Object-Centric Perception for Robot Manipulation

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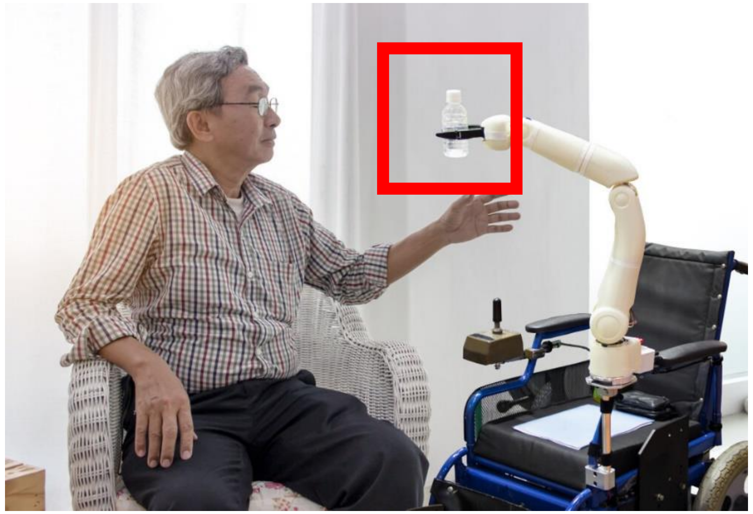
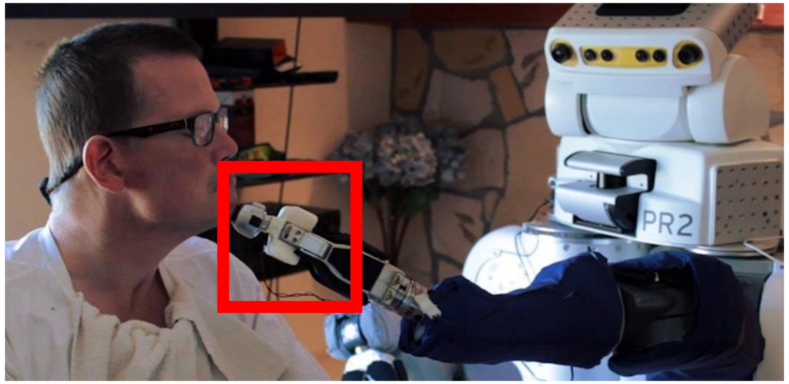
Future Intelligent Robots in Human Environments

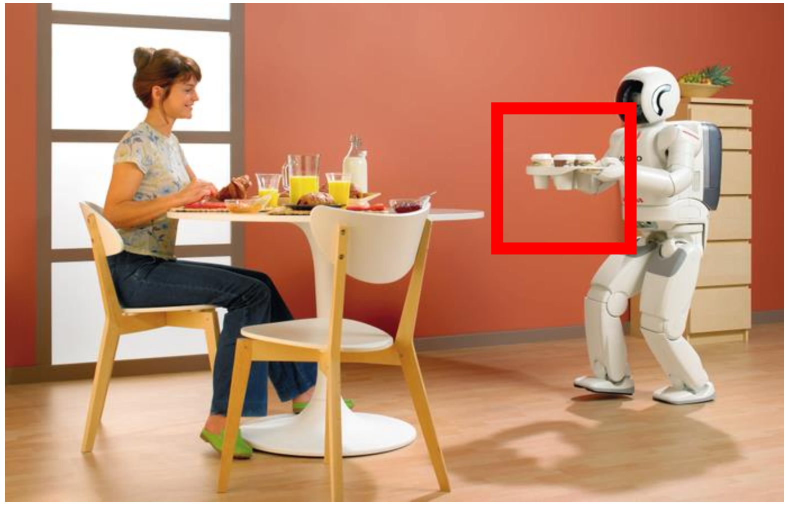
Manipulation



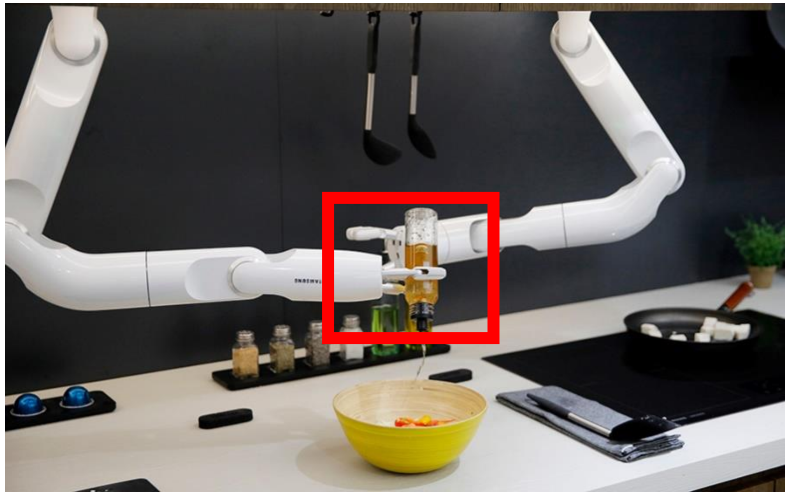
Senior Care



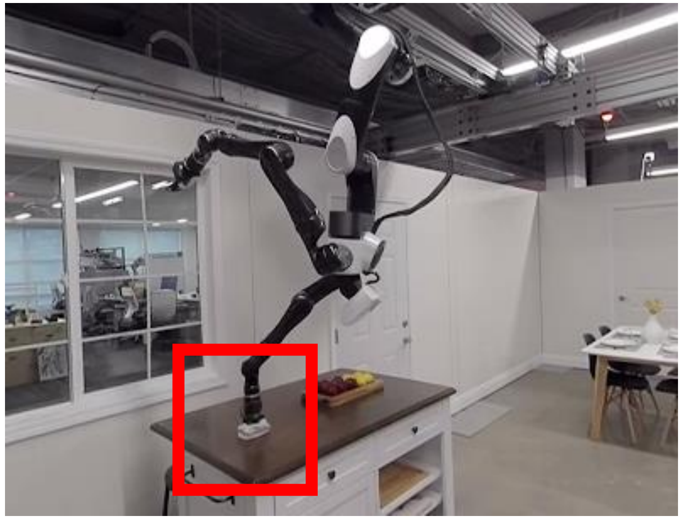
Assisting



Serving



Cooking



Cleaning

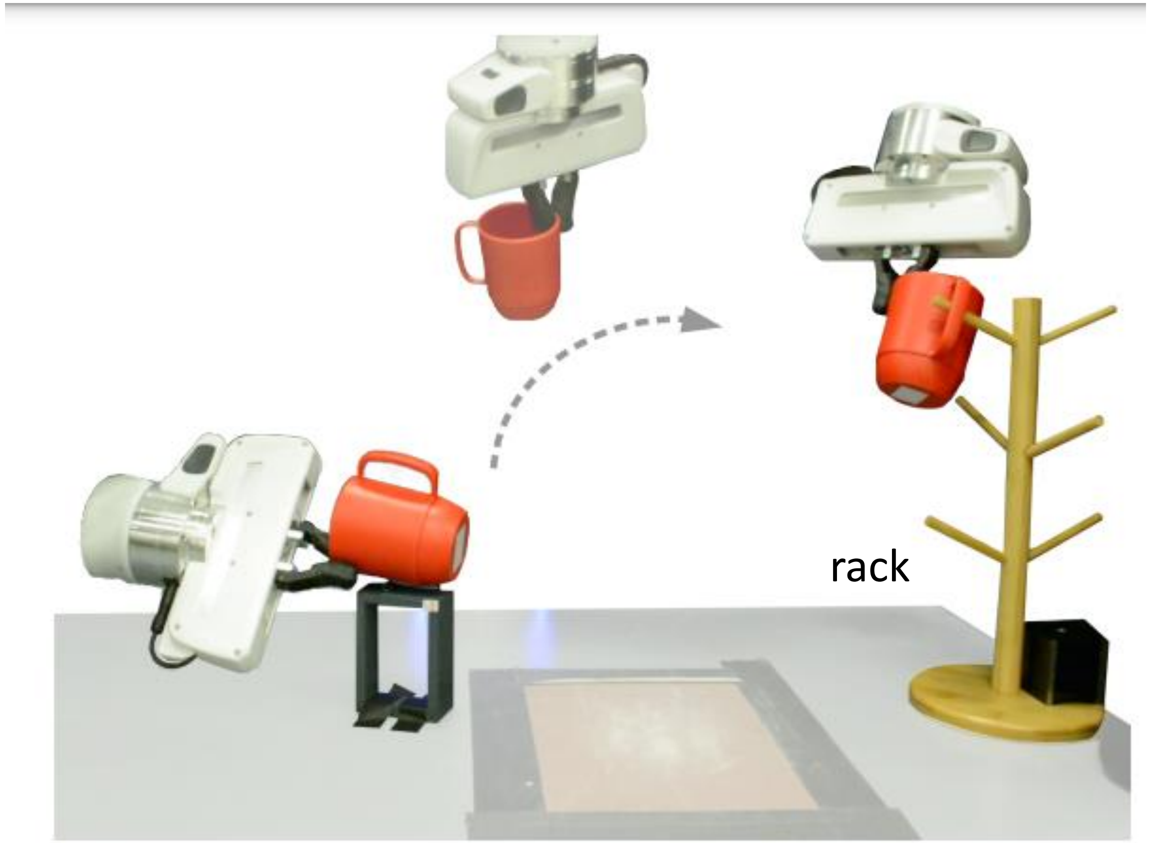
Dish washing

Object-Centric Manipulation vs. Robot-Centric Manipulation

- Object-centric
  - How the object should be controlled
  - Not specific to any robot
  - Require object perception

Generalization

- Robot-centric
  - How the robot should be controlled
  - Difficult to generalize to different robot
  - Can be end-to-end (RL)

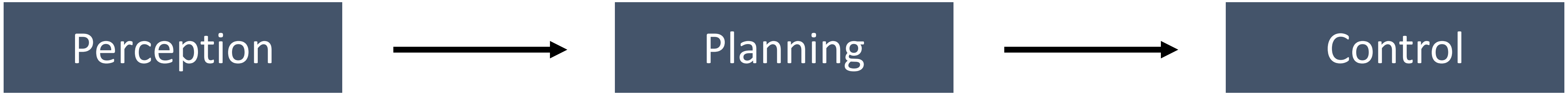


Neural Descriptor Fields. Simeonov, et al. ICRA, 2022.

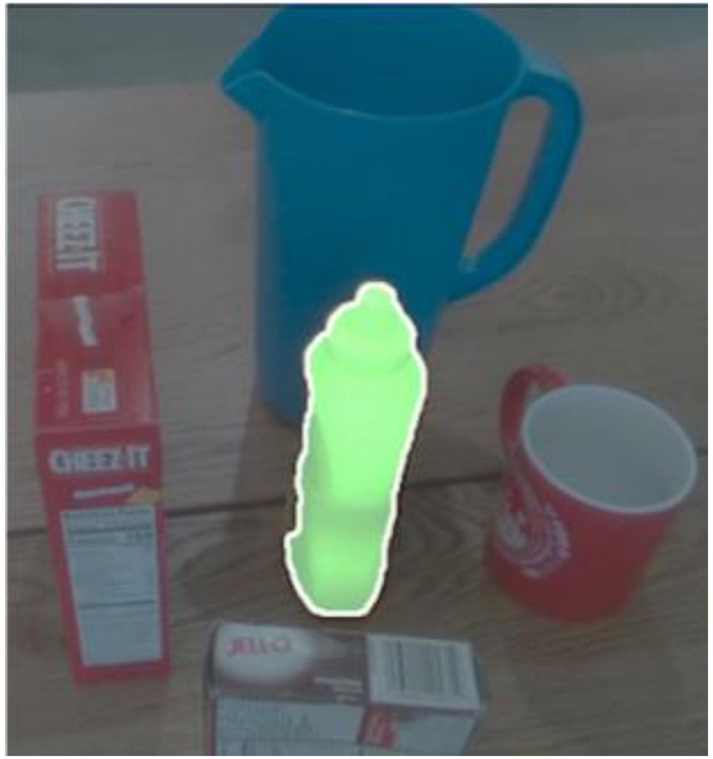
Robots in Unstructured Environments

How can a robot manipulate objects in this cluttered kitchen?

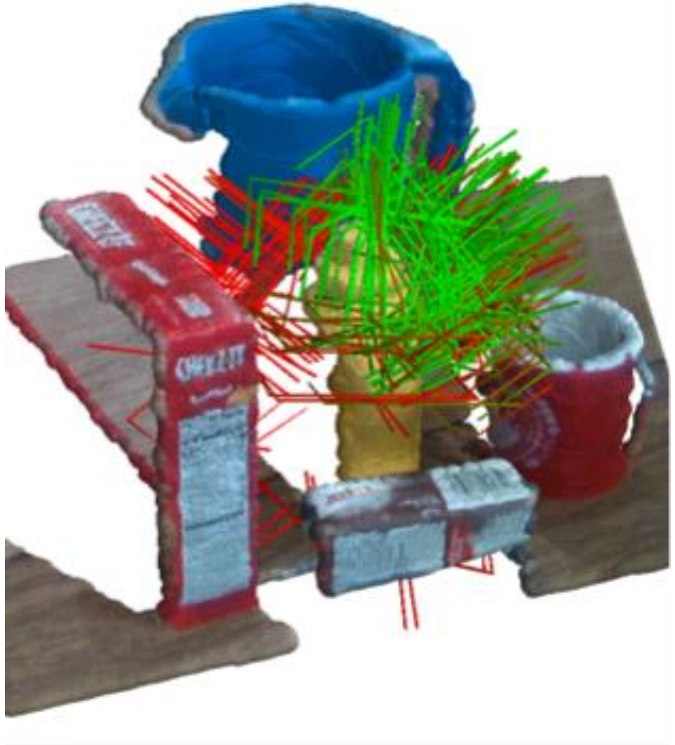
Object Model-free Robotic Grasping



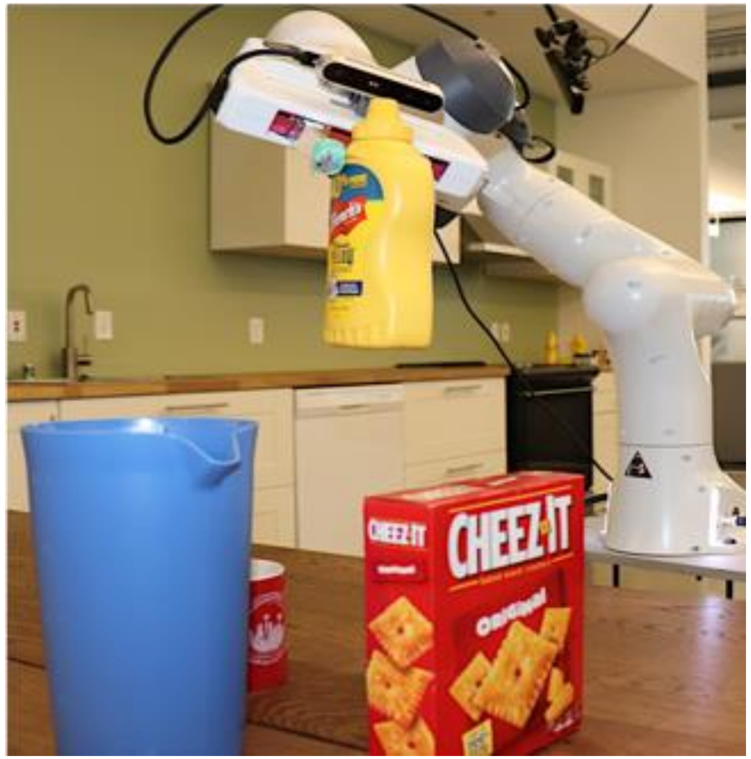
Perception → Planning → Control



Unseen object instance segmentation



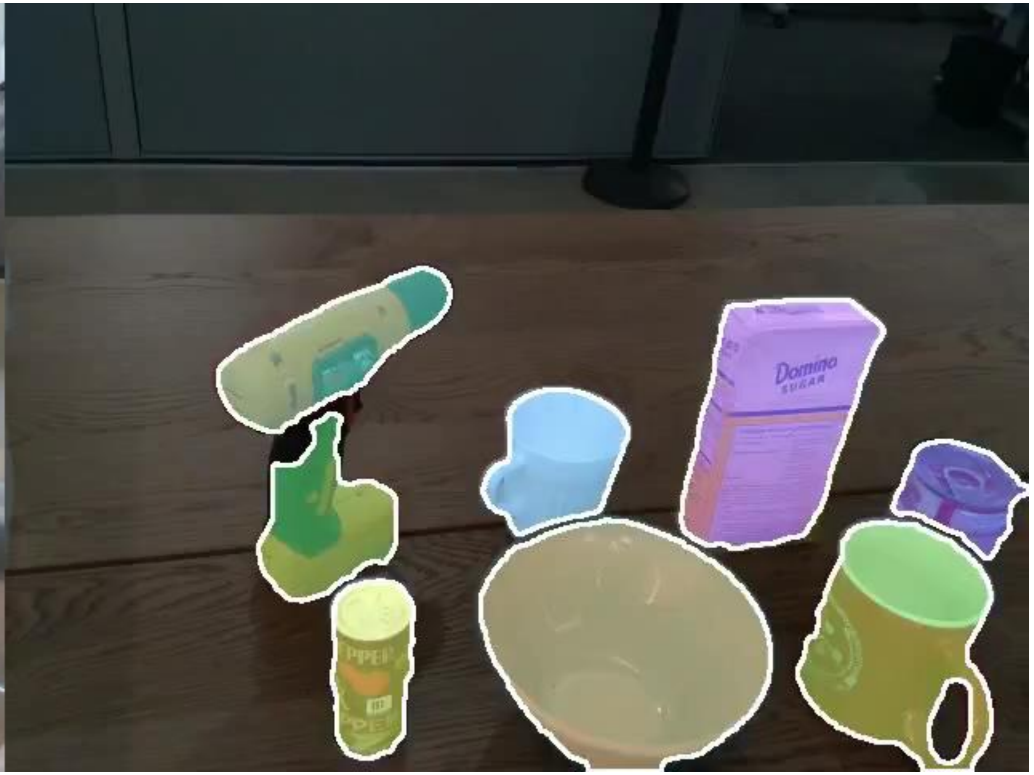
Grasp planning from point clouds



Position control to reach grasp

Figure Credit: Murali-Mousavian-Eppner-Paxton-Fox, ICRA'20

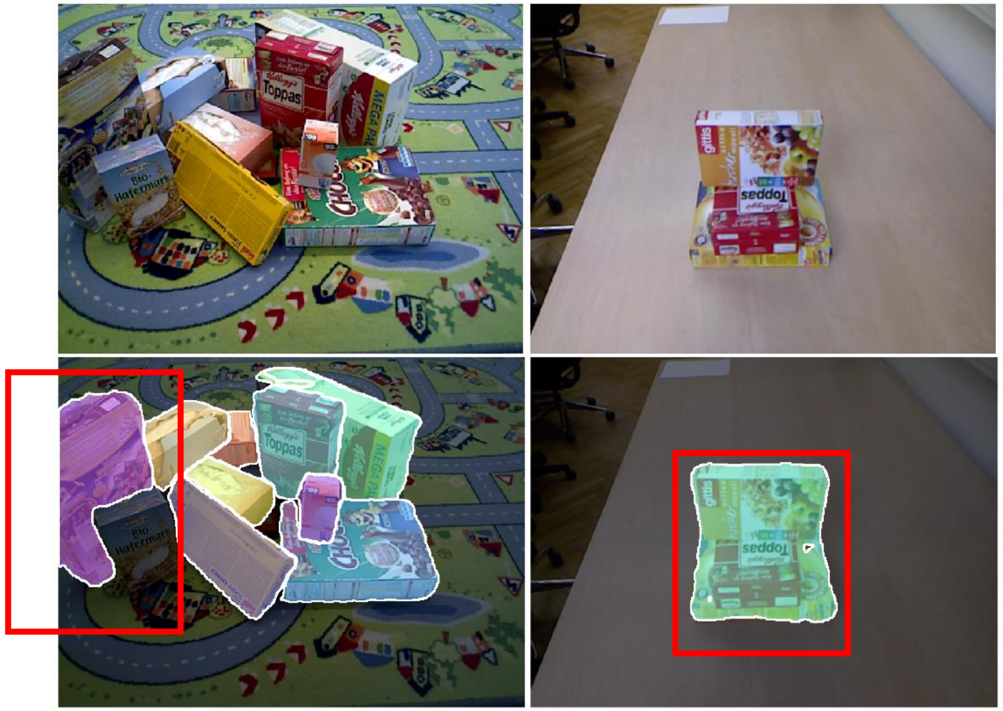
Object Model-free Robotic Grasping



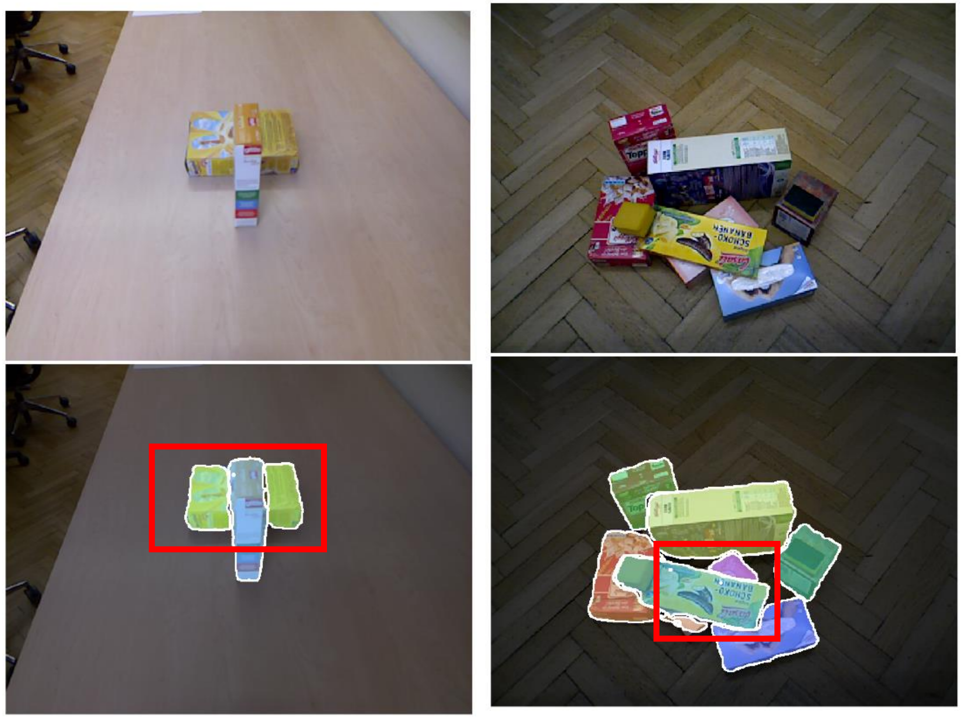
Unseen Object Instance Segmentation:
Xie-Xiang-Mousavian-Fox, CoRL’19, T-RO’21
Xiang-Xie-Mousavian-Fox, CoRL’20

6-DOF GraspNet:
Mousavian-Eppner-Fox, ICCV’19

Segmentation Failure Cases



Under-segmentation



Over-segmentation

How Can We Fix These Failures?

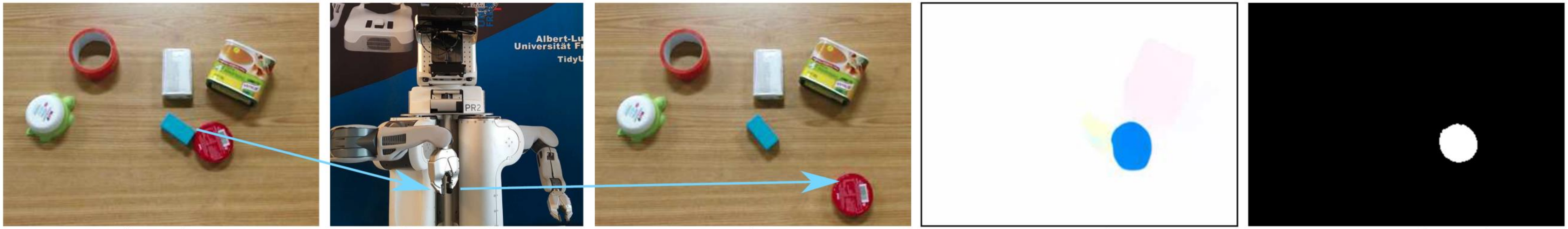
- Better models
  - Swin Transformers
  - OpenAI CLIP
  - ?

- Better training data
  - Photo-realistic synthetic data

UOAIS-Net (Back et al. ICRA’22)

  - Real-world data
    (How can we obtain real-world data for training?)

Self-supervised Segmentation

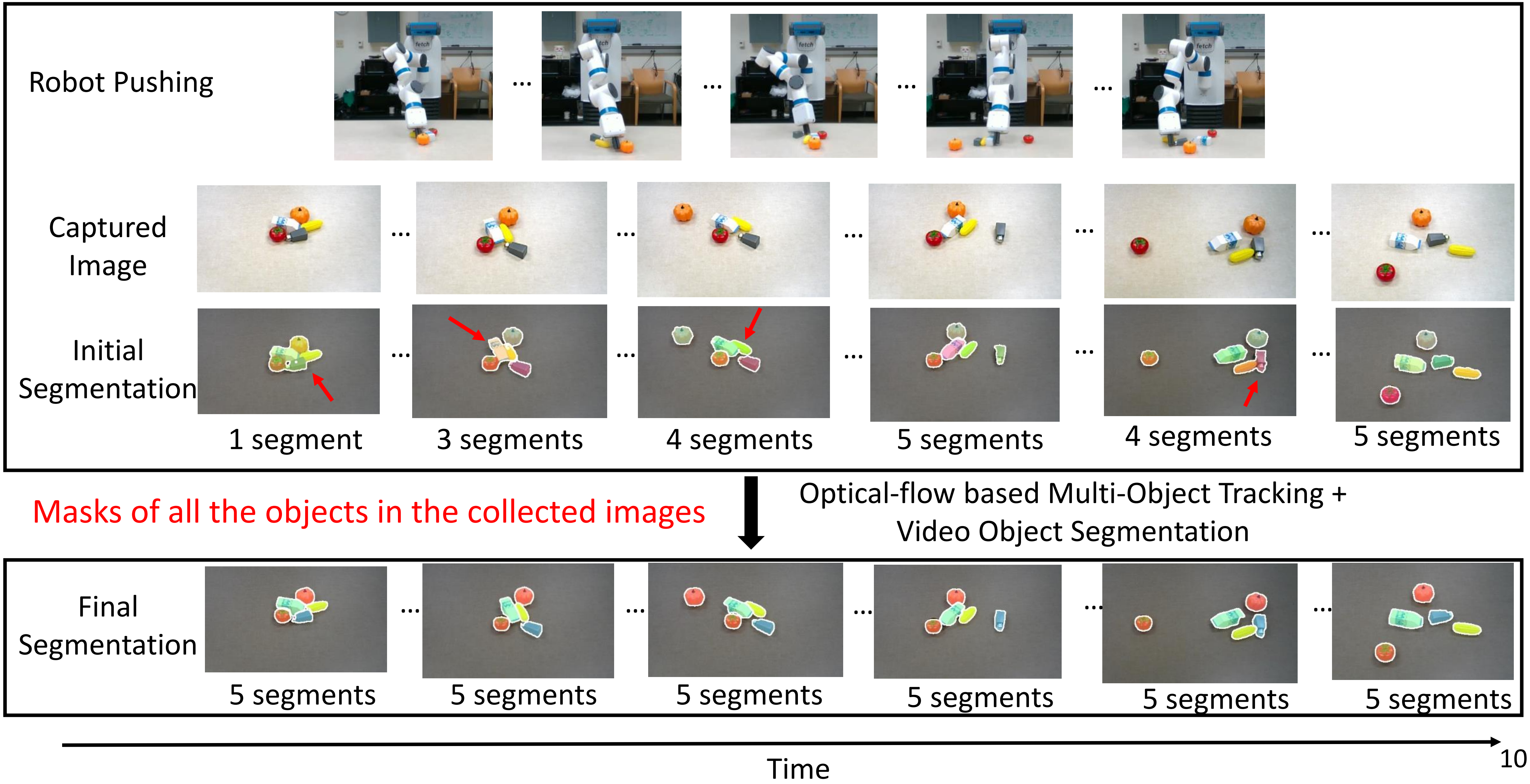


previous image robot pushing next image optical flow generated mask

- One push cannot separate objects sometimes
- These approaches can only obtain one mask in an image

[1] Andreas Eitel, Nico Hauff, and Wolfram Burgard. Self-supervised transfer learning for instance segmentation through physical interaction. IROS, 2019.
[2] Houjian Yu and Changhyun Choi. Self-supervised interactive object segmentation through a singulation-and grasping approach. ECCV, 2022.

Leveraging Long-term Robot Interaction



Robot Pushing ... ...

Captured Image ... ...

Initial Segmentation ... ...

1 segment | 3 segments | 4 segments | 5 segments | 4 segments | 5 segments

Masks of all the objects in the collected images

Optical-flow based Multi-Object Tracking + Video Object Segmentation

Final Segmentation ... ...

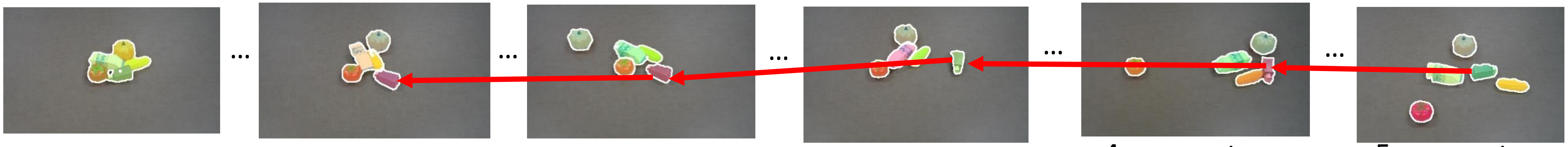
5 segments | 5 segments | 5 segments | 5 segments | 5 segments | 5 segments

Time

Leveraging Long-term Robot Interaction

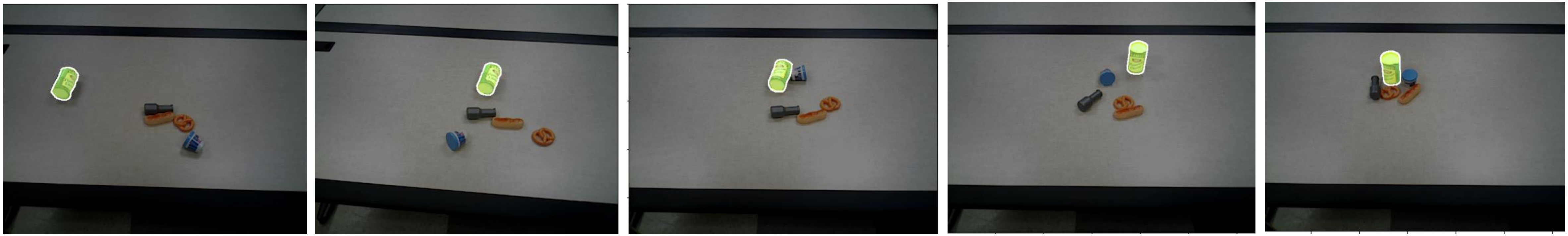
Tracking by Segmentation and Video Object Segmentation

Initial Segmentation



1 segment | 3 segments | 4 segments | 5 segments | 4 segments | 5 segments

Tracklet



Initial mask: frame 20 → frame 10 → frame 7 → frame 4 → frame 0

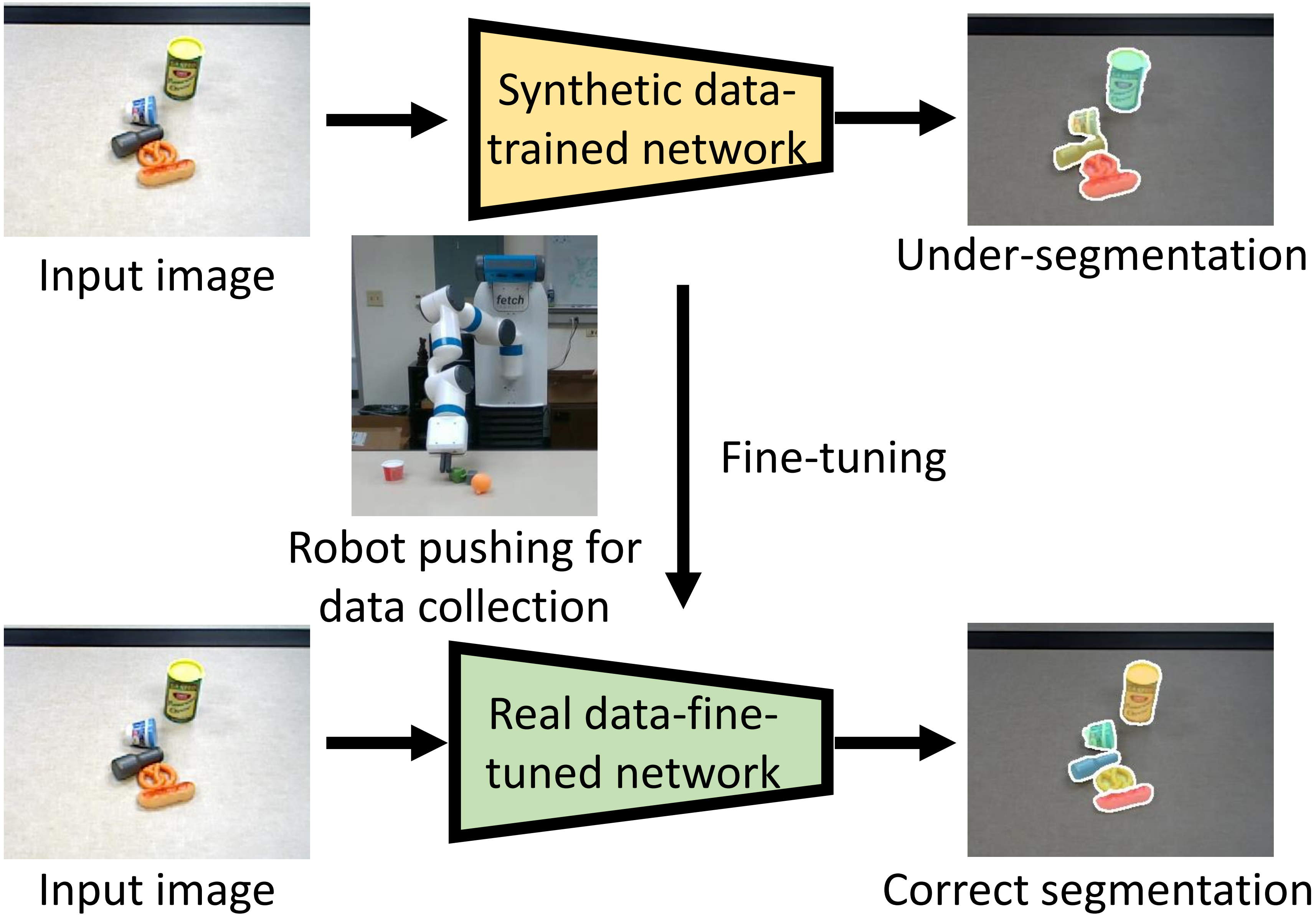
Select the highest score mask in a tracklet

Propagation to other frames

Long-Term Video Object Segmentation with an Atkinson-Shiffrin Memory Model.
Ho Kei Cheng, Alexander Schwing, ECCV, 2022. https://github.com/hkchengrex/XMem

Data Collected by the Robot

Self-supervised Segmentation with Robot Interaction



Synthetic data-trained network

Input image

Under-segmentation

Robot pushing for data collection

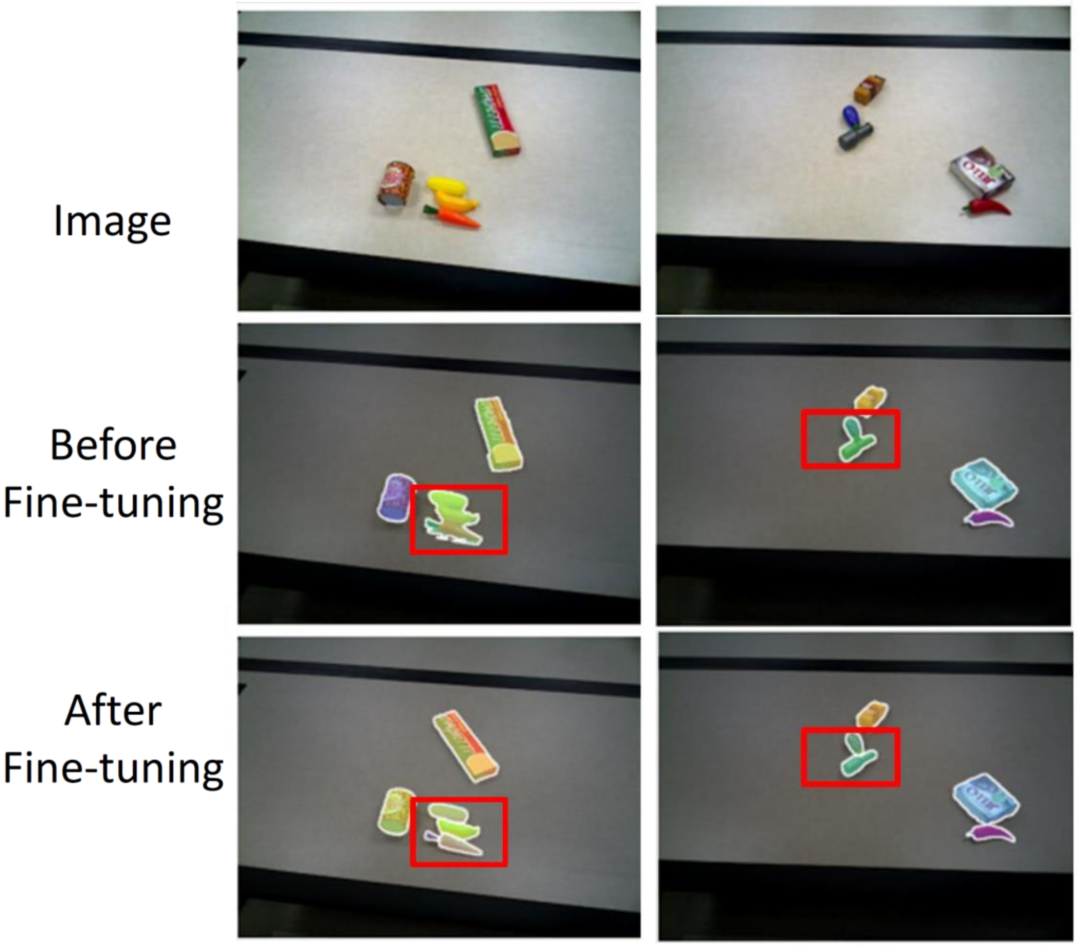
Fine-tuning

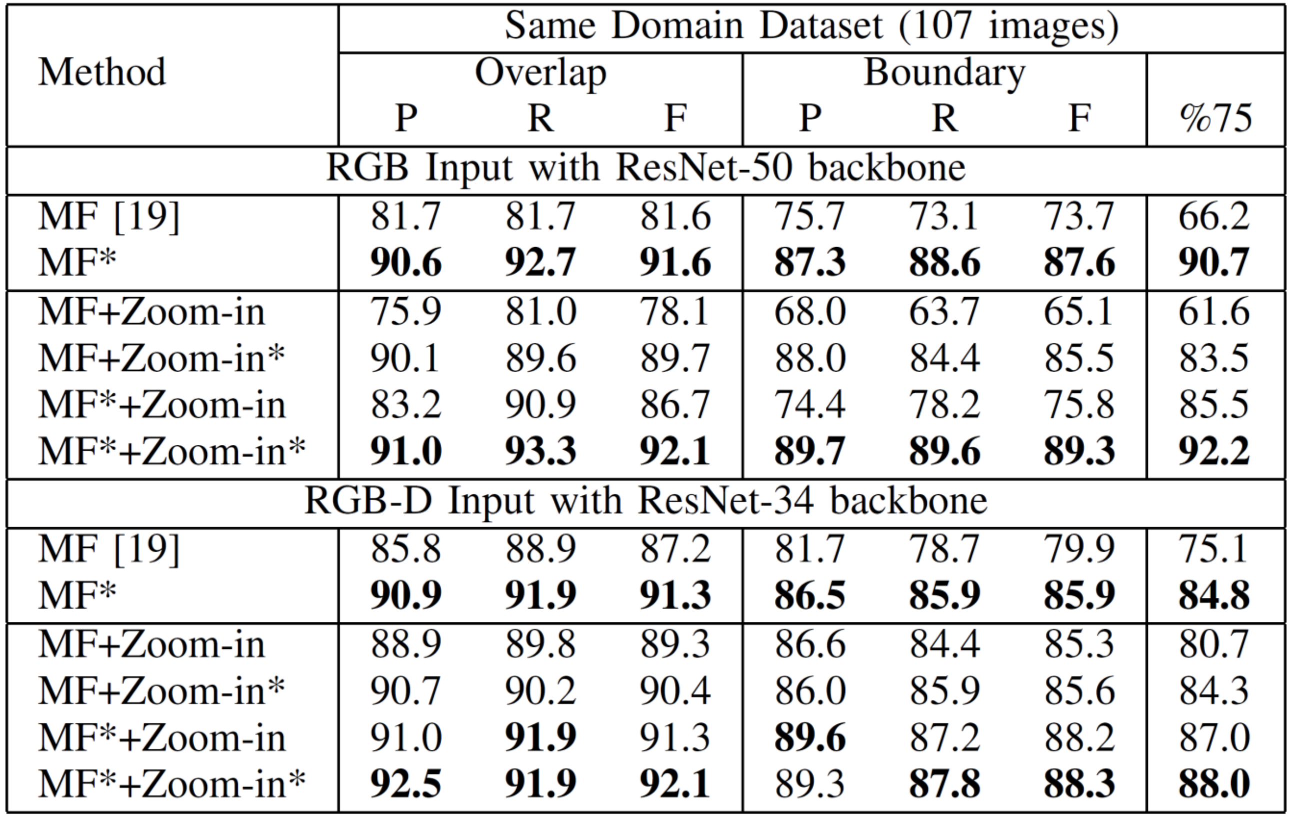
Real data-fine-tuned network

Input image

Correct segmentation

Fine-tuning MSMFormer for Unseen Object Segmentation



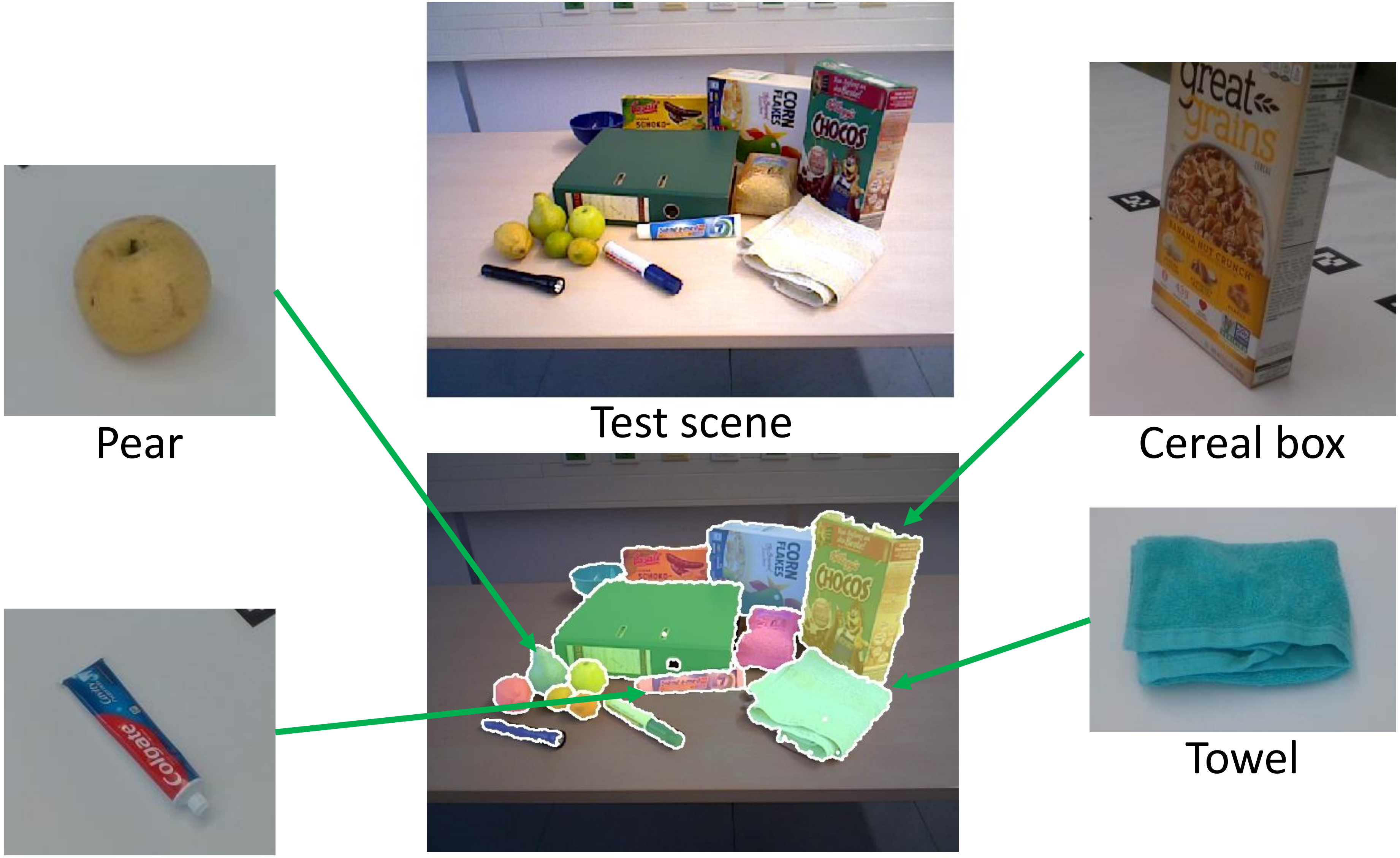


Method	Same Domain Dataset (107 images)						
	Overlap			Boundary			
	P	R	F	P	R	F	%75
RGB Input with ResNet-50 backbone							
MF [19]	81.7	81.7	81.6	75.7	73.1	73.7	66.2
MF*	**90.6**	**92.7**	**91.6**	**87.3**	**88.6**	**87.6**	**90.7**
MF+Zoom-in	75.9	81.0	78.1	68.0	63.7	65.1	61.6
MF+Zoom-in*	90.1	89.6	89.7	88.0	84.4	85.5	83.5
MF*+Zoom-in	83.2	90.9	86.7	74.4	78.2	75.8	85.5
MF*+Zoom-in*	**91.0**	**93.3**	**92.1**	**89.7**	**89.6**	**89.3**	**92.2**
RGB-D Input with ResNet-34 backbone							
MF [19]	85.8	88.9	87.2	81.7	78.7	79.9	75.1
MF*	**90.9**	**91.9**	**91.3**	**86.5**	**85.9**	**85.9**	**84.8**
MF+Zoom-in	88.9	89.8	89.3	86.6	84.4	85.3	80.7
MF+Zoom-in*	90.7	90.2	90.4	86.0	85.9	85.6	84.3
MF*+Zoom-in	91.0	**91.9**	91.3	**89.6**	87.2	88.2	87.0
MF*+Zoom-in*	**92.5**	**91.9**	**92.1**	89.3	**87.8**	**88.3**	**88.0**

*: model after fine-tuning

Top-Down Grasping

Few-Shot Object Recognition



Pear

Test scene

Cereal box

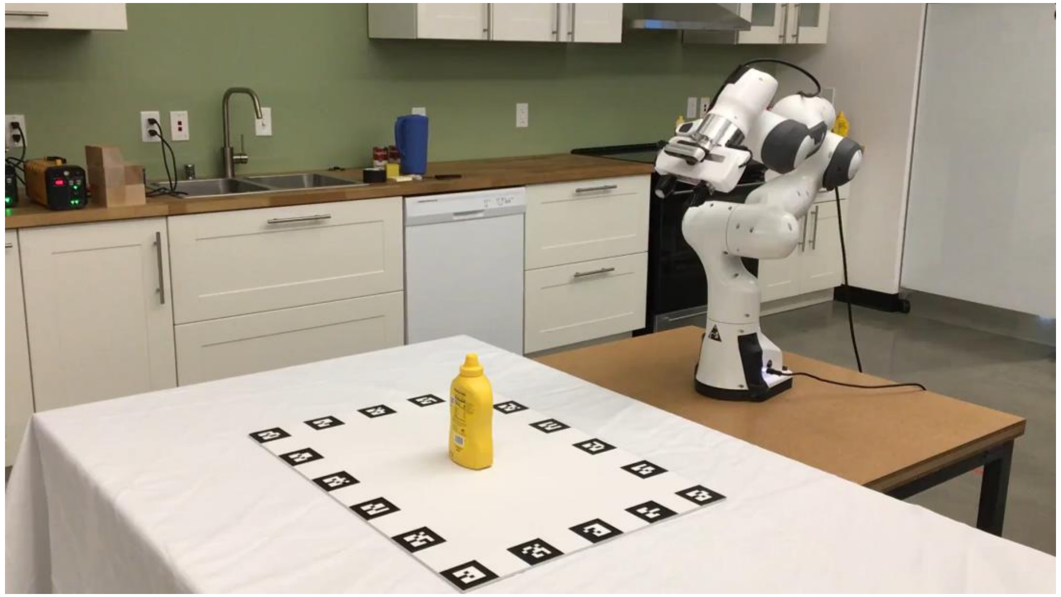
Towel

Toothpaste

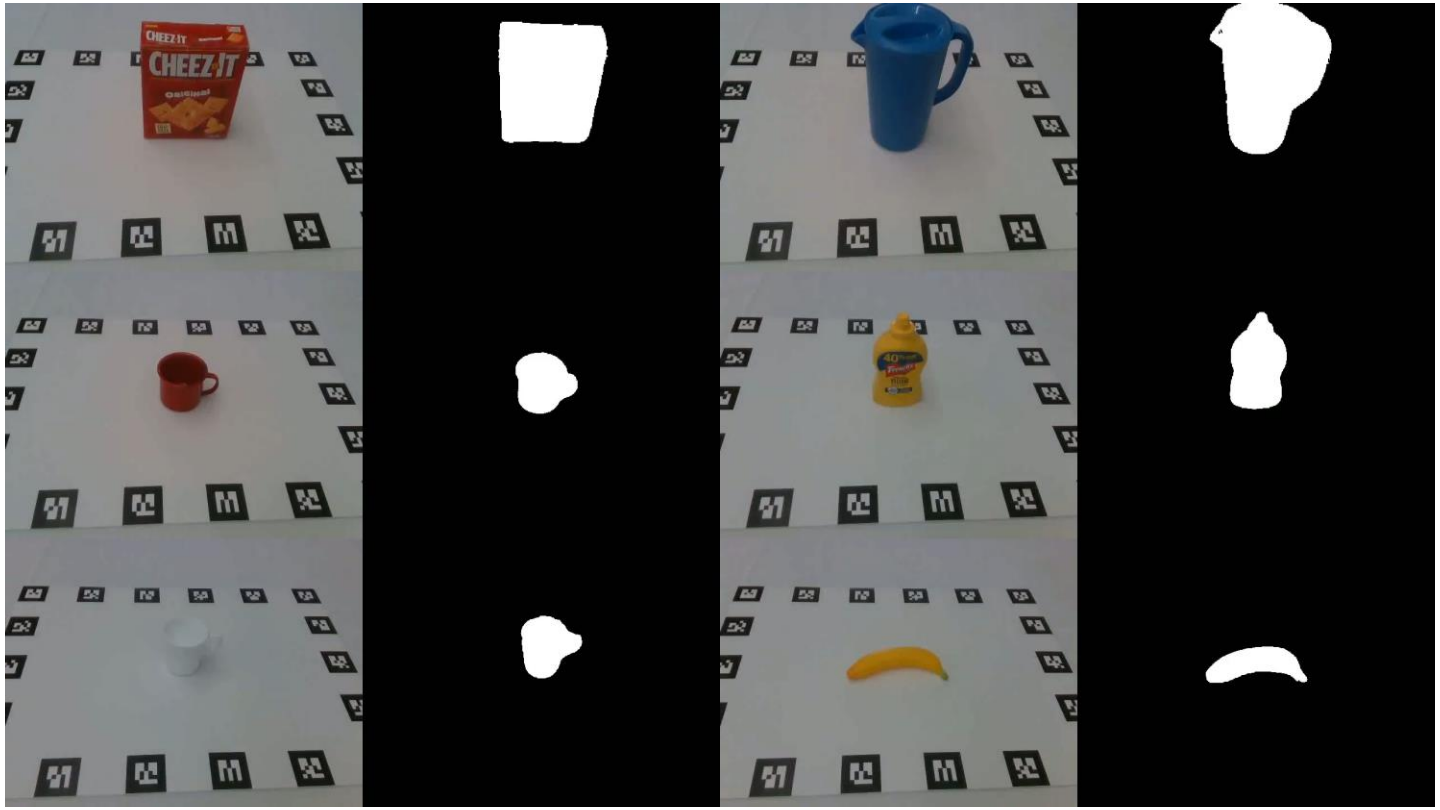
Unseen Object Instance Segmentation

Few-Shot Object Recognition

- A large-scale dataset for few-shot object recognition



Training data collected by a robot

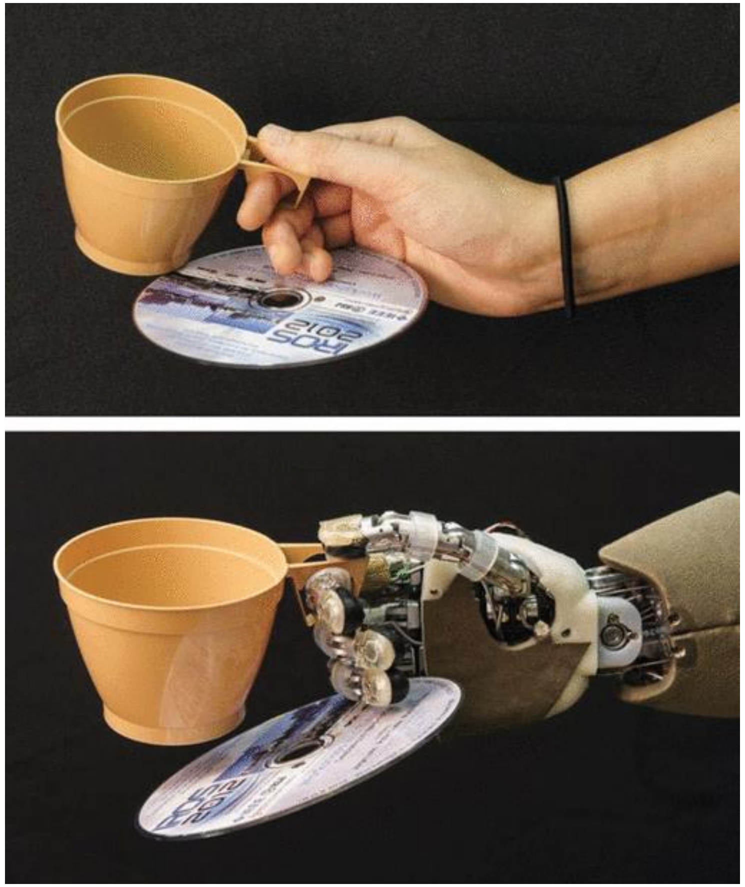


- 336 objects
- 198 object categories
- 9 images per object
- RGB-D images with segmentation masks and camera poses

FewSOL: A Dataset for Few-Shot Object Learning in Robotic Environments
Jishnu Jaykumar P, Yu-Wei Chao, Yu Xiang. ICRA, 2023.

Object-Centric Grasp Transfer

Grasp Transfer



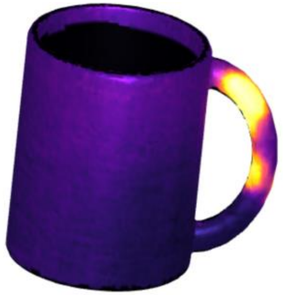
Barrett

Allegro

Human Hand

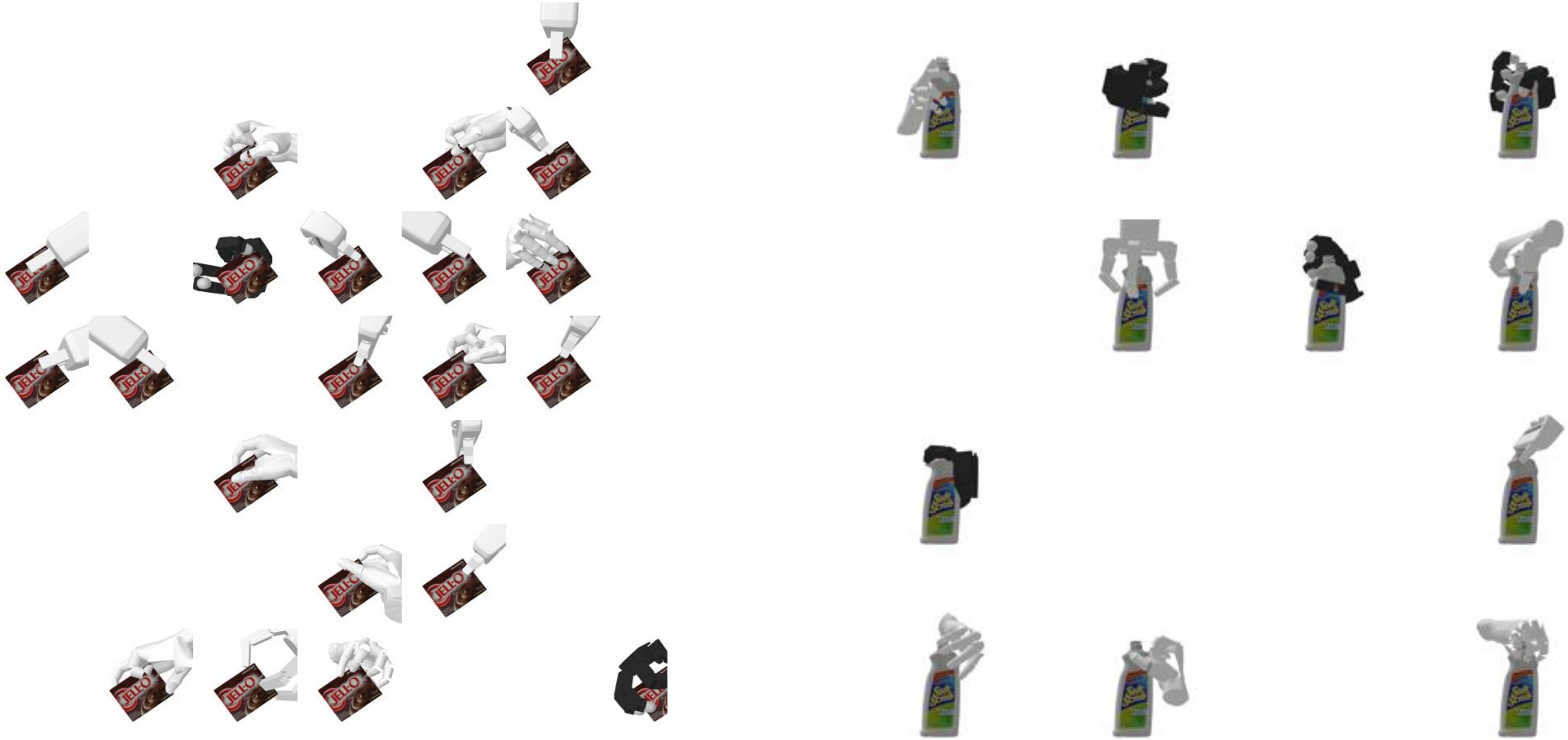
Franka Panda

Fetch Gripper



Object-centric contact regions

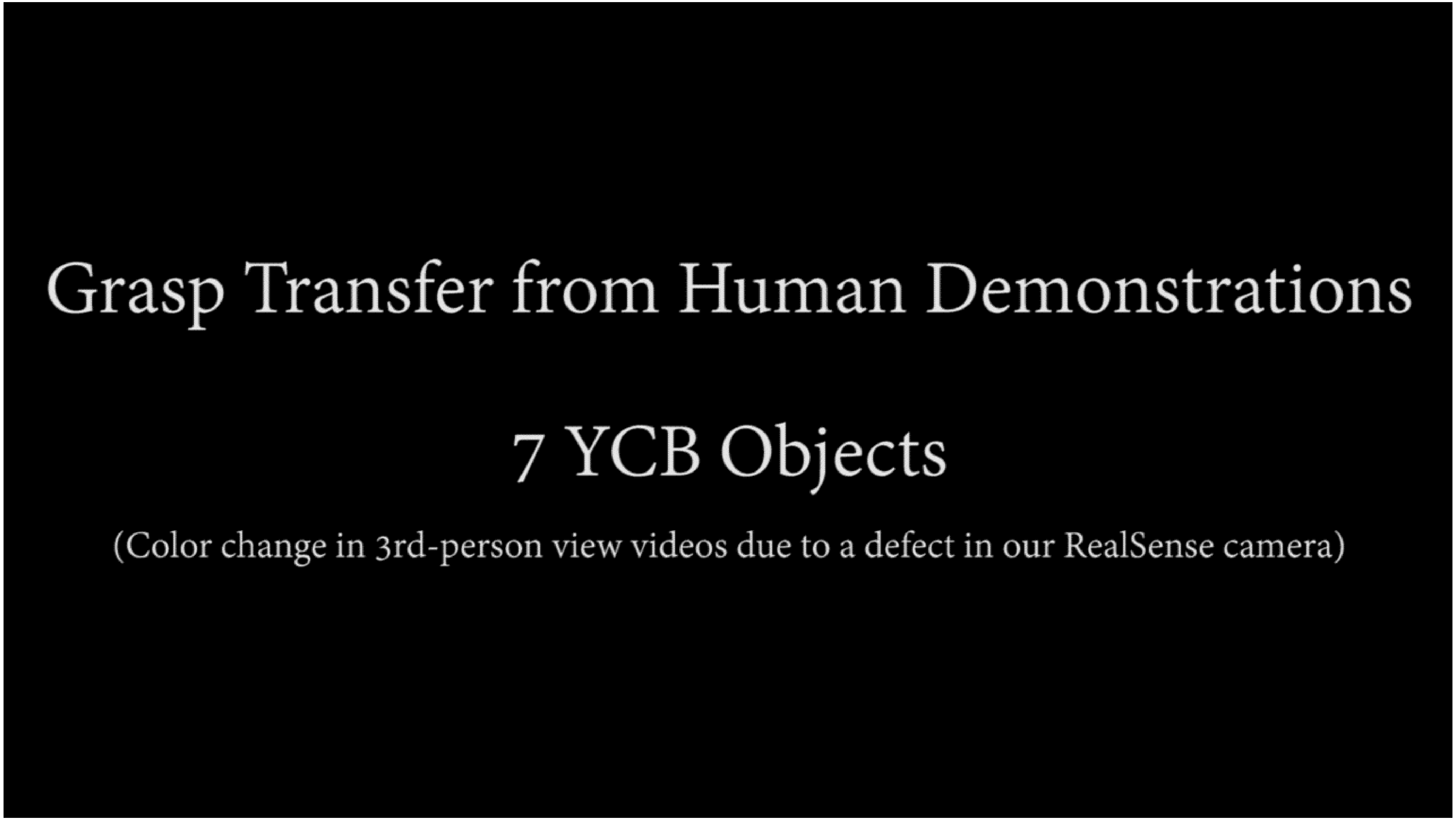
NeuralGrasps



t-SNE visualization of learned latent space

NeuralGrasps: Learning Implicit Representations for Grasps of Multiple Robotic Hands
Ninad Khargonkar, Neil Song, Zesheng Xu, Balakrishnan Prabhakaran, Yu Xiang. CoRL, 2022.

Object-Centric Grasp Transfer



Grasp Transfer from Human Demonstrations

7 YCB Objects

(Color change in 3rd-person view videos due to a defect in our RealSense camera)

Conclusion

- Object-centric perception for manipulation
  - Segmenting unseen objects → Grasping of unseen objects
  - Few-shot object recognition → object grounding in cluttered scenes
  - Grasp transfer among multiple grippers → sharing grasping skills among robots
- End-goal: robots use objects to perform tasks

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Thank you!