

Data-Driven Graphics Jun-Yan Zhu 16-726 Learning-based Image Synthesis

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Subject-specific Data



Photos of Coliseum



Portraits of Bill Clinton





Big Visual Data









100 hours uploaded per minute

3.5 trillion photographs



the simple image sharer 1 billion images served daily

facebook 70 billion images



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





pedestrians

faces







The Internet as a Data Source

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

Is Big Visual Data useful?

A motivating example...











Scene Matching for





The Algorithm



Scene Matching



Scene Descriptor



Scene Descriptor





Scene Descriptor





2 Million Flickr Images







Context Matching





Graph cut + Poisson blending

200

and the first state



Image Blending

Poisson Image Blending





sources/destinations



seamless cloning

More details in the later lectures.

More results




































Why does it work?













































the second se



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





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!







[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 0
- 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









 $\bigcirc \bigcirc \bigcirc \bigcirc$

 $\mathbf{O} \mathbf{O} \mathbf{O}$

 $\mathbf{0}$

Illumination nearest-neighbors













Street accident





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



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



Cosegmentation

Local style transfer

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.

Similar images

Image Database

Sketch2Photo



Sketch2Photo

Sketch-based image retrieval + image blending



User Input

Database images

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

Shape retrieval [Belongie et al. PAMI 2002]



Only based on the extracted contour

Output 09.

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



Multiple Individuals



Sir Francis Galton 1822-1911

[Galton, "Composite Portraits", Nature, 1878]

Composite



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?



Visual Modes

Misaligned

"Object-Centric Averages" (2001) by Antonio Torralba



Manual Annotation and Alignment



With Alignment







Misaligned Aligned



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

Different Cat Breeds (Simple Average)



Abyssinian Sphynx Birman

Bombay

Egyptian Mau



British Persian Maine Russian Siamese Shorthair Blue Coon



Ragdoll



Bengal

Data from [Parkhi et al. 2012]

Different Cat Breeds (Our Result)



Abyssinian

Sphynx

Birman

Bombay

Egyptian Mau



British Shorthair

Persian

Maine Coon

Russian Siamese Blue



Ragdoll



Bengal

Data from [Parkhi et al. 2012]

Application: Online shopping



AverageExplorer



ShadowDraw





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.