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# Breadth-Frist Exploration on Adaptive Grid for Reinforcement Learning

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**Youngsik Yoon**, Gangbok Lee, Sungsoo Ahn, Jungseul Ok

Pohang University of Science and Technology (POSTECH)

{ysyoon97, gangbok2, sungsoo.ahn, jungseul}@postech.ac.kr

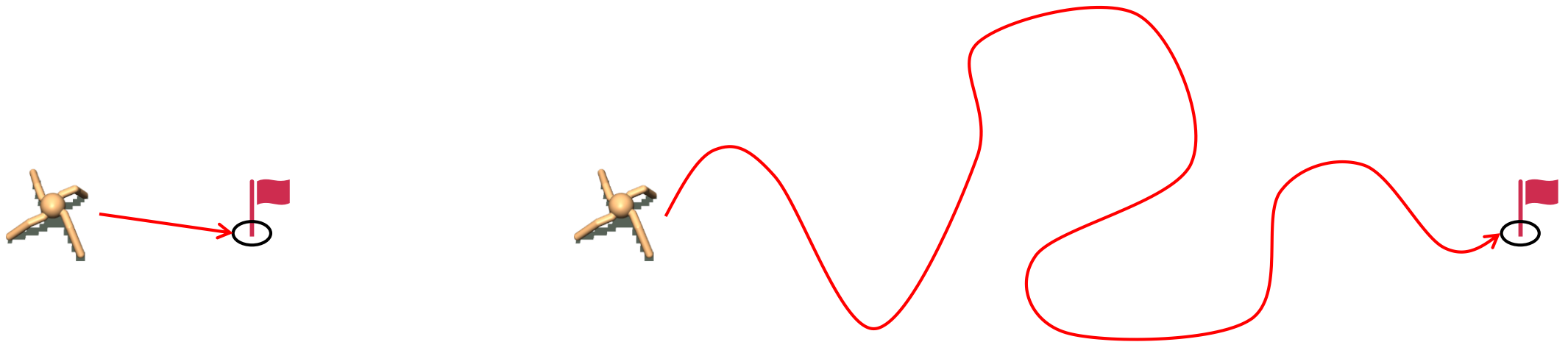
<https://youngsikyoon.github.io/BEAG/>



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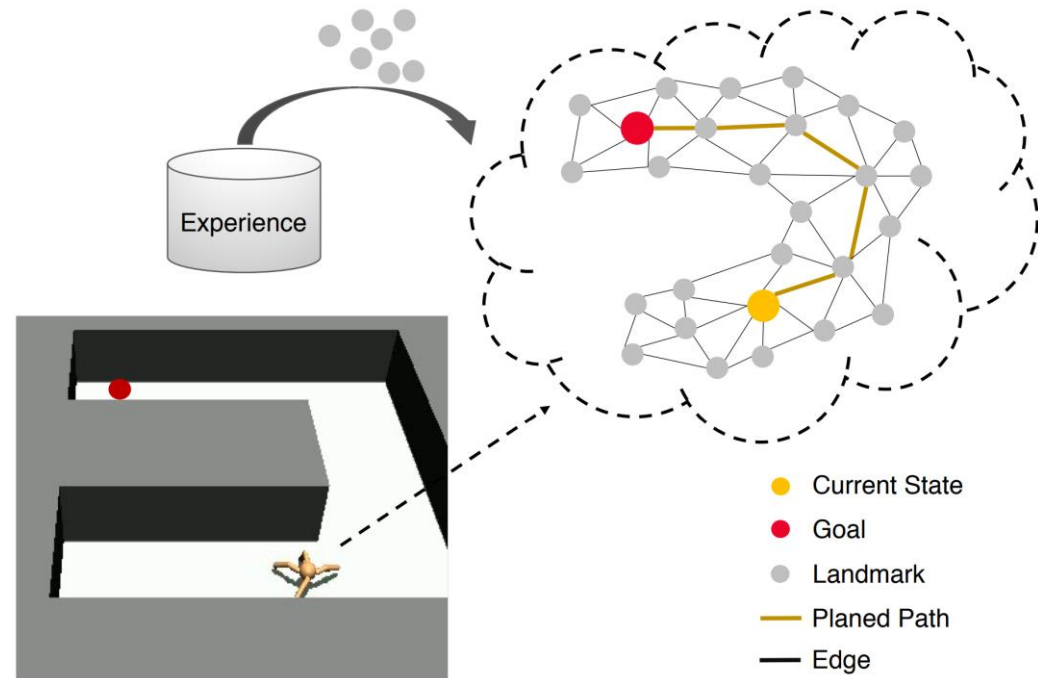
# Goal-conditioned Reinforcement Learning

- Goal-conditioned Reinforcement Learning (GCRL) aims to solve the task of targeting a given goal.



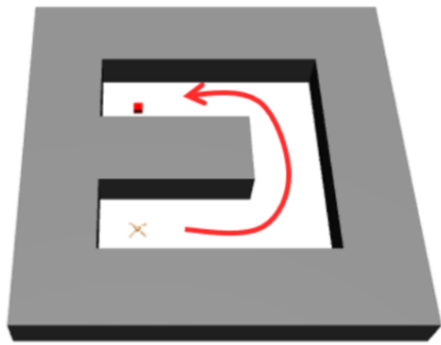
# Graph-based Reinforcement Learning

- Graph-based Reinforcement Learning (GBRL) decomposes long-horizon goals into a series of manageable short-horizon subgoals using a graph structure.

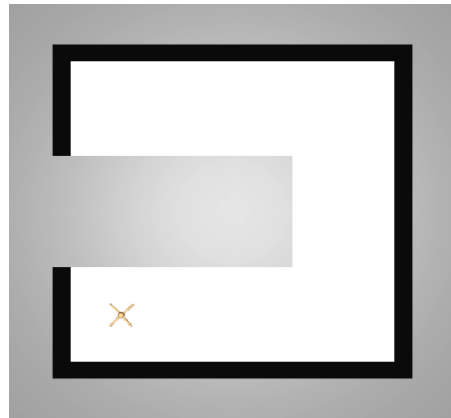


# Motivation

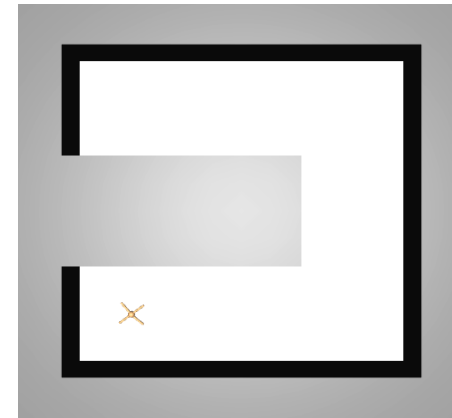
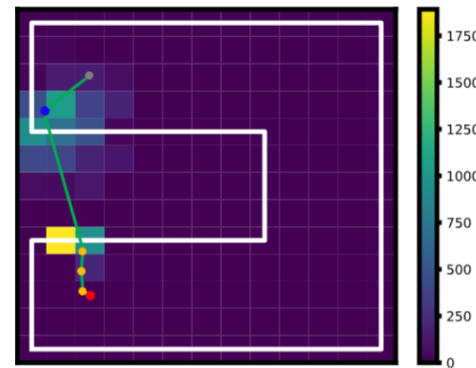
- Existing GBRL methods only manage successful subgoals sampled from the replay buffer without containing failed subgoals and unexplored subgoals, which leads to the problem of repeating the same failure.



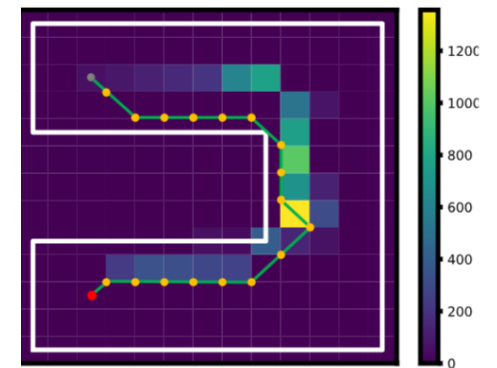
(a) *U-maze* task



(b) DHRL (Lee et al., 2022)

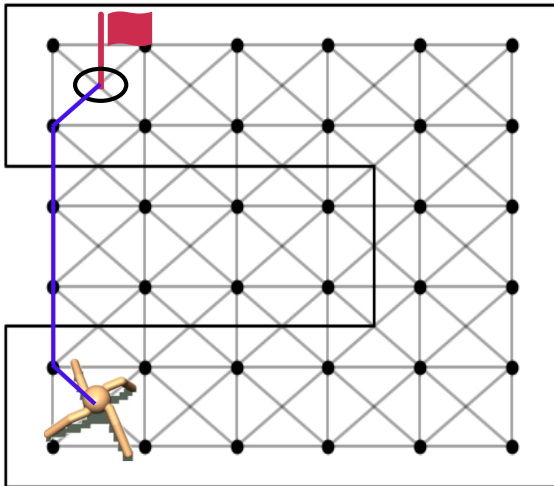


(c) BEAG (ours)



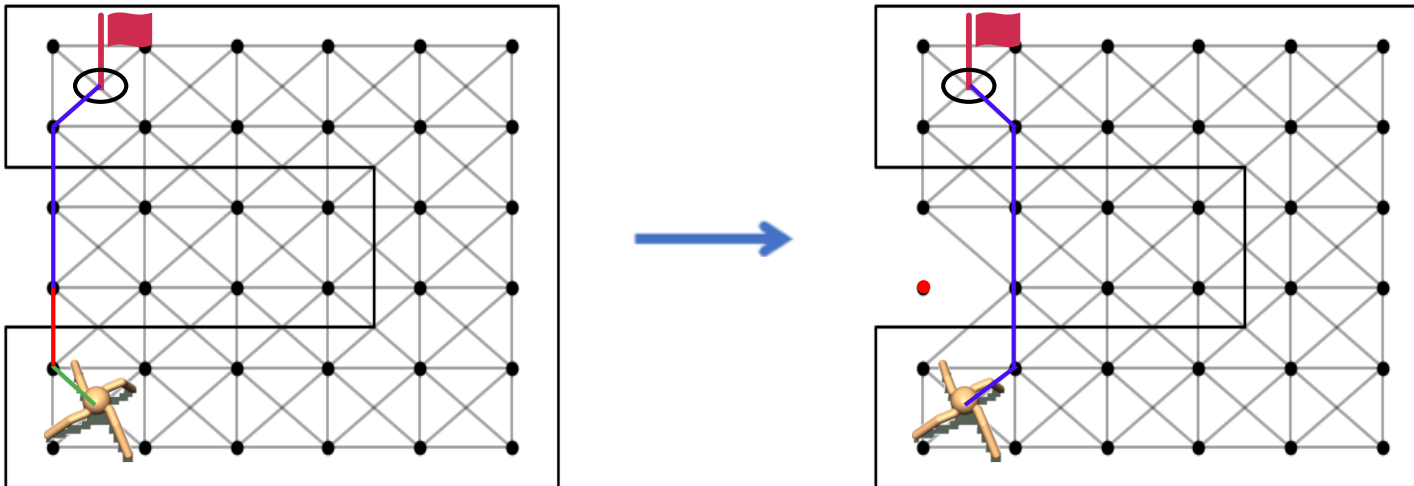
# BEAG: Breadth-First Exploration on Adaptive Grid

- We propose BEAG, which employs a **grid** covering the entire map instead of relying on graphs generated from the replay buffer, which may include **unexplored** or even **impossible** subgoals.



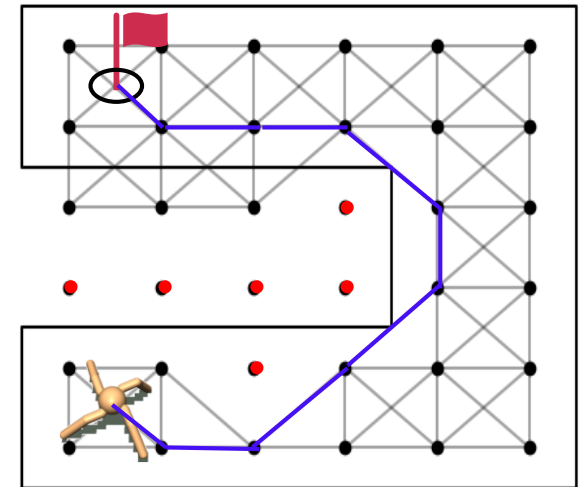
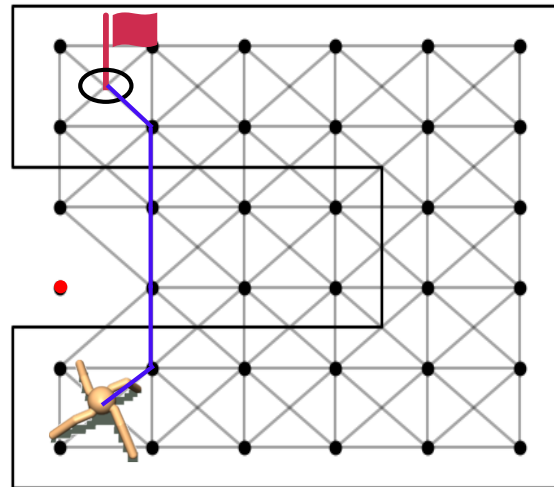
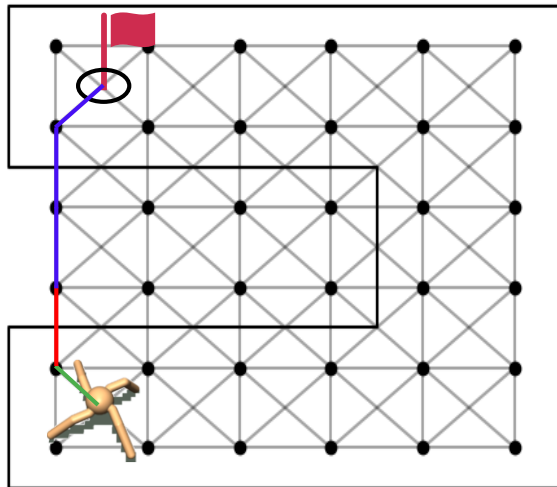
# BEAG: Breadth-First Exploration on Adaptive Grid

- BEAG follows paths generated from the graph and explores promising subgoals by removing edges connected to subgoals that have been experienced repeated failures.



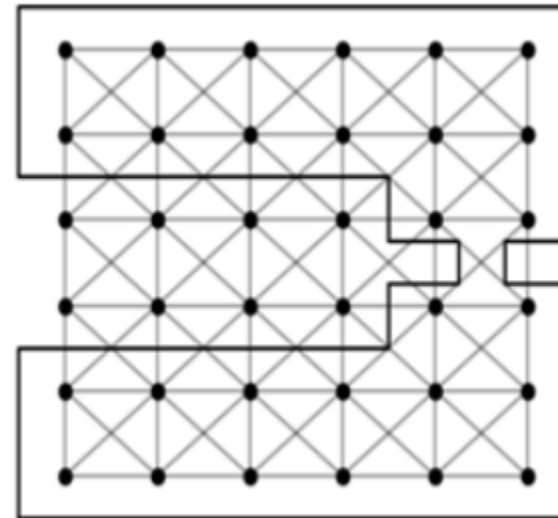
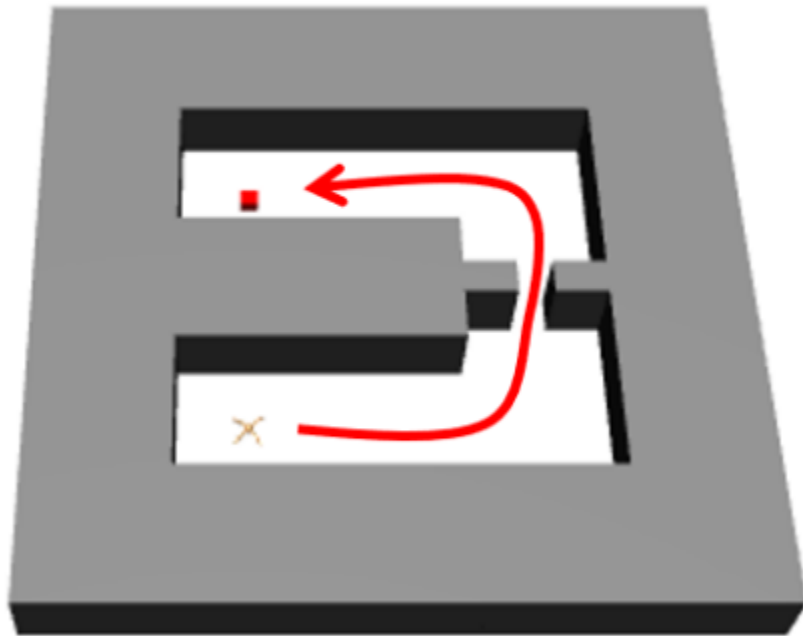
# BEAG: Breadth-First Exploration on Adaptive Grid

- After repeating this process a few times, BEAG will be able to find a successful path.



# Bottleneck Environment

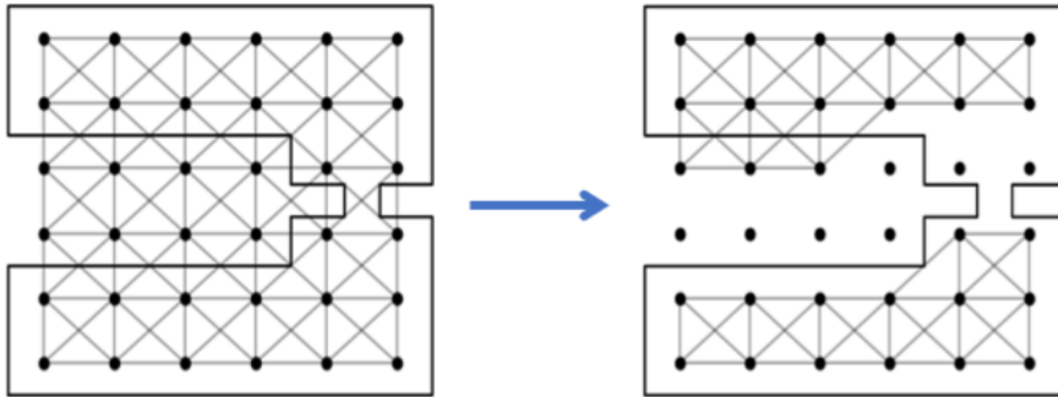
- While generating the grid, there may be issues in creating paths depending on the initial interval.





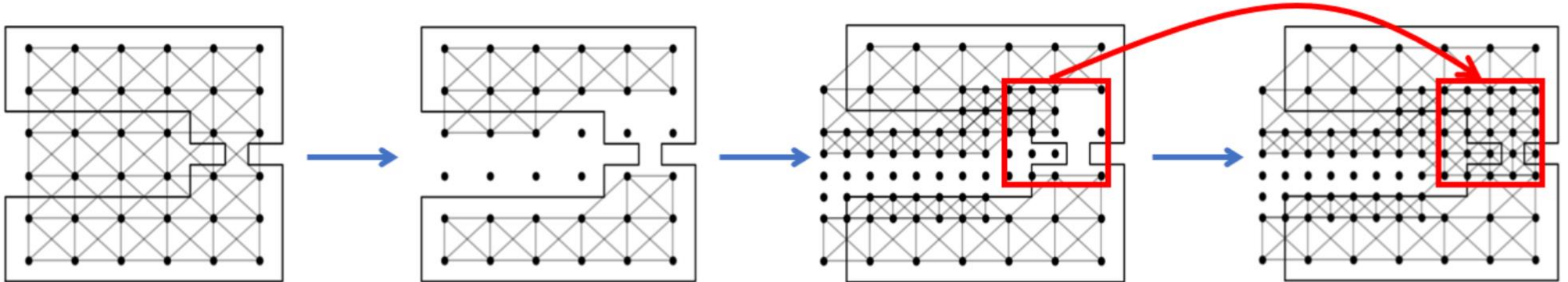
# Adaptive Grid Refinement

- BEAG identifies unattainable subgoals until failing to generate paths.



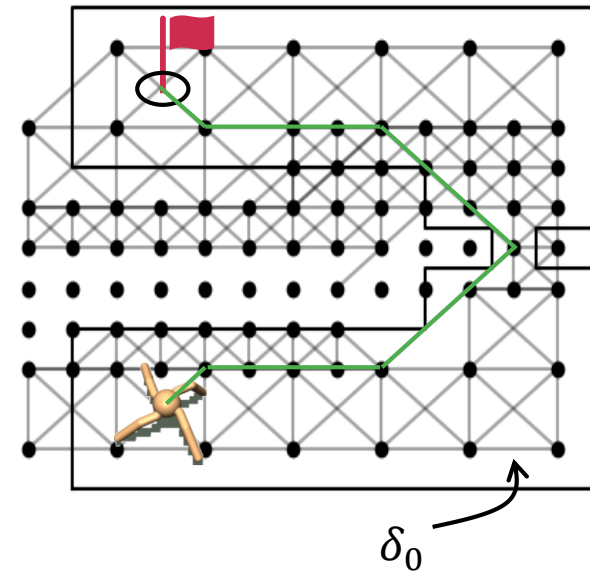
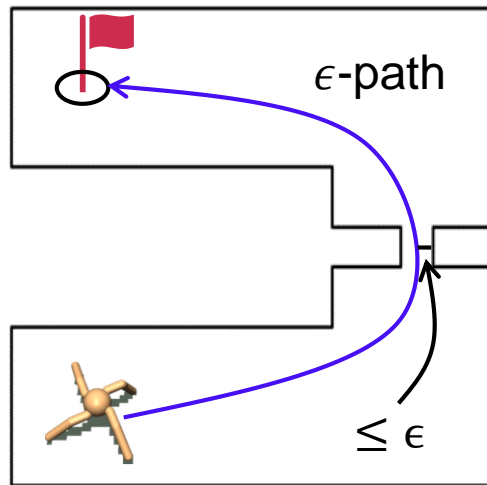
# Adaptive Grid Refinement

- After that, when a path to the goal cannot be generated, we select one of the failed nodes and perform more dense refinement around it.



# Analysis

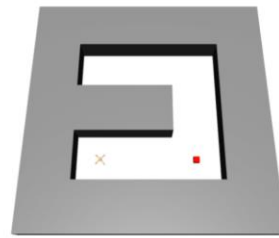
- According to our analysis,
  1. BEAG can always generate a possible path if there exists an  $\epsilon$ -path.
  2. The length of the grid path is at most  $\left(\left\lceil \frac{l}{\delta_0} \right\rceil + 1\right) \delta_0 \sqrt{K}$ , where  $l$  is the length of the  $\epsilon$ -path.



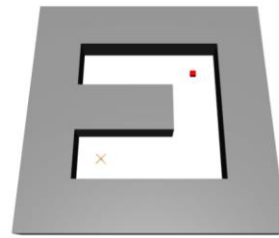
$K$ : dimension of the goal space

# Experimental Environments

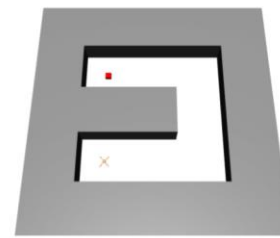
- We conduct experiments in the various maps of the AntMaze environment (a-g) and the Reacher3D environment (h).



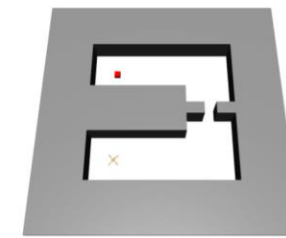
(a) *U-maze-easy*



(b) *U-maze-moderate*



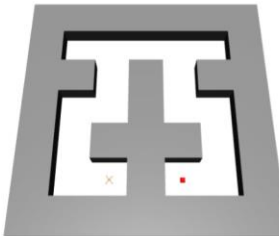
(c) *U-maze*



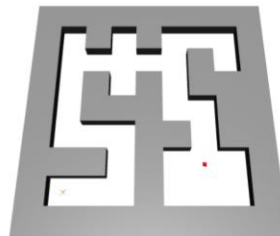
(d) *bottleneck-maze*



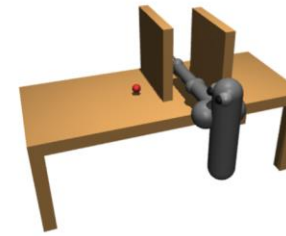
(e) *S-maze*



(f)  *$\pi$ -maze*



(g) *complex-maze*

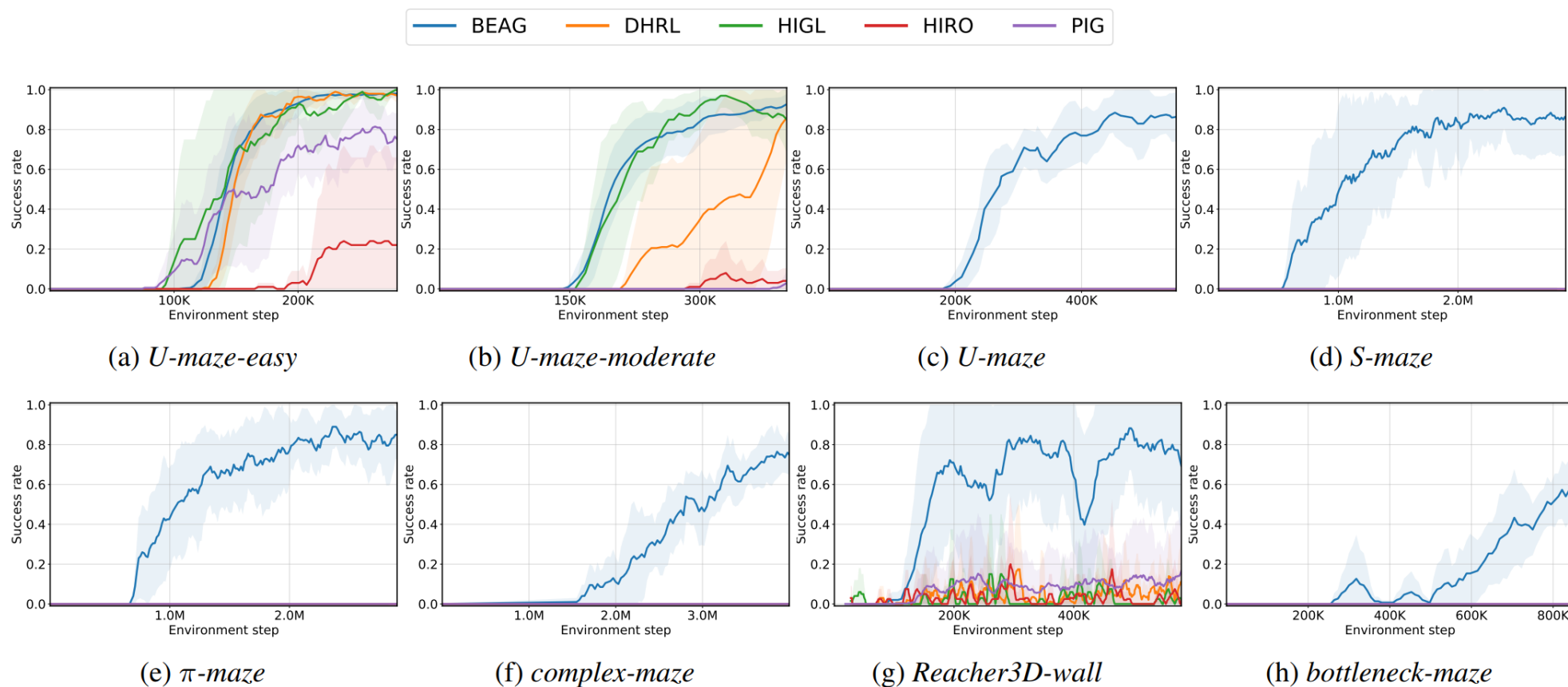


(h) *Reacher3D-wall*

- We compare our method, **BEAG**, with the state-of-the-art hierarchical RL and graph-based RL algorithms: **HIRO** (Nachum et al., 2018), **HIGL** (Kim et al., 2021), **DHRL** (Lee et al., 2022), and **PIG** (Kim et al., 2023)

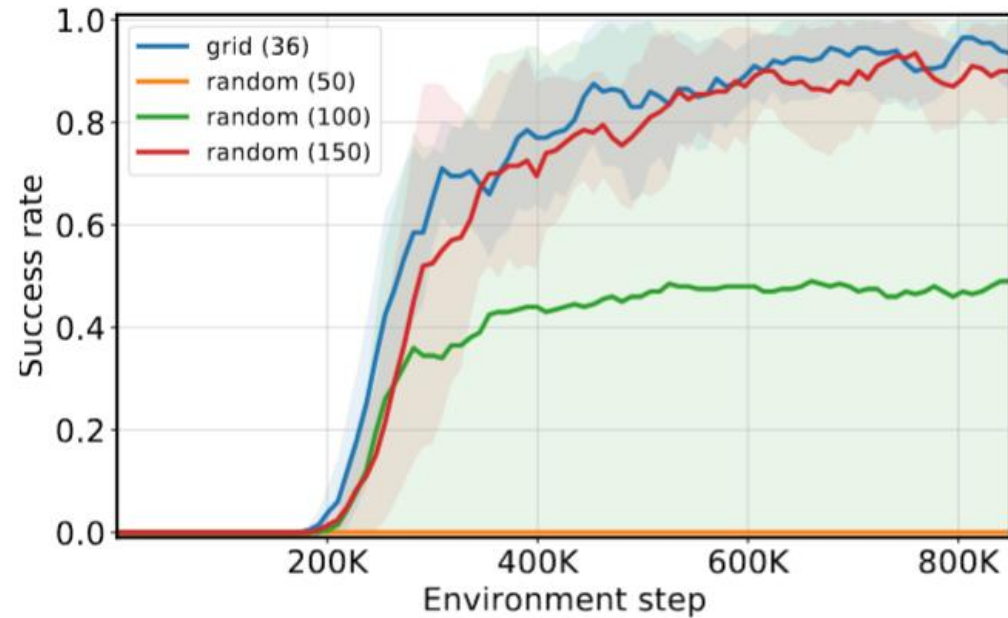
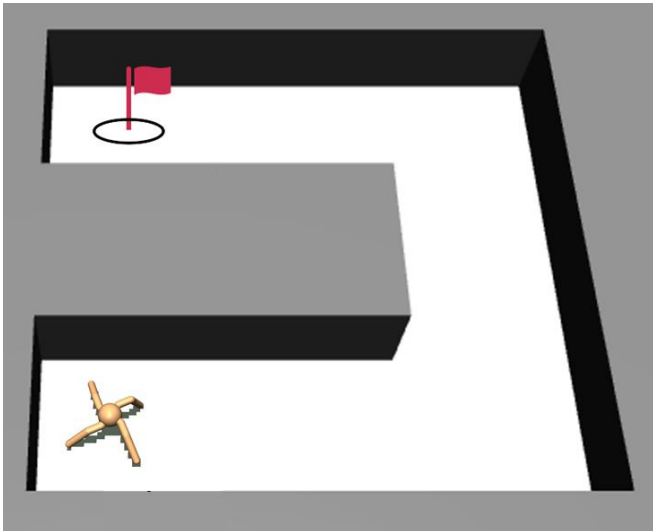
# Experimental Results

- BEAG remarkably outperforms other methods, especially in complex environments that require exploration, only BEAG achieves success.



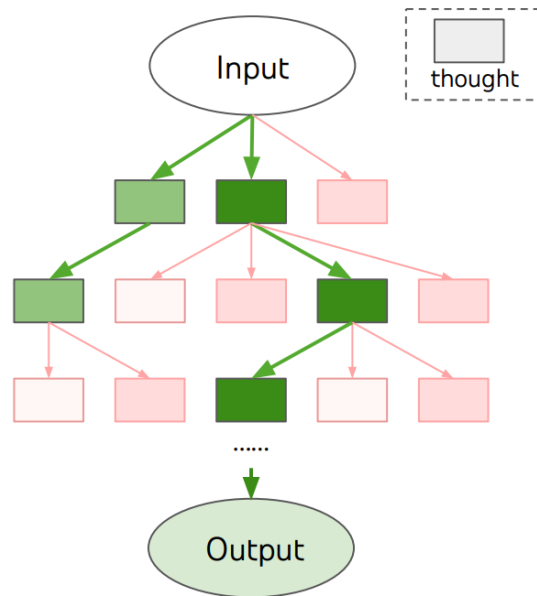
# Justification for Choosing Grid

- We conduct experiments performing a breadth-first search using a uniformly randomly generated graph over the entire map.

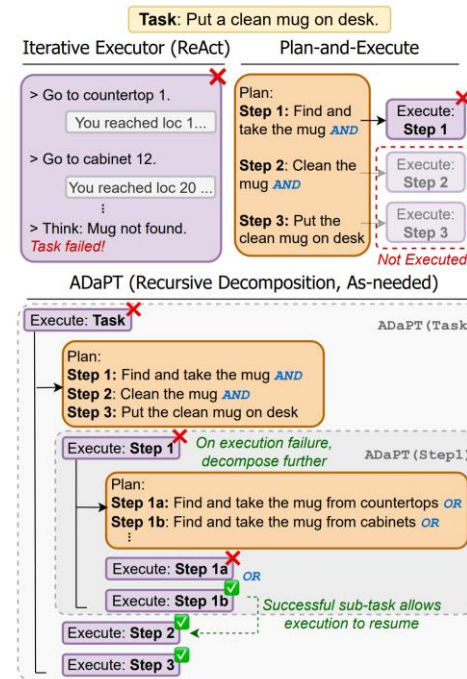


# Take Away

- BEAG has demonstrated the effectiveness of breadth-first search in exploration.
- This approach can be applied not only in the robotics but also in various applications, such as prompt engineering in large language models (LLM).



Tree of Thoughts: Deliberate Problem Solving with Large Language Models, Yao et al., 2023



ADaPT: As-Needed Decomposition and Planning with Language Models, Prasad et al., 2024