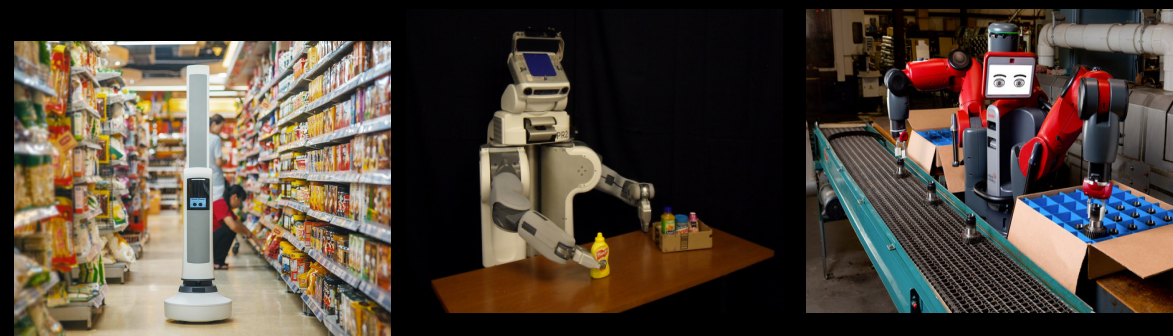


## Problem Statement

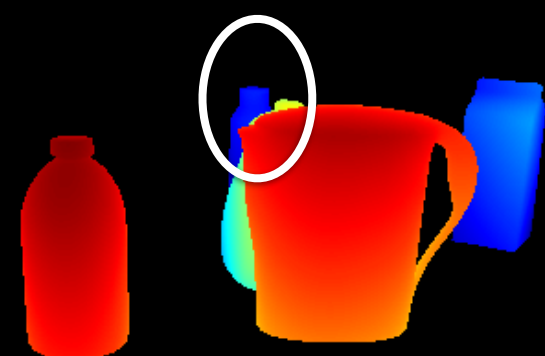


### task:

identify type and 3 DoF pose of all objects in the scene (point cloud/depth image)

### given:

6 DoF camera pose,  
3D models of objects in the scene



- Feature and learning based methods are brittle (e.g., occlusion)
- Learning methods need training data to capture the combinatorics of inter-object interactions
- Generative methods are robust but slow

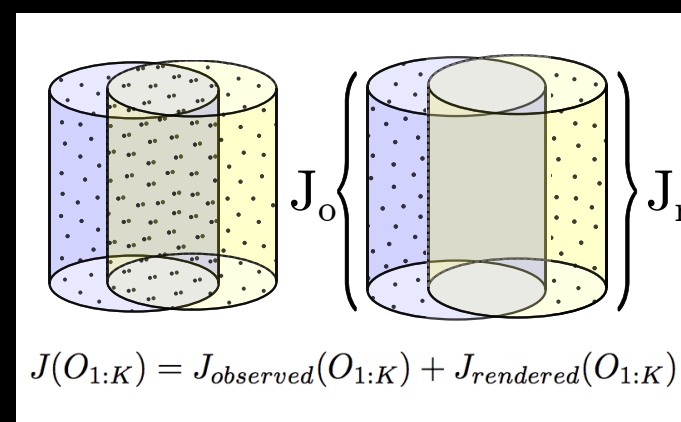
## Contributions

- Framework to guide deliberative global search with *any* and *multiple* discriminative learners
- Theoretical guarantees on solution quality
- Notion of completeness for multi-object recognition and pose estimation
- Lazy Multi-Heuristic A\*

## Perception via Search (PERCH)<sup>[1]</sup>

### minimize over joint object poses

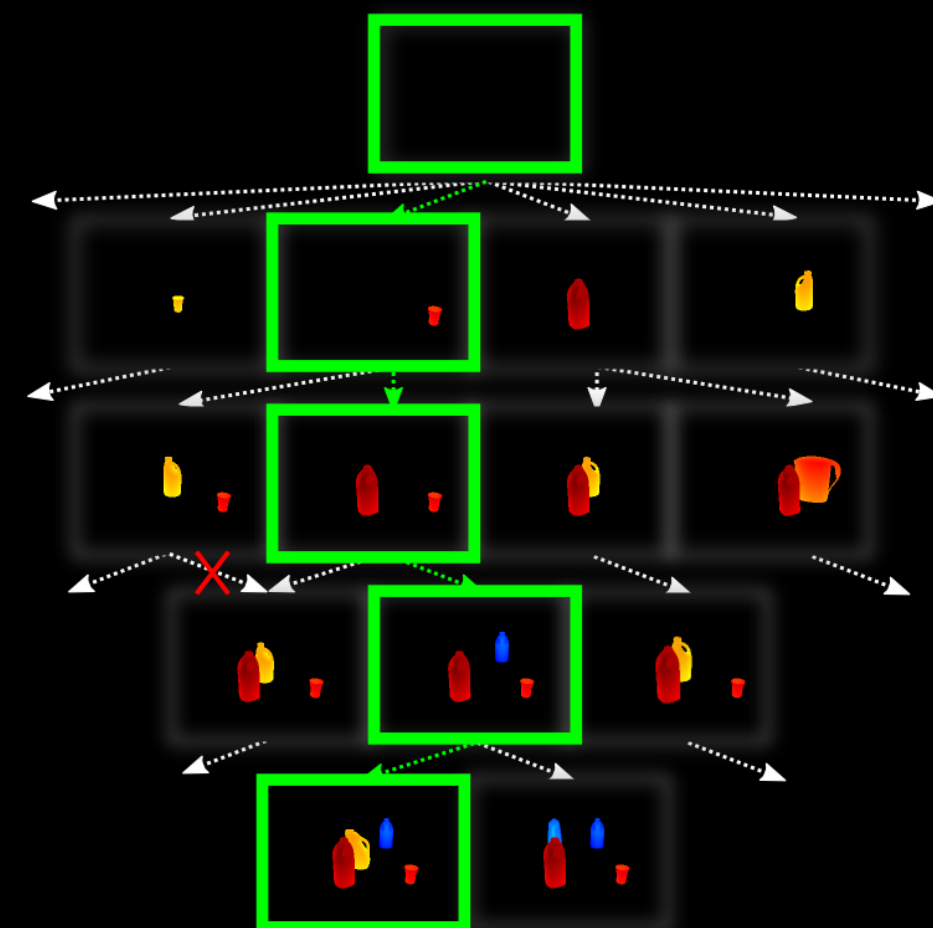
# unexplained points in observed cloud +  
# unexplained points in rendered cloud



$$J(O_{1:K}) = J_{observed}(O_{1:K}) + J_{rendered}(O_{1:K})$$

Render all possible scenes, select the one that  
“best matches” the input point cloud

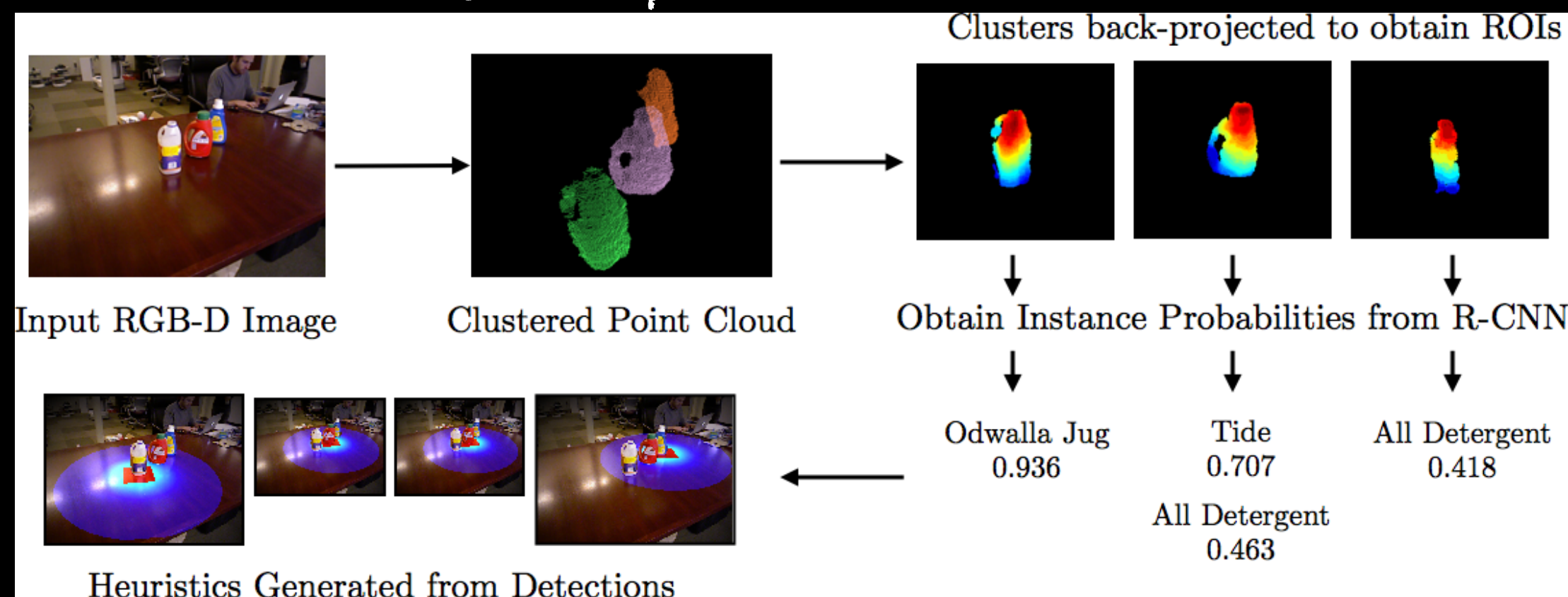
Brute force run time **exponential** in #objects  
(~12 days for 4 objects with 10 (x,y) positions, 10 orientations —  $100^4$  states)



Joint optimization can be cast as tree search, with **monotone constraint!** — still uninformed search

### Key Idea: Guide deliberative search with discriminative learners

## Generating Multiple Discriminative Heuristics

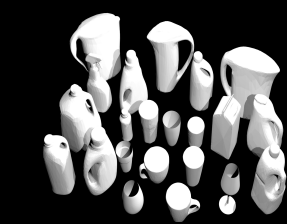


Discriminative heuristics can be **inadmissible** and **unrelated** to optimization objective  
FOCAL Multi-Heuristic A\* <sup>[2]</sup> was developed to handle precisely such heuristics

## Completeness

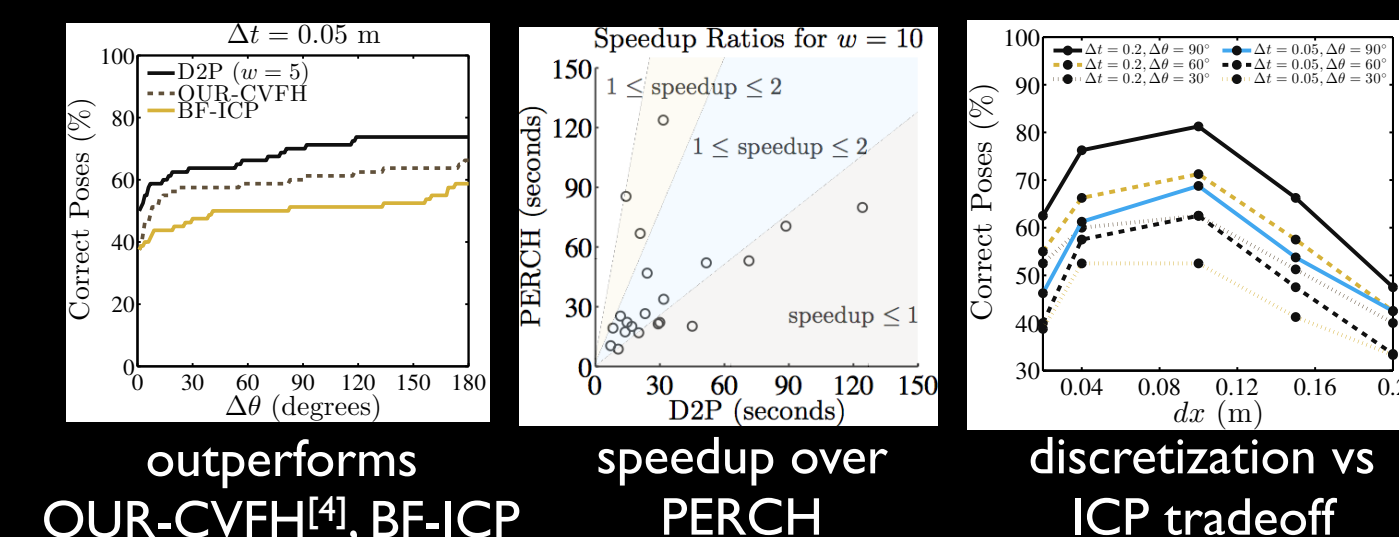
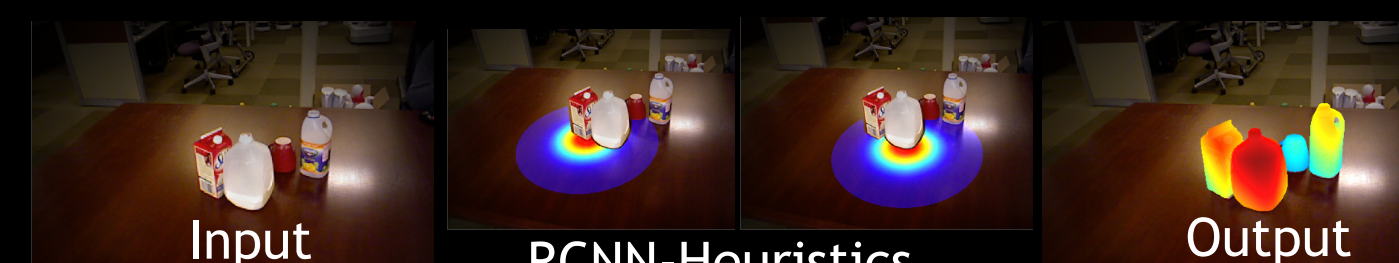
Existing methods based on global hypothesis verification are “**incomplete**”: can fail to produce a feasible solution (set of object poses) even if one exists

## Evaluation



dataset

- Household objects occlusion dataset<sup>[3]</sup>
- 36 objects models, 82 instances in 23 scenes
- Discretization: 4 cm, 22.5 deg; ICP at every stage to compensate for discretization artifacts
- Parallel child node generation (AWS m4.10x, 40 virtual cores); lazy edge evaluation
- R-CNN network (ZF architecture) trained on synthetic depth images of individual objects



outperforms OUR-CVFH<sup>[4]</sup>, BF-ICP      speedup over PERCH      discretization vs ICP tradeoff

code: [github.com/venkatrn/perception](https://github.com/venkatrn/perception)

## References

- [1] Perception via Search Narayanan and Likhachev, ICRA '16
- [2] Improved Muti-Heuristic A\*, Narayanan et al., SoCS '15
- [3] Point Cloud Library, Aldoma et al., IEEE RAM '12
- [4] CAD Model Recognition and 6 DOF Pose Estimation using 3D Cues, Aldoma et al., ICCV Workshops, '11