Object-Centric Perception for Robot Manipulation

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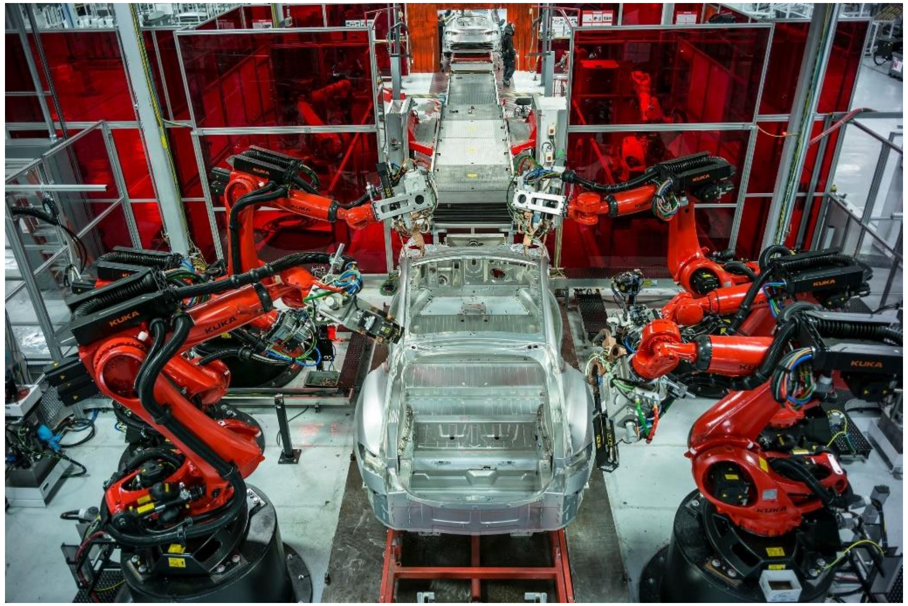
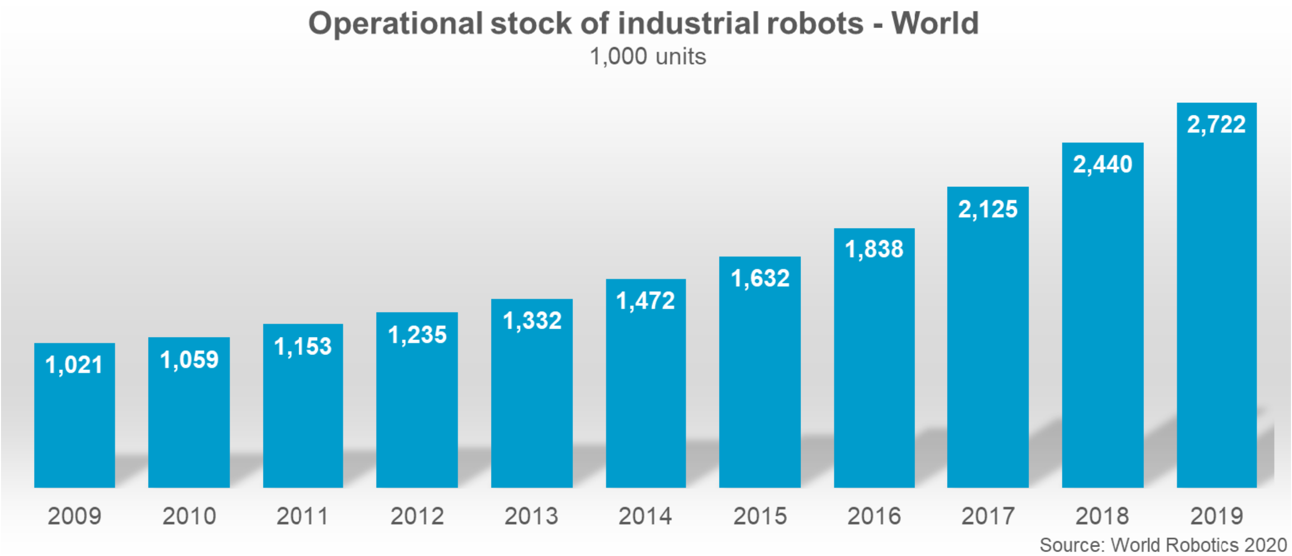
Robots in Factories and Warehouses



Welding and Assembling

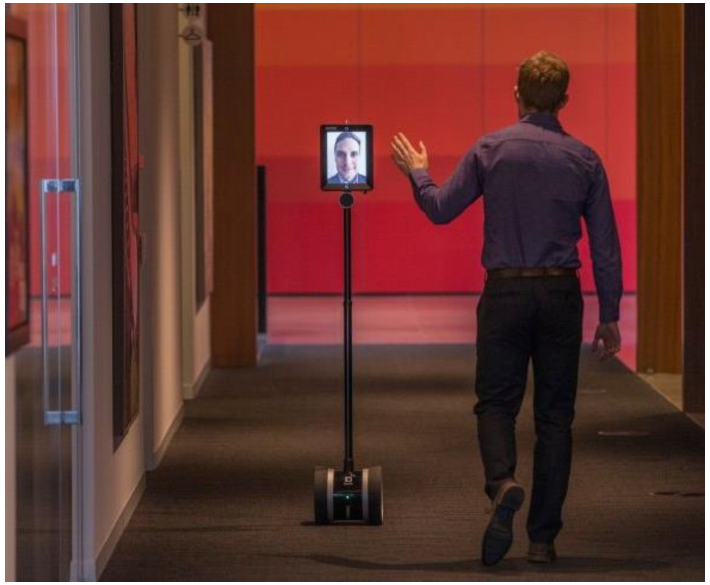
Material Handling

Delivering



Current Robots in Human Environments

Cleaning Robots



Telepresence Robots

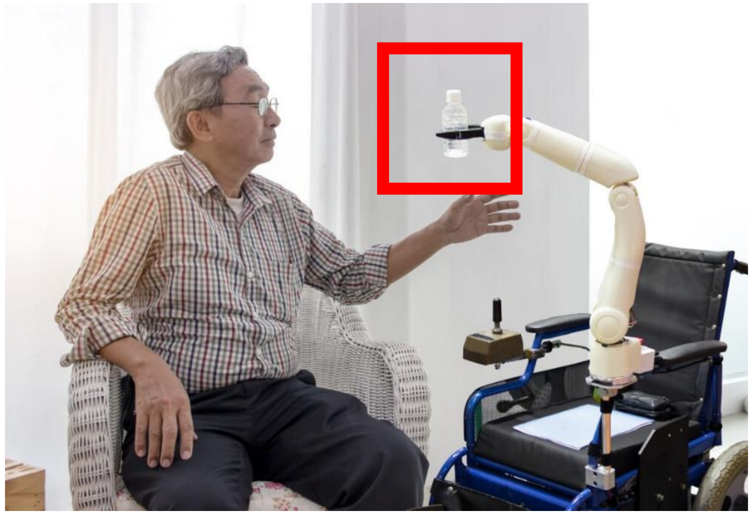
Smart Speakers

How can we have more powerful robots assisting people at homes or offices?

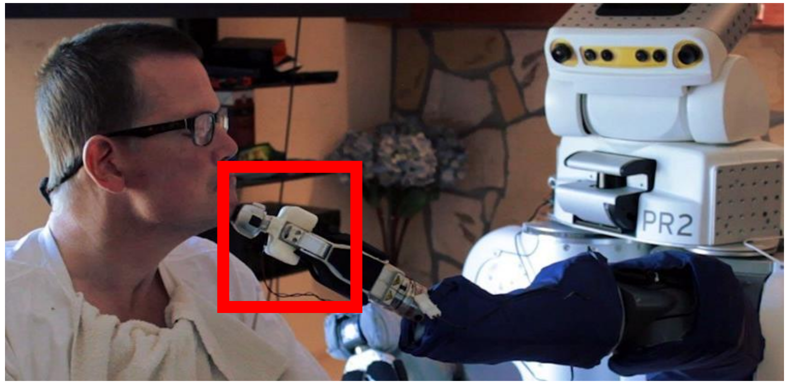
- Mobile manipulators
- Humanoids

Future Intelligent Robots in Human Environments

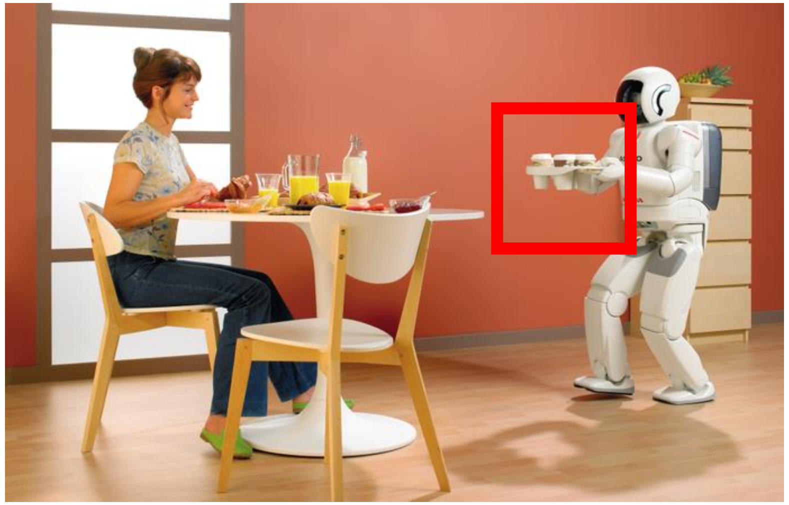
Manipulation



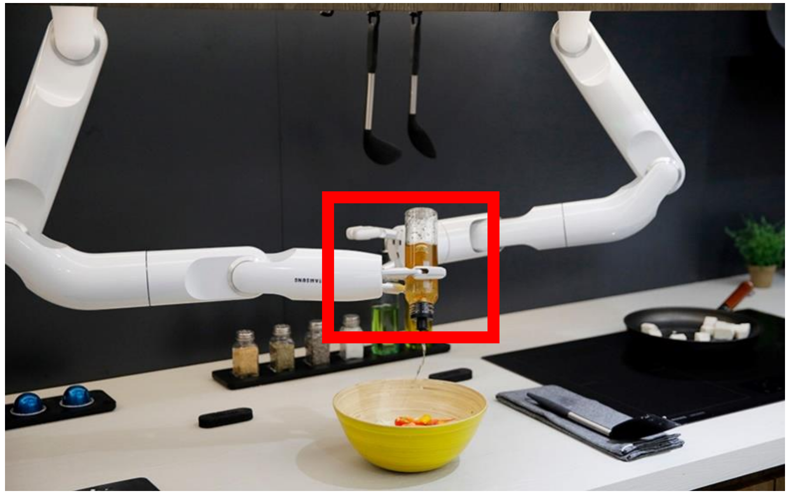
Senior Care



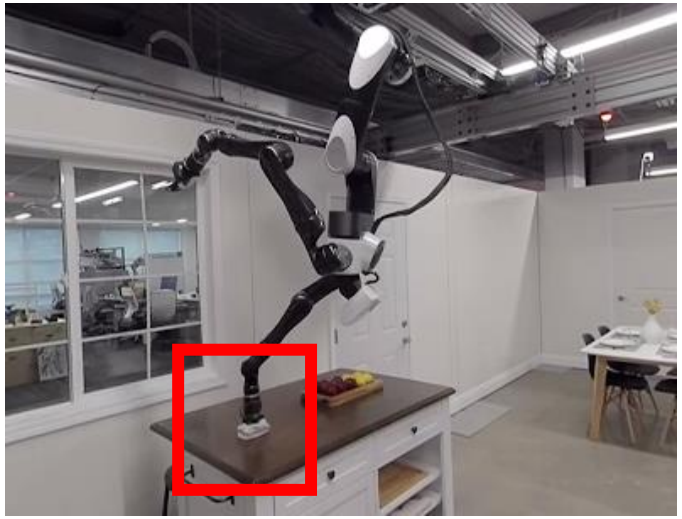
Assisting



Serving



Cooking



Cleaning

Dish washing

The Perception, Planning and Control Loop

Tasks

Perception

Planning

Control

Learning

Sensing

World

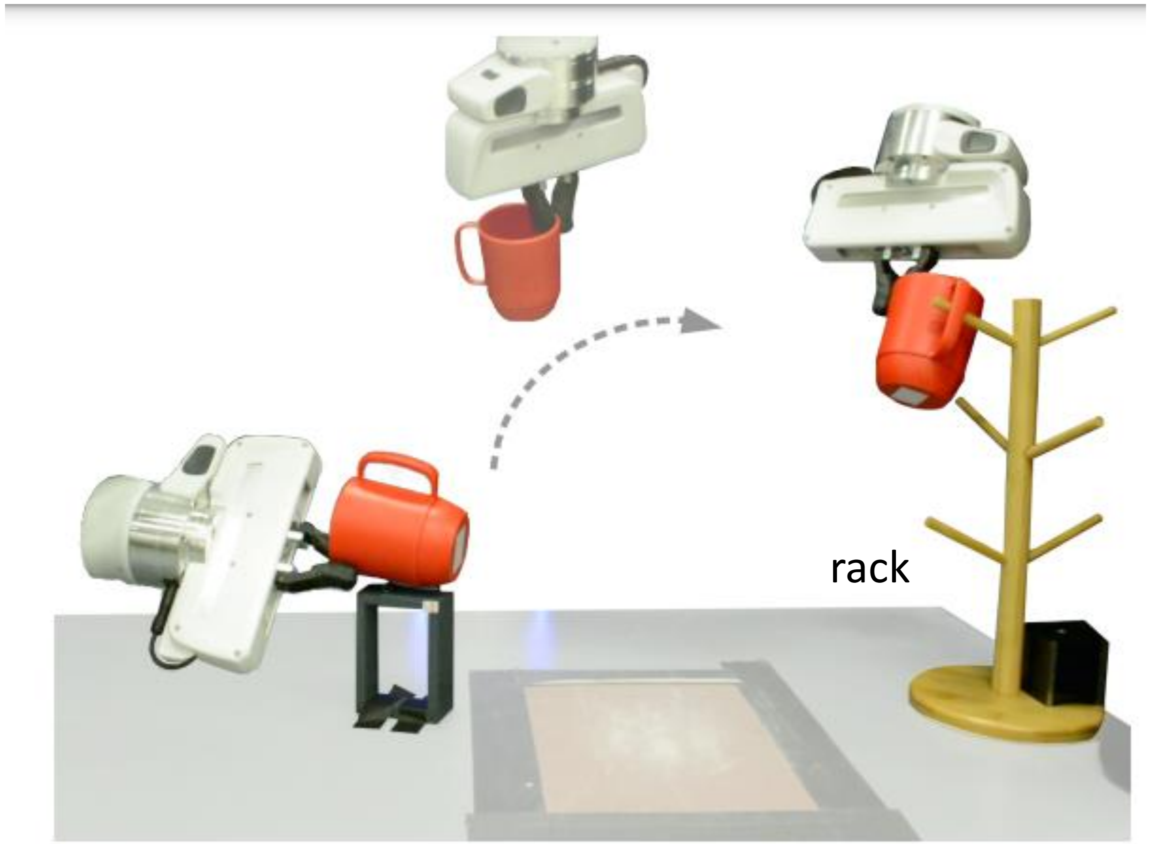
Action

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.

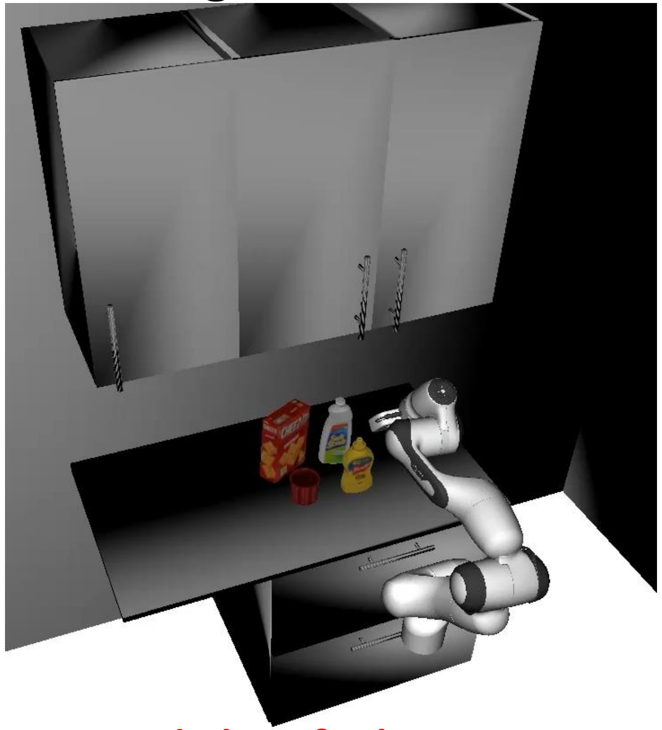
Model-based Robotic Grasping

Perception → Planning → Control

6D Object Pose Estimation | Motion and Grasp Planning | Position Control

Sensed image

Planning scene



Real world execution

We need to have 3D models of objects

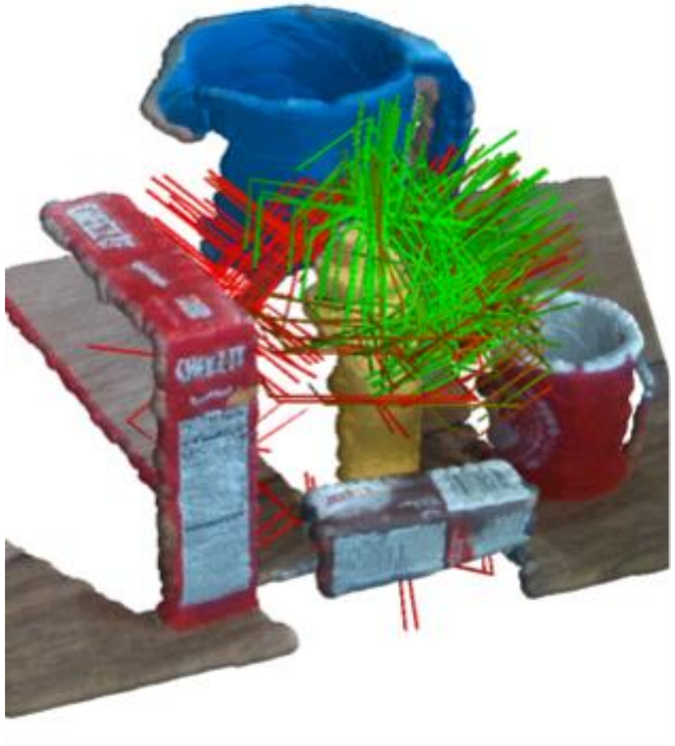
Robots in Unstructured Environments

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

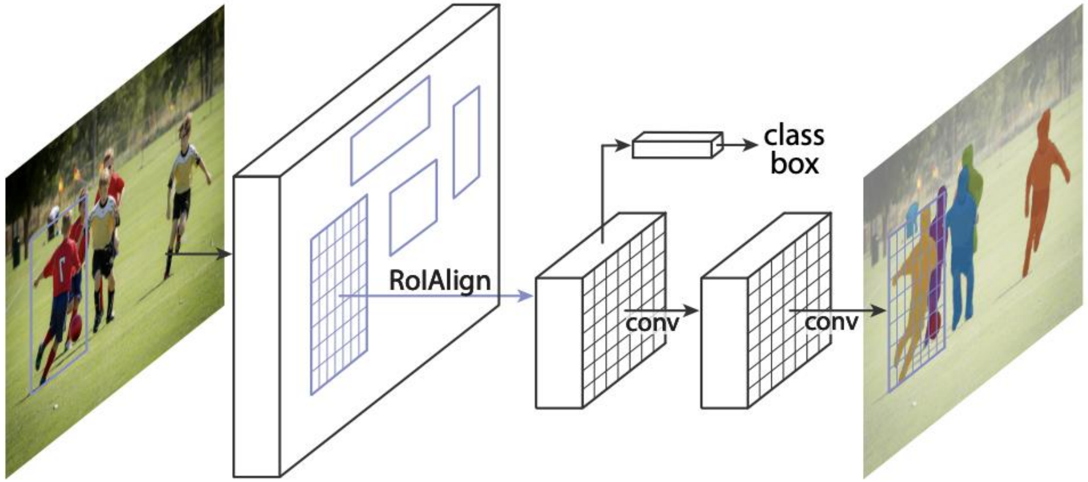
Object Model-free Robotic Grasping

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

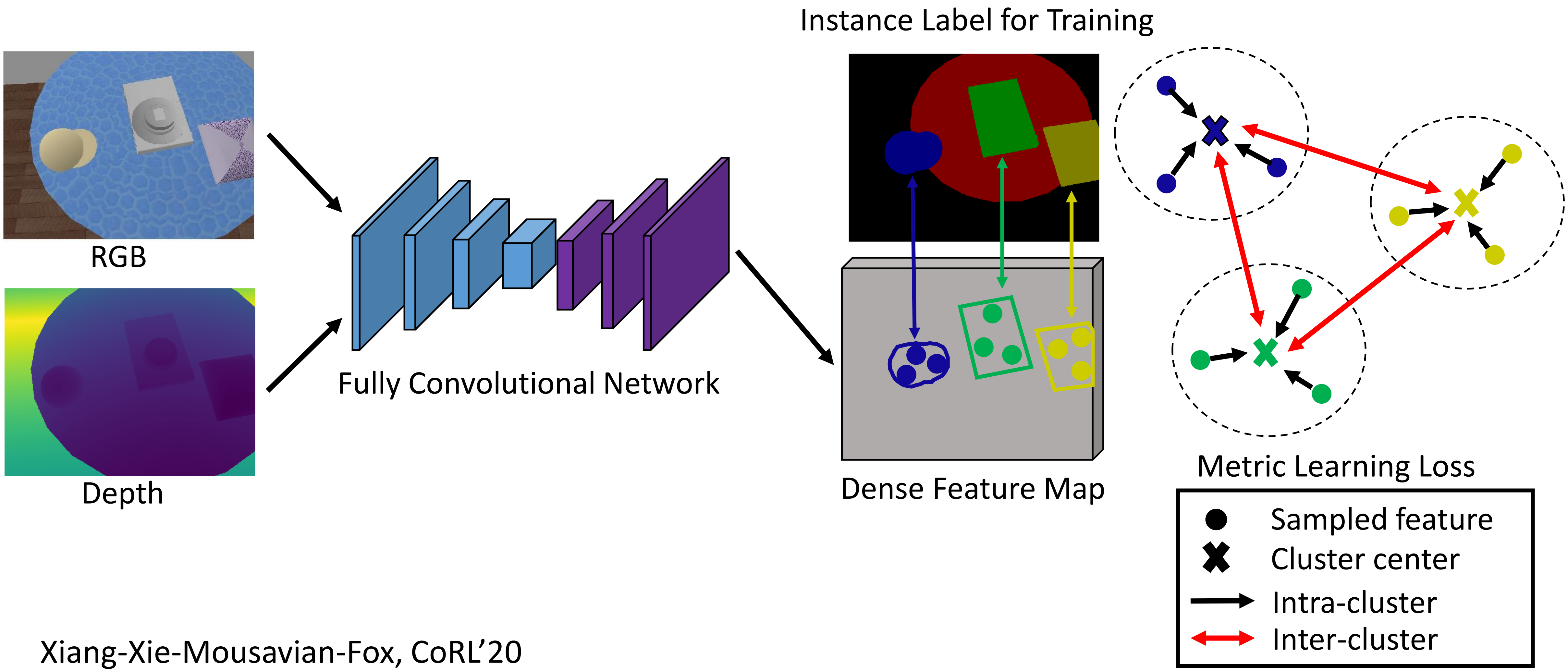
Unseen Object Instance Segmentation

- Top-down approaches
  - Mask R-CNN (objects vs. background)
  - UOAIS-Net (Back et al. ICRA’22)



- Bottom-up approaches
  - UOIS-Net (predicting object centers) Xie et al. CoRL’19, T-RO’21
  - UCN (feature learning + mean shift clustering) Xiang et al. CoRL’20
  - Fully Test-time RGBD Embeddings Adaptation (FTEA) Zhang et al. arXiv’23

Unseen Object Instance Segmentation: Learning RGB-D Feature Embeddings



Xiang-Xie-Mousavian-Fox, CoRL'20

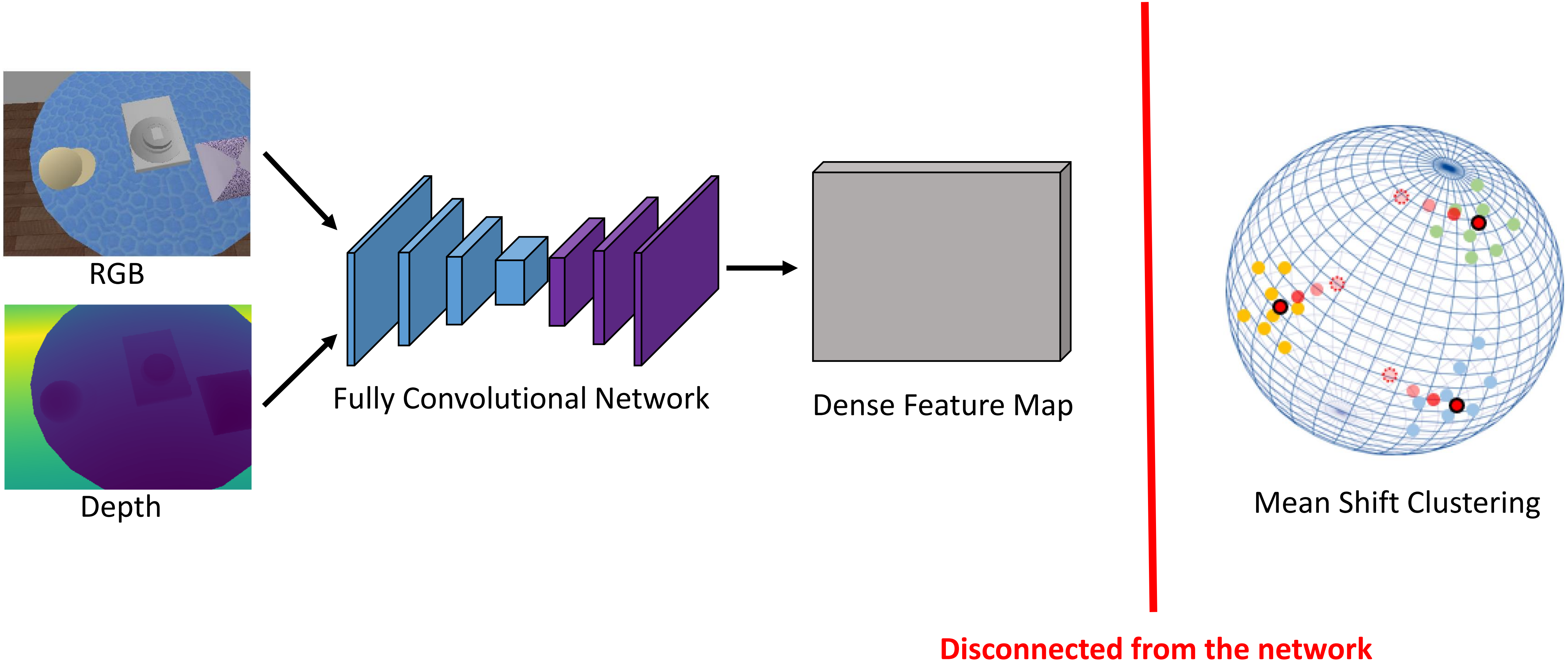
von Mises-Fisher (vMF) Mean Shift Clustering

- Input data points $\mathbf{X} \in \mathbb{R}^{n \times C}$ Unit length vectors
- Sample m initial clustering centers using furthest point sampling

$$\mu^{(0)} \in \mathbb{R}^{m \times C}$$

- For each of the T iterations
  - Compute weight matrix $\underset{m \times n}{\mathbf{W}} \leftarrow \exp(\kappa \mu^{(t-1)} \mathbf{X}^T)$
  - Update clustering centers $\underset{m \times C}{\mu^{(t)}} \leftarrow \mathbf{W}\mathbf{X}$ Normalize each row
- Merge clustering centers with cosine distance smaller than ϵ

Mean Shift Clustering is Non-Differentiable



Can we learn a differentiable clustering module jointly with the image feature embeddings?

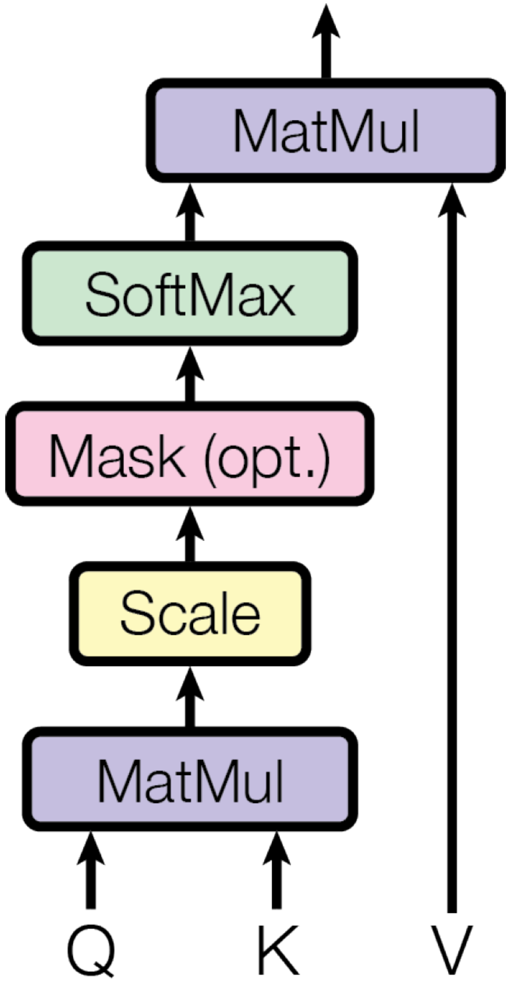
Transformer: Attention

- Scaled Dot-Product Attention
  - Keys $K : m \times d_k$
  - Values $V : m \times d_v$
  - n queries $Q : n \times d_k$

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

$$n \times d_v$$

weights



Attention is all you need. Vaswani et al., NeurIPS'17

vMF Mean Shift vs. Scaled Dot-Product Attention

- vMF mean shift updating rule

$$\mu^{(t)} \leftarrow \exp(\kappa \mu^{(t-1)} \mathbf{X}^T) \mathbf{X}$$

- Scaled Dot-Product Attention

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

Query Q as clustering centers $\mu^{(t)} \in \mathbb{R}^{m \times C}$

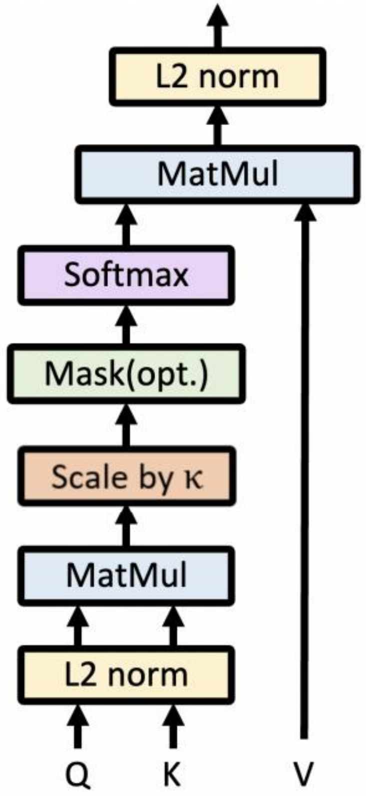
Keys and values as data points $\mathbf{X} \in \mathbb{R}^{n \times C}$

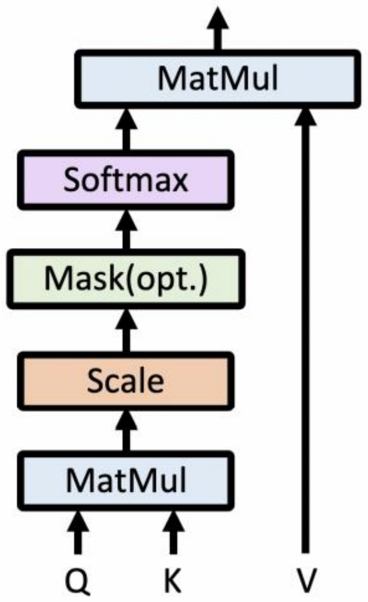
Our Proposed Hypersphere Attention

- Hypersphere Attention

$$\mathrm{HSAtten}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = g(\mathrm{softmax}(\kappa g(\mathbf{Q}) g(\mathbf{K})^T)\mathbf{V}) \qquad g(\mathbf{x}) = \frac{\mathbf{x}}{\|\mathbf{x}\|}$$

hypersphere attention





scaled dot-product attention

$$\mathrm{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \mathrm{softmax}(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}})\mathbf{V}$$

Our Masked Mean Shift Cross-Attention

$$\mu_l = \mu_{l-1} + g(\mathrm{softmax}(\mathcal{M}_{l-1} + \kappa g(\mathbf{Q}_l) g(\mathbf{K}_l)^T)\mathbf{V}_l)$$

$\mu_l \in \mathbb{R}^{m \times C}$ Clustering centers at layer l

$$g(\mathbf{x}) = \frac{\mathbf{x}}{\|\mathbf{x}\|}$$

Query $\mathbf{Q}_l = f_Q(\mu_{l-1}) \in \mathbb{R}^{m \times C}$

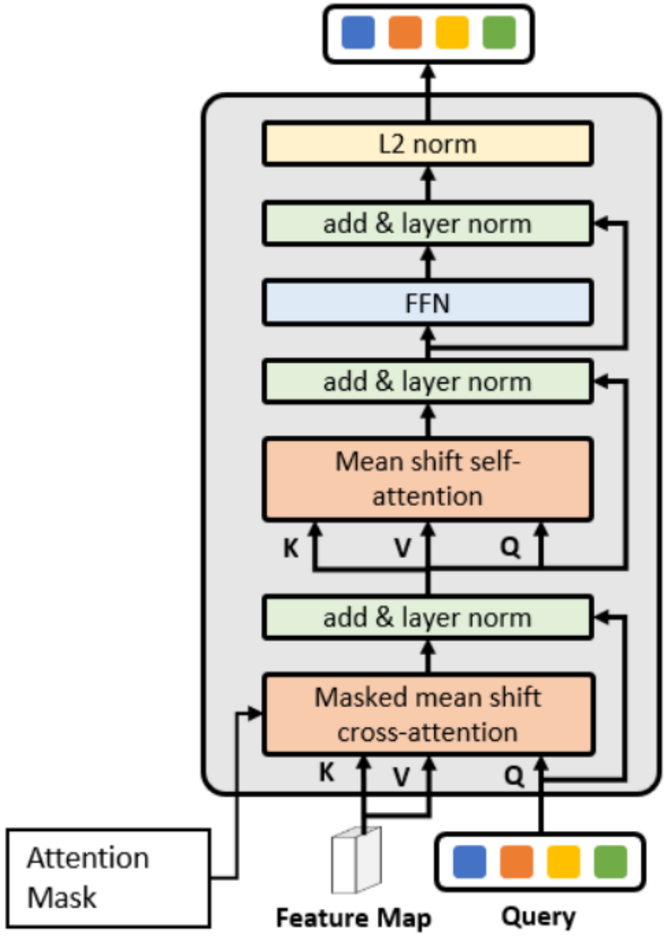
Key, Value $\mathbf{K}_l, \mathbf{V}_l \in \mathbb{R}^{H_l W_l \times C}$ Pixel embeddings

Attention mask $\mathcal{M}_{l-1}(x, y) = \begin{cases} 0 & \text{if } \mathrm{M}_{l-1}(x, y) = 1 \\ -\infty & \text{otherwise} \end{cases}$

Mask prediction $M_{l-1} \in \{0, 1\}^{m \times H_l W_l}$

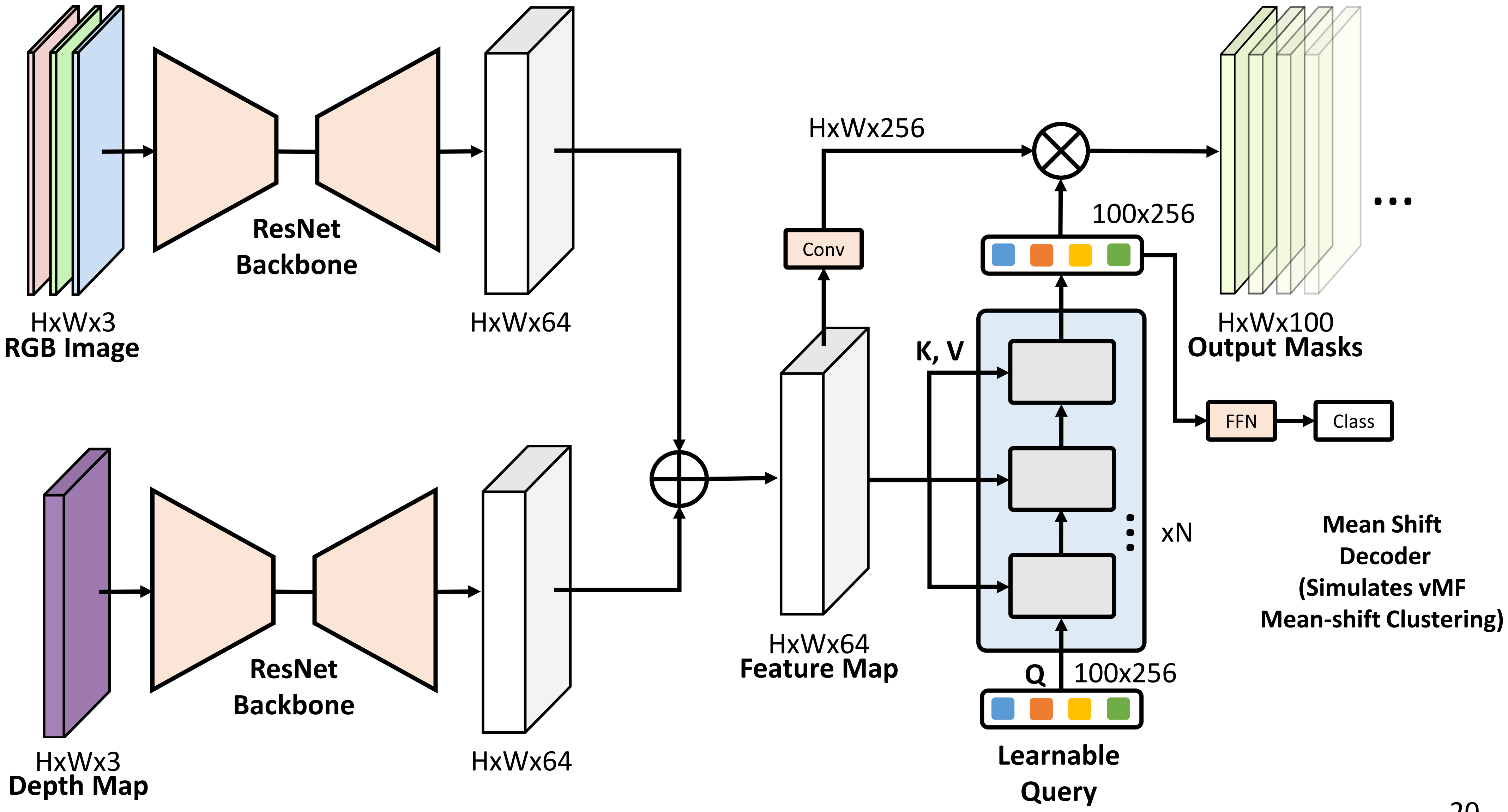
Our Mean Shift Decoder Layer

$$\mu_l = \mu_{l-1} + g(\text{softmax}(\mathcal{M}_{l-1} + \kappa g(\mathbf{Q}_l)g(\mathbf{K}_l)^T)\mathbf{V}_l)$$

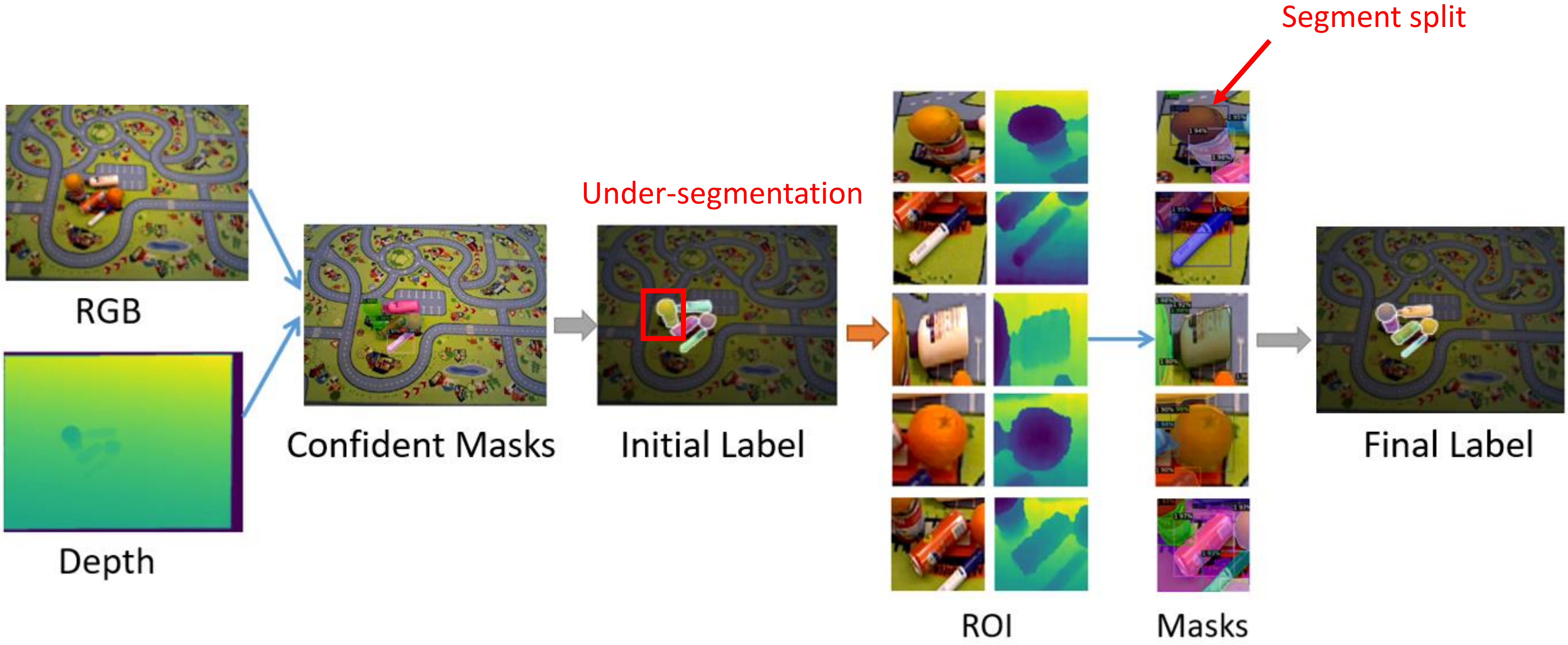


Our Mean Shift Mask Transformer

Can be trained end-to-end



Two-stage Segmentation

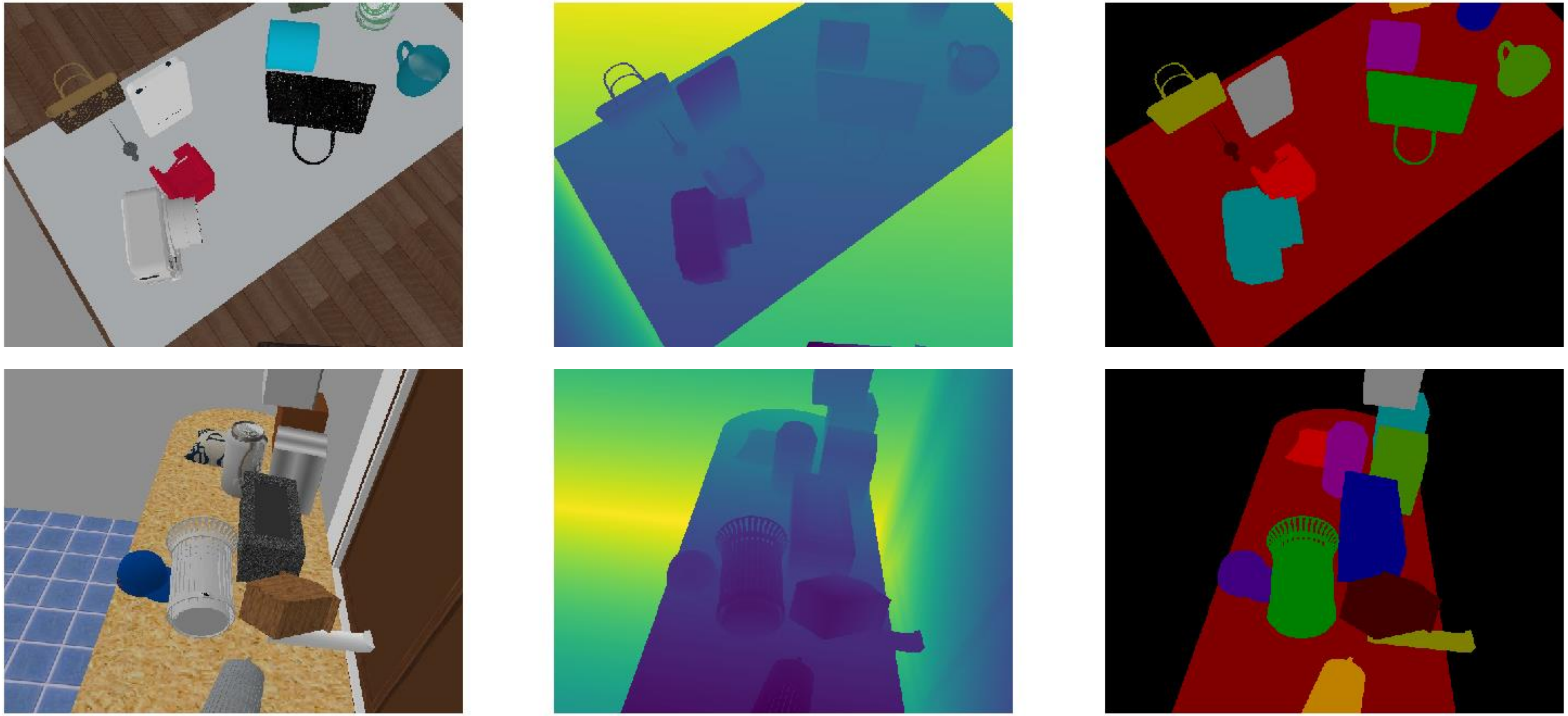


Experiments: Testing Datasets

- Object Cluster Indoor Dataste (OCID), 2,390 RGB-D images   Sushi et al. ICRA'19

- Object Segmentation Database (OSD), 111 RGB-D images   Richtsfeld et al. IROS'12

Experiments: Learning from Synthetic Data



RGB Depth Instance Label

40,000 scenes
7 RGB-D images per scene

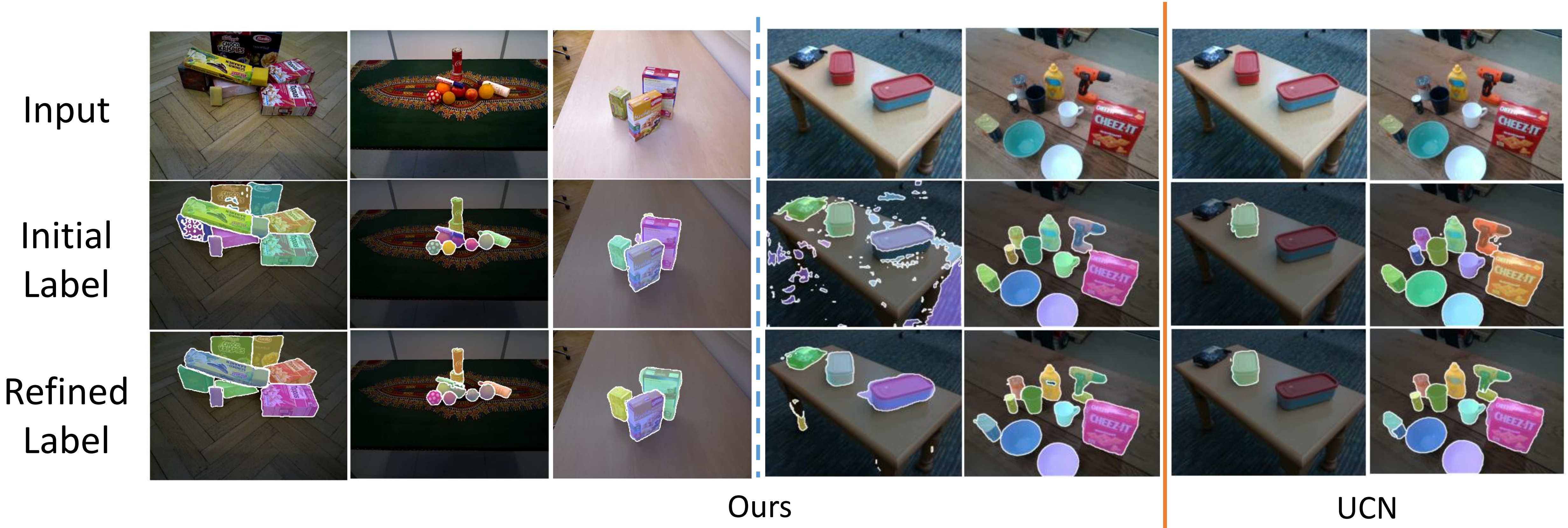
ShapeNet objects in the PyBullet simulator

Xie et al. CoRL'19

Experimental Results

Method	Input	OCID (2390 images)							OSD (111 images)						
		Overlap			Boundary				Overlap			Boundary			
		P	R	F	P	R	F	%75	P	R	F	P	R	F	%75
MRCNN [14]	RGB	**77.6**	67.0	67.2	**65.5**	53.9	54.6	55.8	**64.2**	61.3	62.5	50.2	40.2	44.0	31.9
UCN [40]	RGB	54.8	**76.0**	59.4	34.5	45.0	36.5	48.0	57.2	**73.8**	63.3	34.7	50.0	39.1	52.5
UCN+ [40]	RGB	59.1	74.0	61.1	40.8	55.0	43.8	**58.2**	59.1	71.7	**63.8**	34.3	**53.3**	39.5	**52.6**
Mask2Former [5]	RGB	67.2	73.1	67.1	55.9	**58.1**	54.5	54.3	60.6	60.2	59.5	48.2	41.7	43.3	32.4
MSMFormer (Ours)	RGB	72.9	68.3	**67.7**	60.5	56.3	**55.8**	52.9	63.4	64.7	63.6	48.6	47.4	**47.0**	40.2
MSMFormer+ (Ours)	RGB	73.9	67.1	66.3	64.6	52.9	54.8	52.8	63.9	63.7	62.7	**51.6**	45.3	**47.0**	41.1
MRCNN [14]	Depth	85.3	85.6	84.7	83.2	76.6	78.8	72.7	77.8	85.1	80.6	52.5	57.9	54.6	77.6
UOIS-Net-2D [42]	Depth	88.3	78.9	81.7	82.0	65.9	71.4	69.1	80.7	80.5	79.9	66.0	67.1	65.6	71.9
UOIS-Net-3D [43]	Depth	86.5	86.6	86.4	80.0	73.4	76.2	77.2	85.7	82.5	83.3	**75.7**	68.9	71.2	73.8
UCN [40]	RGBD	86.0	92.3	88.5	80.4	78.3	78.8	82.2	84.3	**88.3**	86.2	67.5	67.5	67.1	79.3
UCN+ [40]	RGBD	91.6	**92.5**	**91.6**	86.5	**87.1**	86.1	**89.3**	**87.4**	87.4	**87.4**	69.1	70.8	69.4	**83.2**
UOAIS-Net [1]*	RGBD	70.7	86.7	71.9	68.2	78.5	68.8	78.7	85.3	85.4	85.2	72.7	**74.3**	**73.1**	79.1
Mask2Former [5]	RGBD	78.6	82.8	79.5	69.3	76.2	71.1	69.3	75.6	79.2	77.3	54.1	64.0	58.0	65.2
MSMFormer (Ours)	RGBD	88.4	90.2	88.5	84.7	83.1	83.0	80.3	79.5	86.4	82.8	53.5	71.0	60.6	79.4
MSMFormer+ (Ours)	RGBD	**92.5**	91.0	91.5	**89.4**	85.9	**87.3**	86.0	87.1	86.1	86.4	69.0	68.6	68.4	80.4

Segmentation Examples



UCN: Xiang-Xie-Mousavian-Fox, CoRL'20

Segmentation Failure Cases

Under-segmentation

Over-segmentation

How Can We Fix These Failures?

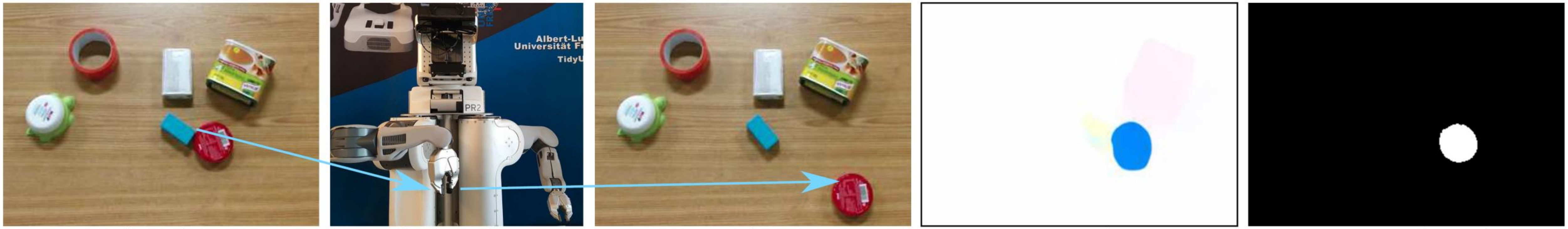
- Better models
  - Swin Transformers
  - OpenAI CLIP
  - ?

- 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

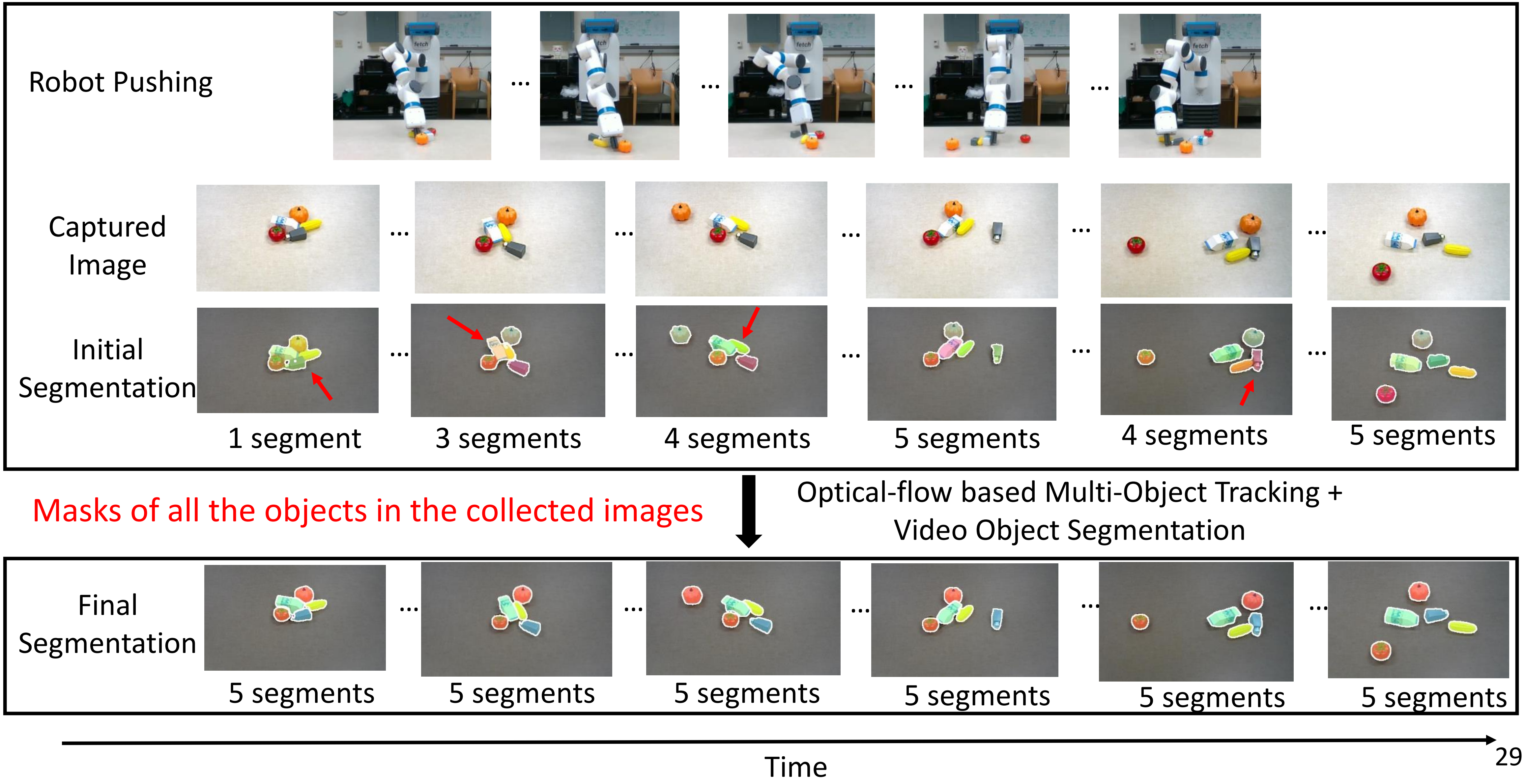


previous image | robot pushing | next image | optical flow | generated mask

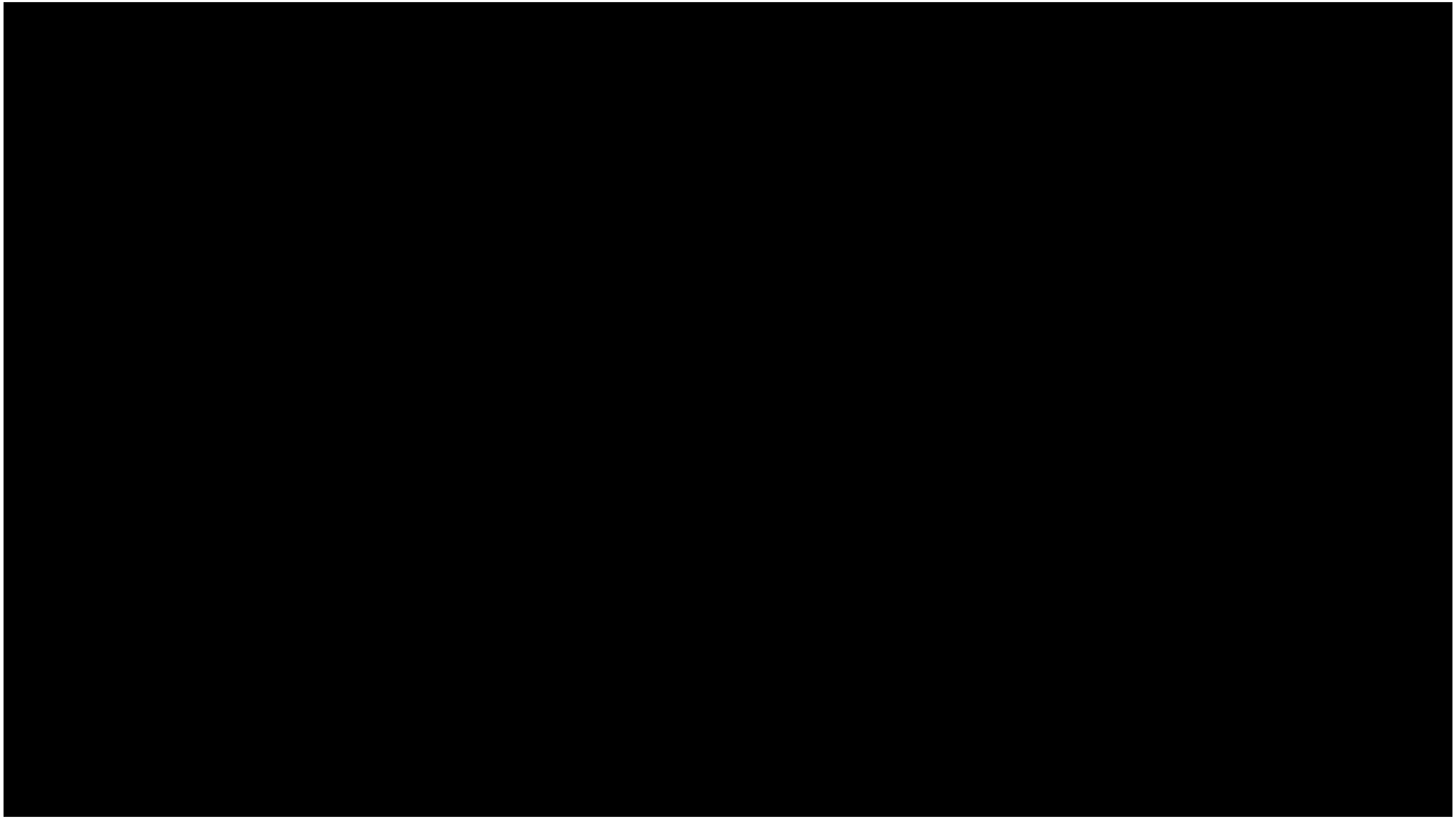
- One push cannot separate objects sometimes
- These approaches can only obtain one mask in an image

[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

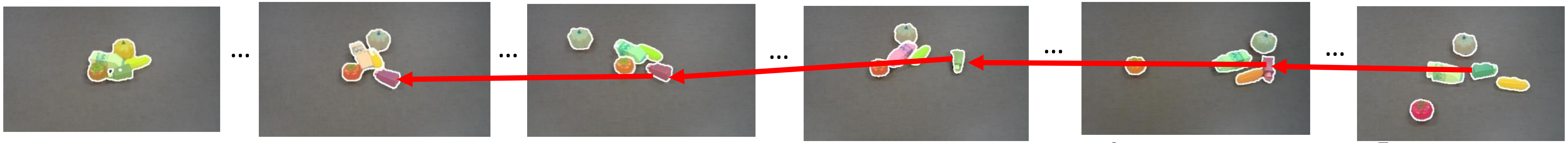


Leveraging Long-term Robot Interaction



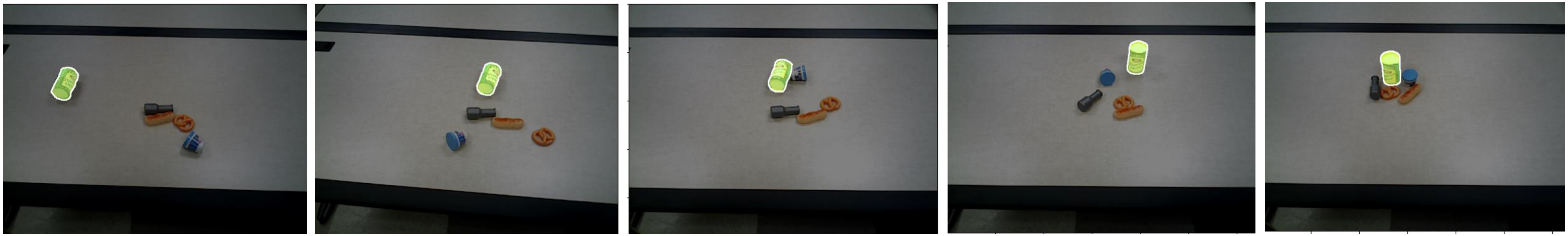
Tracking by Segmentation and Video Object Segmentation

Initial Segmentation



1 segment ... 3 segments ... 4 segments ... 5 segments ... 4 segments ... 5 segments

Tracklet



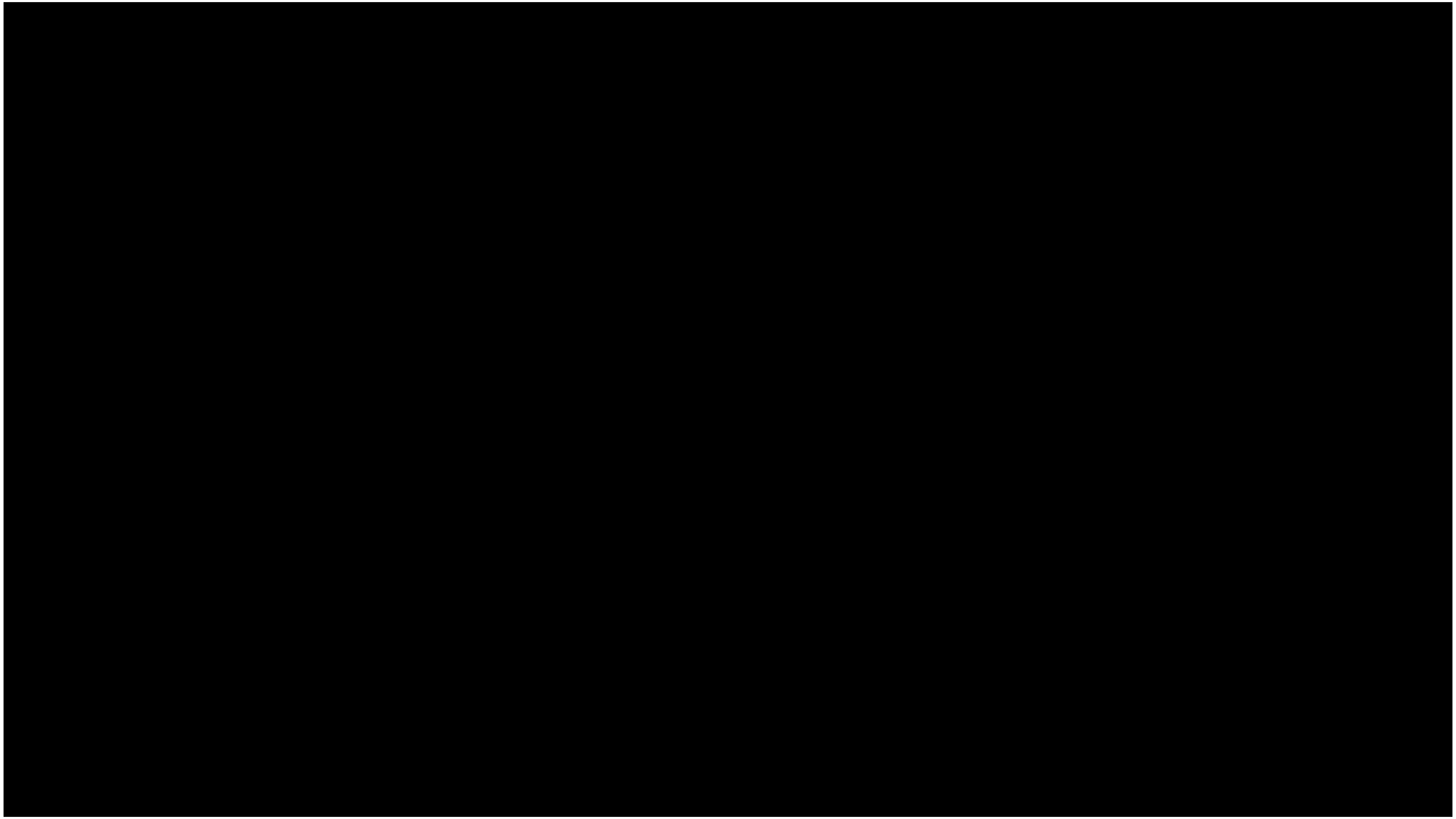
Initial mask: frame 20 → frame 10 → frame 7 → frame 4 → frame 0

Select the highest score mask in a tracklet

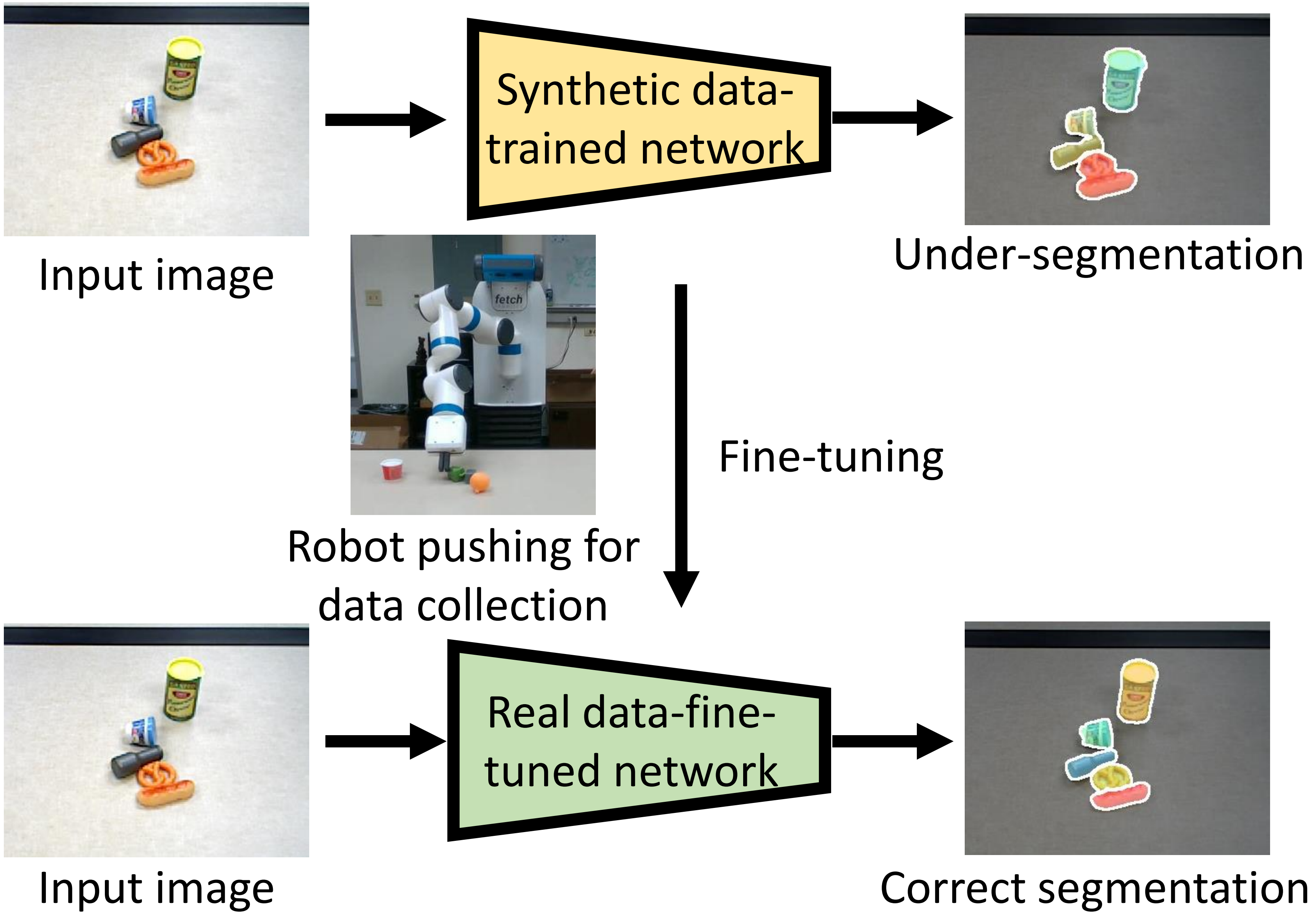
Propagation to other frames

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

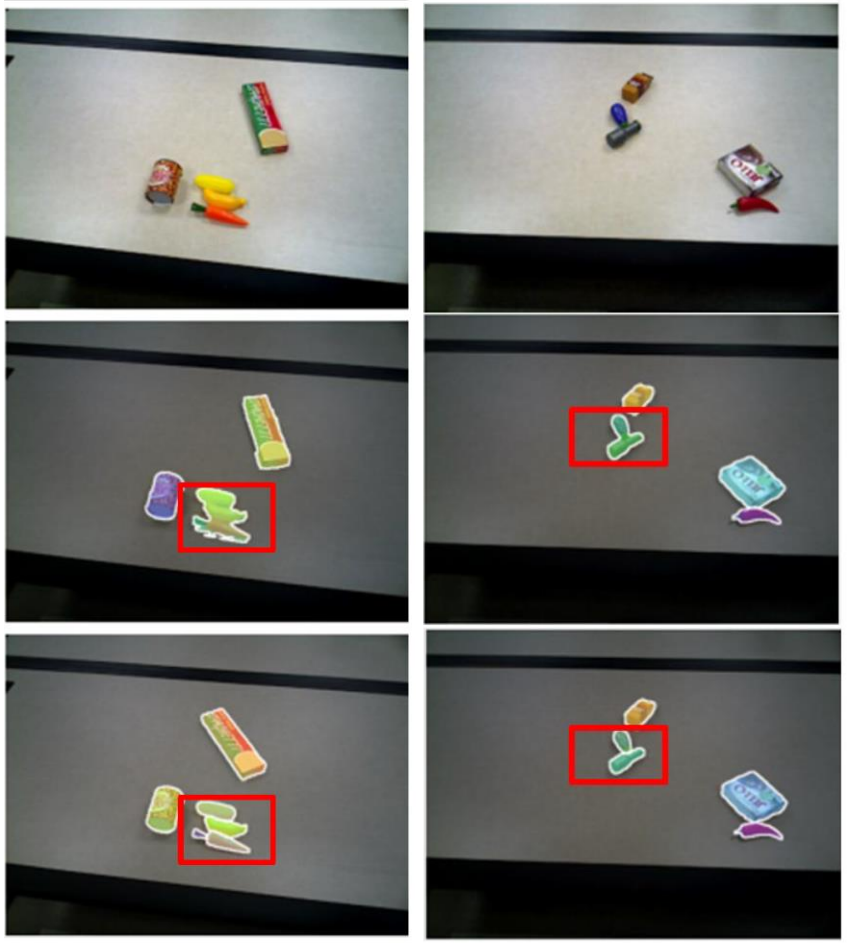
Data Collected by the Robot



Self-supervised Segmentation with Robot Interaction



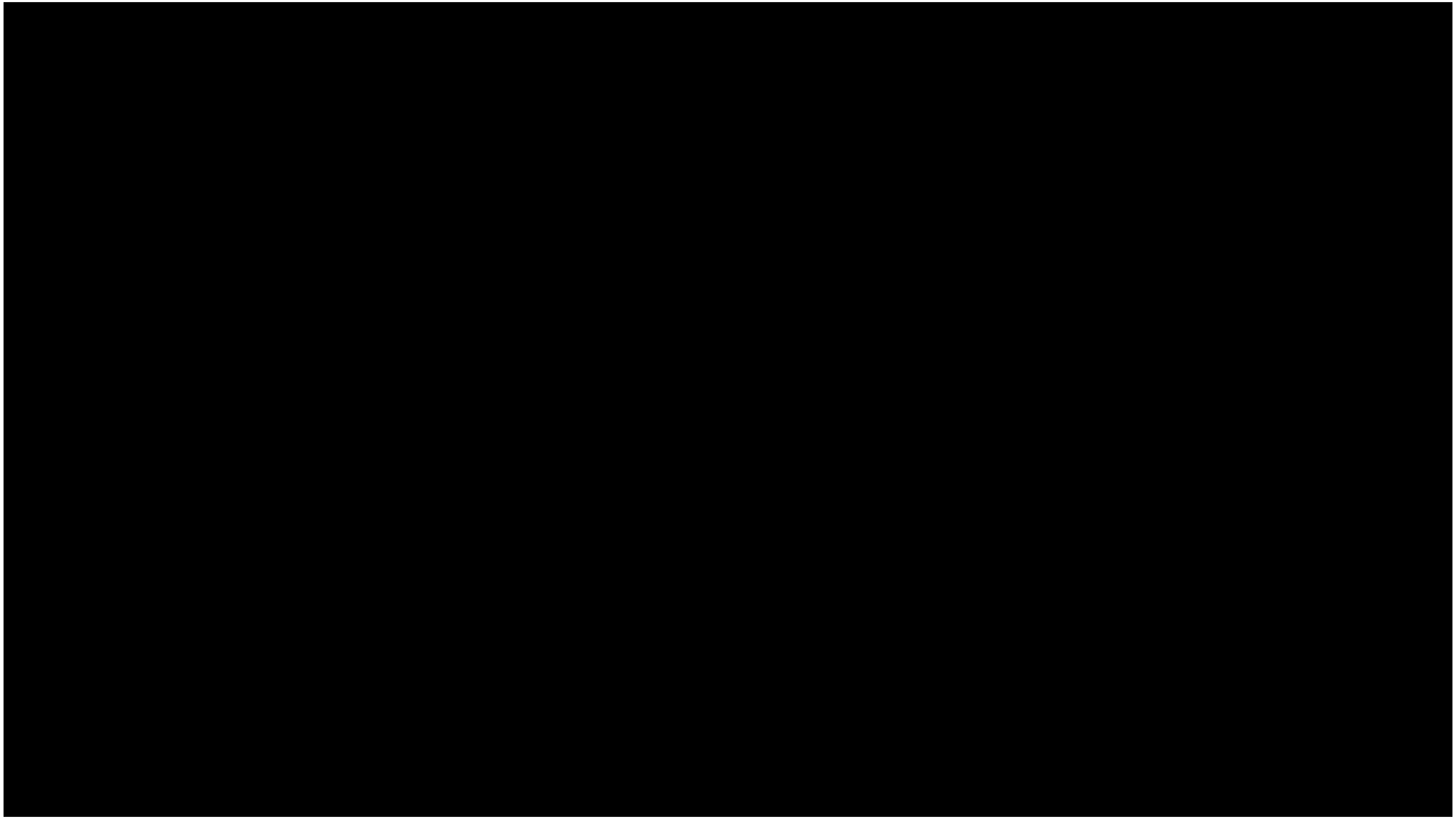
Fine-tuning MSMFormer for Unseen Object Segmentation



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

Test scene

Pear

Cereal box

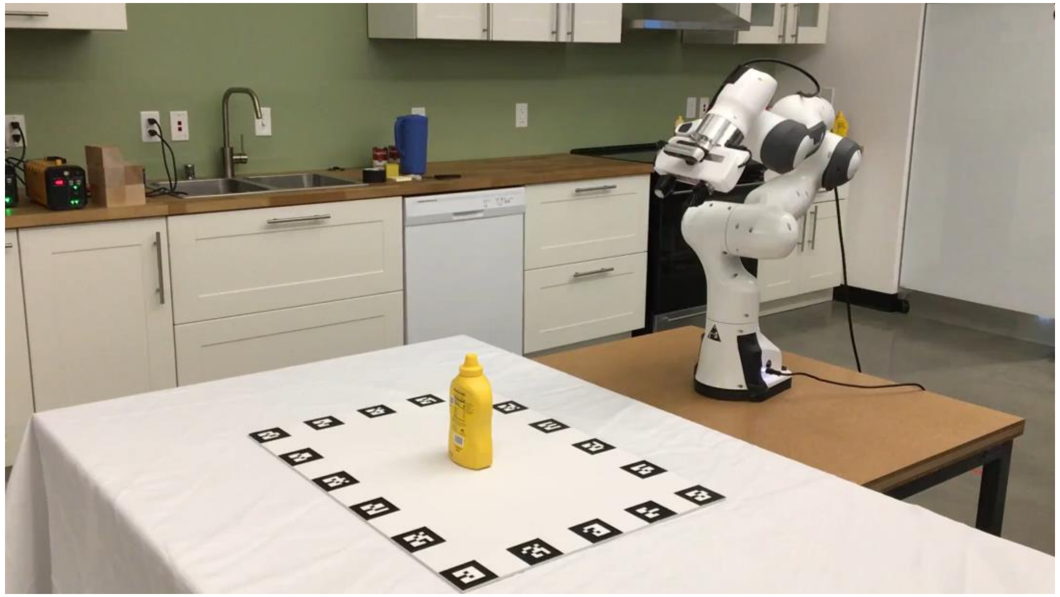
Unseen Object Instance Segmentation

Towel

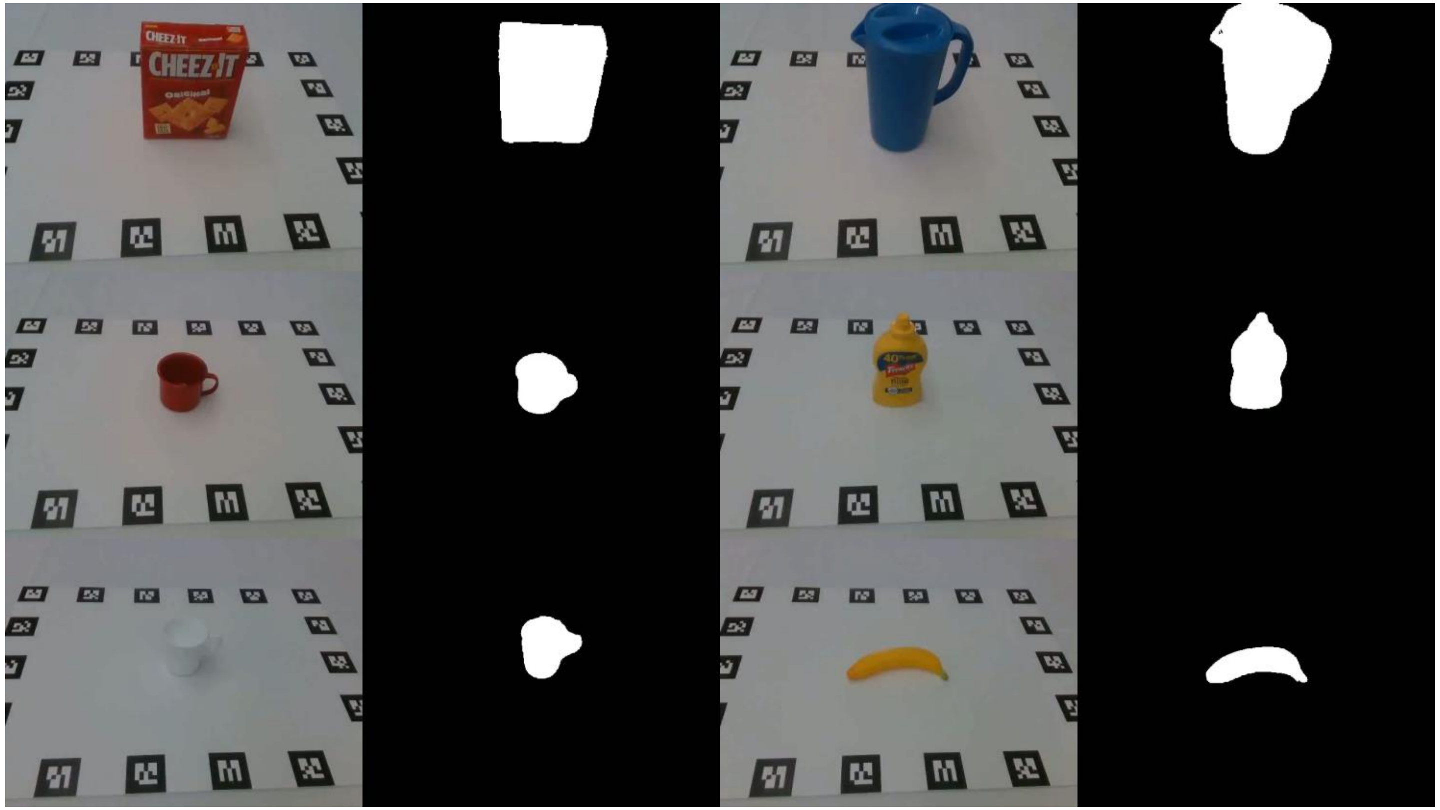
Toothpaste

Few-Shot Object Recognition

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



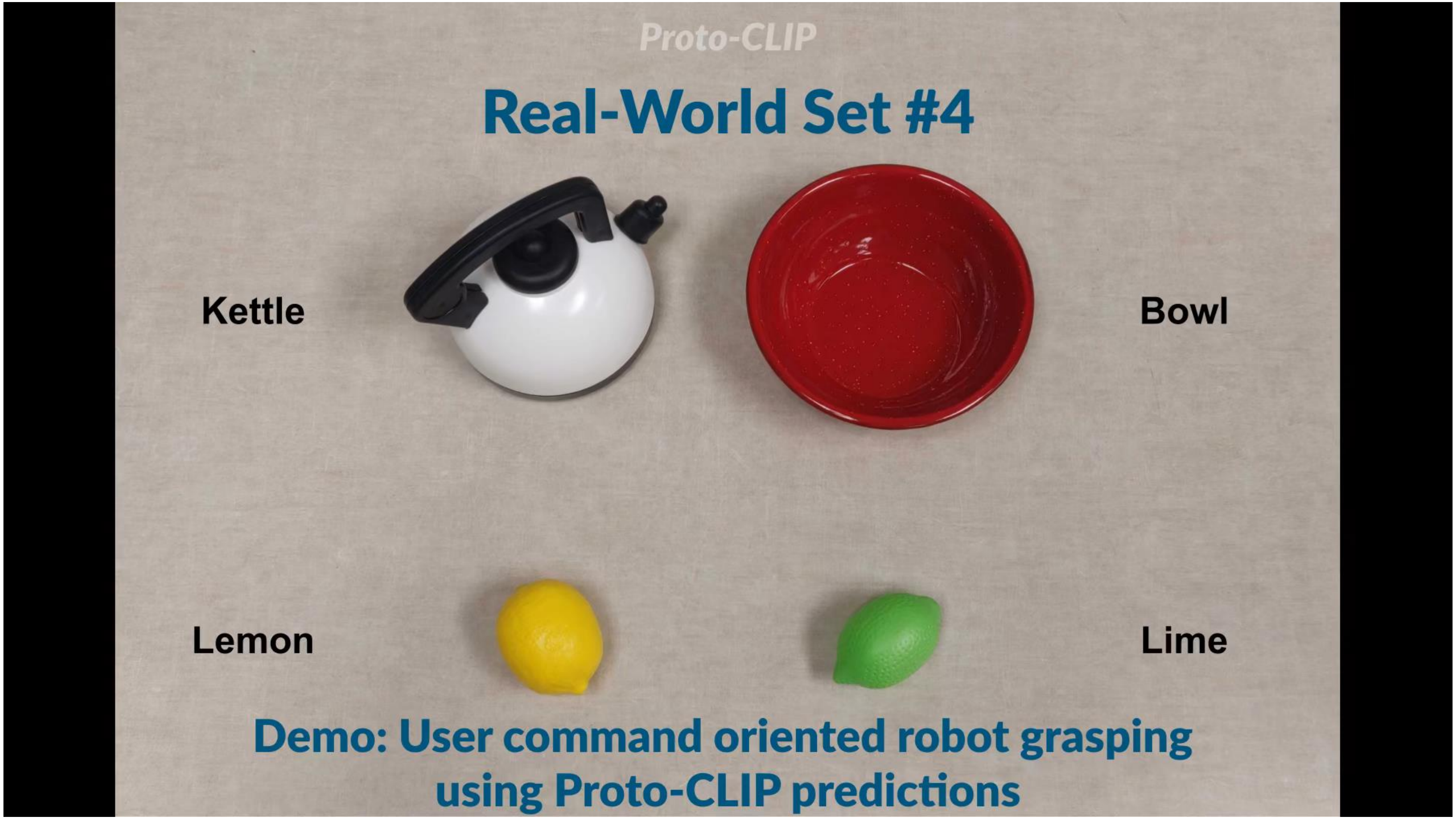
Training data collected by a robot



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

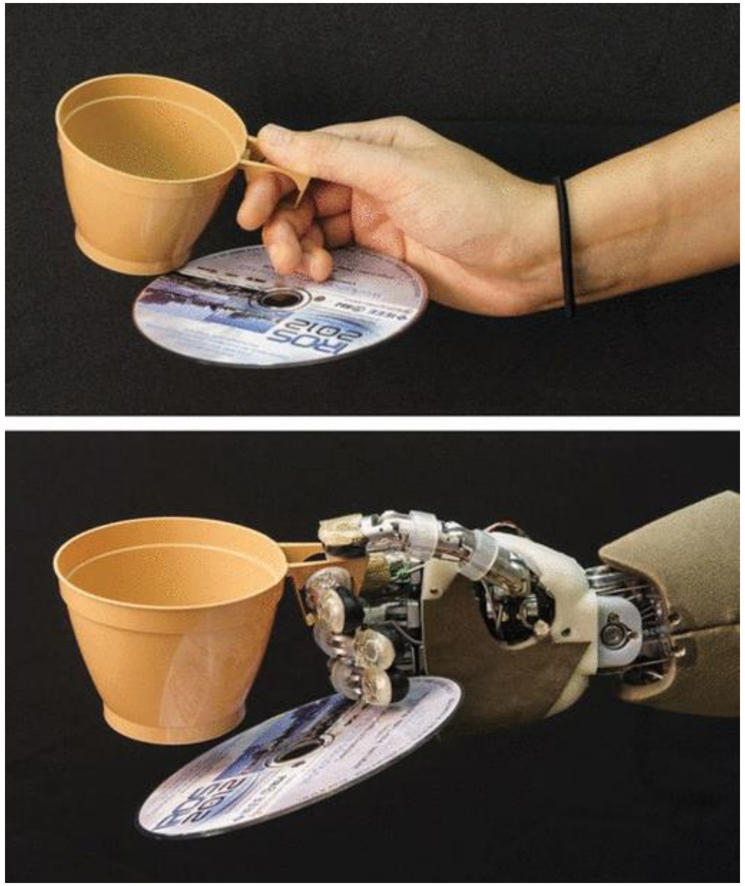
FewSOL: A Dataset for Few-Shot Object Learning in Robotic Environments
Jishnu Jaykumar P, Yu-Wei Chao, Yu Xiang. ICRA, 2023.

Few-Shot Object Recognition



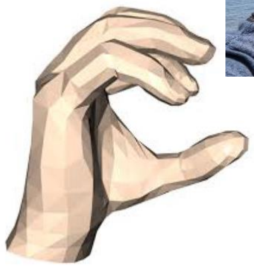
Object-Centric Grasp Transfer

Grasp Transfer



Barrett

Allegro



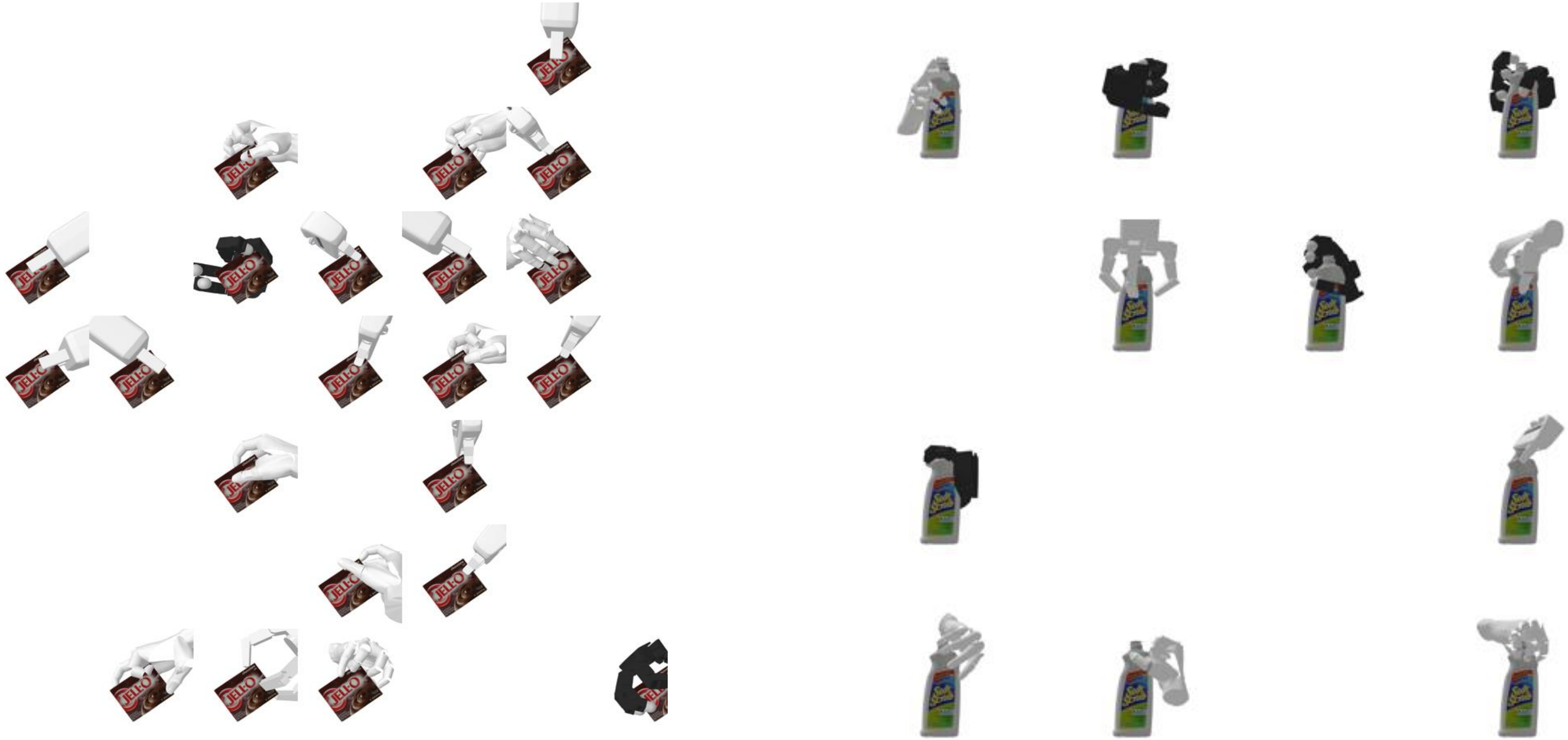
Human Hand

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

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!