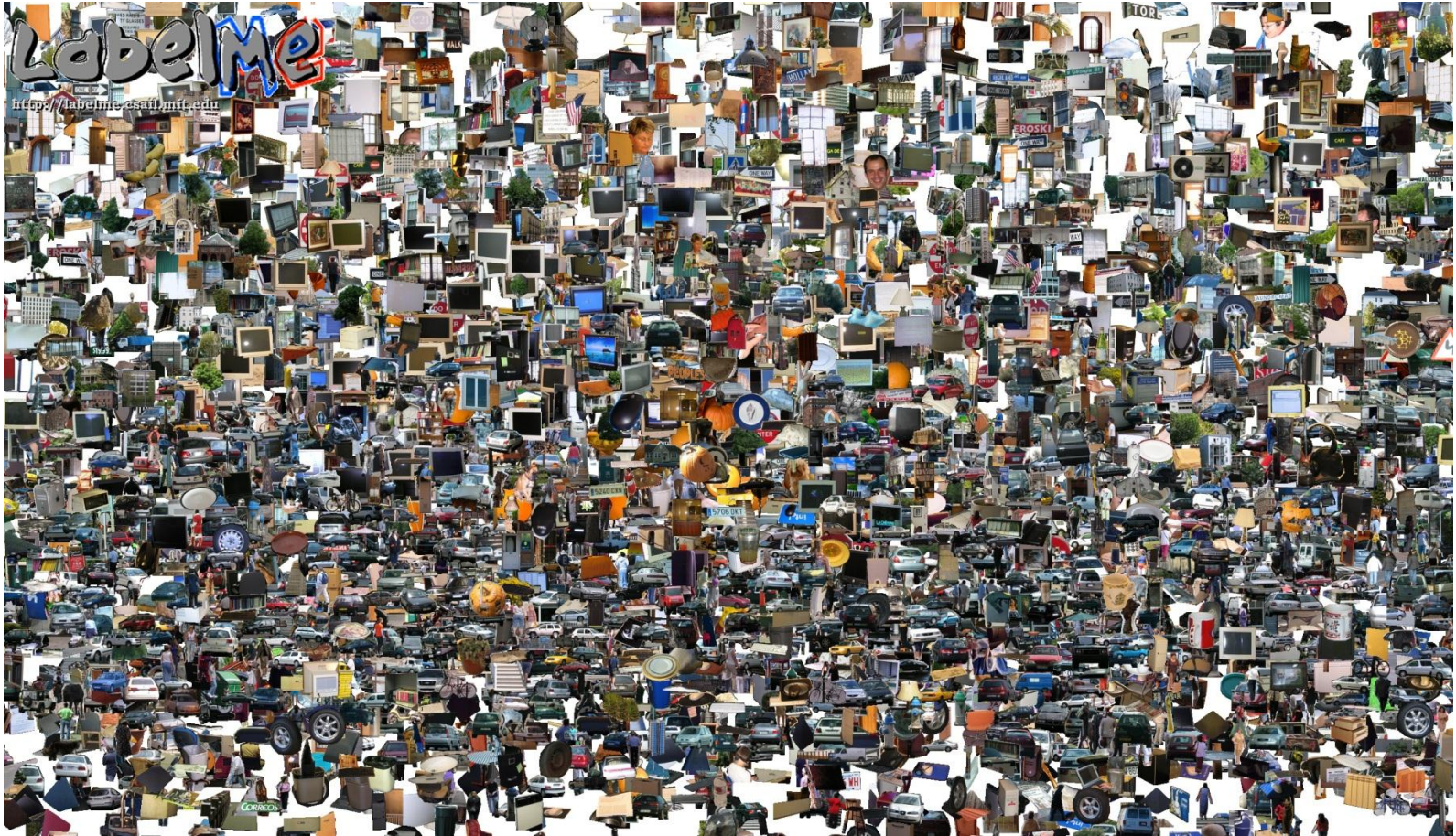


Opportunities of Scale



Computational Photography
Derek Hoiem, University of Illinois

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 in the data



Google Translate



From: English - detected ▼  To: Spanish ▼

My dog once ate three oranges, but then it died.

 [Listen](#)

English to Spanish translation

Mi perro se comió una vez tres naranjas, pero luego murió.

 [Listen](#)

Chinese Room

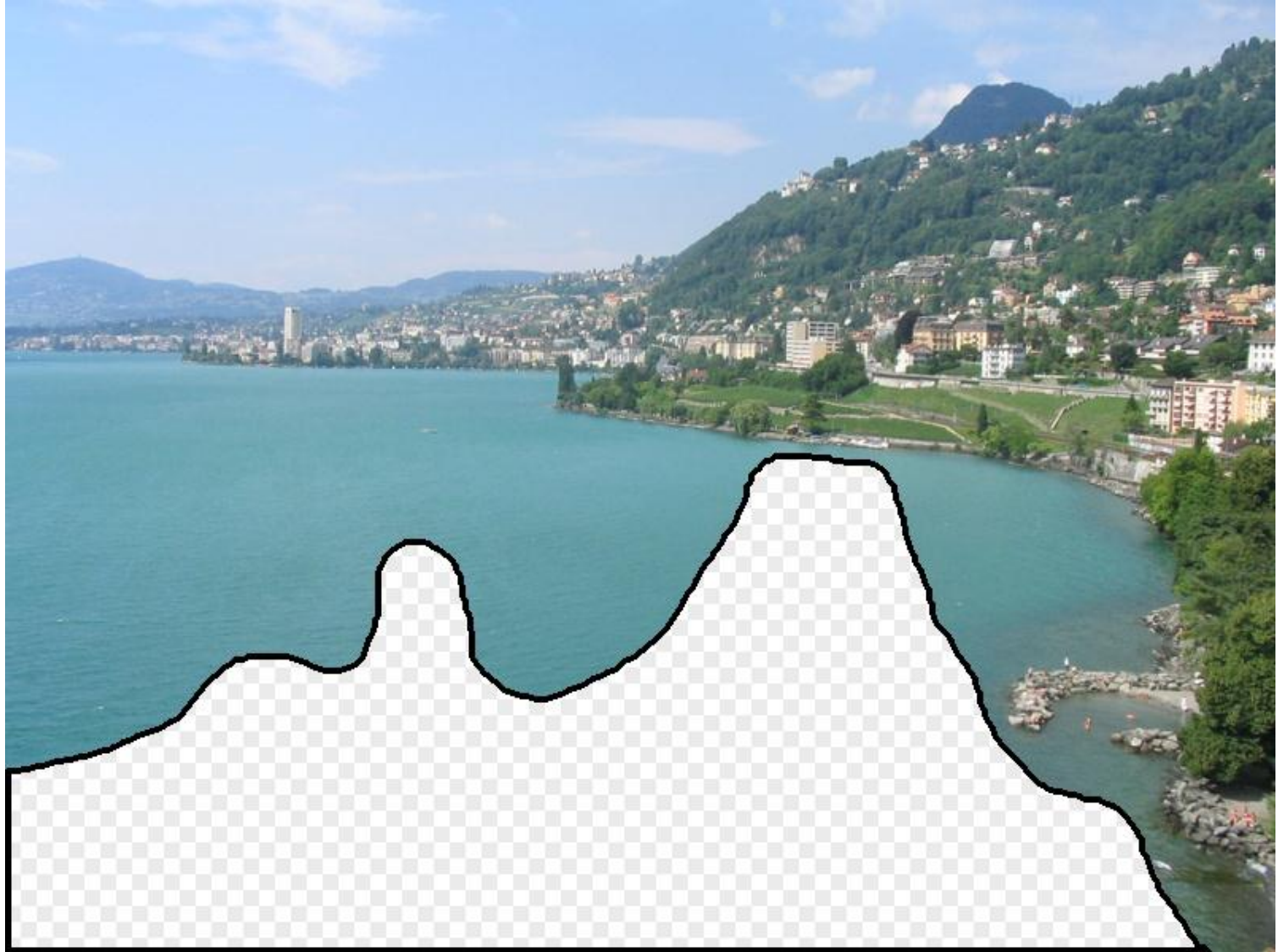
- John Searle (1980)



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)



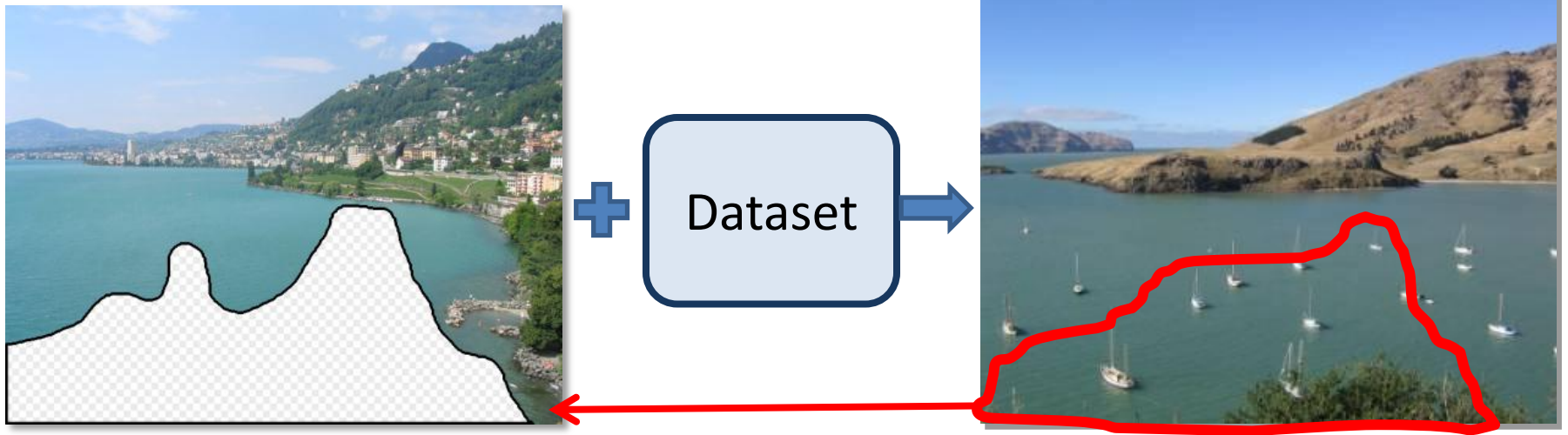
(c)



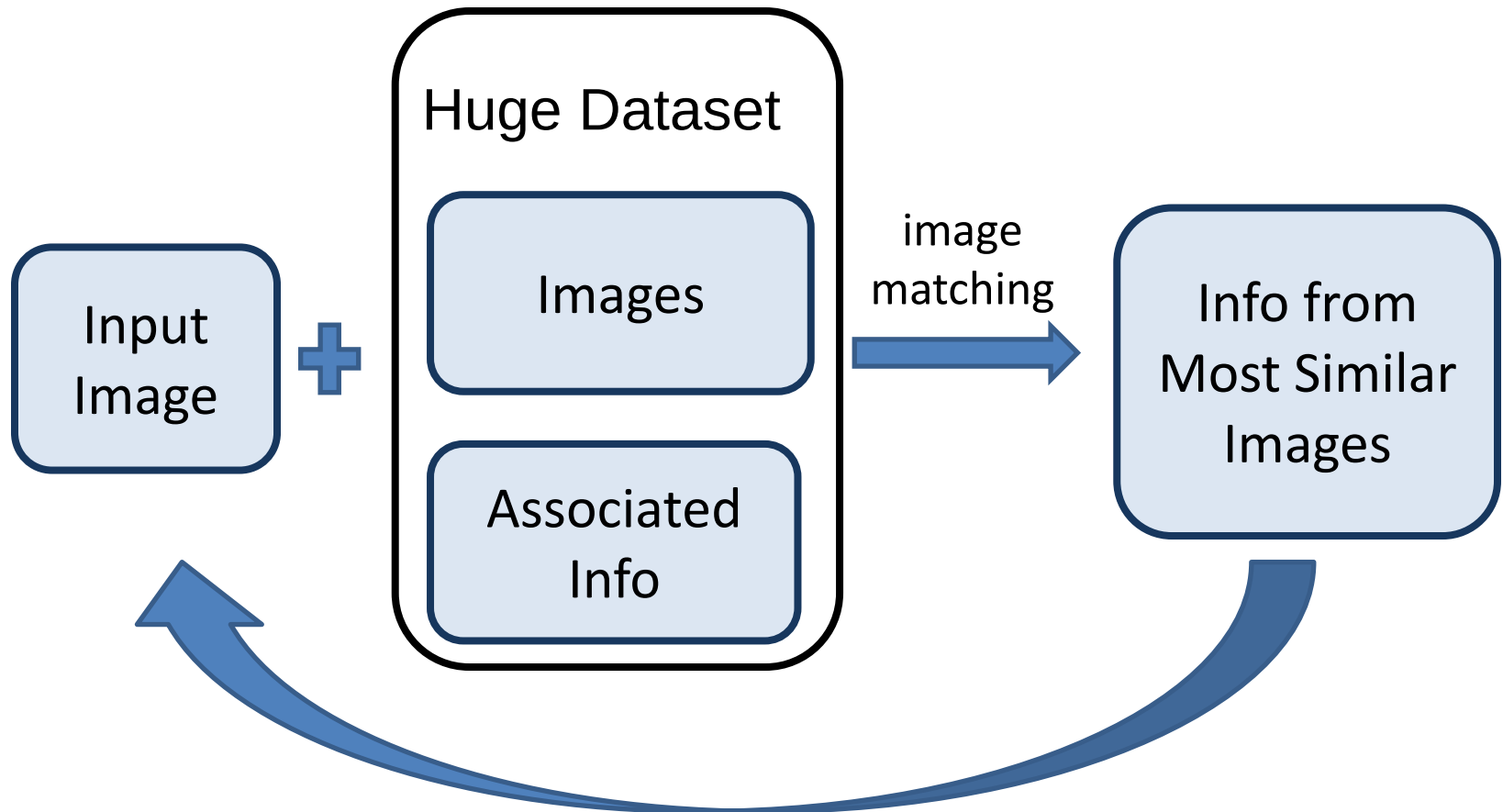
(b)

How it works

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

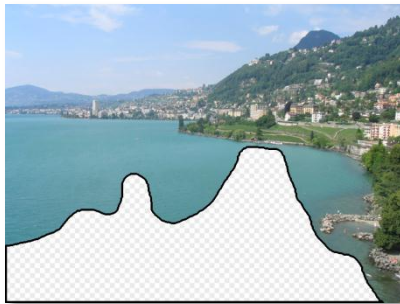


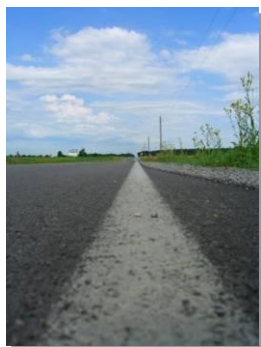
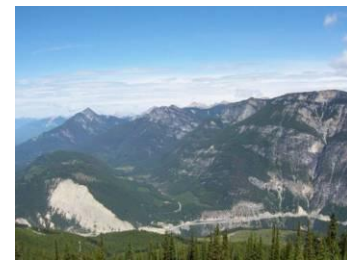
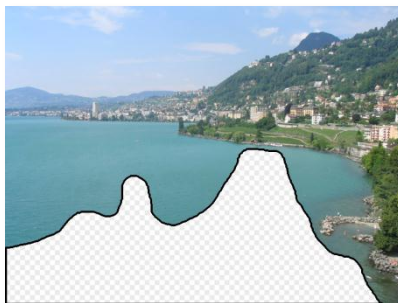
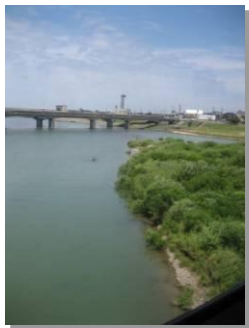
General Principal



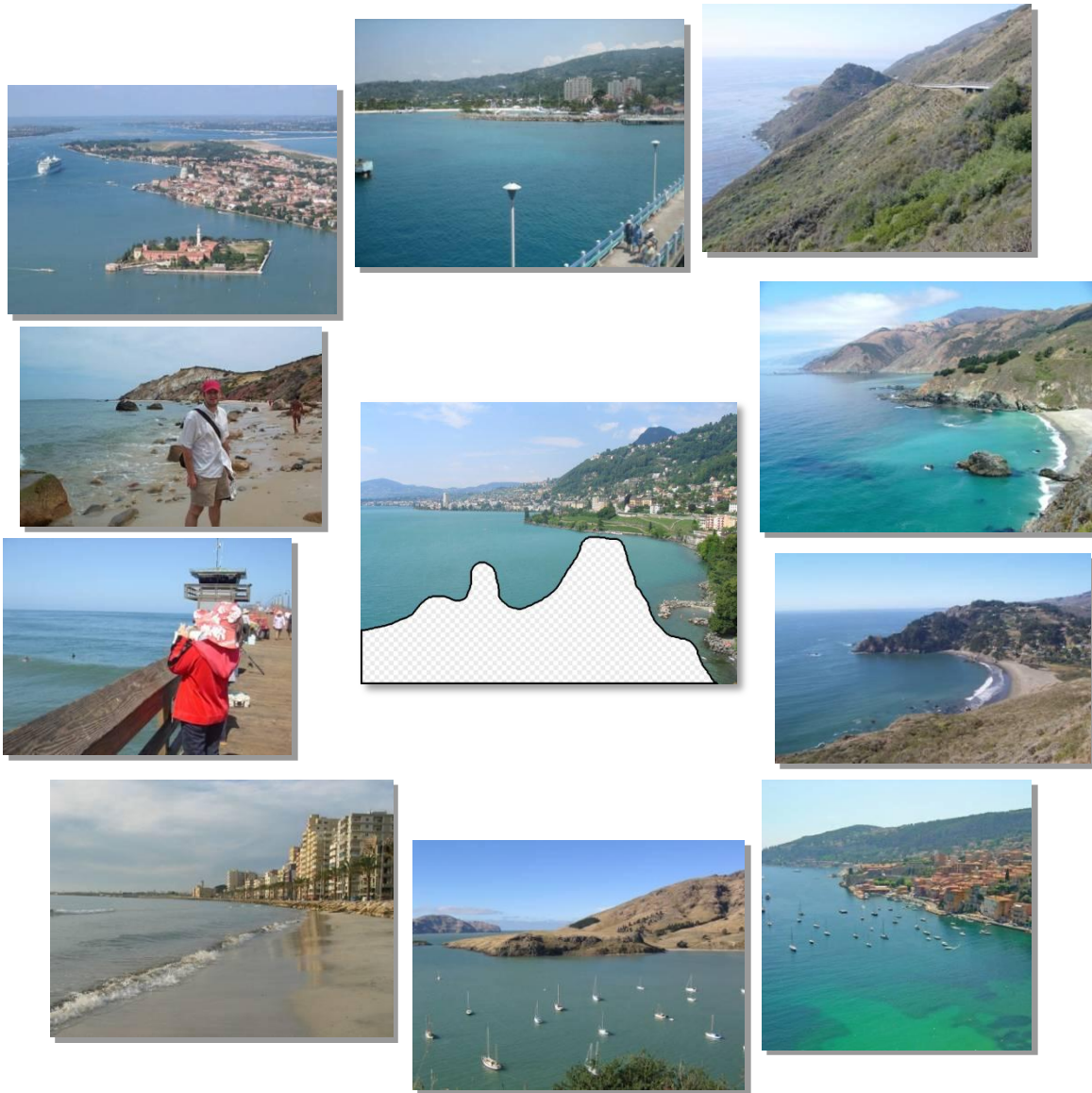
Trick: If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

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

- Flickr (now)
 - 6 billion images per month
 - More than 100 petabytes of images/video
- Flickr (as of Sept. 19th, 2010)
 - 5 billion photographs
 - 100+ million geotagged images
- Imageshack (as of 2009)
 - 20 billion
- Facebook (as of 2009)
 - 15 billion

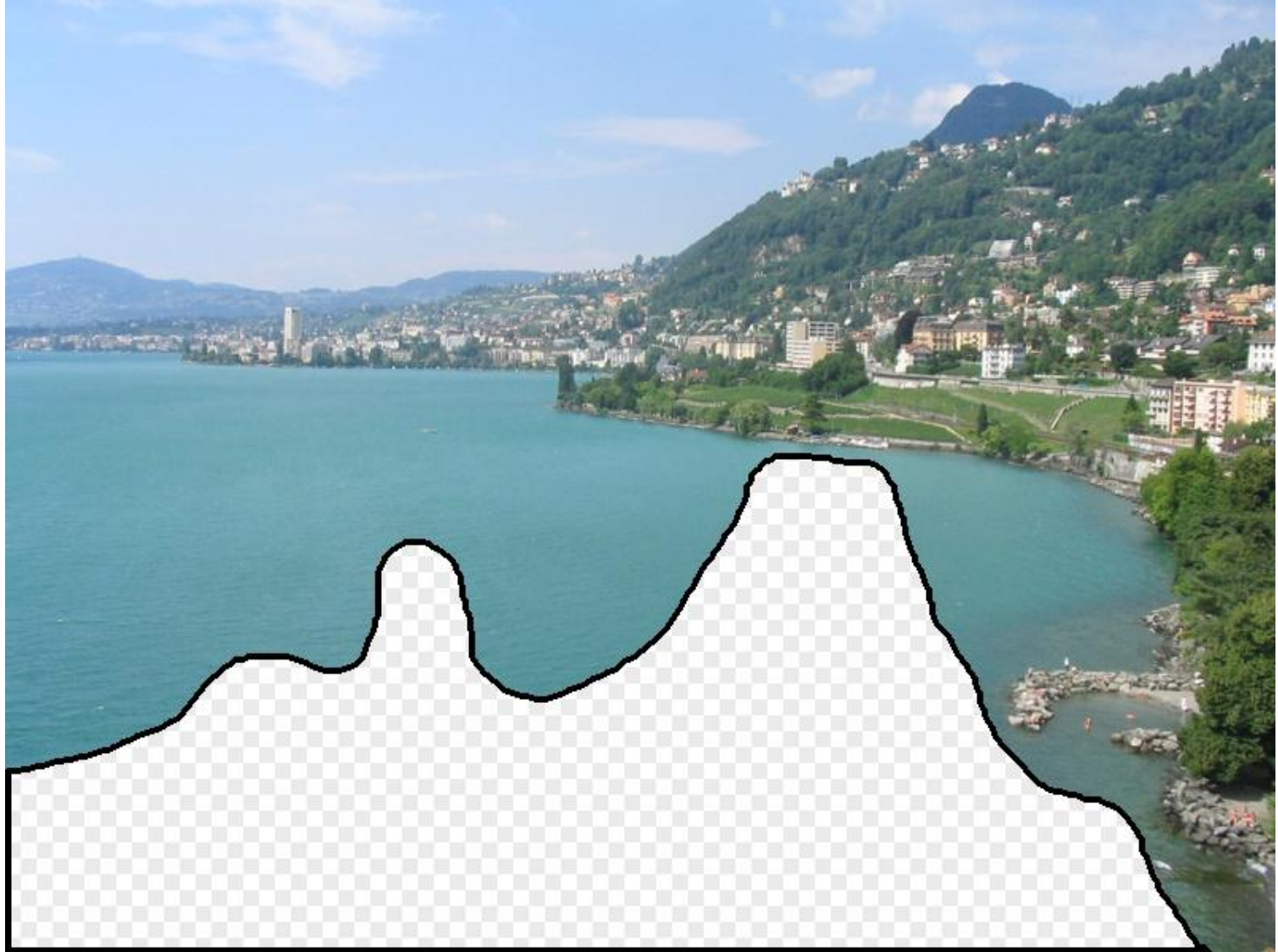
Image completion: how it works

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

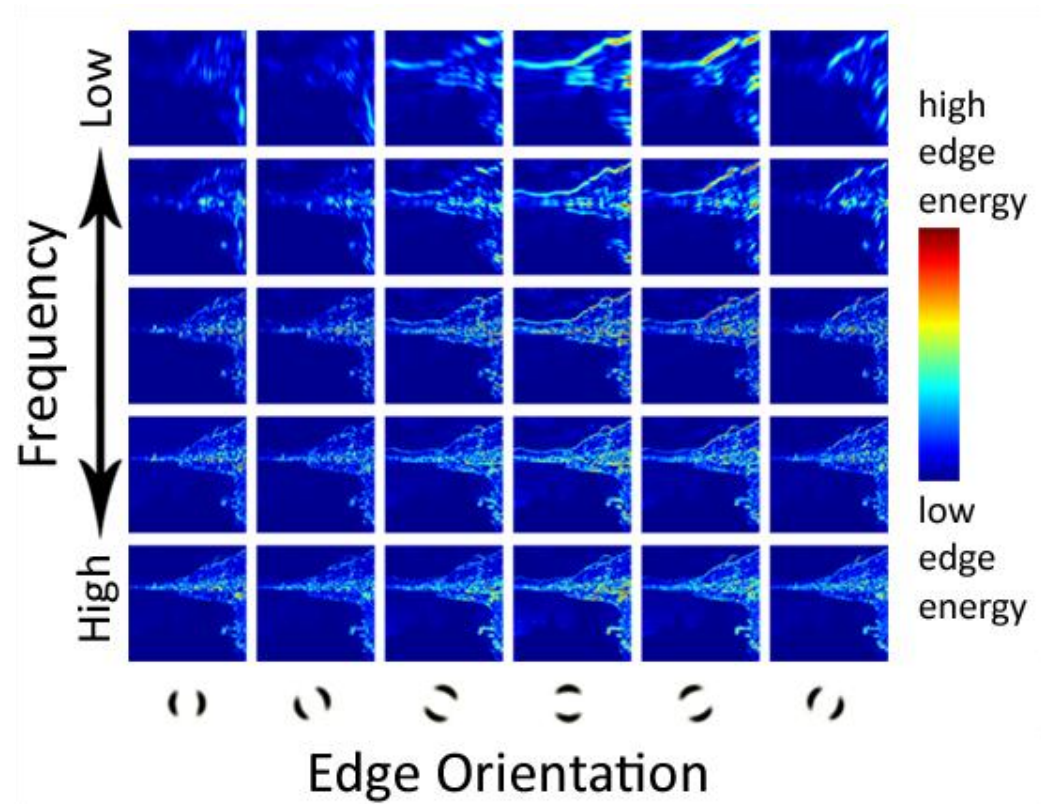
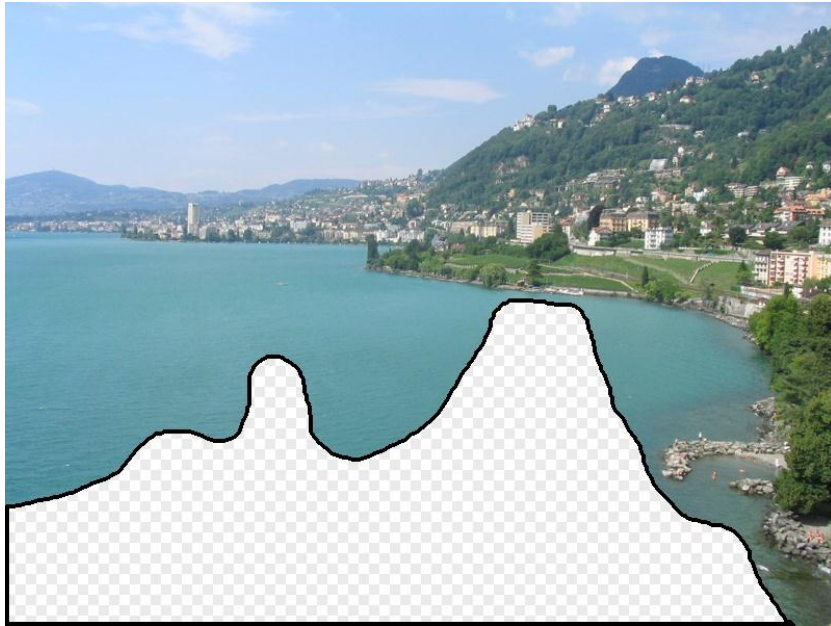
The Algorithm



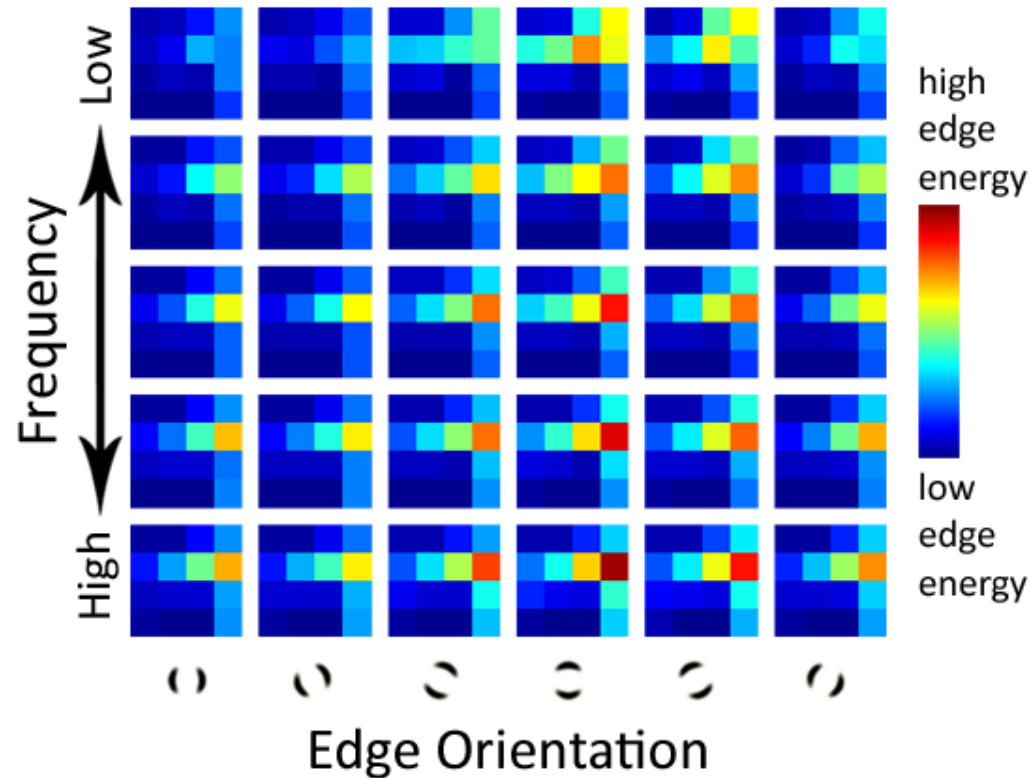
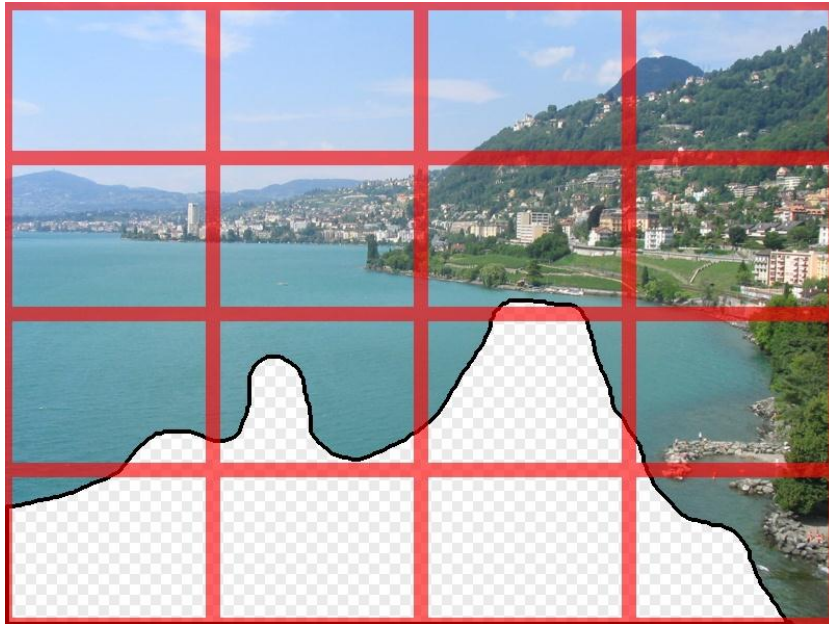
Scene Matching



Scene Descriptor

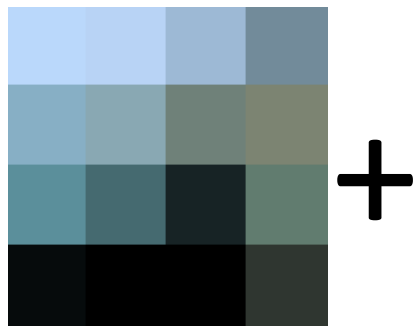


Scene Descriptor

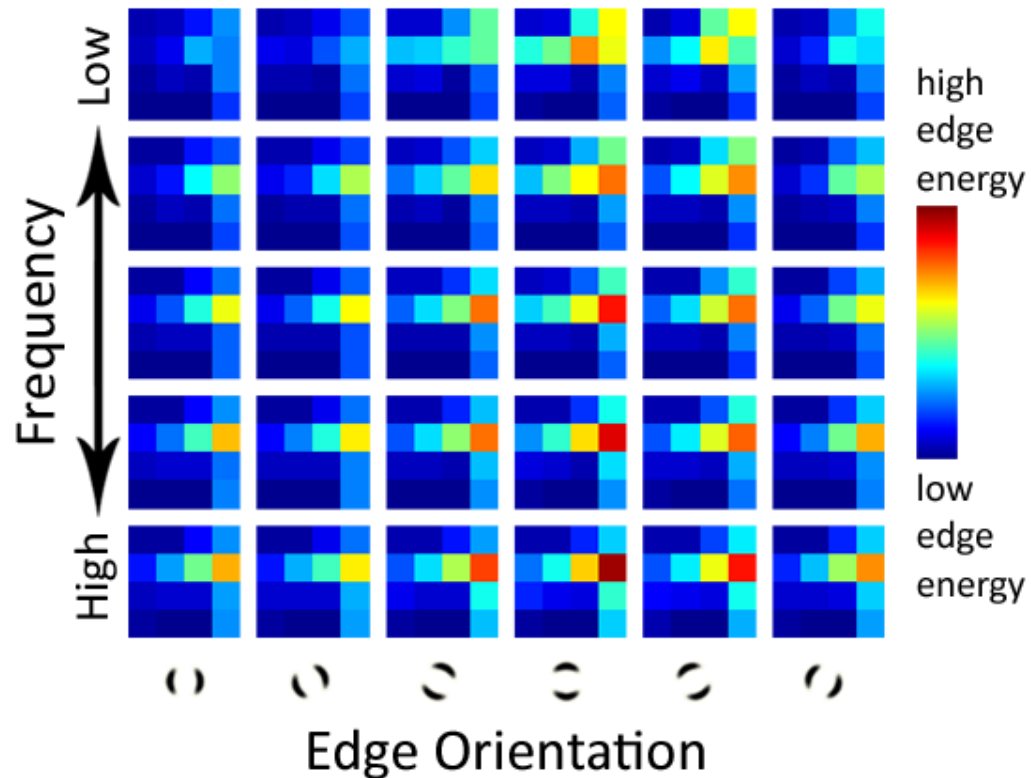


Scene Gist Descriptor
(Oliva and Torralba 2001)

Scene Descriptor

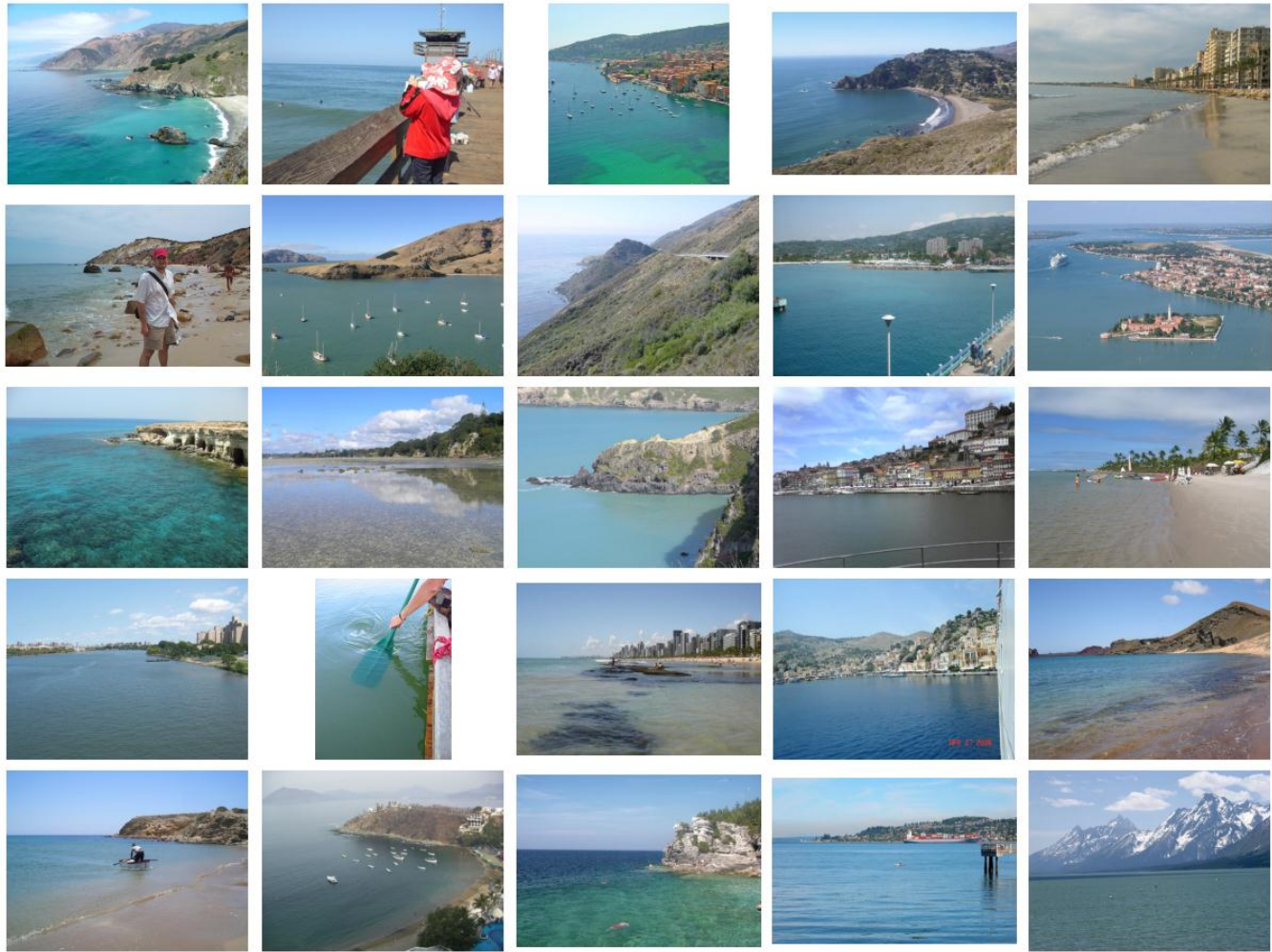
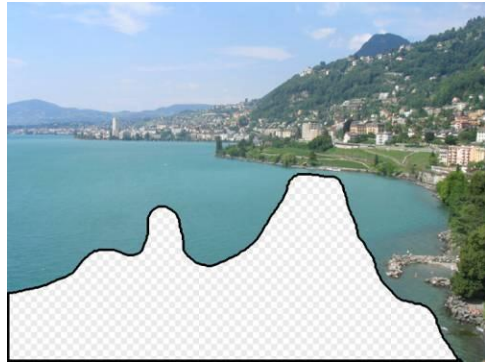


+



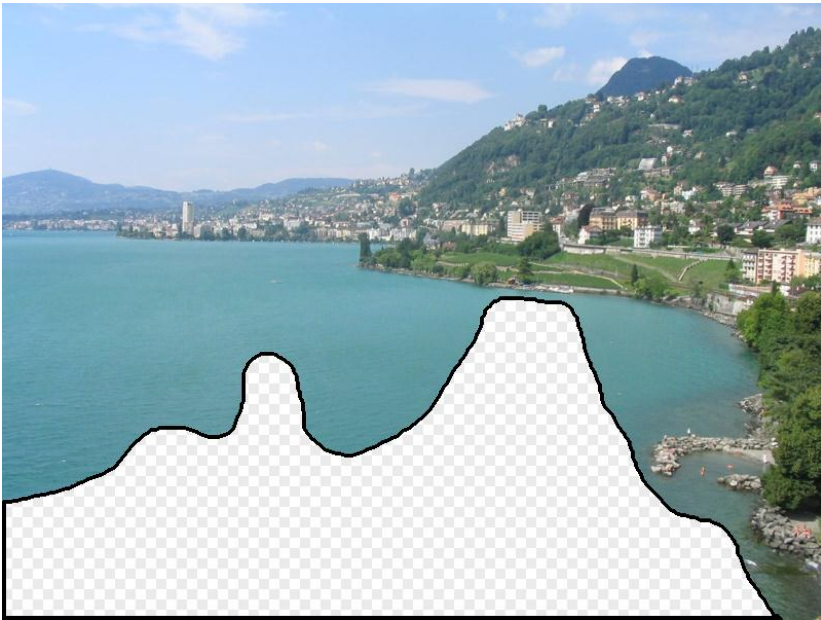
Scene Gist Descriptor
(Oliva and Torralba 2001)

2 Million Flickr Images



... 200 total

Context Matching

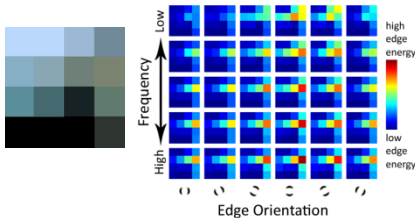




Graph cut + Poisson blending

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

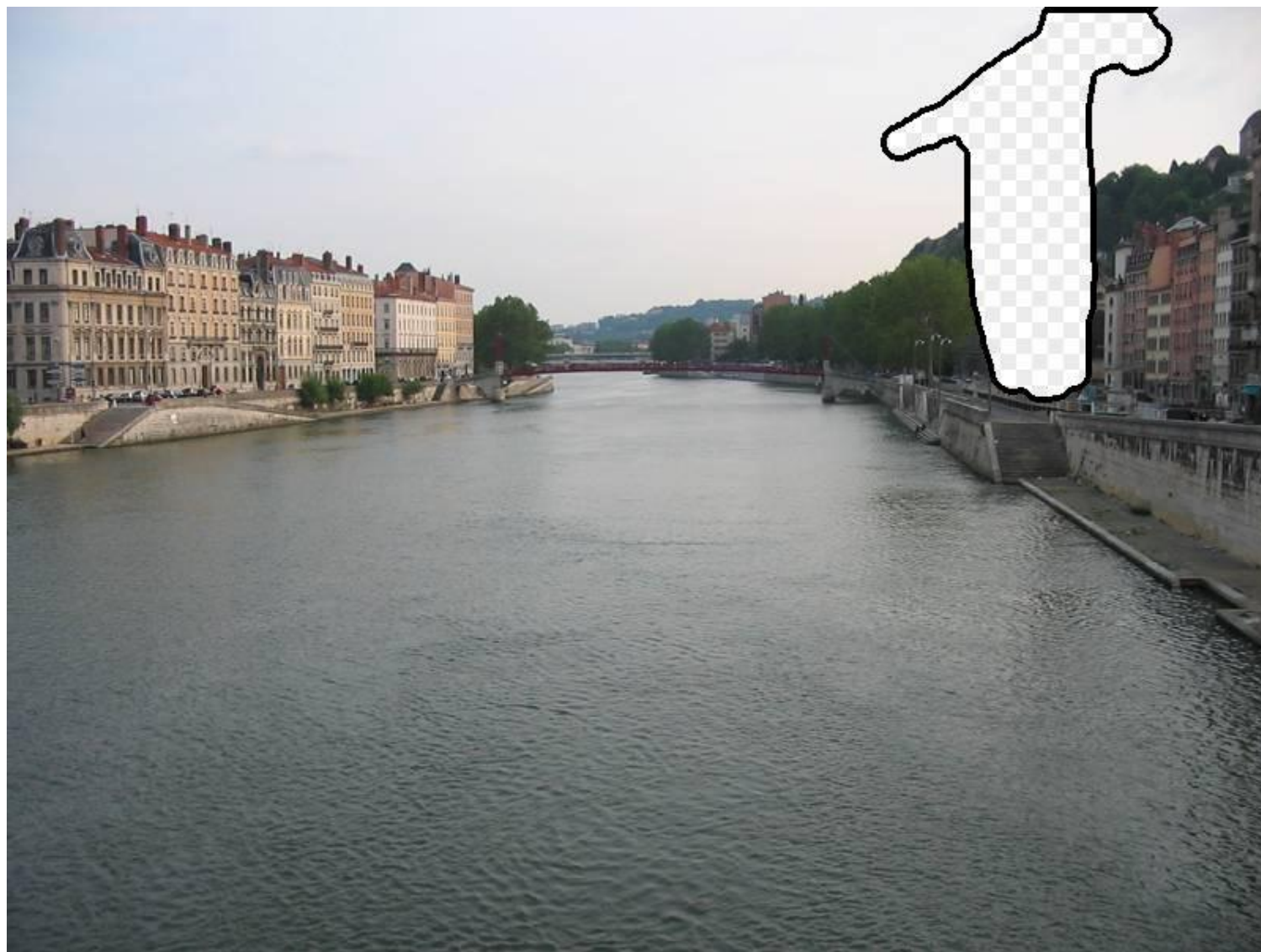




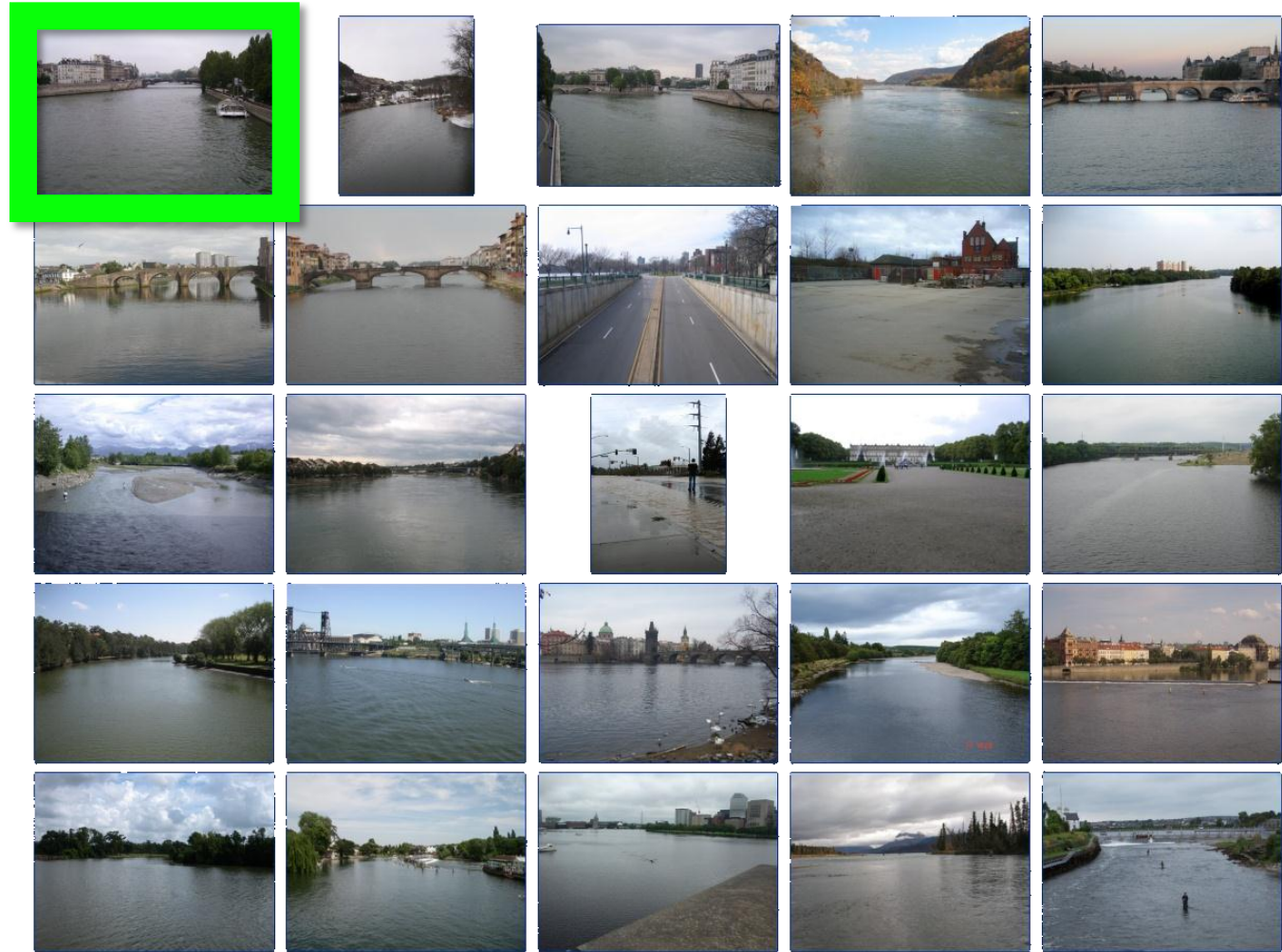








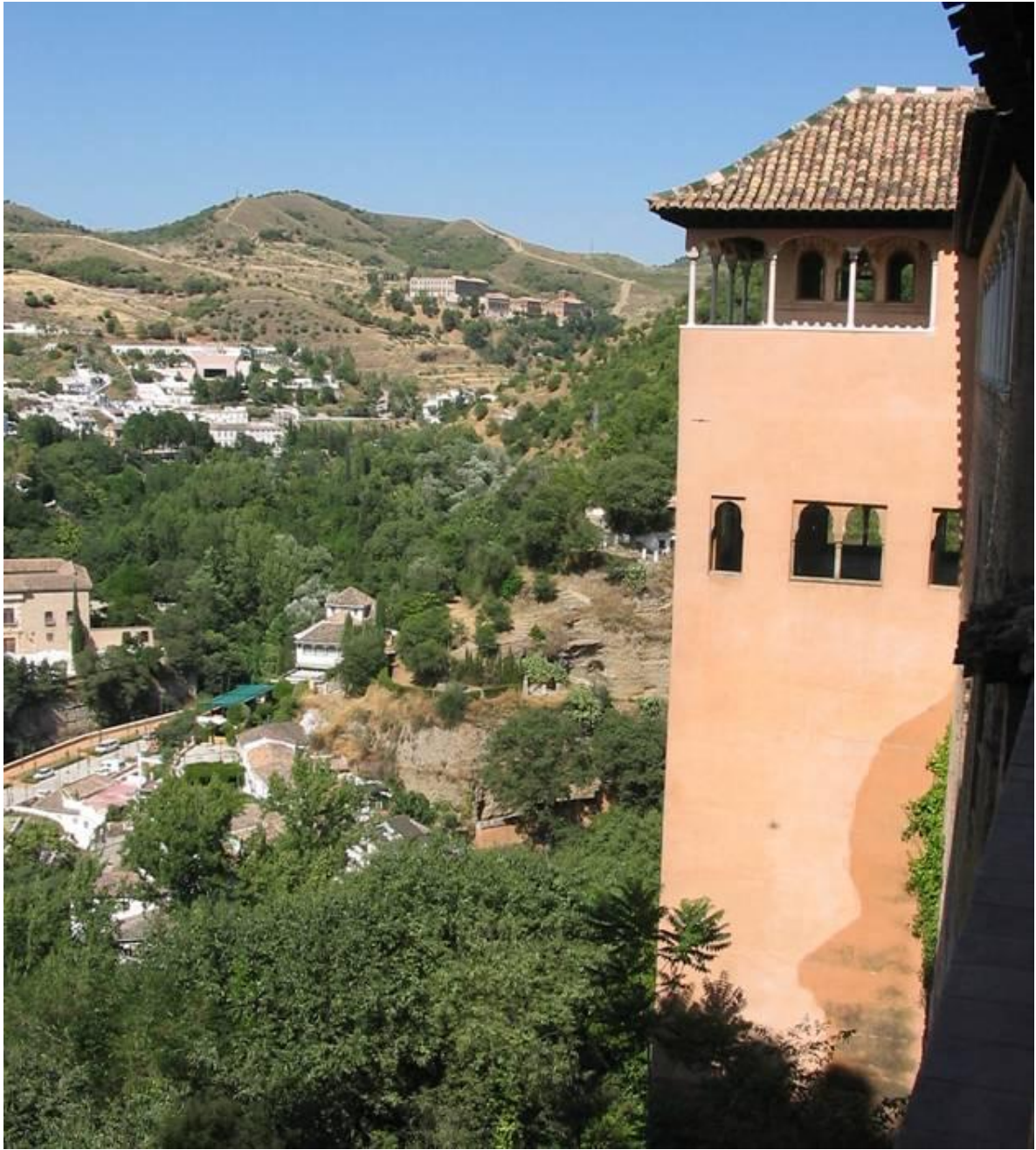




... 200 scene matches











Which is the original?











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



Madrid



england



France



Paris



Croatia



heidelberg



Macau



Malta



Cairo



Italy



Italy



Italy



Latvia



europa

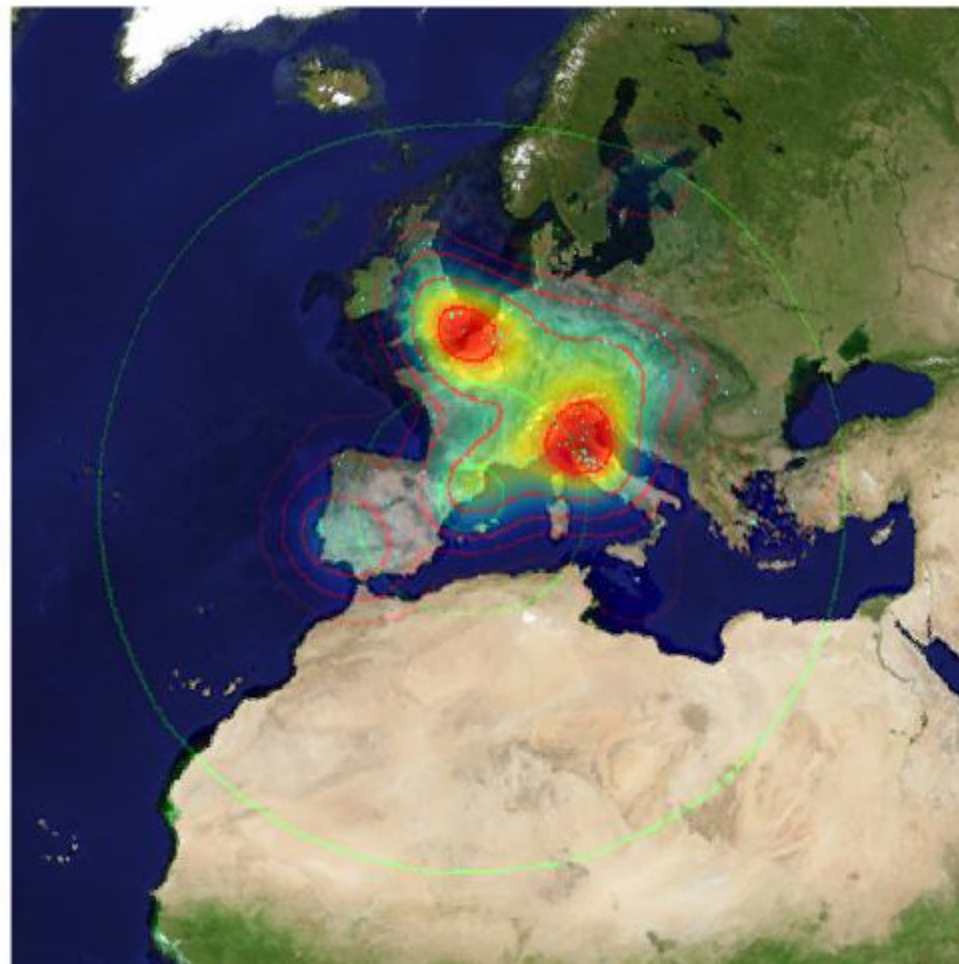
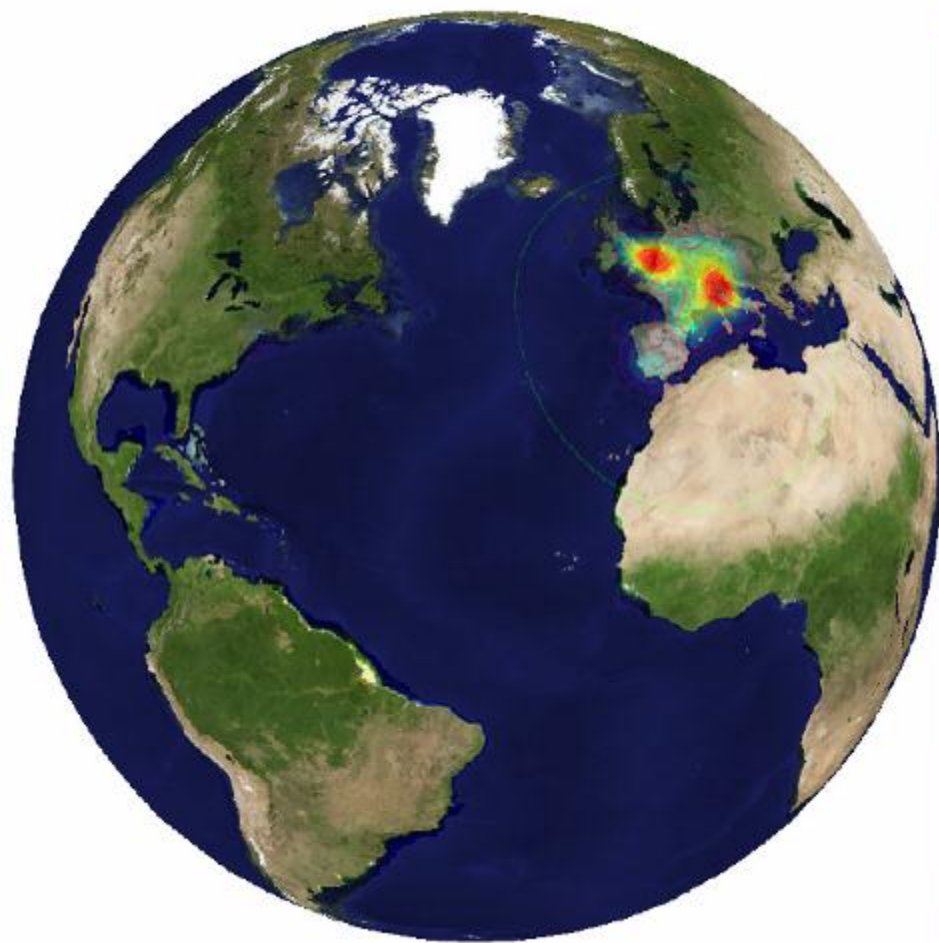


Barcelona



Austria

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?

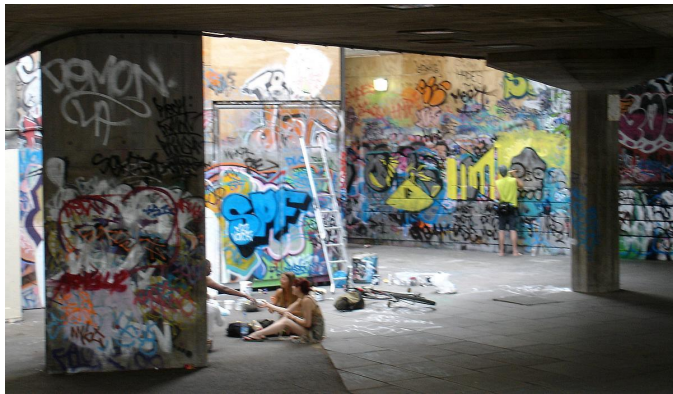


[Olga Vesselova, Vangelis Kalogerakis, Aaron Hertzmann, James Hays, Alexei A. Efros. Image Sequence Geolocation. ICCV'09]

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%

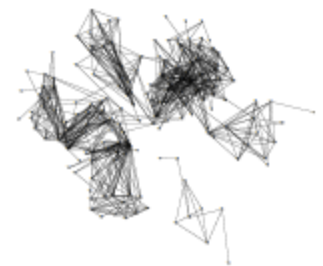
3D Reconstruction from Flickr

- 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](#)

Photo Clip Art [SG'07]

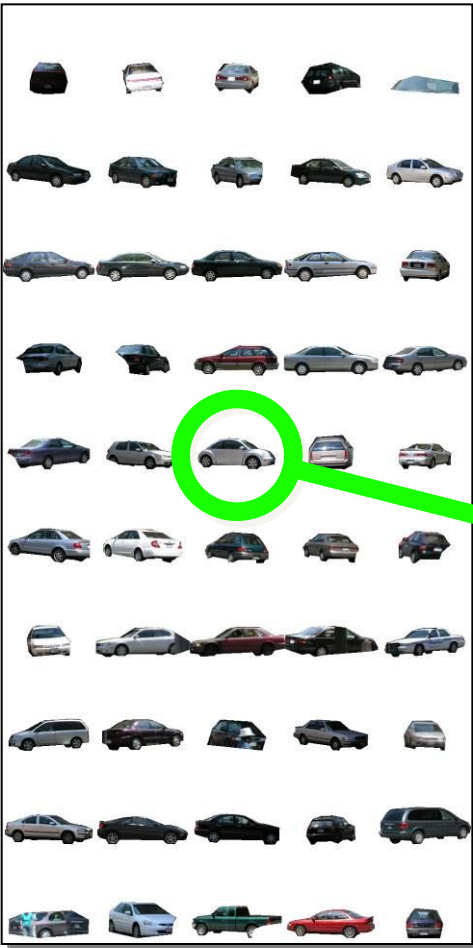
Inserting a single object -- still very hard!



object size, orientation
scene illumination

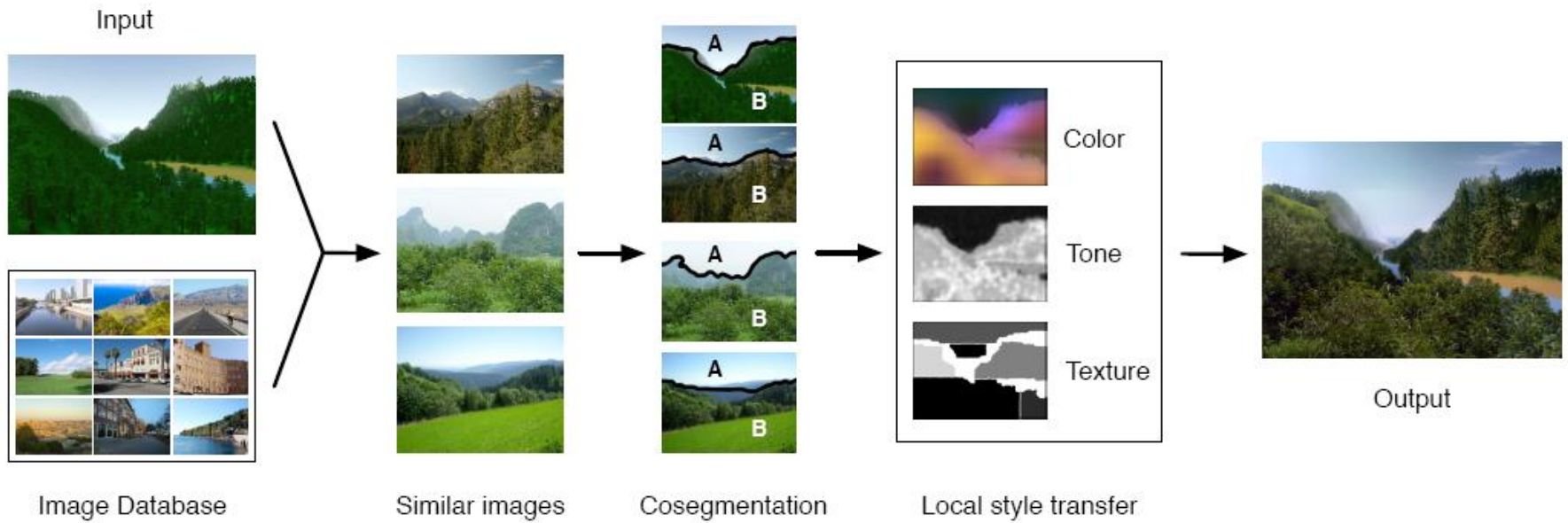
Photo Clip Art [SG'07]

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

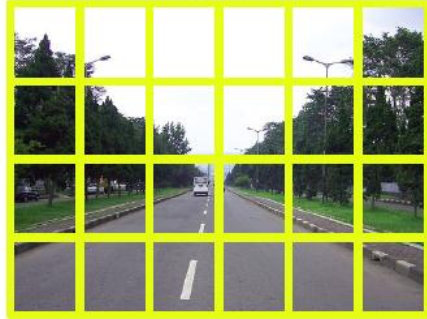
Tour from a single image

Scene matching with camera transformations

Query image



GIST



Best match



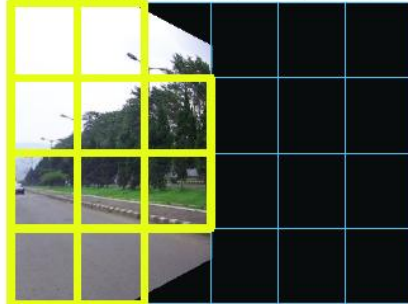
Top matches



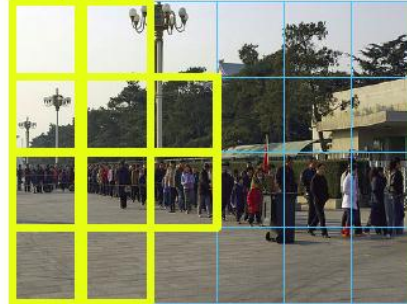
Query image



Camera rotation & GIST



Best match after rotation



Top matches



Tour from a single image

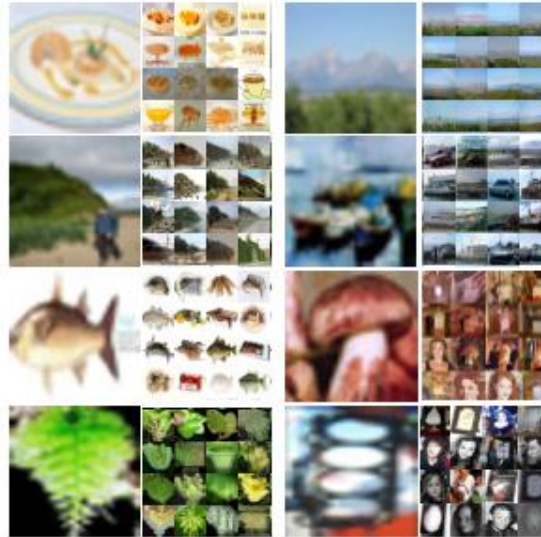


Navigate the virtual space using intuitive motion controls

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/>

256x256



32x32

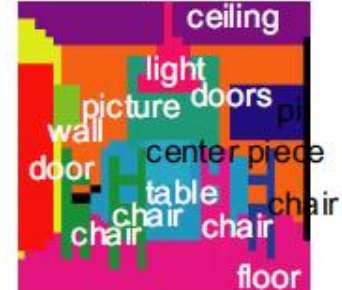
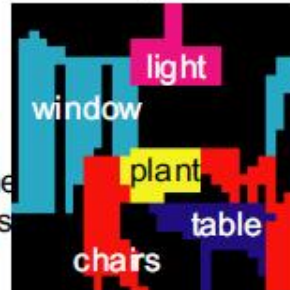
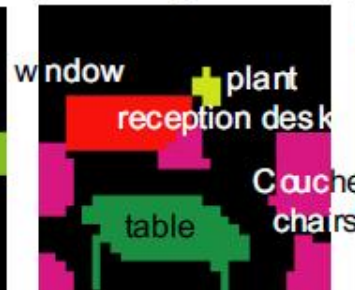
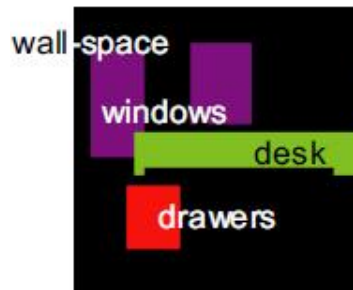


office

waiting area

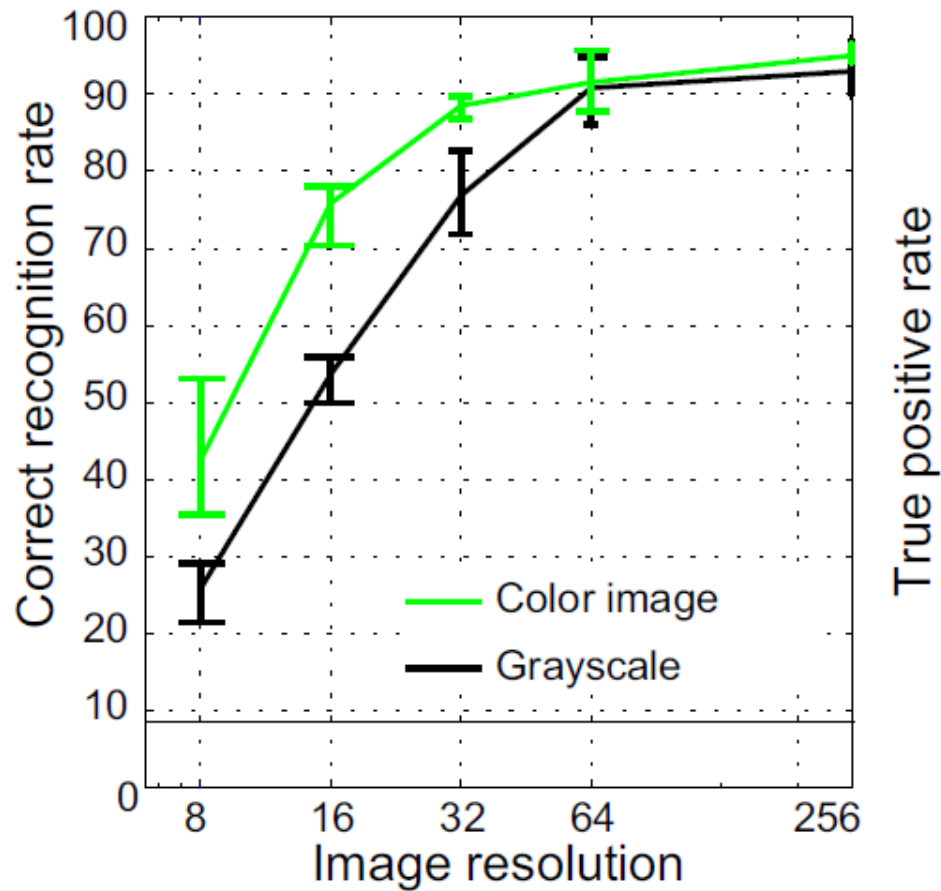
dining room

dining room



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:

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

10^8



Number of images seen by all humanity:

106,456,367,669 humans¹ * 60 years * 3 images/second * 60 * 60 * 16 * 365 =

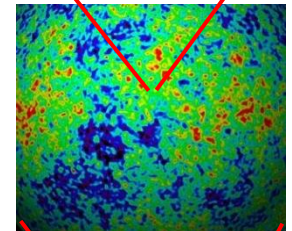
1 from <http://www.prb.org/Articles/2002/HowManyPeopleHaveEverLivedonEarth.aspx>

10^{20}



Number of photons in the universe:

10^{88}



Number of all 32x32 images:

$256^{32 \times 32} \sim 10^{7373}$

10^{7373}



Scenes are unique



But not all scenes are so original



Lots Of Images

Target



7,900



Lots Of Images

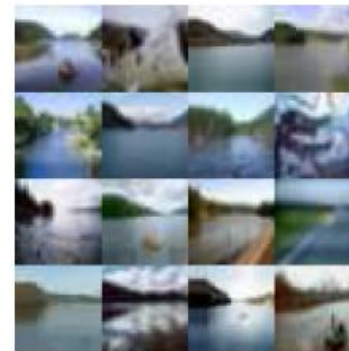
Target



7,900



790,000



Lots Of Images

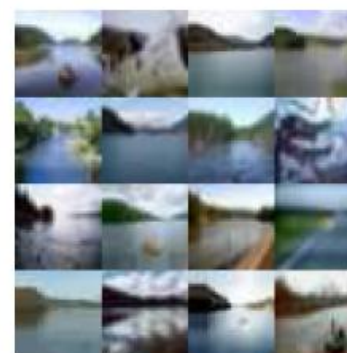
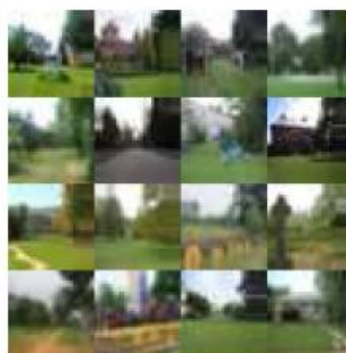
Target



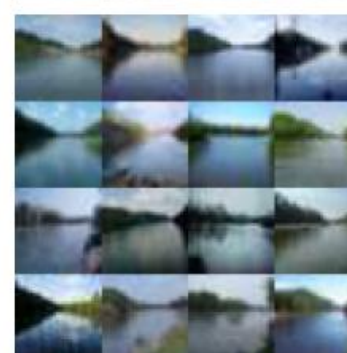
7,900



790,000



79,000,000



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

Summary

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

Upcoming

- Thurs: how Kinect works
 - Contingent on jury duty
- Mon: project 5 due