Context and Spatial Layout

Computer Vision

CS 543 / ECE 549

University of Illinois

Derek Hoiem

Final project reminders

- Posters on Friday, May 11 at 7pm (two rounds, 1.25 hr each) in atrium

- Keep your project topic and group updated here; will be used for scheduling posters https://docs.google.com/spreadsheets/d/1optR3El54YSnsPfuX6sk2FLQ1ZxpjT3eEpm1JjQvieg/edit?usp=drive_web

- 2-page papers and materials due May 12 on compass

- Cannot accept late papers/posters due to grading deadlines

Today’s class: Context and 3D Scenes

Context in Recognition

- Objects usually are surrounded by a scene that can provide context in the form of nearby objects, surfaces, scene category, geometry, etc.

Context provides clues for function

- What is this?

These examples from Antonio Torralba

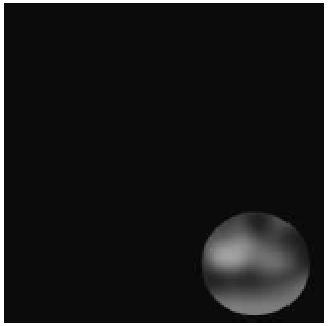
Context provides clues for function

- What is this?

- Now can you tell?

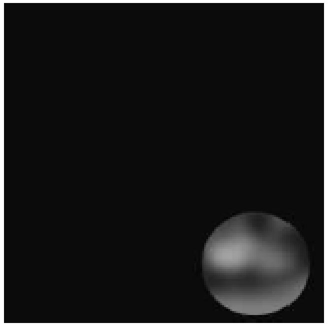
Sometimes context is *the* major component of recognition

- What is this?



Sometimes context is *the* major component of recognition

- What is this?



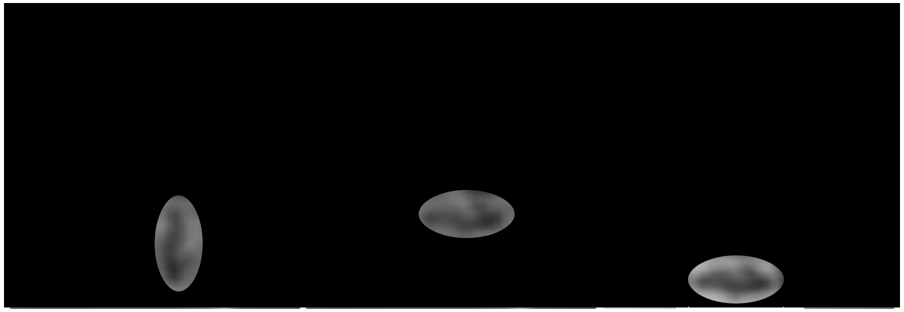
- Now can you tell?

More Low-Res

- What are these blobs?

More Low-Res

- The same pixels! (a car)

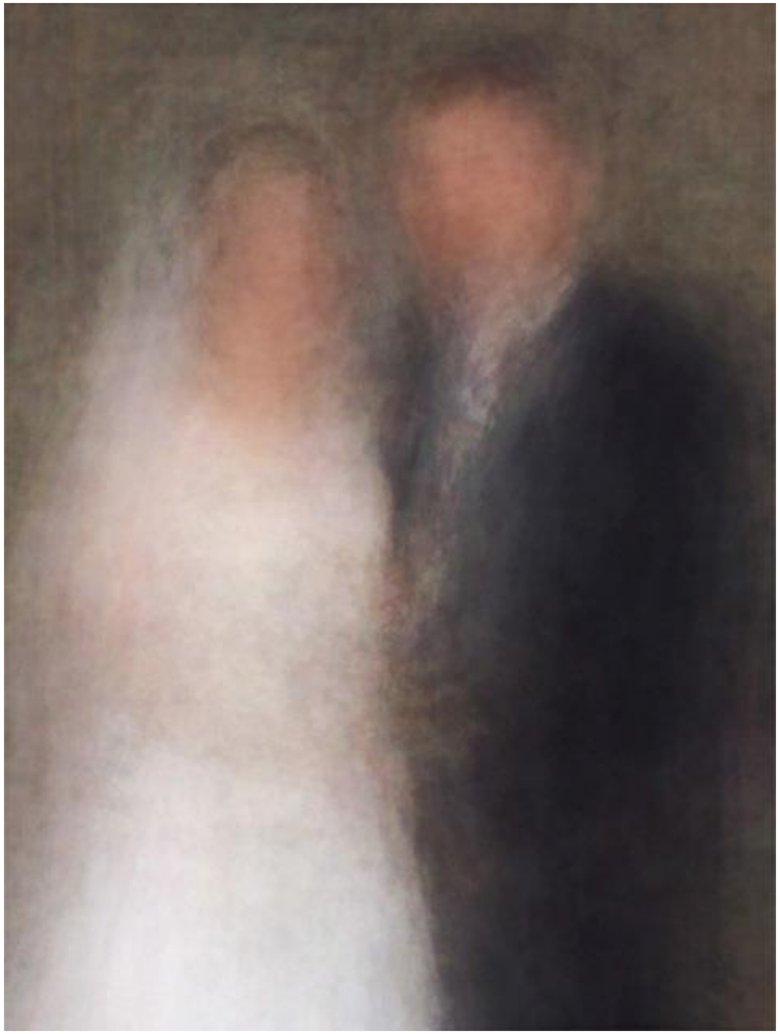


There are many types of context

- **Local pixels**
  - window, surround, image neighborhood, object boundary/shape, global image statistics
- **2D Scene Gist**
  - global image statistics
- **3D Geometric**
  - 3D scene layout, support surface, surface orientations, occlusions, contact points, etc.
- **Semantic**
  - event/activity depicted, scene category, objects present in the scene and their spatial extents, keywords
- **Photogrammetric**
  - camera height orientation, focal length, lens distorition, radiometric, response function
- **Illumination**
  - sun direction, sky color, cloud cover, shadow contrast, etc.
- **Geographic**
  - GPS location, terrain type, land use category, elevation, population density, etc.
- **Temporal**
  - nearby frames of video, photos taken at similar times, videos of similar scenes, time of capture
- **Cultural**
  - photographer bias, dataset selection bias, visual cliches, etc.

from Divvala et al. CVPR 2009

Cultural context



Jason Salavon: http://salavon.com/SpecialMoments/Newlyweds.shtml

Cultural context

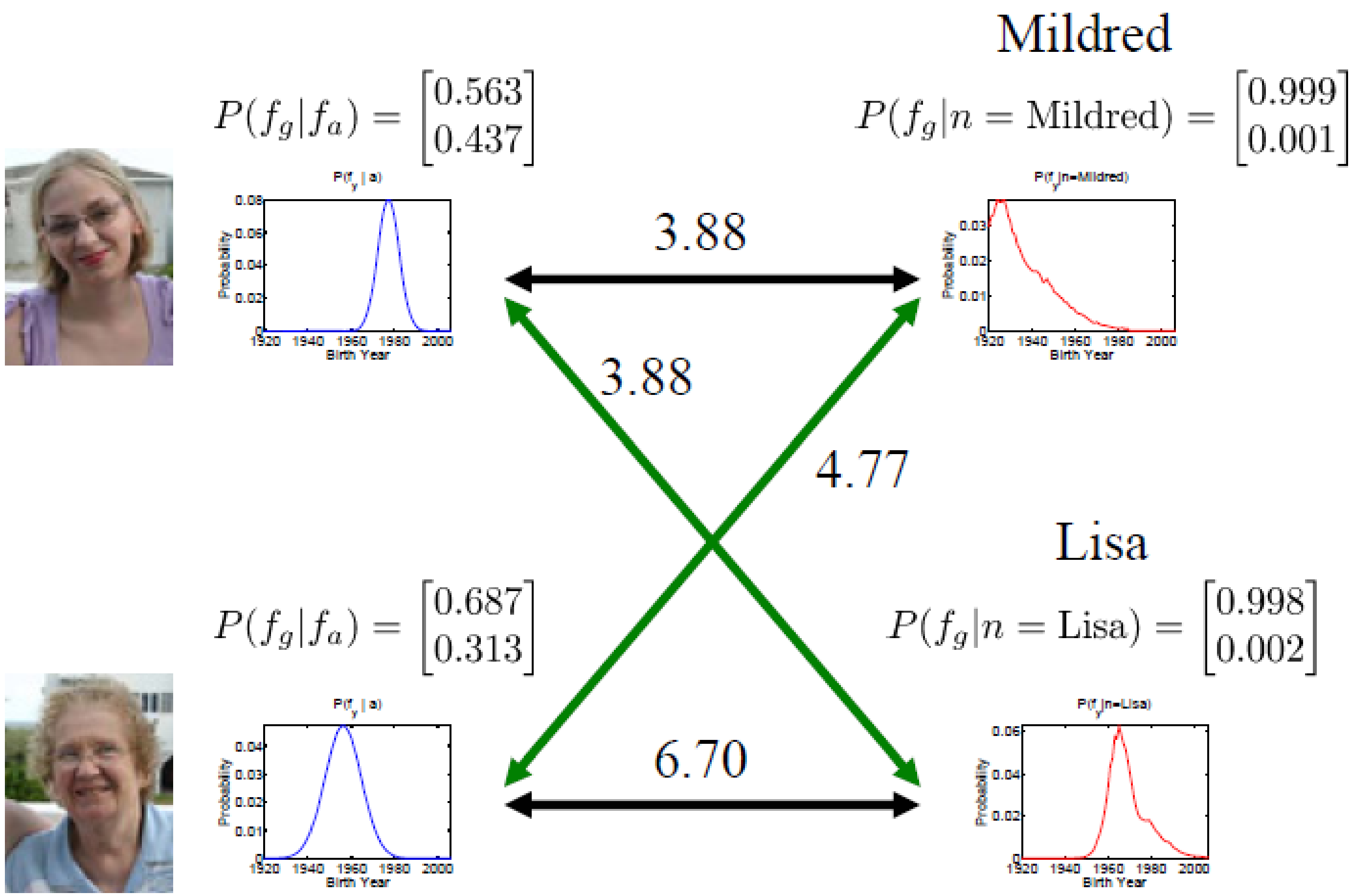
“Mildred and Lisa”: Who is Mildred? Who is Lisa?

Andrew Gallagher: http://chenlab.ece.cornell.edu/people/Andy/projectpage_names.html

Cultural context

Age given Appearance

Age given Name



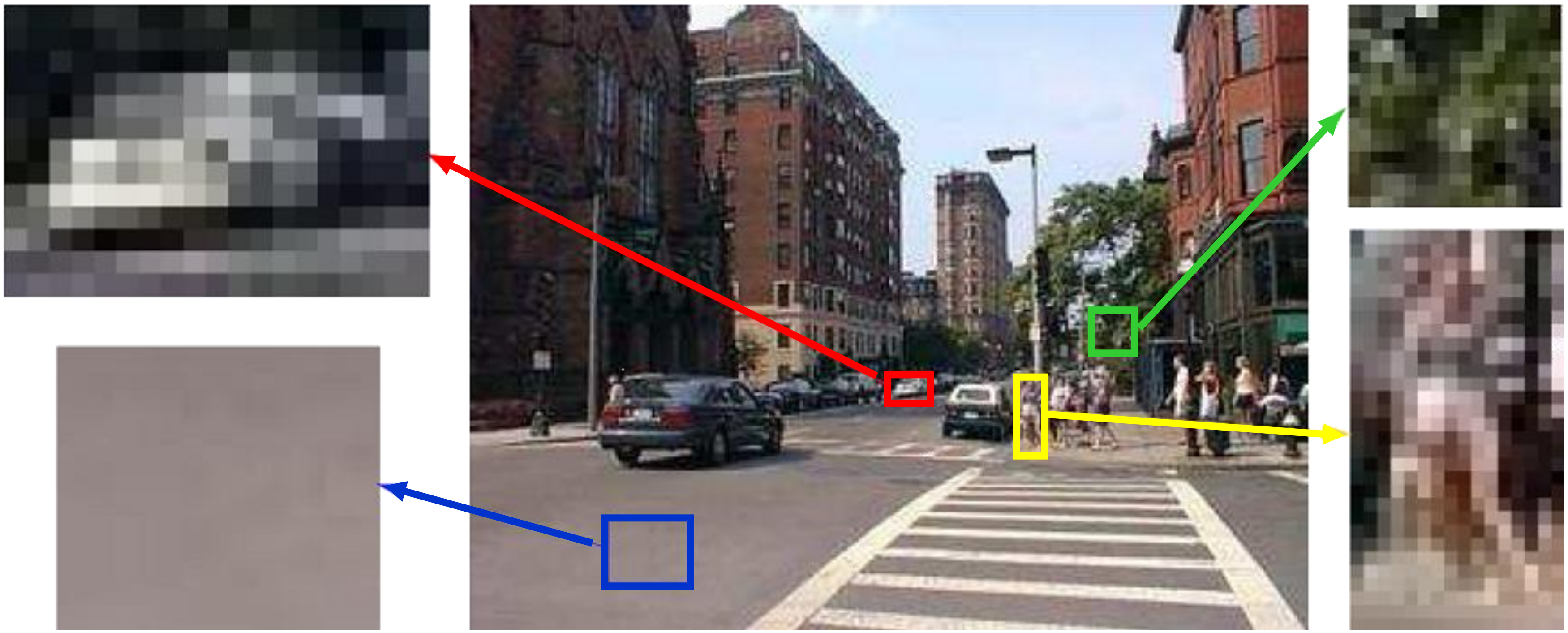
Andrew Gallagher: http://chenlab.ece.cornell.edu/people/Andy/projectpage_names.html

Spatial layout is especially important

1. Context for recognition

Spatial layout is especially important

1. Context for recognition



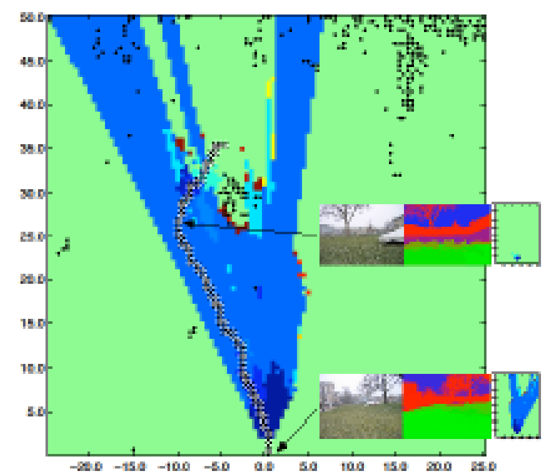
Spatial layout is especially important

1. Context for recognition
2. Scene understanding

Spatial layout is especially important

1. Context for recognition
2. Scene understanding
3. Many direct applications
   a) Assisted driving
   b) Robot navigation/interaction
   c) 2D to 3D conversion for 3D TV
   d) Object insertion

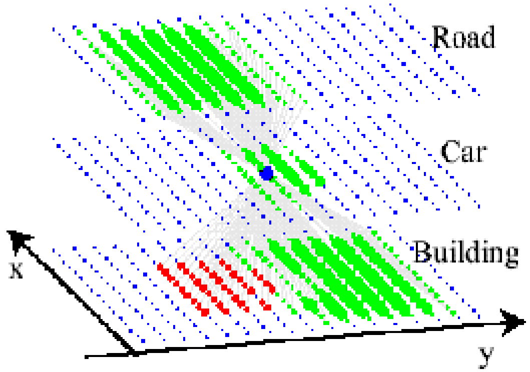
3D Reconstruction: Input, Mesh, Novel View



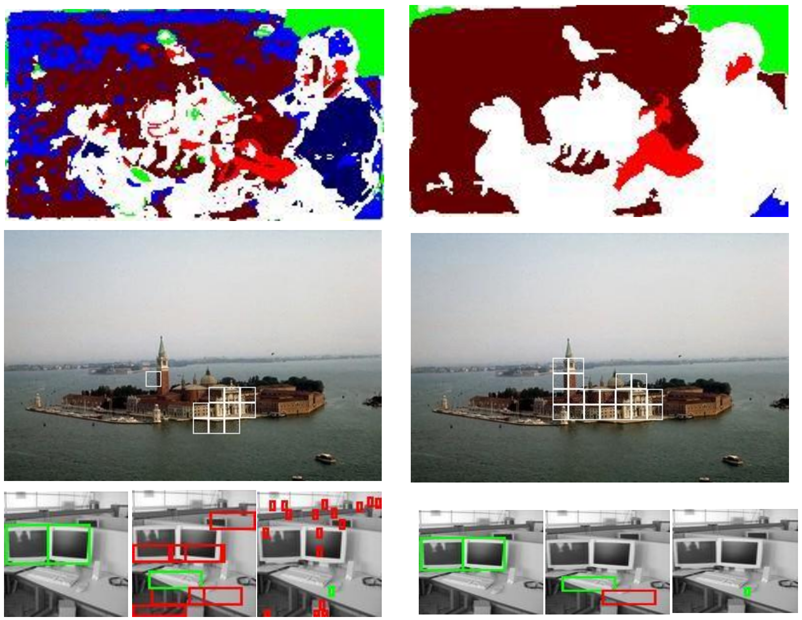
Robot Navigation: Path Planning

Spatial Layout: 2D vs. 3D?

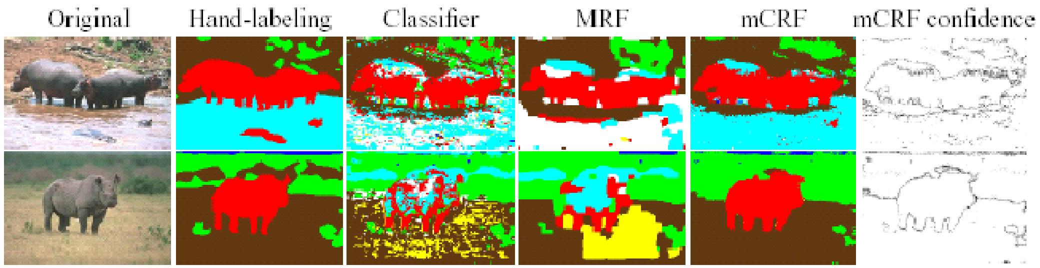
Context in Image Space



[Torralba Murphy Freeman 2004]

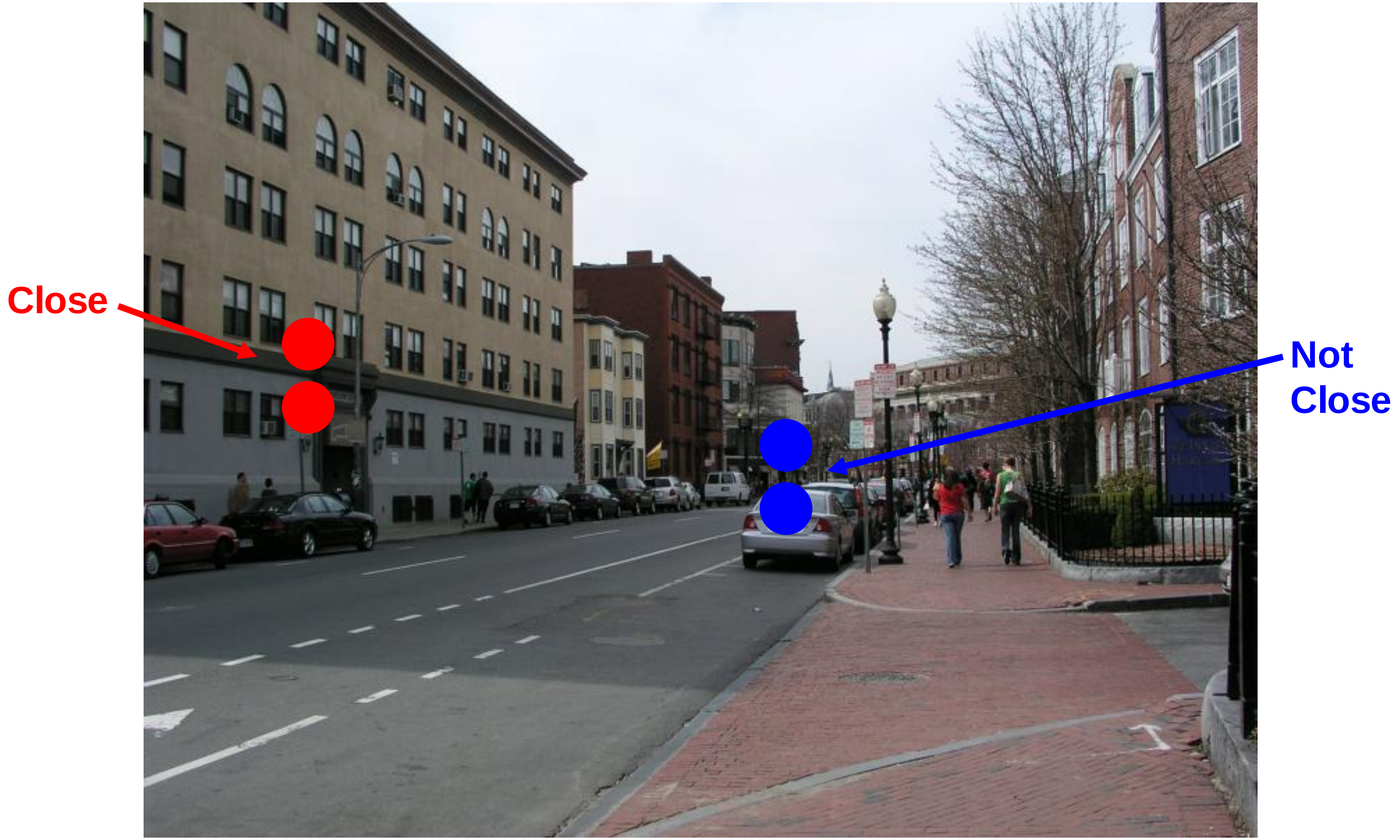


[Kumar Hebert 2005]



[He Zemel Cerreira-Perpiñán 2004]

But object relations are in 3D…



How to represent scene space?

Wide variety of possible representations

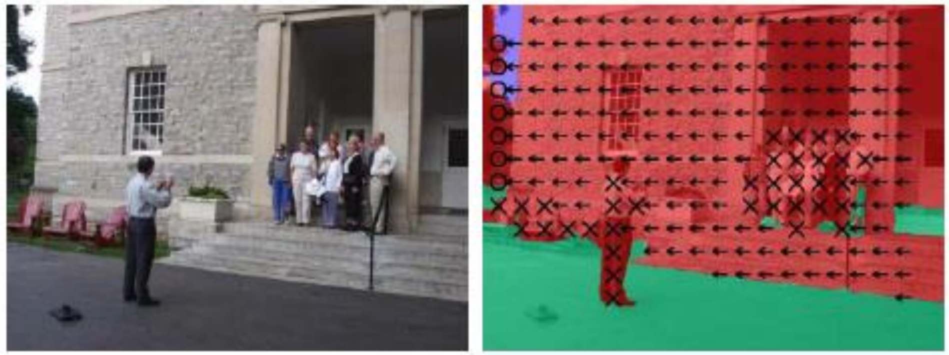
Scene-Level Geometric Description

a) Gist, Spatial Envelope

b) Stages

Figs from Hoiem - Savarese 2011 book

Retinotopic Maps

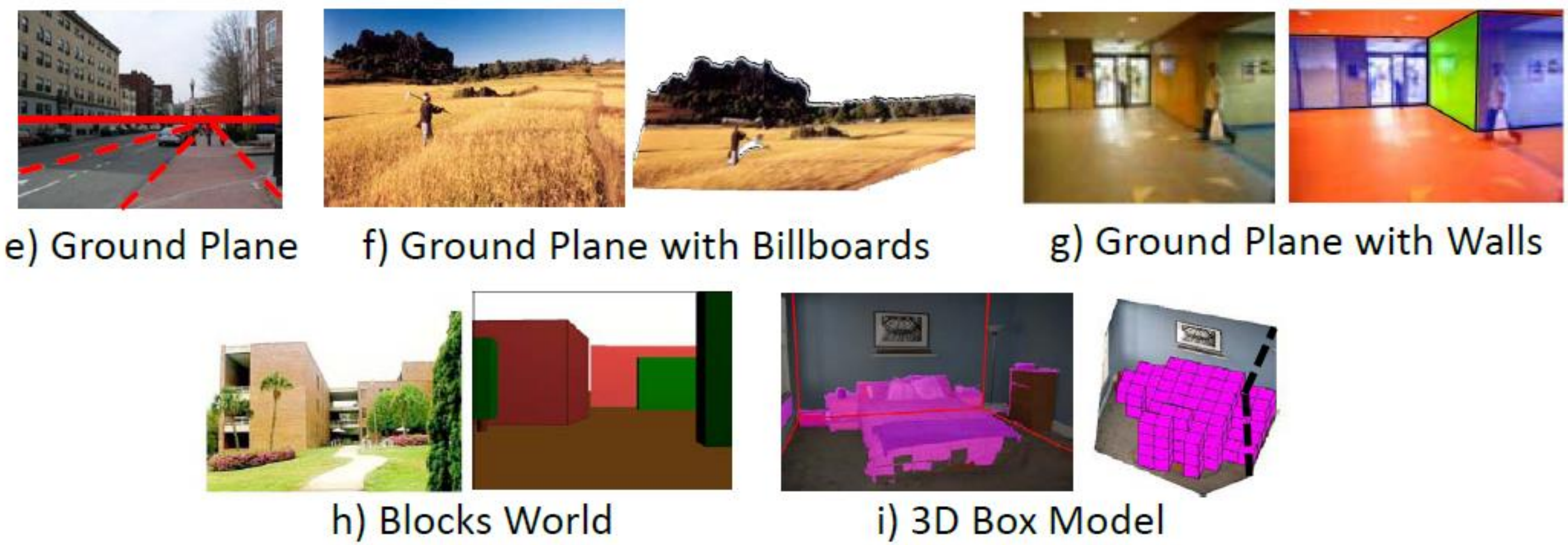


c) Geometric Context

d) Depth Maps

Figs from Hoiem - Savarese 2011 book

Highly Structured 3D Models



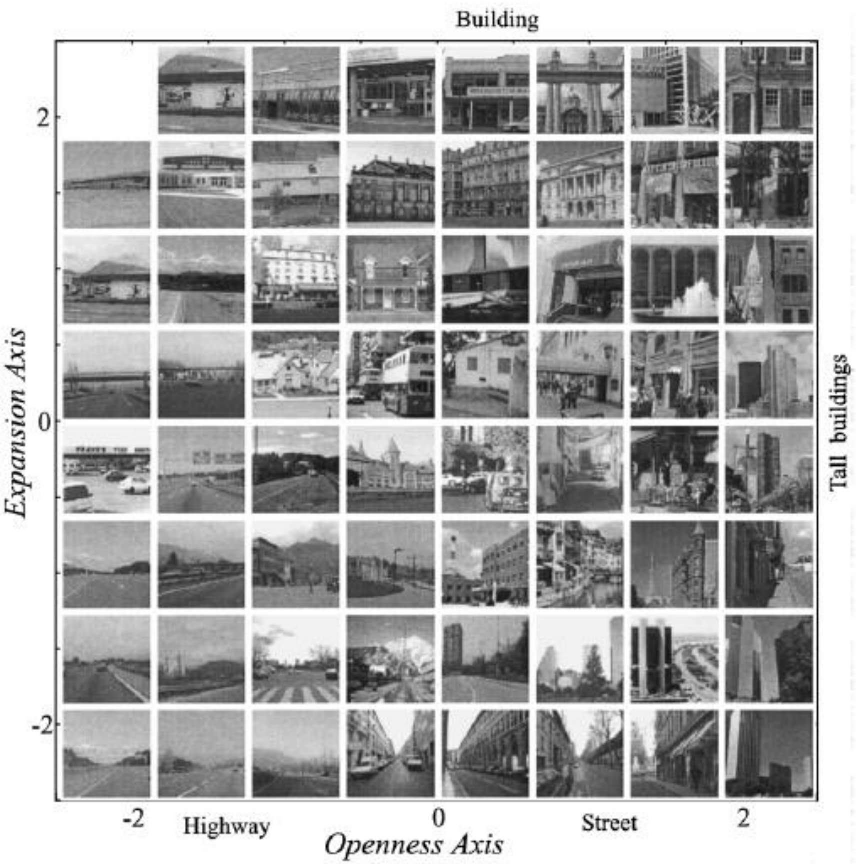
Figs from Hoiem - Savarese 2011 book

Key Trade-offs

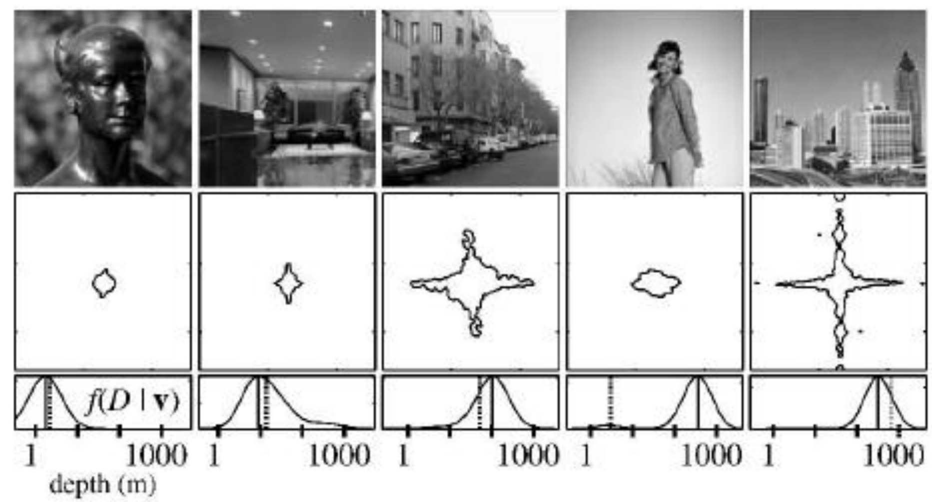
- Level of detail: rough "gist", or detailed point cloud?
  - Precision vs. accuracy
  - Difficulty of inference
- Abstraction: depth at each pixel, or ground planes and walls?
  - What is it for: e.g., metric reconstruction vs. navigation

Low detail, Low/Med abstraction

Holistic Scene Space: "Gist"



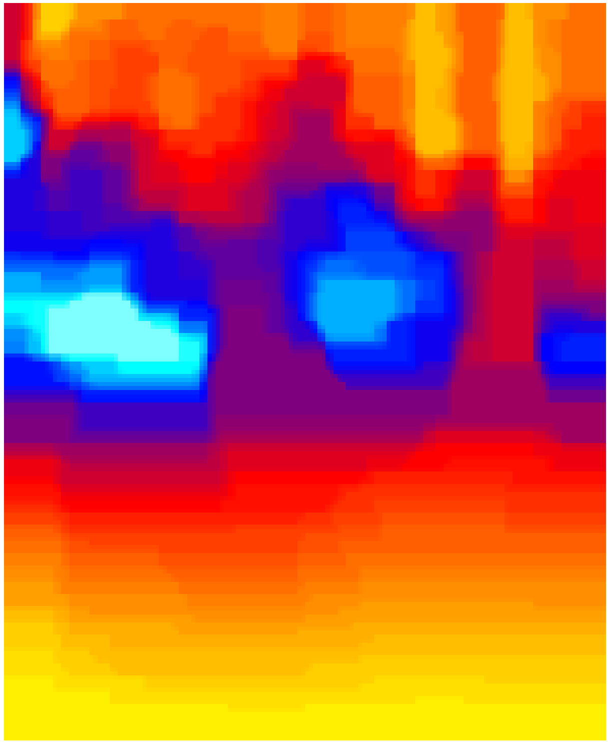
Oliva & Torralba 2001



Torralba & Oliva 2002

High detail, Low abstraction

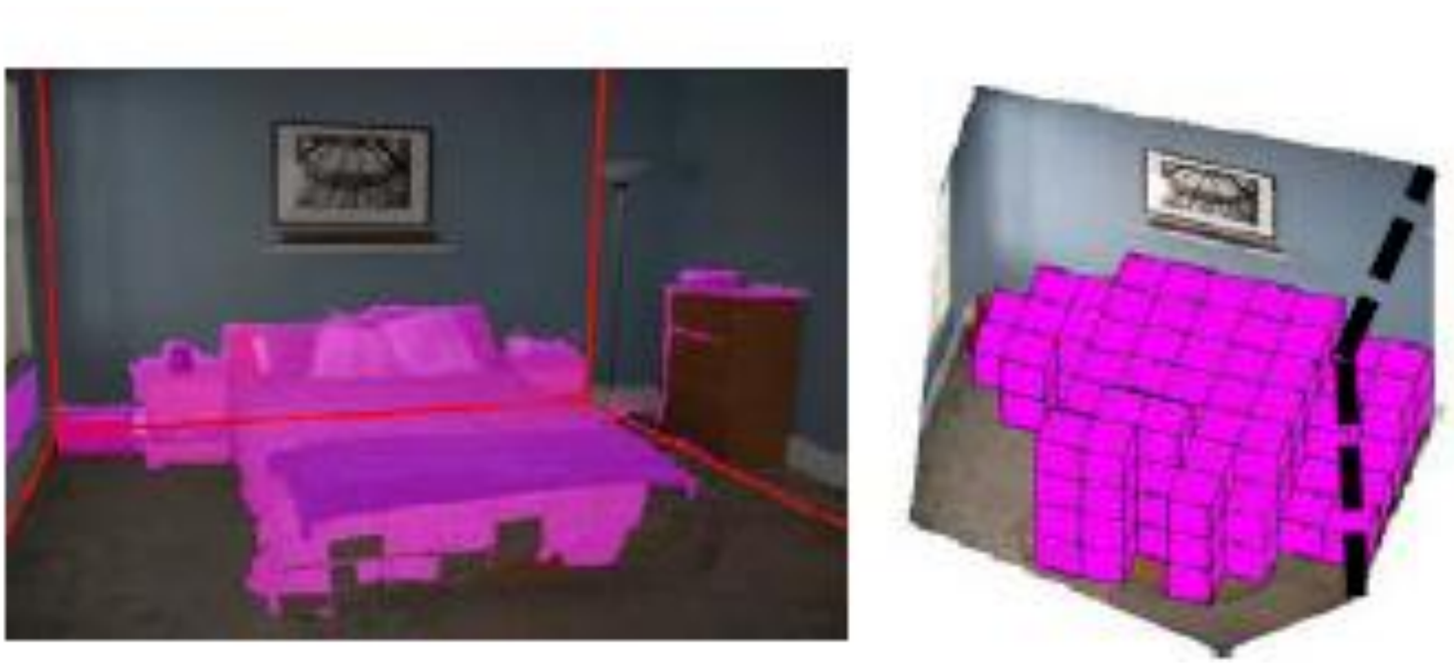
Depth Map



Saxena, Chung & Ng 2005, 2007

Medium detail, High abstraction

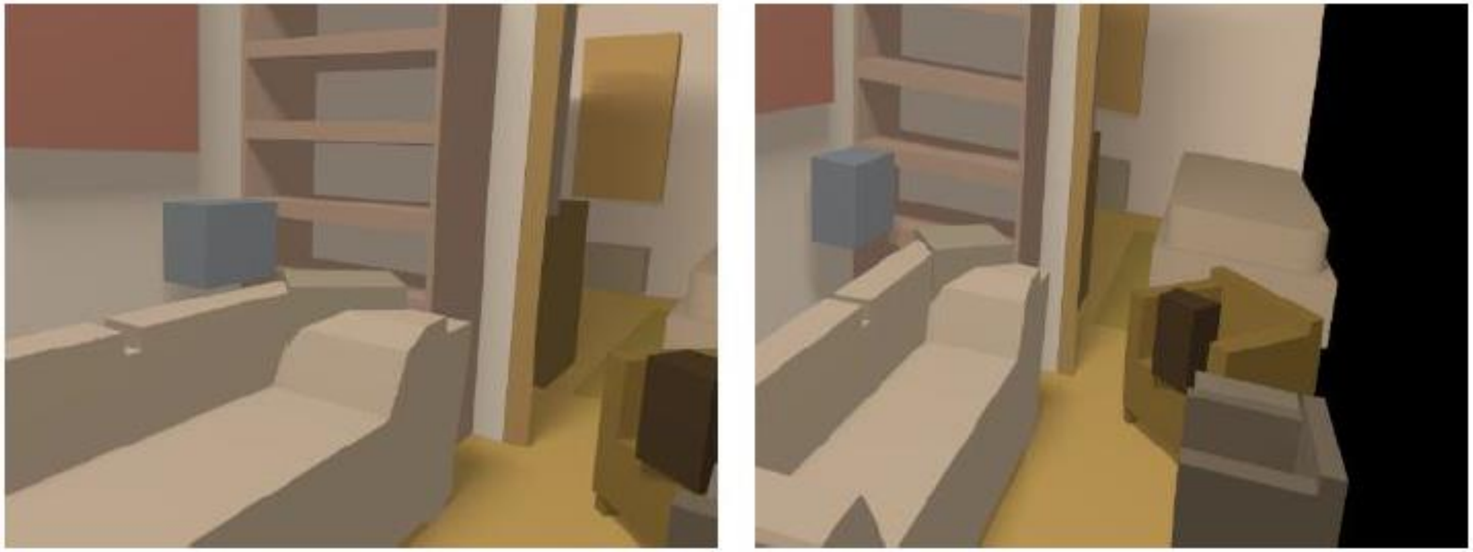
Room as a Box



Hedau Hoiem Forsyth 2009

Med-High detail, High abstraction

Complete 3D Layout

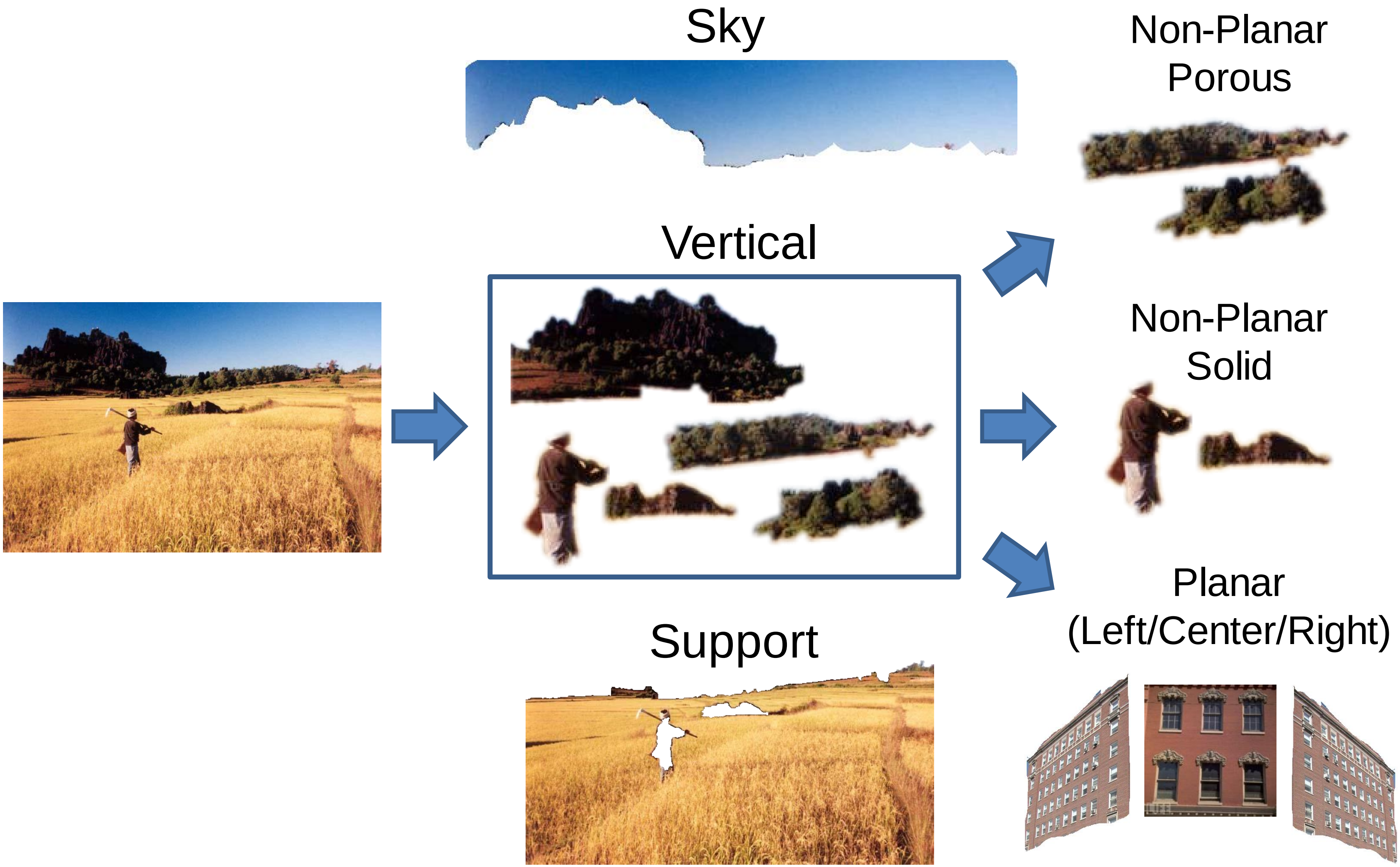


Guo Zou Hoiem 2015

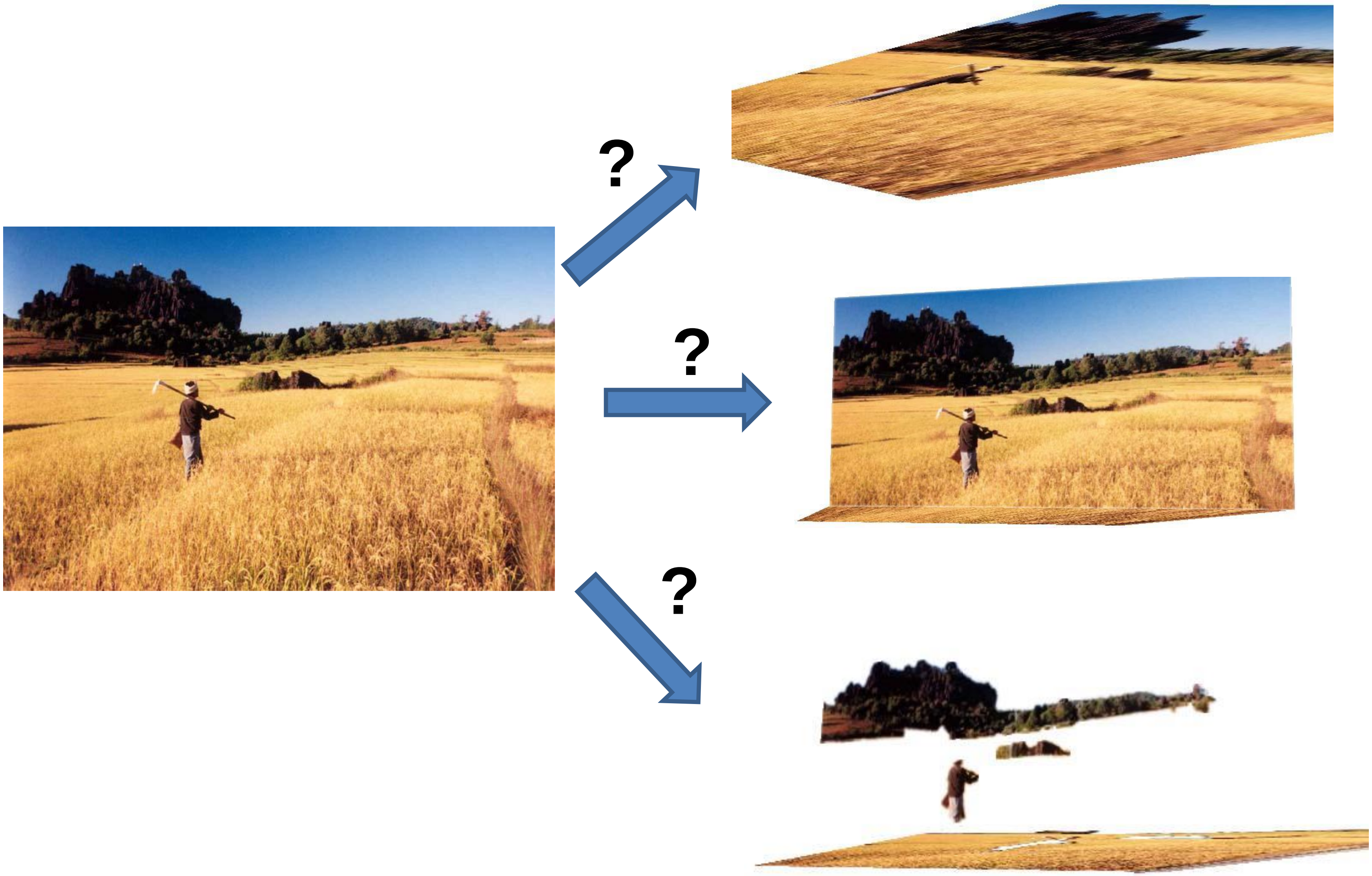
Examples of spatial layout estimation

- Surface layout
  - Application to 3D reconstruction
- The room as a box
  - Application to object recognition
- Complete layout and objects from depth

Surface Layout: describe 3D surfaces with geometric classes

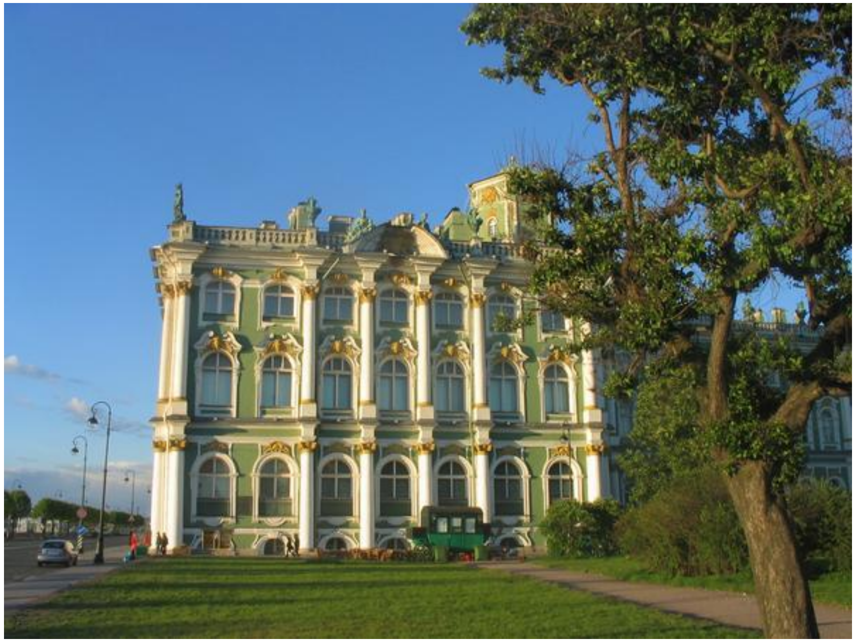


The challenge



Our World is Structured

Abstract World



Our World

Image Credit (left): F. Cunin
and M.J. Sailor, UCSD

Learn the Structure of the World

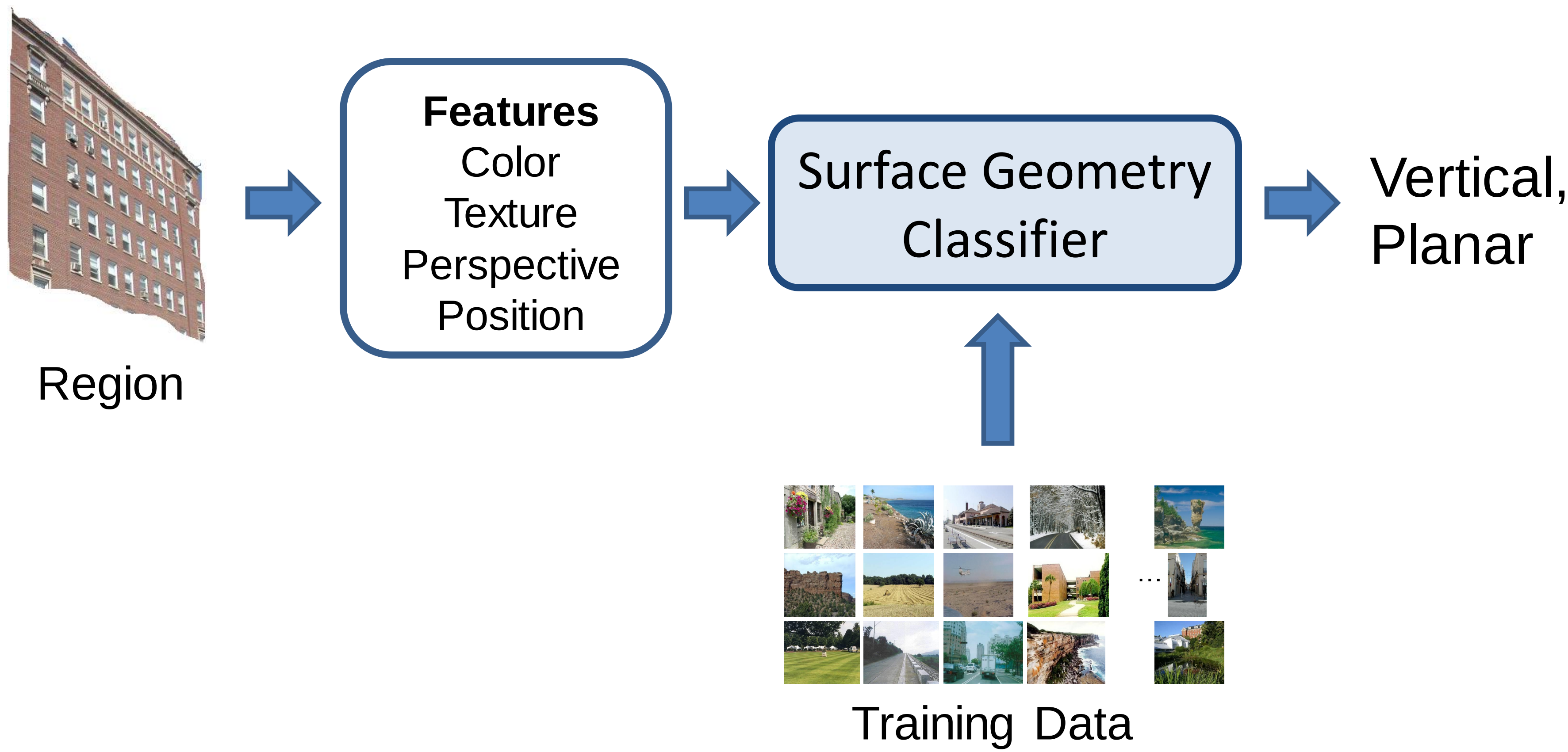
Training Images

Infer the most likely interpretation

Unlikely

Likely

Geometry estimation as recognition



Use a variety of image cues

Vanishing points, lines

Color, texture, image location

Texture gradient

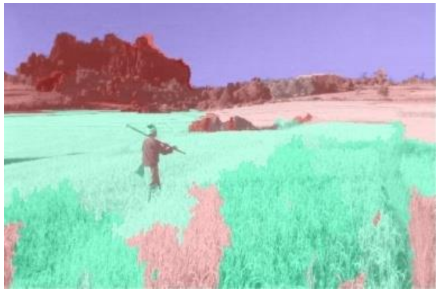
Surface Layout Algorithm

Input Image

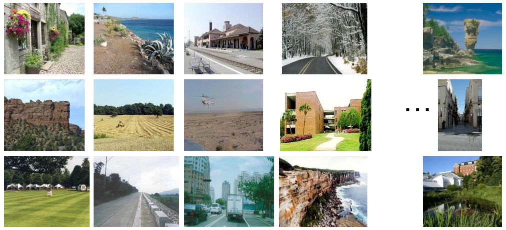
Segmentation

Features
Perspective
Color
Texture
Position

Surface Labels



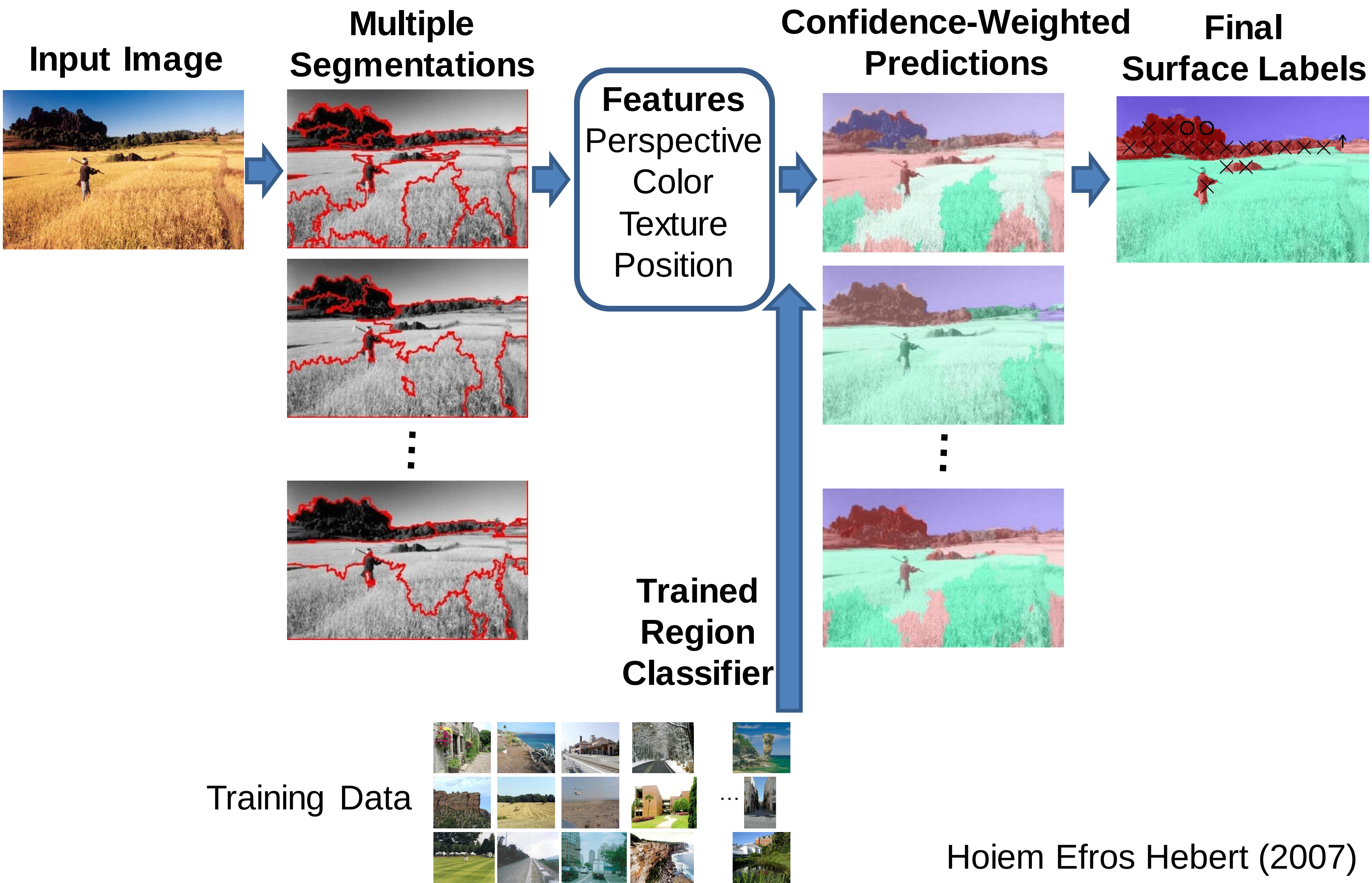
Trained Region Classifier



Training Data

Hoiem Efros Hebert (2007)

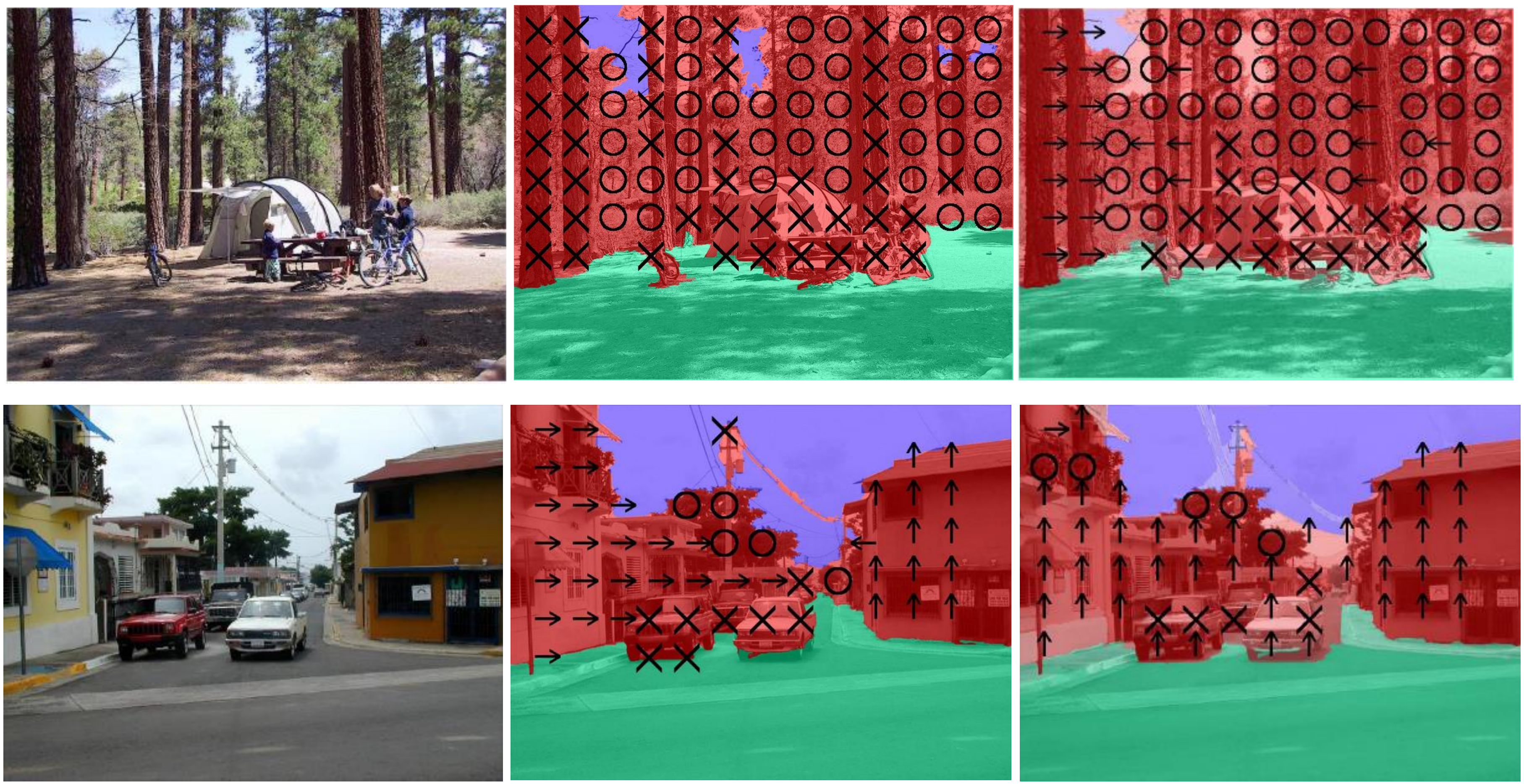
Surface Layout Algorithm



Hoiem Efros Hebert (2007)

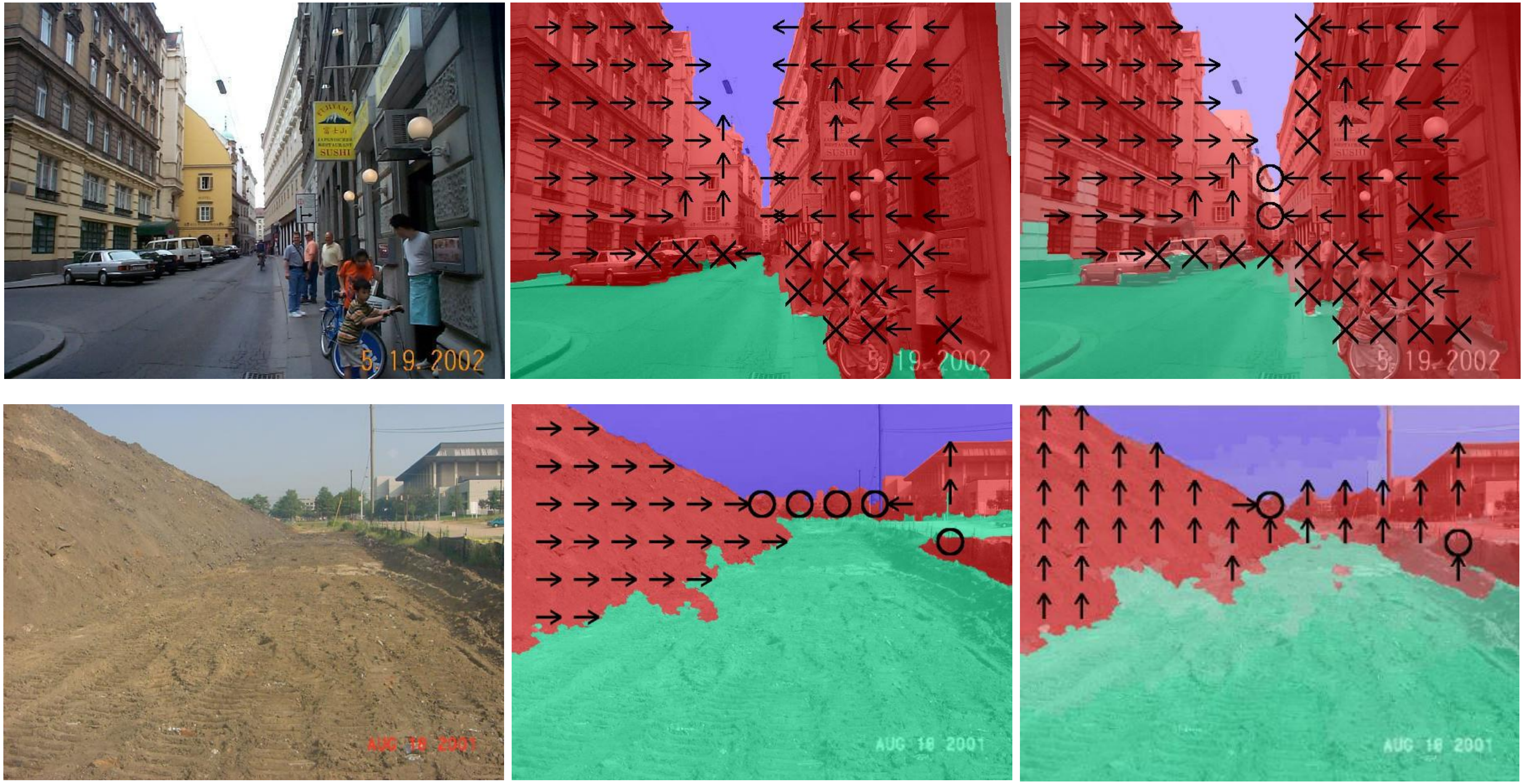
Surface Description Result

Results



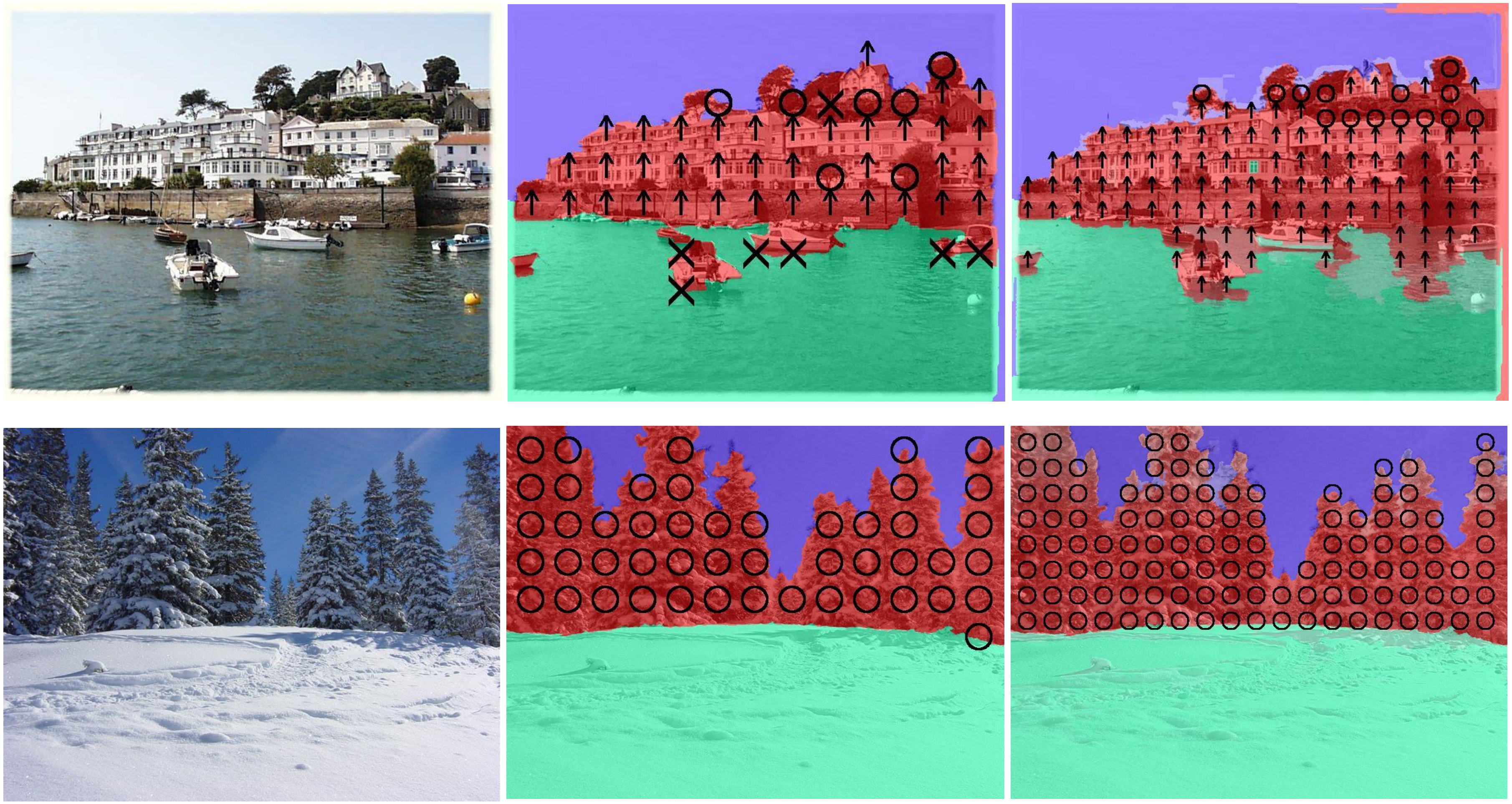
Input Image Ground Truth Our Result

Results



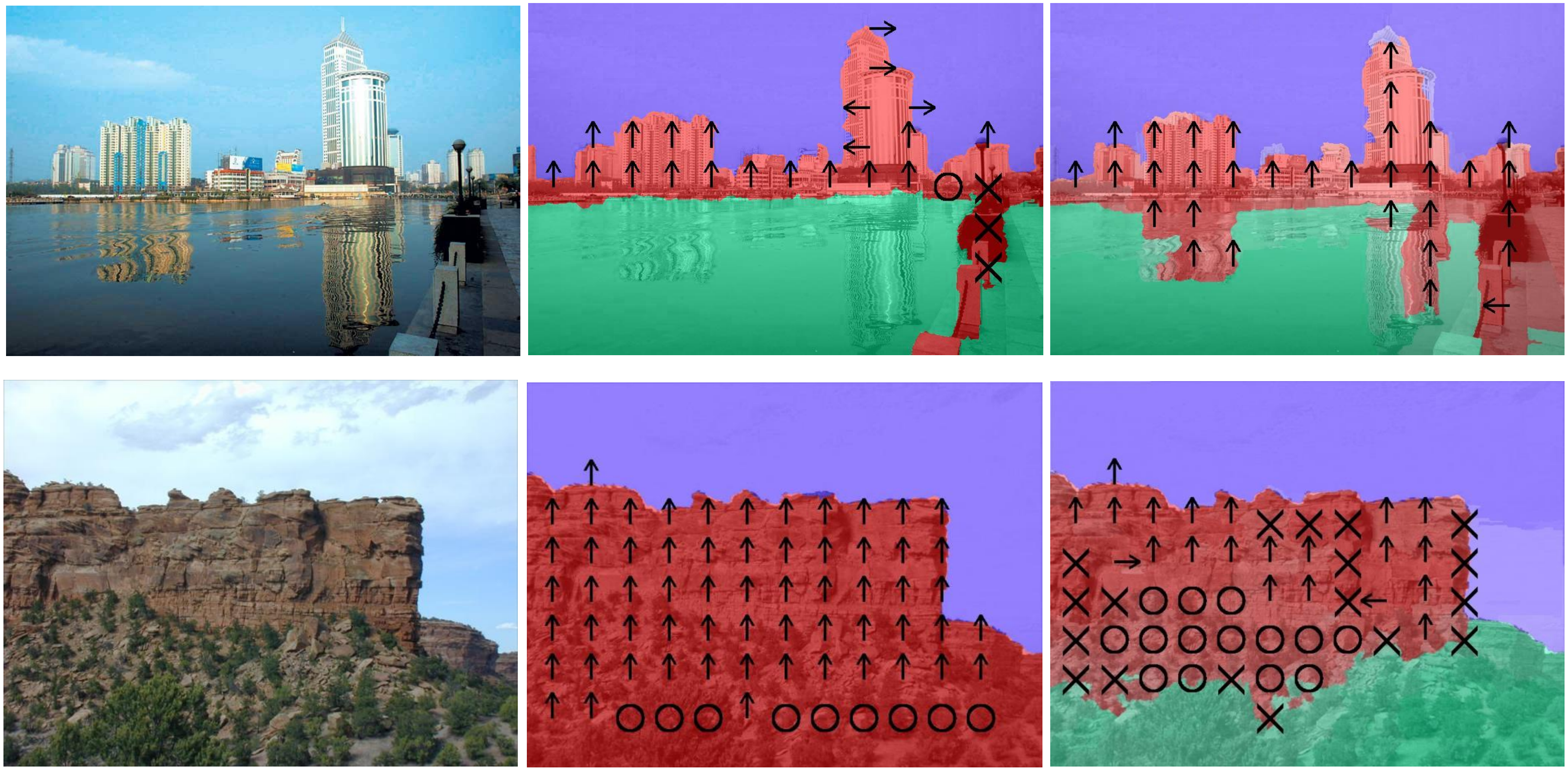
Input Image | Ground Truth | Our Result

Results



Input Image | Ground Truth | Our Result

Failures: Reflections, Rare Viewpoint



Input Image Ground Truth Our Result

Average Accuracy

Main Class: 88%

Subclasses: 61%

Main Class			
	Support	Vertical	Sky
Support	**0.84**	0.15	0.00
Vertical	0.09	**0.90**	0.02
Sky	0.00	0.10	**0.90**

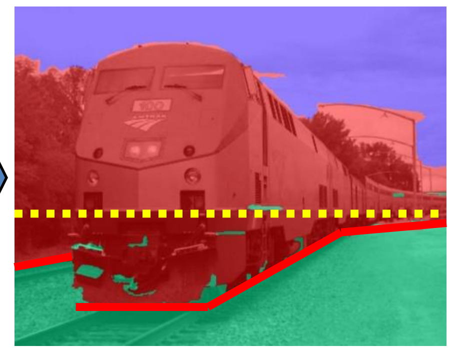
Vertical Subclass					
	Left	Center	Right	Porous	Solid
Left	**0.37**	0.32	0.08	0.09	0.13
Center	0.05	**0.56**	0.12	0.16	0.12
Right	0.02	0.28	**0.47**	0.13	0.10
Porous	0.01	0.07	0.03	**0.84**	0.06
Solid	0.04	0.20	0.04	0.17	**0.55**

Automatic Photo Popup

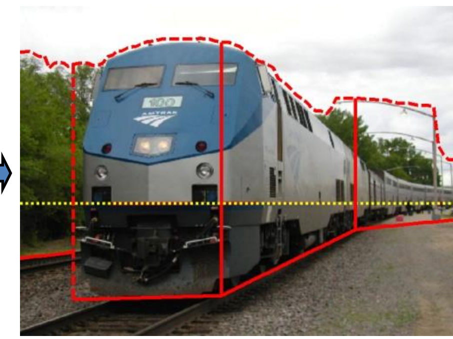
Labeled Image

Fit Ground-Vertical Boundary with Line Segments

Form Segments into Polylines



Cut and Fold

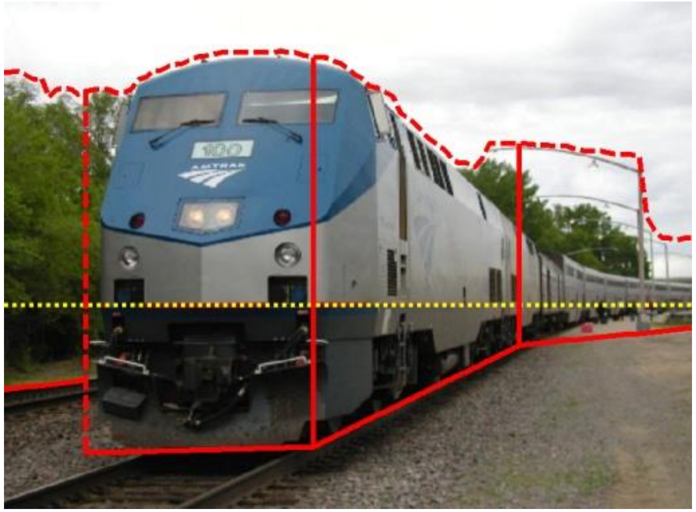


Final Pop-up Model

[Hoiem Efros Hebert 2005]

Automatic Photo Popup

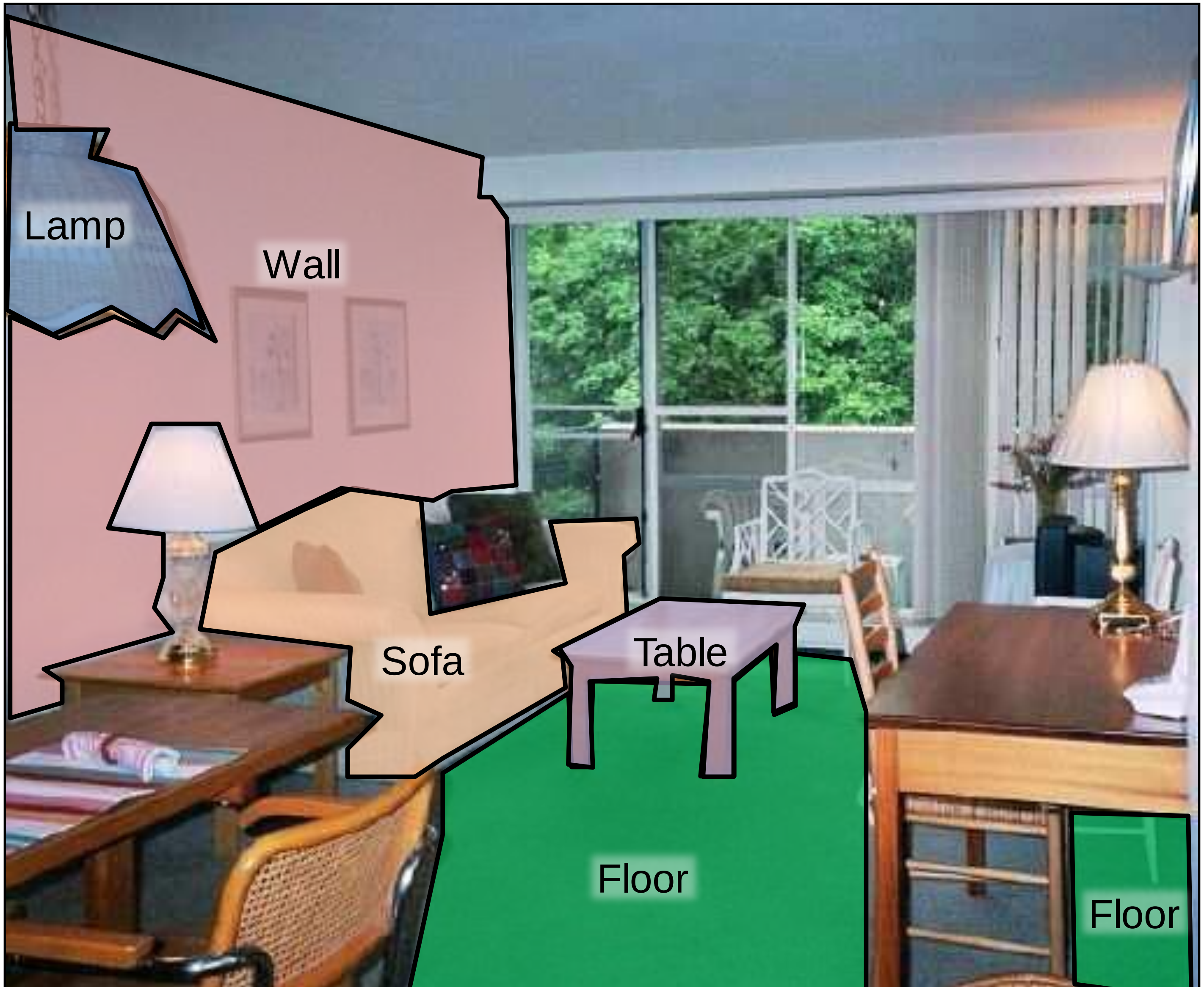
Mini-conclusions



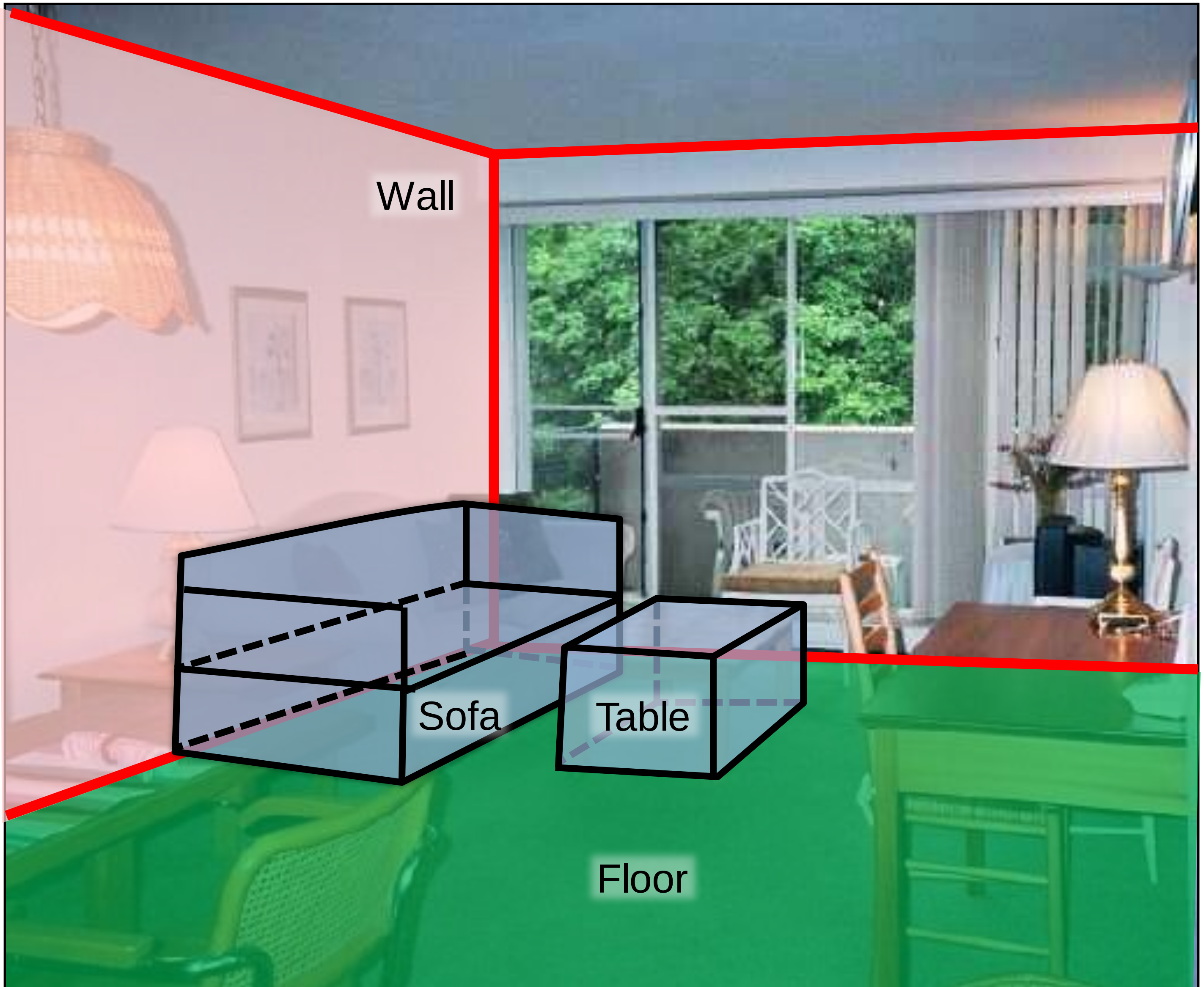
- Can learn to predict surface geometry from a single image

Interpretation of indoor scenes

Vision = assigning labels to pixels?



Vision = interpreting within physical space



Physical space needed for affordance

Is this a good place to sit?

Could I stand over here?

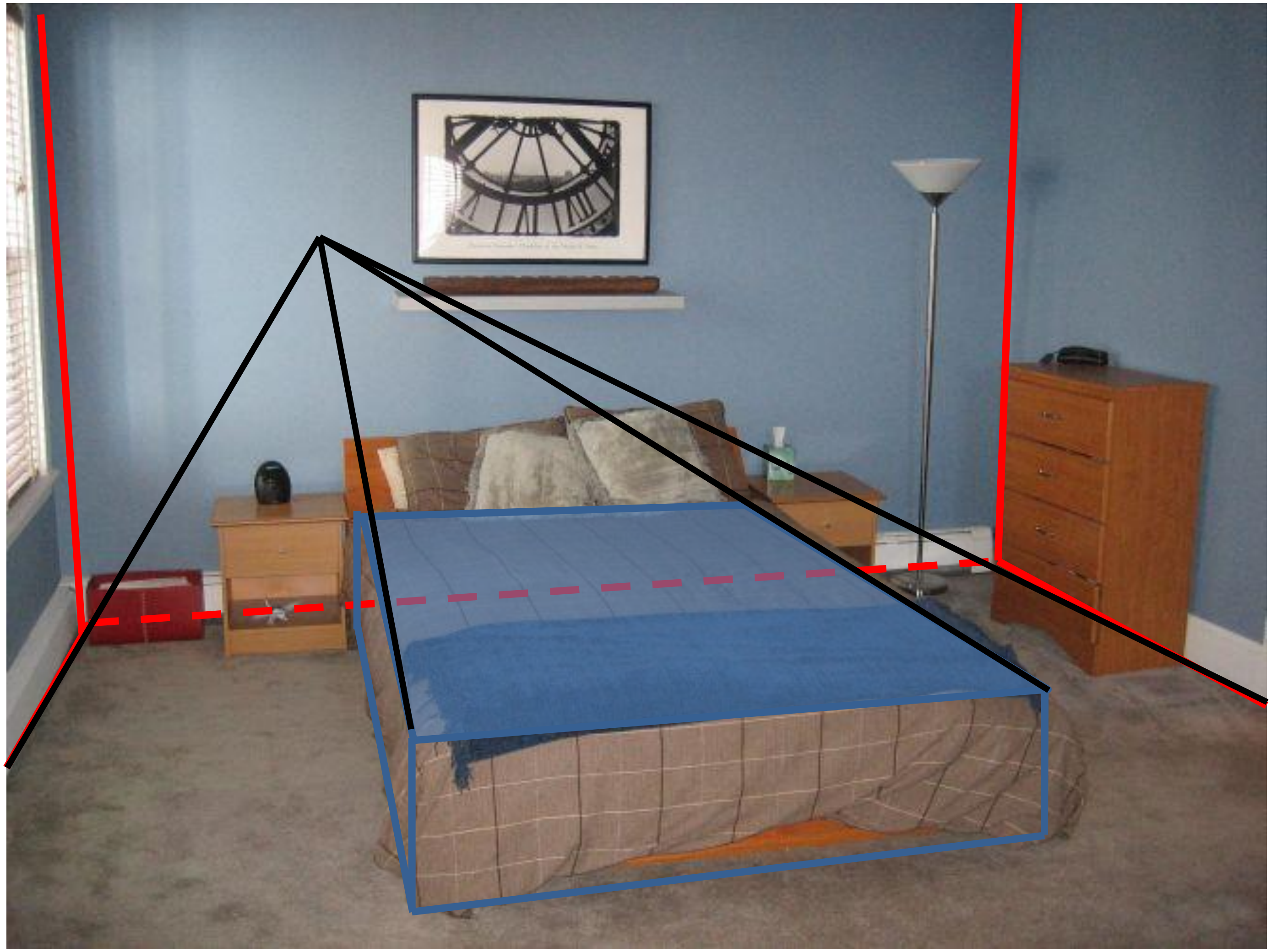
Can I put my cup here?

Walkable path

Physical space needed for recognition

Apparent shape depends
strongly on viewpoint

Physical space needed for recognition



Physical space needed to predict appearance

Physical space needed to predict appearance

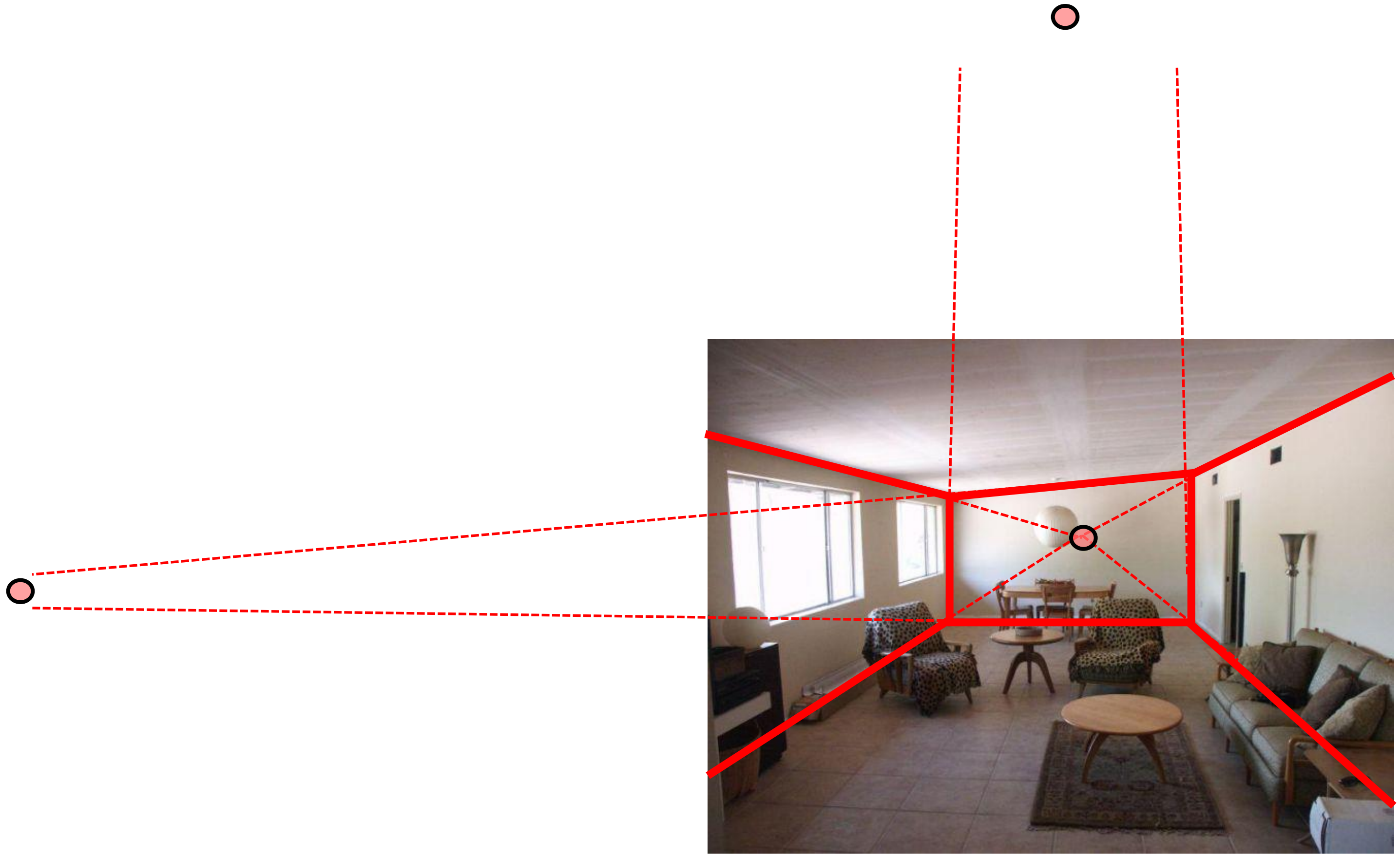
Key challenges

- How to represent the physical space?
  - *Requires seeing beyond the visible*
- How to estimate the physical space?
  - Requires simplified models
  - Requires learning from examples

Hedau Hoiem Forsyth, ICCV 2009

Our Box Layout

- Room is an oriented 3D box
  - Three vanishing points specify orientation
  - Two pairs of sampled rays specify position/size



Our Box Layout

- Room is an oriented 3D box
  - Three vanishing points (VPs) specify orientation
  - Two pairs of sampled rays specify position/size

Another box consistent with
the same vanishing points

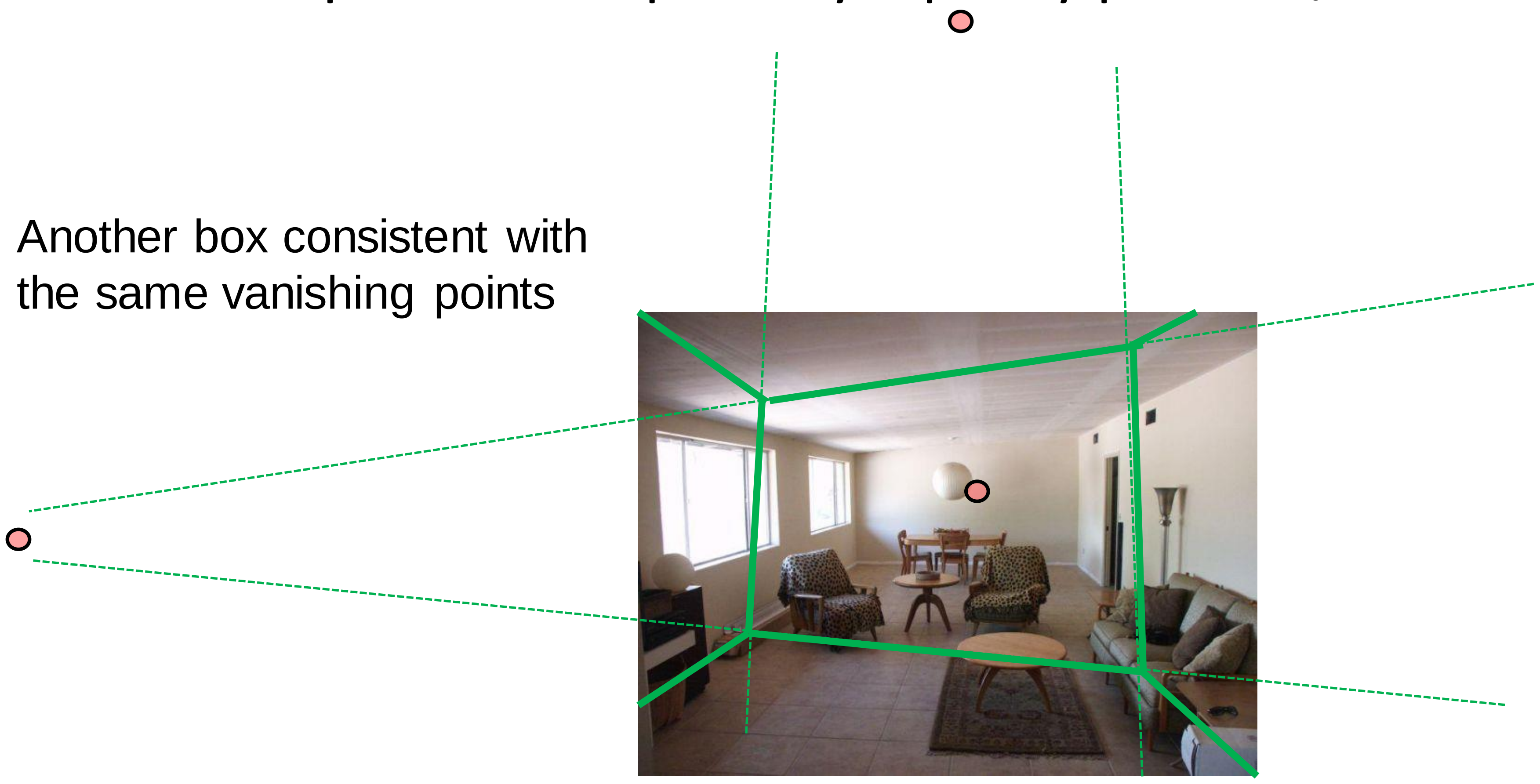
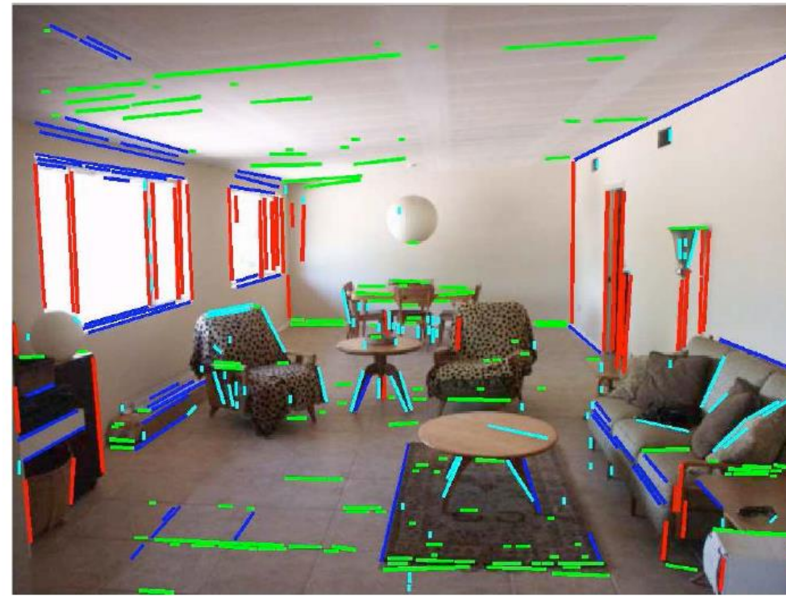
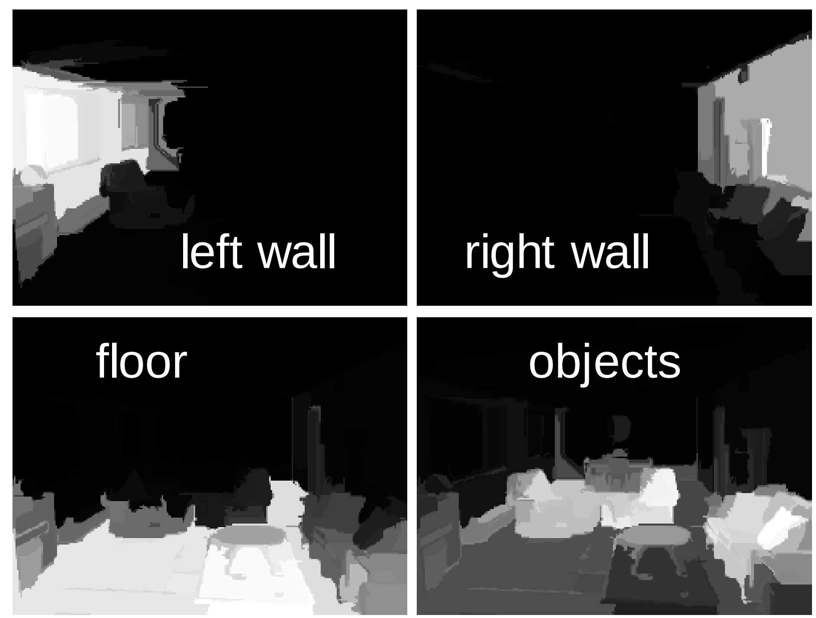


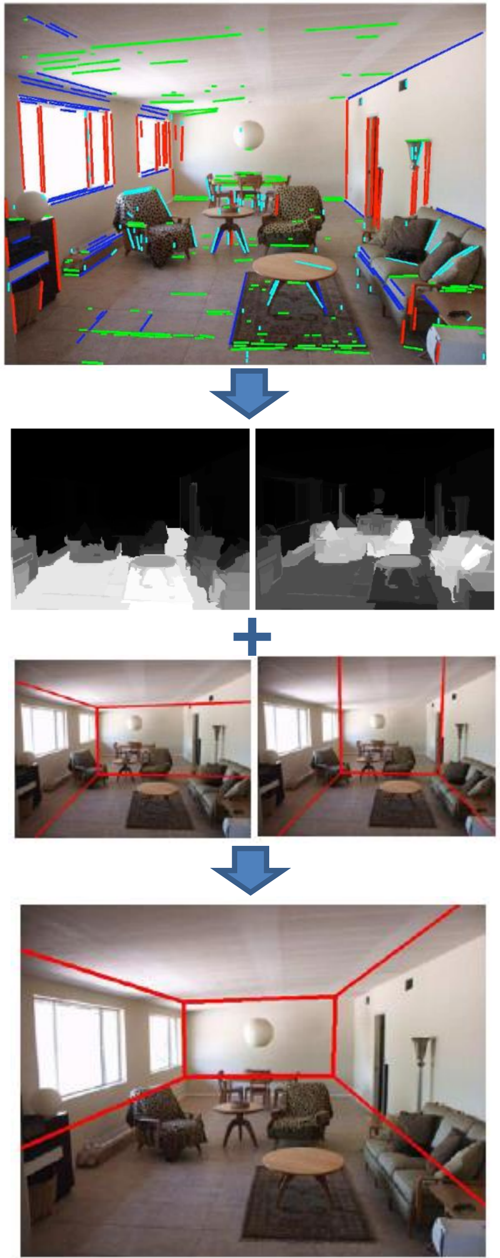
Image Cues for Box Layout

- Straight edges
  - Edges on floor/wall surfaces are usually oriented towards VPs
  - Edges on objects might mislead
- Appearance of visible surfaces
  - Floor, wall, ceiling, object labels should be consistent with box





Box Layout Algorithm



1. Detect edges

2. Estimate 3 orthogonal vanishing points

3. Apply region classifier to label pixels with visible surfaces
   – Boosted decision trees on region based on color, texture, edges, position

4. Generate box candidates by sampling pairs of rays from VPs

5. Score each box based on edges and pixel labels
   – Learn score via structured learning

6. Jointly refine box layout and pixel labels to get final estimate

Evaluation

- Dataset: 308 indoor images
  - Train with 204 images, test with 104 images






Experimental results

Detected Edges

Surface Labels

Box Layout

Detected Edges

Surface Labels

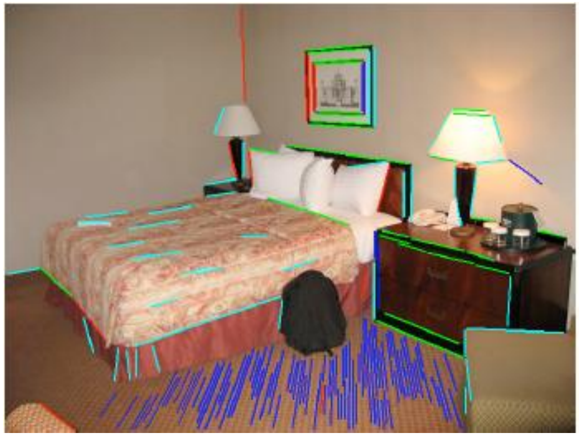
Box Layout

Experimental results


Detected Edges


Surface Labels


Box Layout


Detected Edges


Surface Labels


Box Layout

Experimental results

- Joint reasoning of surface label / box layout helps
  - Pixel error: 26.5% → 21.2%
  - Corner error: 7.4% → 6.3%

- Similar performance for cluttered and uncluttered rooms

Mini-Conclusions

- Can fit a 3D box to the rooms boundaries from one image
  - Make your model as simple as possible to provide robustness

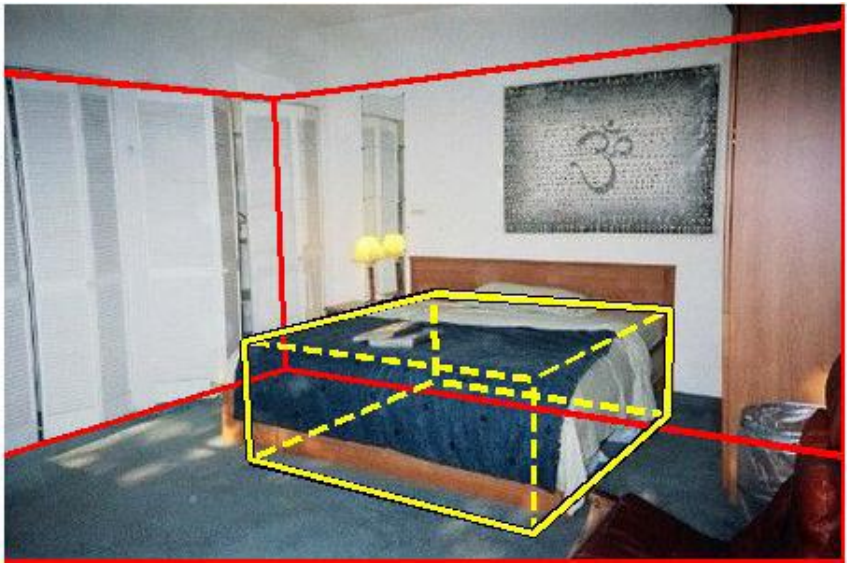
Using room layout to improve object detection

Box layout helps

1. Predict the appearance of objects, because they are often aligned with the room
2. Predict the position and size of objects, due to physical constraints and size consistency

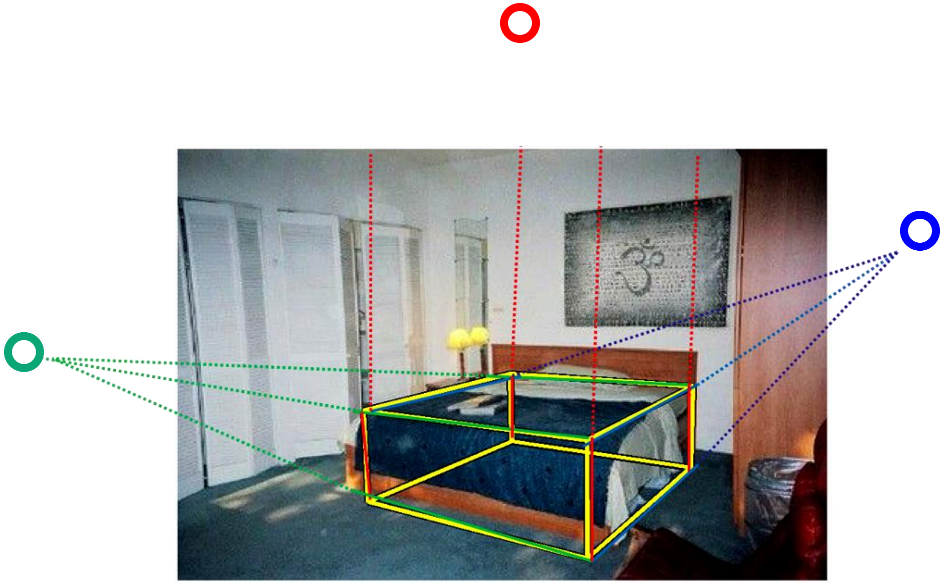
2D Bed Detection

3D Bed Detection with Scene Geometry

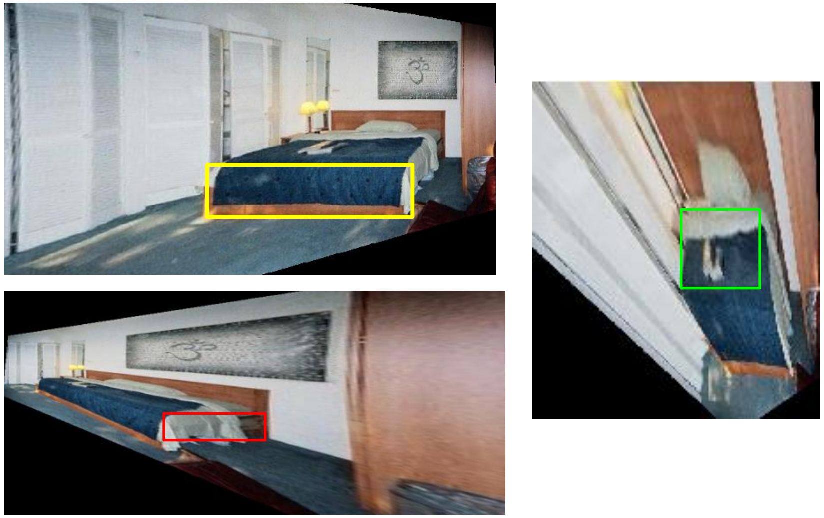


Hedau, Hoiem, Forsyth, ECCV 2010, CVPR 2012

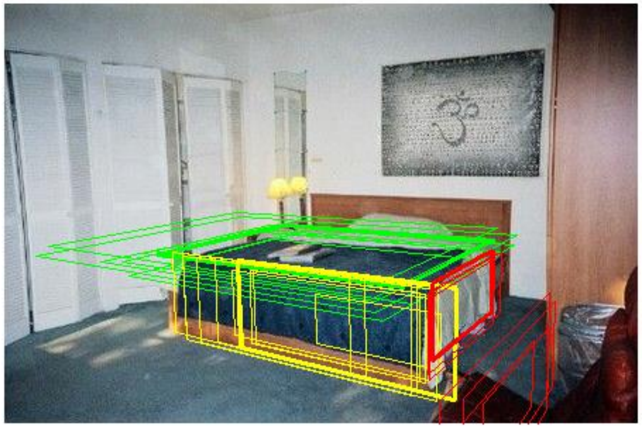
Search for objects in room coordinates



Recover Room Coordinates



Rectify Features to Room Coordinates



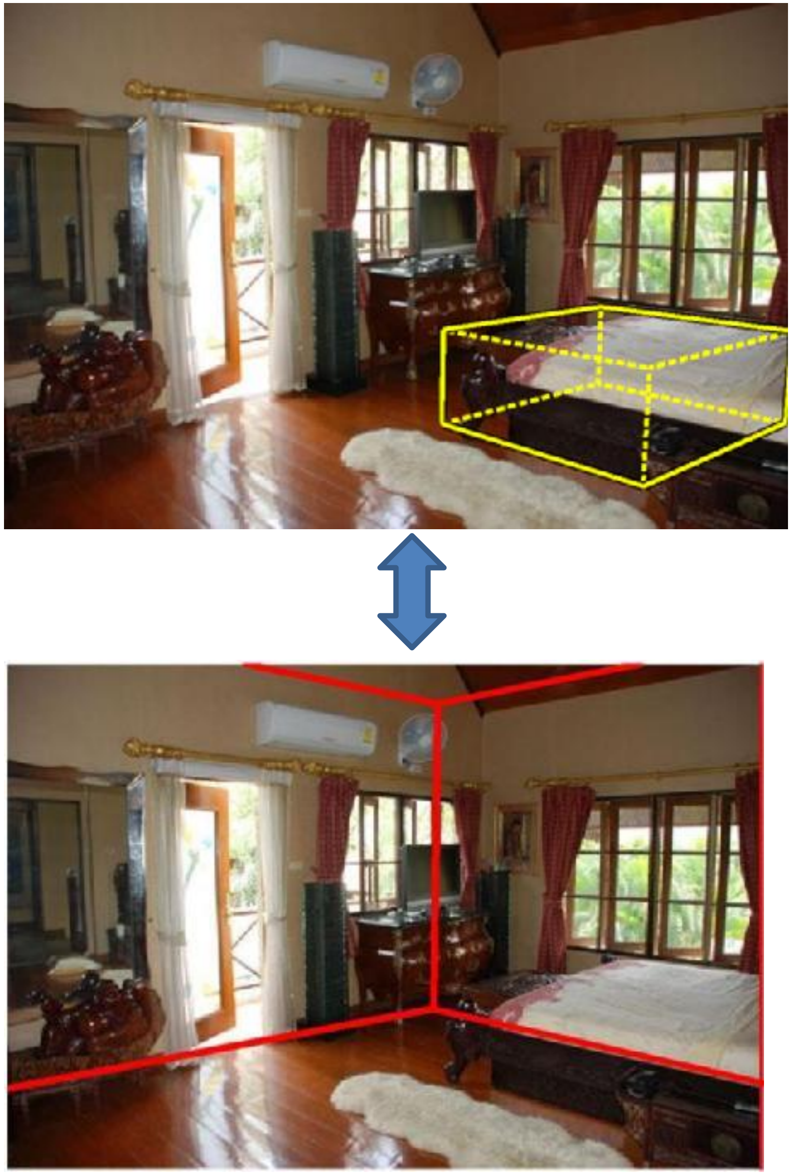
Rectified Sliding Windows

Hedau Forsyth Hoiem (2010)

Reason about 3D room and bed space

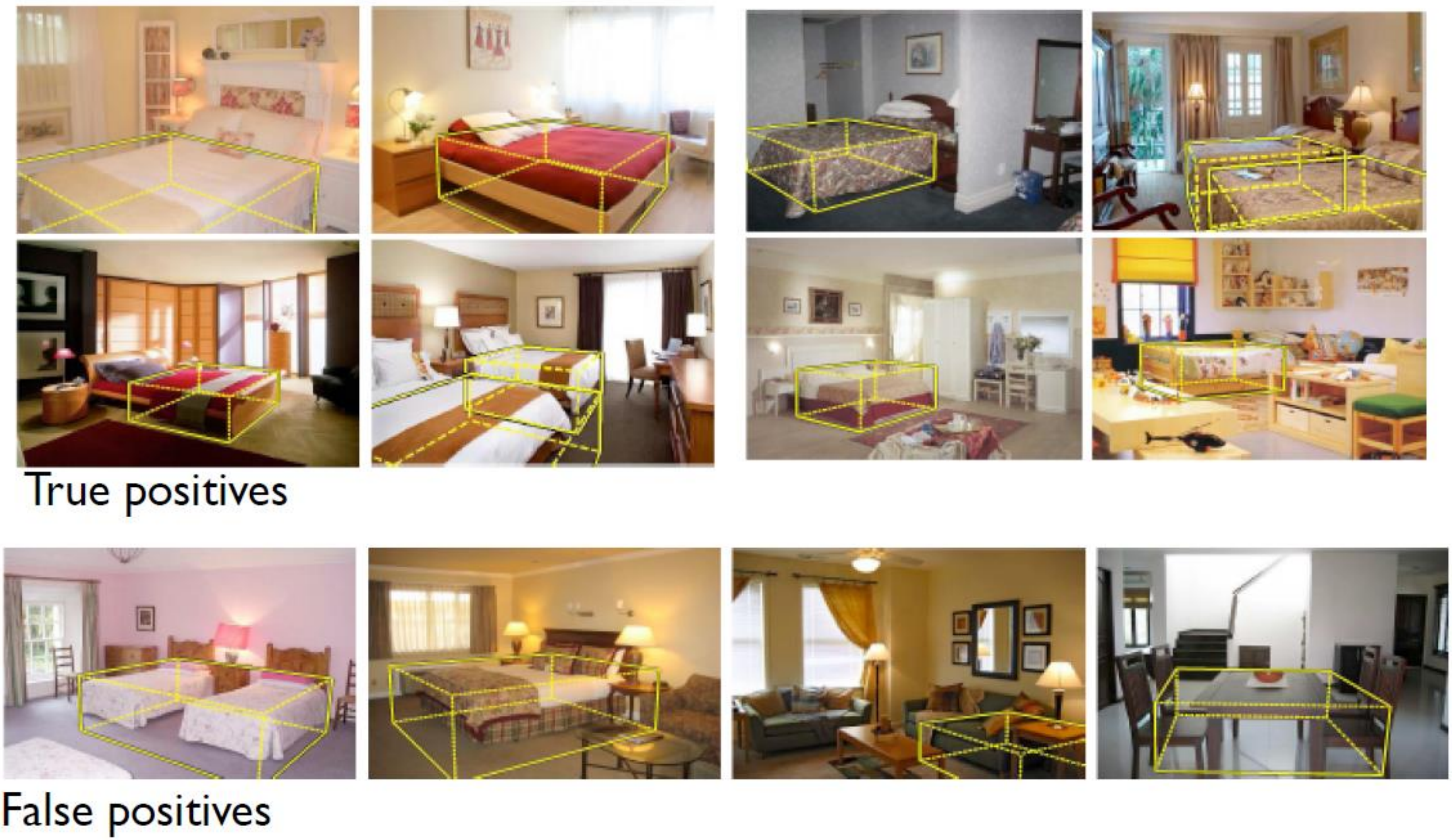
Joint Inference with Priors

- Beds close to walls
- Beds within room
- Consistent bed/wall size
- Two objects cannot occupy the same space

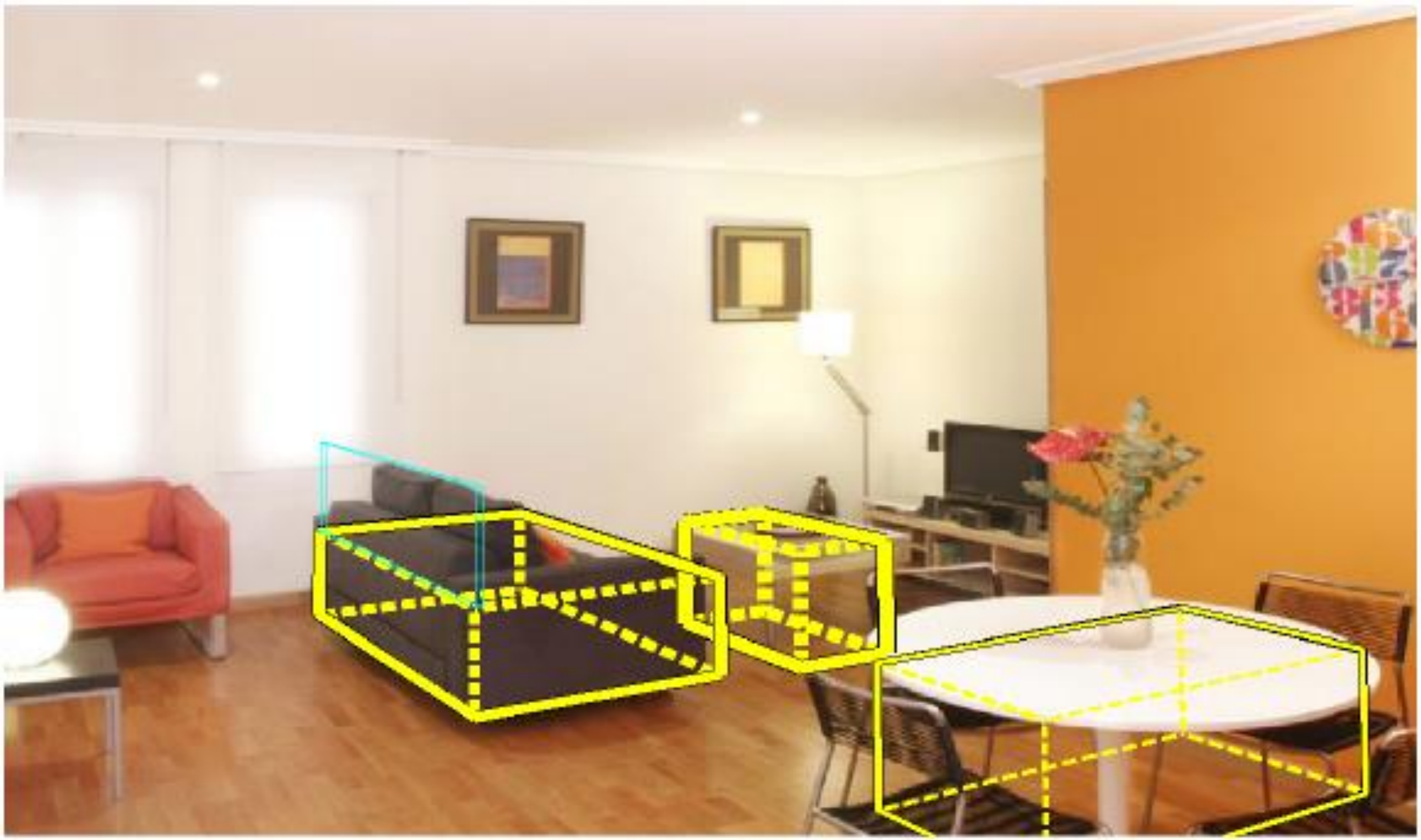


Hedau Forsyth Hoiem (2010)

3D Bed Detection from an Image

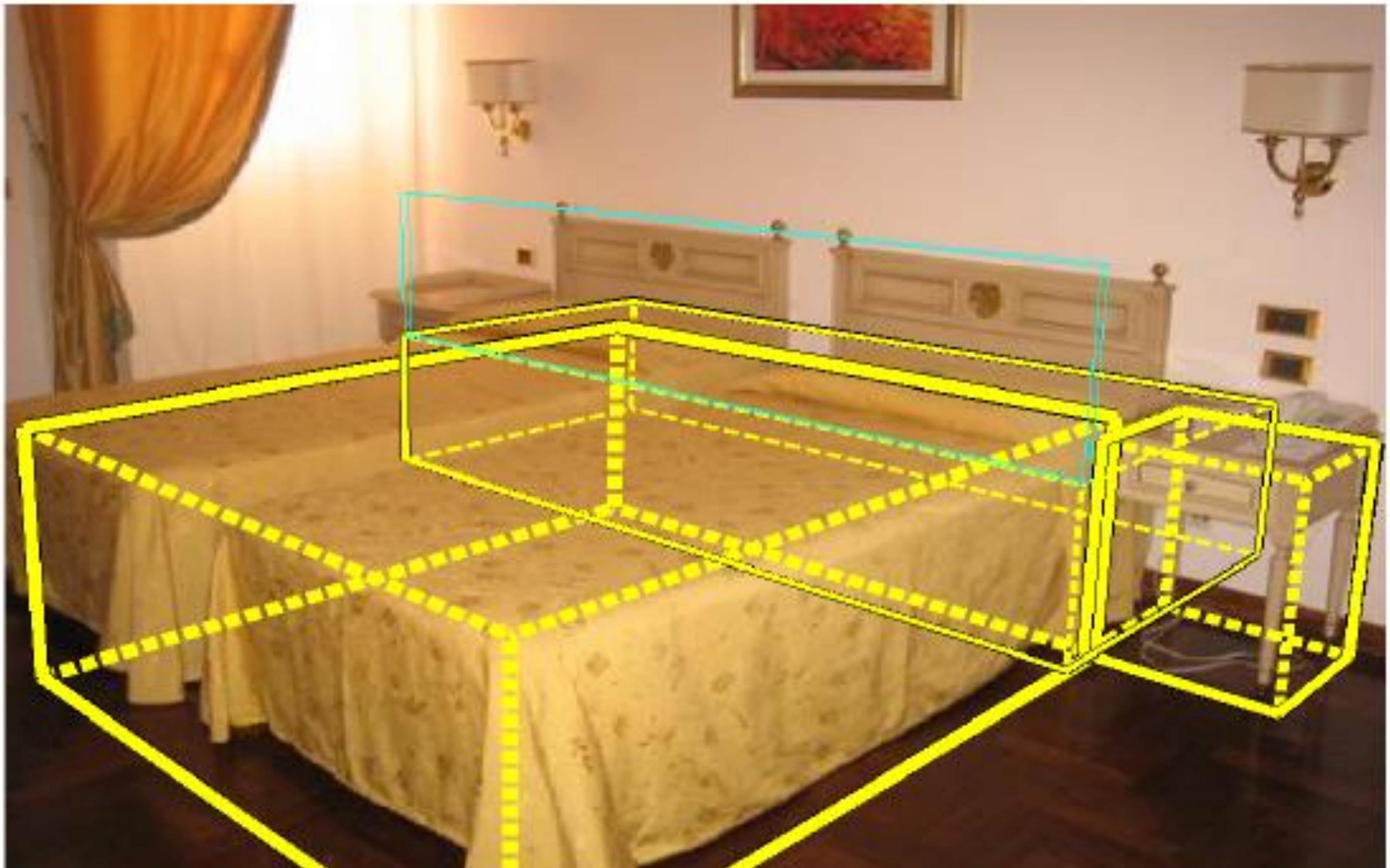


Generic boxy object detection

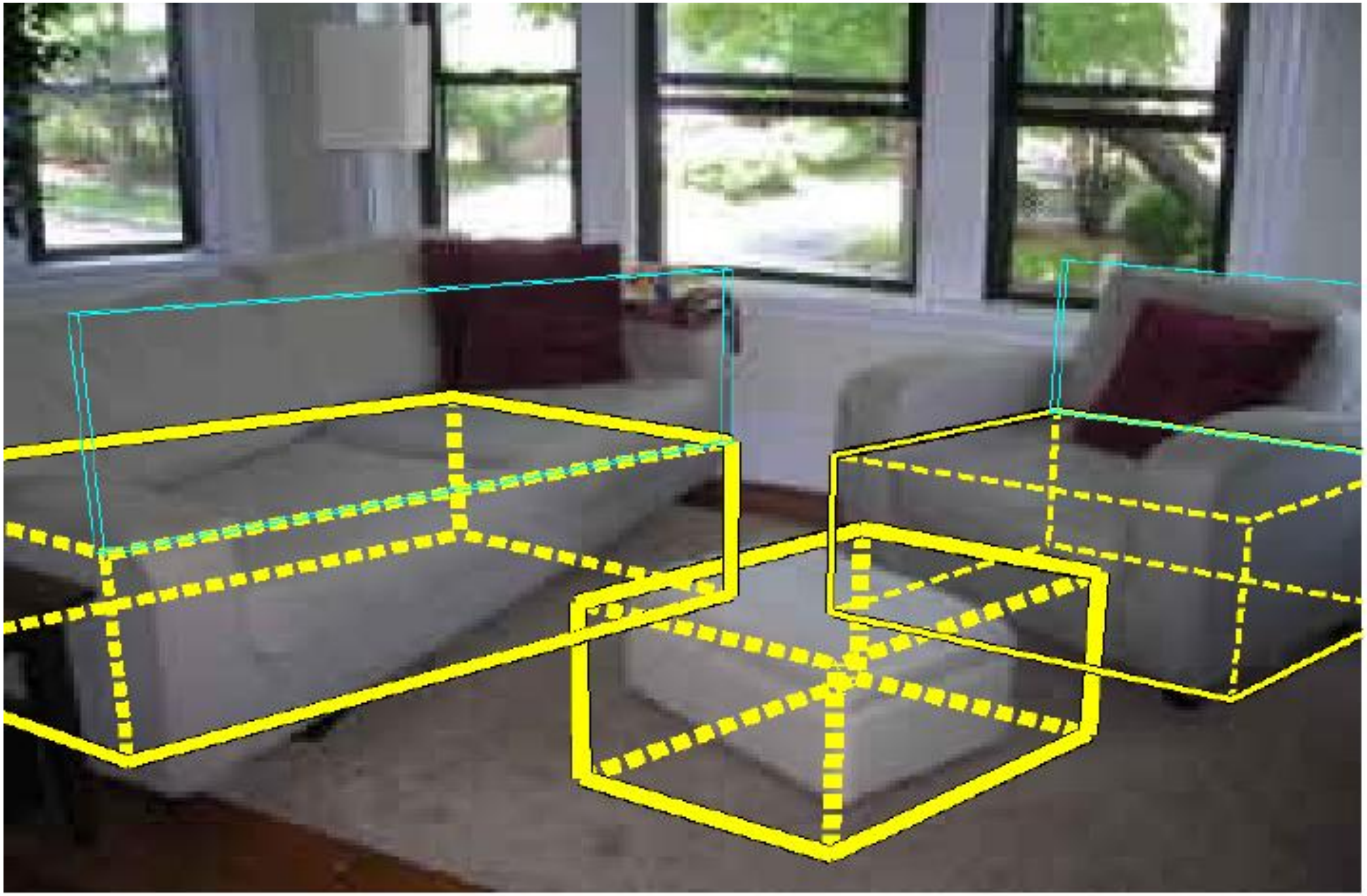


Hedau et al. 2012

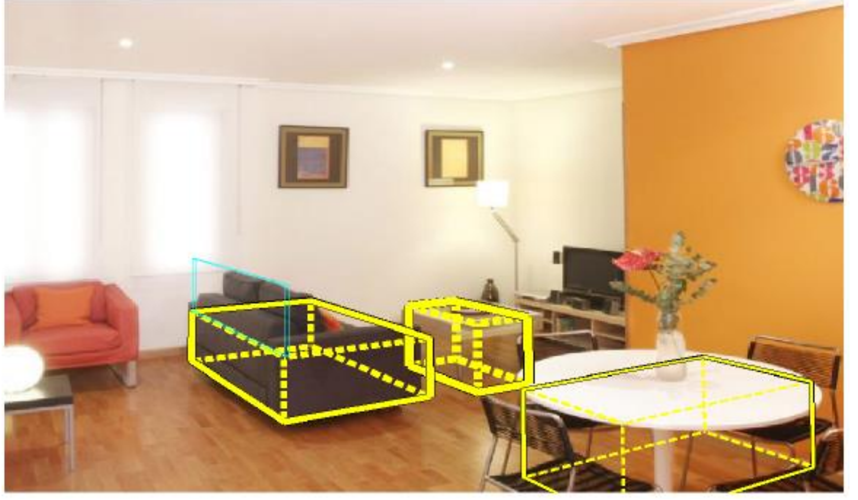
Generic boxy object detection



Generic boxy object detection



Mini-Conclusions

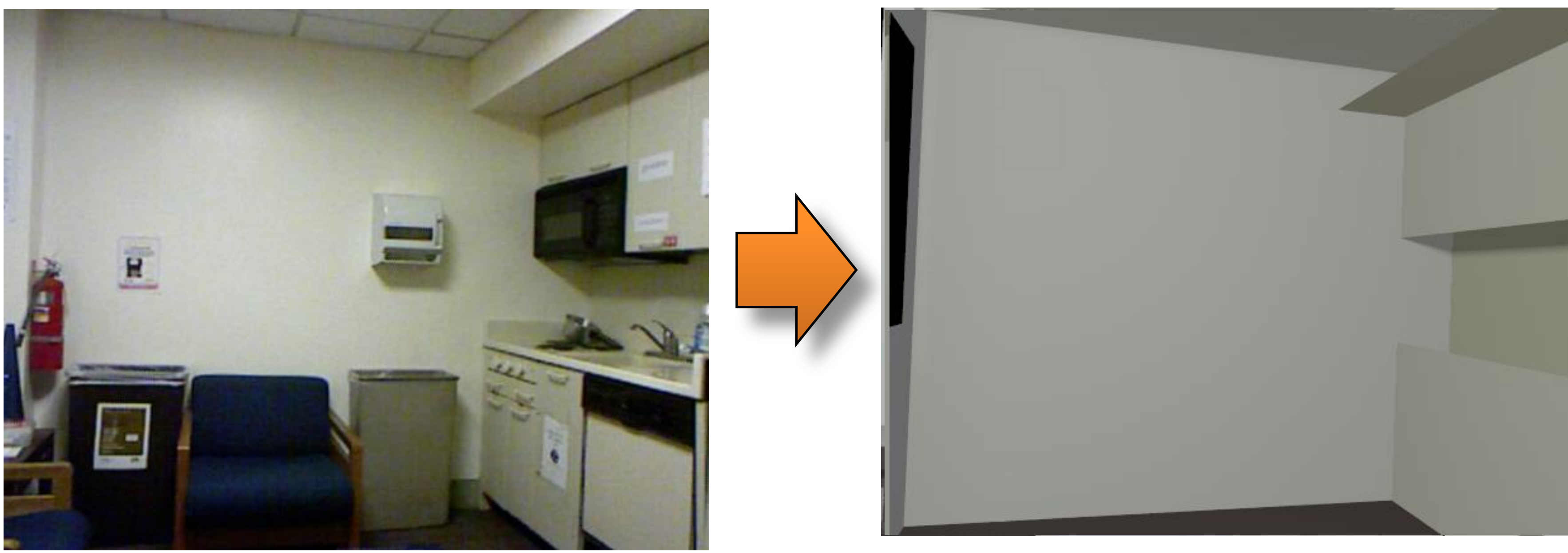


- Simple room box layout helps detect objects by predicting appearance and constraining position

- We can search for objects in 3D space and directly evaluate on 3D localization

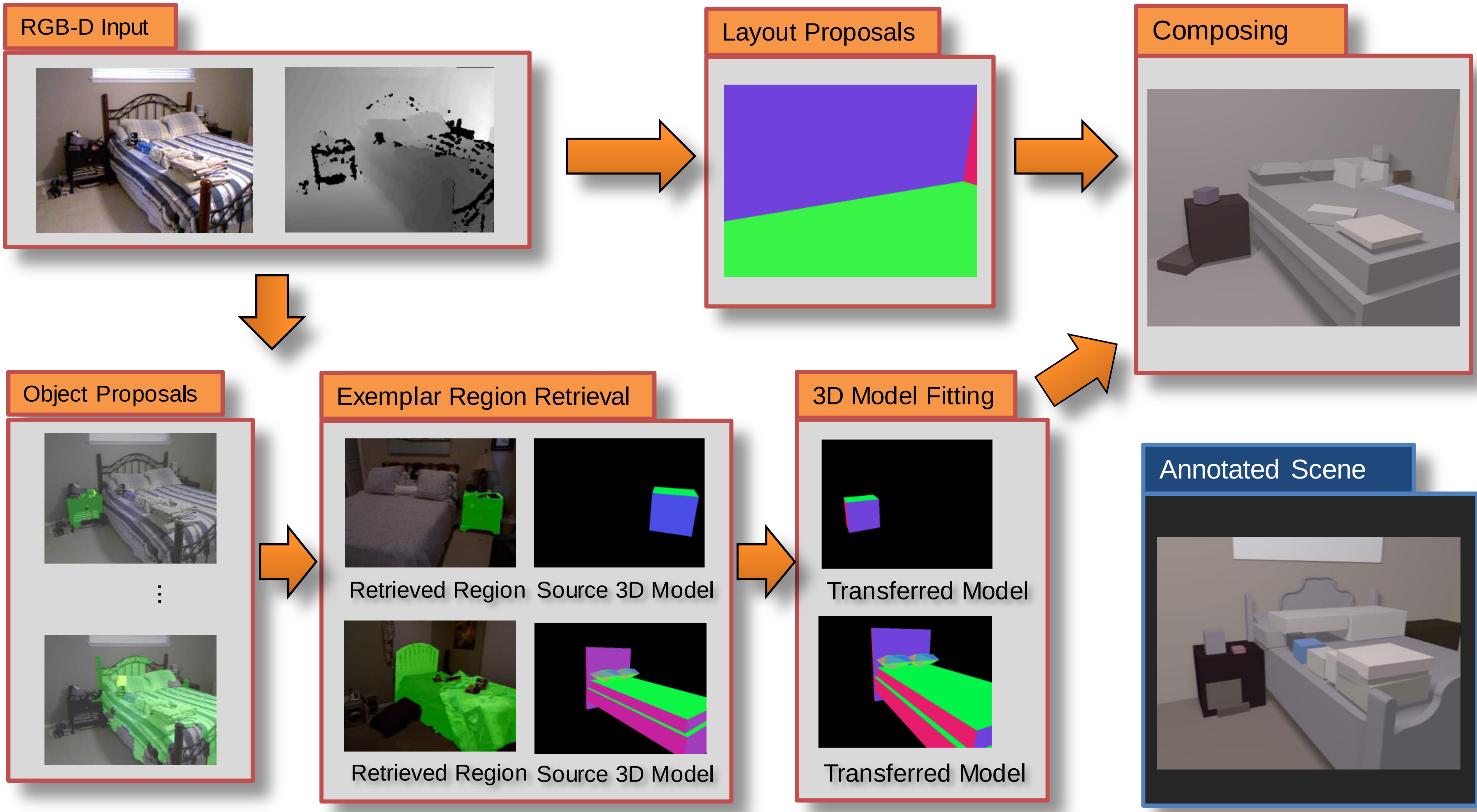
Predicting complete models from RGBD

Key idea: create **complete** 3D scene hypothesis that is **consistent** with observed depth and appearance

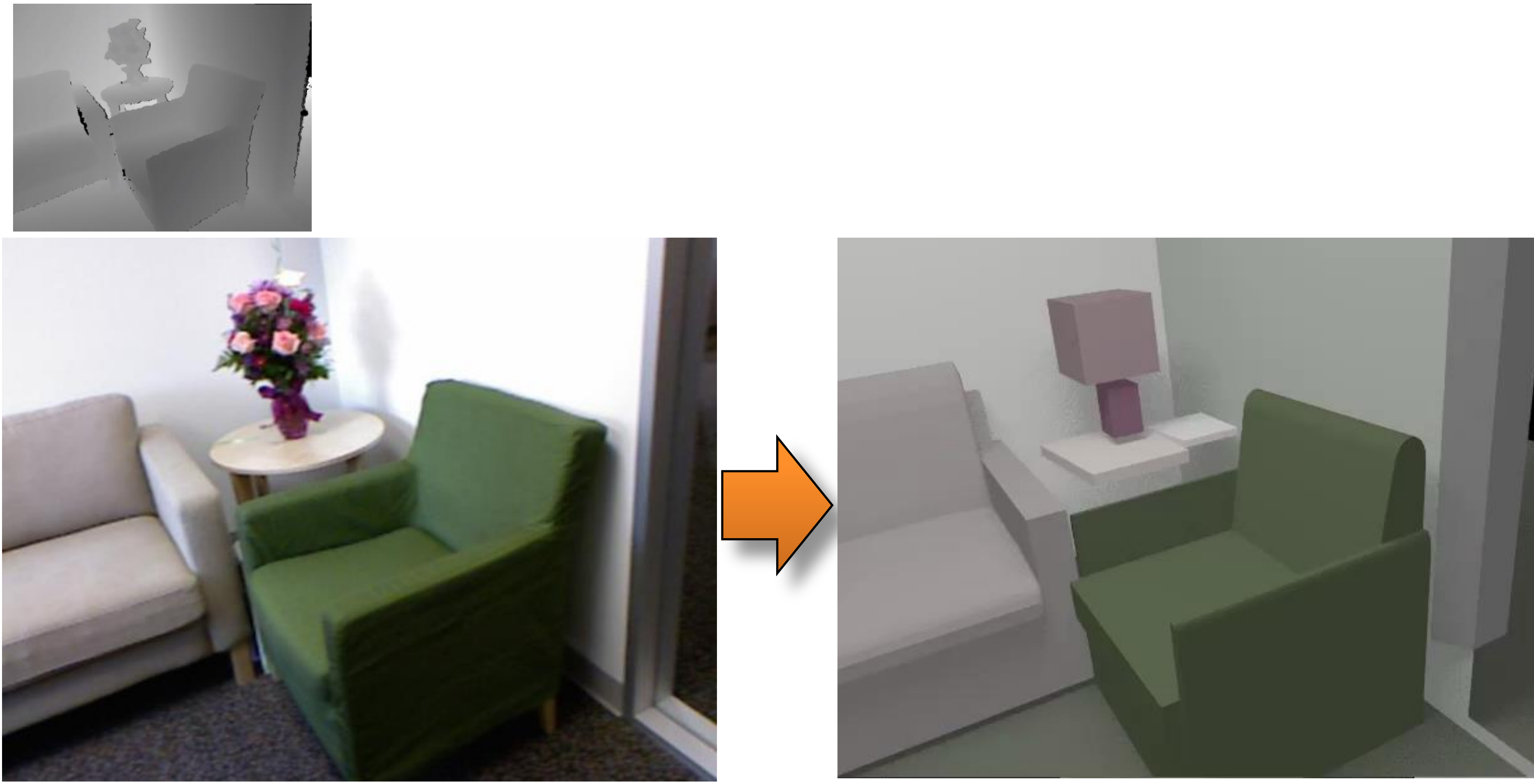


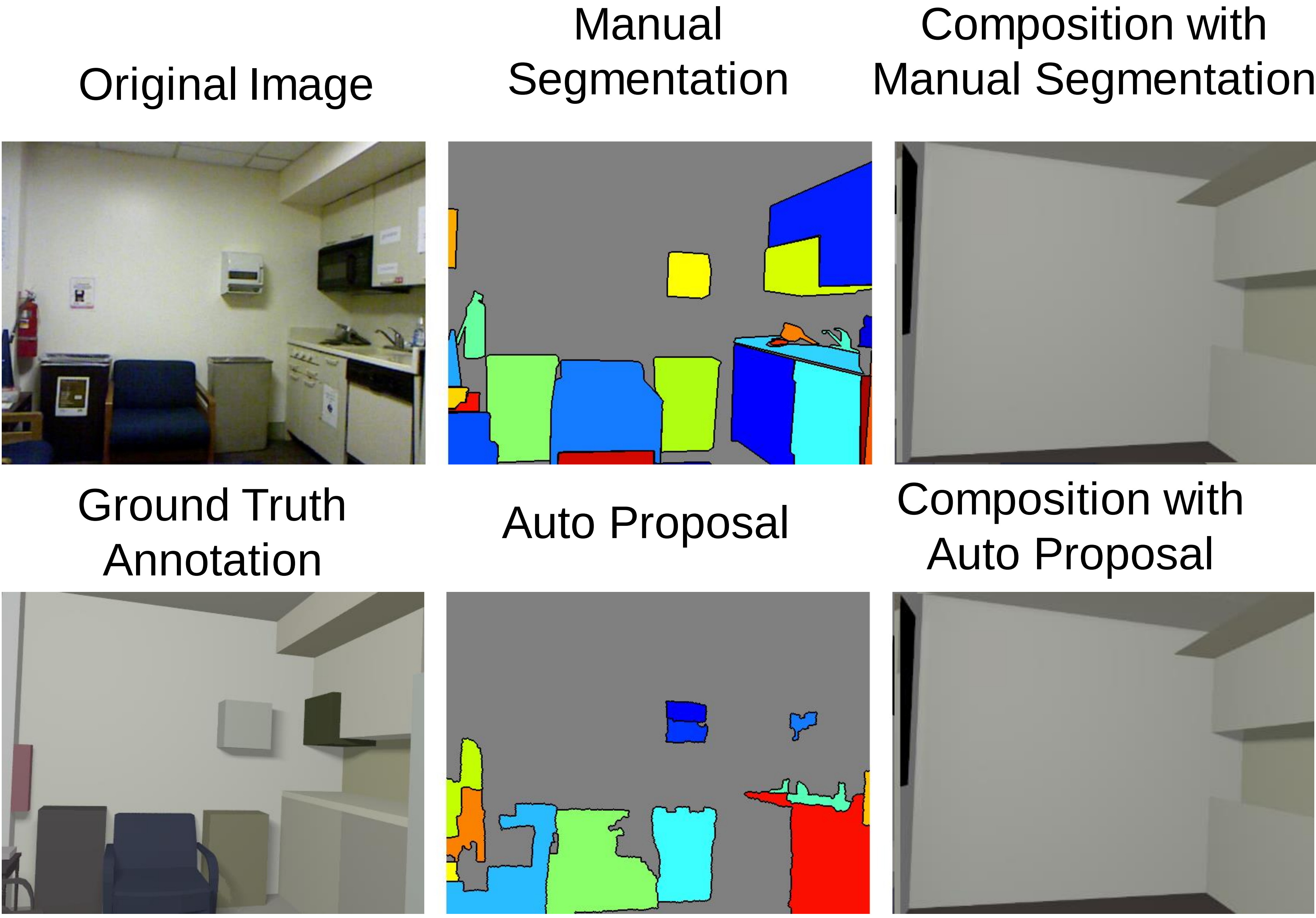
Guo Zou Hoiem 2015, 2016

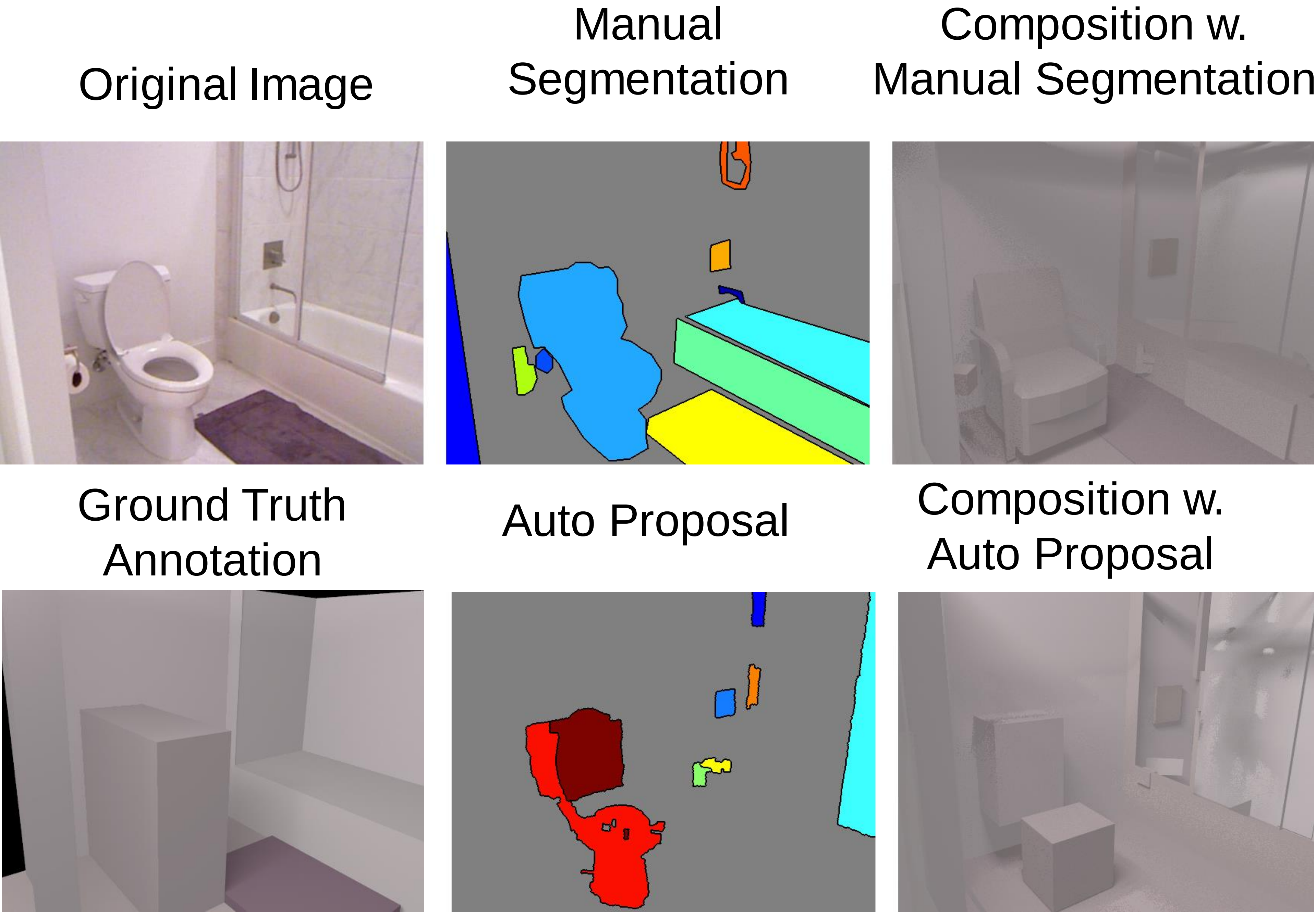
Overview of approach



Example result (fully automatic)




Original Image
Manual Segmentation
Composition with Manual Segmentation
Ground Truth Annotation
Auto Proposal
Composition with Auto Proposal


Original Image
Manual Segmentation
Composition w. Manual Segmentation
Ground Truth Annotation
Auto Proposal
Composition w. Auto Proposal

Things to remember

- Objects should be interpreted in the context of the surrounding scene
  - Many types of context to consider

- Spatial layout is an important part of scene interpretation, but many open problems
  - How to represent space?
  - How to learn and infer spatial models?
  - Important to see beyond the visible

- Consider trade-off of abstraction vs. precision

Next classes

- Thursday
  - Vision and language (Tanmay to present)
- Tuesday
  - Overview of computer vision
  - Important open research problems
  - Feedback / ICES forms