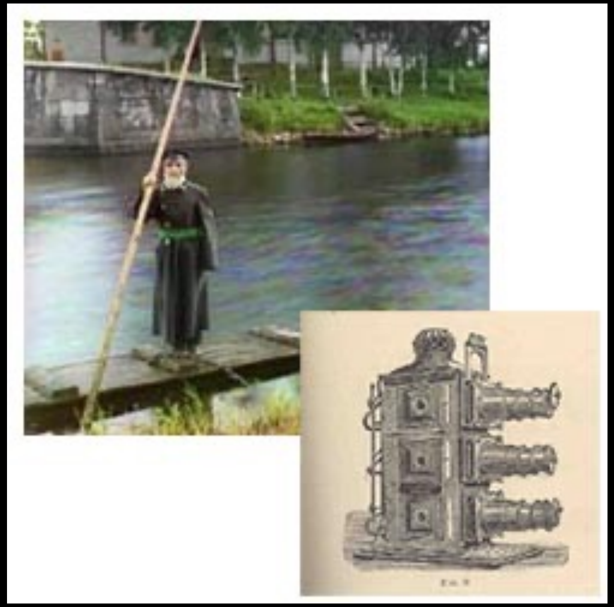
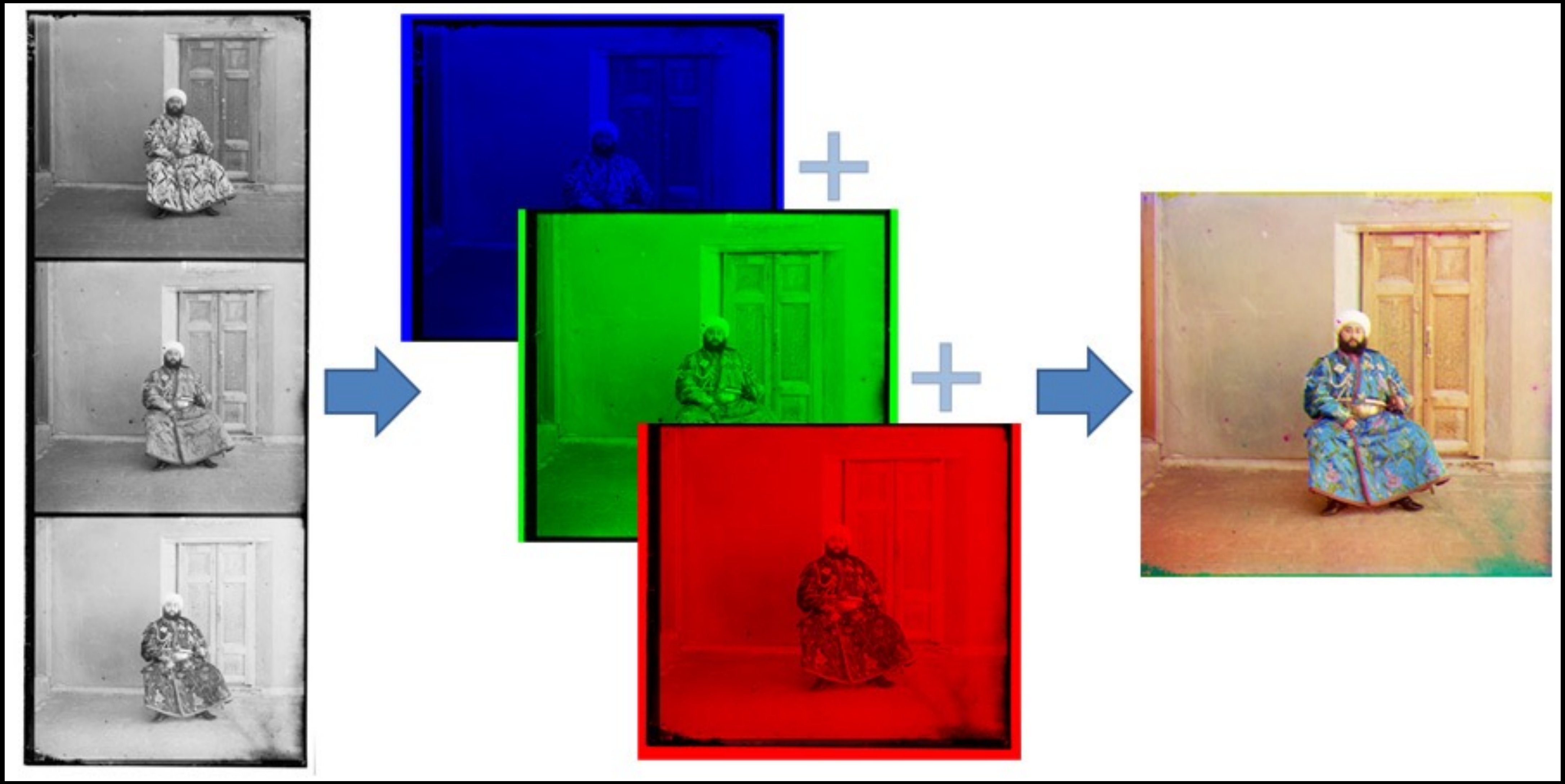
Programming Project #1

- **Prokudin-Gorskii's Color Photography (1907)**



Programming Project #1

- Align R, G, B images (Due 2/15/2022)



Programming Project #1

- How to compare R,G,B channels?
- No right answer
  - Sum of Squared Differences (SSD):

$$ssd(u,v) = \sum_{(x,y)\in N} \left[I(u+x, v+y) - P(x,y) \right]^2$$

  - Normalized Correlation (NCC):

$$ncc(u,v) = \frac{\sum_{(x,y)\in N} \left[I(u+x, v+y) - \bar{I} \right] \left[P(x,y) - \bar{P} \right]}{\sqrt{\sum_{(x,y)\in N} \left[I(u+x, v+y) - \bar{I} \right]^2 \sum_{(x,y)\in N} \left[P(x,y) - \bar{P} \right]^2}}$$

Credit: Berkeley CS194-26

Data-Driven Graphics

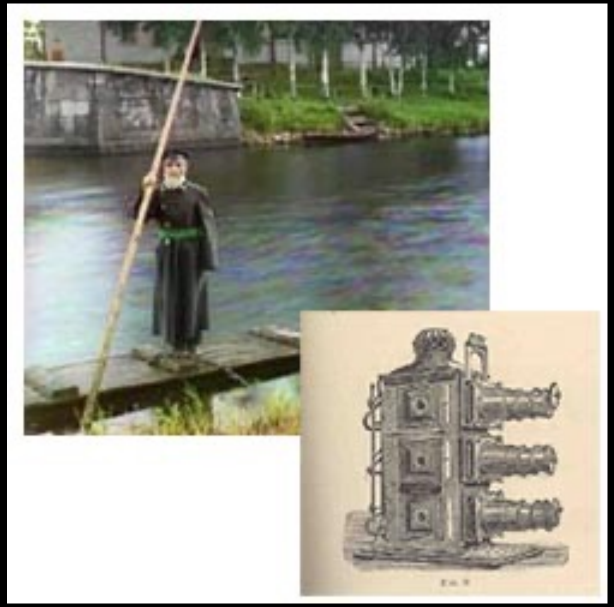
Jun-Yan Zhu

16-726 Learning-based Image Synthesis, Spring 2023

With slides from Alexei. A. Efros, James Hays, Antonio Torralba, and Frederic Heger

Review: Global/Local warping

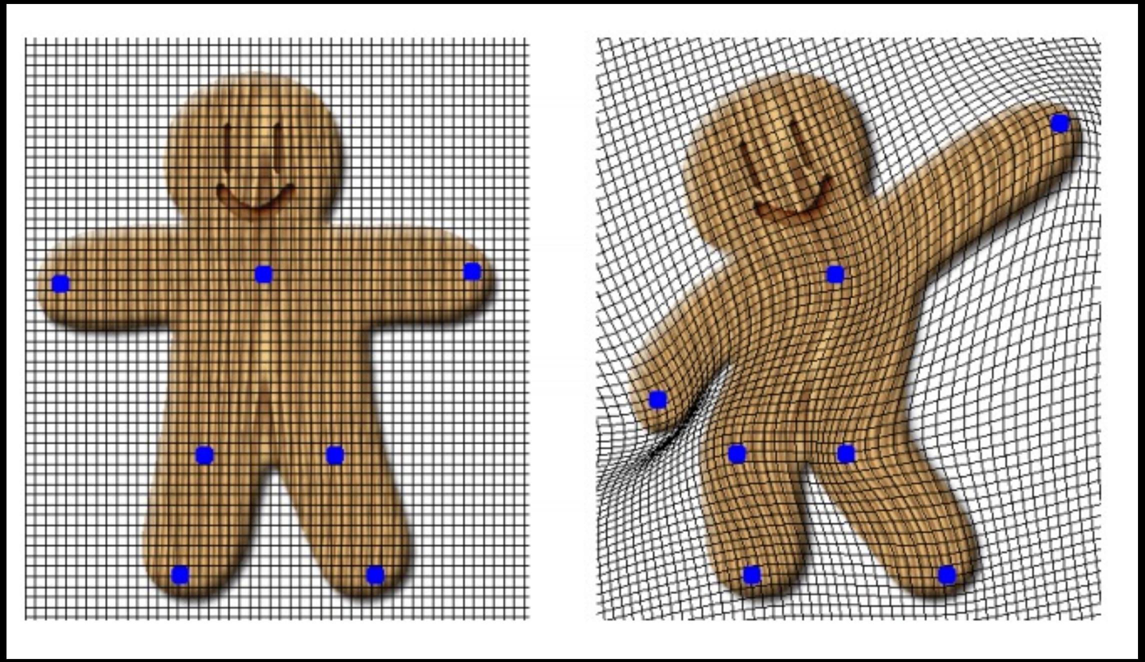
- **Prokudin-Gorskii's Color Photography (1907)**



Review: Global/Local warping

Global vs. Local warping
- Parameter sharing

Dense vs. sparse warping
- Degree of freedom
- Interpolation vs. curve fitting?



Triangulation vs. Moving Least Squares
- Piece-wise function
- Spatially-varying objective functions

Data-Driven Graphics

Jun-Yan Zhu

16-726 Learning-based Image Synthesis, Spring 2023

With slides from Alexei. A. Efros, James Hays, Antonio Torralba, and Frederic Heger

Subject-specific Data

Photos of Coliseum

Portraits of Bill Clinton

Big Visual Data

6 billion images

1 billion images
served daily

3.5 trillion
photographs

100 hours uploaded
per minute

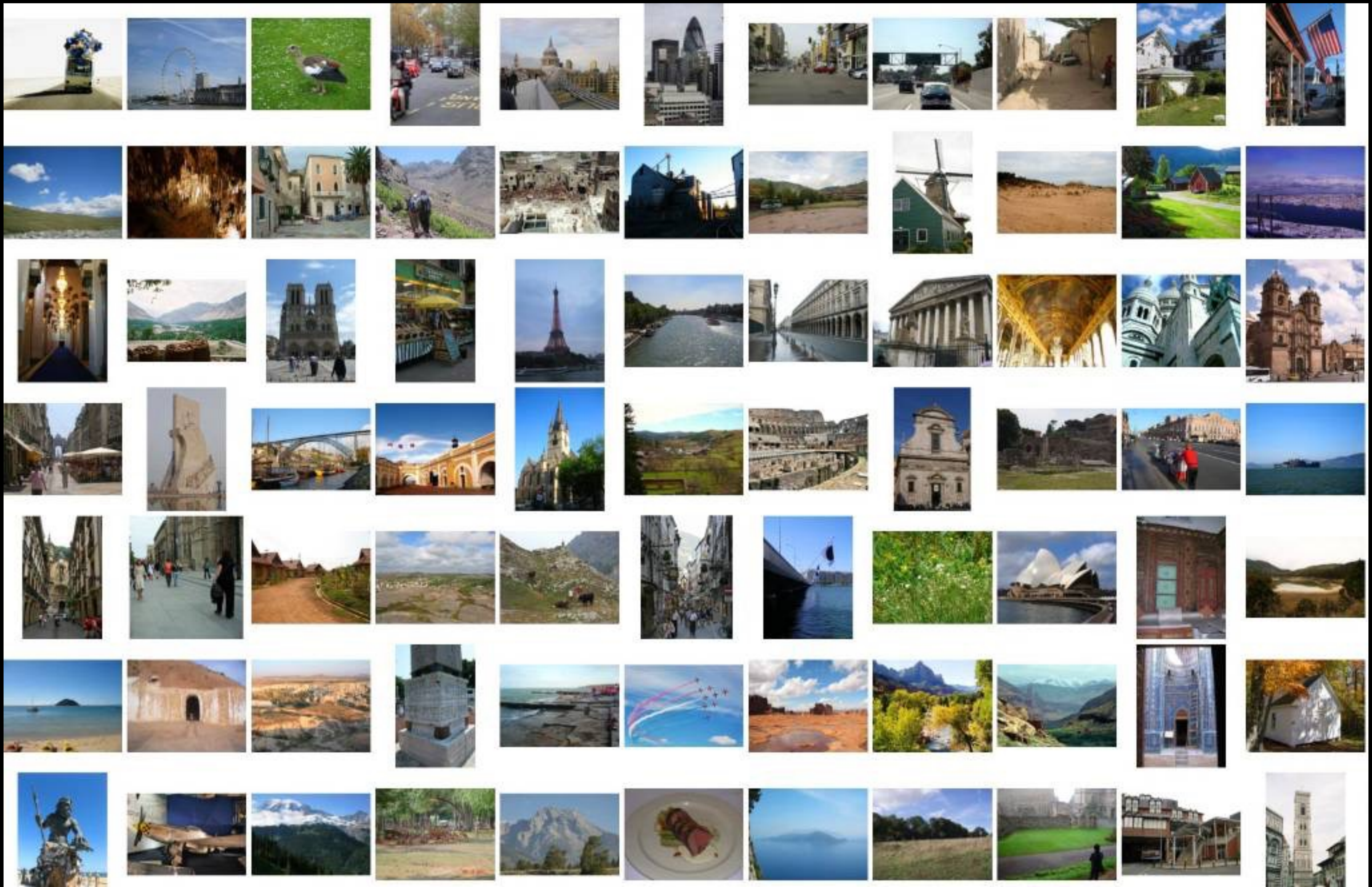
70 billion images


Too Big for Humans
Digital Dark Matter
[Perona 2010]

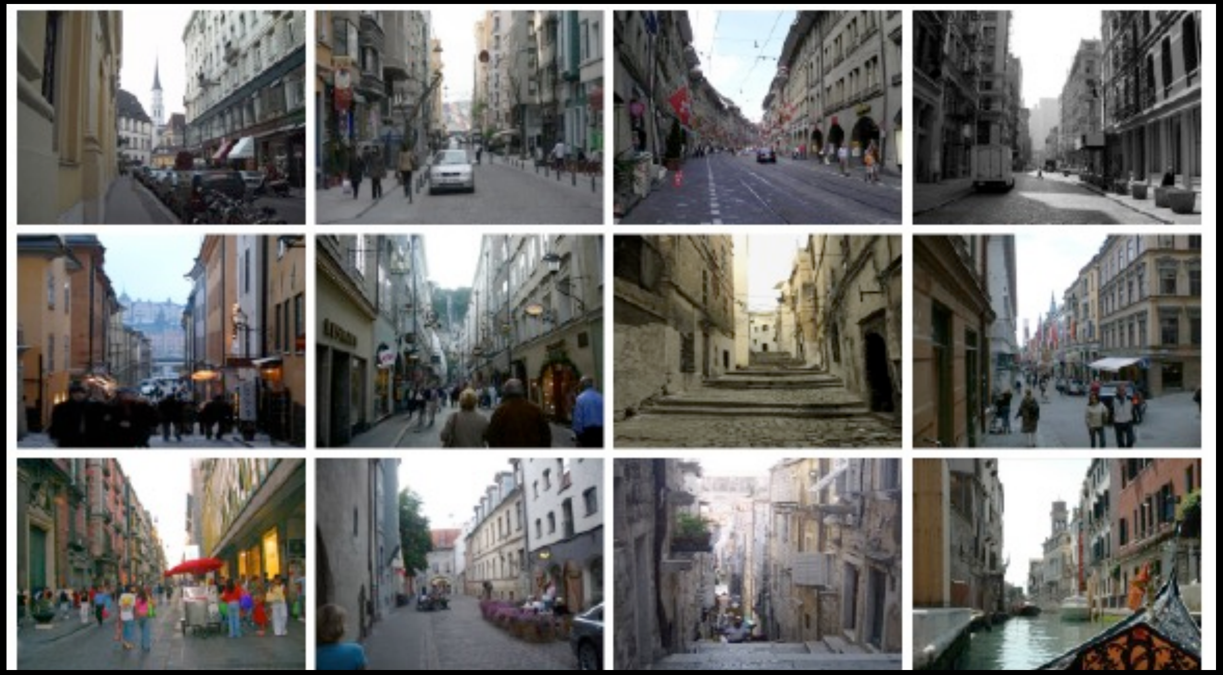
Big issues

- 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?

Much of Captured World is "generic"



Generic Data



street scenes

Food plates

faces

pedestrians

The Internet as a Data Source

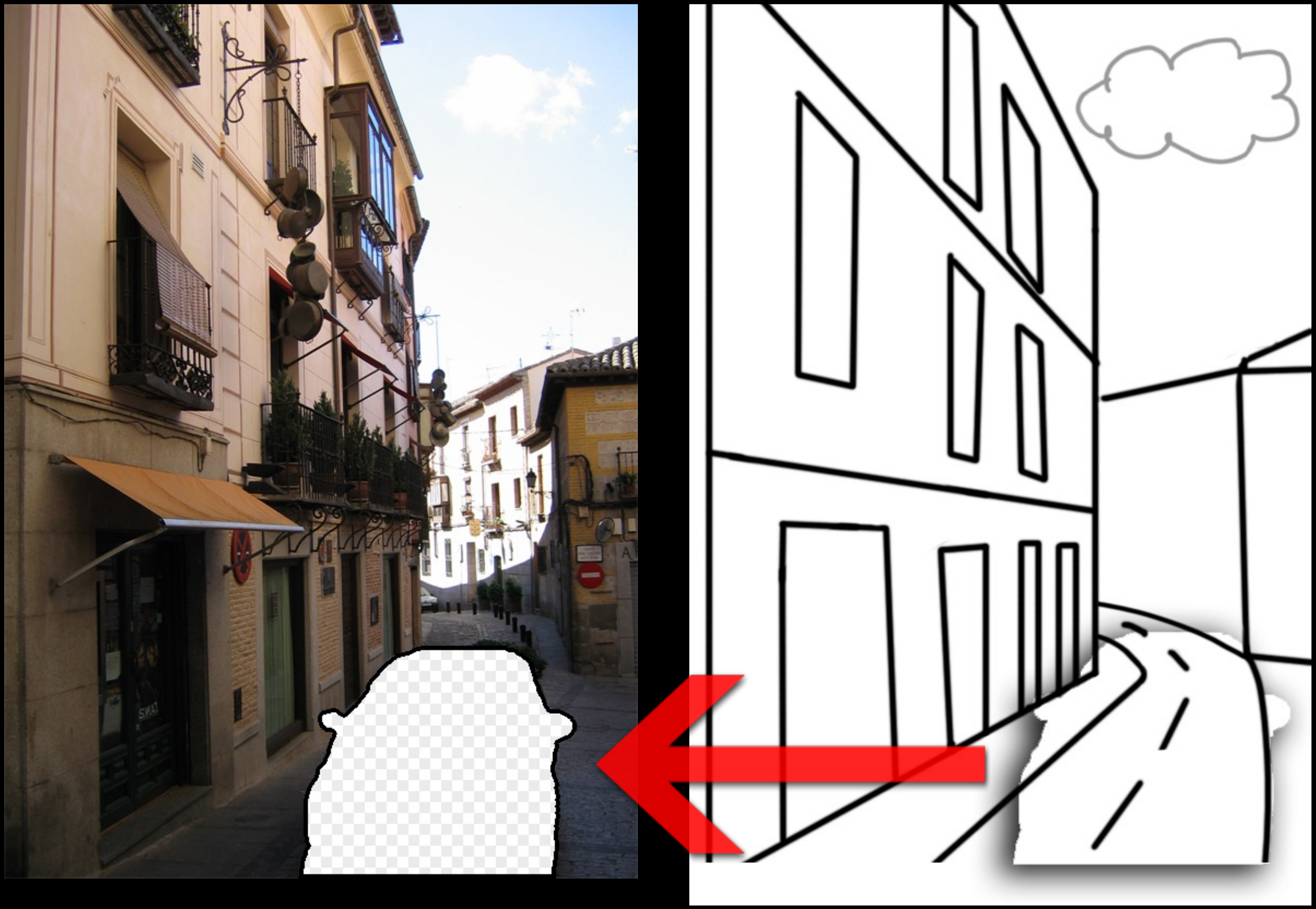
- Social Networking Sites (e.g., Facebook, Snapchat)
- Image Search Engines (e.g., Google, Bing)
- Photo Sharing Sites (e.g., Instagram, Flickr, Adobe Stock)
- Computer Vision Databases (e.g., ImageNet, Places, OpenImages)

Is Big Visual Data useful?

A motivating example…

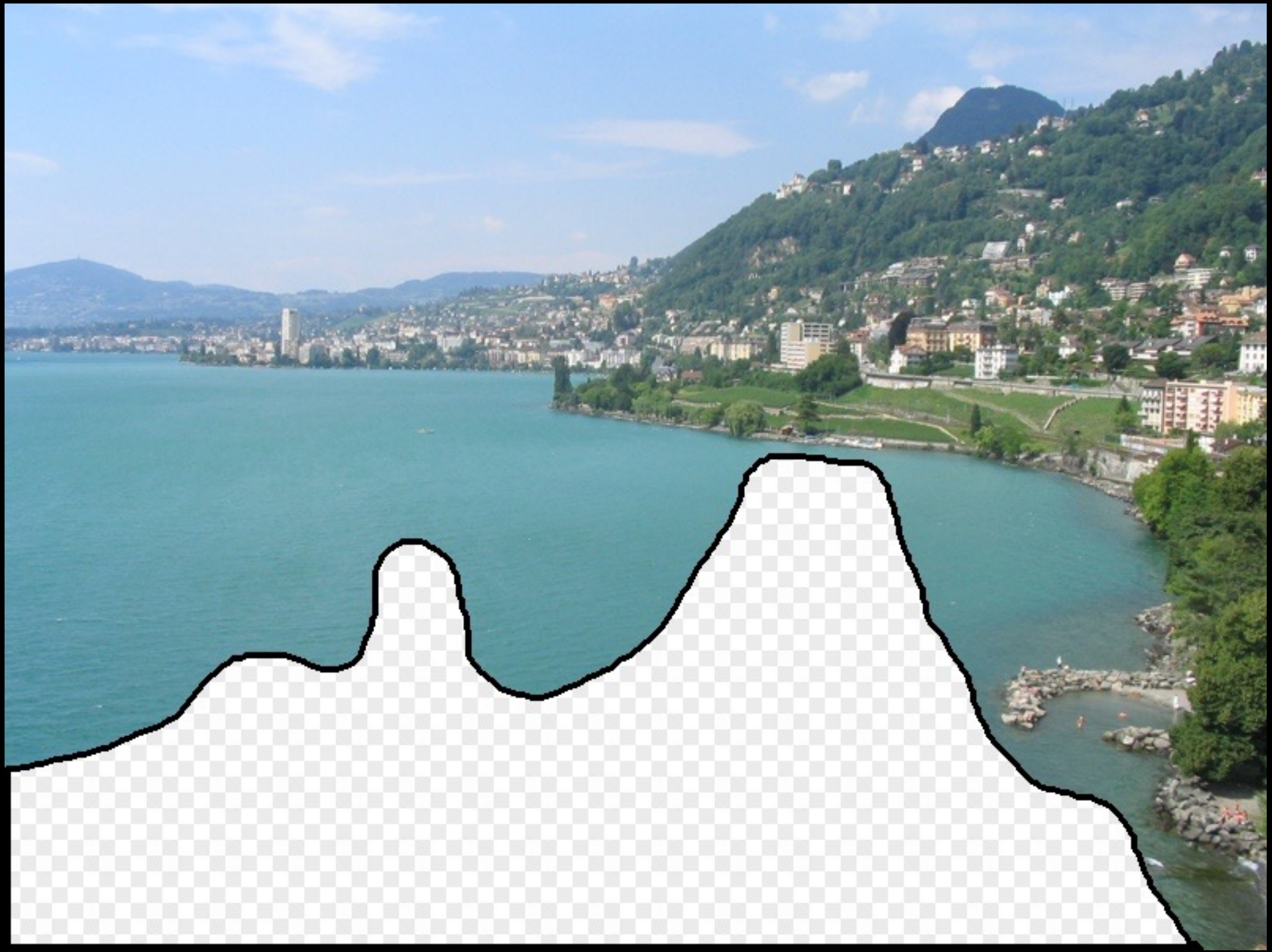

5407 BWL

Scene Matching for Image Completion

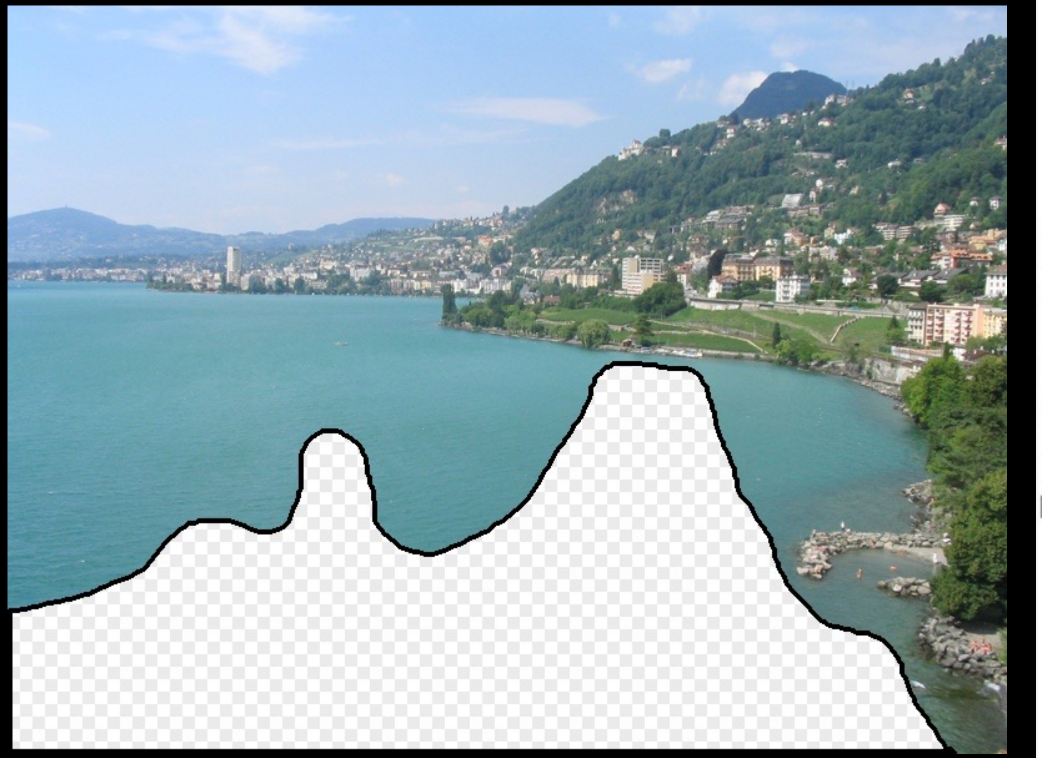


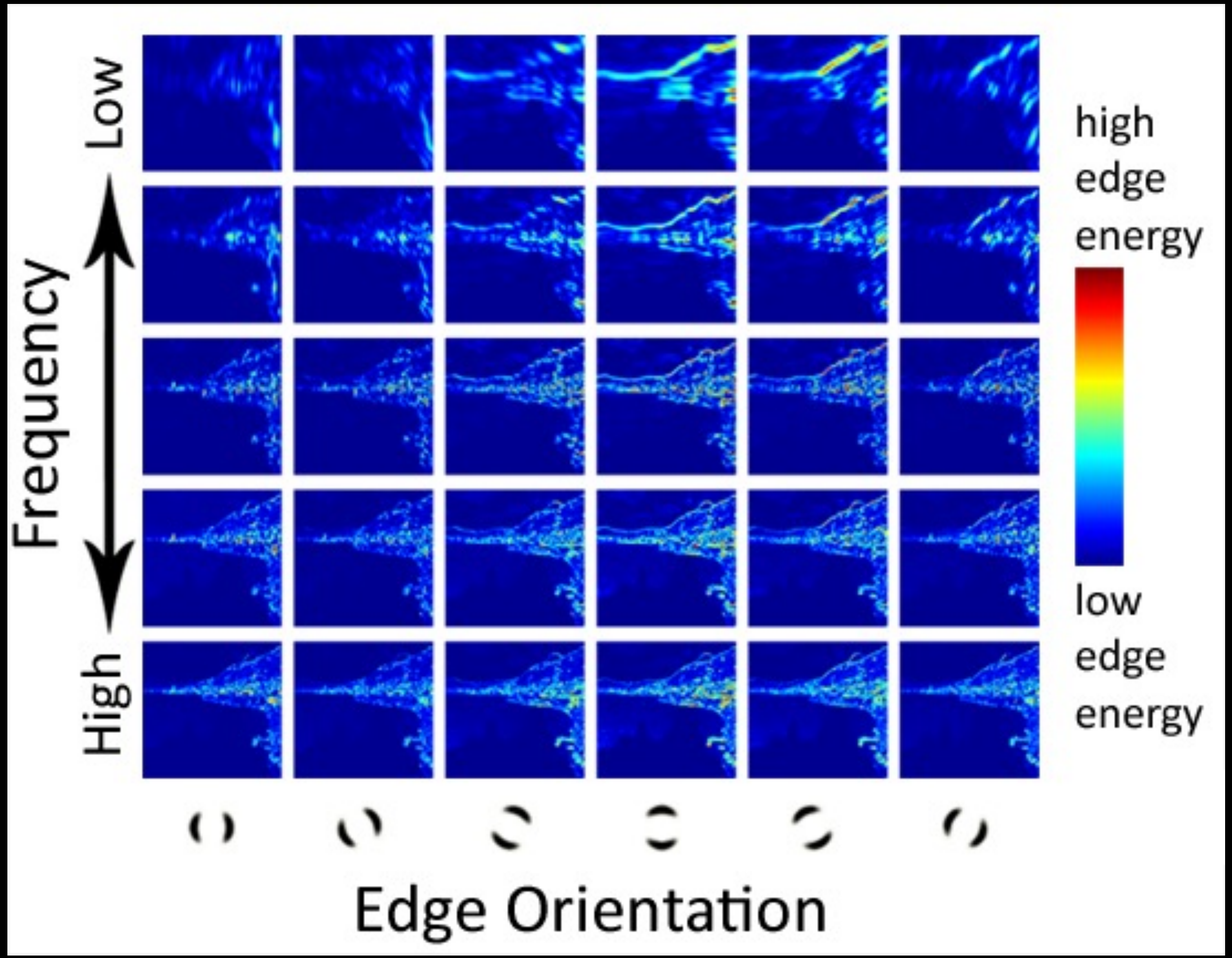
The Algorithm

Scene Matching

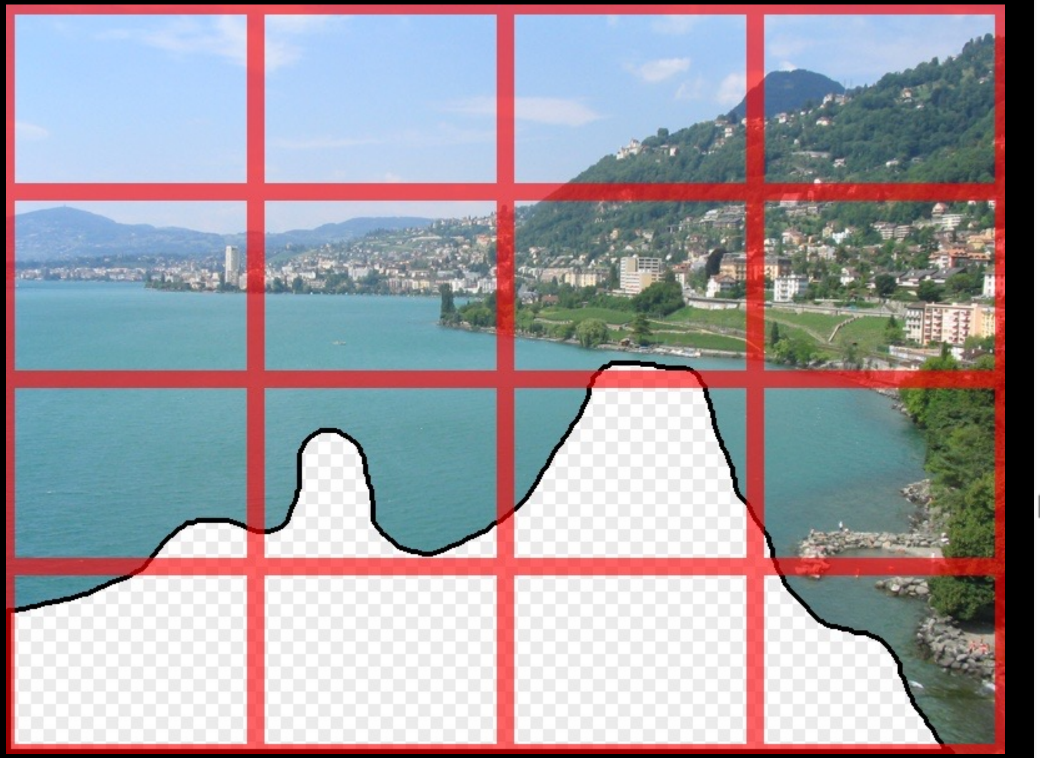


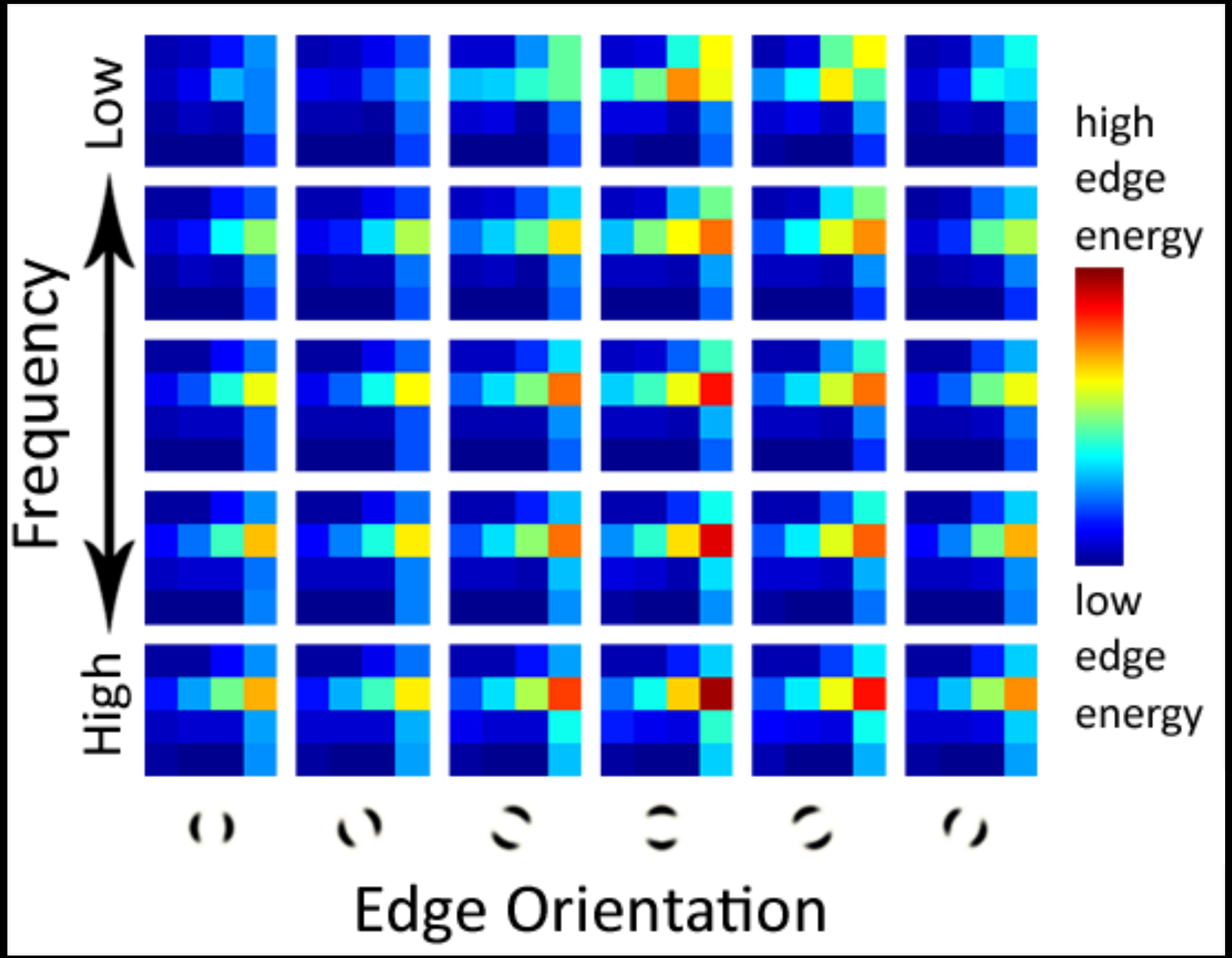
Scene Descriptor



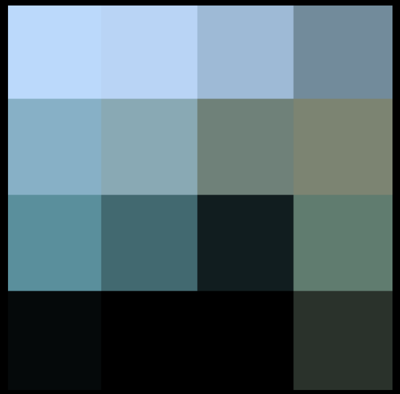


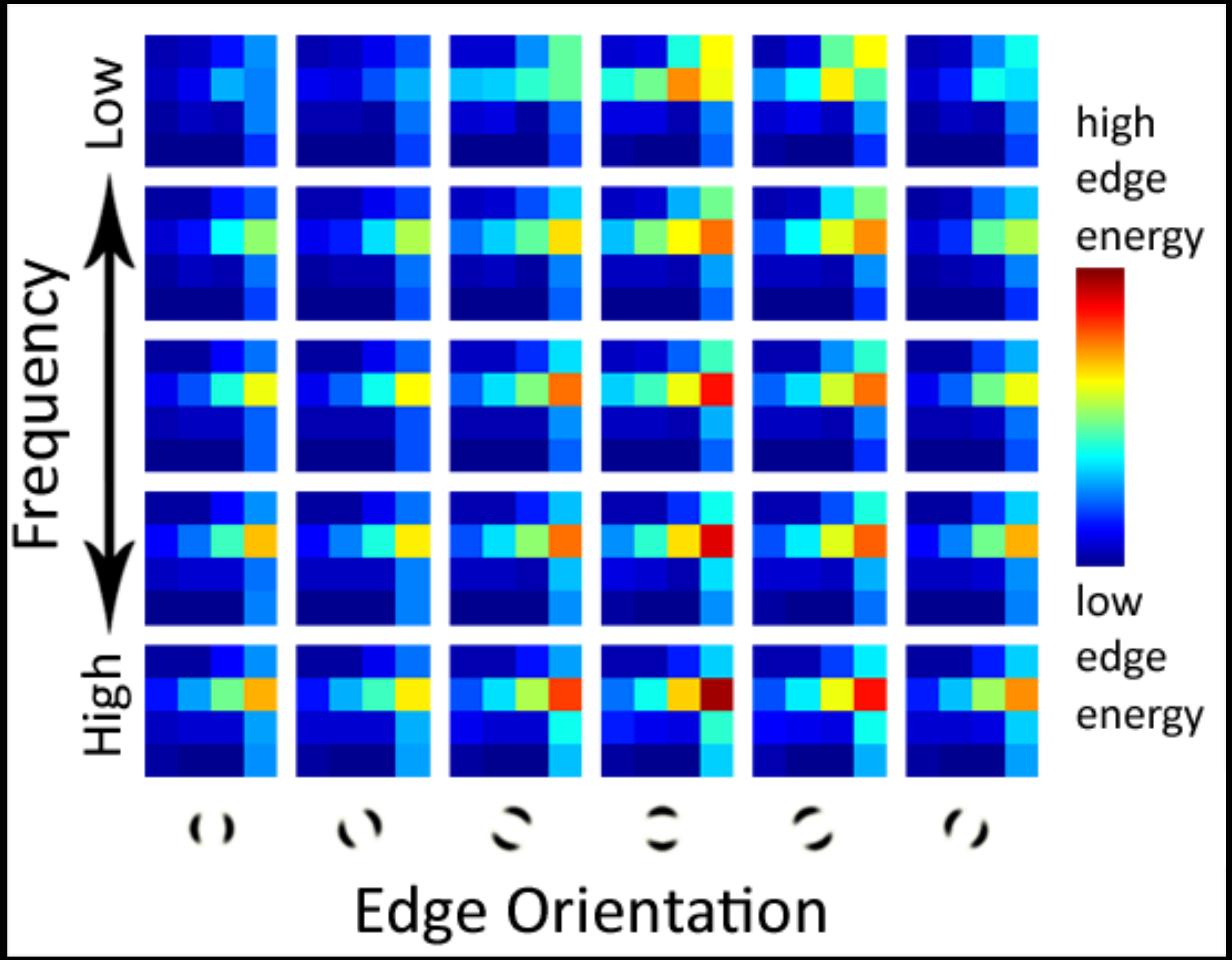
Scene Descriptor



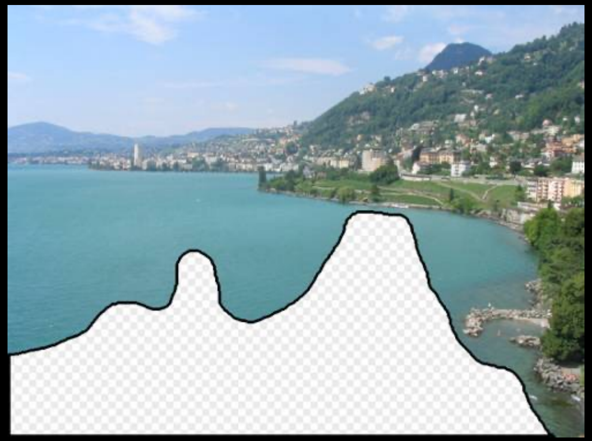


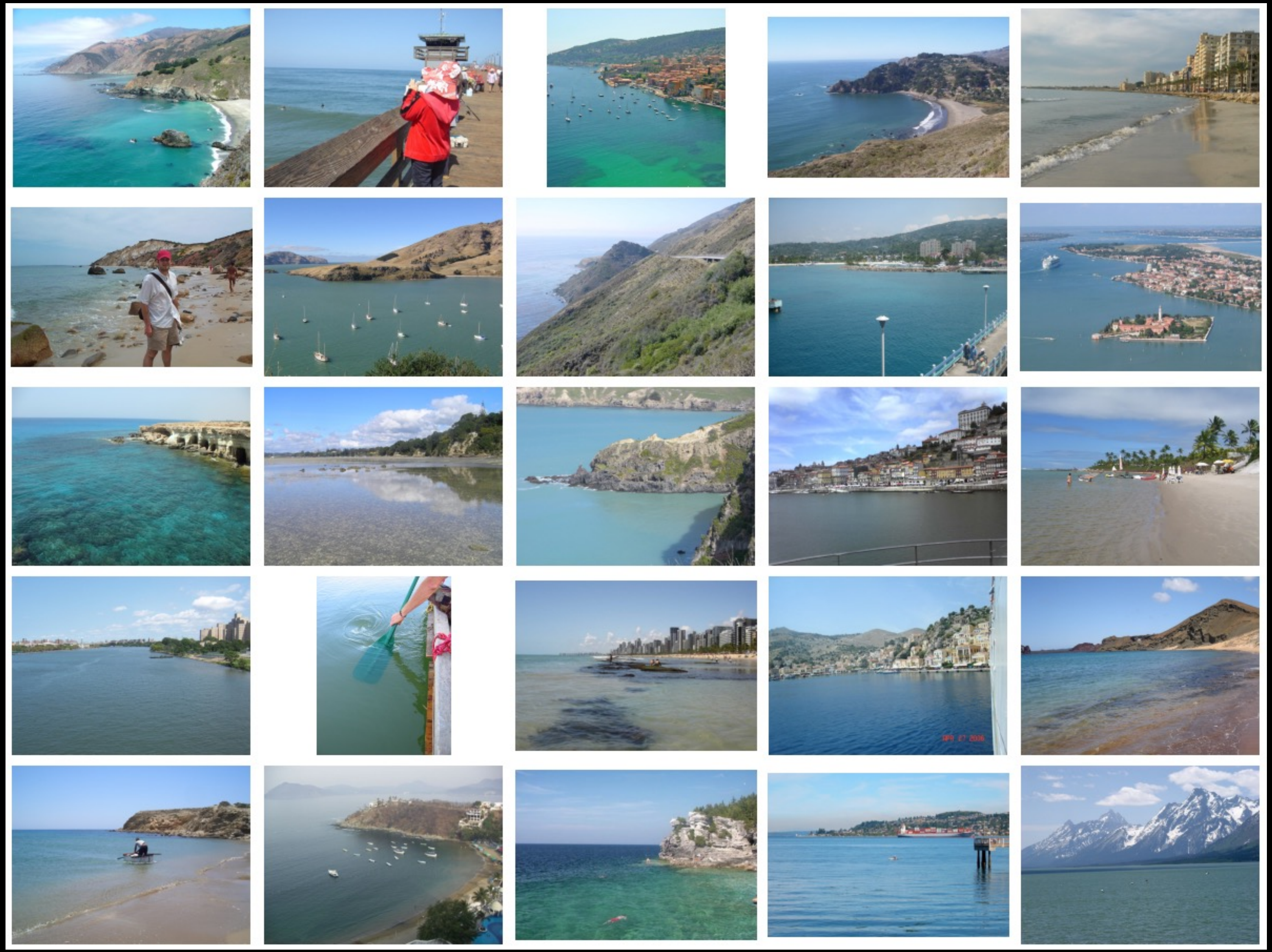
Scene Descriptor



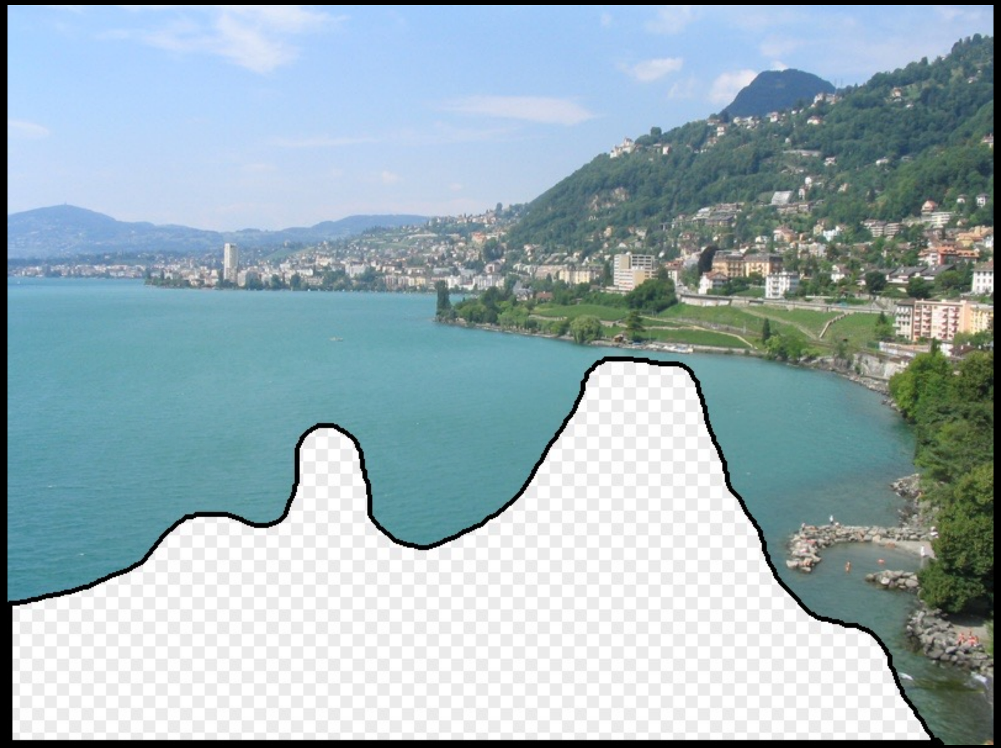


2 Million Flickr Images





Context Matching



Graph cut + Poisson blending

Image Blending

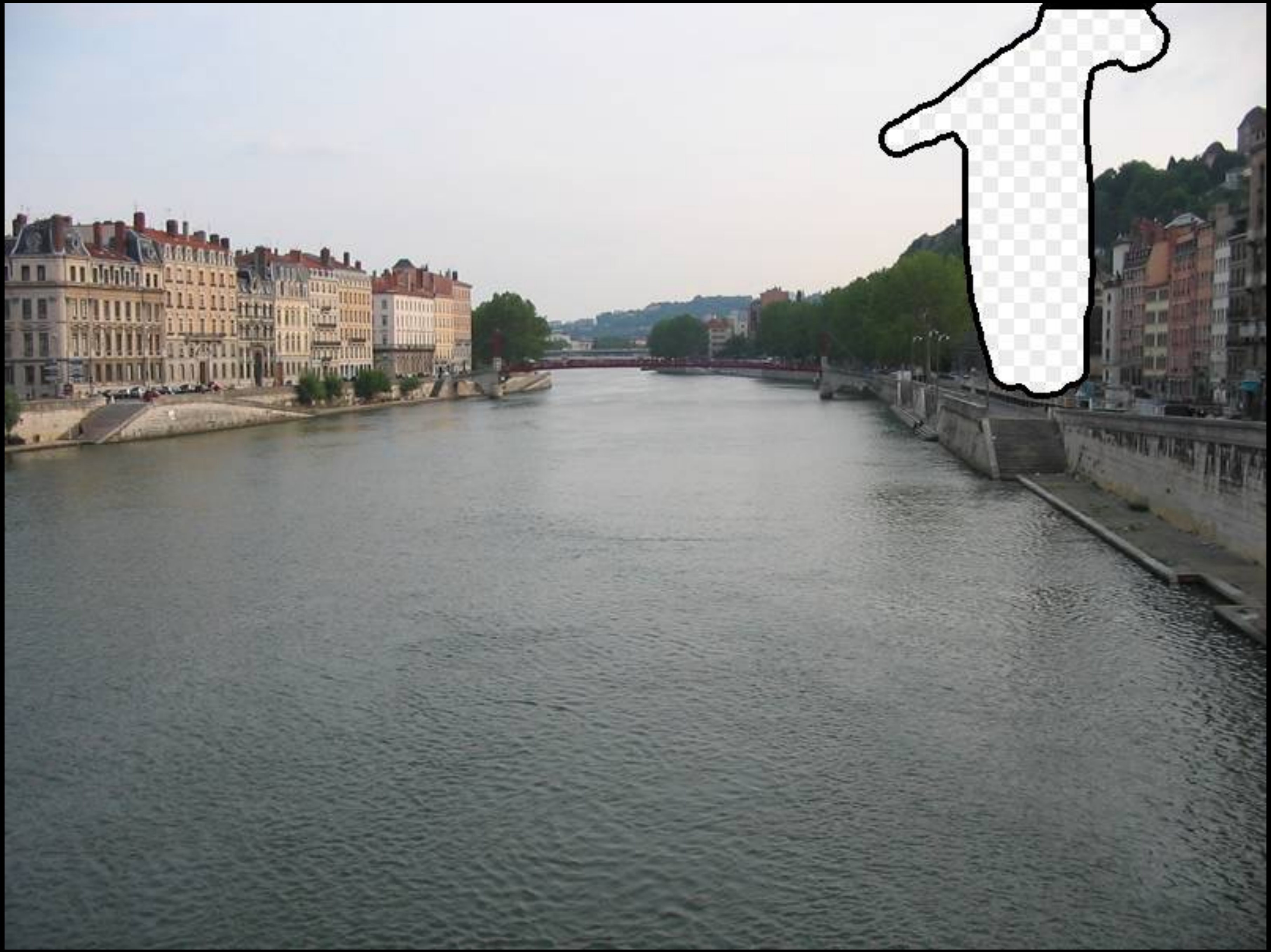
Poisson Image Blending

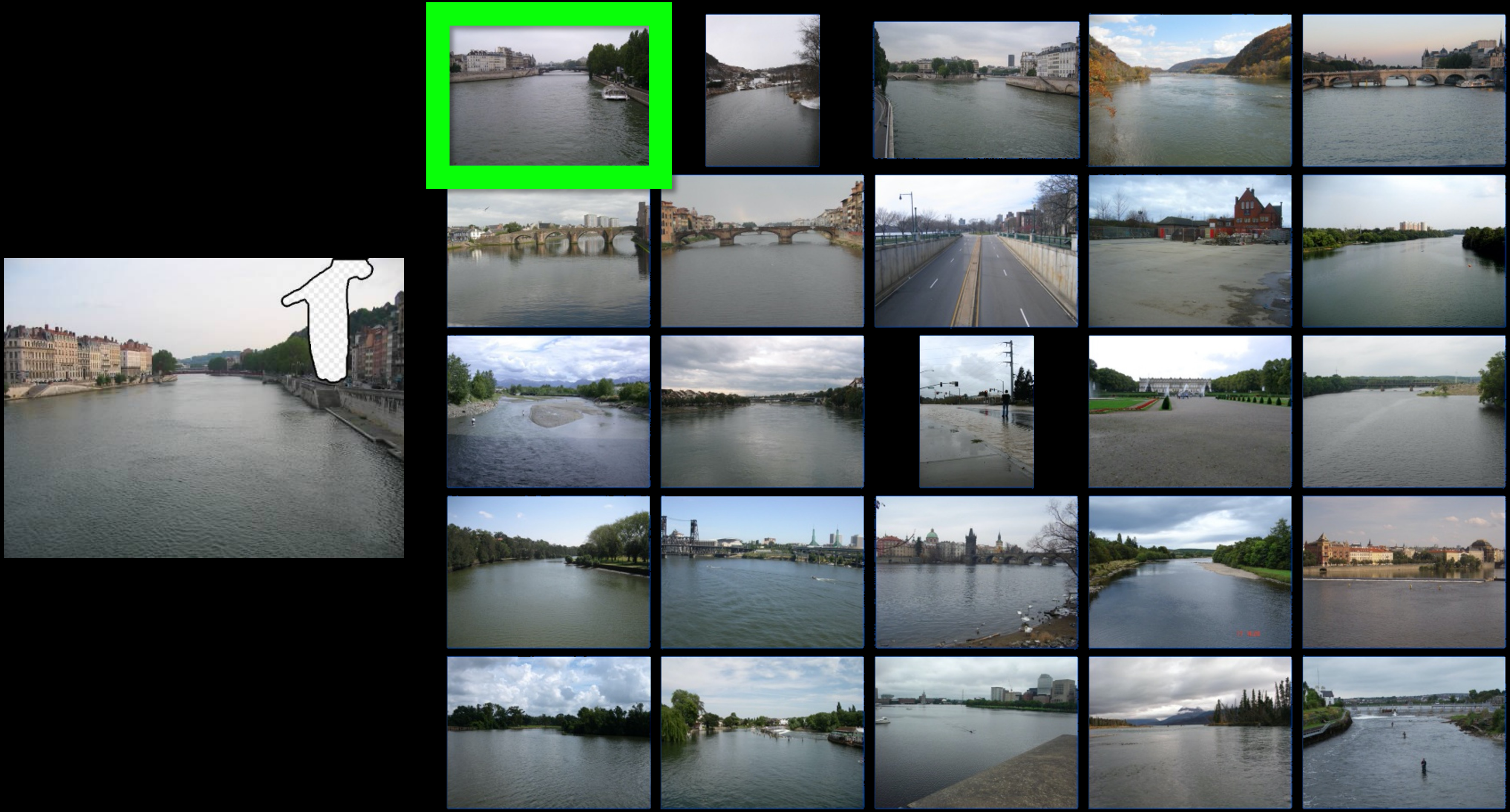
sources destinations cloning seamless cloning

sources/destinations cloning seamless cloning

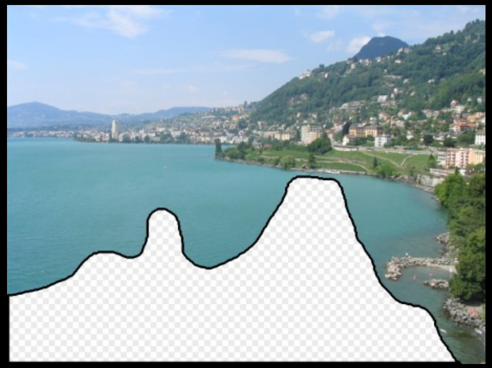
More details in the later lectures.

More results



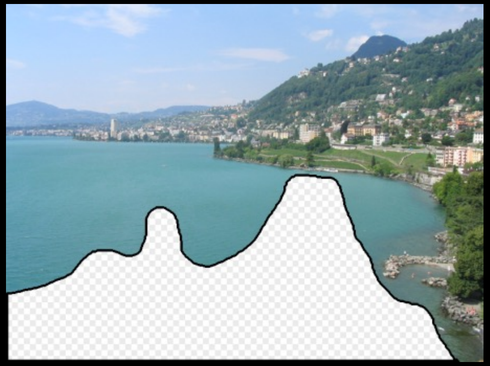


Why does it work?





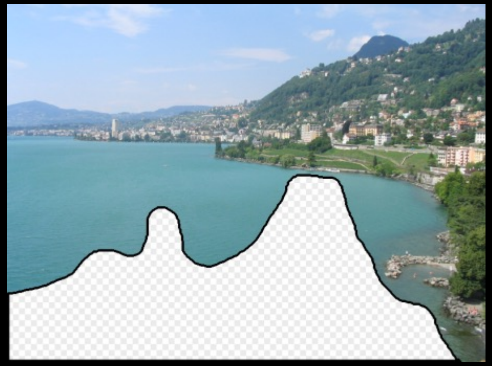






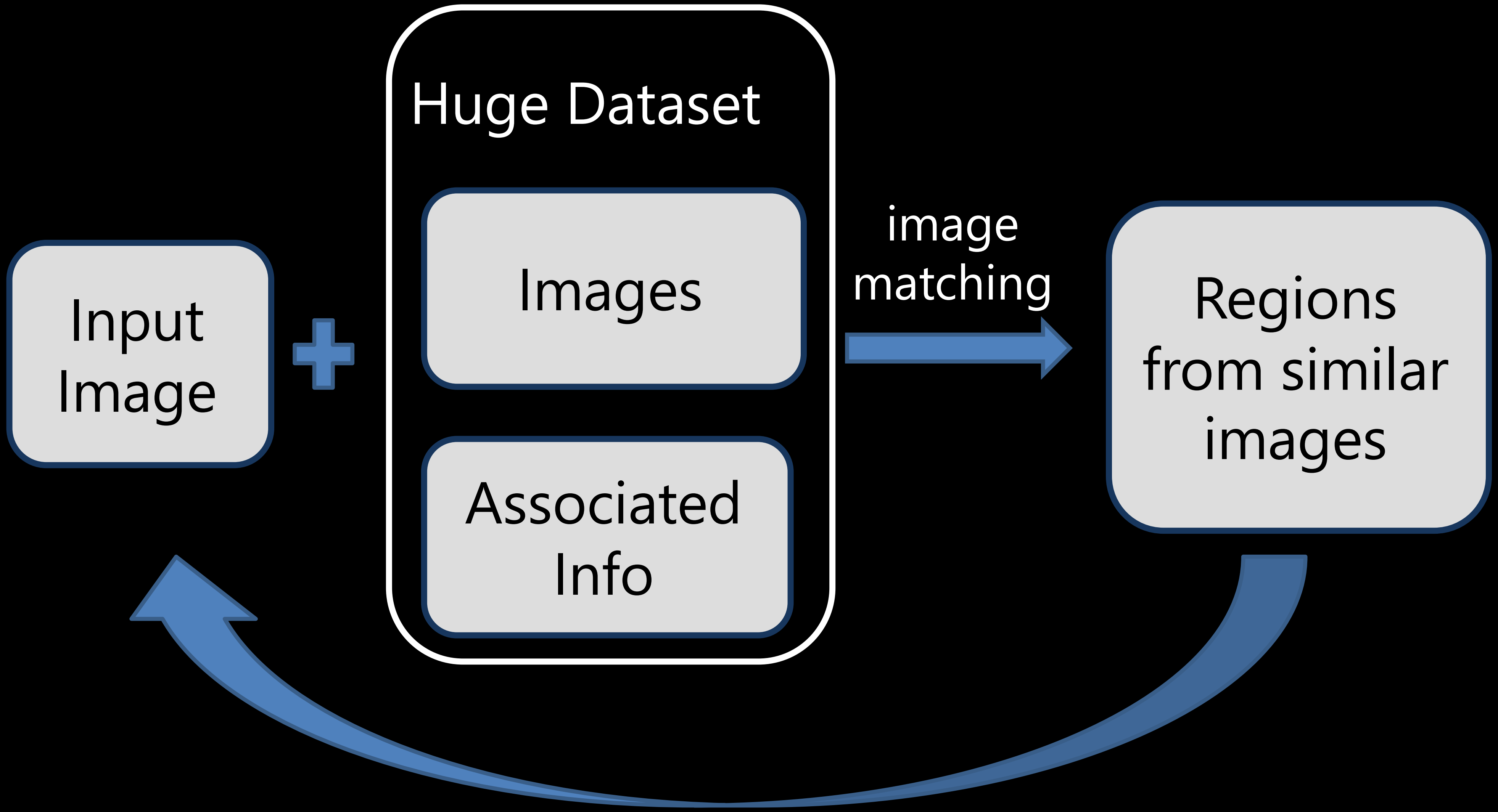




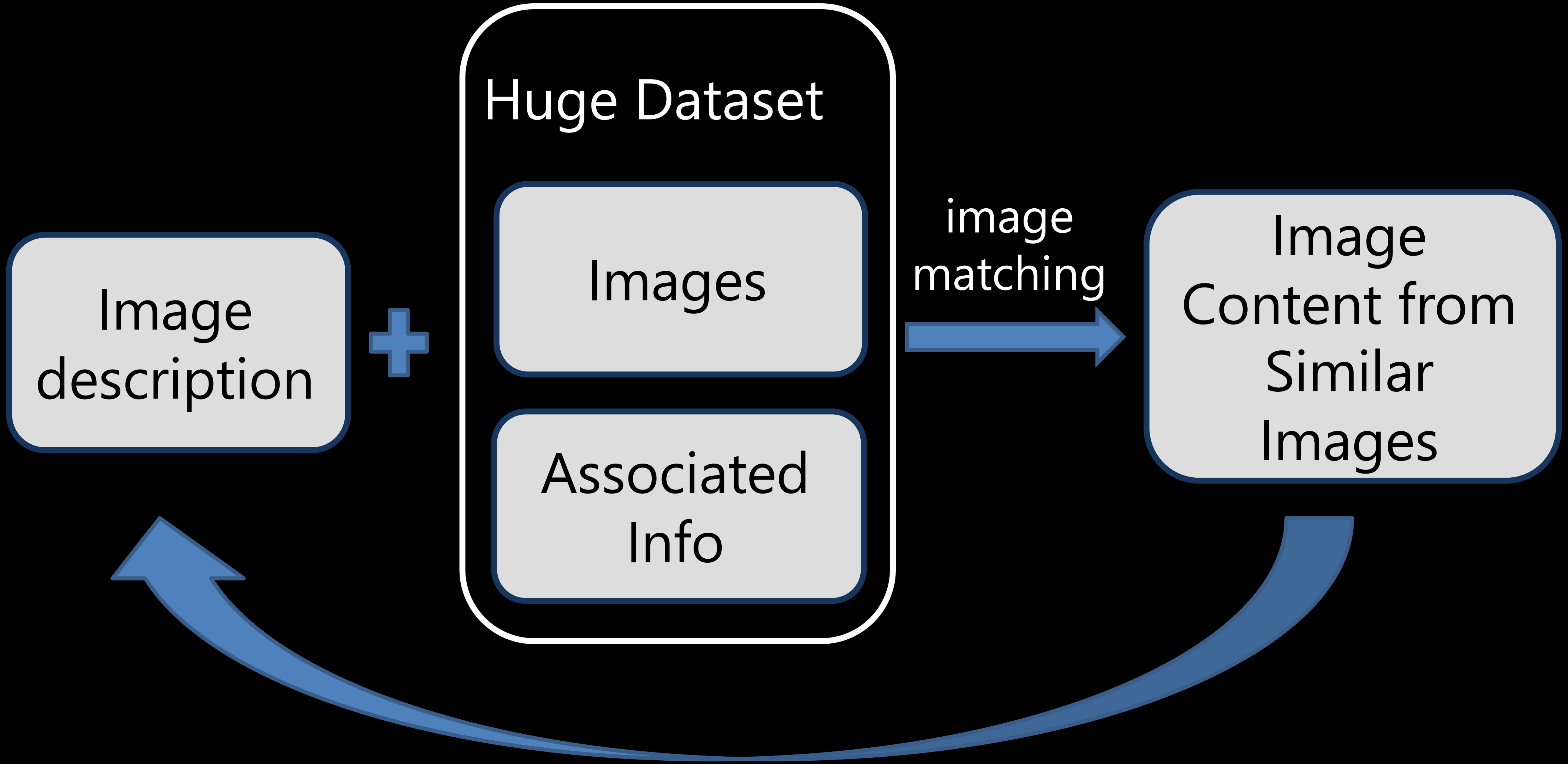


Recap: Using lots of data!



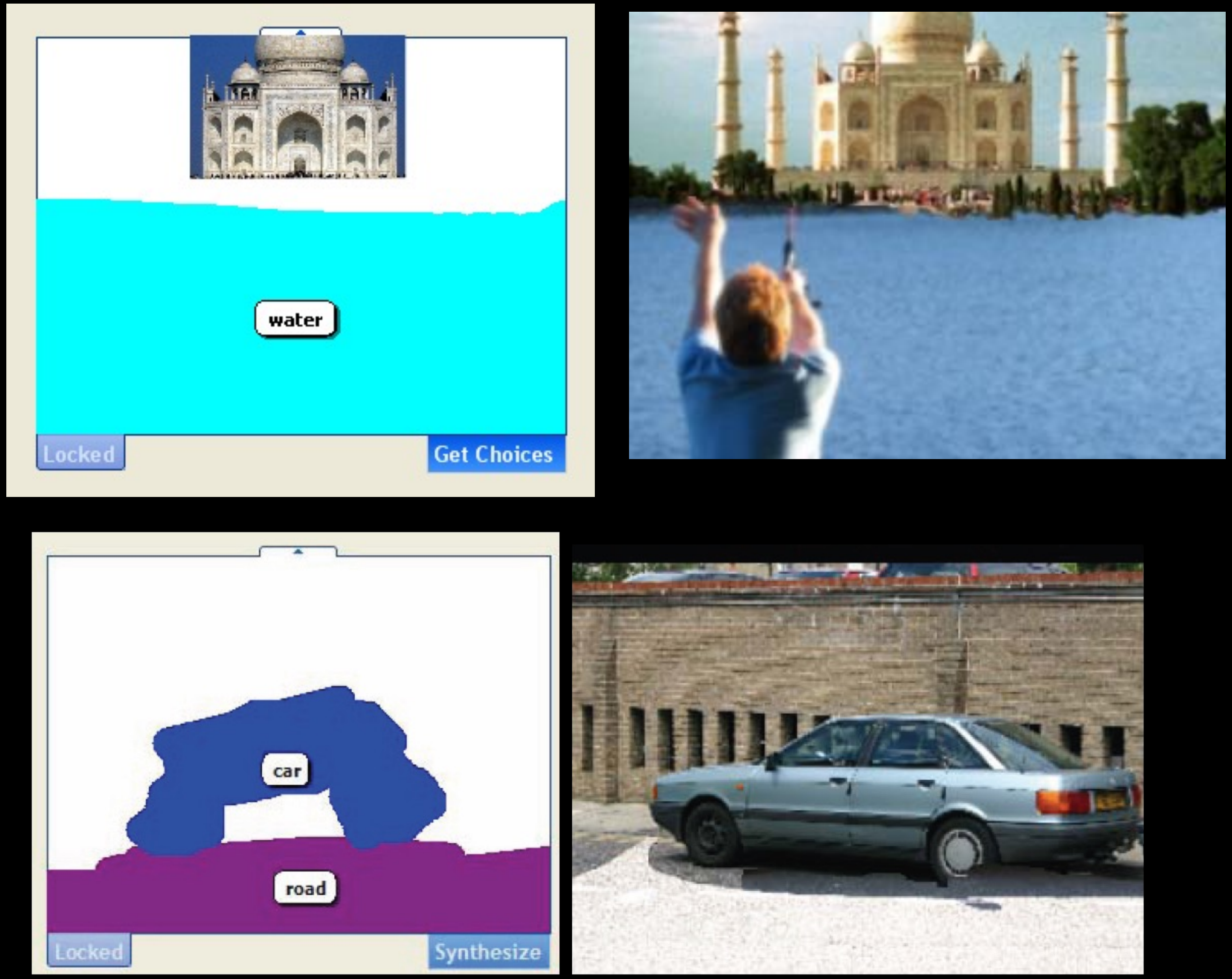
Trick: If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

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

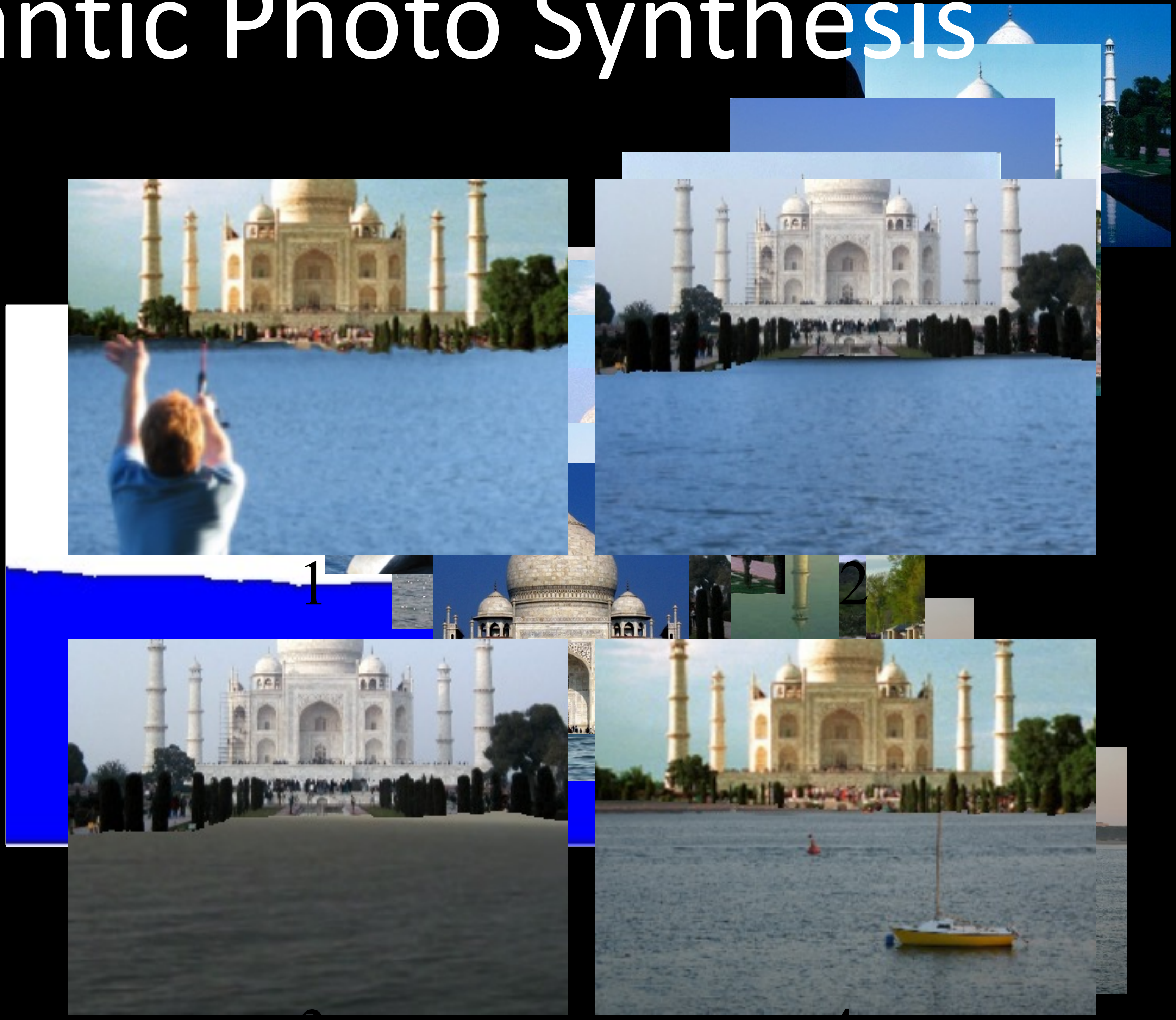
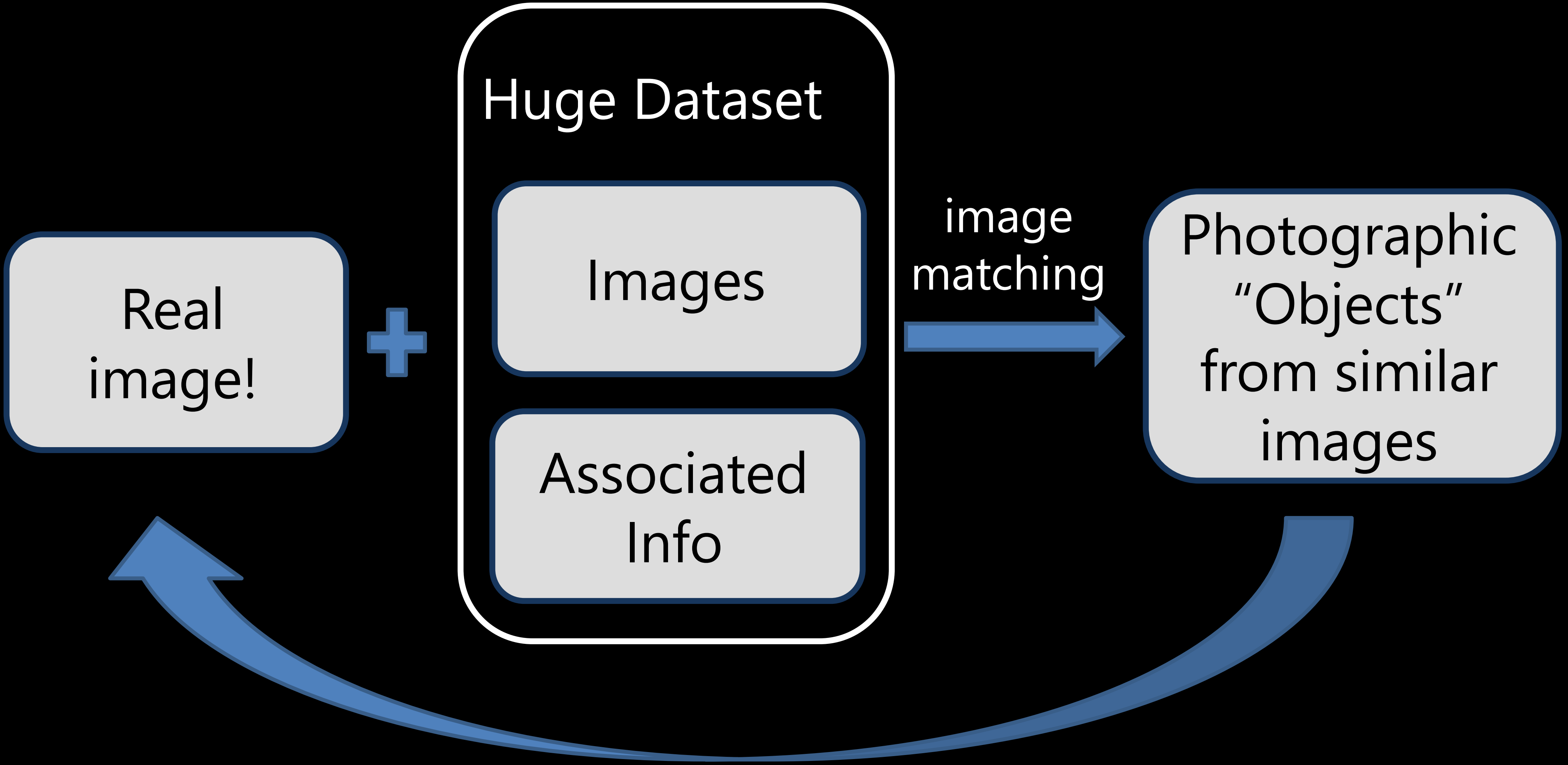


Photo Clip Art



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 [SIGGRAPH 2007]

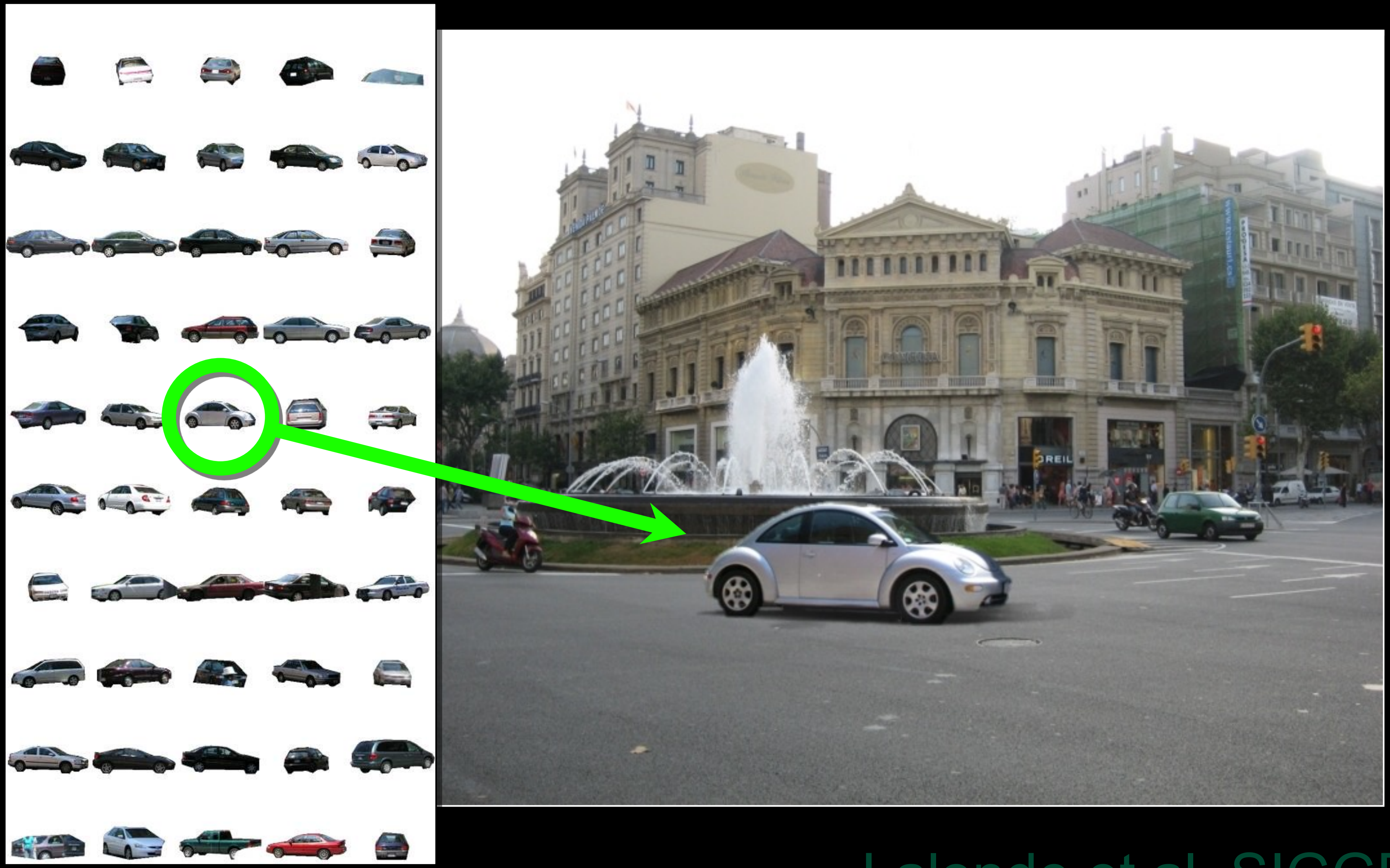
Inserting a single object -- still very hard!

- object size, orientation
- scene illumination

[Lalonde et al, SIGGRAPH 2007]

Photo Clip Art

Use database to find well-fitting object



Lalonde et al, SIGGRAPH 2007

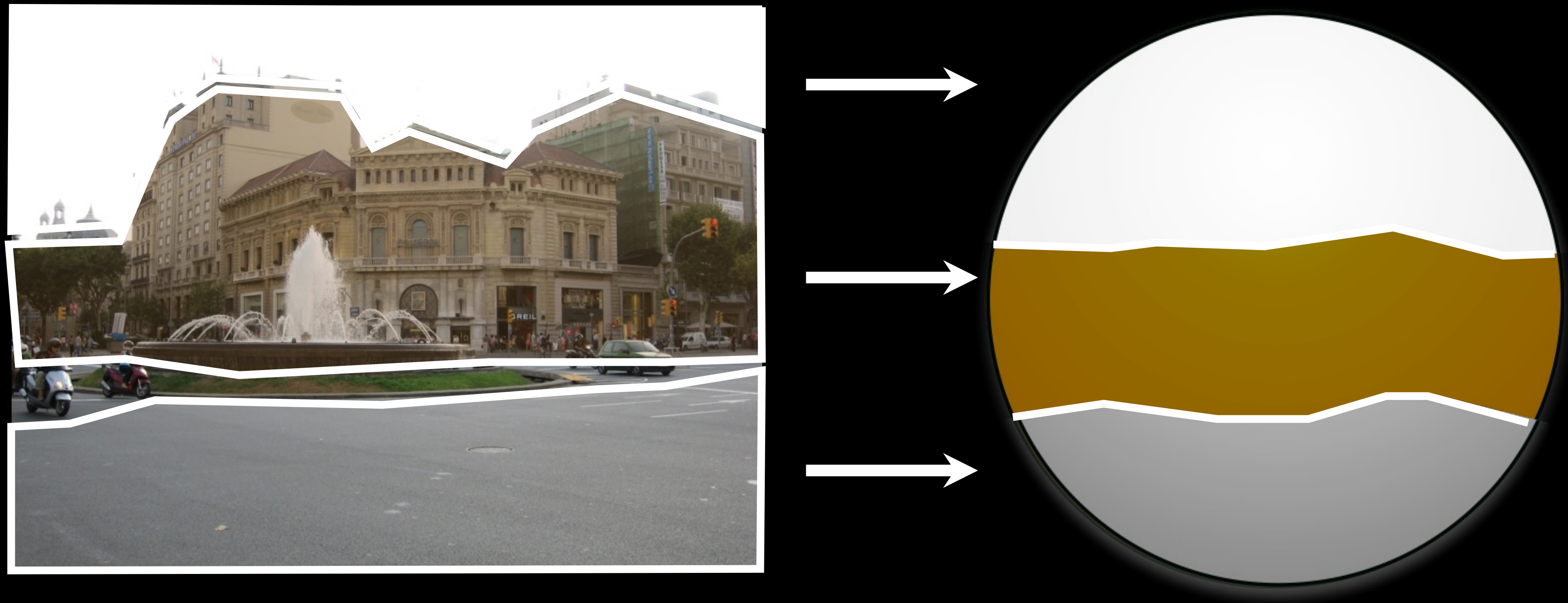
Geometry is not enough

Illumination context

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

Database image

Environment map rough approximation



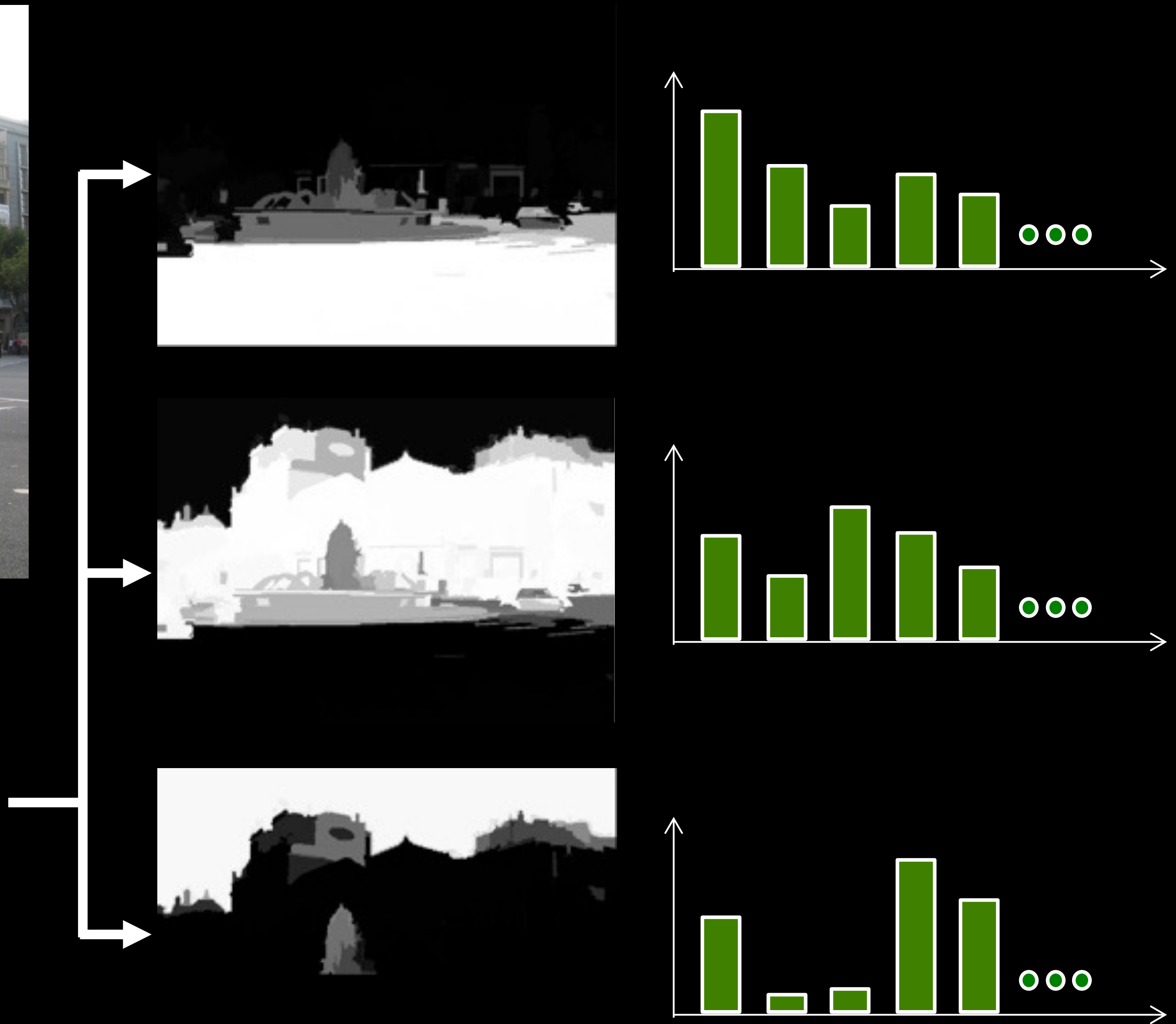
Illumination context

Database image

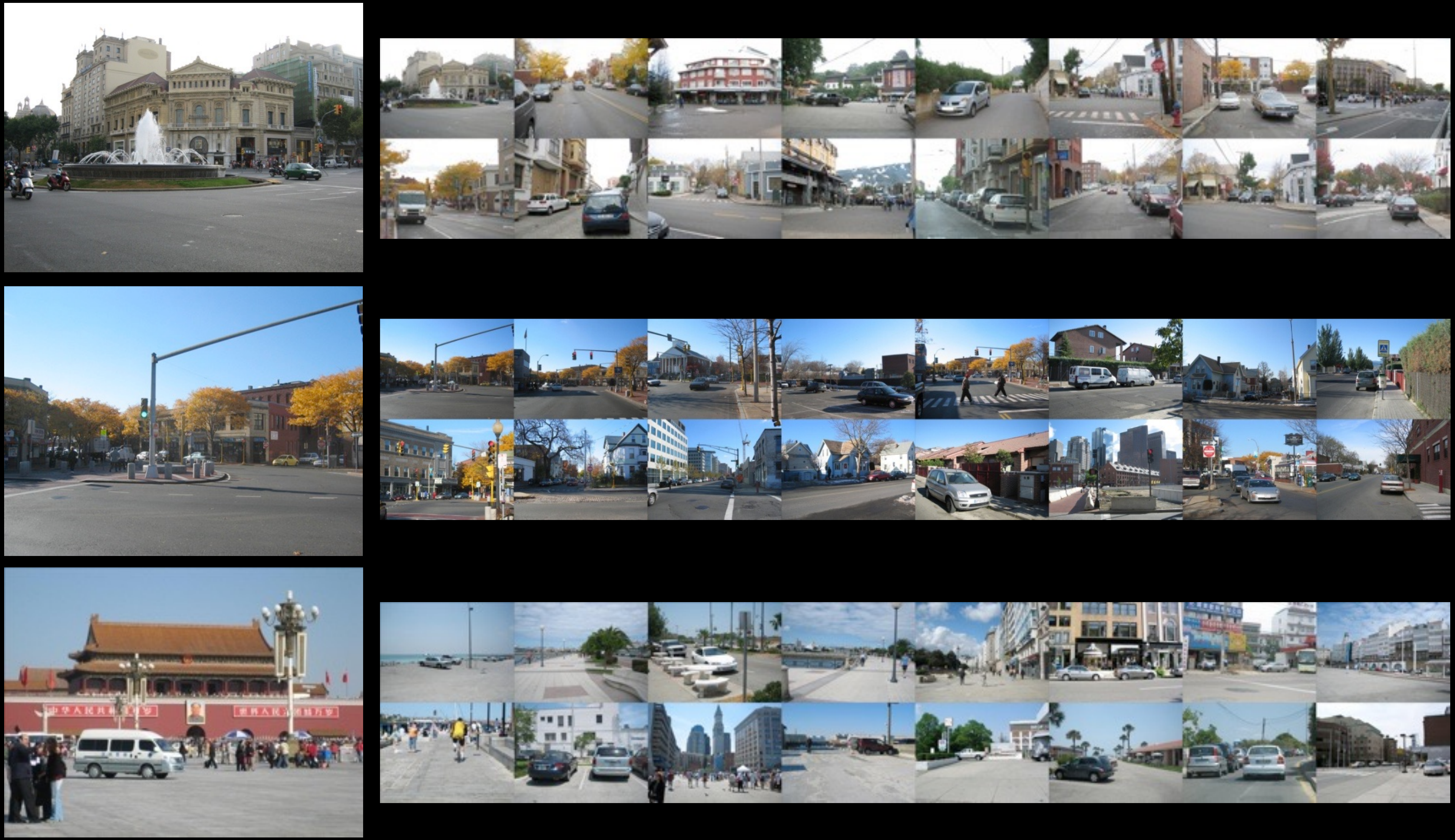
Automatic Photo Popup
Hoiem et al., SIGGRAPH ’05

P(pixel|class)

CIE L*a*b* histograms



Illumination nearest-neighbors



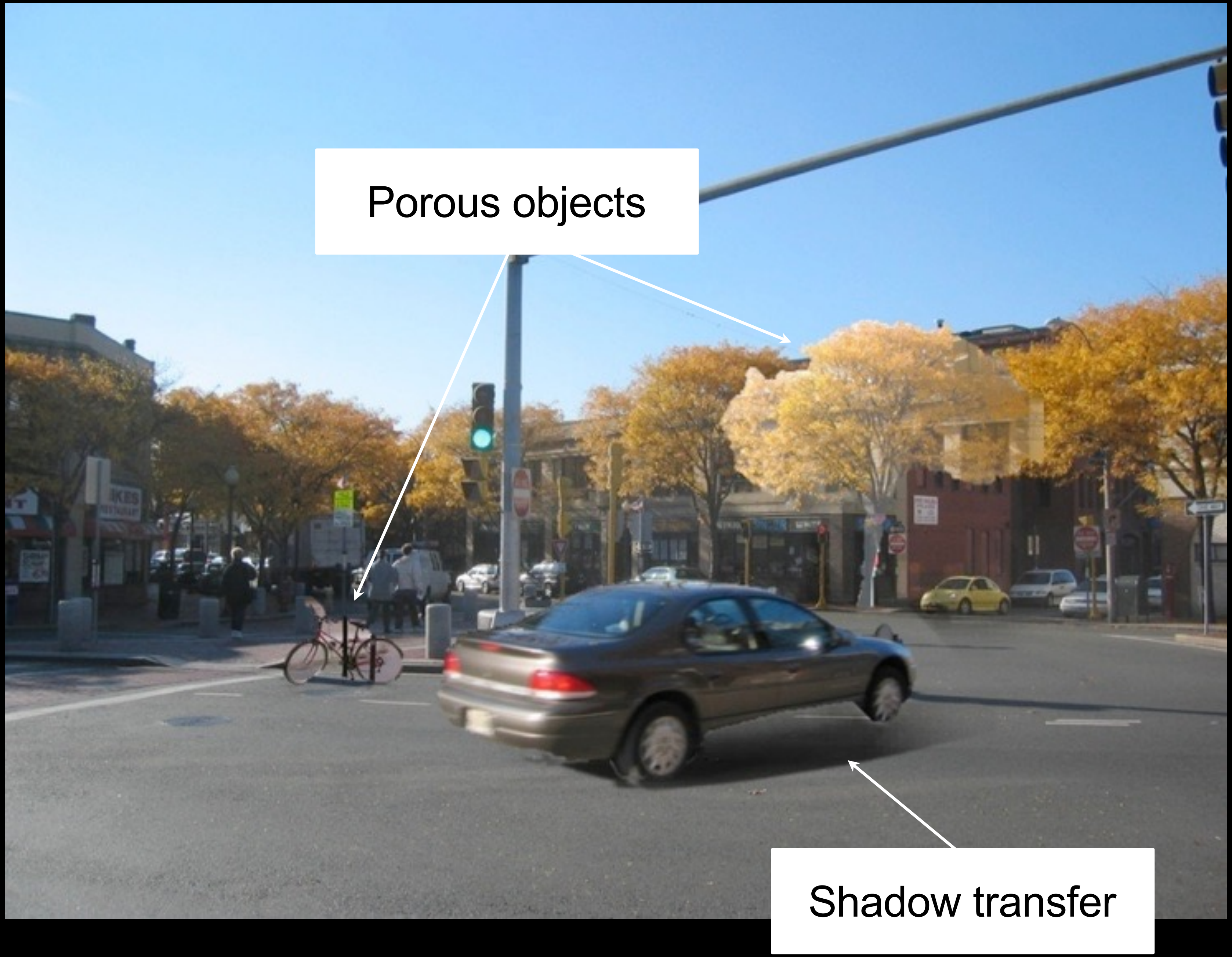
Street accident

Bridge

Painting

Alley

Failure cases



Failure cases

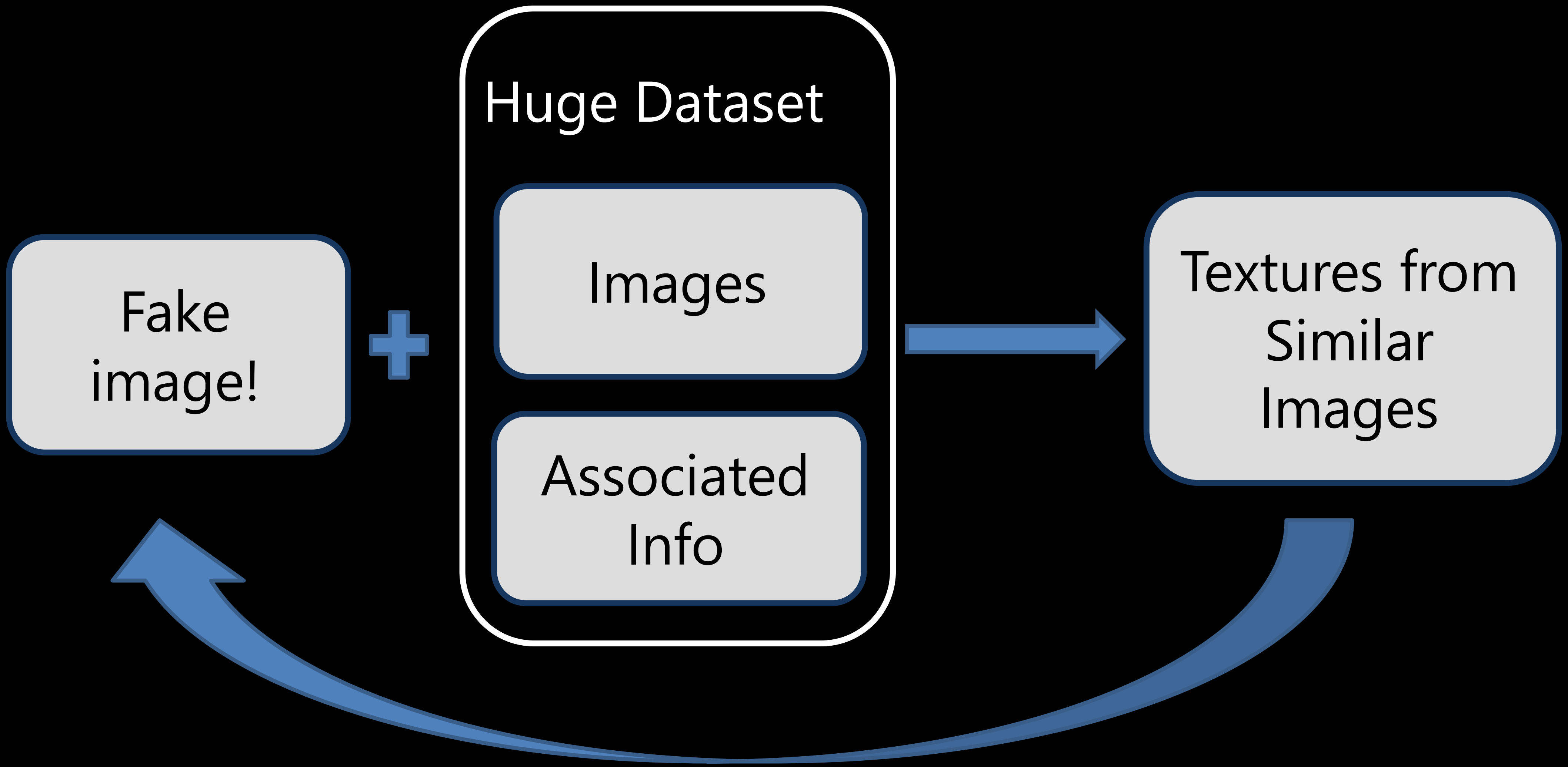
Review (Data-driven Graphics)

- How to find images given a user query?
  - Image Retrieval (Gist descriptor? Deep learning?)
  - Big data helps!
- How to combine images?
  - Image blending (Poisson Equation)

How to Combine Images?

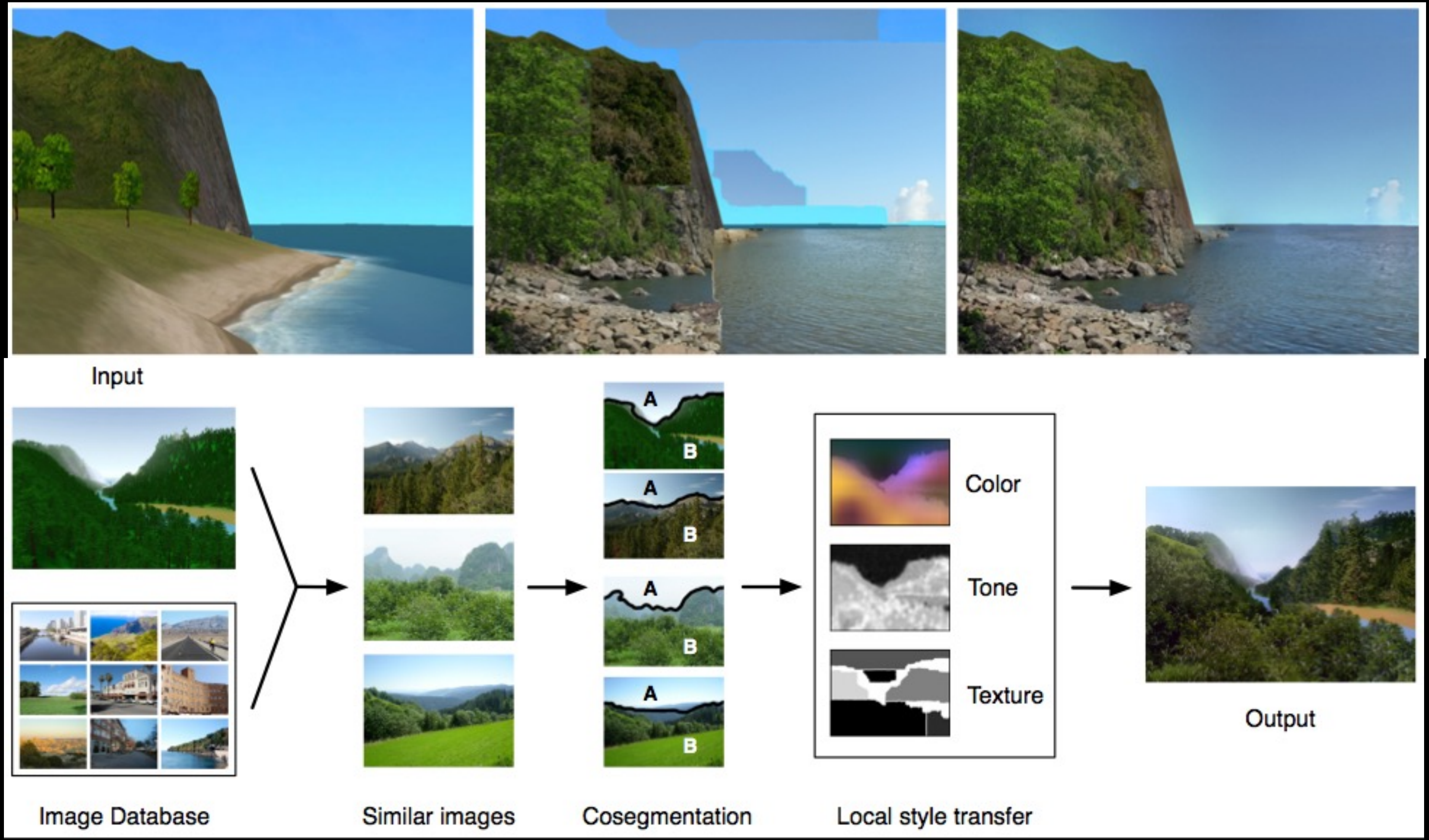
- Image Blending/Compositing:
  - Each piece comes from a different image.
  - Need to hide the boundary

CG2Real



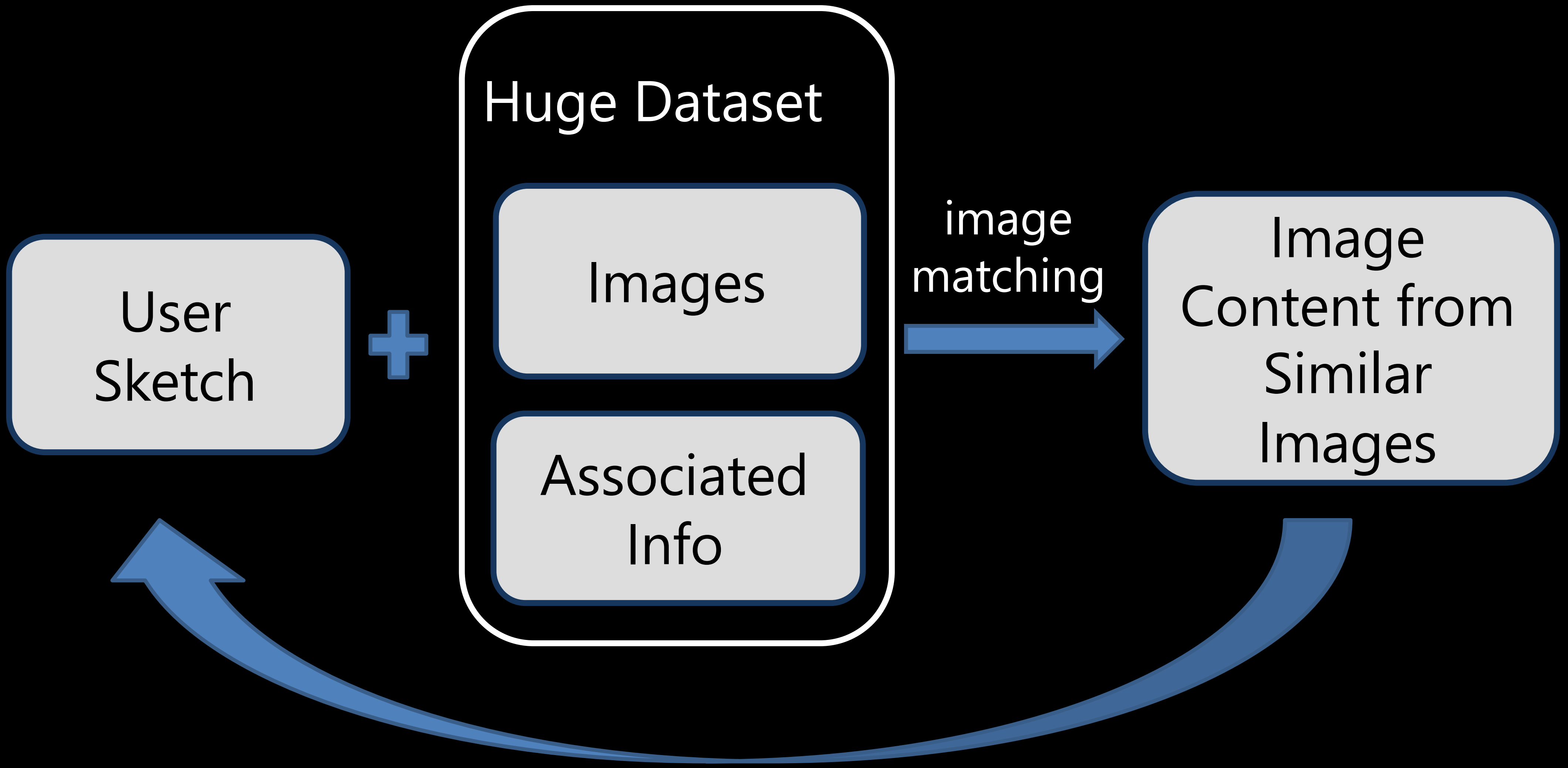
M. K. Johnson, K. Dale, S. Avidan, H. Pfister, W. T. Freeman, and W. Matusik, “CG2Real: Improving the realism of computer generated images using a large collection of photographs,” IEEE TVCG, 2010.

CG2Real



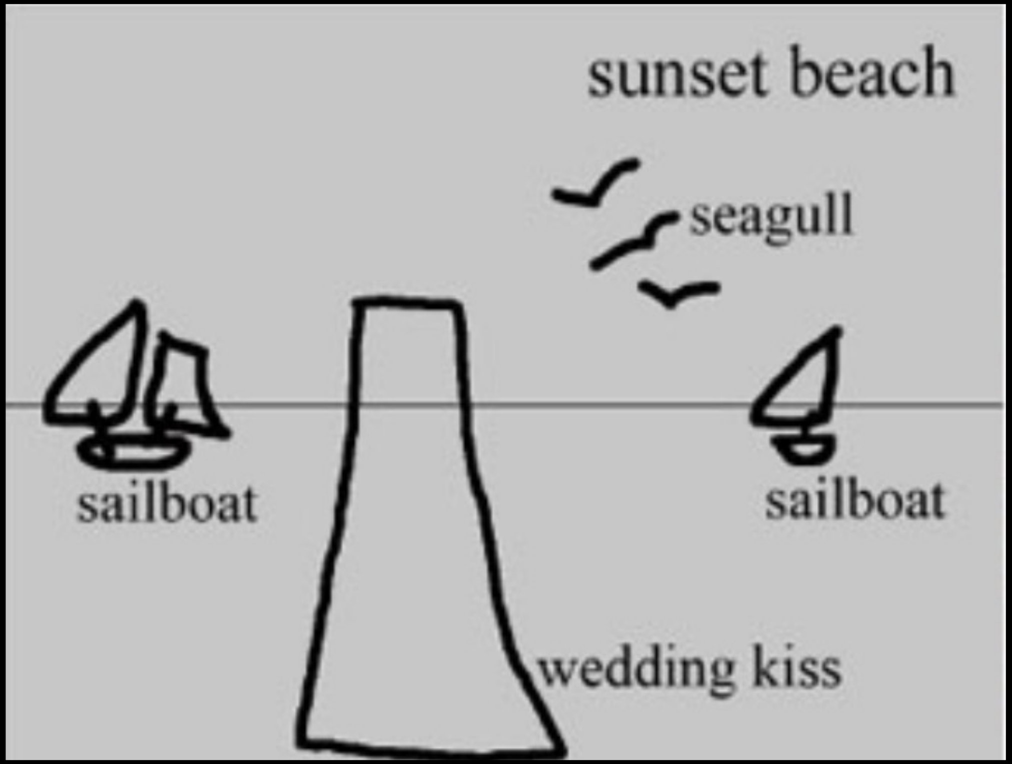
M. K. Johnson, K. Dale, S. Avidan, H. Pfister, W. T. Freeman, and W. Matusik, "CG2Real: Improving the realism of computer generated images using a large collection of photographs," IEEE TVCG, 2010.

Sketch2Photo



Sketch2Photo

Sketch-based image retrieval + image blending



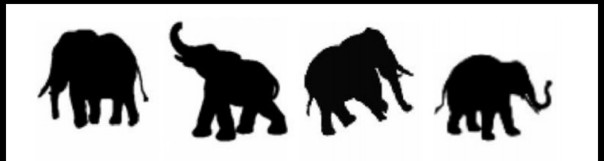
User Input

Database images

Output

Sketch2Photo: Internet Image Montage. Tao et al. SIGGRAPH Asia 2009.

Shape retrieval [Belongie et al. PAMI 2002]

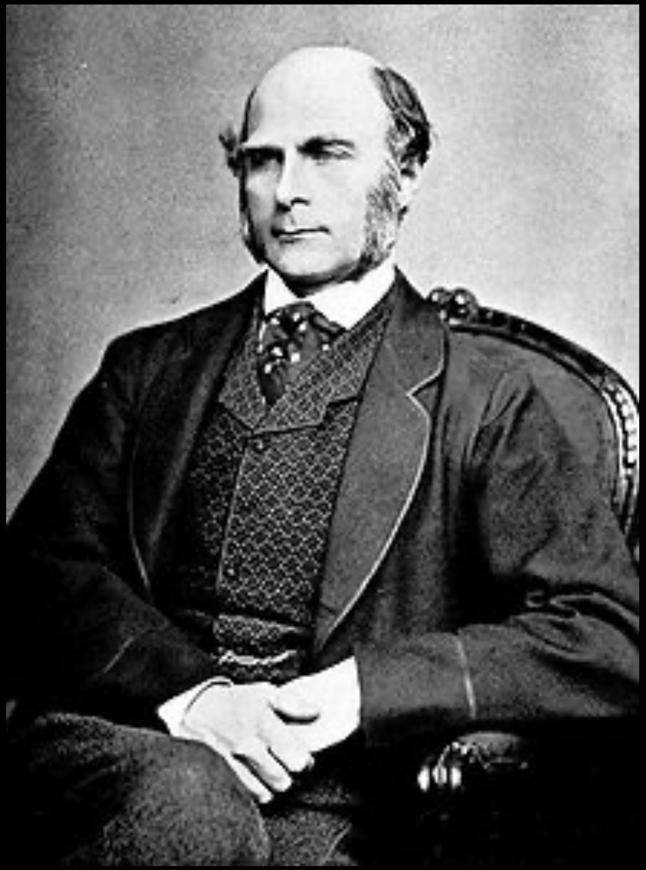


Only based on the extracted contour

How to Combine Images?

- Image Blending/Compositing:
  - Each piece comes from a different image.
  - Need to hide the boundary
- Image Averaging
  - Each pixel is a combination of multiple pixels from different images.
  - Special case: Cross-Dissolve (two images)

Image Averaging



Sir Francis Galton

1822-1911

Multiple Individuals

Composite

[Galton, “Composite Portraits”, Nature, 1878]

Average Images in Art

"60 passagers de 2e classe du metro, entre 9h et 11h"

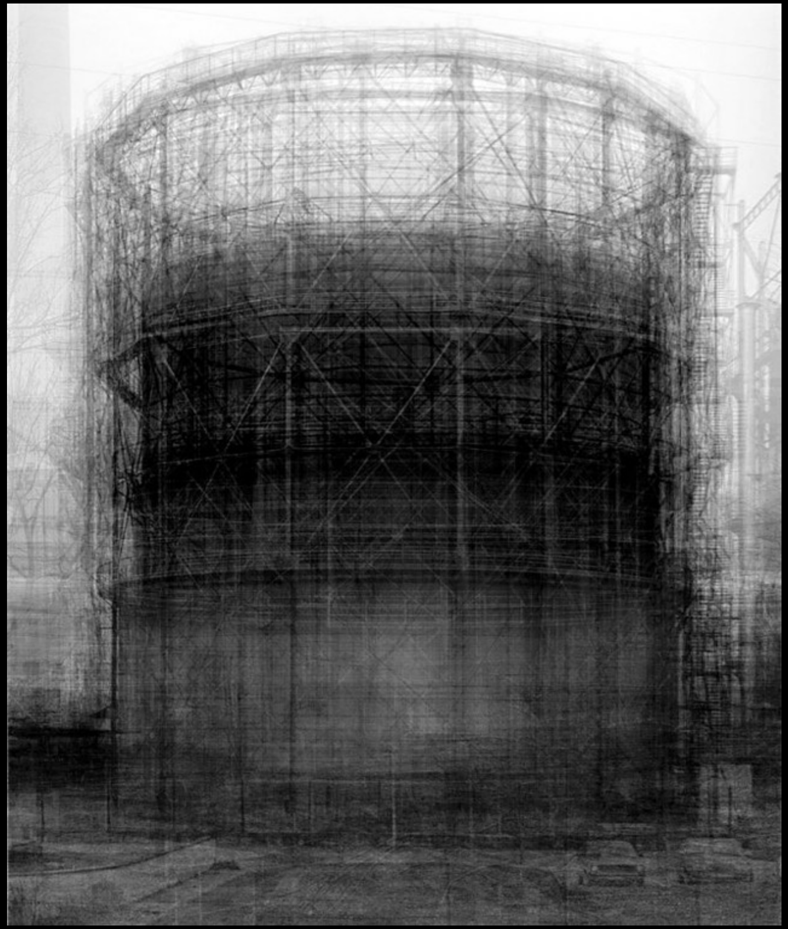
(1985)

Krzysztof Pruszkowski

"Dynamism of a cyclist"

(2001)

James Campbell



"Spherical type gasholders"

(2004)

Idris Khan

"100 Special Moments" (2004) by Jason Salavon

Newlyweds

Little Leaguer

Kids with Santa

Not so simple…

Jason Salavon

“Kids with Santa”

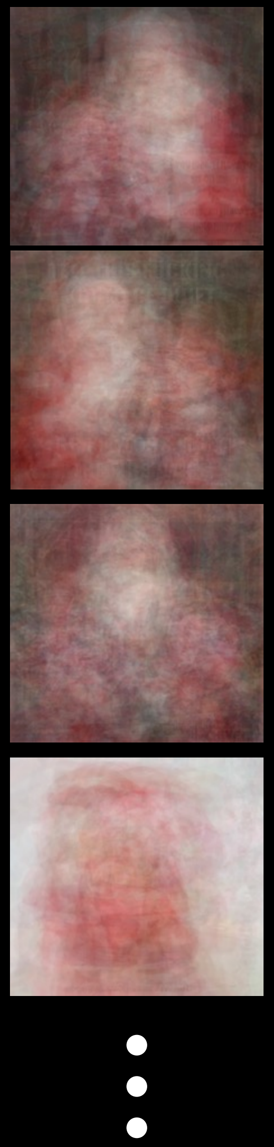
Google query result:

“`kids with Santa`”

Automatic Average

Why Difficult?

Google results



Visual Modes

Misaligned

“Object-Centric Averages” (2001) by Antonio Torralba

…

Manual Annotation and Alignment

Average Image

With Alignment

Goal:

An interactive system to rapidly explore and align a large image collection using ***image averaging***

Zhu, Lee, Efros. AverageExplorer: Interactive Exploration and Alignment of Visual Data Collections, SIGGARPH 2014.

Weighted Averages + Alignment

Overview

Image Collection $\{I_1 \cdots I_N\}$ (e.g. “Kids with Santa” images)

Average I_{avg}

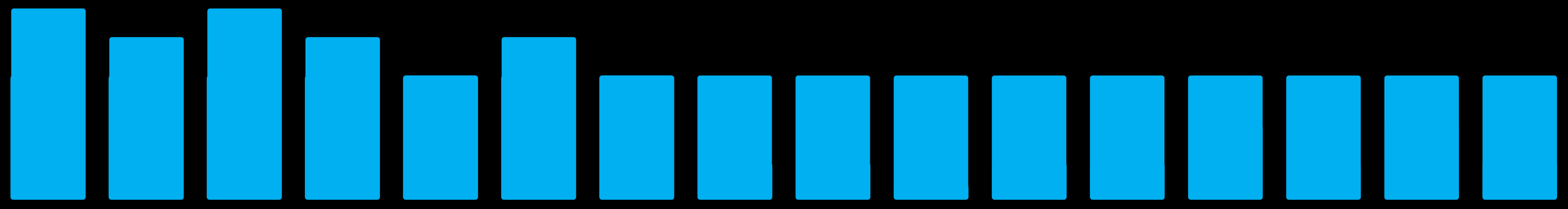
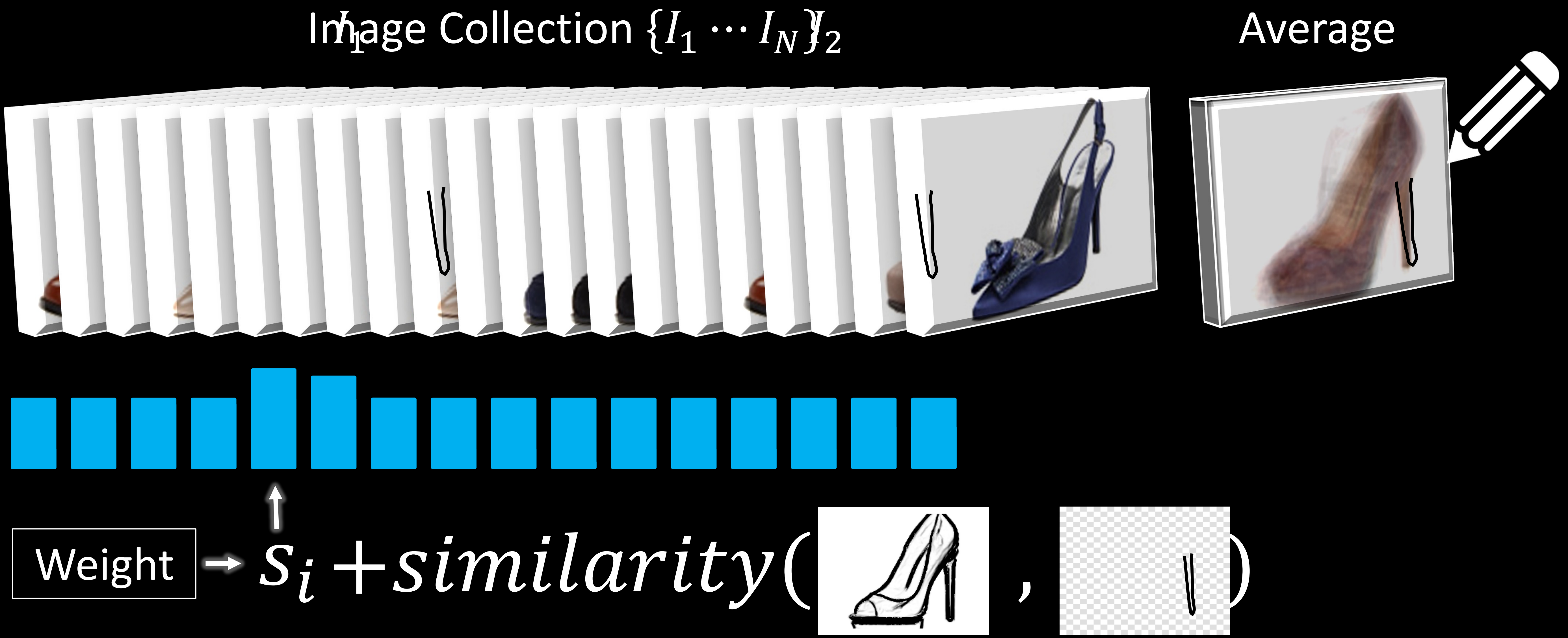


Image Weights $\{s_1 \cdots s_N\}$

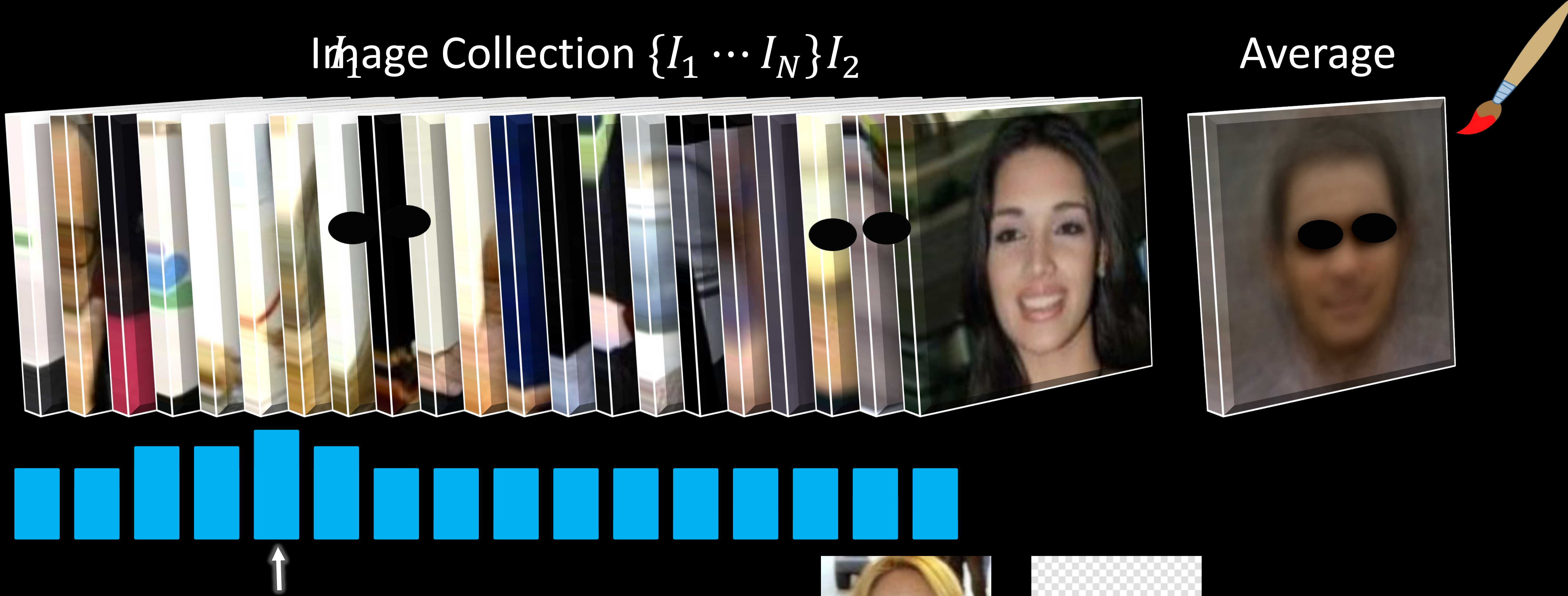
$$I_{avg} = \frac{1}{N}\sum_{i=1}^{N} I_i$$

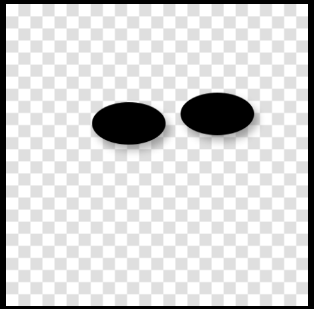
$$I_{avg} = \sum_{i=1}^{N} s_i I_i$$

Sketching Brush



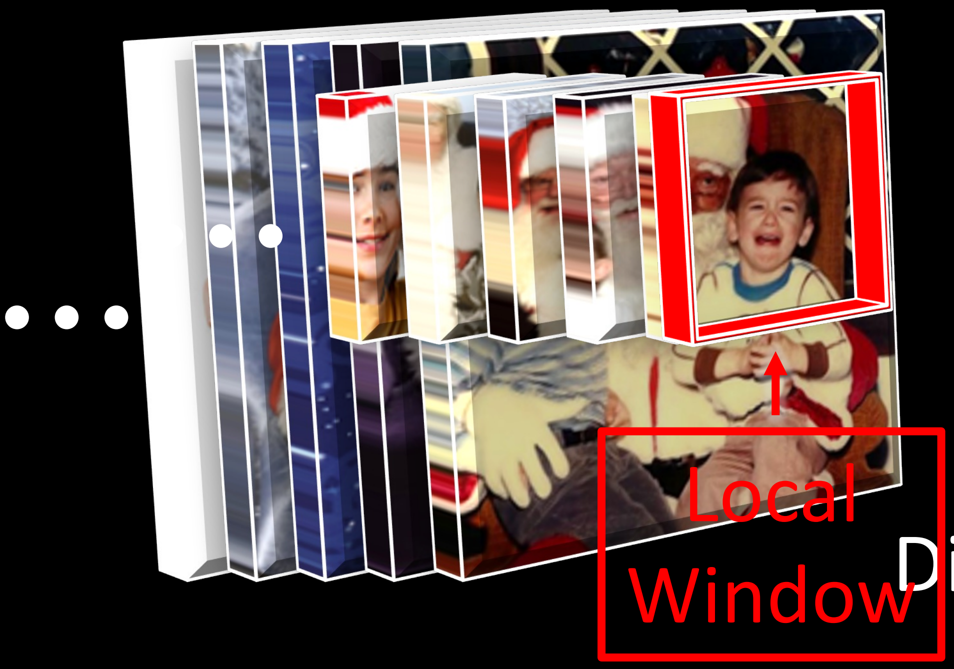
Coloring Brush



Weight → $S_i + similarity($  ,  $)$

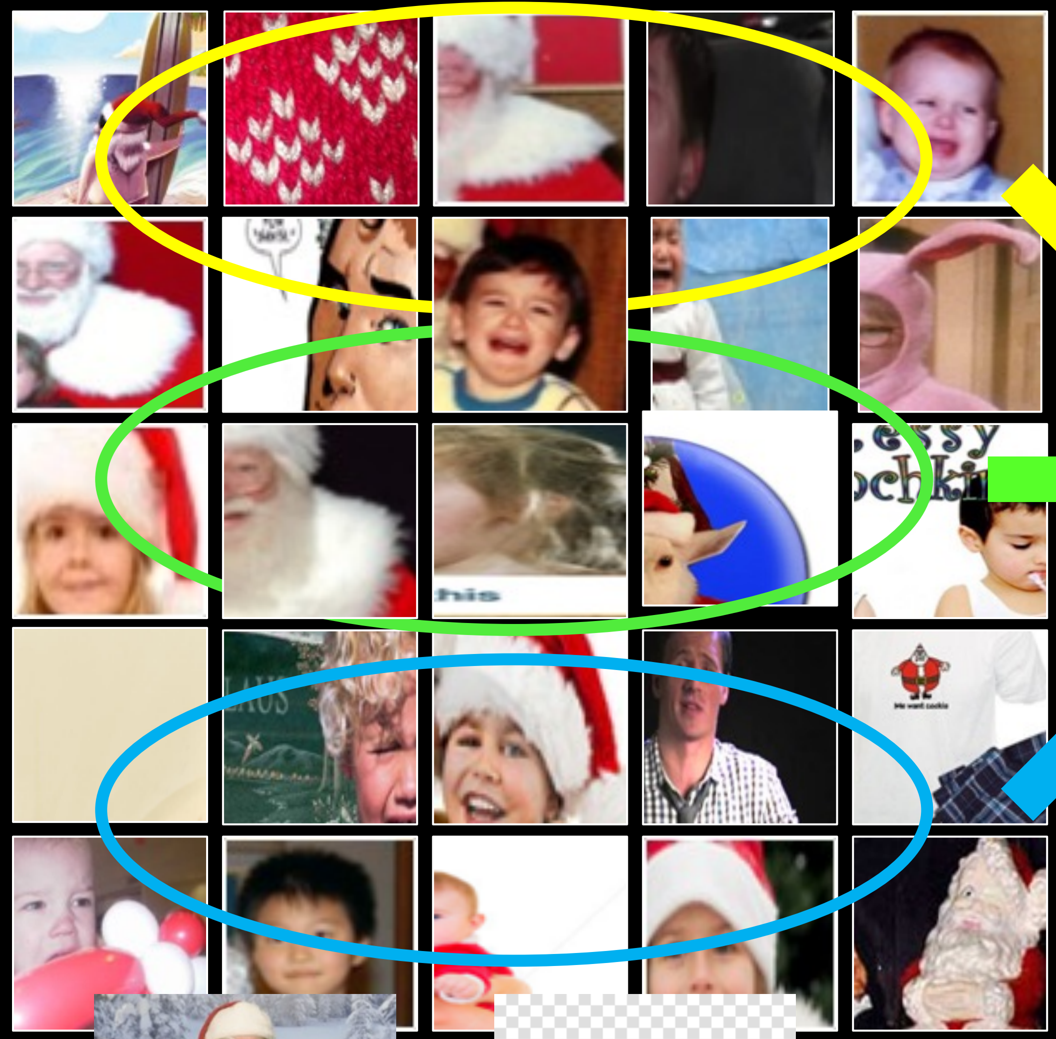
Explorer Brush: Select a Local Mode

N Local Patches

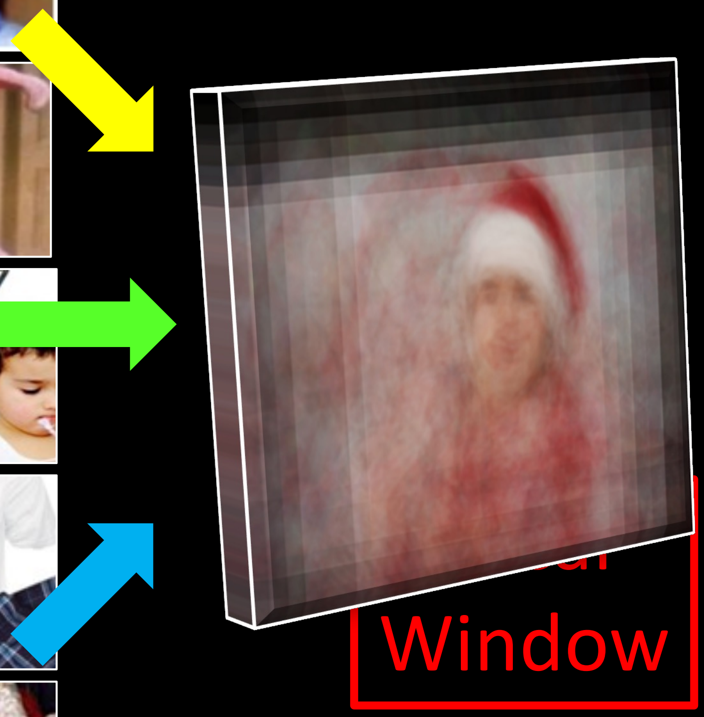


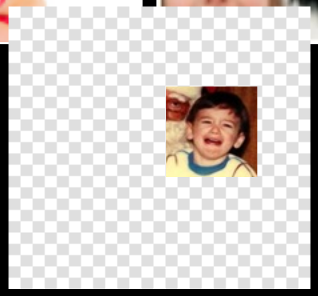
Visual Mode Discovery

Local Visual Modes



Average



$s_i = s_i + similarity($  ,  $)$

Mid-level Discriminative Patch Discovery [Doersch et al. 2012]

Weighted Averages + Alignment

Image Alignment

Image Warping

Moving Least Square [Schaefer et al. 2006]

Different Cat Breeds (Simple Average)


Abyssinian


Sphynx

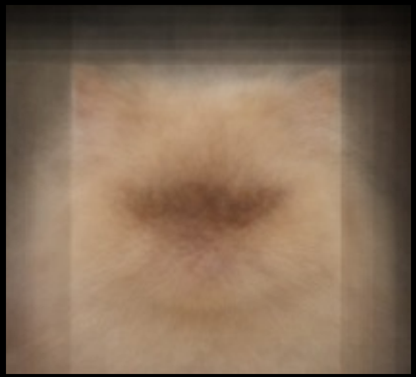

Birman


Bombay


Egyptian Mau


Ragdoll


British Shorthair


Persian


Maine Coon


Russian Blue


Siamese


Bengal

Data from [Parkhi et al. 2012]

Different Cat Breeds (Our Result)


Abyssinian


Sphynx


Birman


Bombay


Egyptian Mau


Ragdoll


British Shorthair


Persian


Maine Coon


Russian Blue

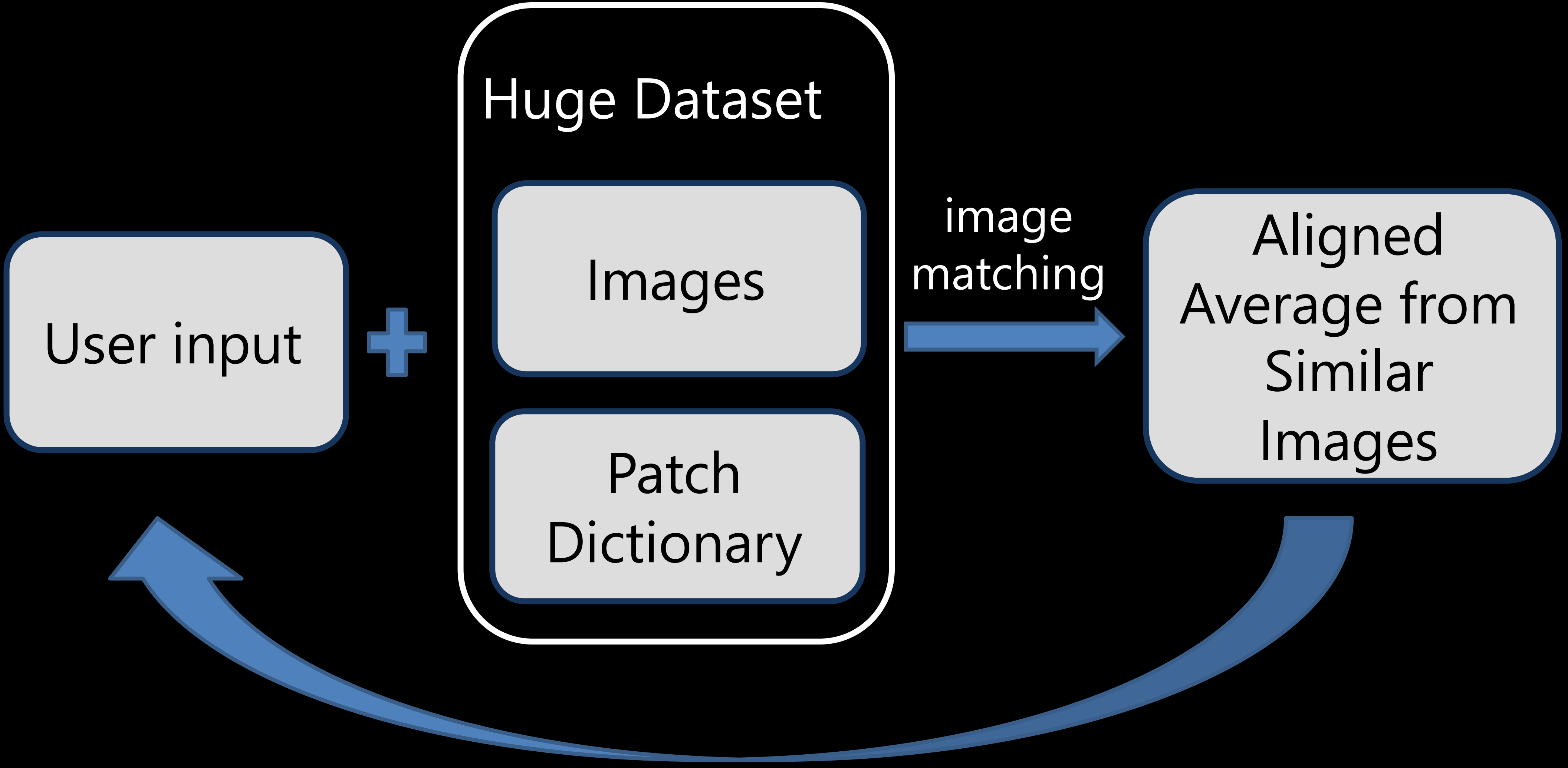

Siamese


Bengal

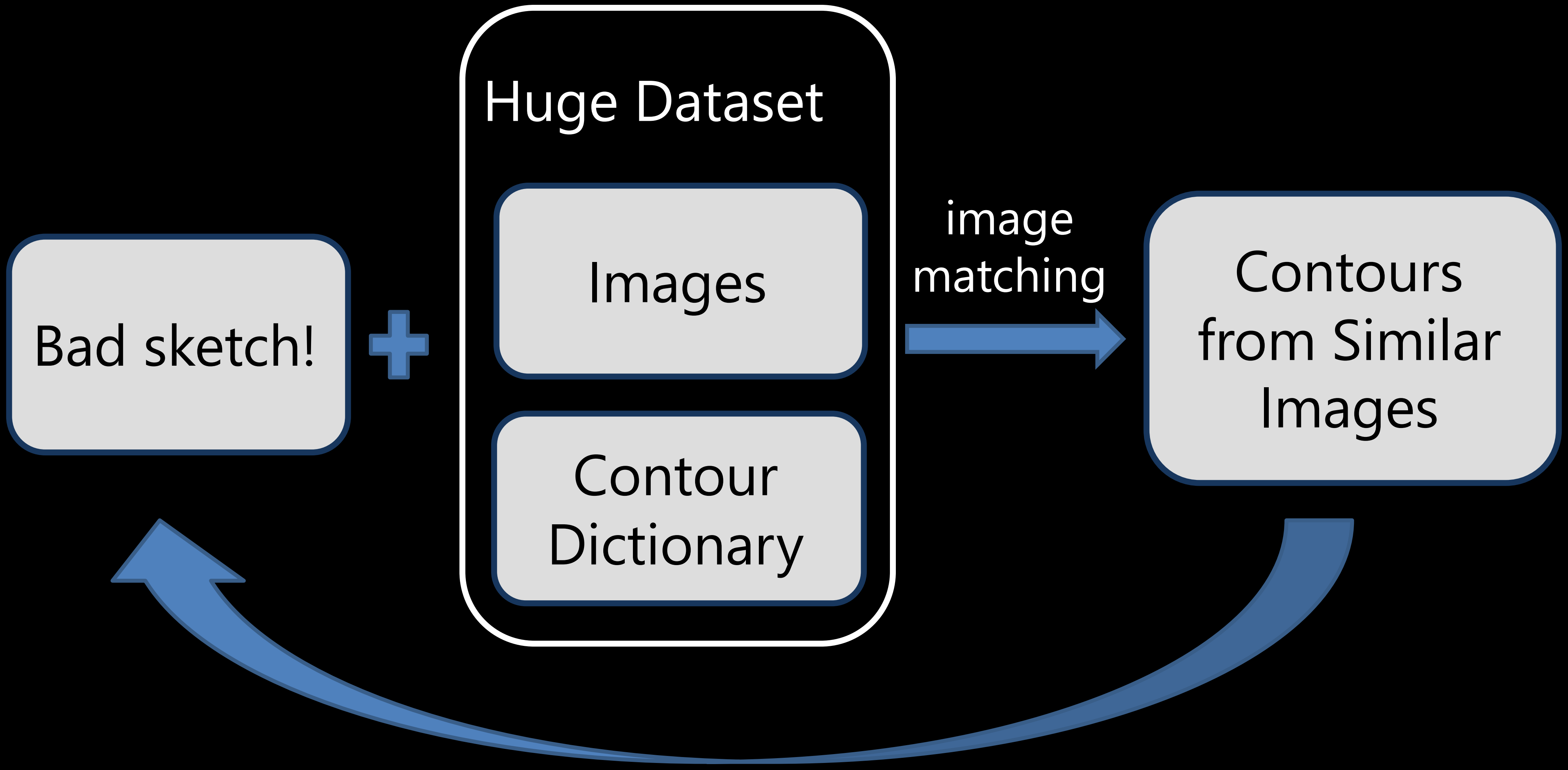
Data from [Parkhi et al. 2012]

Application: Online shopping

AverageExplorer



ShadowDraw


Huge Dataset
Images
Contour Dictionary
Bad sketch!
image matching
Contours from Similar Images


Visible
Not visible
Shadow
Top matches

Limitations

- Realism
  - Blending: locally realistic; globally not (need to handle and hide artifacts)
  - Averaging: globally realistic; locally not (results are blurry)
- Speed
  - Slow; might take minutes to hours for a user input.
  - Requires large-scale external databases.

Thank You!

16-726, Spring 2023

https://learning-image-synthesis.github.io/sp23/