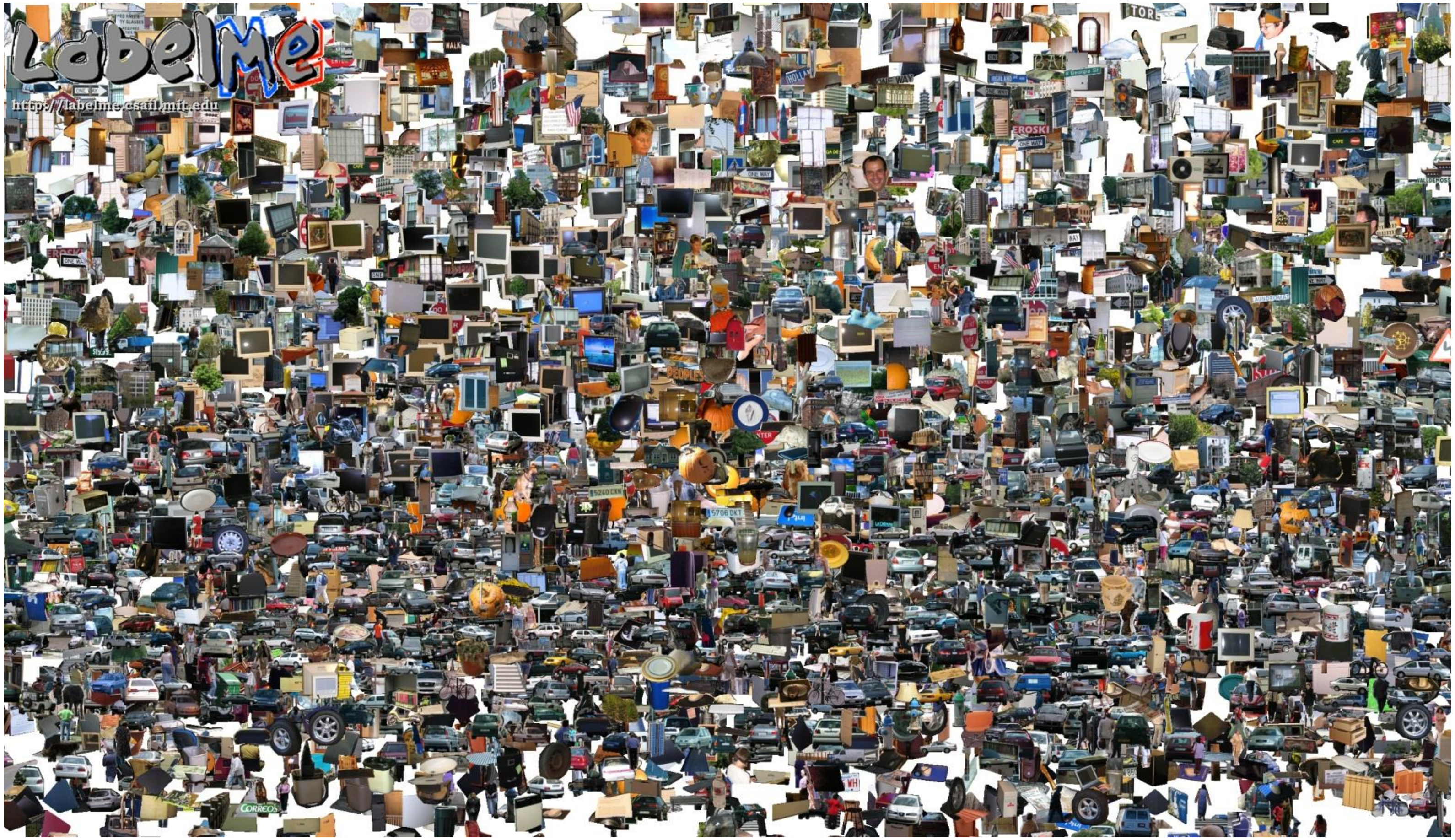
Opportunities of Scale



Computational Photography

Derek Hoiem, University of Illinois

Most slides from Alyosha Efros

Graphic from Antonio Torralba

Today's class

- Opportunities of Scale: Data-driven methods
  - Scene completion
  - Im2gps
  - 3D reconstruction
  - Colorizing
  - Infinite zoom/panorama
  - and much more…

Google and massive data-driven algorithms

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>

Google Translate

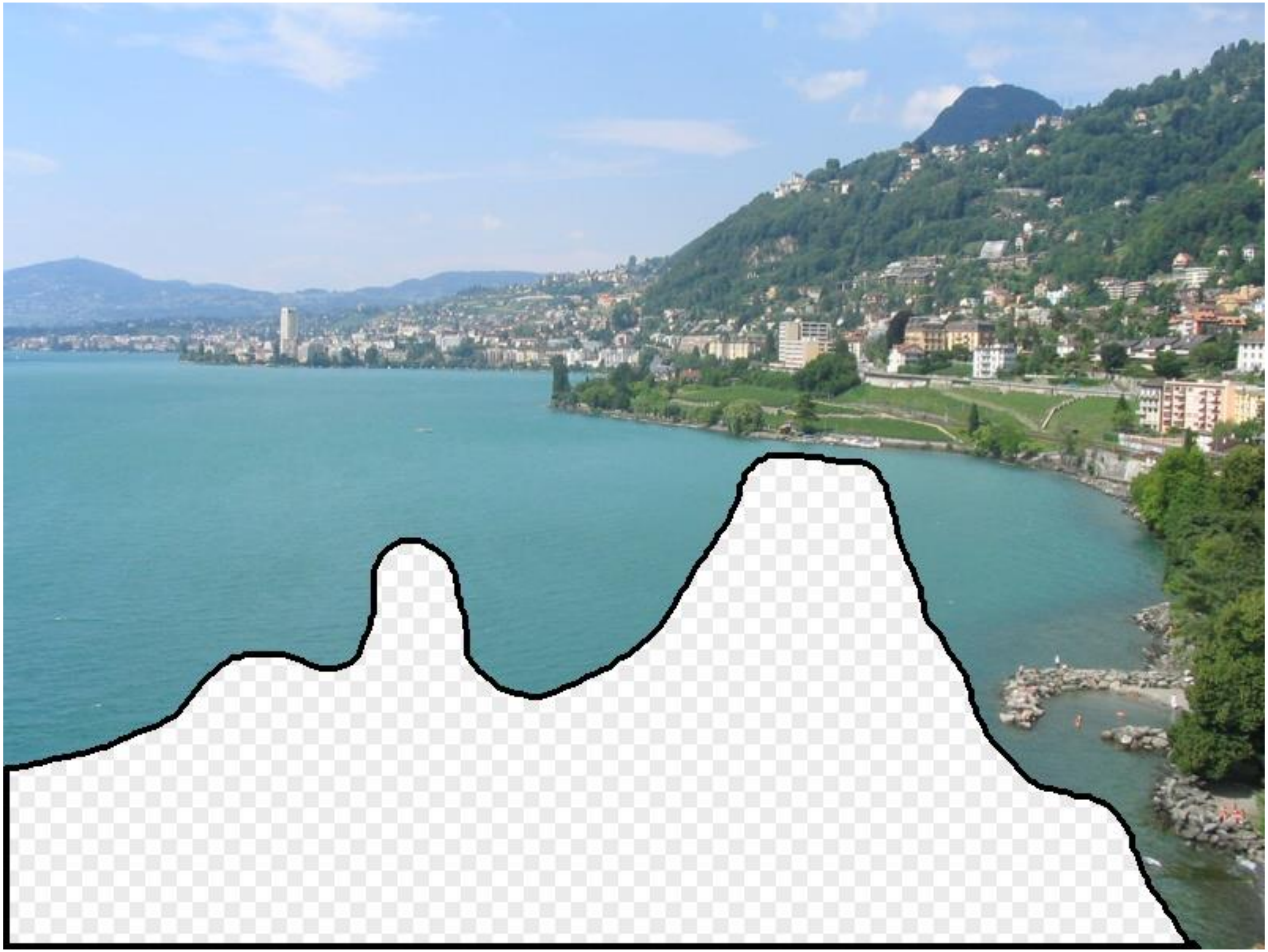
Chinese Room

- John Searle (1980)

Image Completion Example

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

What should the missing region contain?



Which is the original?

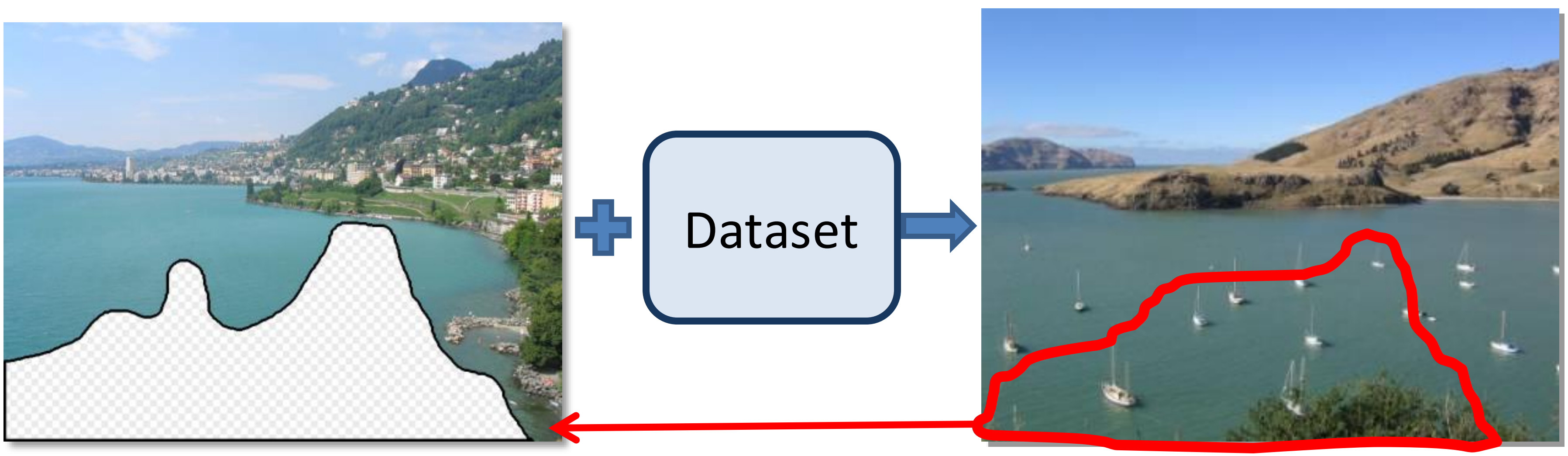
(a)

(b)

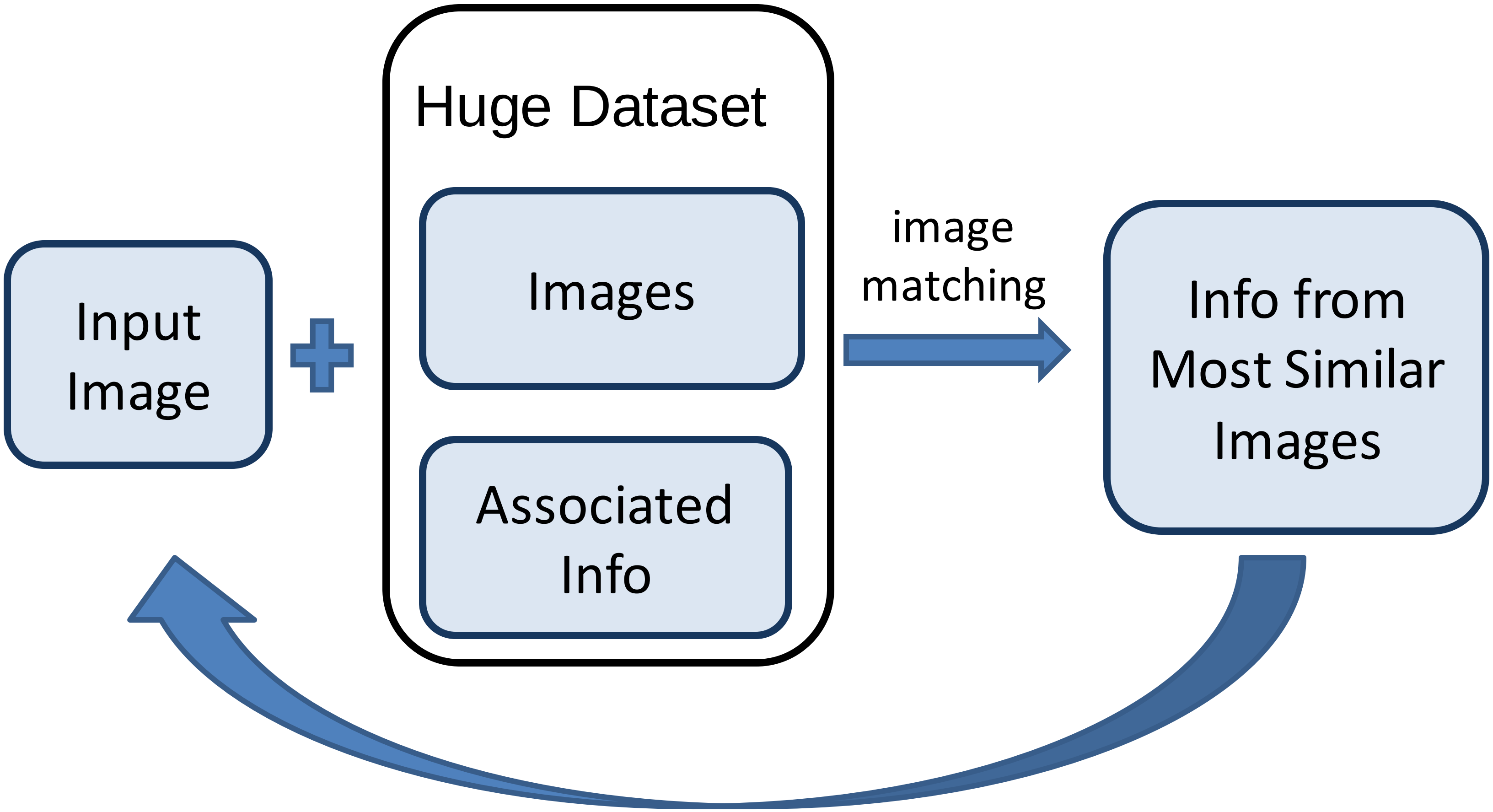
(c)

How it works

- Find a similar image from a large dataset
- Blend a region from that image into the hole

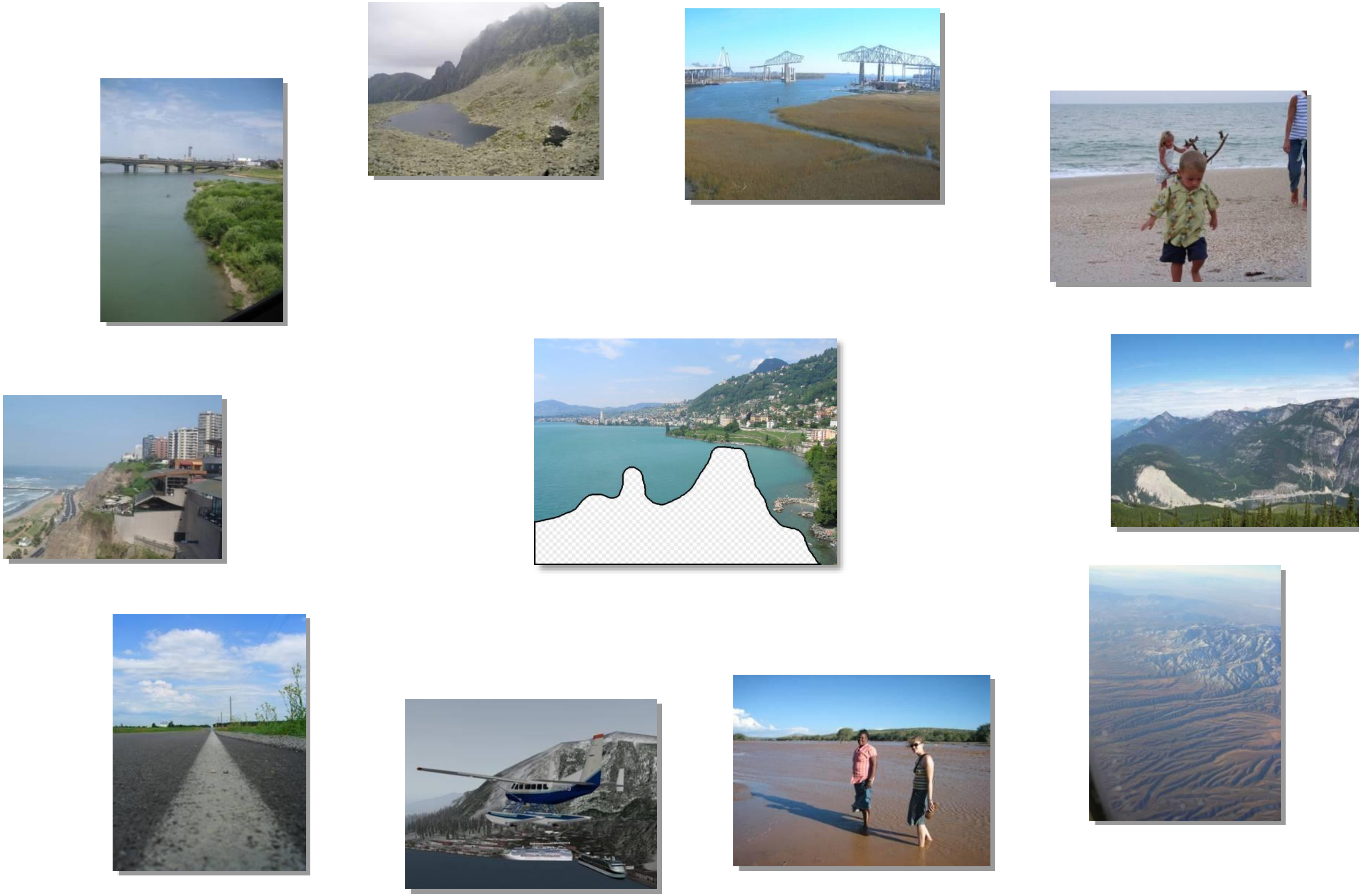


General Principal

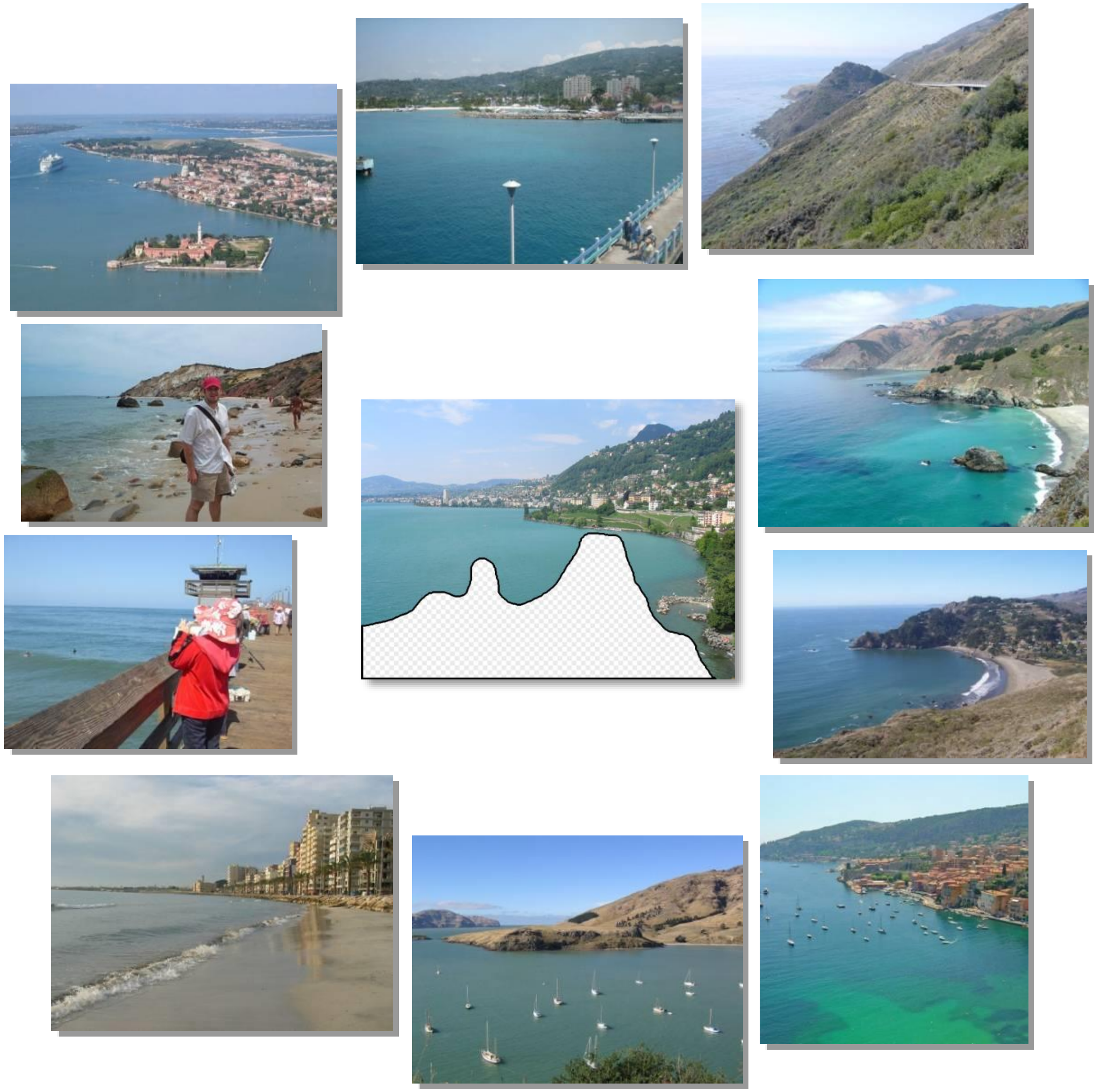


Trick: If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

How many images is enough?



Nearest neighbors from a collection of 20 thousand images



Nearest neighbors from a
collection of 2 million images

Image Data on the Internet

- Facebook (2014)
  - 250 billion total, +350 million per day
- Facebook (2011)
  - 6 billion images per month
  - More than 100 petabytes of images/video
- Flickr (2010)
  - 5 billion photographs
  - 100+ million geotagged images
- Imageshack (as of 2009)
  - 20 billion
- Facebook (as of 2009)
  - 15 billion

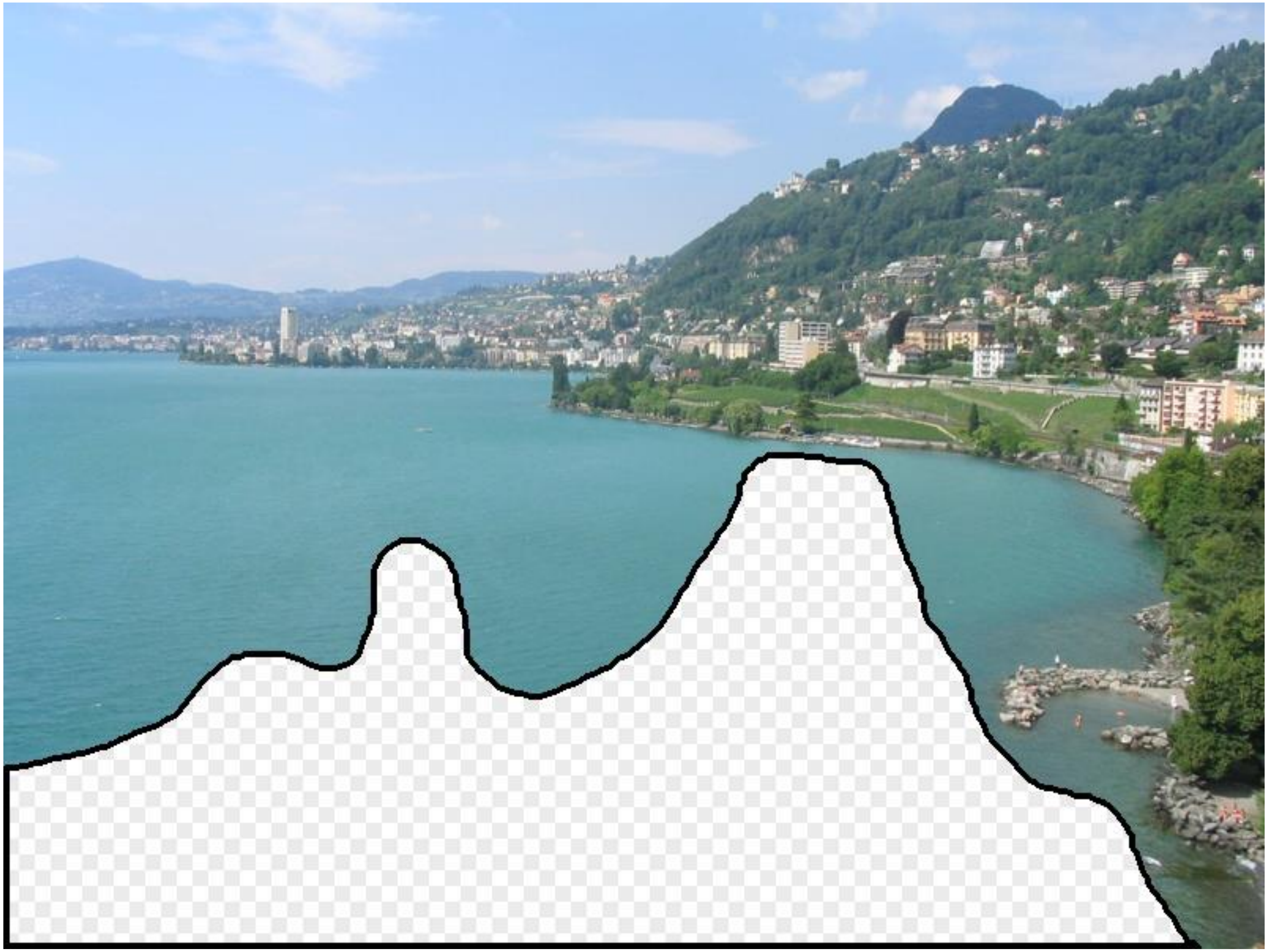
http://royal.pingdom.com/2010/01/22/internet-2009-in-numbers/

Image completion: how it works

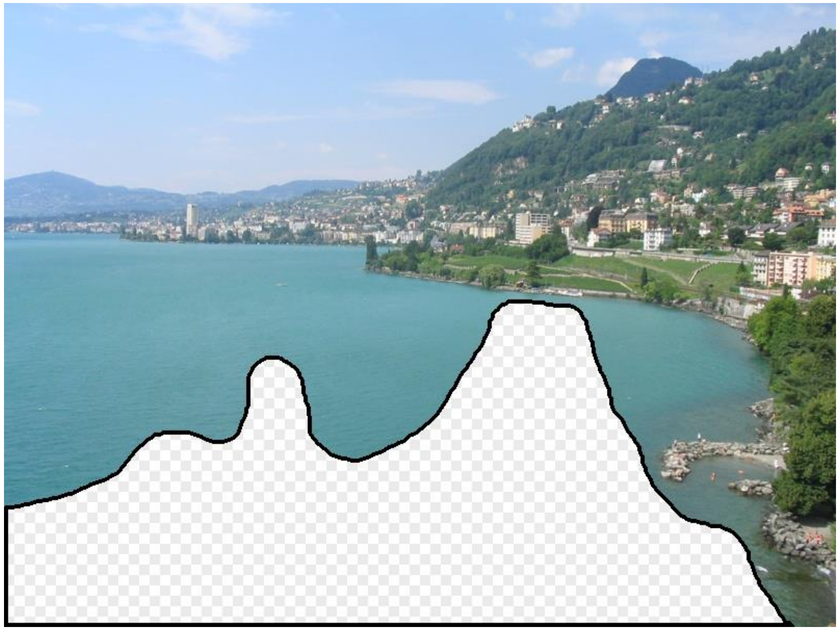
[Hays and Efros. Scene Completion Using Millions of Photographs. SIGGRAPH 2007 and CACM October 2008.]

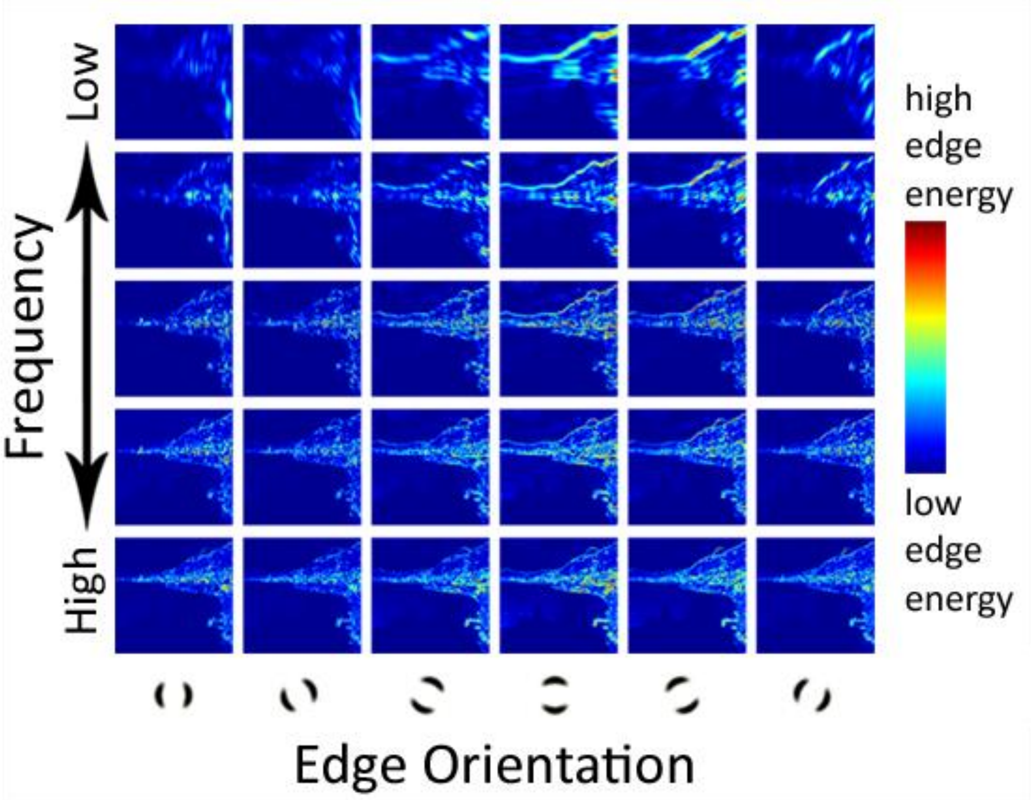
The Algorithm

Scene Matching

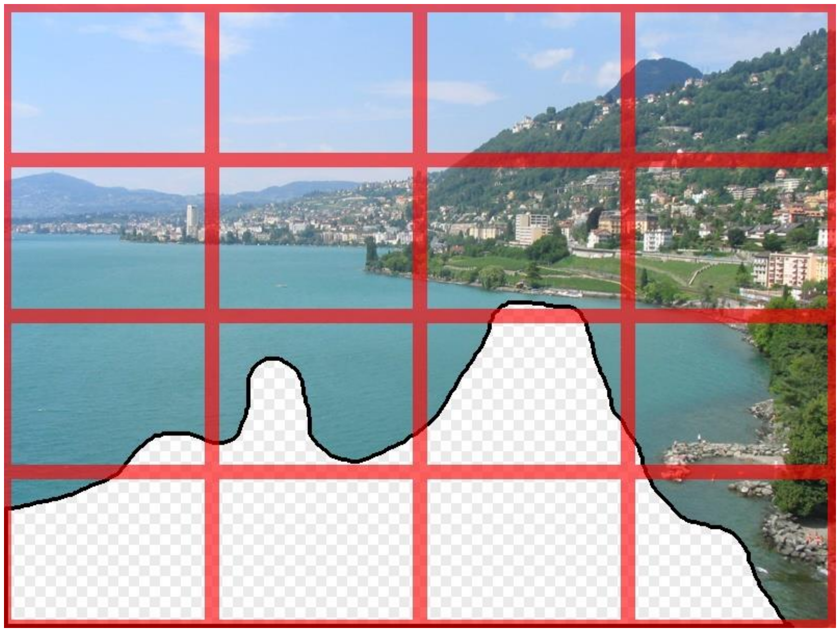


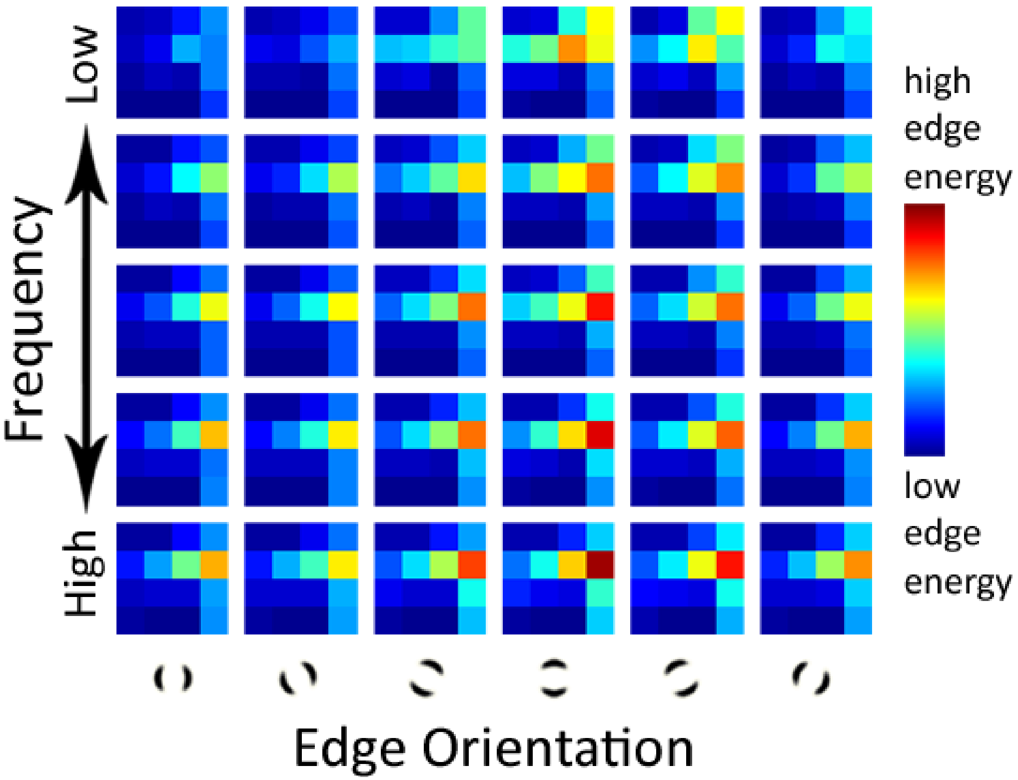
Scene Descriptor





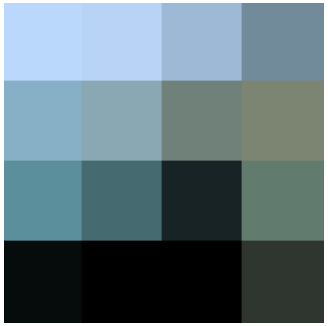
Scene Descriptor



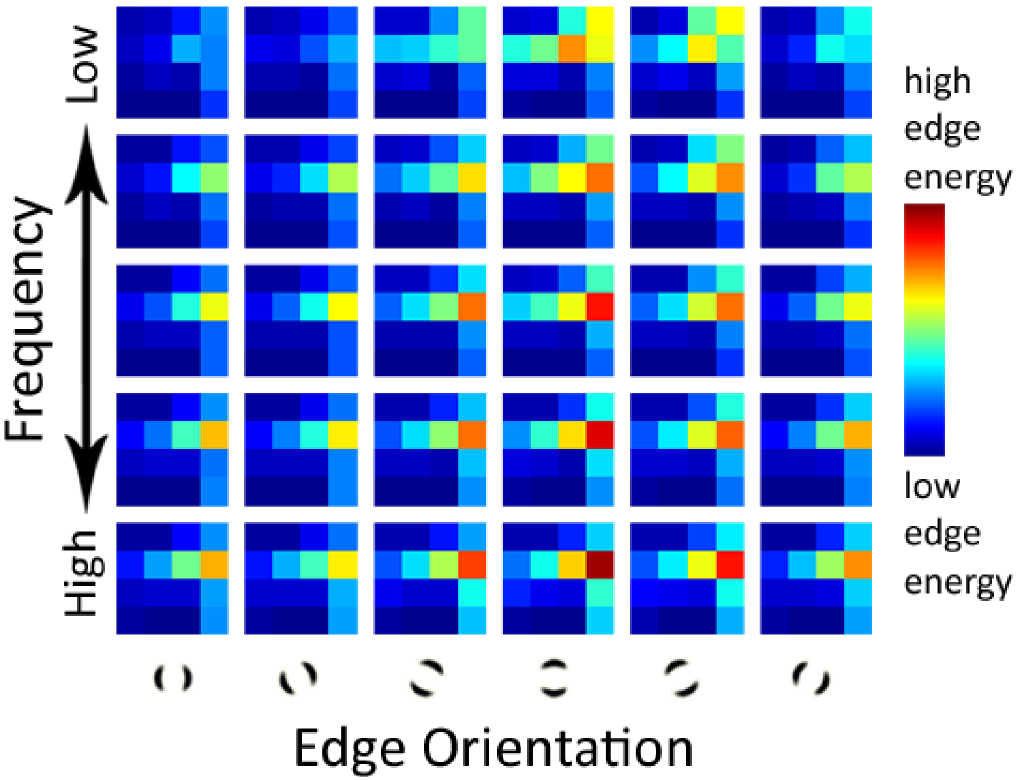


Scene Gist Descriptor
(Oliva and Torralba 2001)

Scene Descriptor

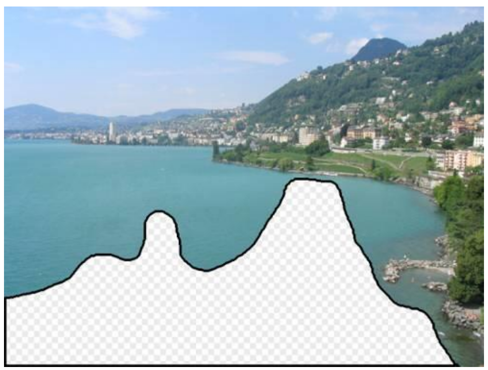


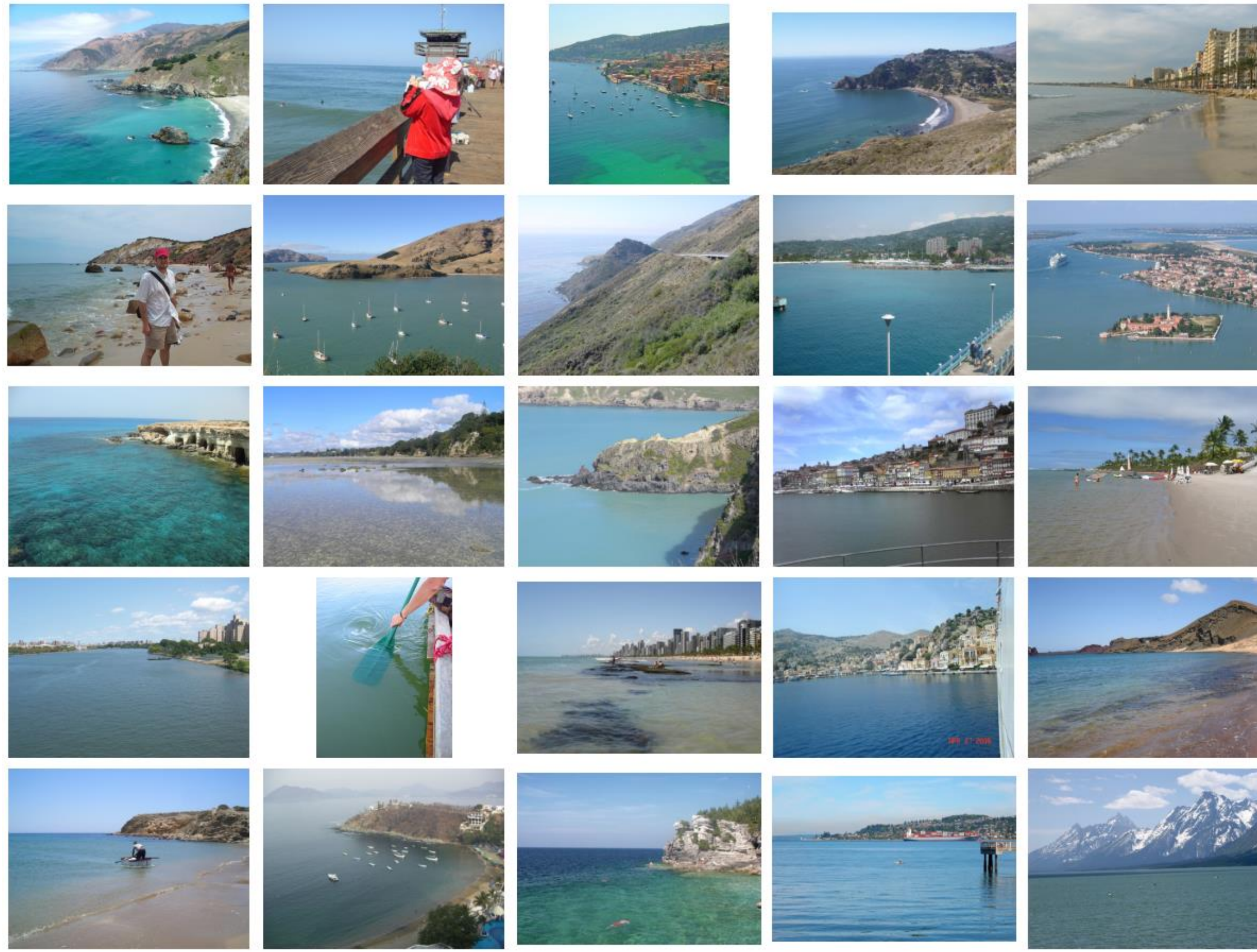
+



Scene Gist Descriptor
(Oliva and Torralba 2001)

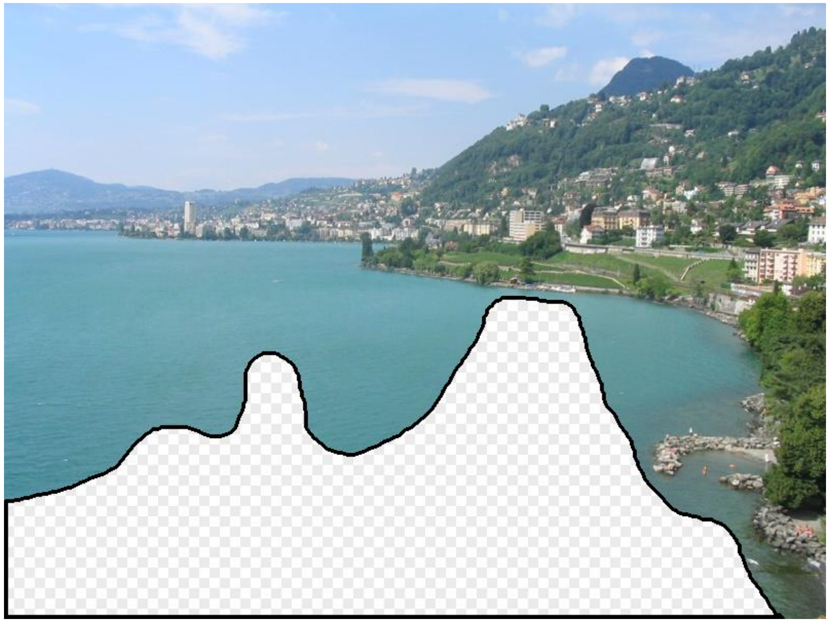
2 Million Flickr Images





… 200 total

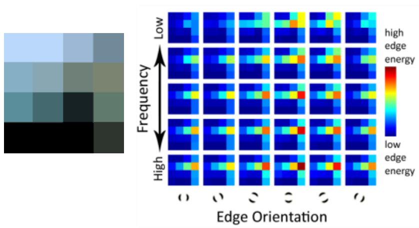
Context Matching




Graph cut + Poisson blending

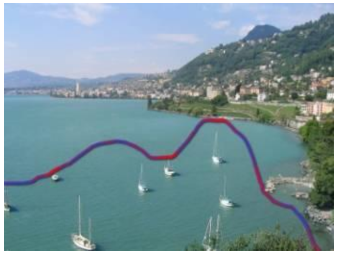
Result Ranking

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

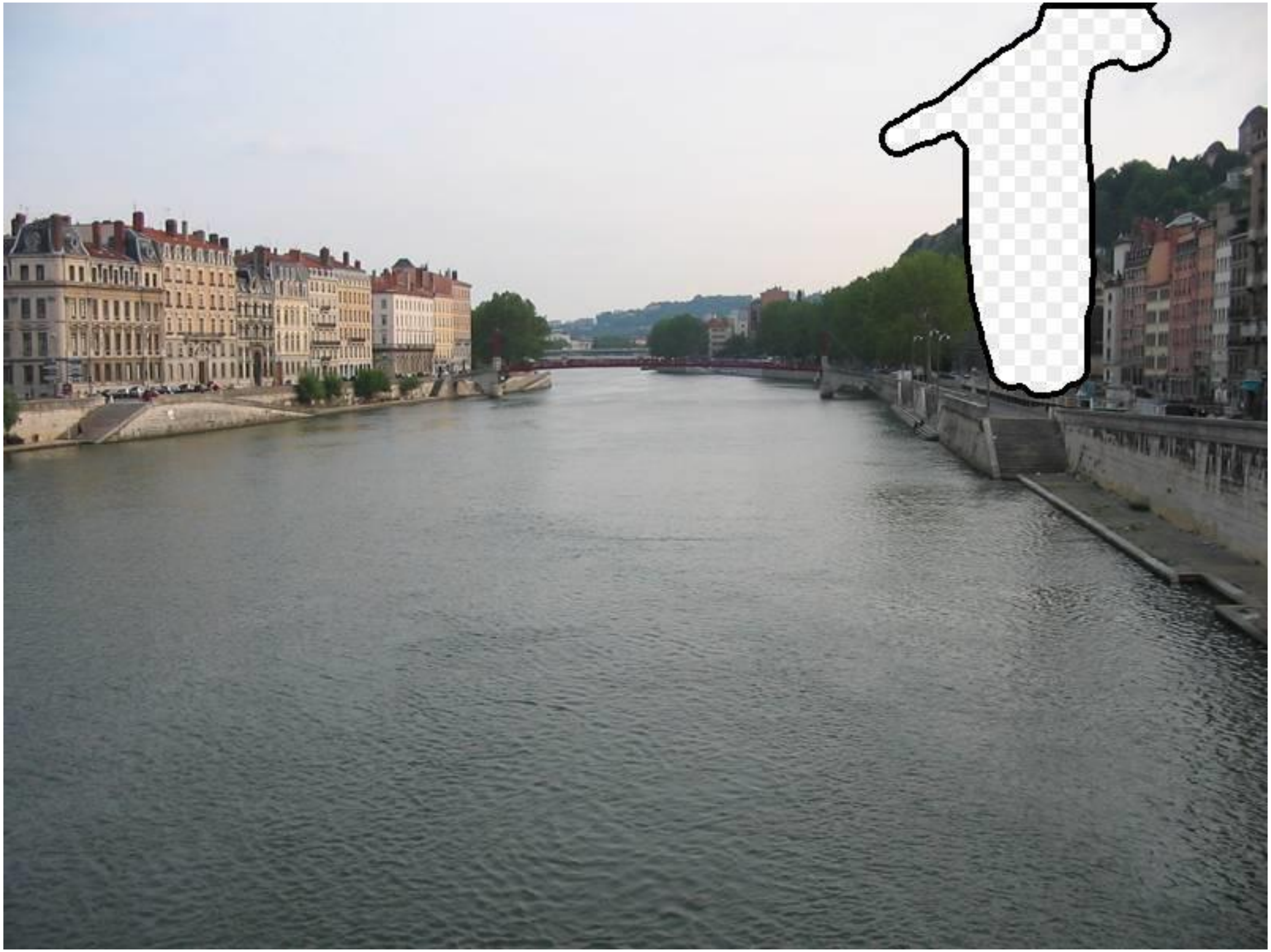


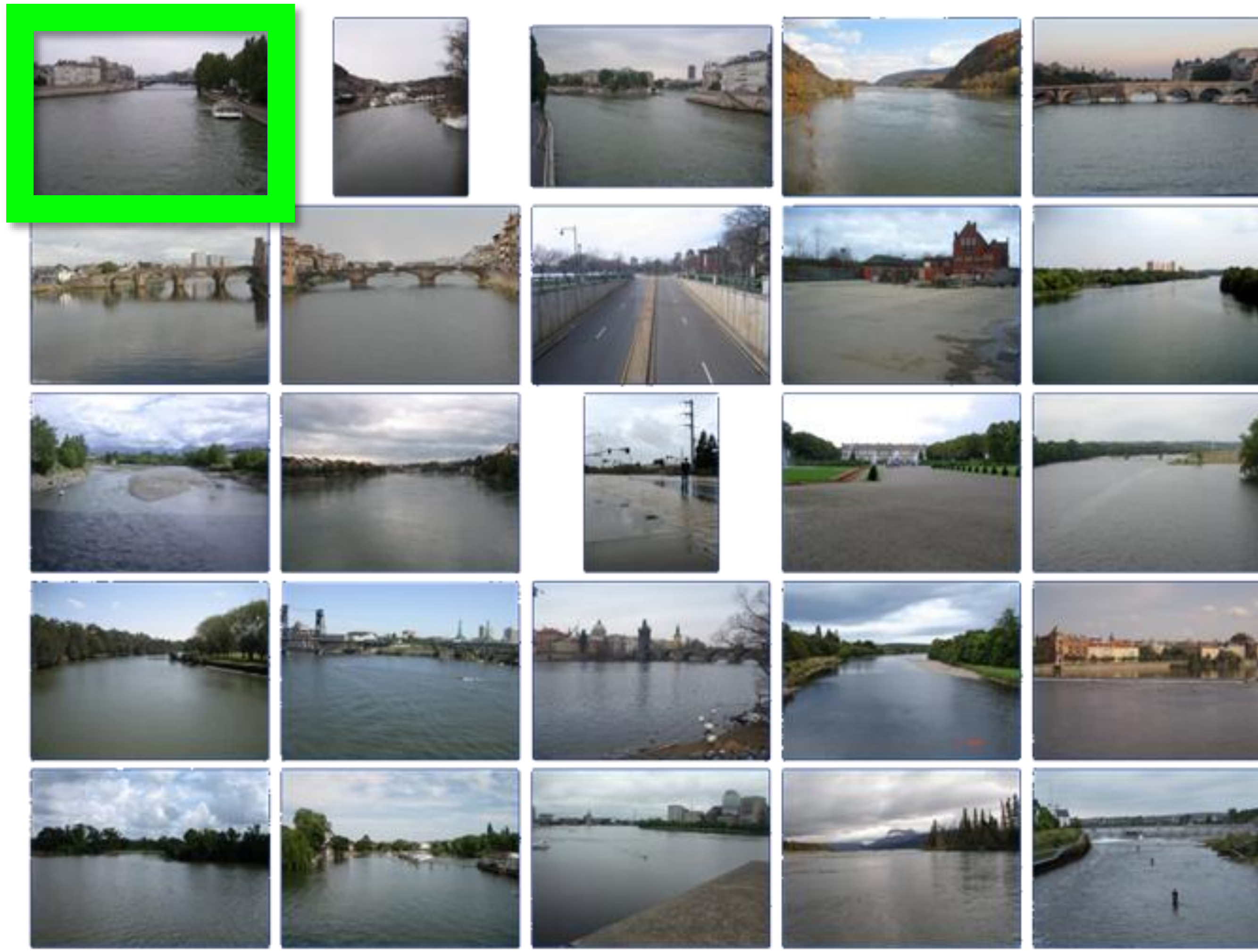
The scene matching distance

The context matching distance
(color + texture)

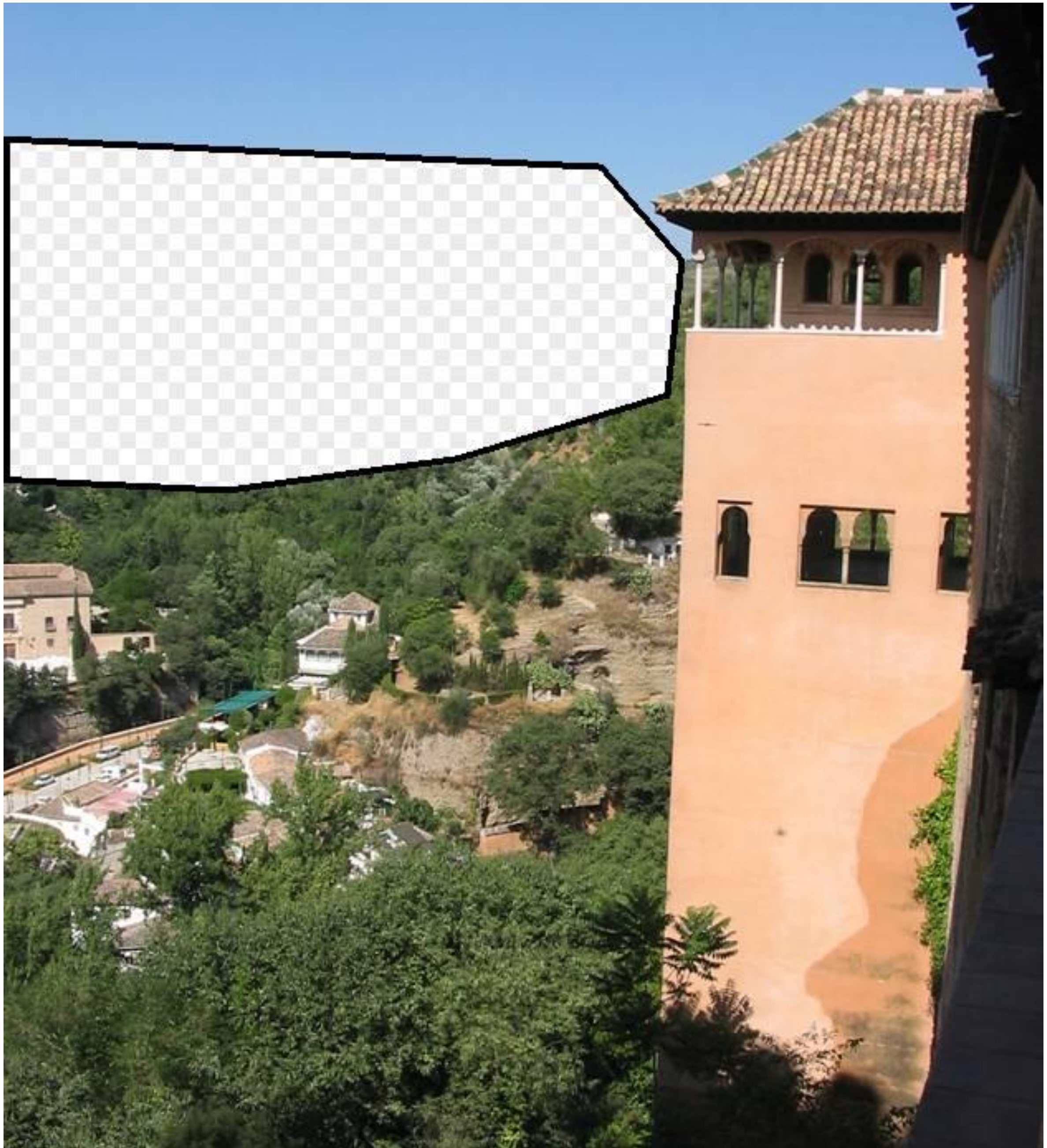


The graph cut cost





… 200 scene matches



Which is the original?


5407 BWL

Diffusion Result

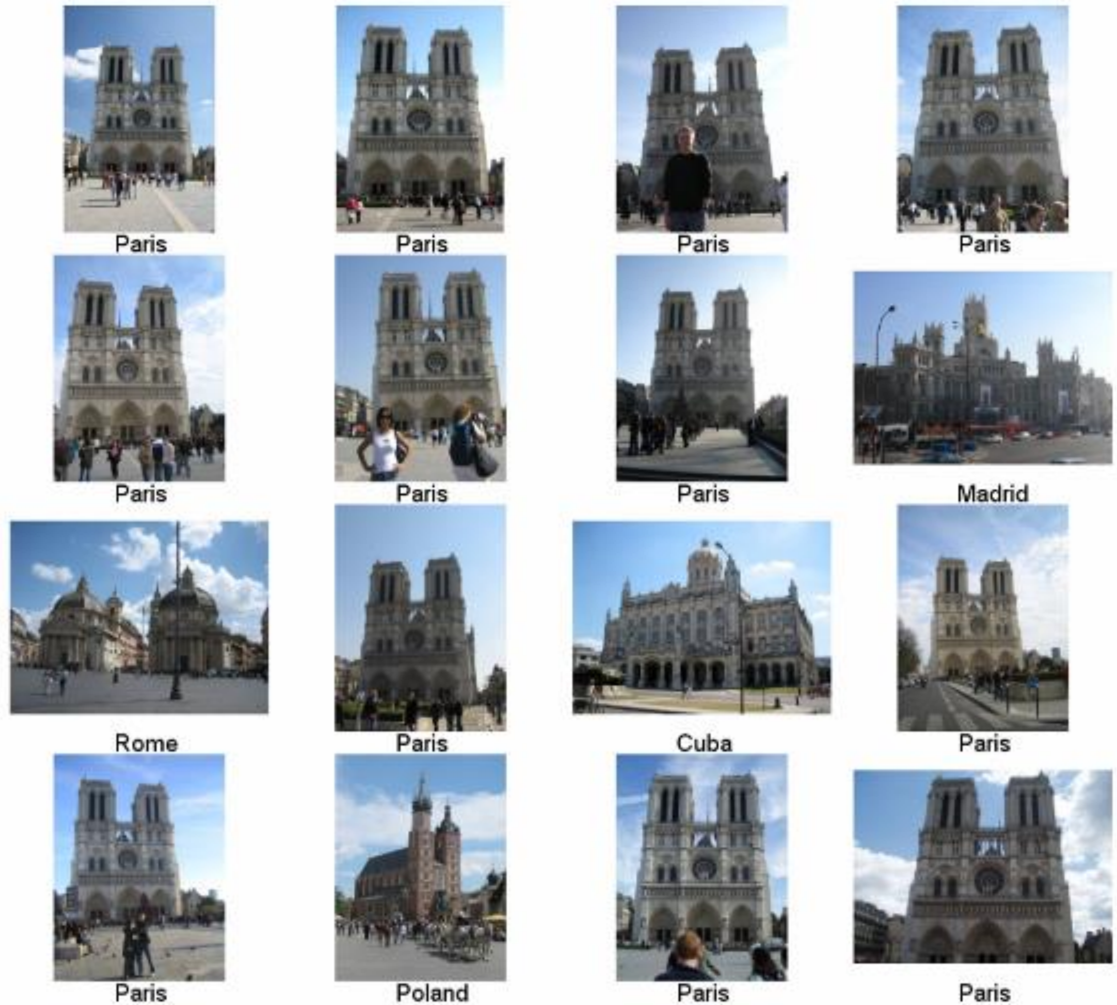
Efros and Leung result

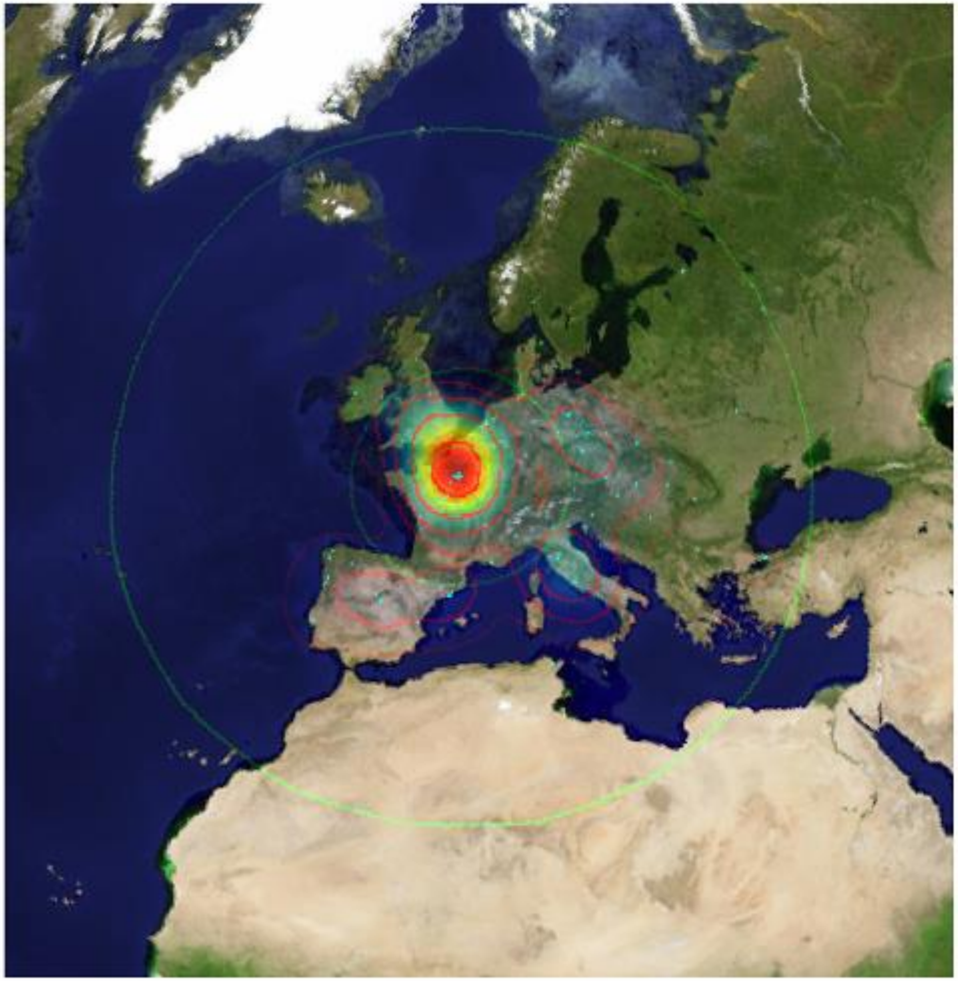
Scene Completion Result

im2gps (Hays & Efros, CVPR 2008)

6 million geo-tagged Flickr images

How much can an image tell about its geographic location?

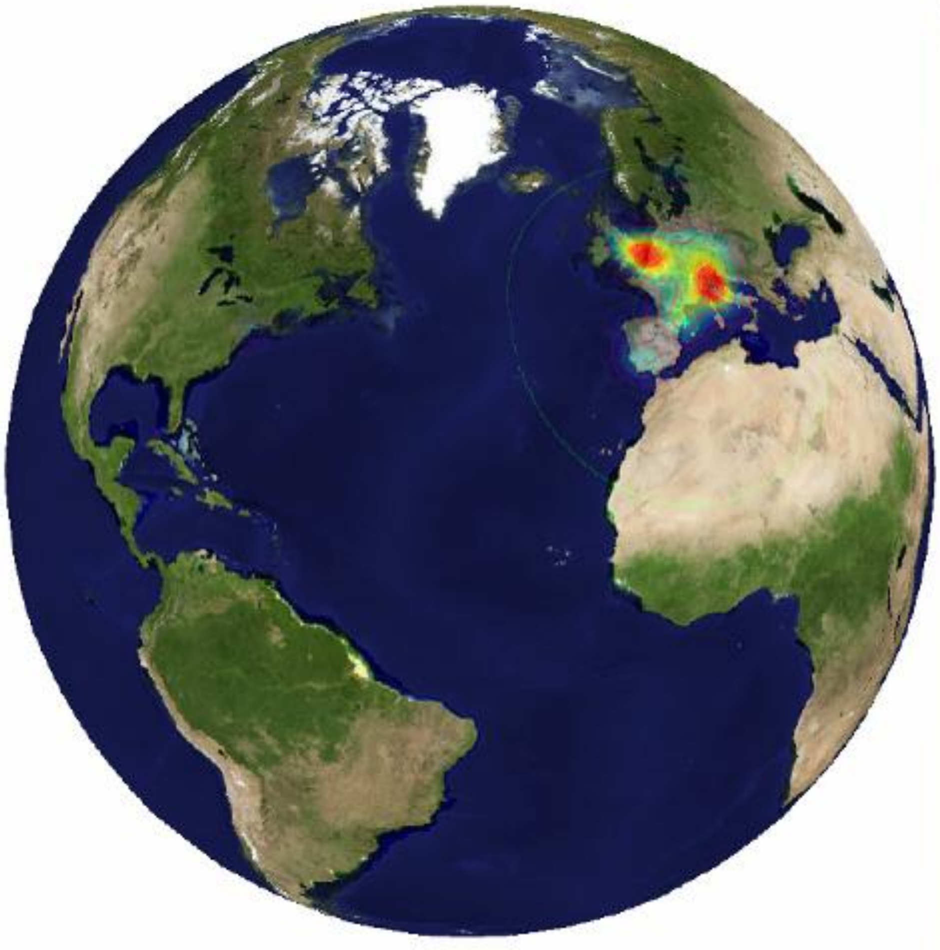

Paris
Paris
Paris
Paris
Paris
Paris
Paris
Madrid
Rome
Paris
Cuba
Paris
Paris
Poland
Paris
Paris

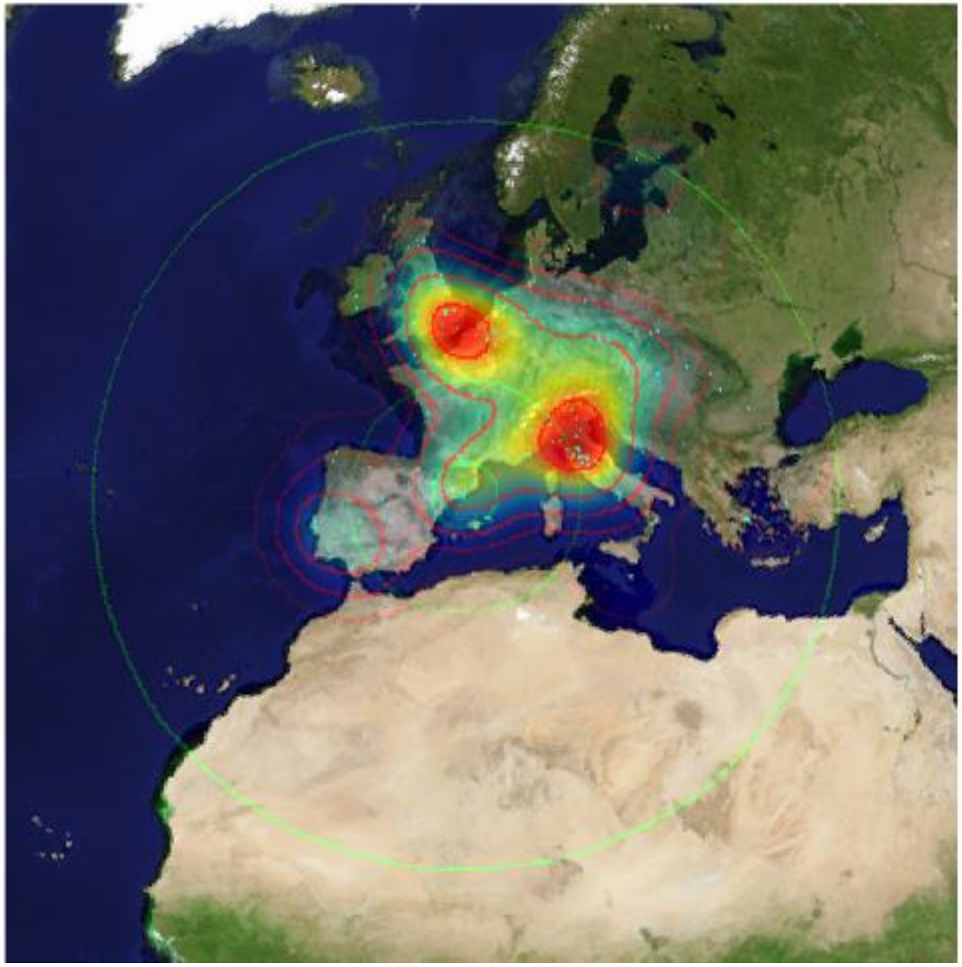


Im2gps

Example Scene Matches

Voting Scheme





im2gps

Philippines

Houston

Thailand

Houston

Maldives

Philippines

NewZealand

Bermuda

Palau

Mexico2

Brazil

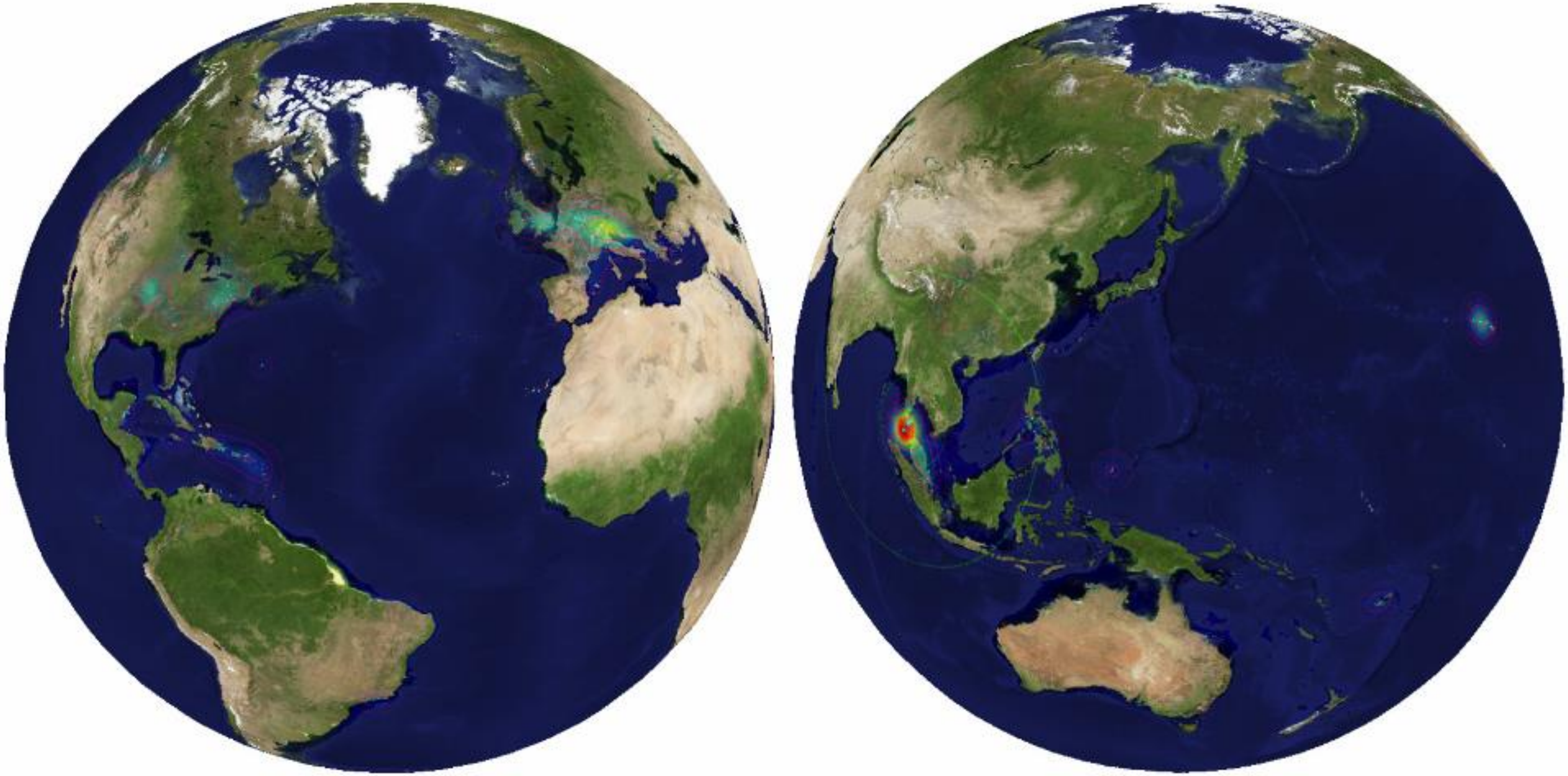
Mendoza

Brazil

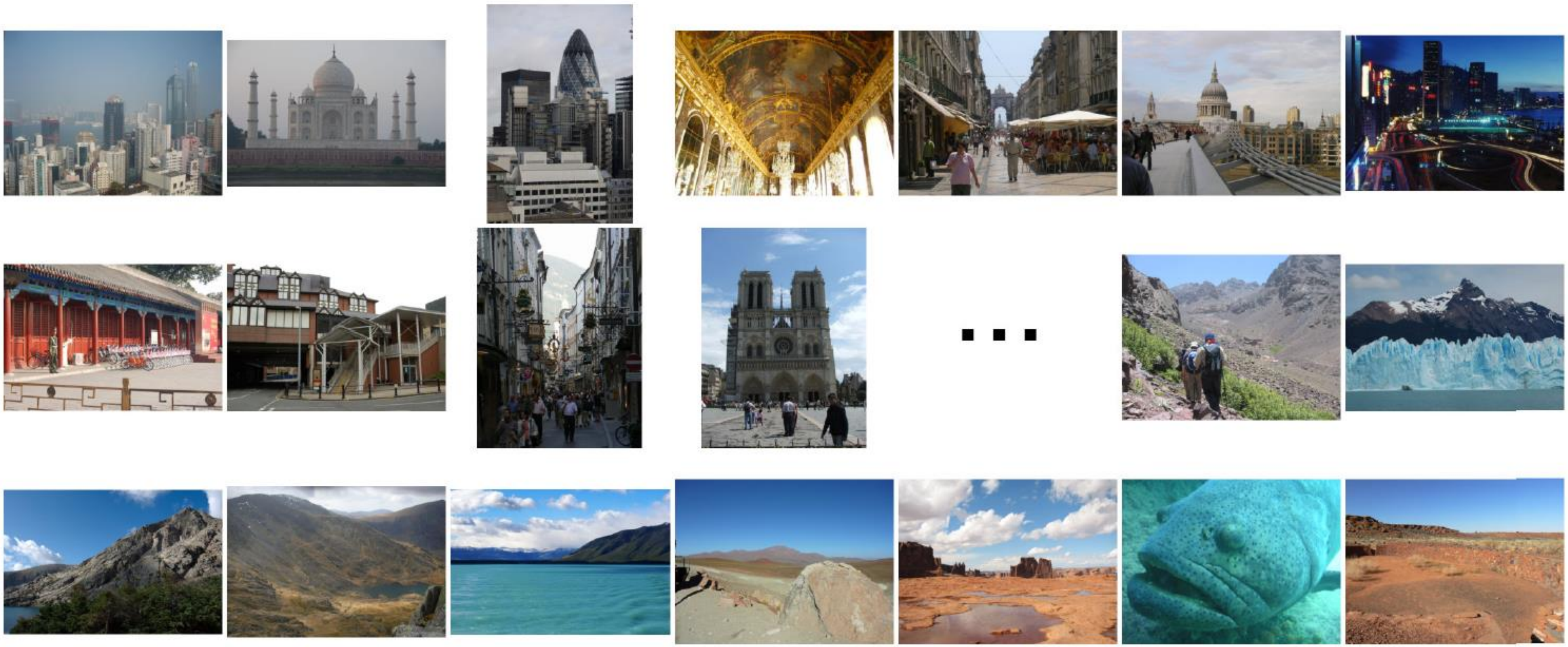
Thailand

Arkansas

Hawaii



Population density ranking

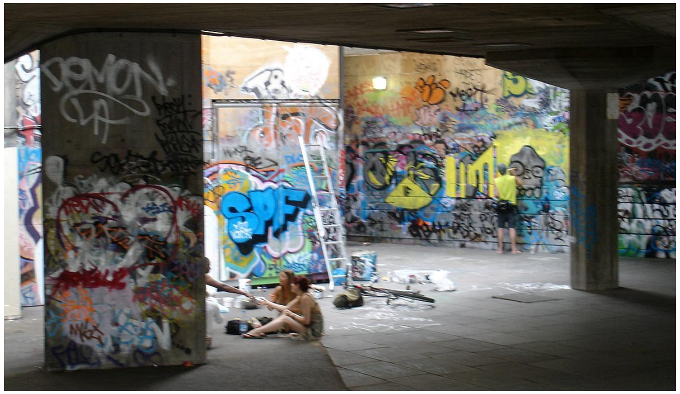


Where is This?

[Olga Vesselova, Vangelis Kalogerakis, Aaron Hertzmann, James Hays, Alexei A. Efros. Image Sequence Geolocation. ICCV’09]

Where is This?

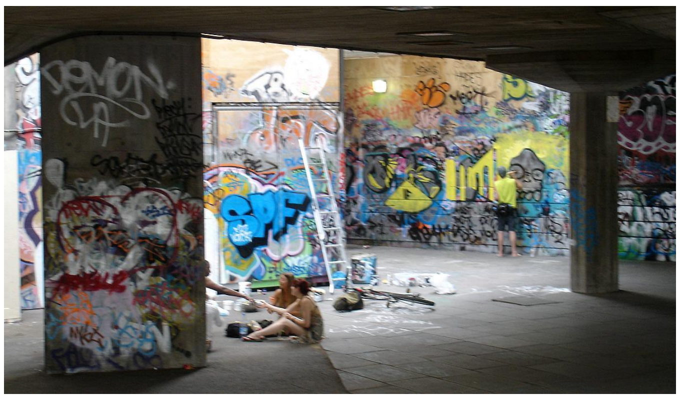
Where are These?



15:14,
June 18th, 2006

16:31,
June 18th, 2006

Where are These?



15:14,
June 18th, 2006

16:31,
June 18th, 2006

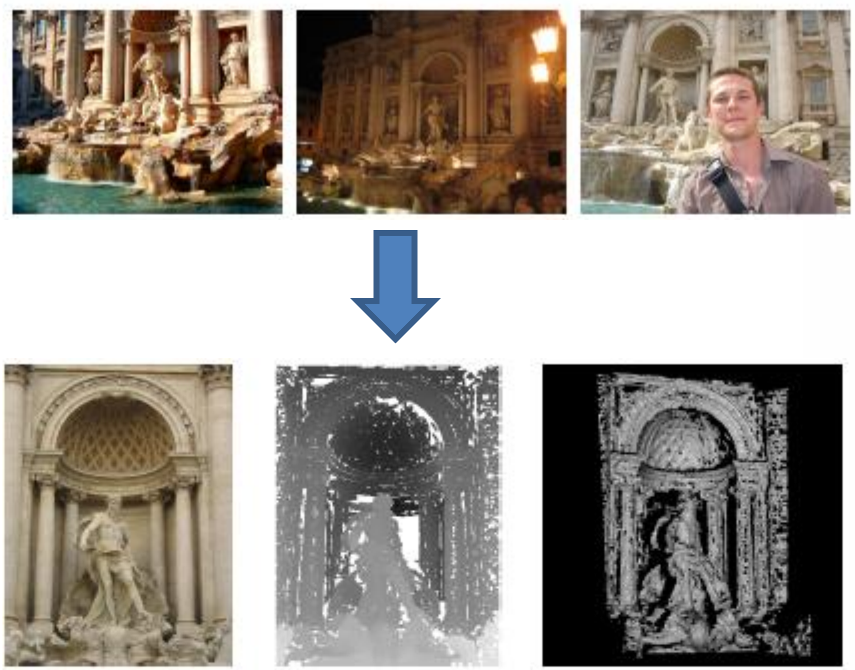
17:24,
June 19th, 2006

Results

- im2gps – 10% (geo-loc within 400 km)
- temporal im2gps – 56%

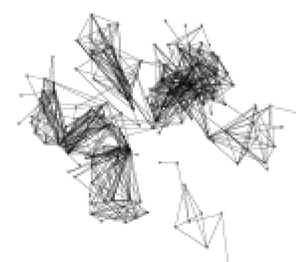
3D Reconstruction from Flickr

- Create detailed 3D scenes from thousands of consumer photographs
- Challenges include variations in season, lighting, occluding objects, etc.



3D Reconstruction from Flickr: How it works

1. Download ~10,000 images, convert to grayscale, compute SIFT keypoints
2. Match images
    1. Get similar images with vocabulary tree (like in recognition from last class)
    2. Match keypoints across similar images and perform geometric verification with RANSAC (similar to photo stitching)
3. Form a graph of matched images
4. 3D Reconstruction by triangulating points, bundle adjustment



Large-scale 3D Reconstruction

Useful references

- Dense reconstruction: "Towards Internet-scale Multi-view Stereo", Furukawa et al., CVPR 2010 http://grail.cs.washington.edu/software/cmvs/

- Sparse reconstruction: "Building Rome in a Day", Goesler et al., ICCV 2009 http://grail.cs.washington.edu/projects/rome/

- Code: Bundler Software, OpenMVG

Photo Clip Art [SG'07]

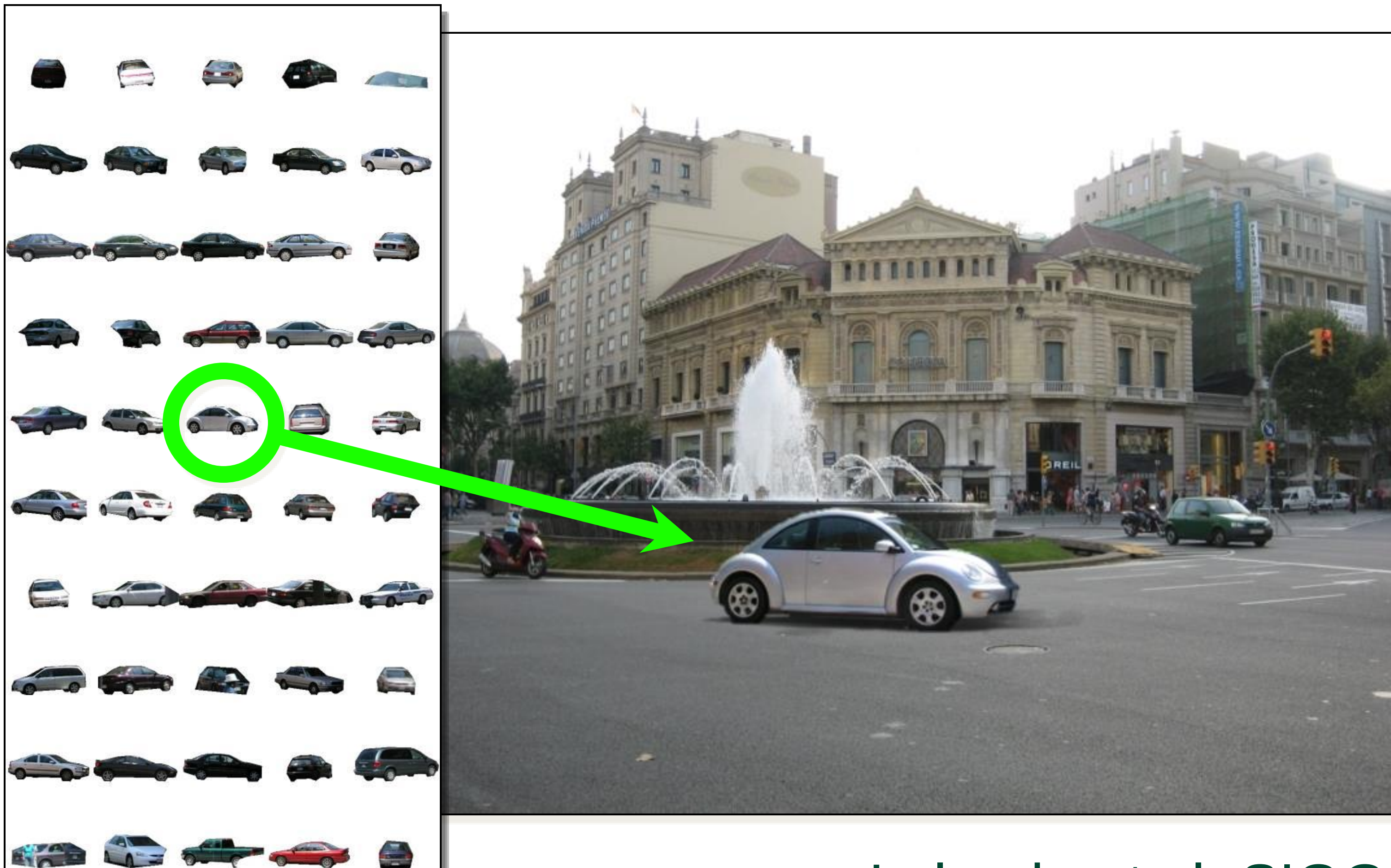
Inserting a single object -- still very hard!

- object size, orientation
- scene illumination

Lalonde et al, SIGGRAPH 2007

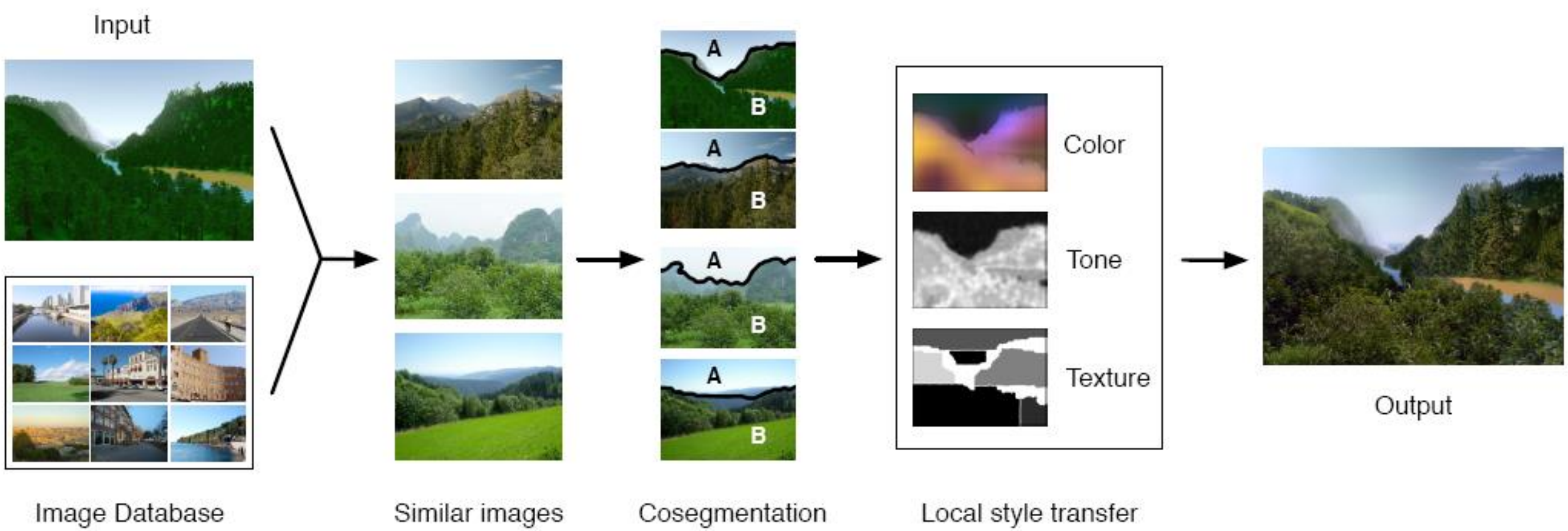
Photo Clip Art [SG'07]

Use database to find well-fitting object



Lalonde et al, SIGGRAPH 2007

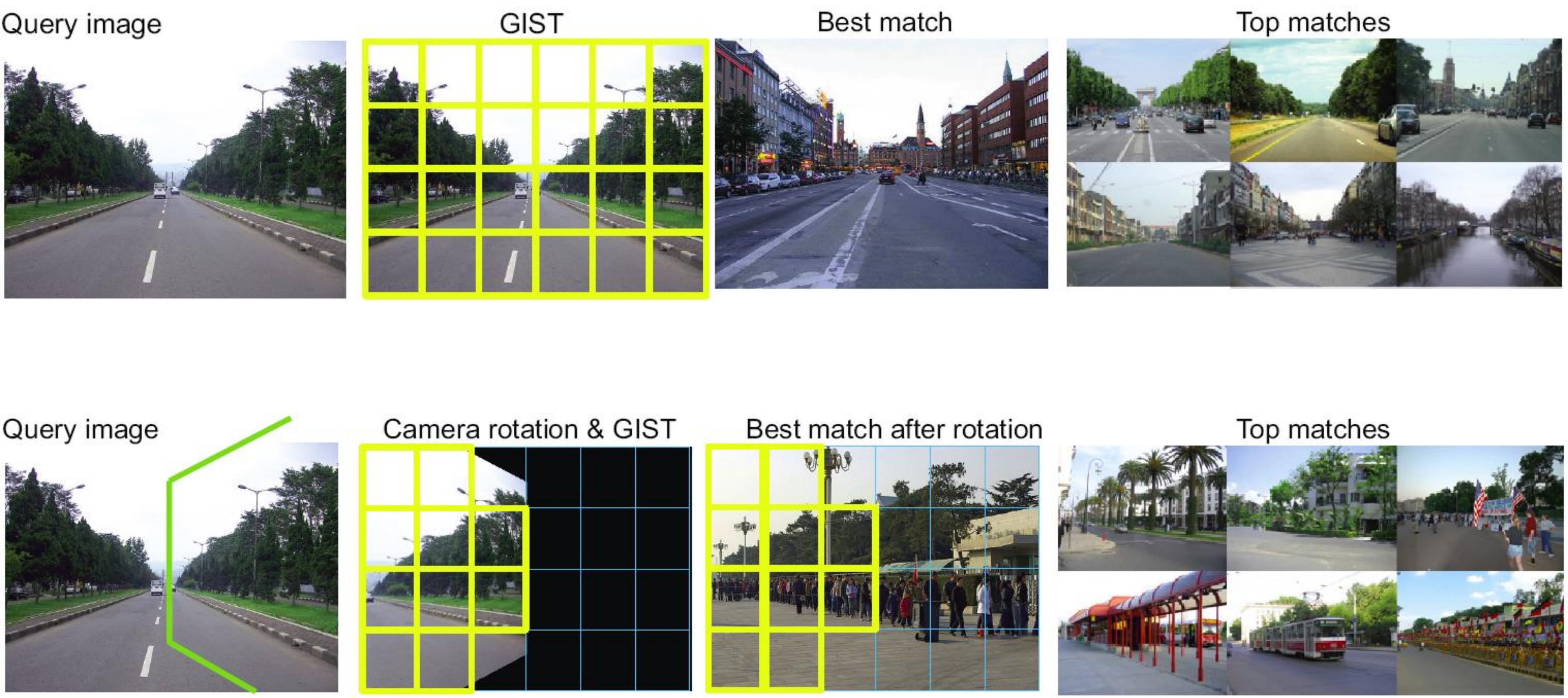
CG2Real



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

Tour from a single image

Scene matching with camera transformations



Tour from a single image

Navigate the virtual space using intuitive motion controls

Video

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

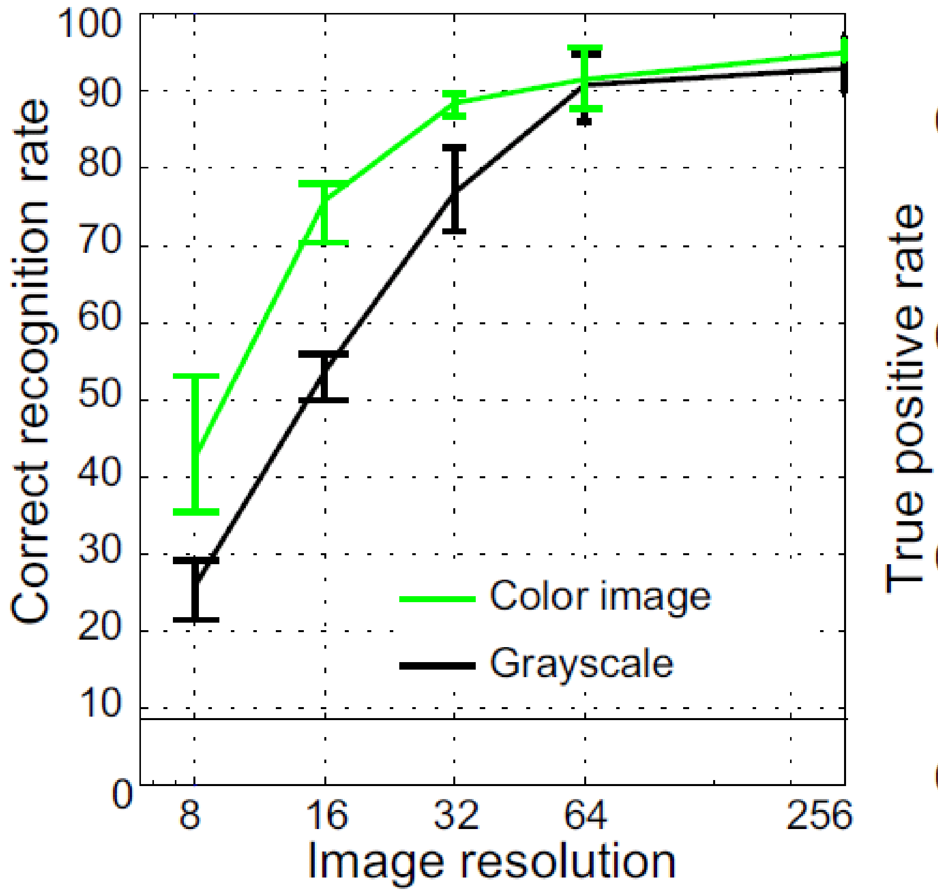
Tiny Images

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

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

c) Segmentation of 32x32 images

Human Scene Recognition



a) Scene recognition

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}

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

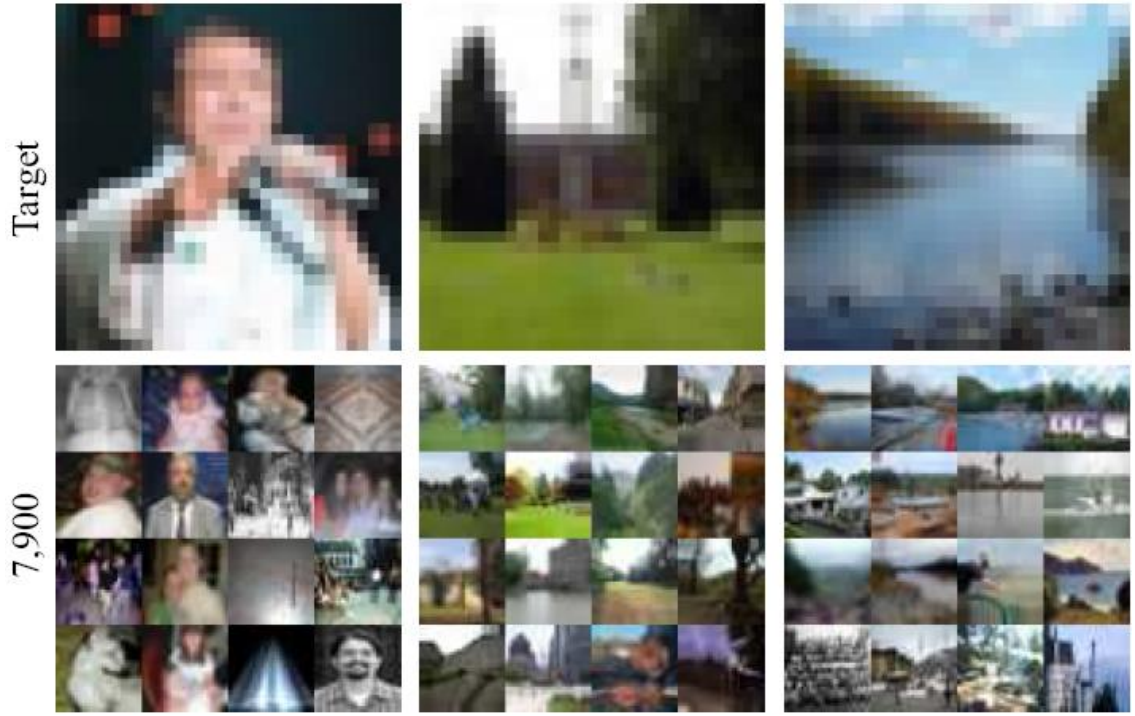
Scenes are unique

But not all scenes are so original

Lots

Of

Images

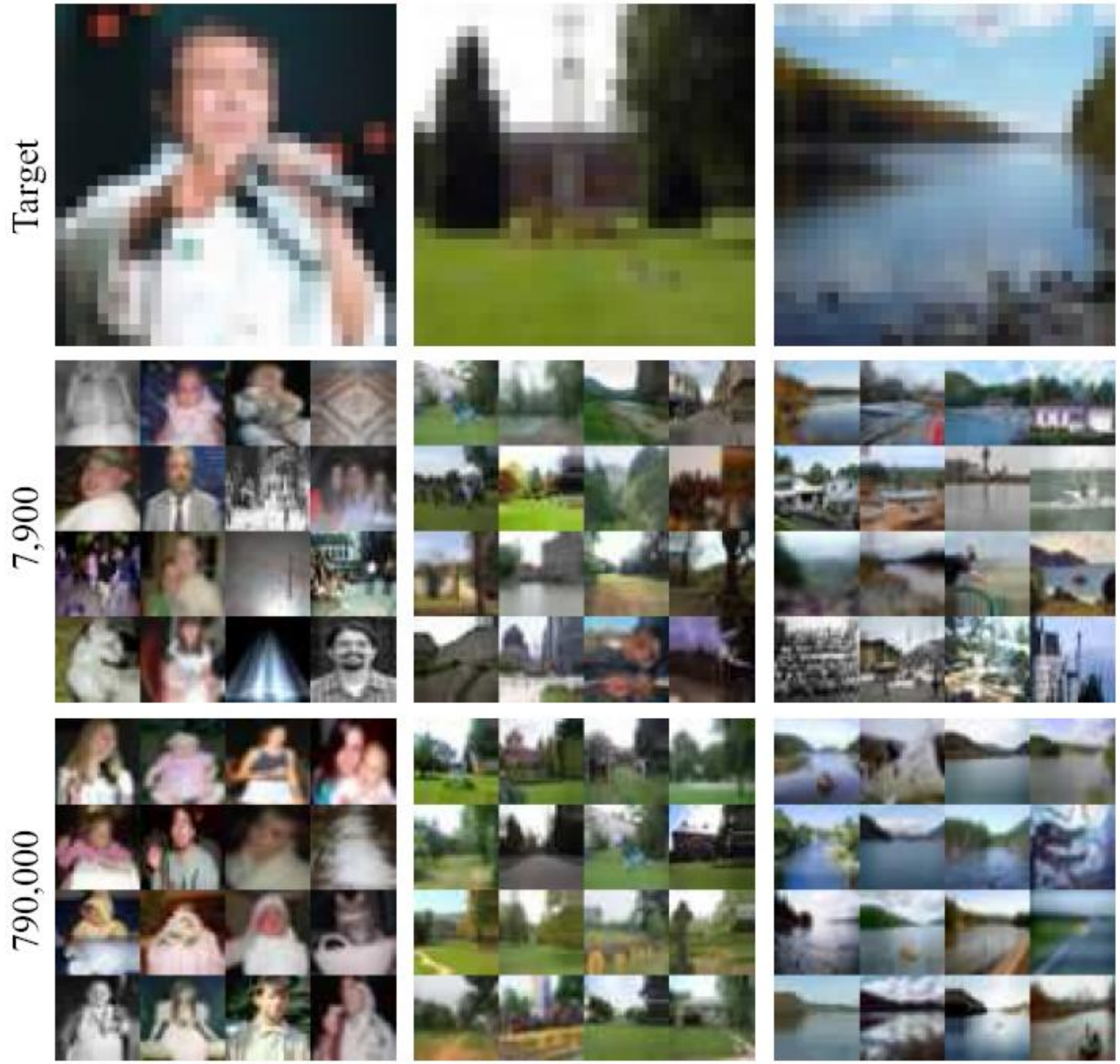


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images

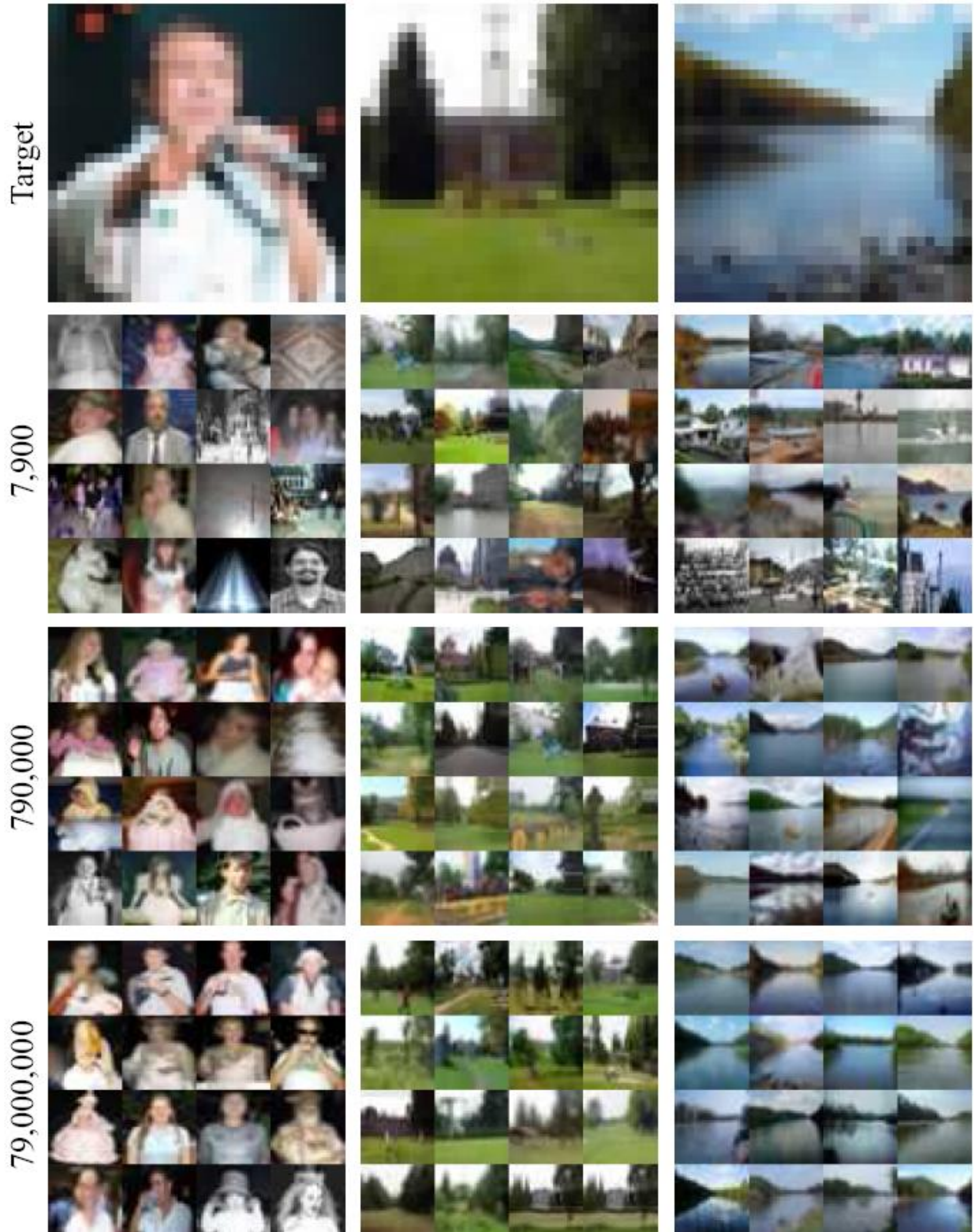


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images



Automatic Colorization

Input

Color Transfer

Color Transfer

Matches (gray)

Matches (w/ color)

Avg Color of Match

Automatic Colorization

Input

Color Transfer

Color Transfer

Matches (gray)

Matches (w/ color)

Avg Color of Match

How Deep Networks Work

- Learn better features to match regions or images
- High capacity to make good use of lots of data

"Revisiting Im2GPS in the Deep Learning Era", Vo, Jacobs, Hays 2017

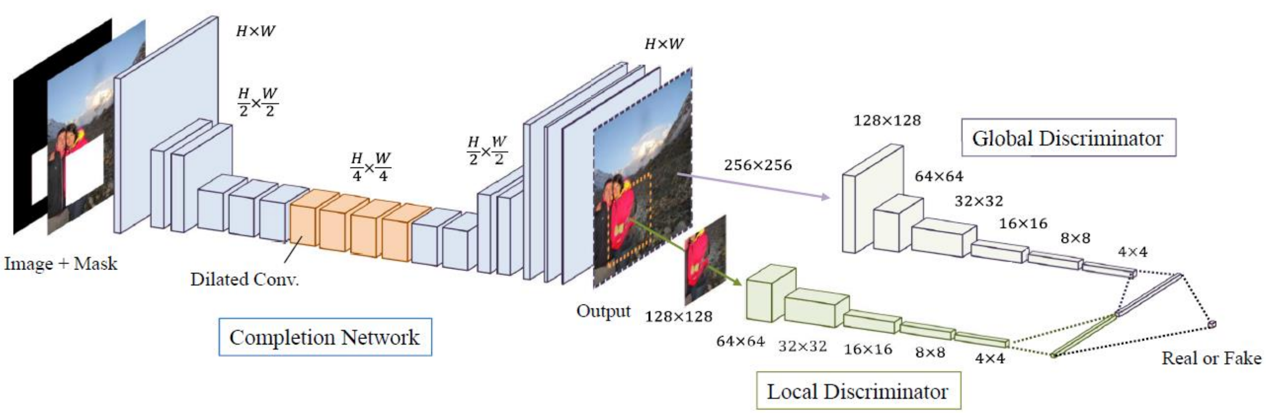
Table 1. Performance on Im2GPS test set. (Human* performance is average from 30 mturk workers over 940 trials, so it might not be directly comparable)

Threshold (km)	Street 1	City 25	Region 200	Country 750	Cont. 2500
Human*			3.8	13.9	39.3
Im2GPS [9]		12.0	15.0	23.0	47.0
Im2GPS [10]	02.5	21.9	32.1	35.4	51.9
PlaNet [36]	08.4	24.5	37.6	53.6	**71.3**
[L] 7011C	06.8	21.9	34.6	49.4	63.7
[L] kNN, σ=4	**12.2**	**33.3**	**44.3**	**57.4**	**71.3**
... 28m database	**14.4**	**33.3**	**47.7**	**61.6**	**73.4**

Globally and Locally Consistent Image Completion

SATOSHI IIZUKA, Waseda University
EDGAR SIMO-SERRA, Waseda University
HIROSHI ISHIKAWA, Waseda University

Fig. 1. Image completion results by our approach. The masked area is shown in white. Our approach can generate novel fragments that are not present elsewhere in the image, such as needed for completing faces; this is not possible with patch-based methods.



SIGGRAPH 2017

Summary

- Many questions have been asked before, photos have been taken before
- Sometimes, we can shortcut hard problems by looking up the answer

Next class

- How the Kinect works