Successor Feature Landmarks for Long-Horizon Goal-Conditioned Reinforcement Learning

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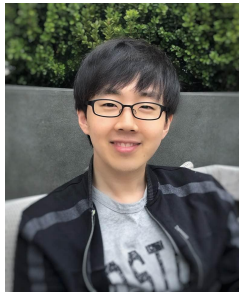

Jongwook Choi
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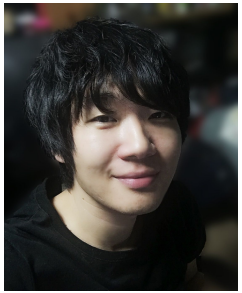

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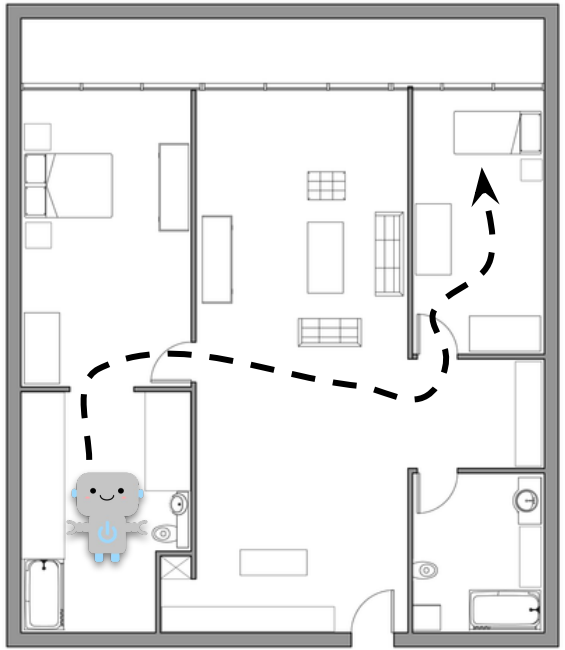
Motivating scenario

Suppose we place a household robot in a *new* home



We would like the robot to be able to do the following

1. Explore the home and understand its layout
2. Reach *any* location (to perform a task) from *any* starting point

Scenario specifications

1. Task can be *long-horizon*, i.e. it can take the robot many steps to move from one room to another
2. Robot only has access to *first-person* images

Long-horizon GCRL

Goal-conditioned reinforcement learning (GCRL)

1. Markov Decision Process extended with set of goals (subset of state space)
2. Goal-conditioned reward function

Problem: find optimal goal-conditioned policy that maximizes expected cumulative *goal-conditioned* reward

Long-horizon: goals can be distant from agent's starting state, requiring policy to operate over longer temporal sequences

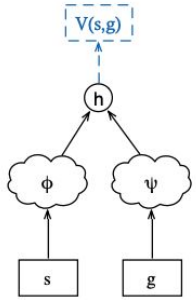
Recent work: GCRL

Universal value function approximator (UVFA; Schaul et al., 2015): value function approximator that generalizes over goal space

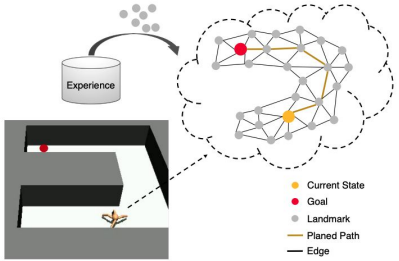
UVFAs have difficulty scaling to long-horizon tasks

Solution: augment UVFAs with planning mechanisms

1. MSS (Huang et al., 2019) and SoRB (Eysenbach et al., 2019): use UVFA as distance metric to build graph of landmarks to conduct planning over
2. LEAP (Nasiriany et al., 2019) - use UVFA to decompose long-horizon tasks as series of reachable subgoals



UVFA architecture with state *s* and goal *g* (Schaul et al., 2015)

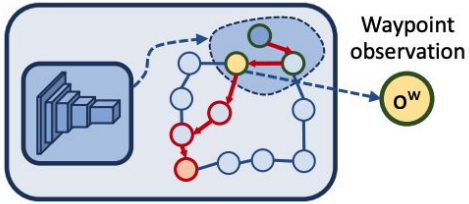


Planning on landmark graph in MSS framework (Huang et al., 2019)

Recent work: graph-based planning

Recent works in navigation have also proposed graph-based planning approaches

1. Conduct planning on high-level graph representations
2. Use low-level controller to move between nodes



Selecting next landmark node to navigate towards in SPTM (Savinov et al., 2018)

Papers

1. SPTM (Savinov et al., 2018): form graph by using reachability network as distance metric
   a. Relies on human demonstrations
2. SGM (Laskin et al., 2020): form sparse graph by merging similar observations
   a. Assumes exploration mechanism

Background: successor features (SF)

Successor representation (SR) of ***(s, a, s')***: expected discounted future occupancy of state ***s'*** starting in state ***s*** and action ***a***, acting under policy π (Dayan, 1993)

$$M_\pi(s, a, s') = \mathbb{E}^\pi \left[\sum_{t'=t}^{\infty} \gamma^{t'-t} \mathbb{I}(S_{t'} = s') \middle| \begin{matrix} S_t = s, \\ A_t = a \end{matrix} \right]$$

SF extend SR to function approximation case where ***s'*** is replaced by feature vector ϕ (Barreto et al., 2017)

SF captures the dynamics of an environment

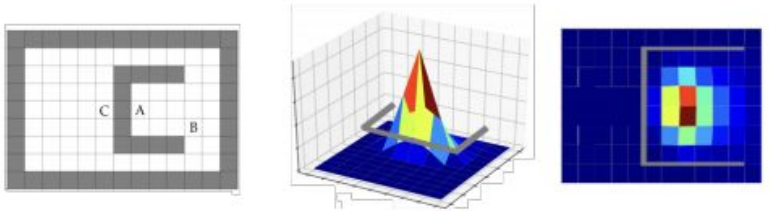


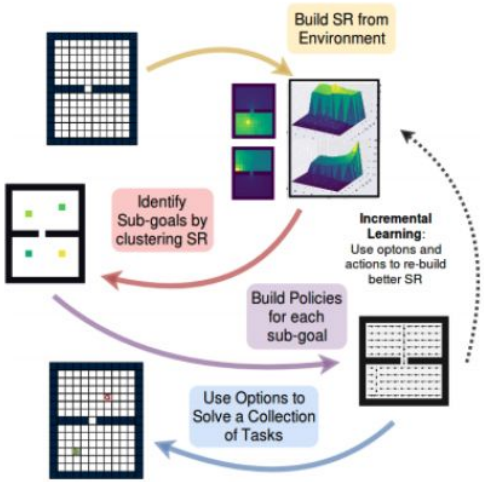
Figure 1: Successor representation, with respect to the uniform random policy, of state A (left). This example is similar to Dayan's (1993). The red color represents larger values while the blue color represents smaller values (states that are temporally further away).

Figure 1 (Machado et al., 2018)

Recent work: SF

Successor Options (Ramesh et al., 2019)

1. Use clustering in SR space to identify subgoals
2. Learn options to subgoals via SR-based option reward function
3. Only qualitative results in high-dimensional state spaces



Successor Options framework (Ramesh et al., 2019)

Idea: leverage SF for graph-based planning

SF: state representation that captures temporally-extended environment dynamics

1. Reflects long-horizon setting
2. Suitable for formulating distance metric
3. Learned via self-supervised training signal

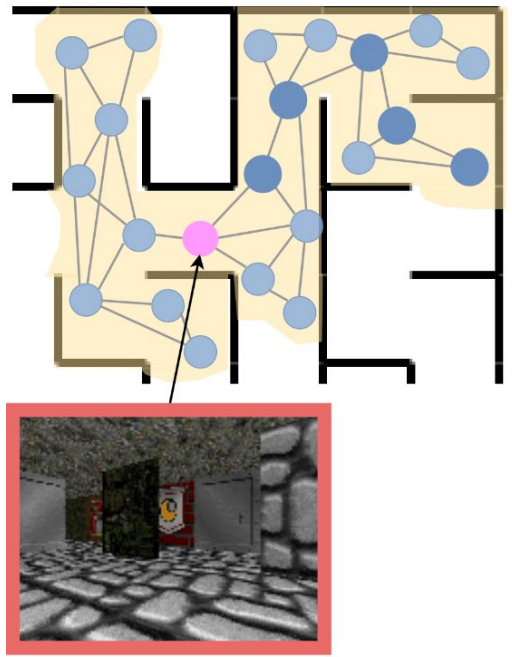
SF enables transfer between goals (Barreto et al., 2016)

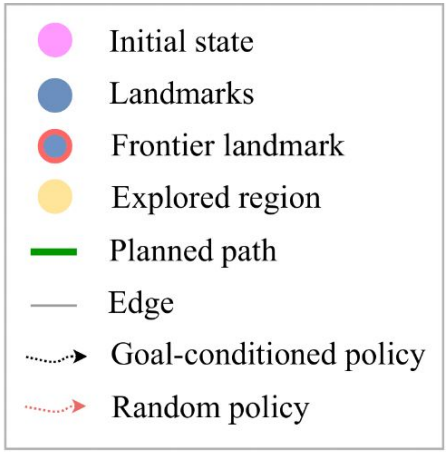
1. Decouples environment dynamics (SF) from task in Q-value formulation

$$r(s, a, s') = \boldsymbol{\phi}(s, a, s')^\top \mathbf{w}$$

$$\begin{aligned} Q^\pi(s, a) &= \mathrm{E}^\pi \left[r_{t+1} + \gamma r_{t+2} + \ldots \,|\, S_t = s, A_t = a \right] \\ &= \mathrm{E}^\pi \left[\boldsymbol{\phi}_{t+1}^\top \mathbf{w} + \gamma \boldsymbol{\phi}_{t+2}^\top \mathbf{w} + \ldots \,|\, S_t = s, A_t = a \right] \\ &= \mathrm{E}^\pi \left[\textstyle\sum_{i=t}^{\infty} \gamma^{i-t} \boldsymbol{\phi}_{i+1} \,|\, S_t = s, A_t = a \right]^\top \mathbf{w} = \boldsymbol{\psi}^\pi(s, a)^\top \mathbf{w} \end{aligned}$$

Overview of Successor Feature Landmarks (SFL)





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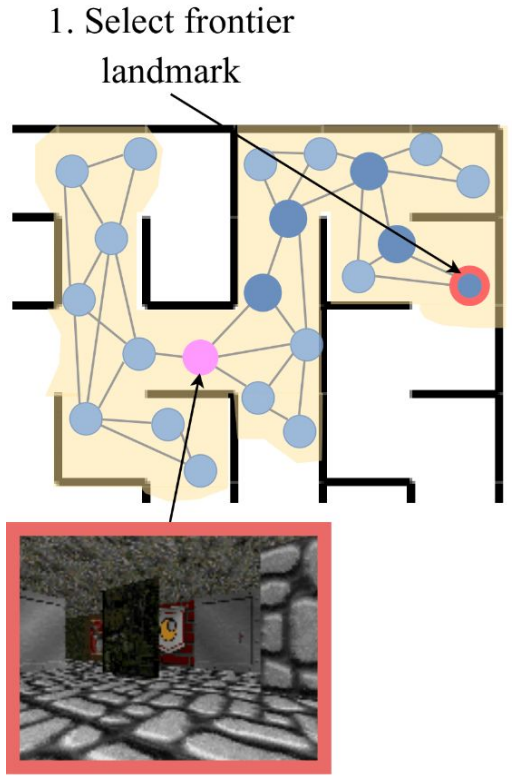

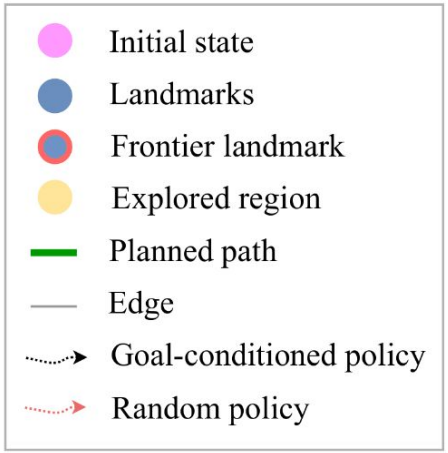

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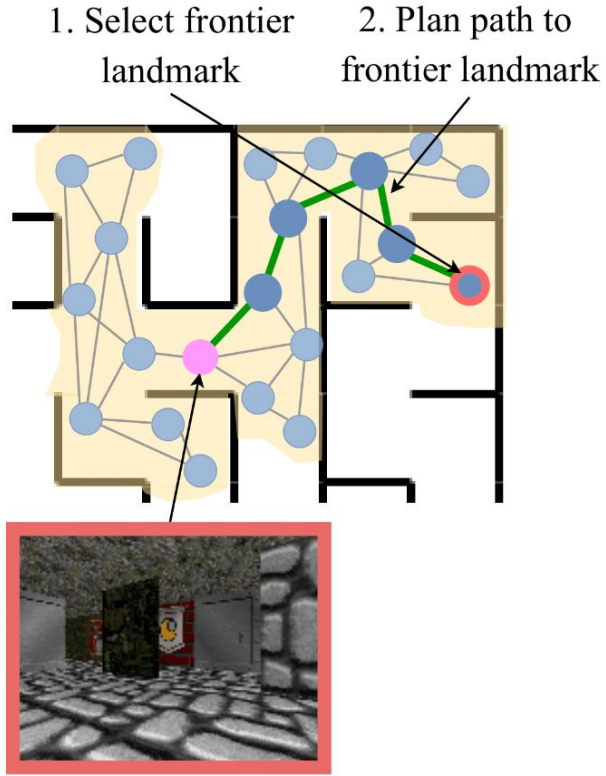

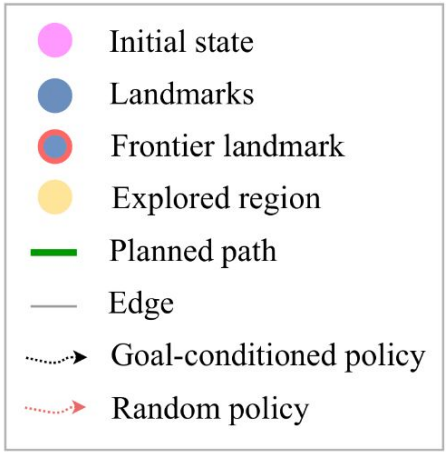

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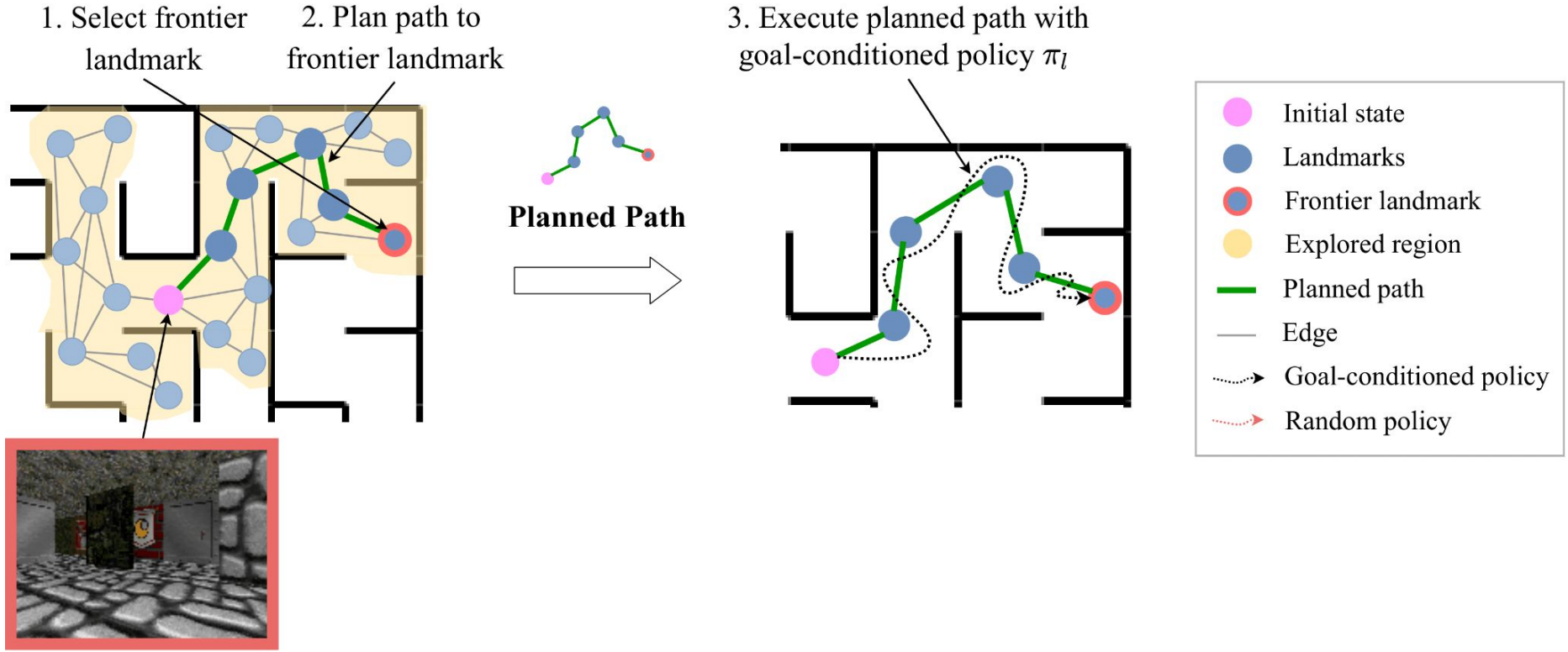

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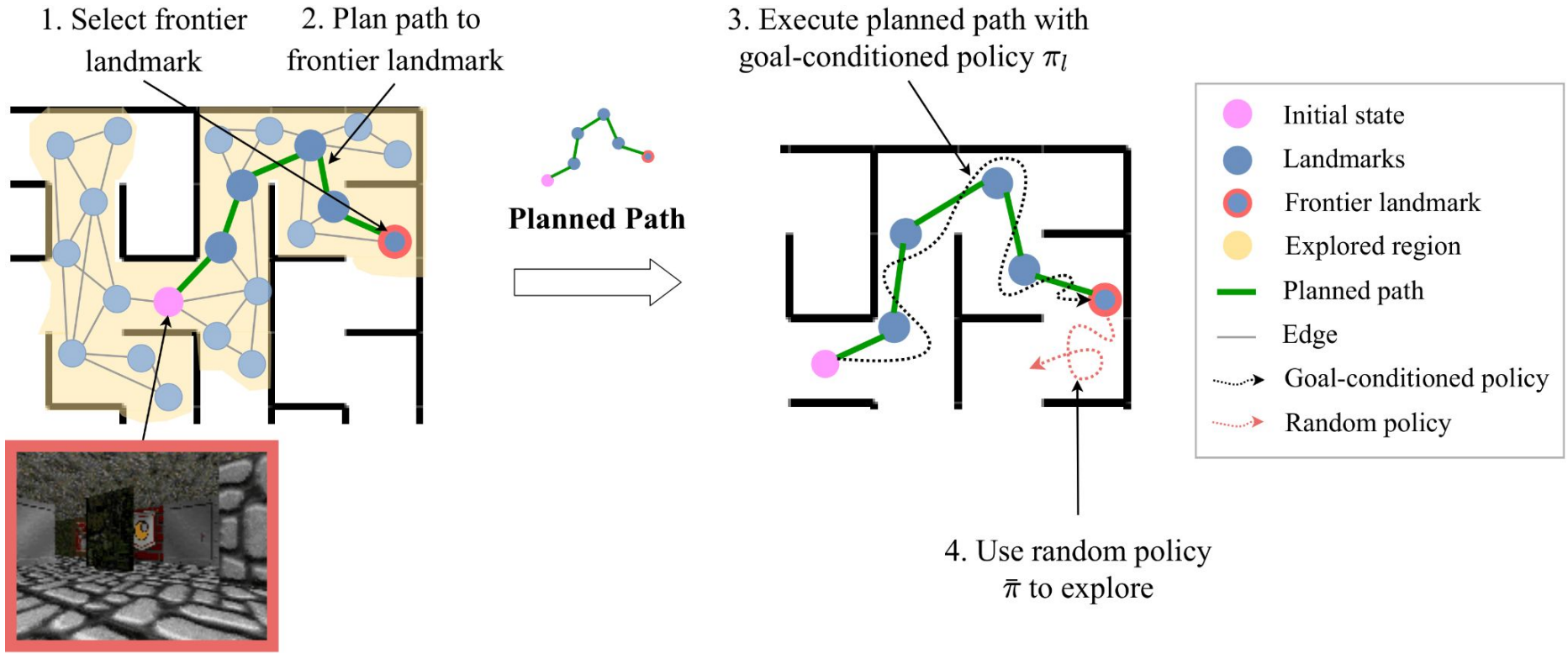

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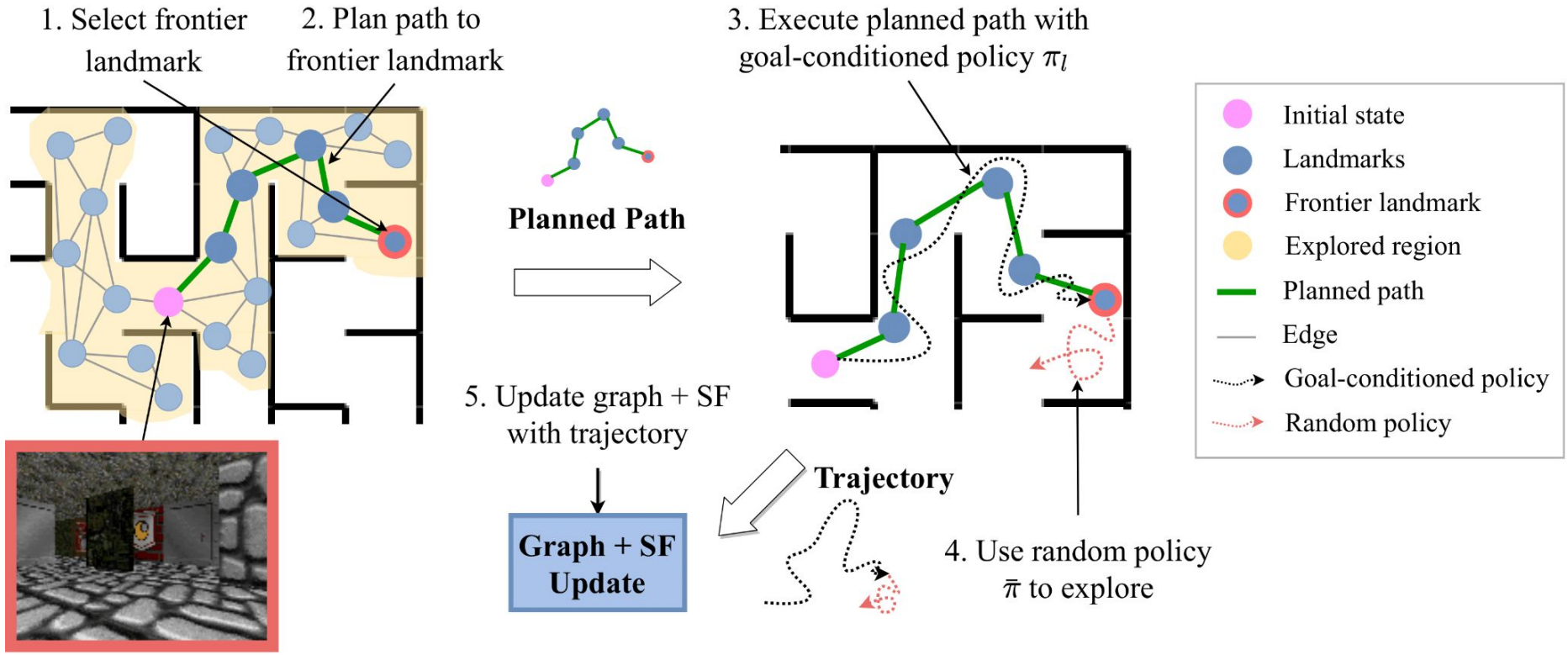

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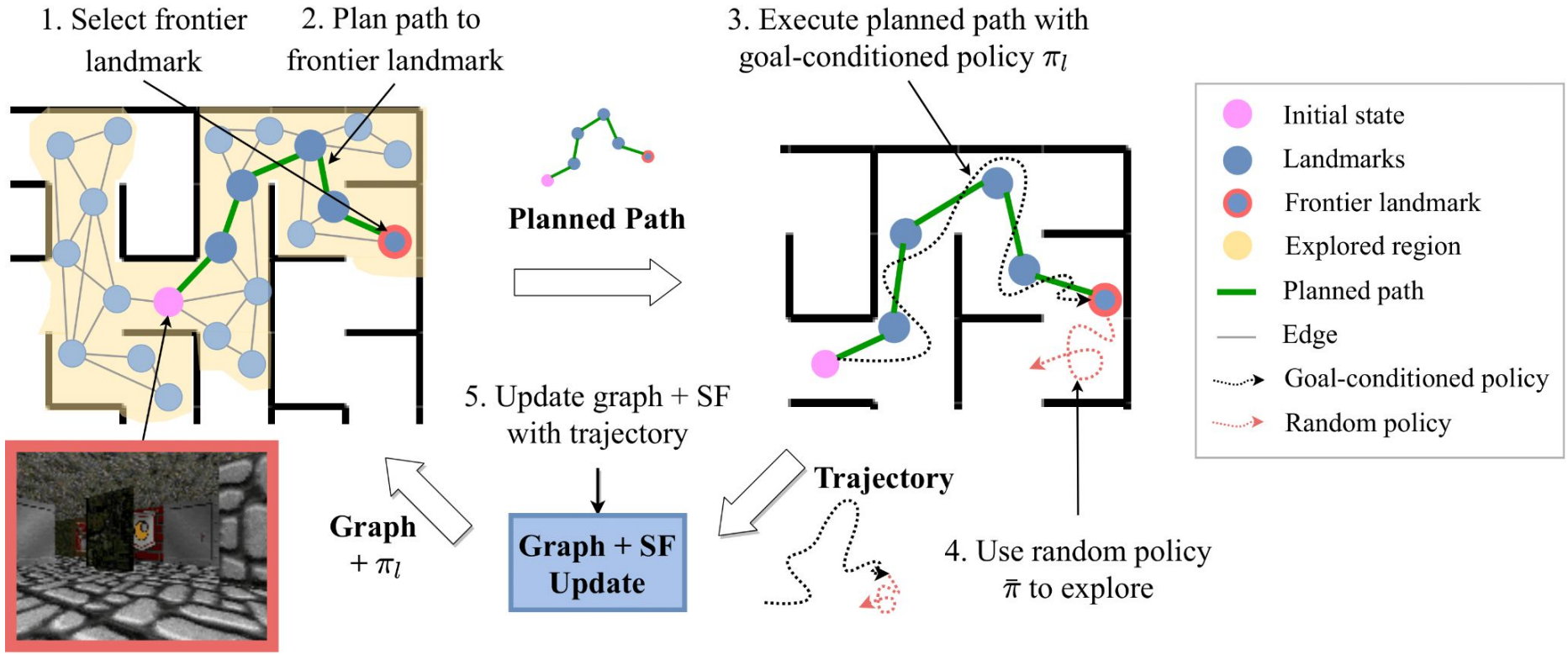


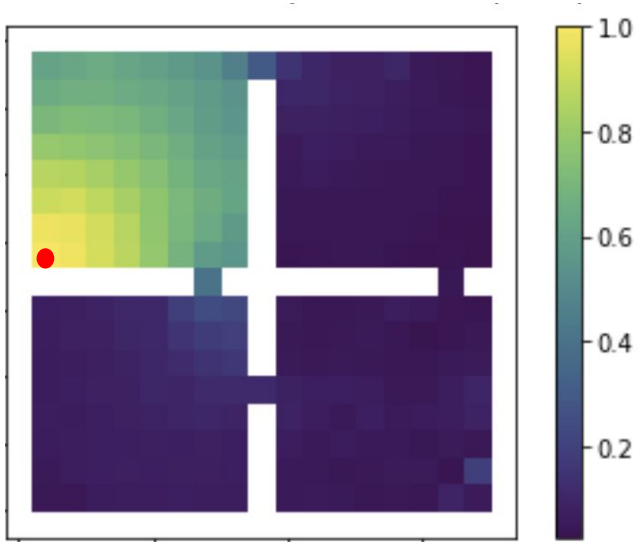
Successor Feature Similarity (SFS)

Defined as cosine similarity in SF space (since $||\psi|| = 1$)

$$\mathrm{SFS}^{\pi}((s_1, a_1), (s_2, a_2)) = \psi^{\pi}(s_1, a_1)^{\top} \psi^{\pi}(s_1, a_2)$$

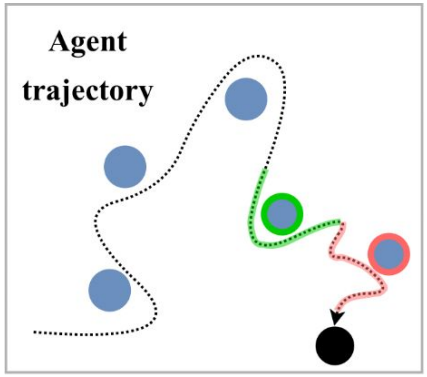
Uses

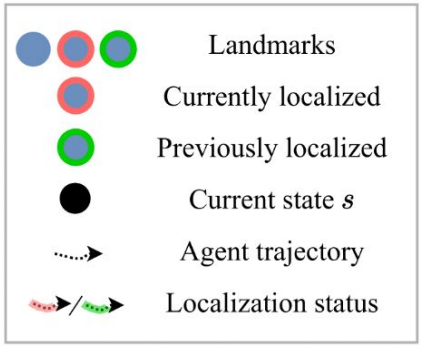
1. Localize agent to nearest landmark
2. Determine which states to add as landmarks
3. Obtain local goal-conditioned policy ***instantly***



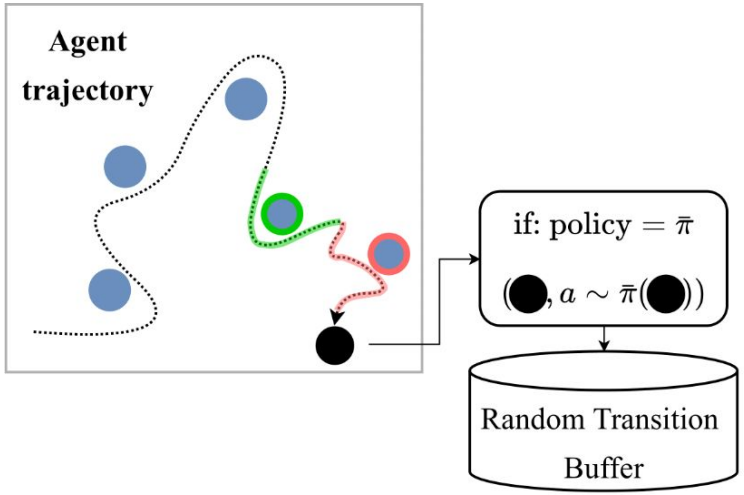
SFS relative to red dot in ***MiniGrid***

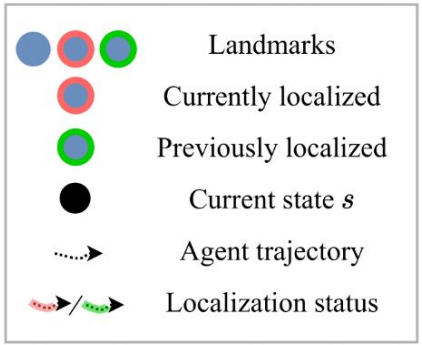
Learning SF


Agent
trajectory


Landmarks
Currently localized
Previously localized
Current state s
Agent trajectory
Localization status

Learning SF


Agent
trajectory
if: policy $= \bar{\pi}$
$(\bullet, a \sim \bar{\pi}(\bullet))$
Random Transition
Buffer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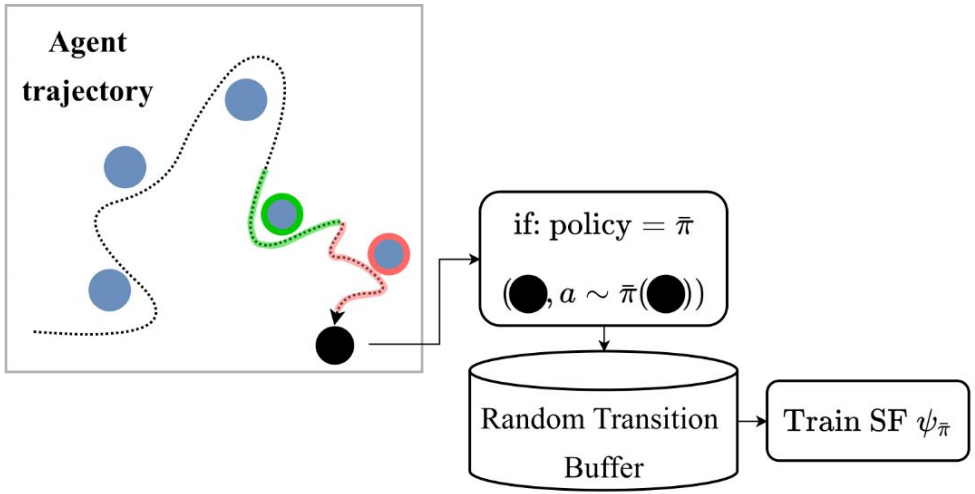
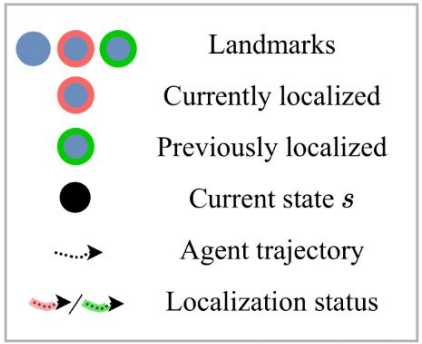

Agent
trajectory
if: policy $= \bar{\pi}$
$(\bullet, a \sim \bar{\pi}(\bullet))$
Random Transition
Buffer
Train SF $\psi_{\bar{\pi}}$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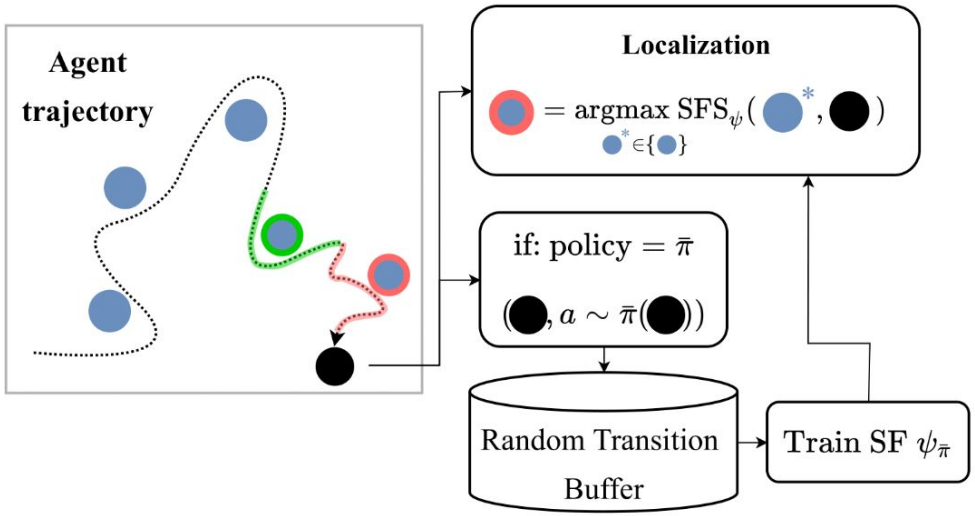
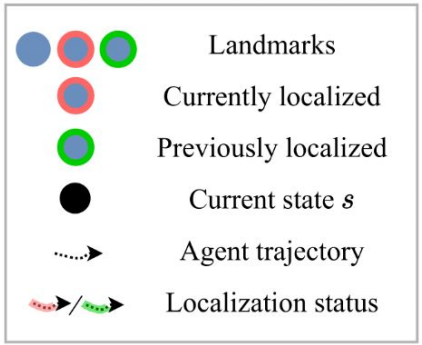
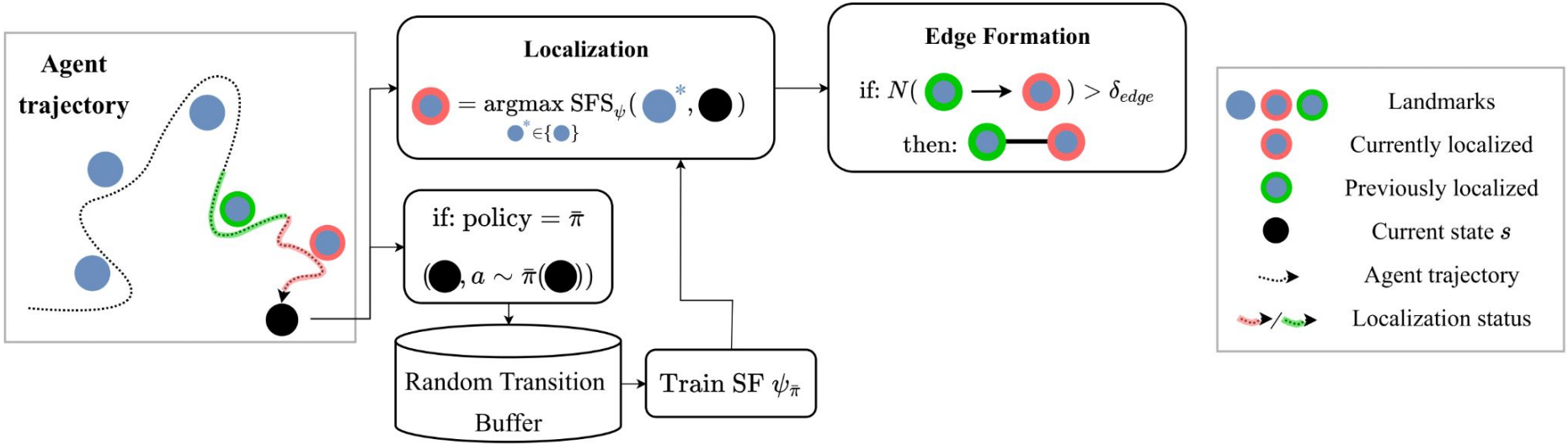
Building landmark graph

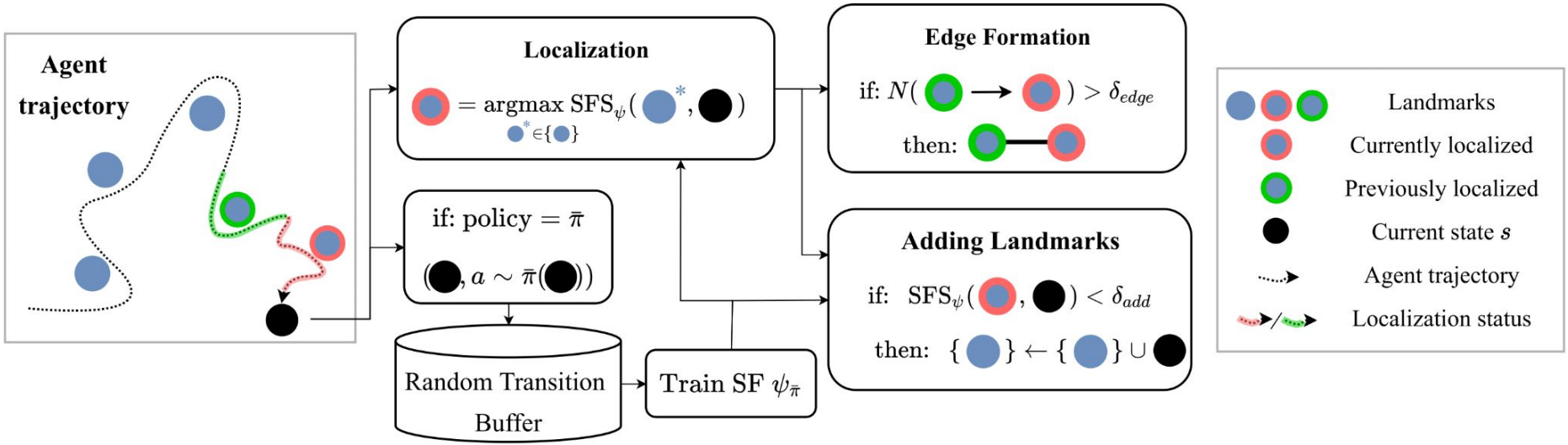




Building landmark graph



Building landmark graph



Local goal-conditioned policy

Goal-conditioned reward function based on features ϕ of current state and SF ψ of goal

$$r(s, a, g) = \phi(s, a)^\top \psi^{\bar{\pi}}(g)$$

Derived Q-value formulation *is equivalent to* SFS

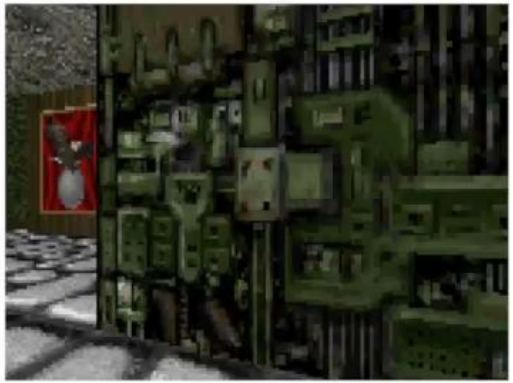
$$\begin{aligned} Q^{\bar{\pi}}(s, a) &= \psi^{\bar{\pi}}(s, a)^\top \psi^{\bar{\pi}}(g) \\ &= \mathrm{SFS}^{\bar{\pi}}(s, a, g). \end{aligned}$$

Policy given by taking action leading to highest SFS

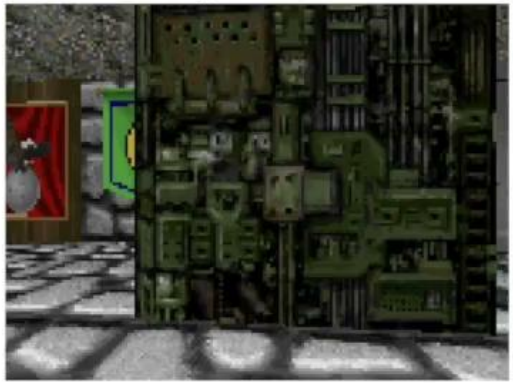
$$\pi = \operatorname*{argmax}_a \mathrm{SFS}^{\bar{\pi}}(s, a, g)$$

Planning

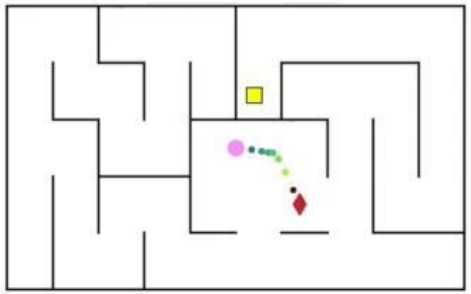
Current Observation



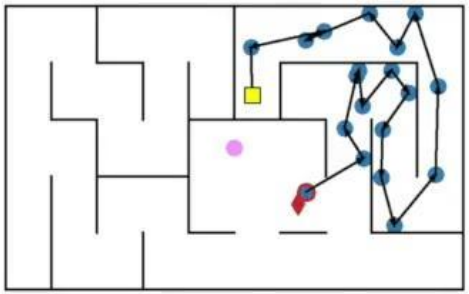
Target Landmark



Agent Trajectory



Landmark Path to Goal



Agent begins at **start** and tries to reach **goal** in **400** steps

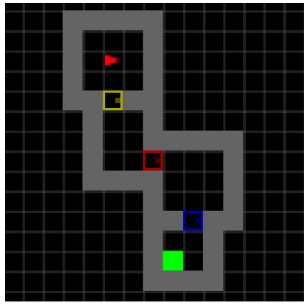
Experimental settings

Problem settings

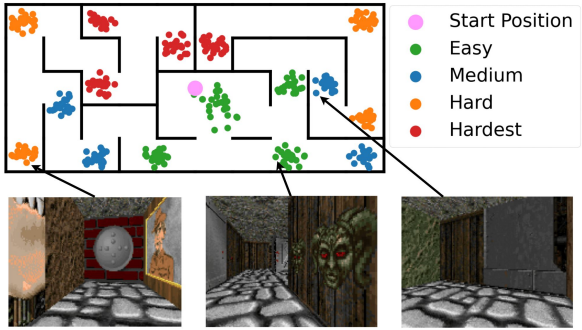
1. *Random spawn*
   a. In training, agent randomly spawned across map
   b. In evaluation, agent tested on random start-goal pairs
2. *Fixed spawn*
   a. In training, agent spawned at fixed starting point
   b. In evaluation, agent tested on random goals with same starting point as in training

Domains

1. ***MiniGrid***: 2D gridworld with top-down view observations
2. ***ViZDoom***: visual navigation environment with 3D first-person observations and large-scale mazes



Four-room MultiRoom ***MiniGrid*** with agent (red arrow) and goal (green square)



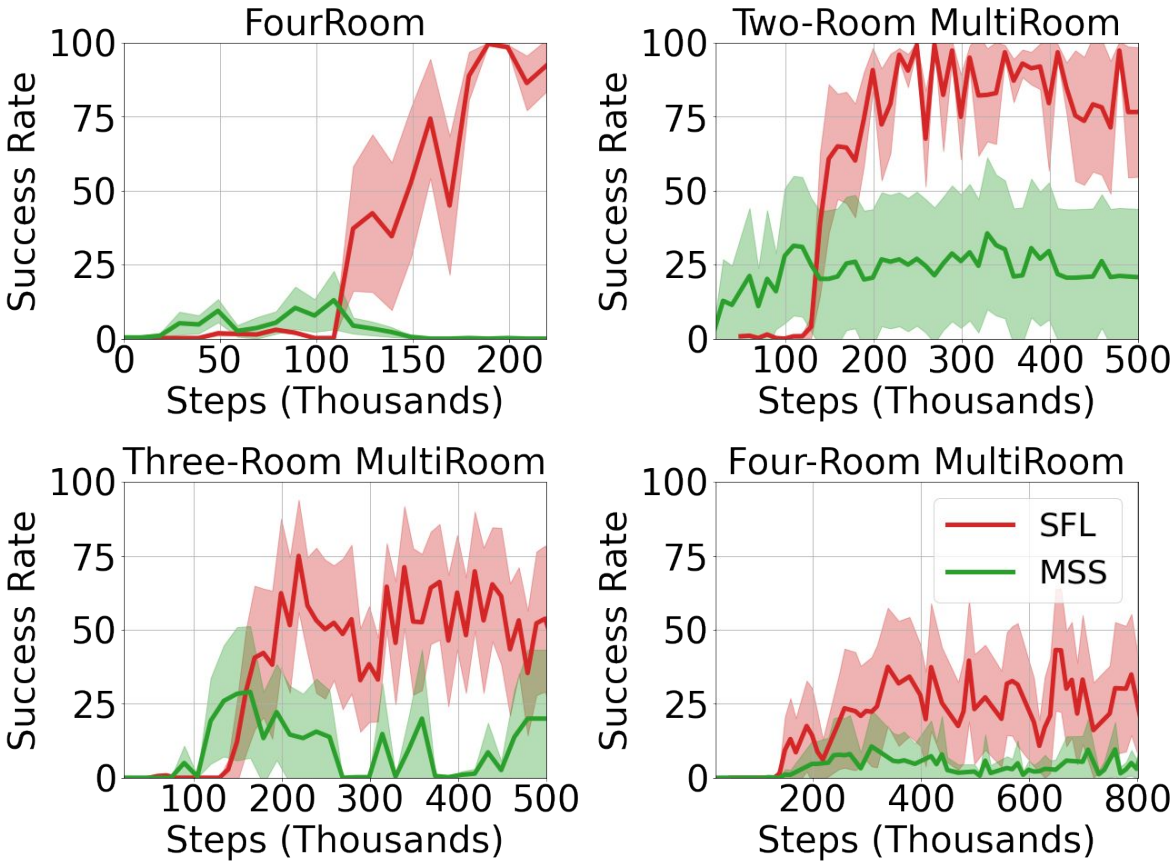
Top-down view of ***ViZDoom*** maze in *fixed spawn* with sampled goals

Baseline methods

Baseline	Local policy	Planning mechanism	Exploration mechanism	Assumptions
Visual controller	Inverse dynamics prediction	*N/A*	*N/A*	Requires random spawning
SPTM	^	Build graph with reachability network	*N/A*	Requires human demonstrations
SGM	^	^ + encourage sparsity in graph with two-way consistency objective	*N/A*	Requires random spawning
Episodic curiosity (EC)* + {SPTM, SGM}	^	^	Curiosity bonus based on reachability network	
MSS	UVFA	Build graph with UVFA distance metric	Select landmarks to be far apart from each other	

*- Savinov et al., 2018

Results on *MiniGrid*



Results on *ViZDoom*

Method	*SGM-Map*			*Test-2*			*Test-6*		
	Easy	Medium	Hard	Easy	Medium	Hard	Easy	Medium	Hard
Random Actions	58%	22%	12%	70%	39%	16%	80%	31%	18%
Visual Controller	75%	35%	19%	83%	51%	30%	89%	39%	20%
SPTM [27]	70%	34%	14%	78%	48%	18%	88%	40%	18%
SGM [15]	**92%**	64%	26%	**86%**	54%	32%	83%	43%	27%
SFL [Ours]	**92%**	**82%**	**67%**	82%	**66%**	**48%**	**92%**	**66%**	**60%**

Table 1: (*Random spawn*) The success rates of compared methods on three **ViZDoom** maps.

Method	*Test-1*				*Test-4*			
	Easy	Medium	Hard	Hardest	Easy	Medium	Hard	Hardest
MSS [10]	23%	9%	1%	1%	21%	7%	7%	7%
EC [28] + SPTM [27]	48%	16%	2%	0%	20%	10%	4%	0%
EC [28] + SGM [15]	43%	3%	0%	0%	28%	7%	4%	1%
SFL [Ours]	**85%**	**59%**	**62%**	**50%**	**66%**	**44%**	**27%**	**23%**

Table 2: (*Fixed spawn*) The success rates of compared methods on three **ViZDoom** maps.

Conclusion

Introduced Successor Feature Landmarks, a graph-based planning framework built *entirely* upon successor features

Experiments on MiniGrid and ViZDoom demonstrated that this method outperforms current graph-based approaches on long-horizon goal-reaching tasks

We hope that future work will explore more properties and uses of successor features