Geometry Beyond 3D

Noah Snavely Google Inc., Cornell University

Bay Area Vision Meeting, 2014

Are we done with 3D modeling?

• Huge progress in the last 10 years



[Pollefeys et al. IJCVo4]

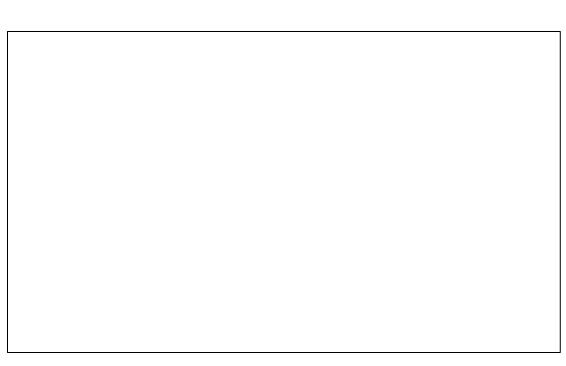


Aerial models

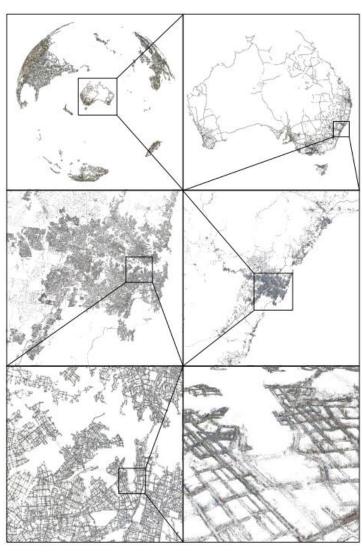


[Zhou & Koltun, SIGGRAPH14]

Are we done with 3D modeling?



[Agarwal et al. ICCV 2009]

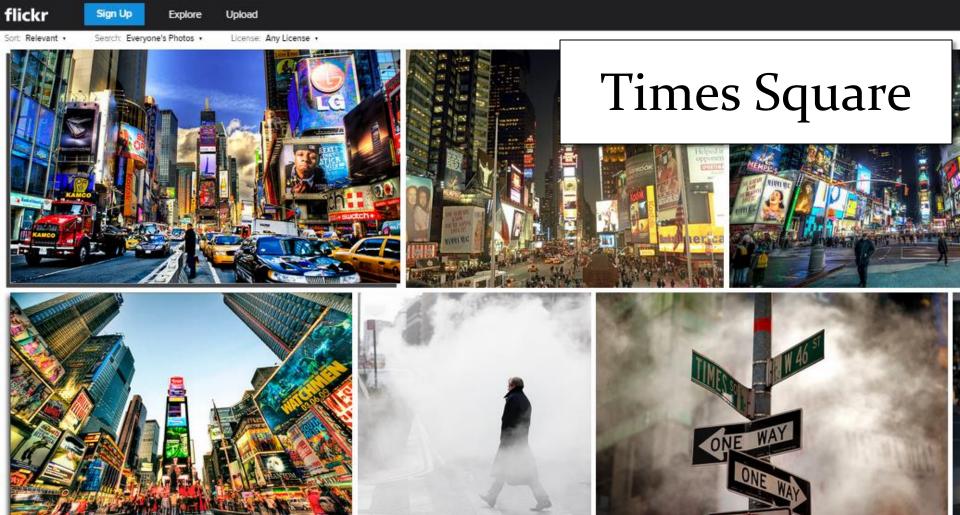


[Klingner et al., ICCV 2013]

Are we done with 3D modeling?

- Not until we have a fully realistic, editable, semantically meaningful model of the entire world
- Realistic = correct geometry, materials, lighting; high-resolution; dynamic

 In other words, a model you can feed into your holodeck









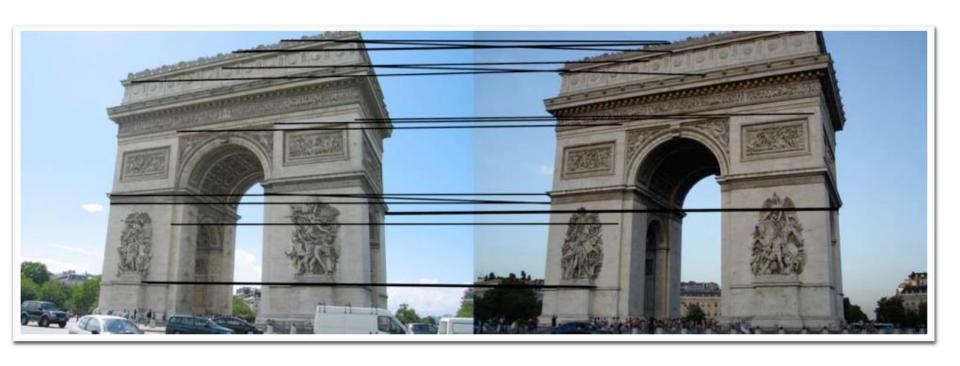
What are the key challenges?

- Scale we have made great progress here
- Robustness
- Time
- Materials
- Semantics / grounding

My own biased view

Robustness

Are two things the same?



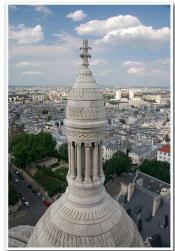
 How do we know what we are looking at is the same or different?

Structural similarities break SfM









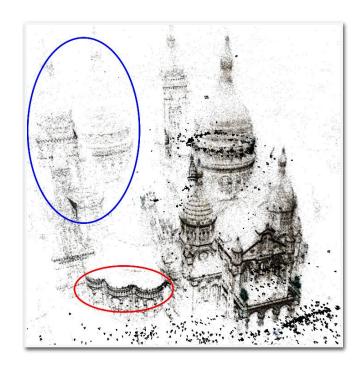




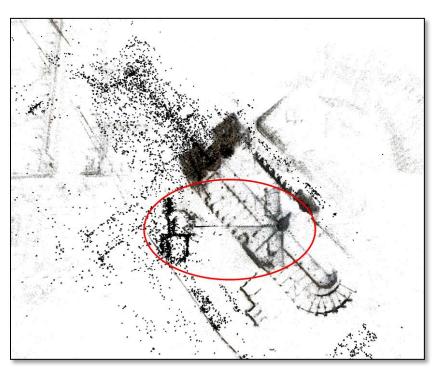
Structural similarities break SfM



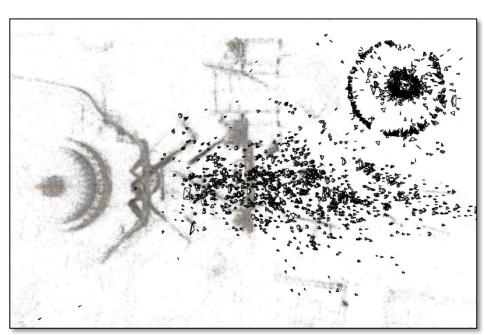




Other examples

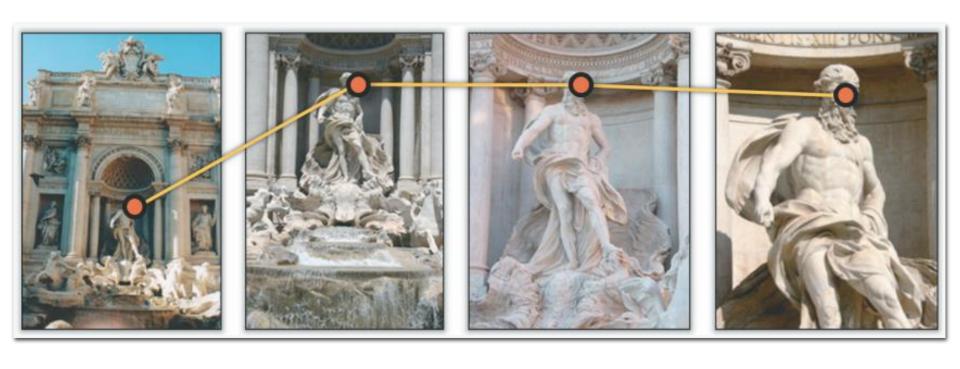


Notre Dame Cathedral

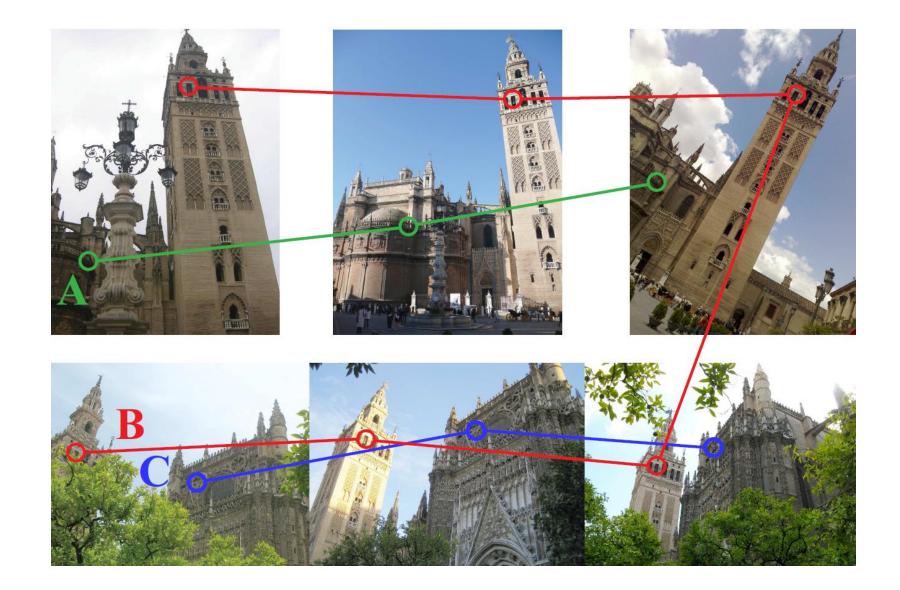


St. Paul's Cathedral

Tracks should contain one 3D point



Tracks can conflate distinct points



SfM Disambiguation

- Most methods reason about inconsistencies across many images
- Inconsistencies in
 - Loops of pairwise geometries
 - Visibility
 - Sequencing
 - Global geometry

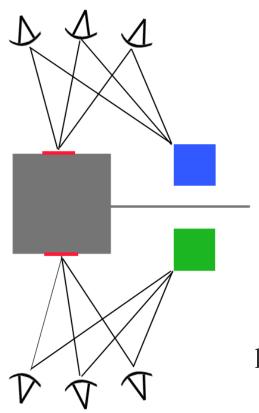
[Zach et al., CVPR 2008], [Zach et al., CVPR 2010], [Roberts et al., CVPR 2011], [Jiang et al., CVPR 2012]

SfM Disambiguation in the Large

- We wanted a solution that was
 - As simple as possible
 - -Scalable to huge image collections

• Intuition: visibility of points is (often) transitive

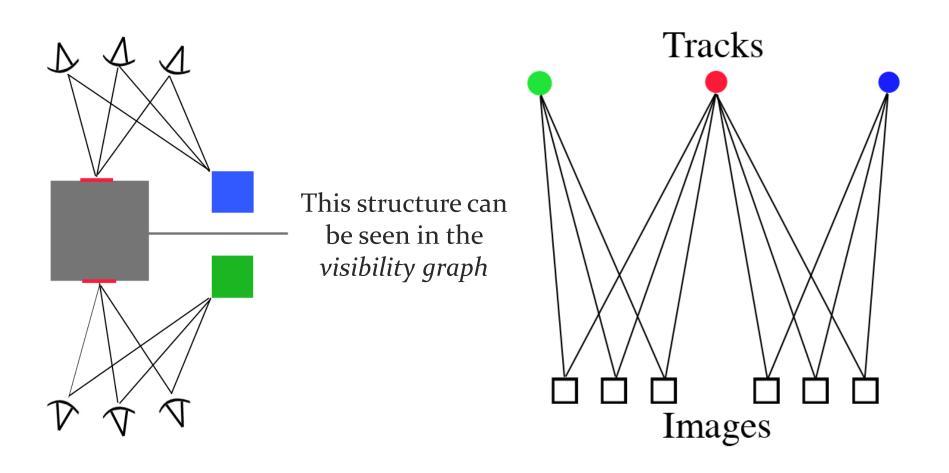
Graph topology is a cue for ambiguities



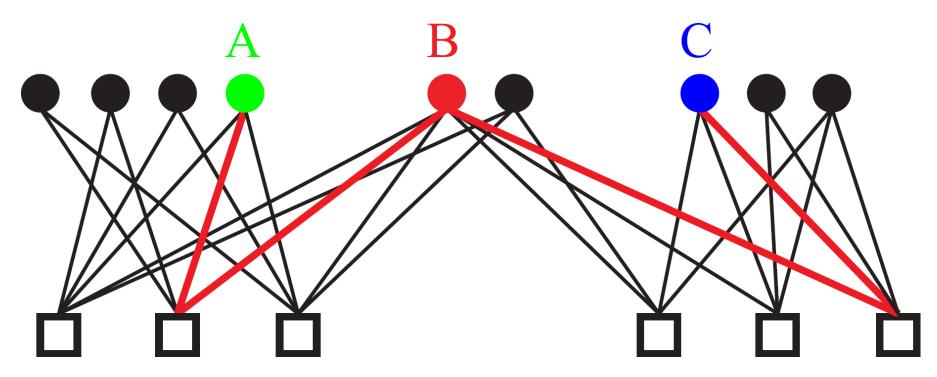
Schematic of a scene with an ambiguous feature (in red)

Note that the two sides of the scene have different background (blue and green)

Graph topology is a cue for ambiguities

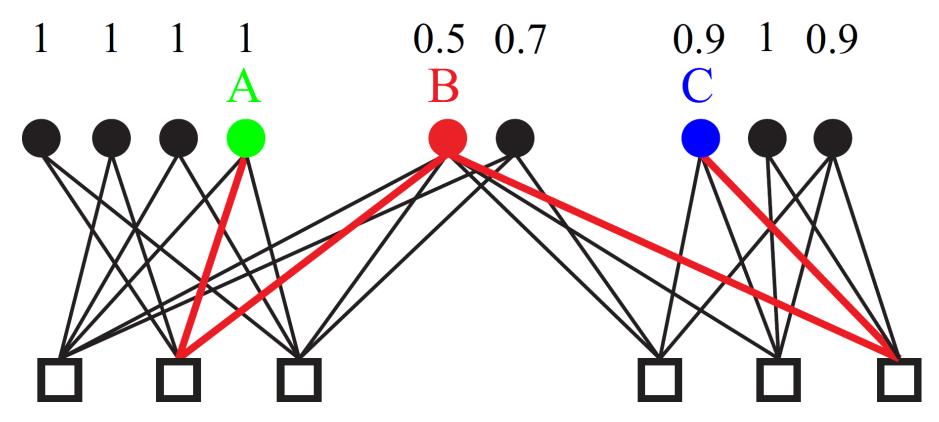


Larger example



Bad tracks have more than one cluster of context. Measure this with the bipartite local clustering coefficient.

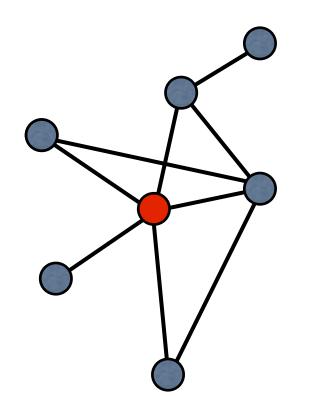
Larger example

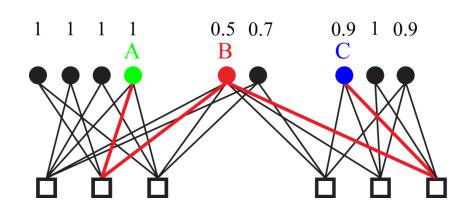


Bad tracks have more than one cluster of context. Measure this with the bipartite local clustering coefficient.

blcc is analagous to the local clustering coefficient

$$lcc(\text{red node}) = \frac{\text{closed triangles}}{\text{possible triangles}} = \frac{3}{10}$$

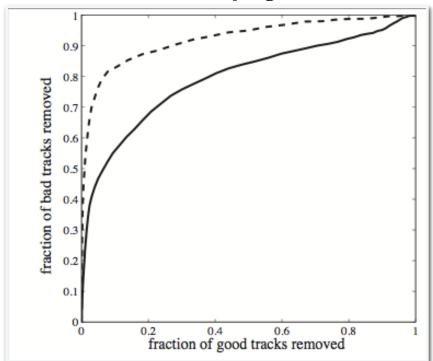




$$blcc(\text{red node}) = \frac{\text{closed 6-paths}}{\text{possible 6-paths}}$$

Filtering by *blcc* removes bad tracks

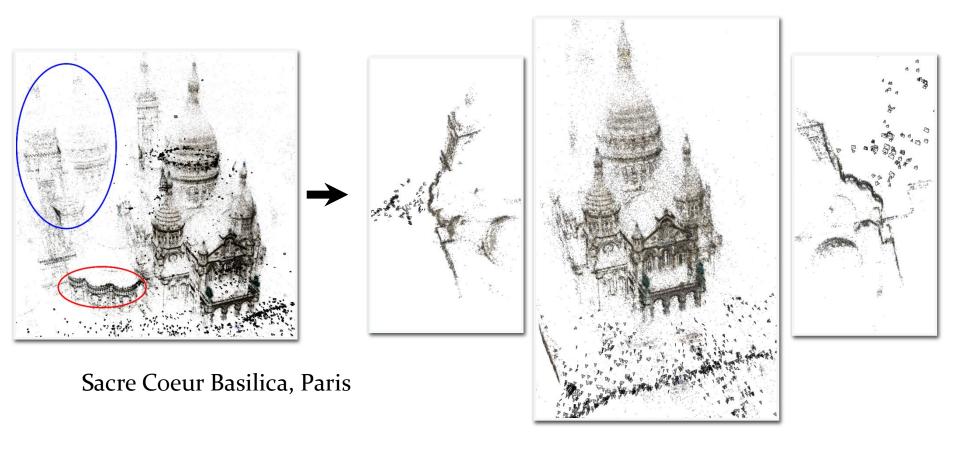
ROC curve for classifying bad tracks



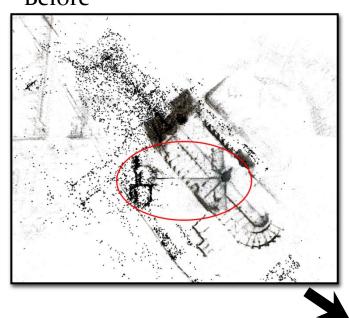
Solid line: thresholding tracks on blcc. Dotted line: same, but on a more uniform subgraph.

Algorithm:

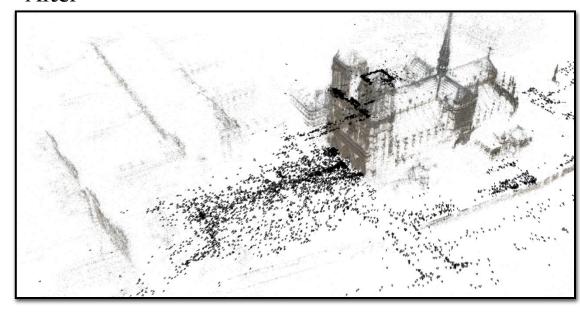
- 1. Compute a covering subgraph
- 2. Compute blcc for each track
- 3. Remove tracks lower than a threshold Use lowest threshold that separates the graph into a user-predetermined number of components.
- 4. Reconstruct each component separately
- 5. Rigidly merge components if possible



Before



After



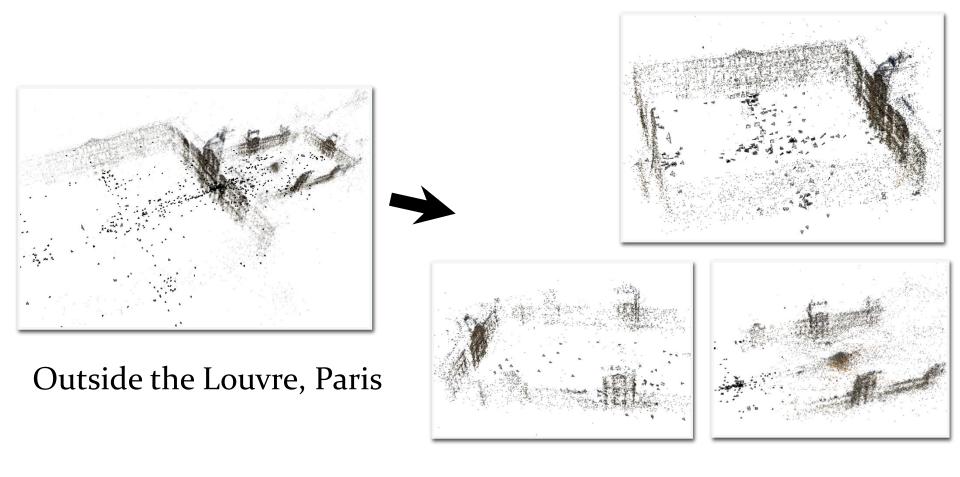
Notre Dame Cathedral, Paris







Seville Cathedral

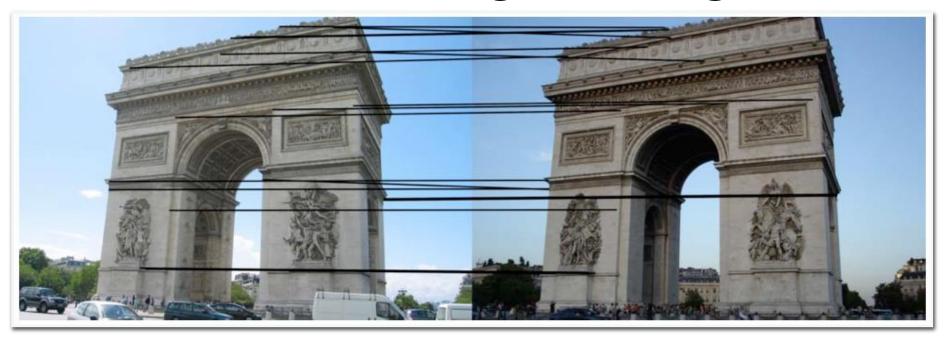


Network Principles for SfM

- + Extremely fast method
- + Based on simple local reasoning
- + Very simple to implement

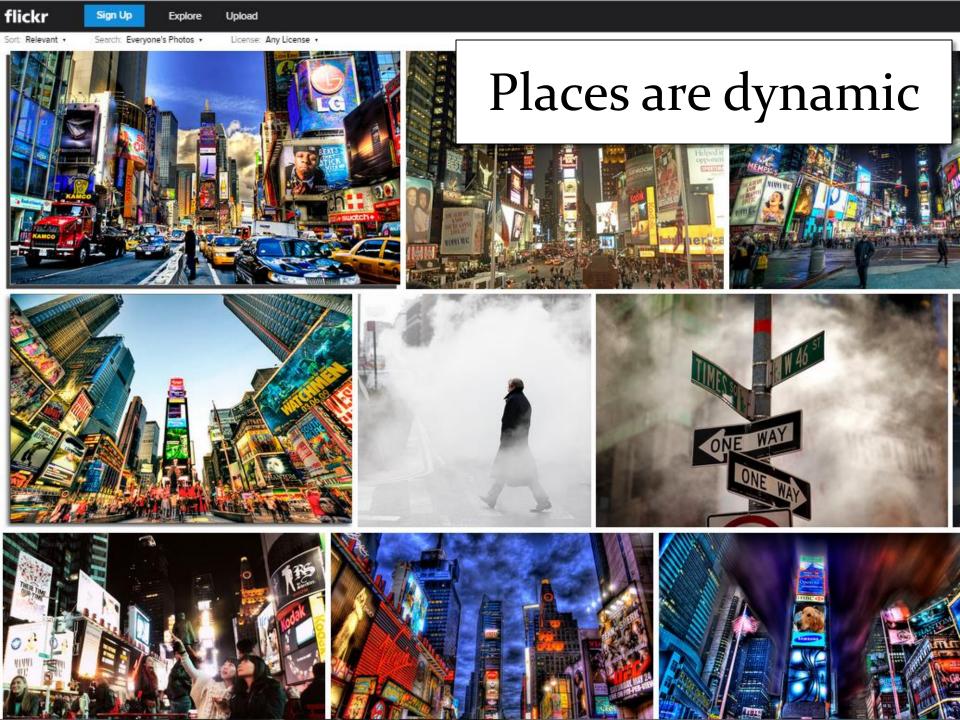
- Can sometimes oversegment models
- Theoretical guarantees?

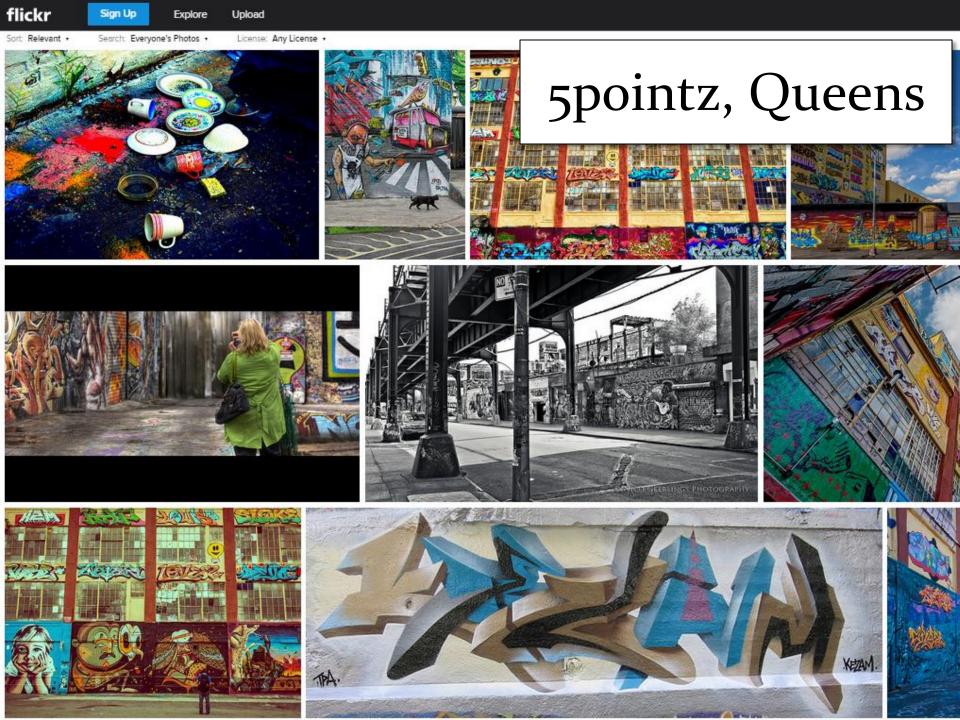
Feature matching as recognition



- Can't we just solve this problem using appearance alone?
- Better features or image metrics?

Time





5pointz



[Graffiti Archaeology, Cassidy Curtis]

4D Cities





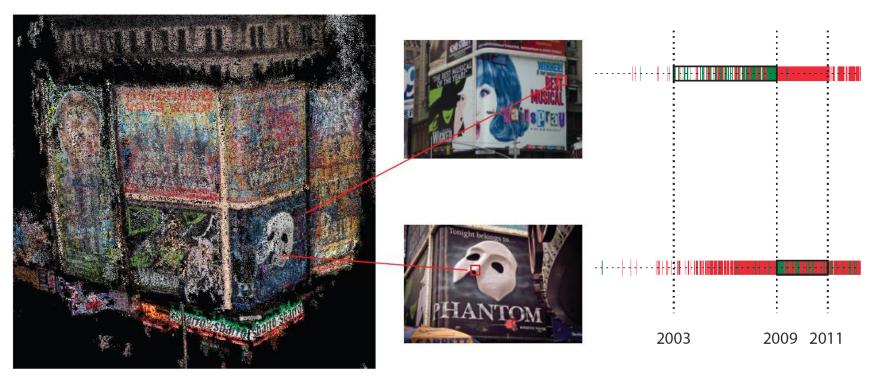
[Frank Dellaert, Grant Schindler, et al.]

Scene Chronology

Step 1: Download photos from Flickr

Step 2: Reconstruct a single 3D model with all times mixed up together

Step 3: Recover the *chronology* of the scene

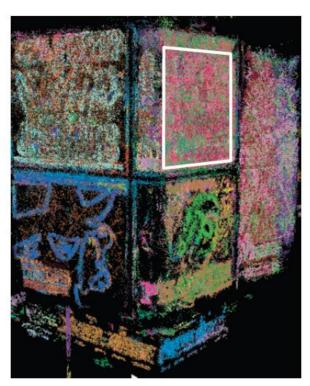


Single 3D Model (from ~100,000 images)

Per-Point Time Observations







Space-Time Point Clustering



Exploded View across Time



Re-time-stamping



Blue: original timestamp

Red: our predicted timestamp



Physics



Weather



People



Times Square, 1922



Eisenstadt, 1945

Materials





OpenSurfaces

Sean Bell, Paul Upchurch, Noah Snavely, Kavita Bala Cornell University

Statistics			Materials	Reflectances	Textures
	Good	AII			一
Labeled Scenes	25,357	91,876			
Whitebalanced Photos	17,839	24,771	- POLITIES	- WWOOI-1062	La Caracteria de la Car
Segmentations	70,005	103,513			イニノイダコーシ
Planar Segmentations	36,482	70,005			
Named Materials	56,625	68,761		4 4 4 - 8 - W = 1	HI TO A TO A
Named Objects	31,697	42,203			5-140JIM
Rectified Textures	16,829	22,219			

Sean Bell, Paul Upchurch, Noah Snavely, Kavita Bala, SIGGRAPH 2013 http://opensurfaces.cs.cornell.edu/



Query









Results: wood floors in kitchens, sorted by diffuse color



Query









Results: fabric sofas in living rooms, sorted by diffuse color similarity

Intrinsic Images in the Wild

Sean Bell, Kavita Bala, Noah Snavely Cornell University







Sean Bell, Kavita Bala, Noah Snavely, SIGGRAPH 2014, http://intrinsic.cs.cornell.edu

Semantics / Grounding

Every image tells a story...

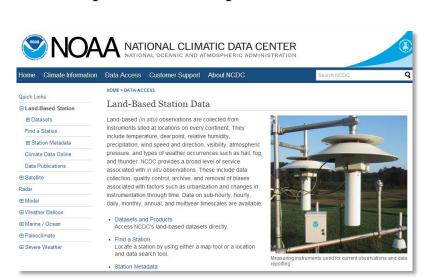




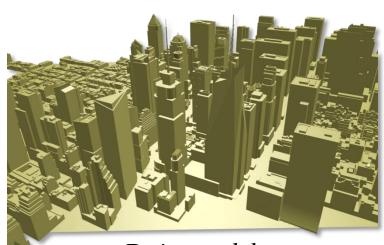
Grounding vision in the world



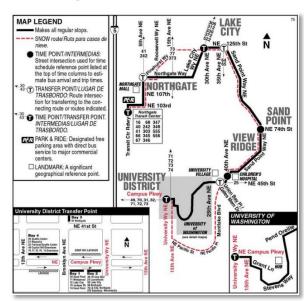
OpenStreetMap



Weather data



3D city models



Bus schedules



	Name
1.	311 Service Requests from 2010 to Present Social Services 311, 311 service requests, 2010, 2011, 2012, All 311 Service Requests from 2010 to present. This information is automatically updated daily.
2.	Electric Consumption by ZIP Code - 2010 Environment electricity, energy, environment, planning, power, 2010 electricity consumption in kWh and GJ, by ZIP code, building type, and utility company.
▼ 3.	Zip Codes Map Social Services geographic, location, map, cartography, zip, code, Polygon representing the boundary of the zip codes in the city.
₹ 4.	MTA Data Transportation traffic, vehicles, route, schedules, clean web Information pertaining to MTA (Metropolitan Transportation Authority of the State of New York) subways, buses, commuter rail,
5.	Restaurant Inspection Results Health restaurant inspection results, NYC restaurant inspection results
6.	Basic Description of Colleges and Universities Education doitt gis, geographic, location, map, cartography, Location of colleges and universities with basic descriptive information.
7.	SAT (College Board) 2010 School Level Results Education lifelong learning New York City school level College Board SAT results for the graduating seniors of 2010. Records contain 2010 College-bound
8.	Mapped In NY Companies Business jobs, tech, jobs and economic mobility Raw data which powers the Mapped In NY site at http://www.mappedinny.com/
9.	Filming Locations (Scenes from the City) Business film, movie, scene, scenes from the city List of filming locations mentioned in the book Scenes from the City
10.	2012 NYC Noise Complaints - Heat Map Other 311, 311 service requests, 2010, 2011, NYC Noise complaints for 2012

https://nycopendata.socrata.com (https://data.sfgov.org/, https://data.seattle.gov/, ...)

Grounding vision in the world



- Which direction is north?
- What is the shape of the buildings?
- What was the weather like?
- Where are streets?
- What is the #51 bus schedule in Rome?

Goal: Integrate images into this ecosystem of geographic data

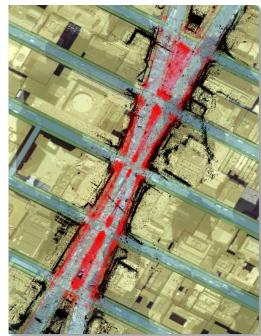
First steps: NYC3DCars











[Kevin Matzen and Noah Snavely, ICCV 2013

NYCOpenData Roadbeds



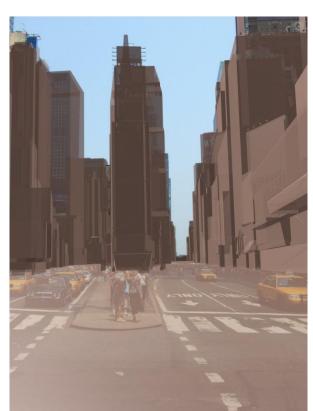
Vision grounded in the real world



Input photo



Overlayed GIS data (roads / sidewalks / medians)



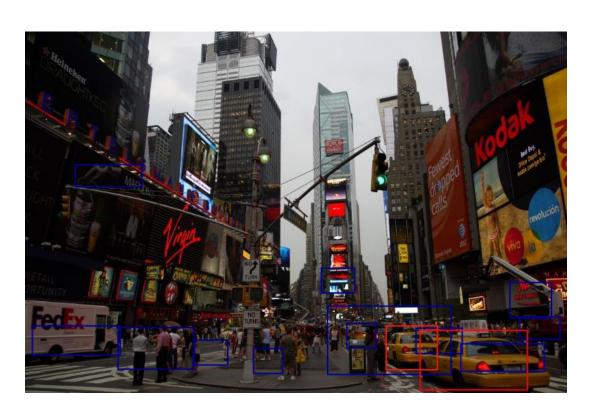
Overlayed Google Earth models

Annotated 3D Vehicles



Video

3D Detection





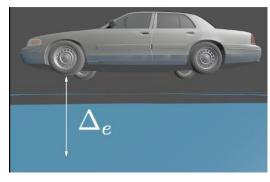




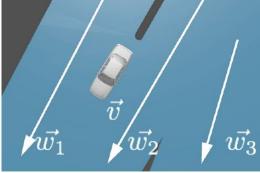
Appearance score



Ground coverage score

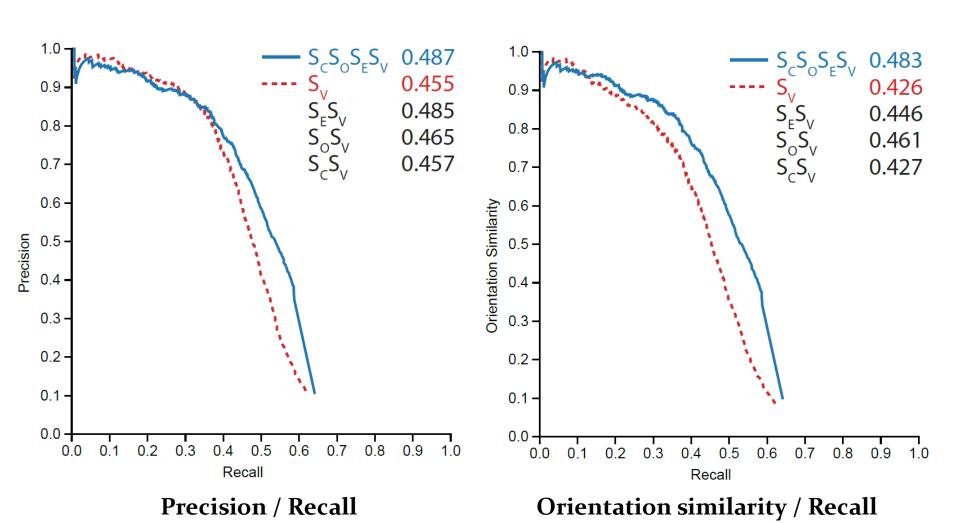


Elevation score



3D orientation score

Results





A vehicle detection database for vision tasks set in the real world.



3D Reconstructions

Each photograph in NYC3DCars has been geo-registered to the Earth, providing full camera intrinsics and extrinsics in an Earth-Centered, Earth-Fixed coordinate system enabling seamless integration with existing geospatial data.



Geographic Data

Companion databases such as those provided by OpenStreetMap and NYC OpenData have been integrated for easy access to geographic features such as road, sidewalk, and median polygons as well as road network connectivity.



Vehicle Annotations

Human annotators have provided detailed descriptions for vehicles contained in the database. Annotations include a full 6 degree of freedom vehicle pose, vehicle type, 2D vehicle bounding box, and approximate photo time of day.

http://nyc3d.cs.cornell.edu/

Summary

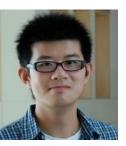
- Many interesting challenges in modeling the world
- Contributions from every area (cf. much wonderful recent work):
 - Scene understanding, object detection, material recognition, illumination modeling, ...
 - Learning?

Acknowledgements

Students



Sean Bell



Song Cao



Daniel Hauagge



Kevin Matzen





Paul Upchurch Chun-Po Wang Scott Wehrwein





Kyle Wilson

- National Science Foundation
- Intel Center for Science and Technology – **Visual Computing**
- Amazon AWS for Education

Collaborators



Kavita Bala



Dan Huttenlocher Yunpeng Li



Dave Crandall

Thank you!

More information at http://www.cs.cornell.edu/~snavely/