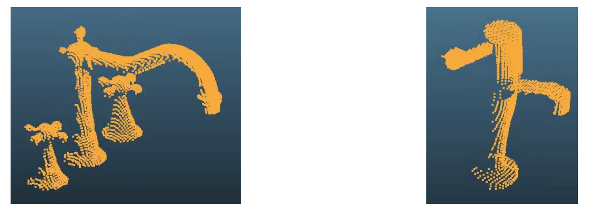
PointPatchRL: Masked Reconstruction Improves RL on Point Clouds

Balázs Gyenes[1] Nikolai Franke[1] Philipp Becker[1] Gerhard Neumann[1]

[1]Autonomous Learning Robots, Karlsruhe Institute of Technology, Karlsruhe

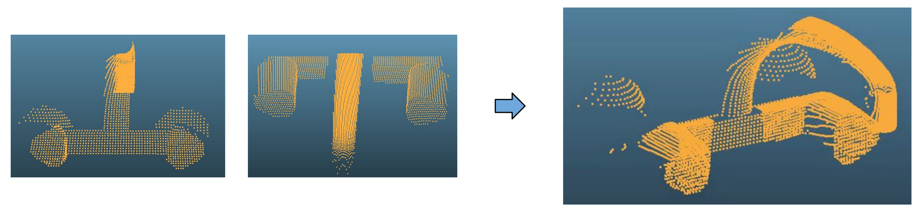
Point Clouds

- capture **task-relevant geometry** of deformable or varying objects



- disentangle **occlusions** in 3D space

- combine **multiple camera** views



Method

(see also main figure)

PointPatchRL builds on point patching paradigm of PointMAE and PointGPT

1. Split point clouds into (overlapping) **patches**

$$C = \text{fps}(X), \quad C \in \mathbb{R}^{n \times 3}$$

$$P = \text{knn}(X, C), \quad P \in \mathbb{R}^{n \times k \times 3}$$

2. Convert each patch into a **token** and add **positional encoding**
3. Copy tokens and **mask** some of them
4. **Encode** both sequences with Transformer layers
5. Compute feature vector using **sequence pooling**, use MLPs to predict value and policy, and compute **SAC critic and actor** losses
6. **Decode** masked sequence
7. Reconstruct point cloud. Loss is chamfer distance for positions and MSE for colors

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} d_{\text{CD}}(P_i^{\text{pd}}, P_i^{\text{gt}}) + \mathcal{L}^{\text{rgb}}(P_i^{pd}, P_i^{\text{gt}})$$

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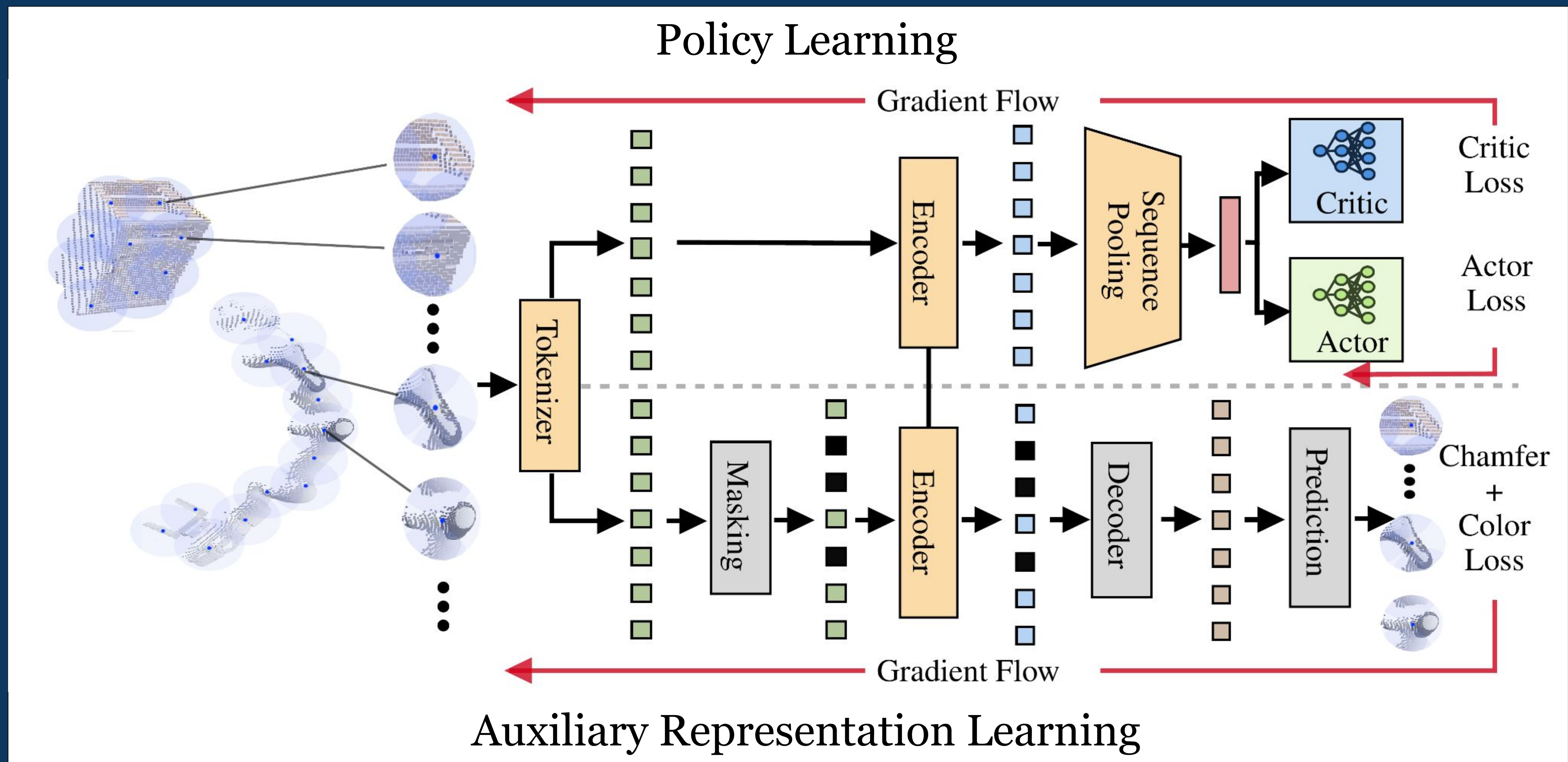
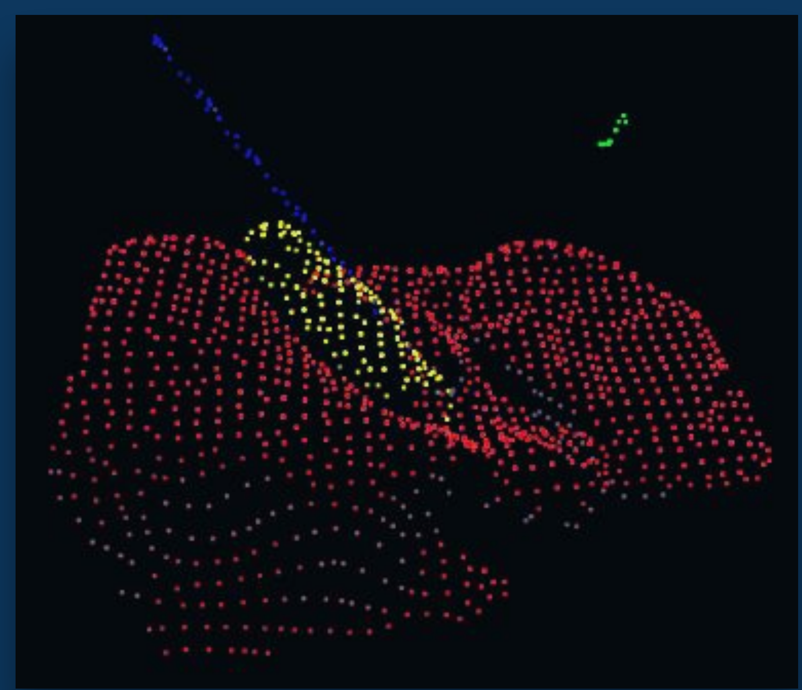
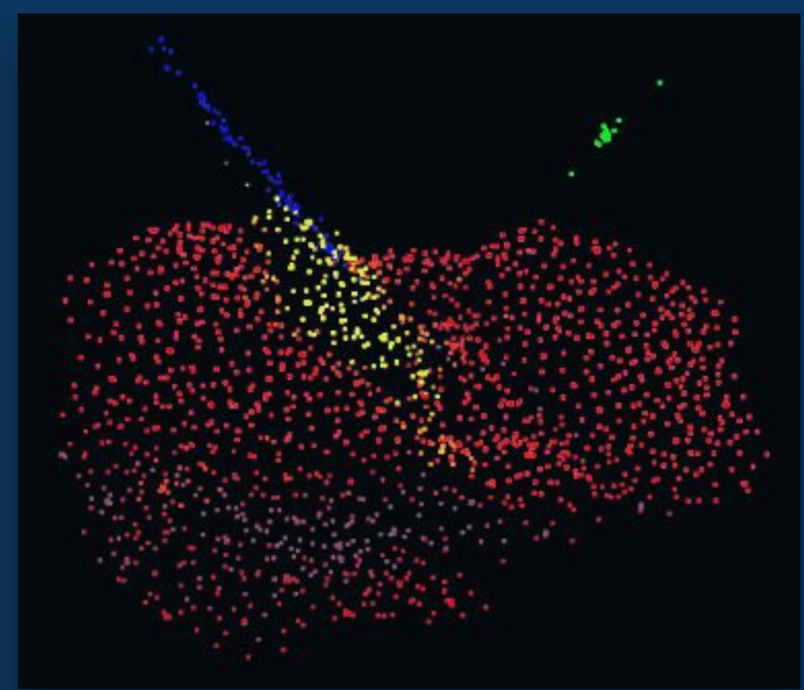




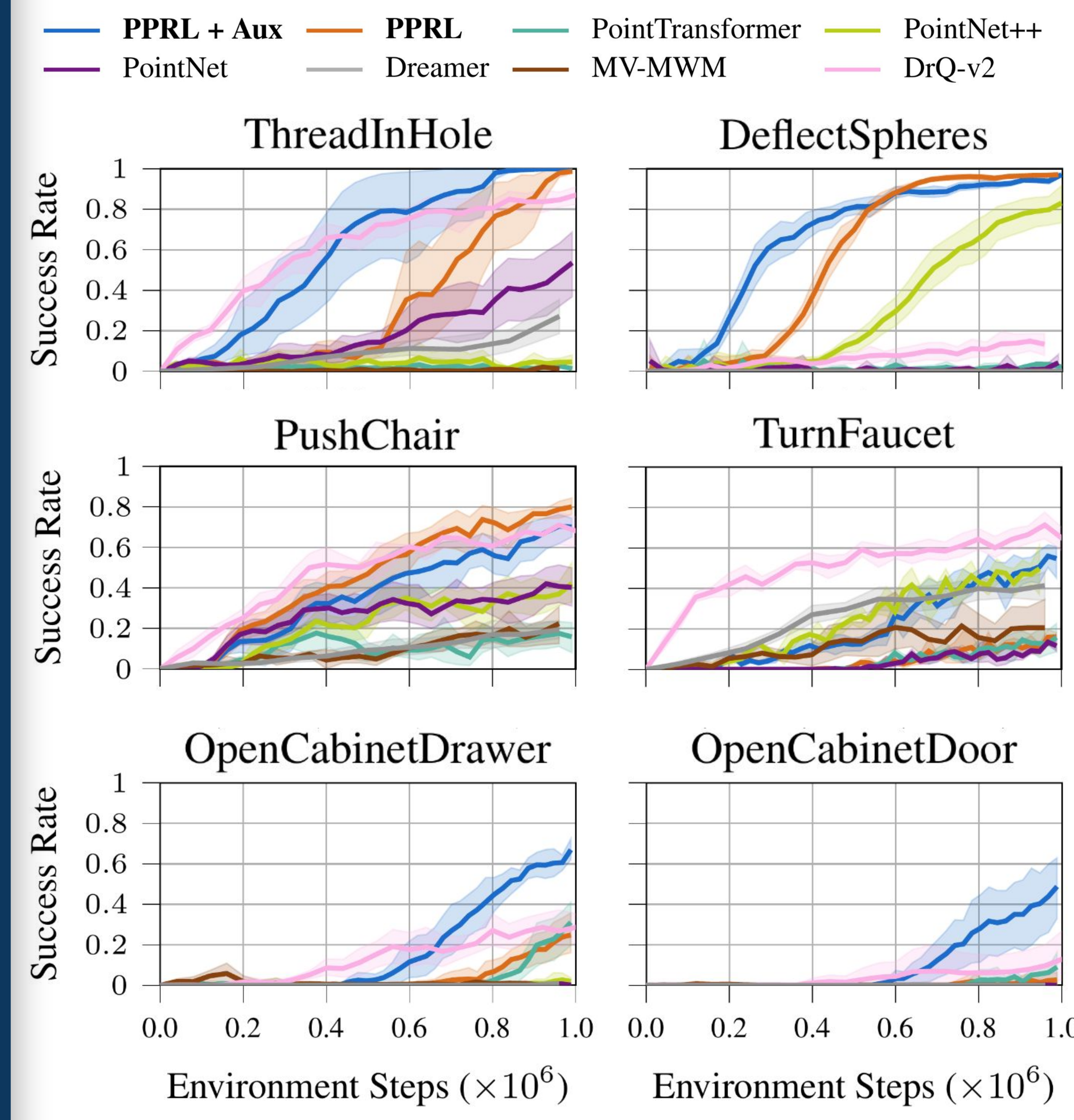
Ground Truth



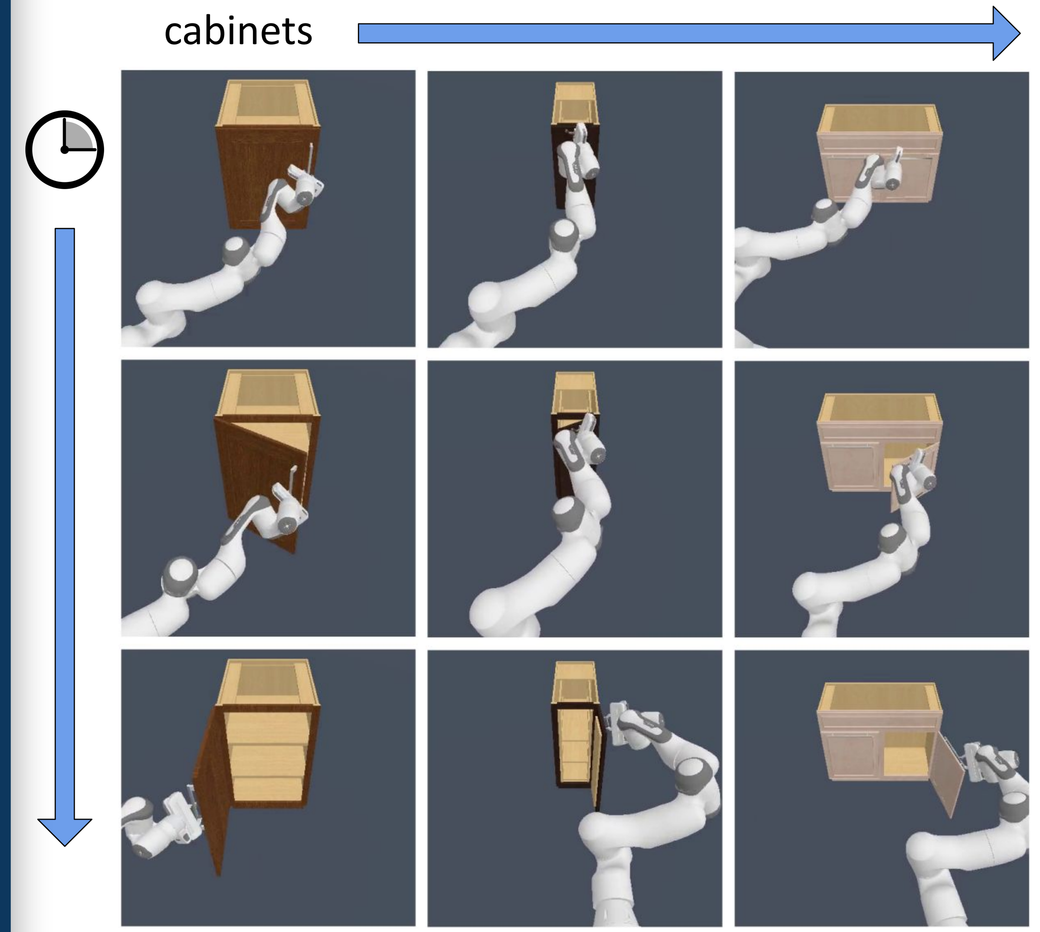
Reconstruction

Experiments

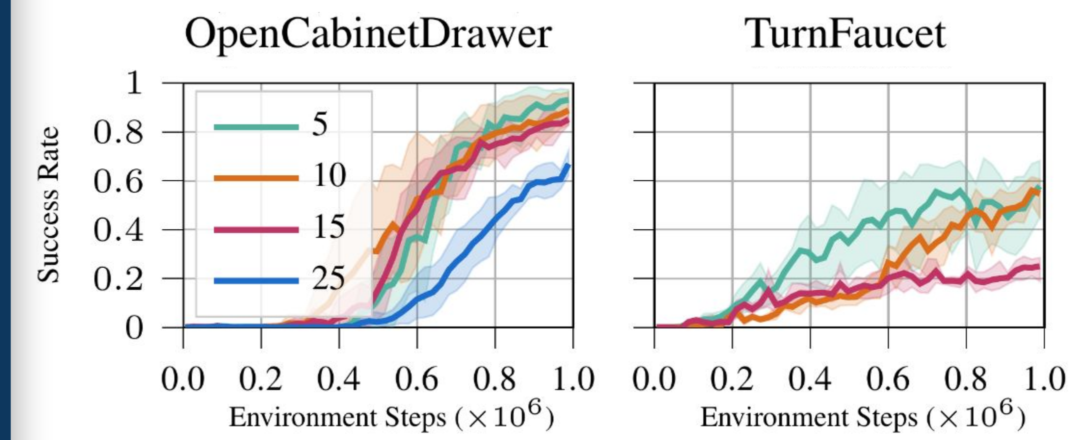
Favourable performance on challenging tasks compared to baselines



Diverse strategies conditioned on object geometry (same policy for each)



Encoder has sufficient capacity to handle more models - up to a critical point



- Train and test agents on increasing numbers of object models [5,10,15,25]