

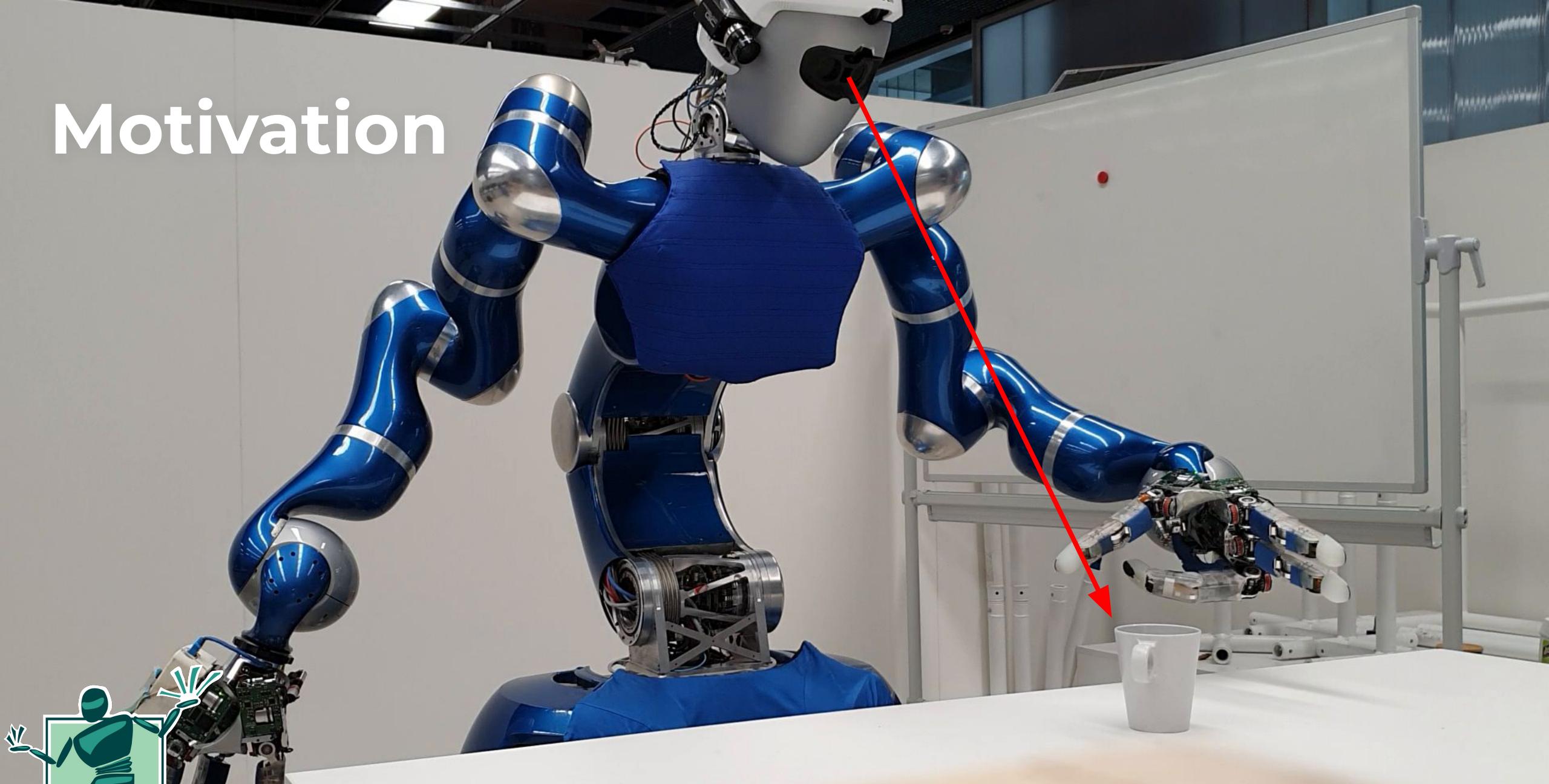
# Shape Completion with Prediction of Uncertain Regions

Matthias Humt, Dominik Winkelbauer and Ulrich Hillenbrand

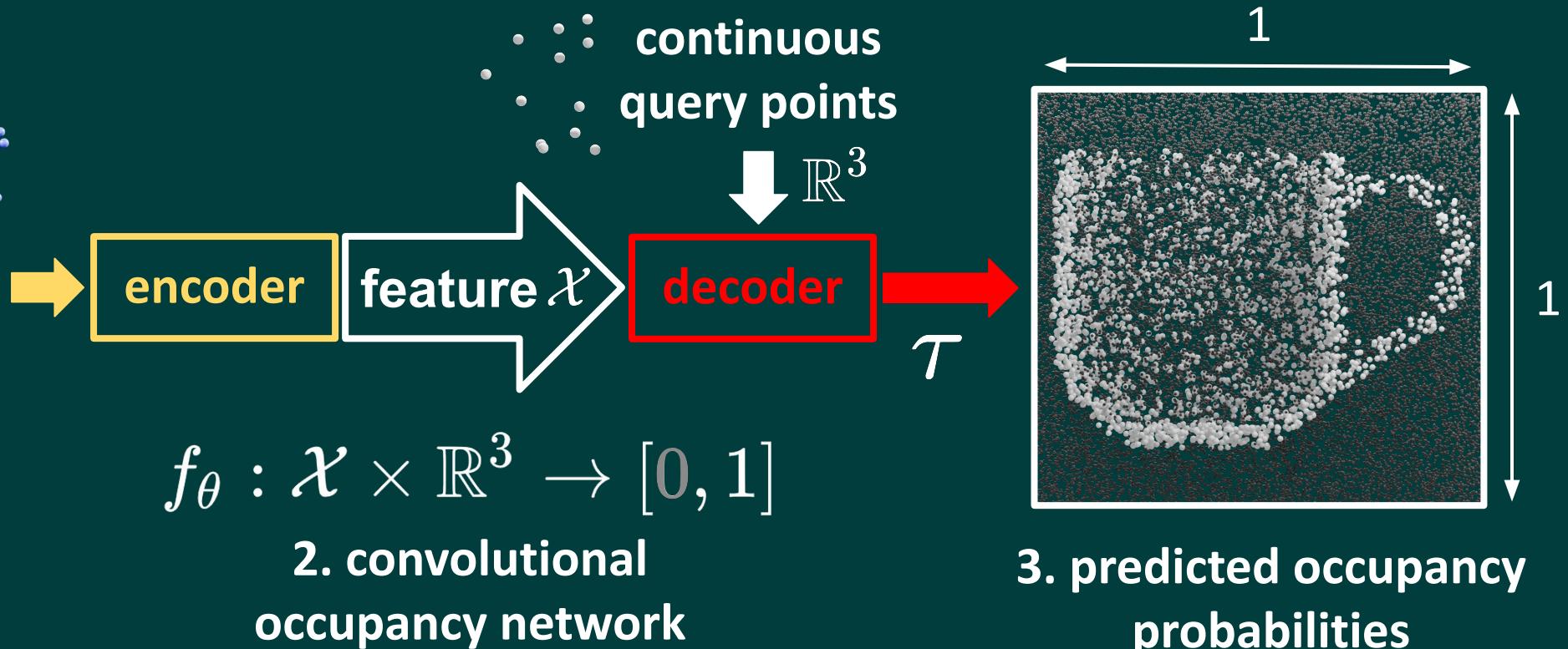
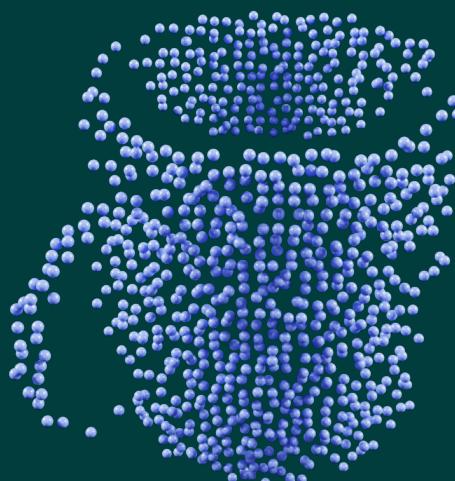


**Deutsches Zentrum  
für Luft- und Raumfahrt**  
German Aerospace Center

# Motivation

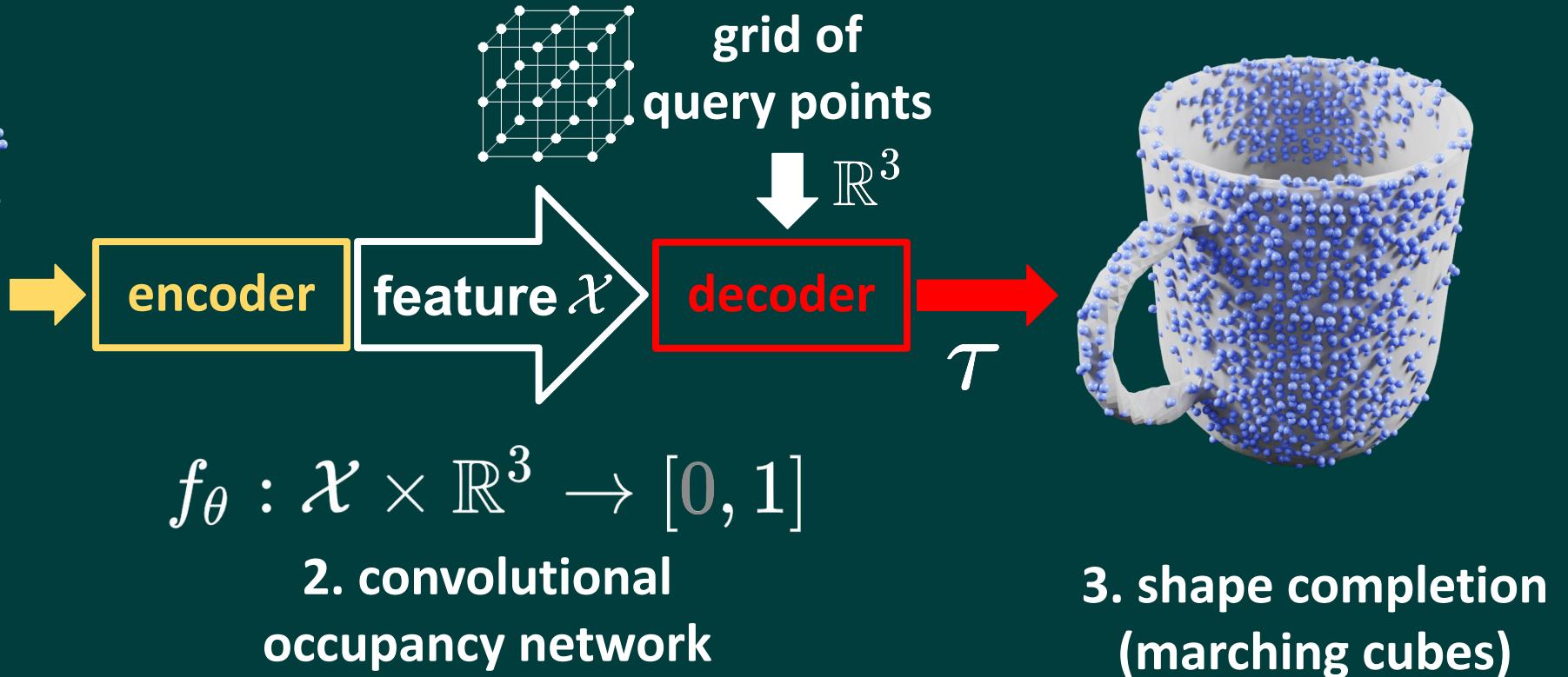
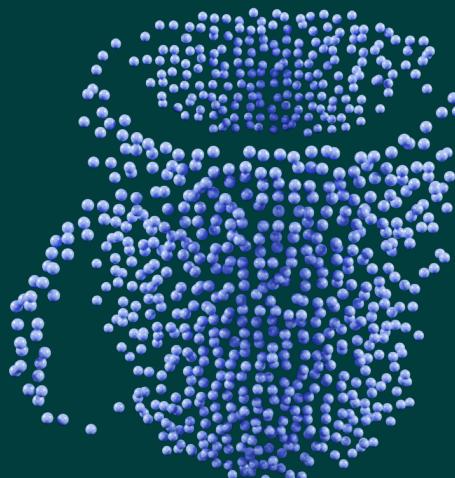


# Shape Completion



[1] [Mescheder et al.: Occupancy Networks: Learning 3D Reconstruction in Function Space](#)  
[2] [Peng et al.: Convolutional Occupancy Networks](#)

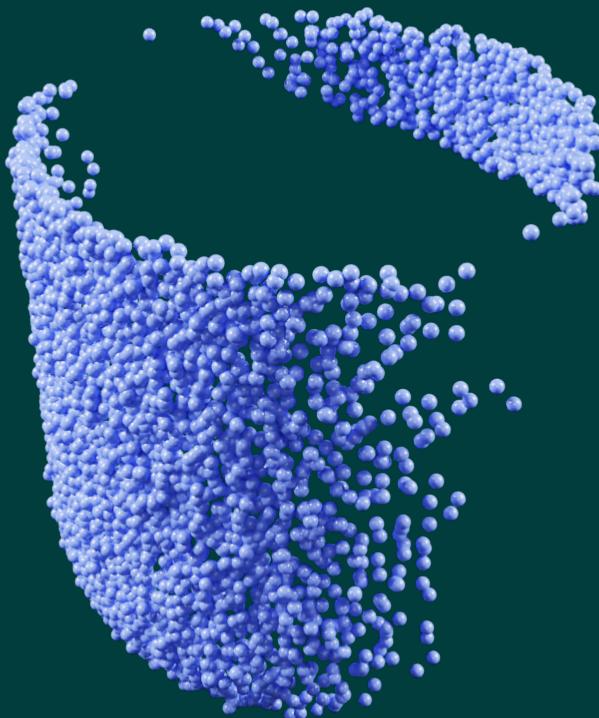
# Shape Completion



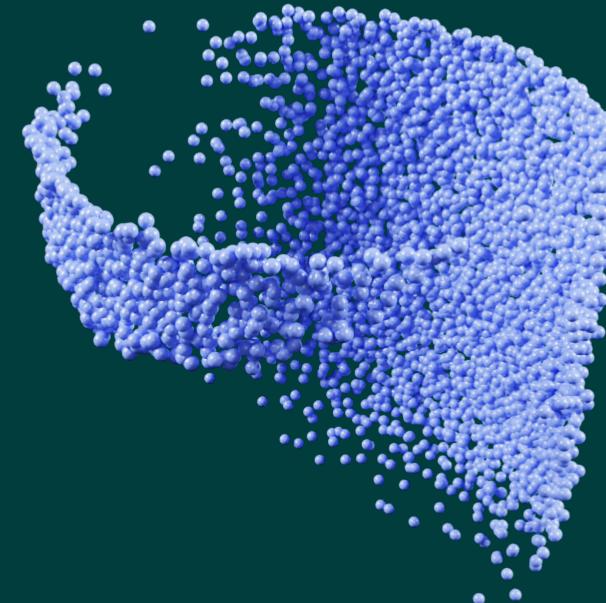
[1] [Mescheder et al.: Occupancy Networks: Learning 3D Reconstruction in Function Space](#)

[2] [Peng et al.: Convolutional Occupancy Networks](#)

# Motivation: Pose Ambiguity



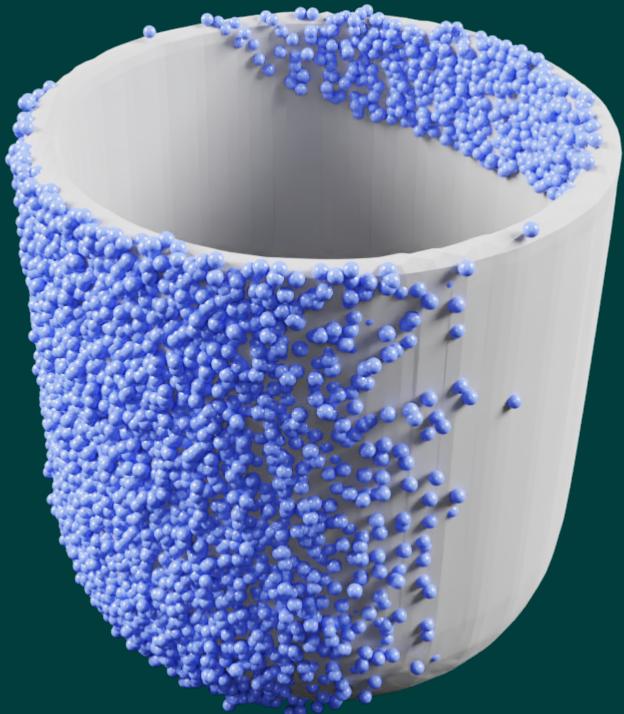
front view



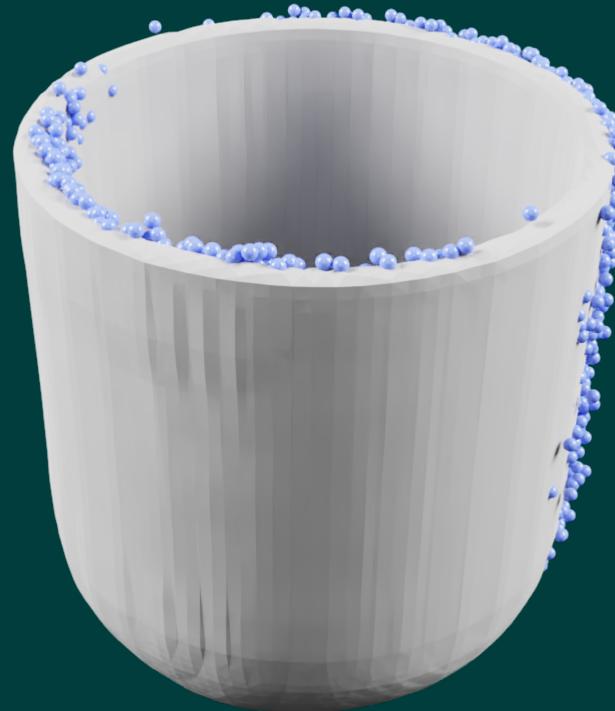
back view



# Motivation: Pose Ambiguity

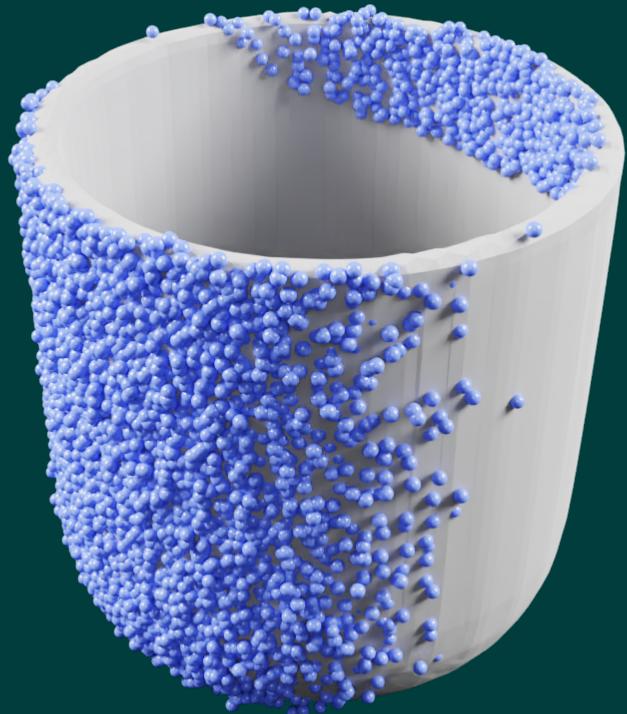


front view

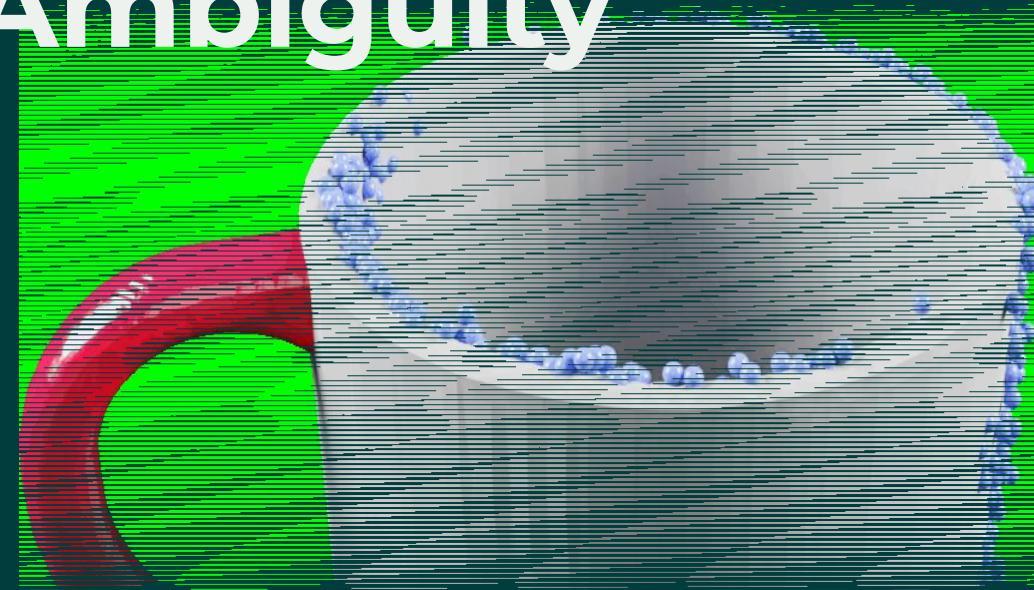


back view

# Motivation: Pose Ambiguity



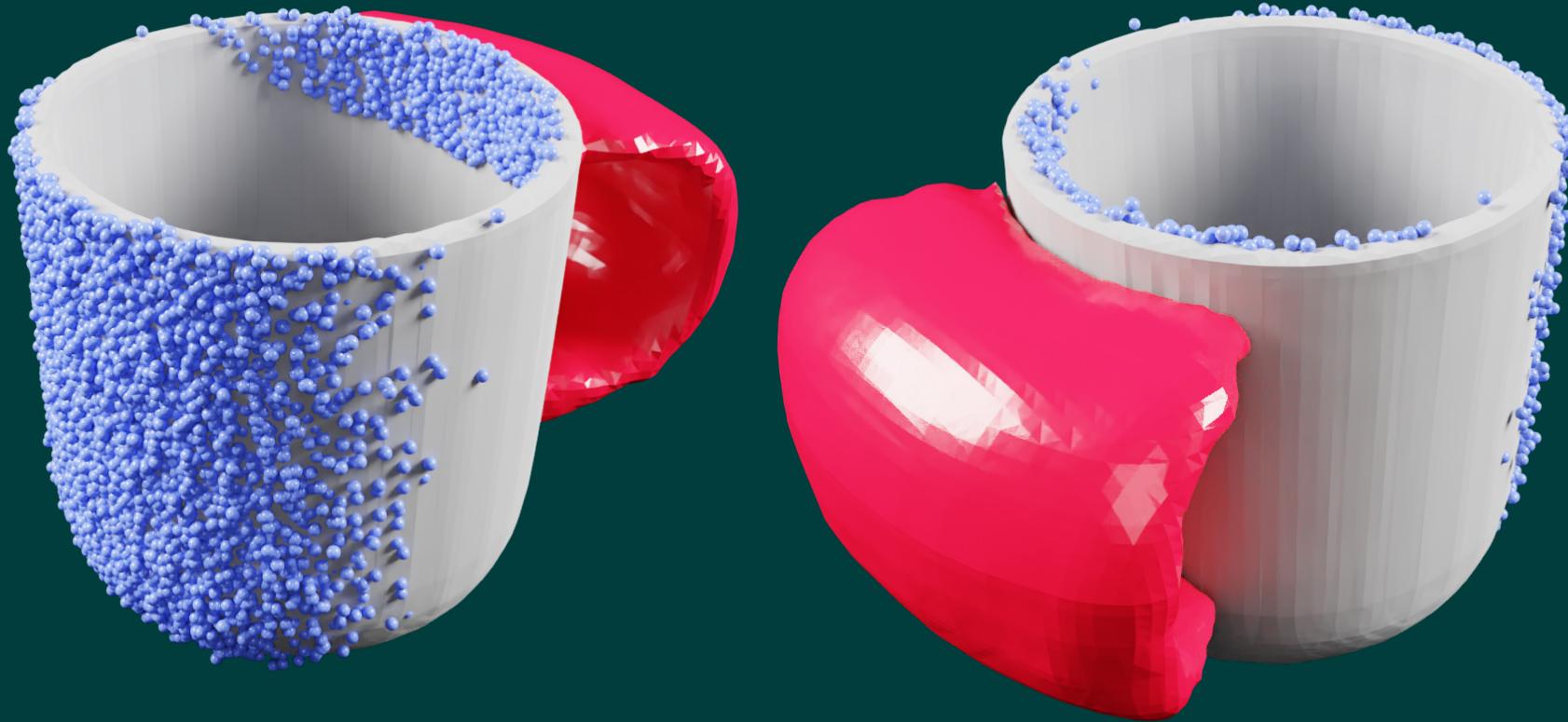
front view



back view



# Motivation: Uncertain Regions



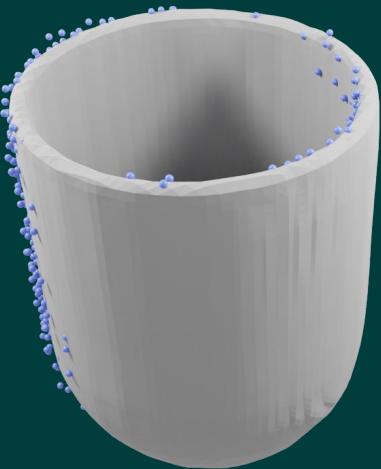
front view

back view

# Approach 1: Gradient Threshold



ground truth



predicted occupied

$$\tau_{\text{occ}} = 0.5$$



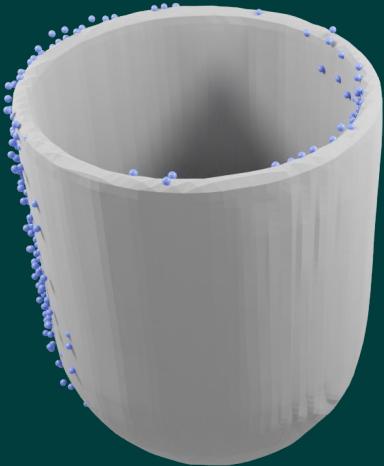
predicted **uncertain**

$$\tau_{\text{min}} < \tau_{\text{max}} \leq \tau_{\text{occ}}$$

# Approach 1: Gradient Threshold



ground truth



predicted occupied

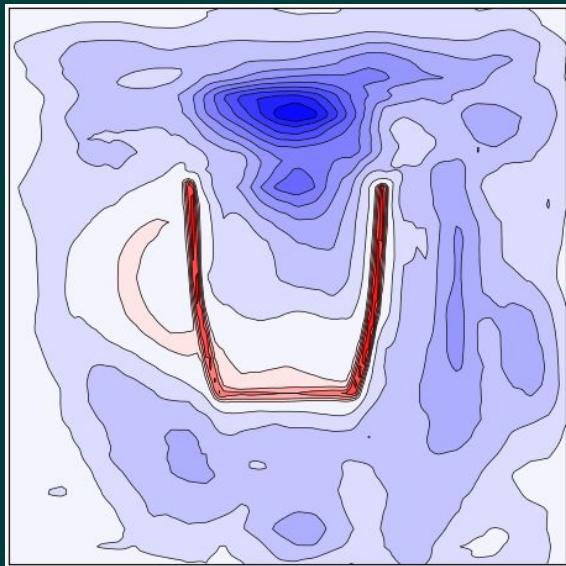
$$\tau_{\text{occ}} = 0.5$$



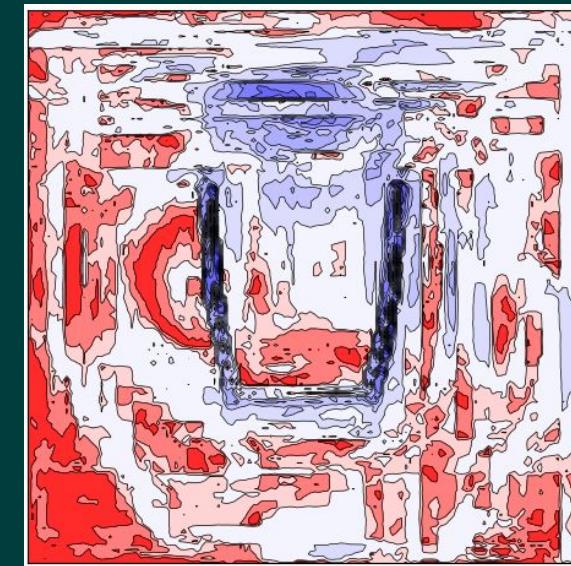
predicted **uncertain**

$$\tau_{\text{min}} < \tau_{\text{max}} \leq \tau_{\text{occ}}$$

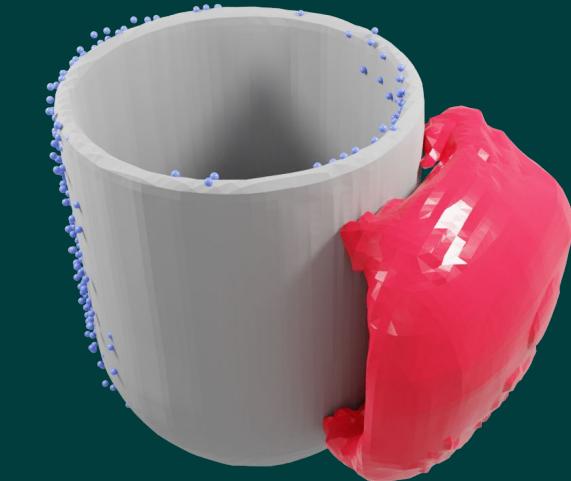
# Approach 1: Gradient Threshold



a: predicted occupancy probability



b: gradient magnitude of (a) w.r.t. the query

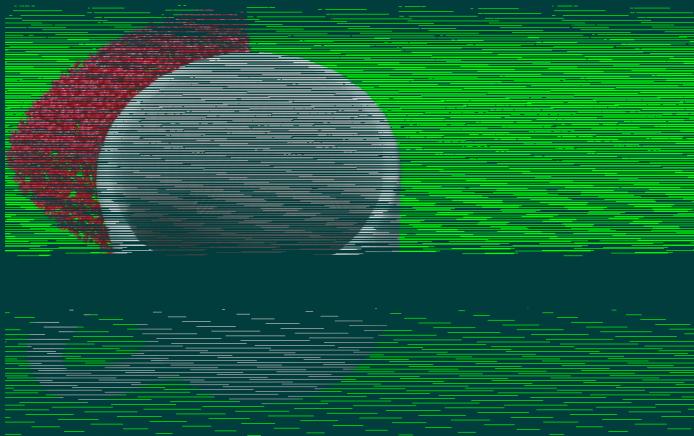


c: shape completion & uncertain region

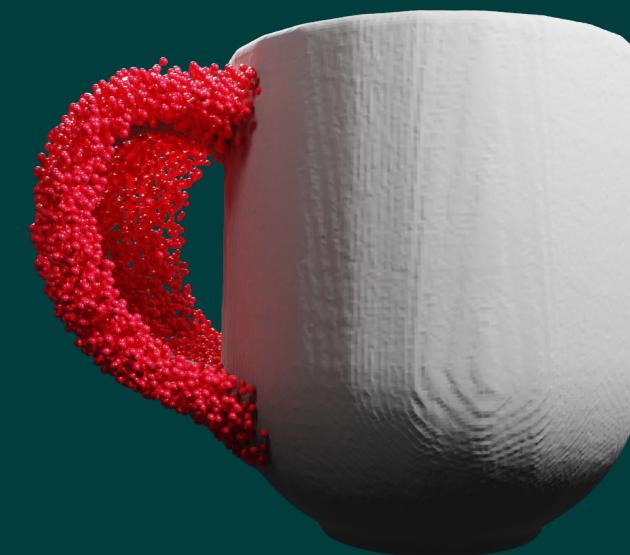


$$\forall q \in \mathcal{Q} : \parallel \nabla_q \sum_{i=1}^N \hat{y}_i \parallel < \frac{1}{|\mathcal{Q}|} \sum_{q \in \mathcal{Q}} \parallel \nabla_q \sum_{i=1}^N \hat{y}_i \parallel$$

# Approach 2: Additional Label

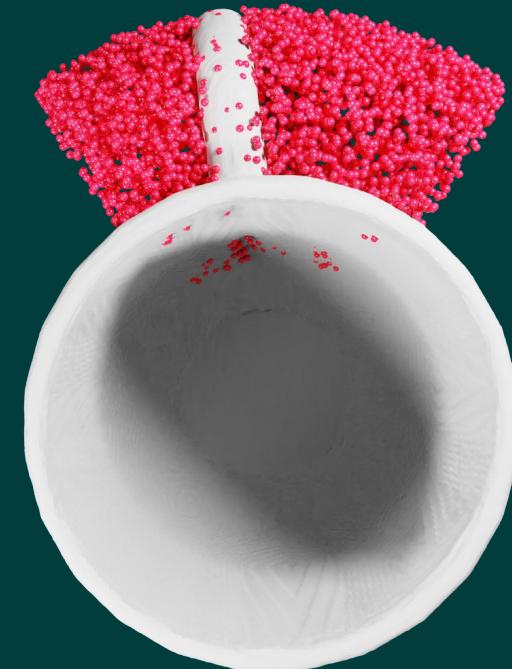


rotations



virtual camera

side view



top view

$$f_{\theta} : \mathcal{X} \times \mathbb{R}^3 \rightarrow [0, 1, 2]$$

# Experiments

1. **Novel View**: Generalize to new viewpoints of known object instances
2. **Novel Instance**: Generalize to new instances of a known class
3. **Sim2Real**: Generalize from simulated to real data



# Evaluation: Metrics

$$IoU = \frac{TP+TN}{TP+TN+FP+FN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



→ harmonic mean between precision & recall

- FN: false negative
- FP: false positive
- TN: true negative
- TP: true positive

confusion matrix

		FN	TN
ground truth	TP		FP

# Evaluation: Grasping

Grasp Collision Risk:

$$GCR = \frac{FN_{occ} + FN_{unc}}{TP_{occ} + FN_{occ} + TP_{unc} + FN_{unc}}$$

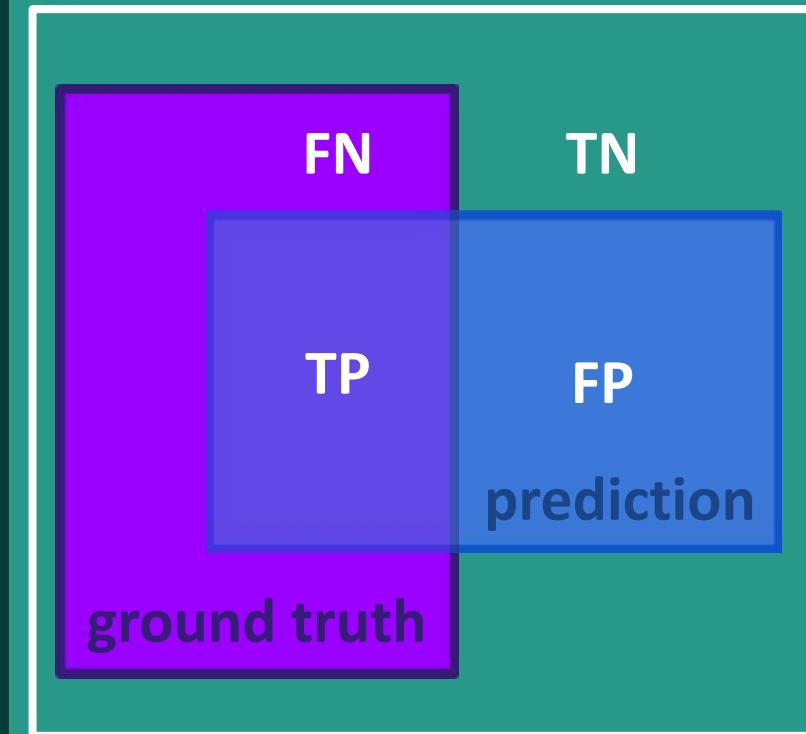
Grasp Miss Risk:

$$GMR = \frac{FP_{occ}}{FP_{occ} + TP_{occ}}$$

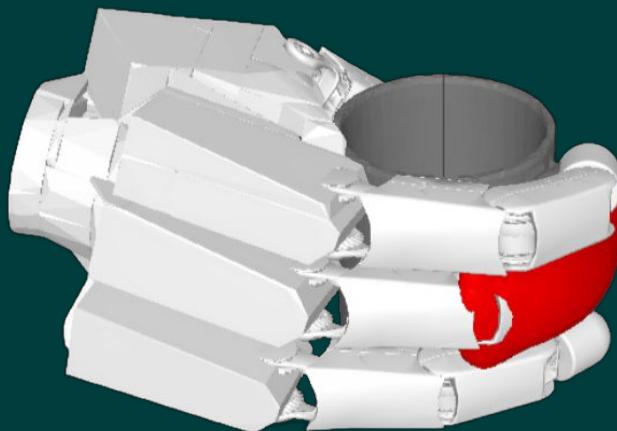
Grasp Exclusion Risk:  $GER = \frac{|\mathcal{FP}_{occ} \cup \mathcal{FP}_{unc}|}{FP_{occ} + TN_{occ}}$



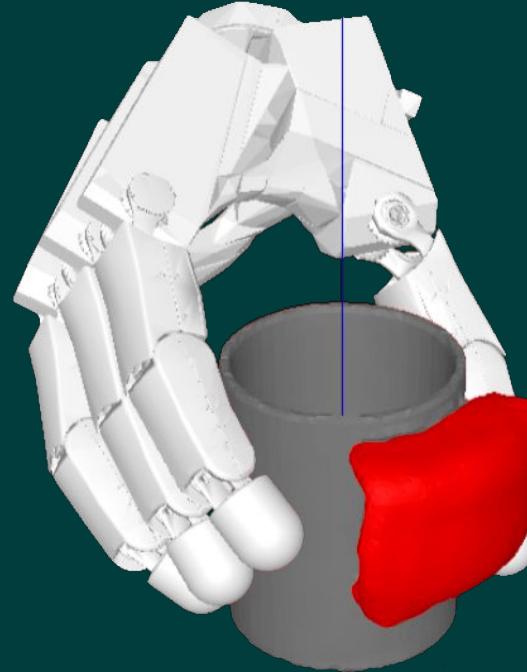
- *occ*: occupied space
  - *unc*: uncertain space
- confusion matrix



# Evaluation: Grasping



ignoring uncertain region



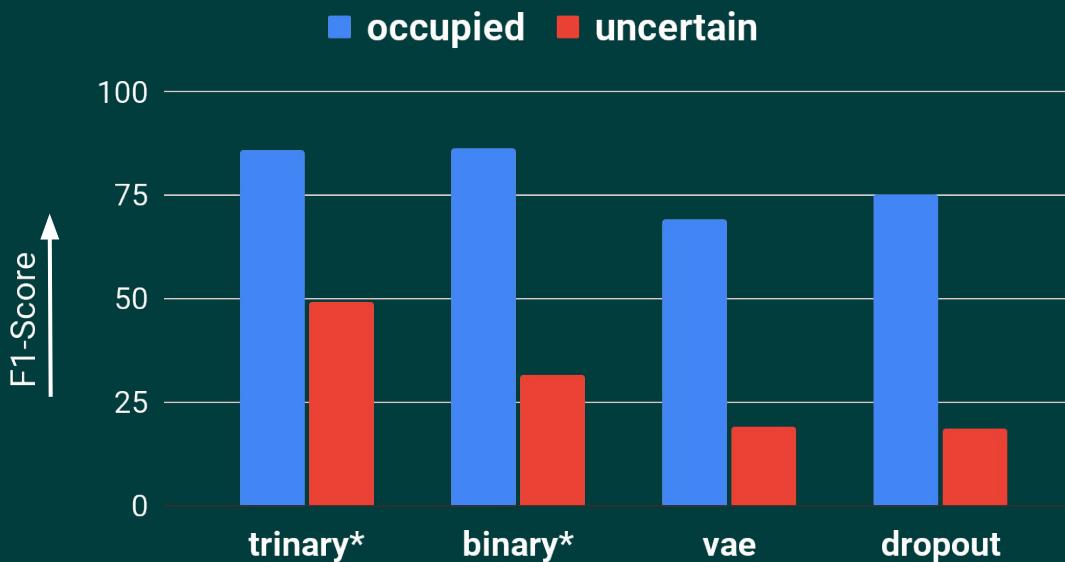
considering uncertain region

**Improved Epsilon Quality metric (IEQ): “*The minimal external force applied to the ground truth object mesh that would break the grasp.*”**

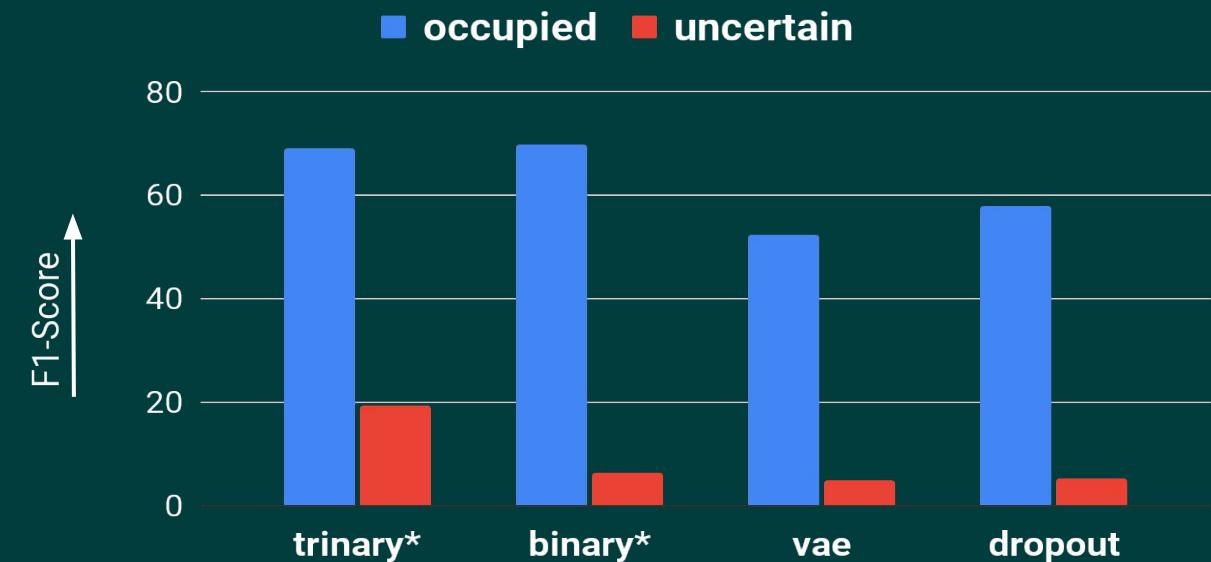
[3] Winkelbauer et al.: A two-stage learning architecture that generates high-quality grasps for a multi-fingered hand

# Results: Novel View & Instance

Novel View - F1



Novel Instance - F1

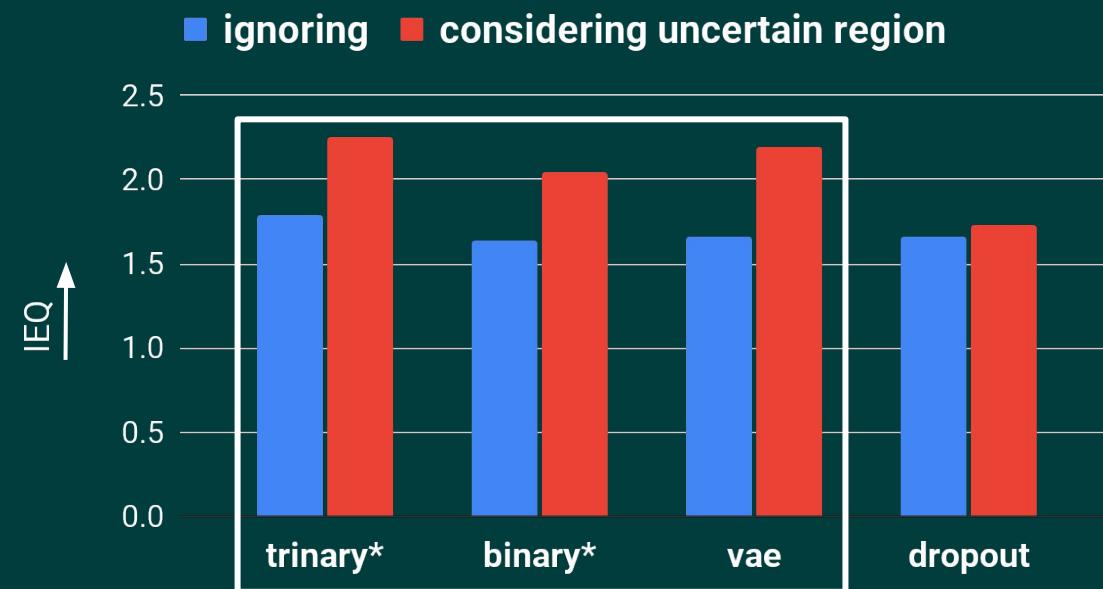


F1-Score

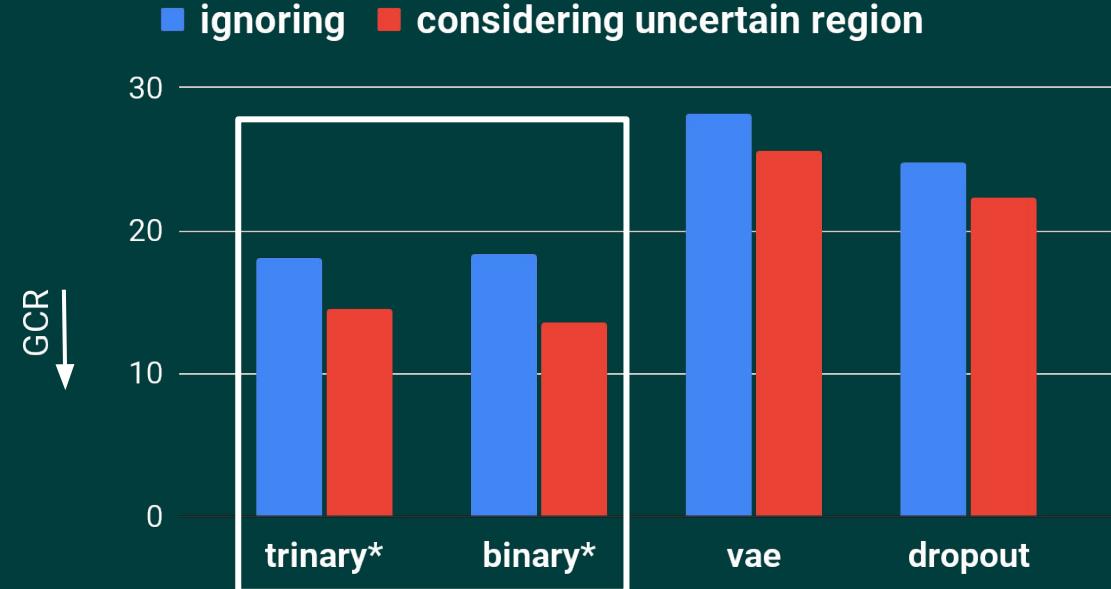
\*ours

# Results: Novel View Grasping

Novel View - IEQ



Novel View - GCR



Improved  $\epsilon$ -Quality



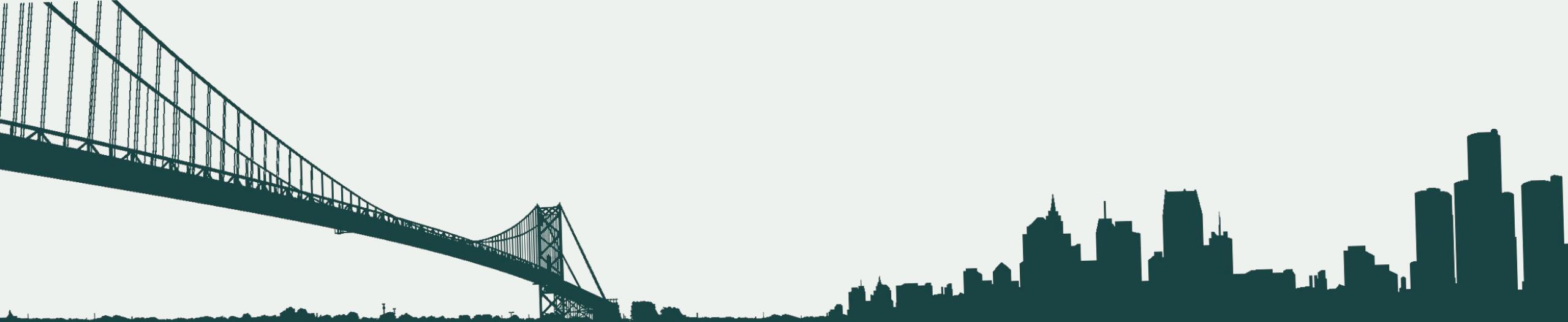
\*ours

# Qualitative Sim2Real Results: Trinary



# Qualitative Sim2Real Results: Binary





# Thank you for your attention!

## Paper



<https://arxiv.org/abs/2308.00377>

## Code & Dataset



<https://github.com/DLR-RM/shape-completion>

## Poster: MoAIP-12.9

