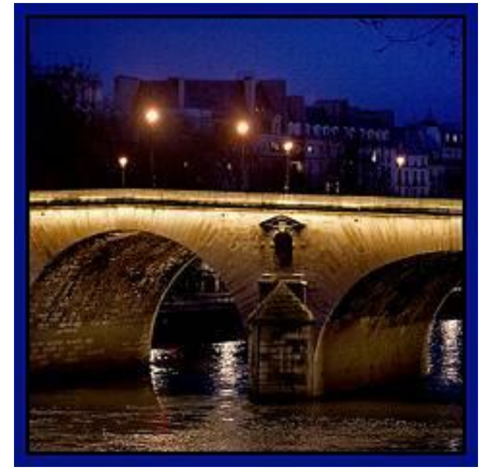
Dale, Johnson, Sunkavalli, Matusik, Pfister, ICCV'09

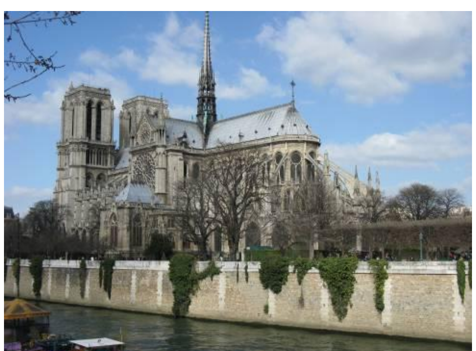
The Dangers of Data

Bias

- Internet is a tremendous repository of visual data (Flickr, YouTube, Picassa, etc)
- But it's <u>not</u> random samples of visual world
- Many sources of bias:
  - Sampling bias
  - Photographer bias
  - Social bias

Flickr Paris

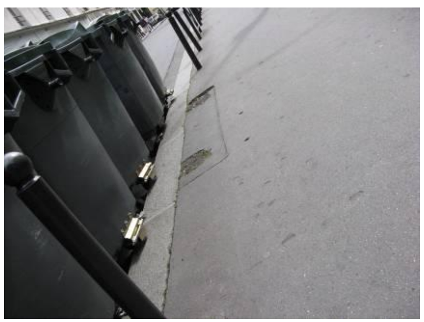


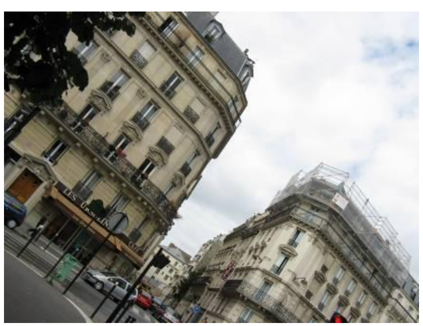


Real Paris

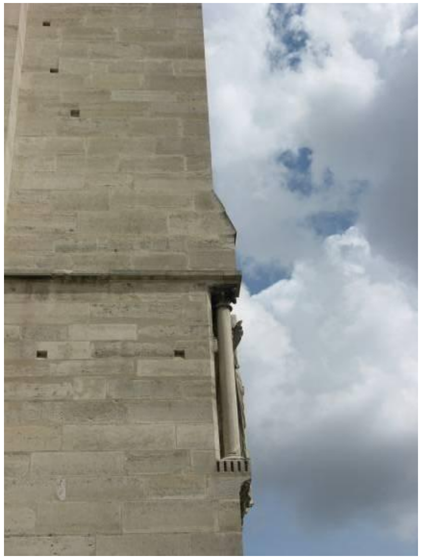







Real Notre Dame

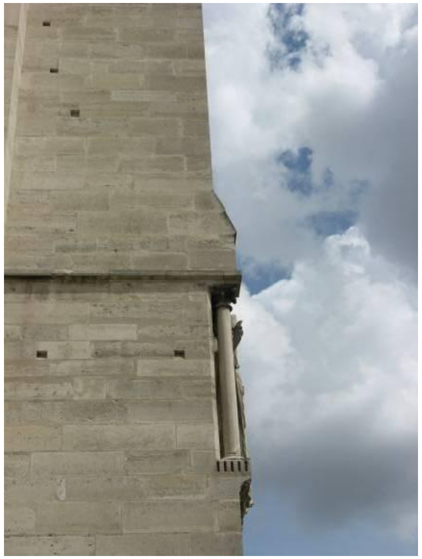


Sampling Bias

- People like to take pictures on vacation

Photographer Bias

- People want their pictures to be recognizable and/or interesting



vs.

Photographer Bias

- People follow photographic conventions

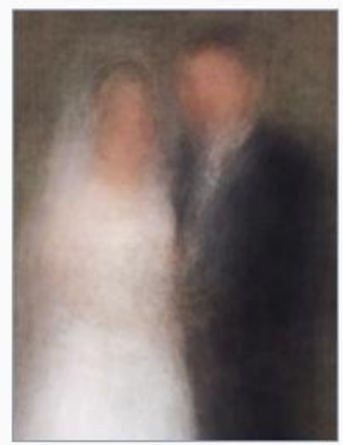
vs.

Social Bias

Little Leaguer

Kids with Santa

The Graduate

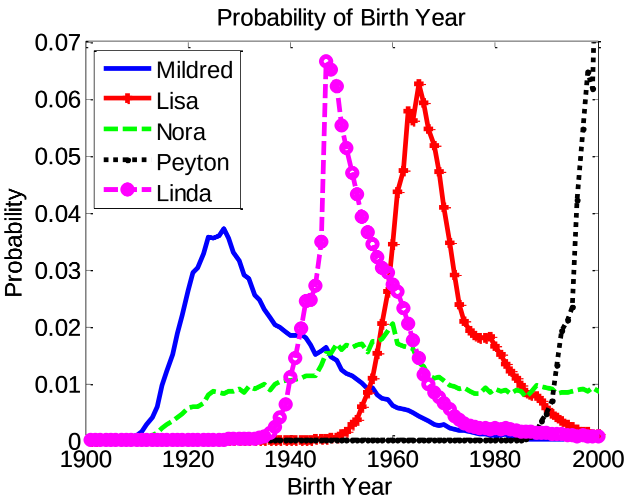


Newlyweds

“100 Special Moments” by Jason Salavon

Social Bias

Mildred and Lisa



Source: U.S. Social Security Administration

Gallagher et al CVPR 2008

Social Bias

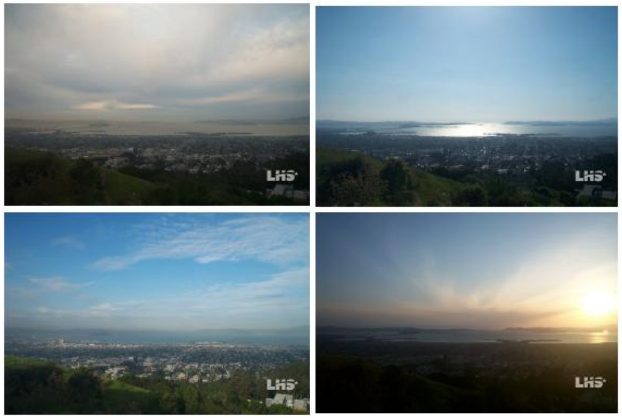
Gallagher et al CVPR 2008

Gallagher et al, CVPR 2009

Reducing / Changing Bias

Street side
Google StreetView

Satellite
google.com



Webcams

- Autonomous capture methods can reduce / change bias
  - But it won't go away completely
- Sometimes you can just pick your data to suit your problem, but not always…