Introduction

- What are we trying to achieve?
- Why are we doing this?
- What do we learn from past history?
- What will we talk about today?

What are we trying to achieve?



Example from Scott Satkin

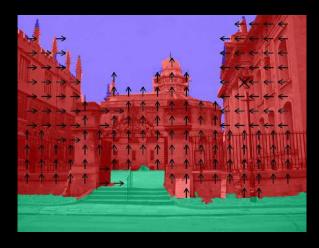


3D interpretation from image

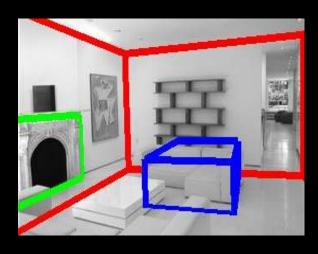
Geometric labels



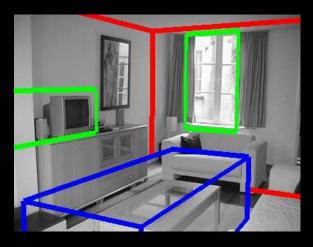




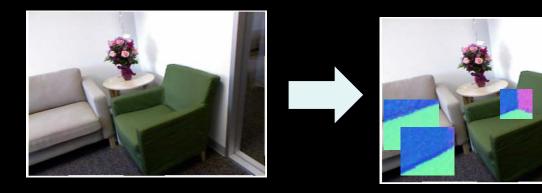
Volumetric layout



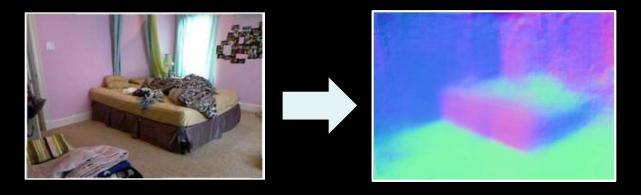




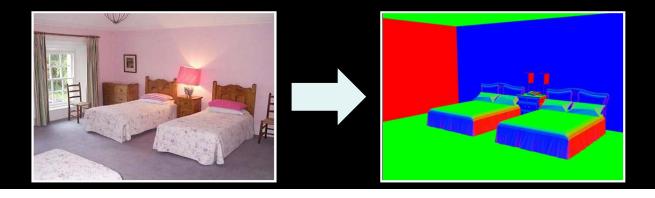
Sparse primitives



Dense reconstruction



3D scene model

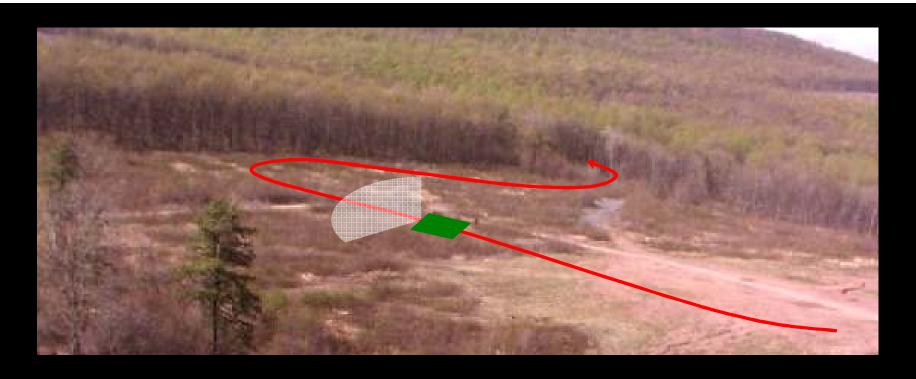


Why are we doing this?

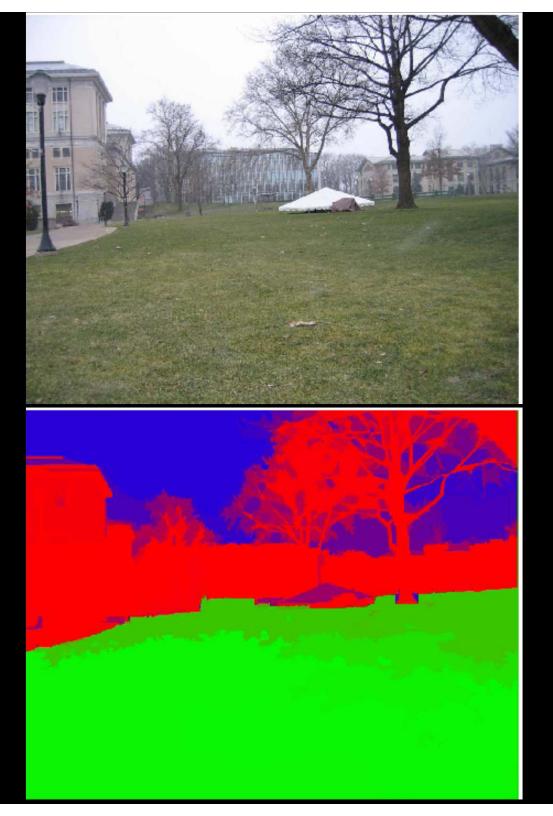
Applications

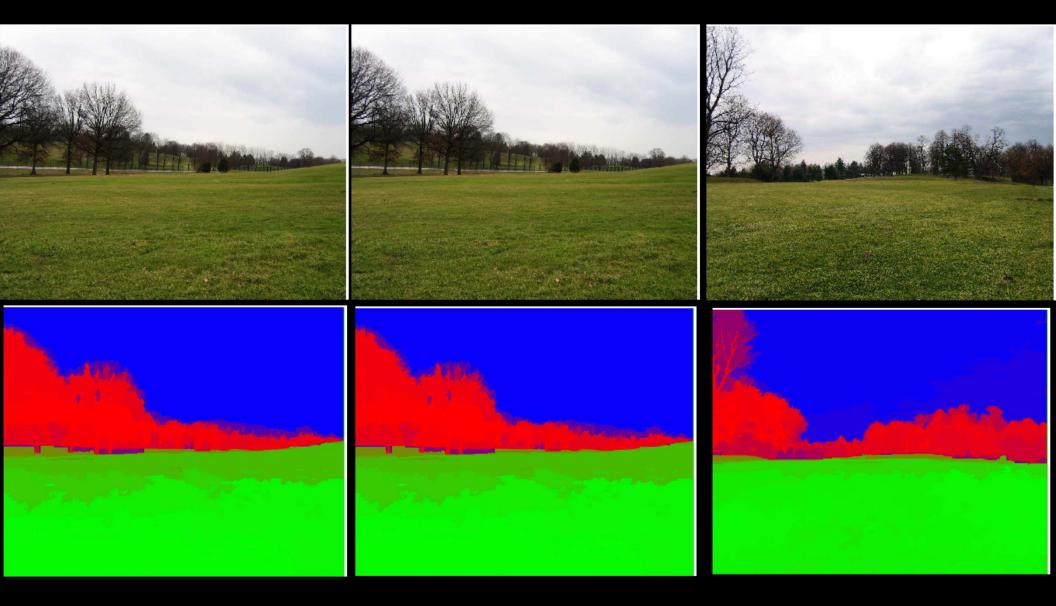
3D for motion

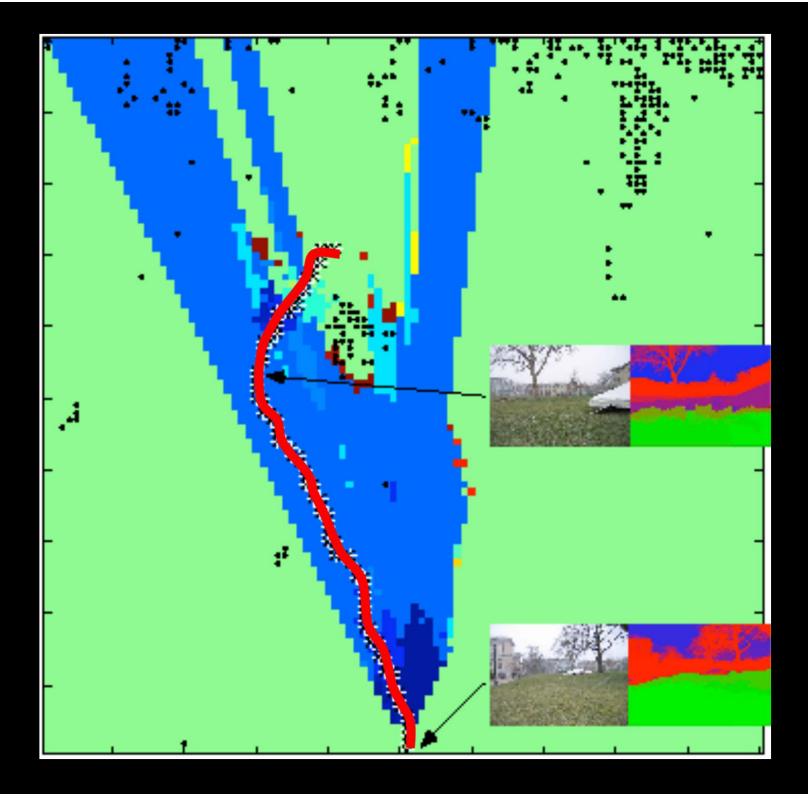
...when there is no direct way to get 3D



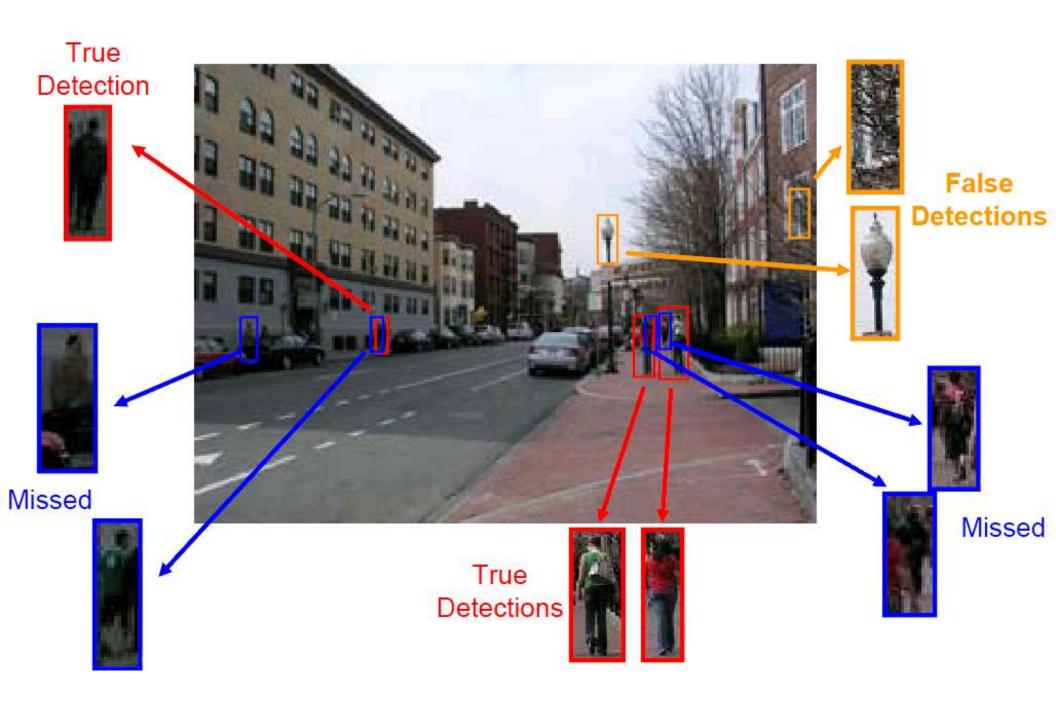


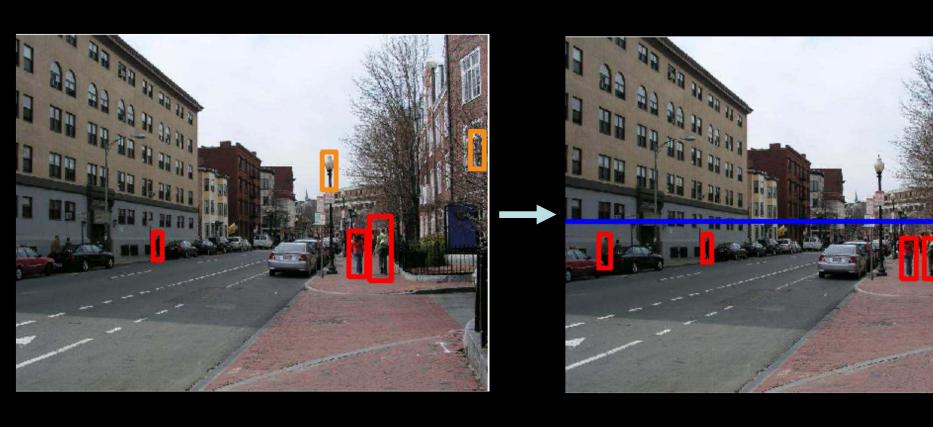






Informing detectors



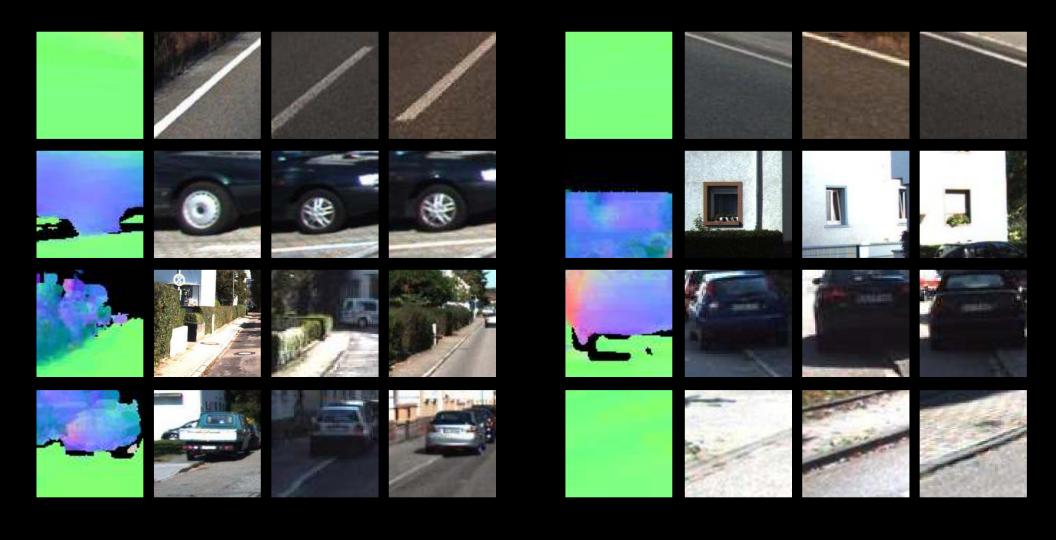


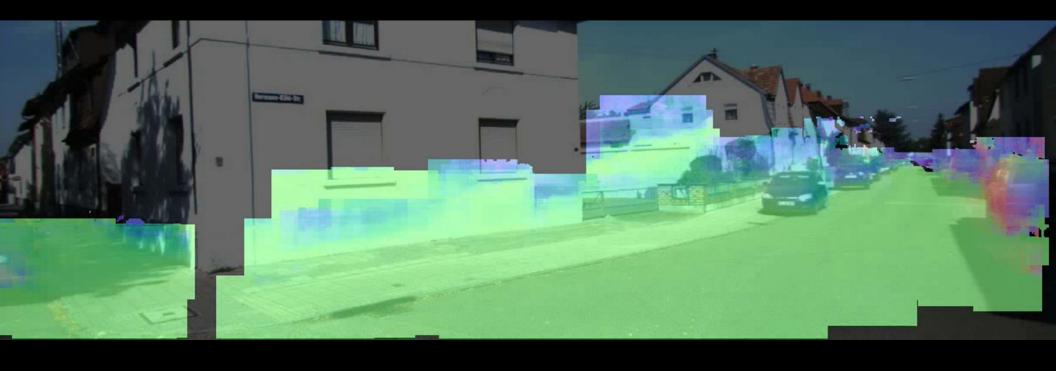
D. Hoiem, A. A. Efros, and M. Hebert. *Putting Objects in Perspective*. International Journal of Computer Vision, Vol. 80, No. 1, October, 2008.



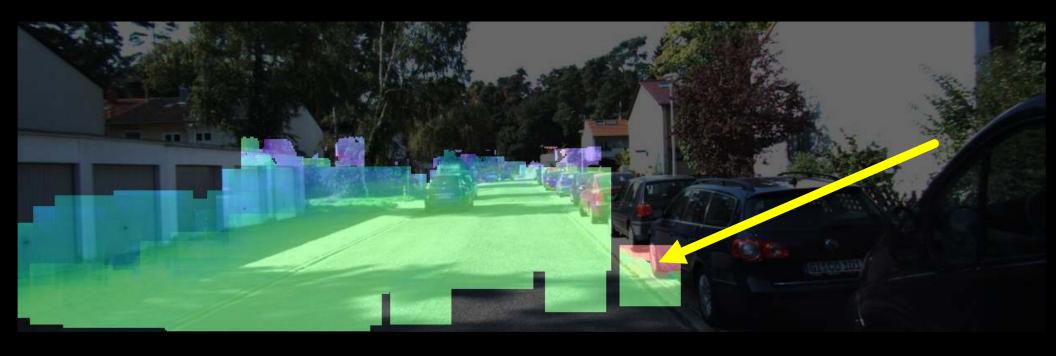


Learned Primitives (Examples)

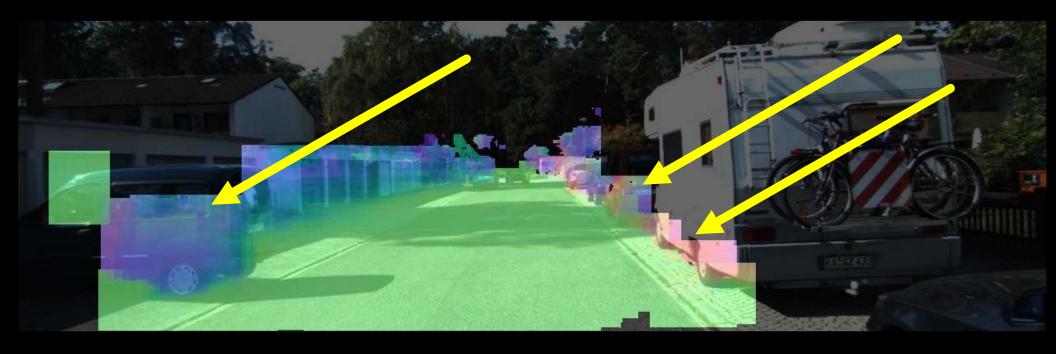




Contact points

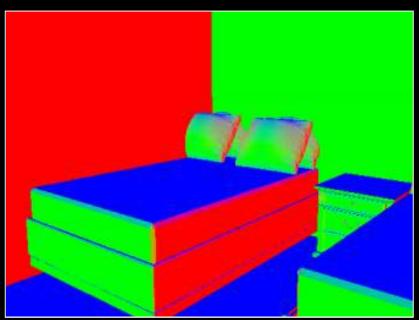


Object surfaces + Contact points

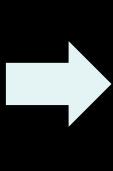


Editing images









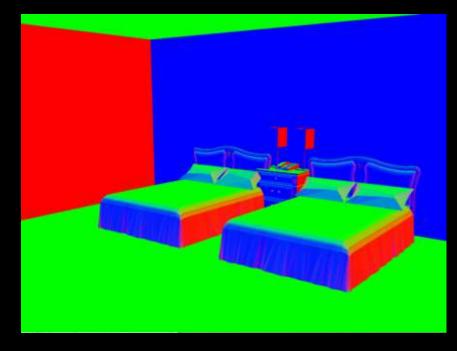




Predicting actions

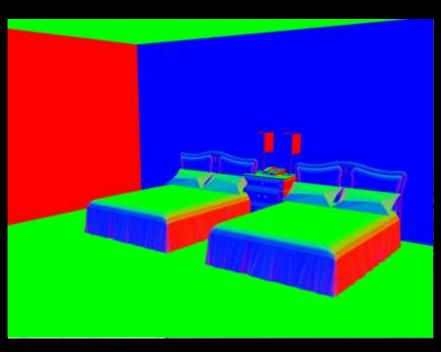


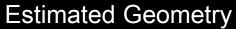




Input Image

Estimated Geometry









Predicted Sitting Locations



Sitting Upright



Laying Down

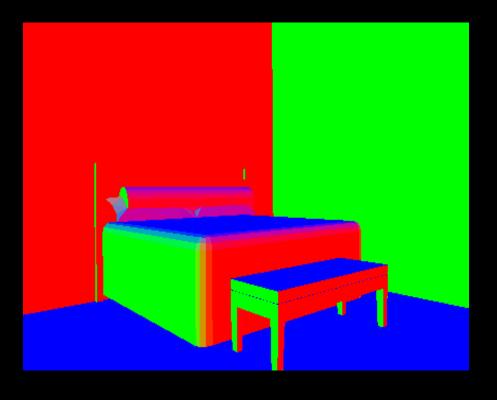


Sitting Reclined



Reaching (4 poses)







Sitting Upright



Laying Down



Sitting Reclined



Reaching (4 poses)

Separating style and structure







Tenenbaum & Freeman. Separating Style and Content with Bilinear Models. Neural Computation. 2000.

Casablanca Hotel, New York









































































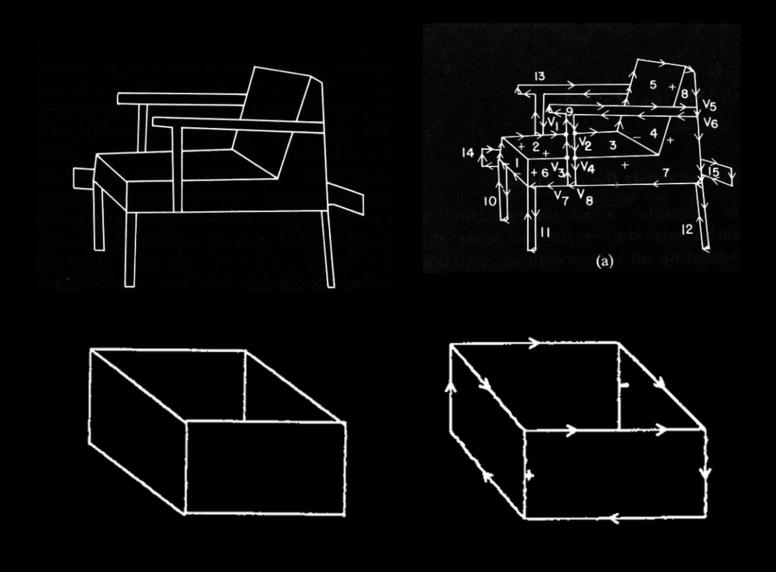




What do we learn from past history?

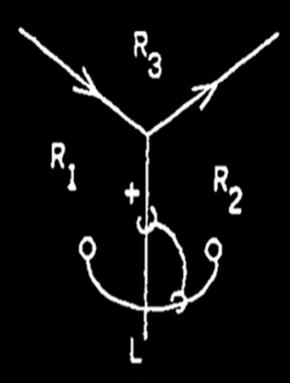
Historical perspective

First era: Geometric/symbolic reasoning

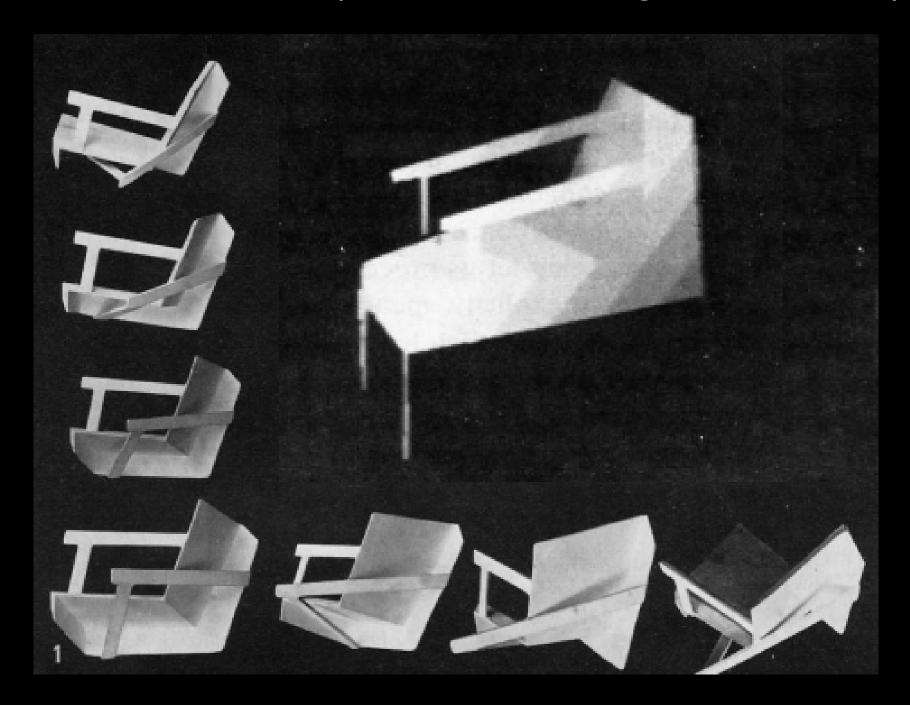


Huffman 71, Clowes 71, Kanade 80, 81 Sugihara 86, Malik 87, etc.

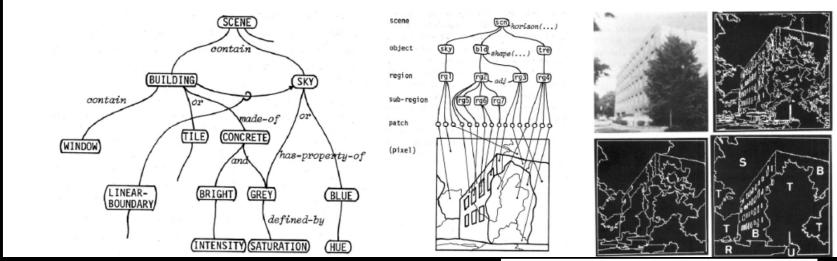
Kanade's Origami World, 1978



Kanade's chair... (Artificial Intelligence, 1981)

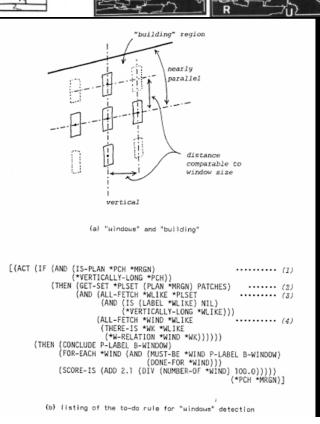


Scene parsing



[Ohta & Kanade 1978]

- Guzman (*SEE*), 1968
- Yakimovsky & Feldman, 1973
- Hansen & Riseman (VISIONS), 1978
- Barrow & Tenenbaum 1978
- Brooks (*ACRONYM*), 1979
- Ohta & Kanade, 1978



Issues

- Assumed "good" (perfect?) geometric elements inferred from the image.
- Limitations on computation, data, inference techniques prevented practical estimation of geometric primitives.

Second era: Statistical machine learning

Input

Learned model





Training data

Classification

- Now we have the opposite problem:
 - Powerful tools to estimate low-level geometric cues (e.g., surface labels)

- Does not incorporate high-level geometric constraints (e.g., orthogonality, intersections, etc.)
- Does not incorporate higher-level reasoning

Now (Part I): learning+reasoning

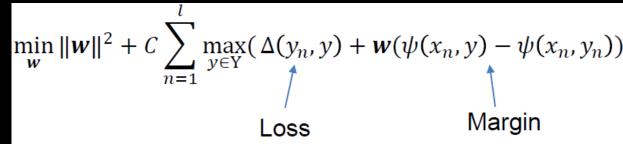
Structured prediction tools

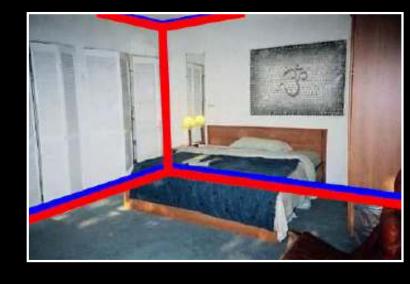


Orientation maps (Lee et al. 2009)



Geometric Context (Hoiem et al. 2007)





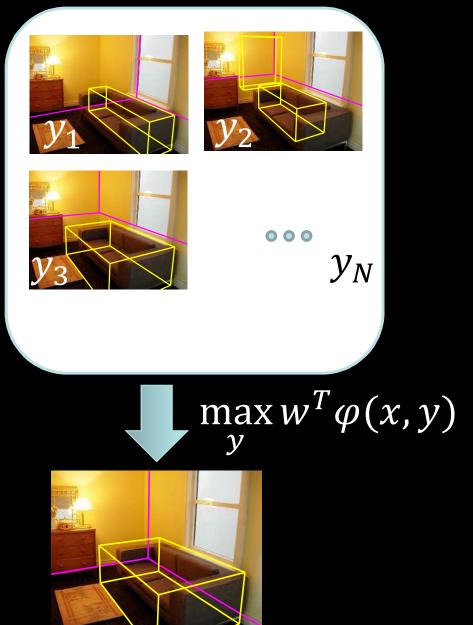
Structured prediction tools+ search

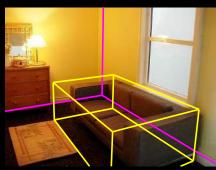
Input image features *x*



Generate hypotheses Search through hypotheses to pick the best one "Best" = maximum score

Score computation learned from data using structured prediction tools



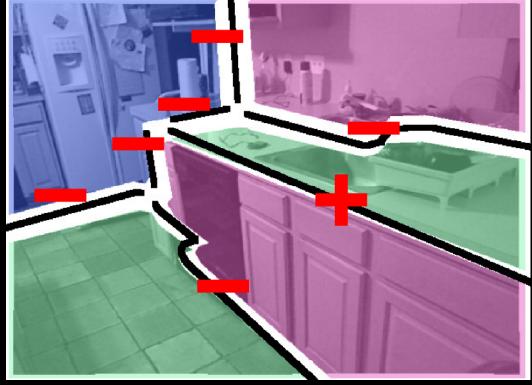


Final scene configuration

Optimization tools

 $\underset{\mathbf{x} \in \{0,1\}^n}{\arg \max } \mathbf{c}^T \mathbf{x} + \mathbf{x}^T \mathbf{H} \mathbf{x} \quad \text{s.t.} \quad \mathbf{A} \mathbf{x} \le \mathbf{1}$





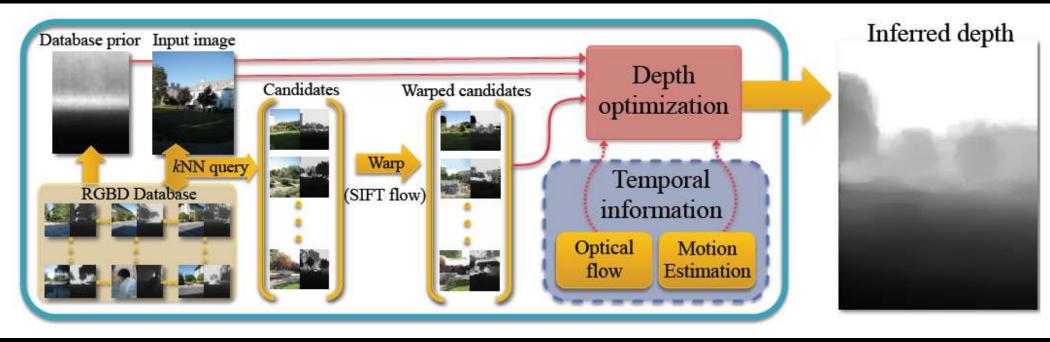
Convex Concave

+ Richer representations, including reasoning about geometric primitives (e.g., relative placement of surfaces, contact relationships, etc.)

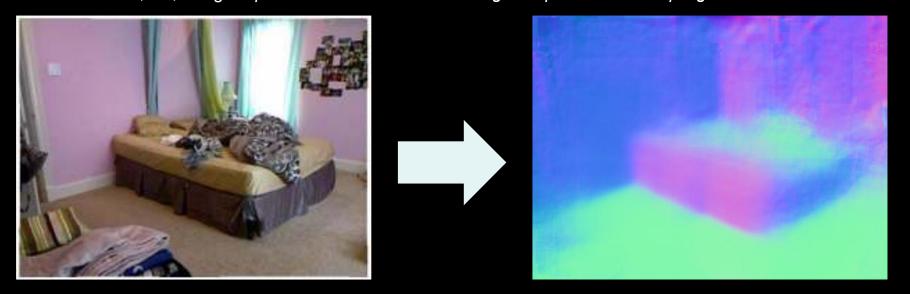
- Taming the combinatorics: How to generate and search hypothesis space efficiently?
- Summarizes a large amount of training data into a "simple" model
- Difficult to capture the richness of big data

Now (Part II): Data-driven interpretation

Label transfer

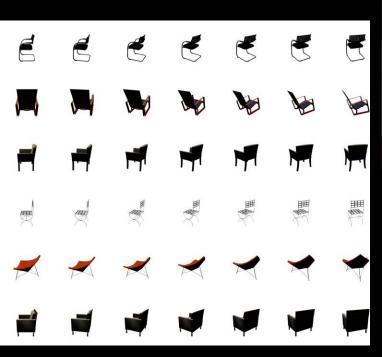


Karsch, Liu, Kang. Depth Extraction from Video Using Non-parametric Sampling. ECCV 2012.



Fouhey, Gupta, Hebert. Data-Driven 3D Primitives for Single-Image Understanding. ICCV 2013.

Object transfer



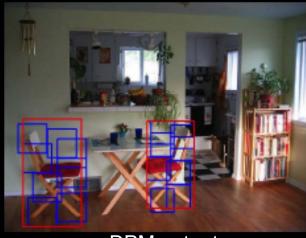
Lots of object models



Input image



Output



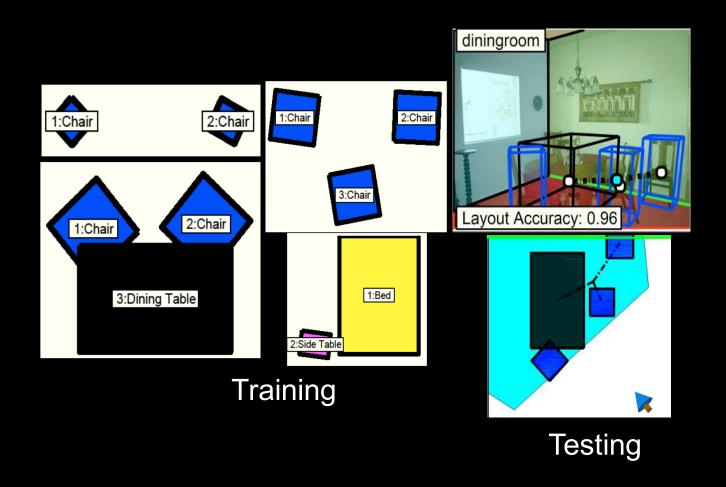
DPM output



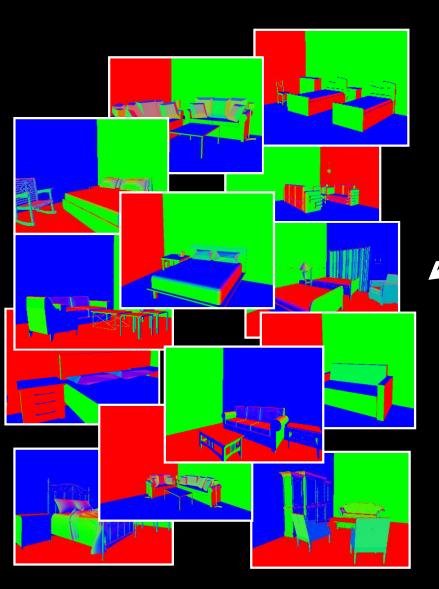
Matched models

Seeing 3D chairs: exemplar part-based 2D-3D alignment using a large dataset of CAD models. M. Aubry, D. Maturana, A. Efros, B. Russell and J. Sivic CVPR, 2014.

Object transfer

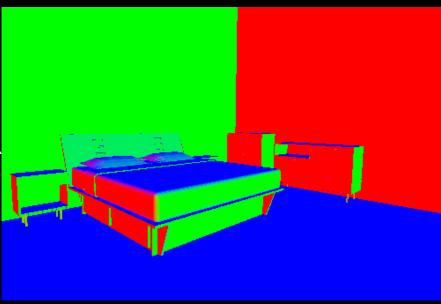


Scene transfer





Nearestneighbor search



Lots of 3D models

 (Arbitrarily) richer description: Transfer of semantics, 3D poses, segmentation, material properties, etc.

- How to relate 2D/appearance features to purely 3D geometric representations?
- What matching score/distance metric should be used?
- How to rank matches?

What will we talk about today?

Tutorial Outline

Bottom up classifiers

More explicit constraint+reasoning

Qualitative

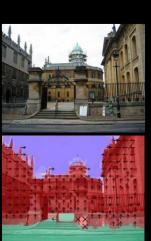
Explicit/Quantitative

Outline

Part 1: Derek
Bottom-up Methods for Regions and
Boundaries, Global Constraints

Part 2: Abhinav Volumetric and Functional Constraints

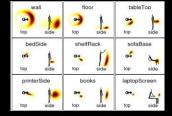
Part 3: David Data-driven Models











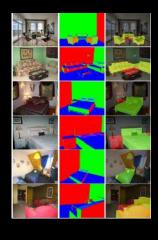


Boundaries and objects

Stronger geometric constraints from domain knowledge + physical constraints +functional constraints



Inferred depth



Big Questions

- How to estimate geometric properties from an image?
- How to incorporate geometric constraints and which ones?
- How to combine reasoning tools with statistical classification/regression tools?
- How to use large-scale 3D data (3D models, kinect)
- How to combine with other 3D estimation methods?