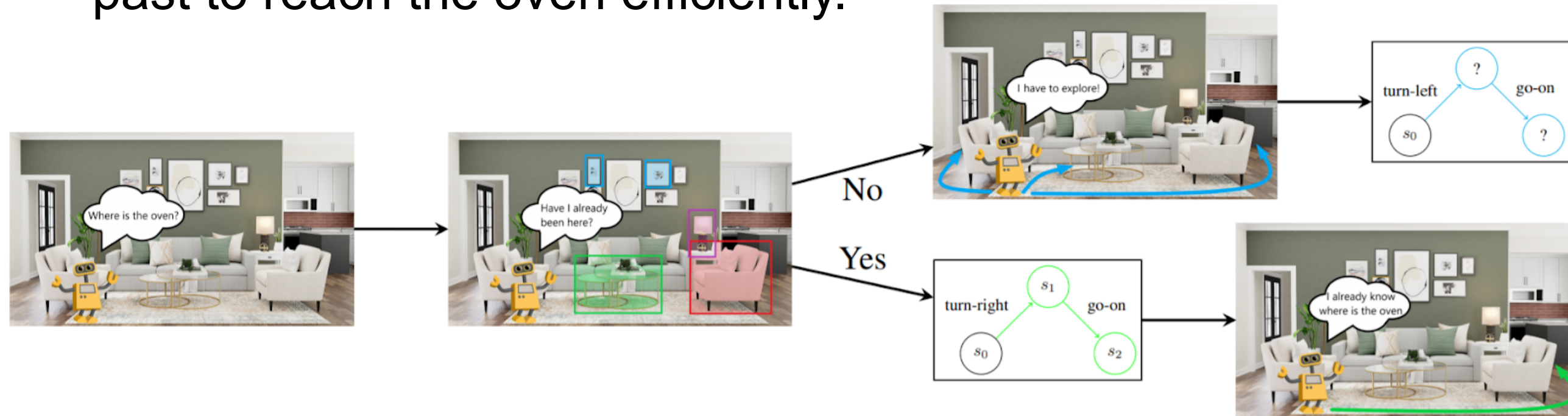


## 1. Core Idea & Contributions

A robot has to find the oven:

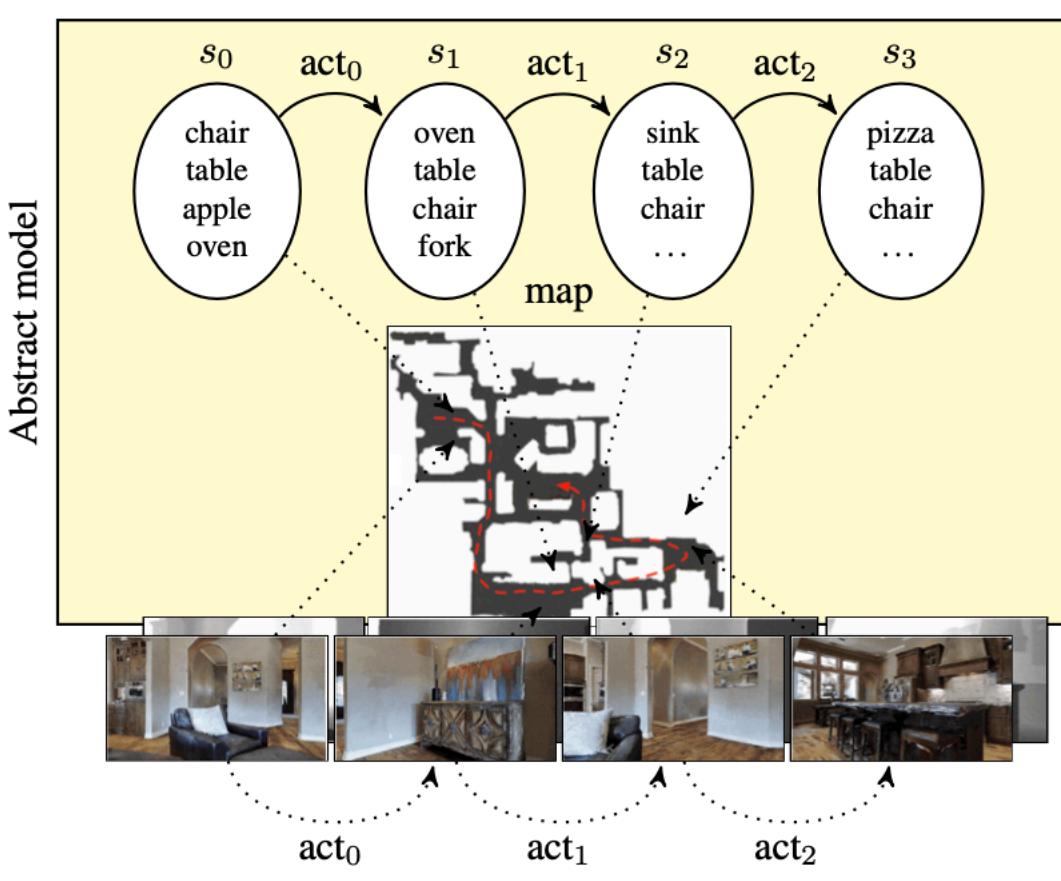
- ◆ If it is in a new environment, it must explore to build a knowledge base;
- ◆ Otherwise, we expect it to leverage the knowledge learned in the past to reach the oven efficiently.



Contributions:

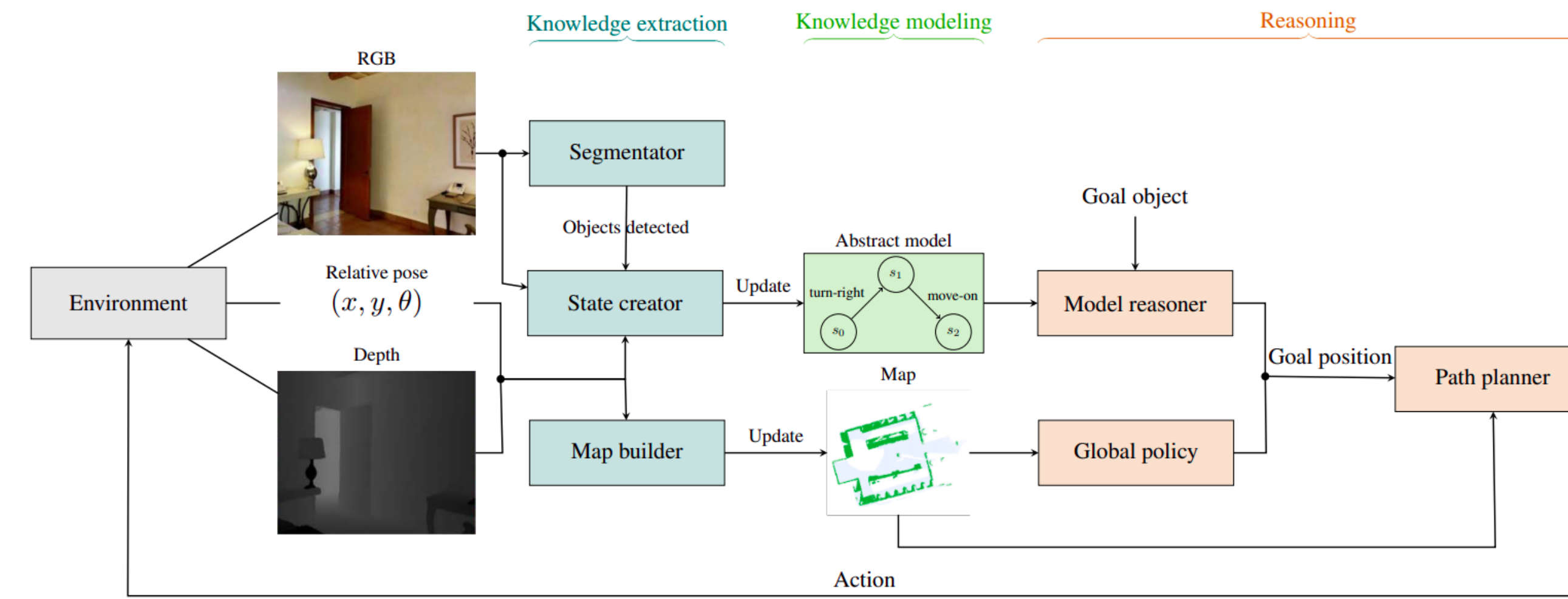
- ◆ Incrementally enhance and reuse previously acquired knowledge, relevant to the current environment;
- ◆ Integrate sub-symbolic techniques with symbolic reasoning on Abstract Models
- ◆ The experiments shows that learning and reusing Abstract Models is an effective way to exploit previously acquired knowledge

## 2. Abstract Model



- ◆ Encodes semantic insights about objects, scene elements, and their relations;
- ◆ The elements of the Abstract Model are grounded to the perceptions
- ◆ Is dynamically updated to incorporate the information the agent acquires
- ◆ The models learned should be reusable whenever the agent is in an environment that corresponds to the stored model

## Method



- ◆ Knowledge extraction: creates an Abstract State from the inputs and updates the egocentric map from the Depth image;
- ◆ Knowledge modeling: updates the current Abstract Model and the global map of the environment;
- ◆ Reasoning: if there is information about the Object Goal in the Abstract Model, its position is set as the target. Otherwise is sampled a target point from the Global Policy. The action is sampled with a Path Planner on the Map.

## Abstract Model Reusage

- ◆ Learned Abstract Model of each episode is stored by the agent for future re-use;
- ◆ When the agent starts a new episode it initializes a new model;
- ◆ At each step the agent checks if the current state is already present in a previously learned model by exploiting cosine distance:

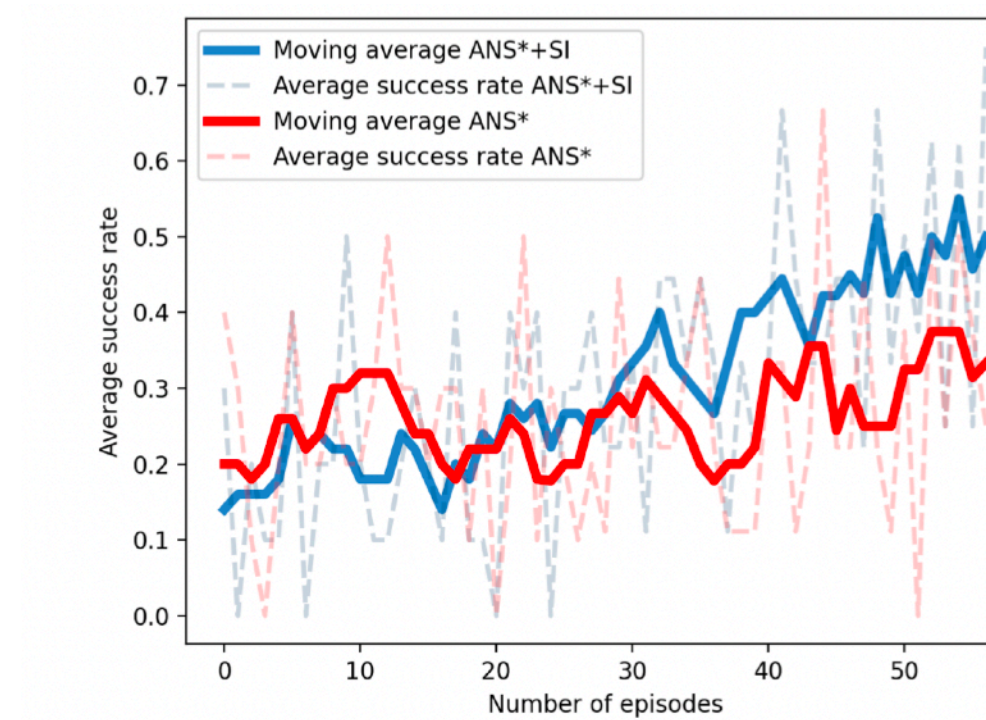
$$s^* = \underset{\substack{s^{(i)} \in \mathcal{S}_d^{(i)} \\ i \in 1, \dots, n}}{\operatorname{argmin}} \operatorname{cos\_dist}(\mathcal{F}_s, \mathcal{F}_{s^{(i)}})$$

- ◆ If a match is found the current model is merged with the older one and current agent's pose is rescaled to match the older Abstract Model coordinate system.

## 3. Experiments

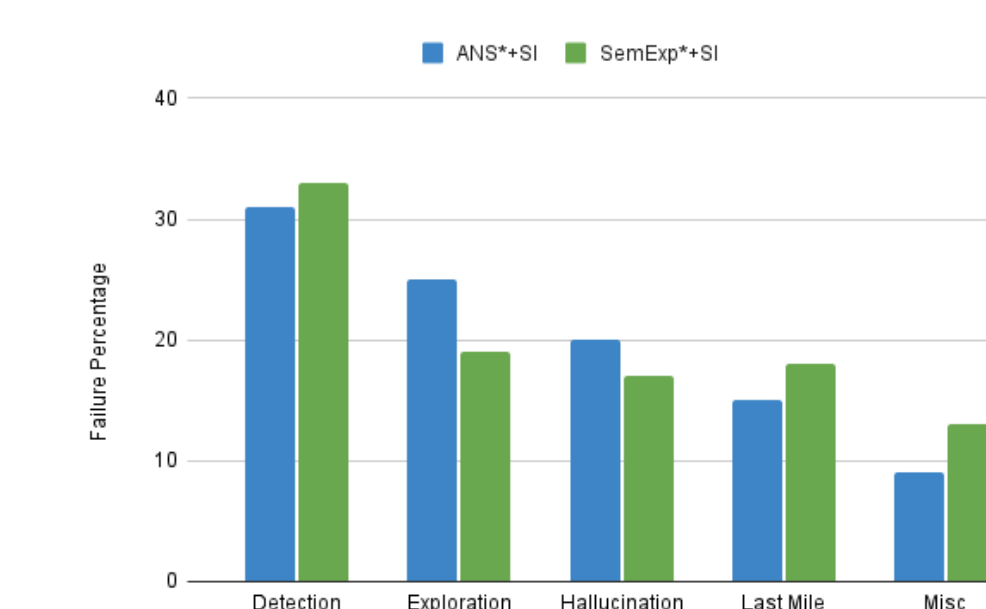
- ANS\*(1): Active Neural SLAM with no Abstract Model reuse across episodes;
- ANS\*+HP/SP: pre-computed and fixed reusable Abstract Models;
- ANS\*+SI: ANS\* + Incrementally learned Abstract Models.
- SemExp\*+SI: SemExp(2) + Incrementally learned Abstract Models.

### Reusing Abstract Models



Method	DTS	Success	SPL	SoftSPL
<b>ANS*</b>	6.417	0.240	0.102	0.191
<b>ANS*+HP</b>	6.352	0.251	0.105	0.206
<b>ANS*+SP</b>	6.294	0.258	0.117	0.214
<b>ANS*+IL</b>	<b>6.155</b>	<b>0.279</b>	<b>0.131</b>	<b>0.233</b>

### Semantic Maps and Abstract Models



Method	DTS	Success	SPL	SoftSPL
<b>SMNet</b>	7.316	0.096	0.057	0.087
<b>SMNet(GT)</b>	5.658	0.312	0.207	0.282
<b>ANS*+IL</b>	6.155	0.279	0.131	0.233
<b>SemExp*+IL</b>	<b>5.785</b>	<b>0.347</b>	<b>0.151</b>	<b>0.274</b>

### References:

- (1) Chaplot et al., "Learning to explore using active neural SLAM" In ICLR, 2019.
- (2) Chaplot et al., "Object goal navigation using goal-oriented semantic exploration" In NeurIPS, 2020.
- (3) Cartillier et al., "Semantic mapnet: Building allocentric semantic maps and representations from egocentric views" In AAAI, 2021
- (4) Chang et al., "Matterport3D: Learning from RGB- D data in indoor environments" In 3DV, 2017
- (5) Savva et al., "Habitat: A plat- form for embodied ai research" In ICCV, 2019

