Visual Data on the Internet

http://www.boingboing.net/2009/07/30/bb-video-send-me-a-l.html (starts at 2:40 min)

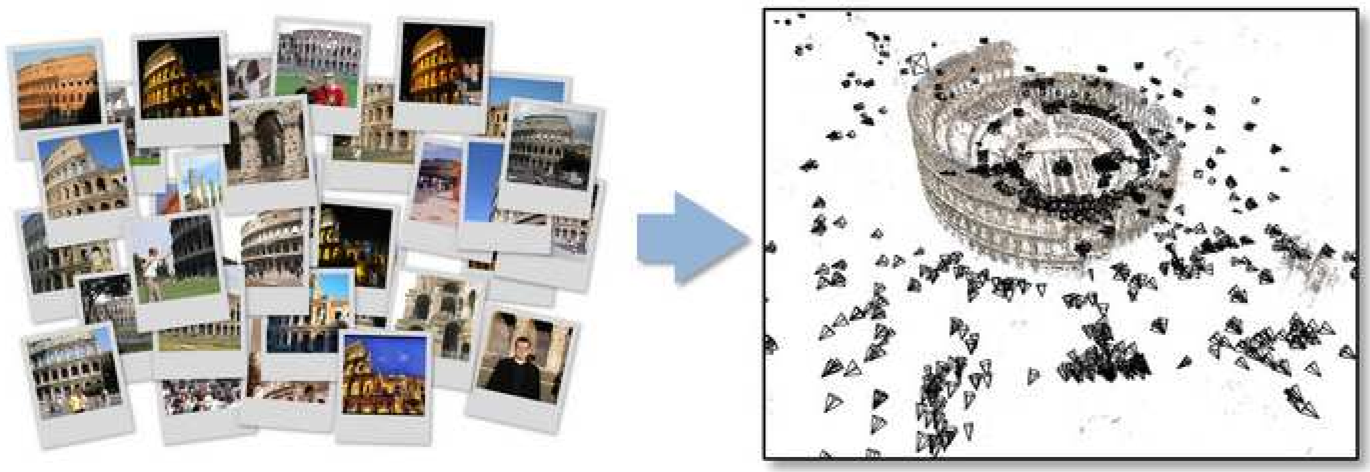
With slides from James Hays, Antonio Torralba, and Frederic Heger

15-463: Computational Photography
Alexei Efros, CMU, Fall 2011

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

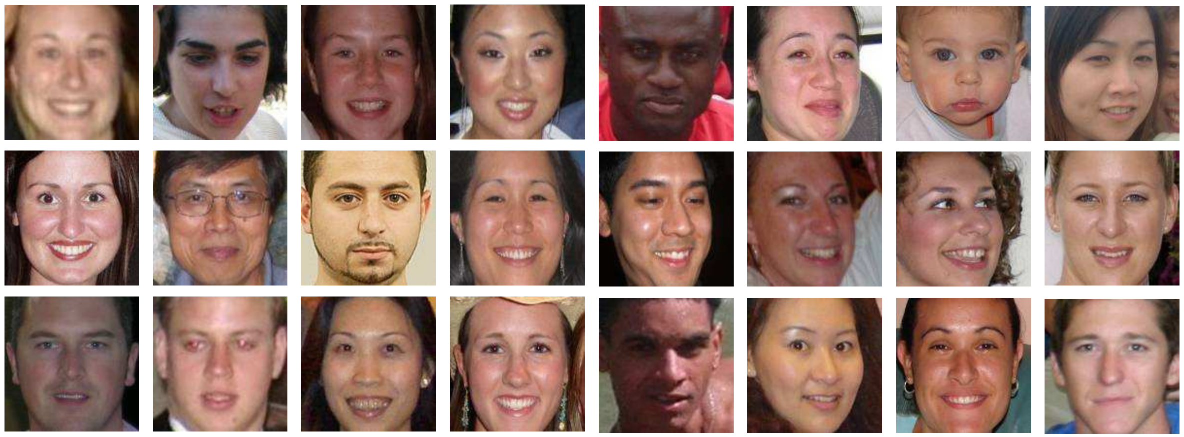
Portraits of Bill Clinton

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. 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)

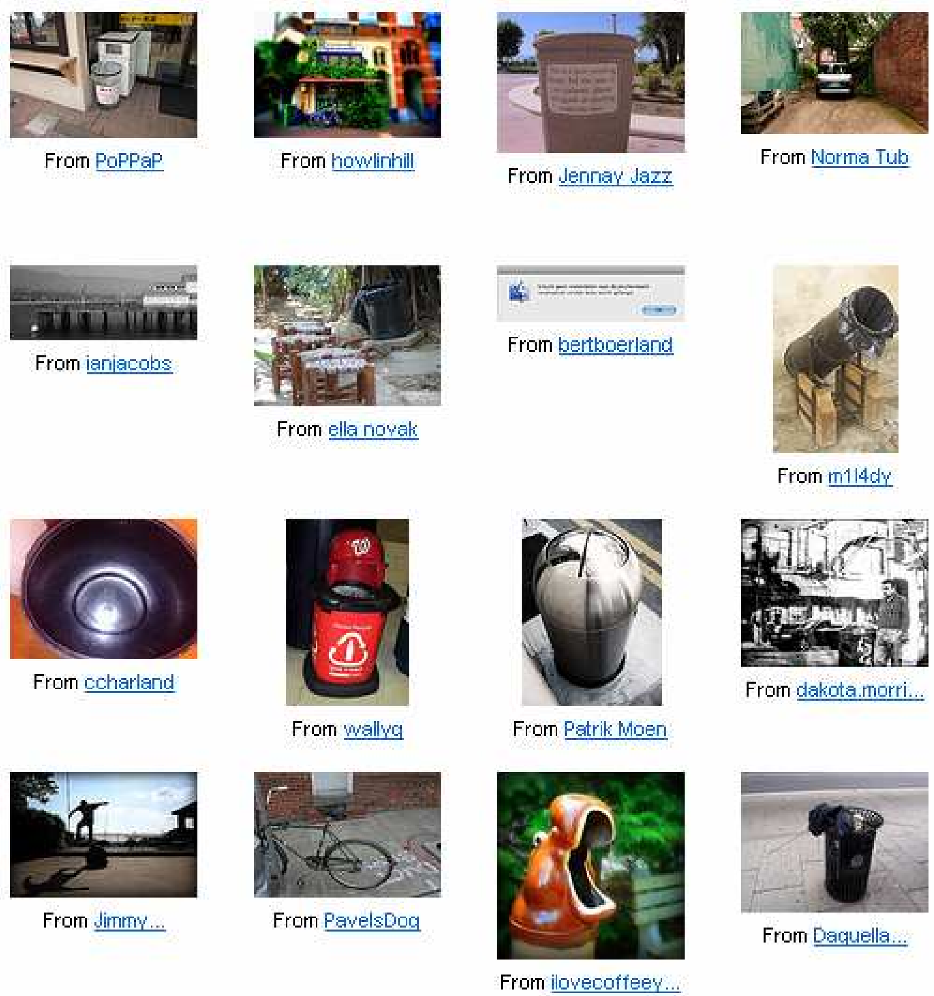
How Big is Flickr?

- 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?

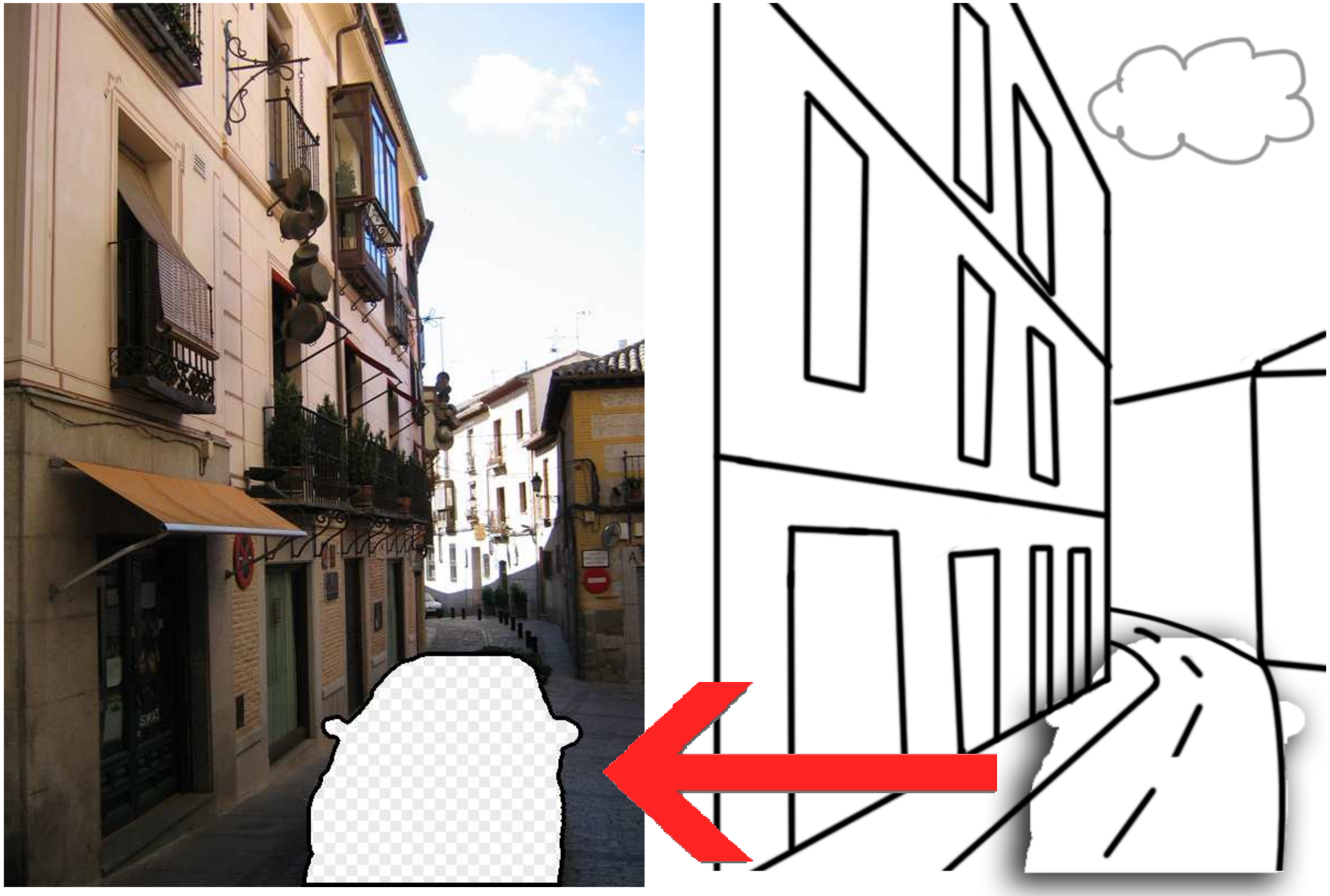
A motivating example…

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

Diffusion Result

Efros and Leung result

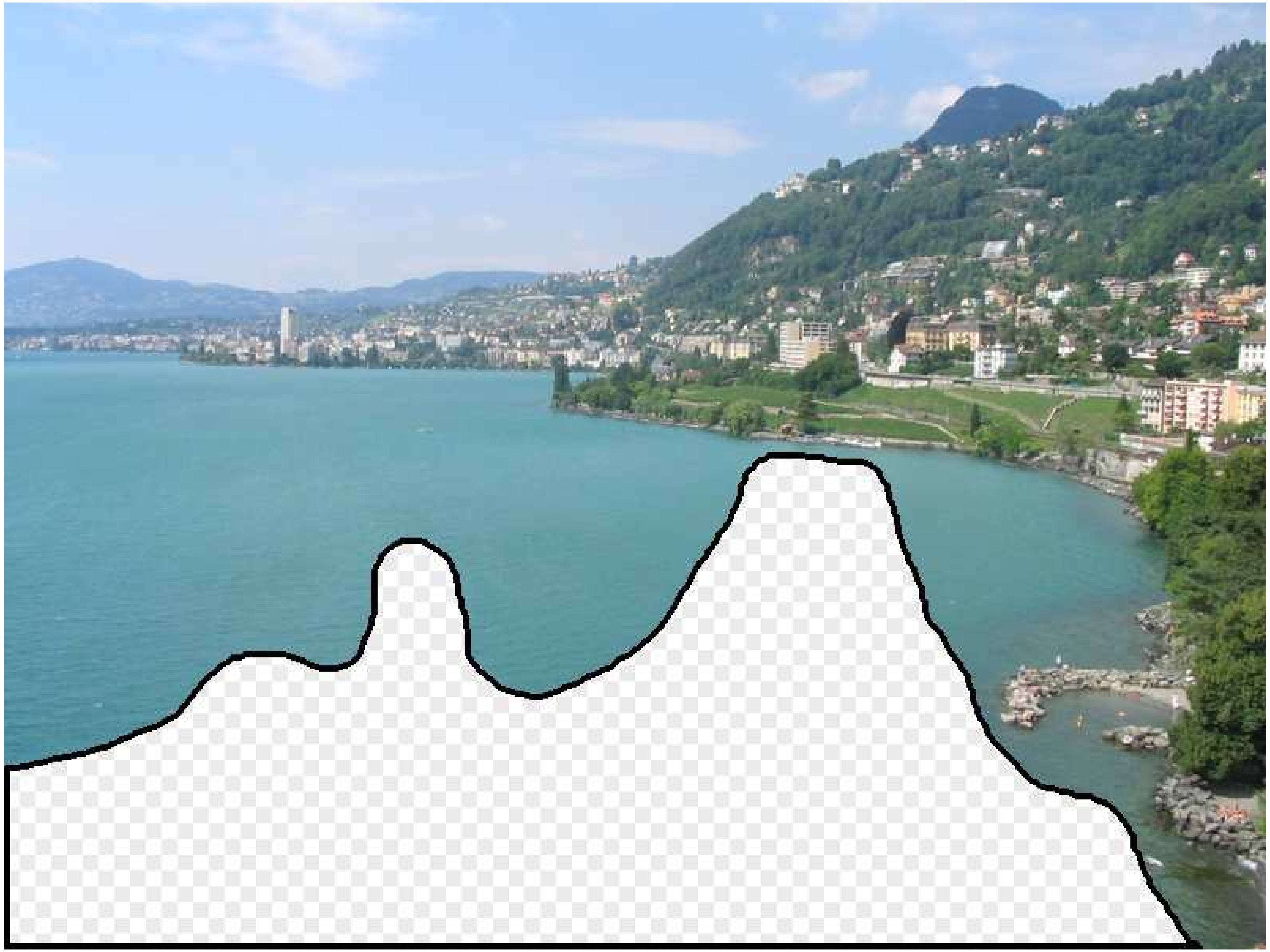
Scene Matching for Image Completion



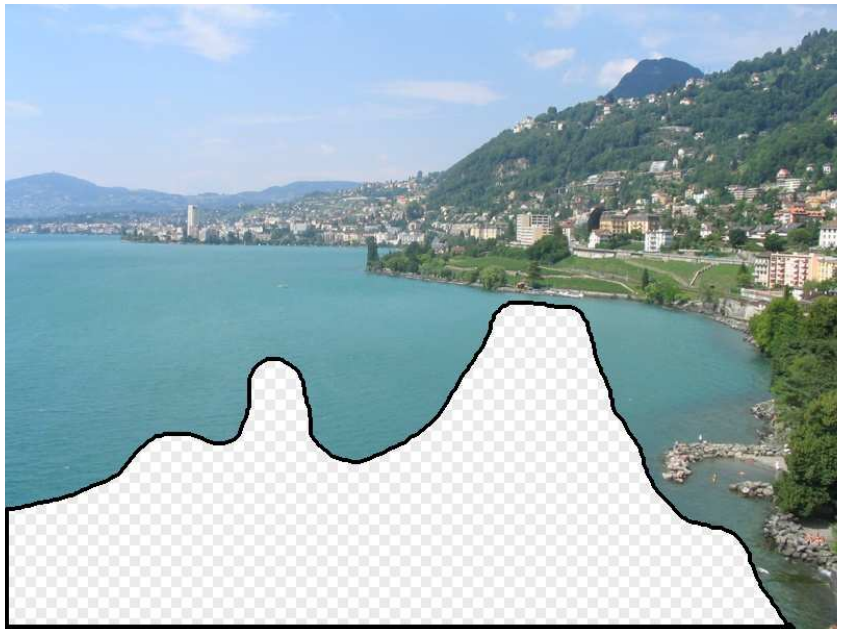
Scene Completion Result

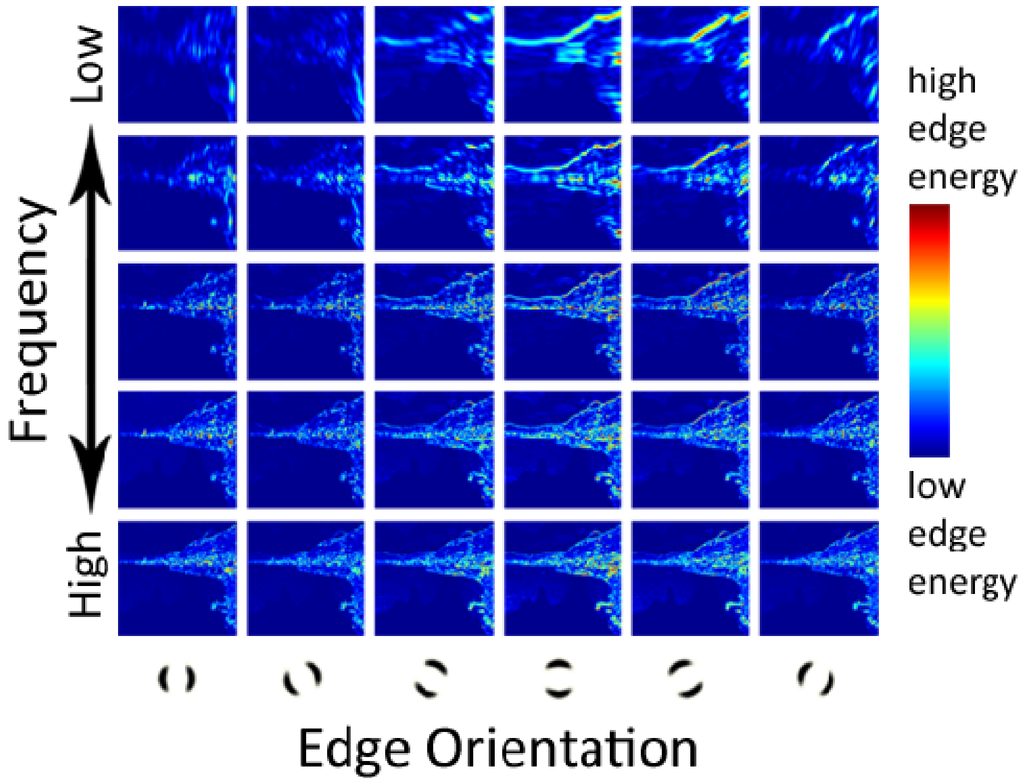
The Algorithm

Scene Matching

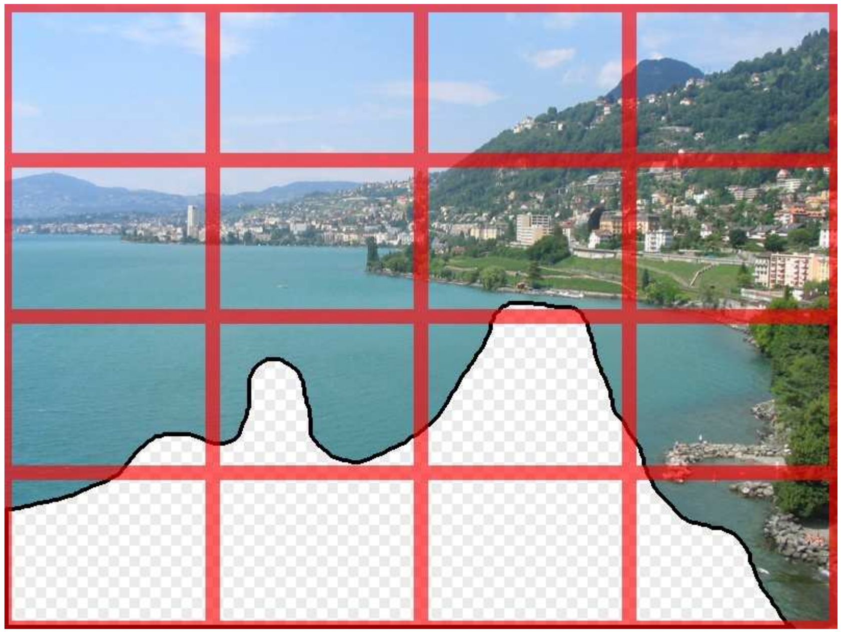


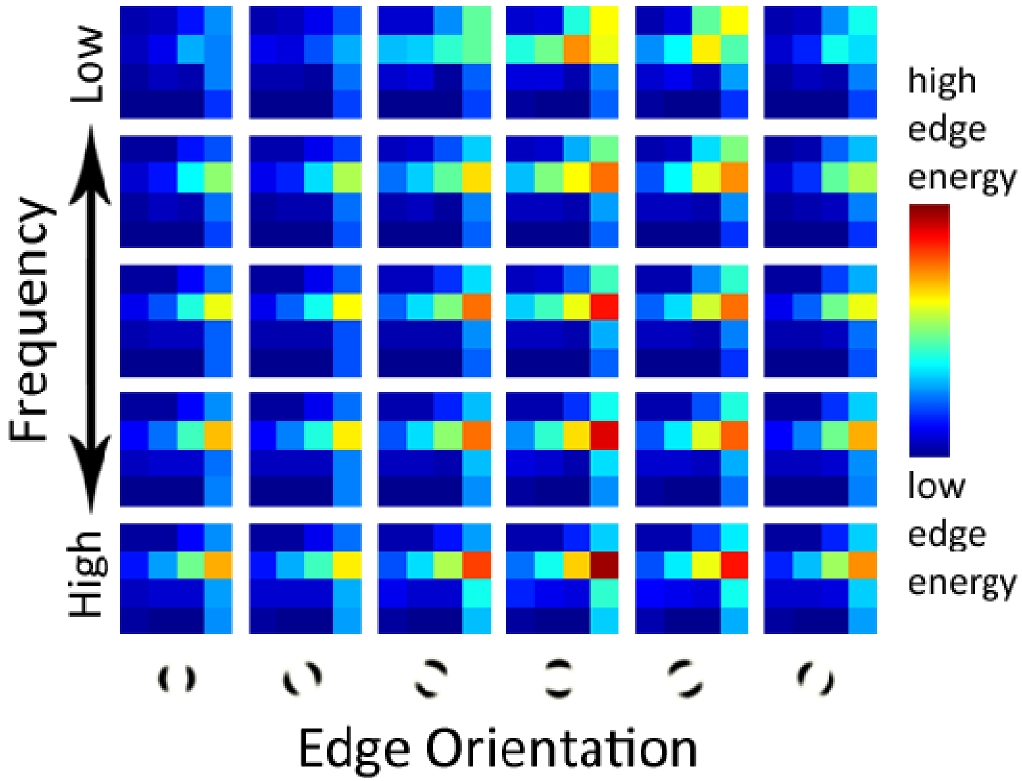
Scene Descriptor





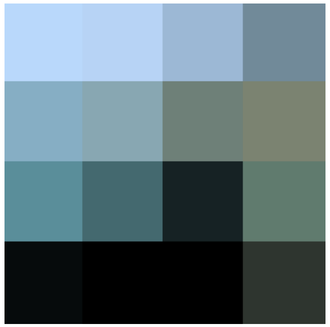
Scene Descriptor

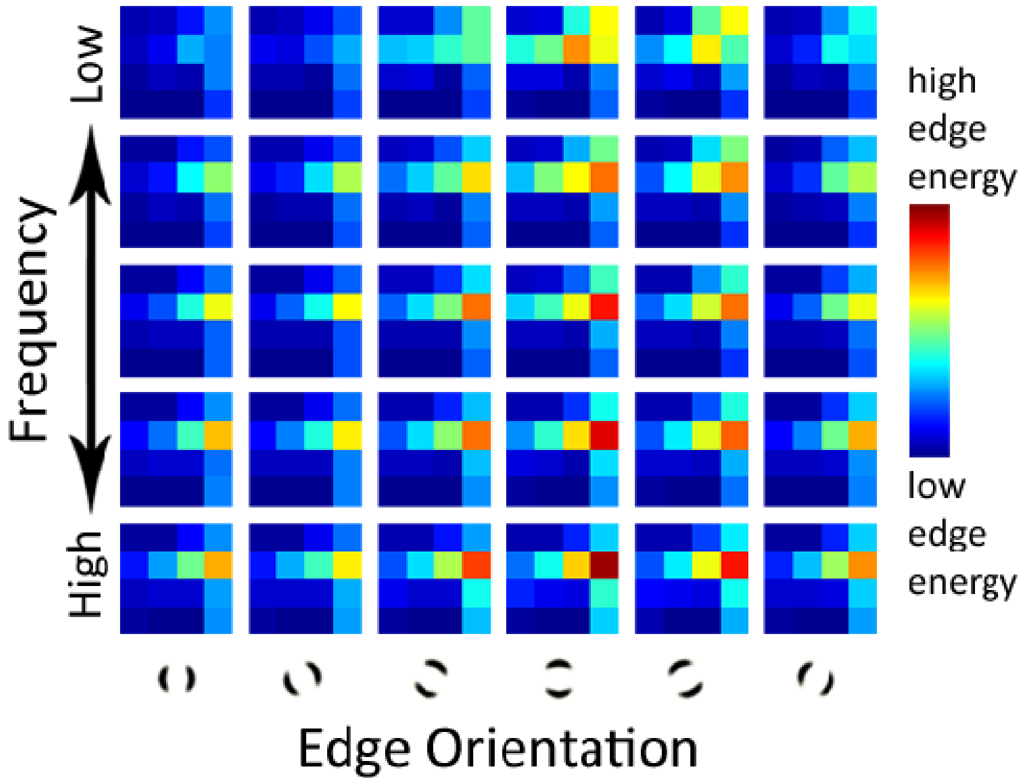




Scene Gist Descriptor
(Oliva and Torralba 2001)

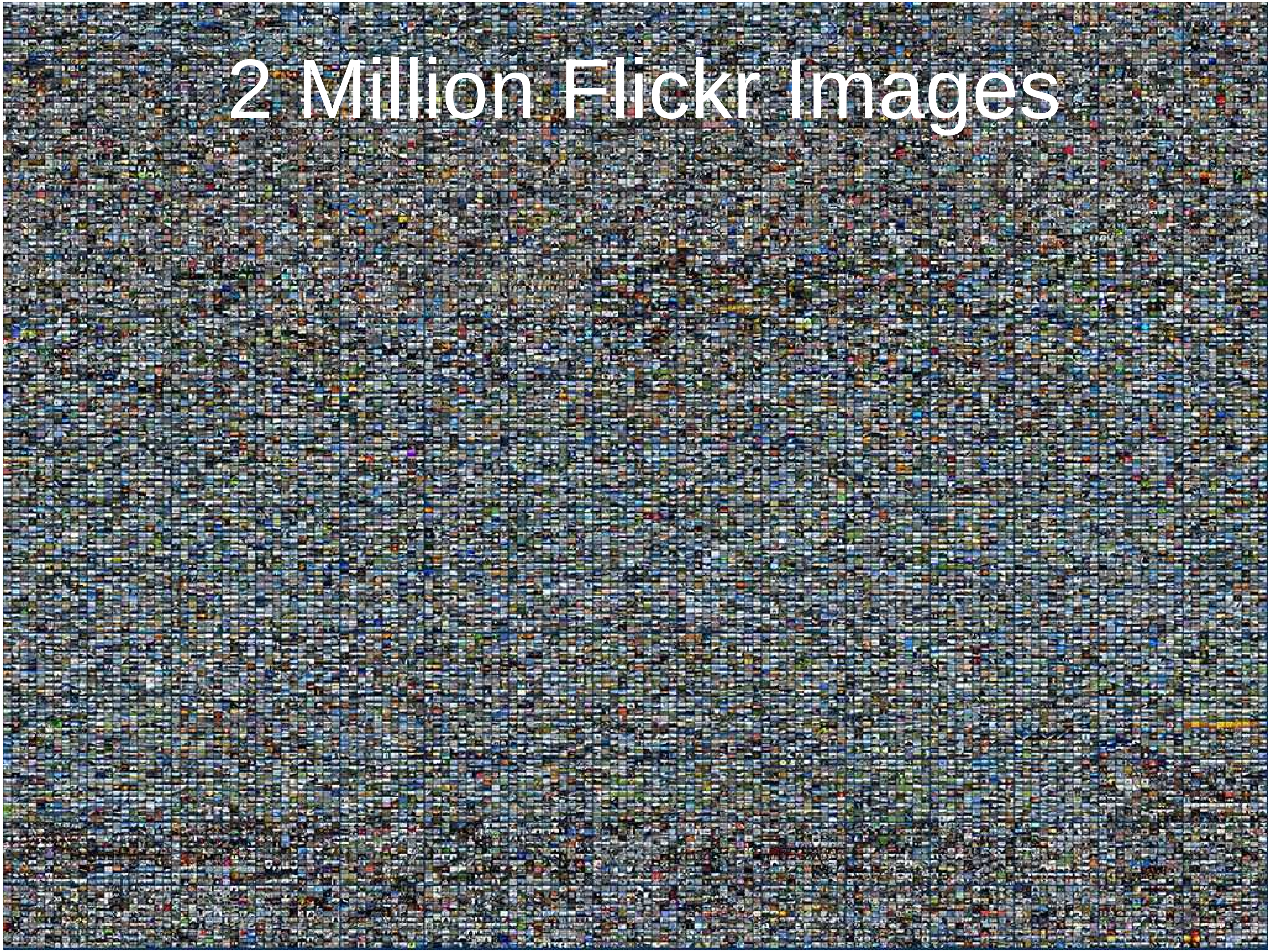
Scene Descriptor

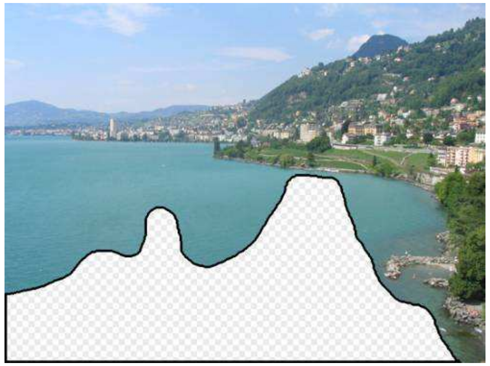


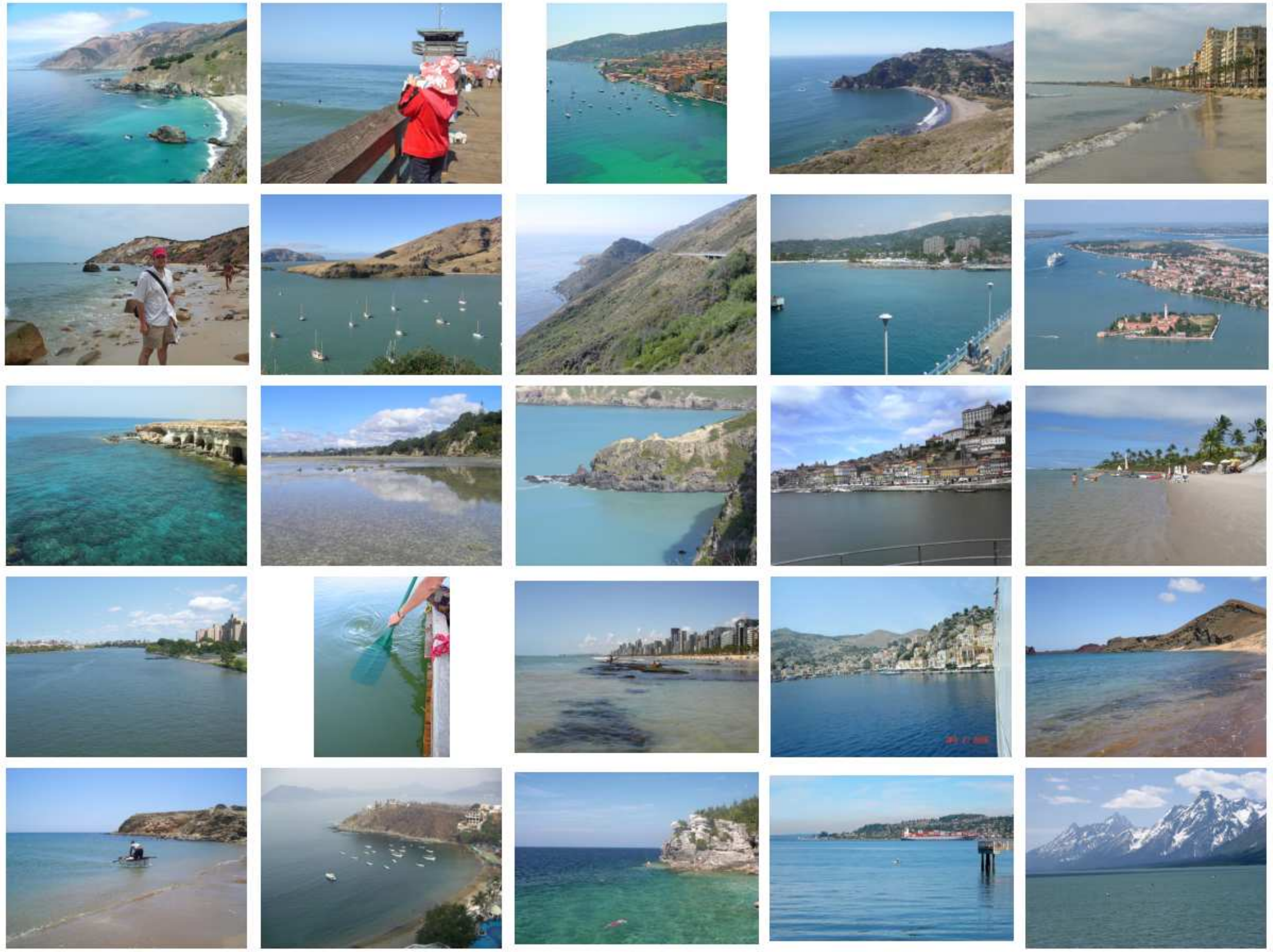


Scene Gist Descriptor
(Oliva and Torralba 2001)

2 Million Flickr Images

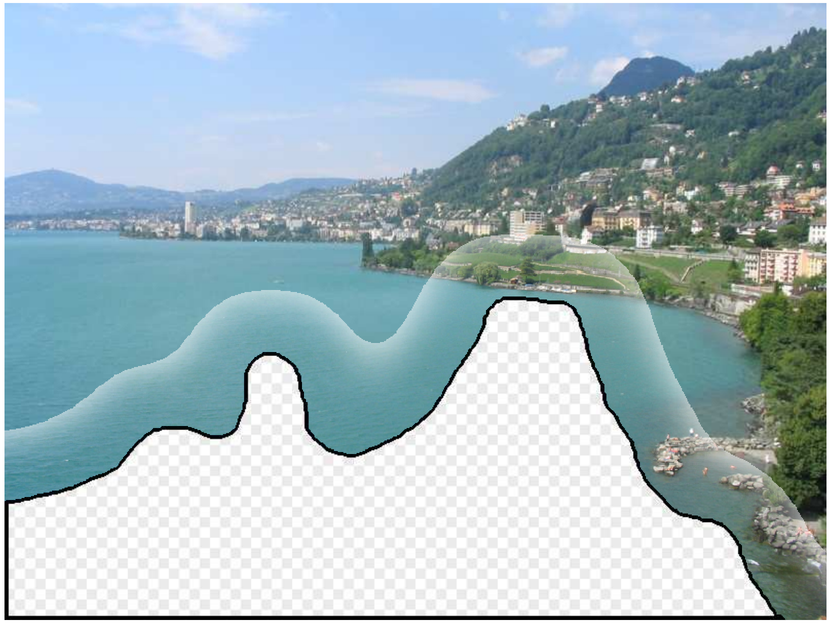






... 200 total

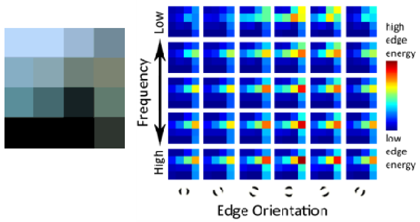
Context Matching



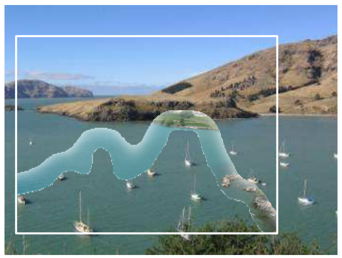
Graph cut + Poisson blending

Result Ranking

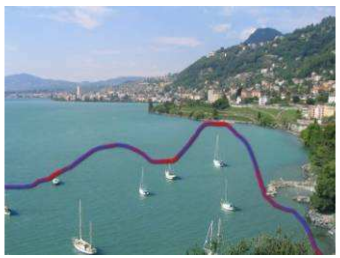
We assign each of the 200 results a score which is the sum of:



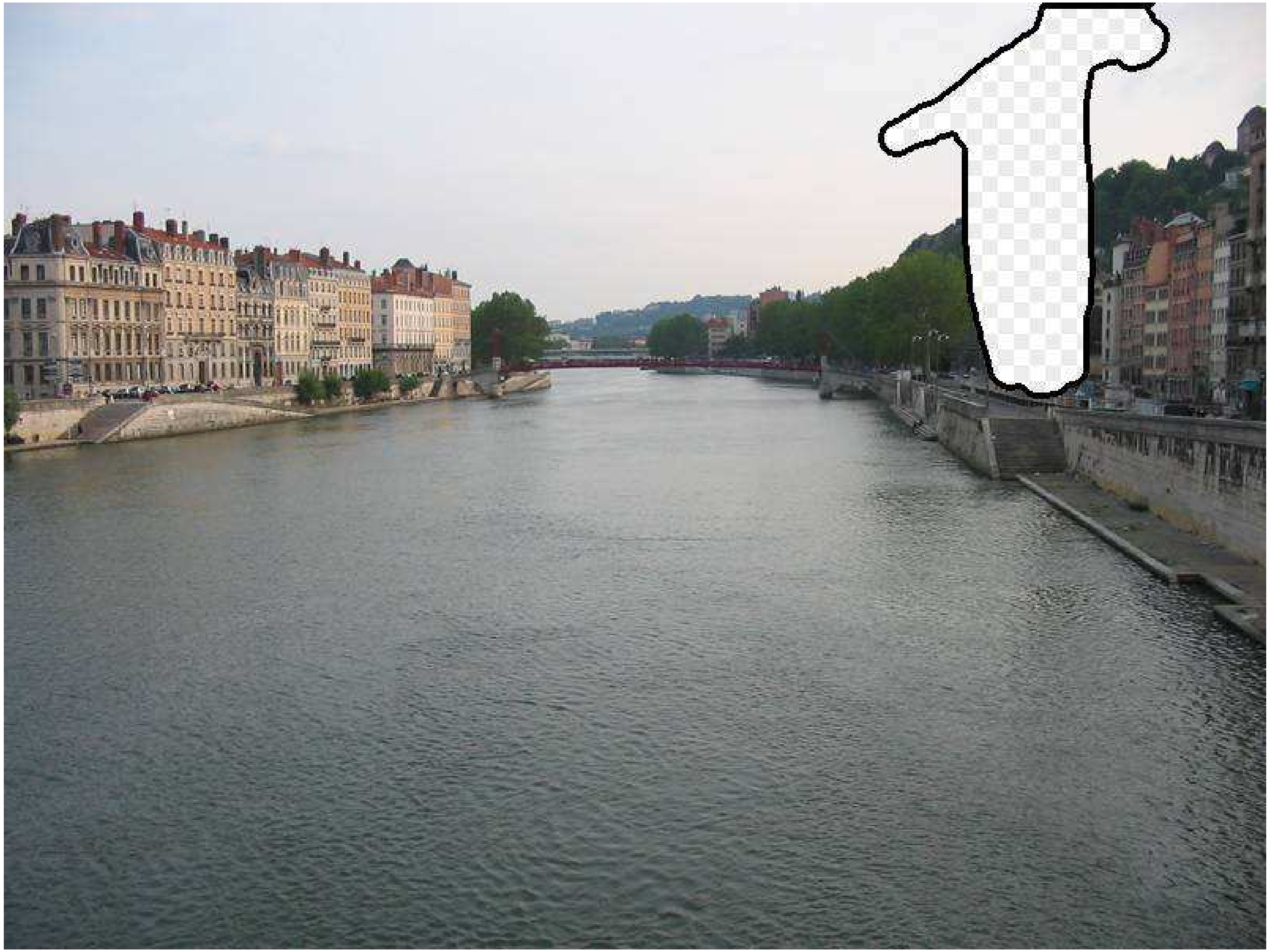
The scene matching distance

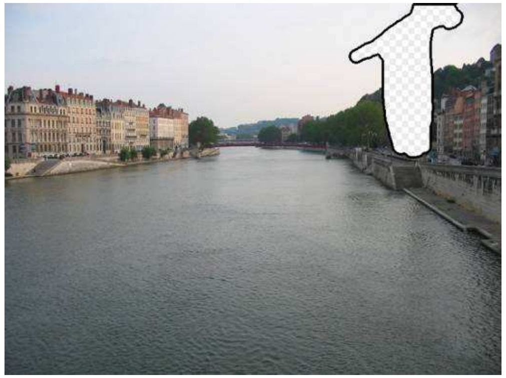


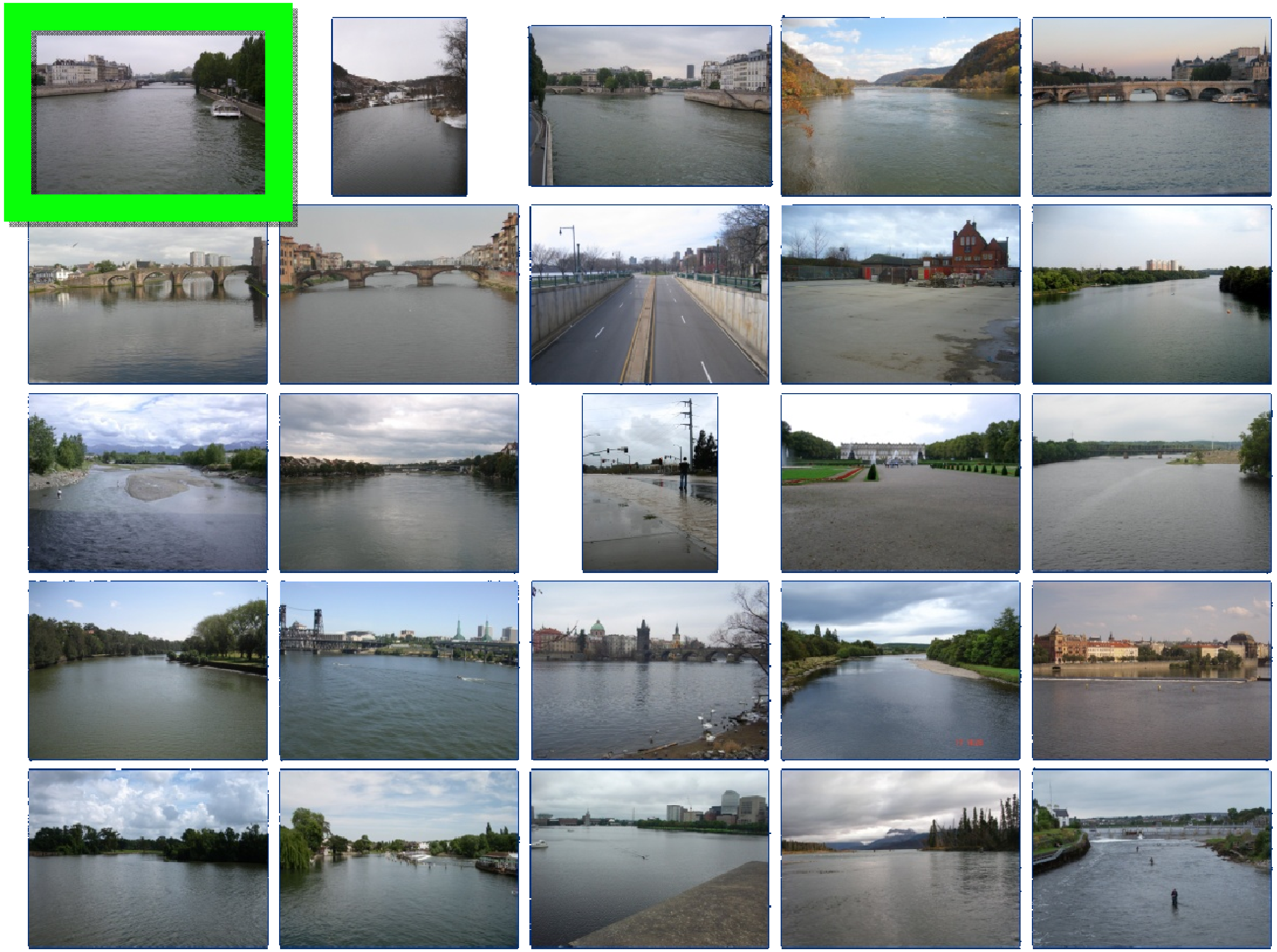
The context matching distance
(color + texture)



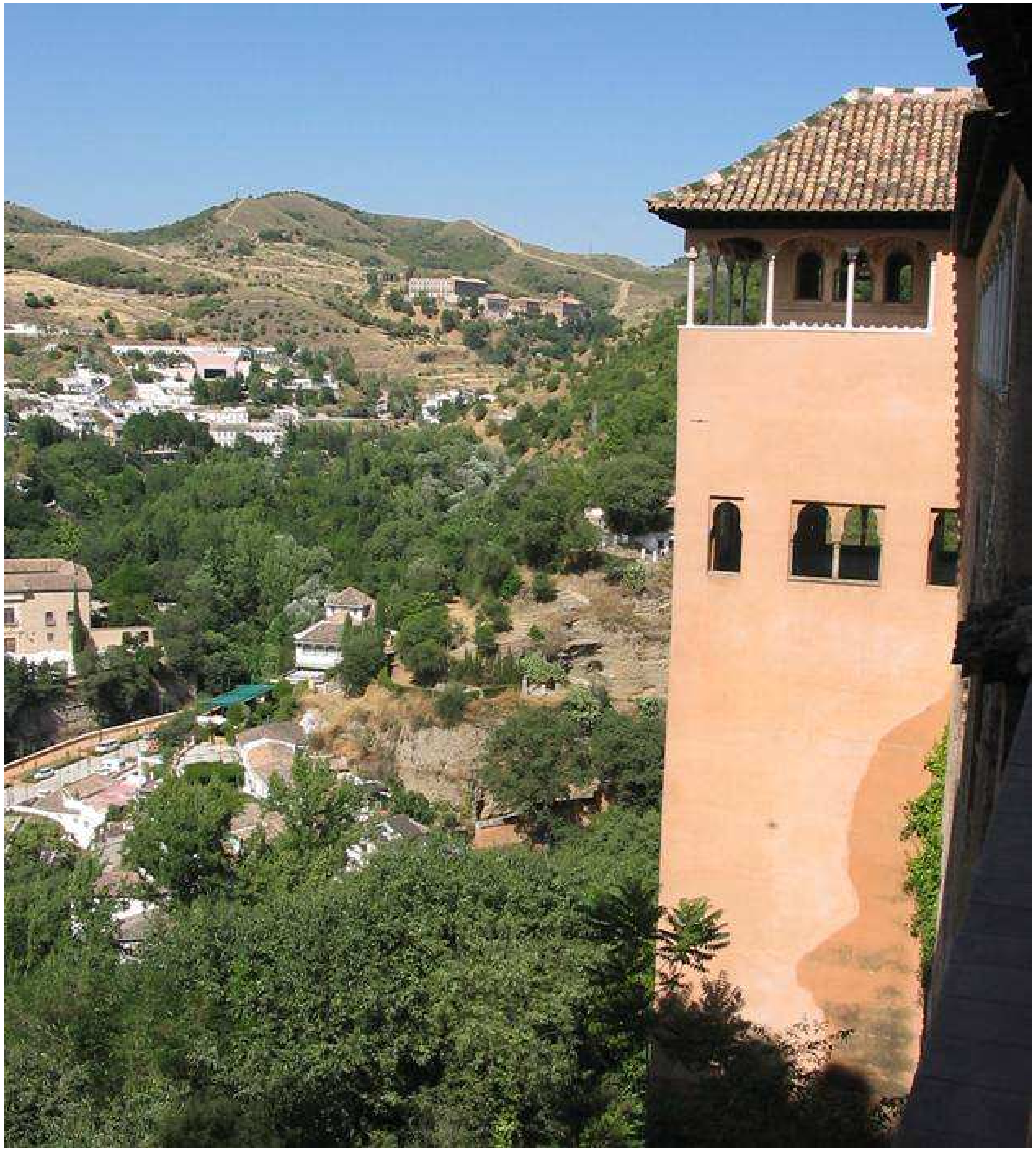
The graph cut cost

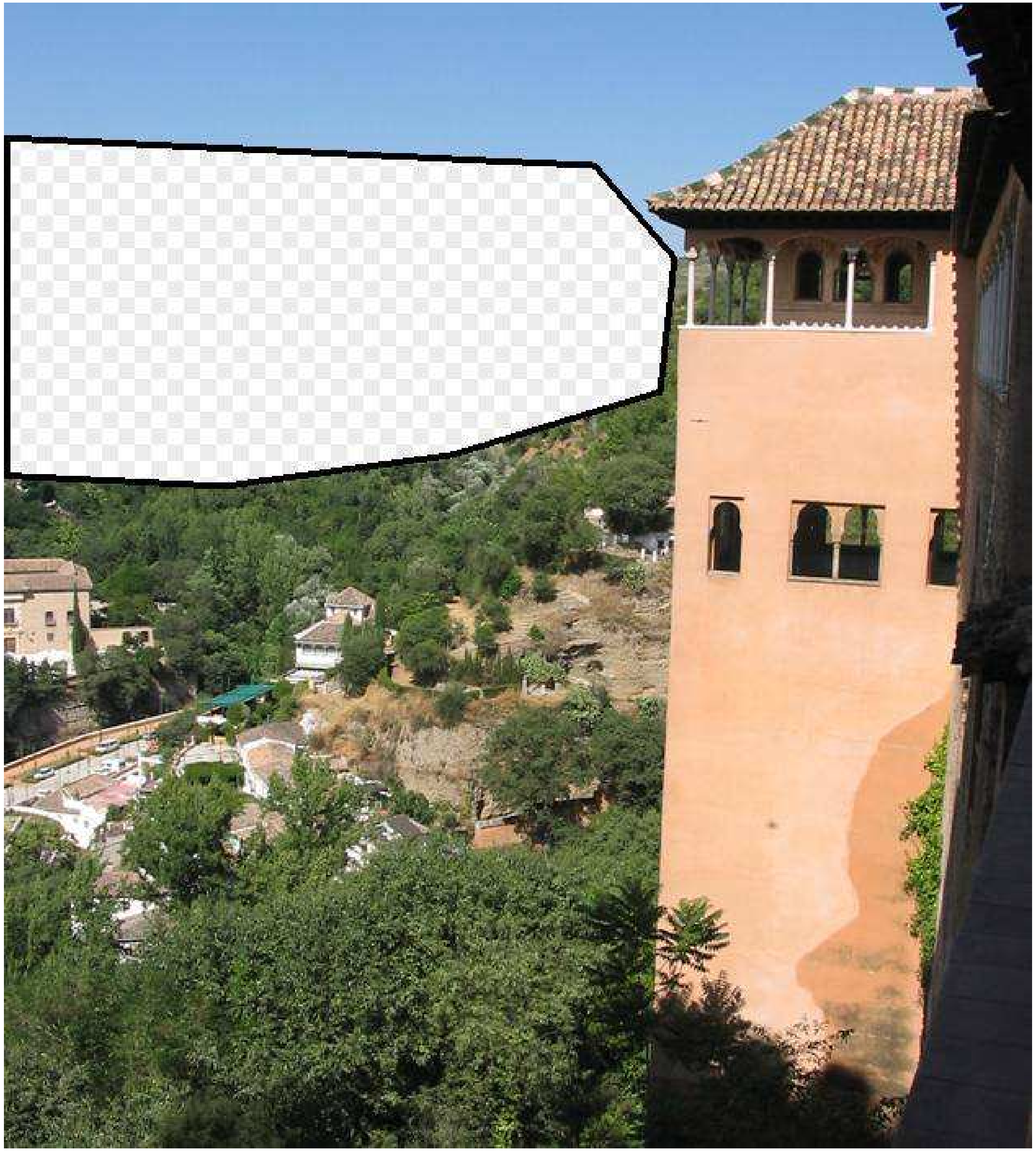


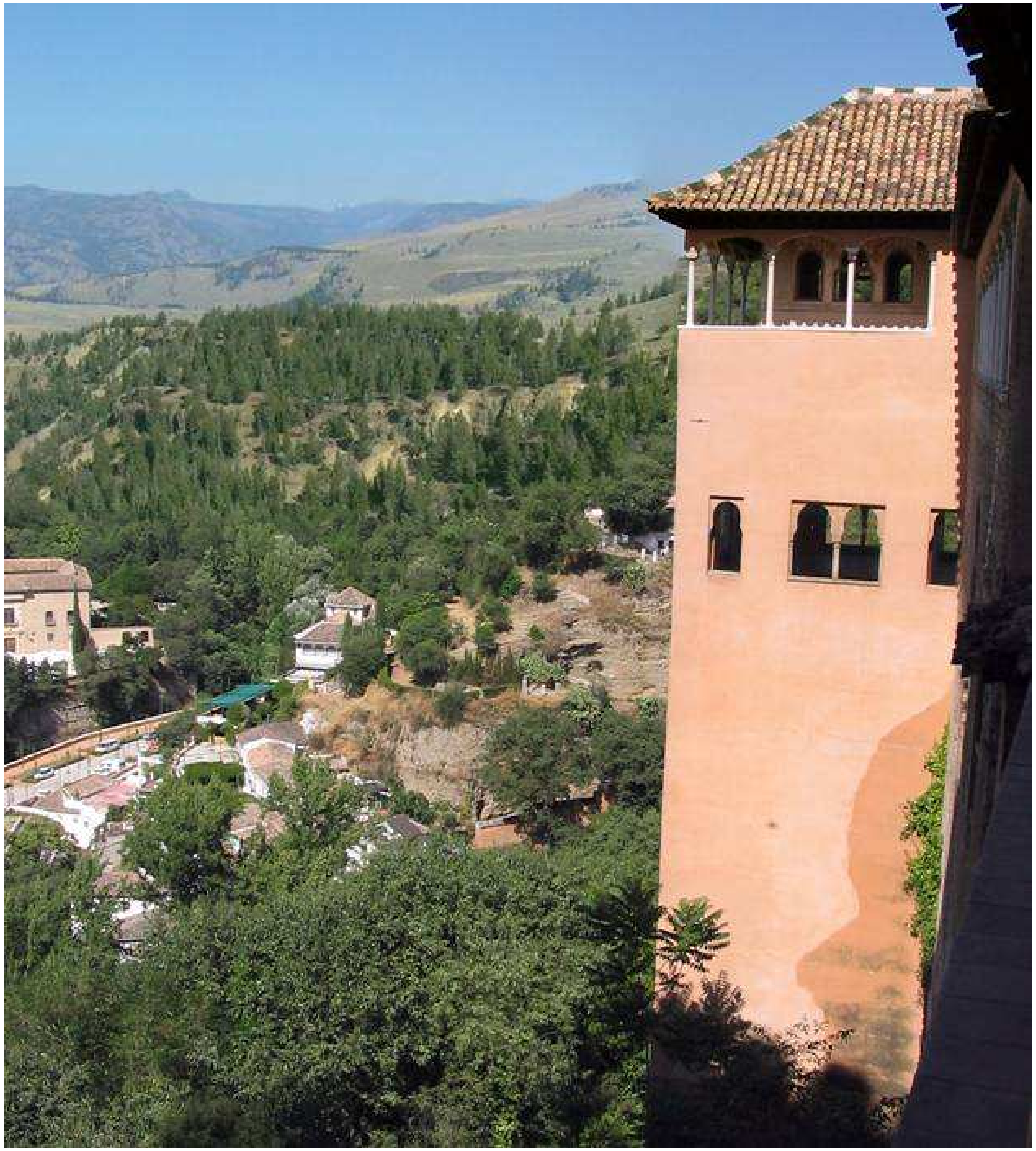




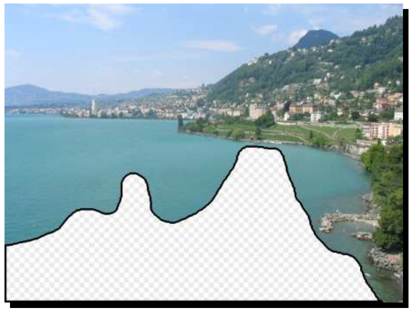
… 200 scene matches

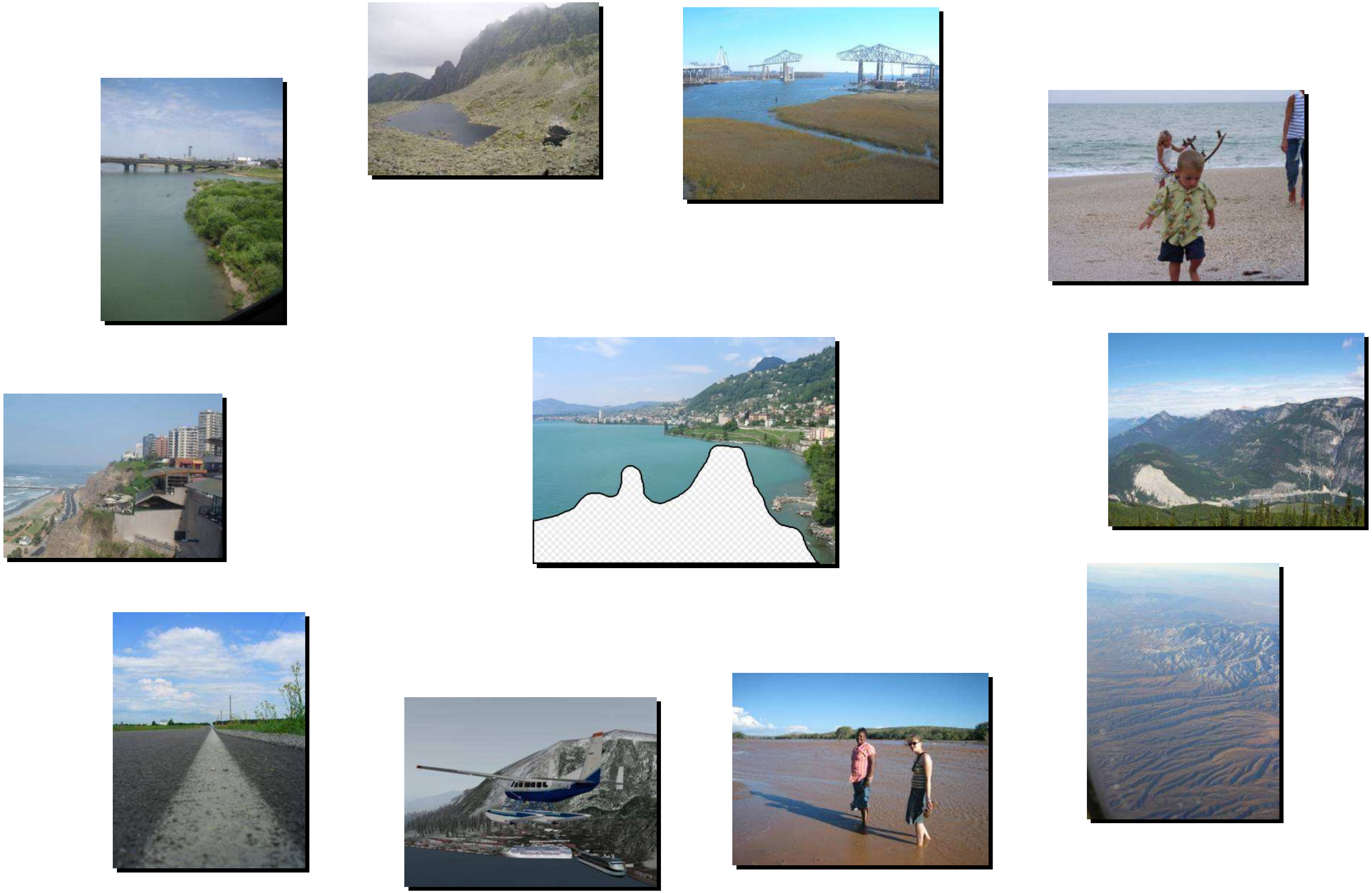




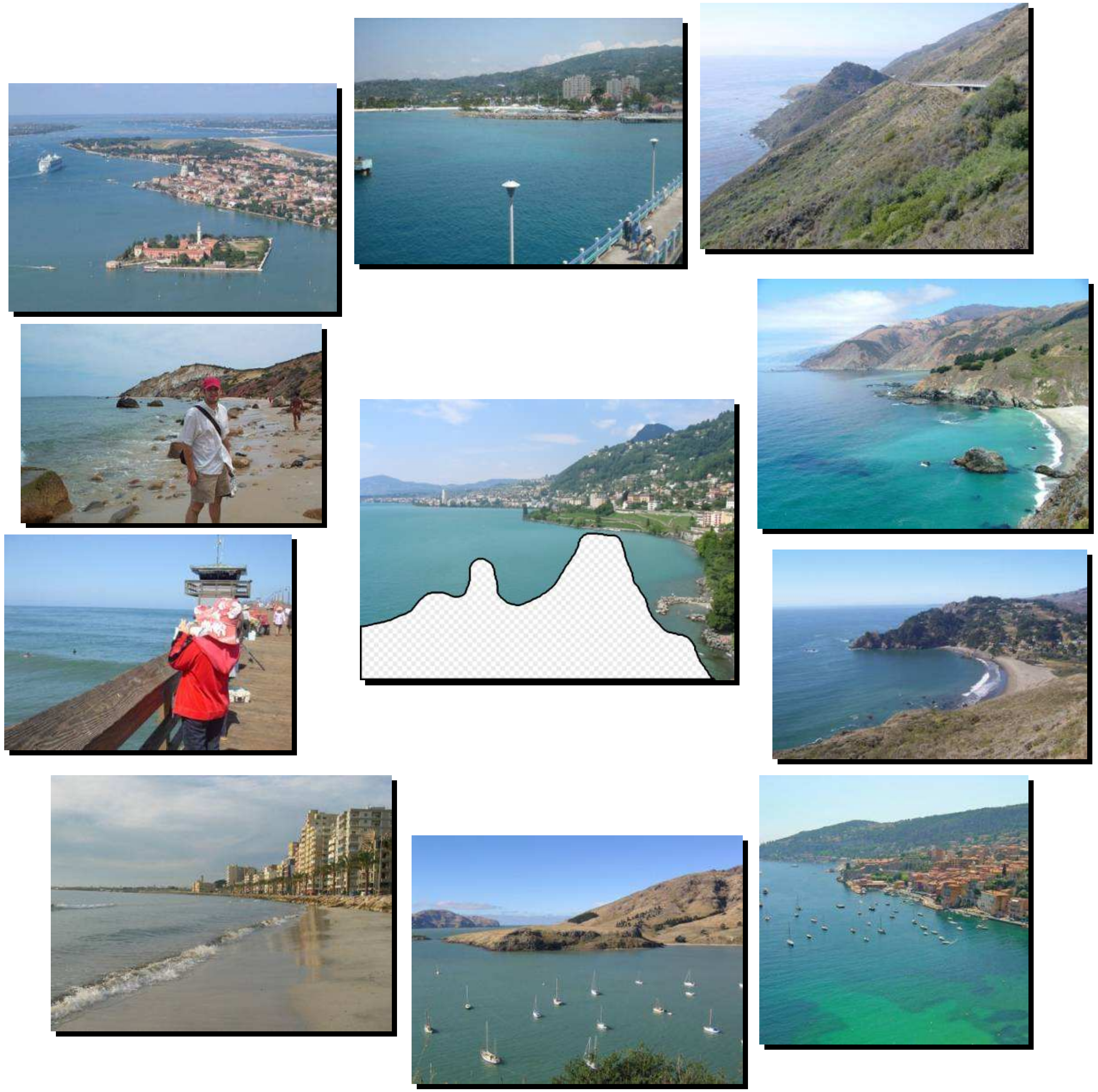


Why does it work?





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

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

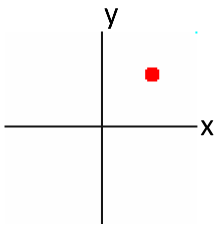
Quick Overview

Comparing Images

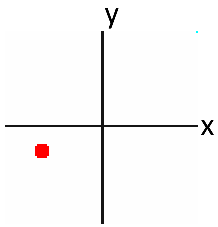
Uses of Visual Data

The Dangers of Data

Distance Metrics



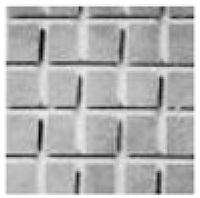
-



= Euclidian distance of 5 units

-

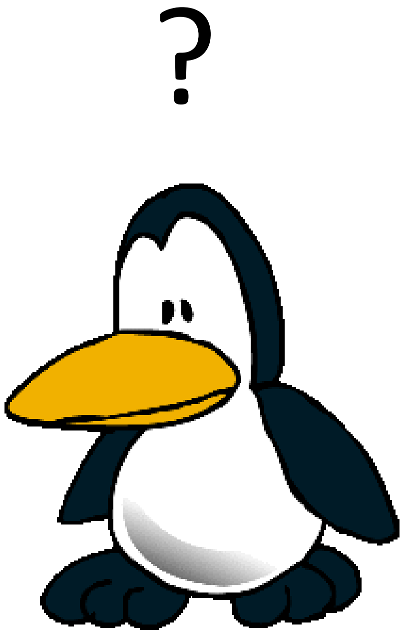
= Grayvalue distance of 50 values



-

= ?

SSD says these are not similar

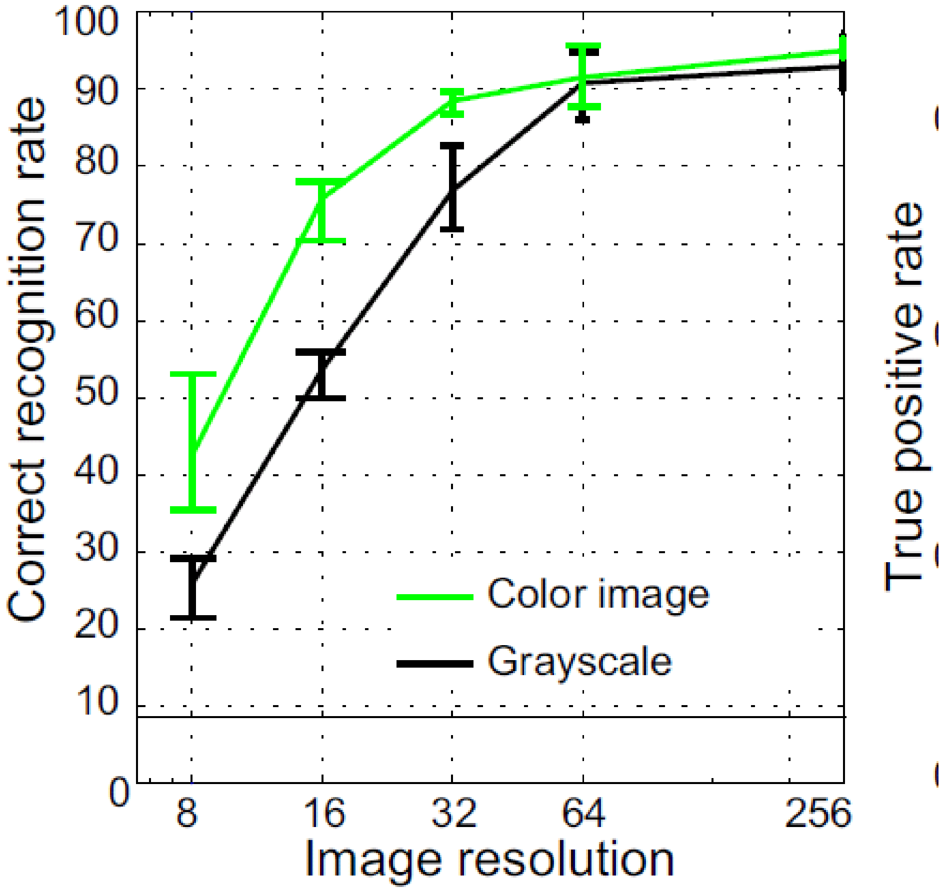


Tiny Images

- 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}

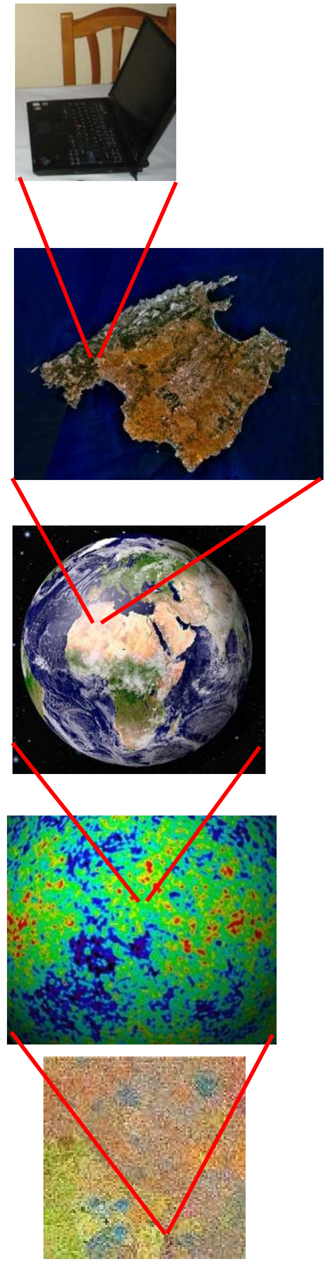
106,456,367,669 humans[1] * 60 years * 3 images/second * 60 * 60 * 16 * 365 =

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

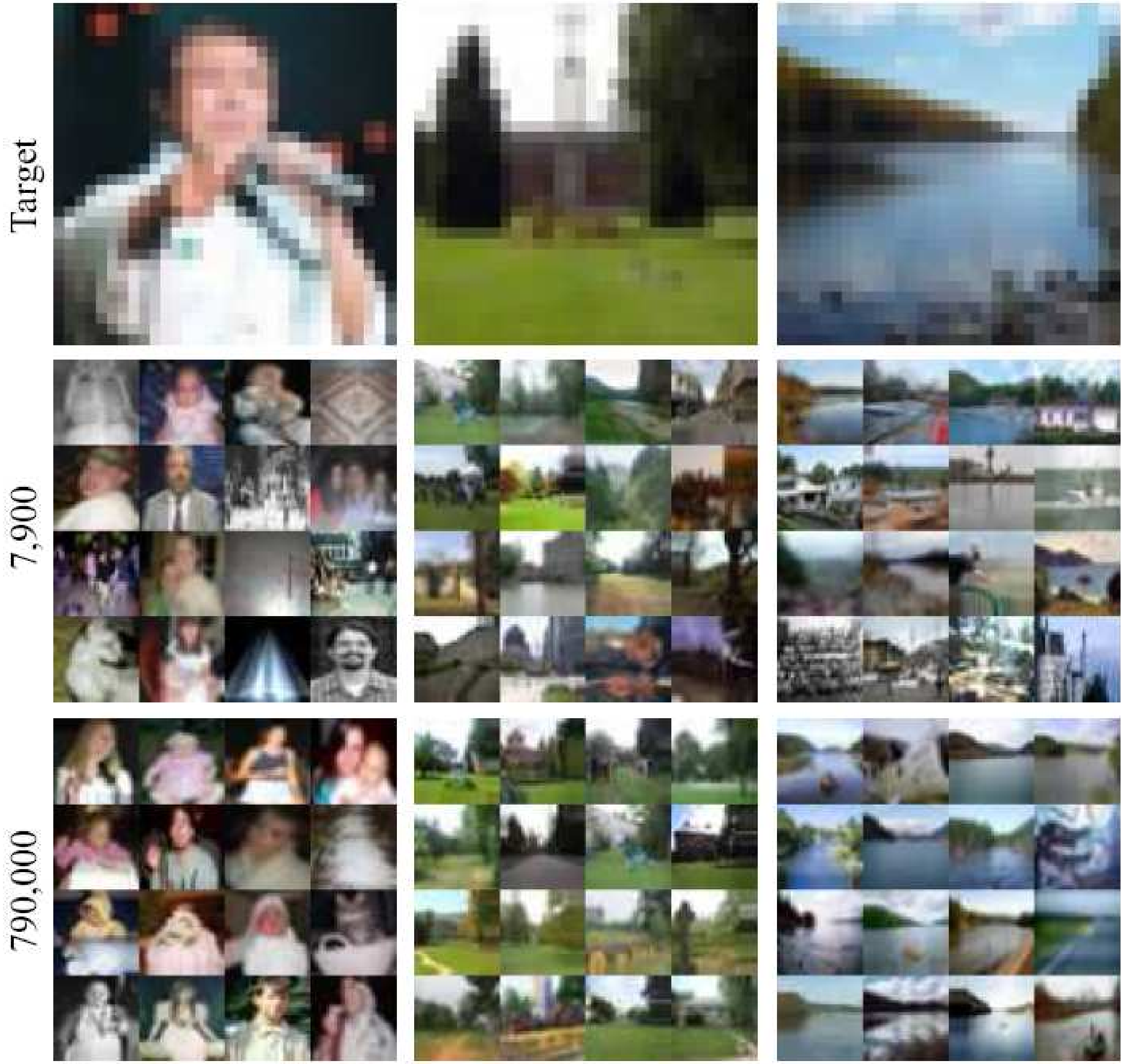
Images

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

Lots

Of

Images

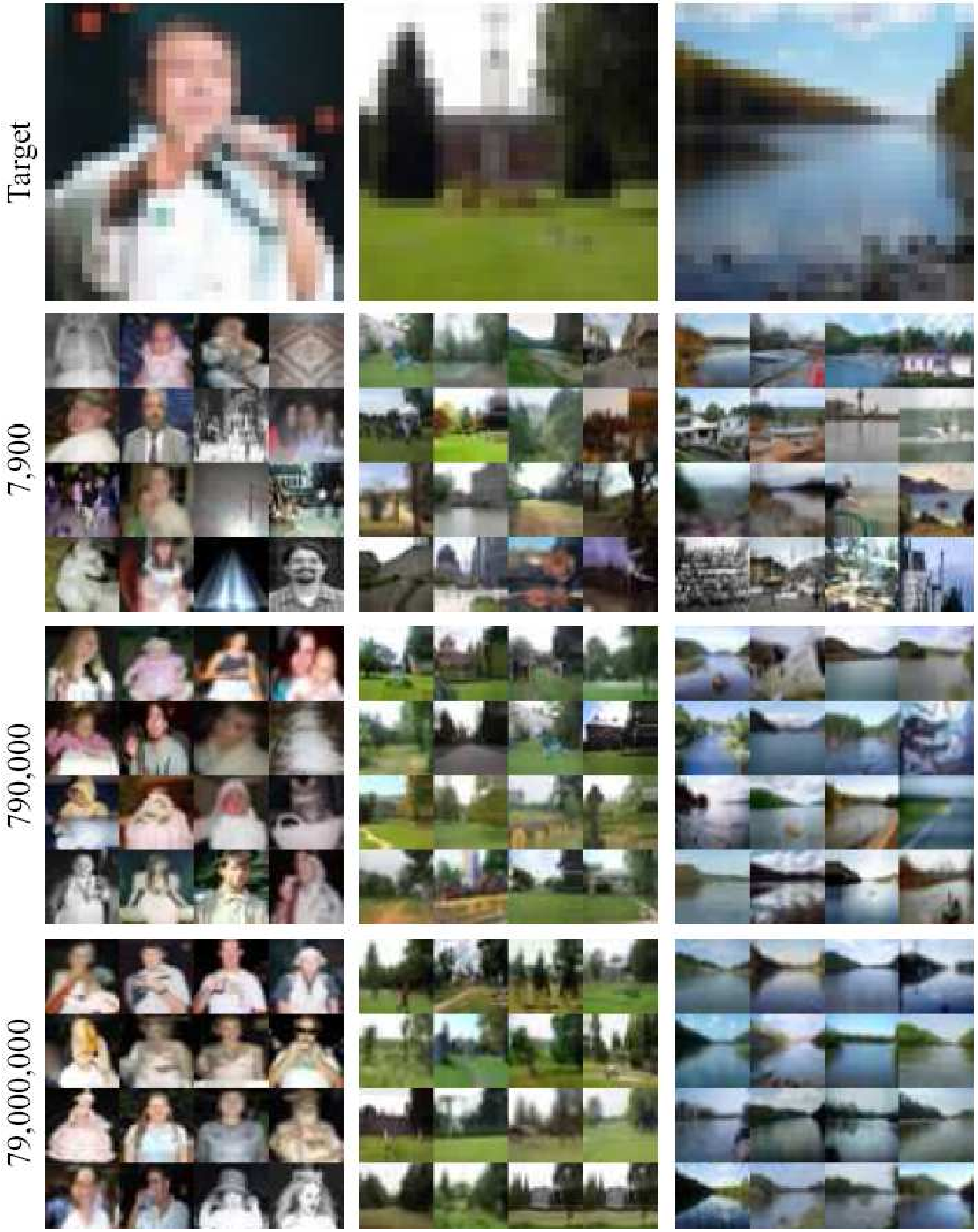


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images



Automatic Colorization Result

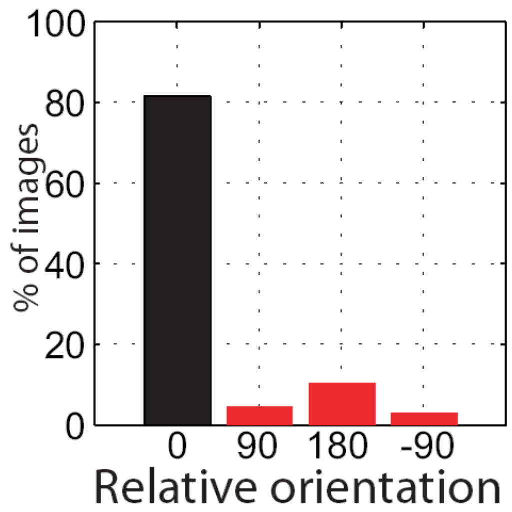
Grayscale input High resolution

Colorization of input using average

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

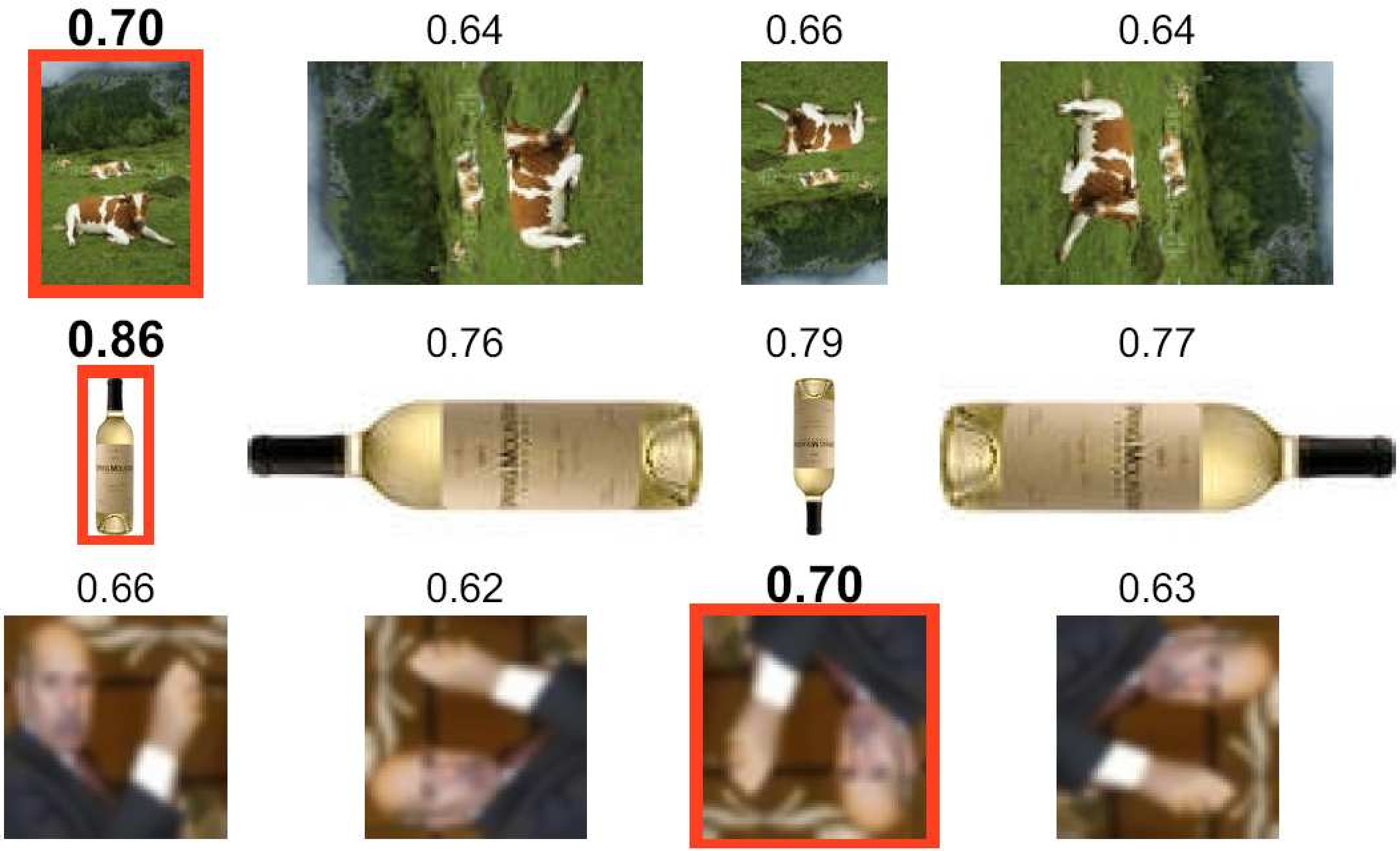
Automatic Orientation

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



- Examples of high and low confidence images:

Automatic Orientation Examples



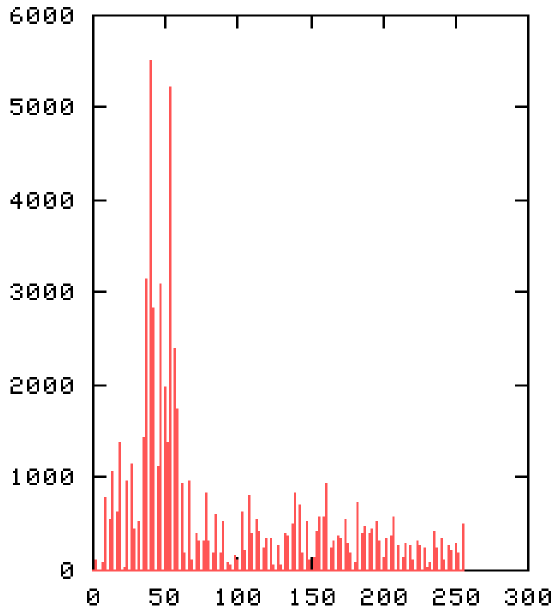
A. Torralba, R. Fergus, W.T.Freeman. 2008

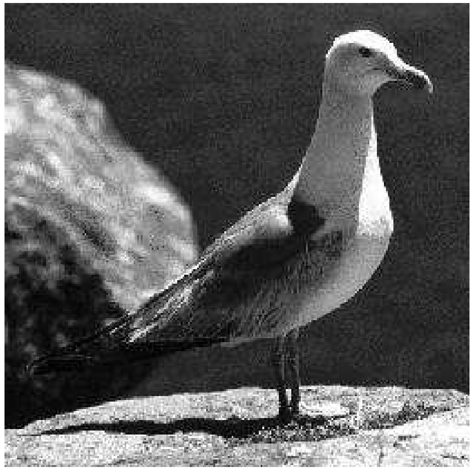
Tiny Images Discussion

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

Image Representations: Histograms

Images from Dave Kauchak



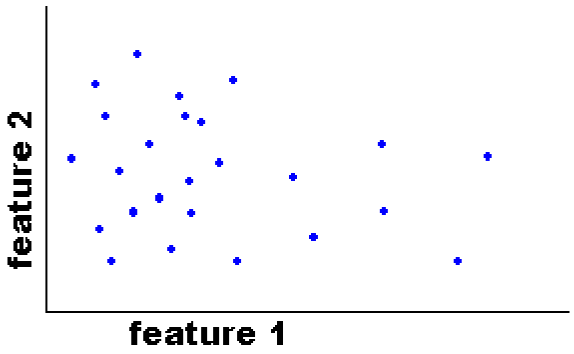


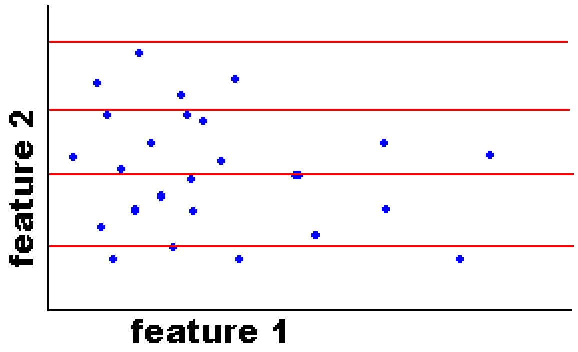
global histogram

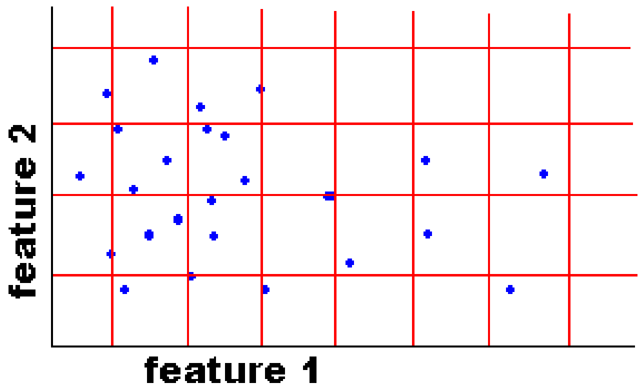
- Represent distribution of features
  - Color, texture, depth, …

Image Representations: Histograms

Images from Dave Kauchak

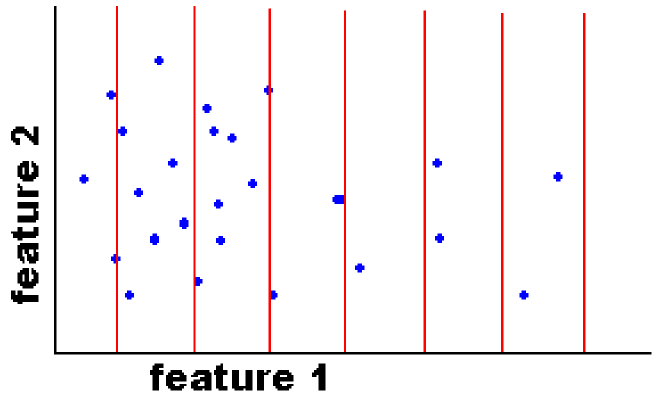






Joint histogram

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

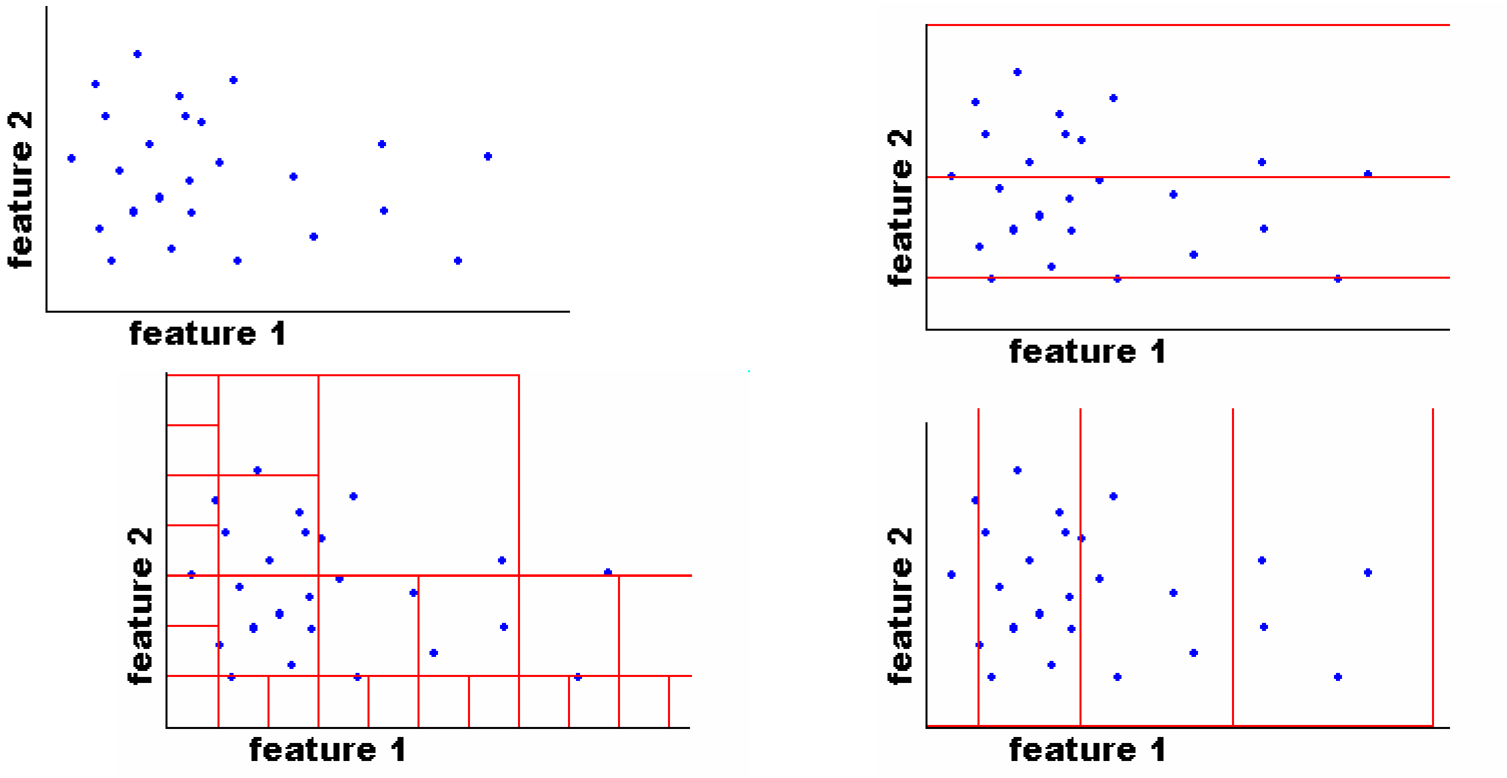


Marginal histogram

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

Image Representations: Histograms

Images from Dave Kauchak

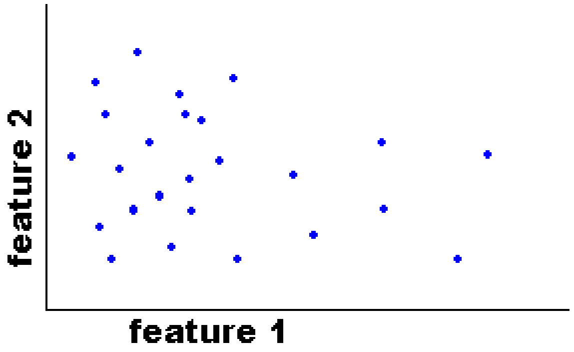


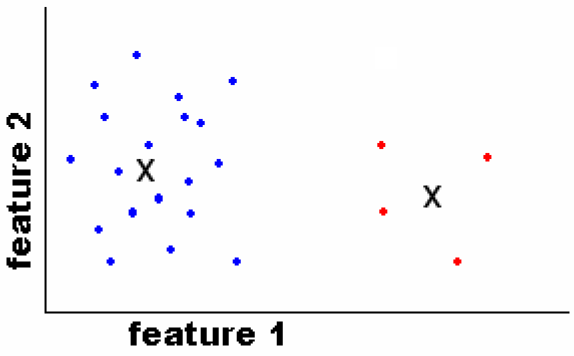
Adaptive binning

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

Image Representations: Histograms

Images from Dave Kauchak

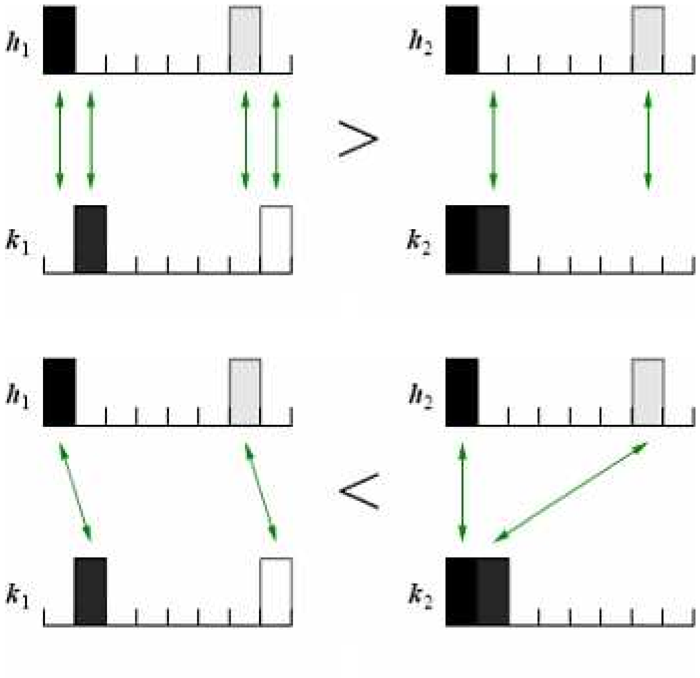


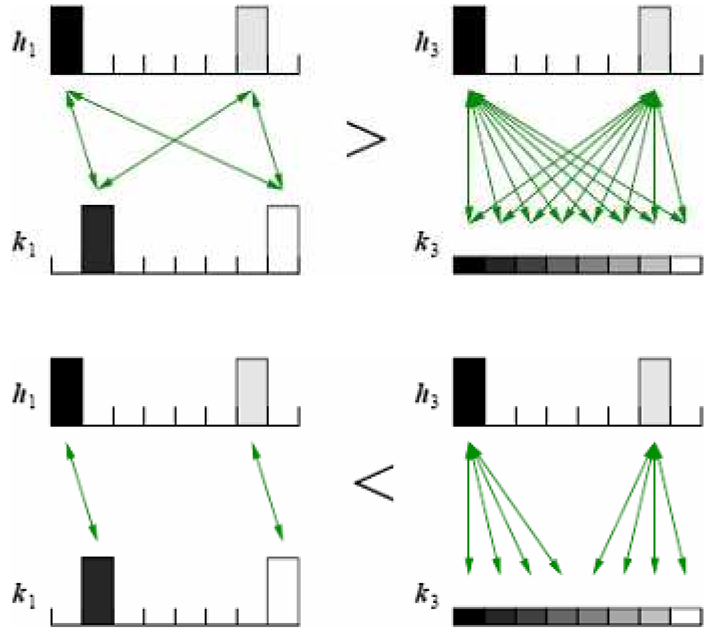


Clusters / Signatures

- “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

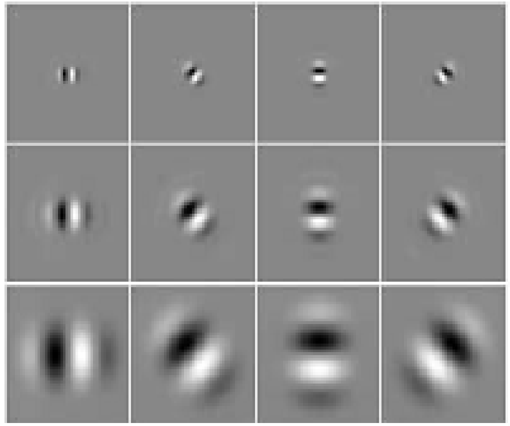
 

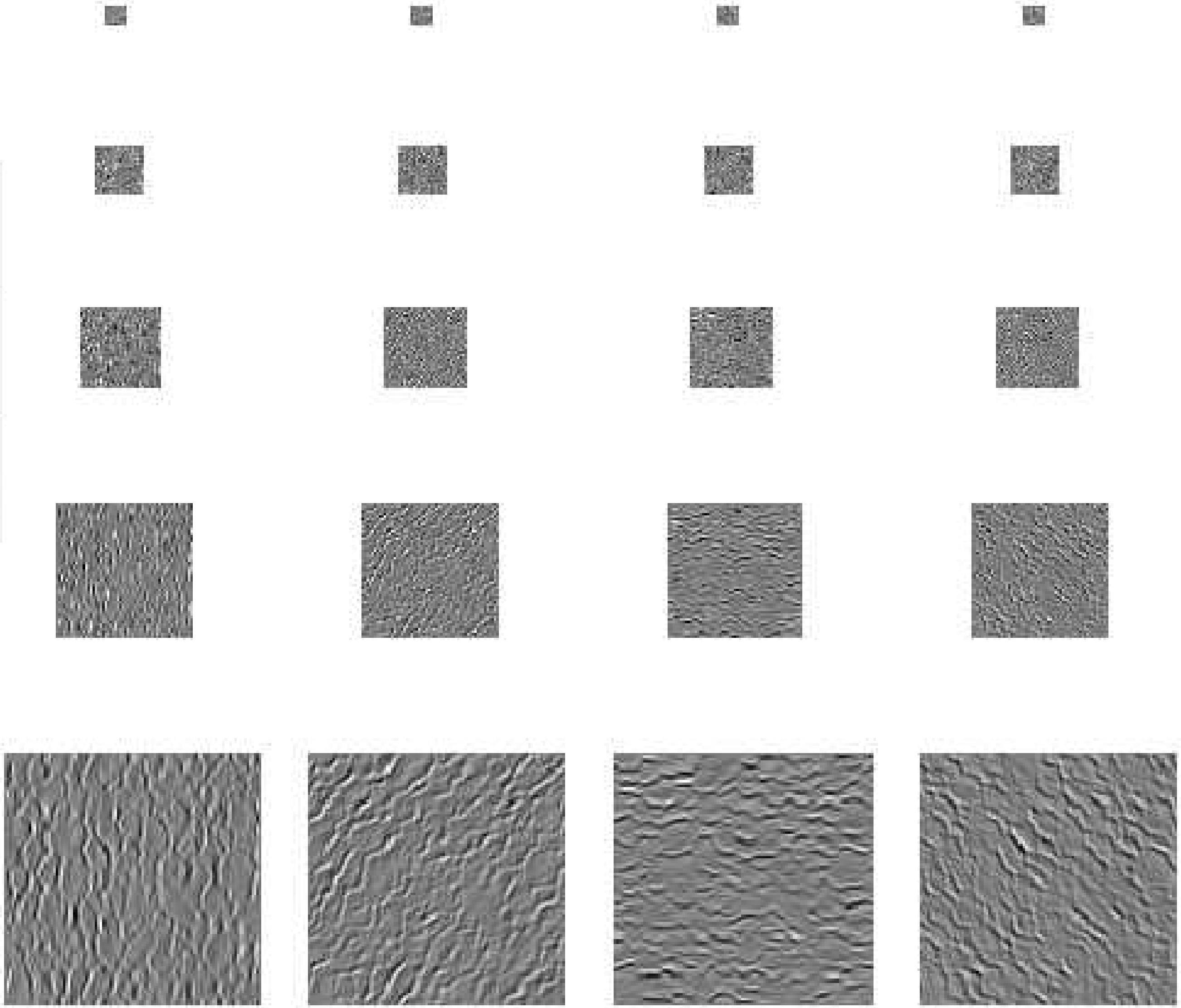
We don’t want an actual texture realization, we want a texture invariant

What are the tools for capturing statistical properties of some signal?

Multi-scale filter decomposition

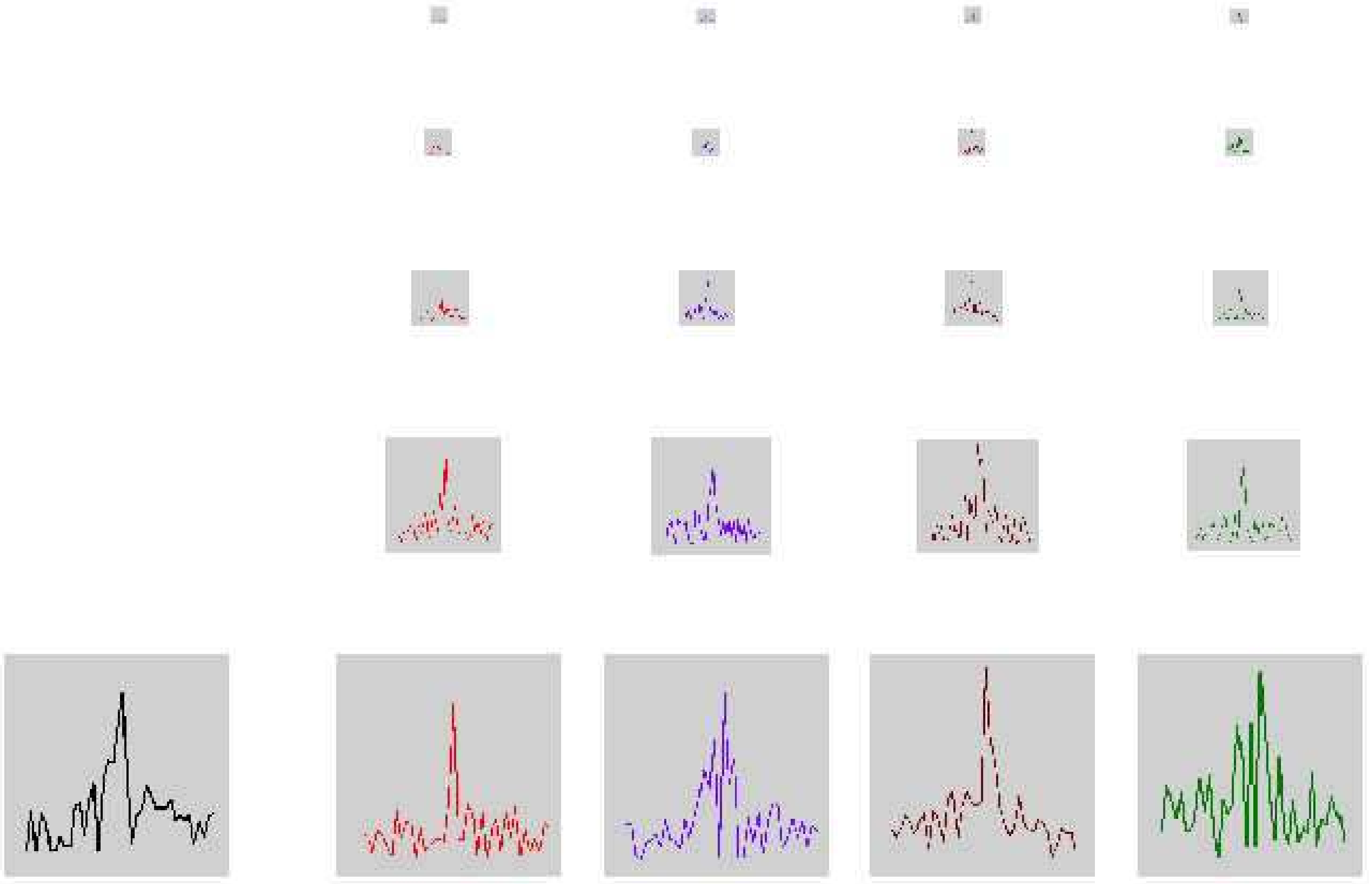
Filter bank





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)

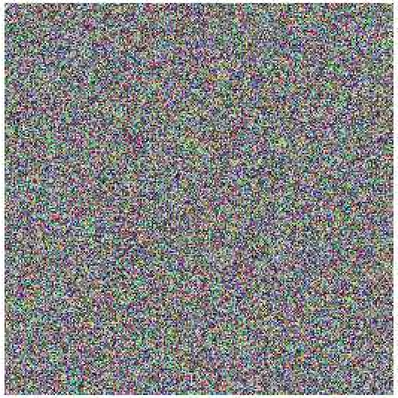
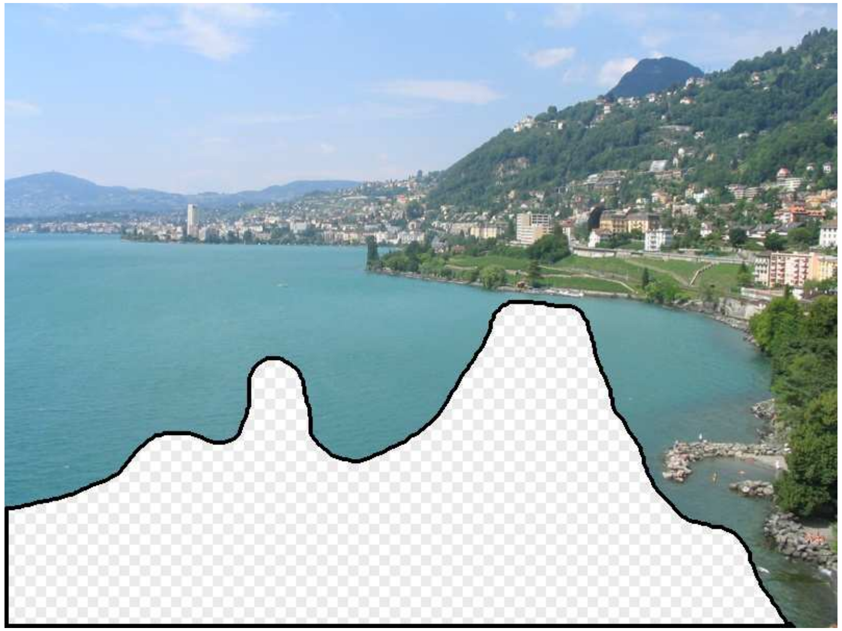
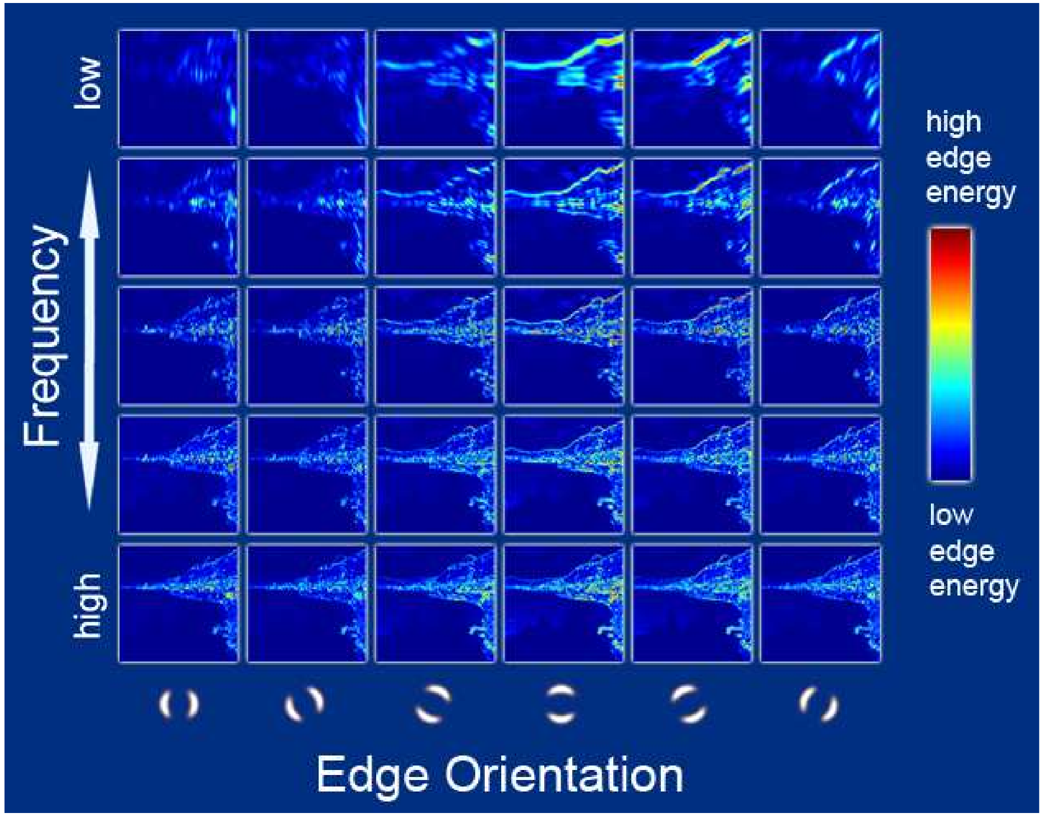


Image Descriptors

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

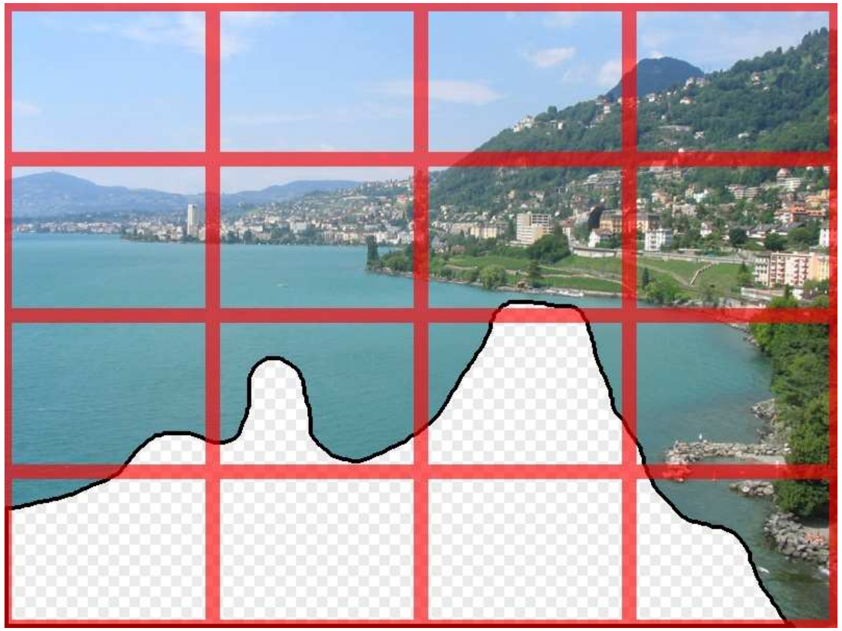
Gist Scene Descriptor

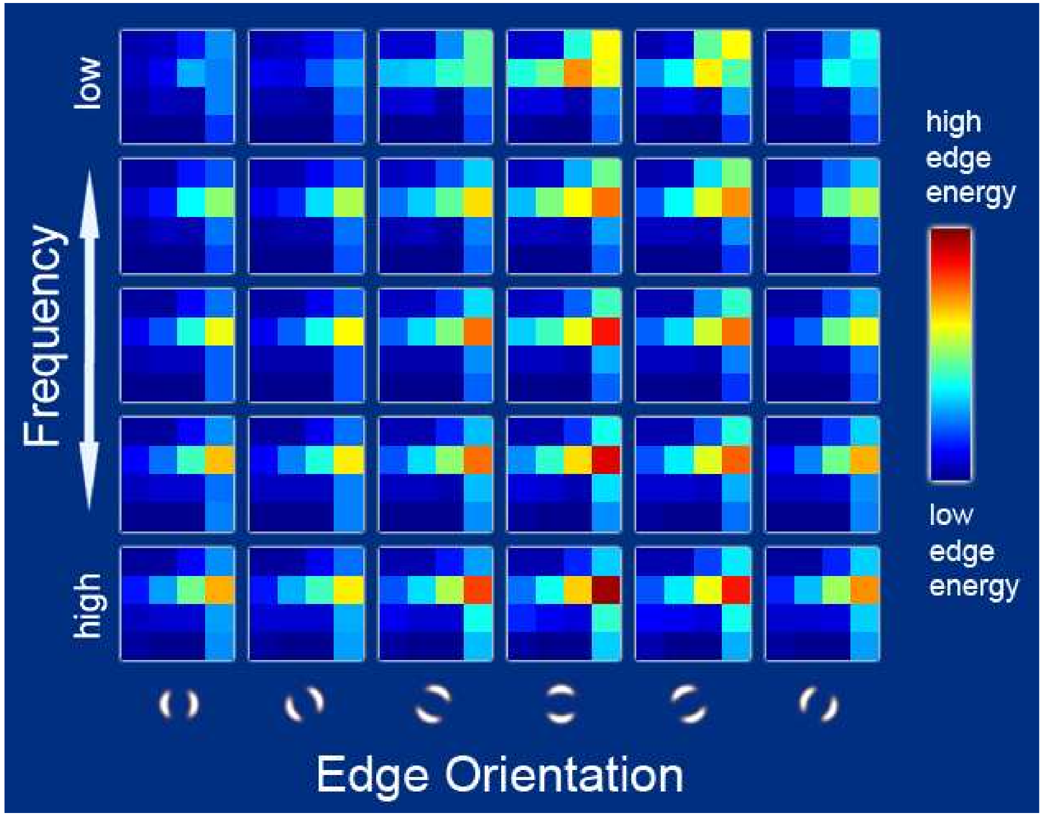




Hays and Efros, SIGGRAPH 2007

Gist Scene Descriptor

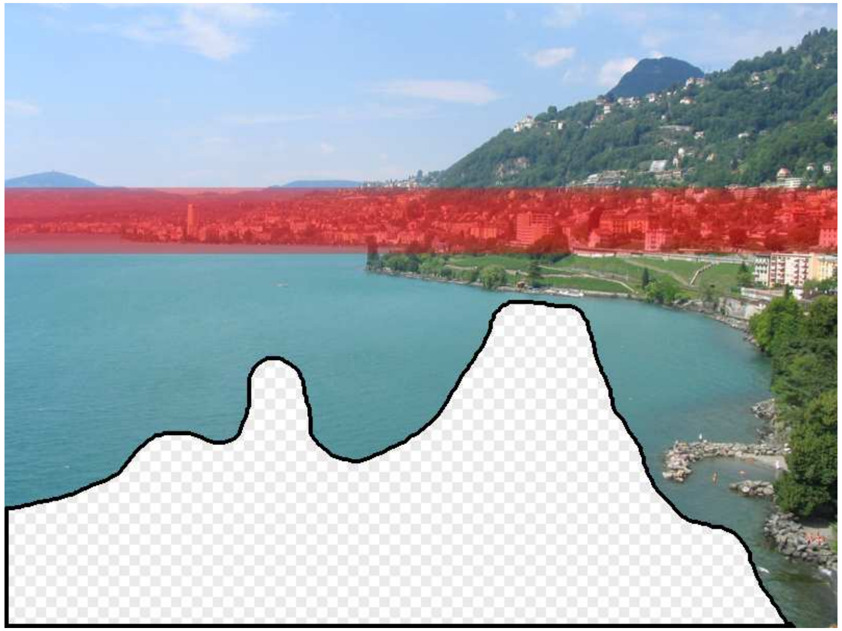


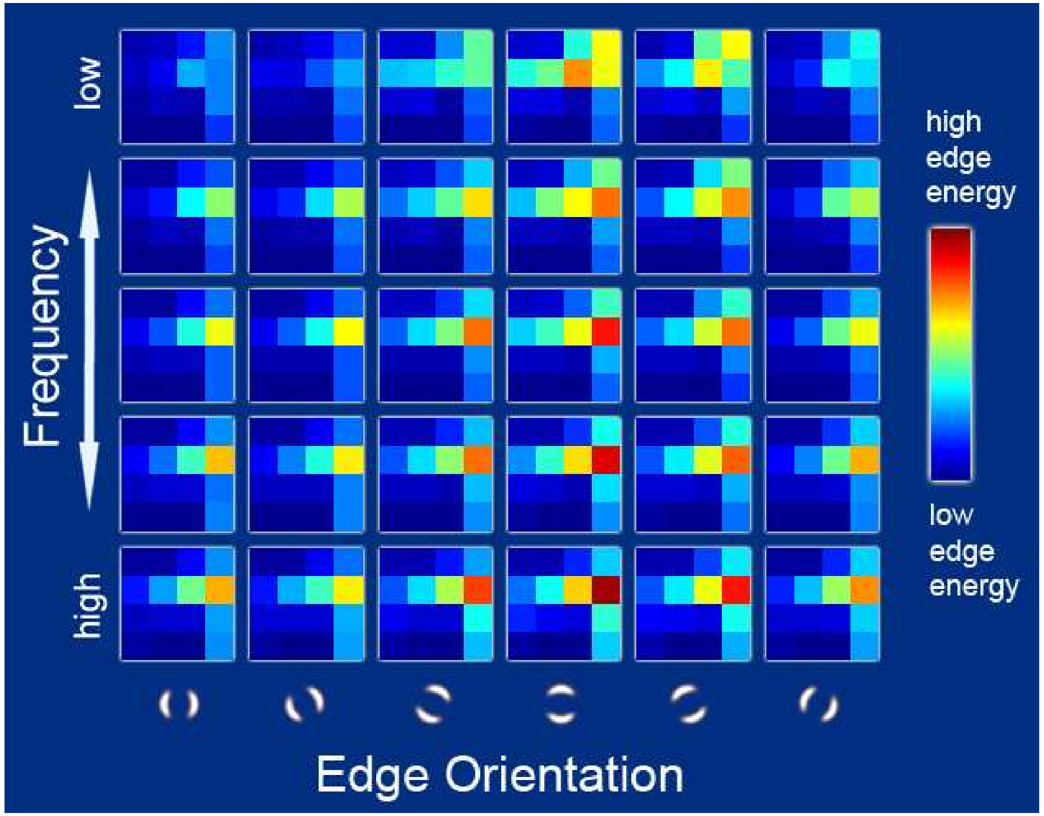


Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

Gist Scene Descriptor

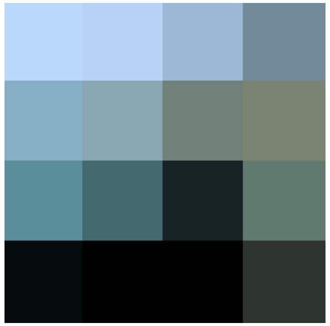




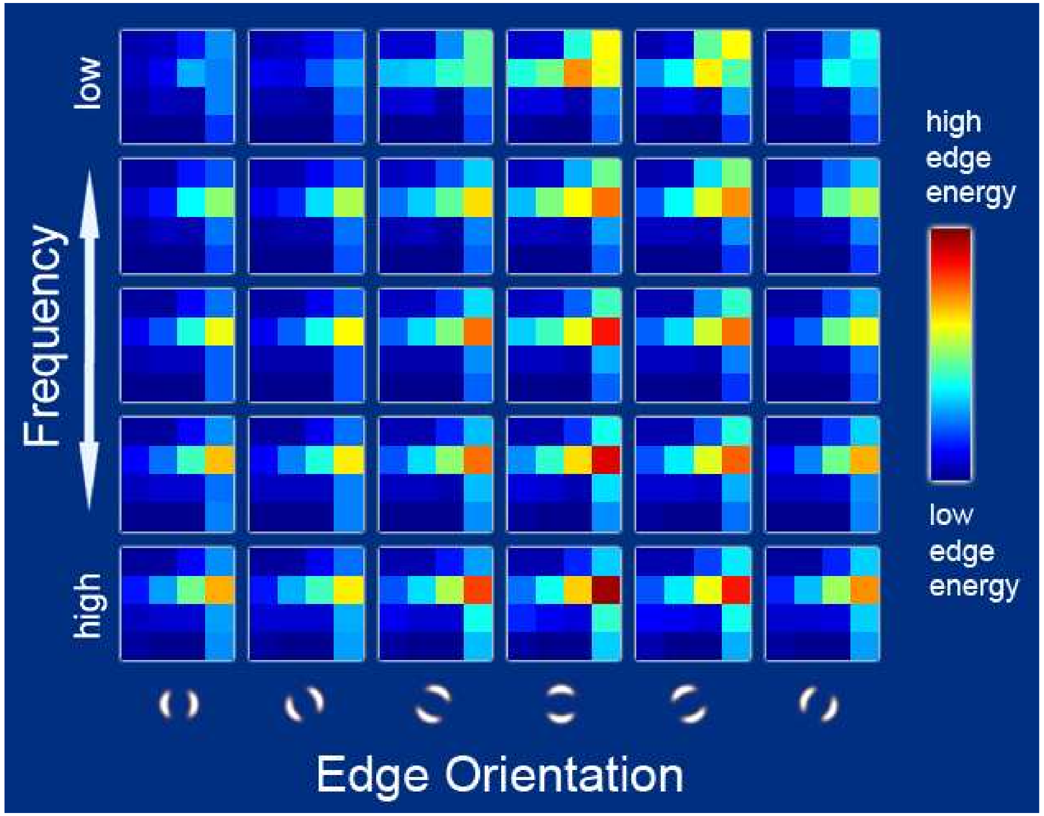
Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

Gist Scene Descriptor



+



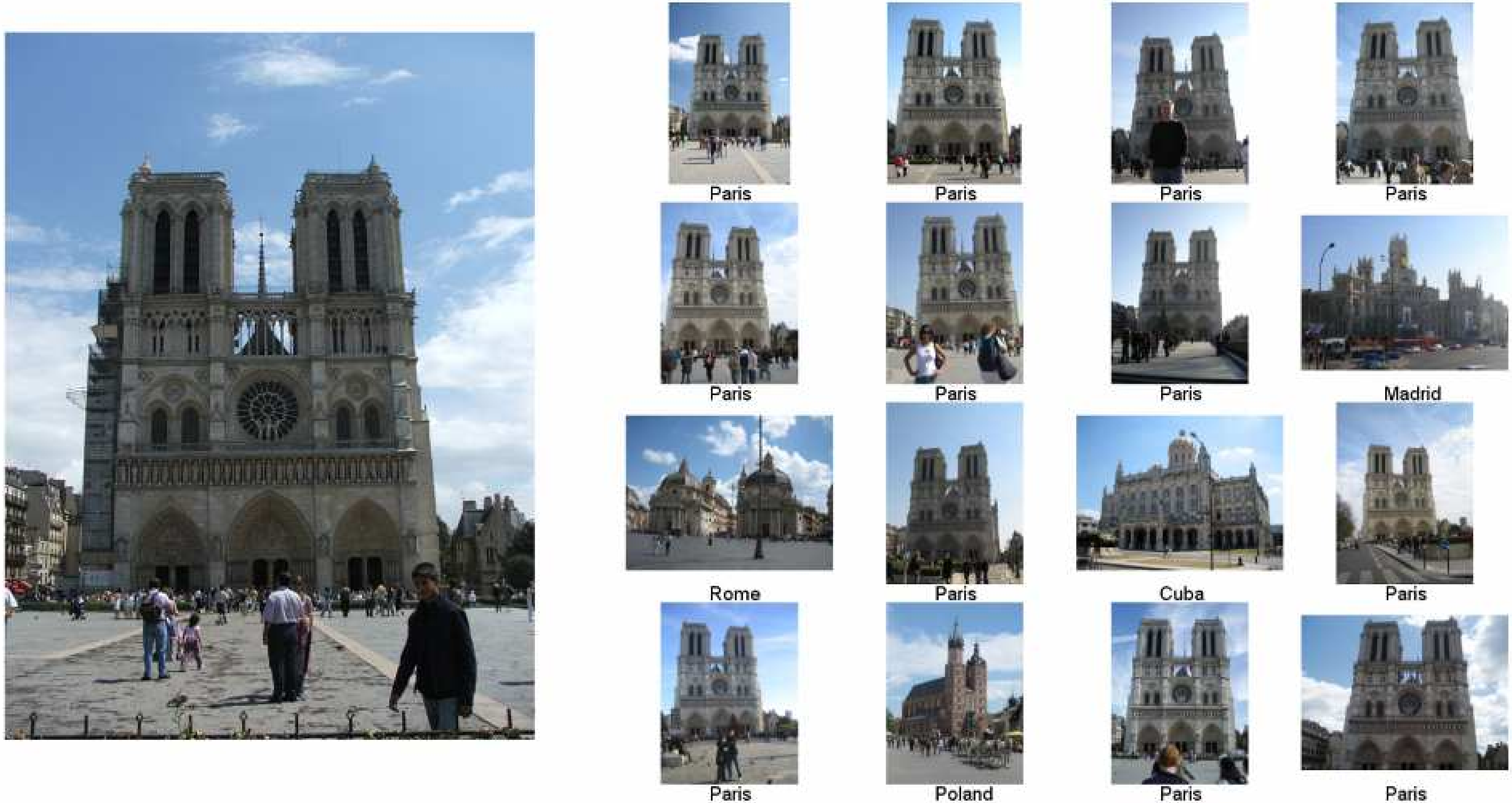
Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

im2gps (Hays & Efros, CVPR 2008)

6 million geo-tagged Flickr images

How much can an image tell about its geographic location?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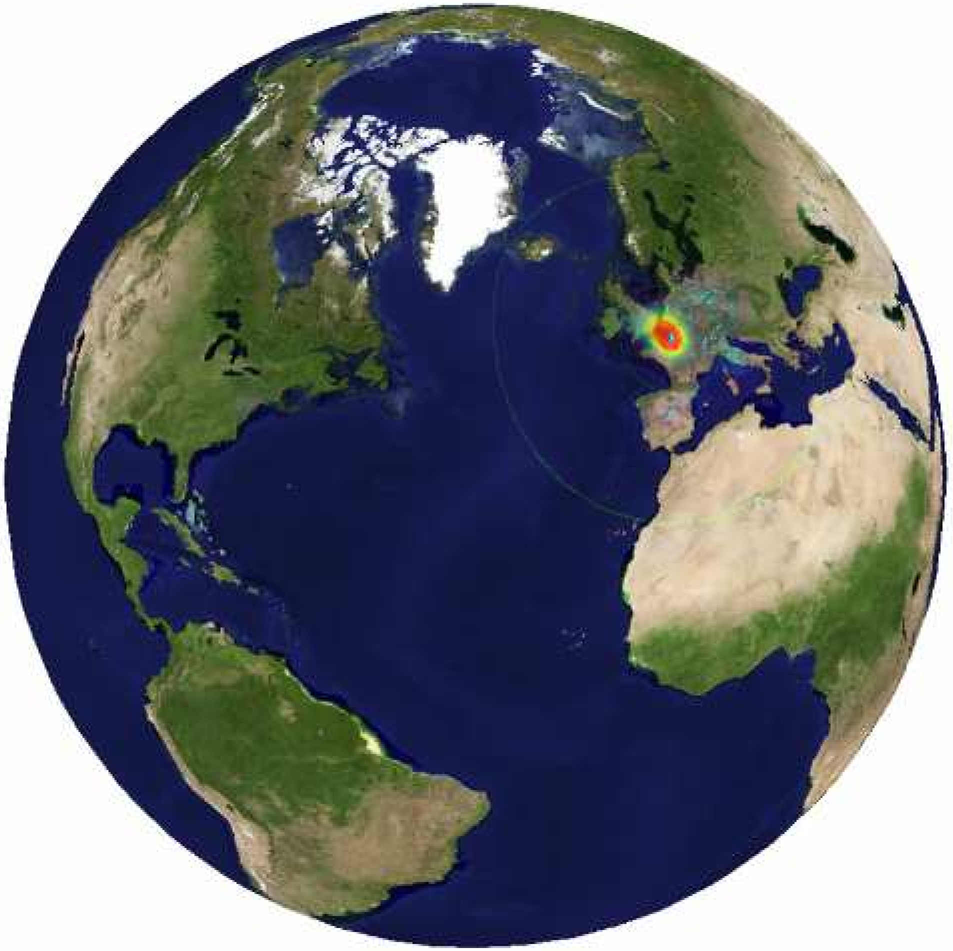
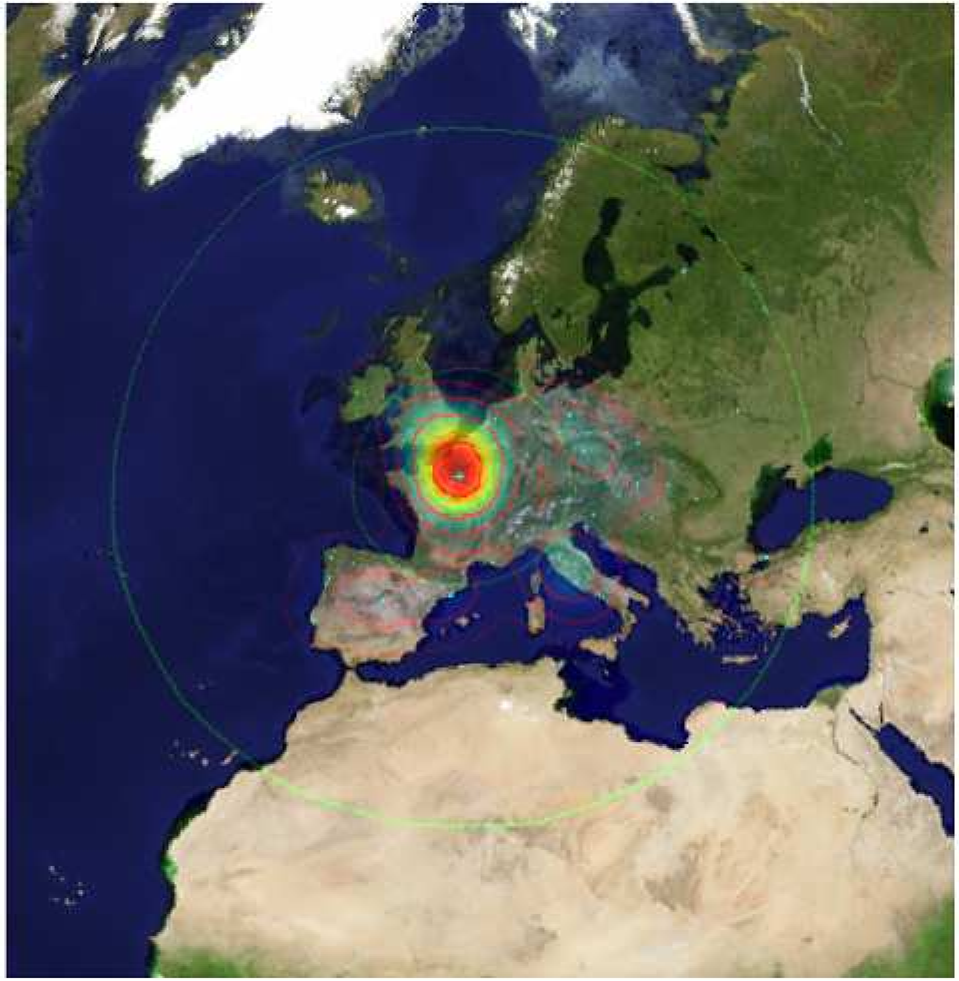
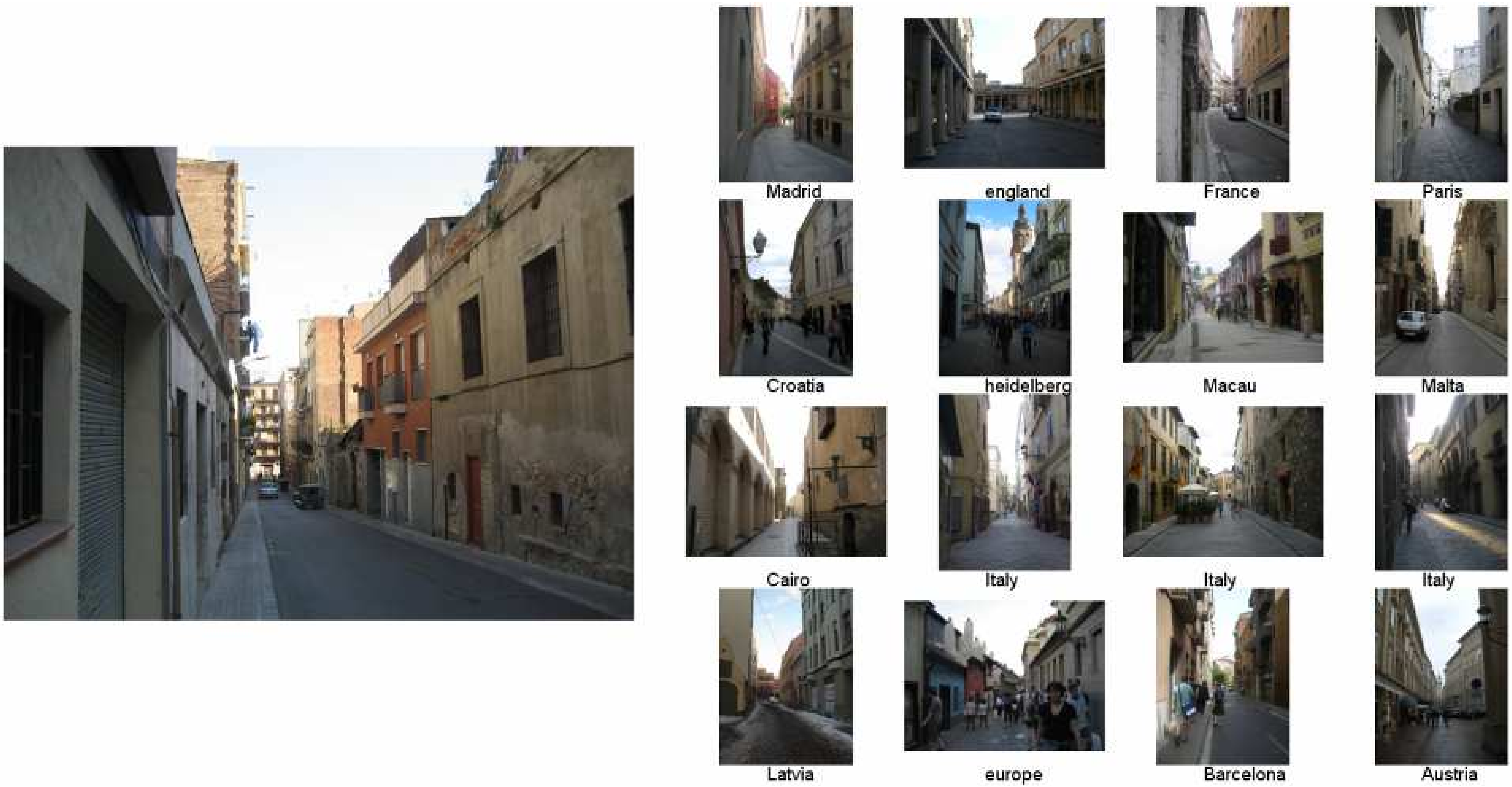
Paris
Paris
Paris
Paris
Paris
Madrid
Rome
Paris
Cuba
Paris
Paris
Poland
Paris
Paris



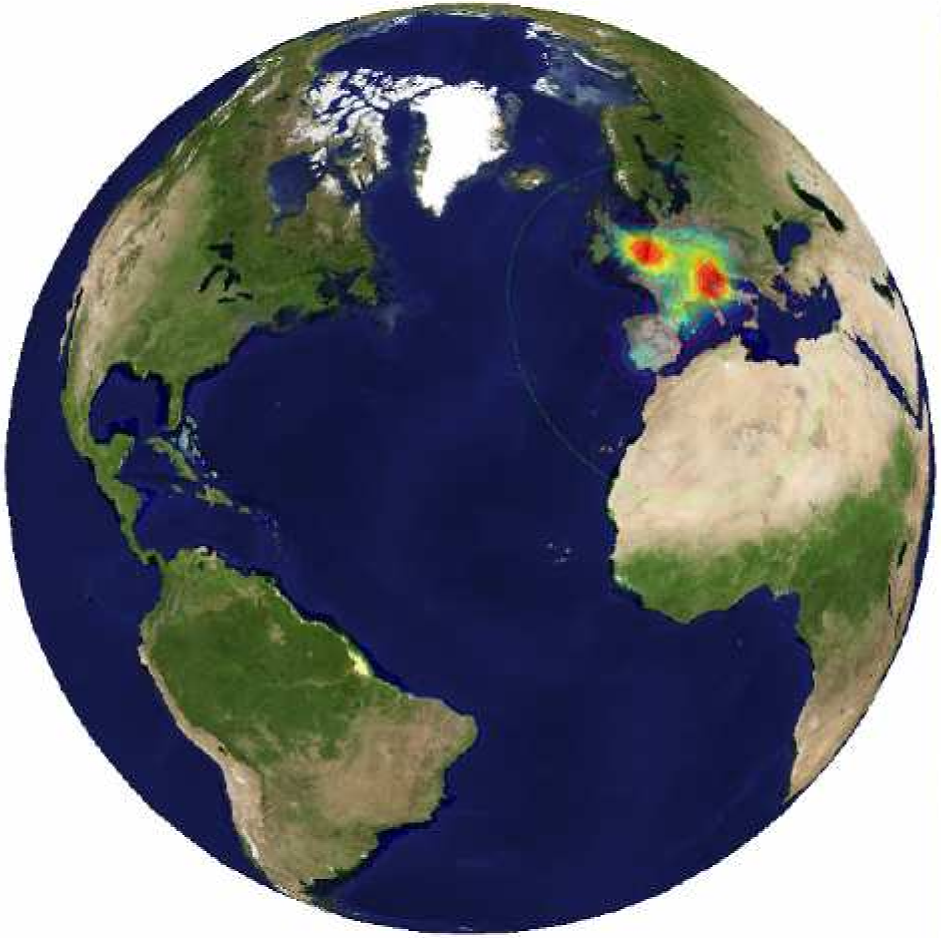


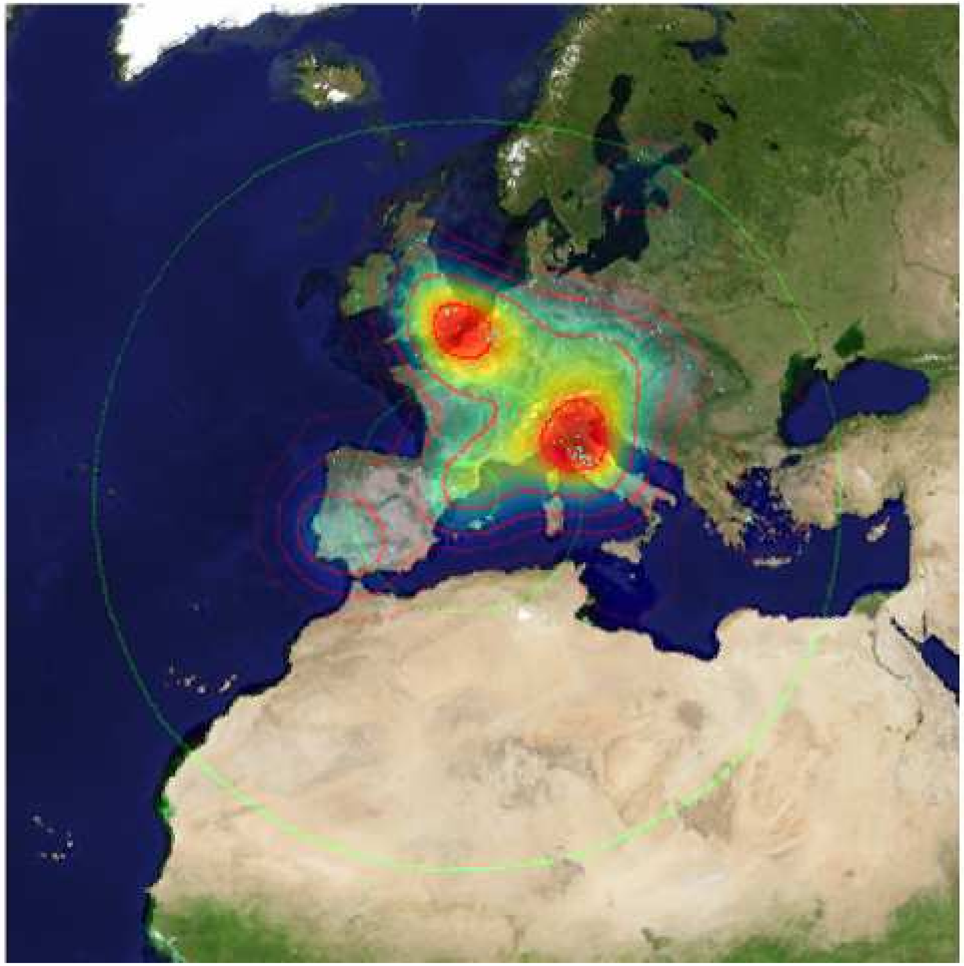
Im2gps

Example Scene Matches



Voting Scheme





im2gps


Philippines


Houston


Thailand

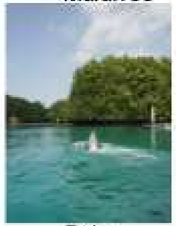

Houston


Maldives


Philippines


NewZealand


Bermuda


Palau


Mexico2


Brazil

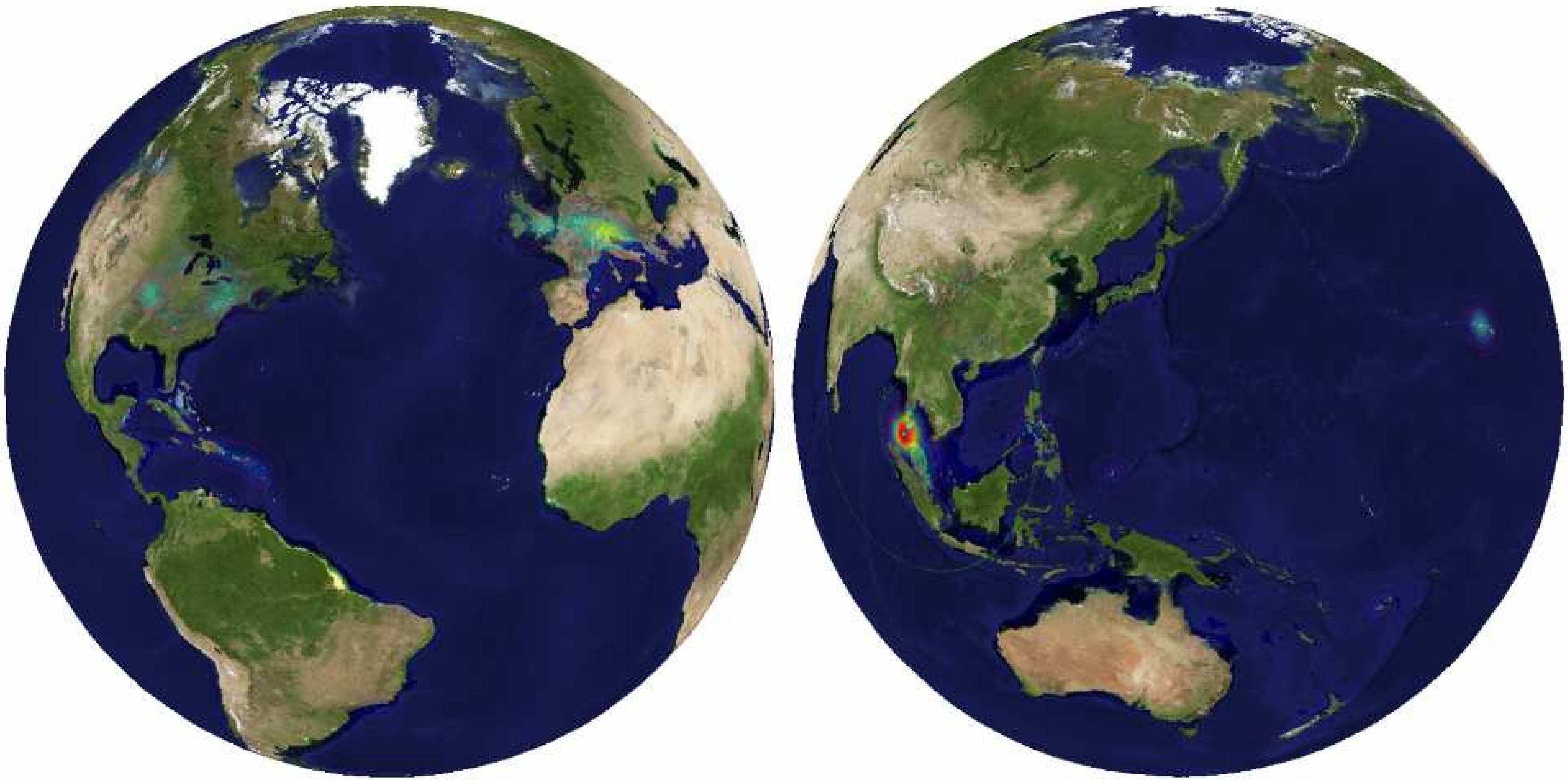

Mendoza


Brazil


Thailand


Arkansas


Hawaii




Switzerland
SouthAfrica
California
Barcelona
Italy
Italy
Nevada
Washington
Paris
Madrid
California
Oregon
SouthDakota
USA
Bangkok
Italy

USA
Utah
Arizona
Utah
Utah
Utah
Tunisia
Kenya
Utah
LosAngeles
Burundi
NewMexico
Utah
Utah
Utah
Mendoza

USA
Utah
Arizona
Utah
Utah
Utah
Tunisia
Kenya
Utah
LosAngeles
Burundi
NewMexico
Utah
Utah
Utah
Mendoza

California

Oklahoma

SouthAfrica

Zambia

Kenya

Hyderabad

Mongolia

SouthAfrica

Kenya

Kenya

Zambia

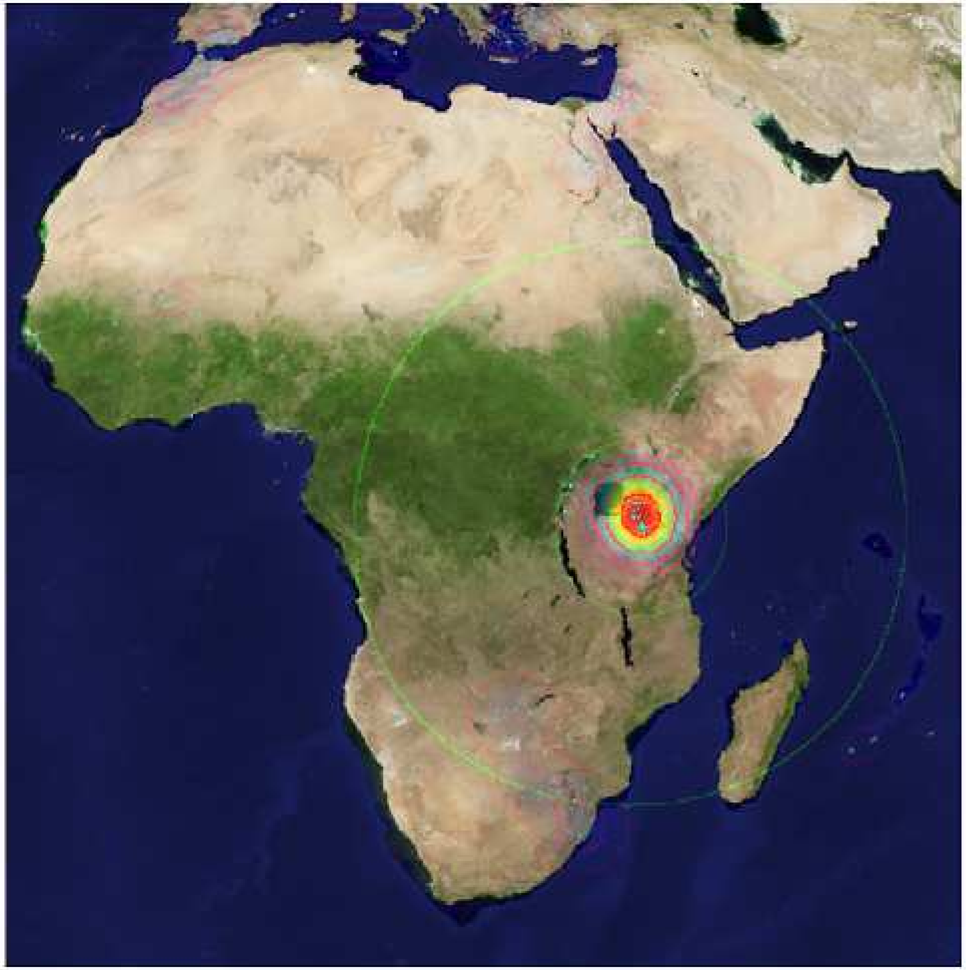
Ethiopia

Nevada

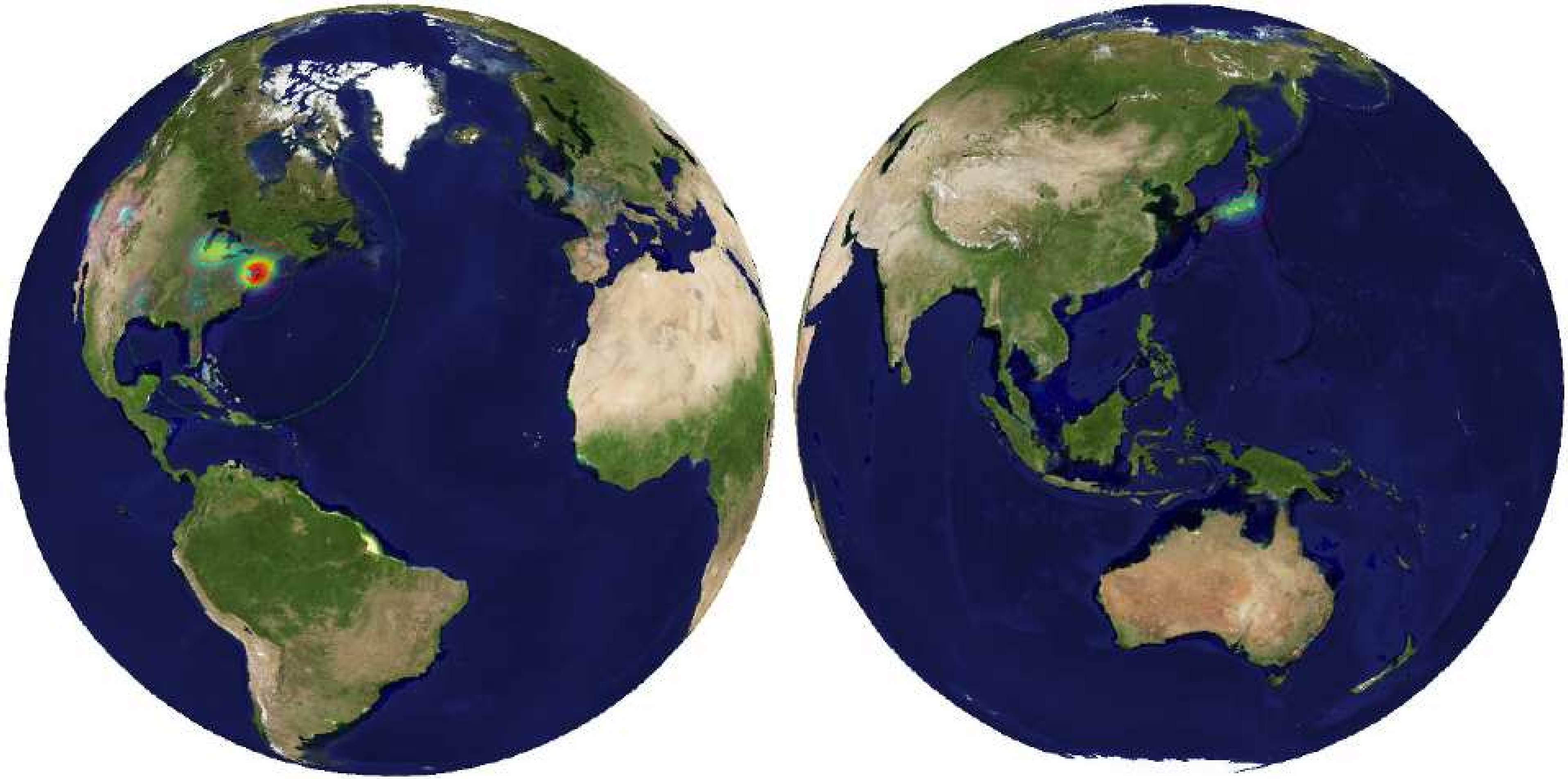
africa

Morocco

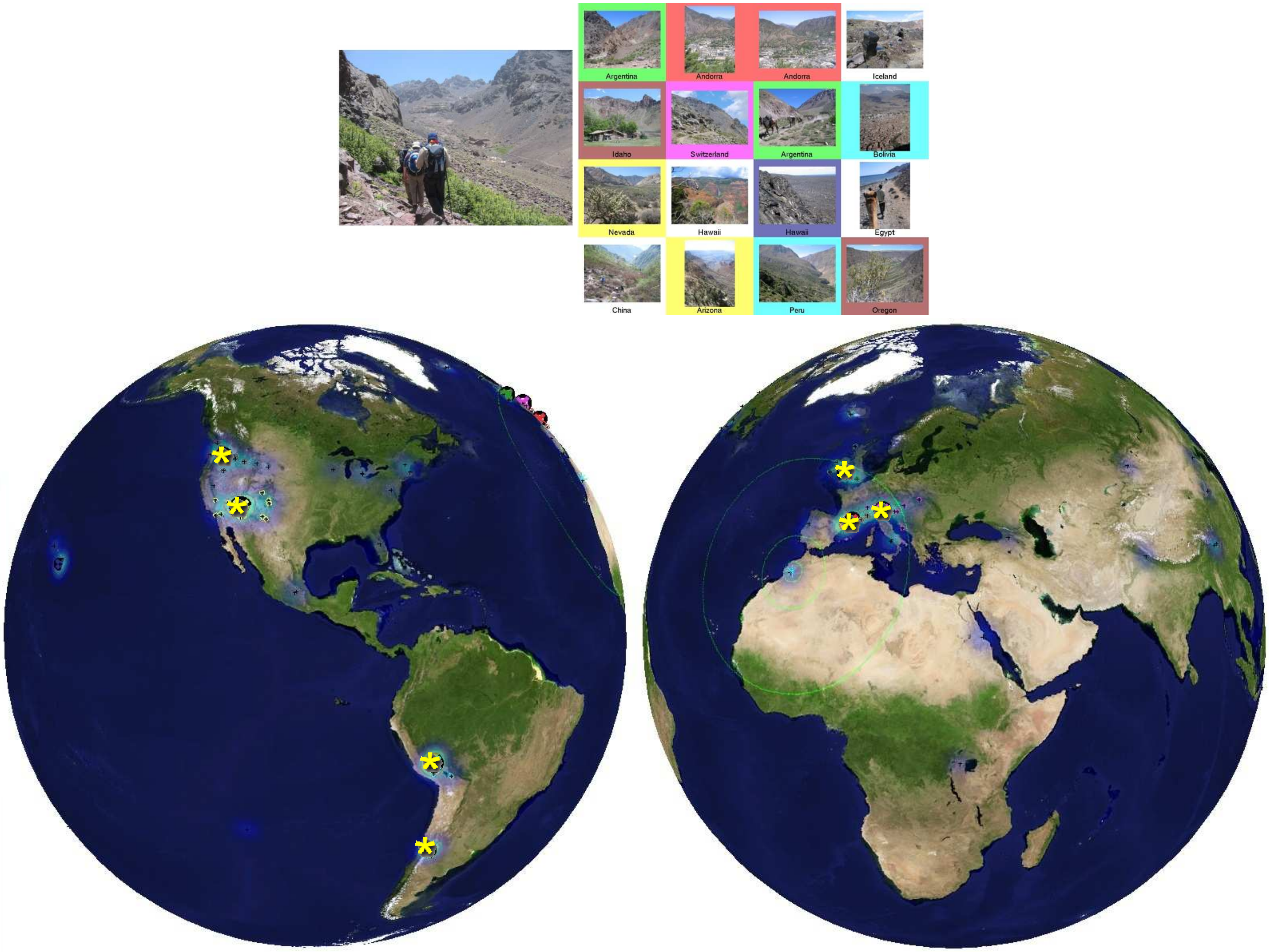
Tennessee

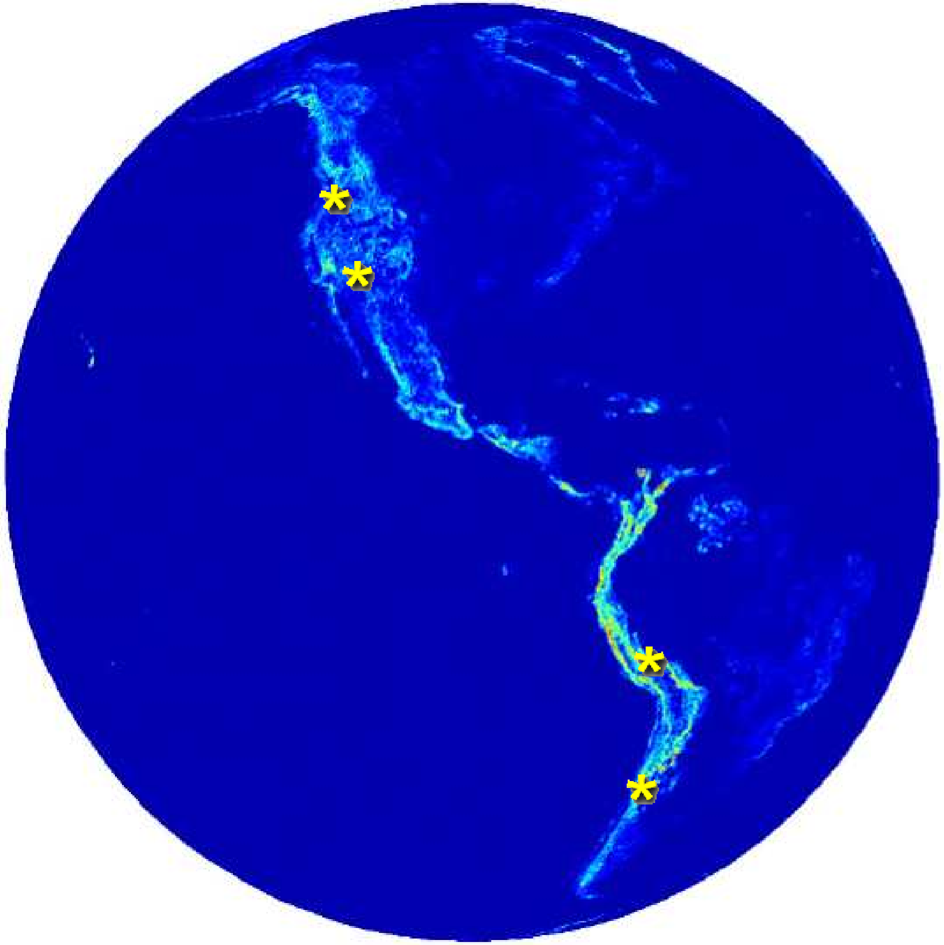

Toronto
Florida
NewYork
Boston
Boston
Oregon
Oregon
Oregon
NewYork
Barcelona
Oregon
Chicago
Ohio
Philadelphia
NewYorkCity
Boston

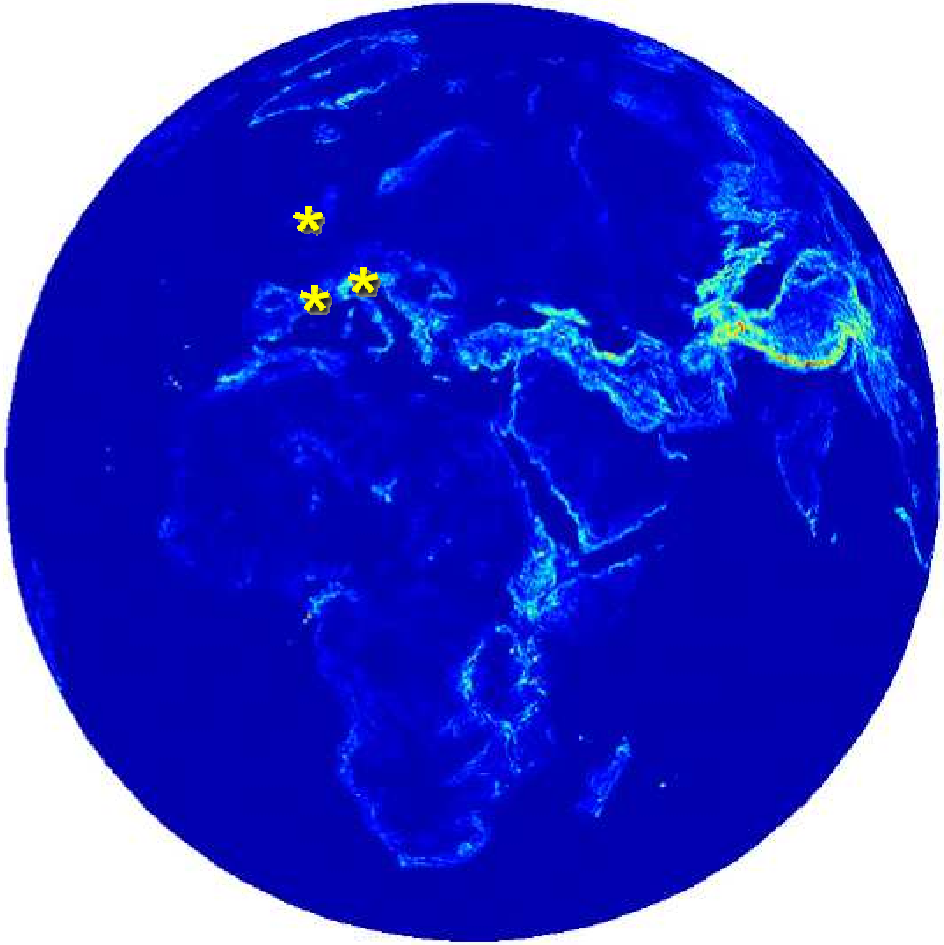


Data-driven categories

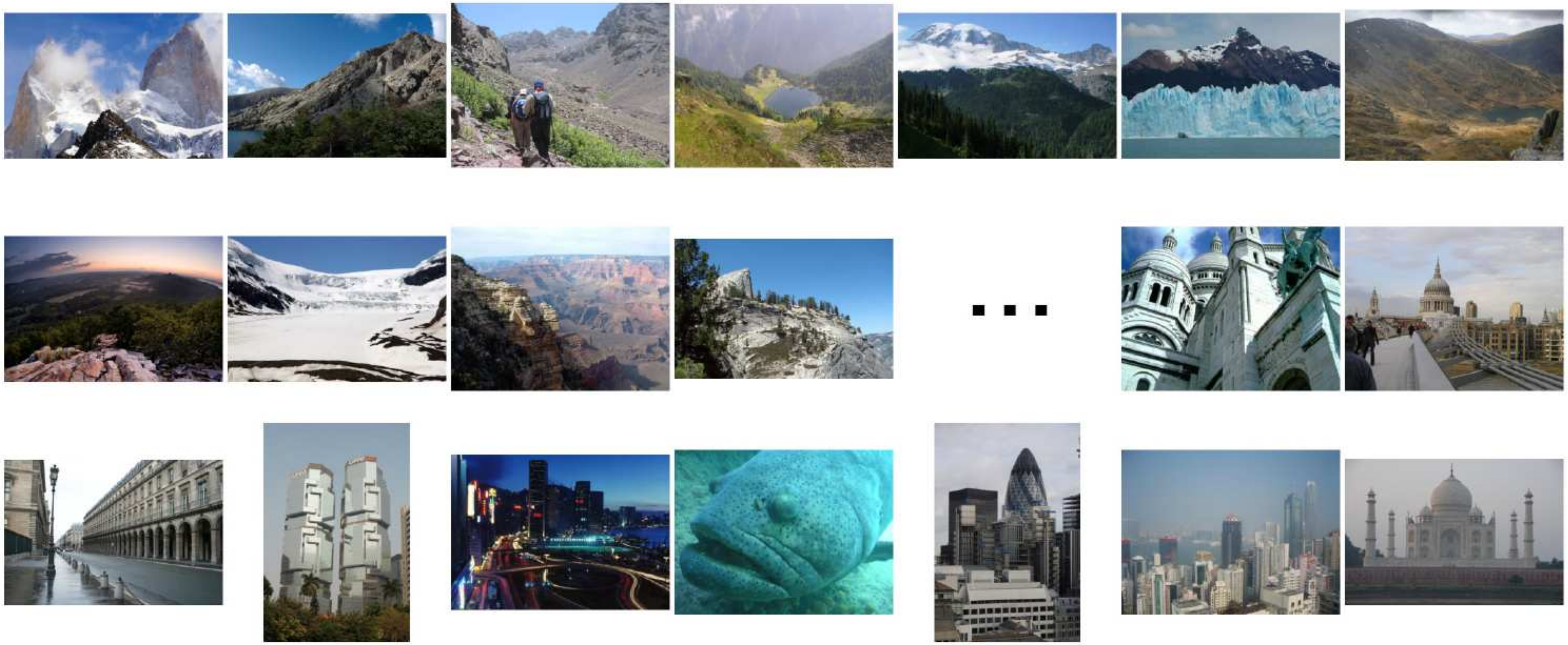

Argentina
Andorra
Andorra
Iceland
Idaho
Switzerland
Argentina
Bolivia
Nevada
Hawaii
Hawaii
Egypt
China
Arizona
Peru
Oregon

Elevation gradient =
112 m / km





Elevation gradient magnitude ranking



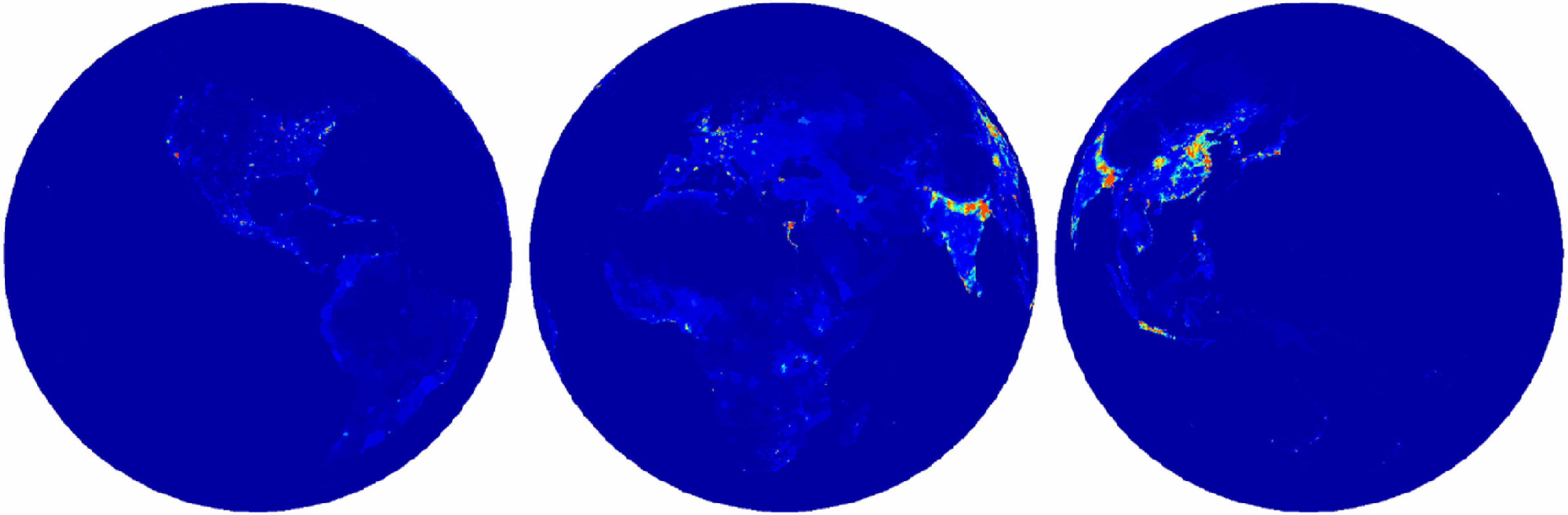
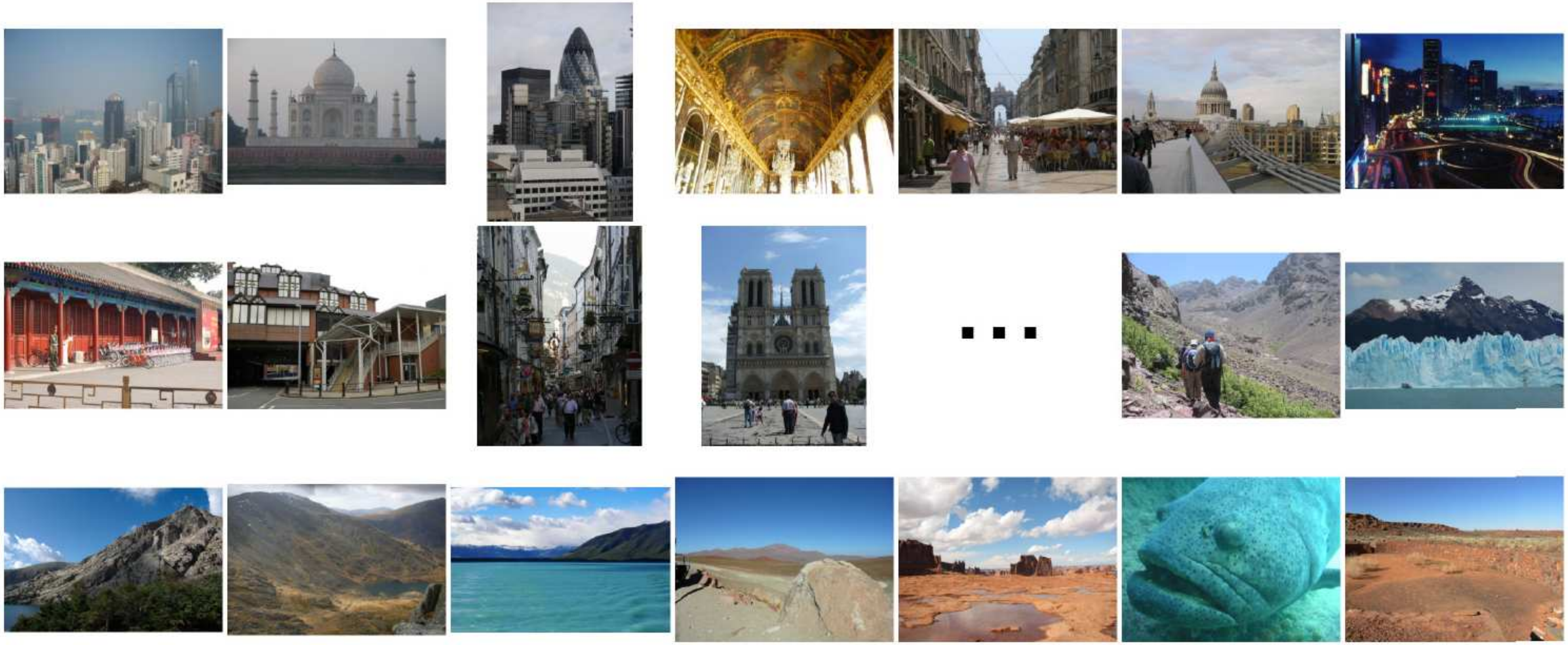


Figure 2. Global population density map.

Population density ranking



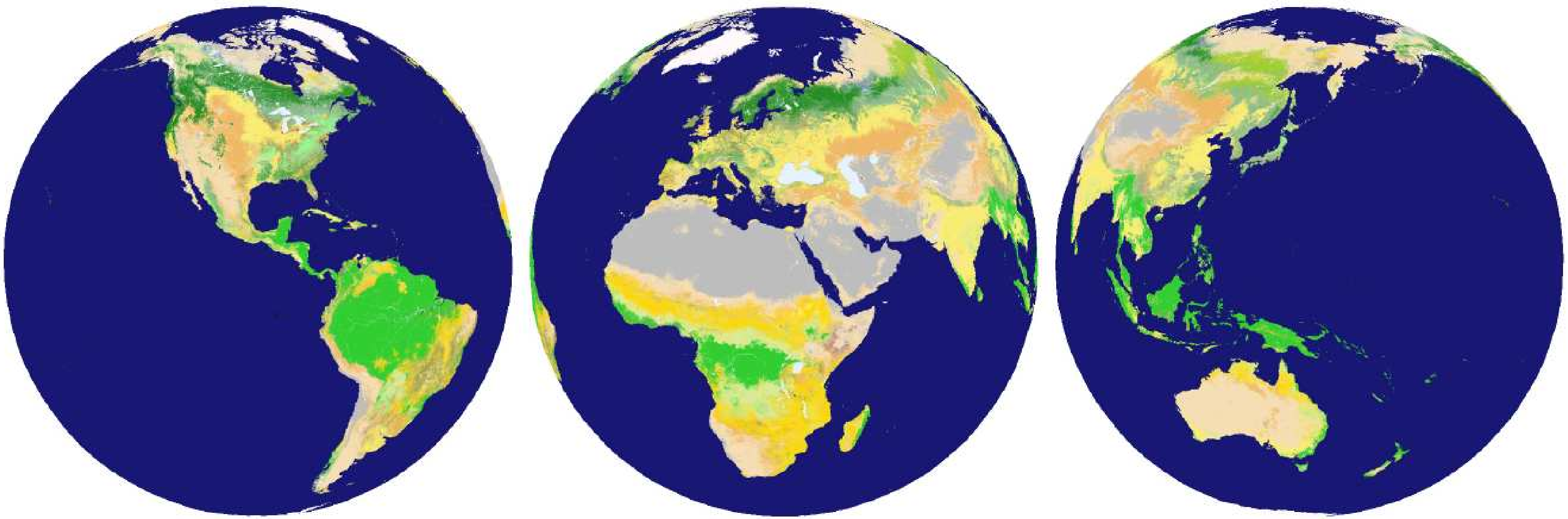
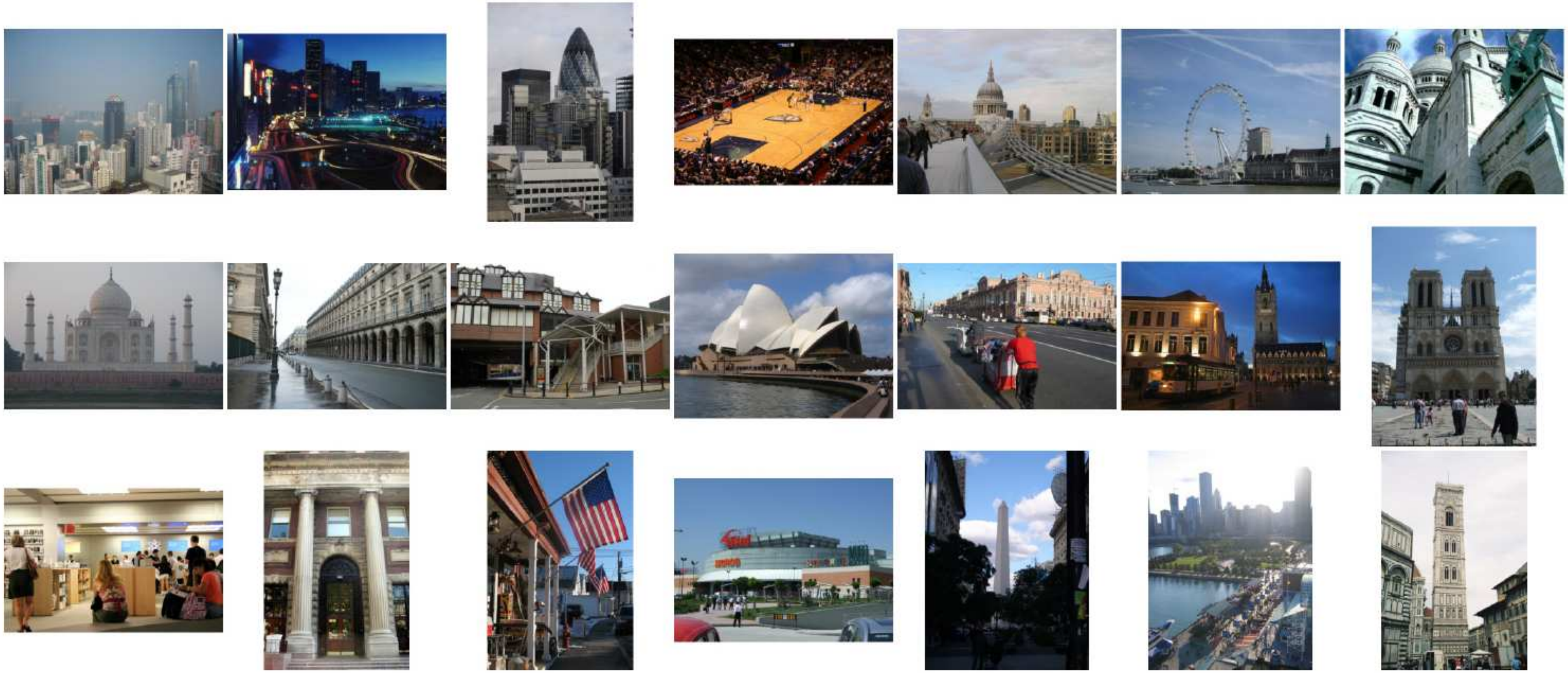


Figure 4. Global land cover classification map.

Barren or sparsely populated

Urban and built up



Snow and Ice





















Savannah













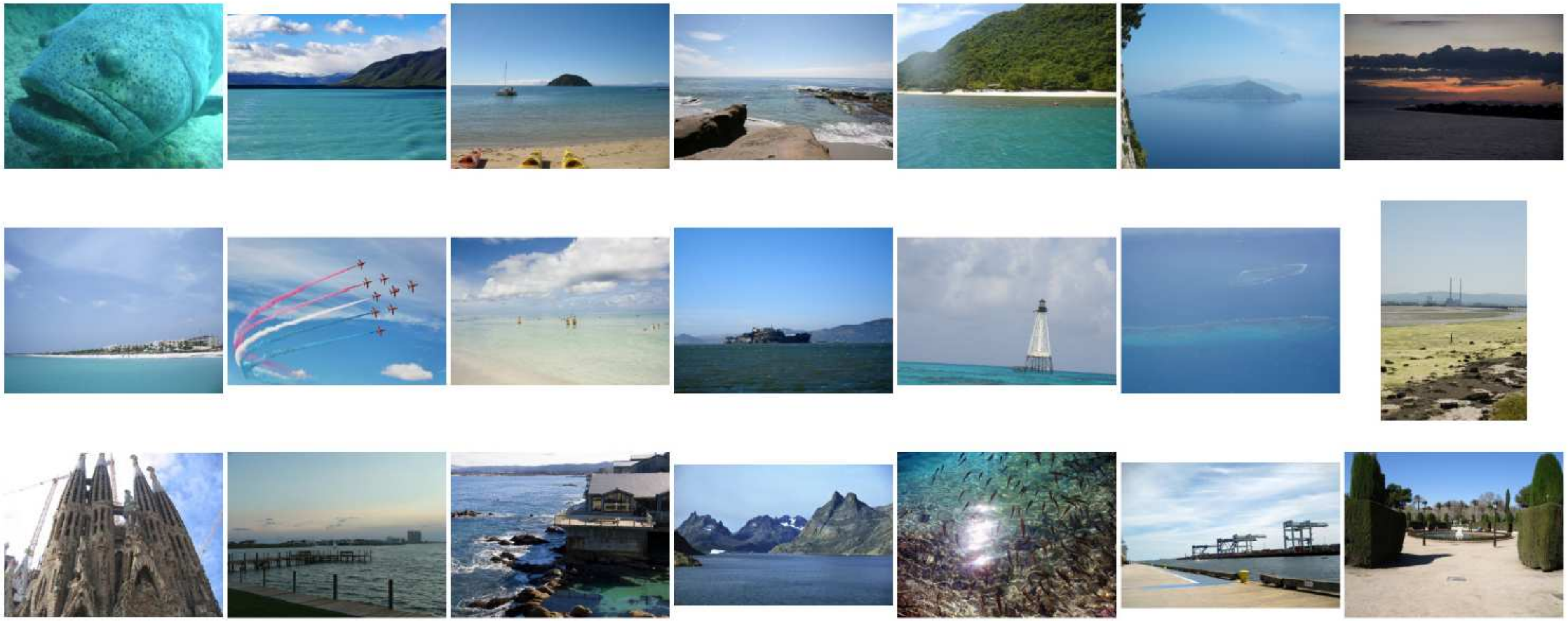








Water



Scene matching with camera transformations

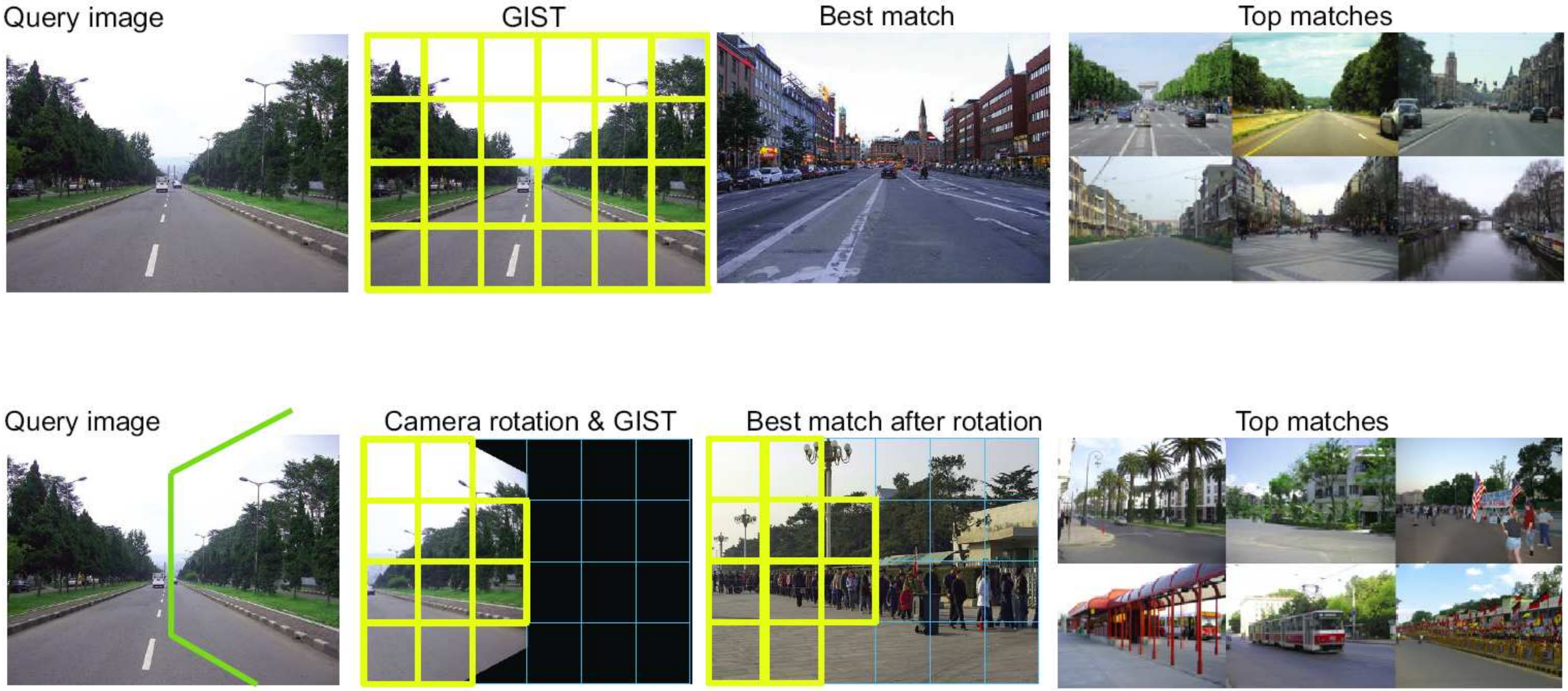
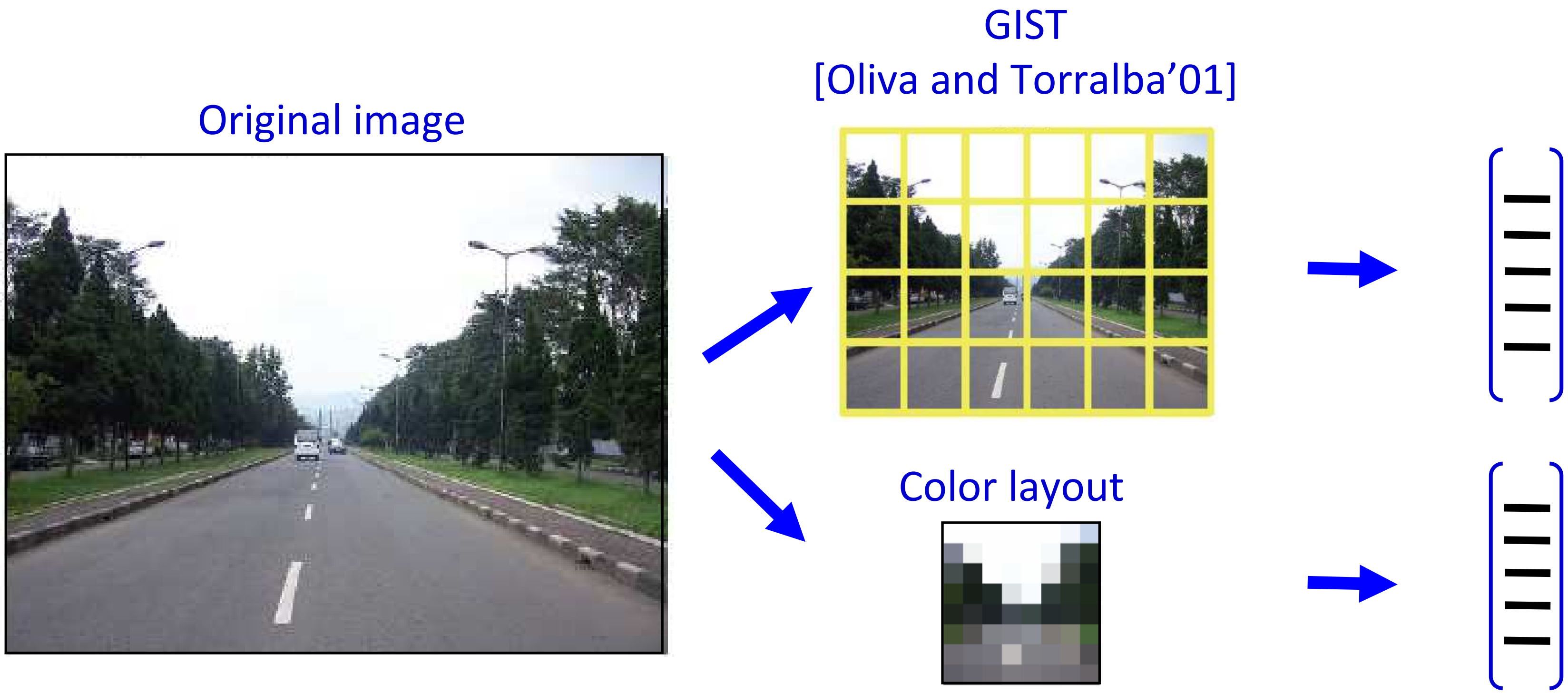
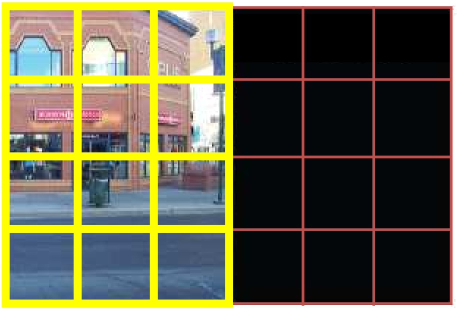


Image representation

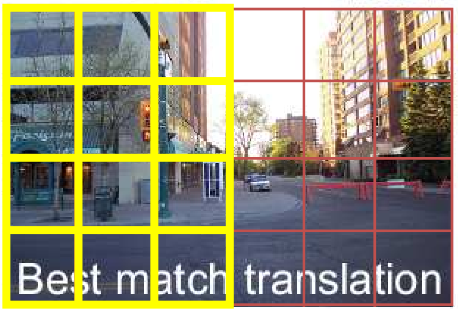


Scene matching with camera view transformations: Translation

1. Move camera



2. View from the virtual camera



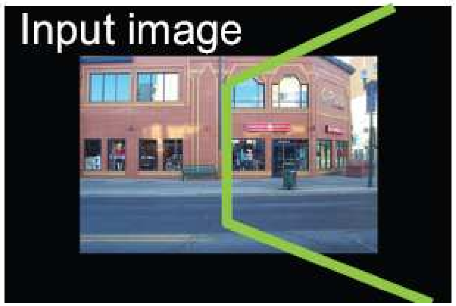
3. Find a match to fill the missing pixels

4. Locally align images

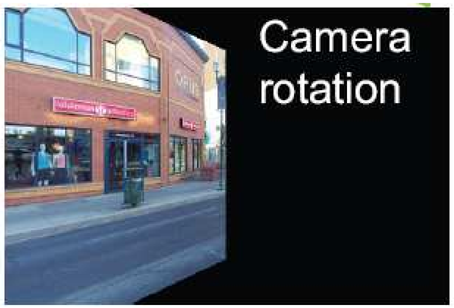
5. Find a seam

6. Blend in the gradient domain

Scene matching with camera view transformations: Camera rotation



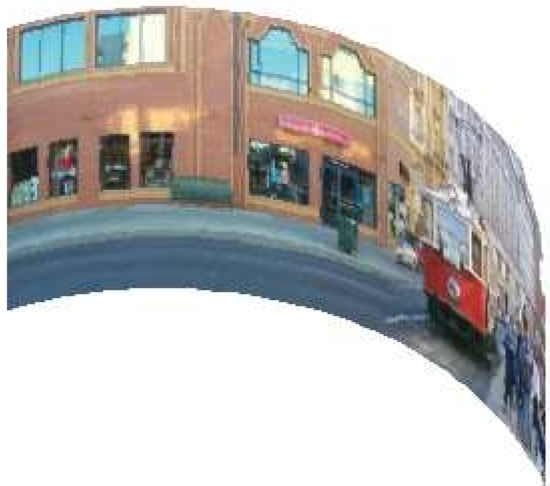
1. Rotate camera



2. View from the virtual camera

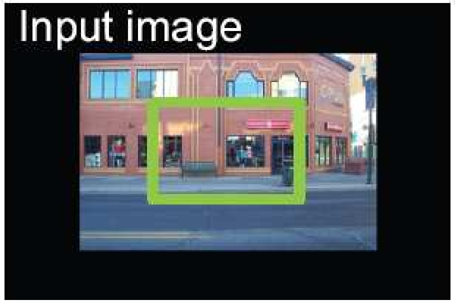
3. Find a match to fill-in the missing pixels

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

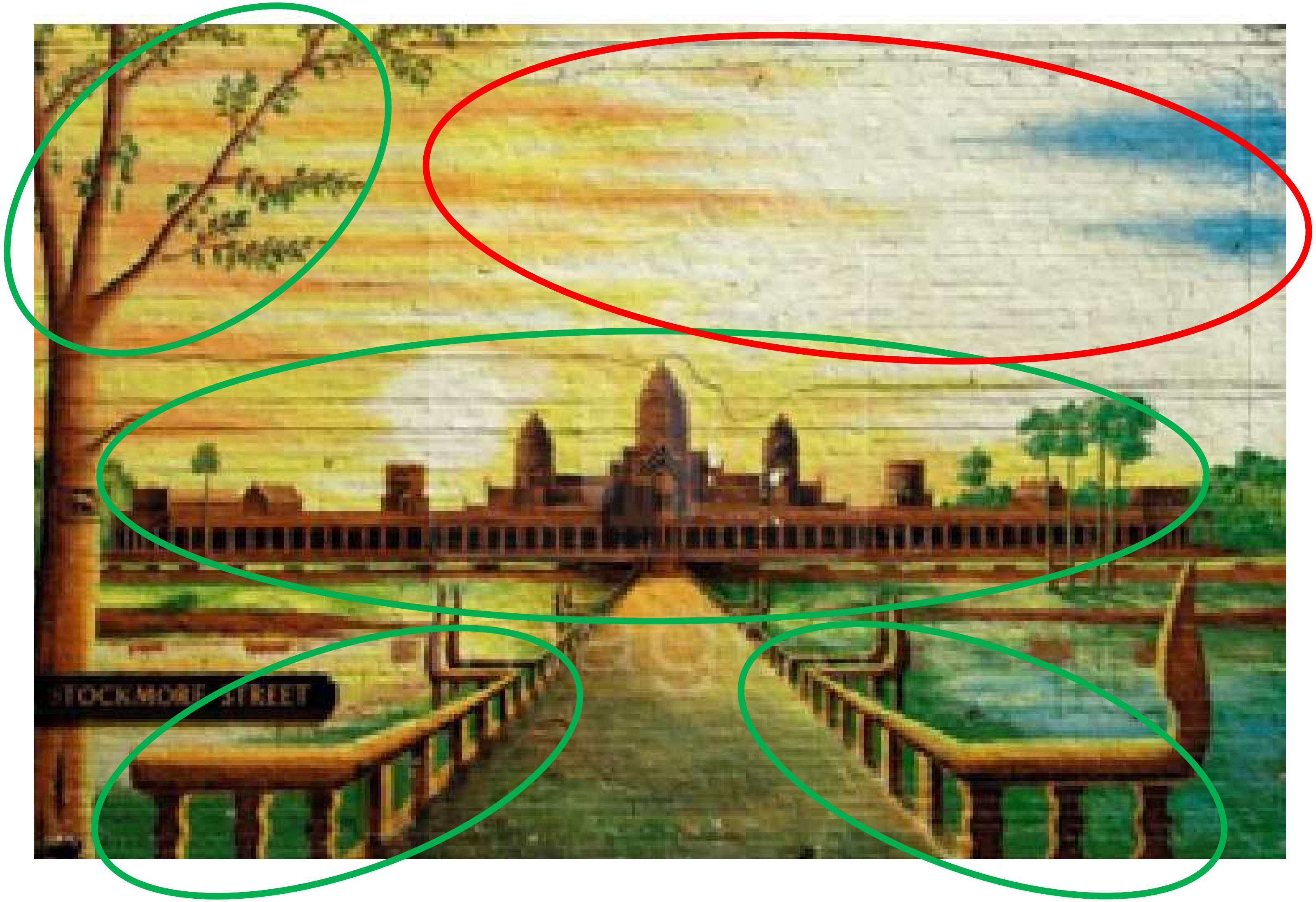
Navigate the virtual space using intuitive motion controls

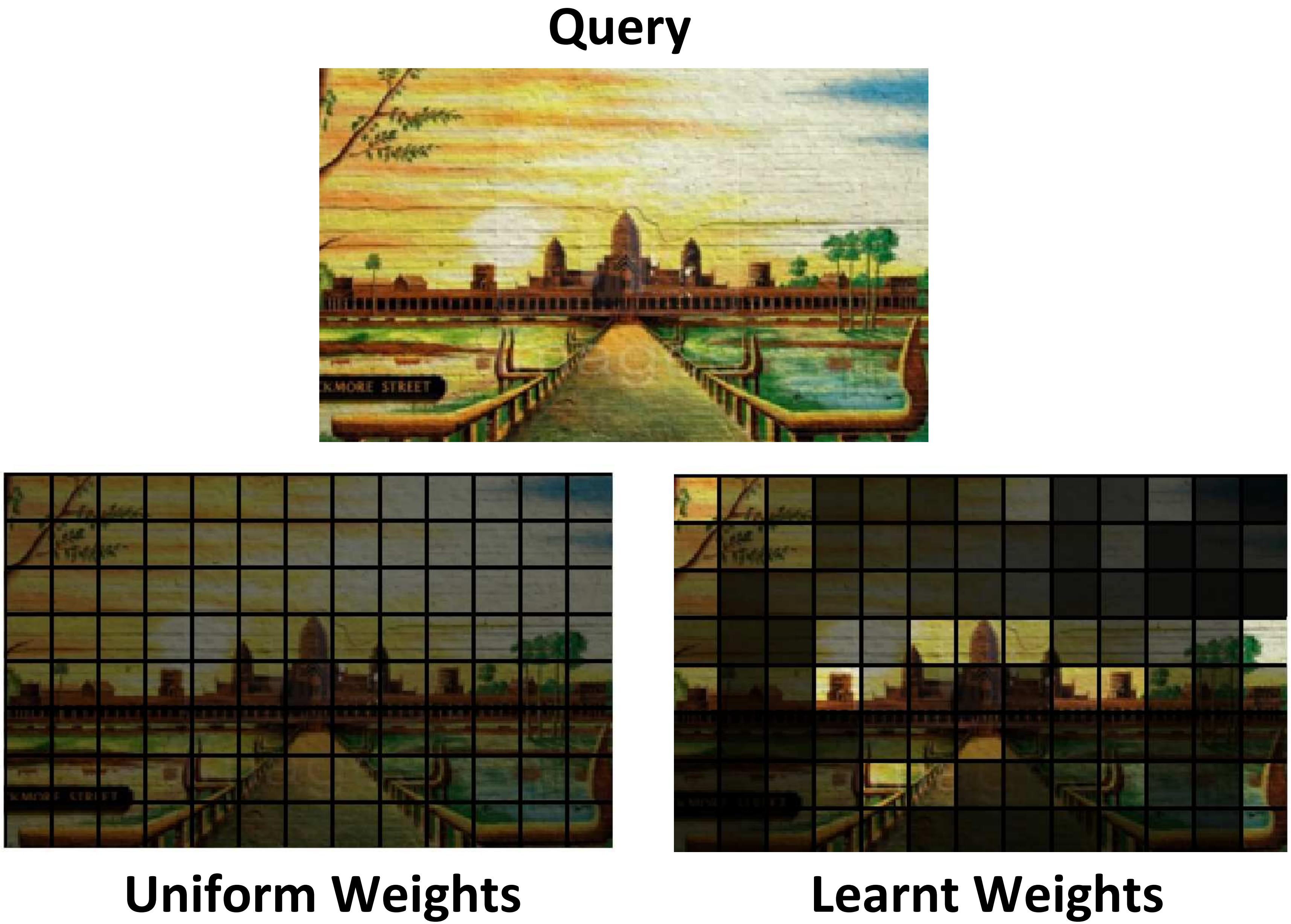
Video

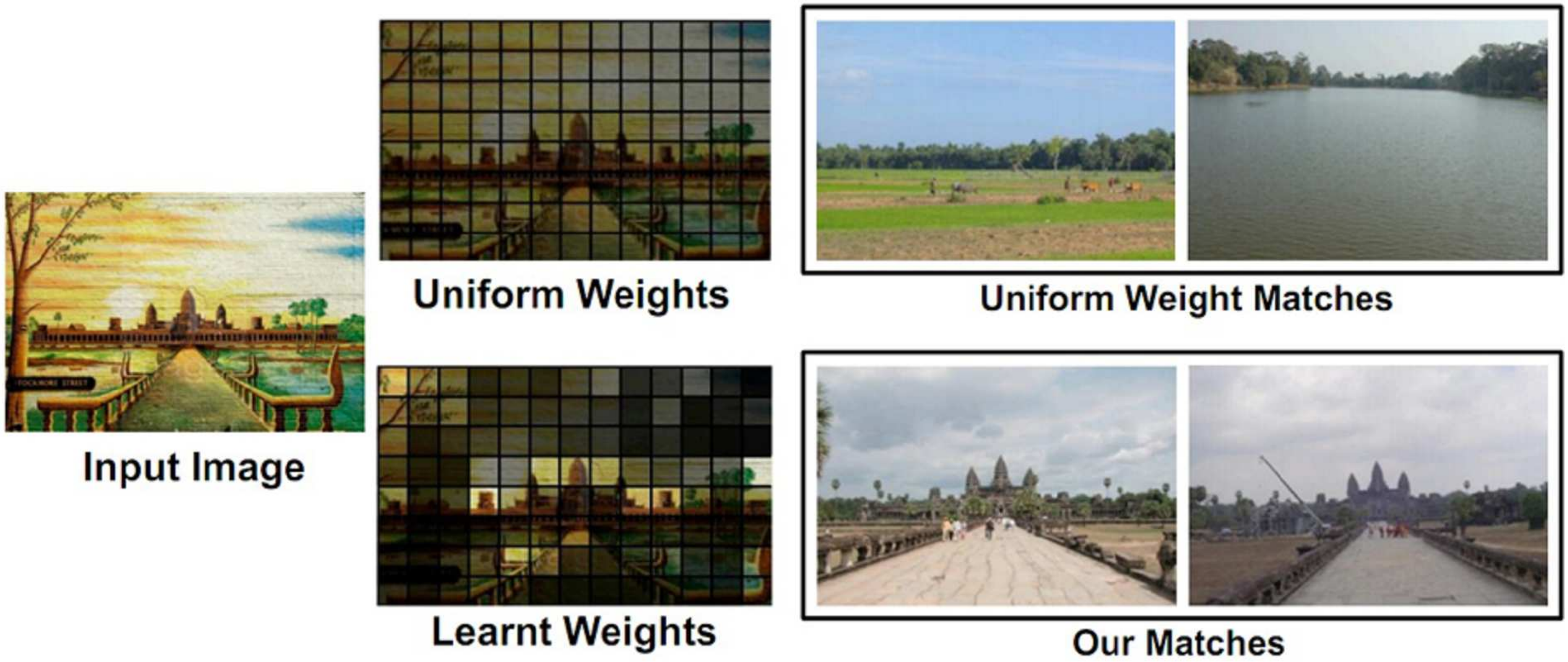
http://www.youtube.com/watch?v=E0rboU10rPo

LEARNING QUERY-CENTRIC VISUAL SIMILARITY

Abhinav Shrivastava, Tomasz Malisiewicz, Abhinav Gupta, Alyosha Efros
Carnegie Mellon University

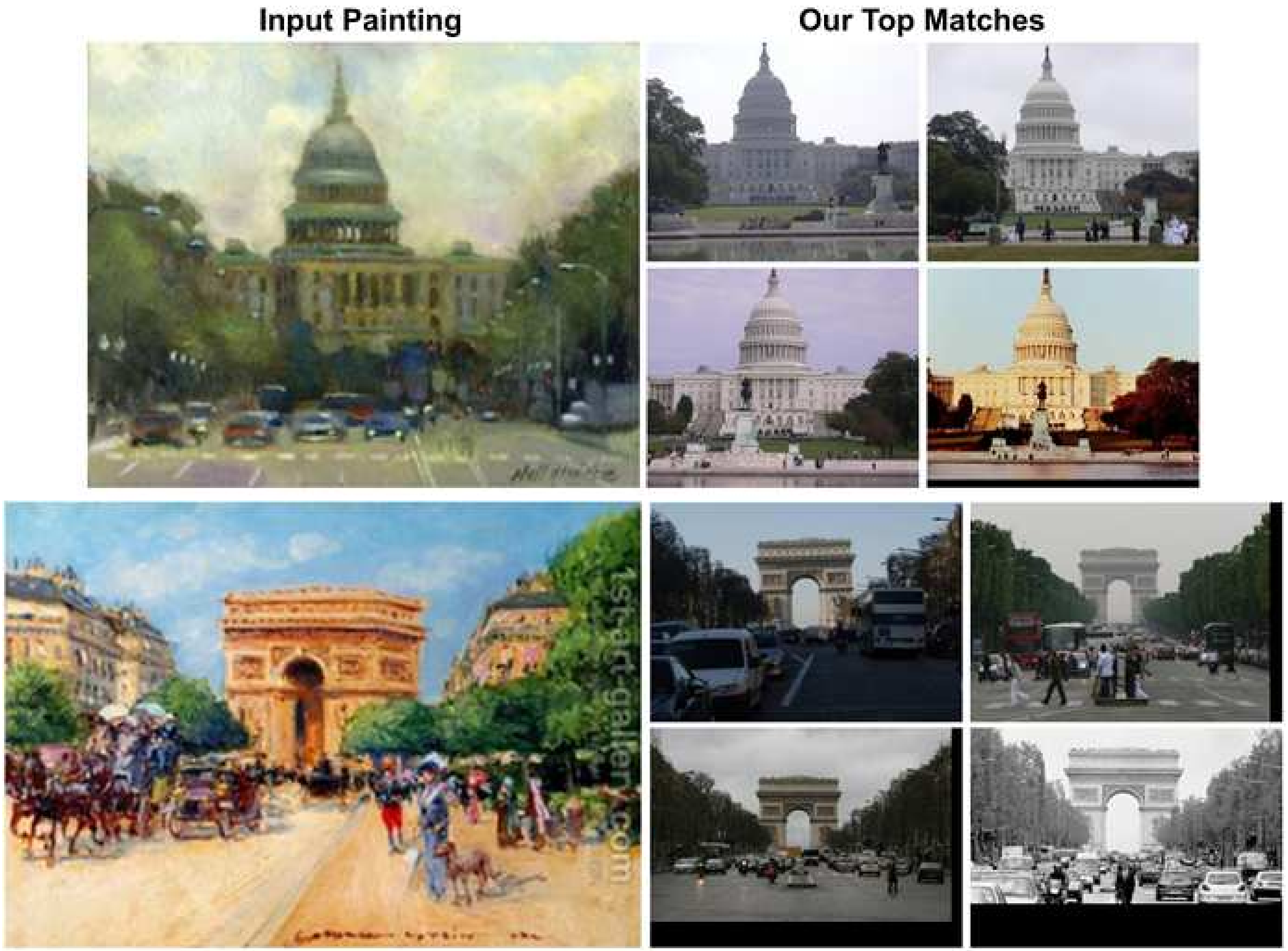

STOCKMORE STREET


Query
KMORE STREET
Uniform Weights
Learnt Weights


Input Image
Uniform Weights
Learnt Weights
Uniform Weight Matches
Our Matches

Sketch based Image Retrieval

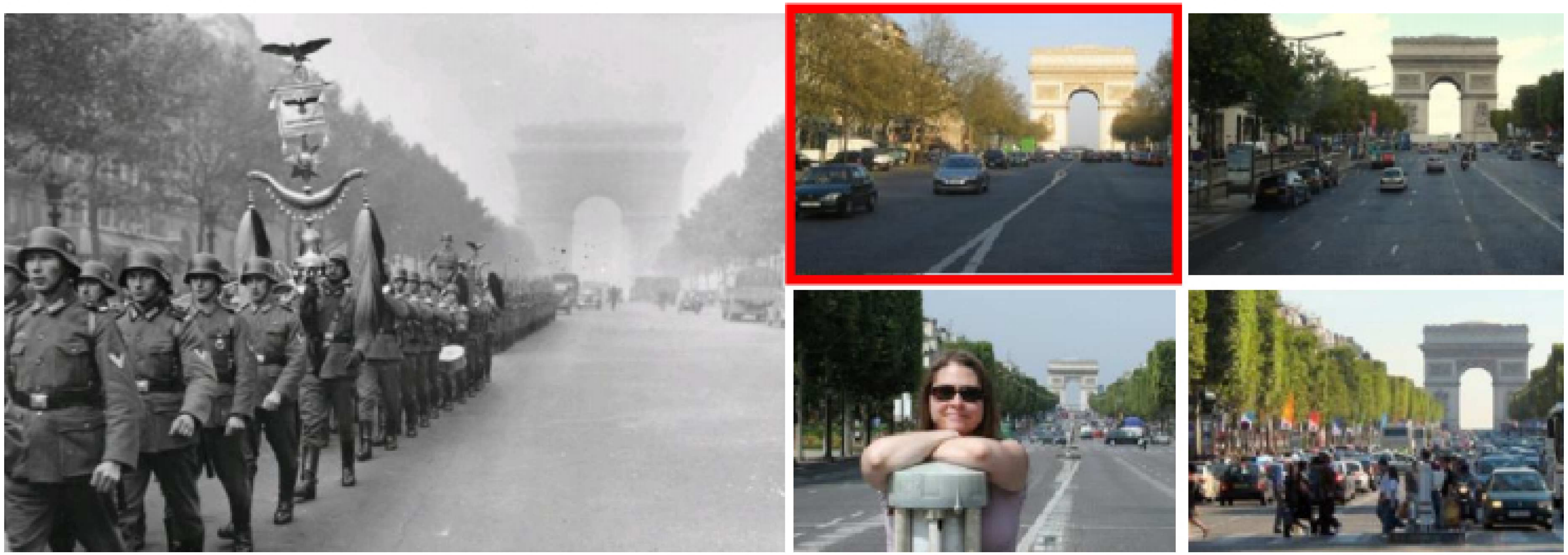
Painting based Image Retrieval



Painting2GPS

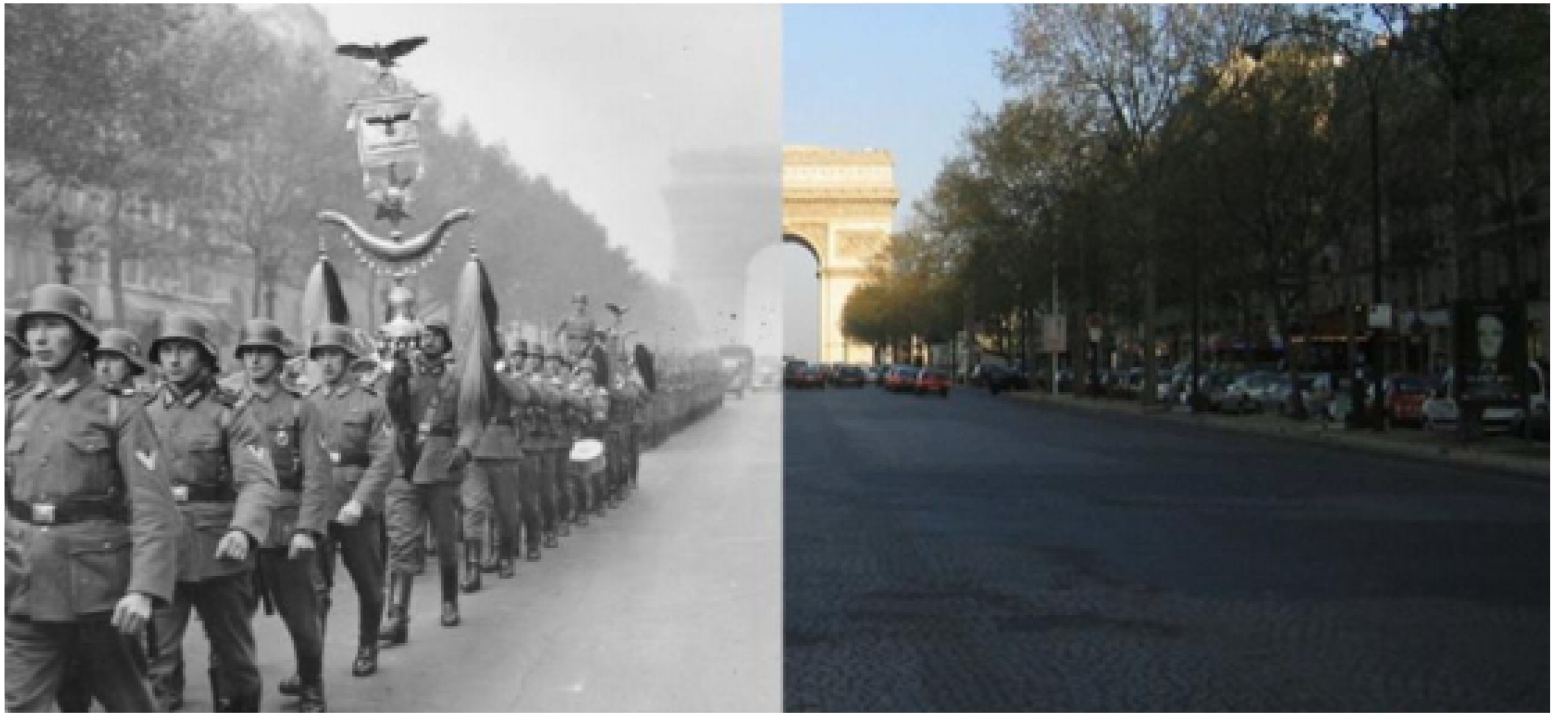
Internet Re-photography

Paris (1940) Top Matches



Internet Re-photography

Manual Alignment



Video

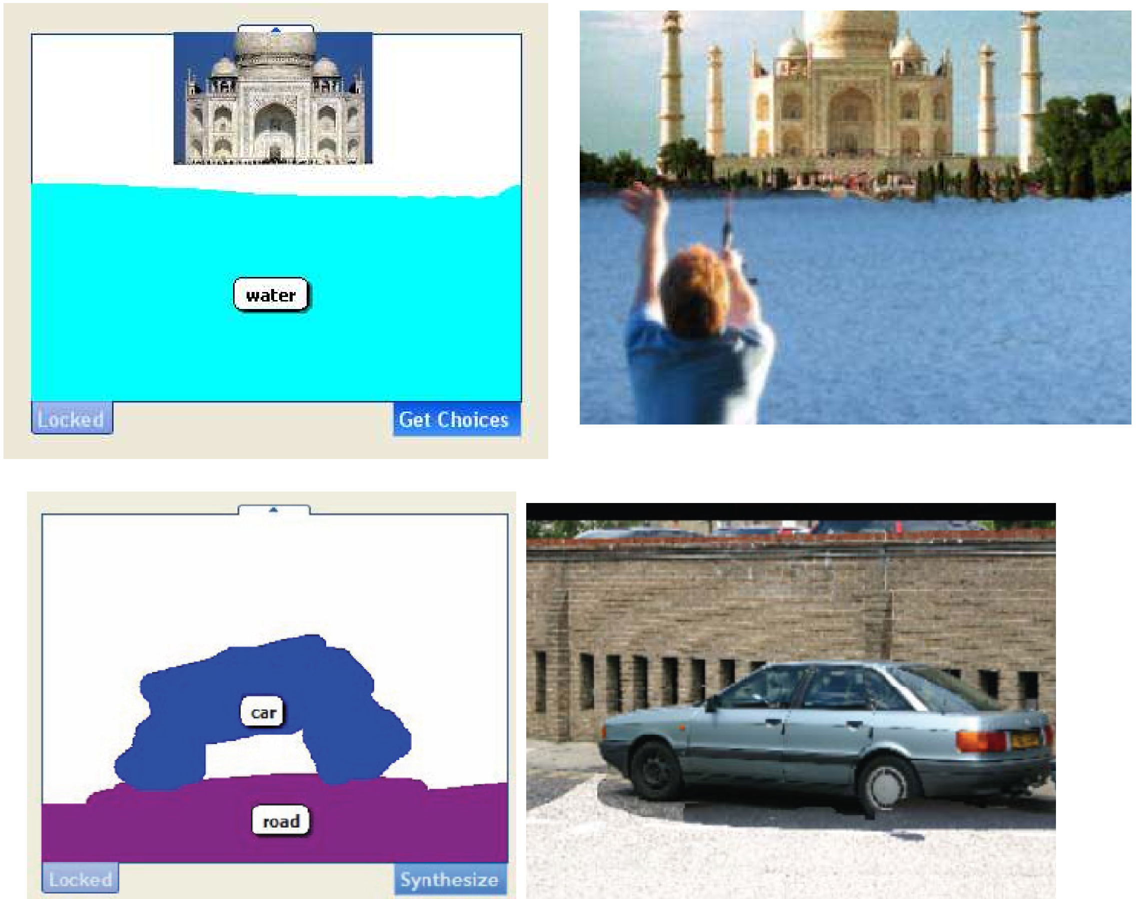
PhotoBios

Ira Kemelmacher-Shlizerman, Eli Shechtman, Rahul Garg, Steven M. Seitz. SIGGRAPH'11

Source Automatically generated transition Target

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

Webcam Clip Art [SG Asia'09]

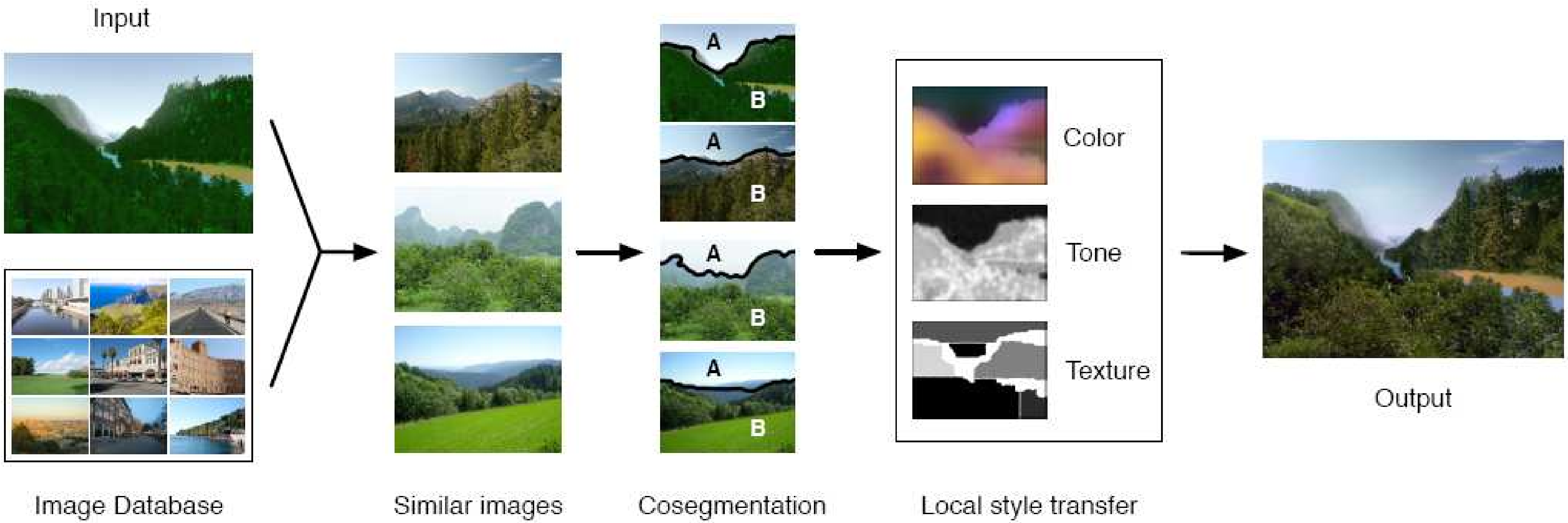
(a) source webcam (b) target webcam (c) transfer results

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

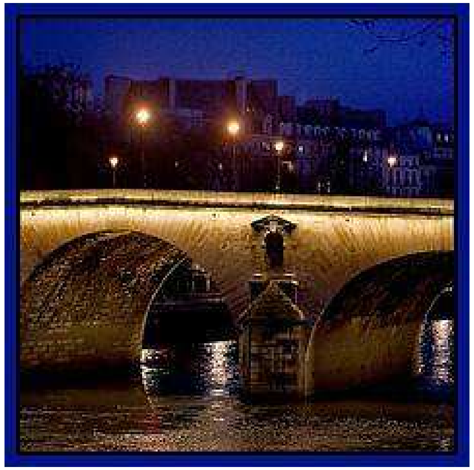
ShadowDraw

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



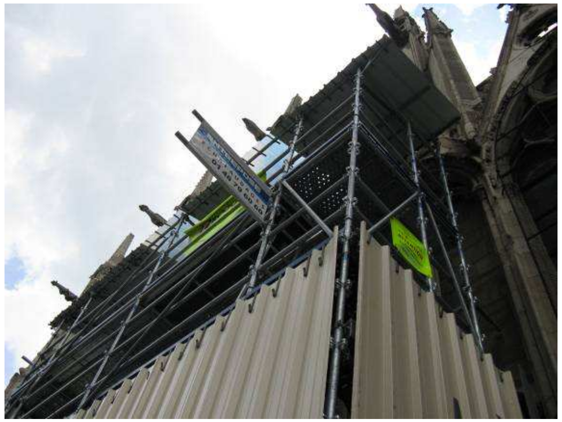









Real Notre Dame



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

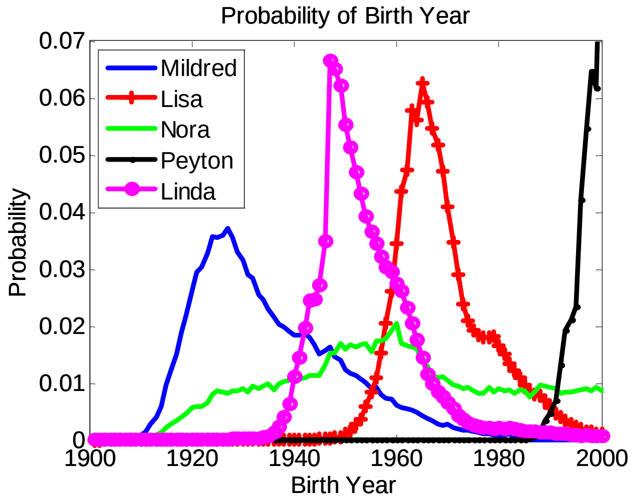
The Graduate

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…