Using Hippocampal Replay to Consolidate Experiences in Memory-Augmented Reinforcement Learning

John Tan Chong Min
johntancm@u.nus.edu

Mehul Motani
motani@nus.edu.sg

Department of Electrical and Computer Engineering
National University of Singapore

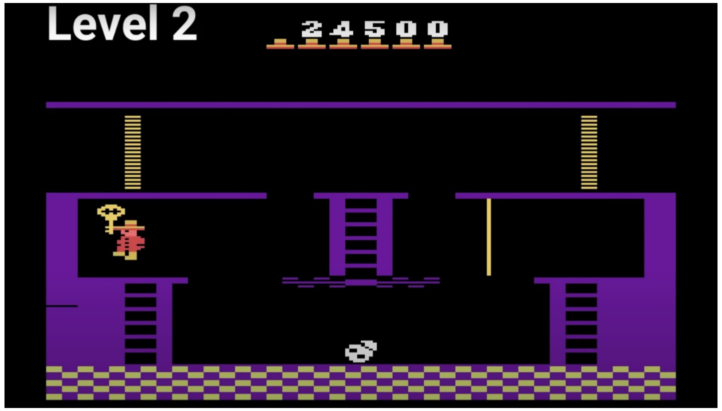
MemARI
NeurIPS 2022 | December 2nd
New Orleans, USA

NeurIPS MemARI Workshop 2022

NUS
National University of Singapore

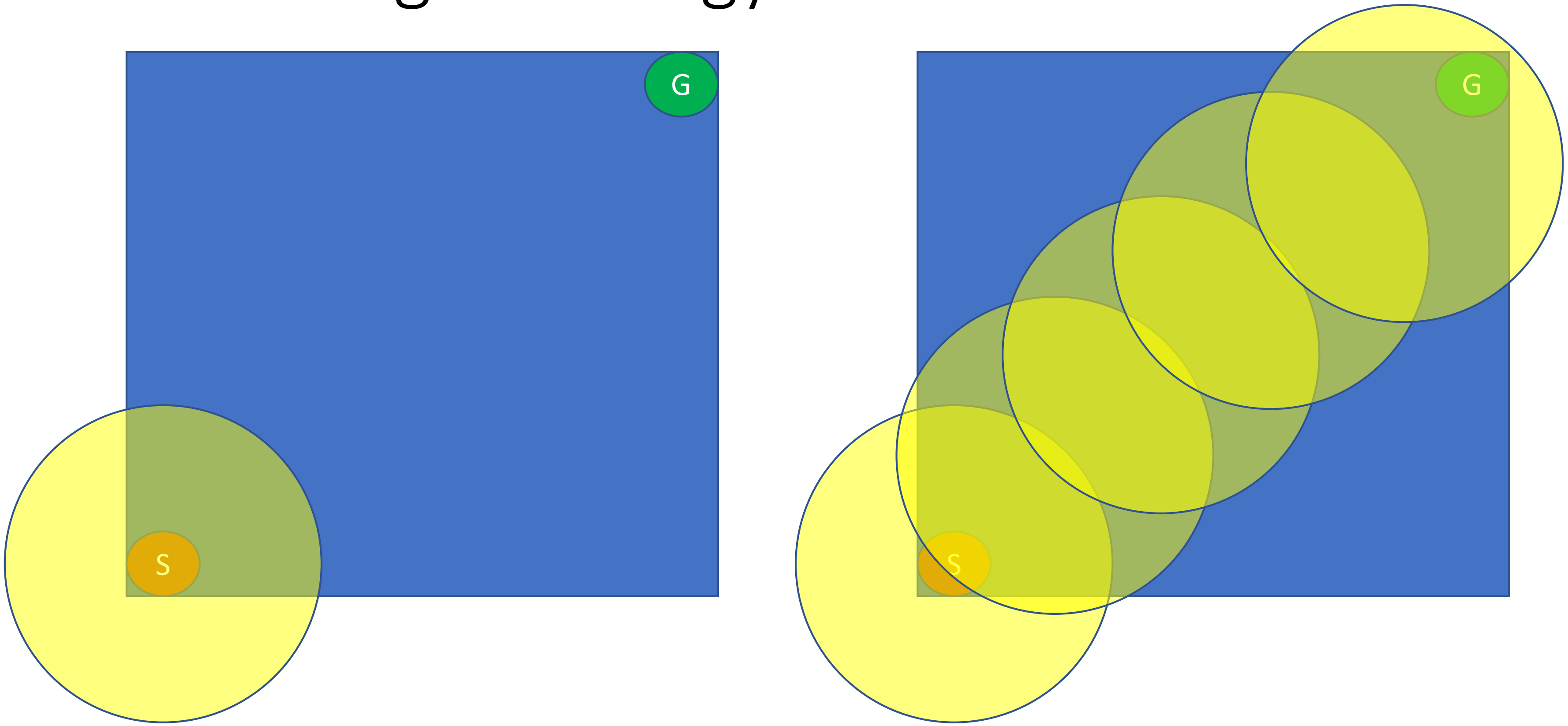
Go-Explore

- Using reward alone may be insufficient for sparse reward settings
- **Go-Explore** (Ecofett, 2019) uses external memory to update states
- In order to explore more states:
  - **Go:** Jump probabilistically to a state
  - **Explore:** Explore randomly from the state



Montezuma's Revenge,
a game with sparse rewards

The torchlight analogy



Exploration from starting state

Exploration from frontier

Agents

1. Random. This agent chooses a valid move randomly, and serves as a worst-case baseline.
2. Go-Explore. Go-Explore was implemented similar to Ecoffet et al. (2019, 2021), except that we select states deterministically in the “Go" phase for faster training.
3. Go-Explore-Count. While Go-Explore uses a random policy for exploration, Go-Explore-Count performs the best action based on a count-based selection function.
4. Explore-Count. Explore-Count is Go-Explore-Count without the “Go" phase.

How to “Go” and “Explore”

- Random exploration can be inefficient

- **Solution –** Use Deterministic Selection to balance explore and exploit

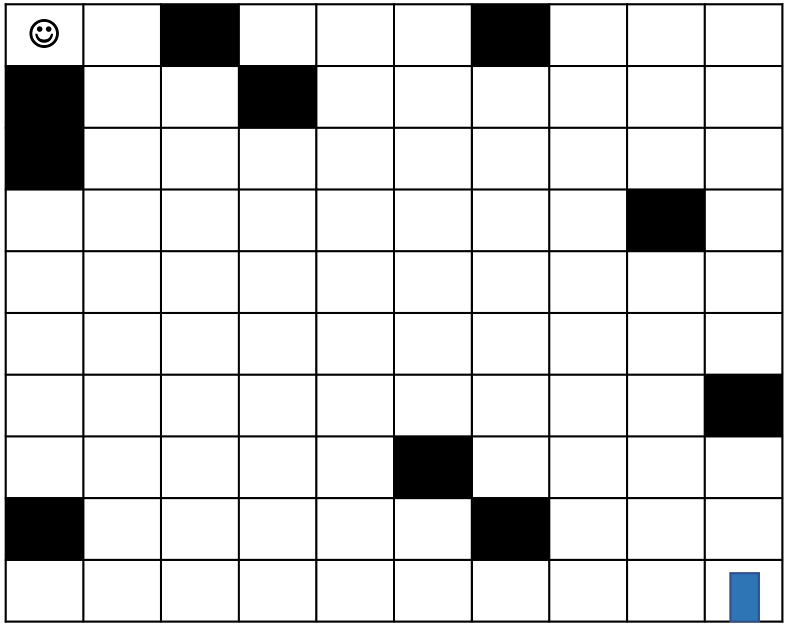
$$\alpha \cdot reward + \kappa\sqrt{moves} - \gamma\sqrt{numselected + numvisited}$$

  - ***reward***: environment reward
  - ***moves***: number of moves to reach state
  - ***numselected***: number of times state is selected in “Go” phase
  - ***numvisited***: number of times state is visited in “Explore” phase

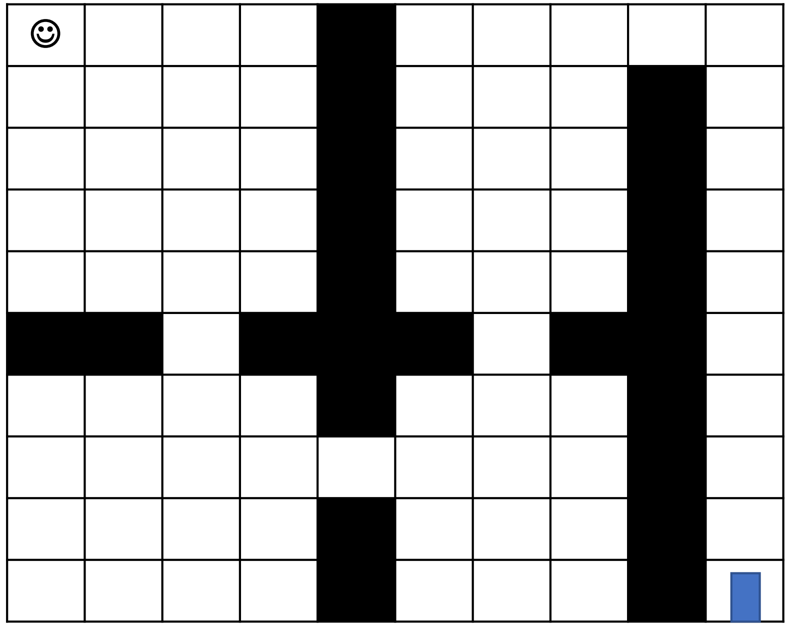
- Similar to Upper Confidence Bounds (UCB) equation and encourages greedy action selection in the long run

Environments

Unwalled Maze



Walled Maze



Legend:

Empty Grid

Obstacle

Agent

Door

Memory Initialization and Updates

- Initialization. For each explored state, store in memory:
  1. Trajectory of actions to reach it
  2. No. of moves to reach it
  3. Reward
  4. No. of selections in the “Go” phase (initialized at 0)
  5. No. of visits in the “Explore” phase (initialized at 0)

- Updating Current State. Increment selection and visit counts upon selection in “Go” and visitation in “Explore” phase respectively

- Updating Next State. Update the memory of the next state if current trajectory:
  - Has a higher reward
  - Has the same reward with a shorter trajectory

Hippocampal Replay

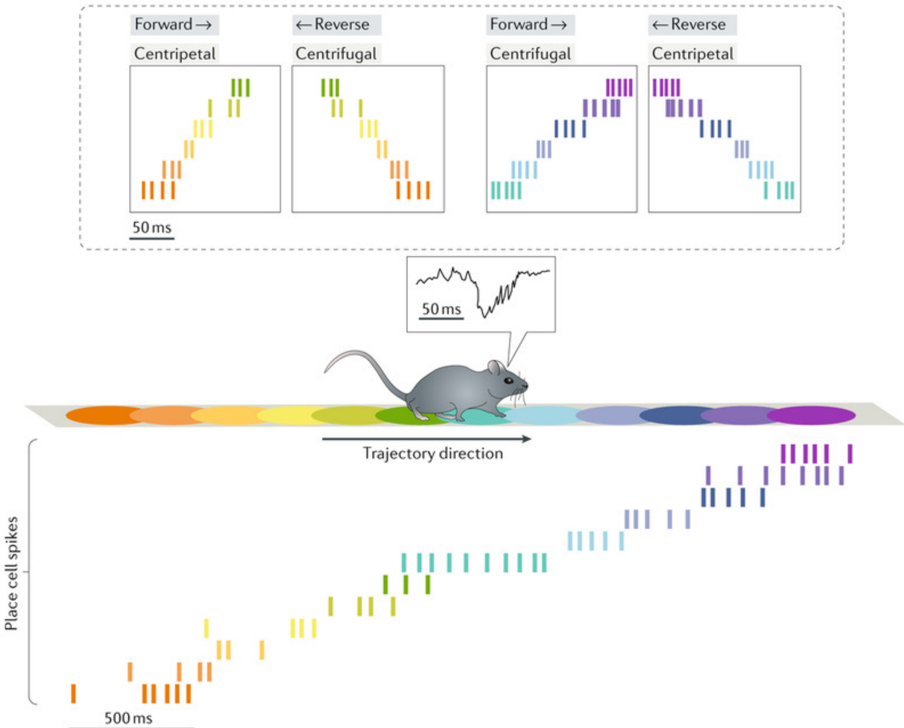


Figure extracted from Joo, H. R., & Frank, L. M. (2018). The hippocampal sharp wave-ripple in memory retrieval for immediate use and consolidation. Nature reviews. Neuroscience, 19(12), 744–757. https://doi.org/10.1038/s41583-018-0077-1

Algorithm 1 Hippocampal Replay

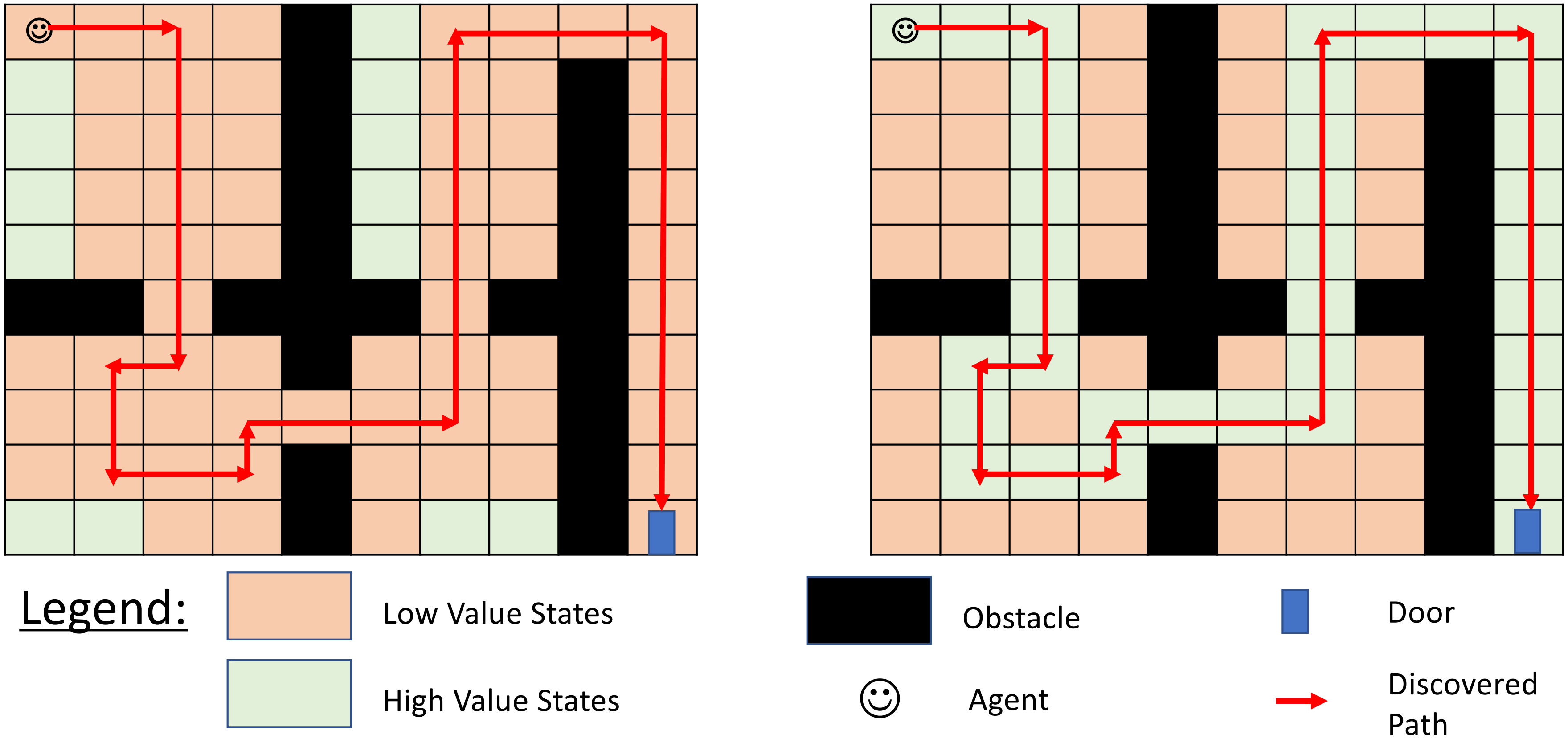
```
procedure HIPPOCAMPALREPLAY(env, trajectory):
    Consolidate the list of states in the successful trajectory, in chronological order   ▷ Pre-play
    Visit states in reverse order from the goal, and update the memory of each state      ▷ Replay
```

- Inspired from sharp wave-ripple in mice
- Pre-play to retrieve states along successful trajectory
- Replay to reset state selection and visit counts to 0 to create an “Exploration Highway”
- Replay can also be used to update intrinsic reward of state for better performance

Hippocampal Replay creates Exploration Highway

Before Hippocampal Replay:

After Hippocampal Replay:



Results

Table 1: Performance results for Unwalled Maze 100x100 with and without hippocampal replay. '-HR' represents with hippocampal replay. Bolded text represents better performance.

Overall		First Solve		Steps to Solve		
Agent	**Solve Rate**	**Run**	**Memory size**	**Avg**	**Min**	**Max**
Random	1/100	15	-	9980.0	9980.0	9980.0
Go-Explore	0/100	-	-	-	-	-
Go-Explore-HR	0/100	-	-	-	-	-
Go-Explore-Count	78/100	**1**	**7597**	**5533.1**	**4312.0**	9498.0
Go-Explore-Count-HR	**100/100**	**1**	**7597**	6003.3	5984.0	**7854.0**
Explore-Count	98/100	**1**	**7597**	**3501.8**	**1436.0**	8286.0
Explore-Count-HR	**100/100**	**1**	**7597**	5984.0	5984.0	**5984.0**

Table 2: Performance results for Walled Maze 100x100 with and without hippocampal replay. '-HR' represents with hippocampal replay. Bolded text represents better performance.

Overall		First Solve		Steps to Solve		
Agent	**Solve Rate**	**Run**	**Memory size**	**Avg**	**Min**	**Max**
Random	0/100	-	-	-	-	-
Go-Explore	0/100	-	-	-	-	-
Go-Explore-HR	0/100	-	-	-	-	-
Go-Explore-Count	**100/100**	**1**	**7552**	4918.2	**4718.0**	6362.0
Go-Explore-Count-HR	**100/100**	**1**	**7552**	**4912.0**	4912.0	**4912.0**
Explore-Count	52/100	**1**	**7552**	7039.0	**3094.0**	9758.0
Explore-Count-HR	**100/100**	**1**	**7552**	**4912.0**	4912.0	**4912.0**

- Our count-based approaches (Go-Explore-Count, Explore-Count) perform better than vanilla Go-Explore
- Hippocampal Replay leads to more consistent performance (higher solve rate) and less exploration (higher minimum number of steps to solve)

Hyperparameter Effects

Selection equation: $\alpha \cdot reward + \kappa\sqrt{moves} - \gamma\sqrt{numselected + numvisited}$

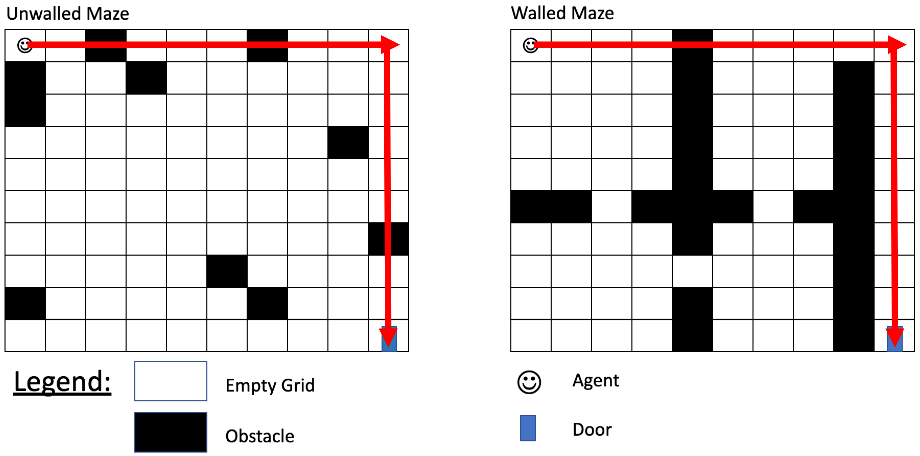
Table 3: Performance results for Walled Maze 100x100 with and without hippocampal replay using various hyperparameters. '-HR' represents with hippocampal replay. 'X' refers to any value in {0, 1, 10}. Bolded text refers to best performance within the given hyperparameters.

			Overall		First Solve		Steps to Solve		
α	κ	γ	**Agent**	**Solve Rate**	**Run**	**Mem**	**Avg**	**Min**	**Max**
X	1	1	Go-Explore-Count	**100/100**	**1**	**7454**	4831.3	4620.0	6704.0
			Go-Explore-Count-HR	**100/100**	**1**	**7454**	4804.0	4804.0	**4804.0**
			Explore-Count	41/100	**1**	**7454**	**3940.8**	**2510.0**	9098.0
			Explore-Count-HR	**100/100**	**1**	**7454**	4804.0	4804.0	**4804.0**
X	0	1	Go-Explore-Count	0/100	-	-	-	-	-
			Go-Explore-Count-HR	0/100	-	-	-	-	-
			Explore-Count	17/100	**2**	**7476**	8031.8	**5730.0**	9746.0
			Explore-Count-HR	**99/100**	**2**	**7476**	**7286.0**	7286.0	**7286.0**
X	10	1	Go-Explore-Count	0/100	-	-	-	-	-
			Go-Explore-Count-HR	0/100	-	-	-	-	-
			Explore-Count	14/100	**19**	**8581**	**2782.6**	**2260.0**	**3596.0**
			Explore-Count-HR	**82/100**	**19**	**8581**	3596.0	3596.0	**3596.0**
X	1	0	All	0/100	-	-	-	-	-
X	1	10	Go-Explore-Count	**100/100**	**1**	**7552**	4918.2	4718.0	6362.0
			Go-Explore-Count-HR	**100/100**	**1**	**7552**	**4912.0**	4912.0	**4912.0**
			Explore-Count	52/100	**1**	**7552**	7039.0	**3094.0**	9758.0
			Explore-Count-HR	**100/100**	**1**	**7552**	**4912.0**	4912.0	**4912.0**

- Reward term not significant due to sparse reward setting
- Moves term should just be at 1 for tie-breaker to discover frontier. Any lower or higher leads to less efficient solution
- Higher exploration term (*numselected + numvisited*) leads to consistency at the expense of a less efficient solution

Goal-Directed Intrinsic Reward (GDIR)

- Possible to improve goal-seeking by adding a potential-function term to let agent know how close it is to goal
- Only serves as guide, does not tell us how to get there
- For maze environments, it can be Manhattan distance
- Scaled term between –1 to 0:
  - −(Manhattan Distance of agent to door position)/(Height+Width − 2)



Results for GDIR

Table 4: Performance results for Unwalled Maze 100x100 with and without GDIR. Results are with hippocampal replay. Bolded text represents better performance.

Overall		First Solve		Steps to Solve		
Agent	**Solve Rate**	**Run**	**Memory size**	**Avg**	**Min**	**Max**
Go-Explore-Count	**100/100**	**1**	7597	6003.3	5984.0	7854.0
Go-Explore-Count-GDIR	**100/100**	**1**	**499**	**230.0**	**230.0**	**230.0**
Explore-Count	**100/100**	**1**	7597	5984.0	5984.0	5984.0
Explore-Count-GDIR	**100/100**	**1**	**499**	**224.1**	**224.0**	**230.0**

Table 5: Performance results for Walled Maze 100x100 with and without GDIR. Results are with hippocampal replay. Bolded text represents better performance.

Overall		First Solve		Steps to Solve		
Agent	**Solve Rate**	**Run**	**Memory size**	**Avg**	**Min**	**Max**
Go-Explore-Count	**100/100**	**1**	7552	**4912.0**	**4912.0**	**4912.0**
Go-Explore-Count-GDIR	**100/100**	**1**	**5105**	8922.0	8922.0	8922.0
Explore-Count	**100/100**	**1**	7552	4912.0	4912.0	**4912.0**
Explore-Count-GDIR	**100/100**	**1**	**5105**	**2298.8**	**2184.0**	8922.0

- GDIR leads to shorter solutions in most situations
- Walled Maze Go-Explore-Count-GDIR ends up with a longer solution – GDIR guidance may lead to wrong path followed initially in presence of wall

Discussion

- Should count-based explore-exploit selection be used as the baseline policy, or just as the action selection branch?

- How to incorporate with neural networks to help with action selection?

- How does our brain generate goals for an agent to move towards? How are these goals then quantified with an intrinsic reward?