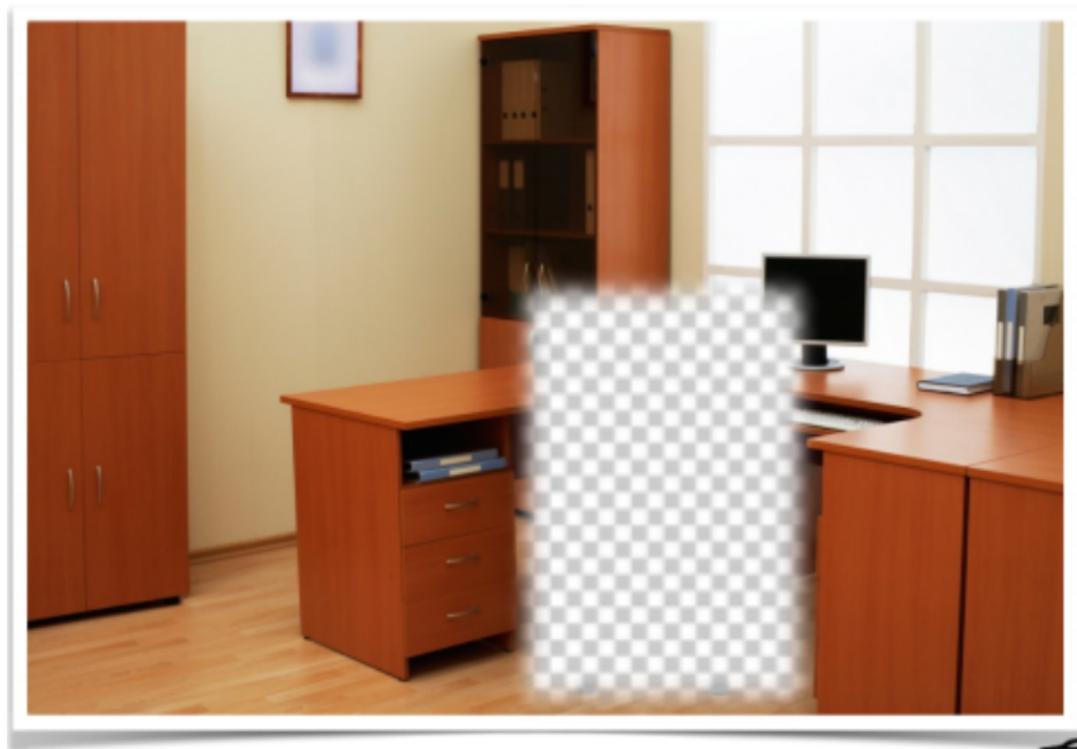


PanoContext: A Whole-room 3D Context Model for Panoramic Scene Understanding

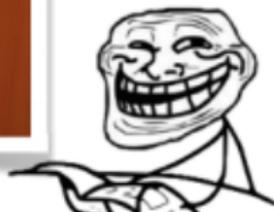
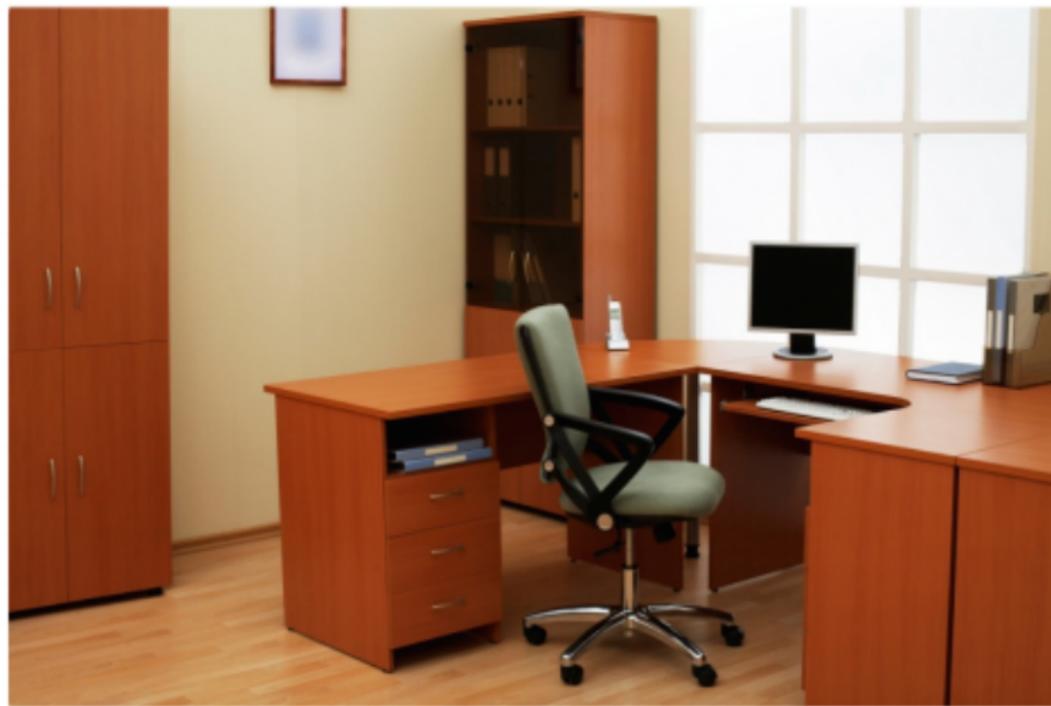
Yinda Zhang Shuran Song Ping Tan[†] Jianxiong Xiao

Princeton University [†] Simon Fraser University

Importance of Context in Image Processing



Importance of Context in Image Processing



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Importance of Context in Image Processing



Importance of Context in Image Processing

Context Models

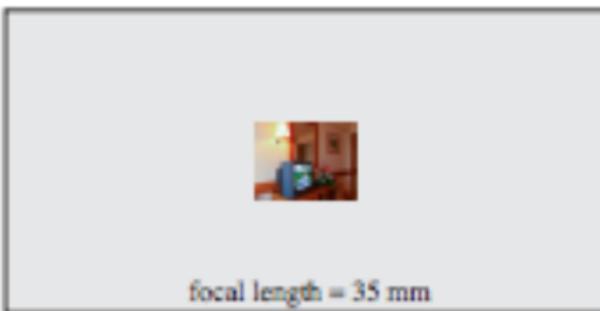
- Proposed in the past, but they do not work as well as expected
- WHY?

Field of View (FOV)

Small FOV \implies Hinders the contextual information



What your eyes see

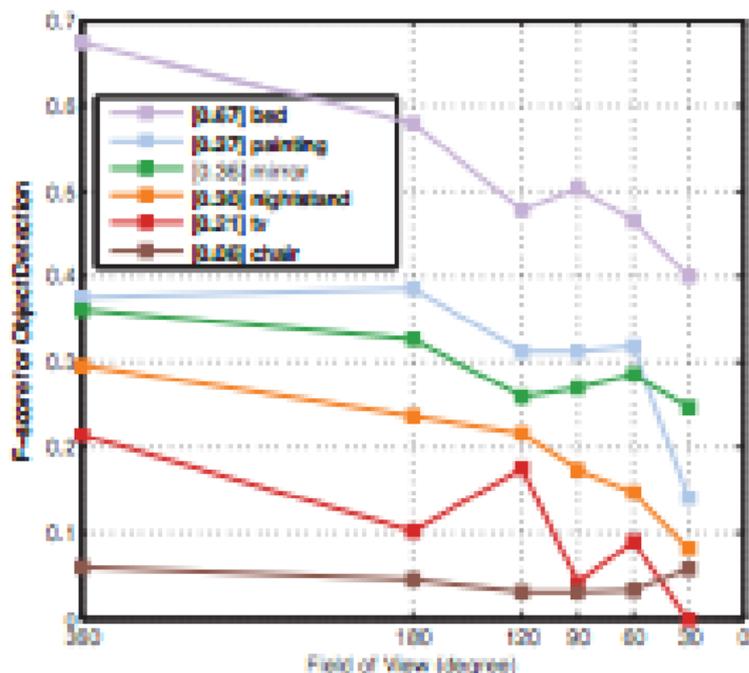


What a camera sees

Field of View (FOV)



Field of View (FOV)



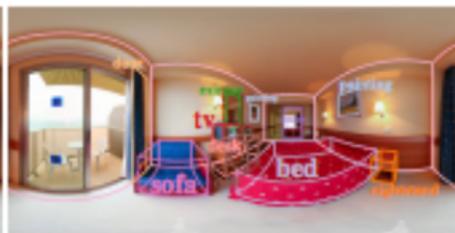
F-score with different FOV

Panorama - 360° Horizontal and 180° Vertical

- Easily obtained by smartphones, special lenses, or image stitching
- All objects are usually visible despite occlusion
 - Enables the detection of the room layout and of the contextual information
- Panorama \implies Object Detection \implies Whole-room 3D Context Model



Input: a single-view panorama



Output: object detection



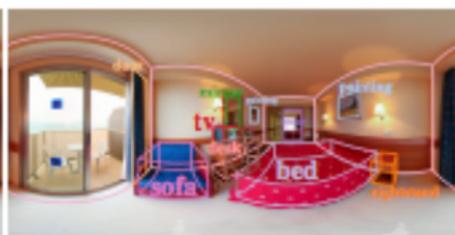
Output: 3D reconstruction

Panorama - 360° Horizontal and 180° Vertical

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Input: a single-view panorama



Output: object detection



Output: 3D reconstruction

¹Manhattan world assumption: assumes the scene consists of 3D cuboids aligned with the three principle directions

²Assume no floating objects

Algorithm

- 1 Generate a set of hypotheses for room layout and objects
- 2 Rank these whole-room hypotheses holistically to determine the best hypothesis

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses

Input



Room

Object

*Whole
Room*

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses

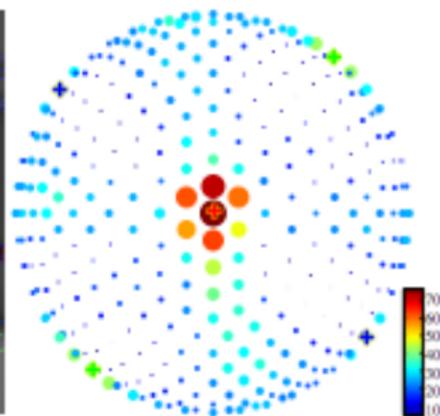
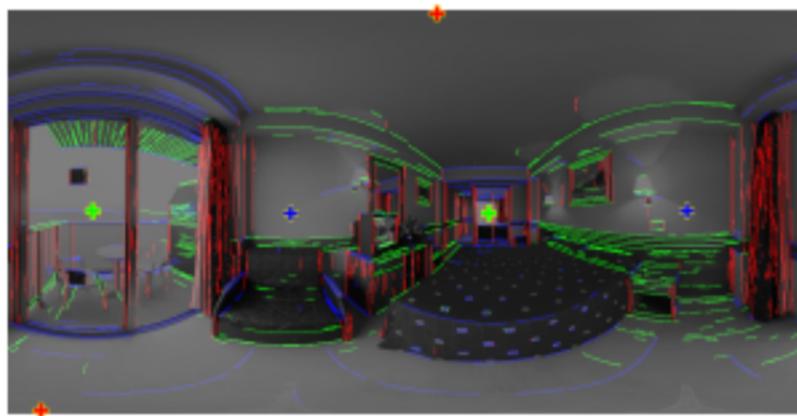
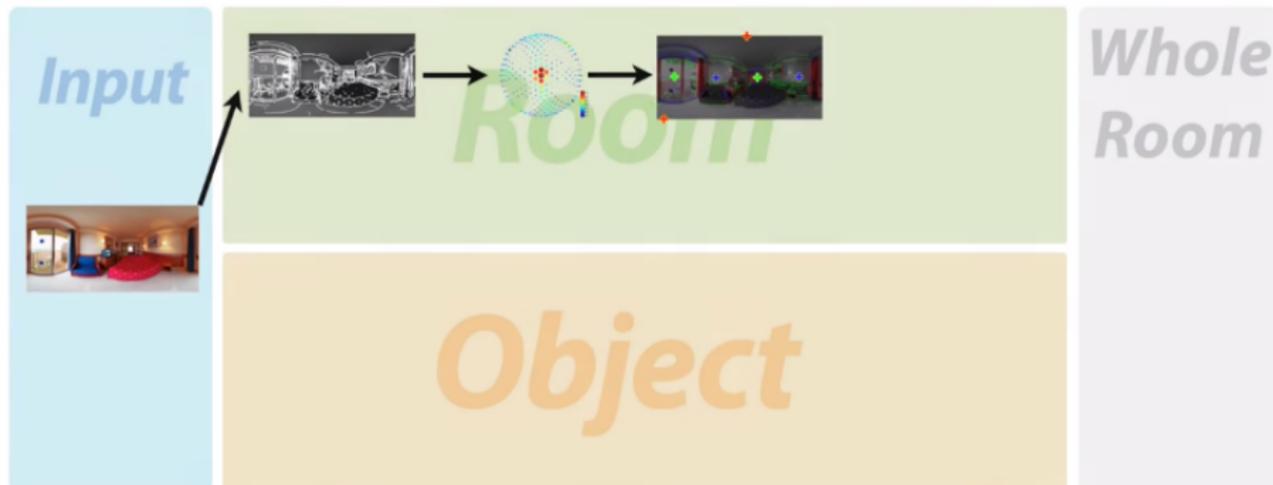


Figure : Hough transform for vanishing point detection

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses

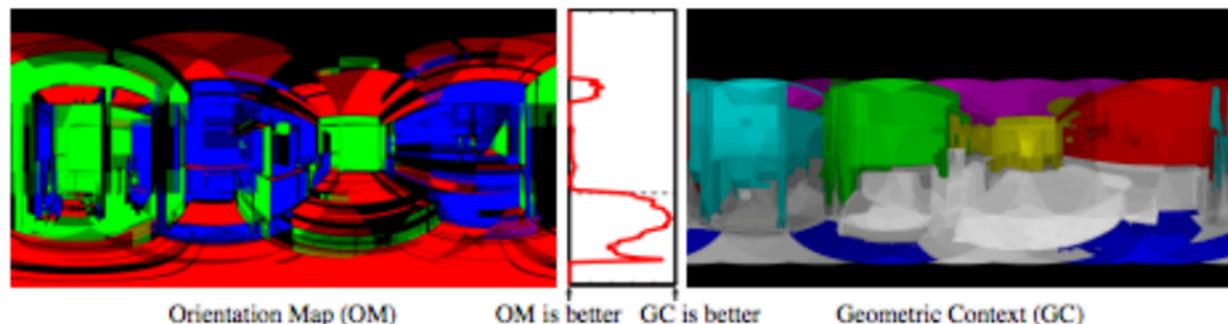
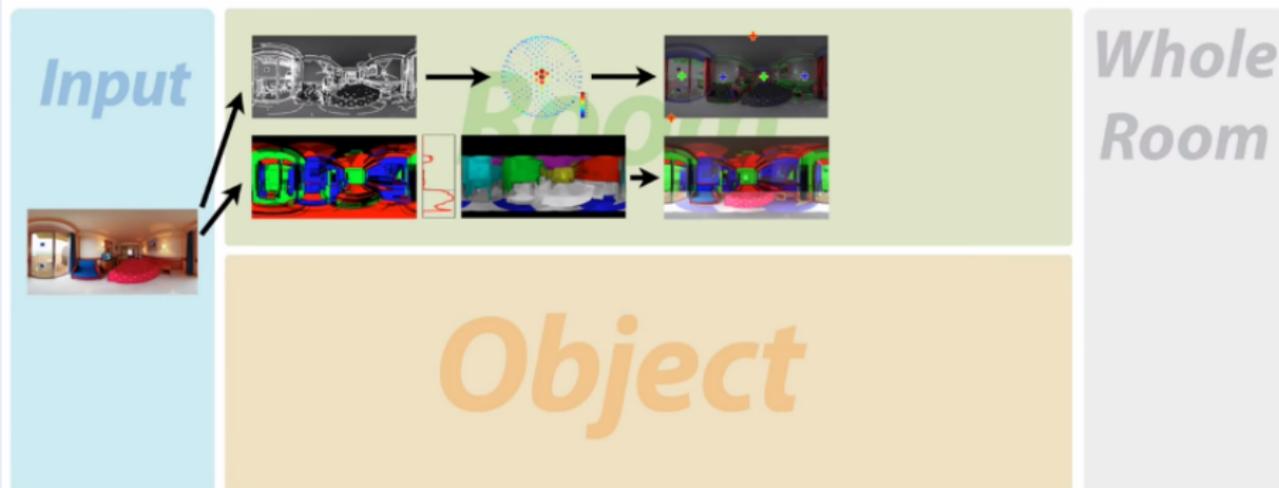


Figure : Comparison of OM and GC. OM works better on the top half of the image, while GC provides better normal estimation at the bottom

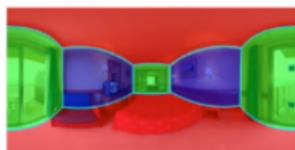
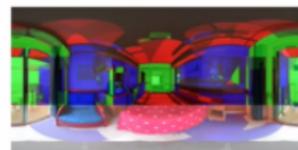
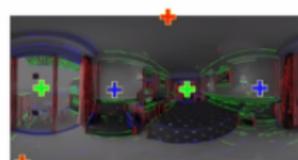
PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



Consistency Score:

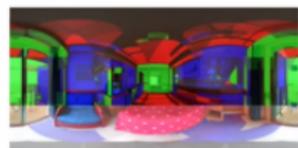
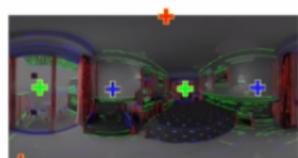
0.770

0.711

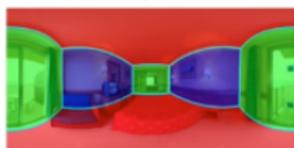
0.504

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



Consistency Score:



0.770



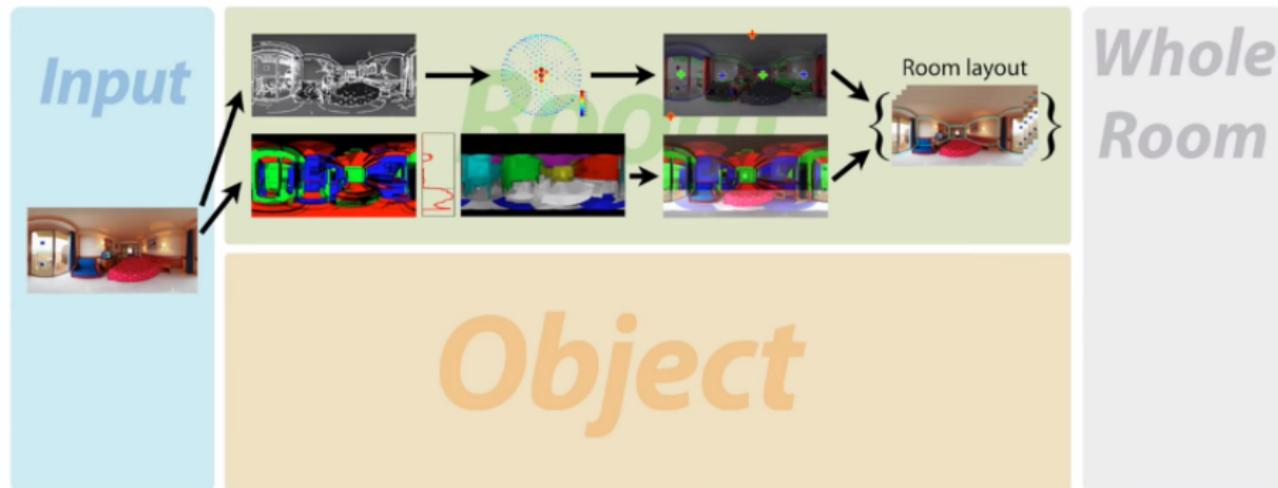
0.711



0.504

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



PanoContext: A Whole-Room 3D Context Model

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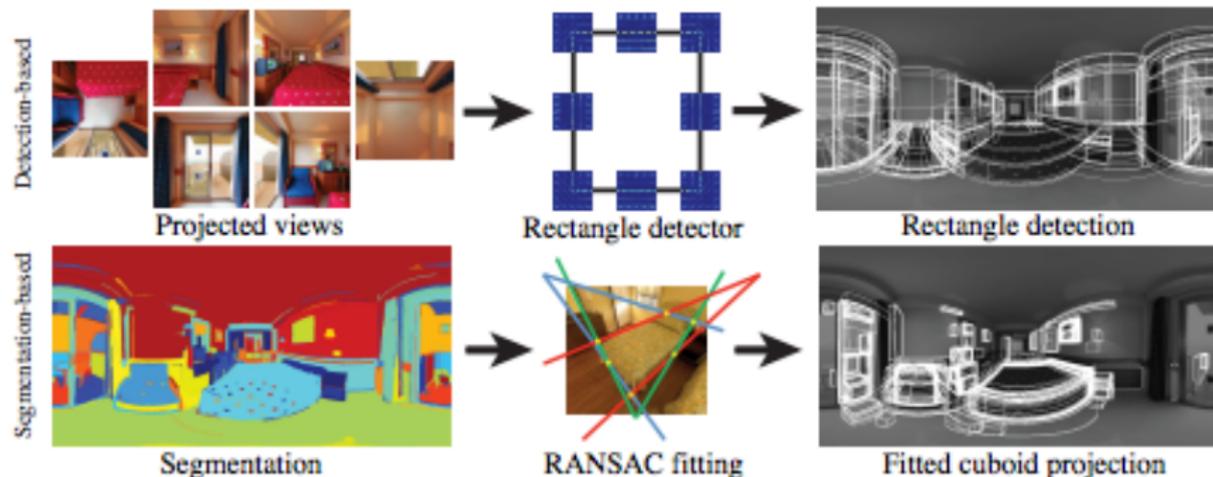
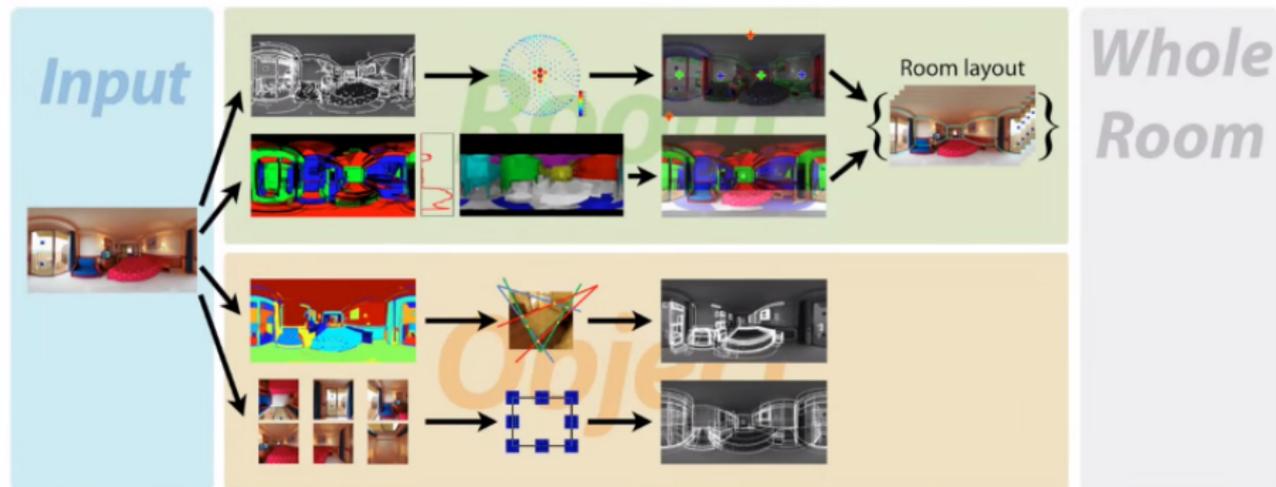


Figure : Two ways to generate object hypotheses

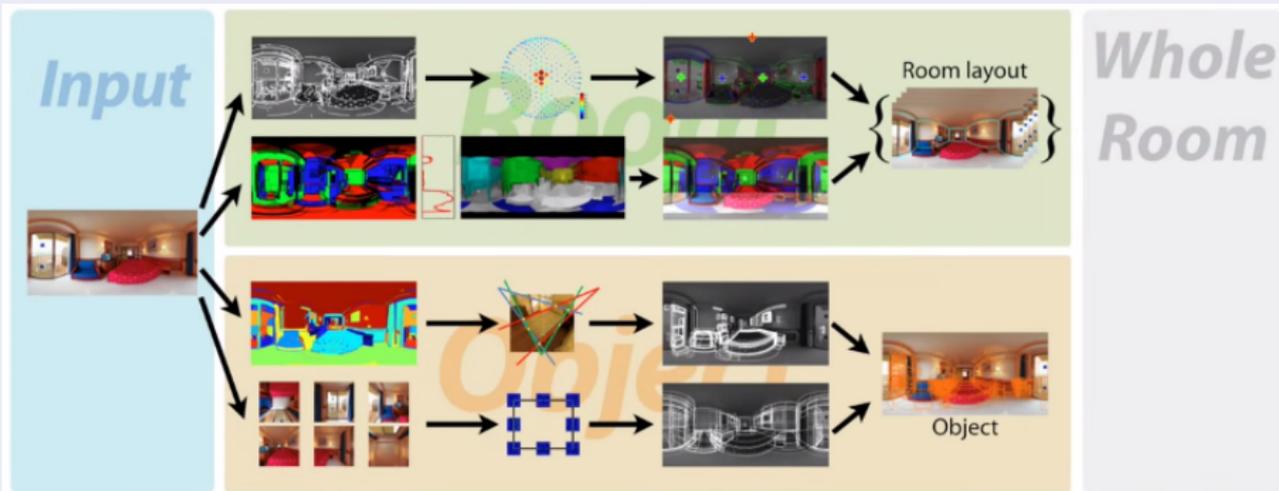
PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



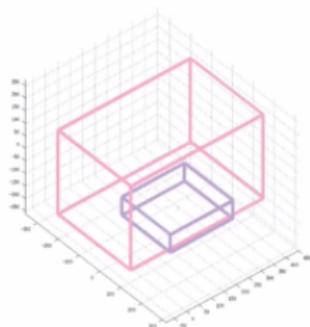
PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



PanoContext: A Whole-Room 3D Context Model

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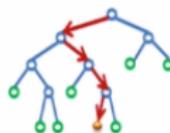


3D cuboid feature

- Size
- Aspect ratio & Area
- Distance to walls



Classifier



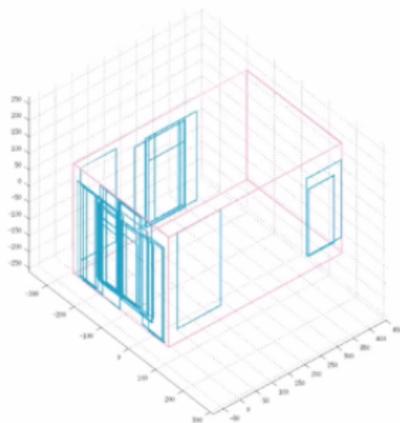
Label likelihood

- bed 
- desk 
- sofa 
- ...
- chair 

¹Semantic Label

PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses



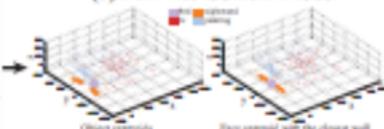
PanoContext: A Whole-Room 3D Context Model

1. Generate a set of whole-room hypotheses

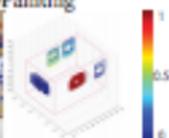
Sampled Bed in Last Step



(b) Pairwise Context Model



(c) Pairwise Context: Bed->Painting



↑
bed

All Hypotheses



(a) Bottom-up Score: Painting



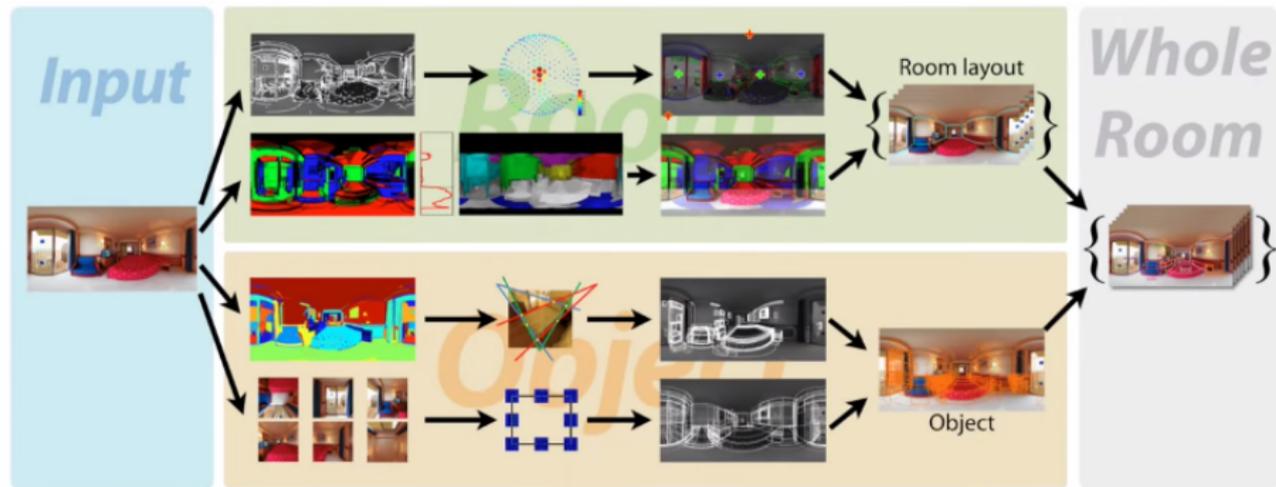
(d) Merged Score: Painting



¹Pairwise Constraint

PanoContext: A Whole-Room 3D Context Model

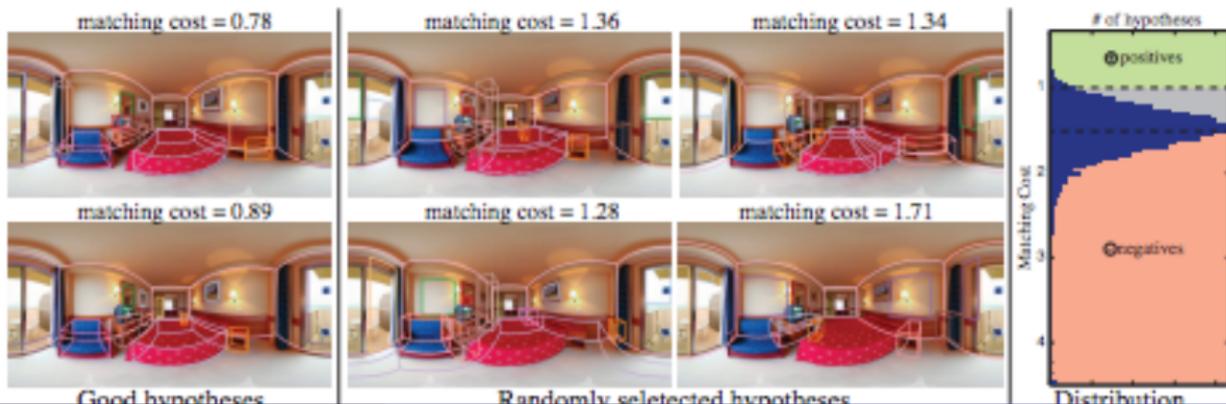
1. Generate a set of whole-room hypotheses



PanoContext: A Whole-Room 3D Context Model

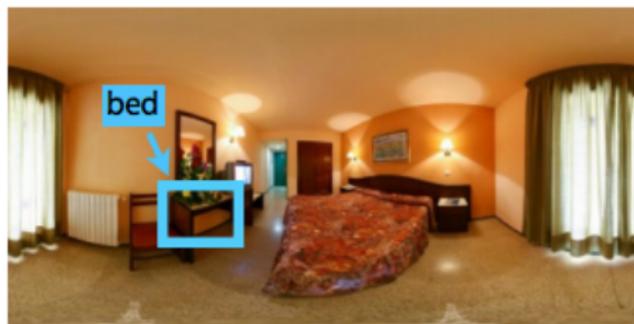
2. Determine the best whole-room hypotheses

- Train a linear SVM model to rank the whole-room hypotheses and choose the best hypothesis
- Want the matching cost (difference between whole-room hypothesis and its ground truth) to be as low as possible

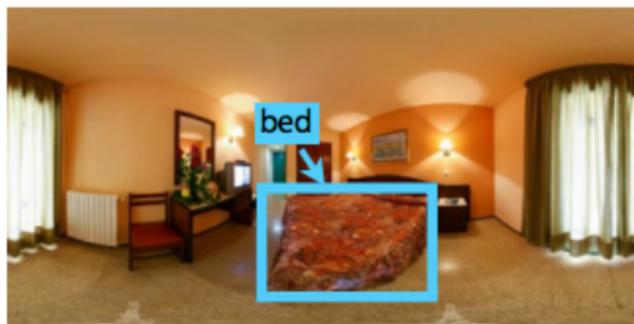


Summary: How does context help?

- Helps to determine the size of objects



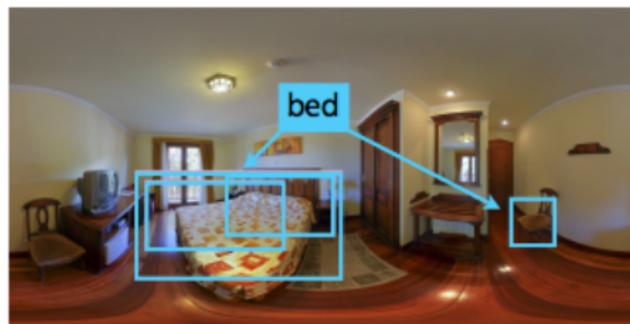
DPM: Wrong relative size



PanoContext

Summary: How does context help?

- Helps to determine the size of objects
- Helps to determine the correct number of objects



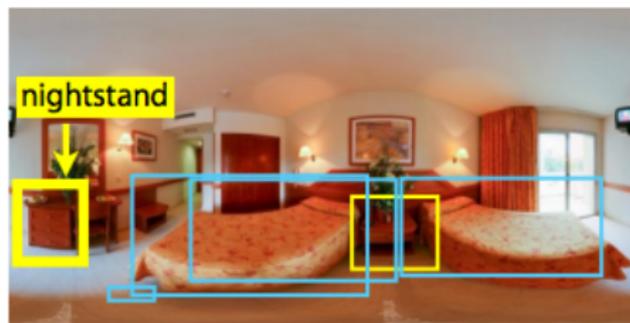
DPM: Wrong number of objects



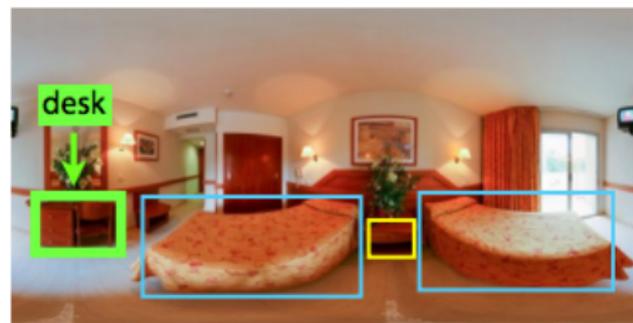
Our detection

Summary: How does context help?

- Helps to determine the size of objects
- Helps to determine the correct number of objects
- Helps the determine the relative position of objects

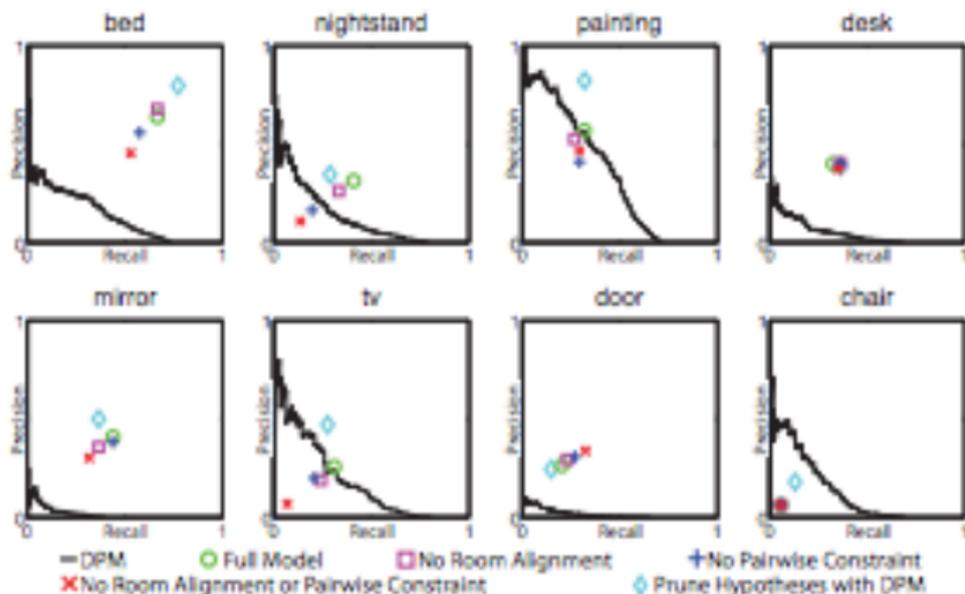


DPM: Wrong relative position



Our detection

Summary: How does context help?



Precision-recall comparison with DPM

¹DPM: Deformable Part Model

²Felzenszwalb et. al: Discriminative training with partially labeled data

Contributions

- Context model is fully in 3D
- First annotated panorama dataset

Questions?