Visual Data on the Internet

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

Cassandra Jones:
https://youtu.be/5H7WrIBrDRg?t=161

CS194: Image Manipulation & Computational Photography
Alexei Efros, UC Berkeley, Fall 2015

facebook

140 billion images
6 billion added monthly

flickr

6 billion images

the simple image sharer
imgur

1 billion images
served daily

YouTube

72 hours uploaded
every minute

3.5 trillion photographs

90% of net traffic will be visual!

Too Big for Humans

Digital Dark Matter

[Perona 2010]

Big issues

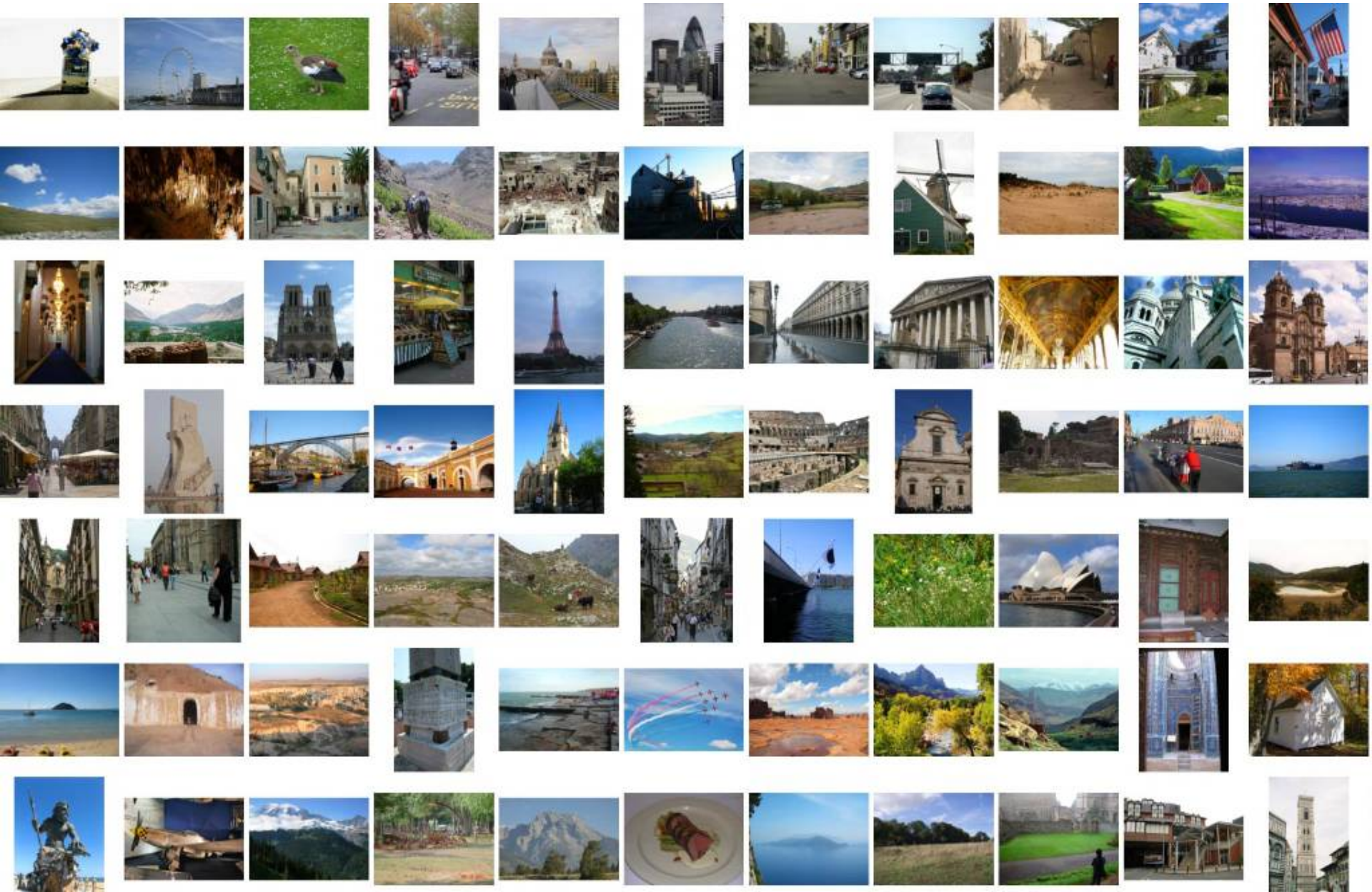
- What is out there on the Internet? How do we get it? What can we do with it?
- How do we compute distances between images?

Subject-specific Data

Photos of Coliseum

Portraits of Bill Clinton

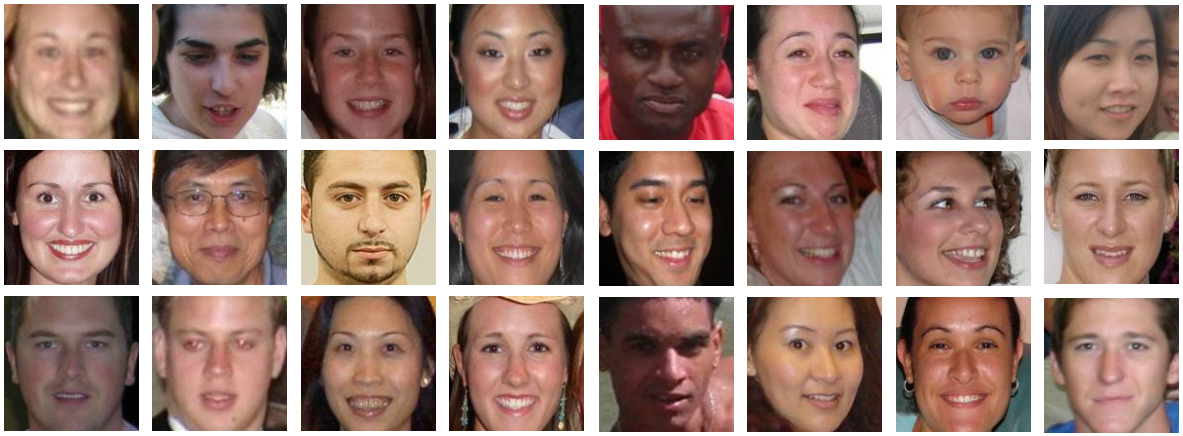
Much of Captured World is “generic”



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. 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)

Is Generic Data useful?

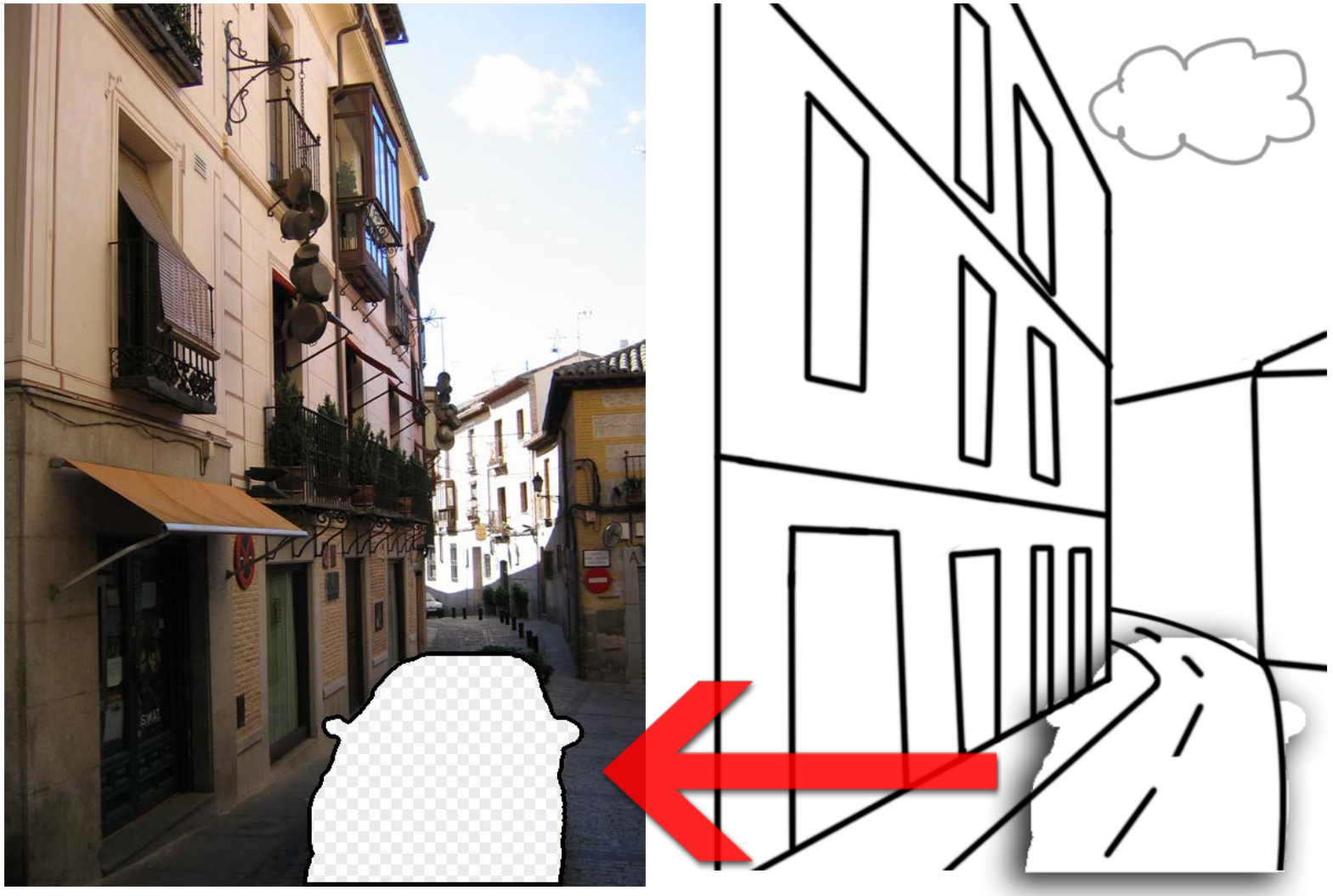
A motivating example…

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

Diffusion Result

Efros and Leung result

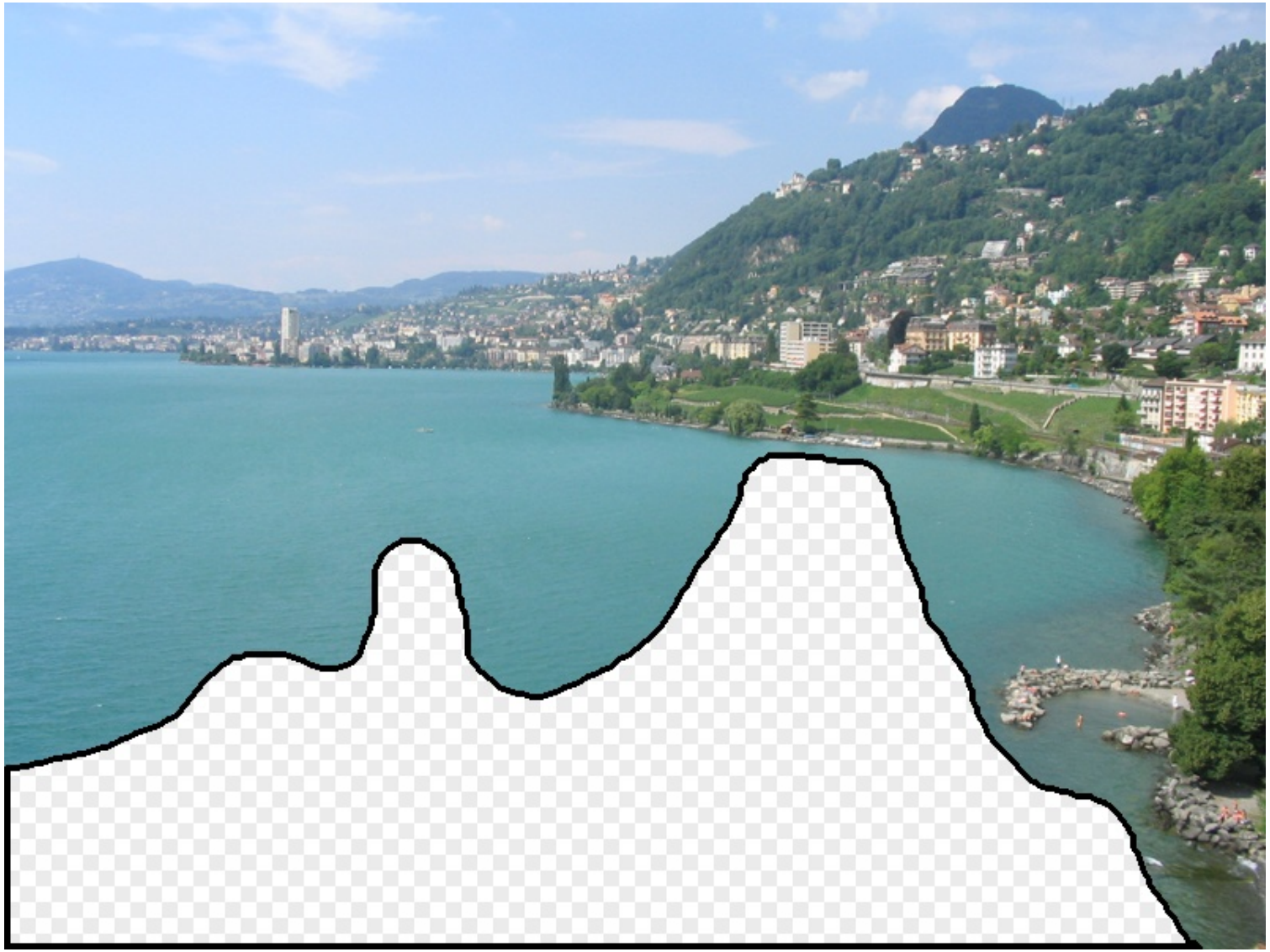
Scene Matching for Image Completion



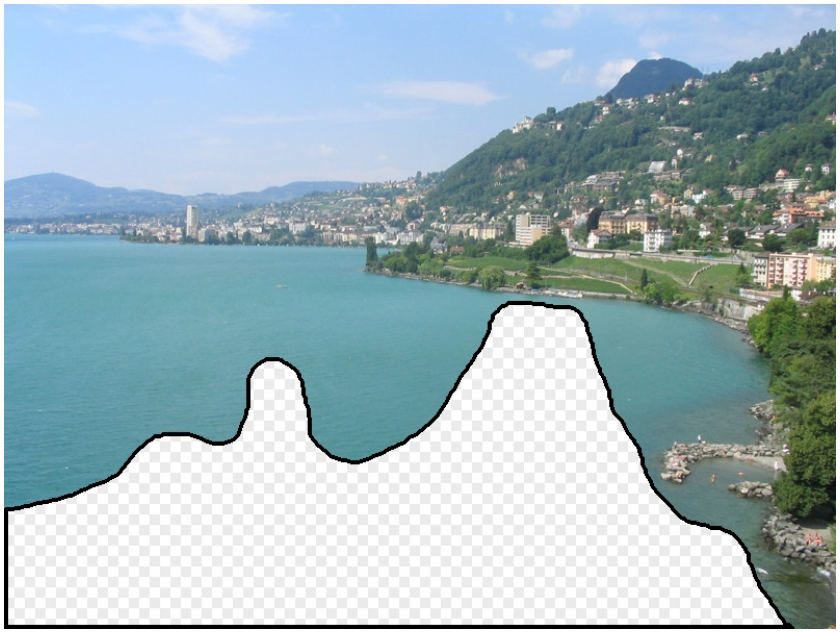
Scene Completion Result

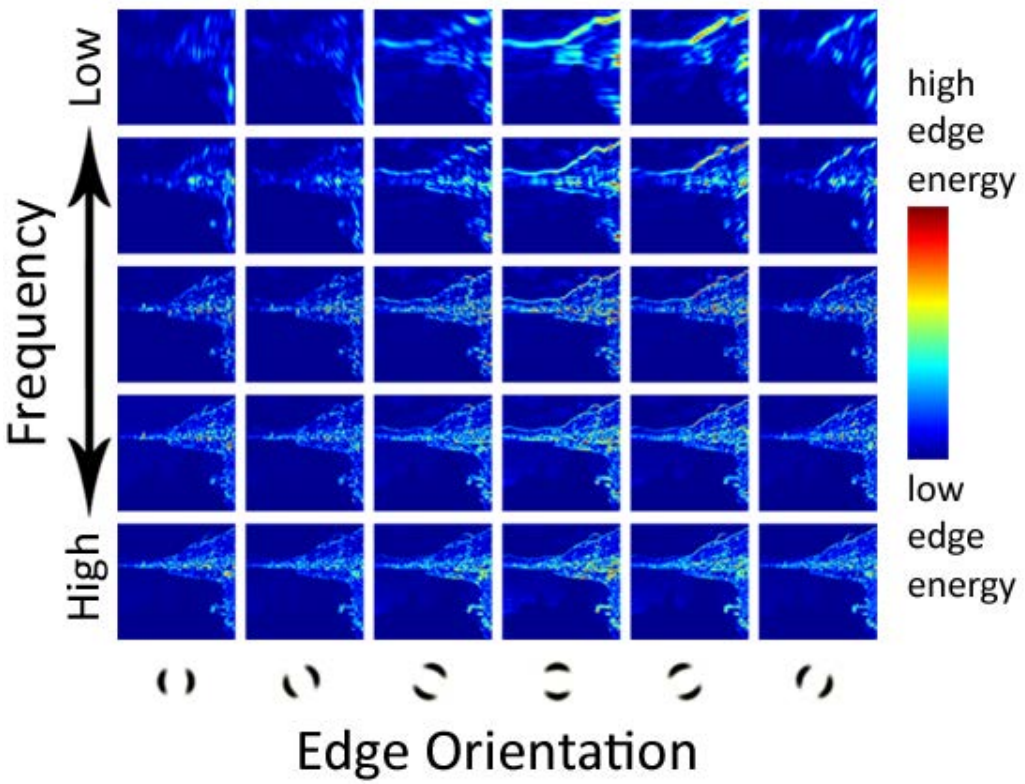
The Algorithm

Scene Matching

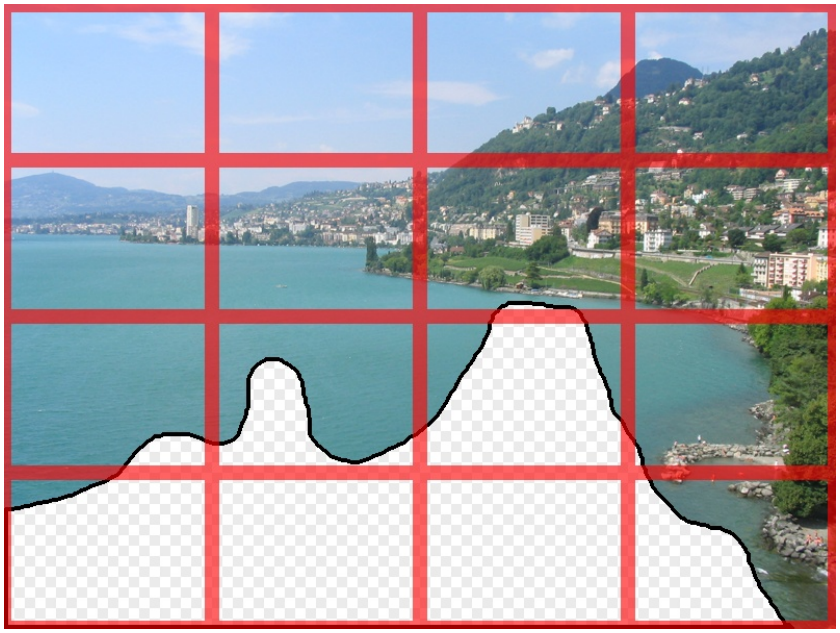


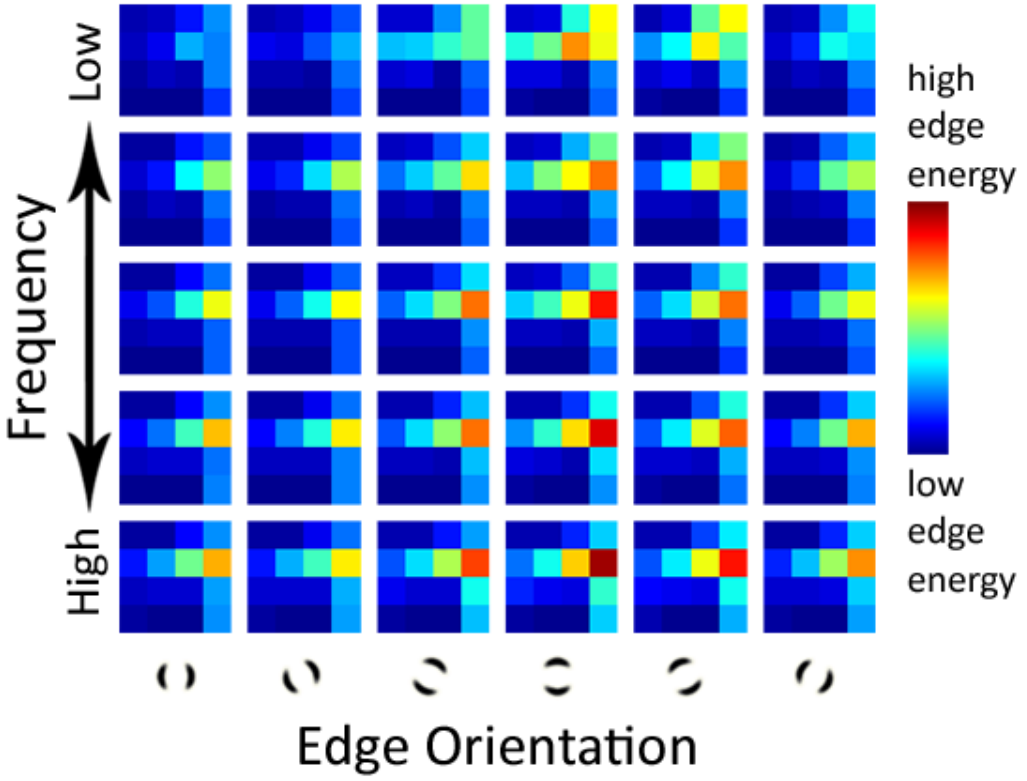
Scene Descriptor





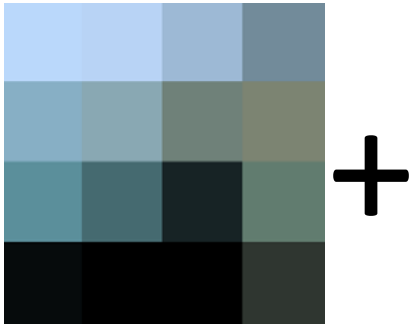
Scene Descriptor



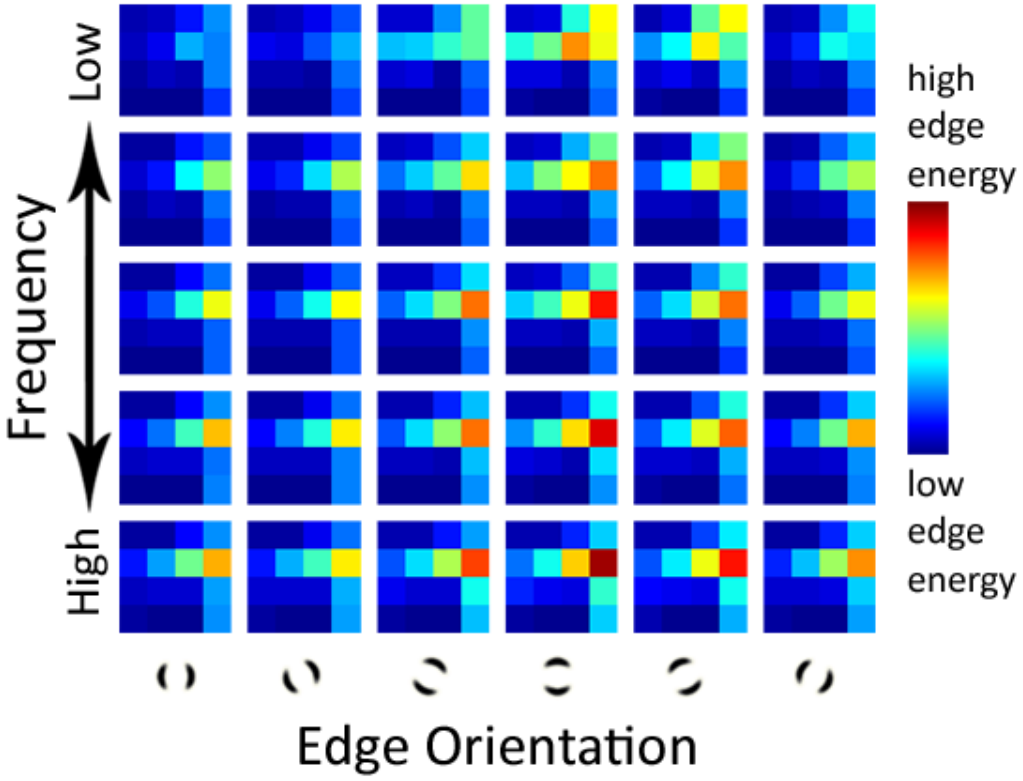


Scene Gist Descriptor
(Oliva and Torralba 2001)

Scene Descriptor

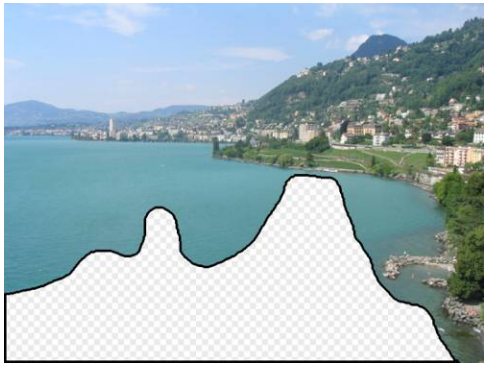


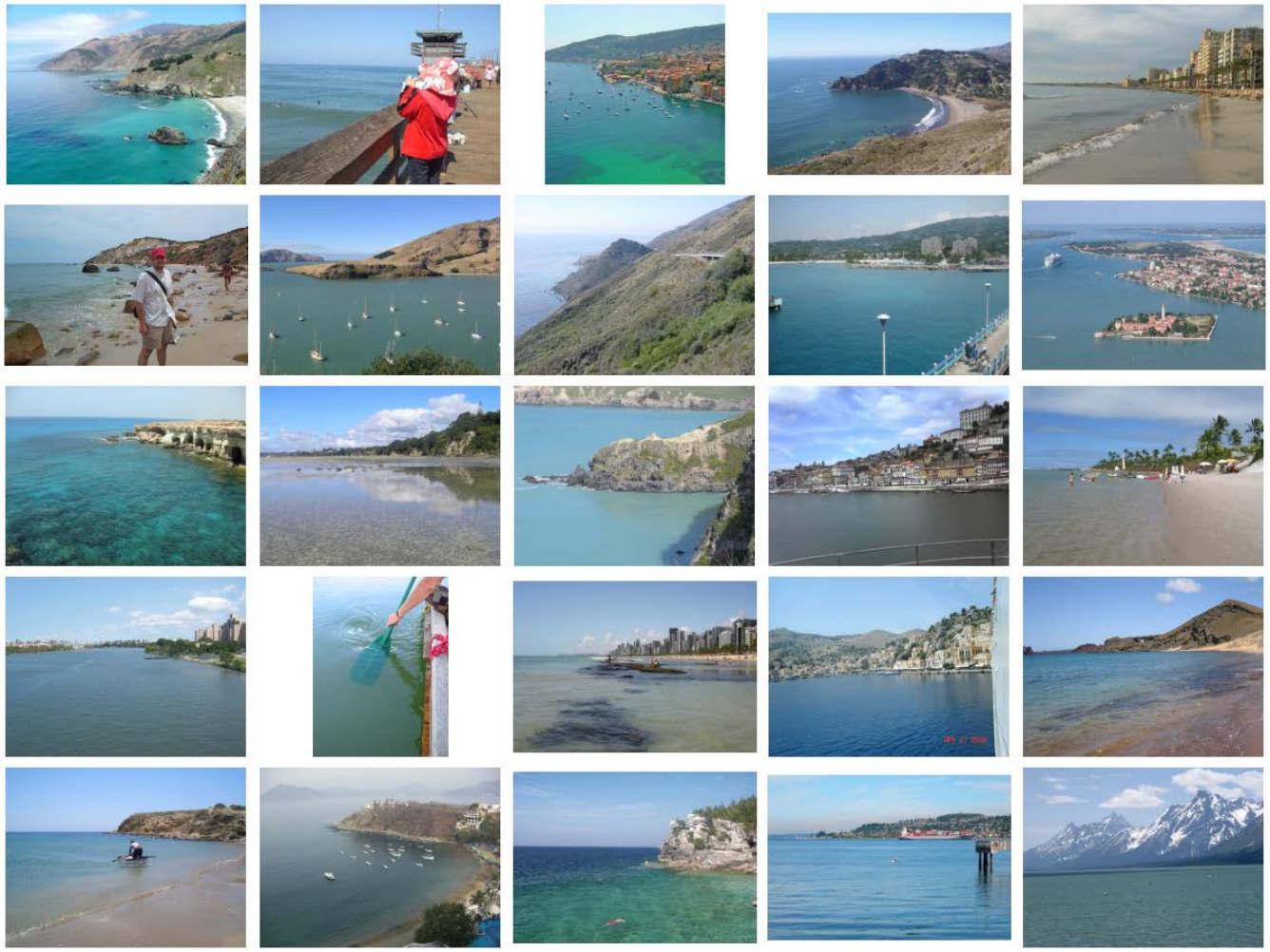
+



Scene Gist Descriptor
(Oliva and Torralba 2001)

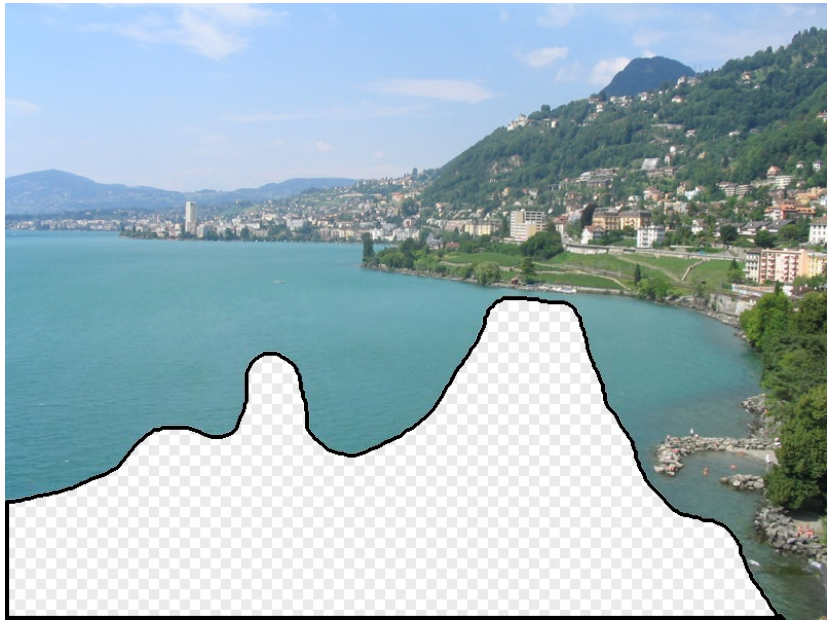
2 Million Flickr Images





… 200 total

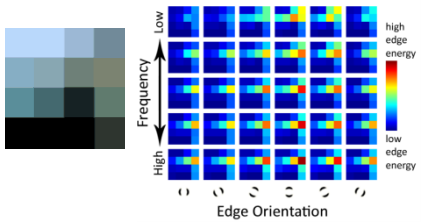
Context Matching



Graph cut + Poisson blending

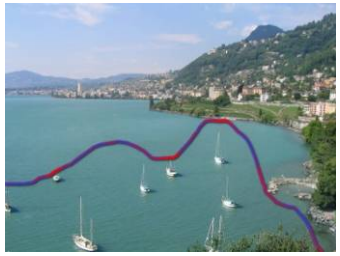
Result Ranking

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

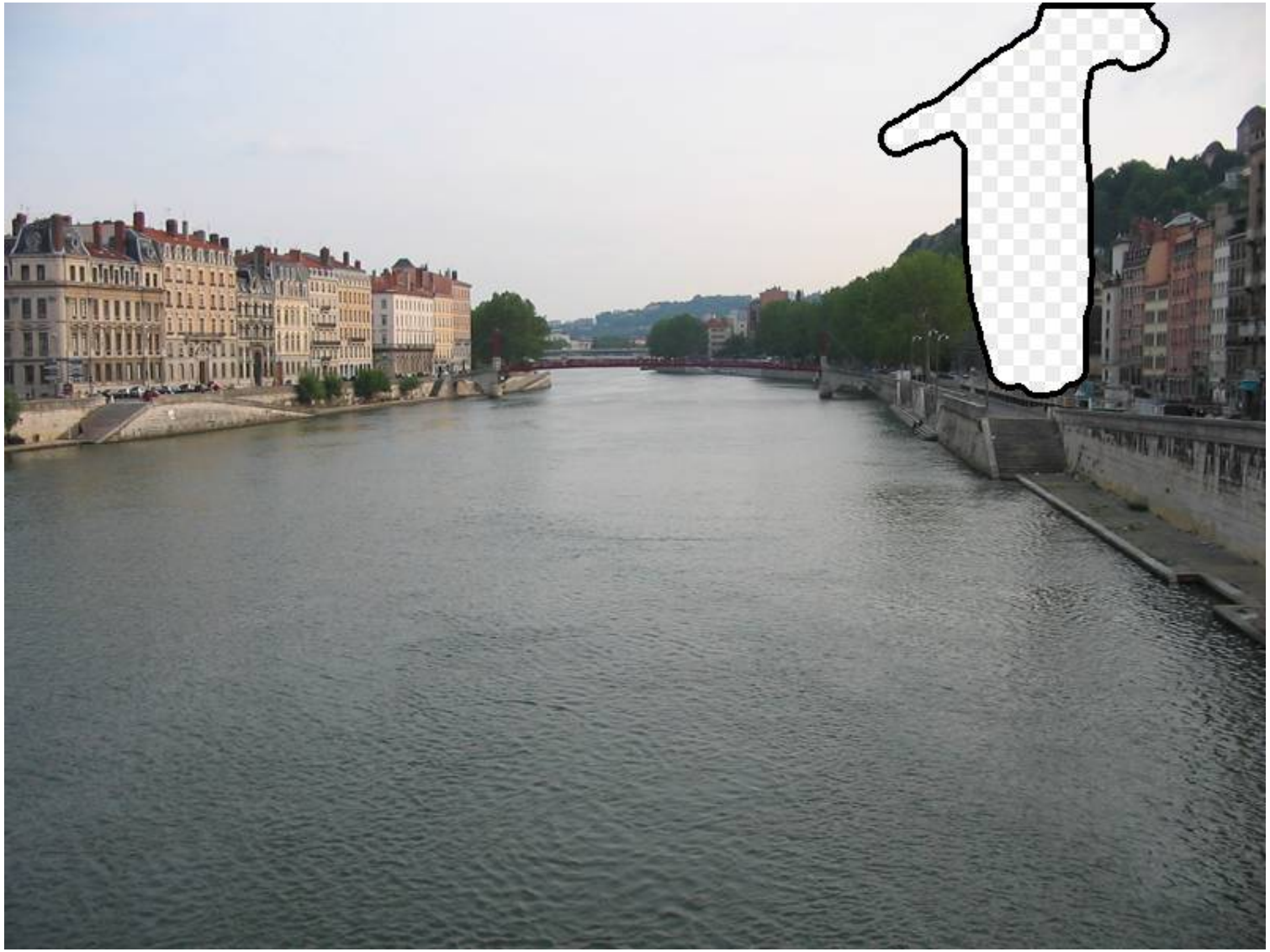


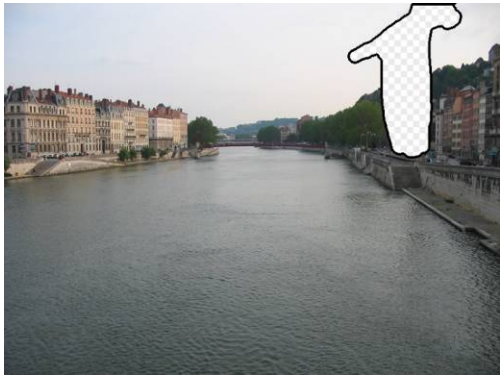
The scene matching distance

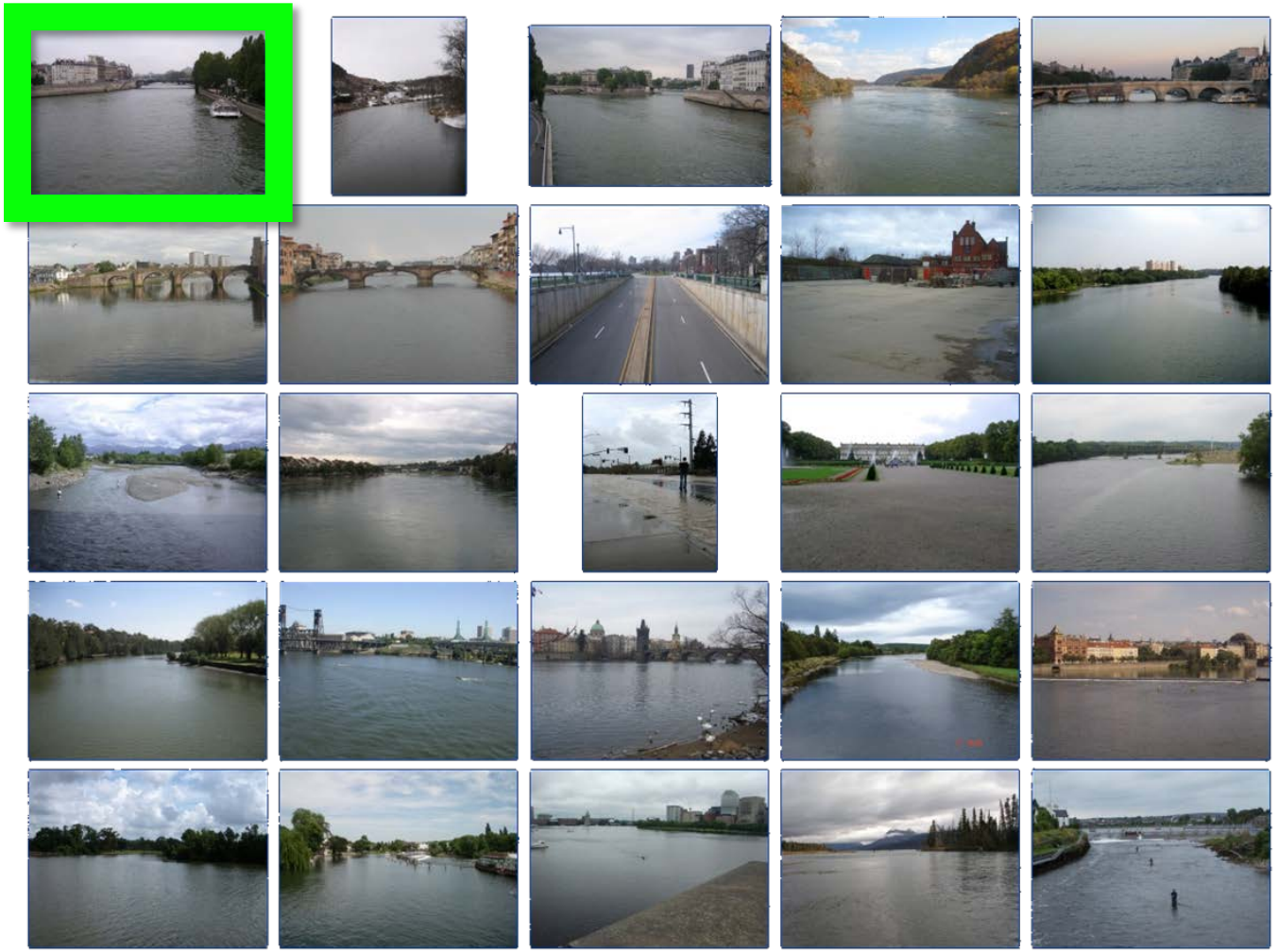
The context matching distance (color + texture)



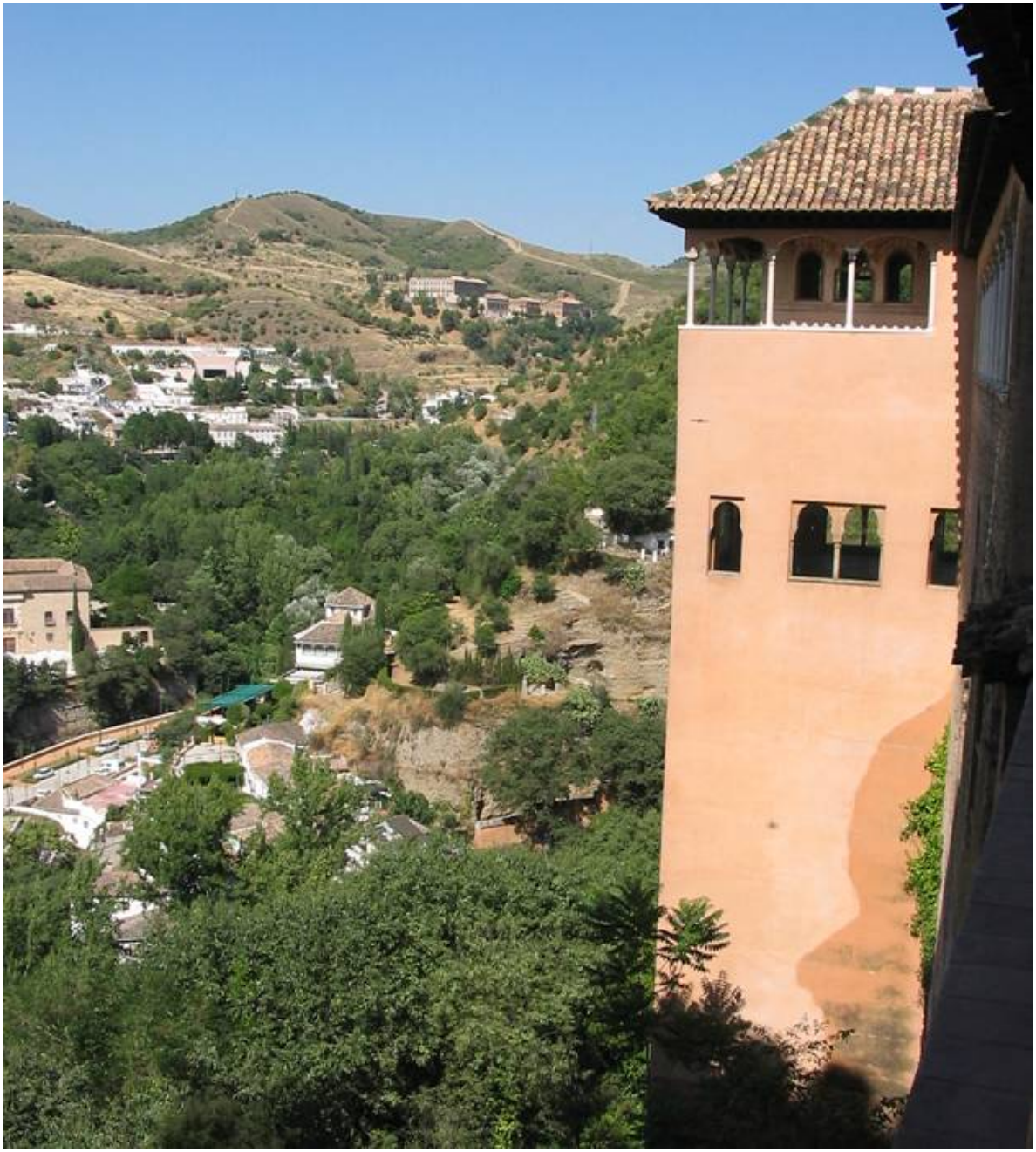
The graph cut cost

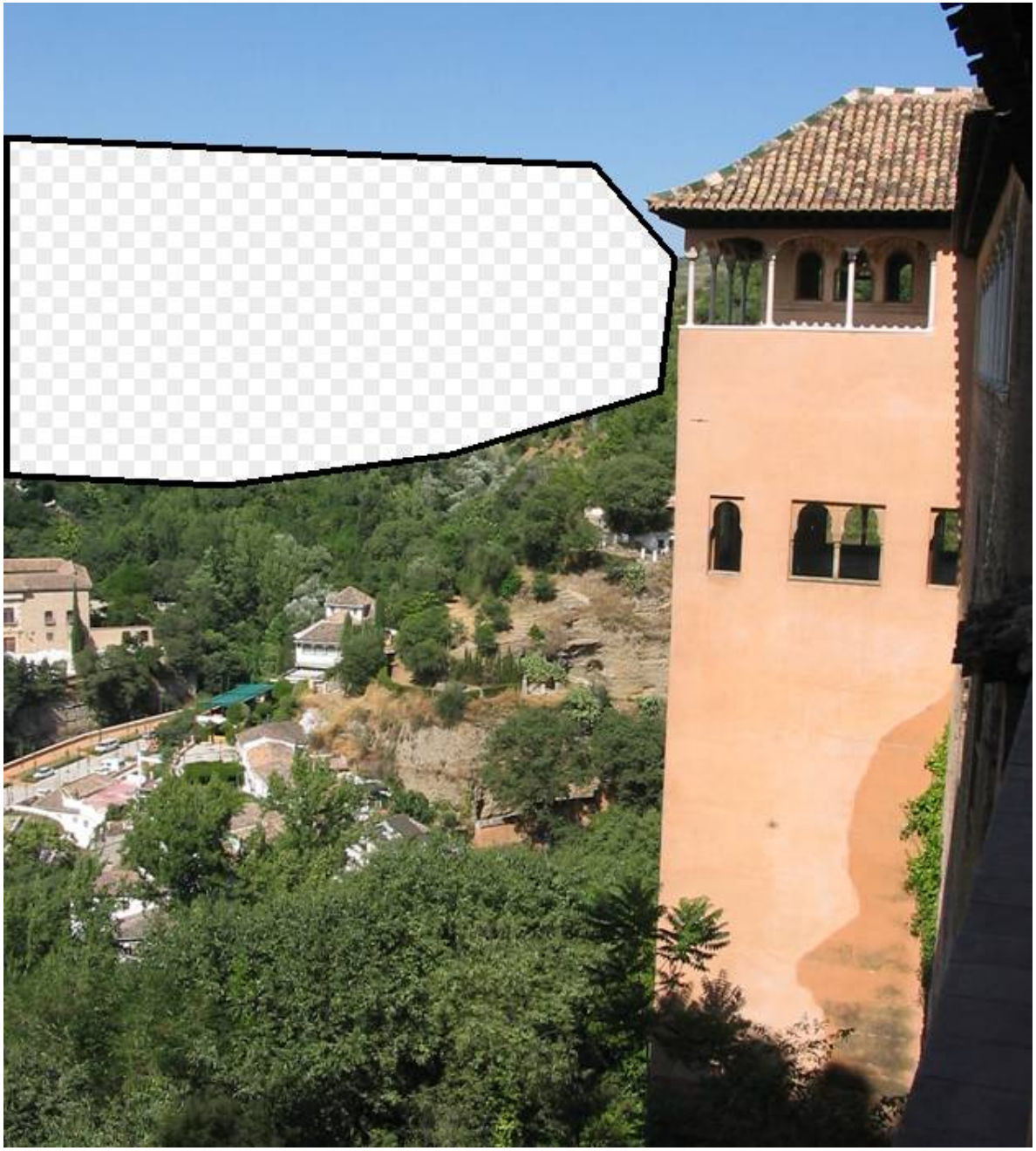




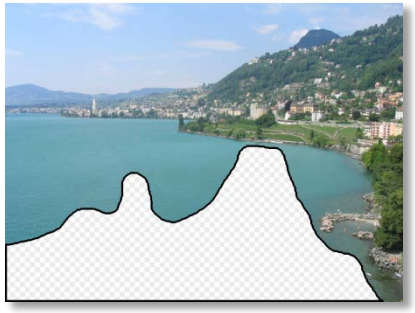


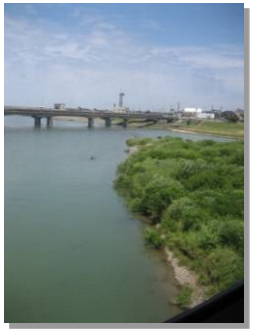
… 200 scene matches

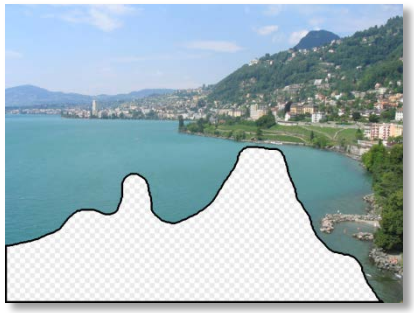




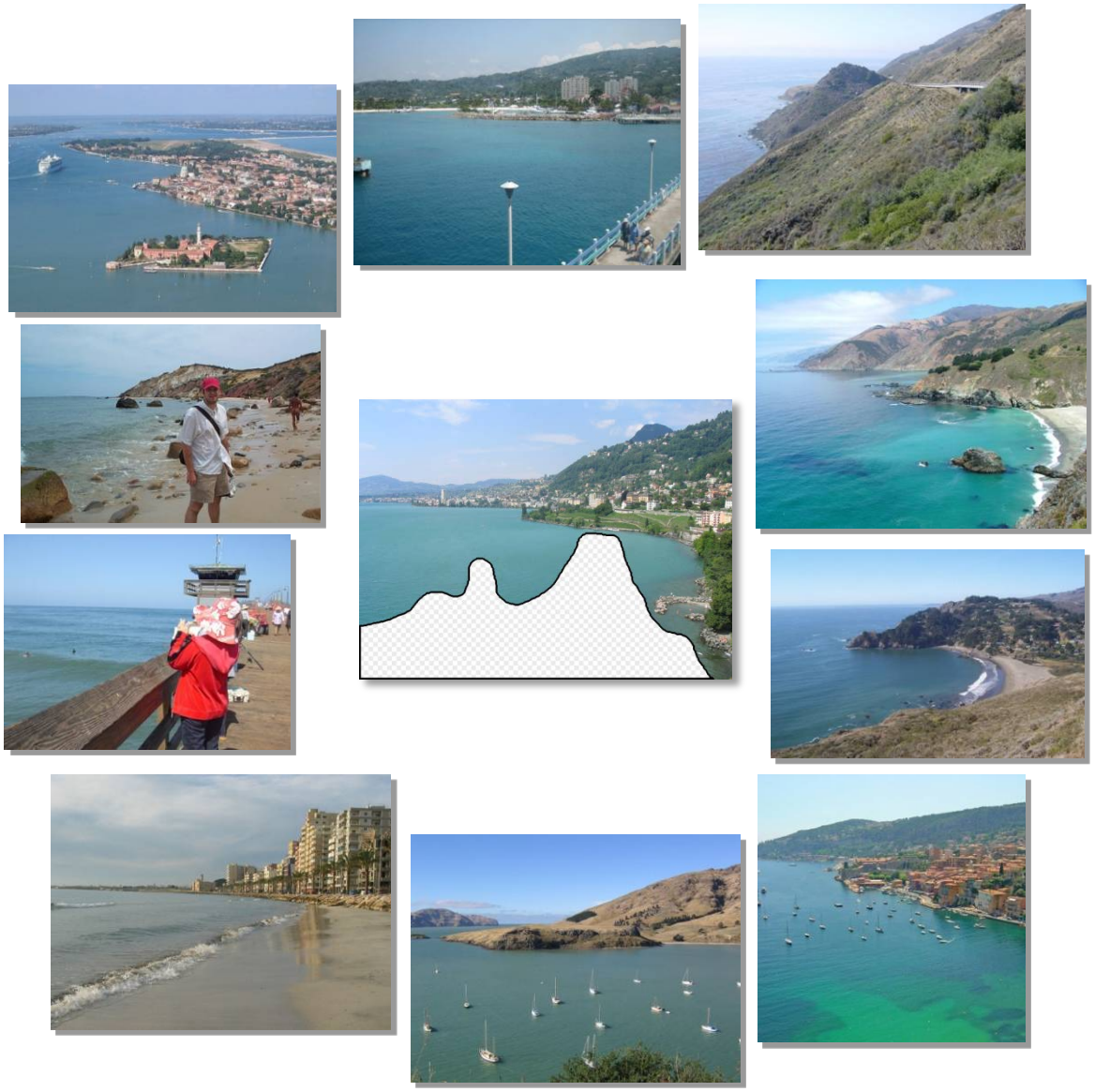
Why does it work?







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 The Data!
  - 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 in the data

How about visual data?

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

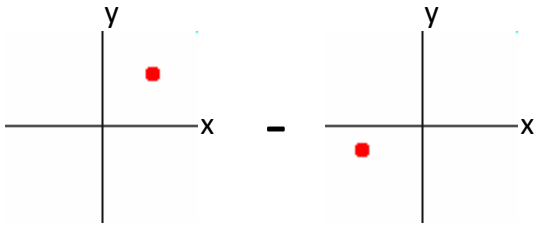
Quick Overview

Comparing Images

Uses of Visual Data

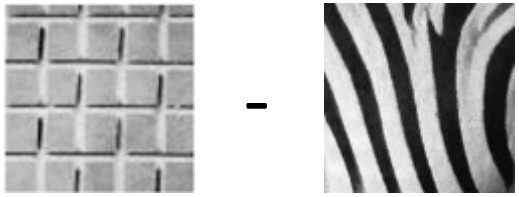
The Dangers of Data

Distance Metrics



= Euclidian distance of 5 units

= Grayvalue distance of 50 values



= ?

SSD says these are not similar

?

Gist of a scene

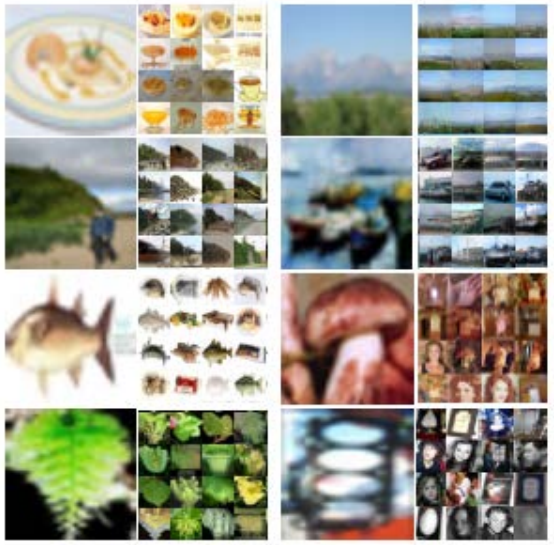
- Need a full image descriptor, to capture the context

- But still want it to be not too high-dimentional (else nothing will look similar)

Make them tiny!

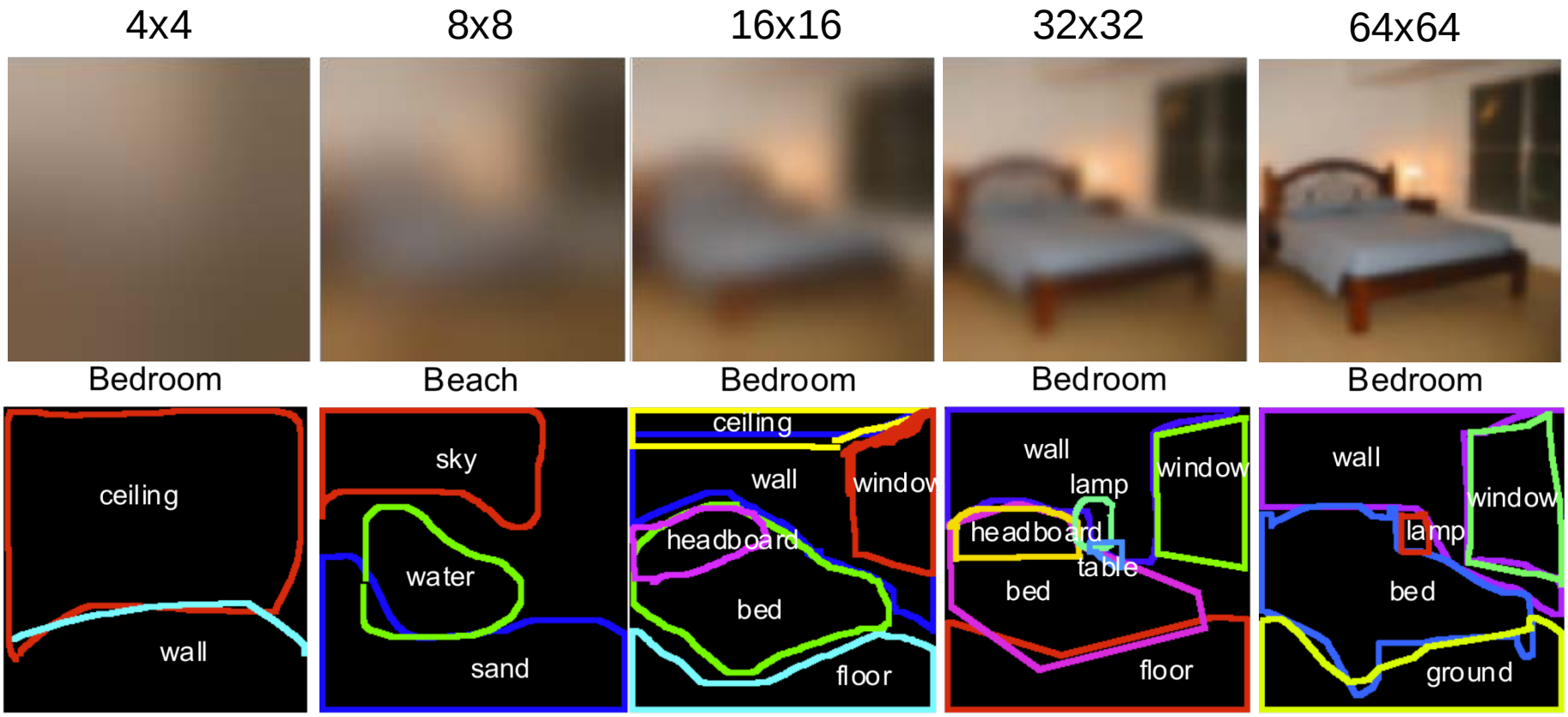
?

Tiny Images



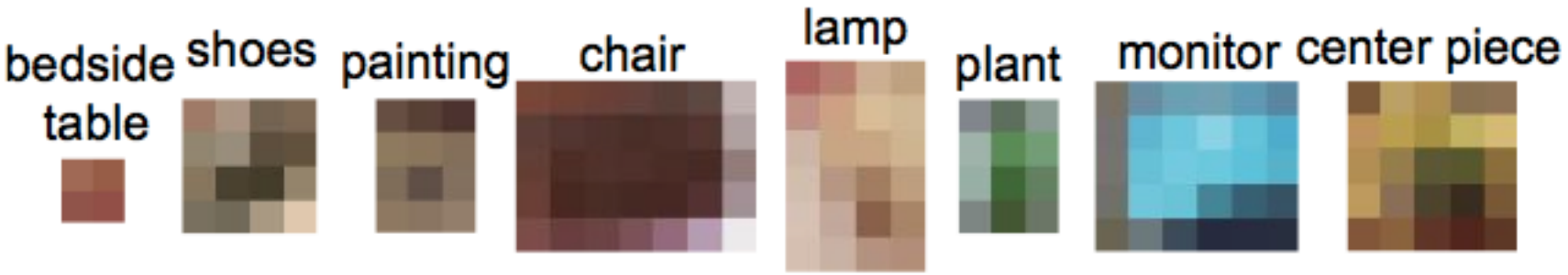
- 80 million tiny images: a large dataset for non-parametric object and scene recognition Antonio Torralba, Rob Fergus and William T. Freeman. PAMI 2008.

Tiny Images pack a punch!

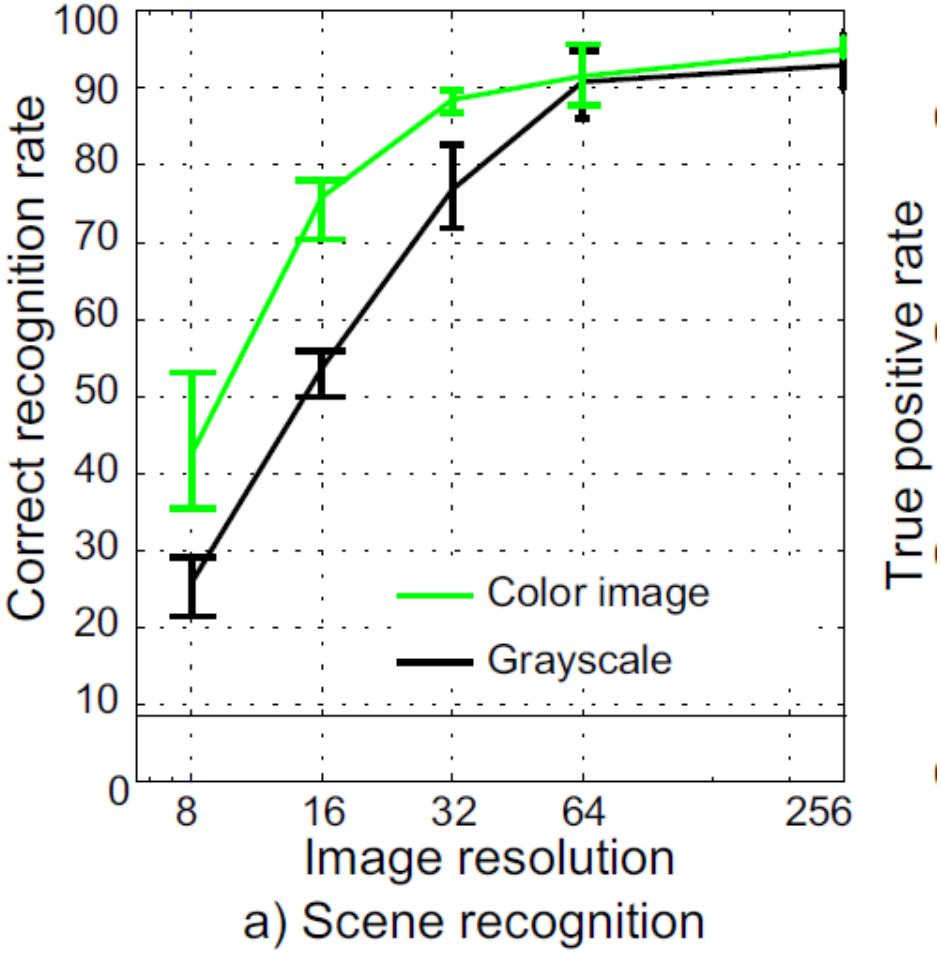


c) Segmentation of 32x32 images

Image Segmentation (by humans)



Human Scene Recognition



Tiny Images Project Page

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

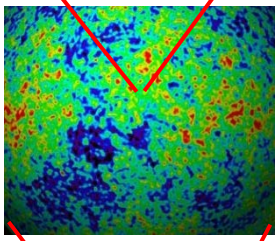
Powers of 10

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

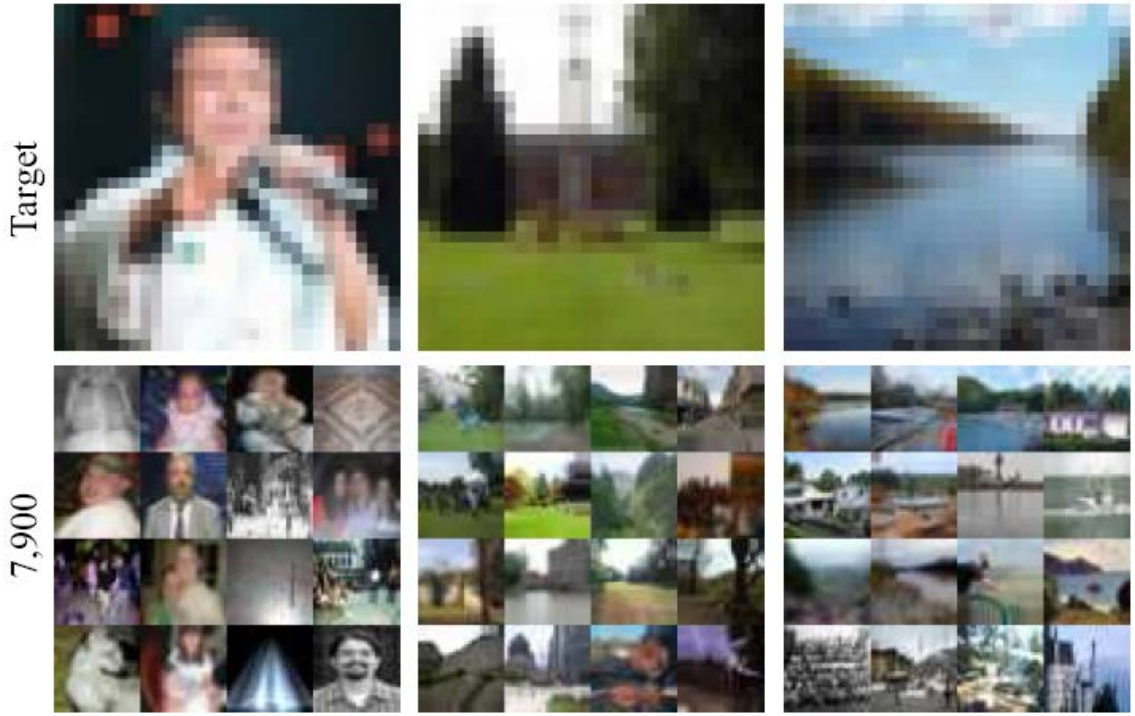
But not all scenes are so original

But not all scenes are so original

Lots

Of

Images

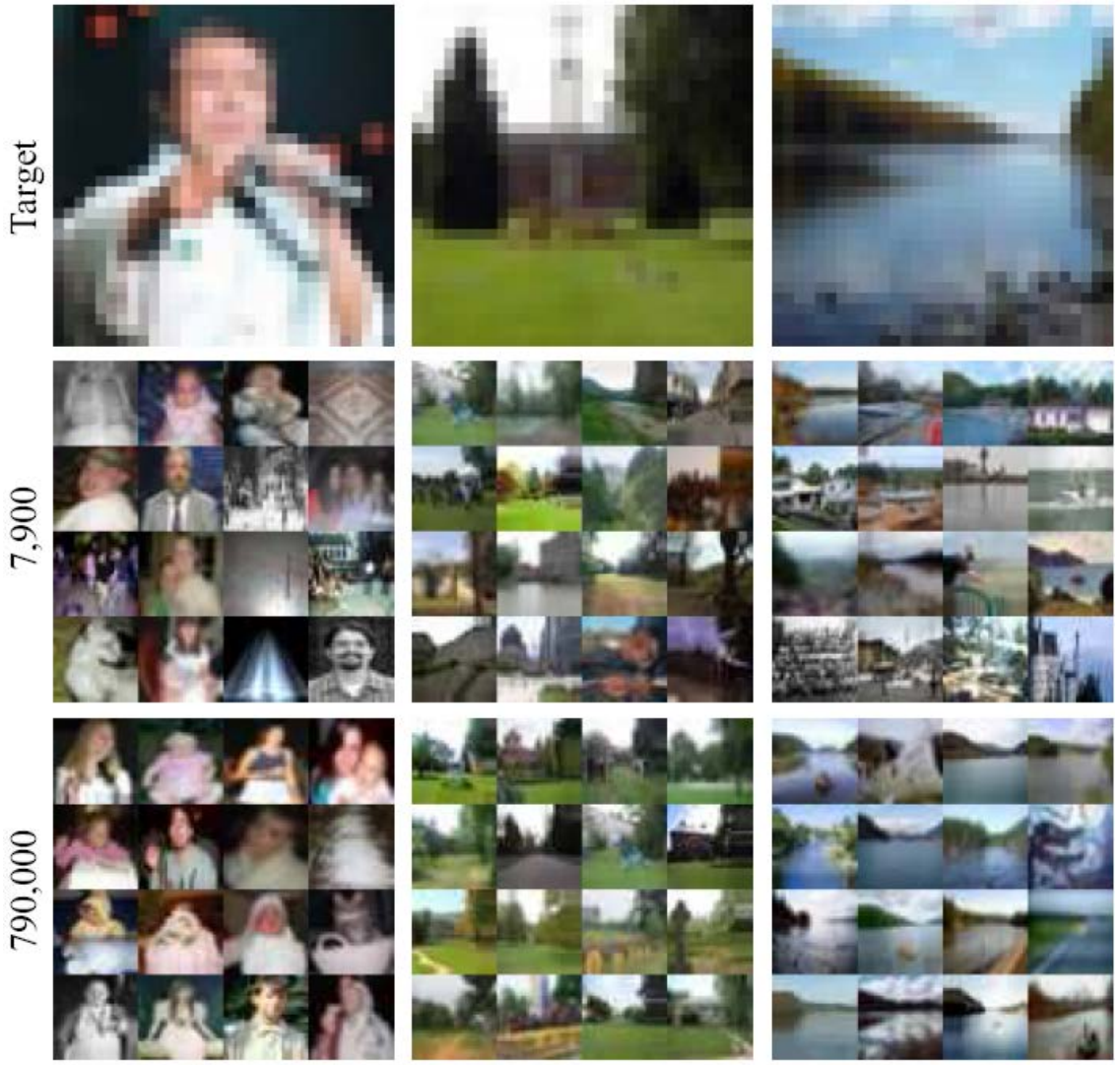


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images

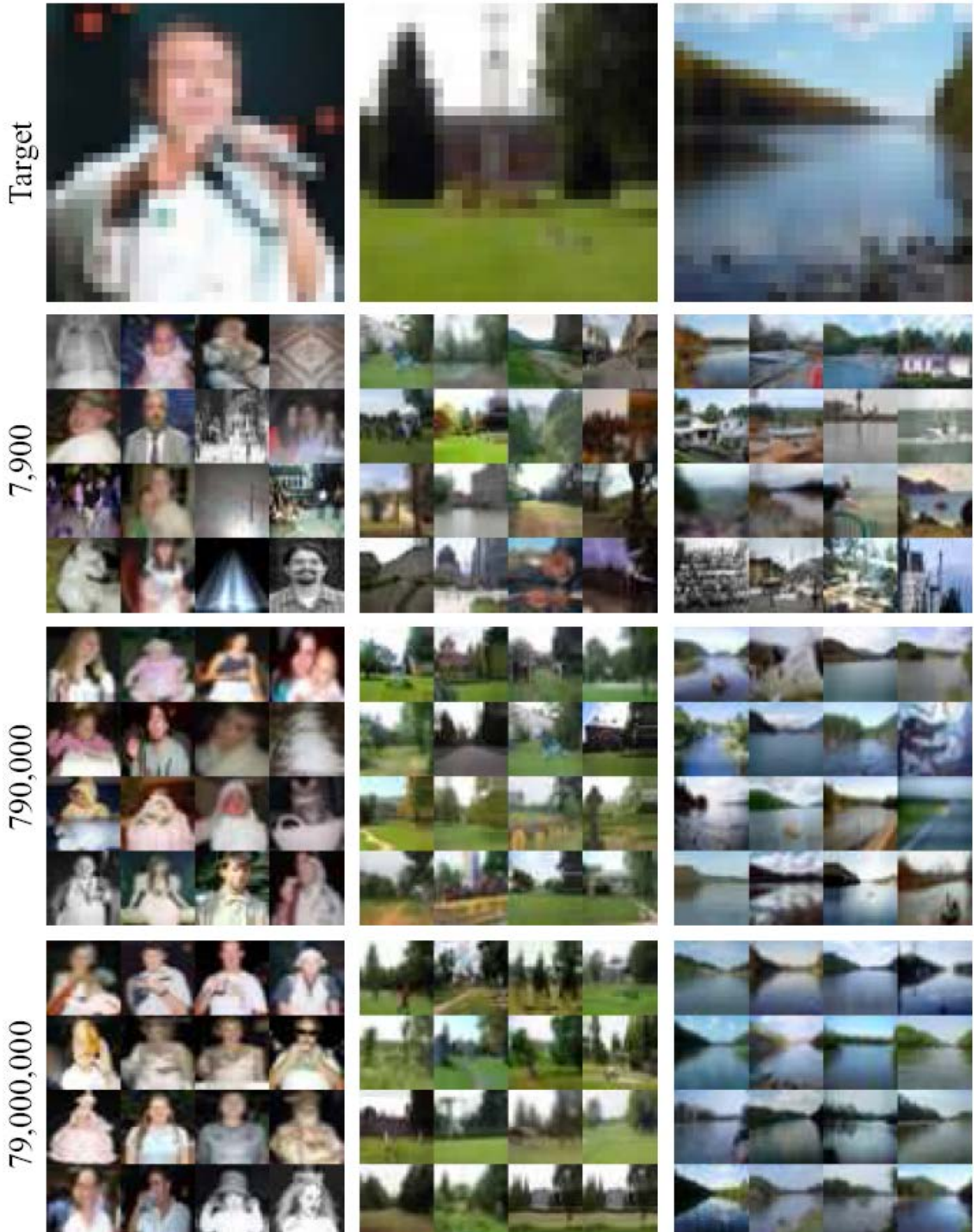


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images



Automatic Colorization Result

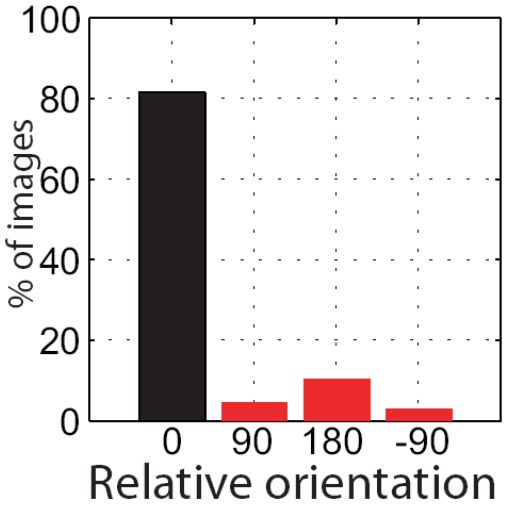
Grayscale input High resolution

Colorization of input using average

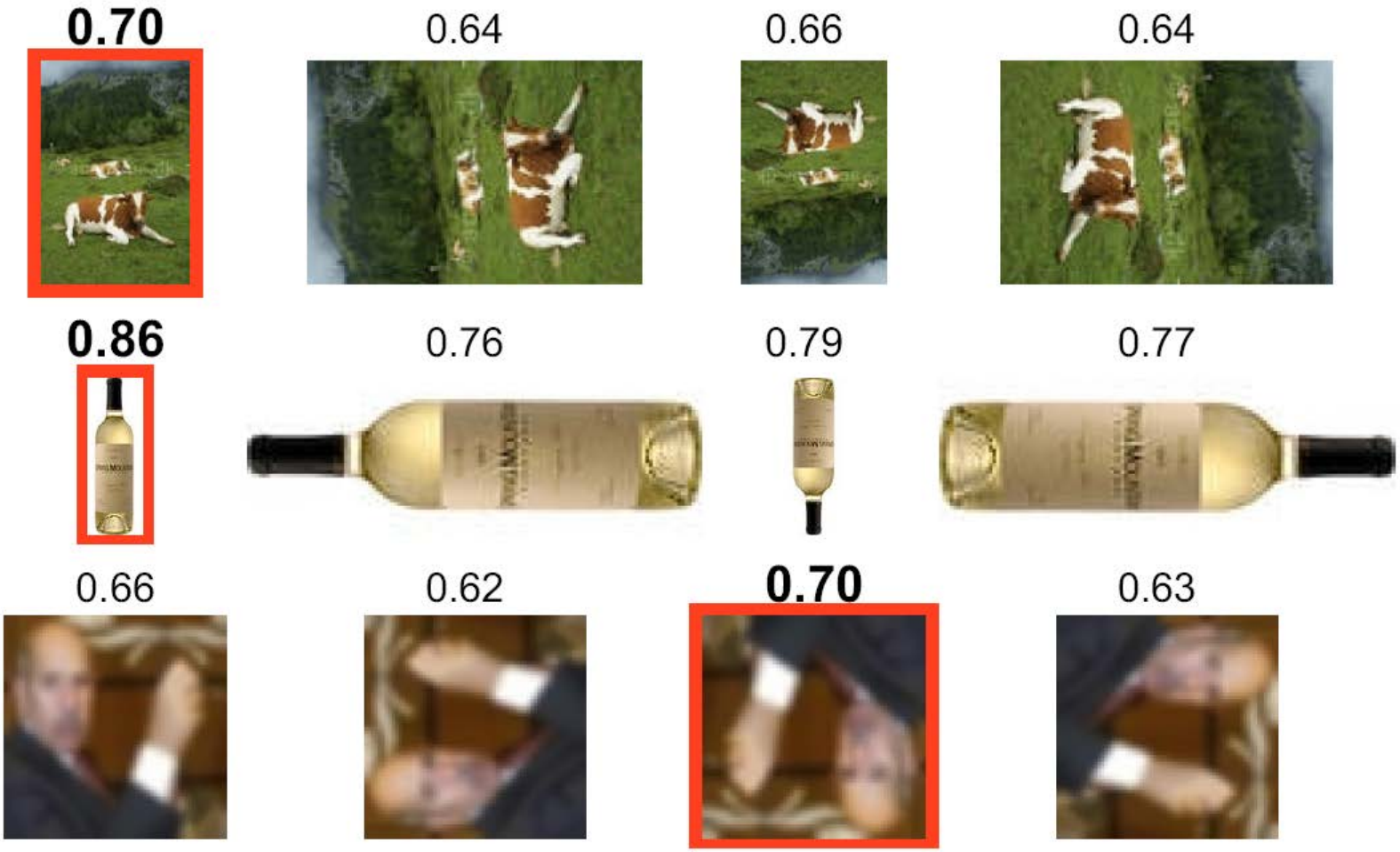
A. Torralba, R. Fergus, W.T.Freeman. 2008

Automatic Orientation

- Many images have ambiguous orientation
- Look at top 25% by confidence:
- Examples of high and low confidence images:



Automatic Orientation Examples



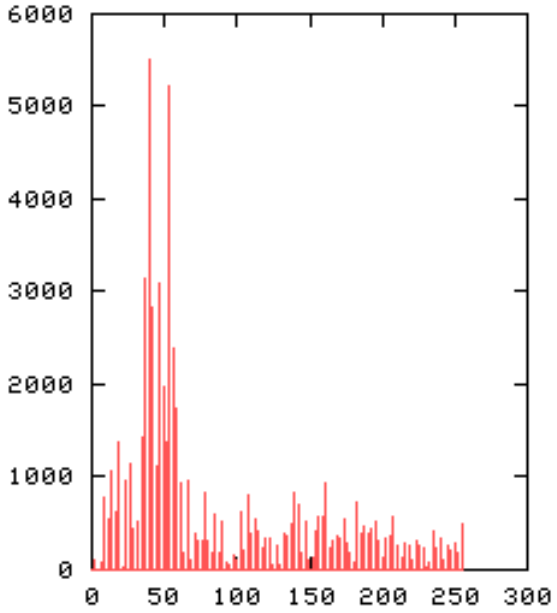
A. Torralba, R. Fergus, W.T.Freeman. 2008

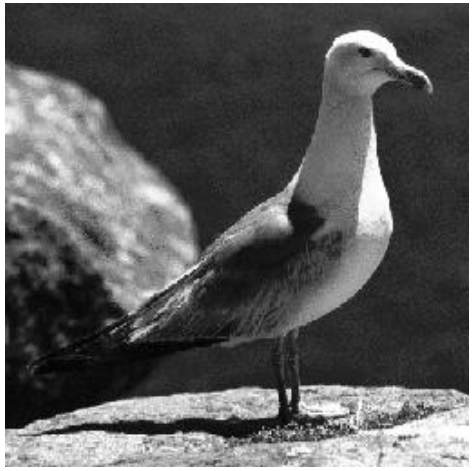
Tiny Images Discussion

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

Image Representations: Histograms

Images from Dave Kauchak



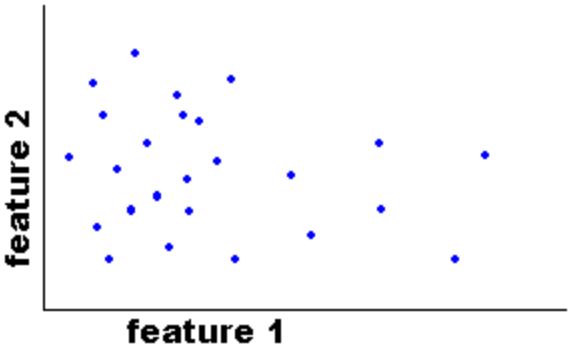


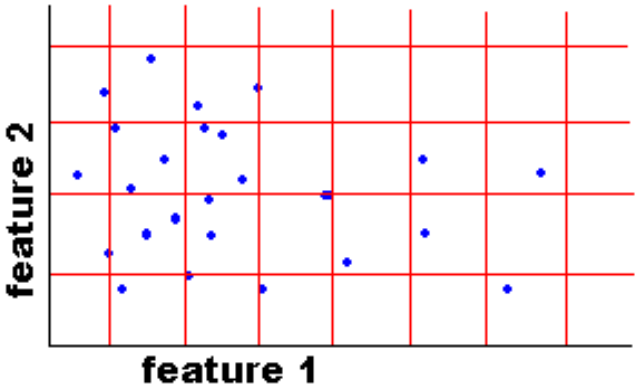
global histogram

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

Image Representations: Histograms

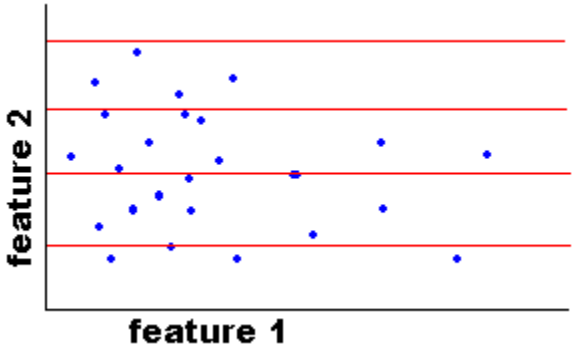
Images from Dave Kauchak

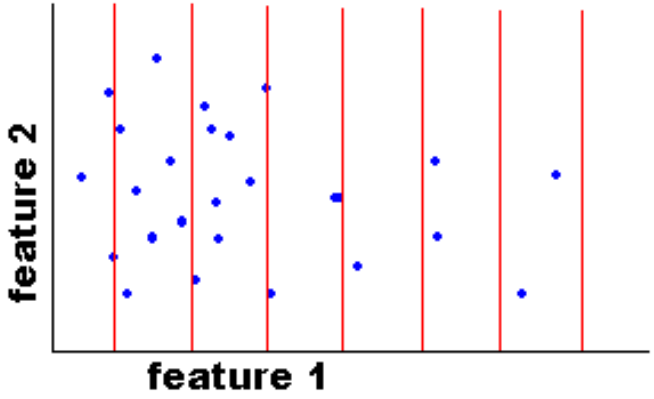




Joint histogram

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





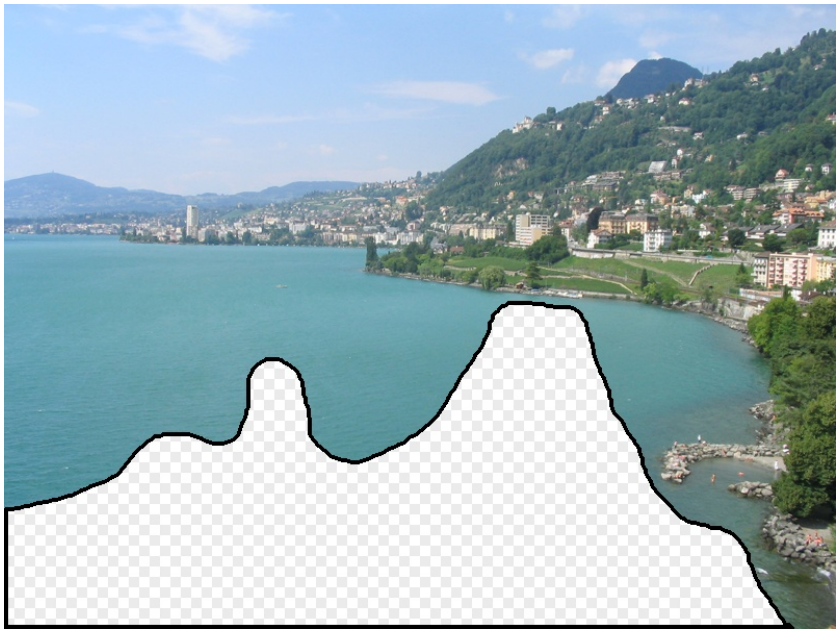
Marginal histogram

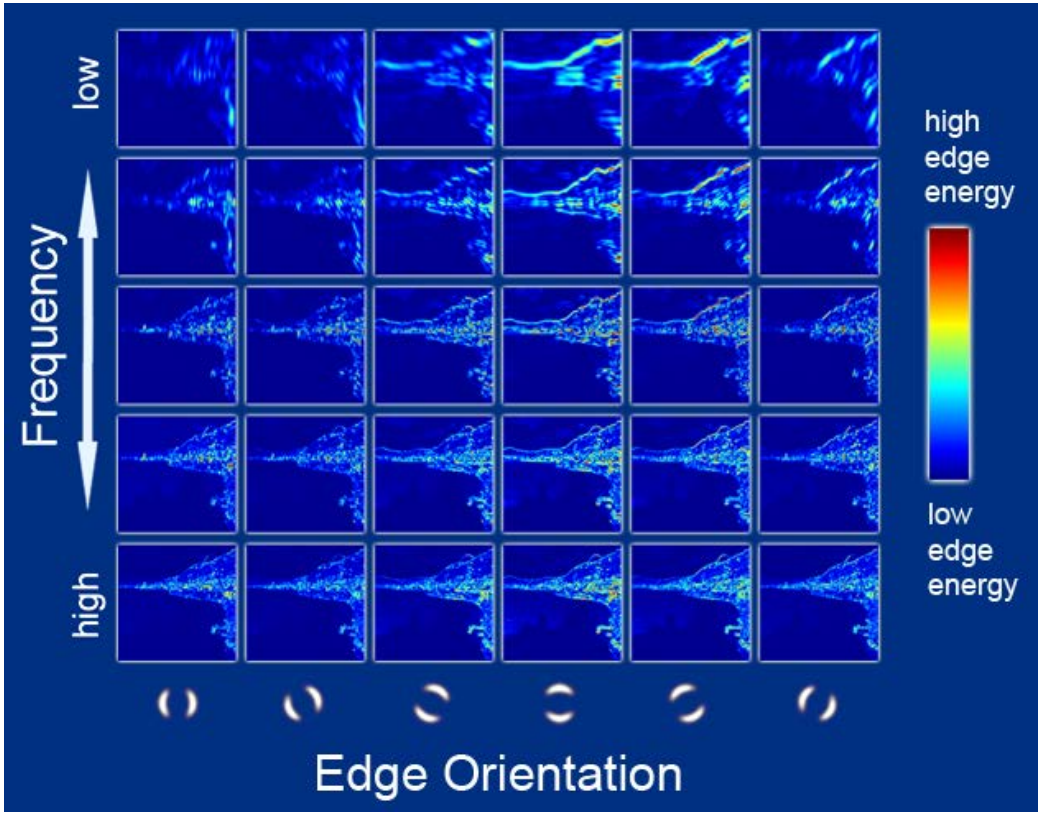
- Requires independent features
- More data/bin than joint histogram

Image Descriptors (more later)

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

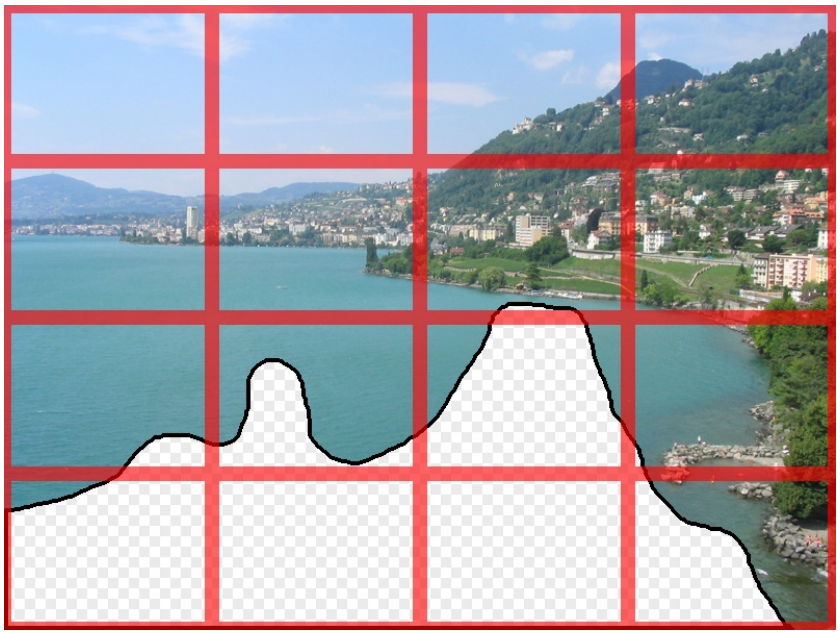
Gist Scene Descriptor

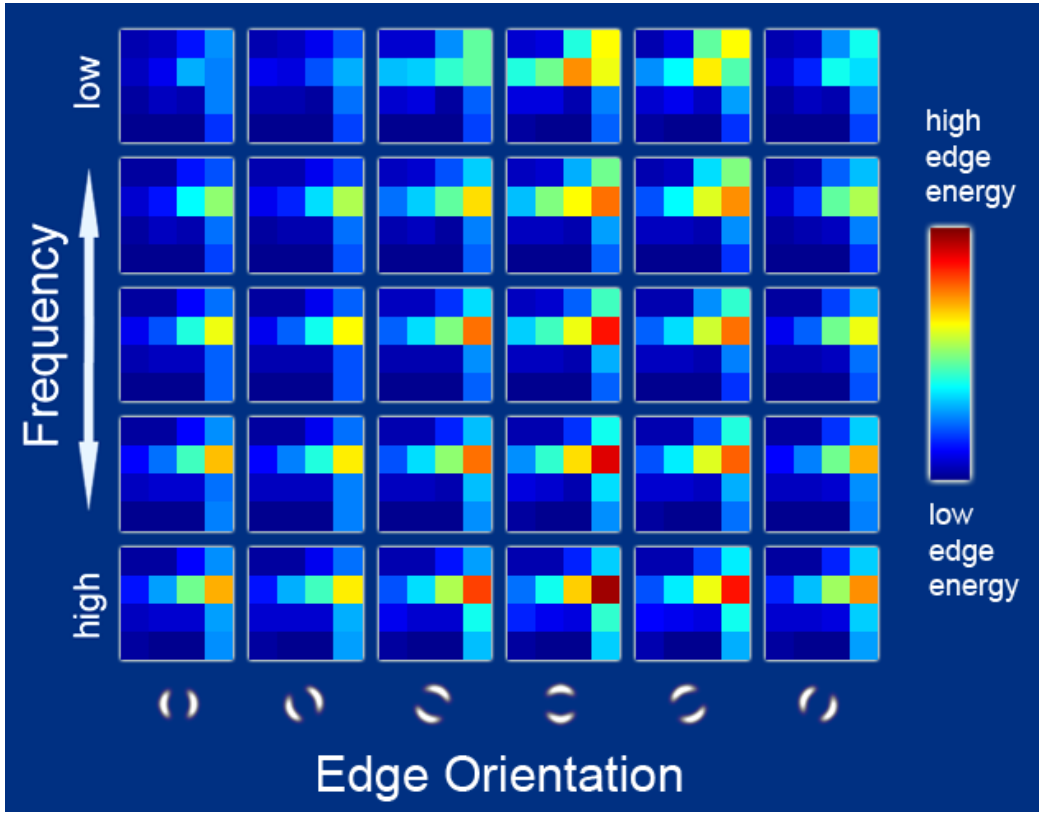




Hays and Efros, SIGGRAPH 2007

Gist Scene Descriptor

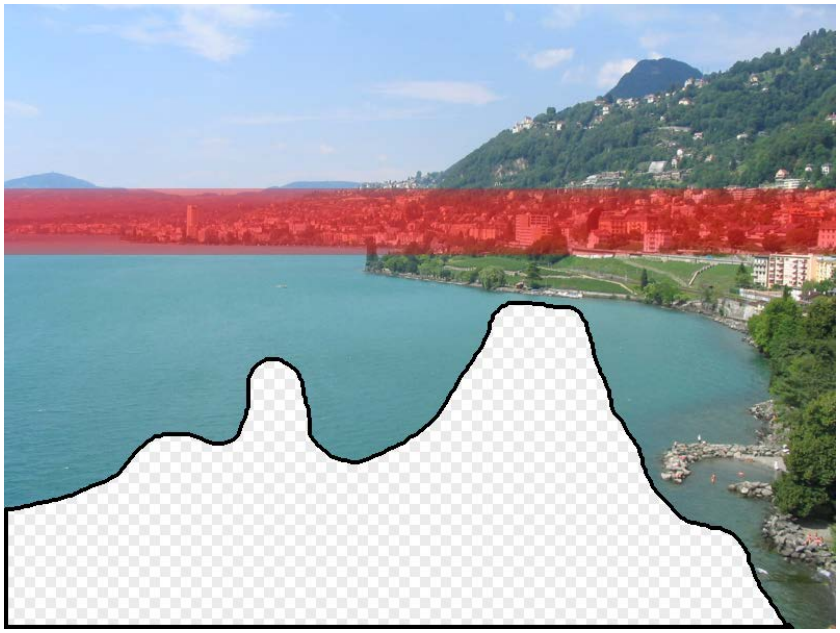


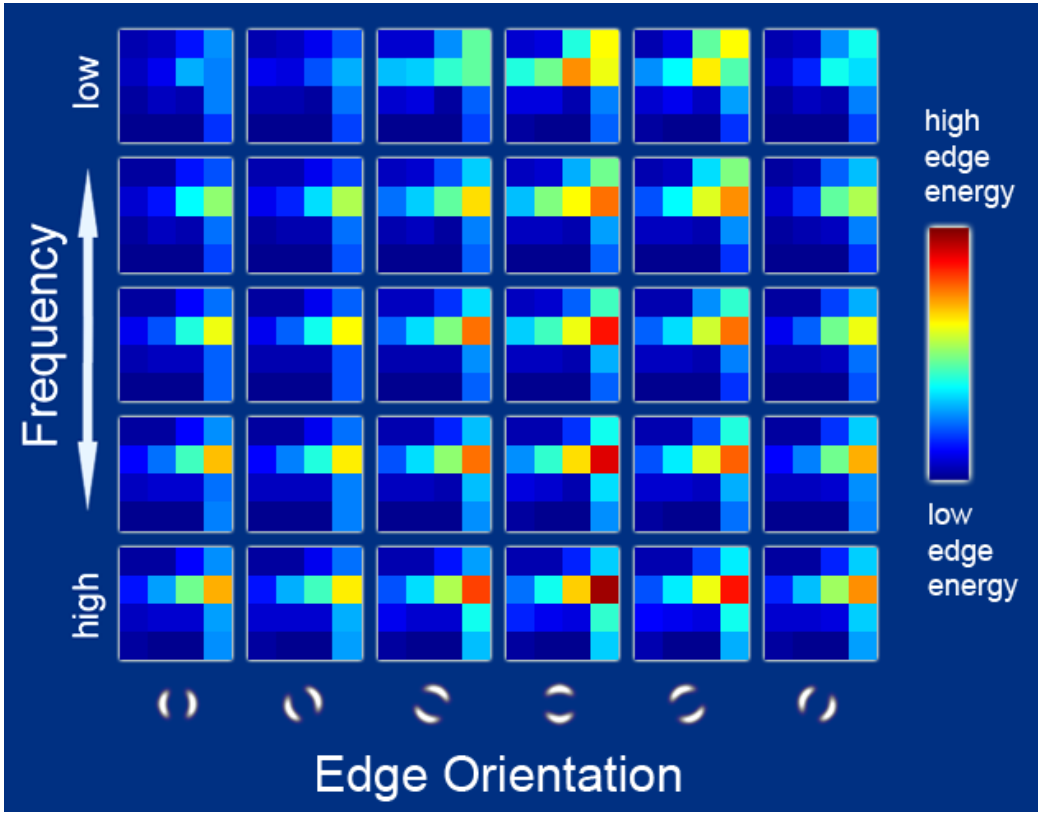


Gist scene descriptor
(Oliva and Torralba 2001)

Hays and Efros, SIGGRAPH 2007

Gist Scene Descriptor

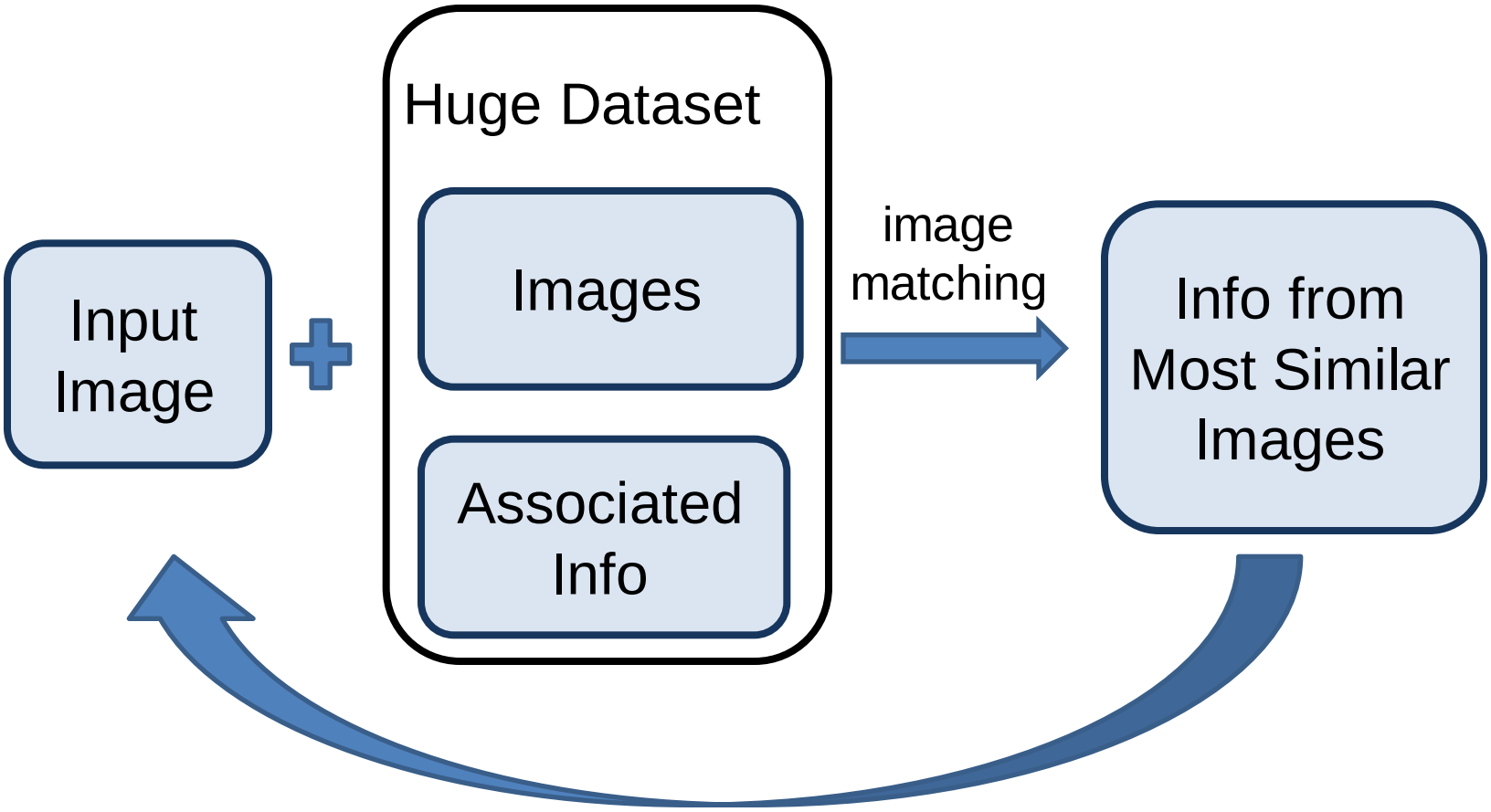




Gist scene descriptor
(Oliva and Torralba 2001)

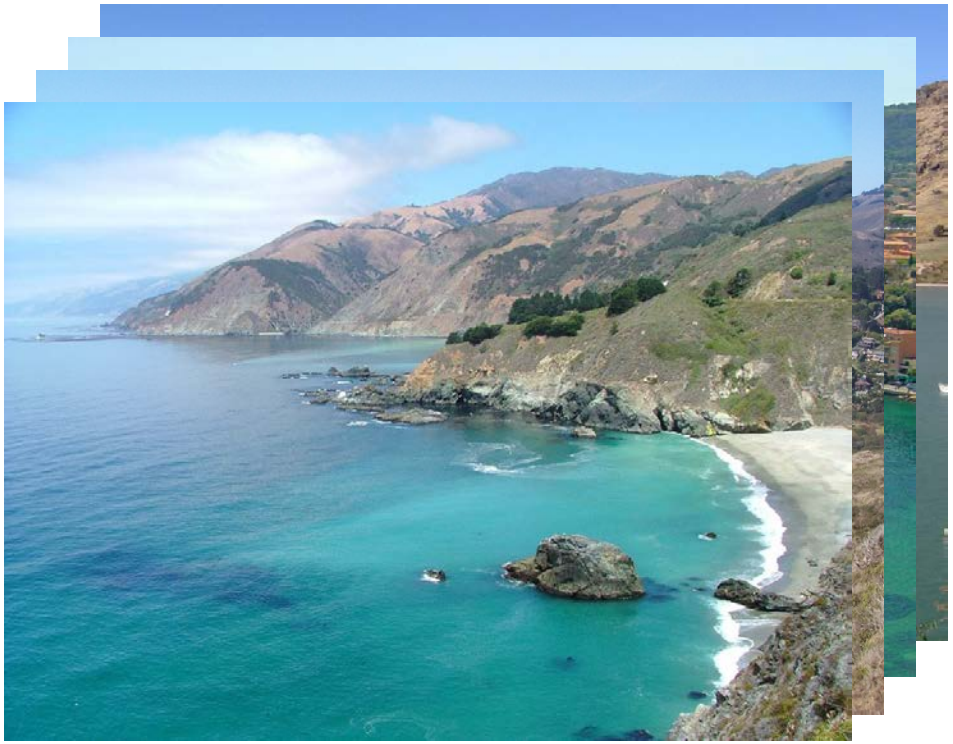
Hays and Efros, SIGGRAPH 2007

Recap: Using lots of data!



Trick: If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

Label Transfer



Label Transfer

Tags: Sky, Water, Beach, Sunny, …
Time: 1pm, August, 2006, …
Location: Italy, Greece, Hawaii …
Photographer: Flickrbug21, Traveller2

im2gps (Hays & Efros, CVPR 2008)

6 million geo-tagged Flickr images

How much can an image tell about its geographic location?

Paris

Paris

Paris

Paris

Paris

Paris

Paris

Madrid

Rome

Paris

Cuba

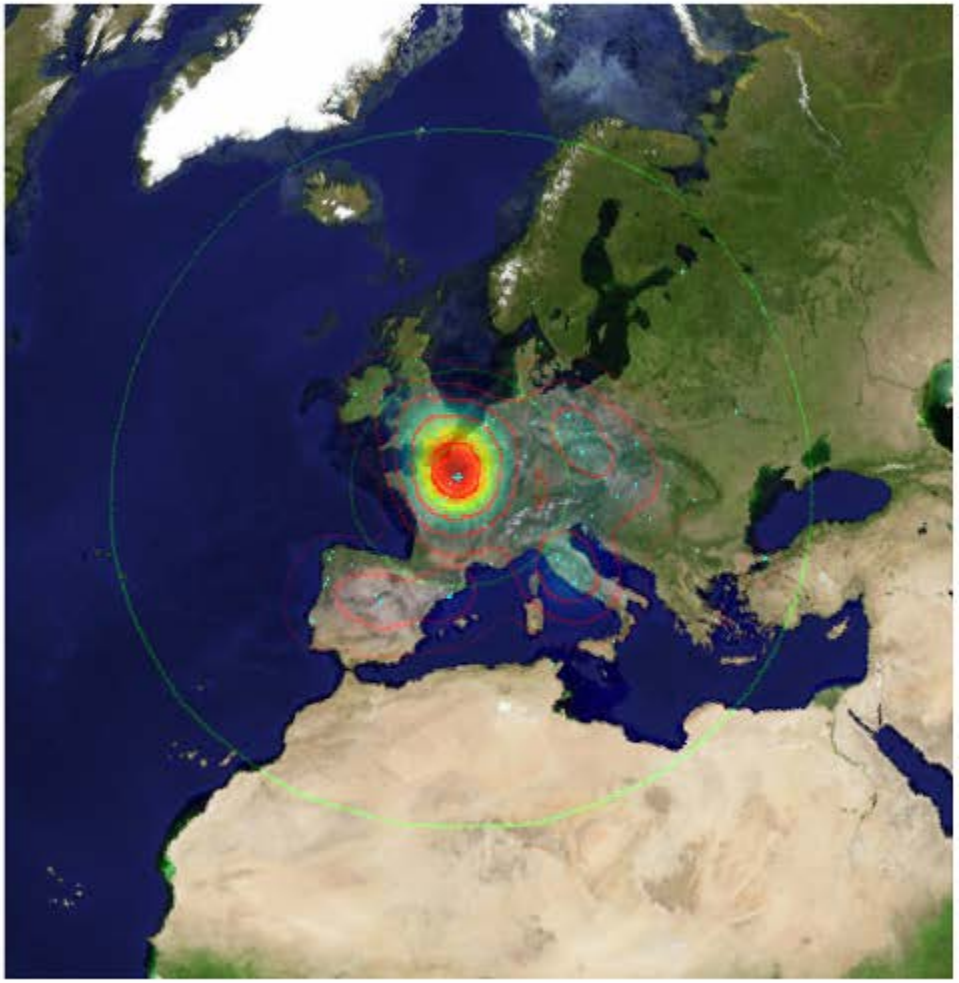
Paris

Paris

Poland

Paris

Paris



Im2gps

Example Scene Matches

Madrid

england

France

Paris

Croatia

heidelberg

Macau

Malta

Cairo

Italy

Italy

Italy

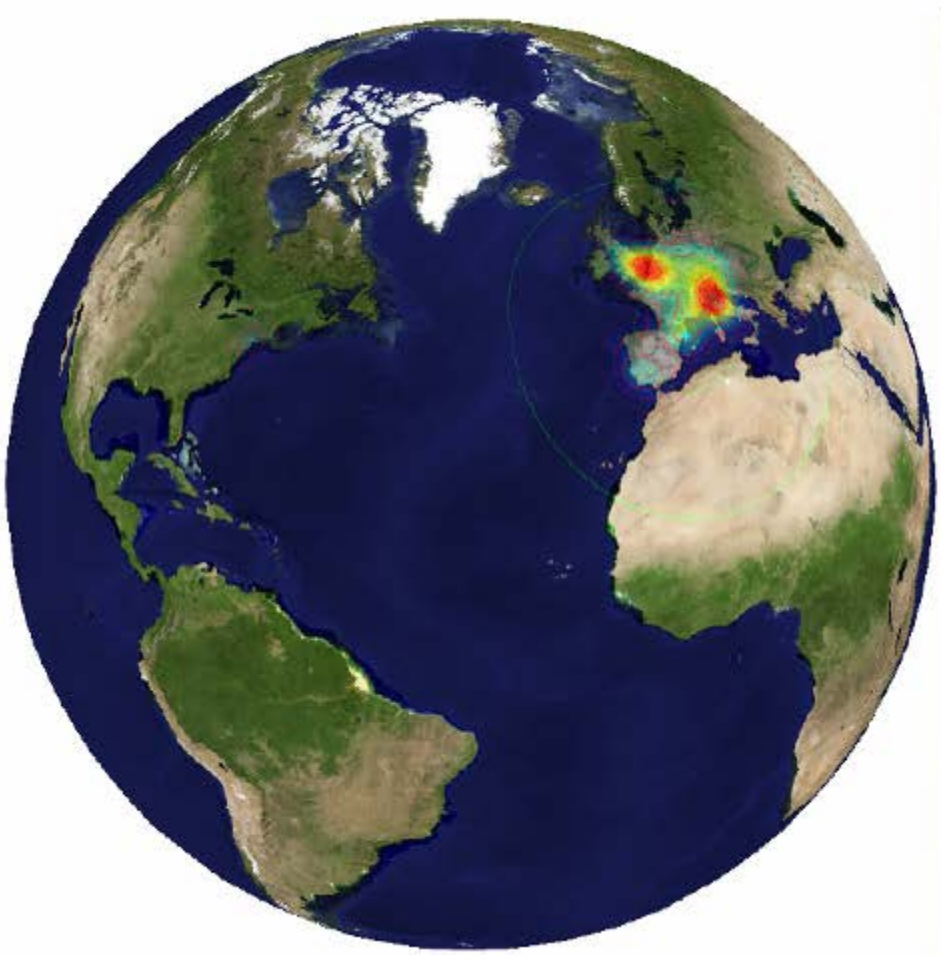
Latvia

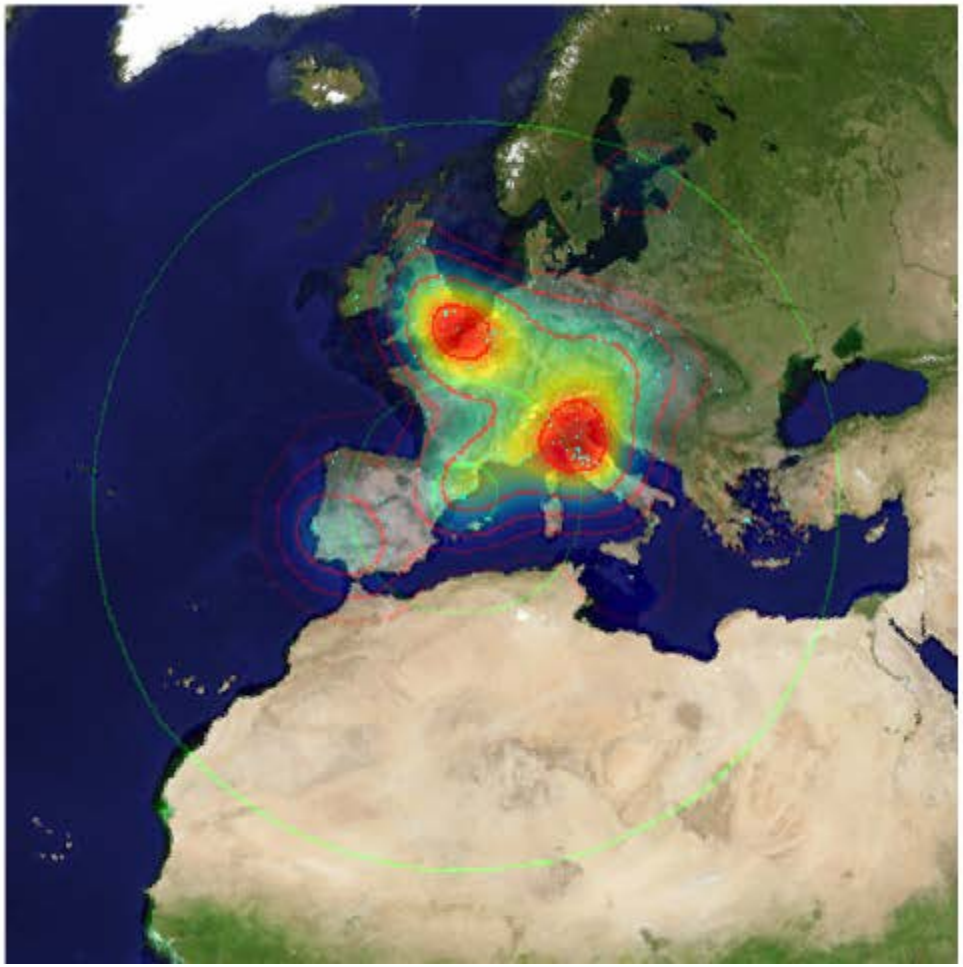
europe

Barcelona

Austria

Voting Scheme





im2gps

Philippines

Houston

Thailand

Houston

Maldives

Philippines

NewZealand

Bermuda

Palau

Mexico2

Brazil

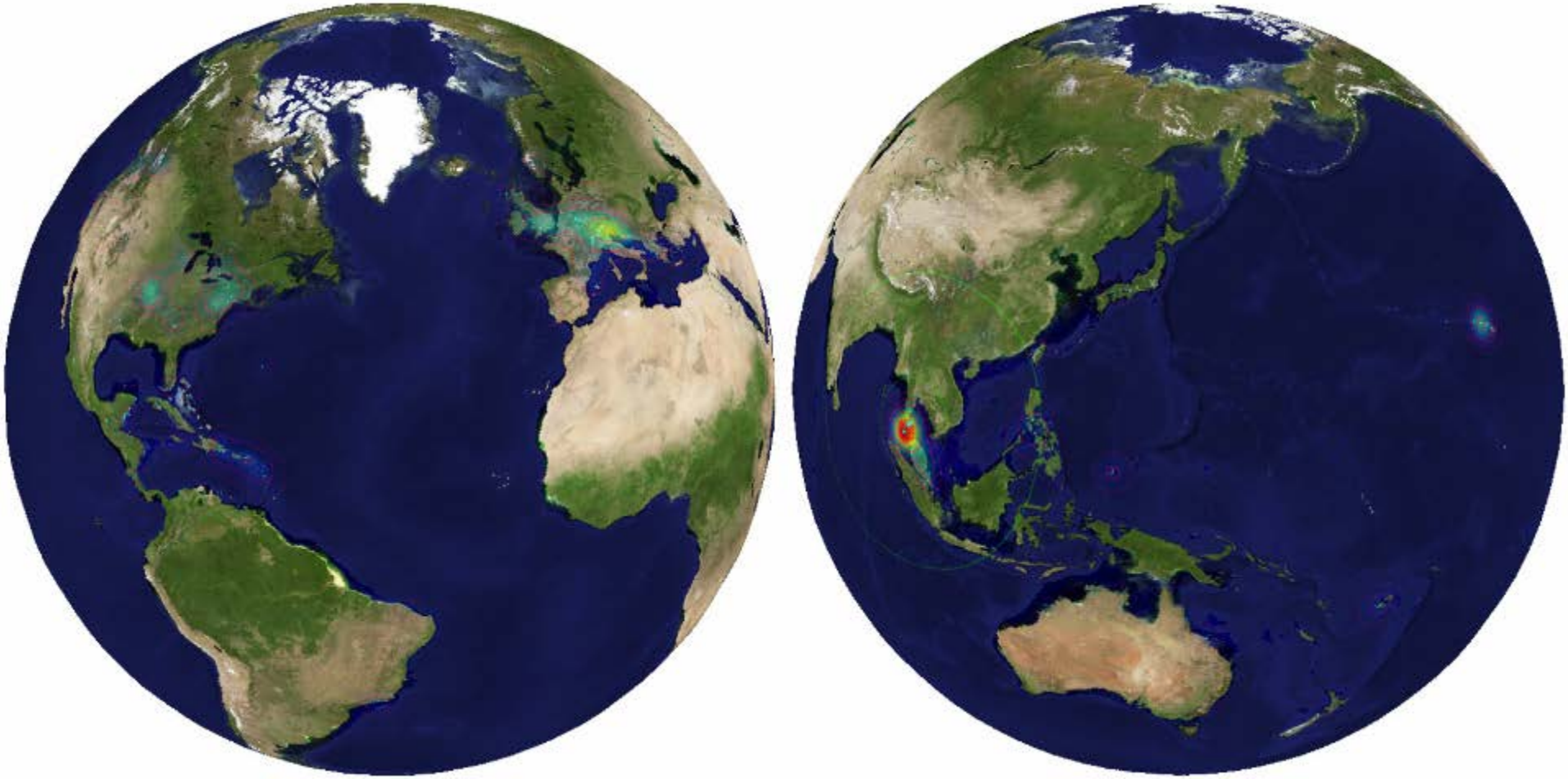
Mendoza

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

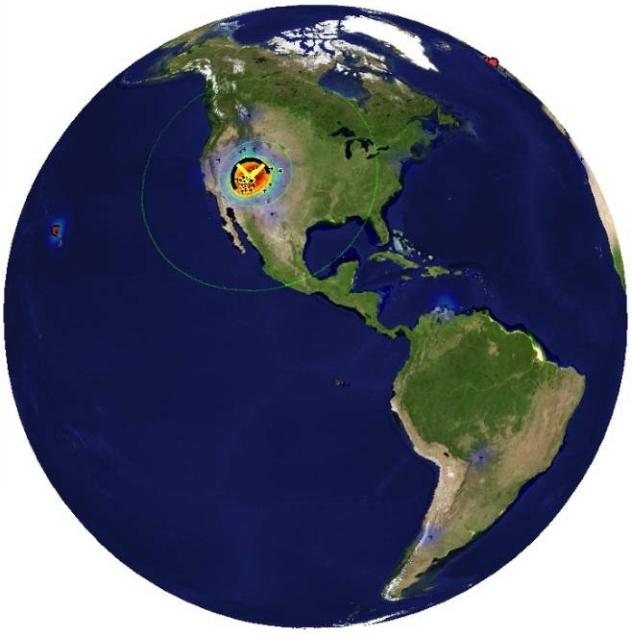
Utah

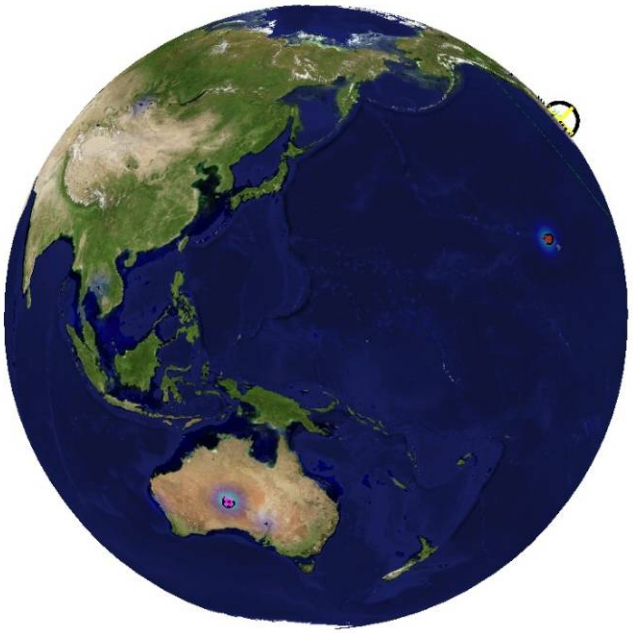
Utah

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

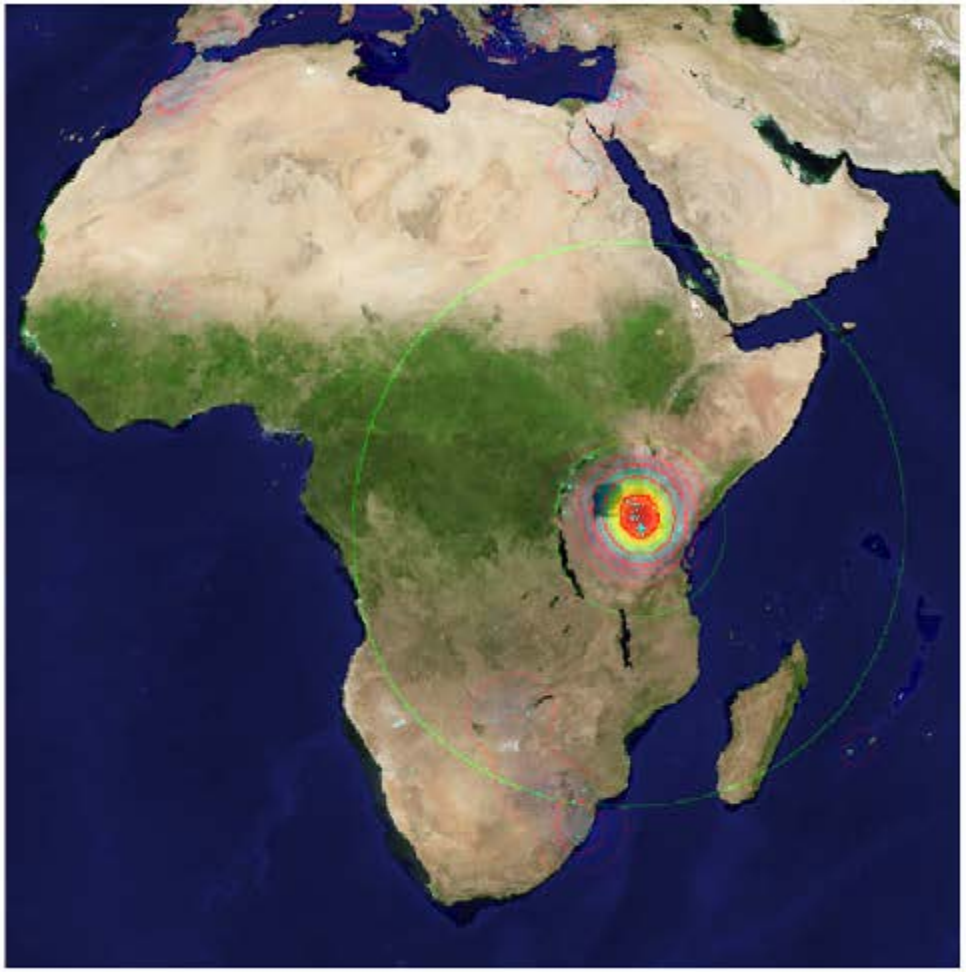
Ethiopia

Nevada

africa

Morocco

Tennessee



Toronto

Florida

NewYork

Boston

Boston

Oregon

Oregon

Oregon

NewYork

Barcelona

Oregon

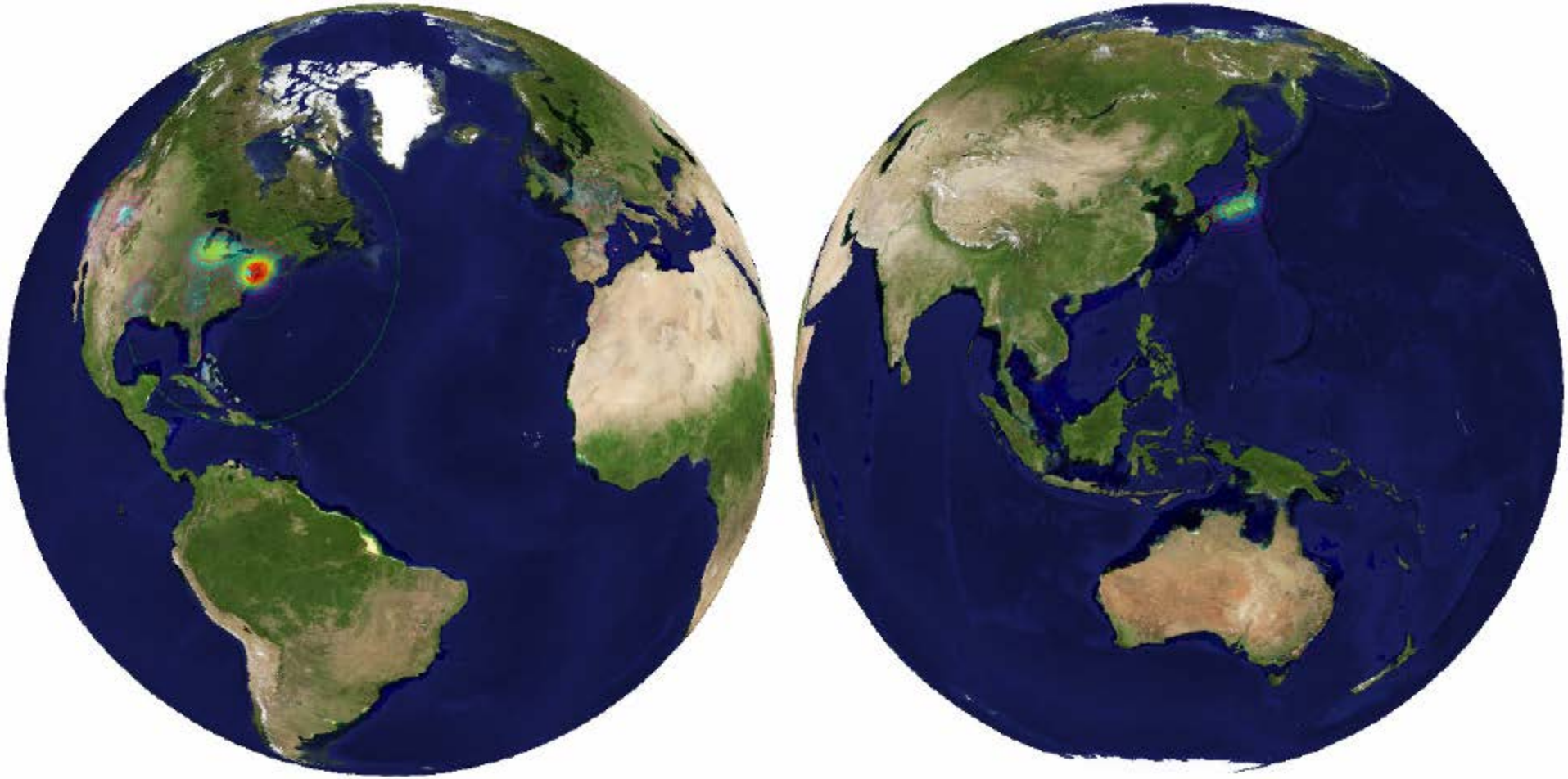
Chicago

Ohio

Philadelphia

NewYorkCity

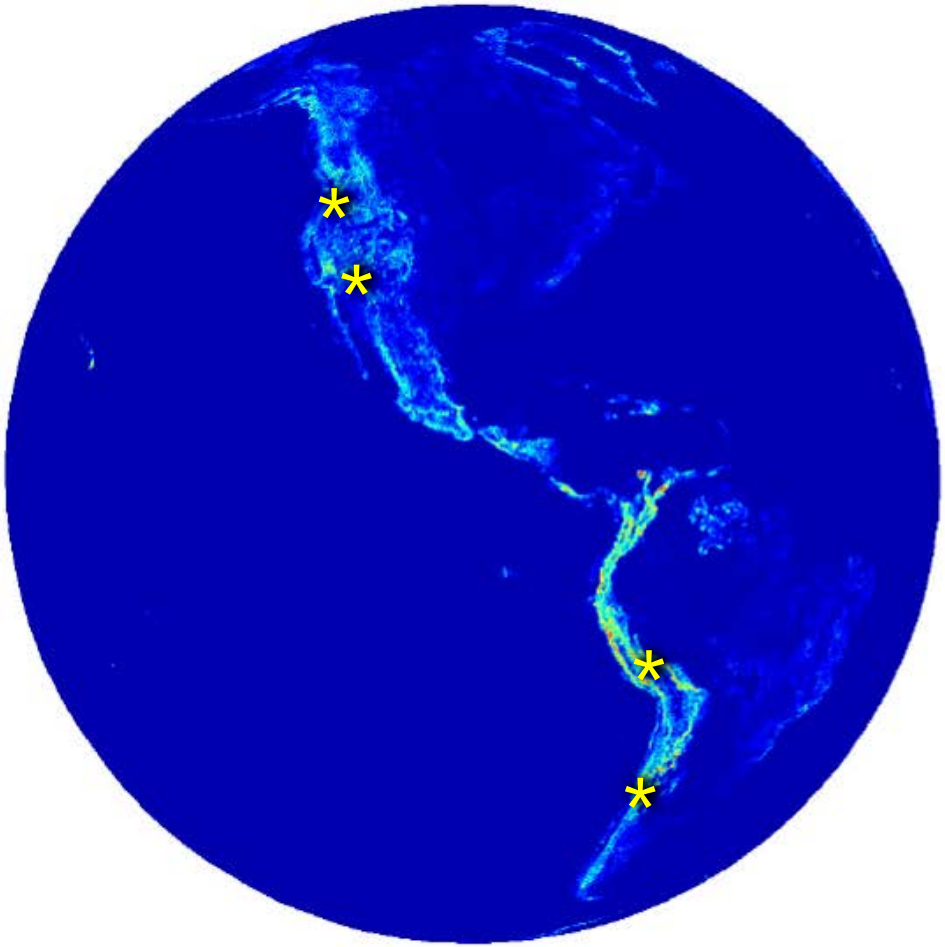
Boston

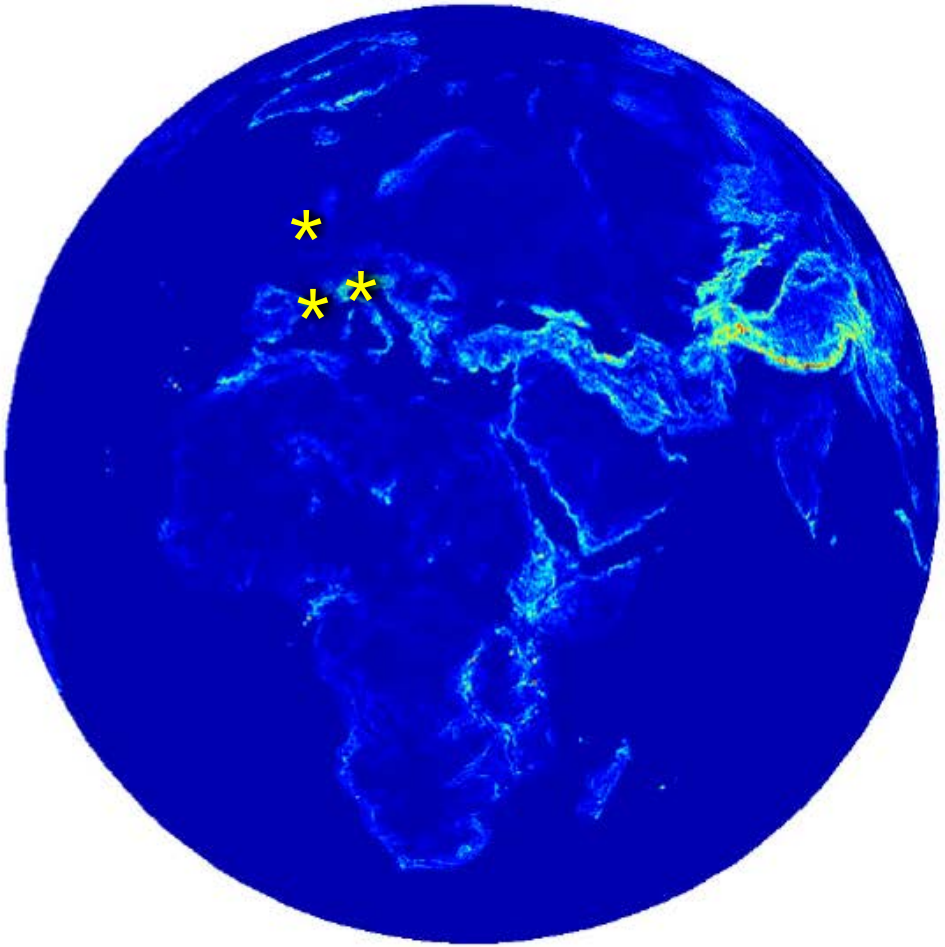


Data-driven categories

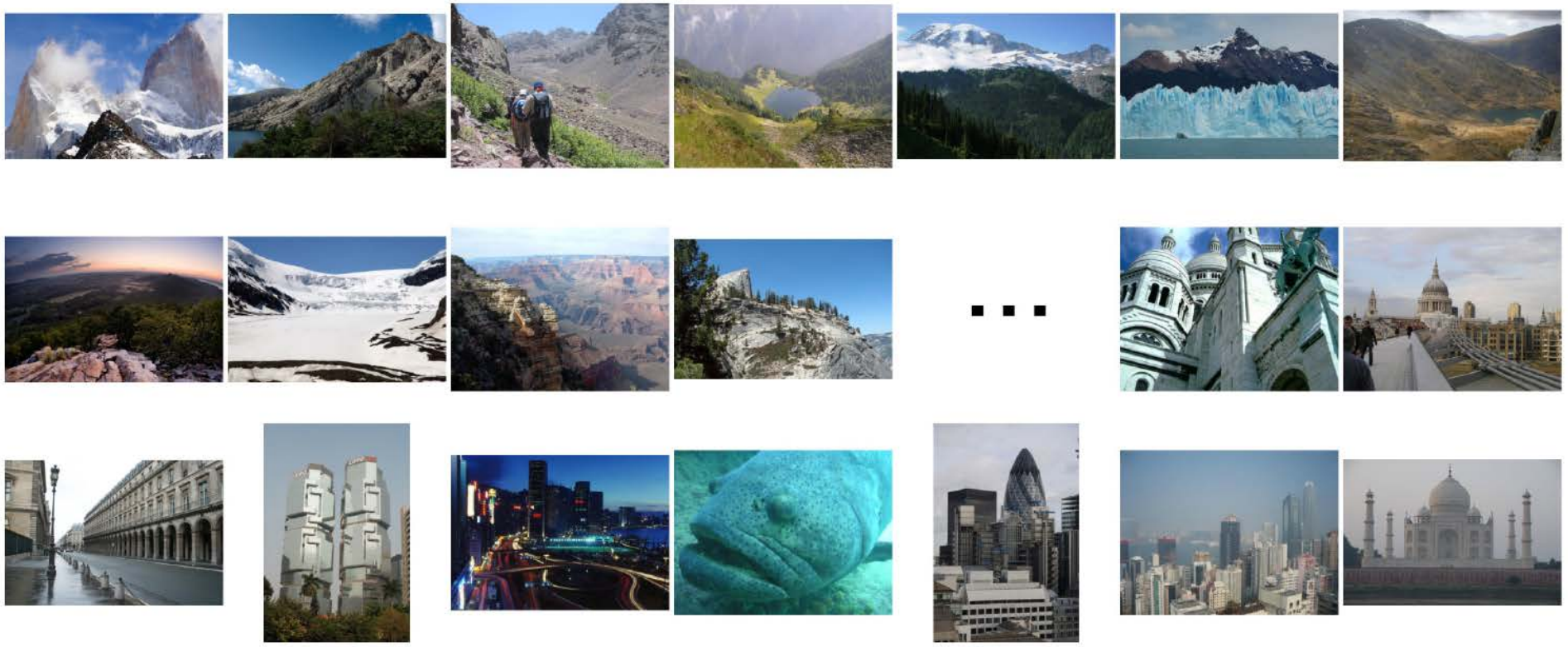
Argentina
Andorra
Andorra
Iceland
Idaho
Switzerland
Argentina
Bolivia
Nevada
Hawaii
Hawaii
Egypt
China
Arizona
Peru
Oregon

Elevation gradient =
112 m / km





Elevation gradient magnitude ranking



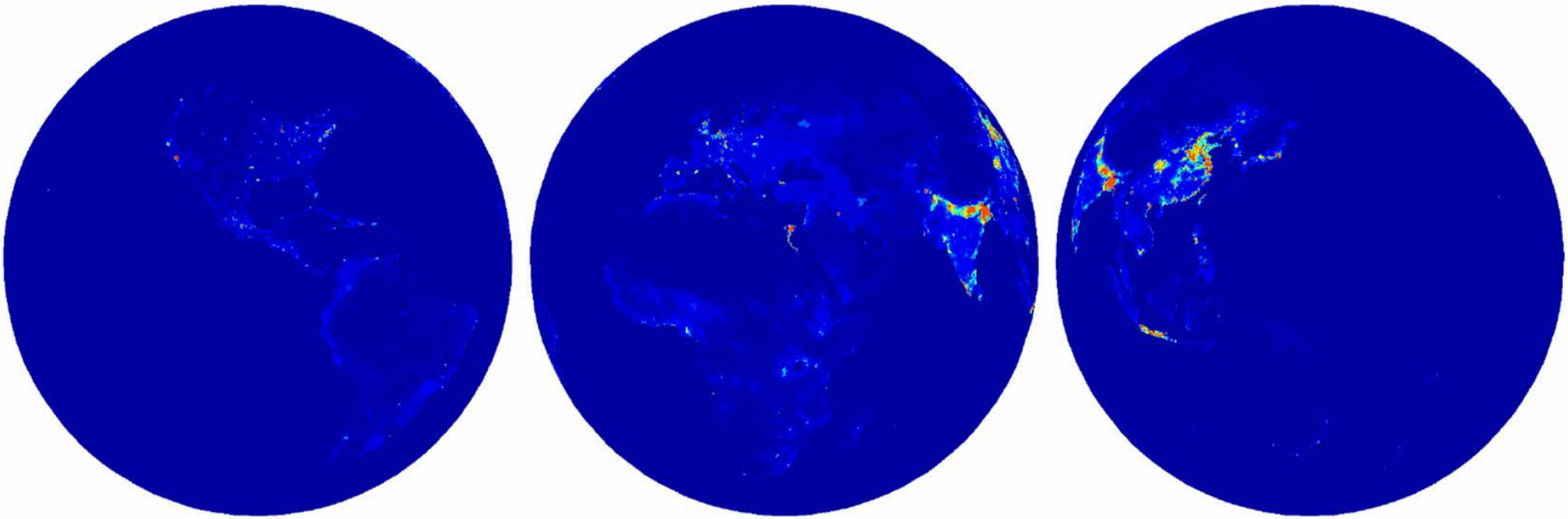


Figure 2. Global population density map.

Population density ranking

...

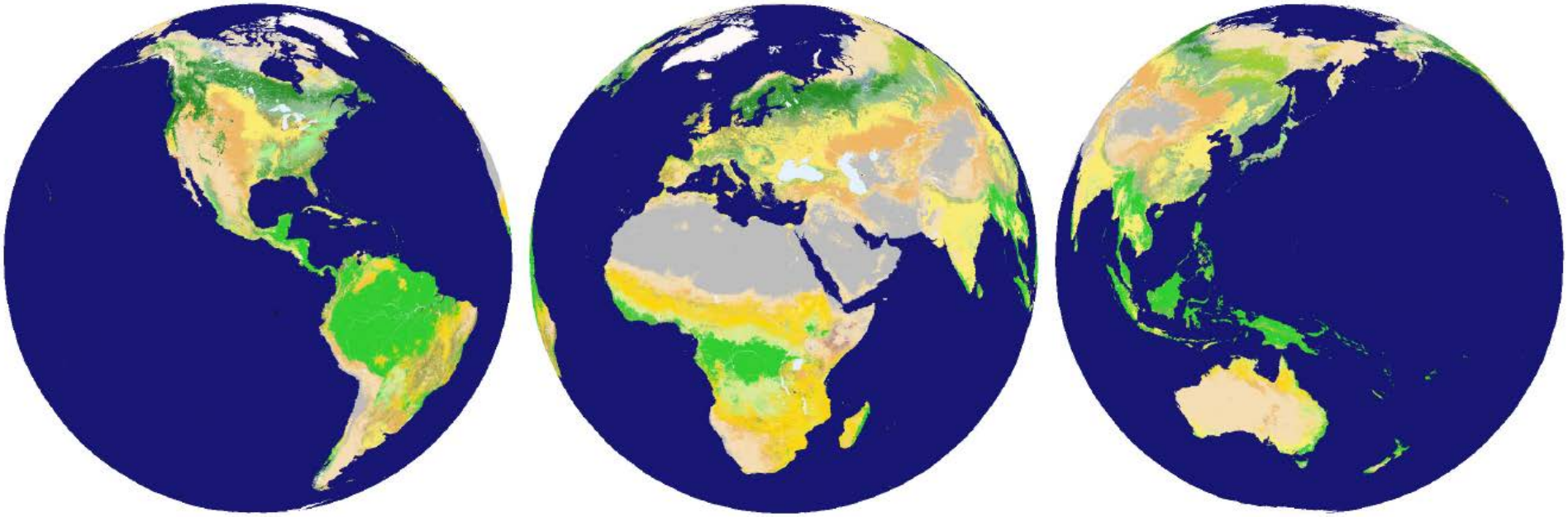


Figure 4. Global land cover classification map.

Barren or sparsely populated

Urban and built up

Snow and Ice

Savannah

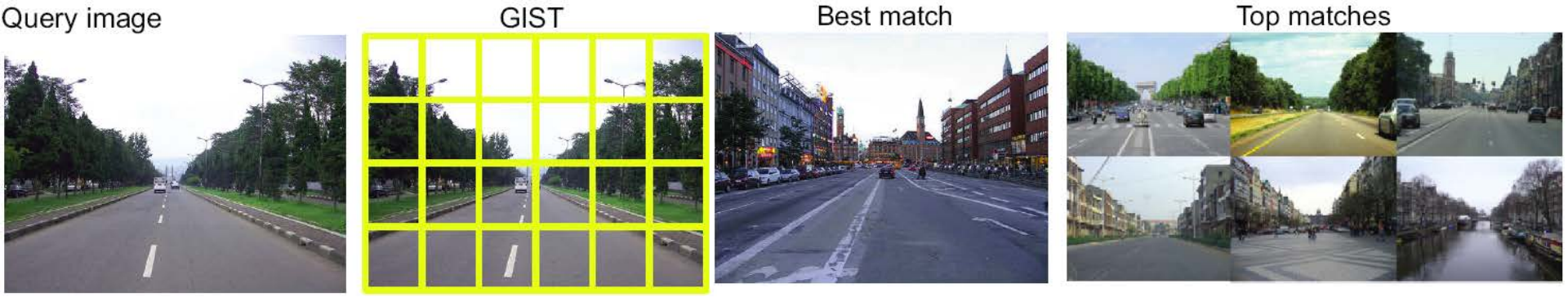
Water

Using Data for Image Creation…

Michel Gondry, *Je Danse la Mia*

https://www.youtube.com/watch?v=7ceNf9qJjgc

Scene matching with camera transformations



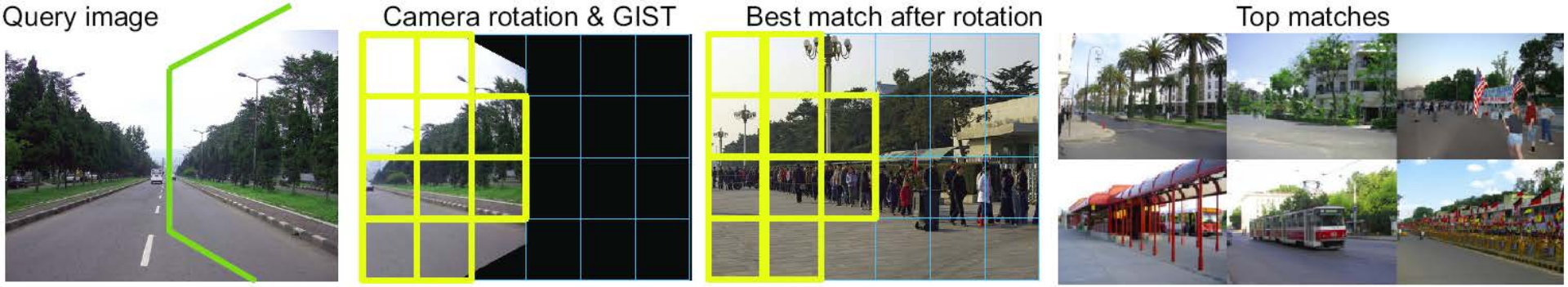
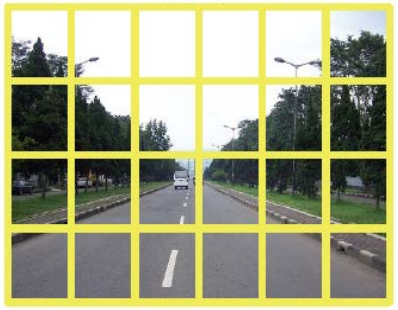
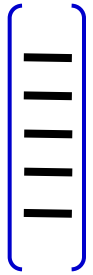


Image representation

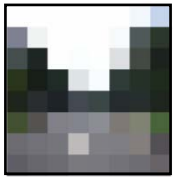
Original image

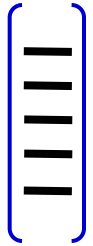
GIST
[Oliva and Torralba'01]



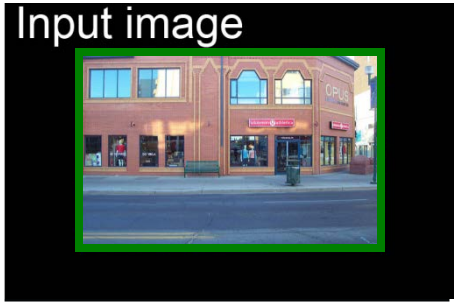


Color layout

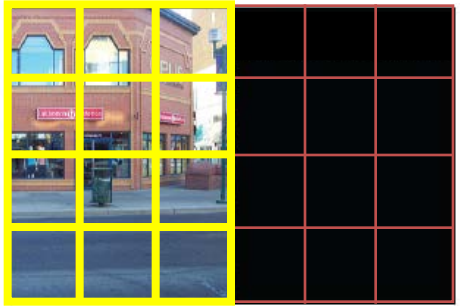




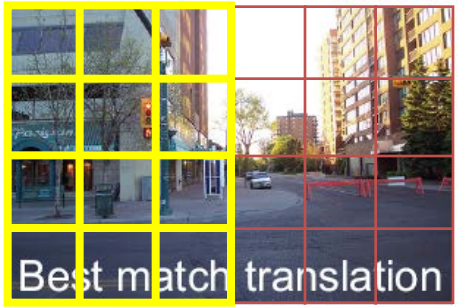
Scene matching with camera view transformations: Translation



1. Move camera



2. View from the virtual camera



3. Find a match to fill the missing pixels

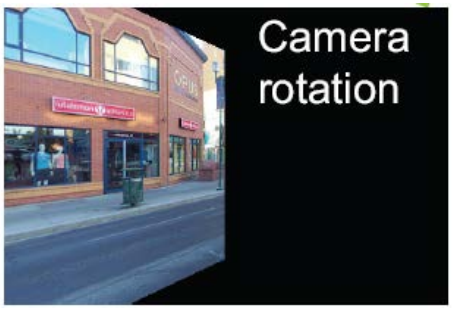
4. Locally align images

5. Find a seam

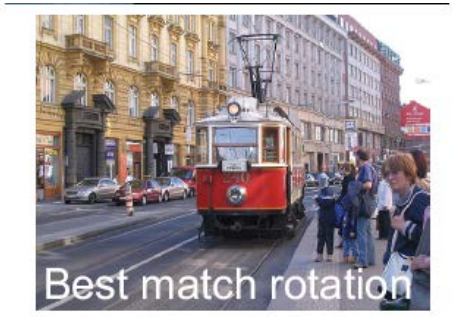
6. Blend in the gradient domain

Scene matching with camera view transformations: Camera rotation

1. Rotate camera



2. View from the virtual camera

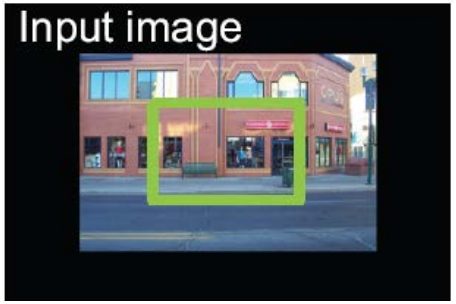


3. Find a match to fill-in the missing pixels

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

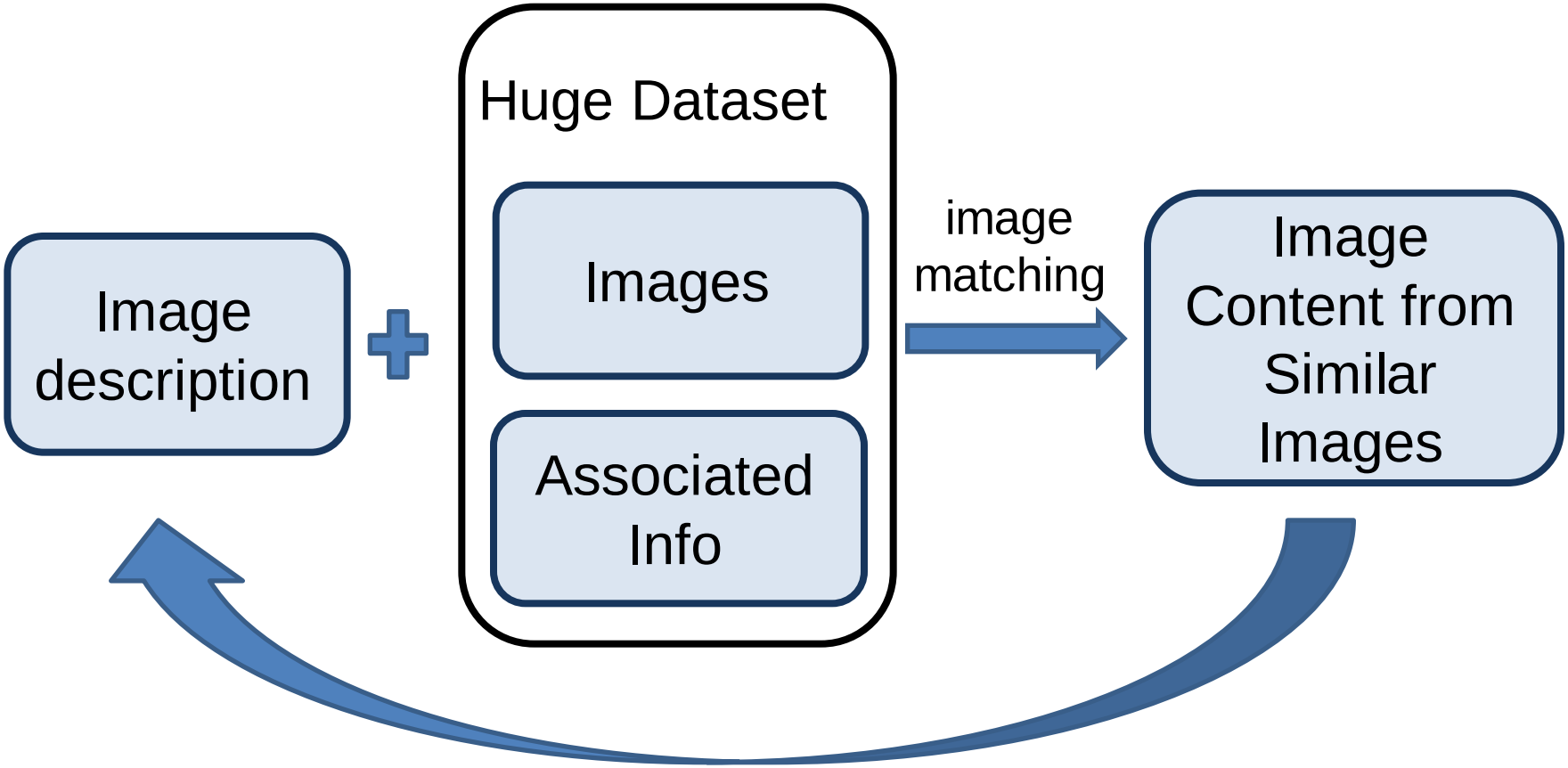
Tour from a single image

Navigate the virtual space using intuitive motion controls

Video

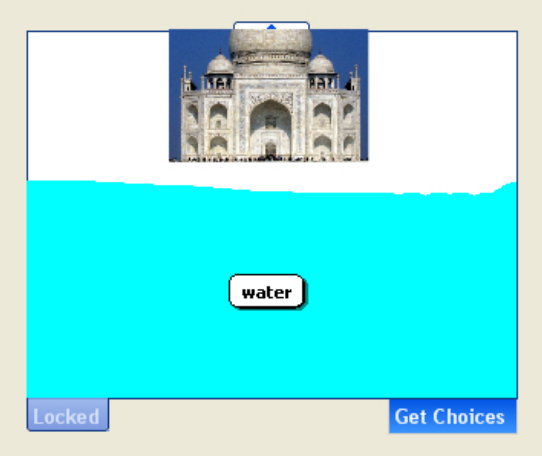
http://www.youtube.com/watch?v=E0rboU10rPo

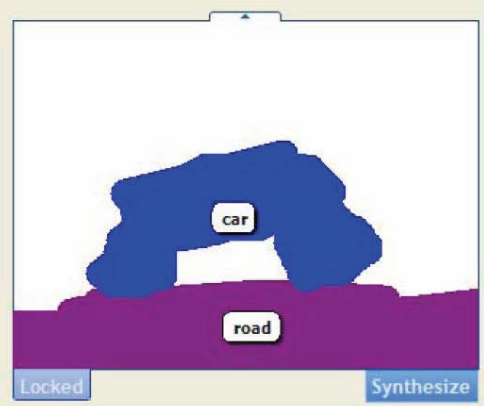
Semantic Photo Synthesis



M. Johnson, G. Brostow, J. Shotton, O. A. c, and R. Cipolla, “Semantic Photo Synthesis,” Computer Graphics Forum Journal (Eurographics 2006), vol. 25, no. 3, 2006.

Semantic Photo Synthesis [EG'06]





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

Semantic Photo Synthesis

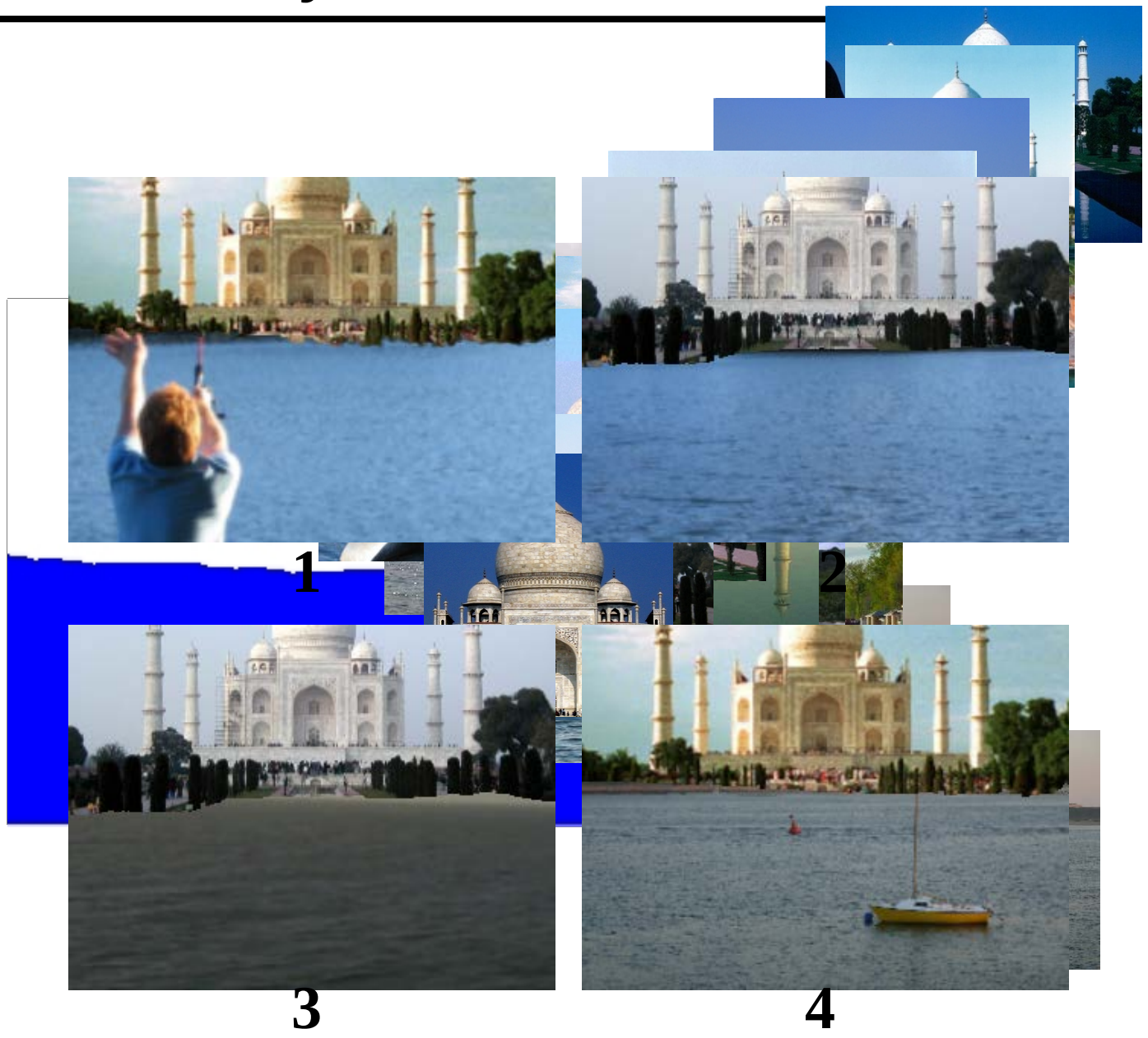
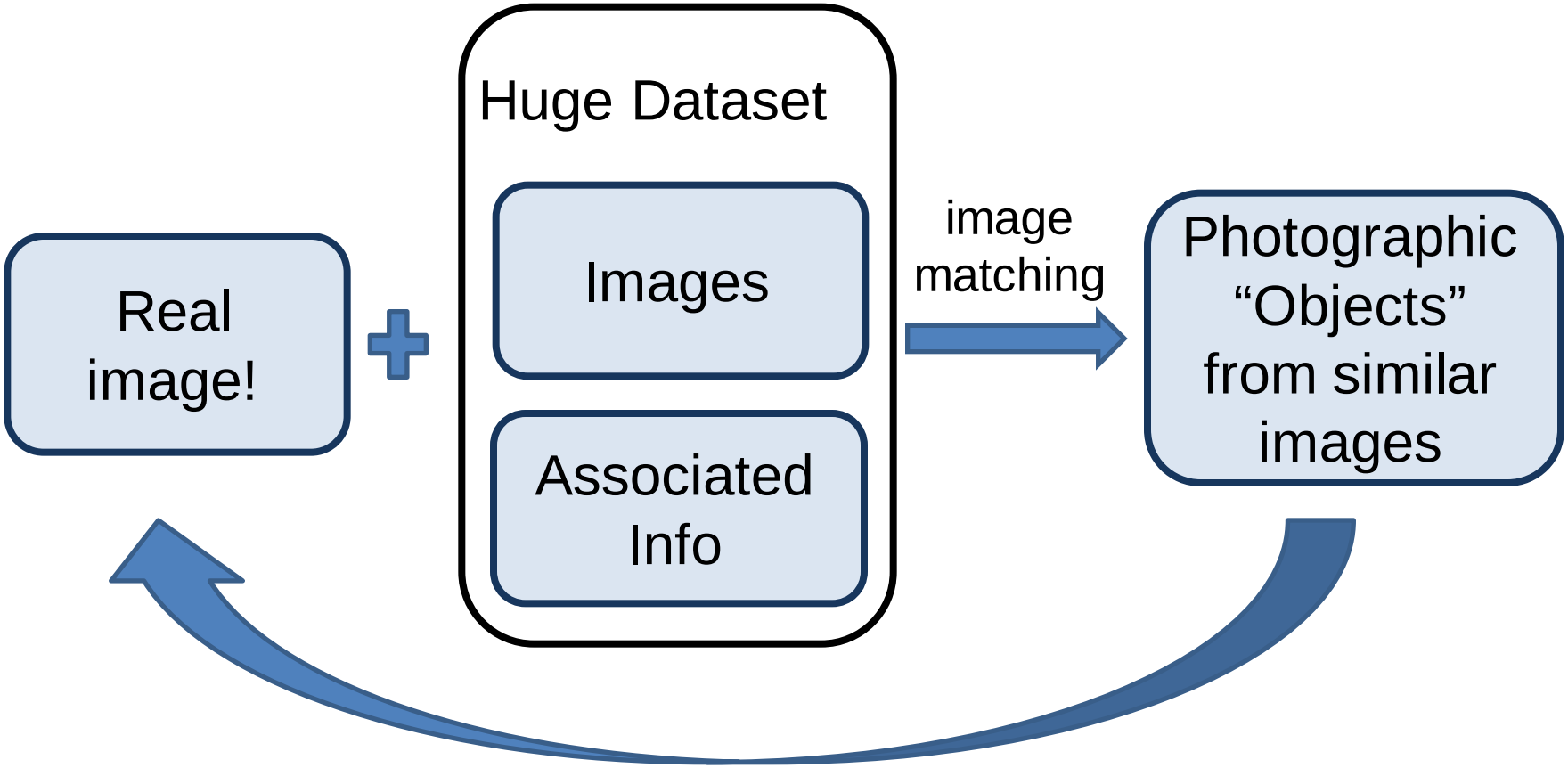


Photo Clip Art



J.-F. Lalonde, D. Hoiem, A. A. Efros, C. Rother, J. Winn, and A. Criminisi, "Photo Clip Art," ACM Transactions on Graphics (SIGGRAPH 2007), vol. 26, no. 3, Aug. 2007.

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

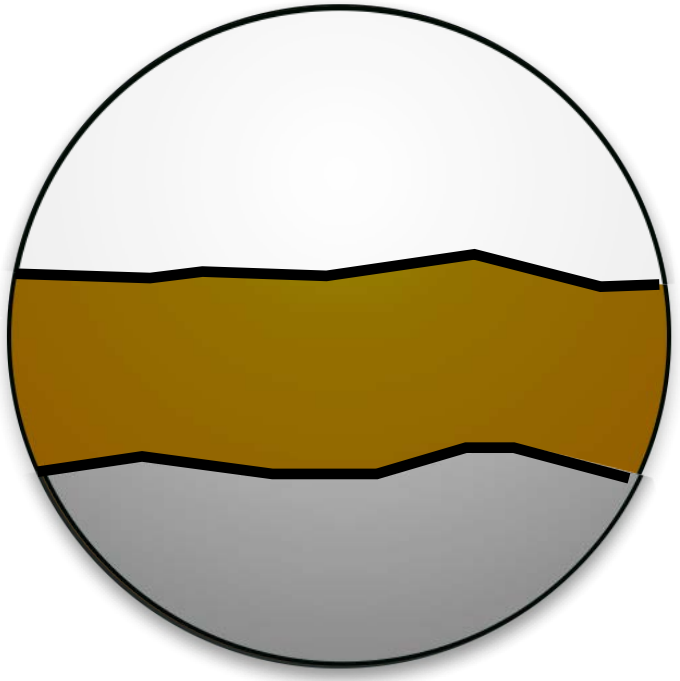
Geometry is not enough

Illumination context

- Exact environment map is impossible
- Approximations [Khan et al., ‘06]

Database image

Environment map rough approximation

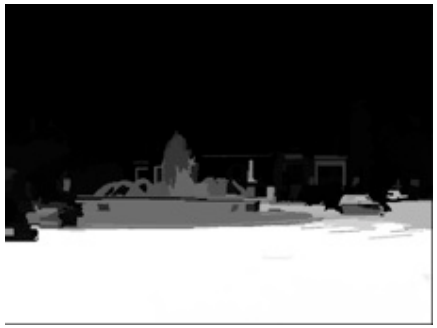


Illumination context

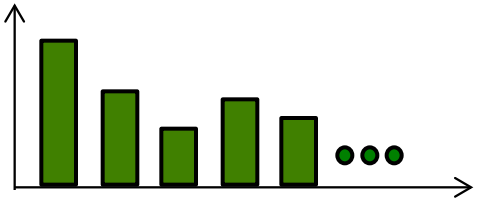
Database image

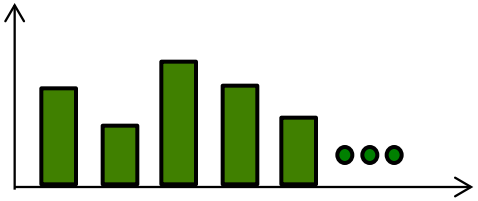
Automatic Photo Popup
Hoiem et al., SIGGRAPH ’05

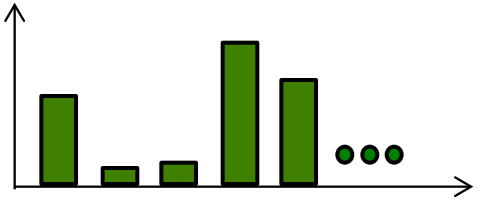
P(pixel|class)



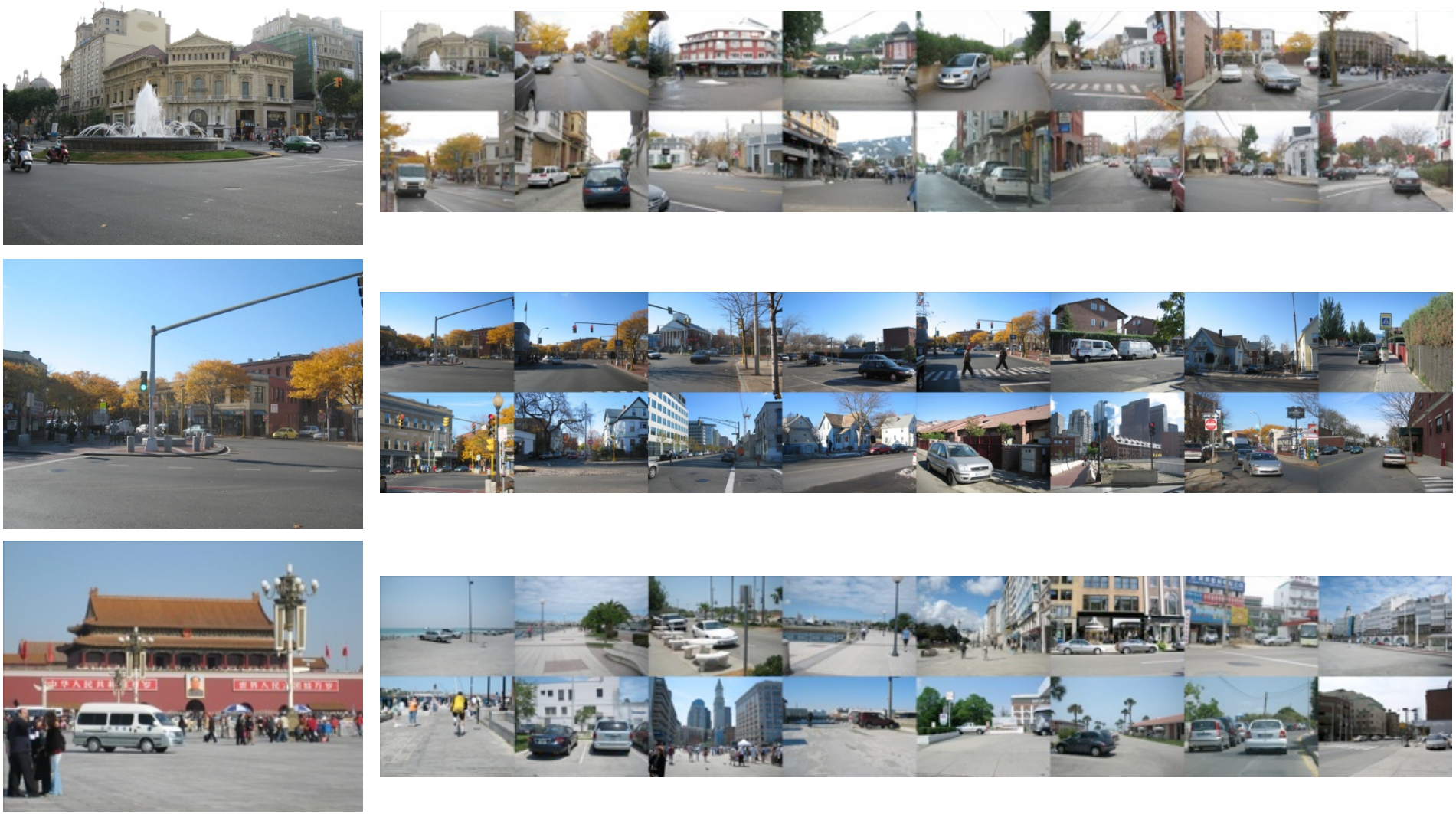
CIE L*a*b* histograms







Illumination nearest-neighbors



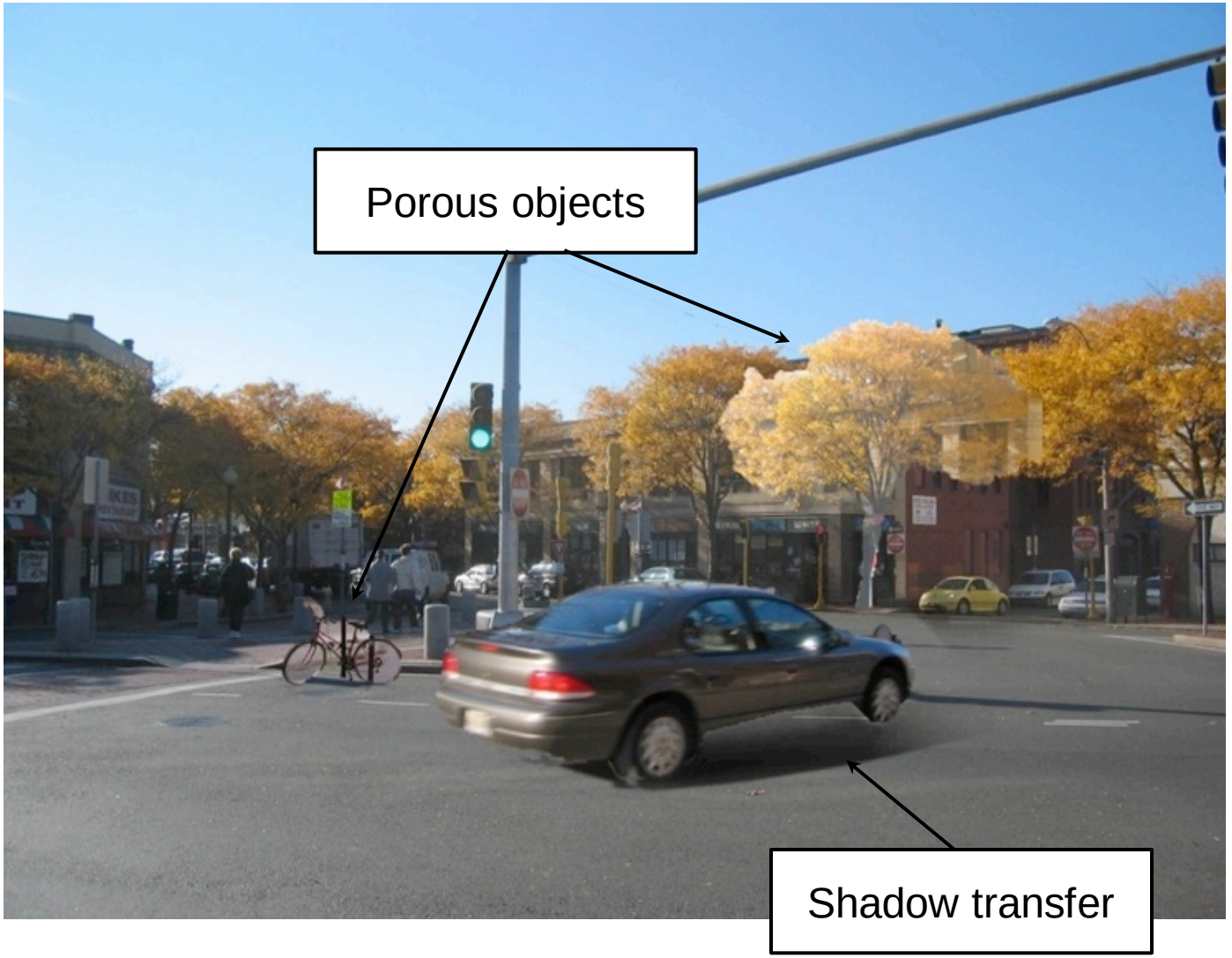
Street accident

Bridge

Painting

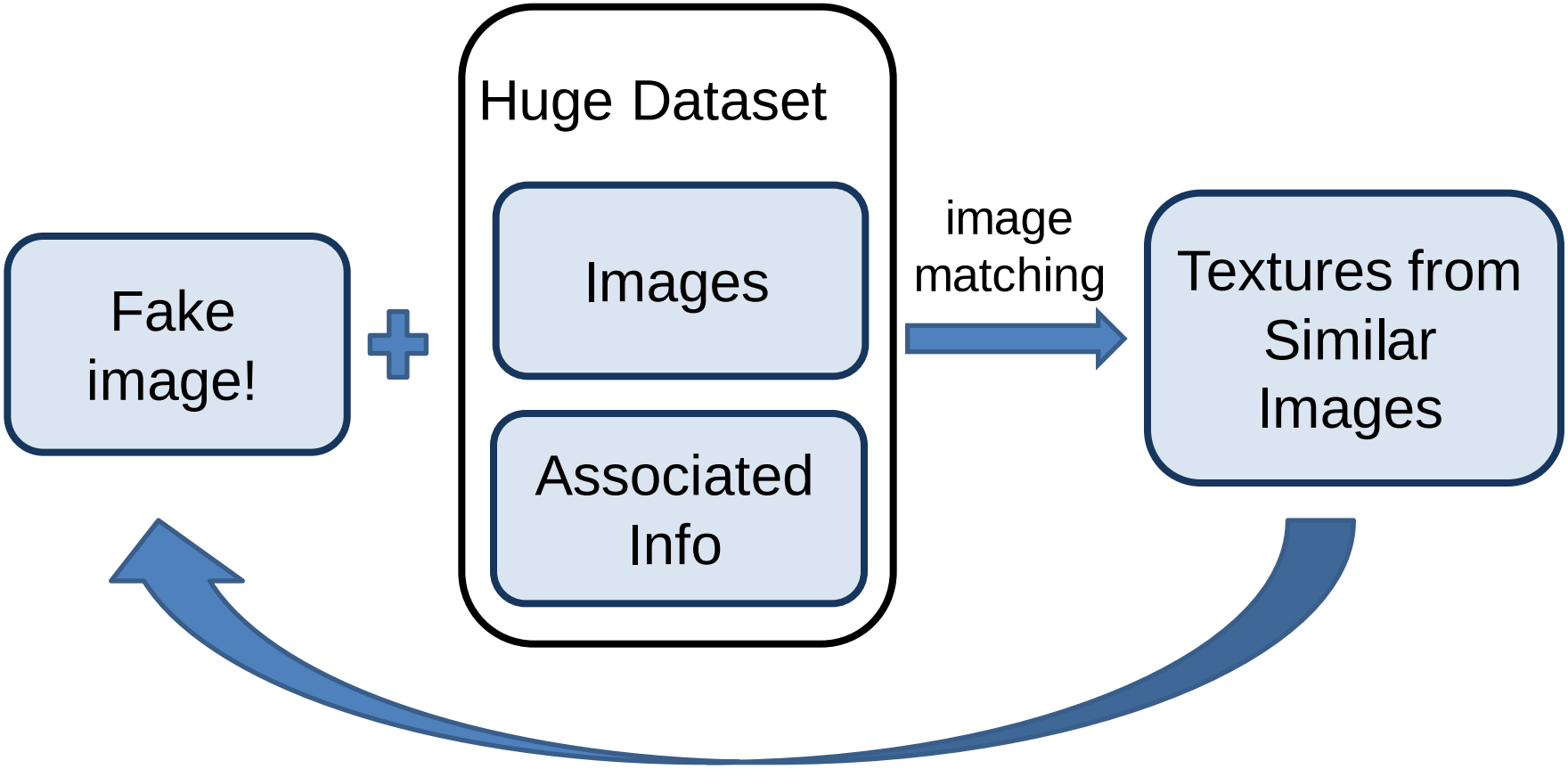
Alley

Failure cases



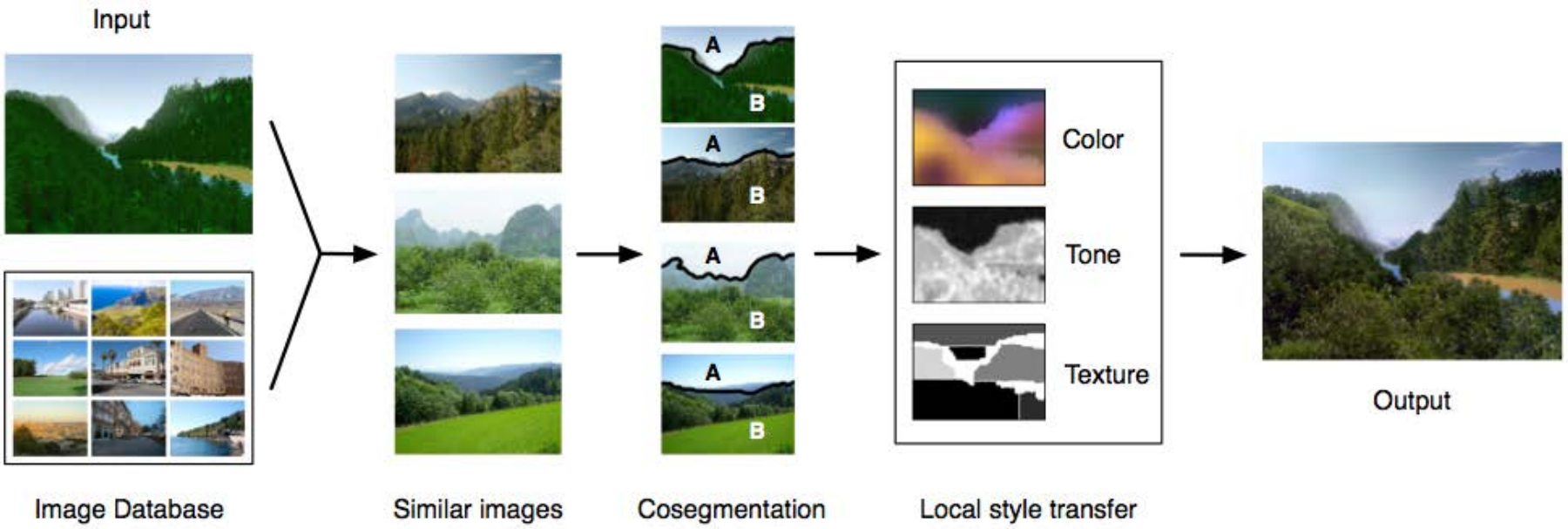
Failure cases

CG2Real



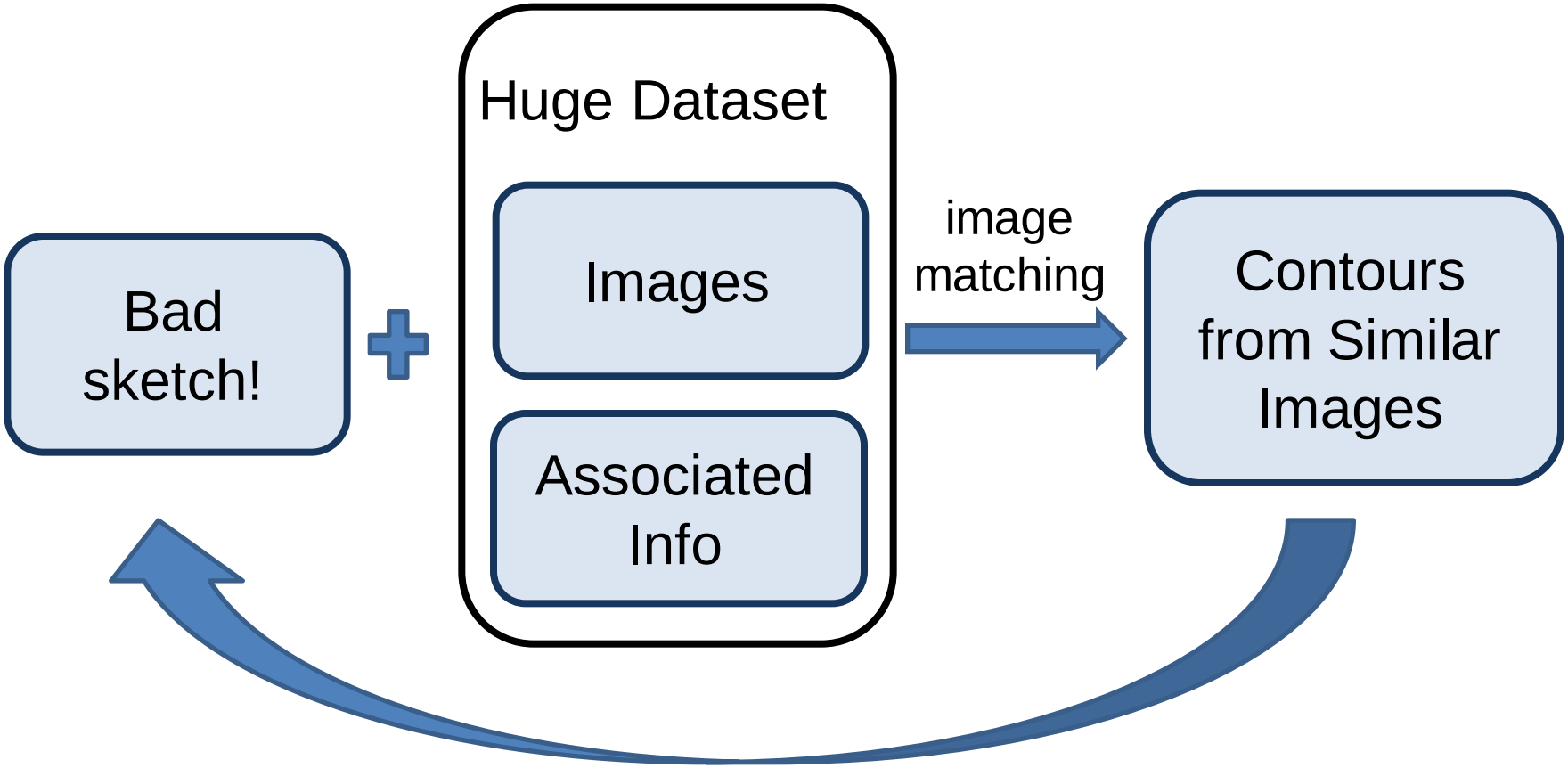
M. K. Johnson, K. Dale, S. Avidan, H. Pfister, W. T. Freeman, and W. Matusik, “CG2Real: Improving the realism of computer generated images using a large collection of photographs,” IEEE Transactions on Visualization and Computer Graphics, 2010.

CG2Real



M. K. Johnson, K. Dale, S. Avidan, H. Pfister, W. T. Freeman, and W. Matusik, “CG2Real: Improving the realism of computer generated images using a large collection of photographs,” IEEE Transactions on Visualization and Computer Graphics, 2010.

ShadowDraw


Huge Dataset
Images
Associated Info
Bad sketch!
image matching
Contours from Similar Images

ShadowDraw

http://www.youtube.com/watch?v=zh_-HUdQwow

Explore Visual Data

AverageExplorer

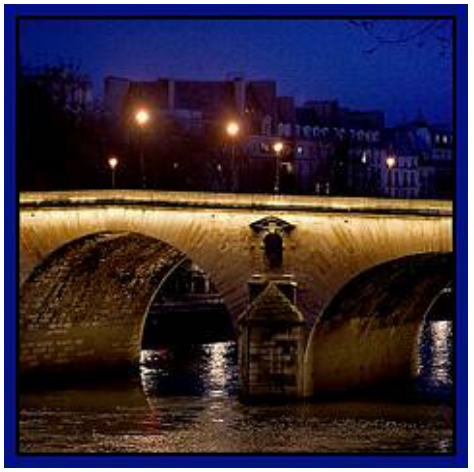
http://www.youtube.com/watch?v=1QgL_aPPCpM

The Dangers of Data

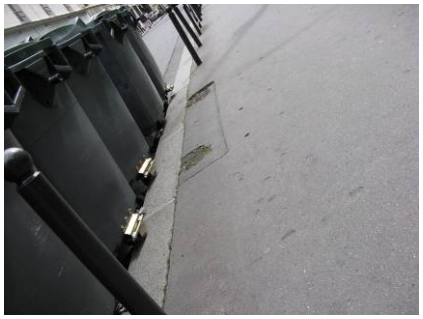
Bias

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

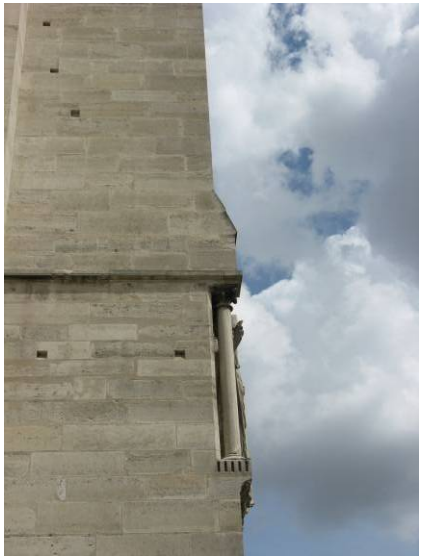
Flickr Paris



Real Paris



Real Notre Dame

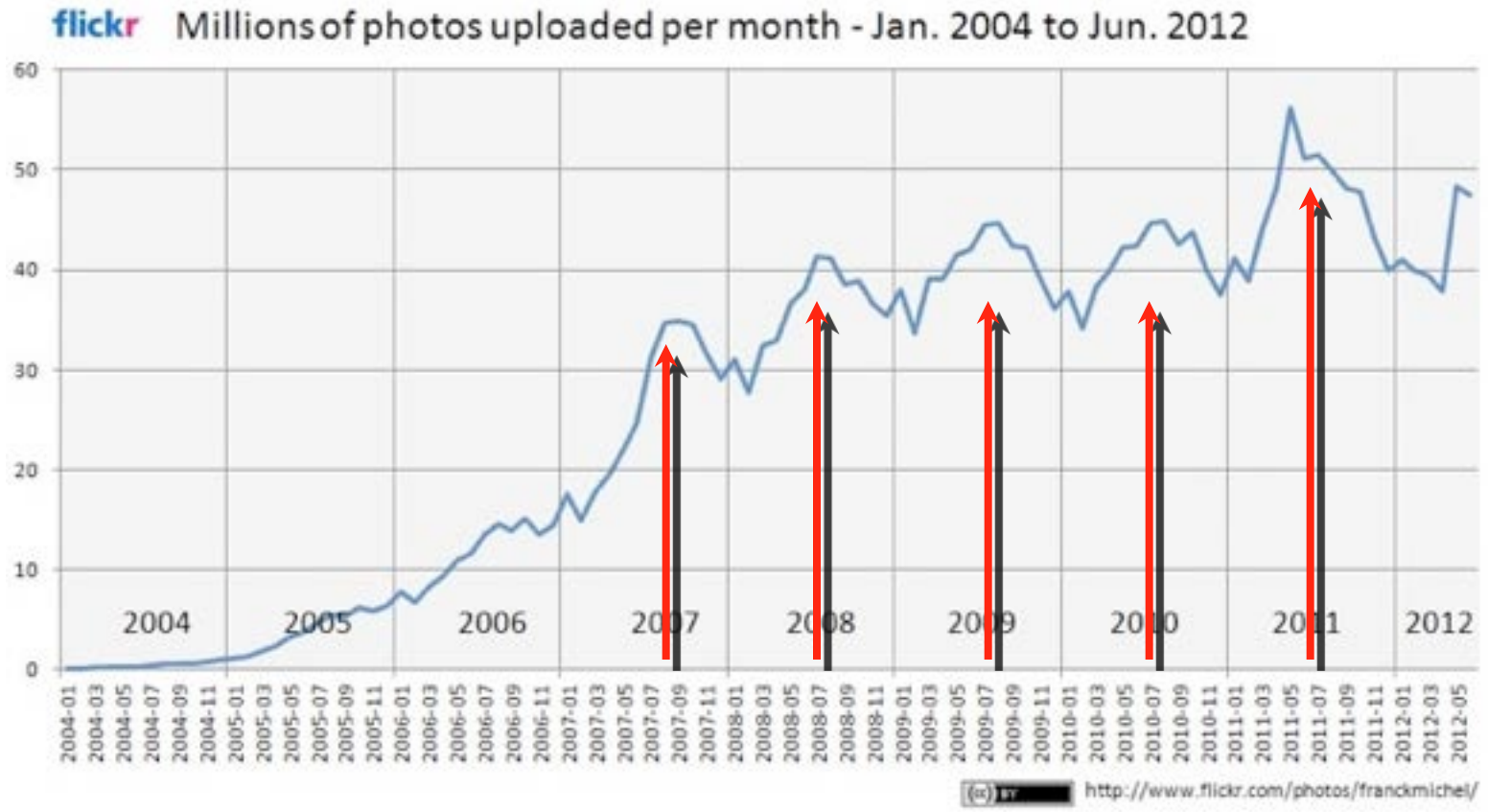


Sampling Bias

- People like to take pictures on vacation

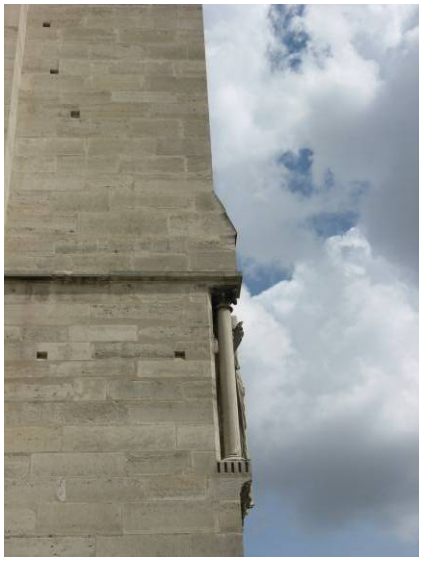
Sampling Bias

People like to take pictures on vacation



Photographer Bias

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



vs.

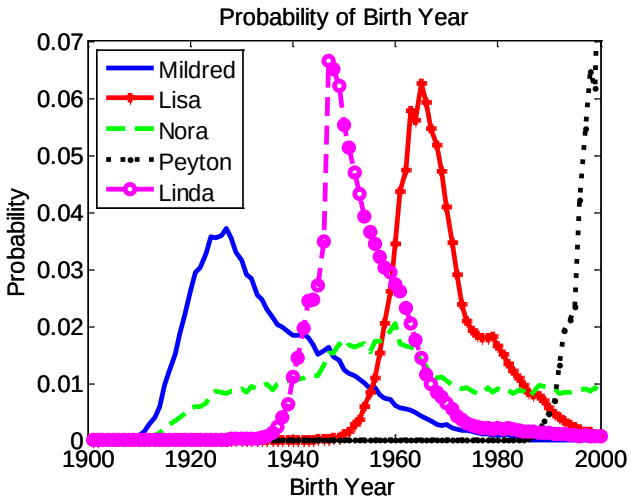
Photographer Bias

- People follow photographic conventions

vs.

Social Bias

Mildred and Lisa



Source: U.S. Social Security Administration

Gallagher et al CVPR 2008

Social Bias

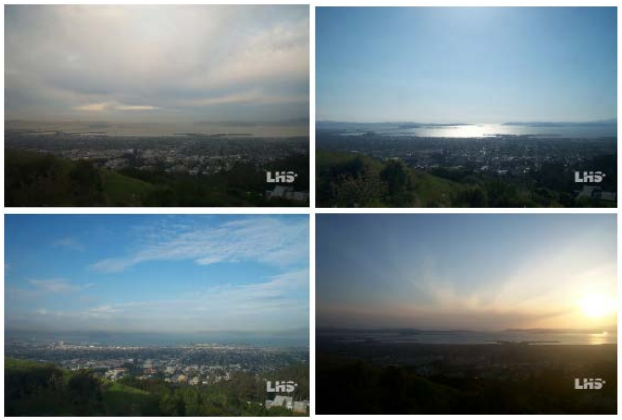
Gallagher et al CVPR 2008

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…