

Category-Level Object Pose Estimation

Shuran Song



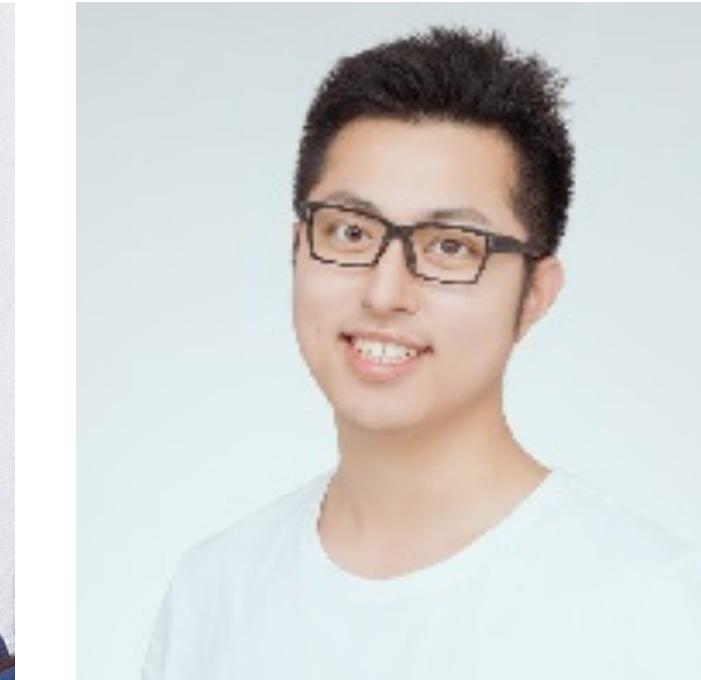
Acknowledgment



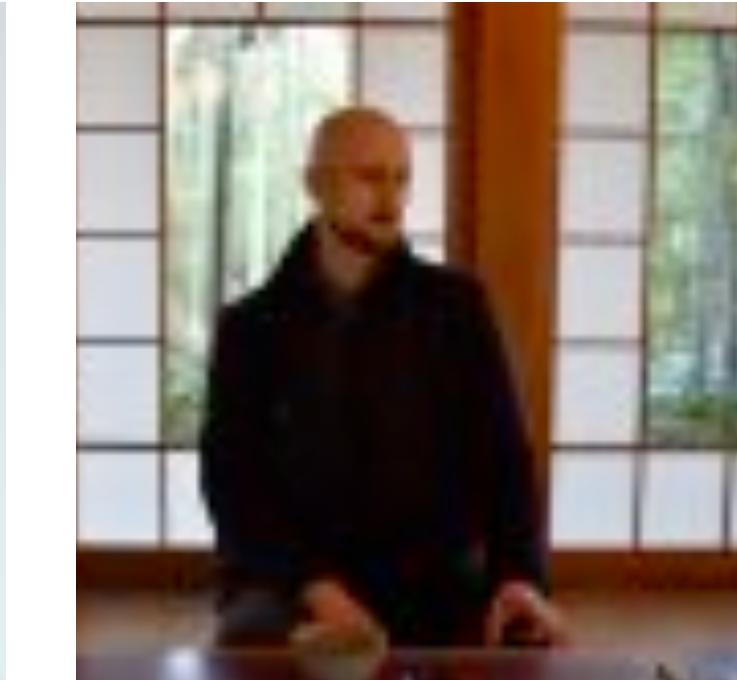
He Wang



Srinath Sridhar



Jingwei Huang



Julien Valentin



Xiaolong Wang



Yi Li

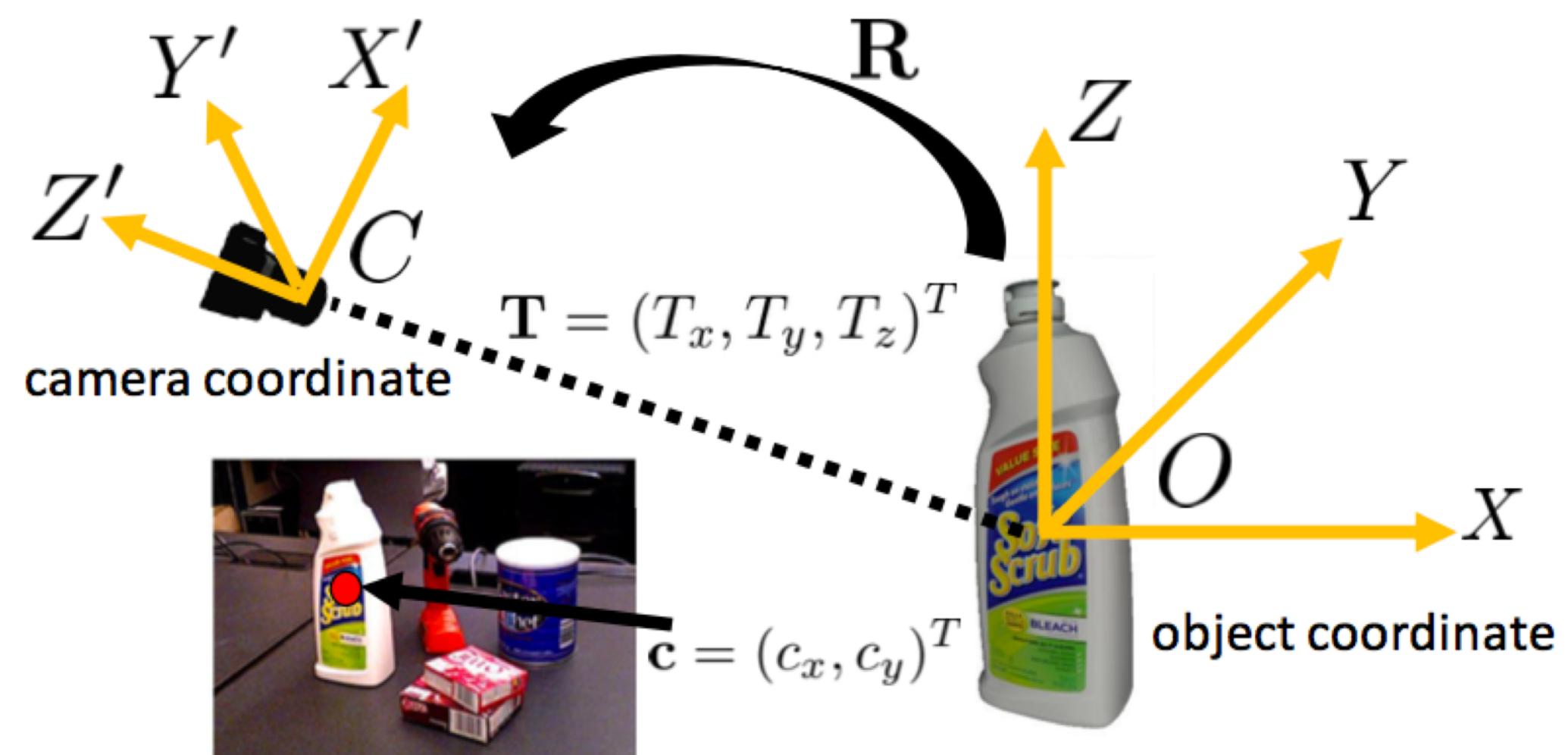


A. Lynn Abbott



Leonidas Guibas

Instance-level 6DoF Pose Estimation



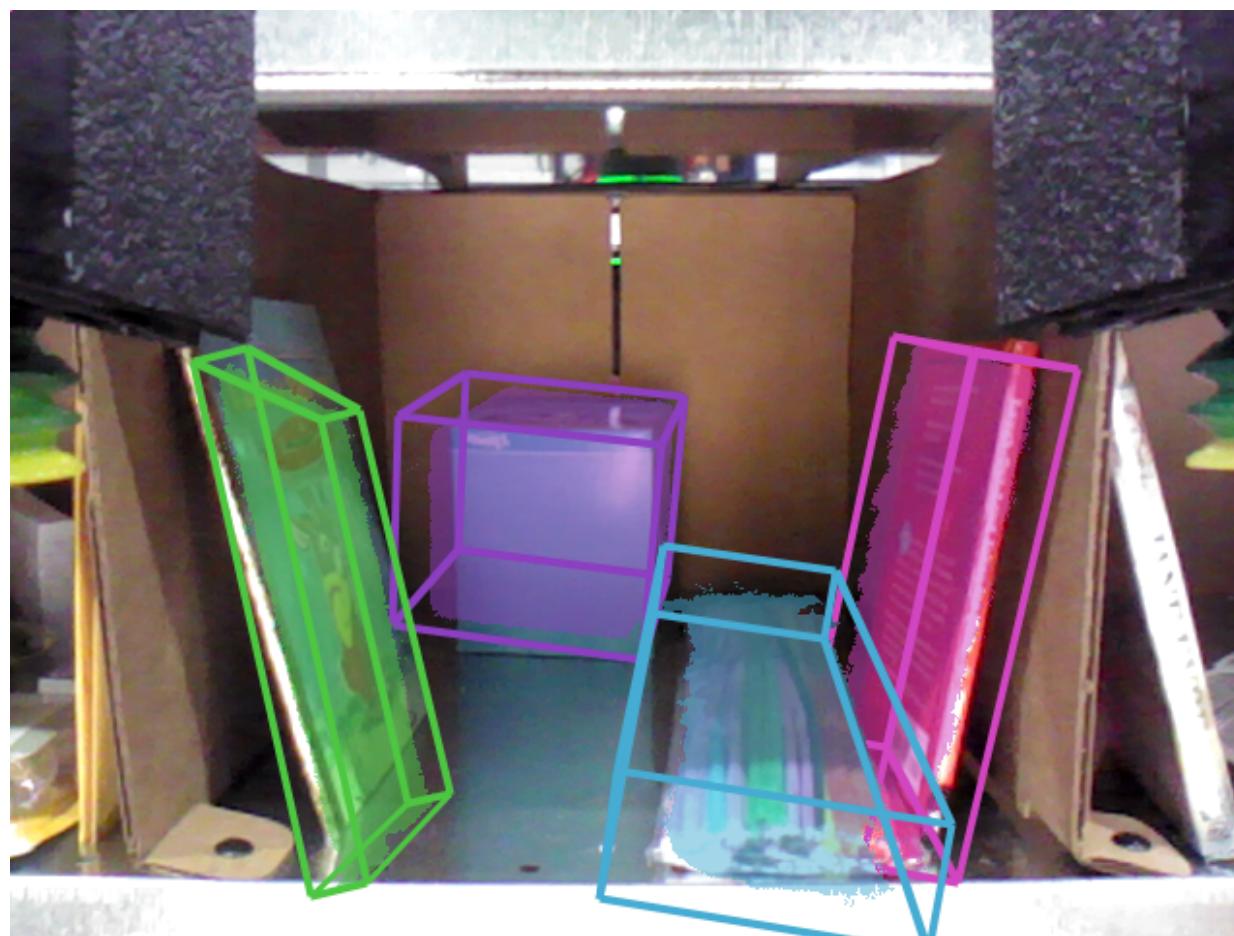
- Instance-level 6DoF pose estimation
 - 3DoF translation
 - 3DoF rotation

Xiang, et al. 2017

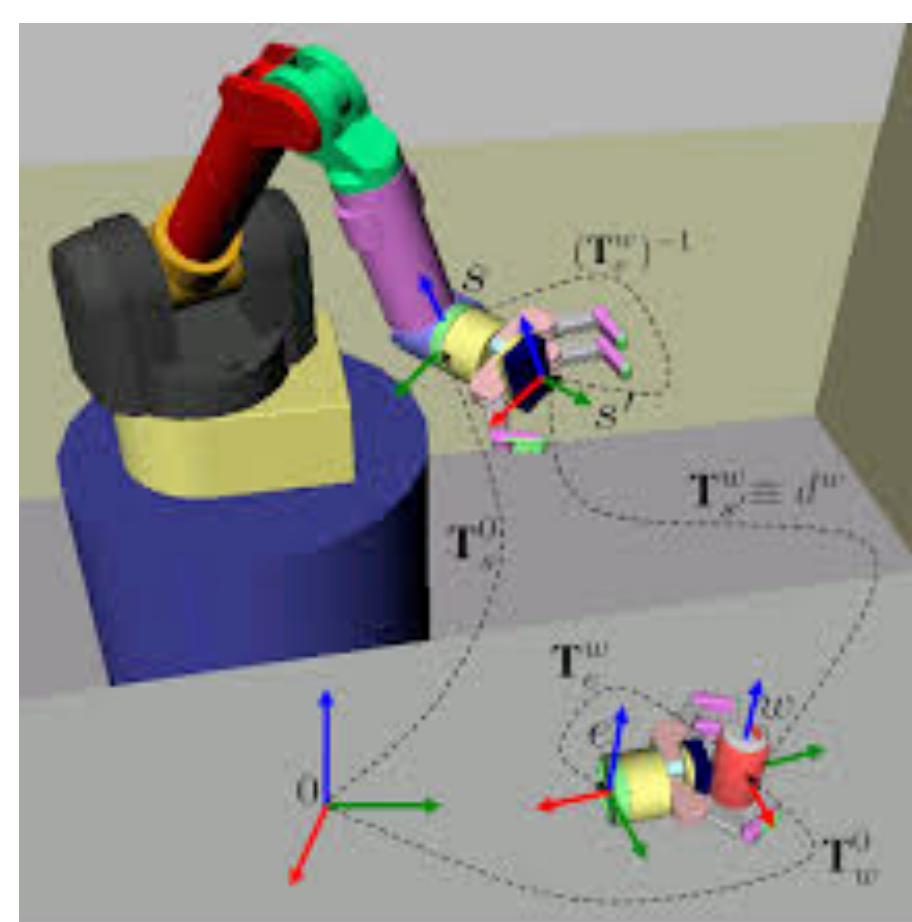
Instance-level 6DoF Pose Estimation

Why it is useful?

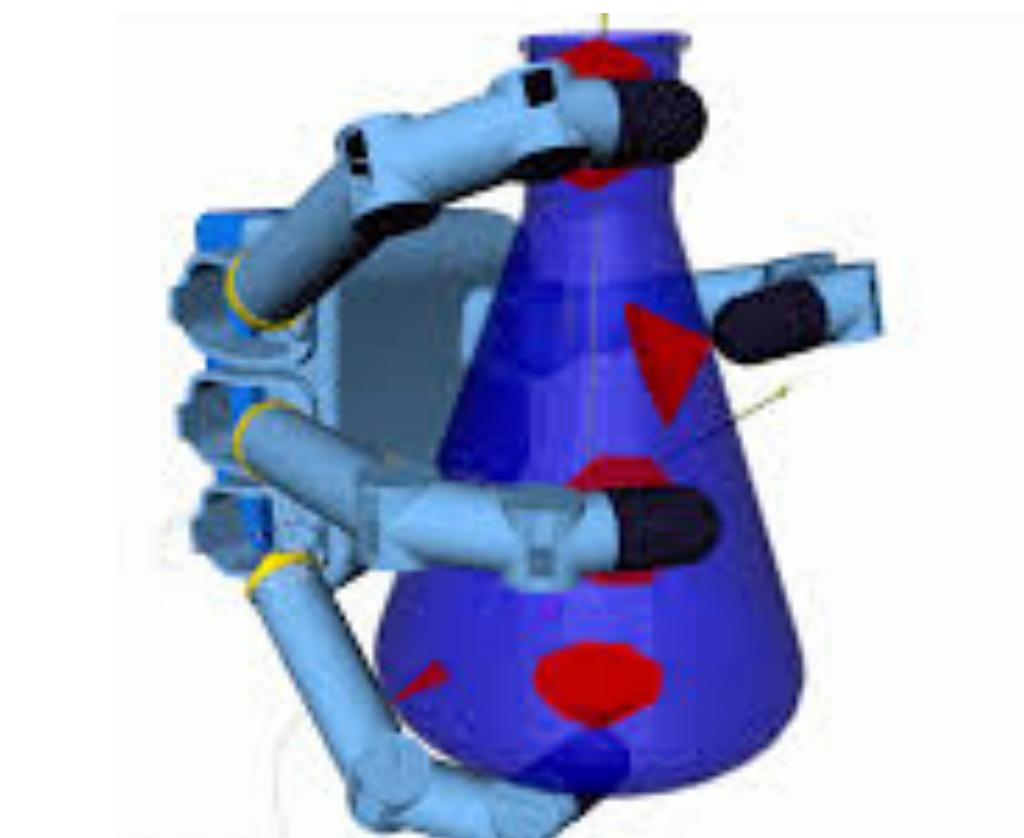
- Concise description of scene and state
- Can be easily used by planning algorithm



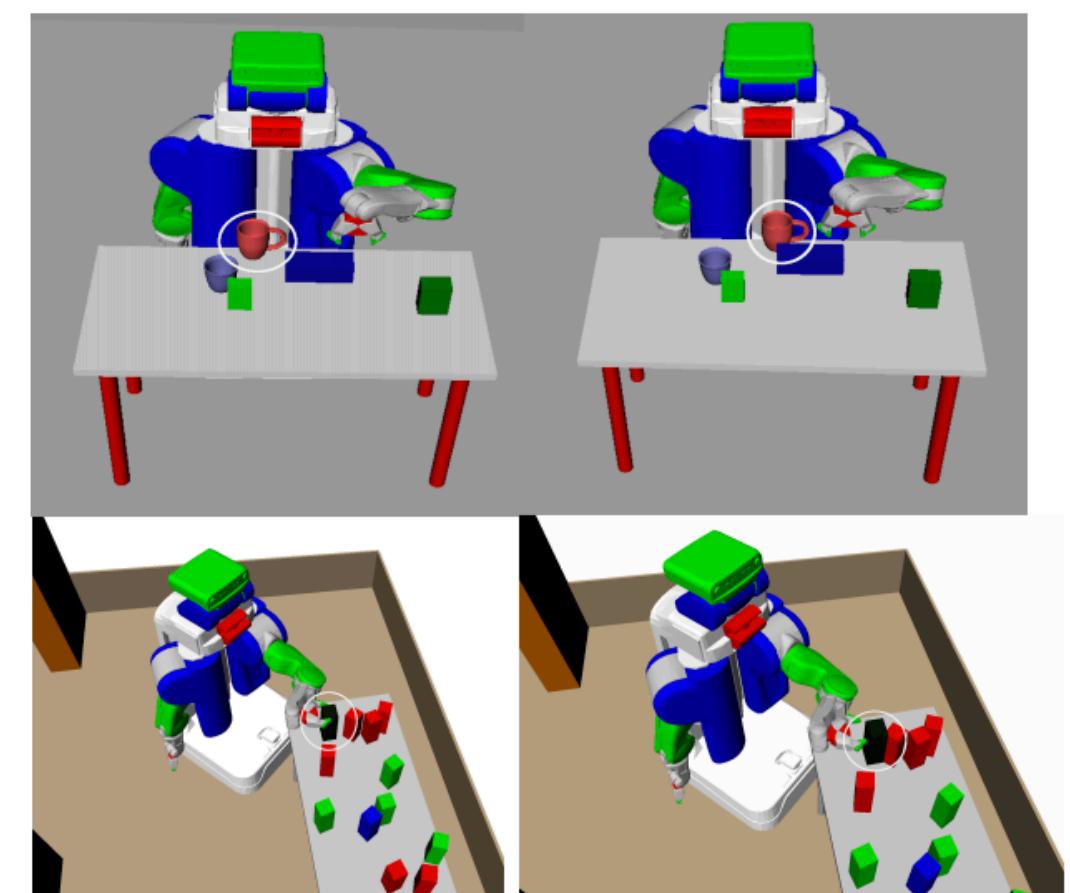
6D Poses Estimation



Berenson et al., 2009



Miller and Allen 2009

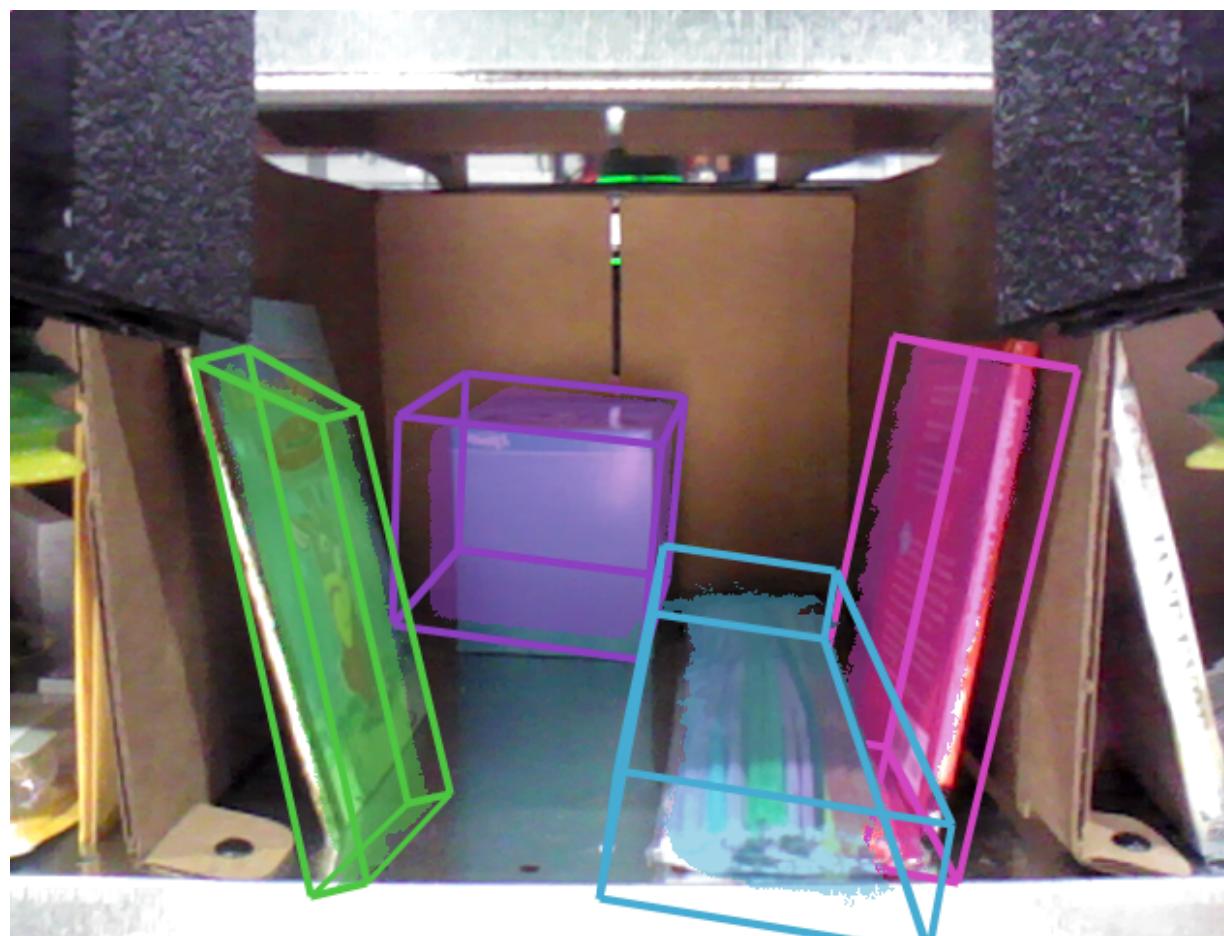


Kimm et al 2019

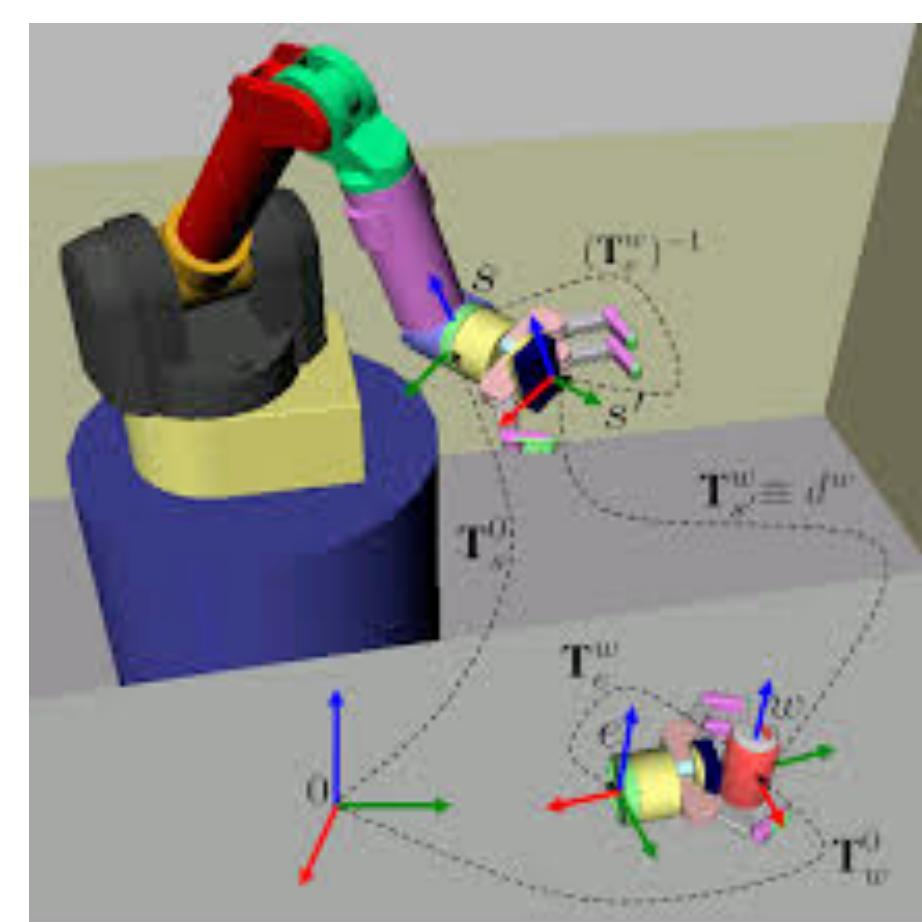
Instance-level 6DoF Pose Estimation

Why it is useful?

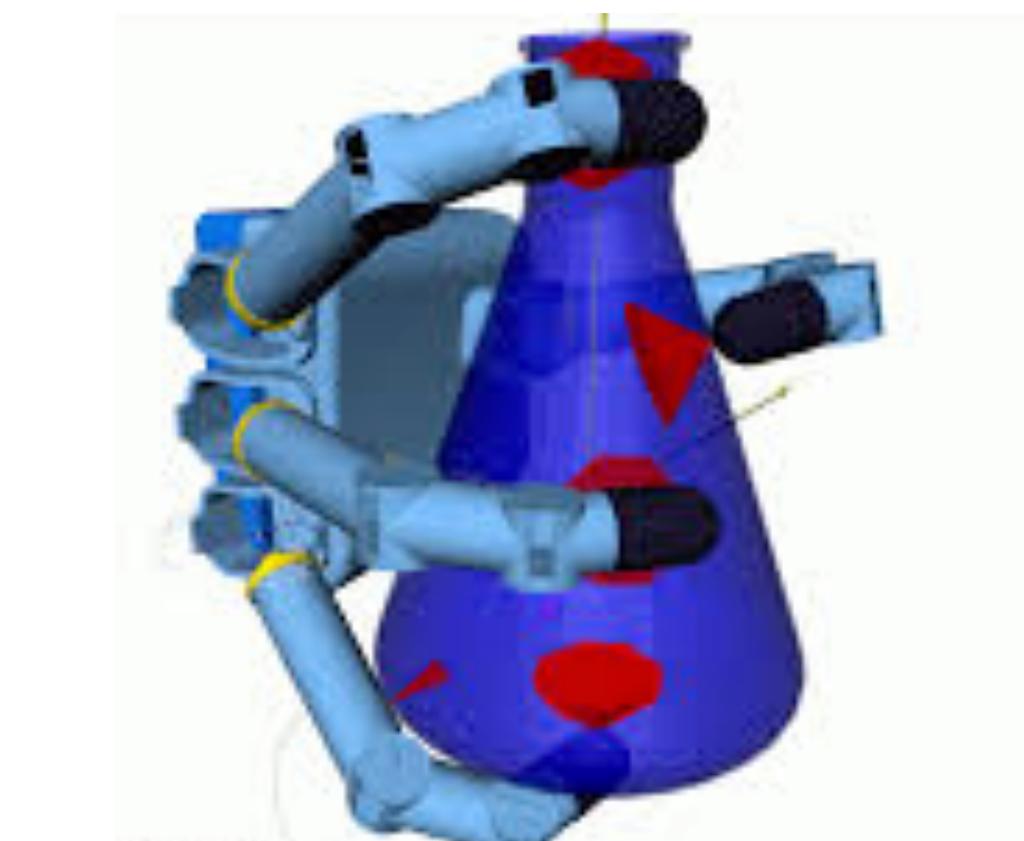
- Concise description of scene and state
- Can be easily used by planning algorithm



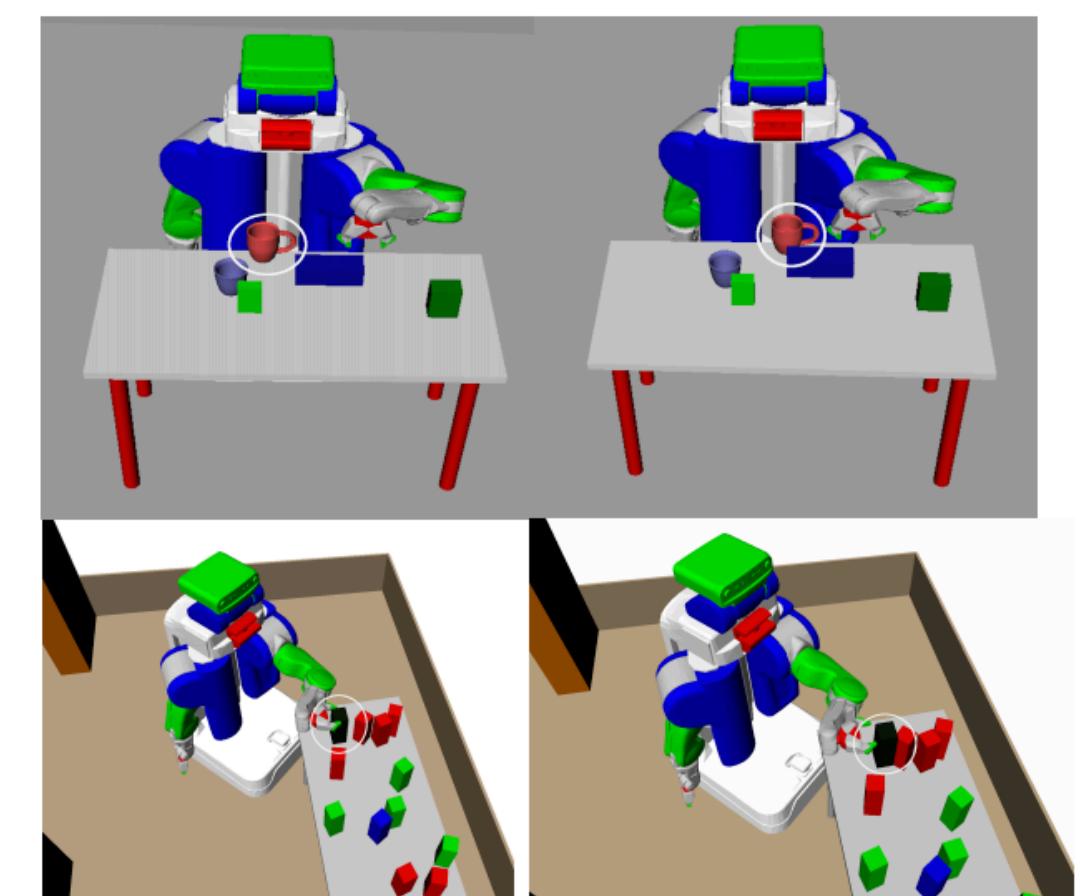
6D Poses Estimation



Berenson et al., 2009



Miller and Allen 2009



Kimm et al 2019

Good for structured **known** settings with **rigid** objects

Instance-level 6DoF Pose Estimation

Why it is limiting?

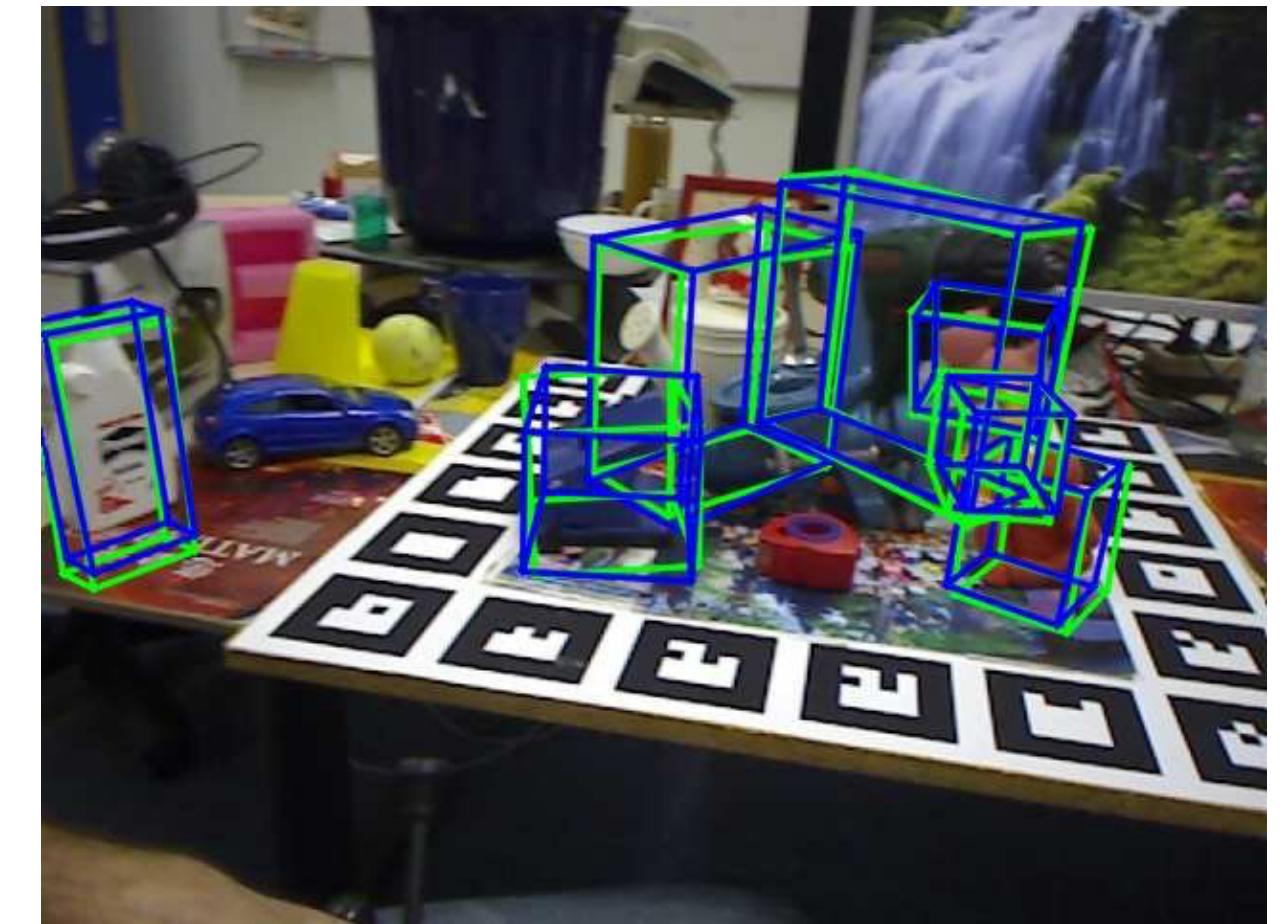
- Need 3D models of the exact objects
- Cannot generalize to unseen objects instances



Instance-level 6DoF Pose Estimation

Why it is limiting?

- Need 3D models of the exact objects
- Cannot generalize to unseen objects instances
- Handles a small collection of known instances.



LINEKIT dataset



YCB dataset

Today's Talk

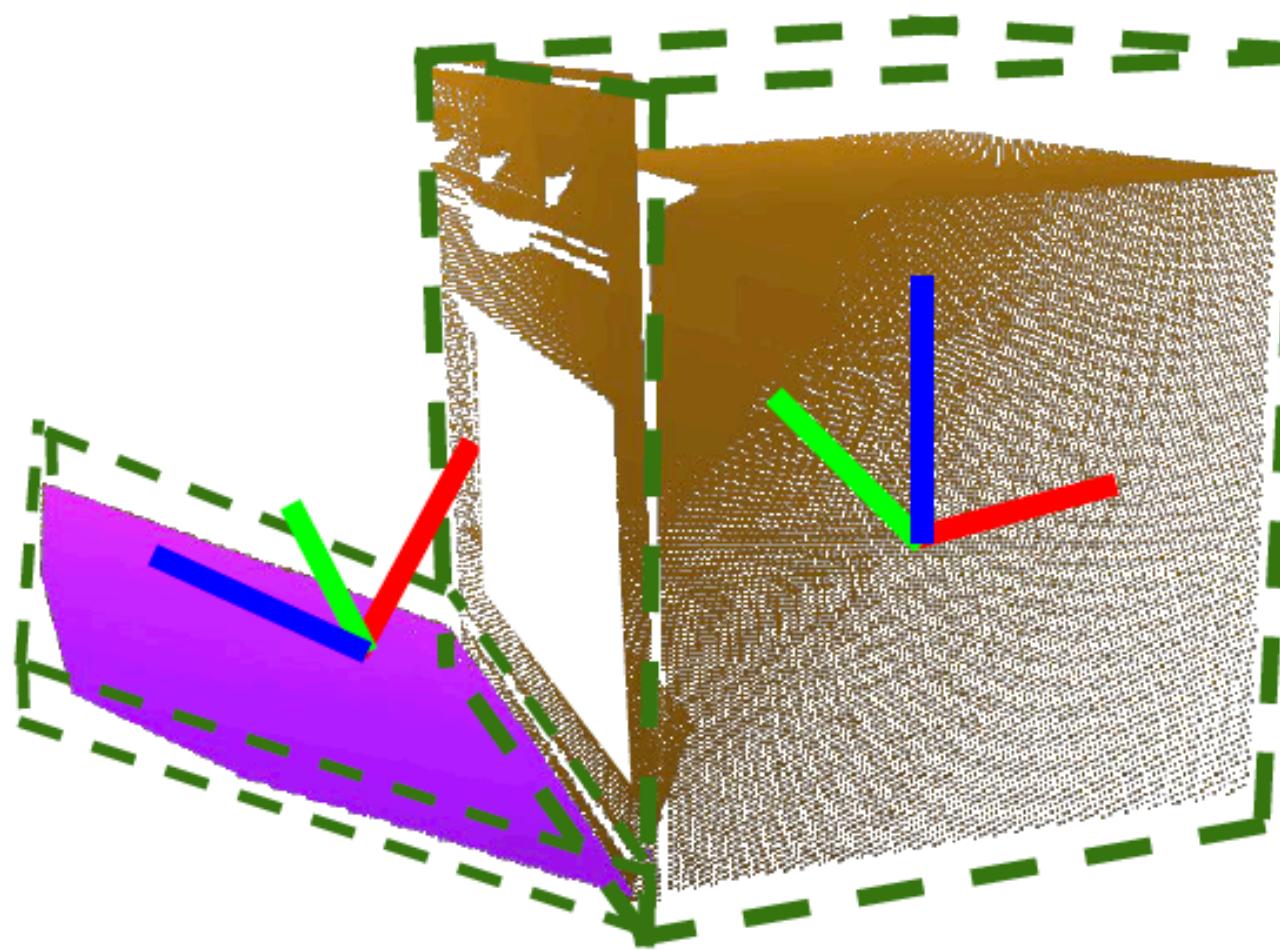
Category-level pose estimation that enables algorithm to generalize to
unseen object instance by leveraging category prior.

Today's Talk

Category-level pose estimation for



Rigid Object



Articulated Object



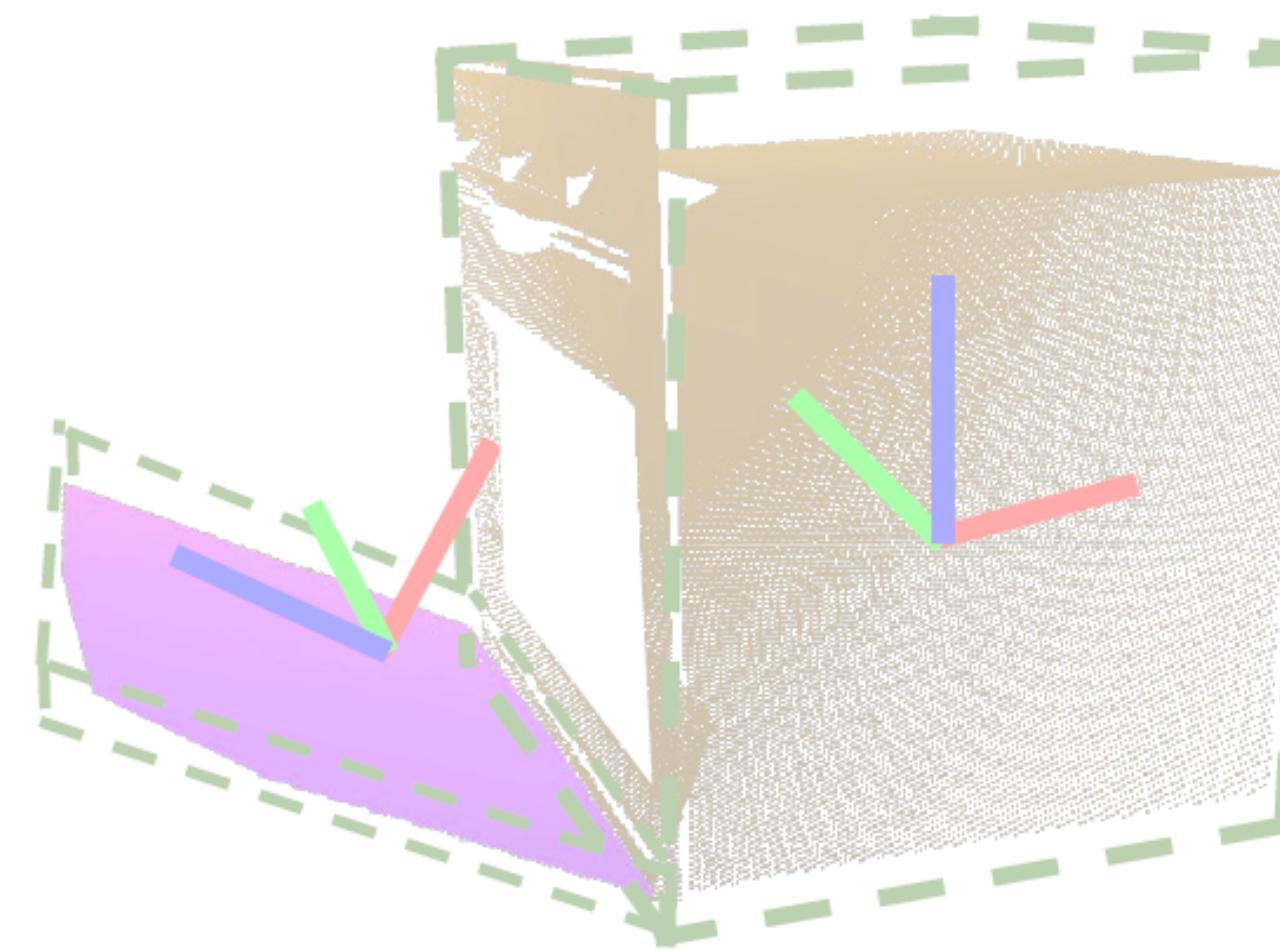
What's next?

Today's Talk

Category-level pose estimation for



Rigid Object



Articulated Object

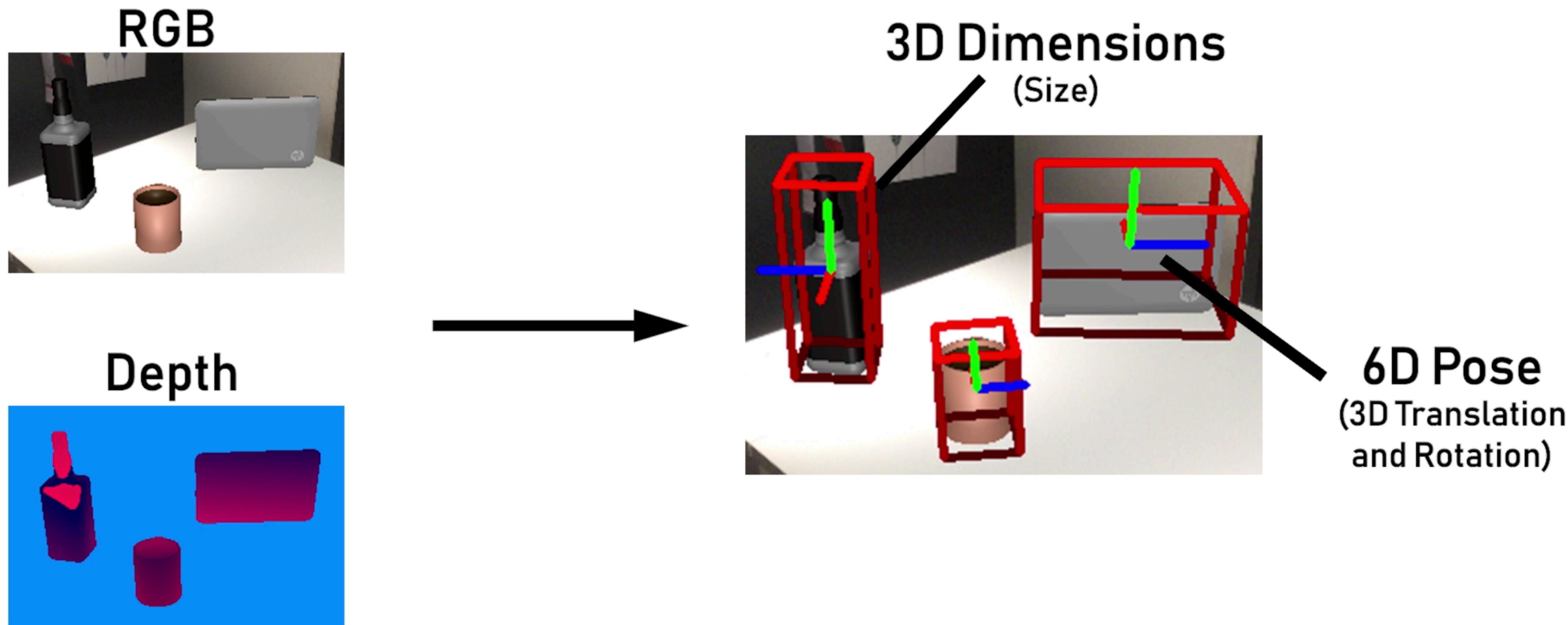


What's next?

Normalized Object Coordinate Space for Category-Level 6D Object Pose and Size Estimation
He Wang, Srinath Sridhar, Jingwei Huang, Julien Valentin, Shuran Song, Leonidas Guibas CVPR'19

Problem Formulation

Task: detecting and estimating **6D pose** and **3D size** of **novel** objects in certain categories from RGBD images.

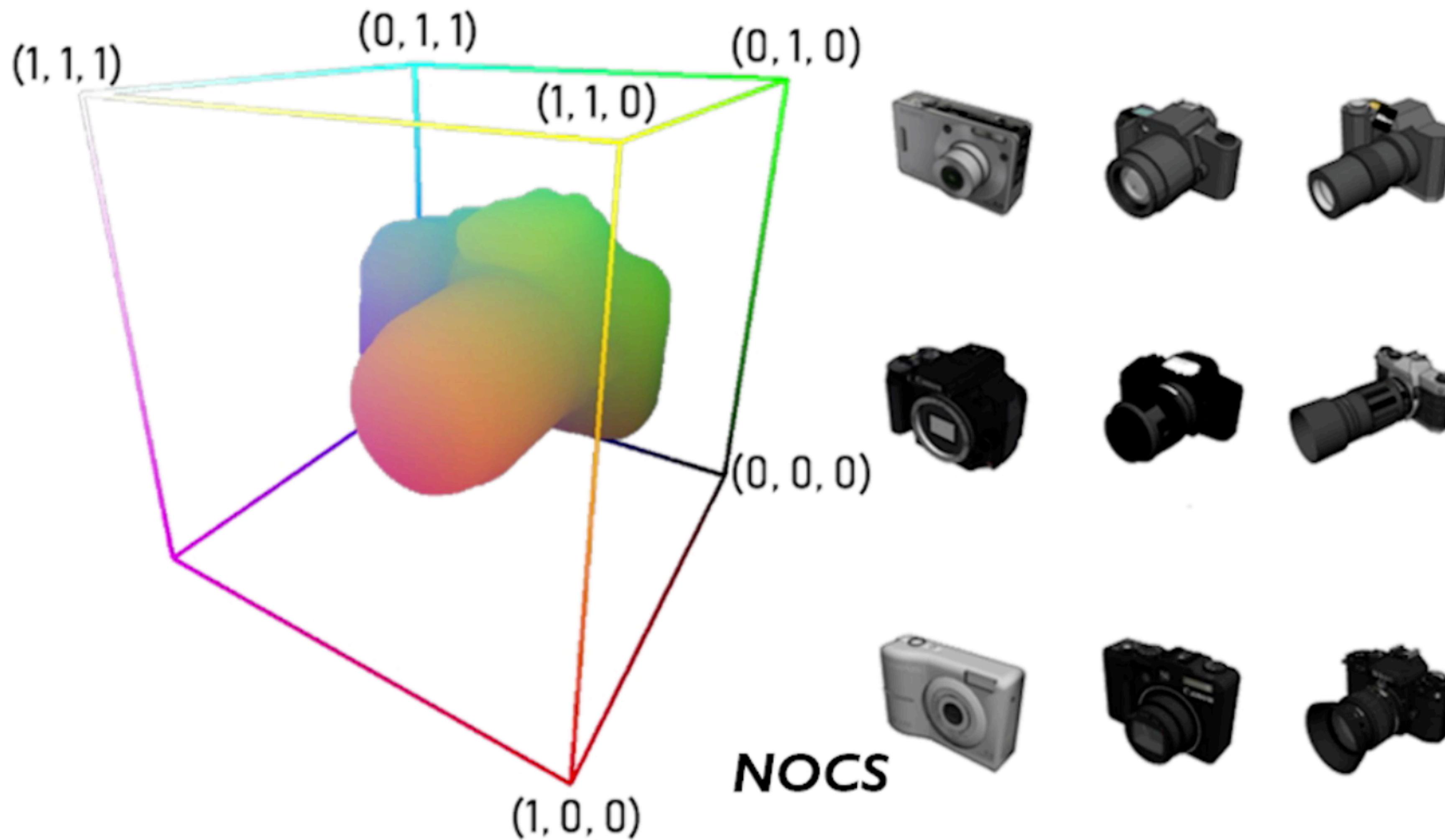


Challenges

- Defining and representing category-level object poses
- Intra-category shape variations
- Training data collection



Normalized Object Coordinate Space (NOCS)

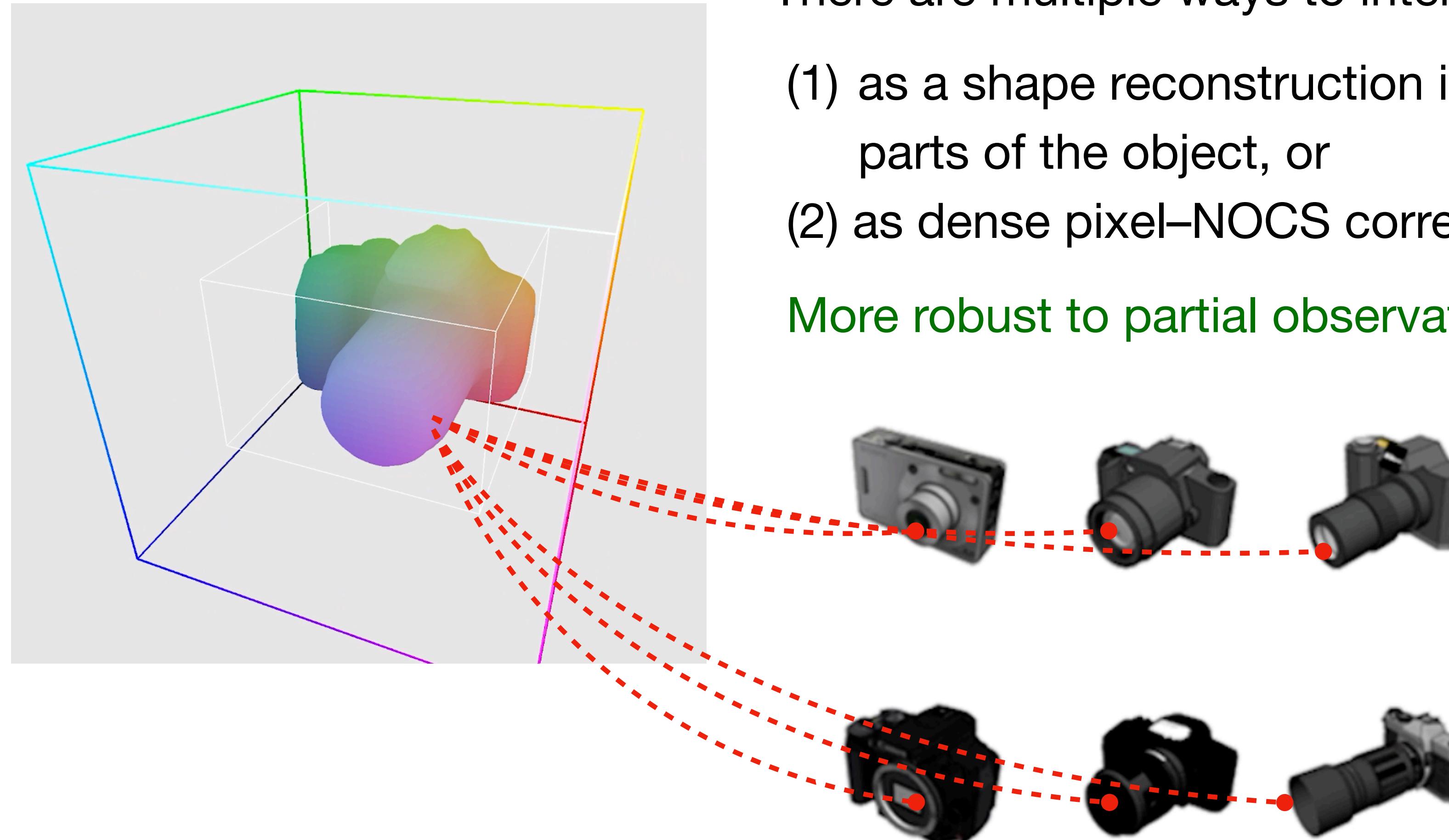


Normalized Object Coordinate Space (NOCS)

Category-level object orientation can be defined for each category up to the limit of global symmetry in the category.



Normalized Object Coordinate Space (NOCS)

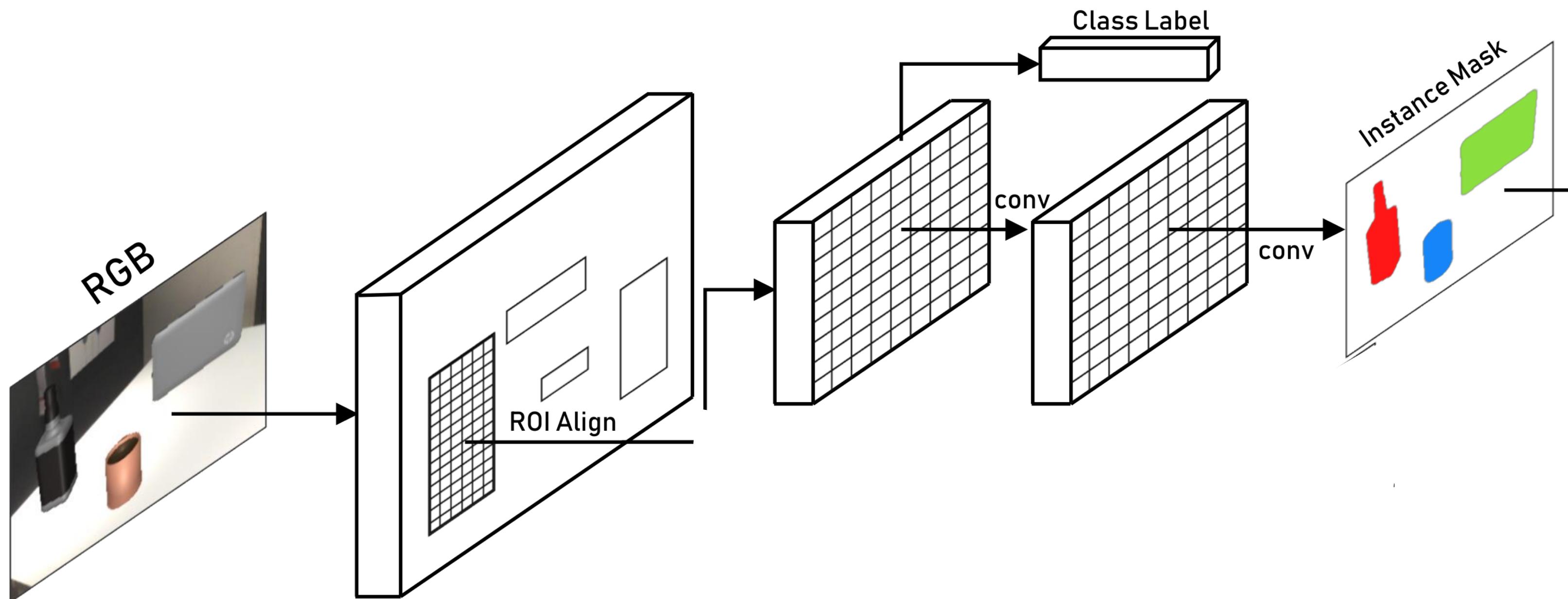


There are multiple ways to interpret a NOCS map:

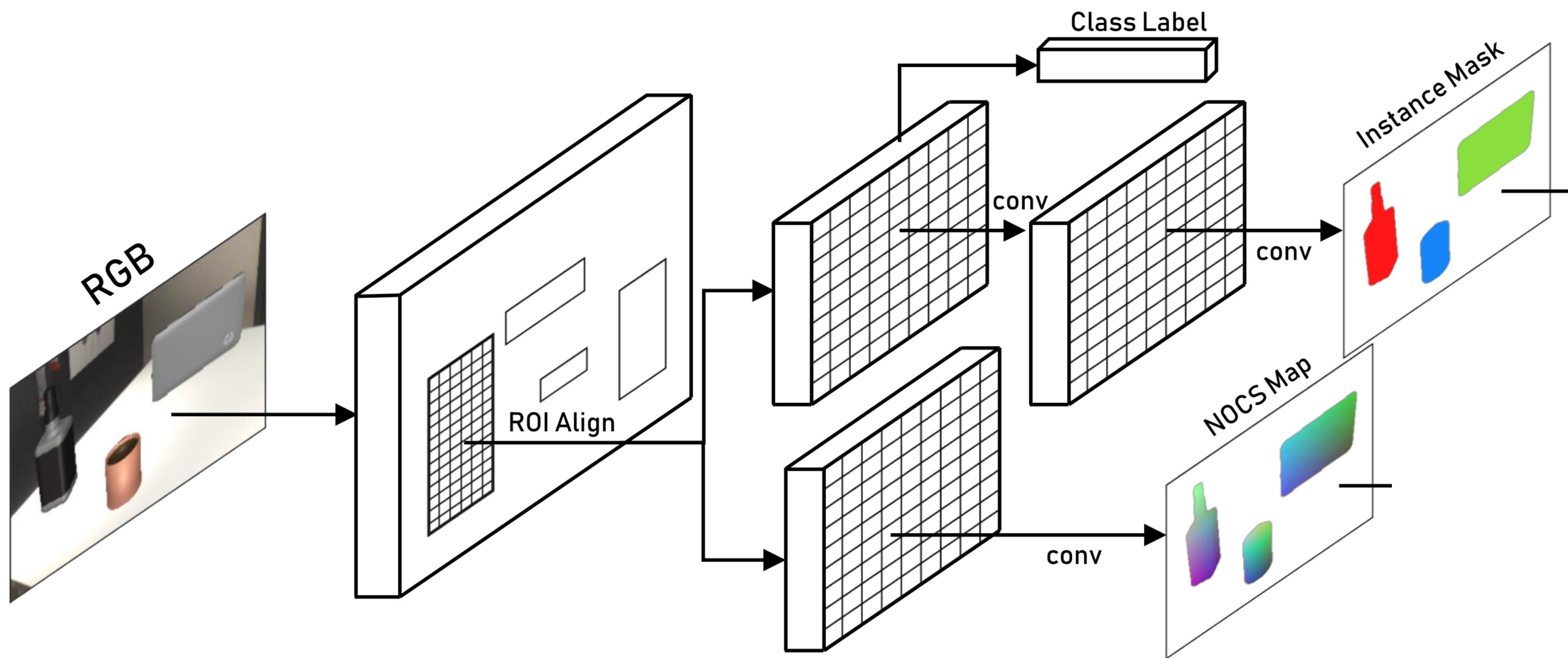
- (1) as a shape reconstruction in NOCS of the observed parts of the object, or
- (2) as dense pixel-NOCS correspondences.

More robust to partial observation

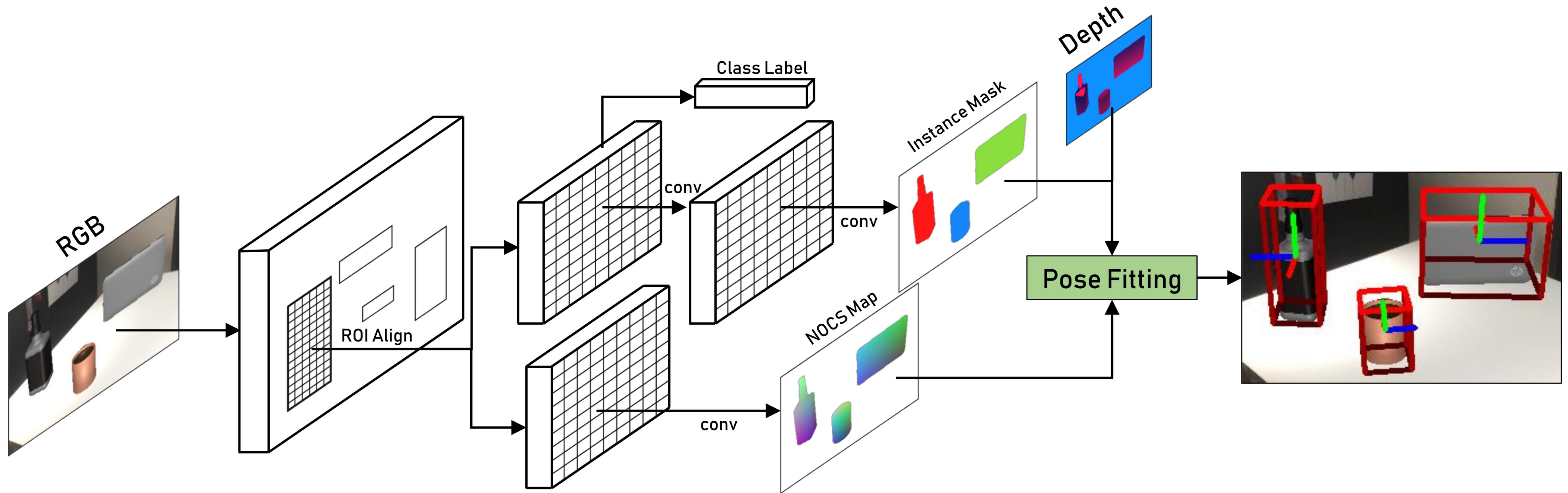
Method Overview



Method Overview



Method Overview



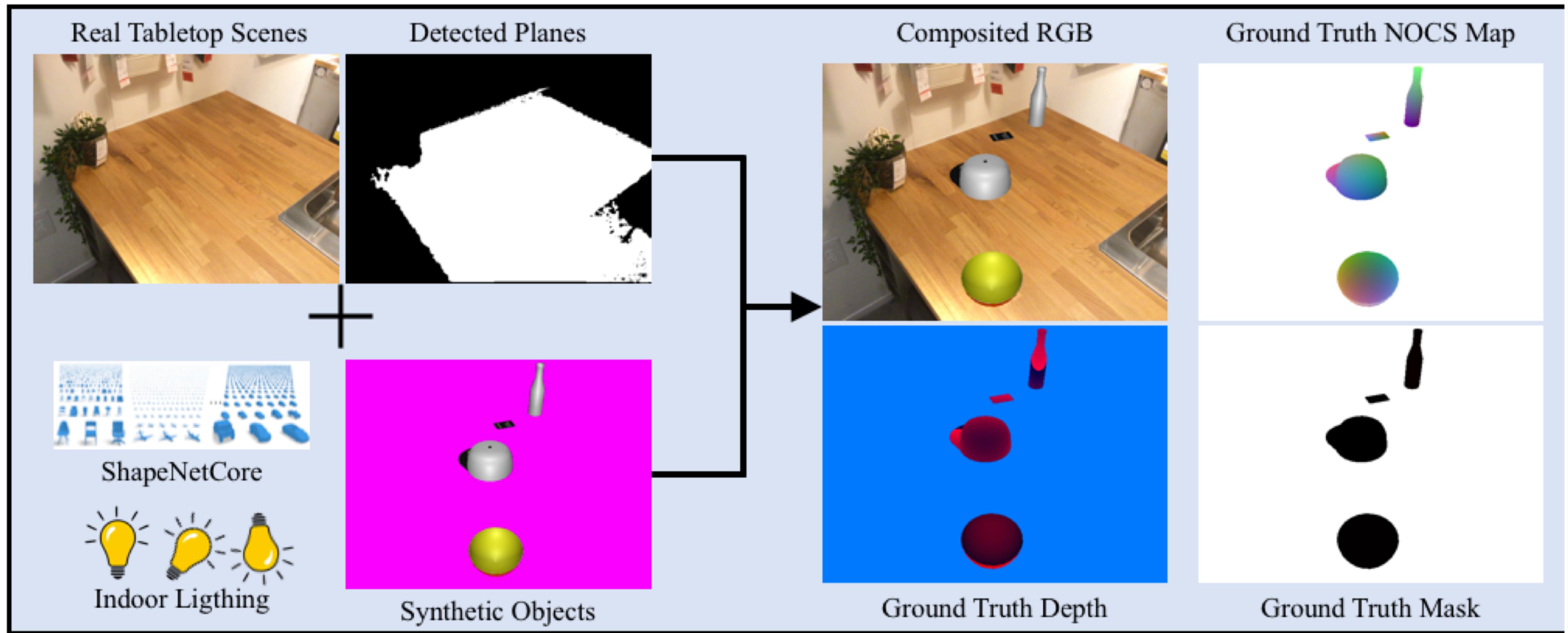
Handling Symmetry

Symmetry-aware loss function: $L_s = \min_{i=1,\dots,|\theta|} L(\tilde{\mathbf{y}}_i, \mathbf{y}^*)$

min-of-N loss



Context-Aware MixEd ReAlity (CAMERA)



Mixed-reality data generation pipeline

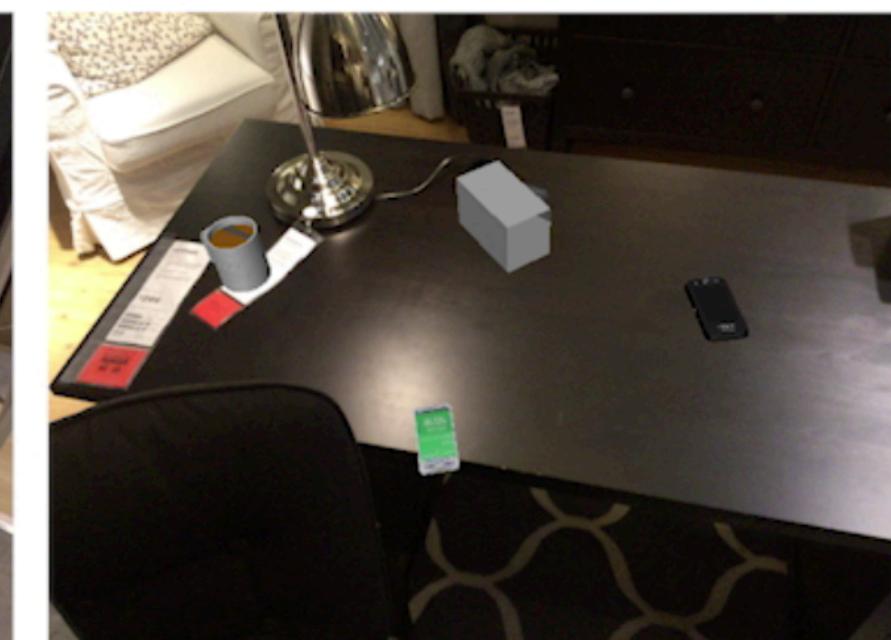
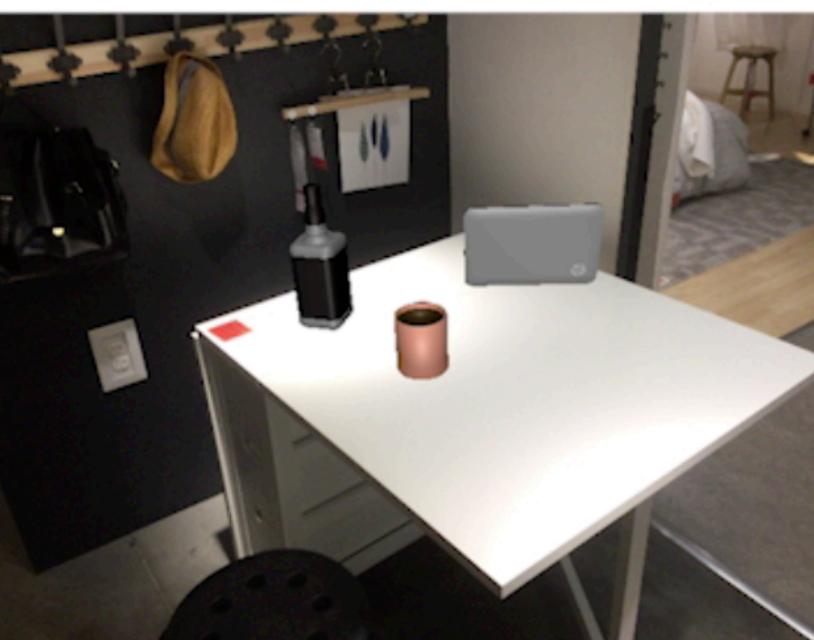
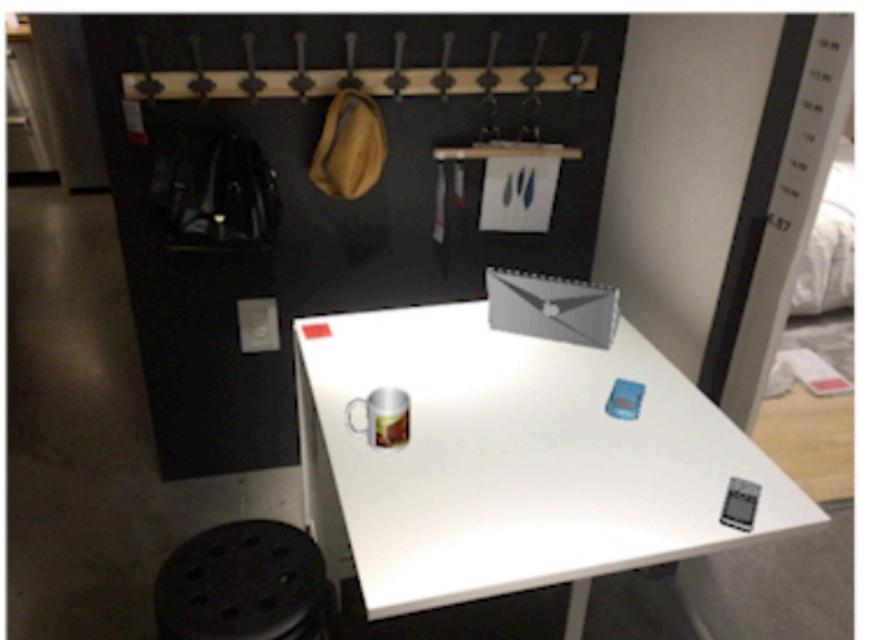
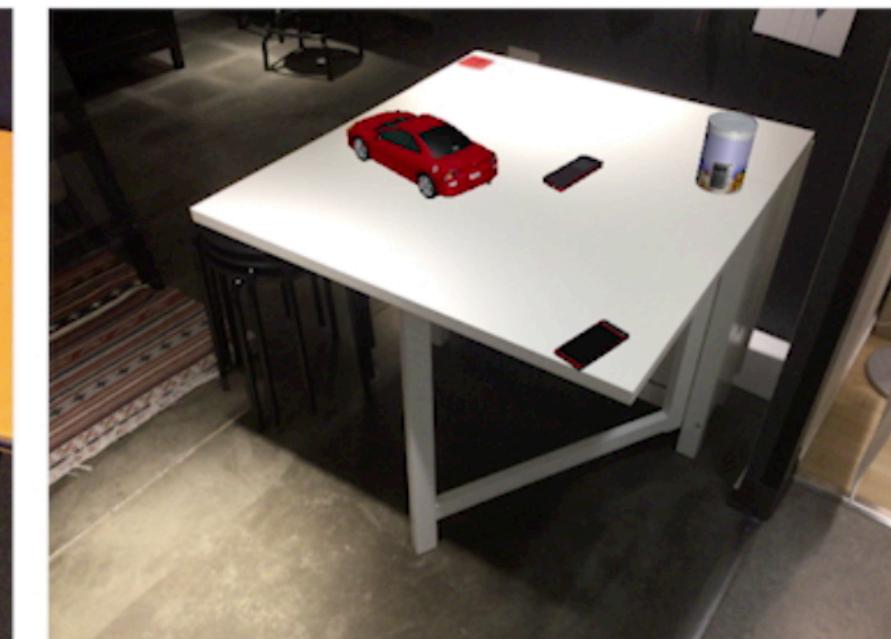
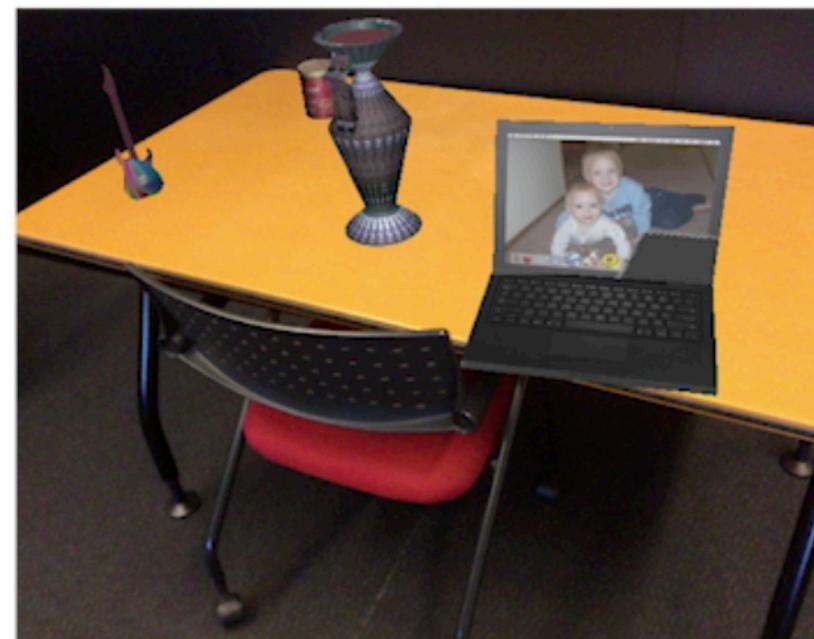
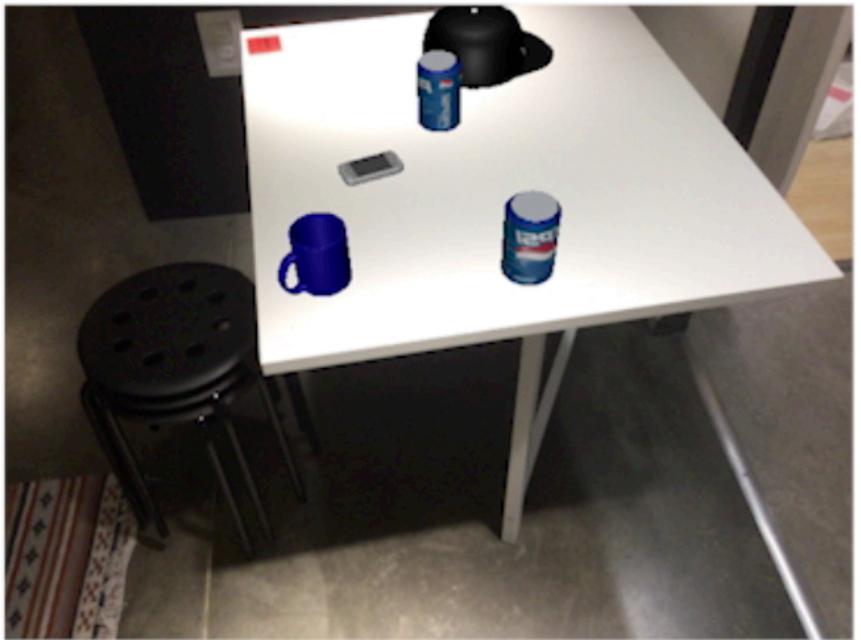
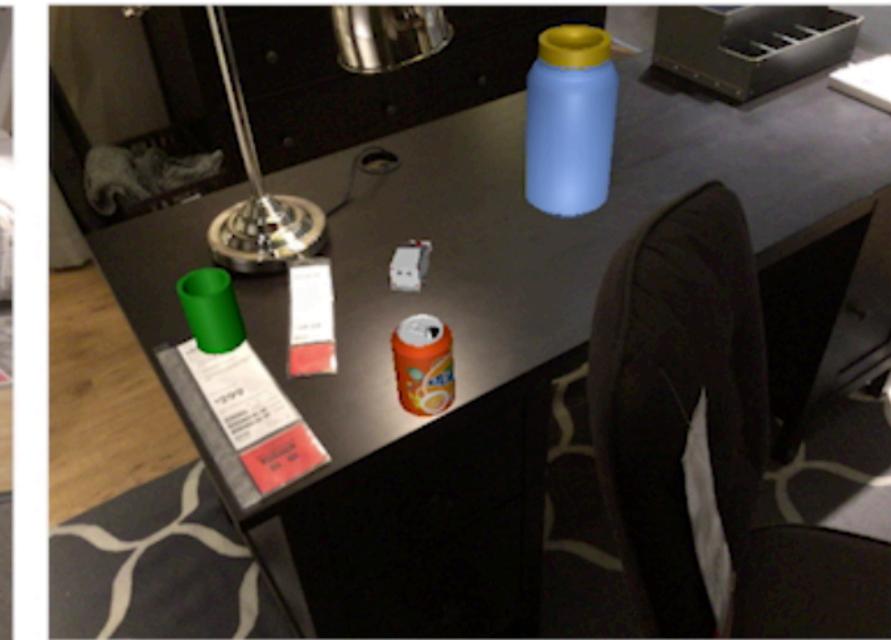
Dataset Statistics

- **Context-Aware MixEd ReAlity**

- 300K images (275K/25K)
- 31 real-world tabletop scenes
- 1085 ShapeNet models



Mixed Reality Data



Real-World Dataset

* markers not used for prediction



Dataset Statistics

- **Real Dataset (Train/Val/Test)**
 - 8K RGB-D (4K/0.95K/3.75K)
 - 18 real scenes (6/6/6)
 - 42 unique instances (3/1/3)

- **6 Object Categories**

- bottle, bowl, camera, laptop, mug
- symmetric vs. asymmetric



Results on Real Test Data

Training Data:

275K CAMERA

20K COCO (without NOCS)

4.3K real images

CAMERA data



Real data



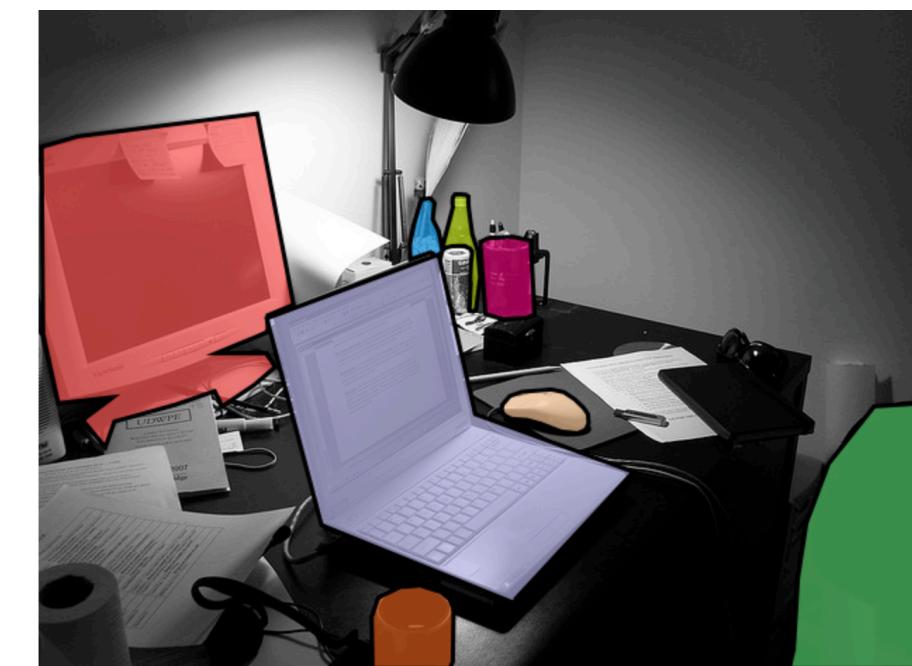
Performance:

3D IoU @ 50%: **76.4%**

5°, 5cm: **10.2%**

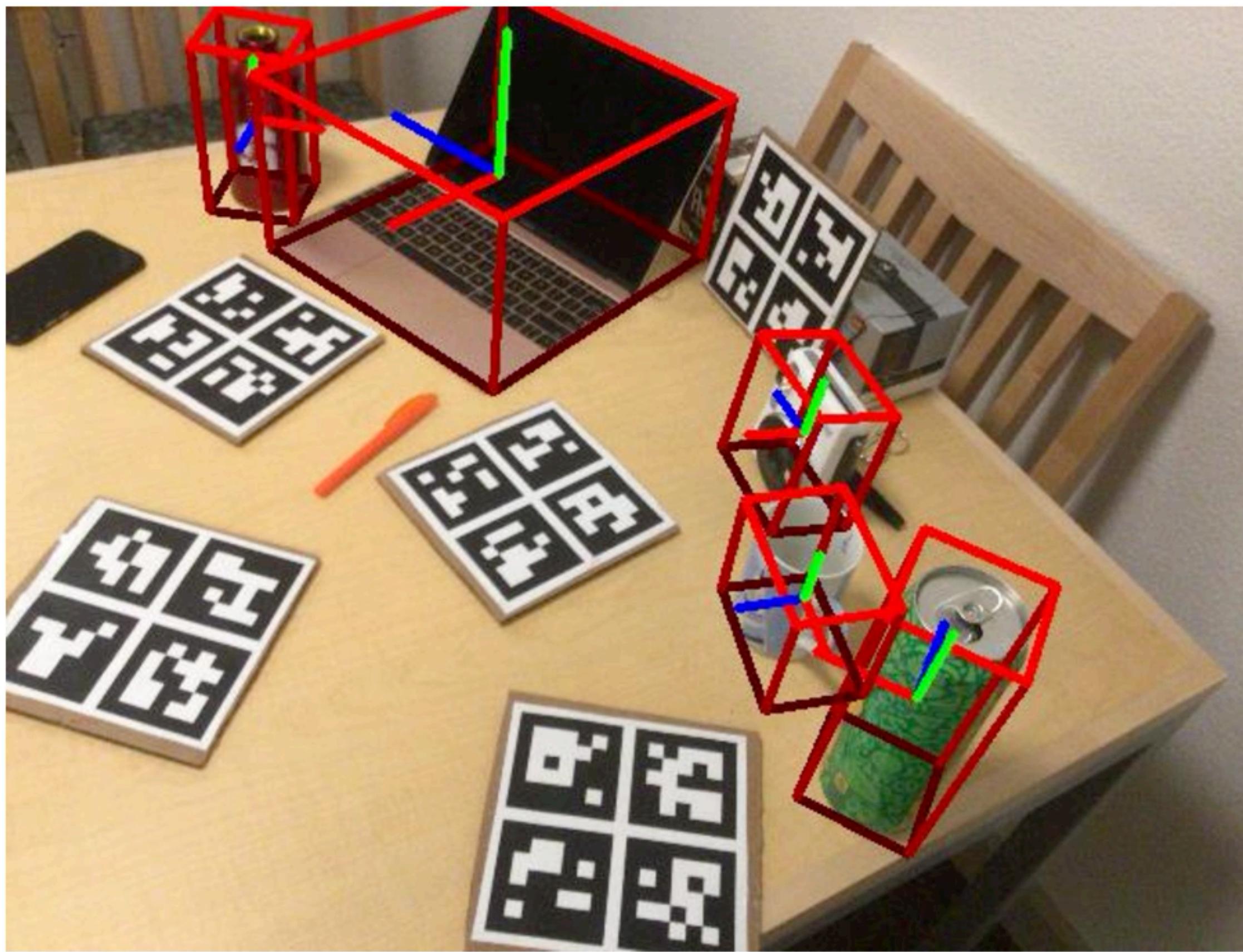
10°, 10cm: **23.1%**

MS COCO data

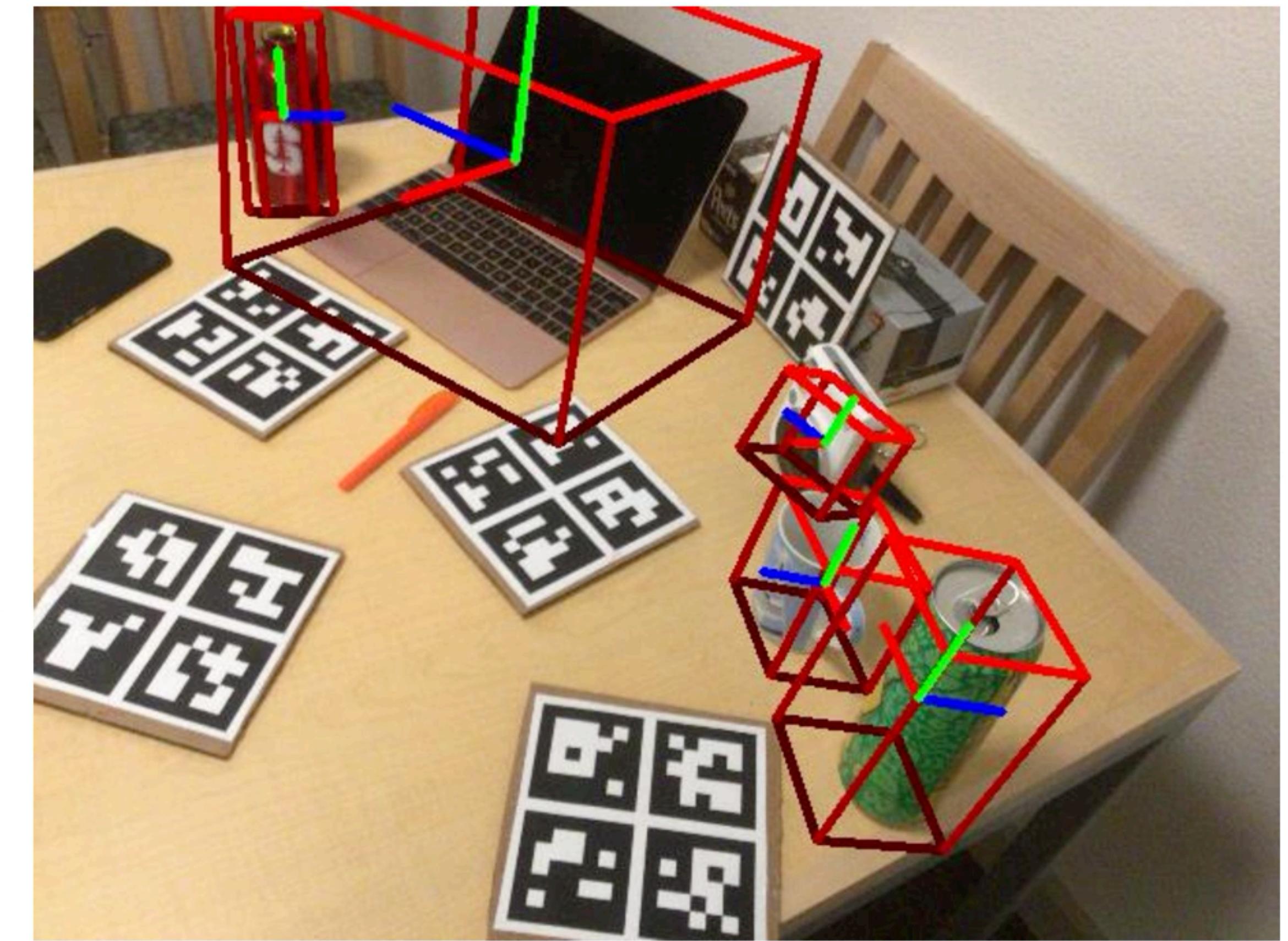


Result Visualization

Ground Truth



Prediction (Ours)



Recap

Category-level pose estimation for



Rigid Object

Normalized object coordinate space (NOCS)
*defines a shared space with consistent
object scaling and orientation.*

Recap

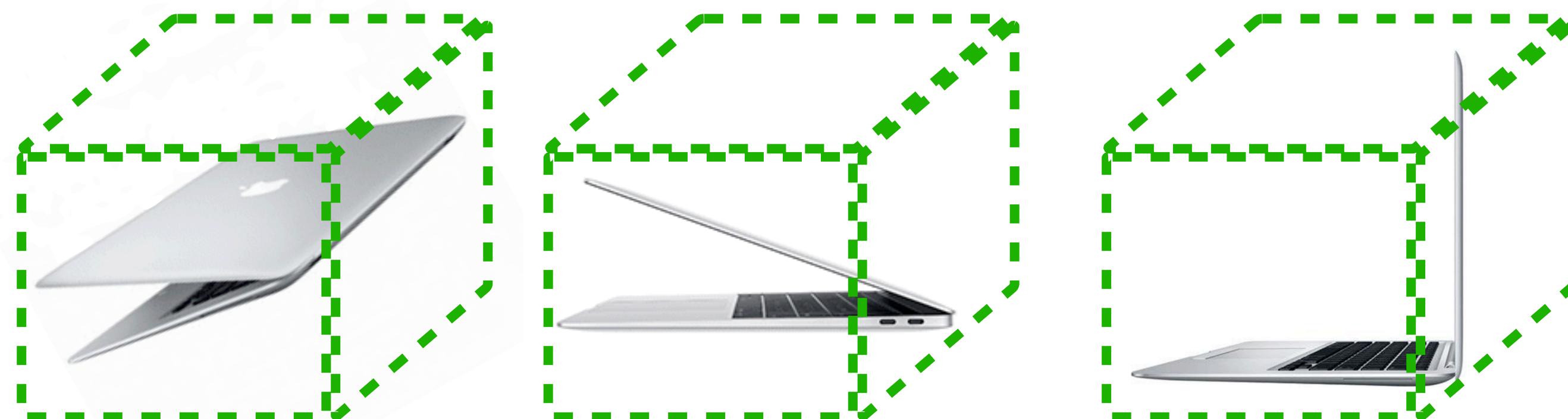
Category-level pose estimation for



Rigid Object

Normalized object coordinate space (NOCS)
*defines a shared space with consistent
object scaling and orientation.*

x Rigid object Assumption

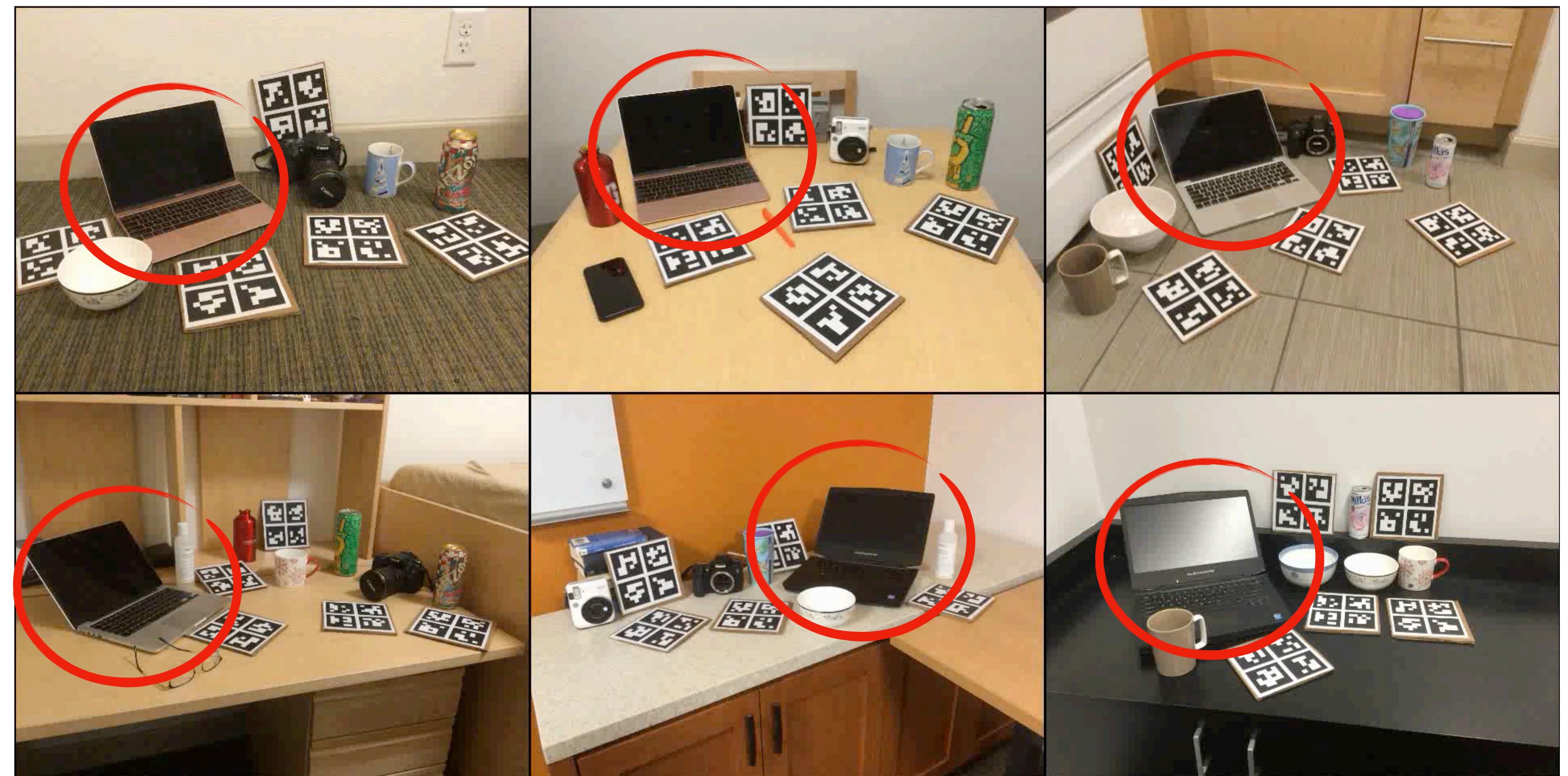


Recap

Category-level pose estimation for



Rigid Object

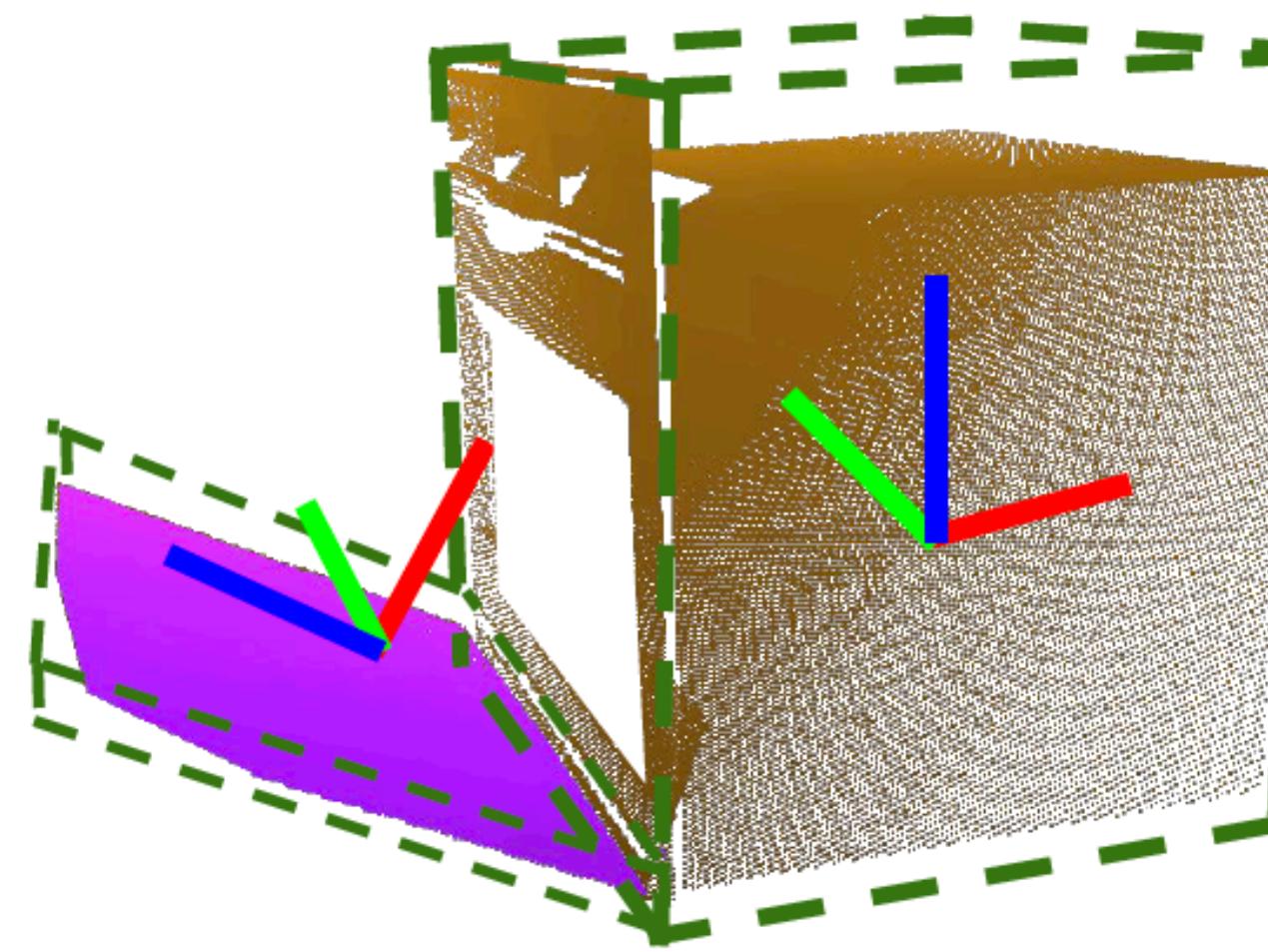


Today's Talk

Category-level pose estimation for



Rigid Object



Articulated Object

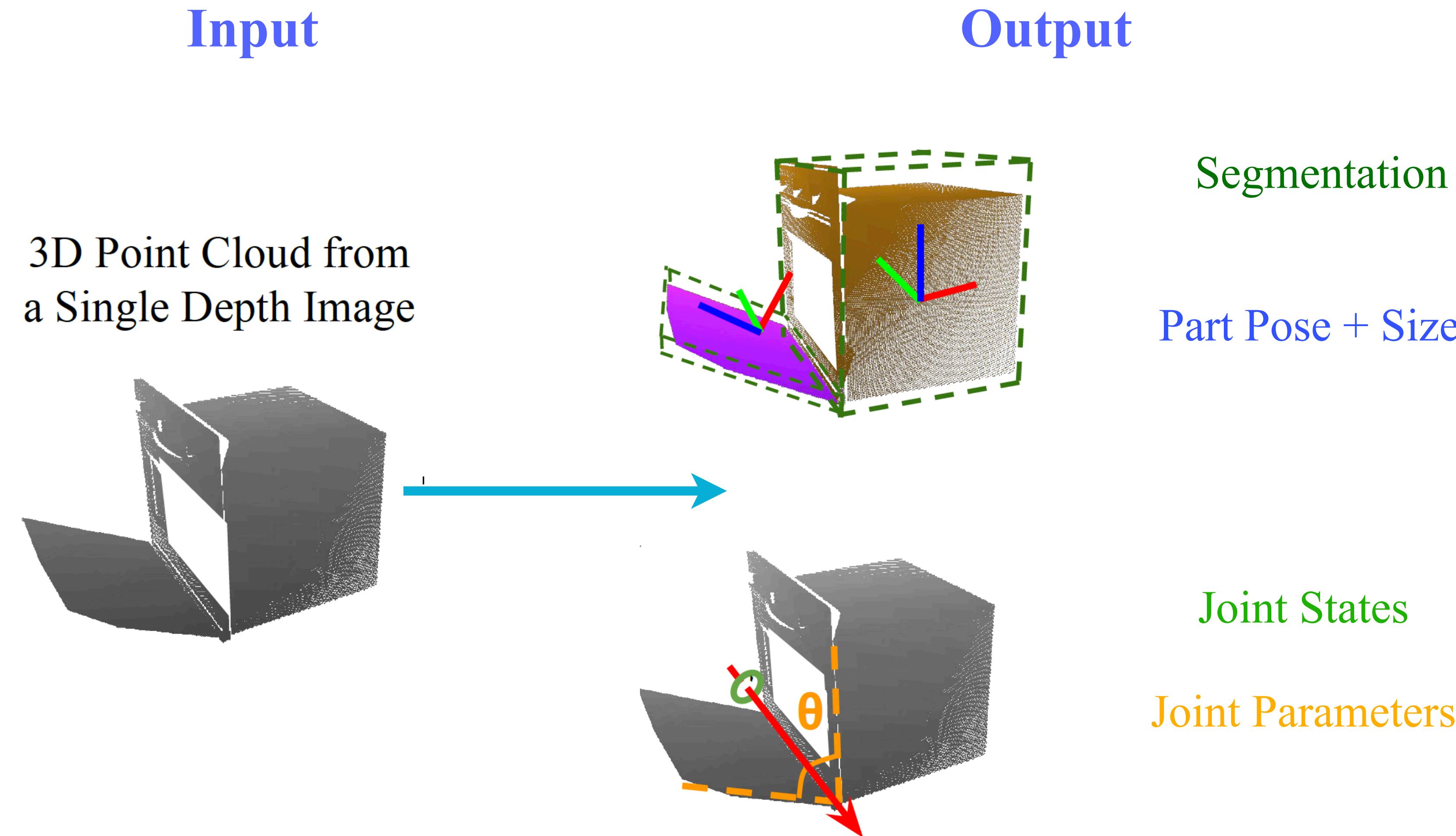


What's next?

Category-level Articulated Object Pose Estimation (CVPR'20)

Xiaolong Li*, He Wang*, Li Yi, Leonidas Guibas, A. Lynn Abbott, Shuran Song

Problem definition



Representation: ANCSH

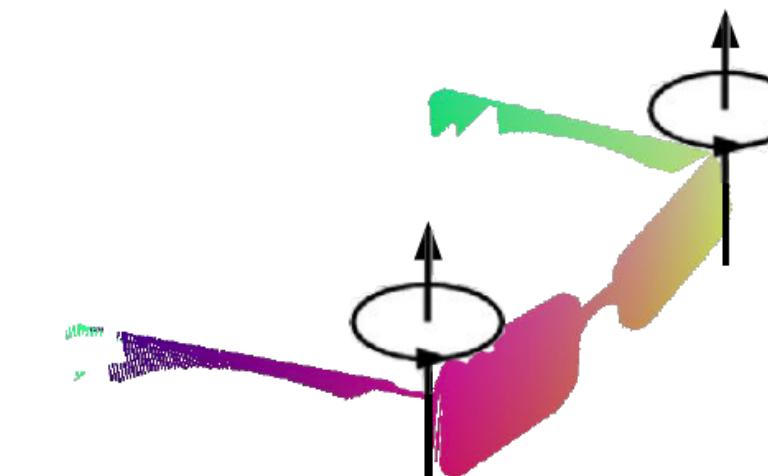
Articulation-aware Normalized Coordinate Space Hierarchy

Normalized Articulated
Object Coordinate Space
(NAOCS)

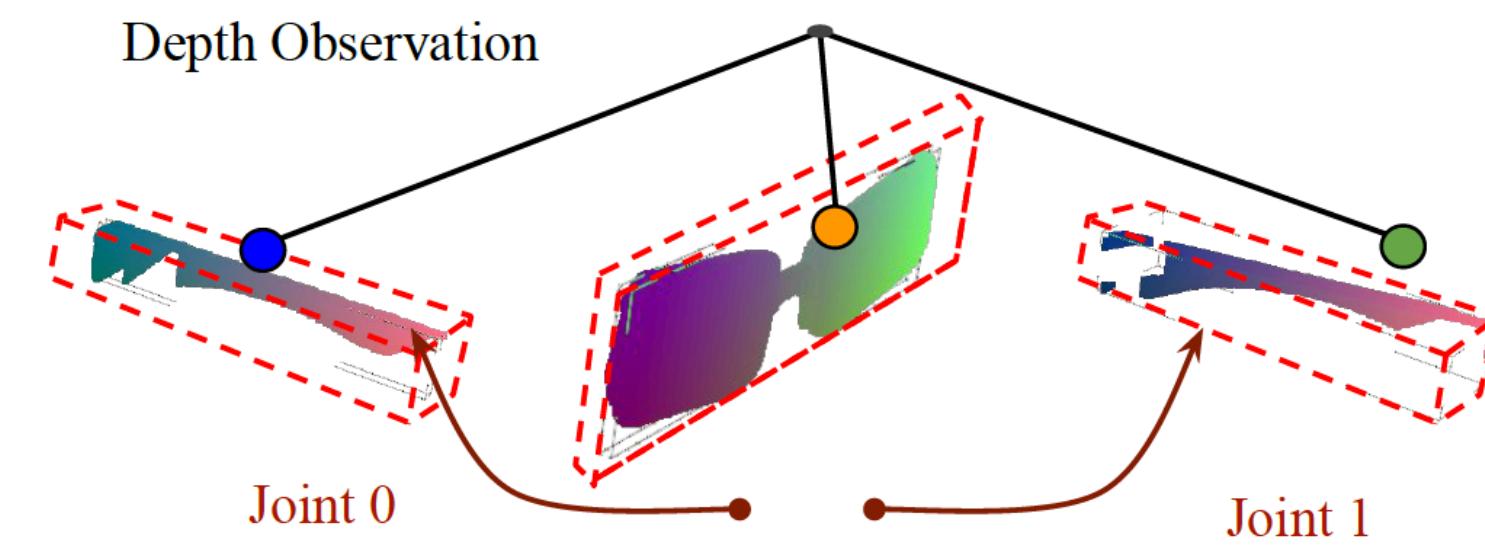
Normalized Part Coordinate
Space
(NPCS)



Depth Observation

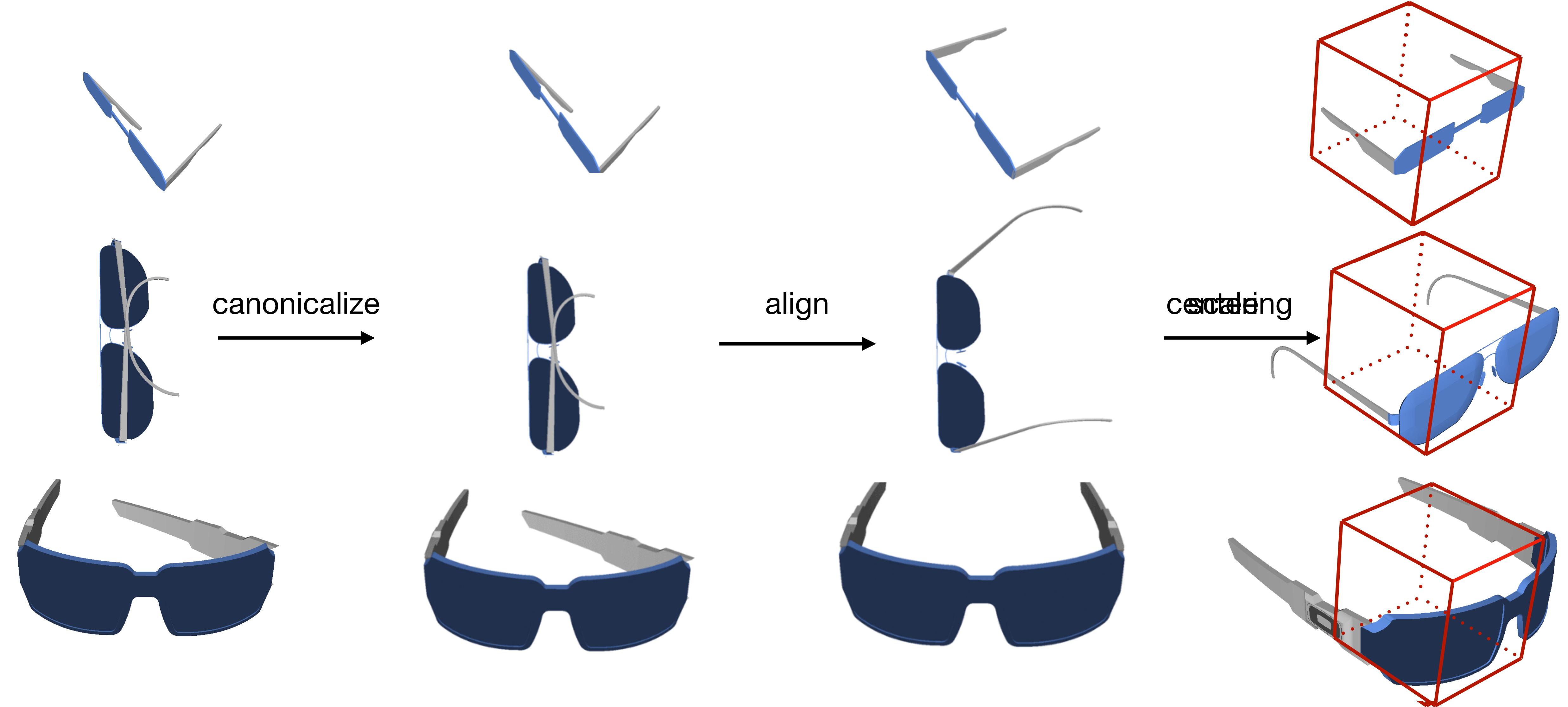


Depth Observation



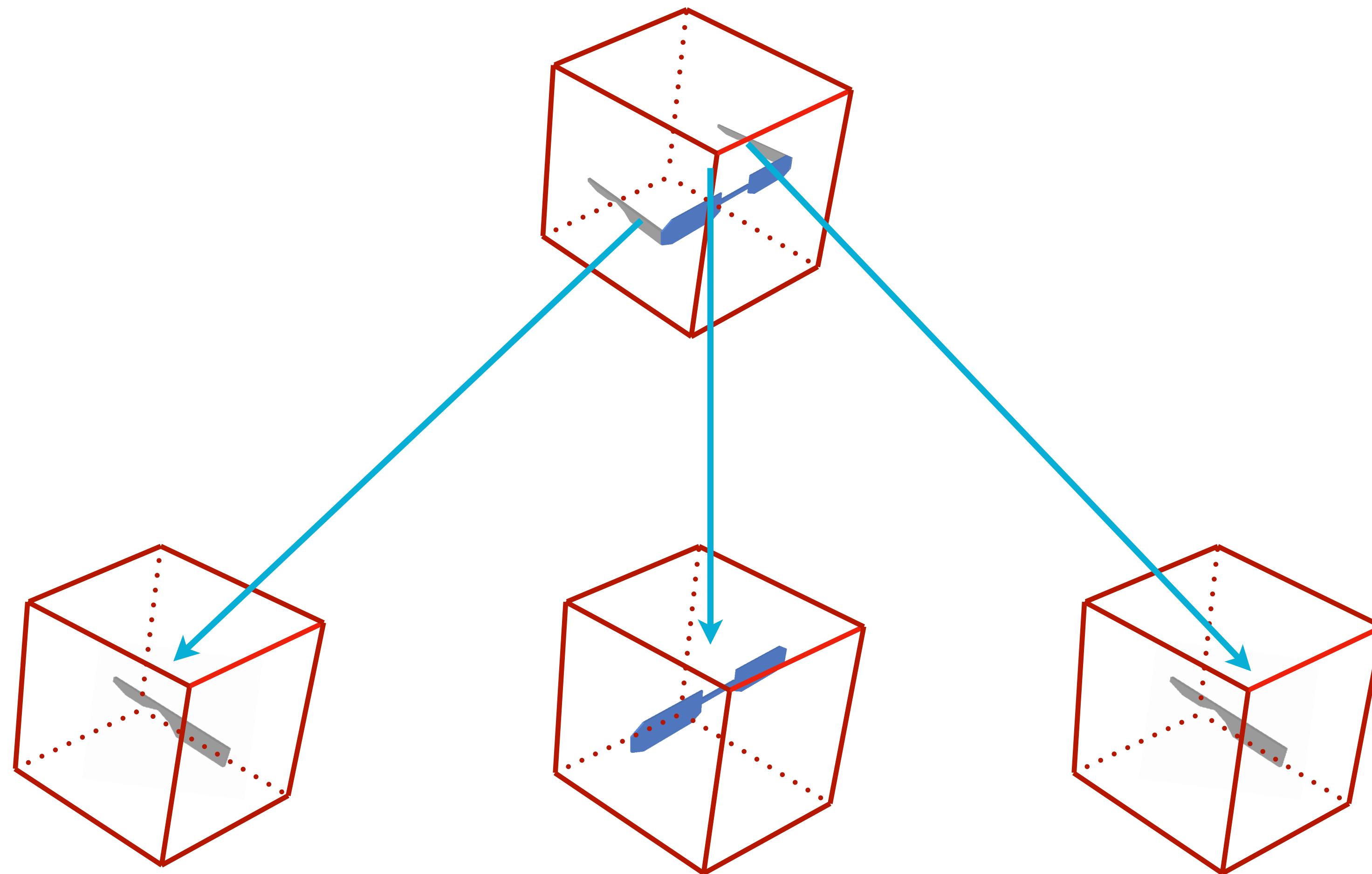
Hierarchical Normalization in ANCSH

Normalized Articulated Object Coordinate Space(NAOCS)

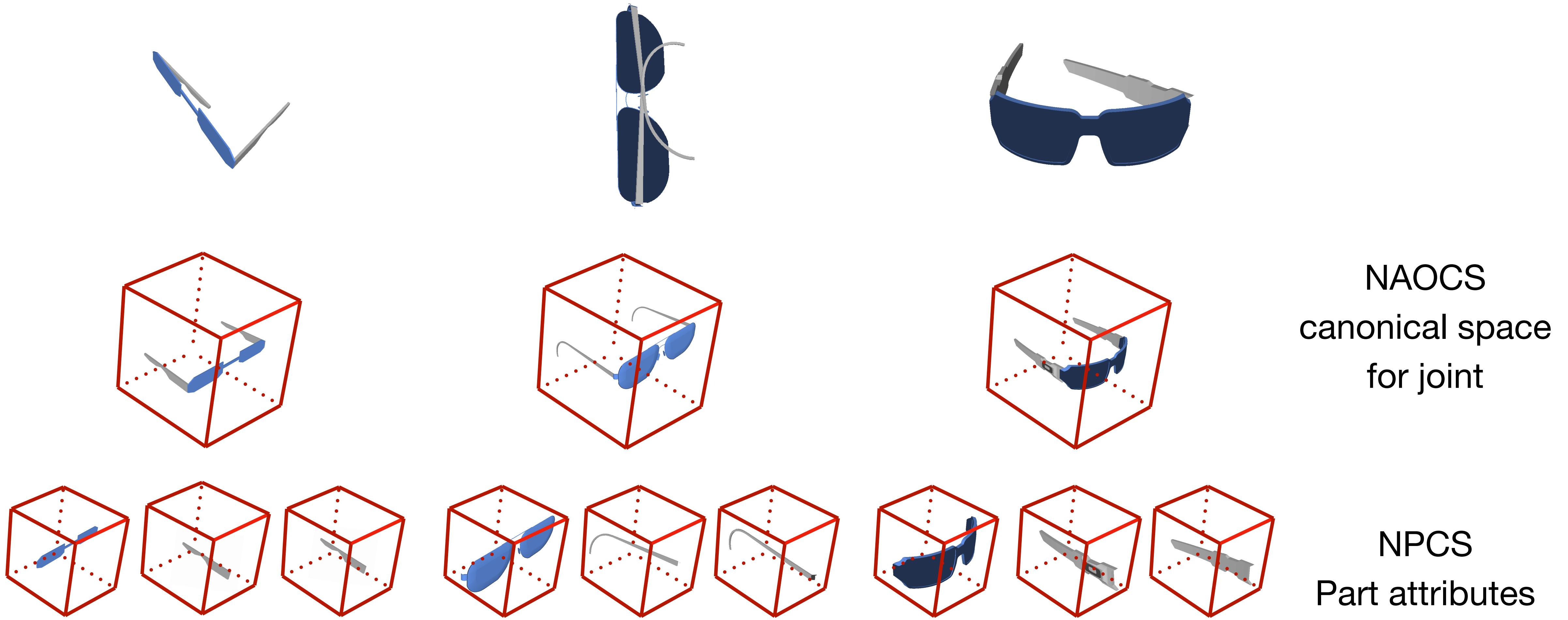


Hierarchical Normalization in ANCSH

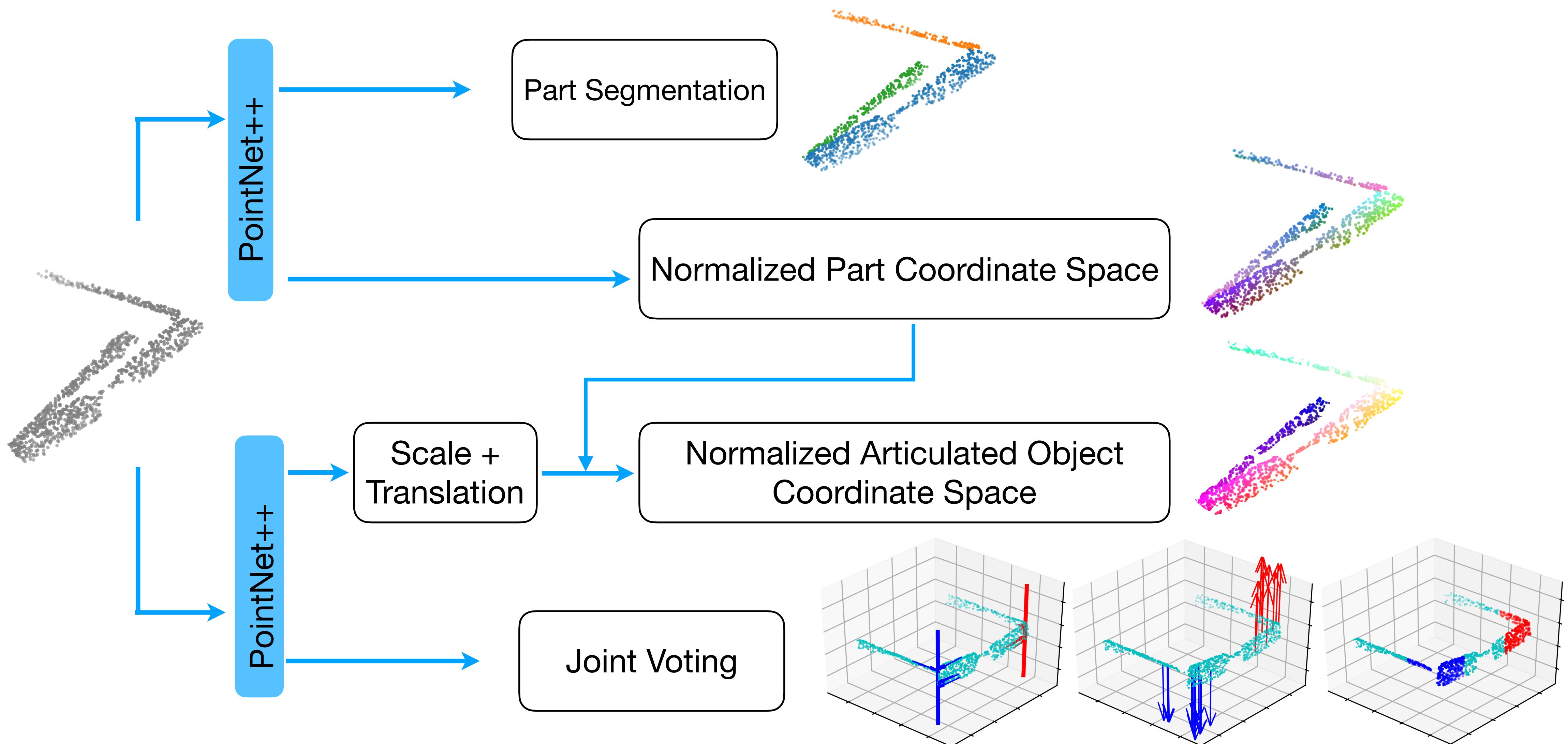
Normalized Part Coordinate Space(NPCS)



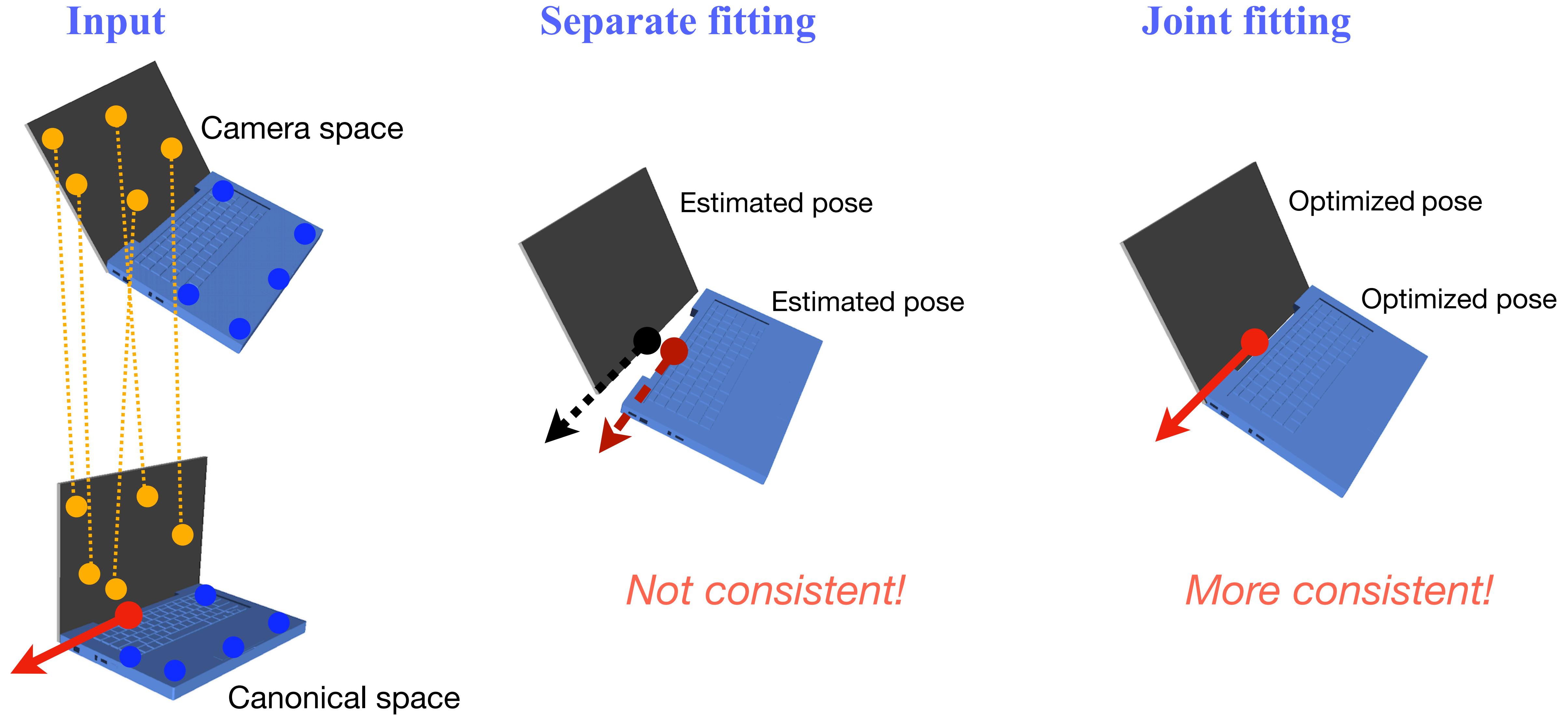
Representation: ANCSH



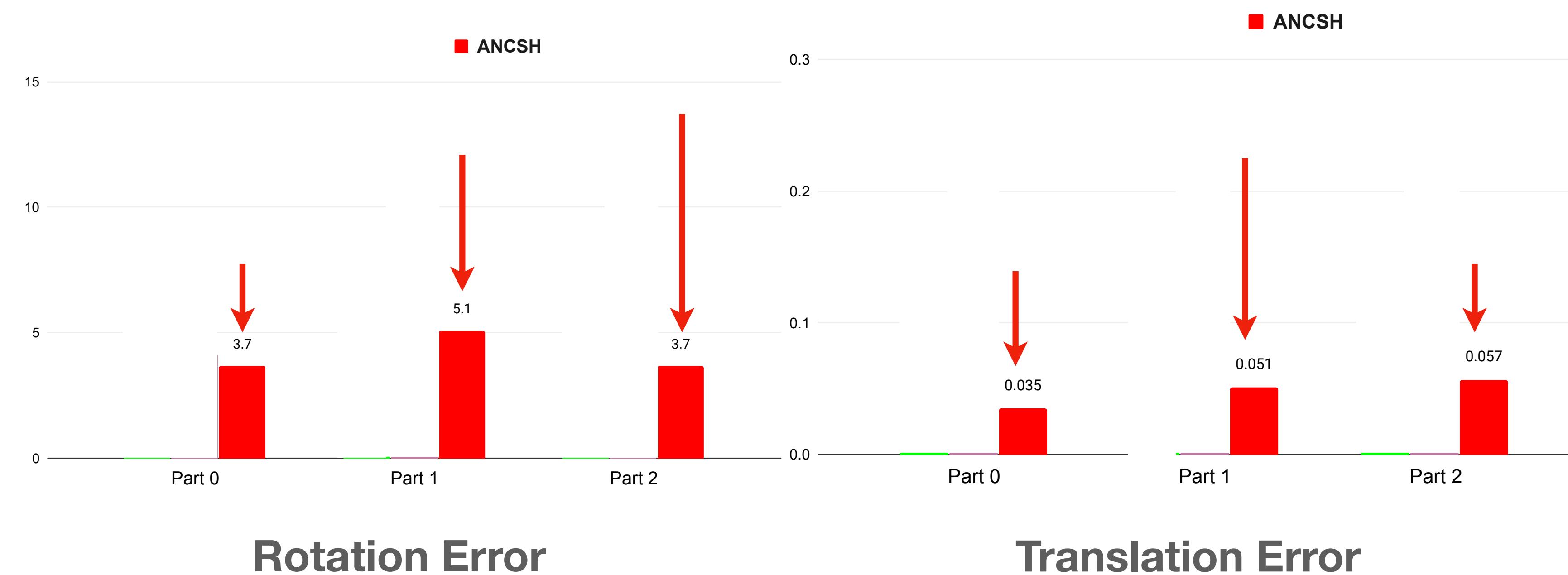
Method: ANCSH Network



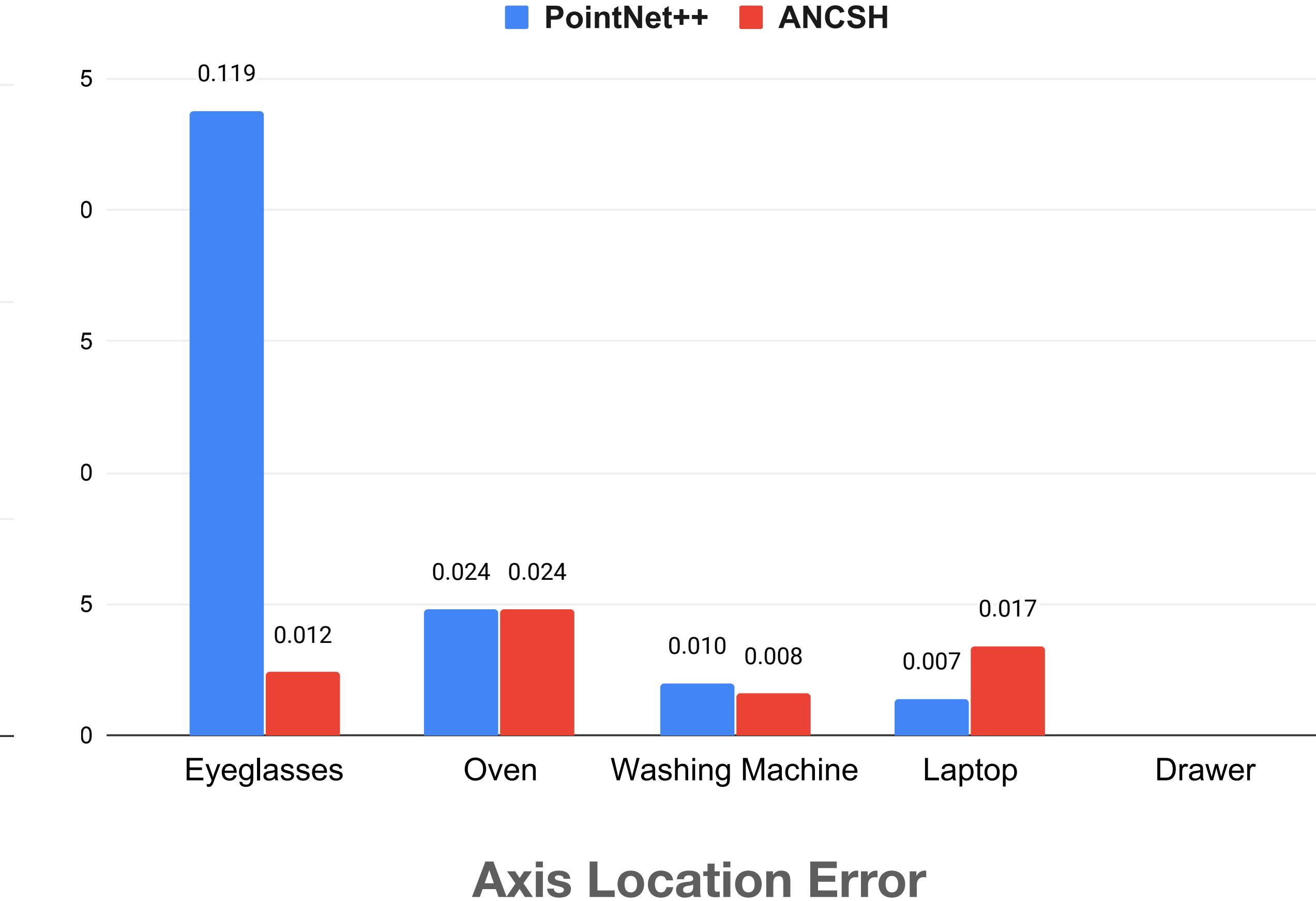
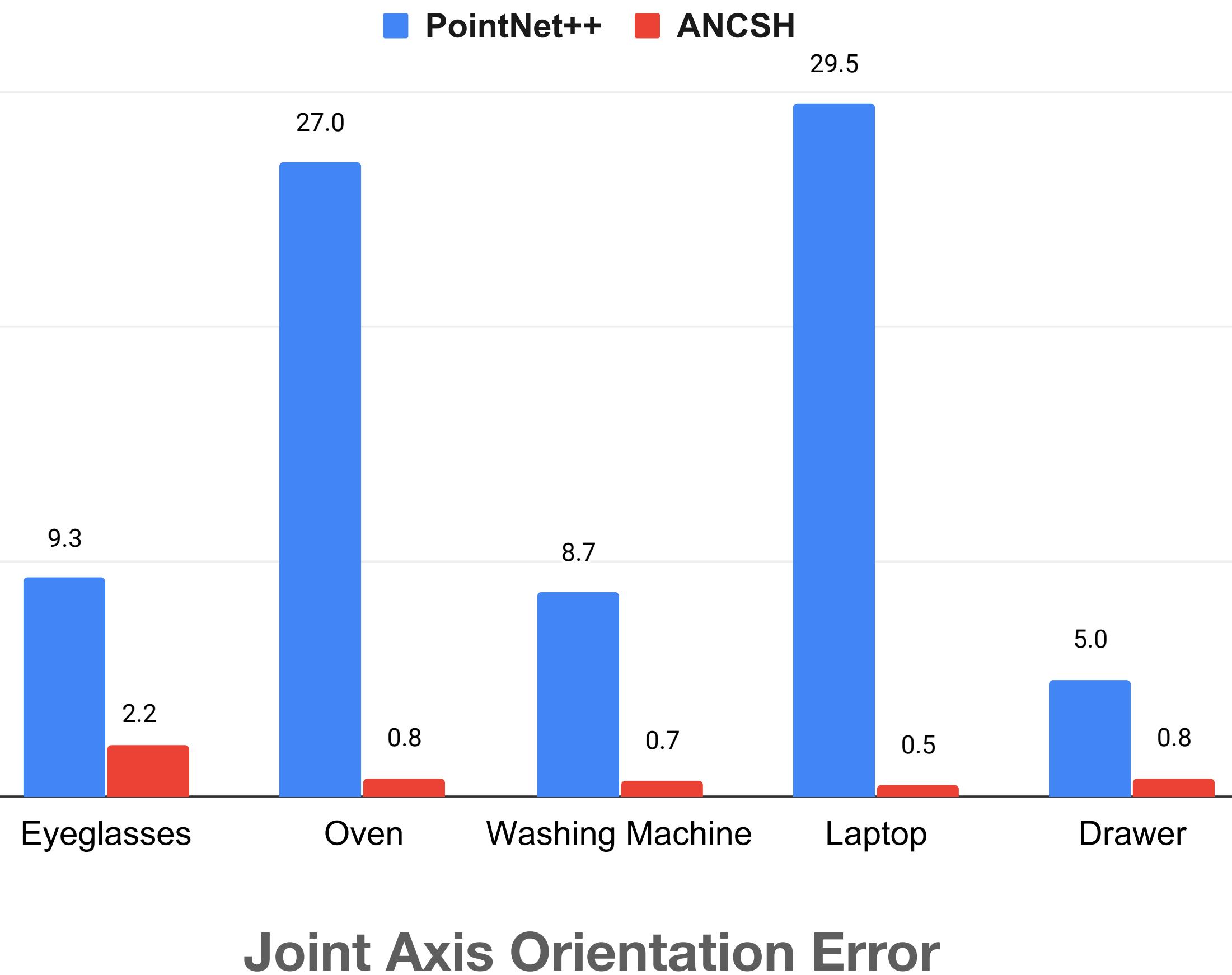
Method: Pose Fitting with Kinematic Chain Constraint



Results: Pose Estimation



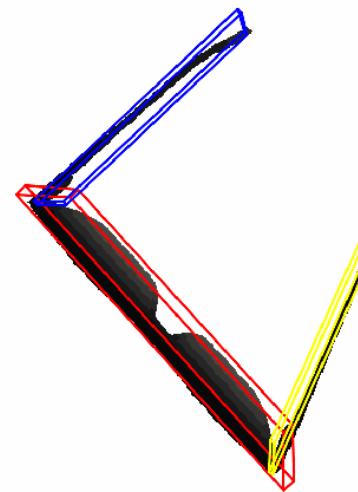
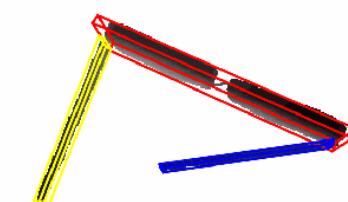
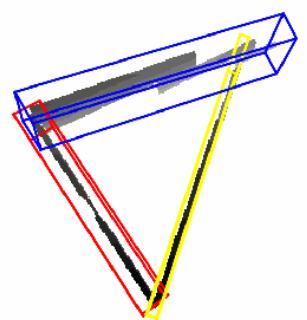
Results: Joint Parameters Estimation



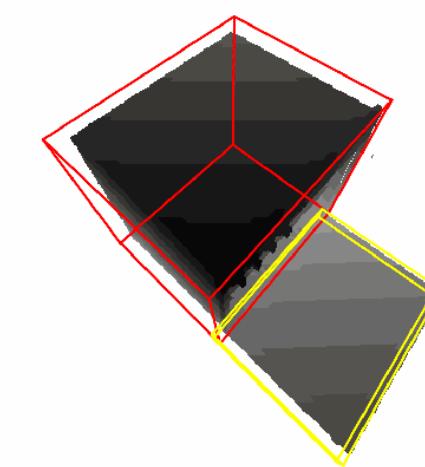
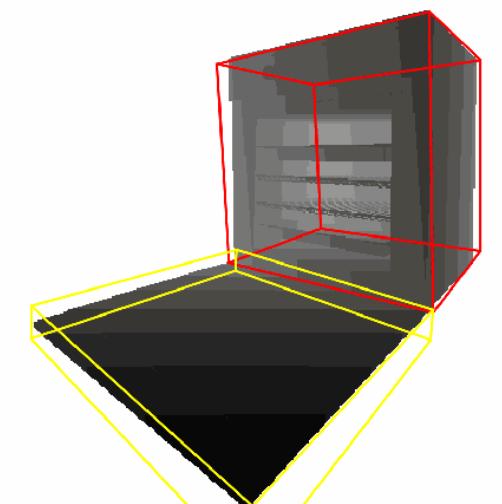
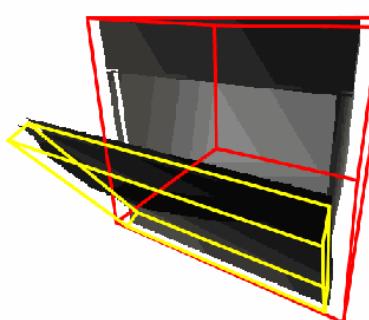
Our method achieves *high-accuracy* joint parameters estimation!

Results visualization of Hold-Out Instances

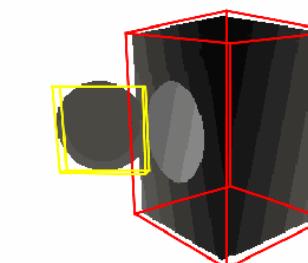
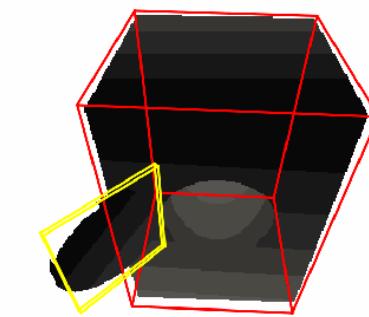
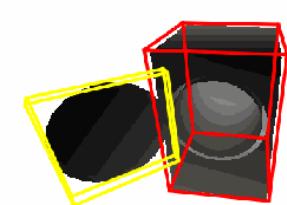
Eyeglasses



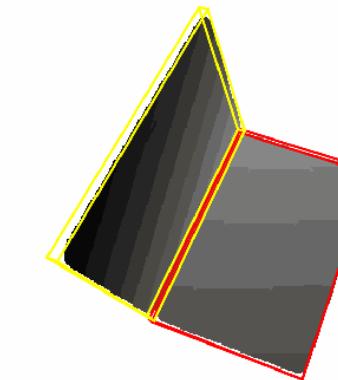
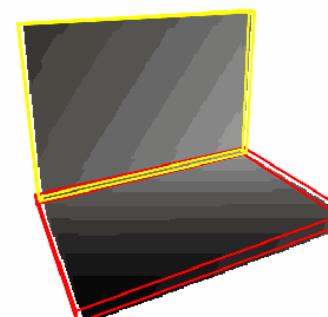
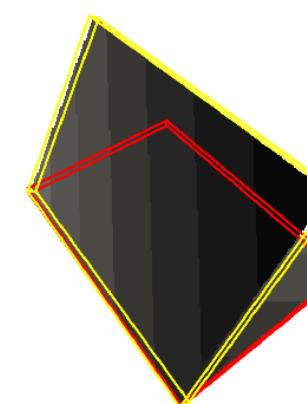
Oven



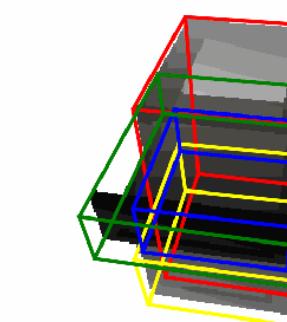
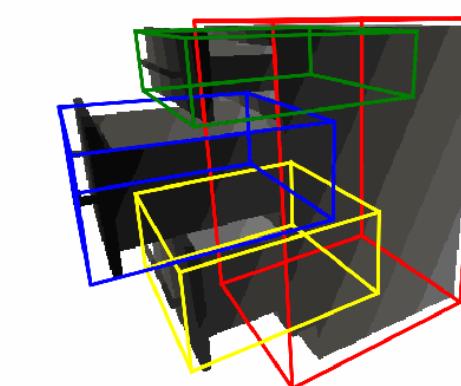
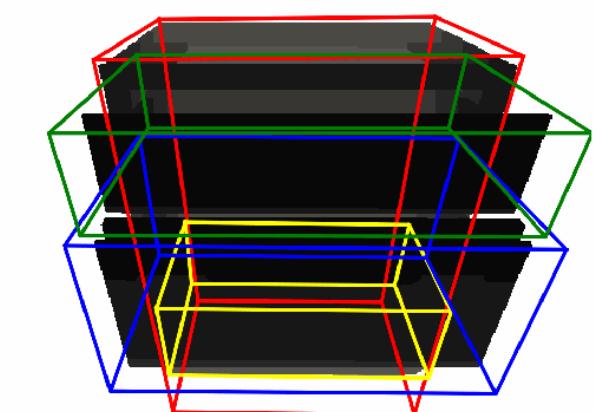
Washing Machine



Laptop



Drawer

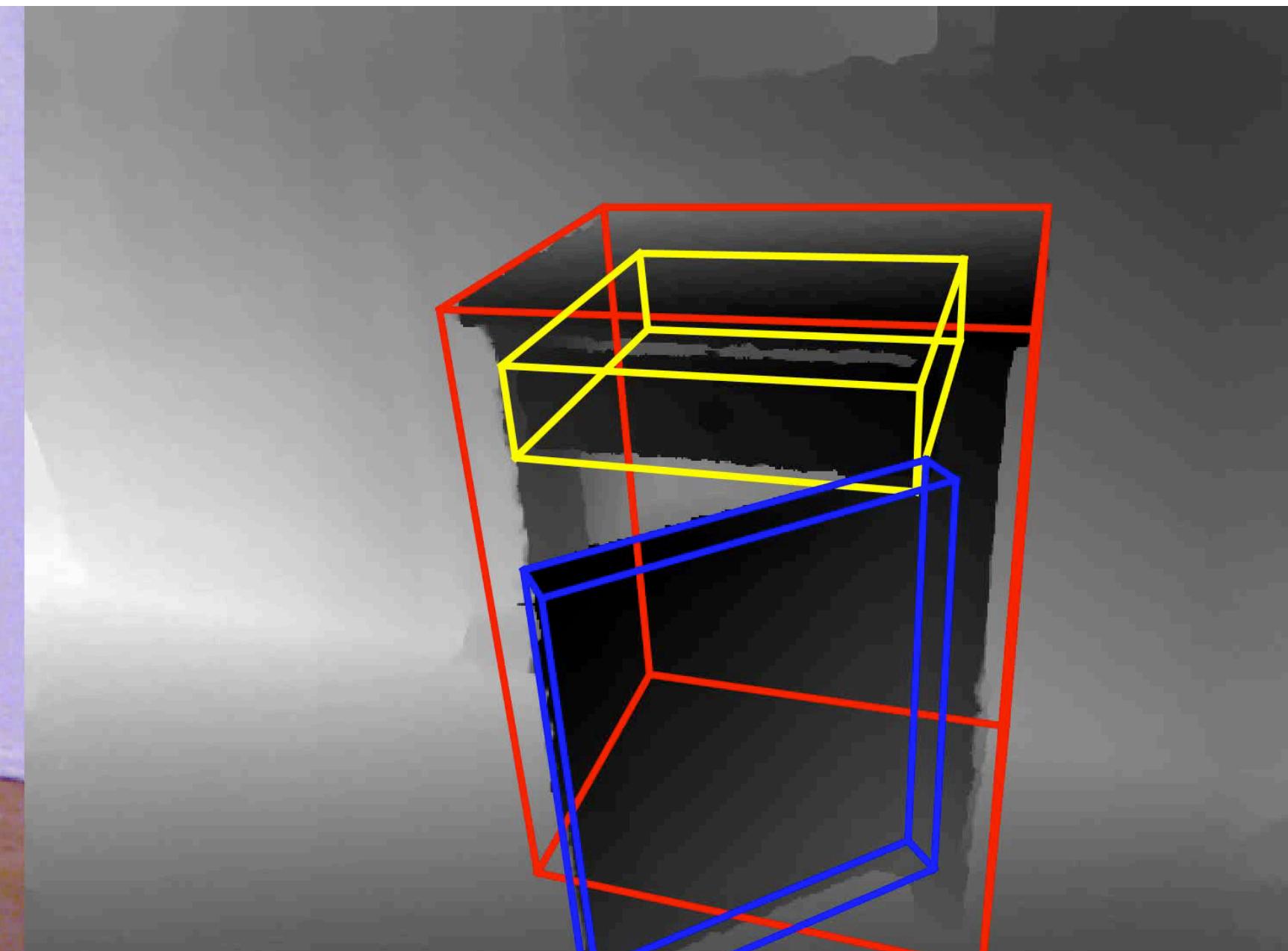


Results: ICCV 2015 Articulated Pose Estimation Dataset

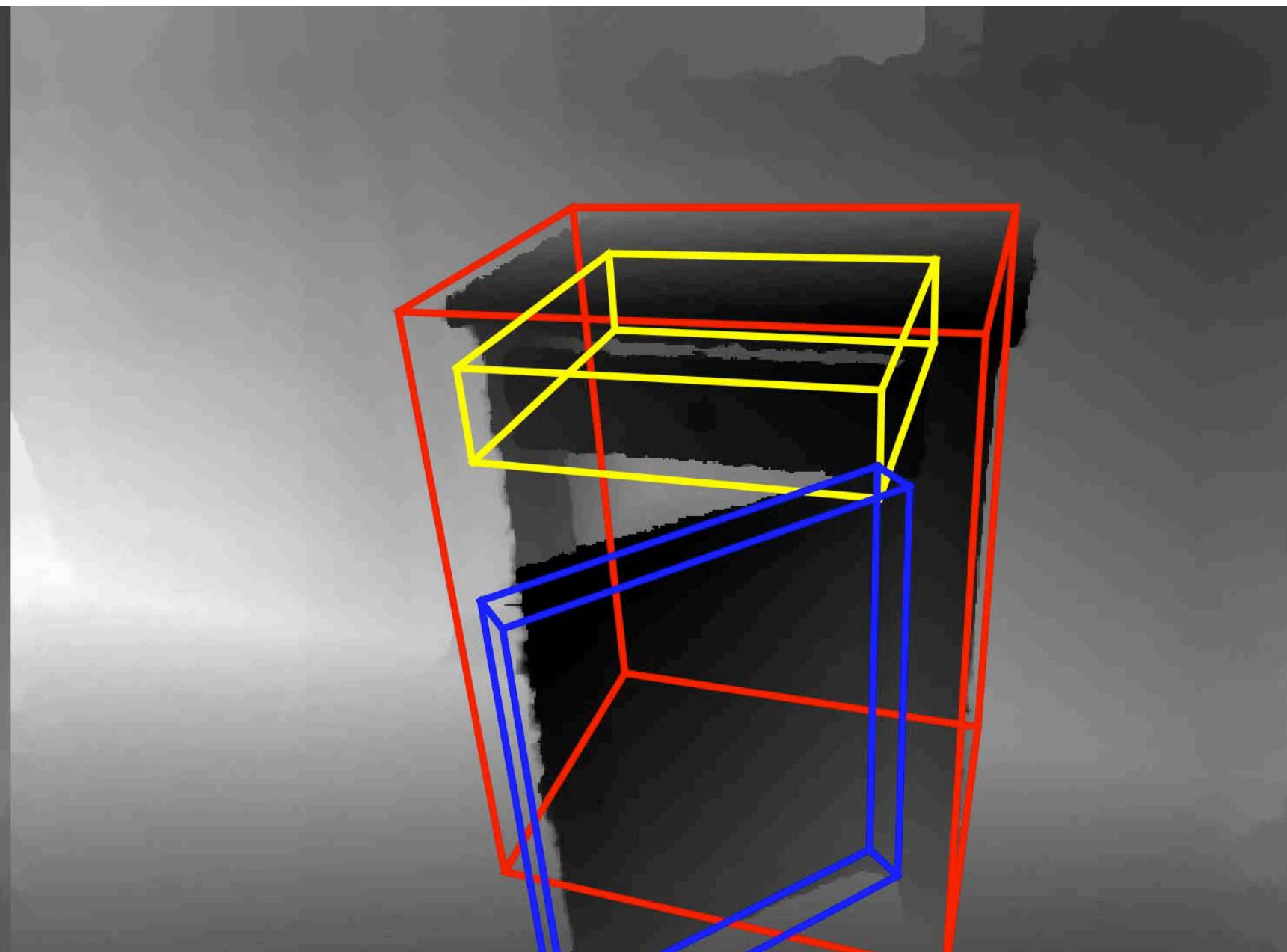
RGB reference



Predicted Pose



Labeled GT Pose

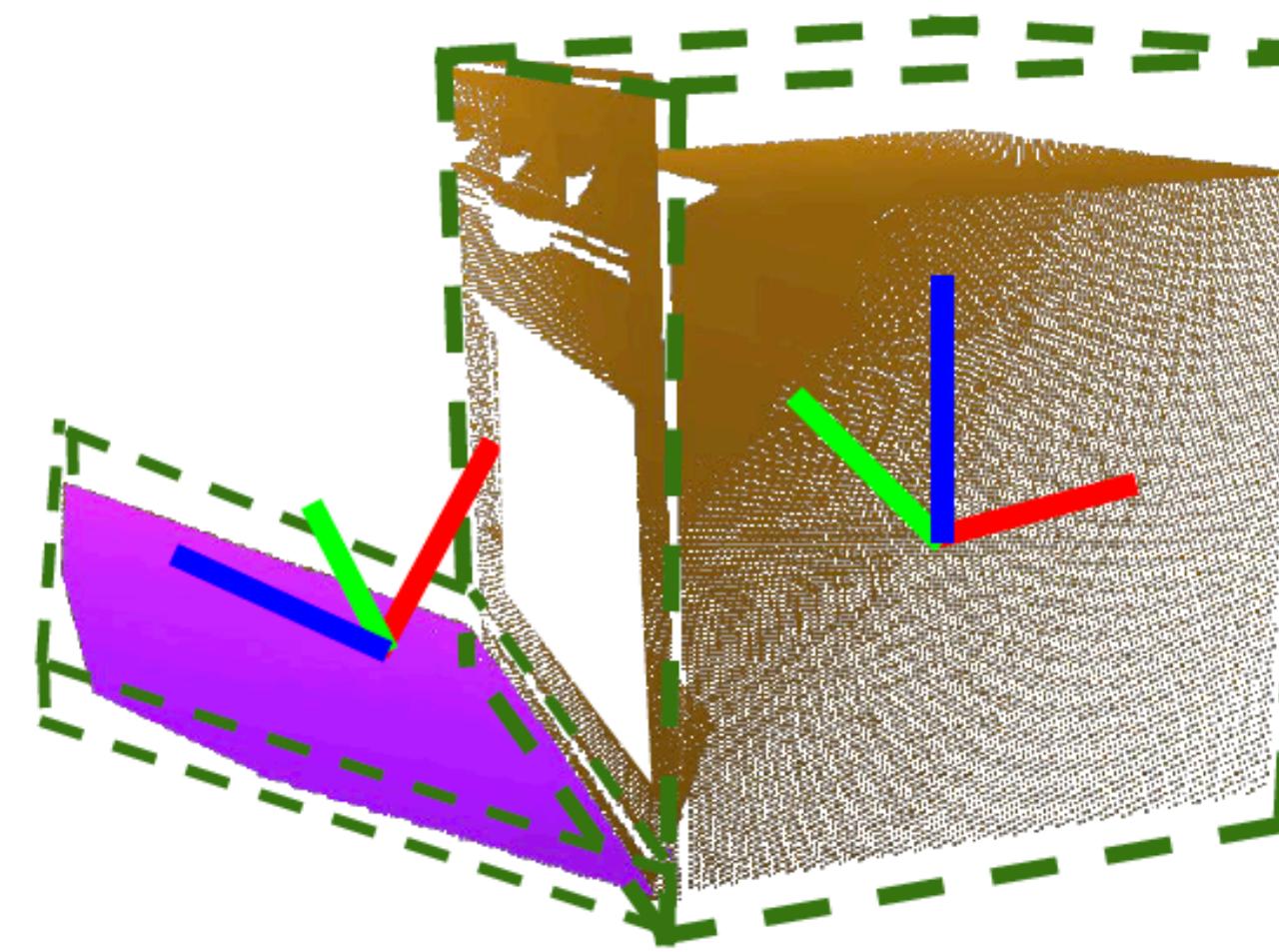


Recap

Category-level pose estimation for



Rigid Object



Articulated Object



What's next?

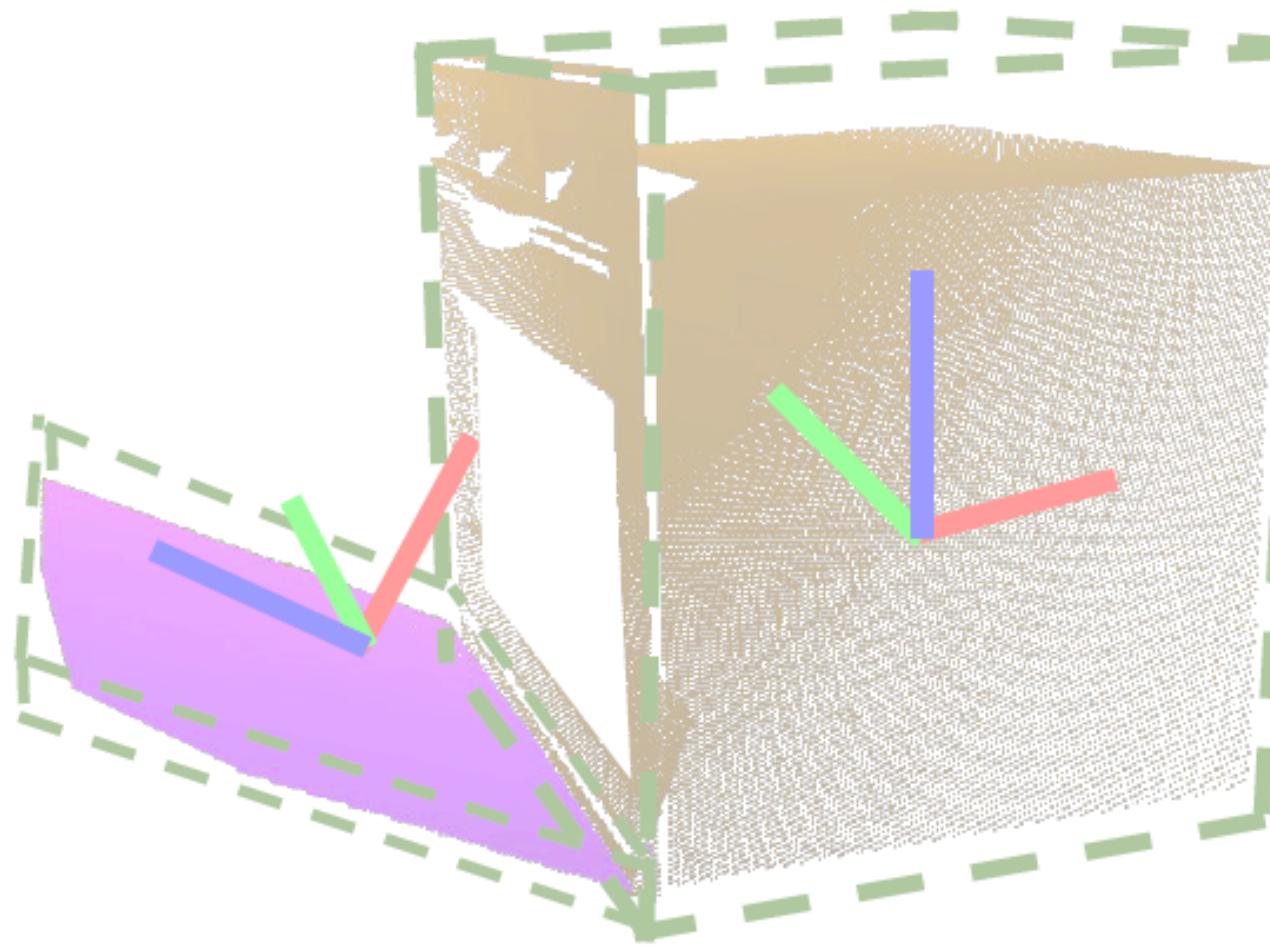
- A novel representation for category level articulated objects—**—ANCSH;**
- Joint optimization of part poses with kinematic chain constraints improves accuracy

What's next?

Category-level pose estimation for



Rigid Object



Articulated Object



What's next?

Not everything in the world is a rigid body with a canonical pose!

Deformable?



“piles” of stuff?



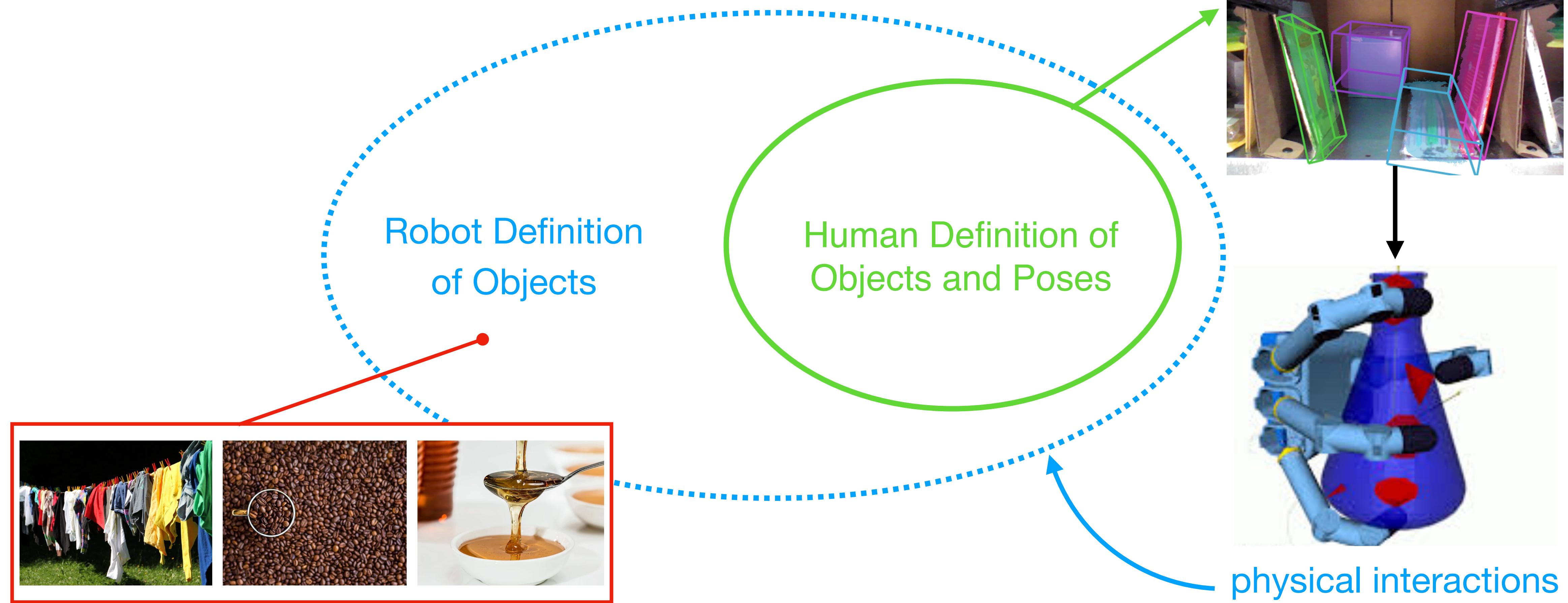
Fluid?



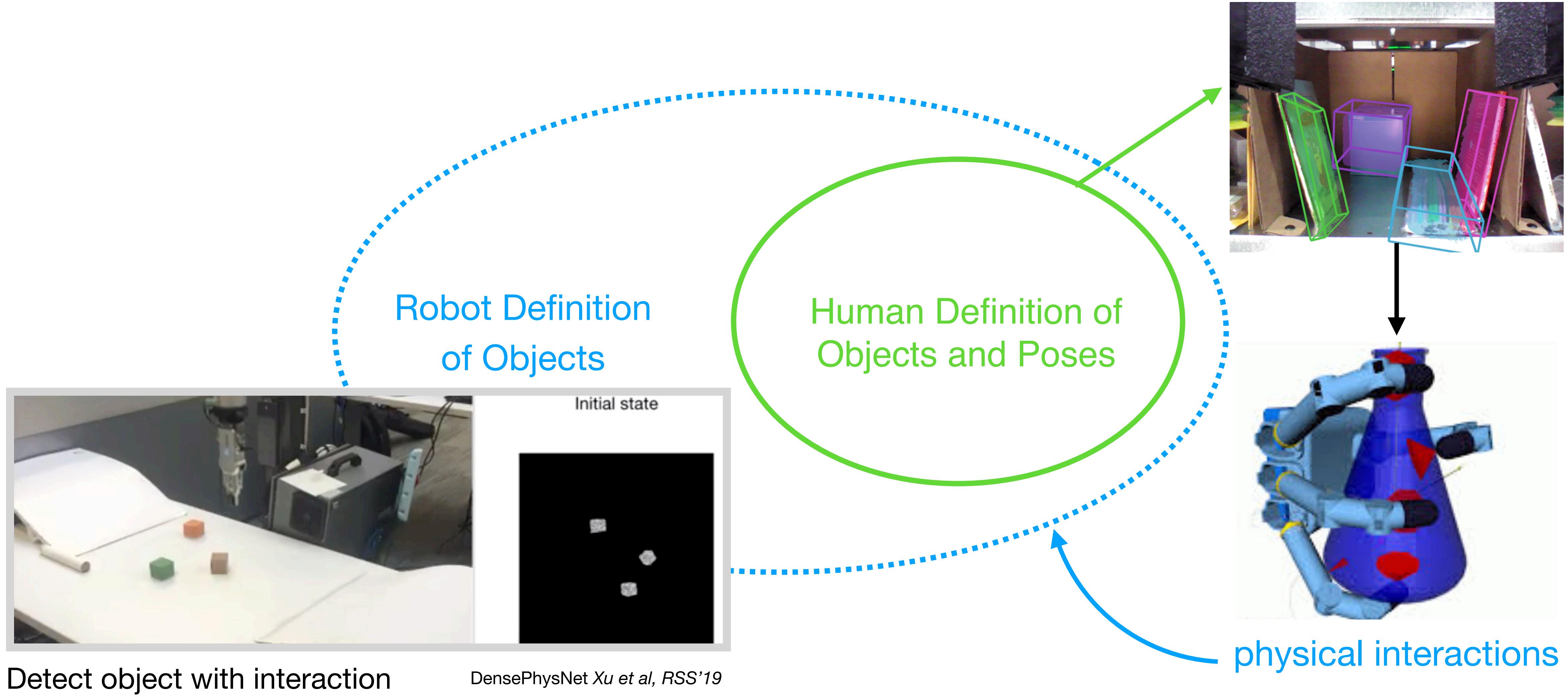
Unknown Category



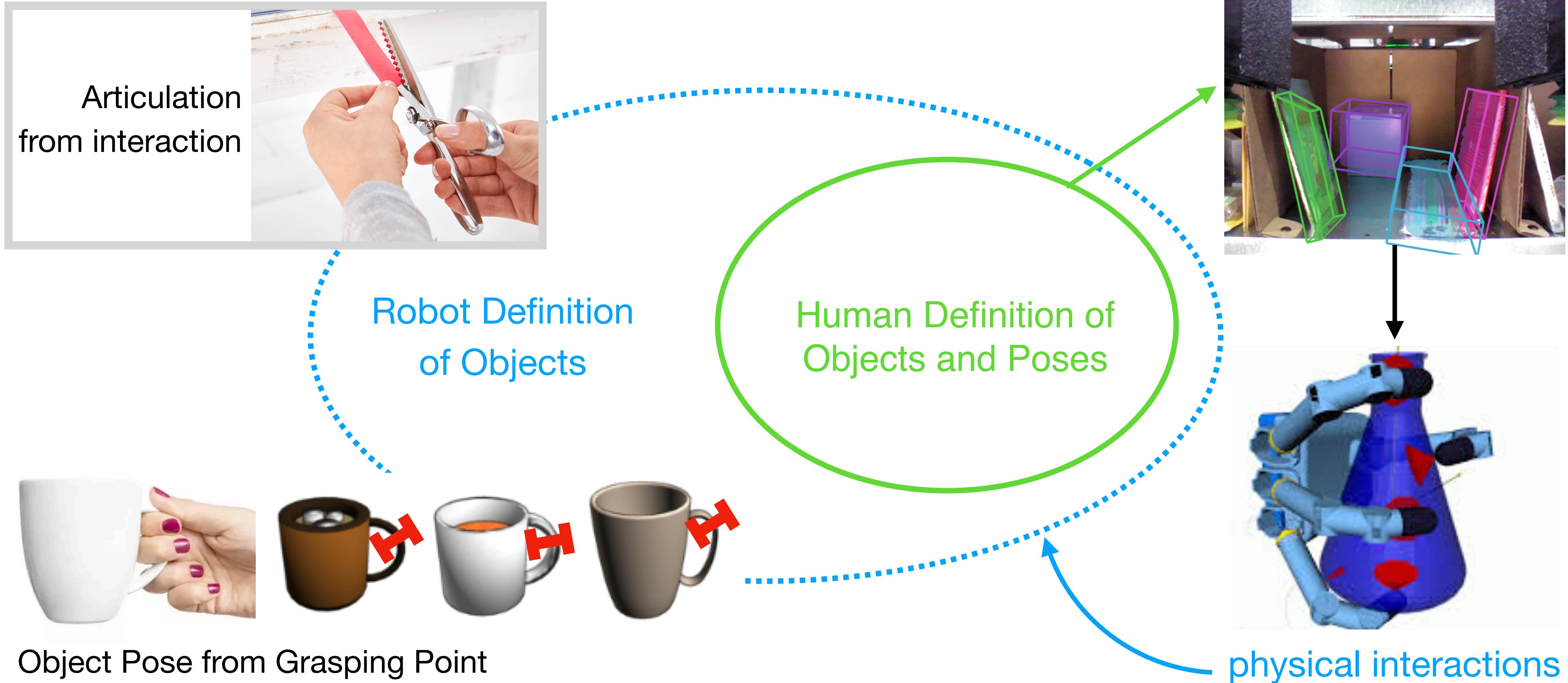
Beyond object pose estimation



Beyond object pose estimation

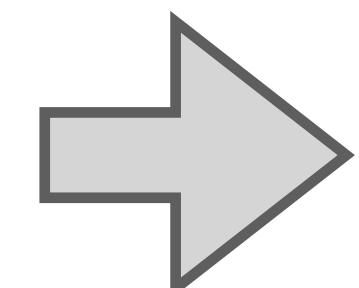


Beyond object pose estimation

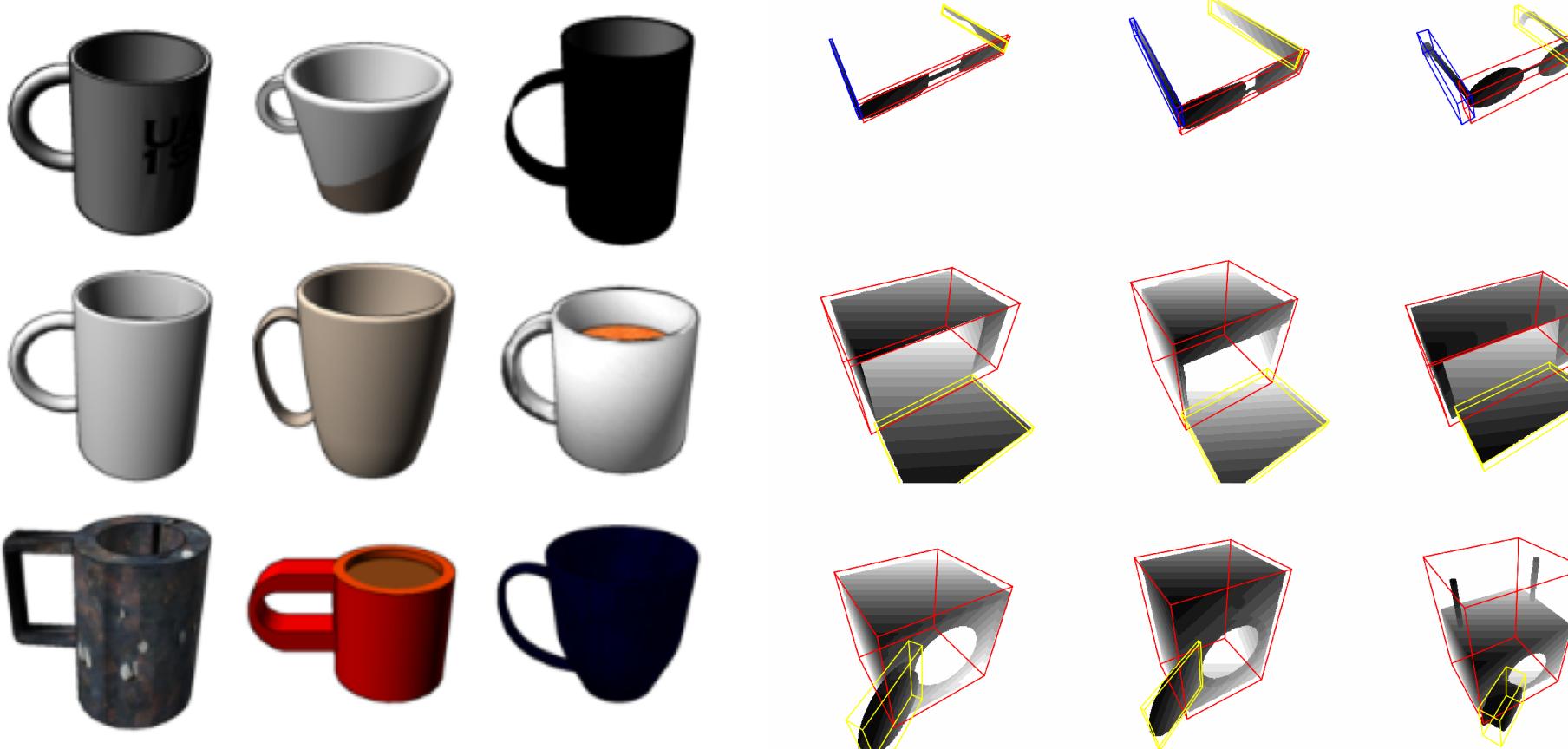


Summary

Instance-level



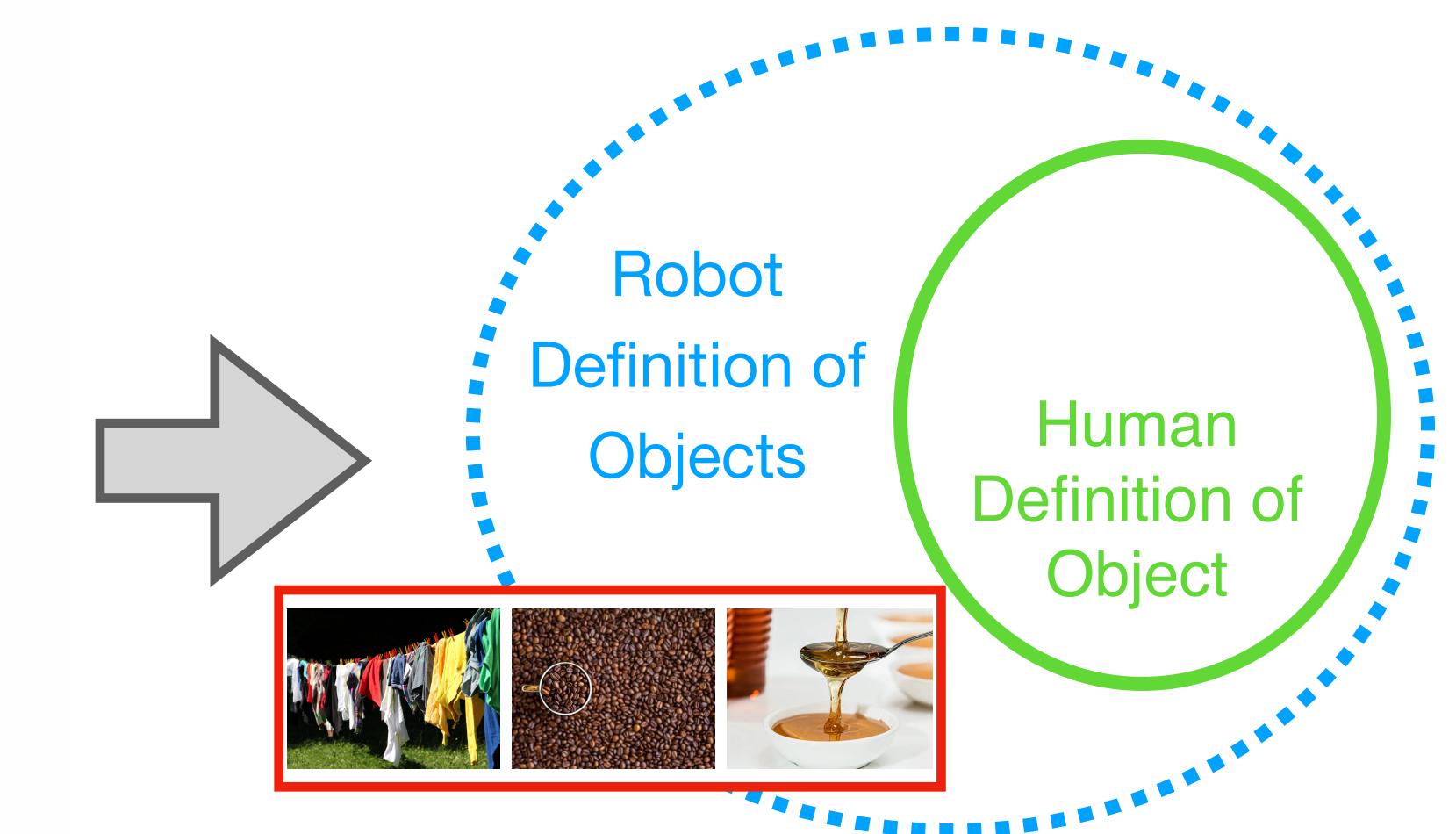
Category-level Pose Estimation



Rigid object

Articulated object

Beyond Category-level



Deformable, Granular, Fluid,
unknown category...

Acknowledgment



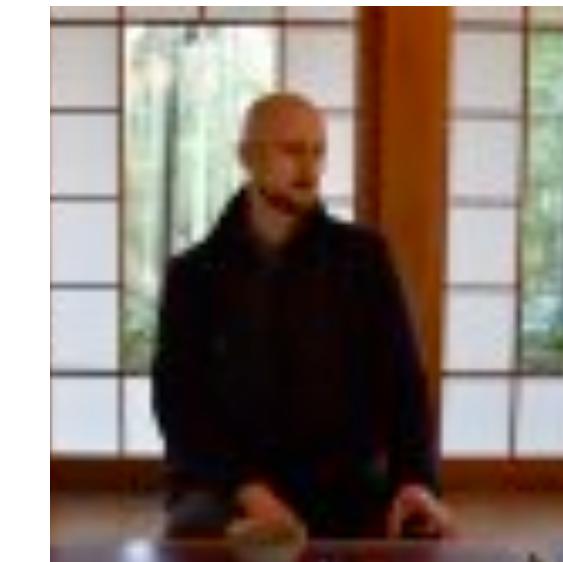
He Wang



Srinath Sridhar

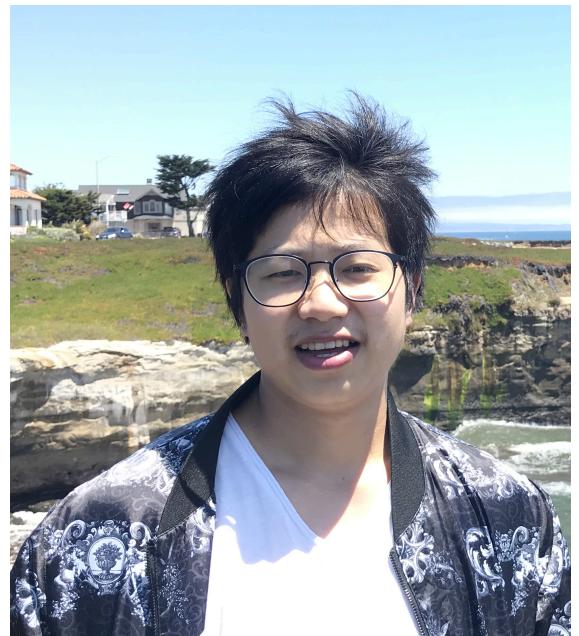


Jingwei Huang



Julien Valentin

Normalized Object Coordinate Space for Category-Level
6D Object Pose and Size Estimation
He Wang, Srinath Sridhar, Jingwei Huang, Julien Valentin, Shuran Song,
Leonidas J. Guibas
CVPR 2019



XiaoLong Wang



Yi Li



A. Lynn Abbott



Leonidas Guibas

Category-level Articulated Object Pose Estimation
He Wang*, Xiaolong Li*, Li Yi, Leonidas Guibas, A. Lynn Abbott, Shuran
Song
CVPR 2020

