

Navigating to Objects in the Real World



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Unseen environment: No experience, No map

Inputs

Toilet

Goal Category

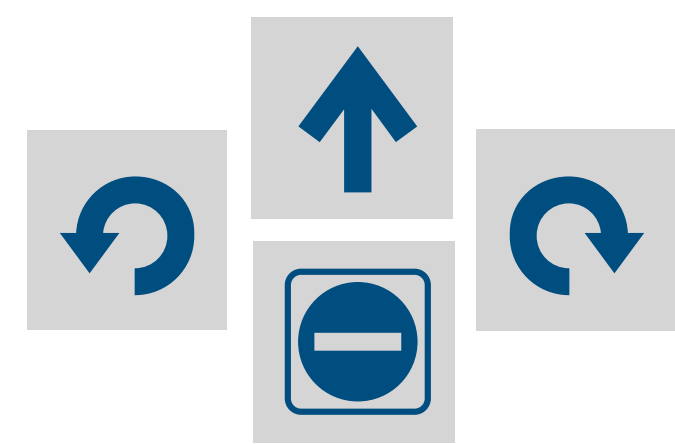


Observation
(RGBD)

(x, y, θ)

Pose Sensor

Output



Action

Spatial Scene Understanding

Navigable Space Detection



Spatial Scene Understanding
Navigable Space Detection

Semantic Scene Understanding
Object Detection

Chair

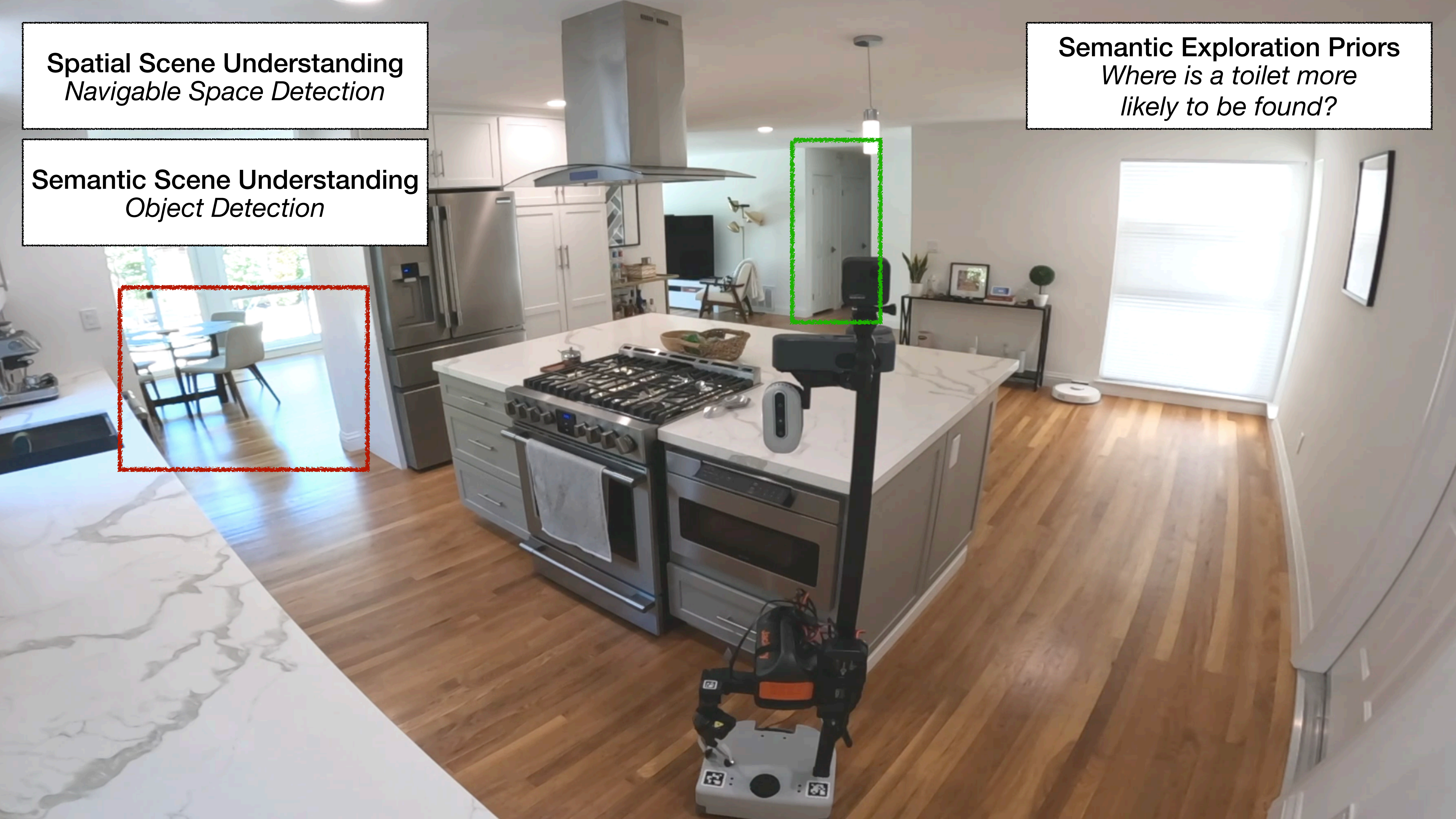
Oven



Spatial Scene Understanding
Navigable Space Detection

Semantic Scene Understanding
Object Detection

Semantic Exploration Priors
Where is a toilet more likely to be found?



Spatial Scene Understanding
Navigable Space Detection

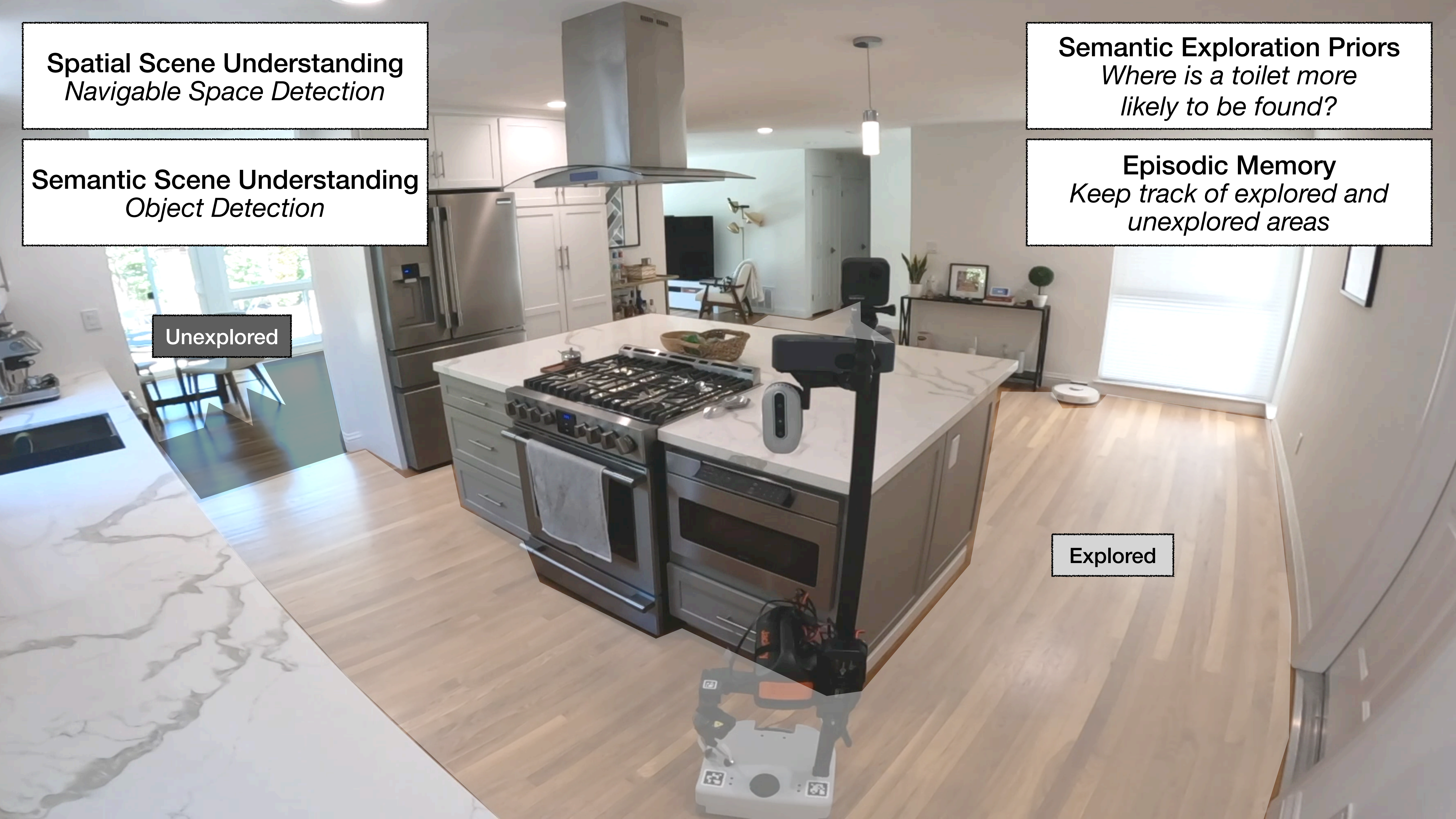
Semantic Scene Understanding
Object Detection

Semantic Exploration Priors
Where is a toilet more likely to be found?

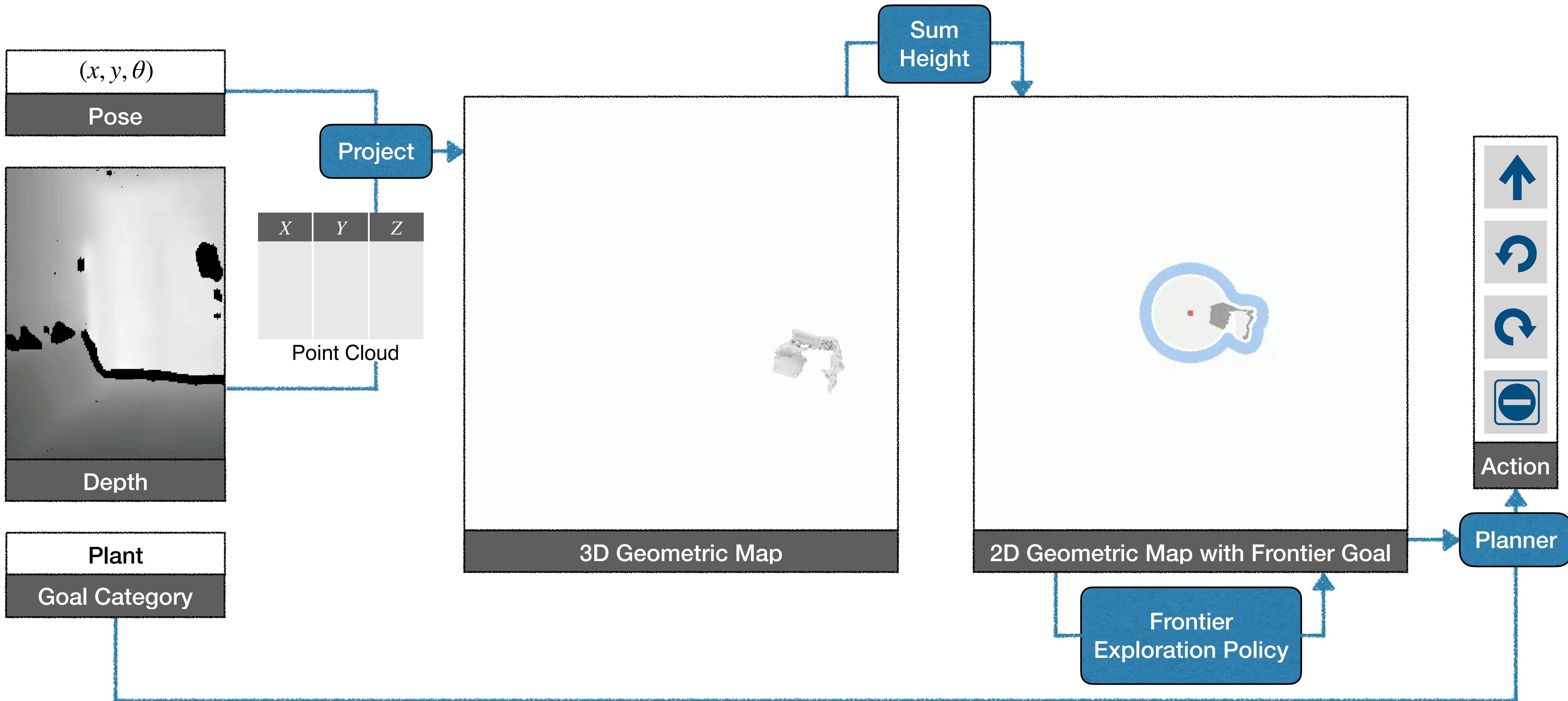
Episodic Memory
Keep track of explored and unexplored areas

Unexplored

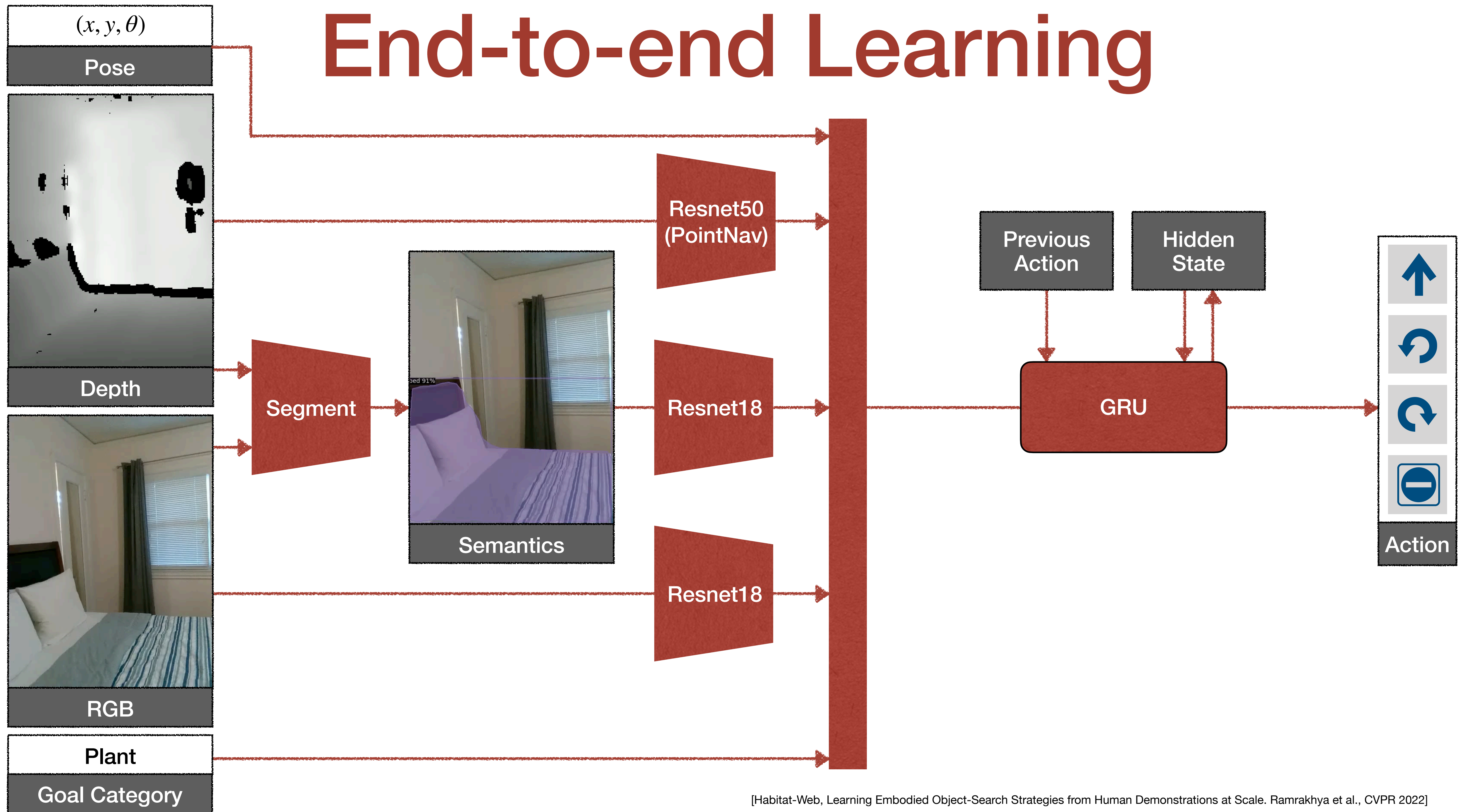
Explored



Classical Navigation

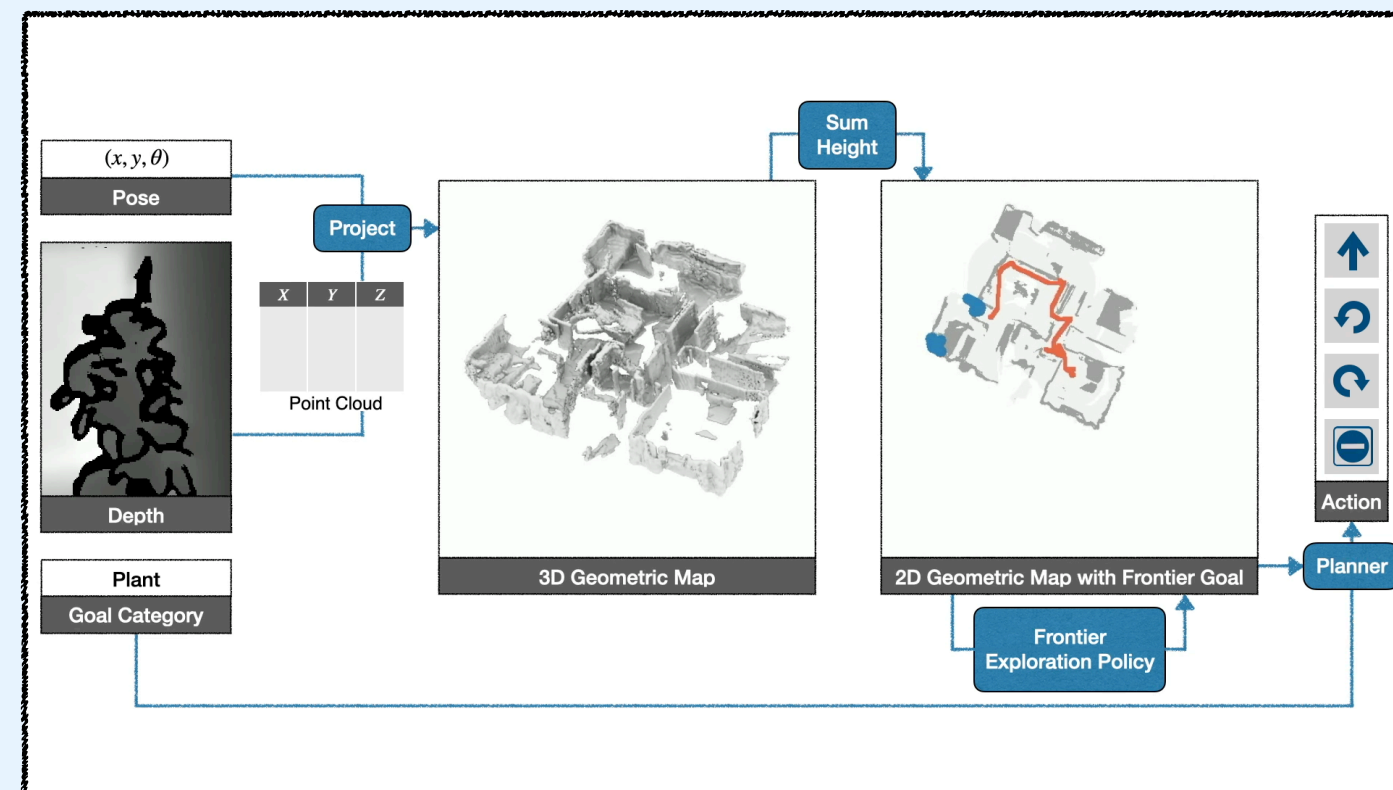


End-to-end Learning



Modular Learning

Classical

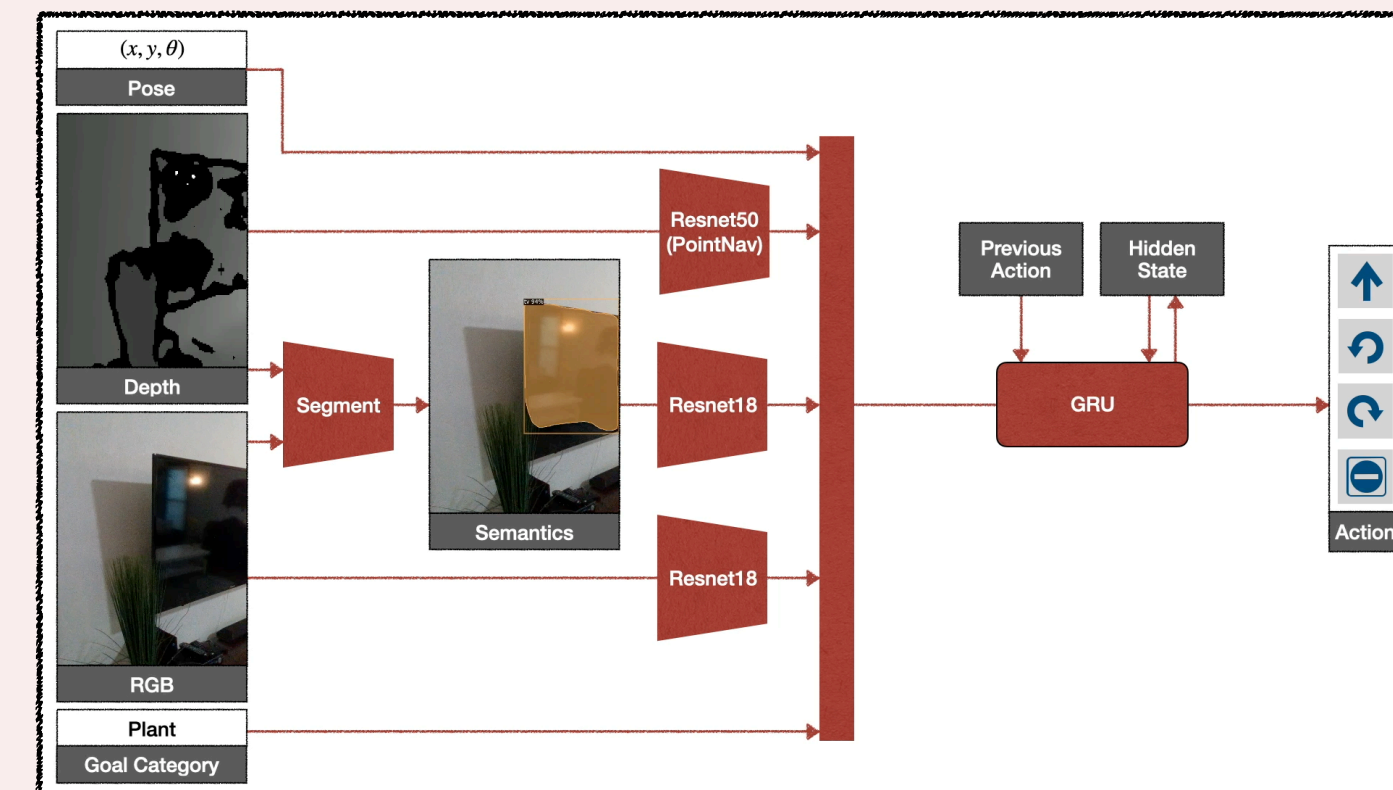


- ▶ Modular
- ▶ Explicit Memory/Maps & Planning
- ▶ Heuristic Policy

+ Long-term Memory and Planning

- Semantic Exploration Priors

End-to-end Learning

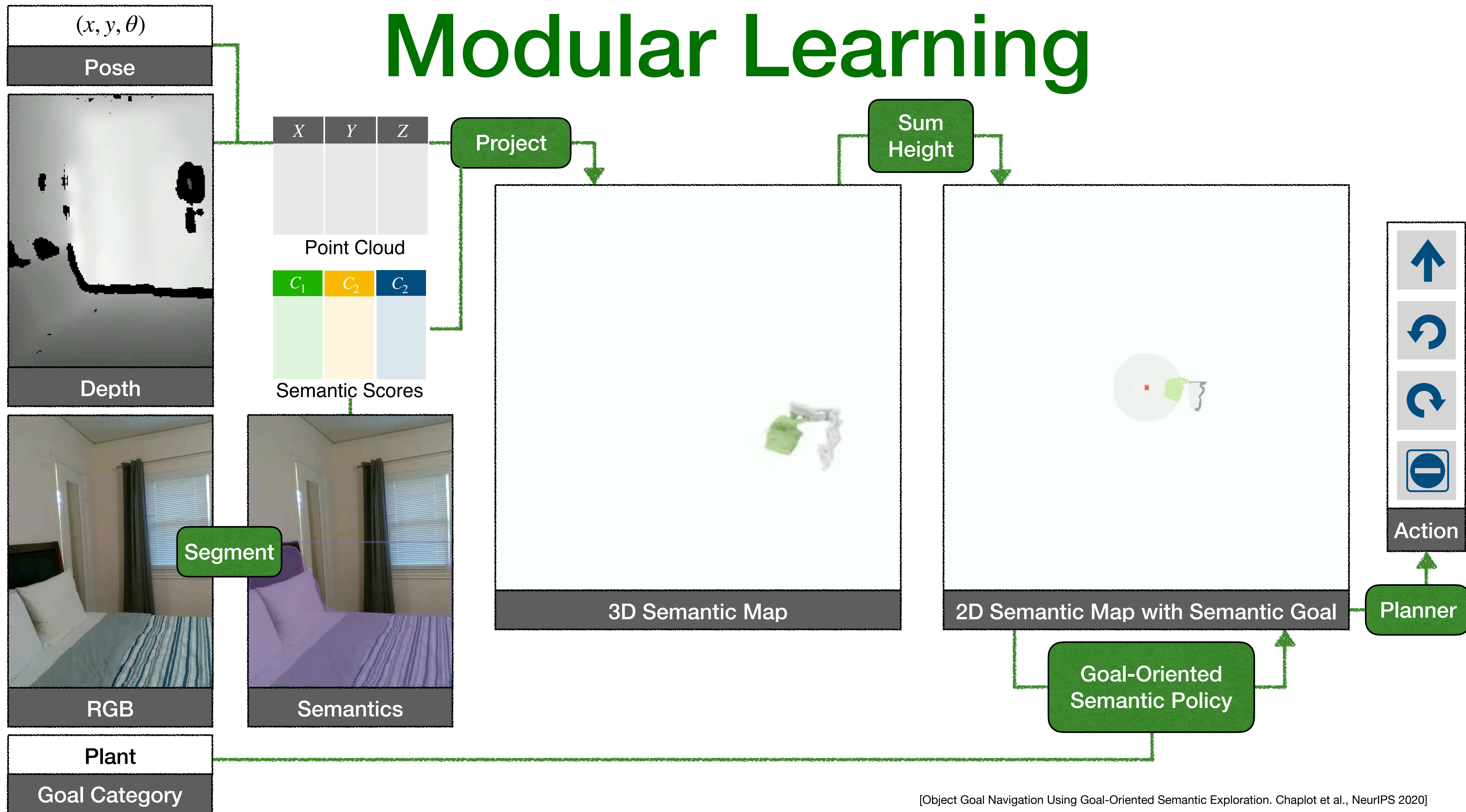


- ▶ End-to-end
- ▶ Implicit Memory & Planning
- ▶ Learned Policy

- Long-term Memory and Planning

+ Semantic Exploration Priors

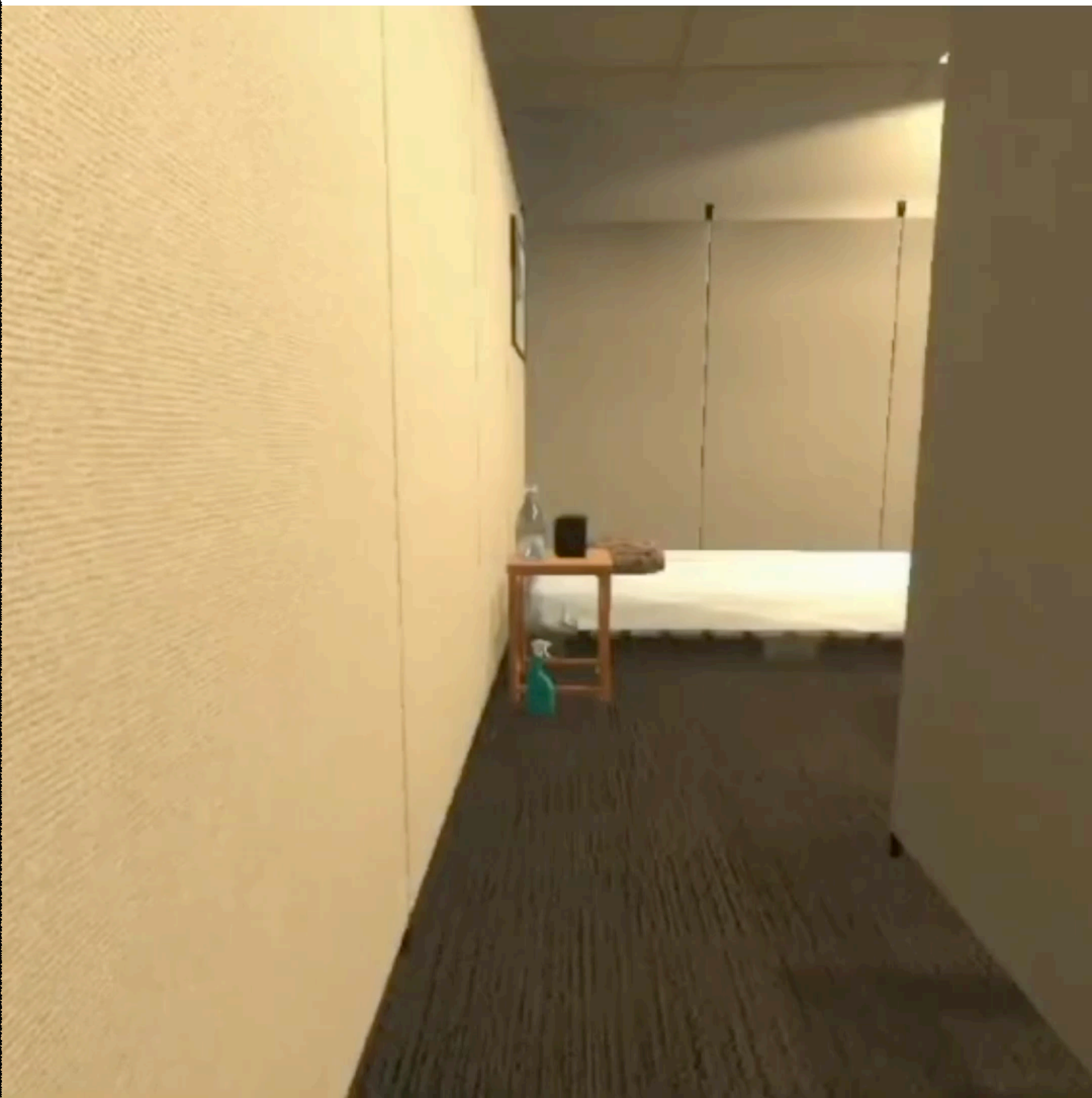
Modular Learning



Habitat

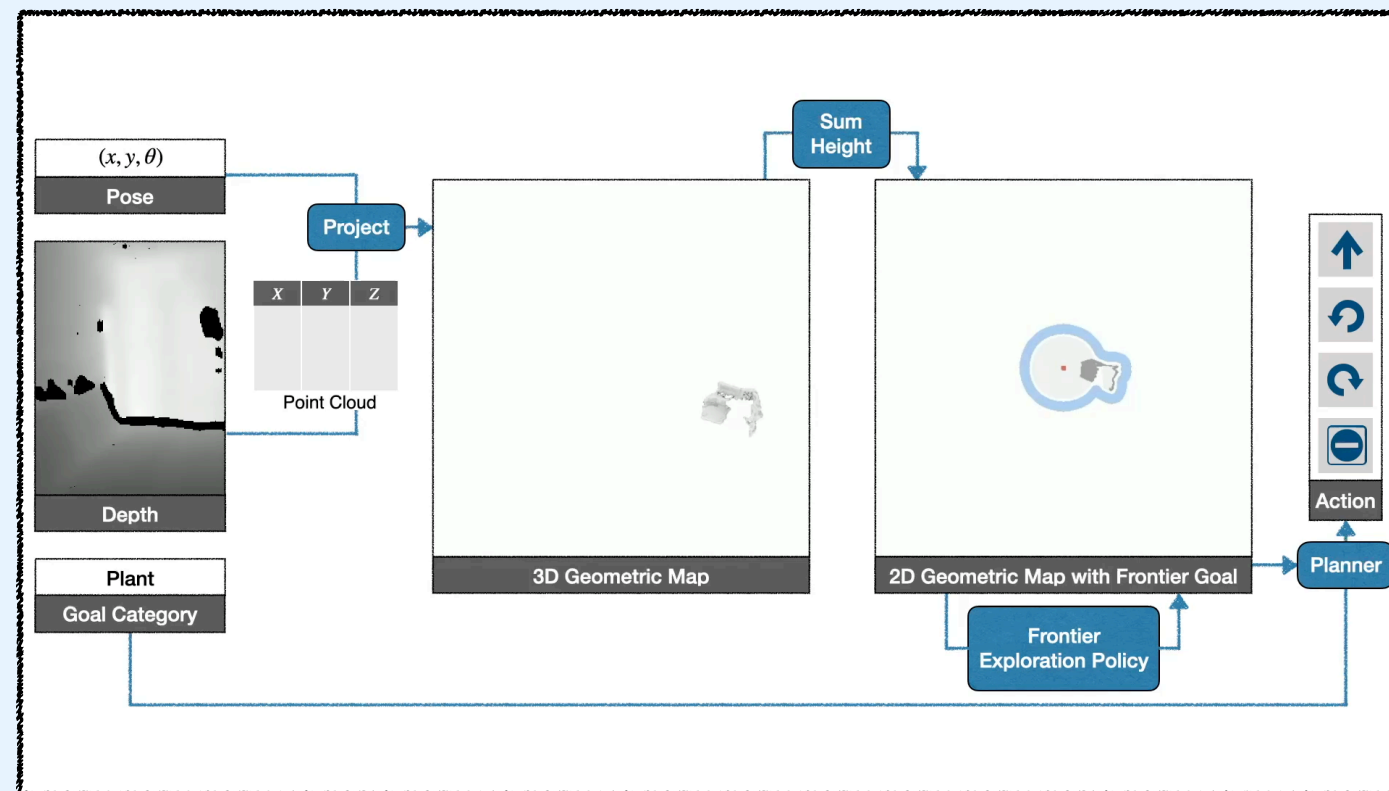


AI2-Thor



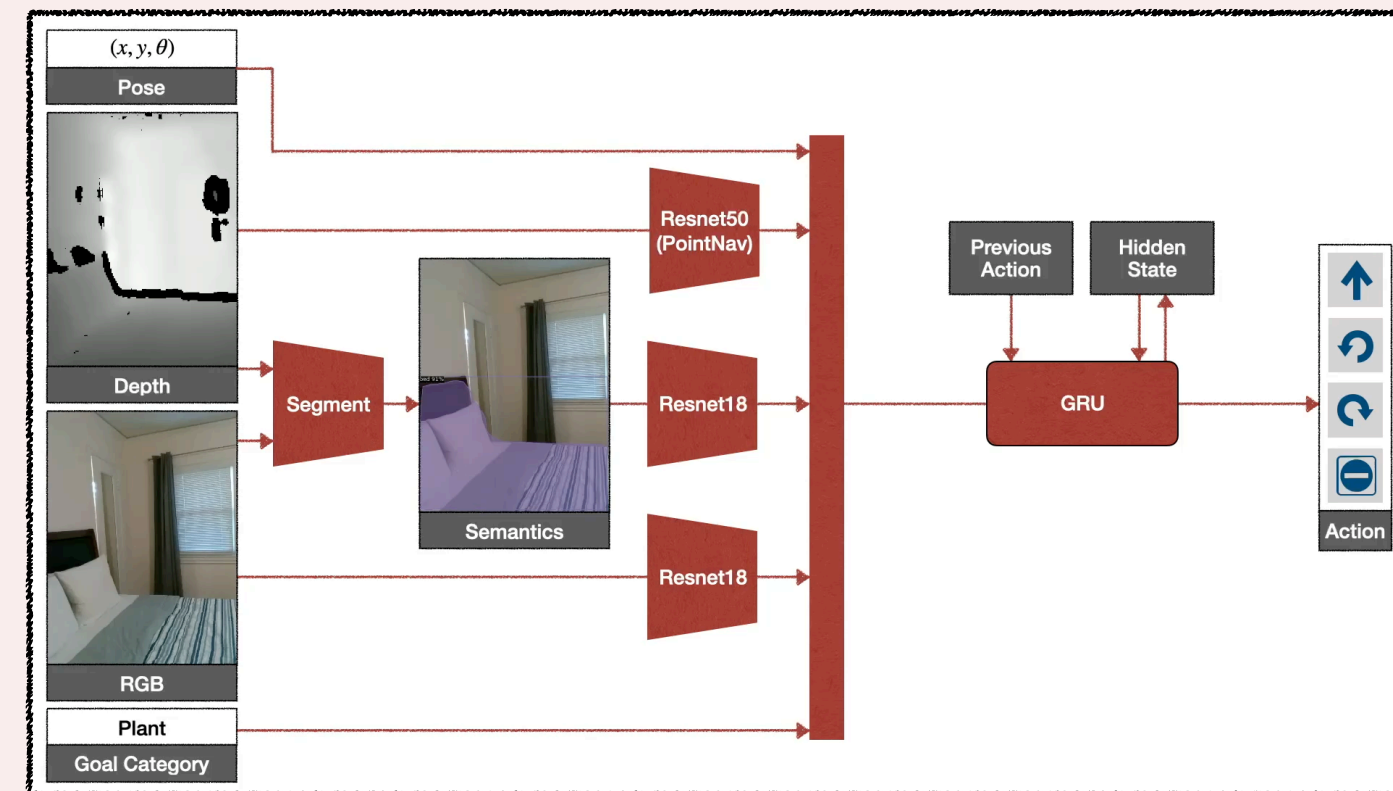
Methods

Classical



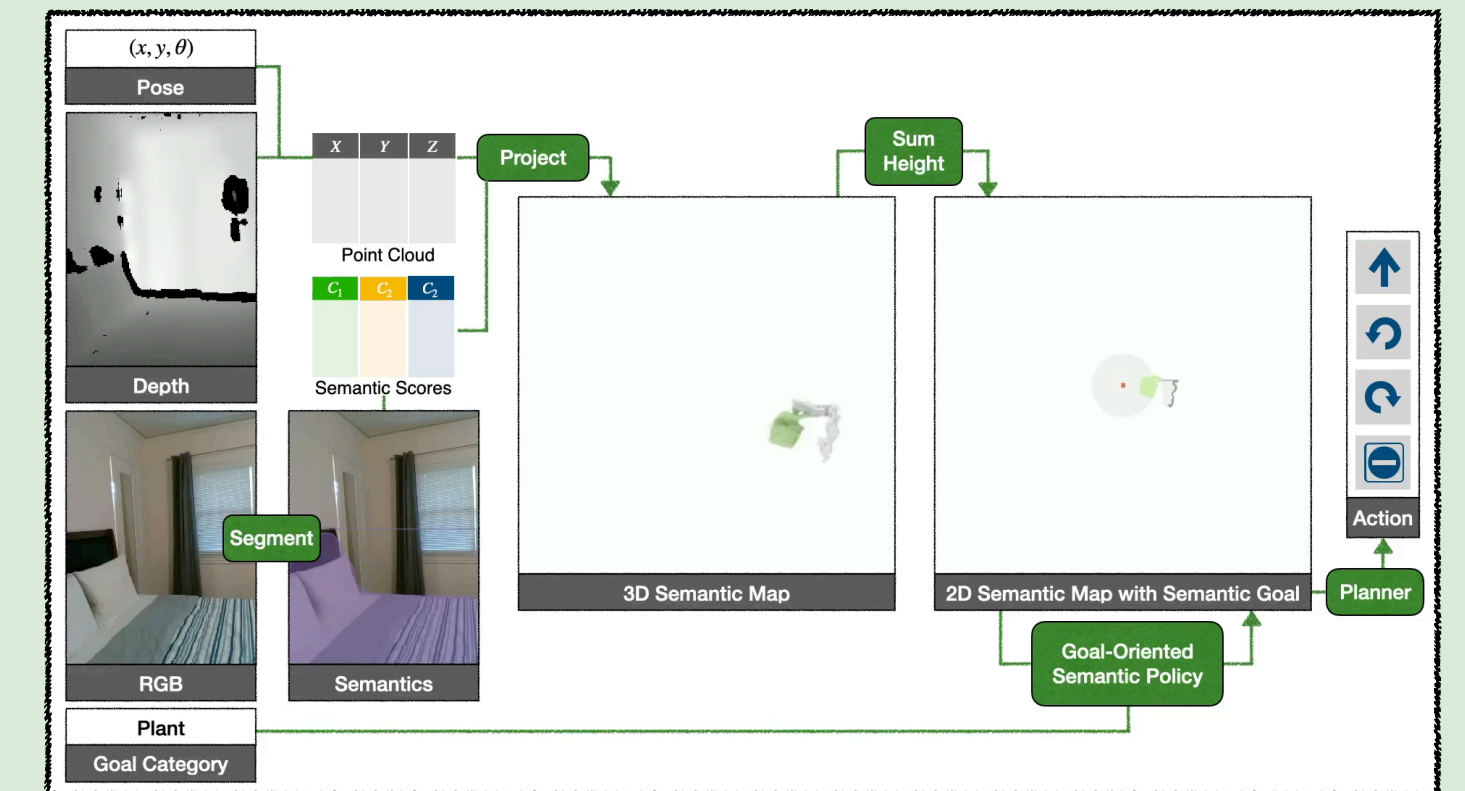
- ▶ Geometric Map
- ▶ Heuristic Exploration
 - ▶ No Training

End-to-end Learning

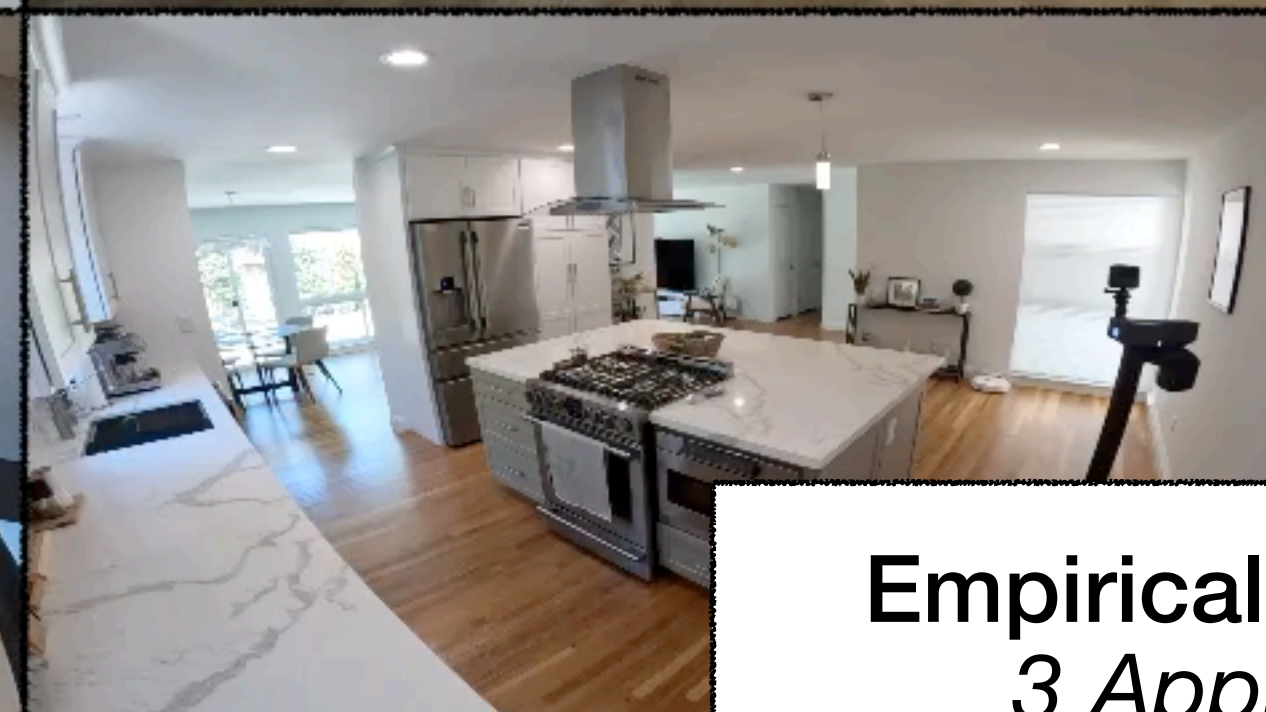


- ▶ End-to-end
- ▶ Large-scale IL + RL fine-tuning
 - ▶ 77,000 human trajectories
 - ▶ 200M frames of RL

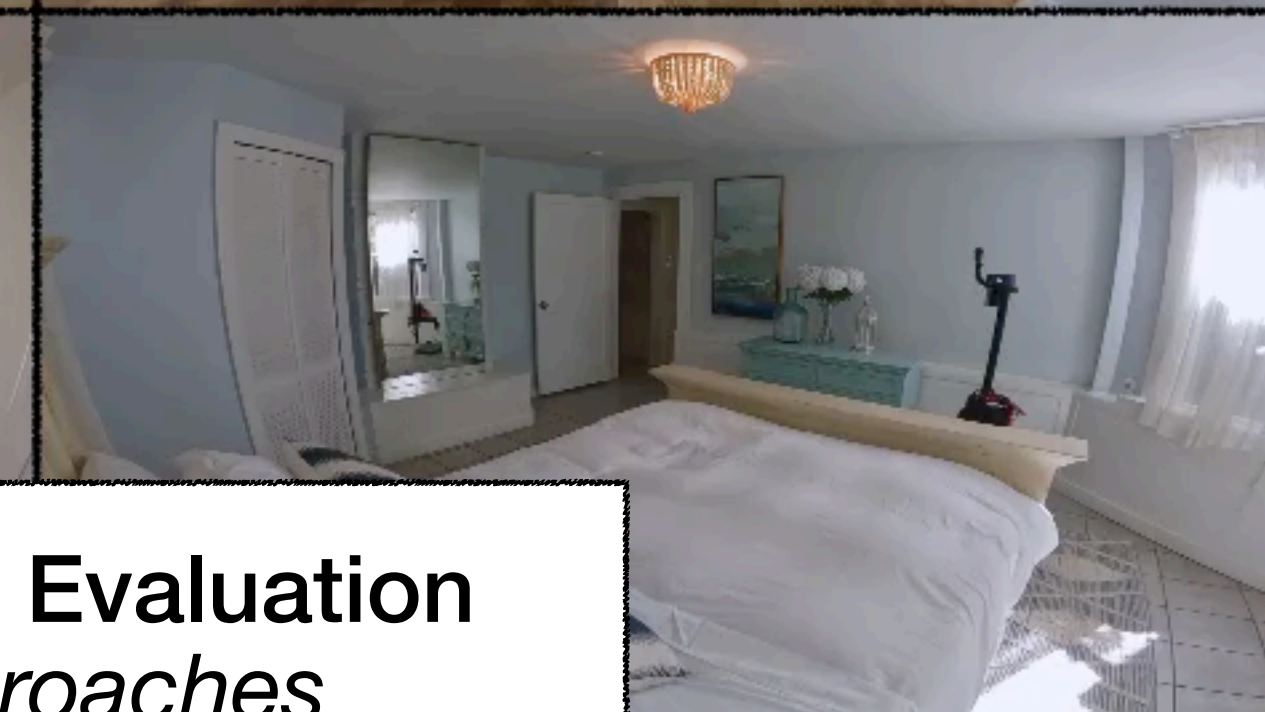
Modular Learning



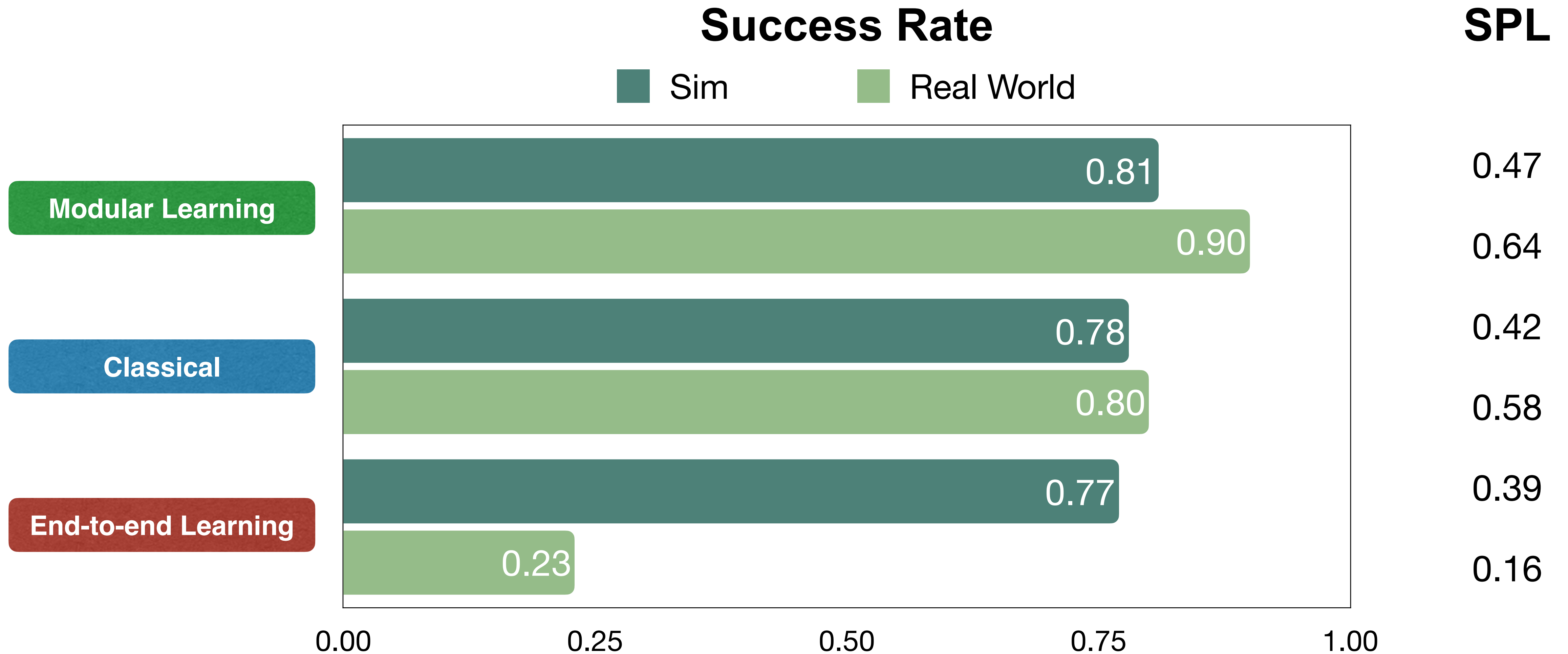
- ▶ Semantic Map
- ▶ Goal-Oriented Exploration
 - ▶ 10M frames of RL



Empirical Evaluation
3 Approaches
6 Unseen Homes
6 Goal Object Categories



Results

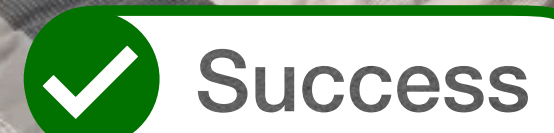


Goal: *couch*

SPL: 0.74, 78 steps

Modular

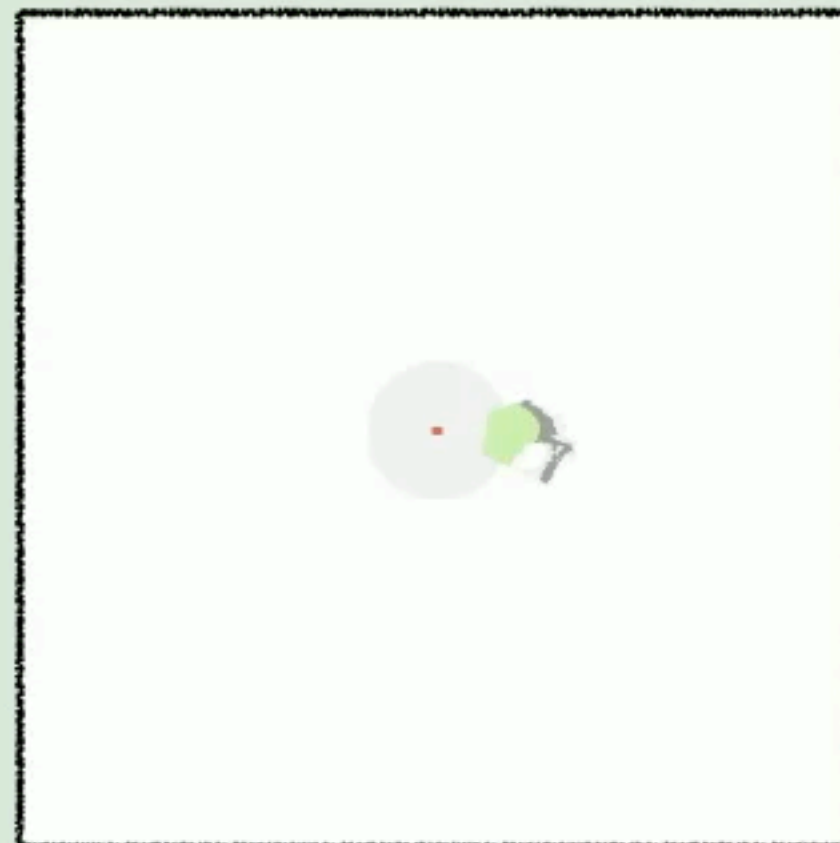
Third-person view



Success



Observation



Predicted
Semantic Map

SPL: 0.0, 121 steps

End-to-End

Third-person view



Failure



SPL: 0.33, 181 steps

Classical

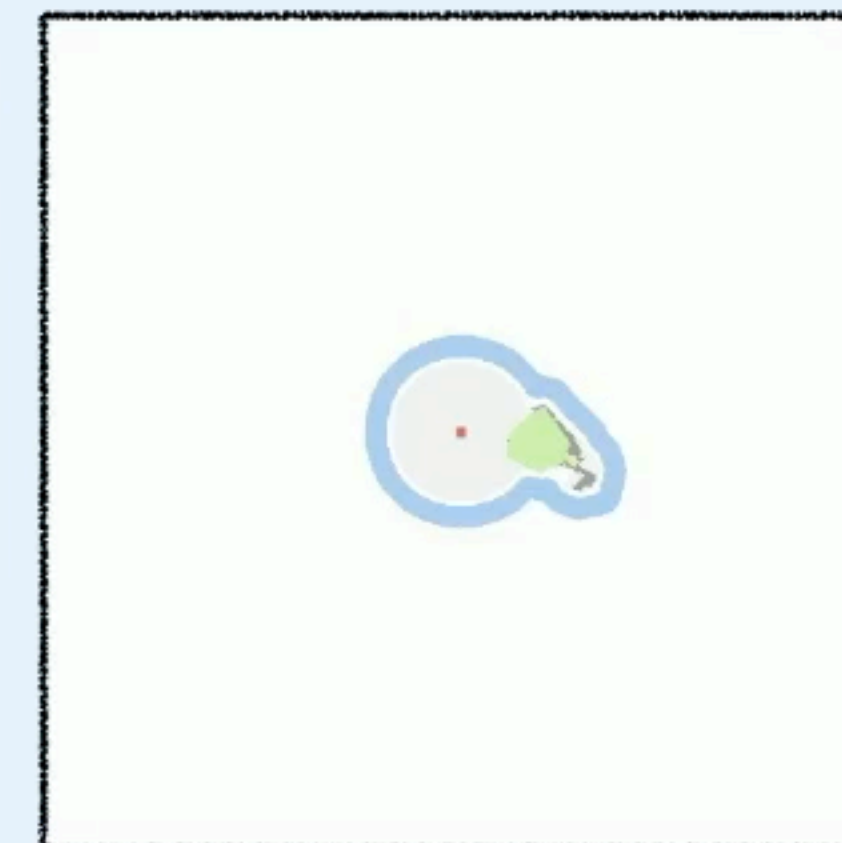
Third-person view



Success

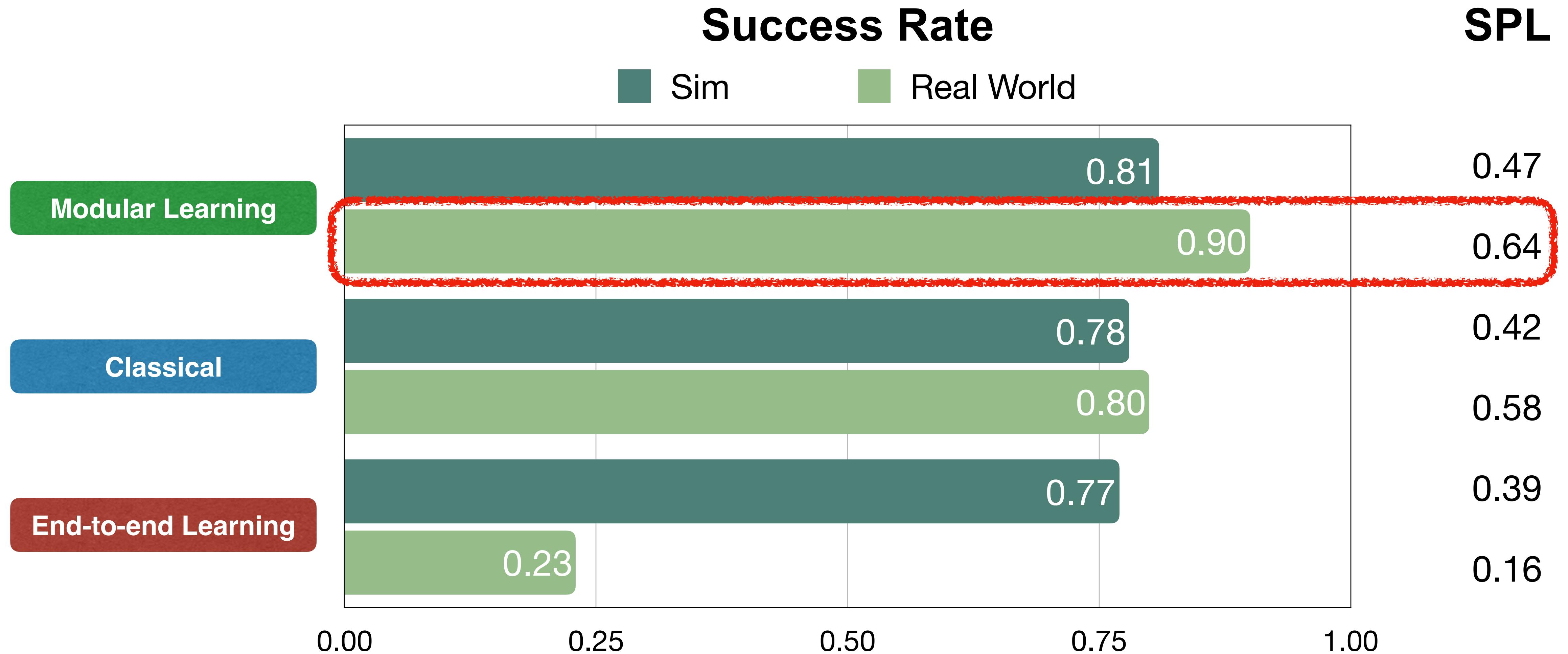


Observation

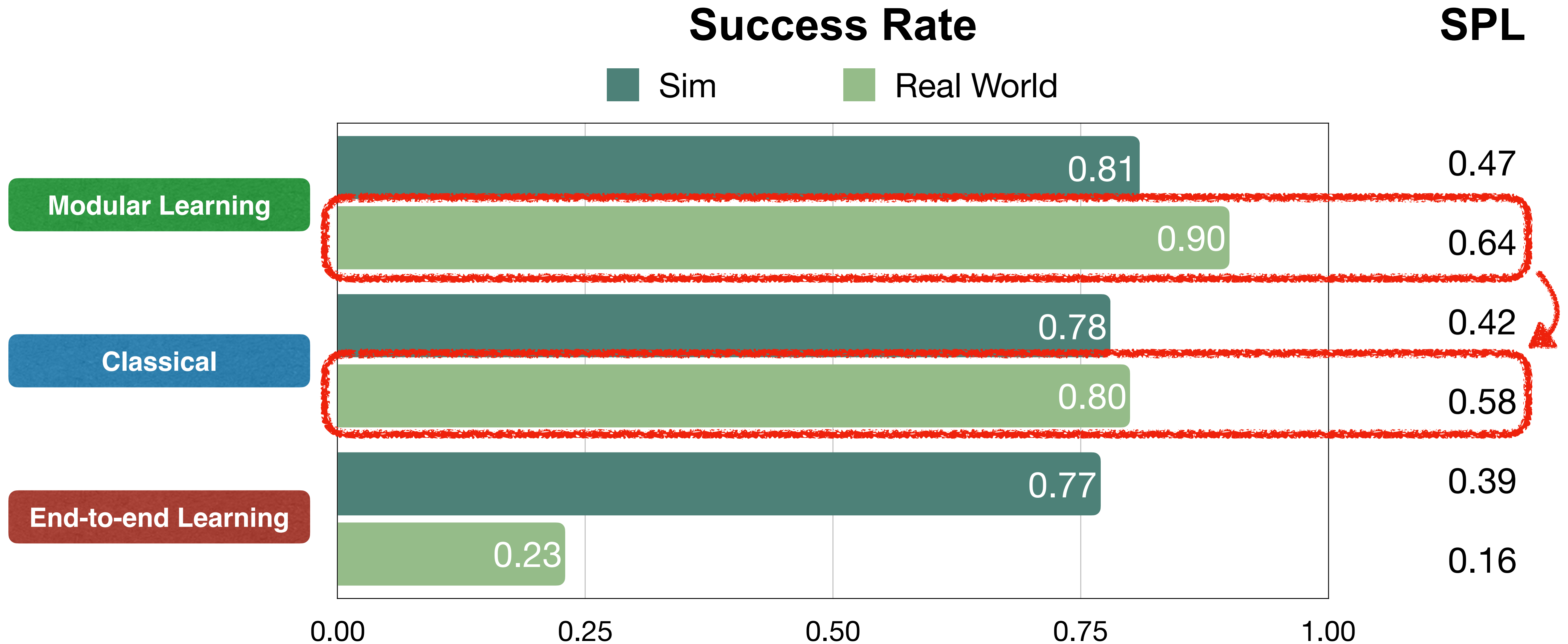


Predicted
Semantic Map

Modular Learning is Reliable



Classical vs Modular Learning



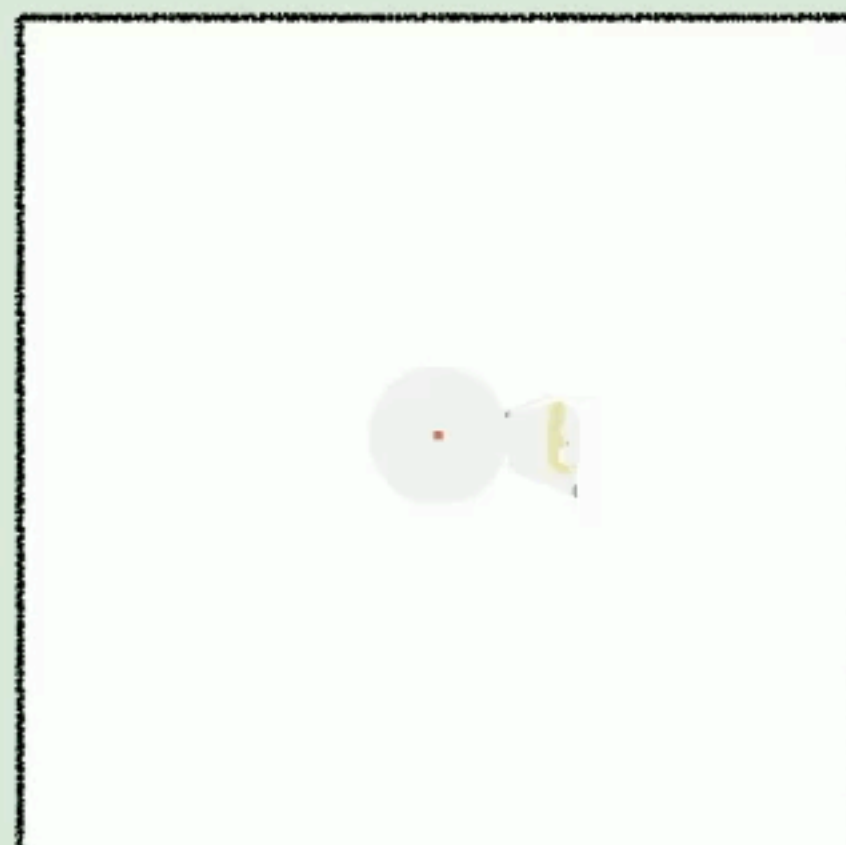
Classical vs Modular Learning

Goal: *bed*

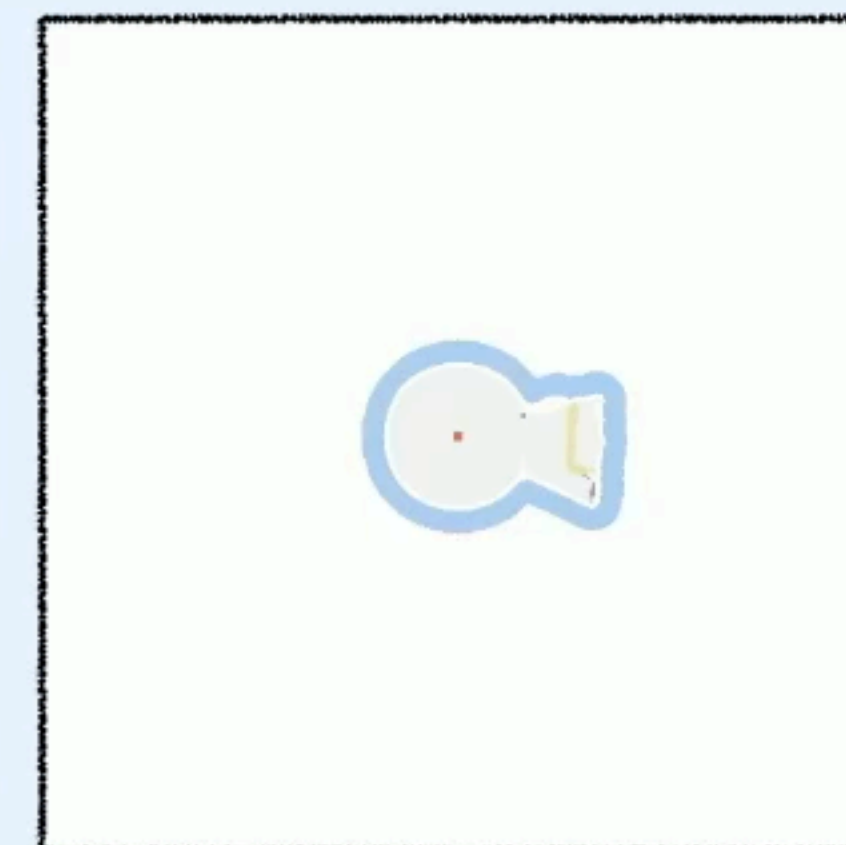
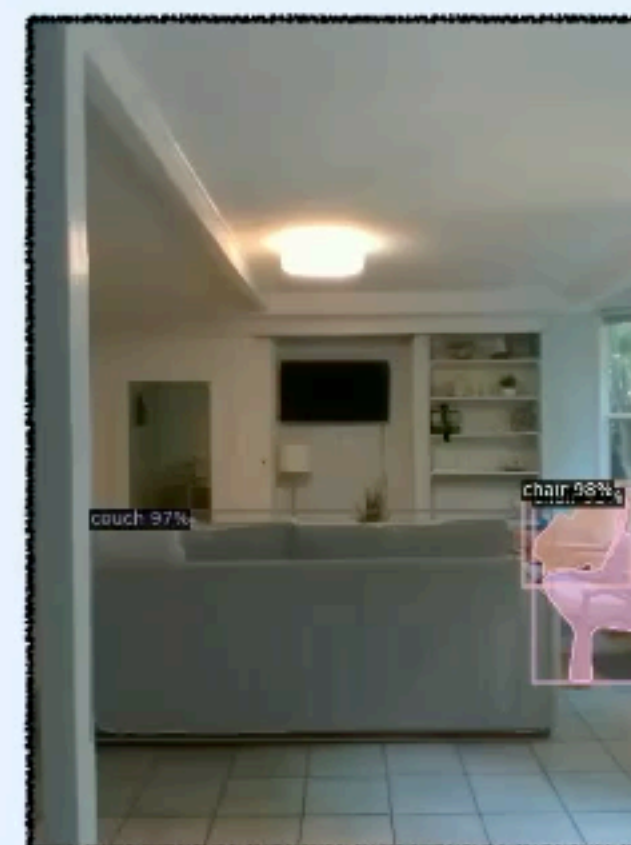
SPL: 0.90, 98 steps

SPL: 0.52, 152 steps

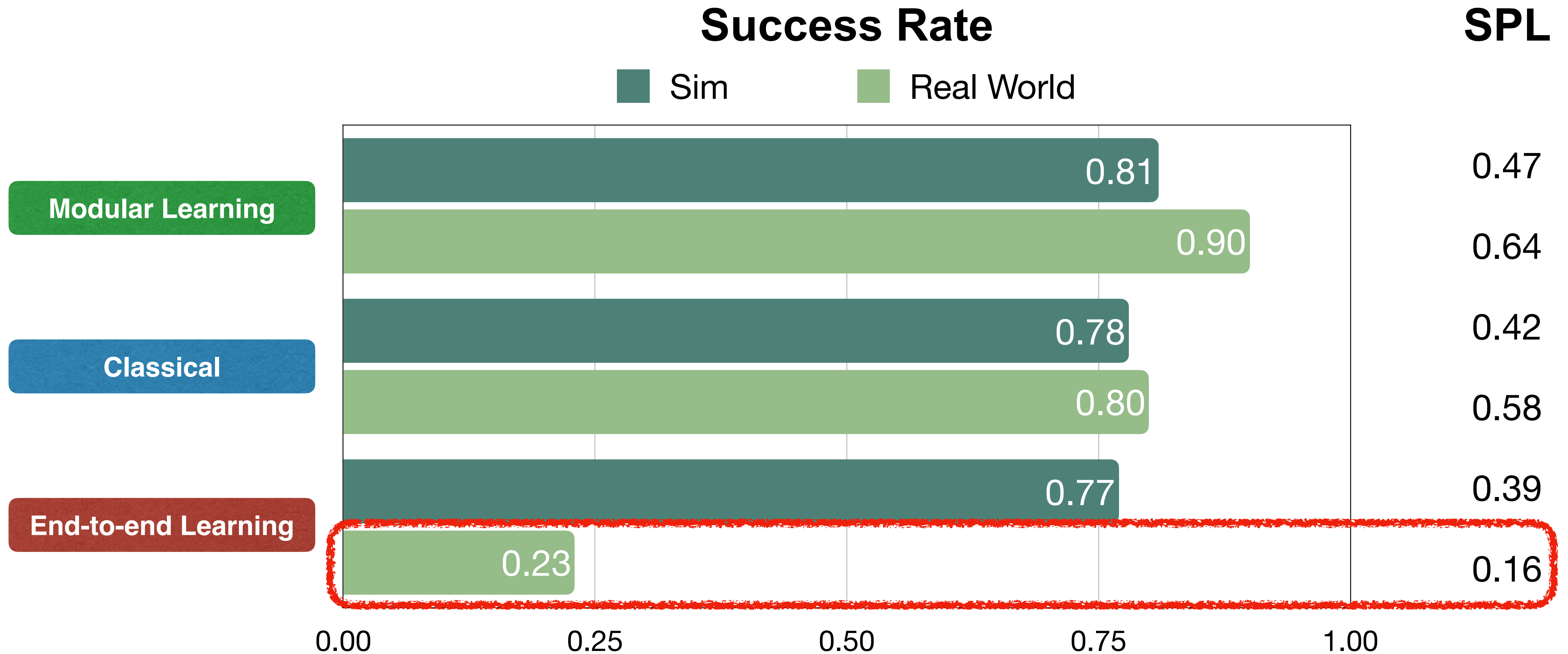
Semantic Exploration



Frontier Exploration



End-to-end fails to Transfer



End-to-end Failures

Goal: *TV*



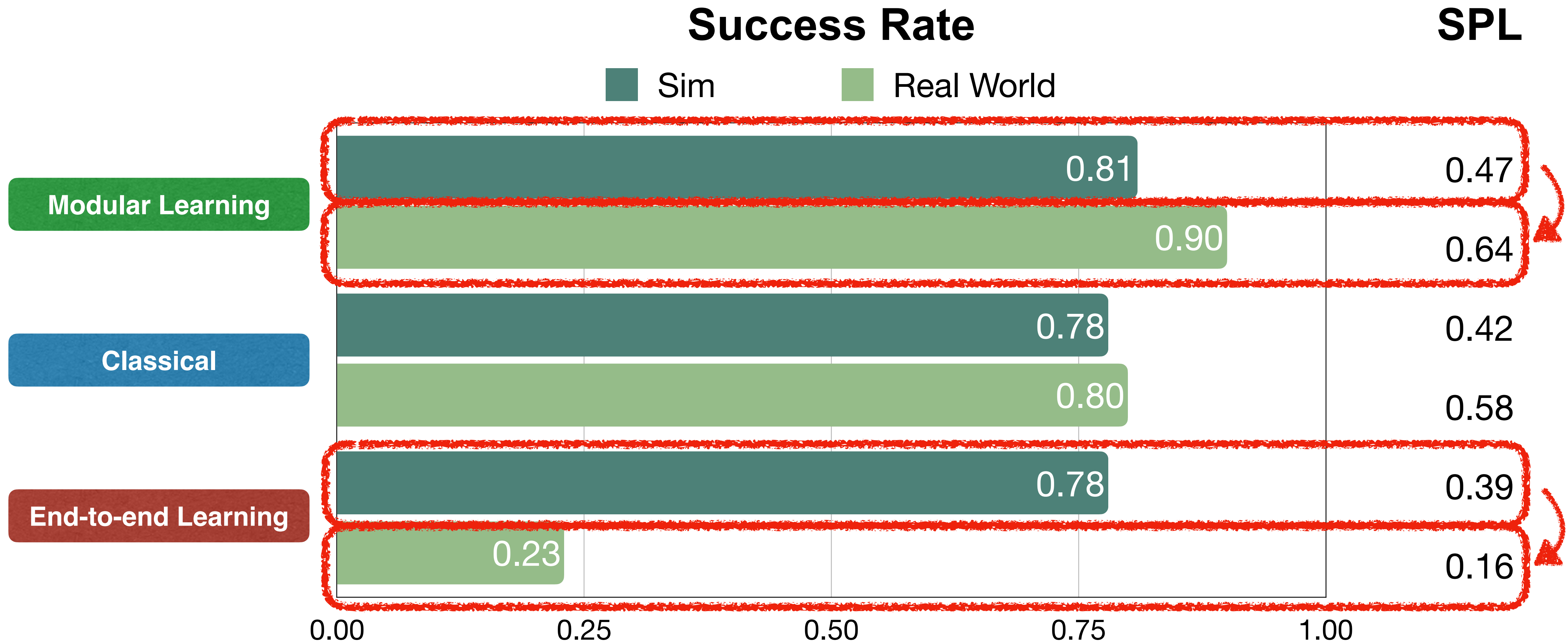
Goal: *Toilet*



Goal: *Plant*



Modular vs End-to-end Transfer

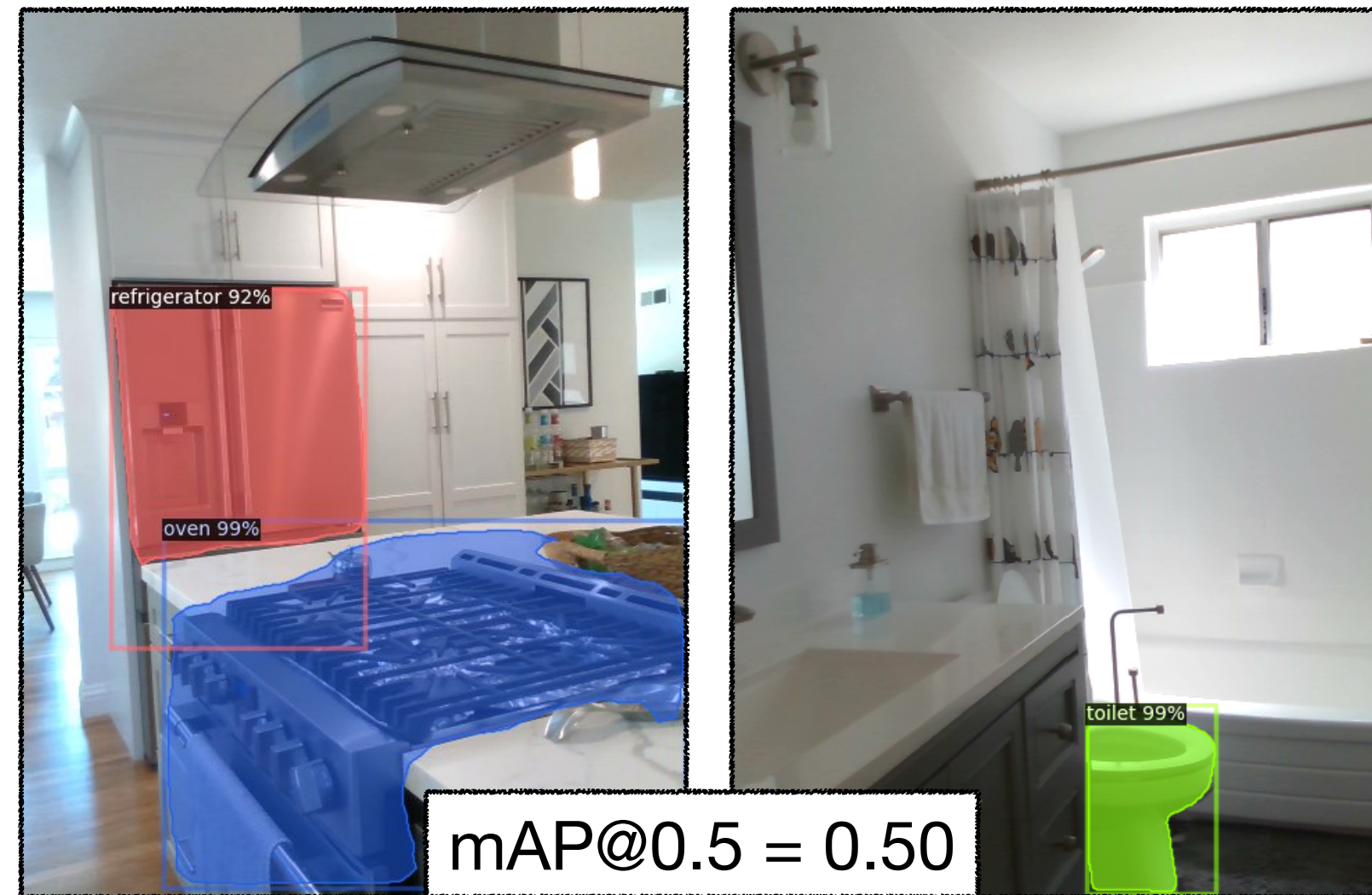


Real World

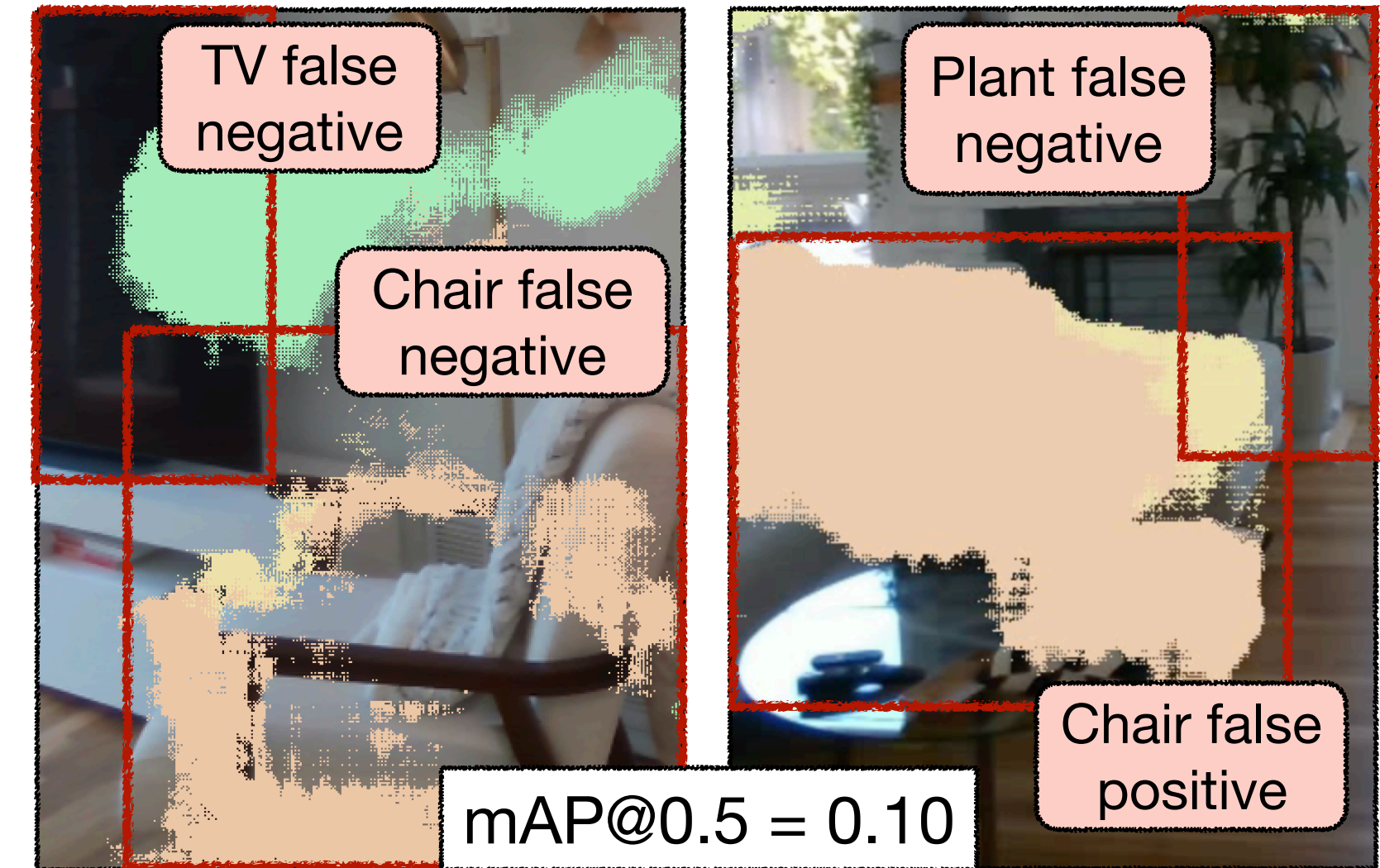
Predicted
Semantic Map



Segmentation Model
Trained in Real World



Segmentation Model
Trained in Simulation



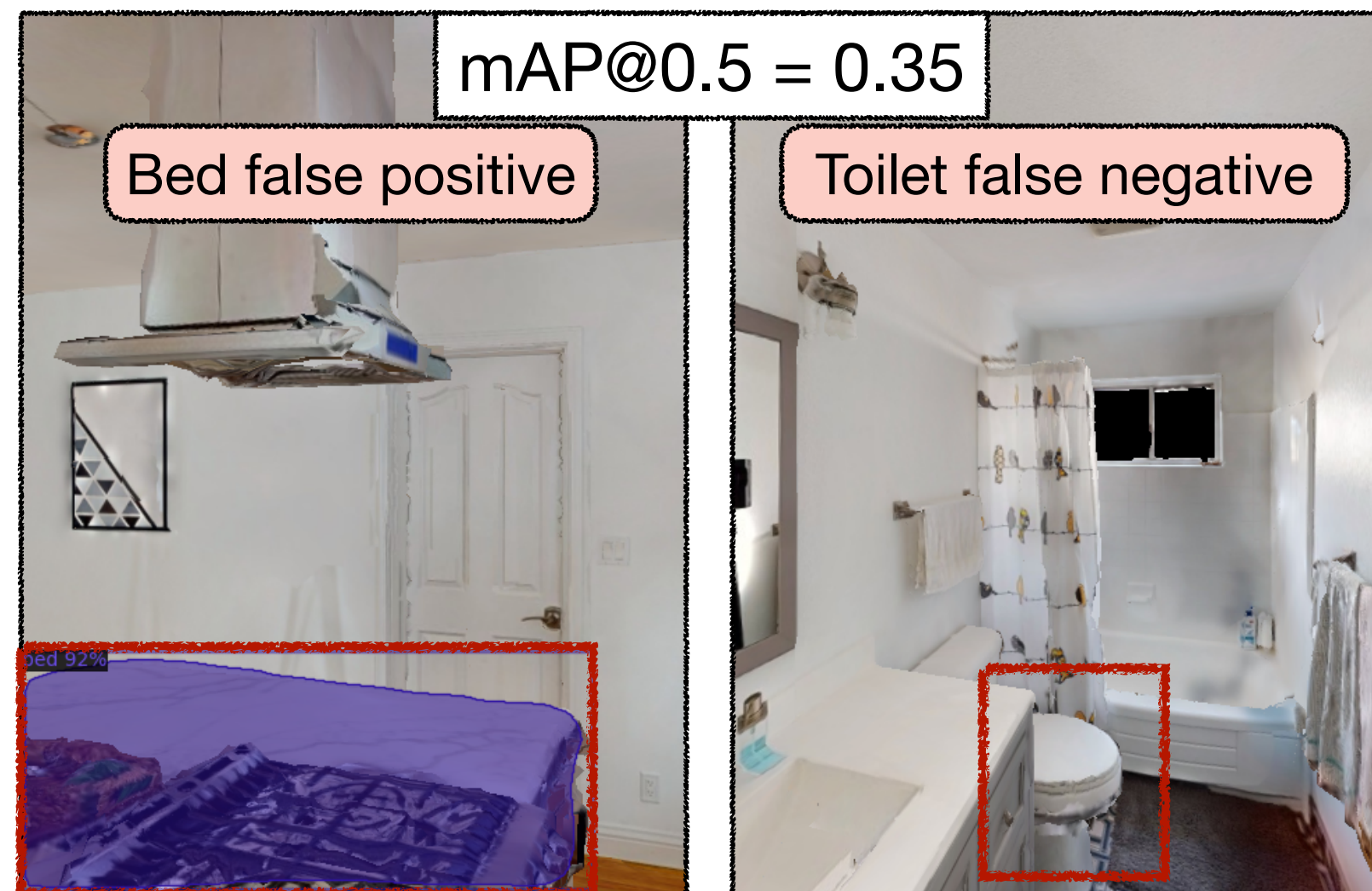
Domain
Invariance

Domain Gap

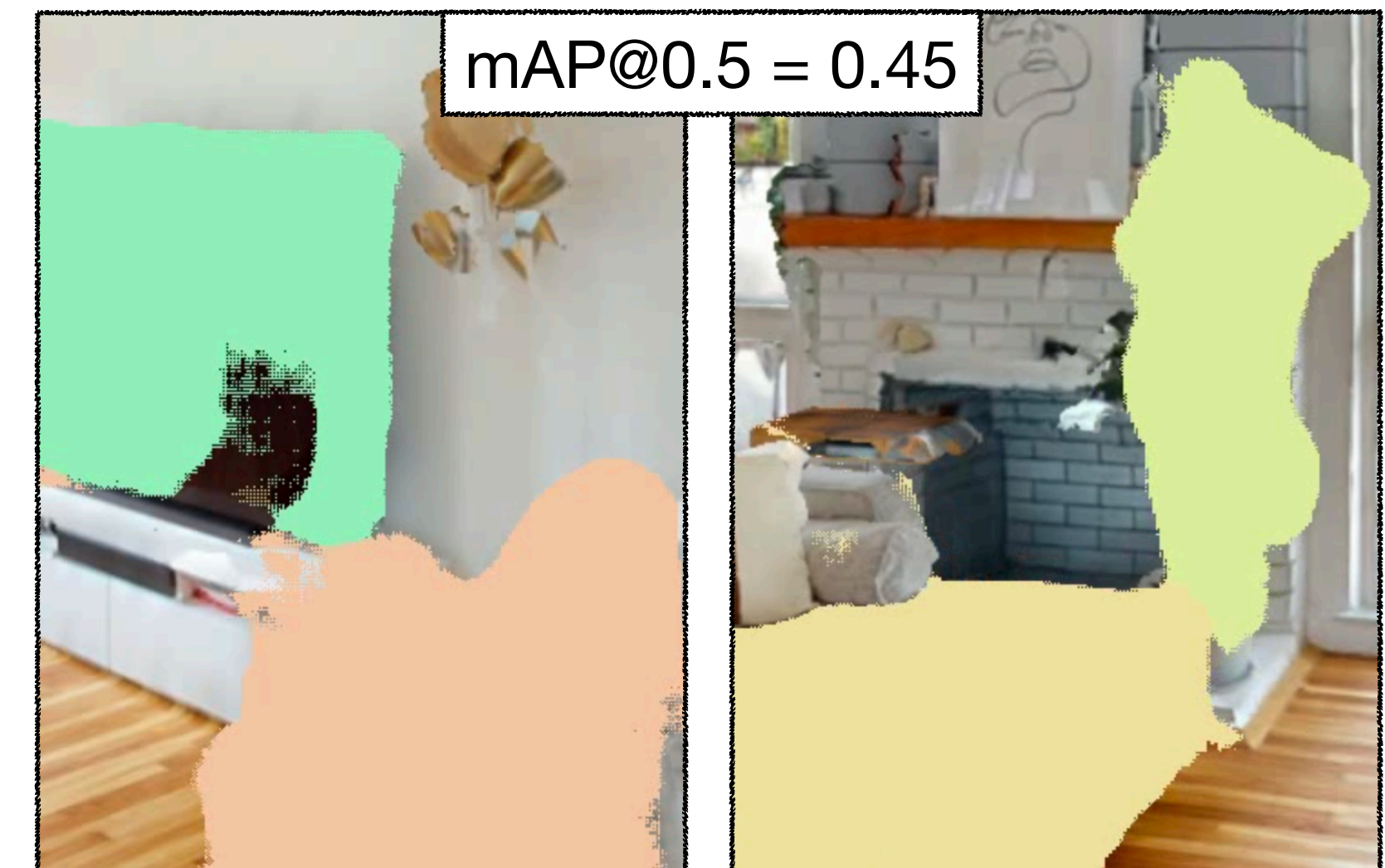
Domain Gap

- 0: chair
- 1: couch
- 2: potted plant
- 3: bed
- 4: toilet
- 5: tv

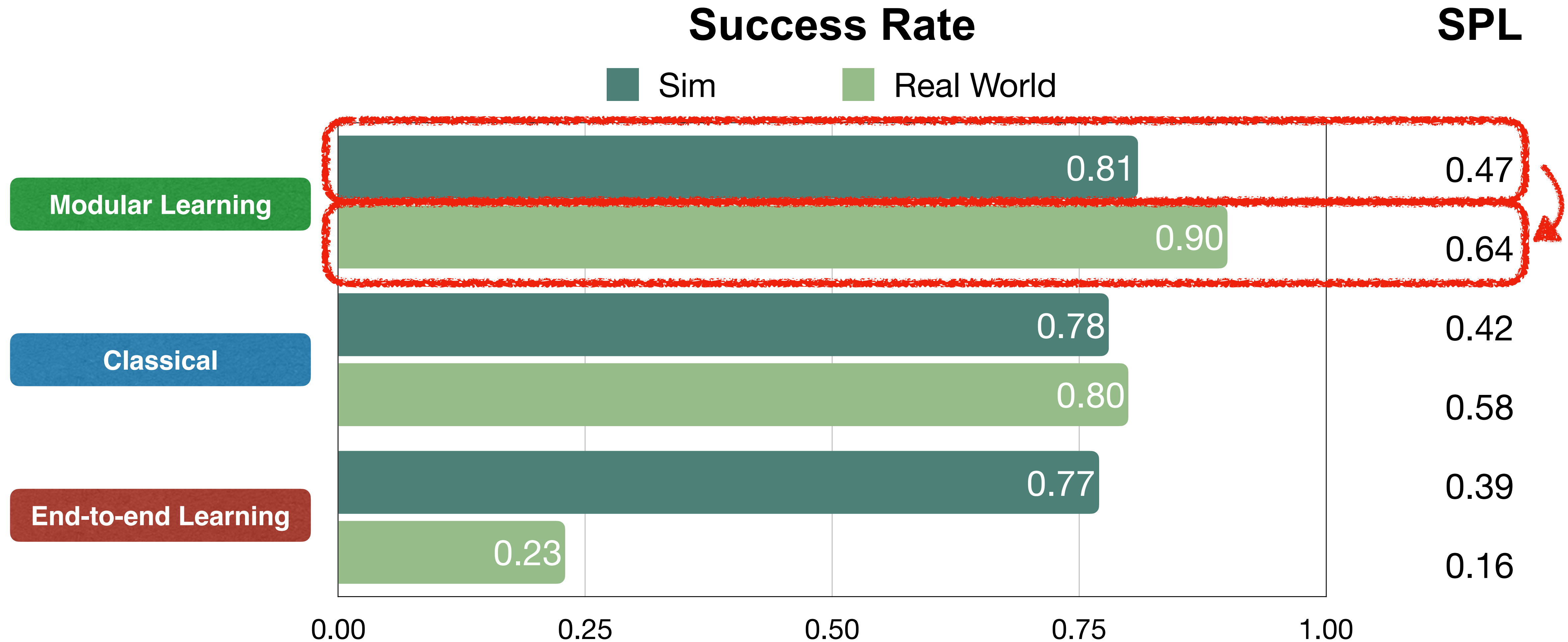
Simulation



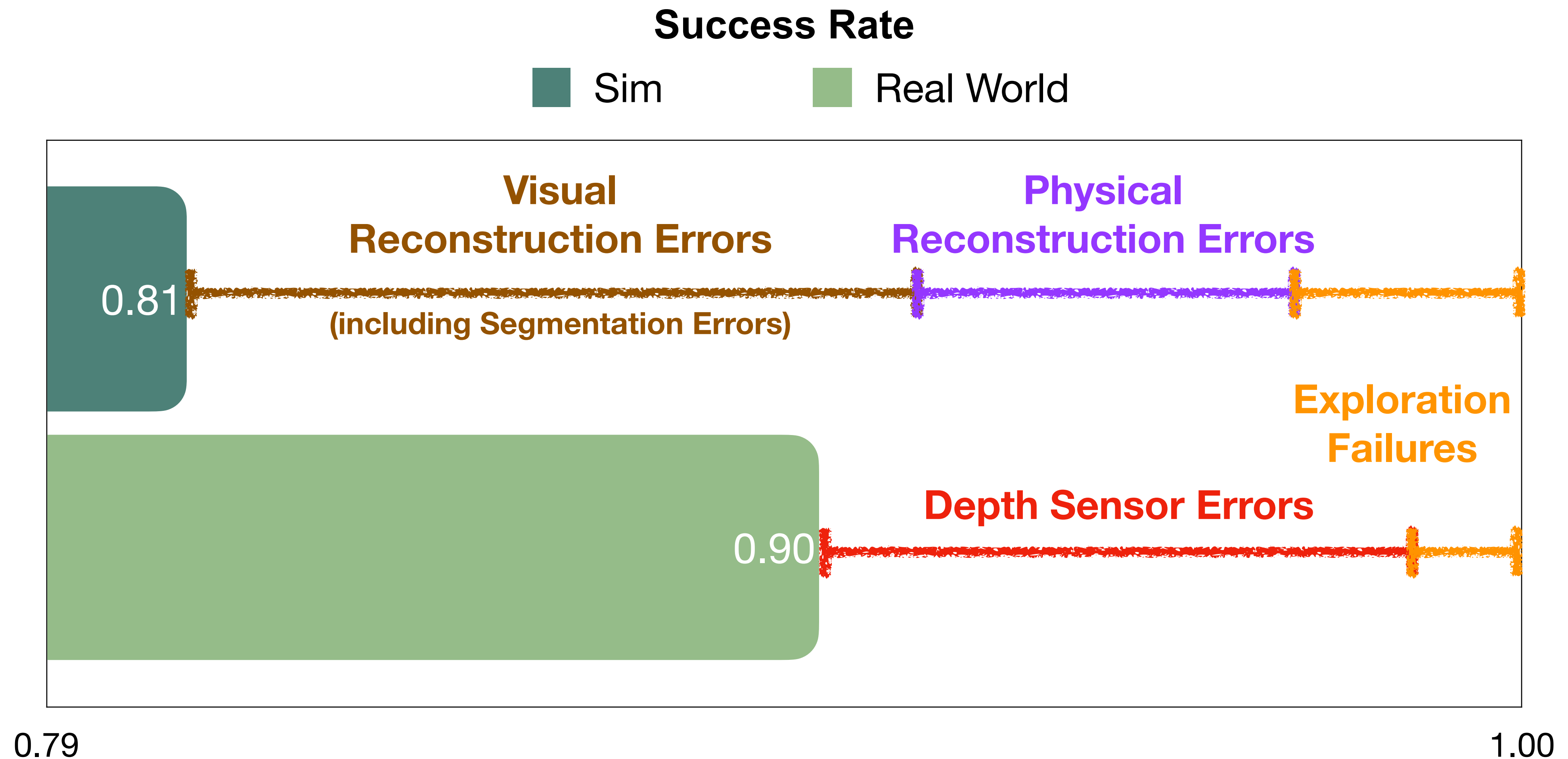
mAP@0.5 = 0.45

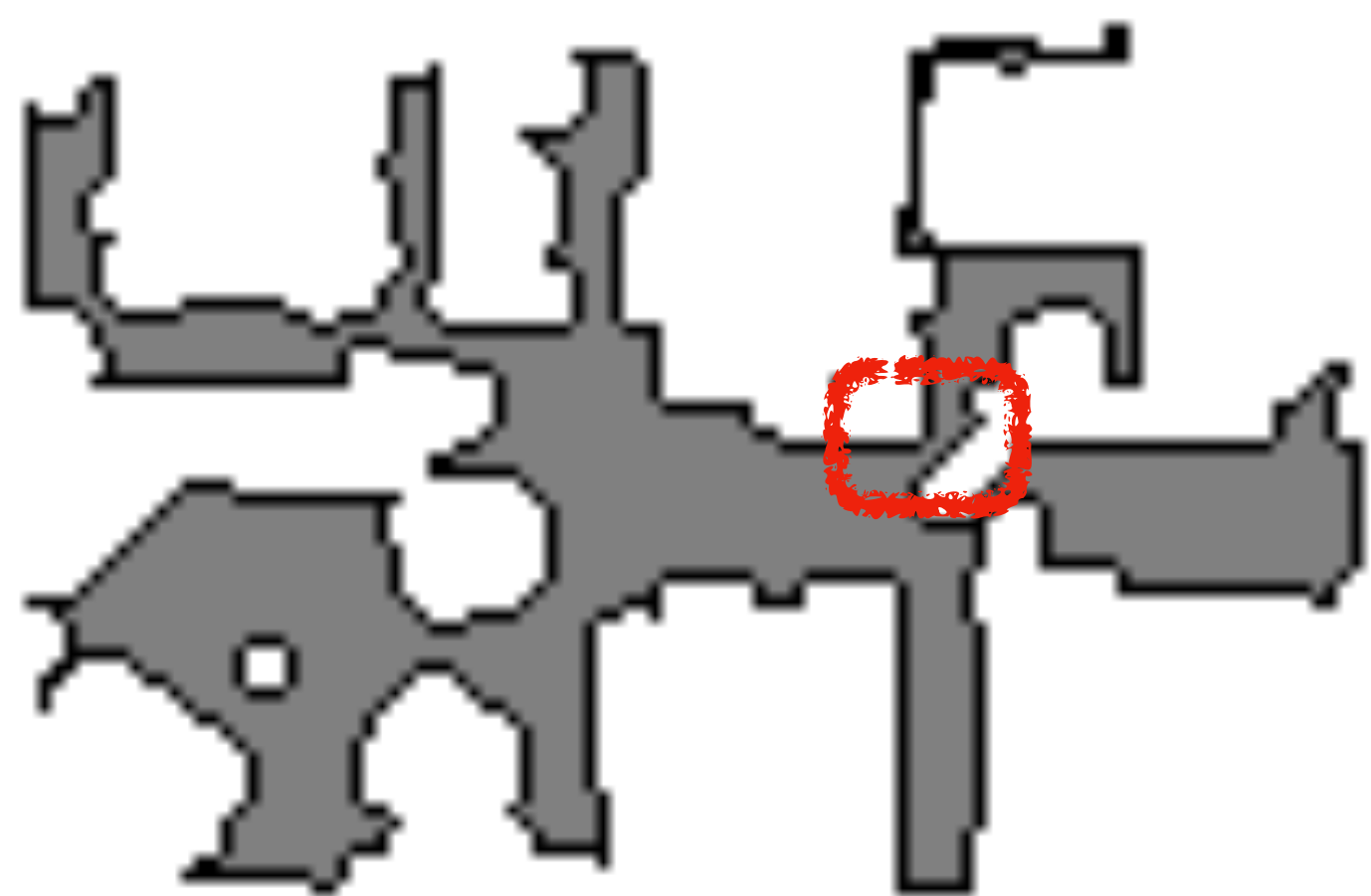


Modular Learning Sim vs Real



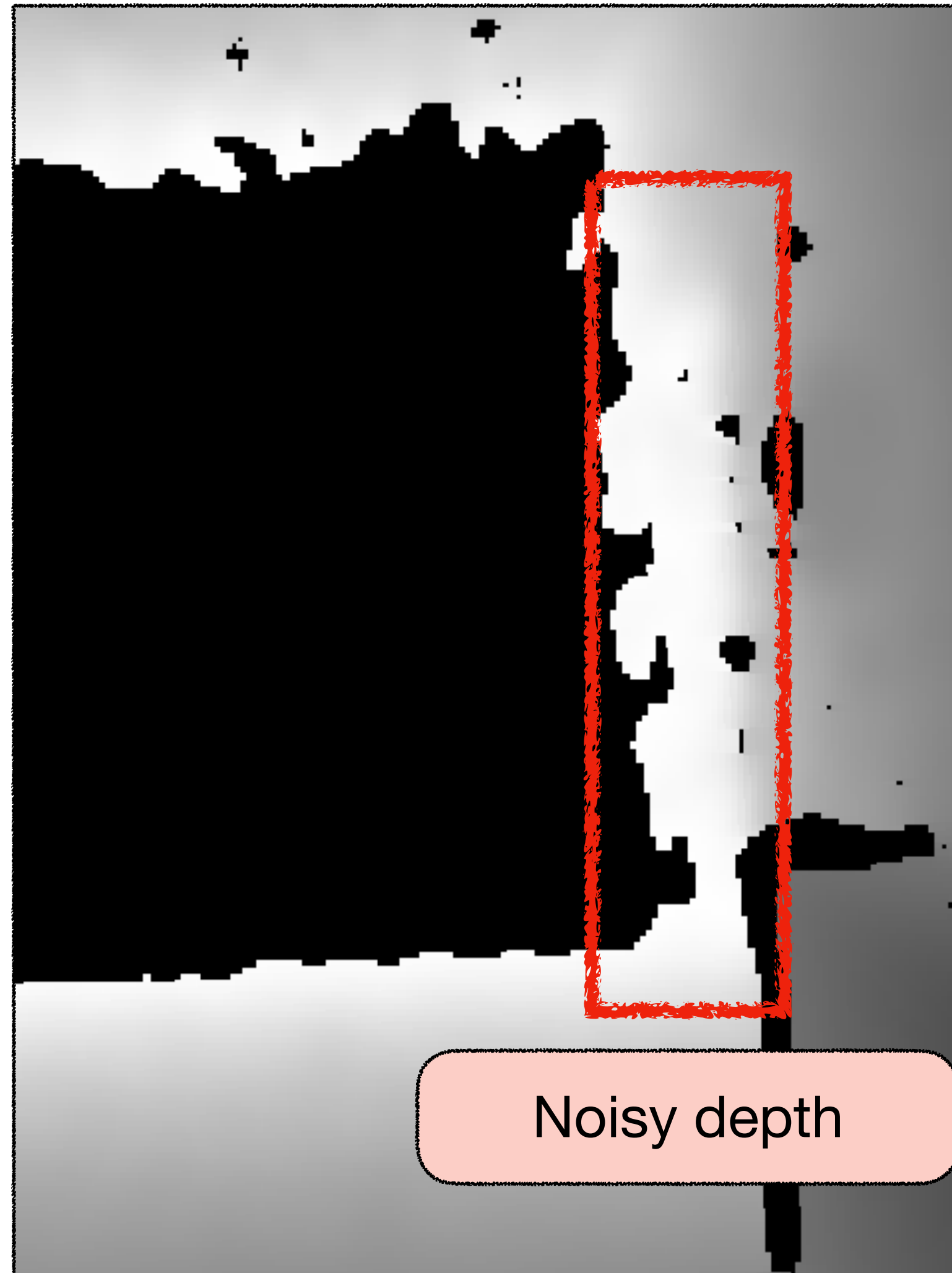
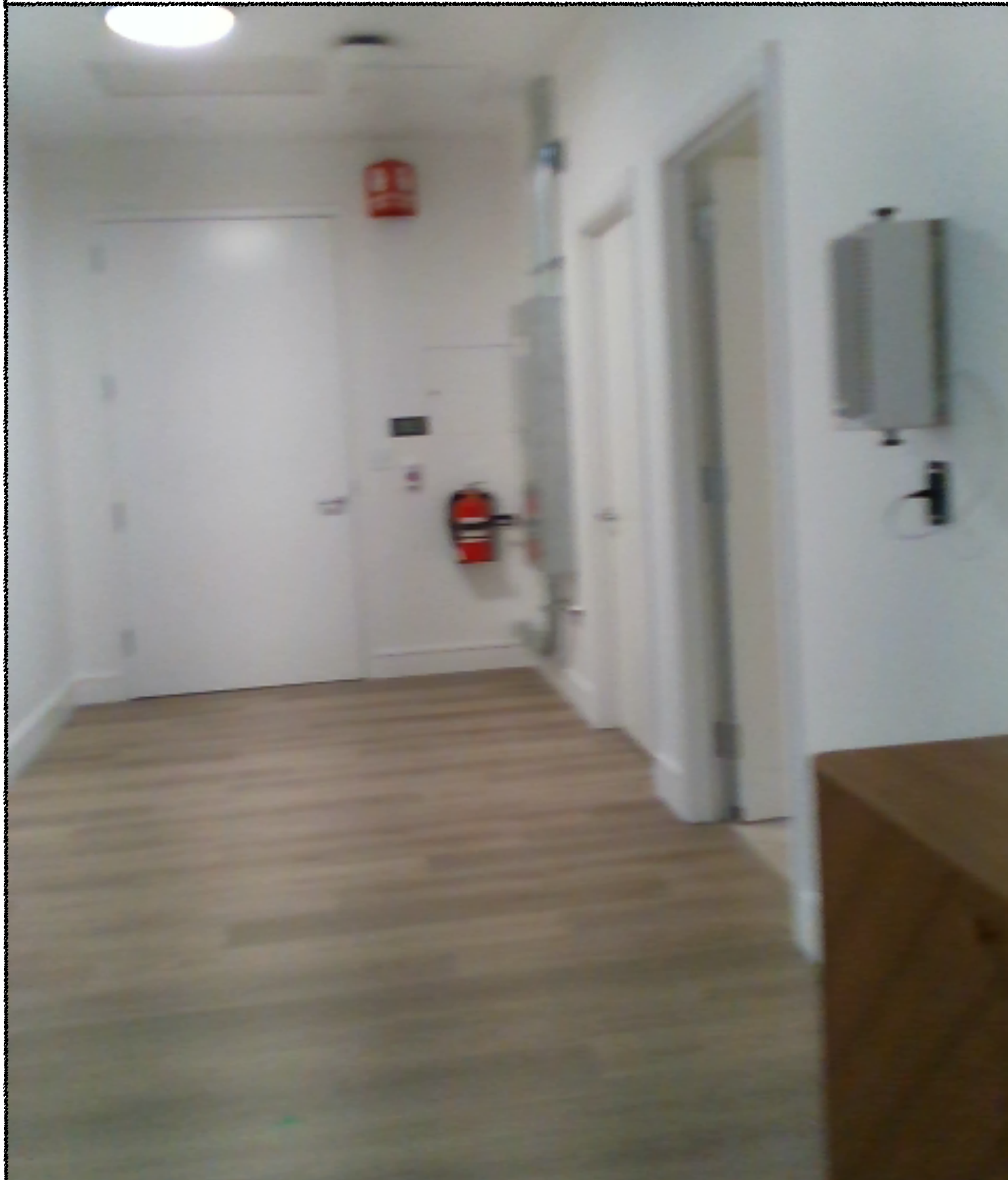
Modular Learning Sim vs Real



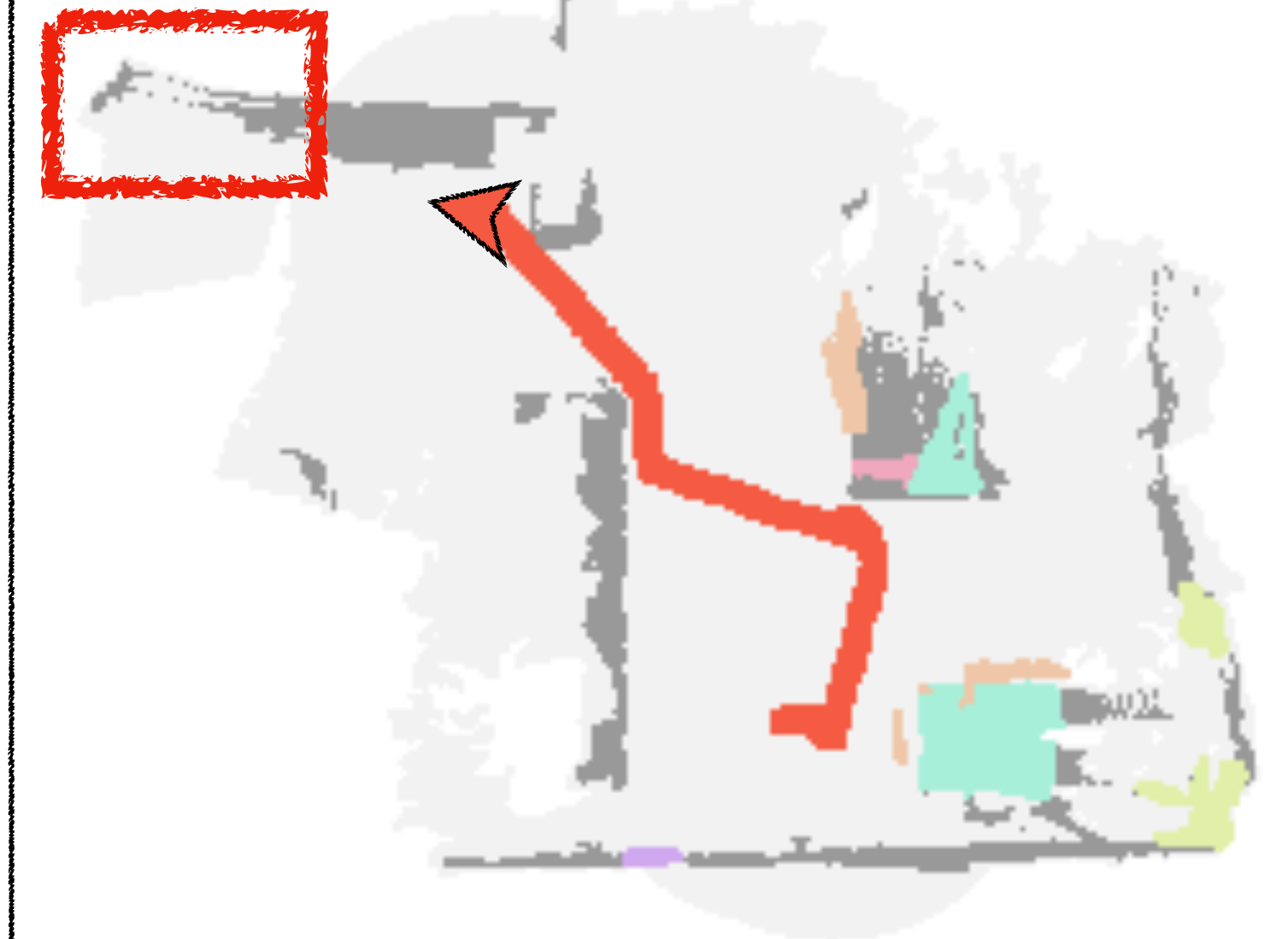


Real-world Depth Sensor Errors

Door approach at an angle



Closed door



Real-world Depth Sensor Errors

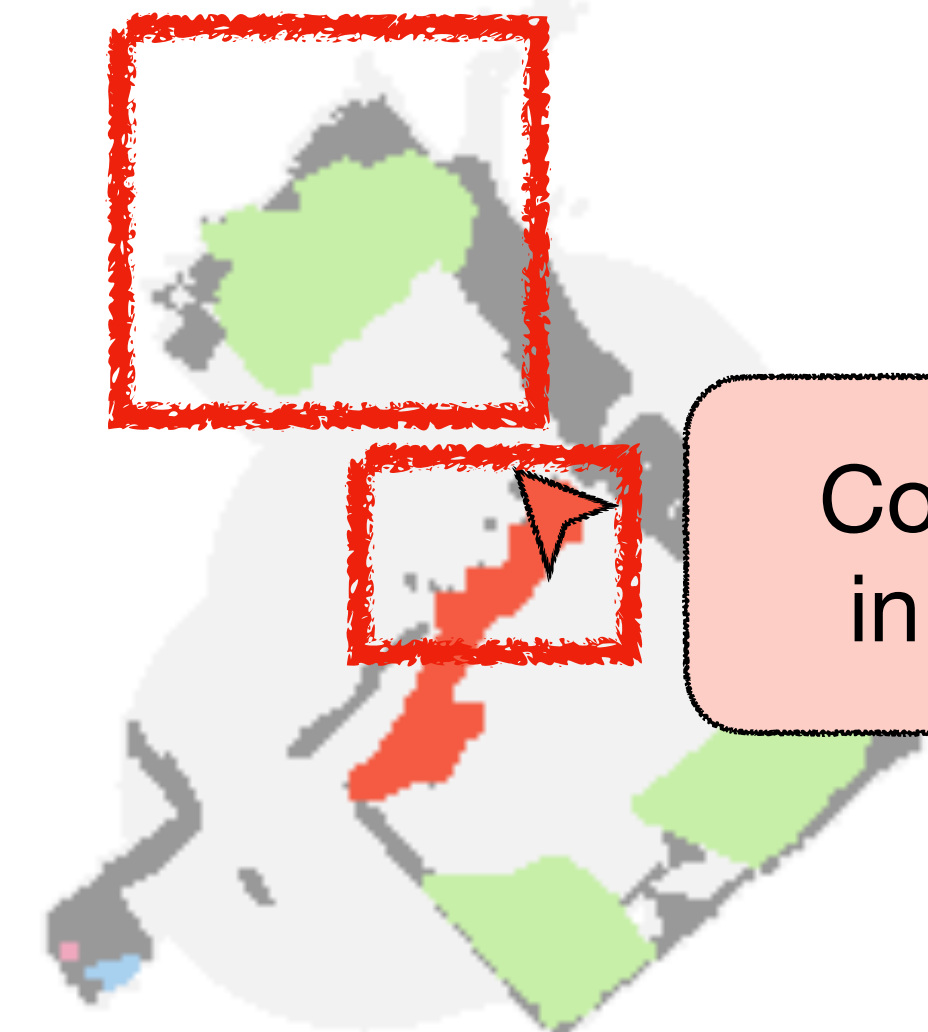
Mirror reflection



Reflected depth



Hallucinated bed mapped



Collisions in mirror



Takeaways

For practitioners:

- Modular learning can reliably navigate to objects with 90% success

For researchers:

- Models relying on RGB images are hard to transfer from sim to real → *leverage modularity and abstraction in policies*
- Disconnect between sim and real error modes → *evaluate semantic navigation on real robots*



Thank you!

Webpage: <https://theophilegervet.github.io/projects/real-world-object-navigation>