Visual Navigation

Deep Reinforcement Learning and Control

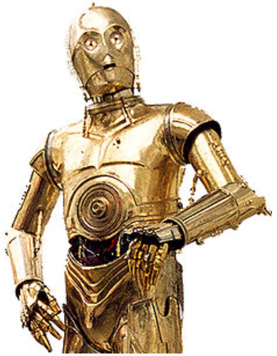
Fall 2021, CMU 10703

Carnegie Mellon University

MACHINE LEARNING DEPARTMENT

Learning Behaviors

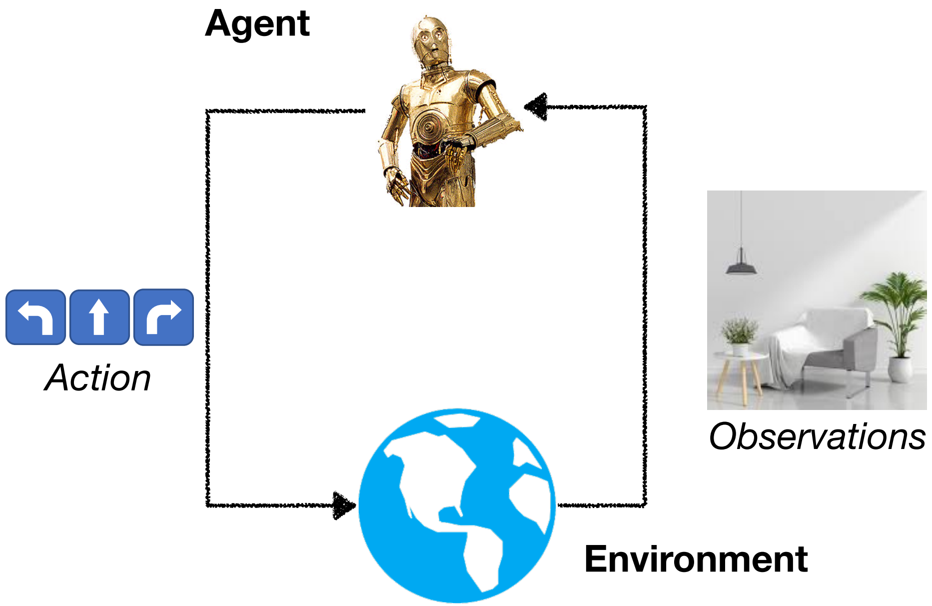
Observation $\xrightarrow{\hspace{2em}}$ o_t



Action $\xrightarrow{\hspace{2em}}$ a_t

Learning to map sequences of observations to actions, for a particular goal

Physical Intelligence

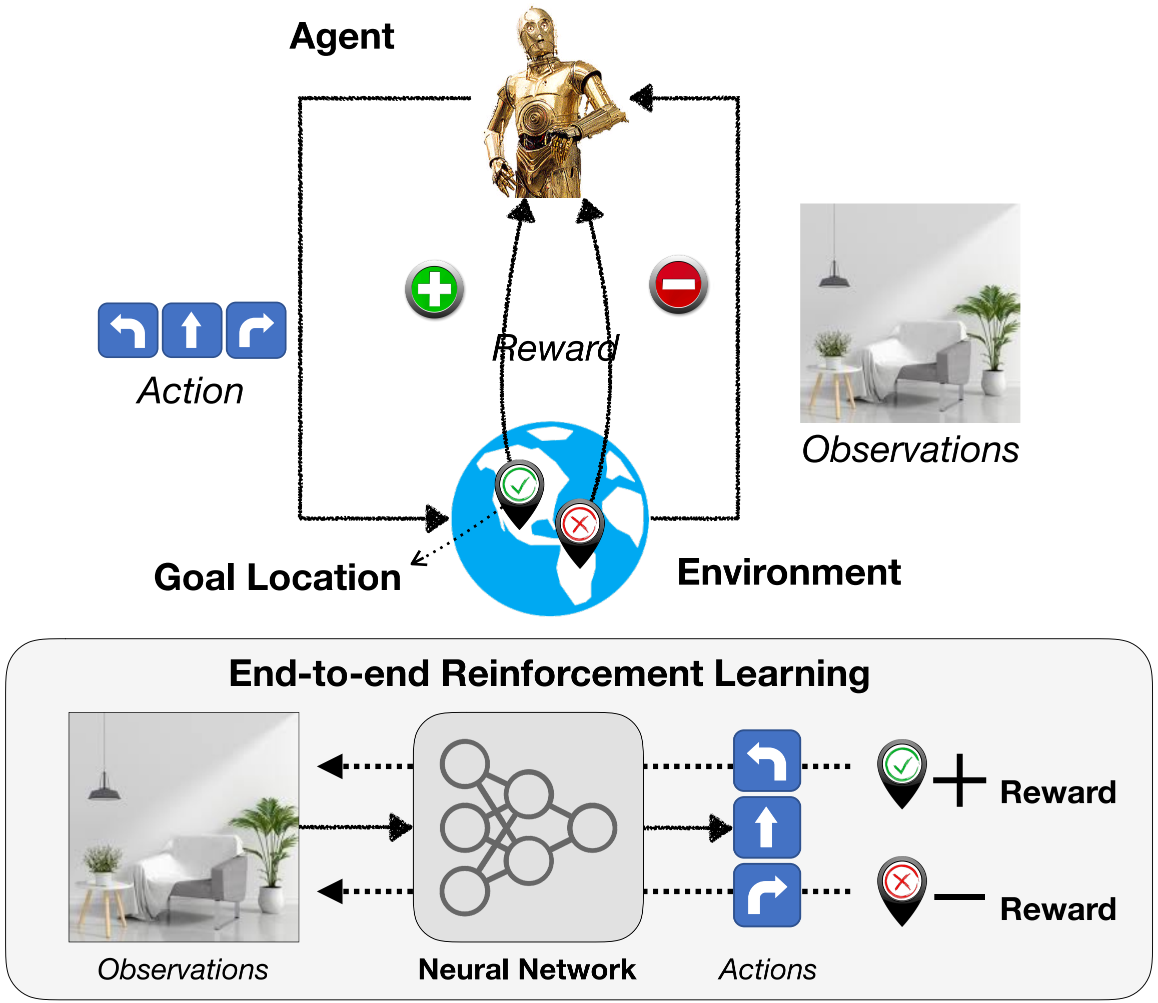


Agent needs to move in the world physically.

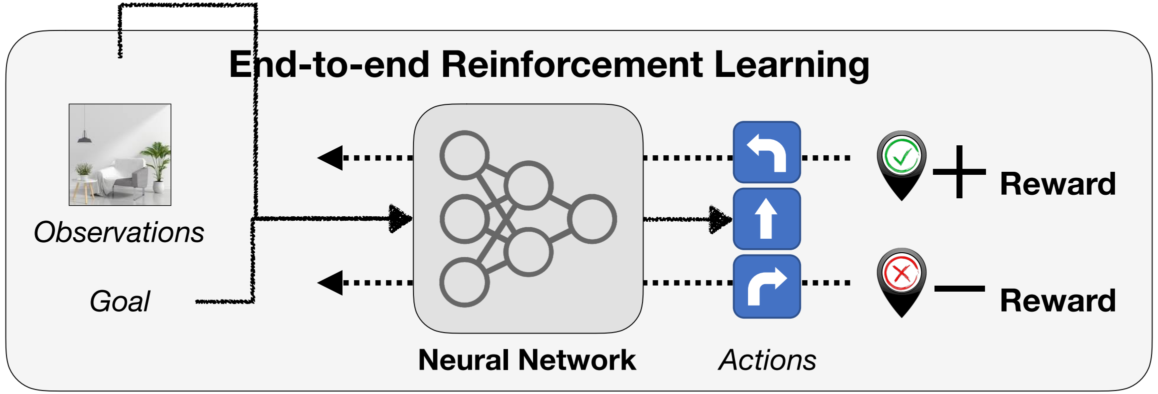
Current actions affect future observations.

Require Spatial and Semantic Understanding.

Navigation


Agent
Action
Reward
Observations
Goal Location
Environment
End-to-end Reinforcement Learning
Observations
Neural Network
Actions
Reward
Reward

Goal-conditioned Navigation



Point Goal

(x, y) *coordinate*

Image Goal

Object Goal

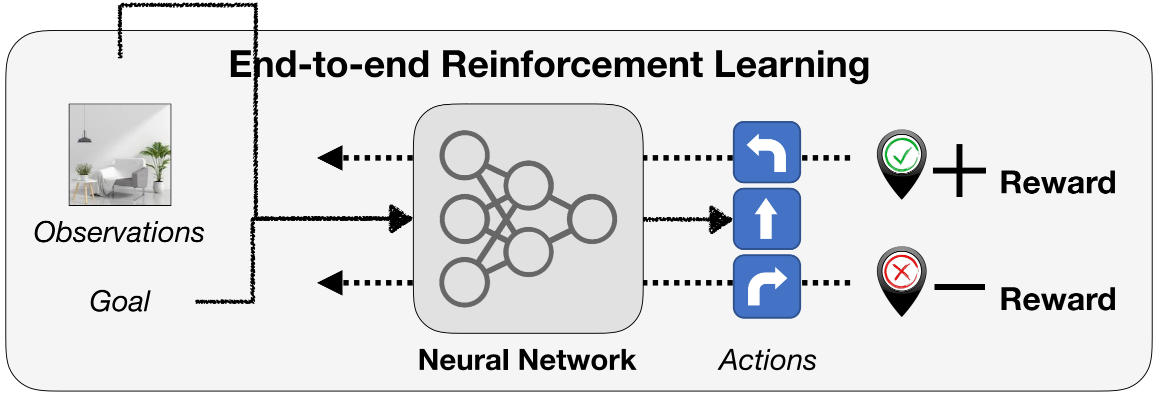
Chair
TV
Sofa

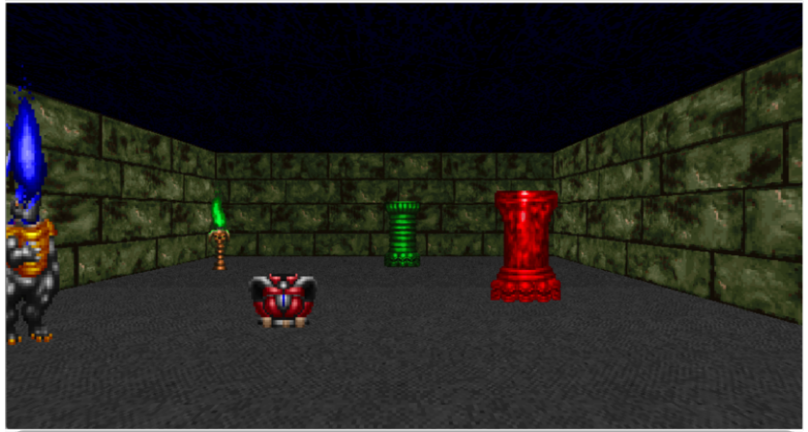
Language Goal

Blue Chair
Largest TV
White Sofa

- Convenient for humans
- Compositionality

Goal-conditioned Navigation





Go to the green torch

Train

Go to the short red torch
Go to the blue keycard
Go to the largest yellow object
Go to the green object

Test

Go to the tall green torch
Go to the red keycard
Go to the smallest blue object

Language Goal

Blue Chair
Largest TV
White Sofa

- Convenient for humans
- Compositionality

Navigation Tasks

Known goal location

- Require efficient navigation to the goal
- Tasks
  - Pointgoal [1, 2, 3]
  - Language Instructions describing path to goal [4]

[1] Anderson et al. *arXiv:1807.06757*, 2018.
[2] Mirowski et al. In *NeurIPS*, 2018.
[3] Savva et al. arXiv:1712.03931, 2017.
[4] Anderson et al. In *CVPR*, 2018.

Navigation Tasks

Known goal location

- Require efficient navigation to the goal
- Tasks
  - Pointgoal [1, 2, 3]
  - Language Instructions describing path to goal [4]

Unknown goal location

- Require exhaustive exploration
- Tasks
  - Exploration: Maximize explored area [5]
  - Object/Area Goal [3, 6, 7]
  - Semantic Goal Navigation [8]
  - Embodied Question Answering [9, 10]

[1] Anderson et al. *arXiv:1807.06757*, 2018.
[2] Mirowski et al. In *NeurIPS*, 2018.
[3] Savva et al. arXiv:1712.03931, 2017.
[4] Anderson et al. In *CVPR*, 2018.
[5] Chen et al. *ICLR*, 2019.
[6] Lample et al. In *AAAI*, 2017.
[7] Mirowski et al. *ICLR*, 2017.
[8] Chaplot et al. *AAAI*, 2018.
[9] Gordon et al. *CVPR*, 2018.
[10] Das et al. *CVPR*, 2018.

Desirable Characteristics of a Navigation model

- Effective at both types of Navigation tasks:
  - Known goal location (Pointgoal) and
  - Unknown goal location (Exploration)
- Generalization: domains, task, goals
- Sample efficiency

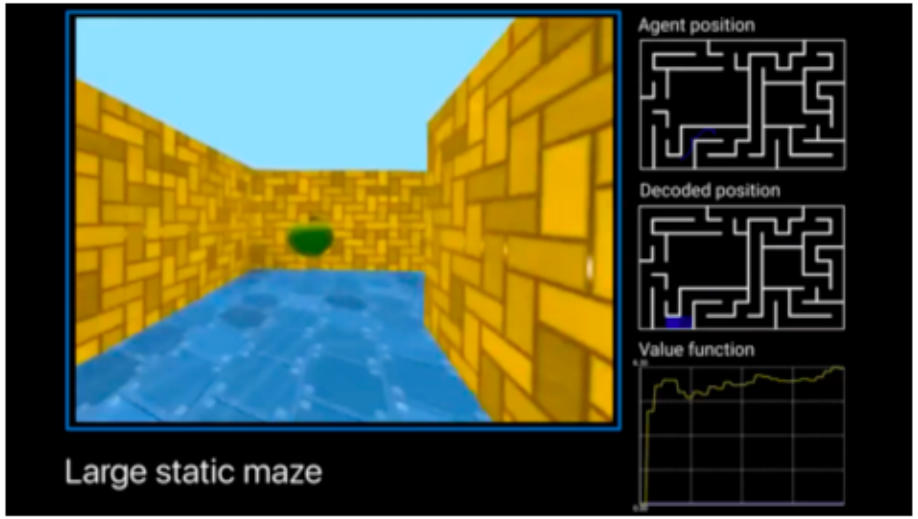
Limitations of Classical SLAM

- Generalization
  - Robustness to environment conditions [Maddern et al. 2016]
  - Robustness to dynamic objects [Zou and Tan, 2012]
  - Failure cases of keypoint tracking [Cadena et al. 2016]

- Passiveness
  - Unable to decide the actions taken by the agent in order to map the environment or localize as accurately and efficiently as possible.

Deep RL?

[Lample & Chaplot, 2016]



[Mirowski et al. 2017]

Limitations of “end-to-end” Deep RL

- Ineffective at long-term planning
- Sample inefficiency
- Poor transferability

Navigation Tasks

Point Goal

(x, y) *coordinate*

Image Goal

Object Goal

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Sofa

Language Goal

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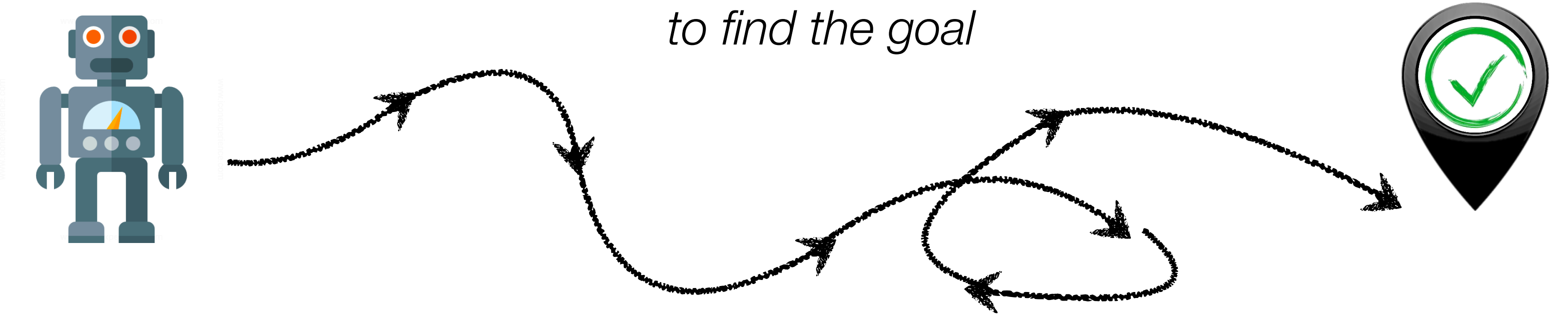
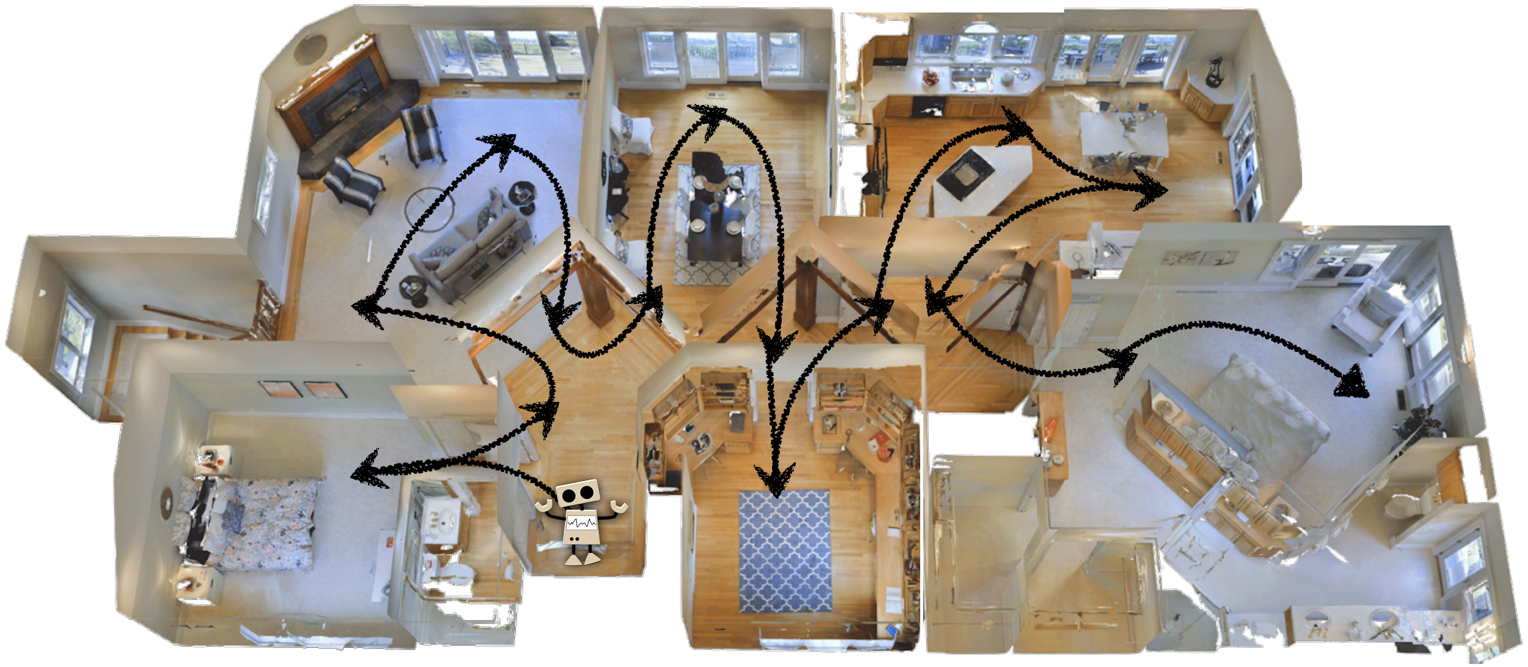
Largest TV

White Sofa

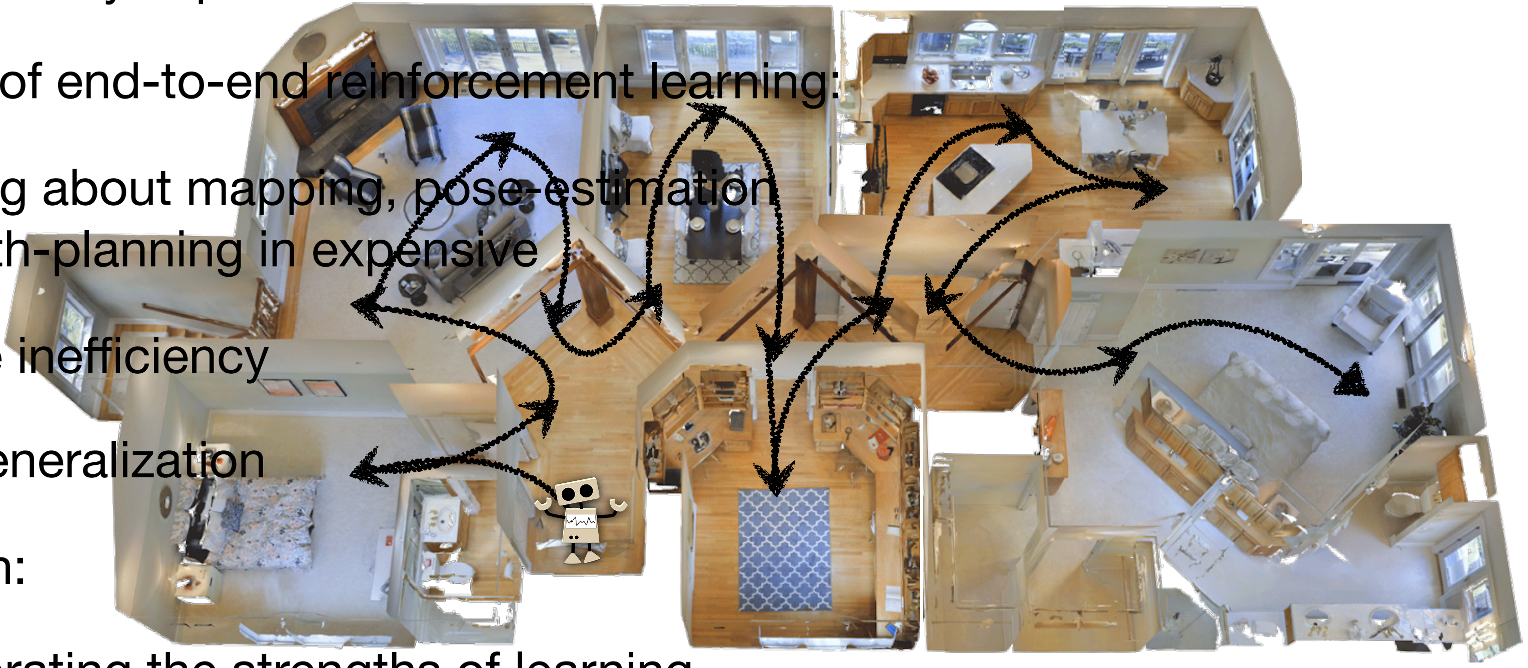
Require exploring the environment to find the goal



Exploration

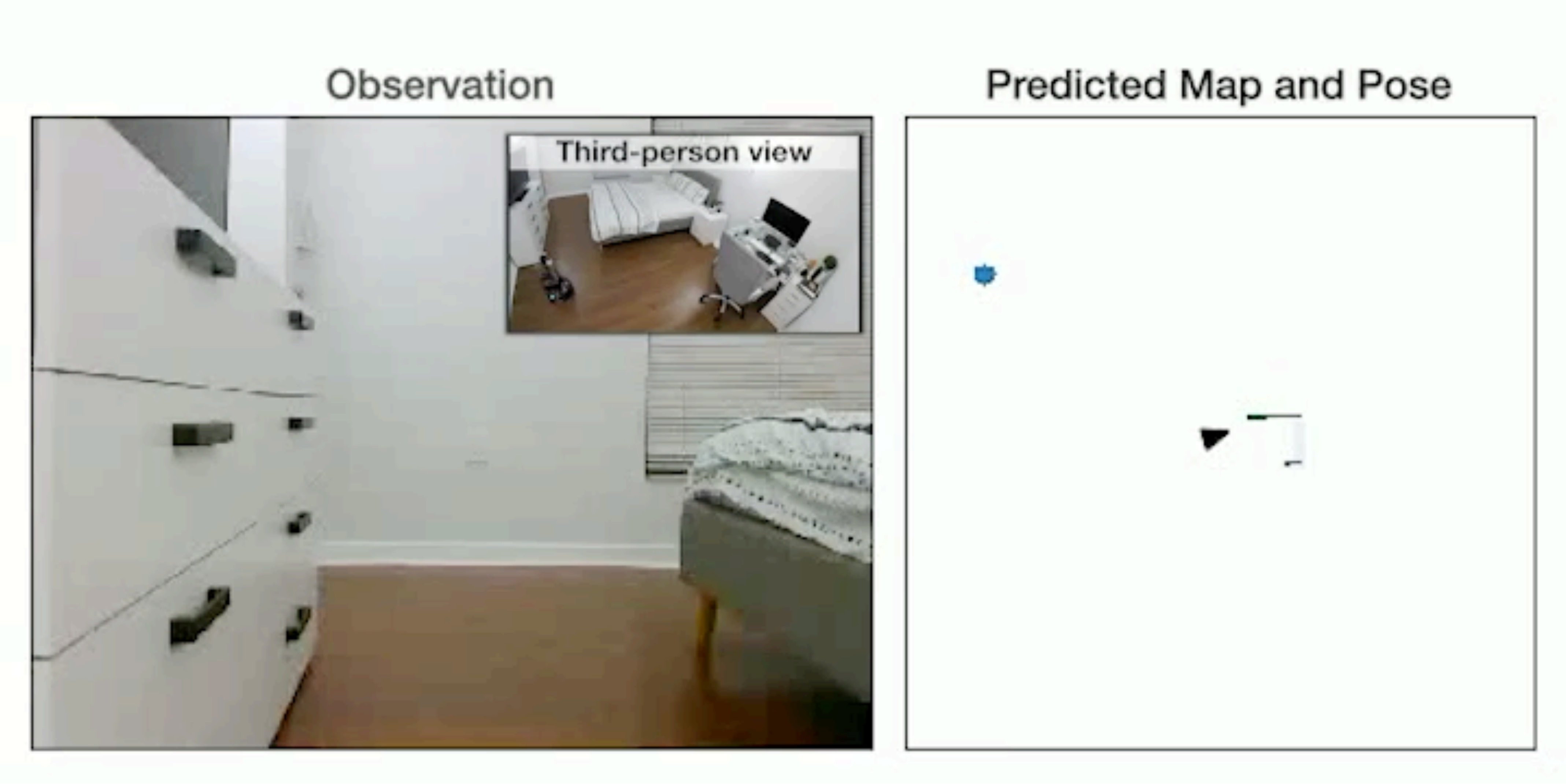


Exploration

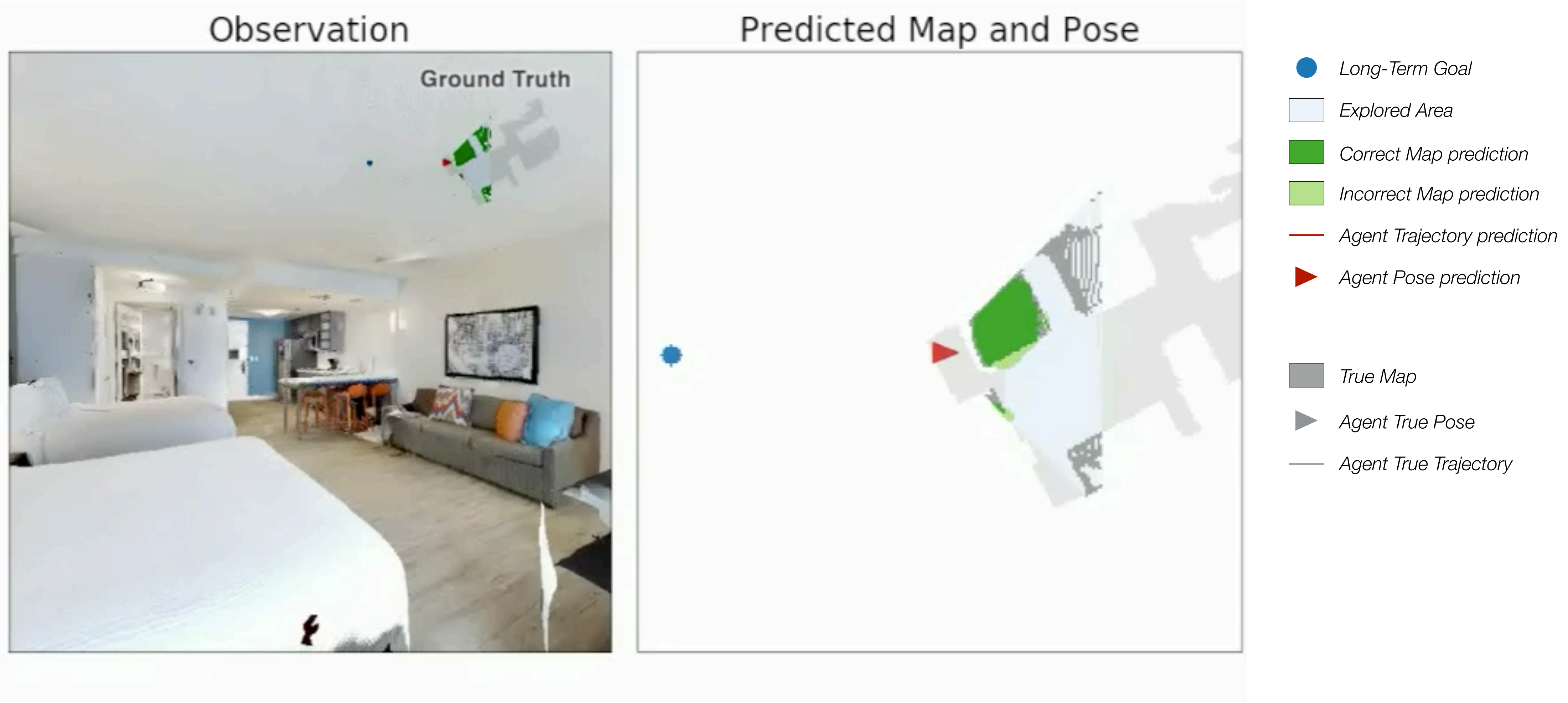


- How to efficiently explore an unseen environment?
- Limitations of end-to-end reinforcement learning:
  - Learning about mapping, pose-estimation and path-planning in expensive
  - Sample inefficiency
  - Poor generalization
- Our solution:
  - Incorporating the strengths of learning
  - Modular and hierarchical system

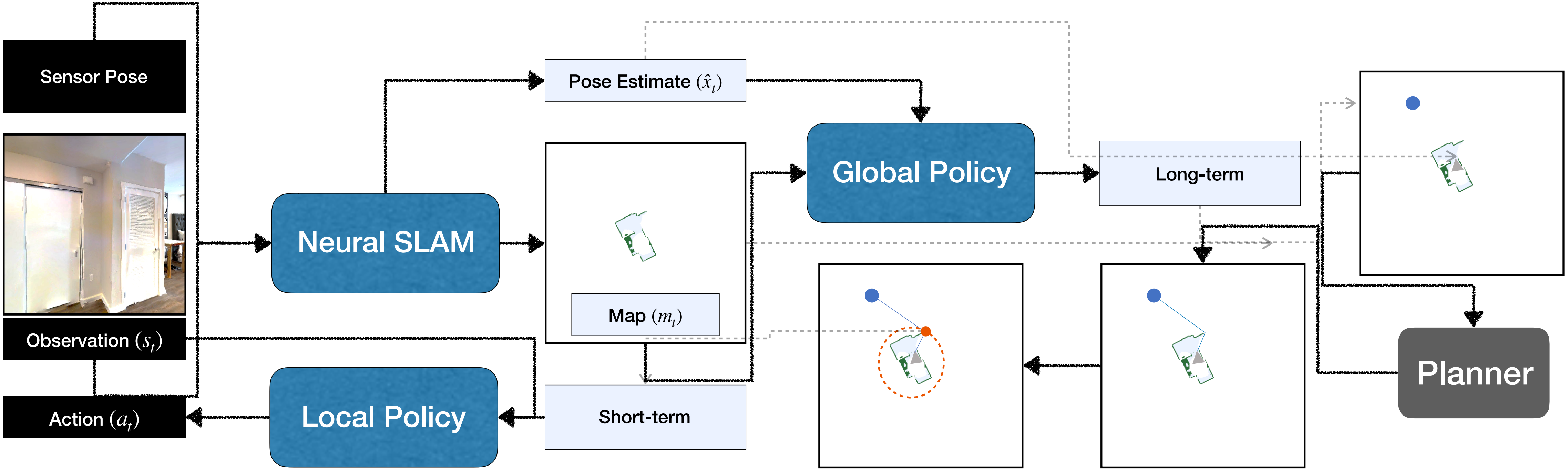
Preview: Visual Navigation in the Real World



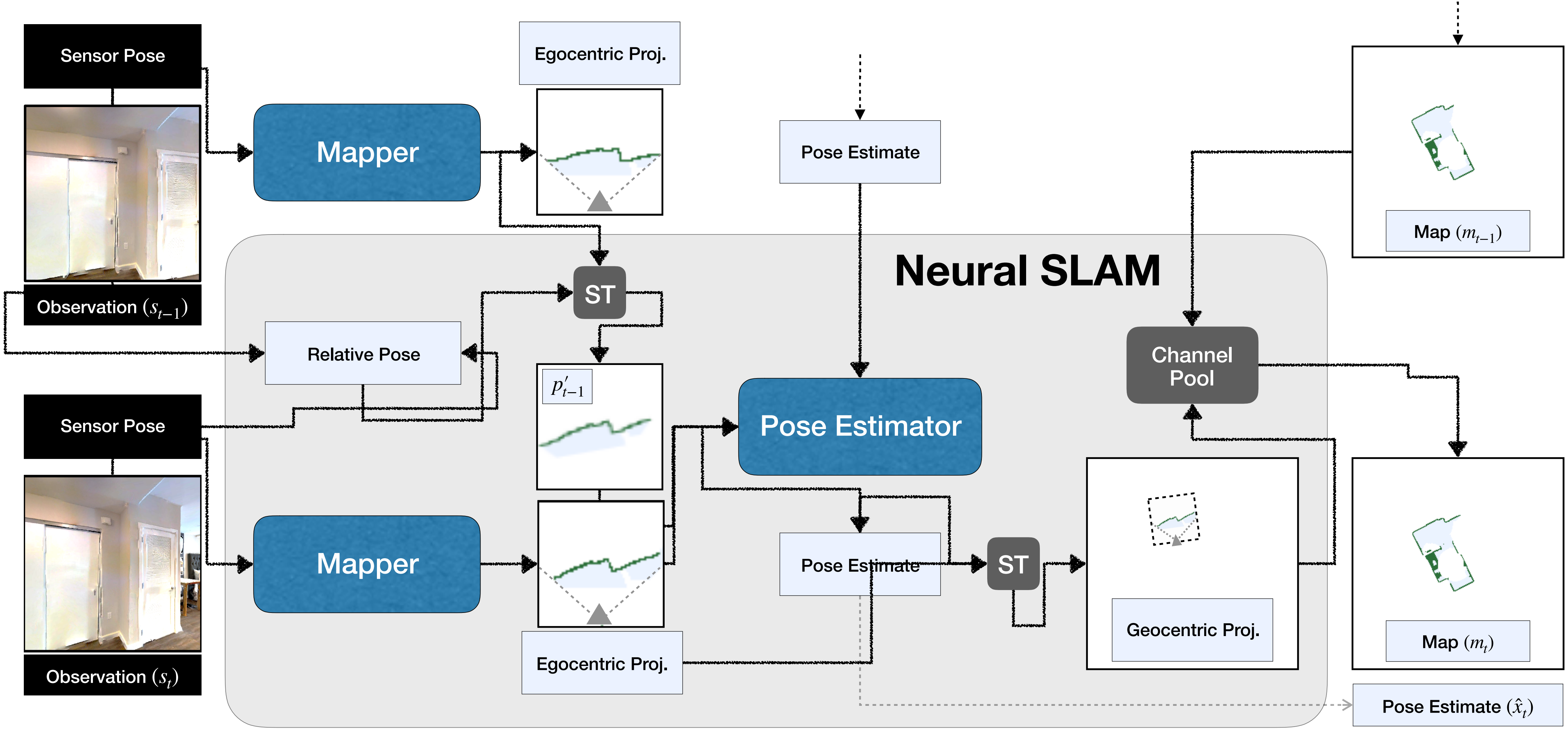
Exploration in Gibson Environment



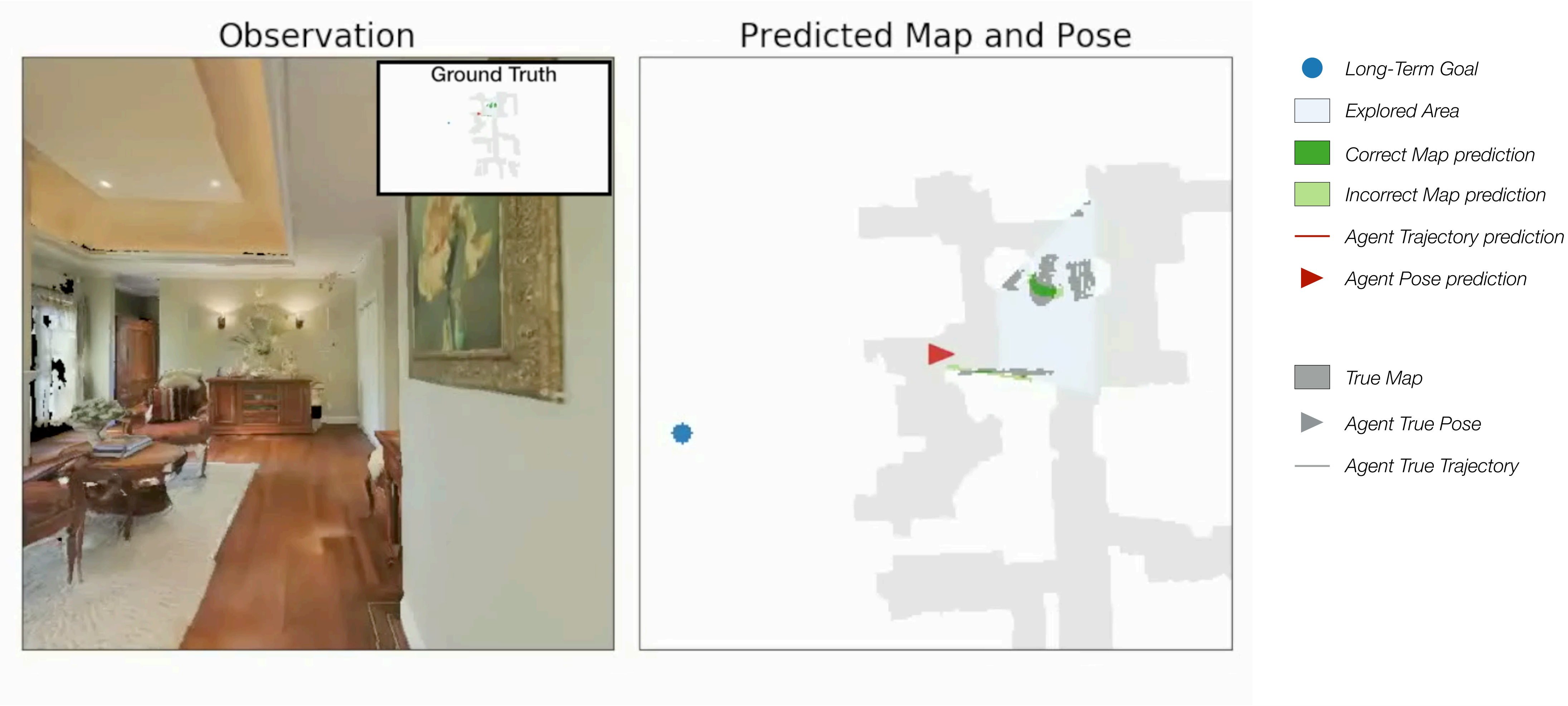
Active Neural SLAM: Overview



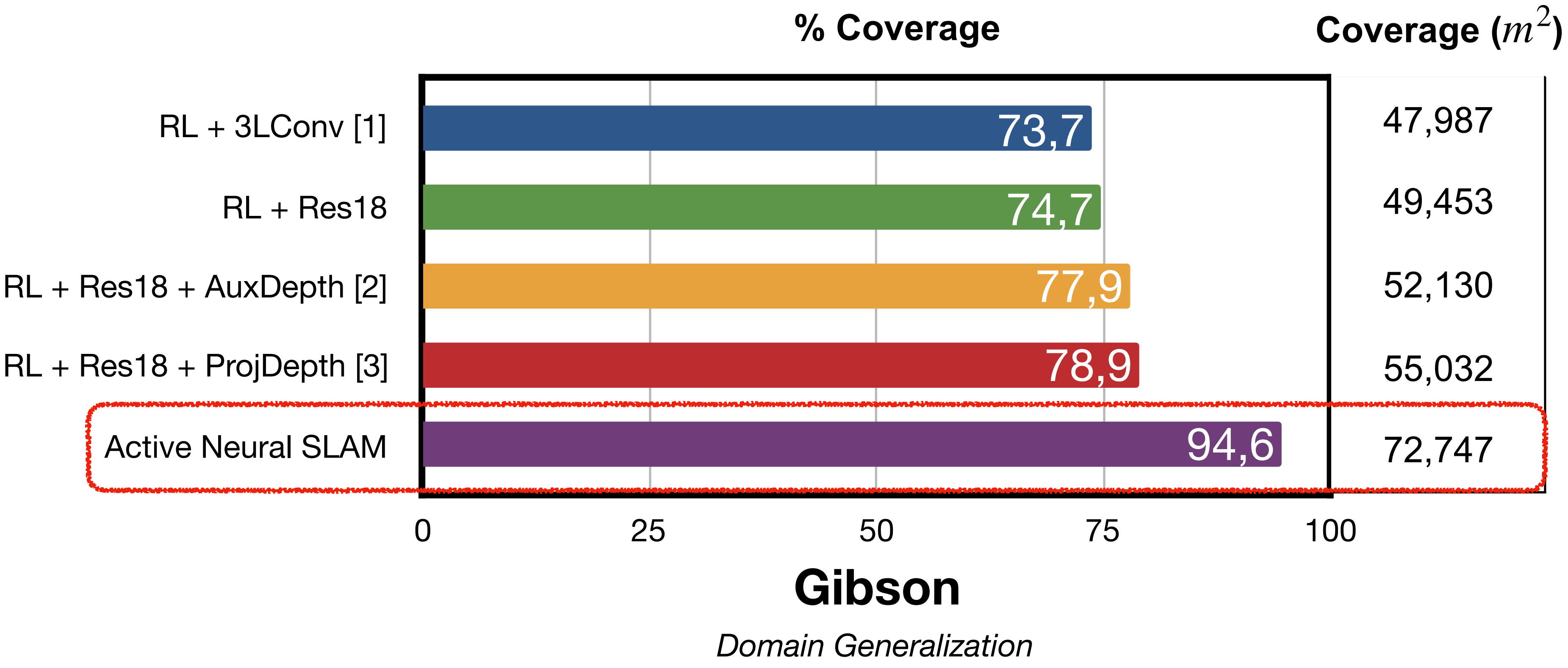
Neural SLAM Module



Domain Generalization: Matterport3D



Exploration Results



**Adapted from [1] Lample & Chaplot. AAAI-17, [2] Mirowski et al. ICLR-17, [3] Chen el al. ICLR-19*

Goal-conditioned Navigation

Point Goal

(x, y) *coordinate*

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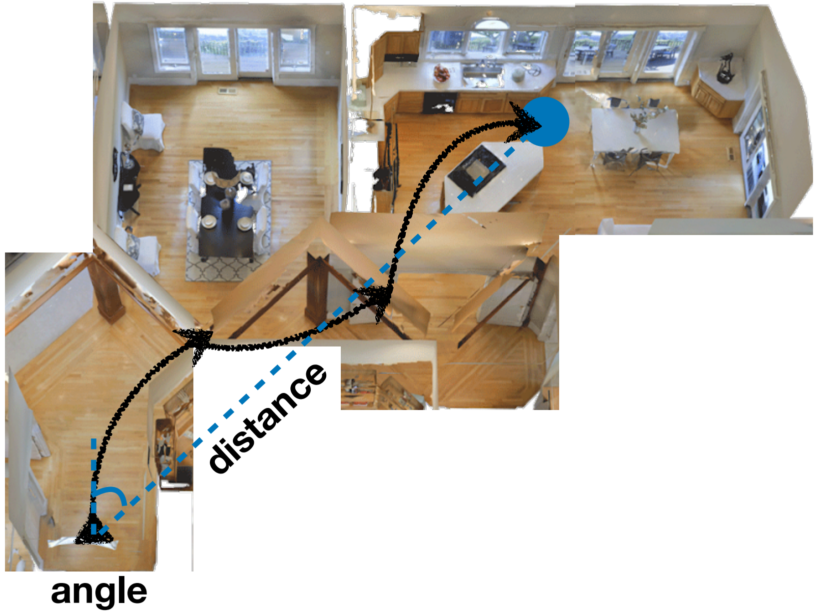
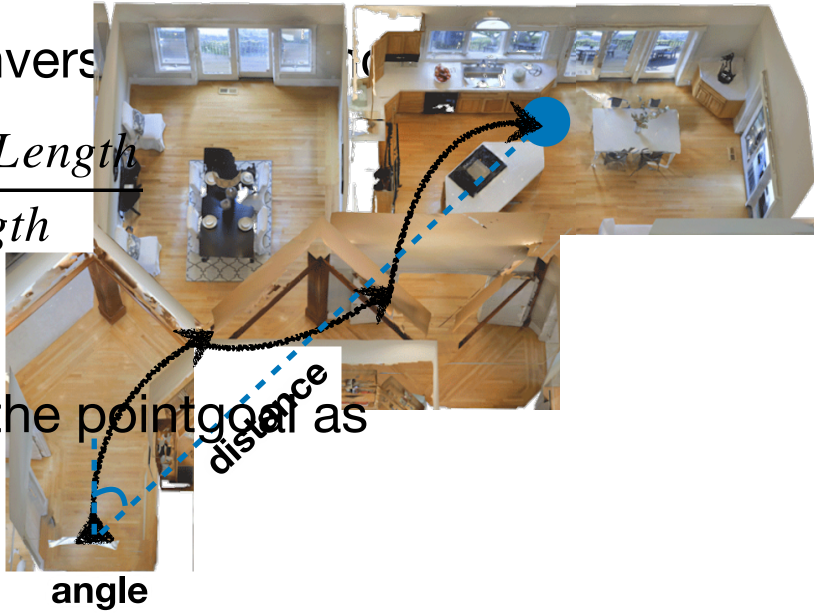
Point-Goal Navigation



Point-Goal Navigation

- Objective: Navigate to goal coordinates
- Metric: Success weighted by invers

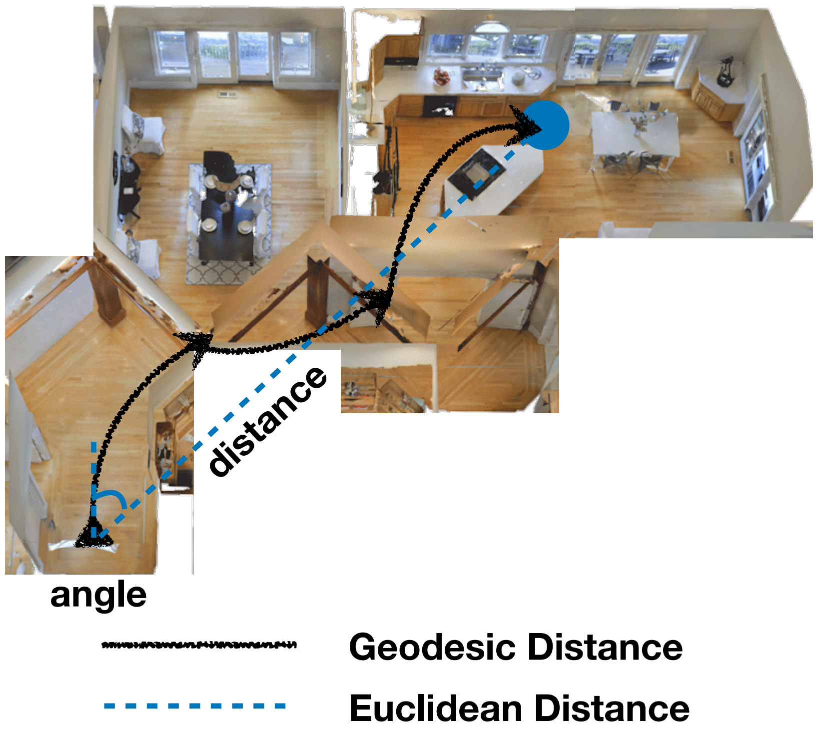
$$\frac{1}{N}\sum_{i=1}^{N} Success * \frac{ShortestPathLength}{PathLength}$$



- Global Policy -> always gives the pointgoal as the long-term goal

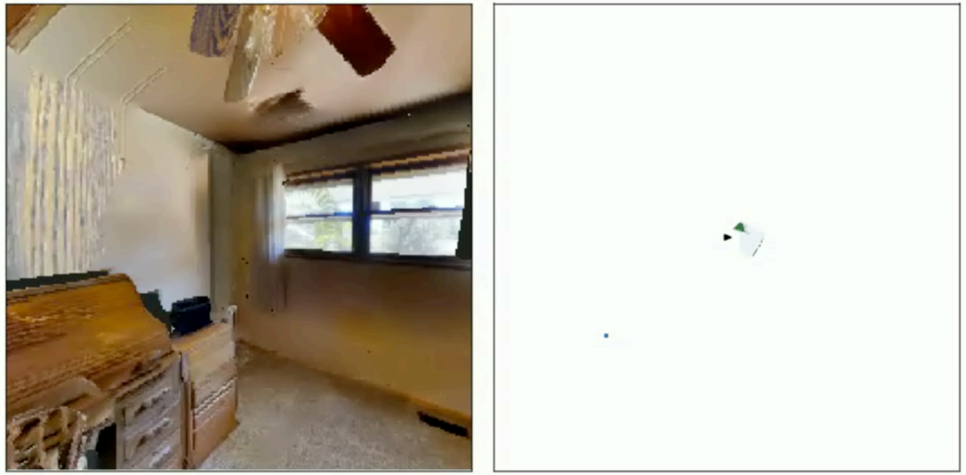
Harder Datasets

- **Hard-GEDR**
  - Higher Geodesic to Euclidean distance ratio (GEDR)
  - Avg GEDR 2.5 vs 1.37, minimum GEDR is 2
- **Hard-Dist**
  - Higher Geodesic distance
  - Avg Dist 13.5m vs 7.0m, minimum Dist is 10m



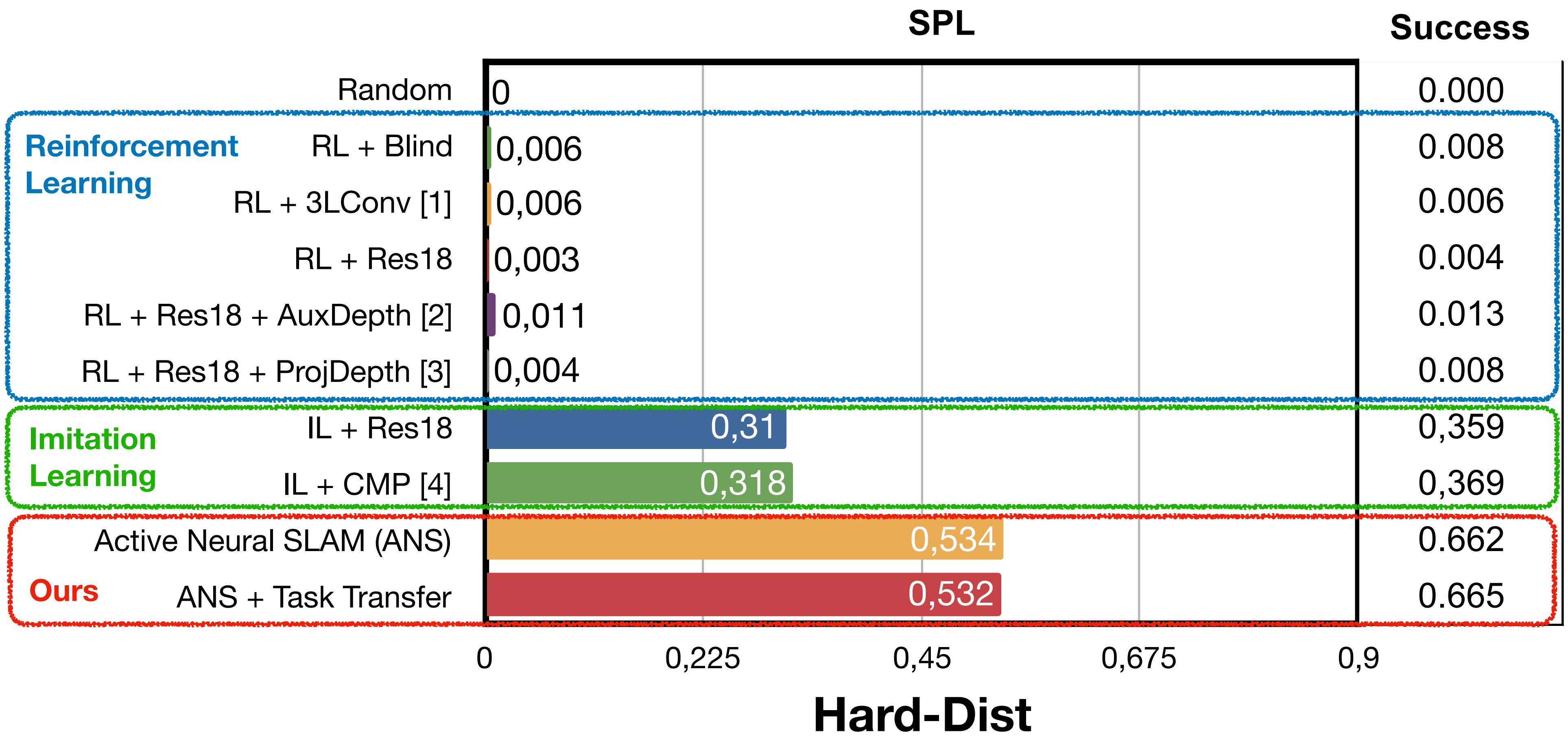
Point-Goal Navigation

Gibson



MP3D

Results



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Navigation Tasks

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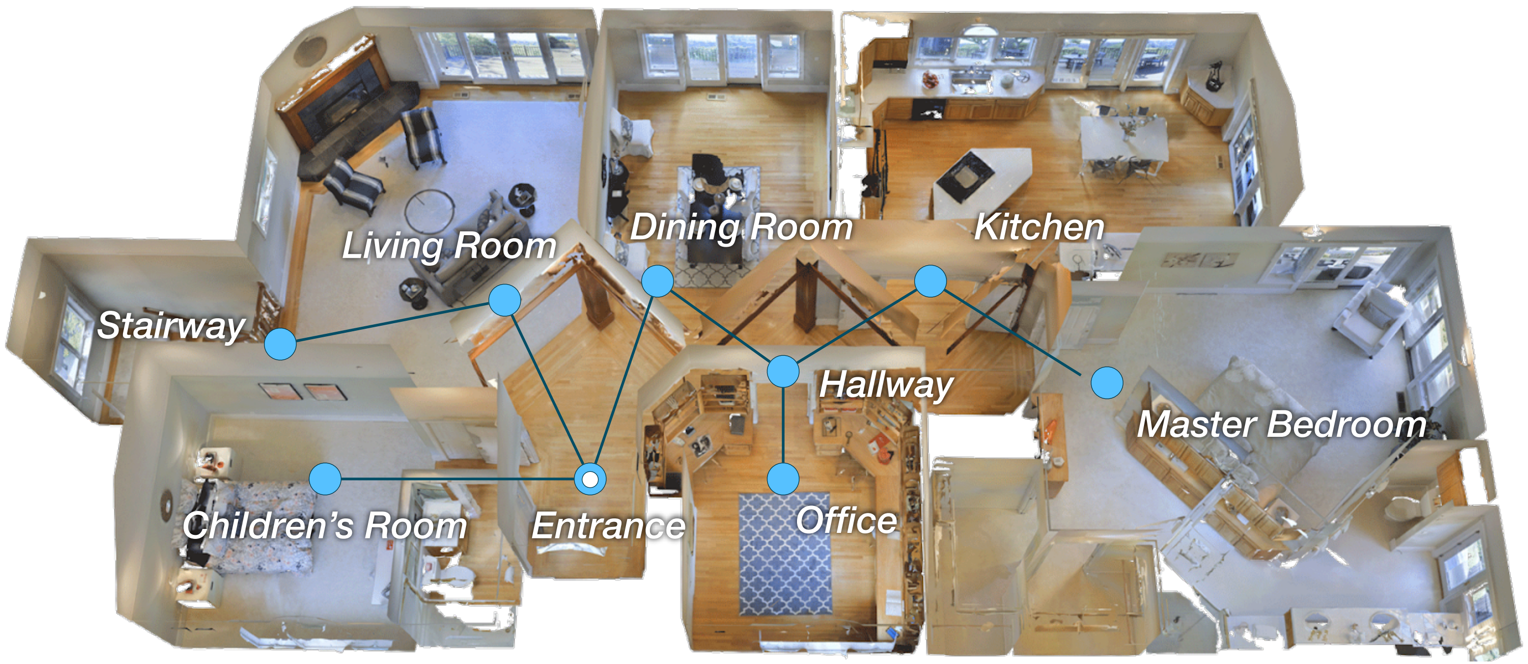
Semantic Priors and Common-Sense

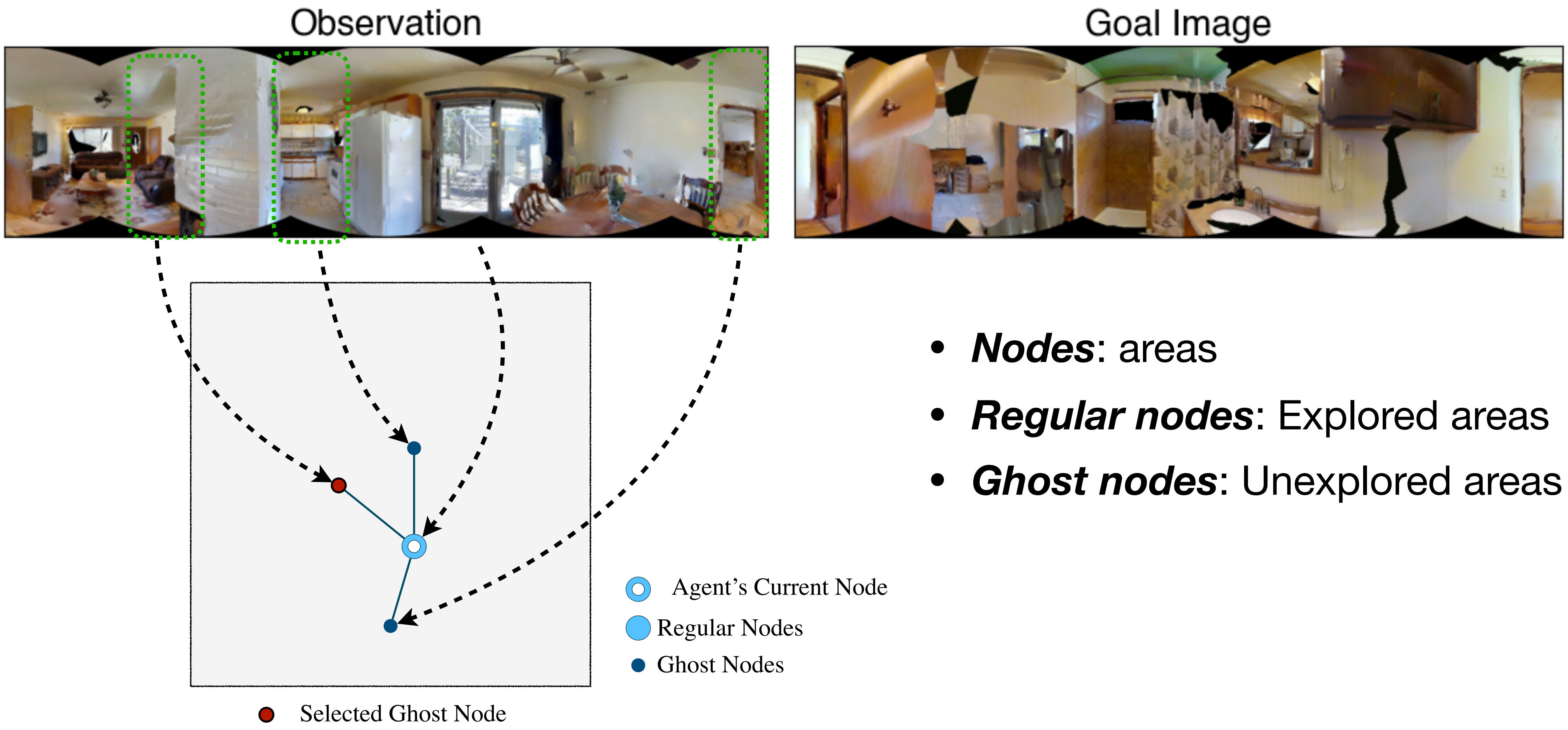
- Humans use semantic priors and common-sense to explore and navigate everyday
- Most navigation algorithms struggle to do so

Object Goal Navigation using Goal-oriented Semantic Exploration
Devendra Singh Chaplot, Dhiraj Gandhi, Abhinav Gupta, Ruslan Salakhutdinov, NeurIPS 2020

Topological Maps

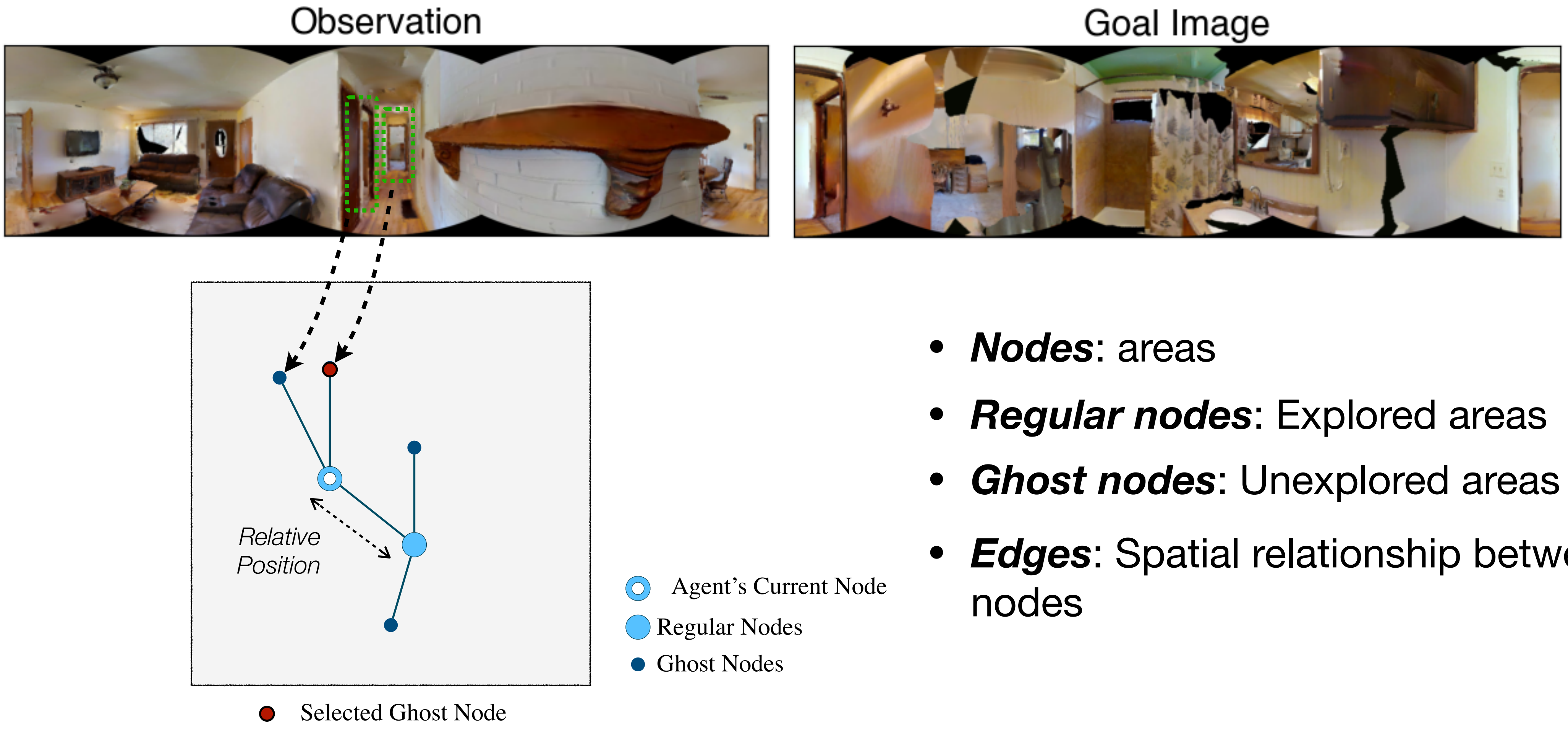


Topological Graph Representation



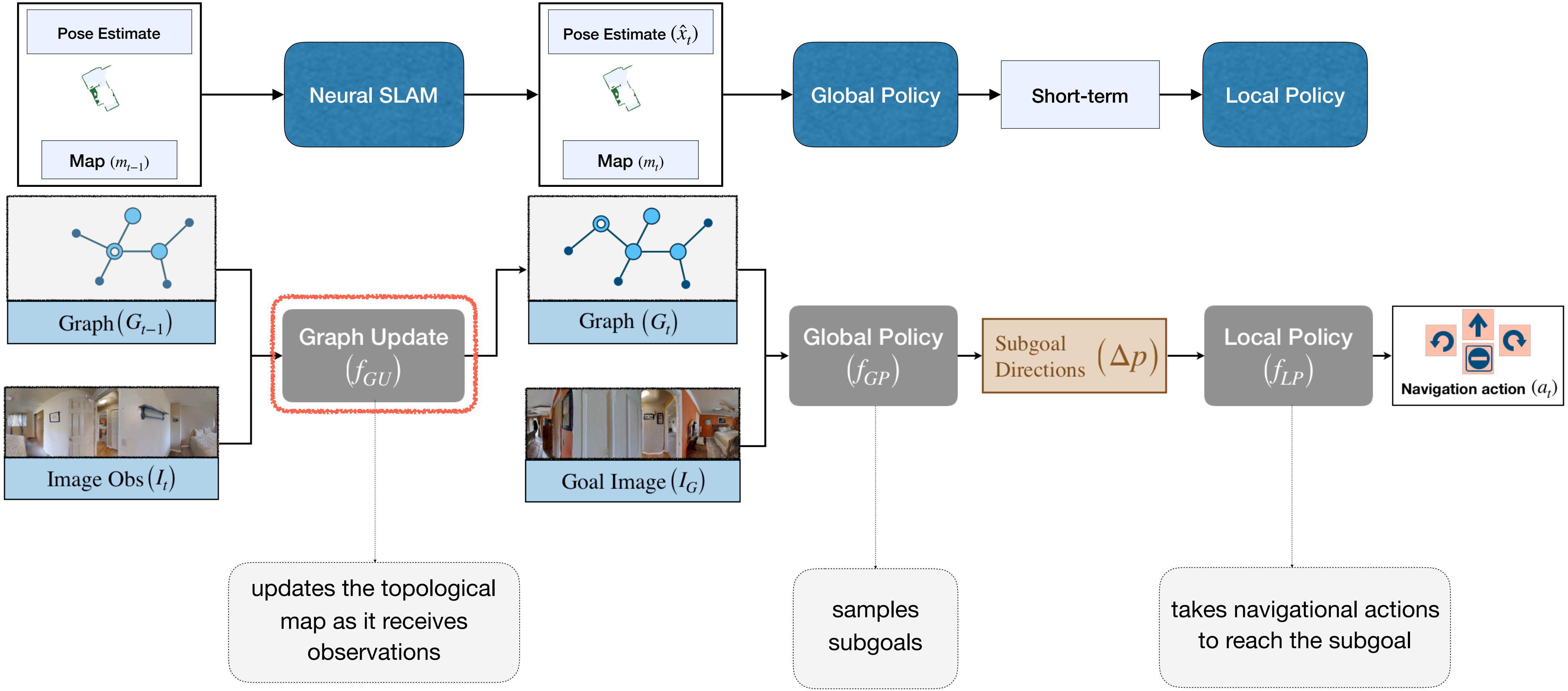
- ***Nodes***: areas
- ***Regular nodes***: Explored areas
- ***Ghost nodes***: Unexplored areas

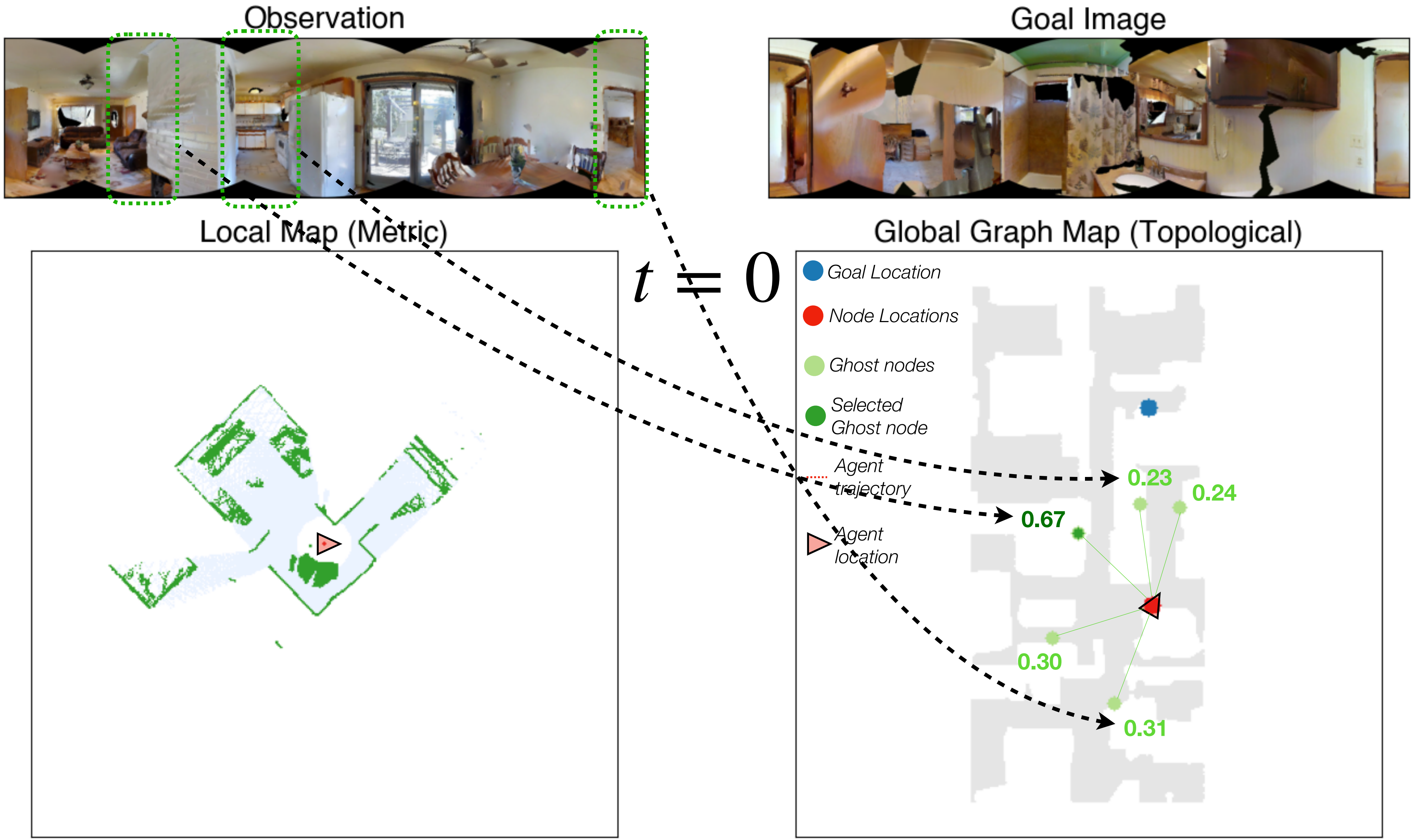
Topological Graph Representation



- ***Nodes***: areas
- ***Regular nodes***: Explored areas
- ***Ghost nodes***: Unexplored areas
- ***Edges***: Spatial relationship between nodes

Neural Topological SLAM

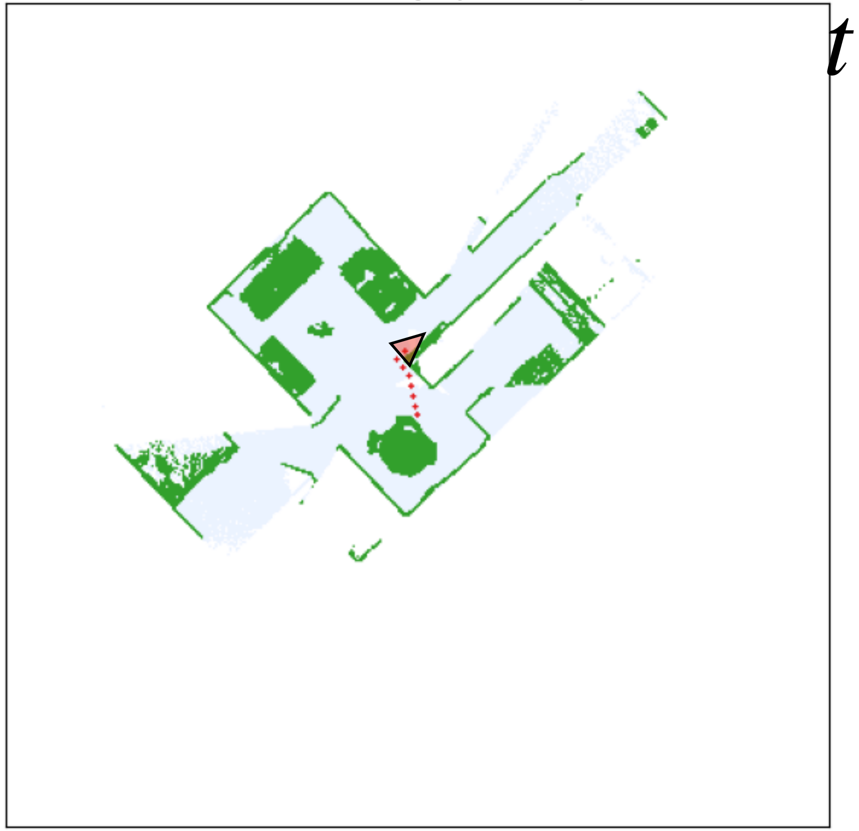



Observation
Goal Image
Local Map (Metric)
Global Graph Map (Topological)
$t = 0$
Goal Location
Node Locations
Ghost nodes
Selected Ghost node
Agent trajectory
Agent location
0.23
0.24
0.67
0.30
0.31

Observation

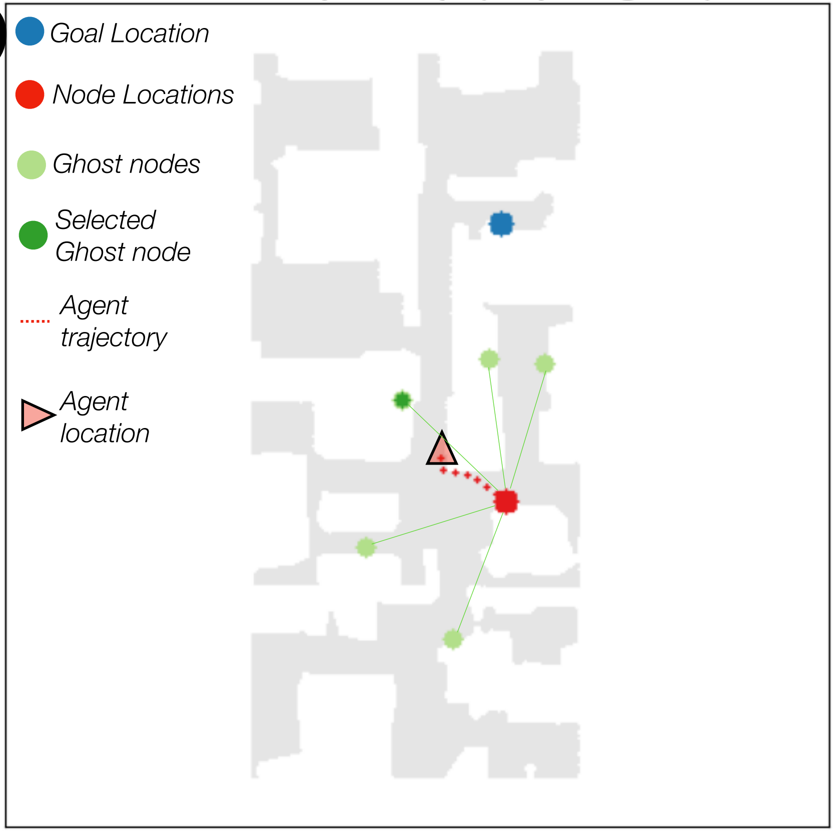
Goal Image

Local Map (Metric)



$t = 29$

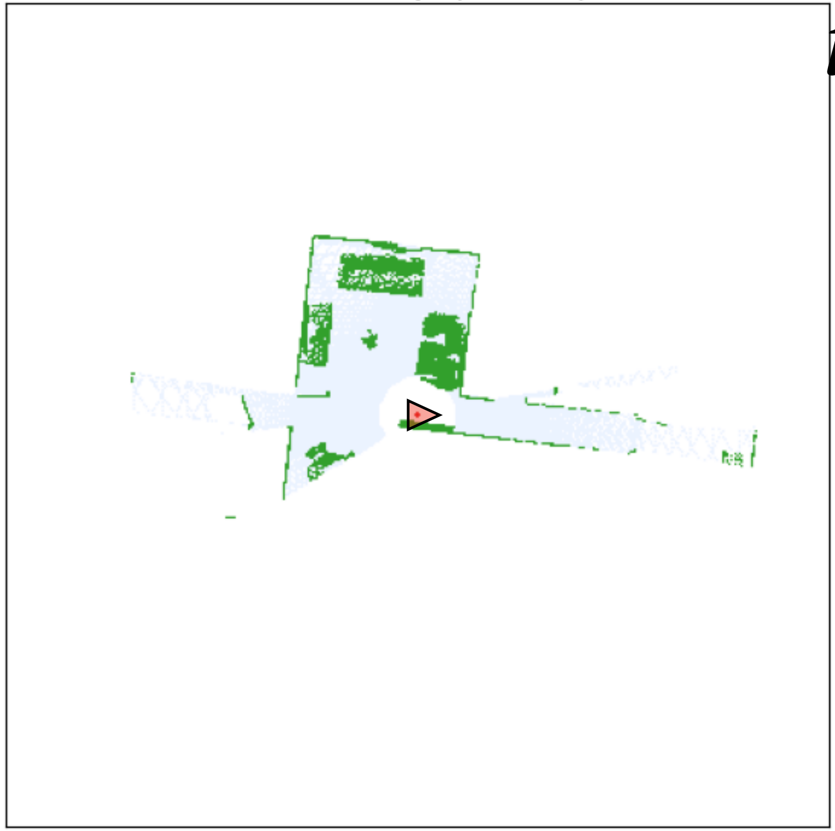
Global Graph Map (Topological)



Observation

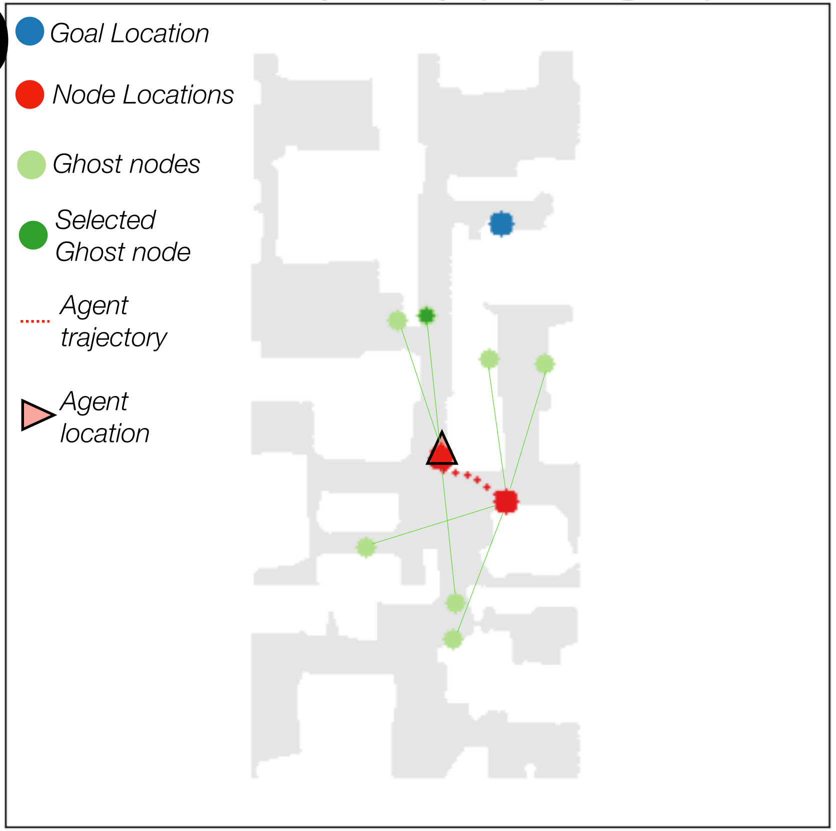
Goal Image

Local Map (Metric)



$t = 30$

Global Graph Map (Topological)

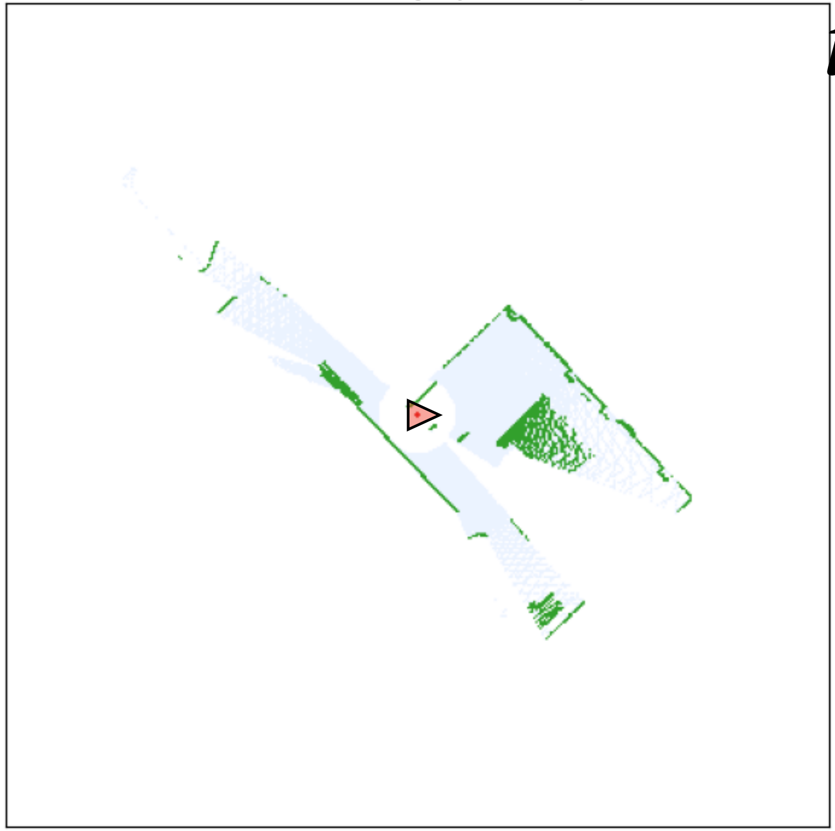


Observation

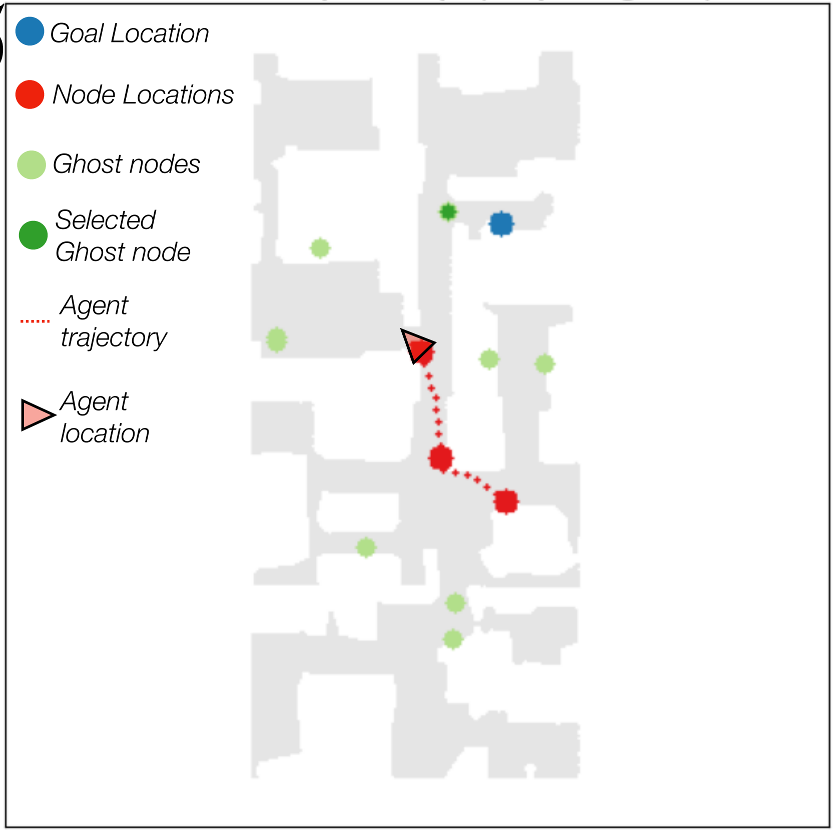
Goal Image

Local Map (Metric)

$t = 45$



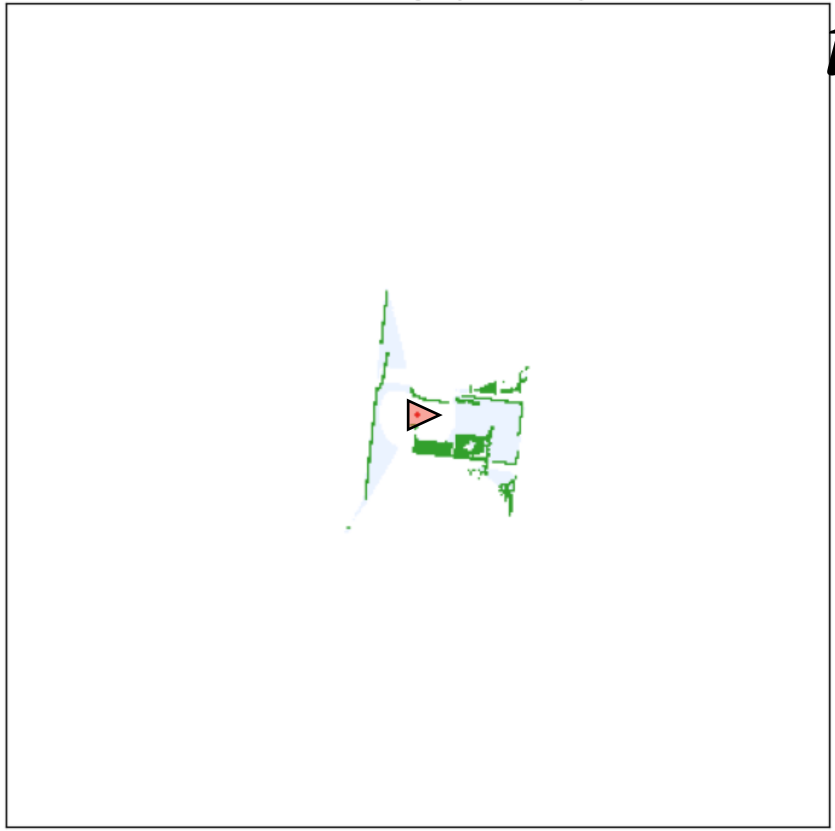
Global Graph Map (Topological)



Observation

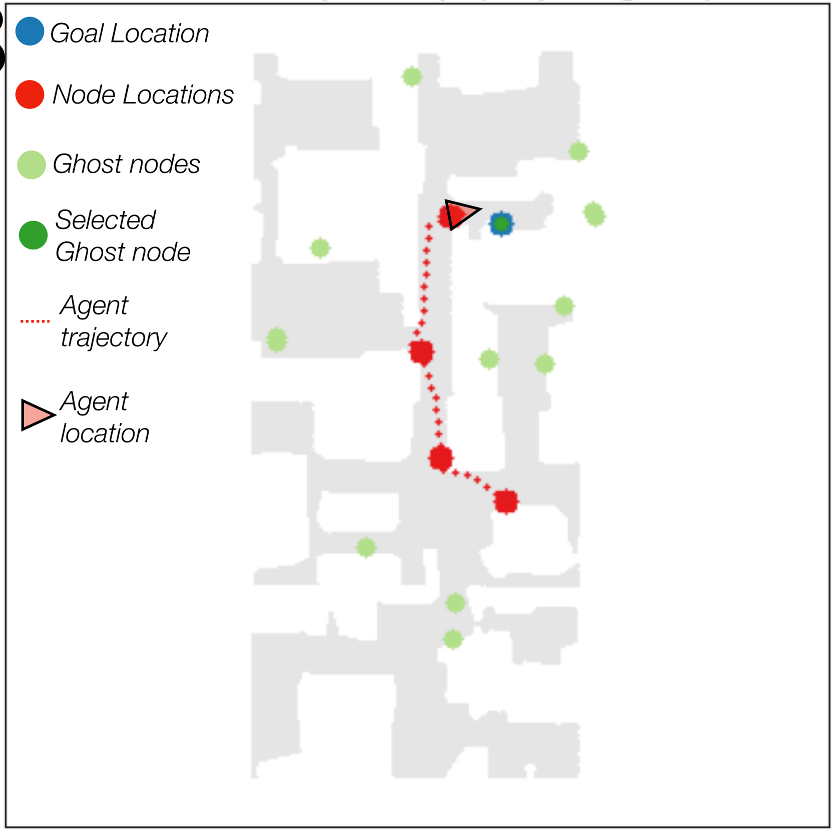
Goal Image

Local Map (Metric)



$t = 78$

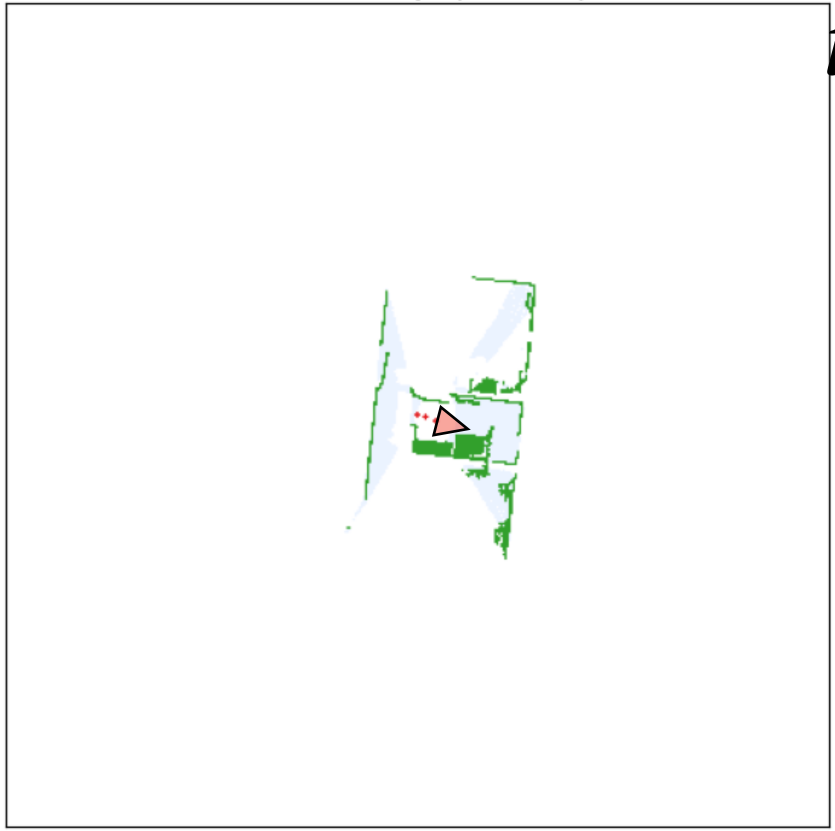
Global Graph Map (Topological)



Observation

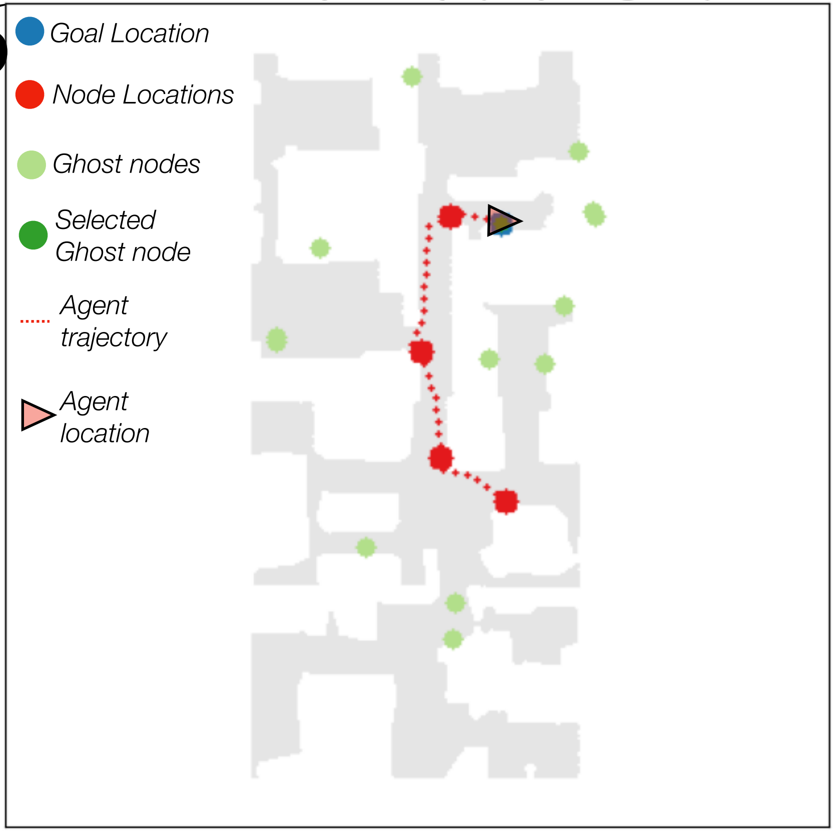
Goal Image

Local Map (Metric)



$t = 86$

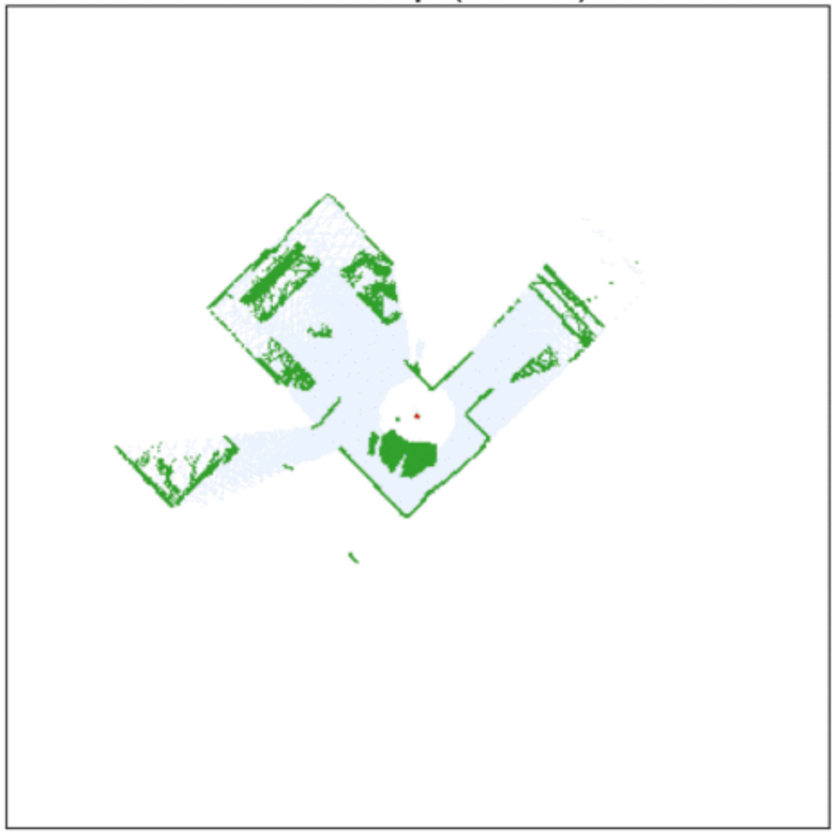
Global Graph Map (Topological)



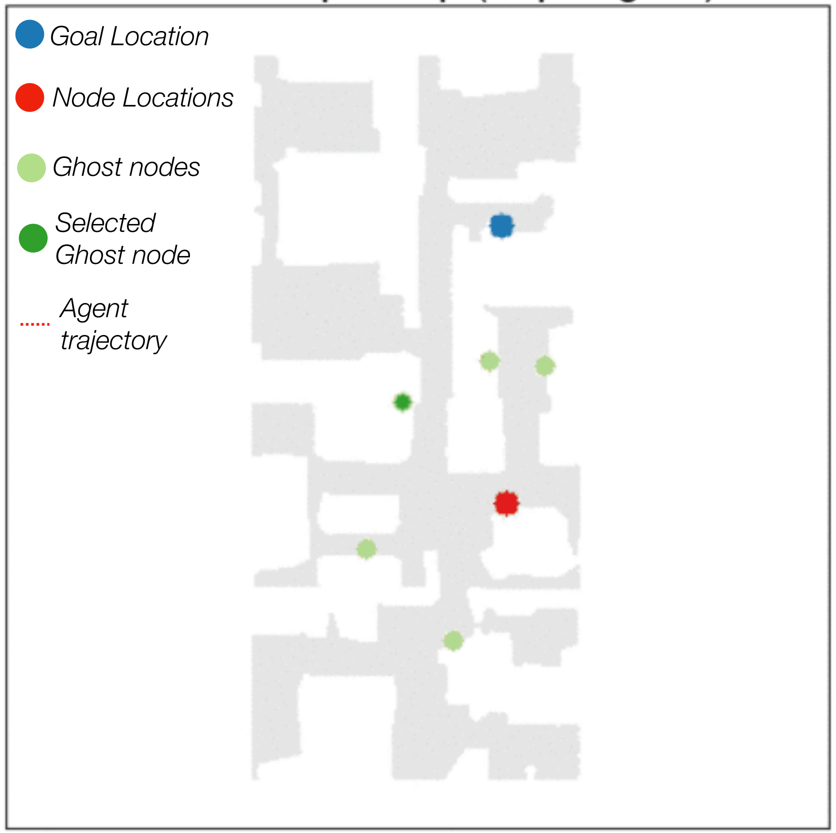
Observation

Goal Image

Local Map (Metric)



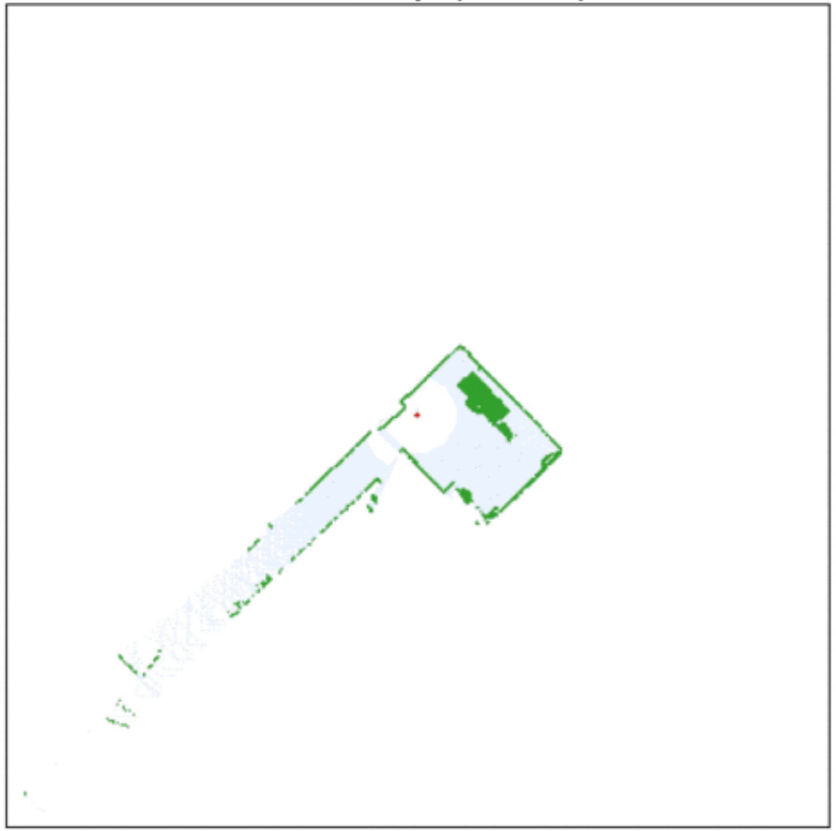
Global Graph Map (Topological)



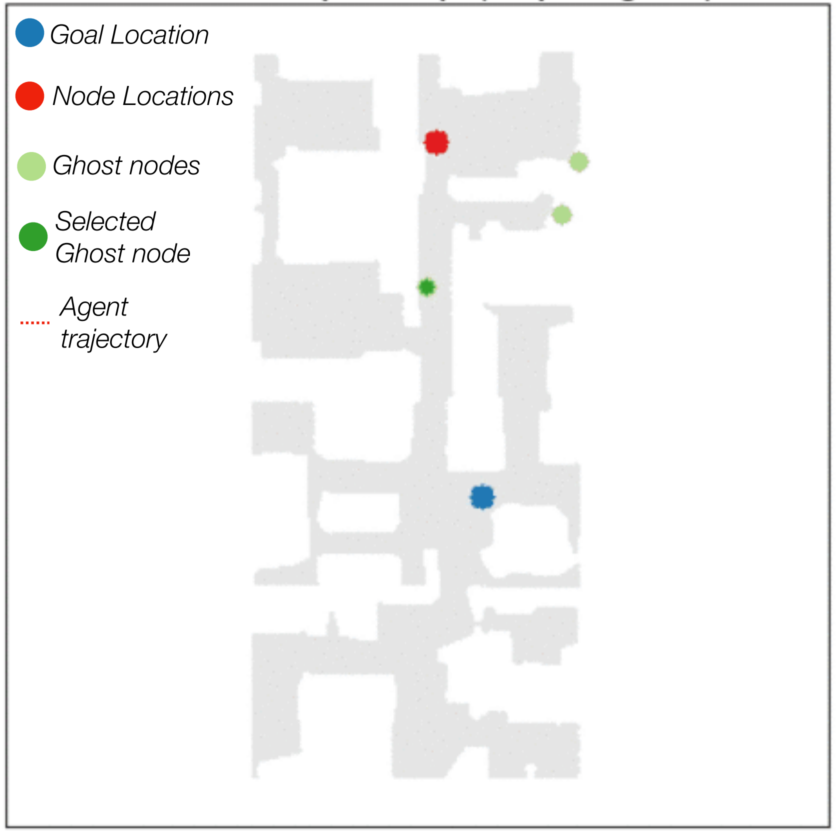
Observation

Goal Image

Local Map (Metric)



Global Graph Map (Topological)



Results

Robustness to Pose Noise

		RGB	RGBD	RGBD (No Noise)	RGBD (No Stop)
End-to-end Learning	LSTM + Imitation	0,10	0,14	0,15	0,18
	LSTM + RL	0,10	0,13	0,14	0,17
Modular Metric Maps	Occupancy Maps + FBE + RL	N/A	0,26	0,31	0,24
	Active Neural SLAM	0,23	0,29	0,35	0,39
Topological Maps	**Neural Topological SLAM**	**0,38**	**0,43**	**0,45**	**0,60**

Map based methods are better than vanilla learning methods even in presence of noise

NTS is better than occupancy map models, captures and uses semantic priors.

Internet vs Embodied Data

Static Internet Data

Active Embodied Data

Using Internet models for Embodied Agents

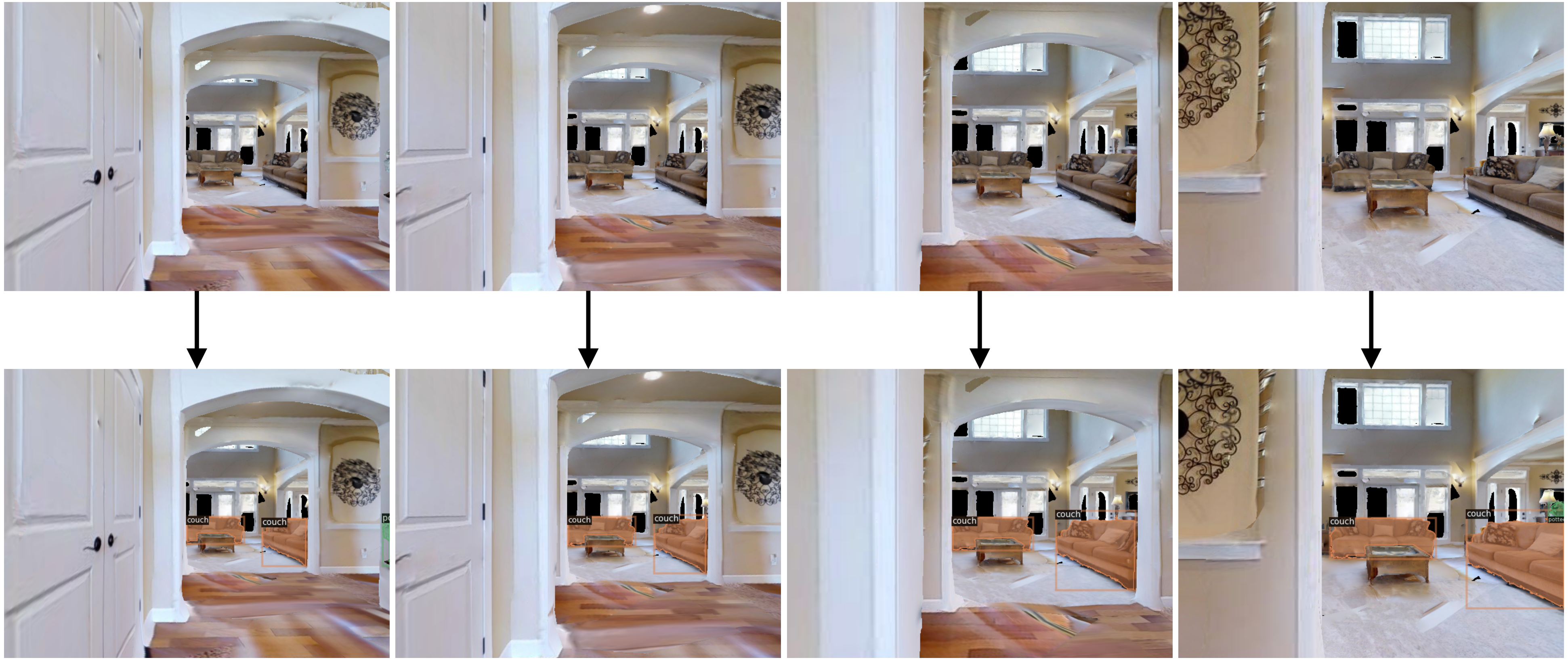
False positives

False negatives

Savva et al, Habitat: A platform for embodied AI research, ICCV 2019

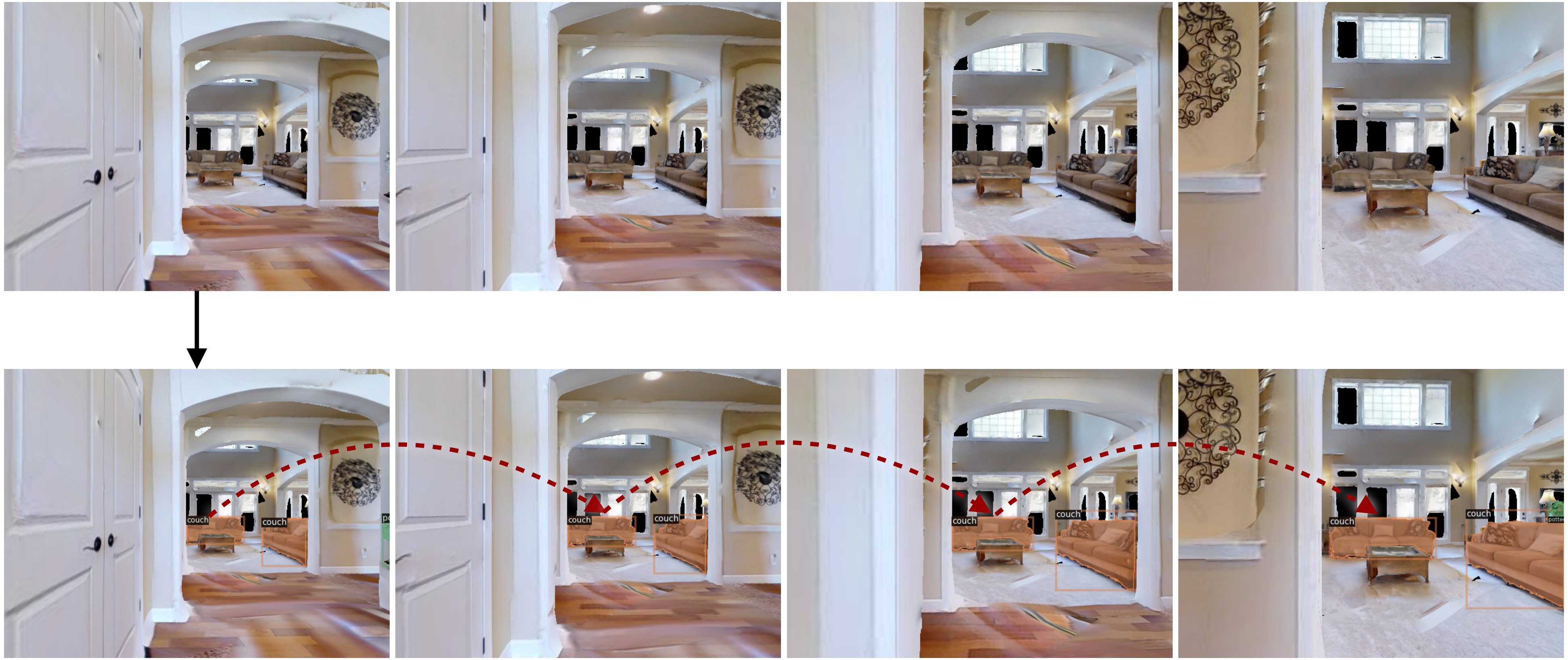
Embodied Perception

Active Embodied data

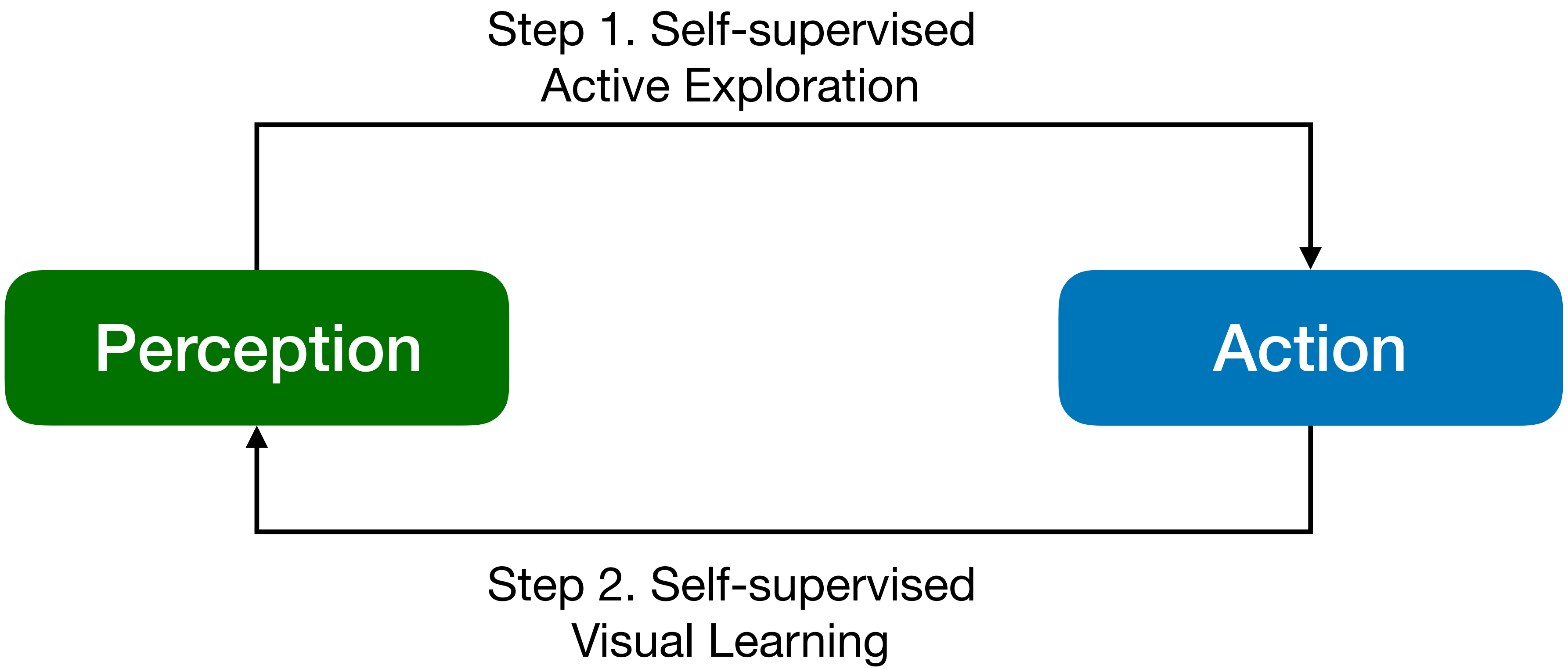


Embodied Perception

Active Embodied data

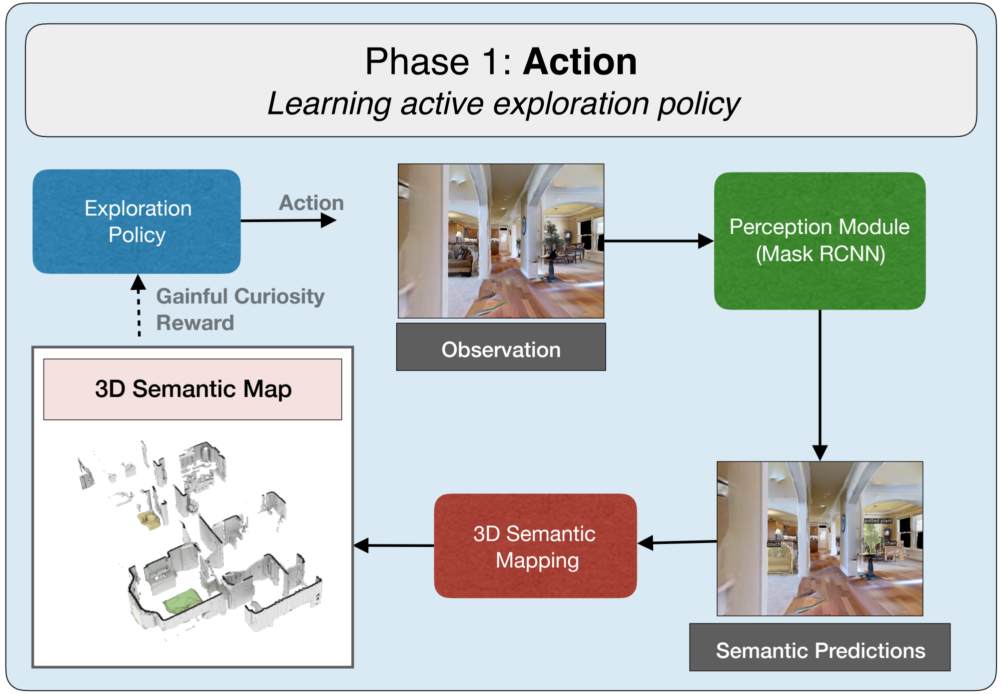


Perception-Action Loop



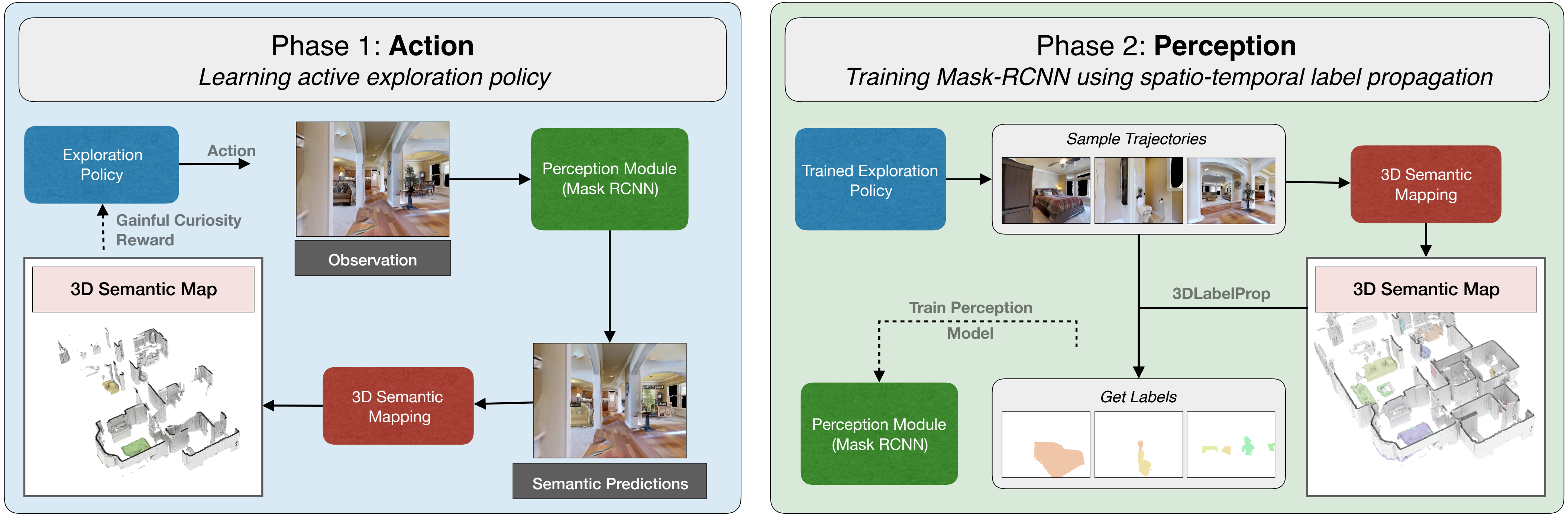
Pathak et al, Learning instance segmentation by interaction, 2018
Jang et al, Grasp2vec: Learning object representations from self-supervised grasping, 2018
Eitel et al, Self-supervised transfer learning for instance segmentation through physical interaction, 2019
Fang et al.,Move to See Better: Self-Improving Embodied Object Detection, 2021

SEAL: Self-supervised Embodied Active Learning



SEAL: Self-supervised Embodied Active Learning using Exploration and 3D Consistency
Devendra Chaplot, Murtaza Dalal, Saurabh Gupta, Jitendra Malik, Russ Salakhutdinov, NeurIPS 2021

SEAL: Self-supervised Embodied Active Learning

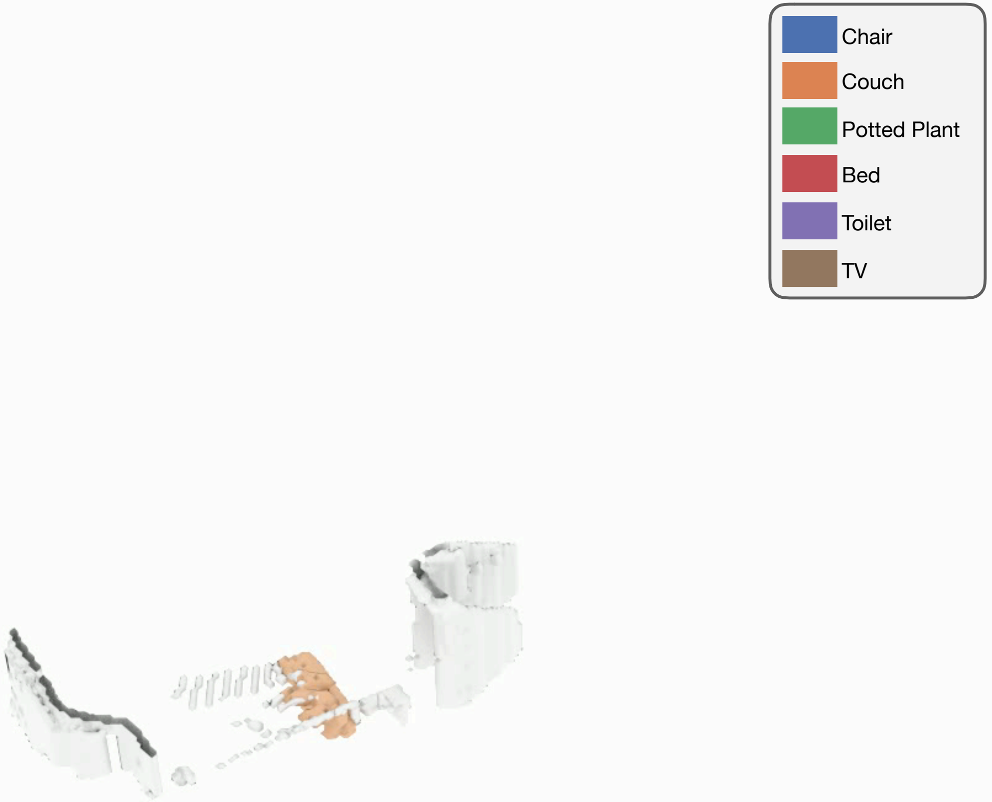


Both phases do not require any additional labelled data

SEAL: Self-supervised Embodied Active Learning using Exploration and 3D Consistency
Devendra Chaplot, Murtaza Dalal, Saurabh Gupta, Jitendra Malik, Russ Salakhutdinov, NeurIPS 2021

3D Semantic Mapping

3D Semantic Map $M = K \times L \times W \times H$



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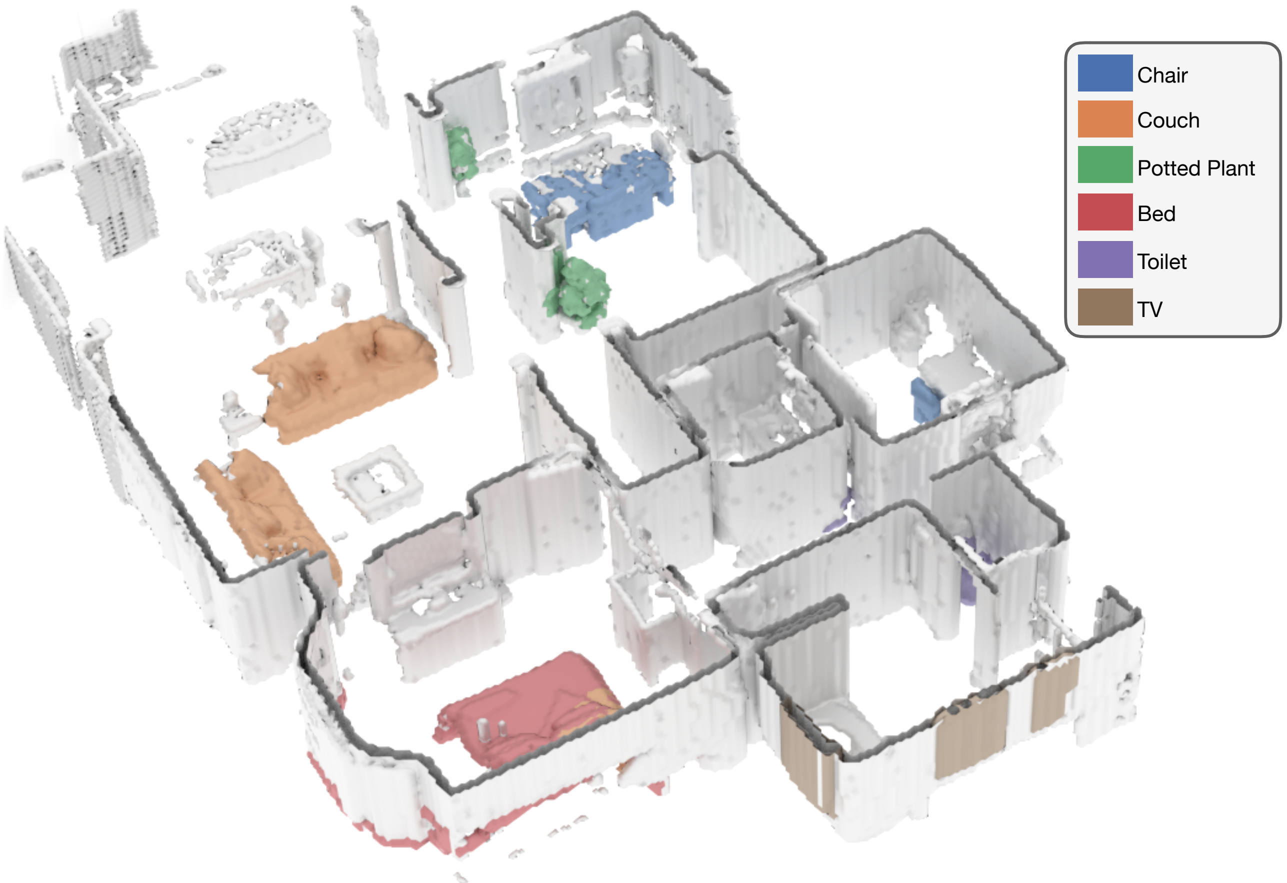
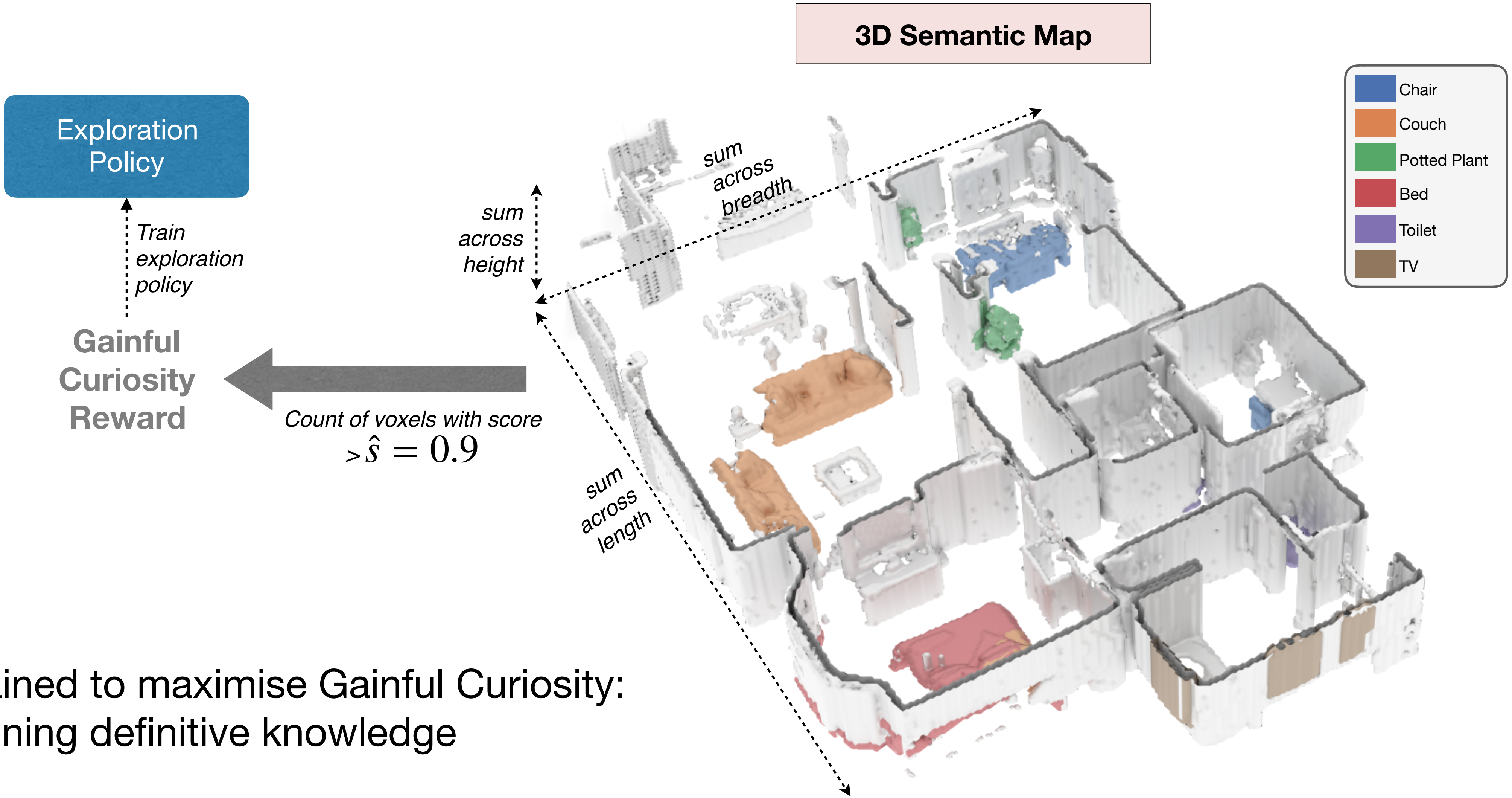
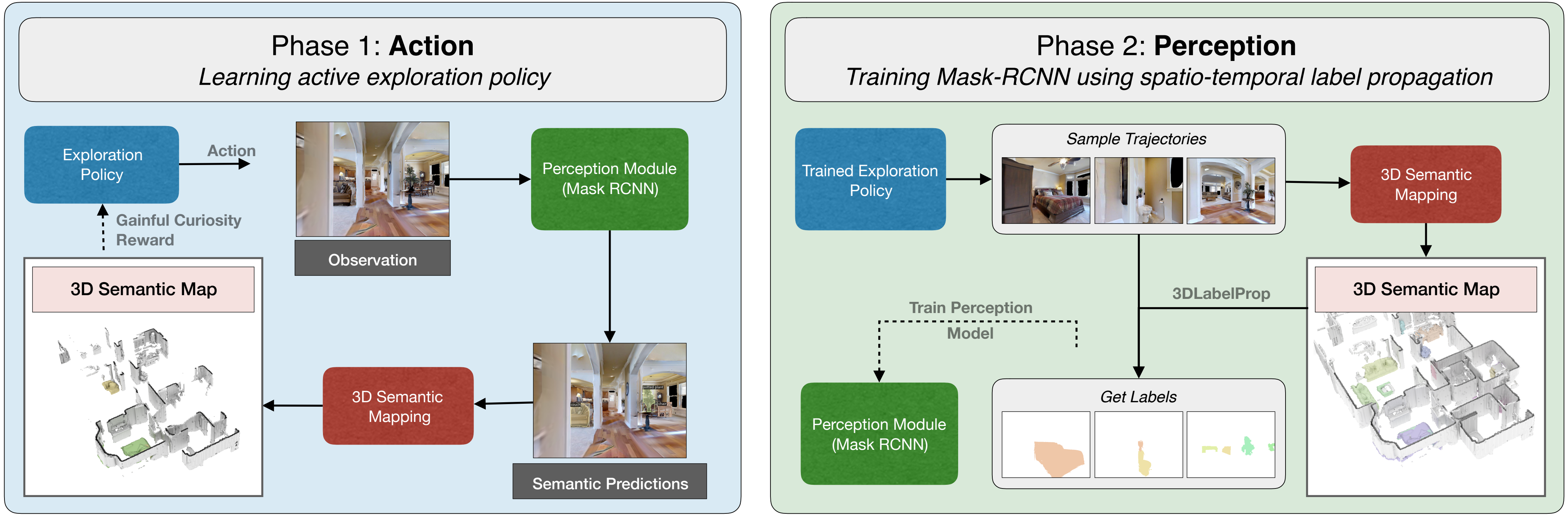


Gainful Curiosity



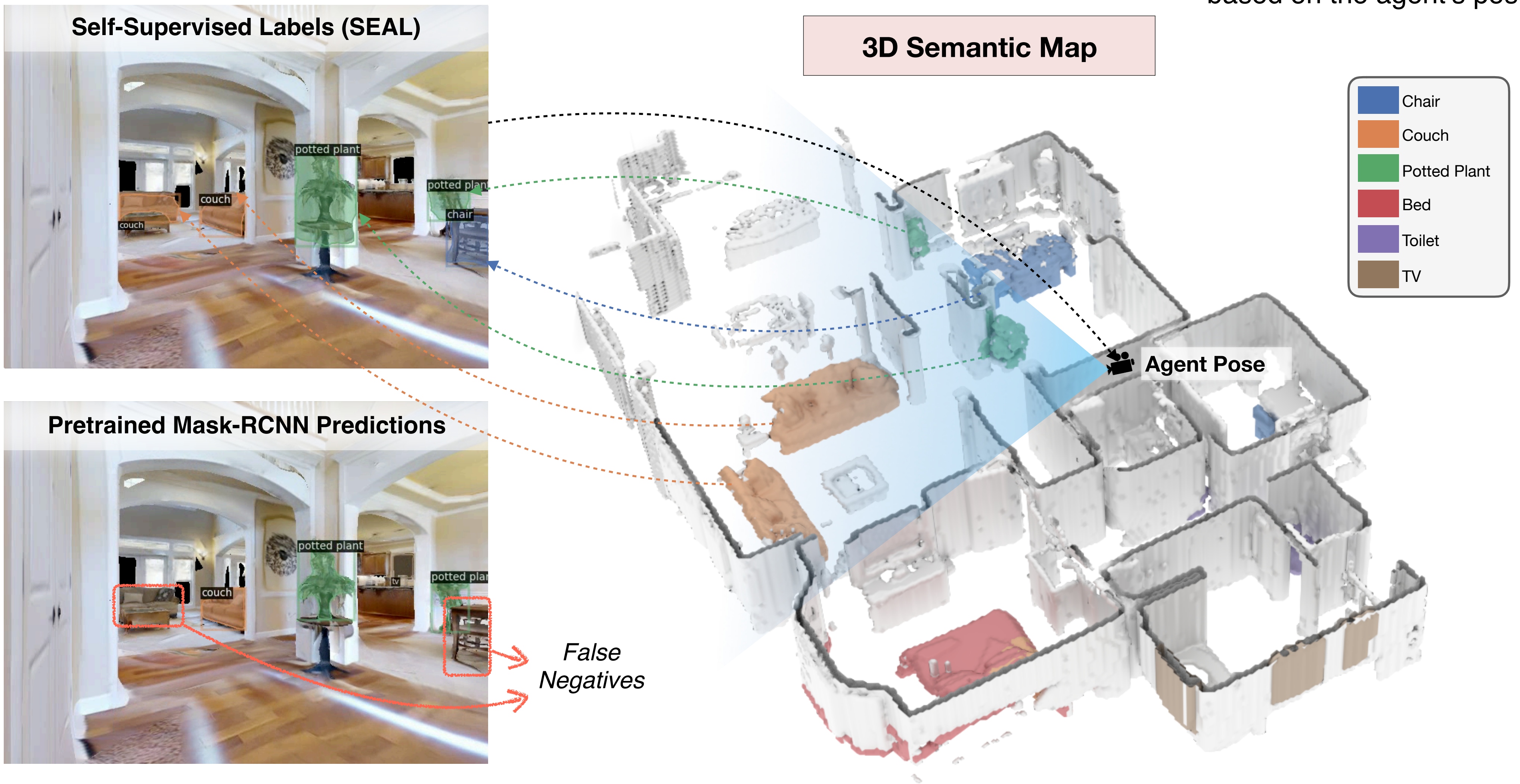
- Trained to maximise Gainful Curiosity: gaining definitive knowledge

SEAL: Self-supervised Embodied Active Learning

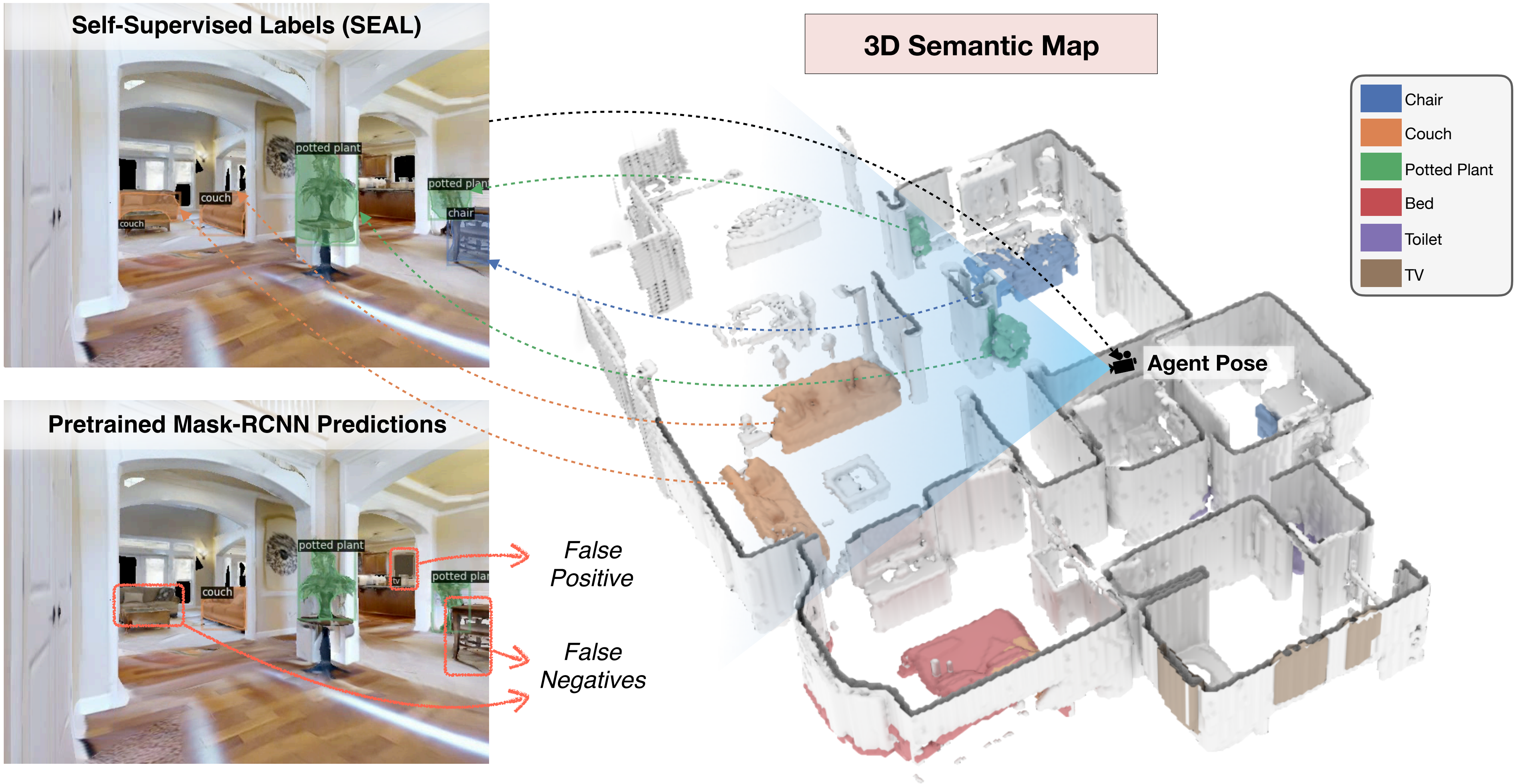


3D Label Propagation

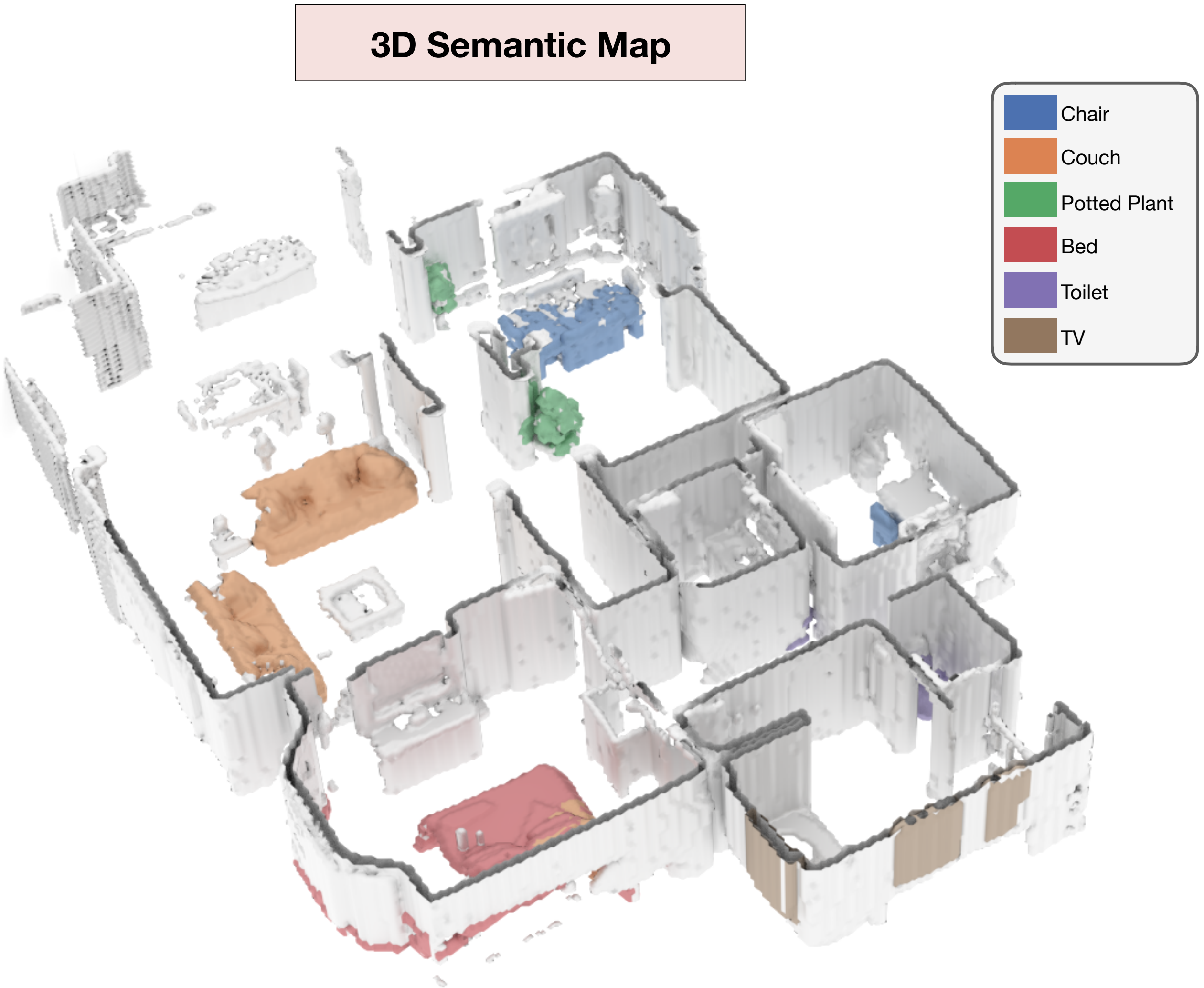
Instance label for each pixel is obtained using ray tracing based on the agent's pose



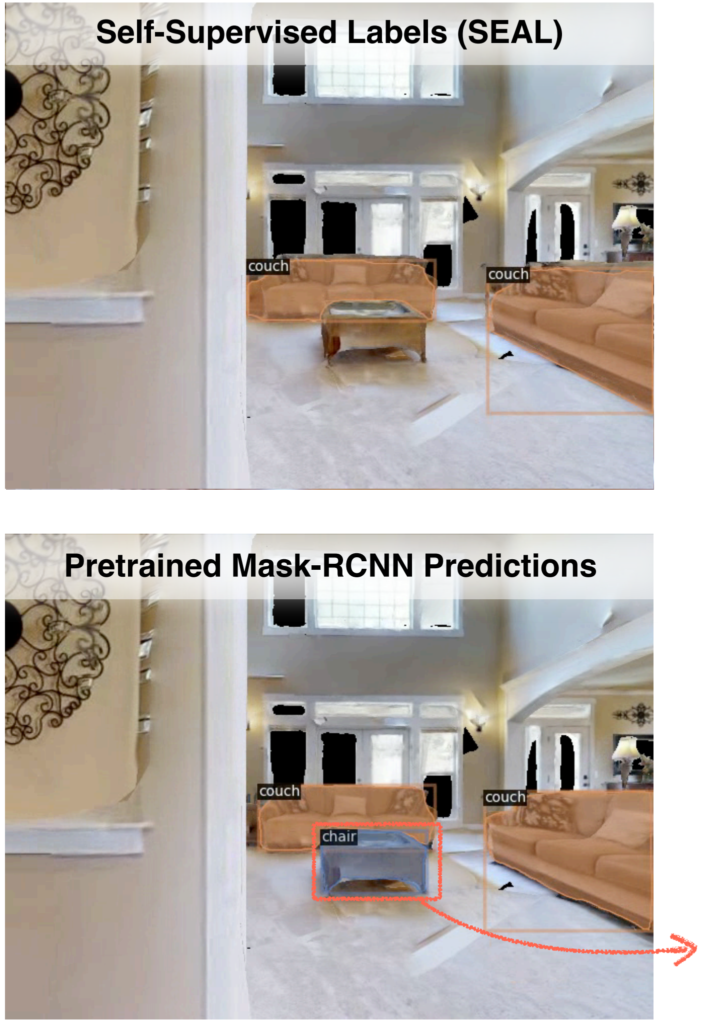
3D Label Propagation



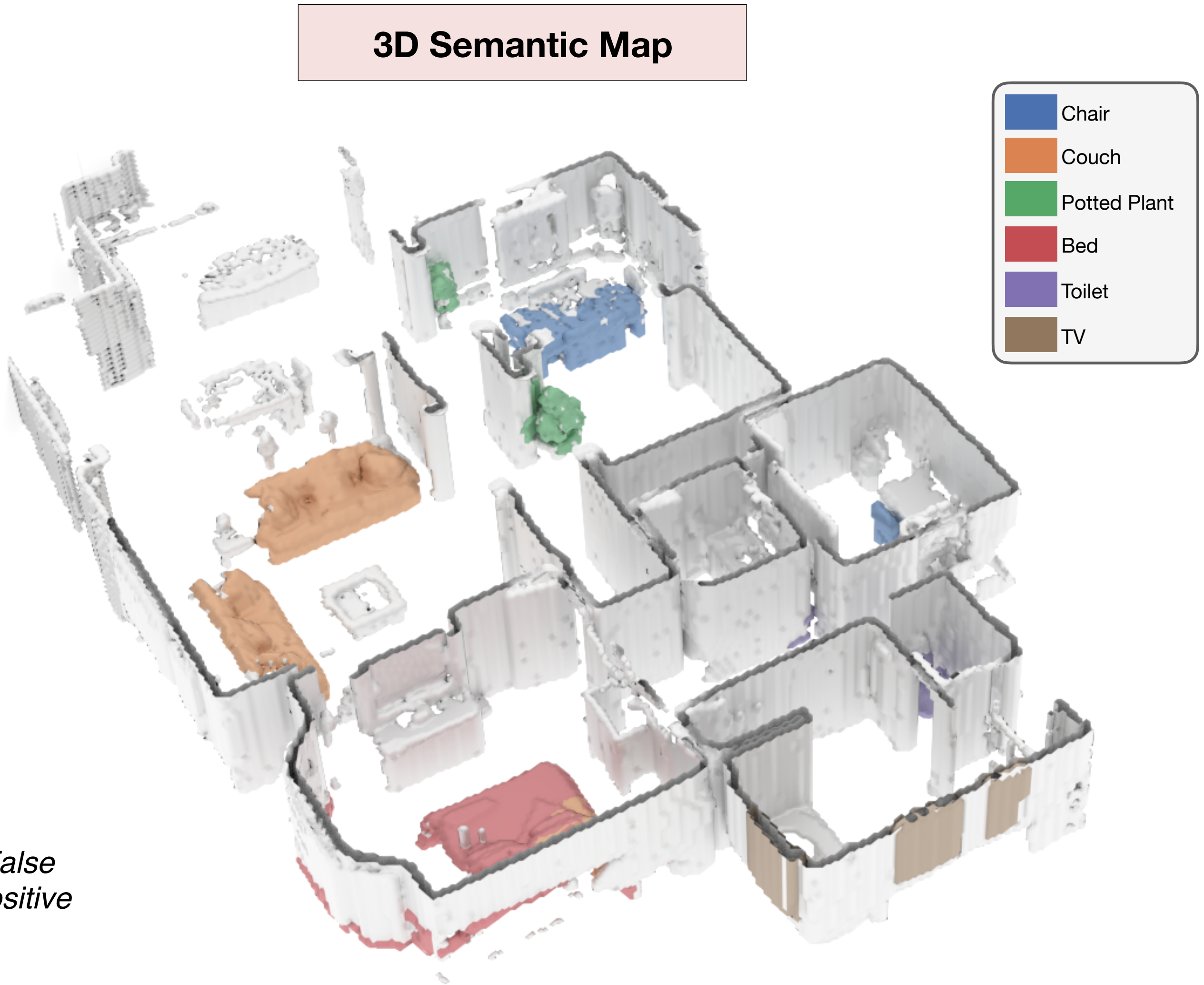
3D Label Propagation



3D Label Propagation



False Positive

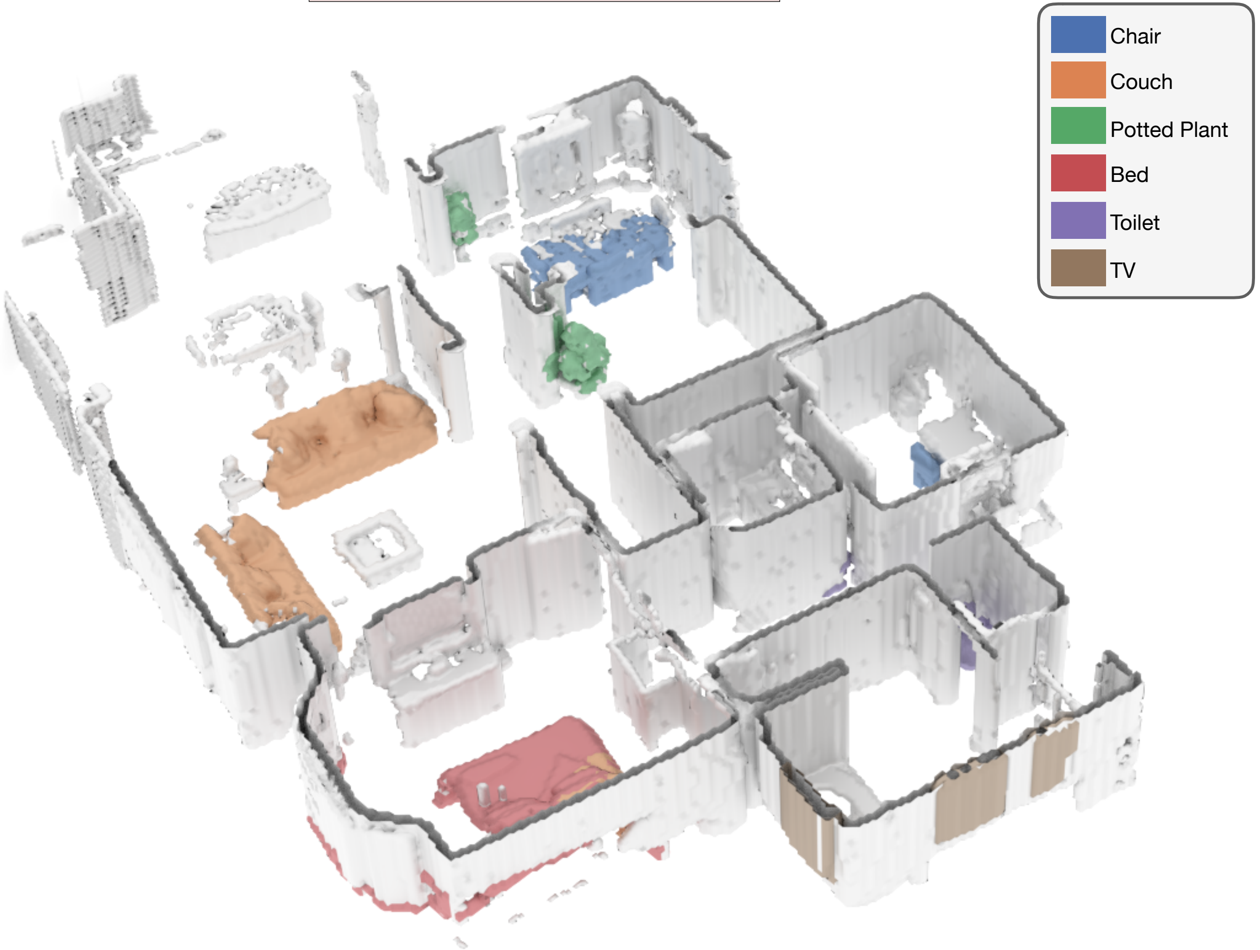


3D Label Propagation

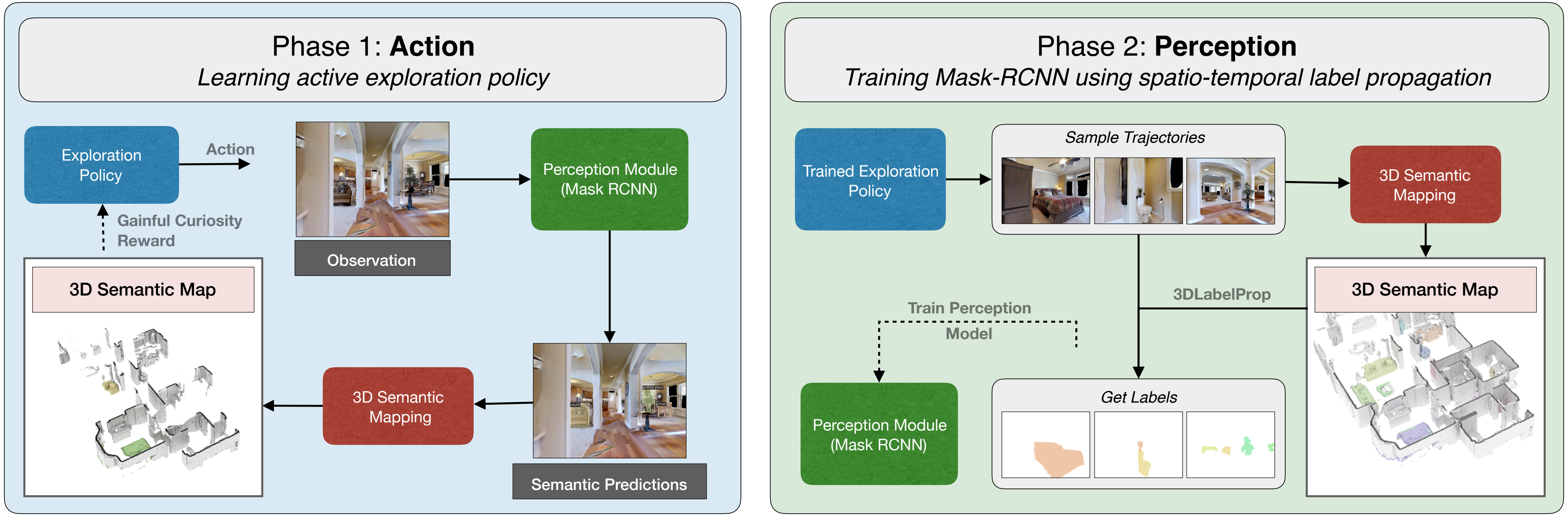
Train Perception Model

Perception Model (Mask RCNN)

3D Semantic Map



SEAL: Self-supervised Embodied Active Learning



	Action	Perception
Generalization	Train	Train
Specialization	Train	Train + 1 episode test

Dataset

- Gibson dataset: 25 training and 5 test scenes
- 6 object categories: chair, couch, bed, toilet, TV, potted plant.
- Training Set: randomly sample 2500 images (500 per test scene)
- Evaluation Set: randomly sample 12,500 images (500 per training scene)
- Report bounding box and mask AP50 scores for detection and instance segmentation

Armeni et al , 3d scene graph: A structure for unified semantics, 3d space, and camera, ICCV 2019

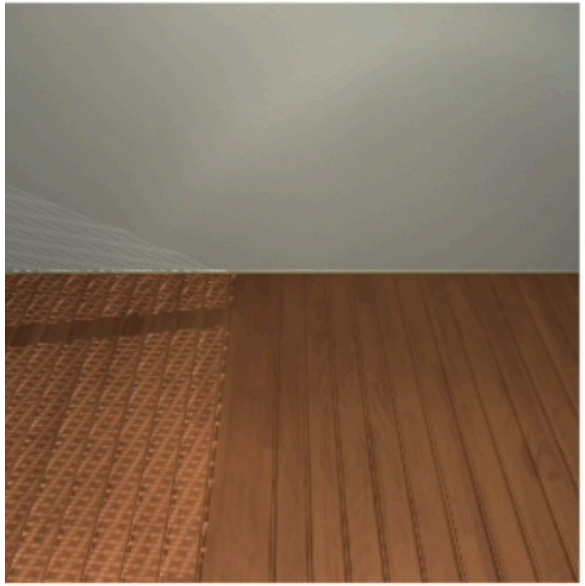
Results

Method	Generalization		Specialization	
	Object Detection	Instance Segmentation	Object Detection	Instance Segmentation
Pretrained Mask-RCNN	34.82	32.54	34.82	32.54
Random Policy + Self-training [51]	33.41	31.89	34.11	31.23
Random Policy + Optical Flow [22]	33.97	32.34	34.33	32.22
Frontier Exploration [52] + Self-training [51]	33.78	32.45	33.29	32.50
Frontier Exploration [52] + Optical Flow [22]	35.22	31.90	34.19	32.12
Active Neural SLAM [10] + Self-training [51]	34.35	31.20	34.84	32.44
Active Neural SLAM [10] + Optical Flow [22]	35.85	32.22	35.90	33.12
Semantic Curiosity [11] + Self-training [51]	35.04	32.19	35.23	32.88
Semantic Curiosity [11] + Optical Flow [22]	35.61	32.57	35.71	33.29
SEAL	**40.02**	**36.23**	**41.23**	**37.28**

EIF: Embodied Instruction Following: ALFRED

Instruction: place a cold lettuce slice in a waste basket.

RGB



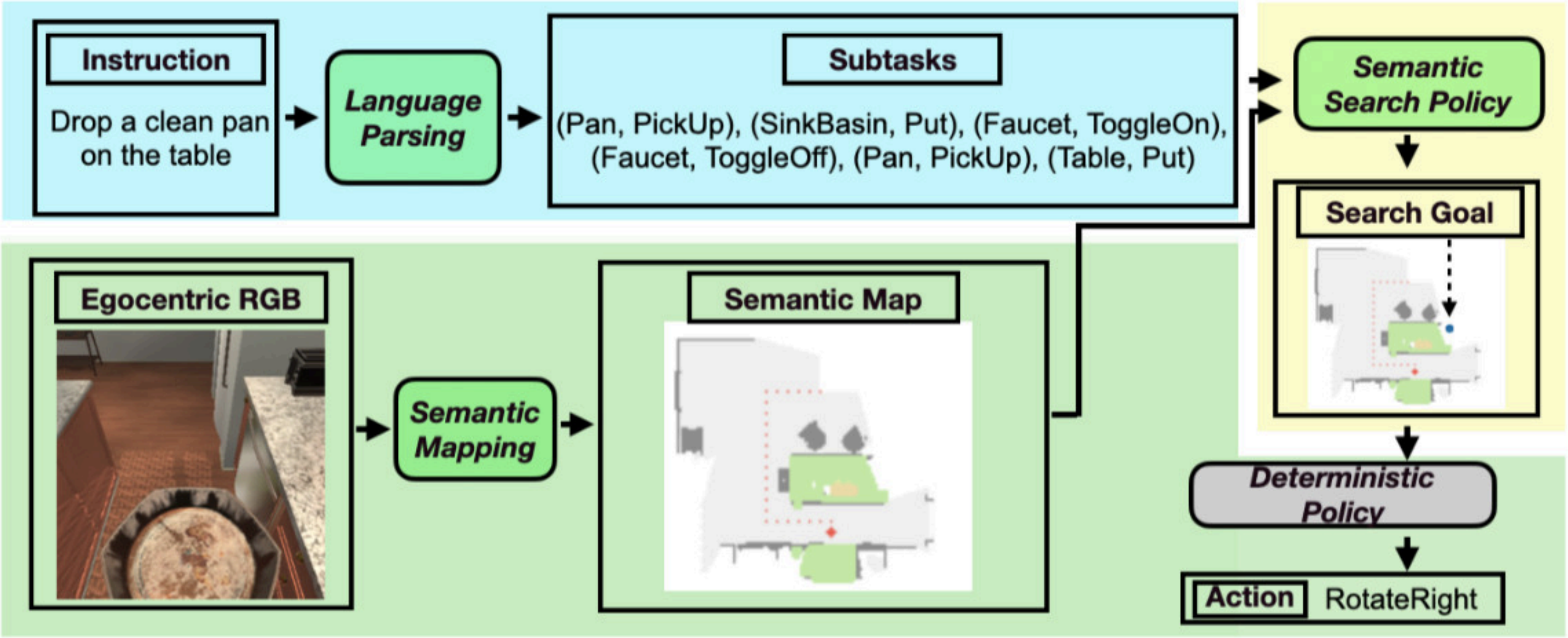
Completed Subgoals

- X PickUp, Knife
- X Slice, Lettuce
- X Put, Knife, Sink
- X PickUp SlicedLettuce
- X Open, Fridge
- X Put, SlicedLettuce, Fridge
- X Close, Fridge
- X Open, Fridge
- X PickUp, SlicedLettuce
- X Close, Fridge
- X Put, SlicedLettuce, GarbageCan

Predicted Action RotateLeft_90

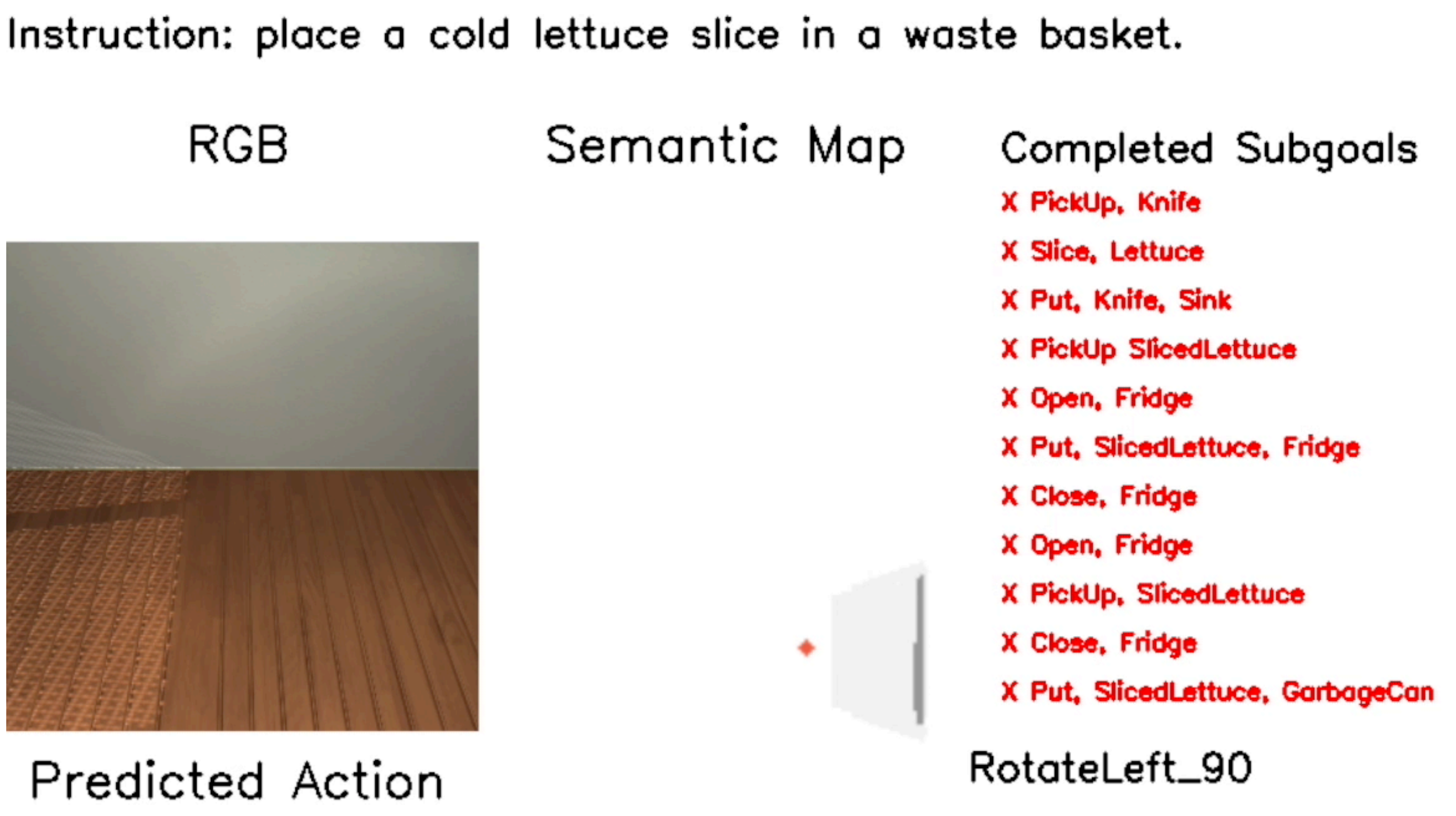
Mohit Shridhar, Jesse Thomason, Daniel Gordon, Yonatan Bisk, Winson Han, Roozbeh Mottaghi, Luke Zettlemoyer, and Dieter Fox. Alfred: A benchmark for interpreting grounded instructions for everyday tasks

FILM: Following Instructions in Language with Modular Methods

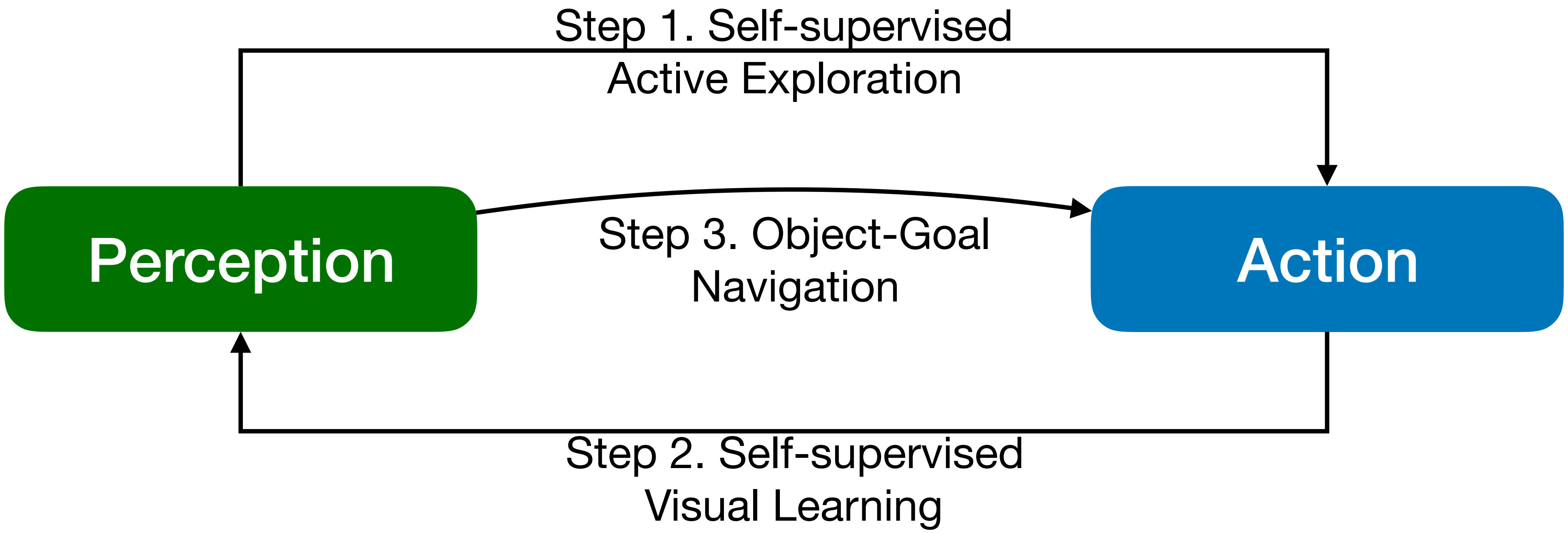


FILM: Following Instructions in Language with Modular Methods
So Yeon Min, Devendra Singh Chaplot, Pradeep Ravikumar, Yonatan Bisk, Ruslan Salakhutdinov

FILM: Following Instructions in Language with Modular Methods



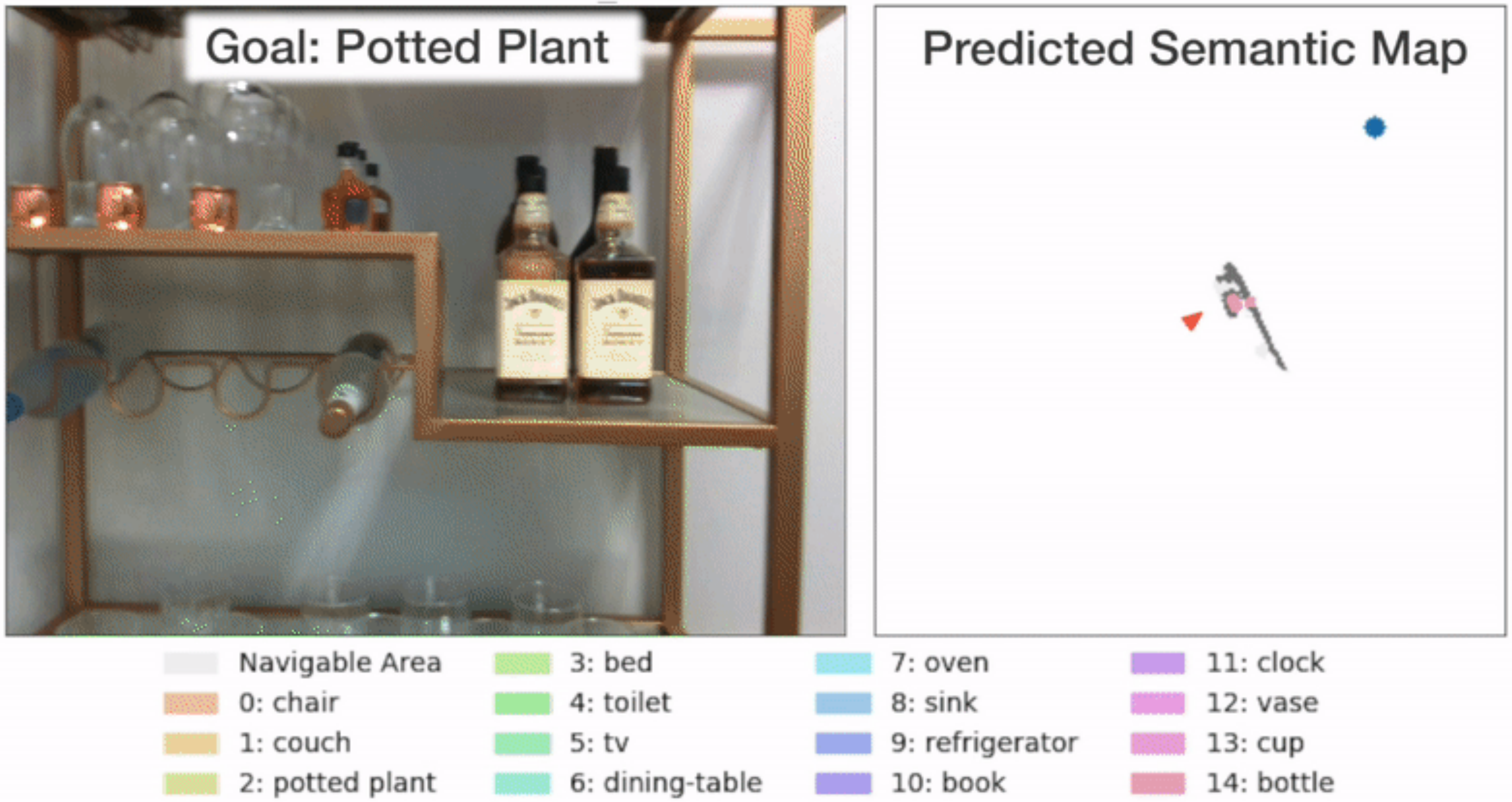
Perception-Action Loop



Explicit Semantic Mapping

Chaplot et al, . Object Goal Navigation using Goal-Oriented Semantic Exploration. NeurIPS-20

Explicit Semantic Mapping



Chaplot et al, . Object Goal Navigation using Goal-Oriented Semantic Exploration. NeurIPS-20

Results: Object Goal Navigation

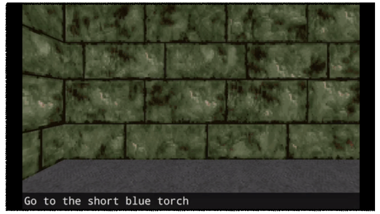
Method	Success	SPL
SemExp [9]	0.544	0.199
SemExp + SEAL (Gen.)	0.611	0.323
SemExp + SEAL (Spec.)	**0.627**	**0.331**

Simulation to Real

Games

ViZDoom

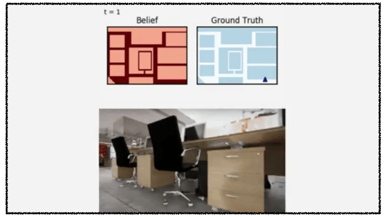
[CL *AAAI-17*]



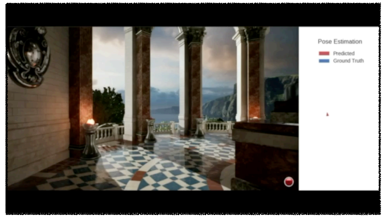
[CMPRS *AAAI-18*]

Photorealistic simulation

Unreal



[CPS *ICLR-18*]

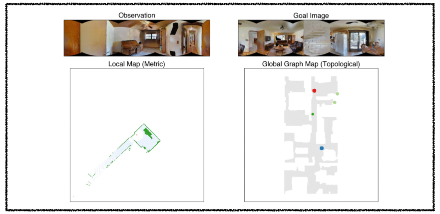


[PCZS *CVPR-18 (w)*]

Reconstructed simulation

Habitat (Gibson, MP3D)

[CGSGG *ICLR-20*]



[CSGG *CVPR-20*]

Physical Domain Gap

Visual Domain Gap

Real-world

?

Simulation to Real

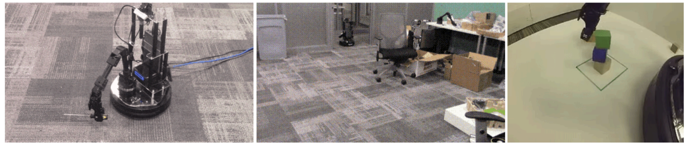
- Physical Domain Gap
  - Actuation noise models
  - Sensor noise models
- Visual Domain Gap
  - Image Translation
  - Policy-based

PyRobot

PyRobot is a light weight, high-level interface which provides hardware independent APIs for robotic manipulation and navigation. This repository also contains the low-level stack for LoCoBot, a low cost mobile manipulator hardware platform.

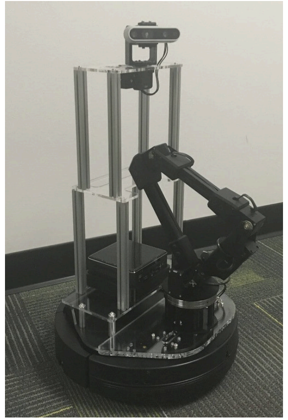
- What can you do with PyRobot?
- Installation
- Getting Started
- The Team
- Citation
- License
- Future features

What can you do with PyRobot?



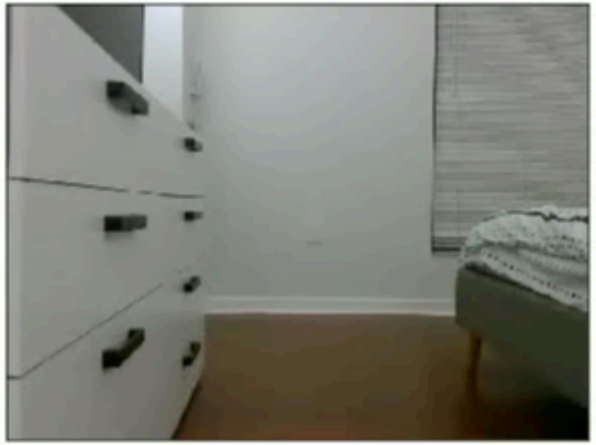
pyrobot.org

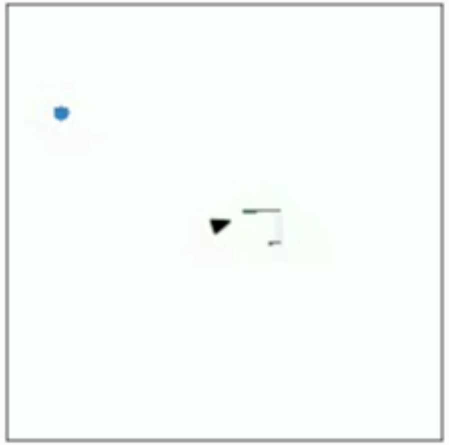
LoCoBot



locobot.org

Simulation to Real





Building Intelligent Agents

Navigate Autonomously
Localize and Plan
Multi-modal Input
Perceptive Human Speech
Reason & Understand Language
Recognize objects