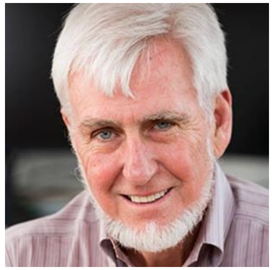
Grid Cell-Inspired Fragmentation and Recall for Efficient Map Building

Jaedong Hwang

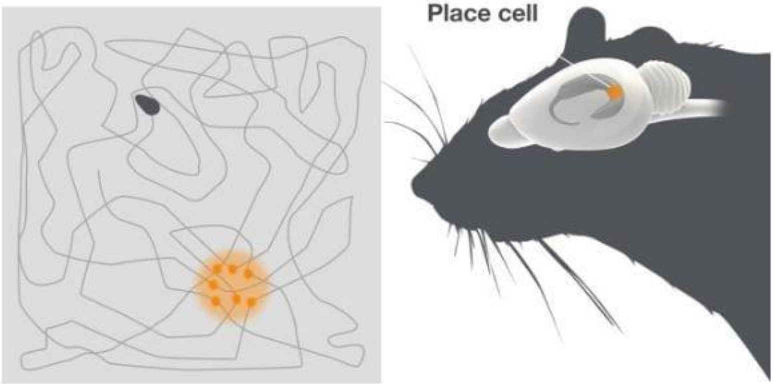
NeuroAI Workshop @ NeurIPS 2024

Conferences are held in various locations and usually very complex

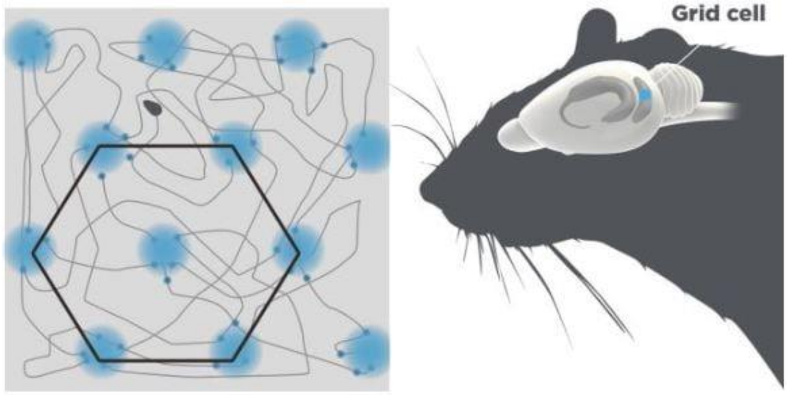
Place Cell and Grid Cell

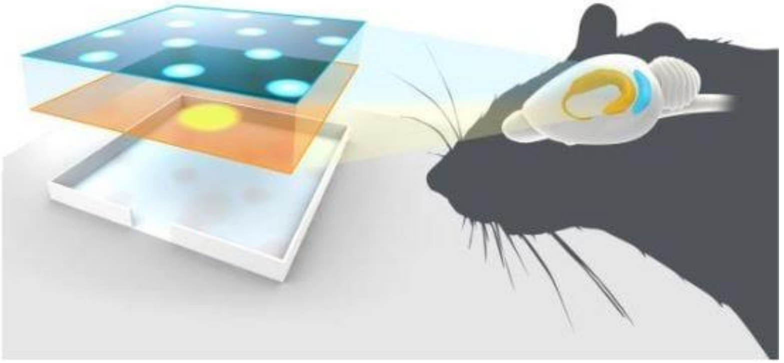


John O'Keefe
(1971)



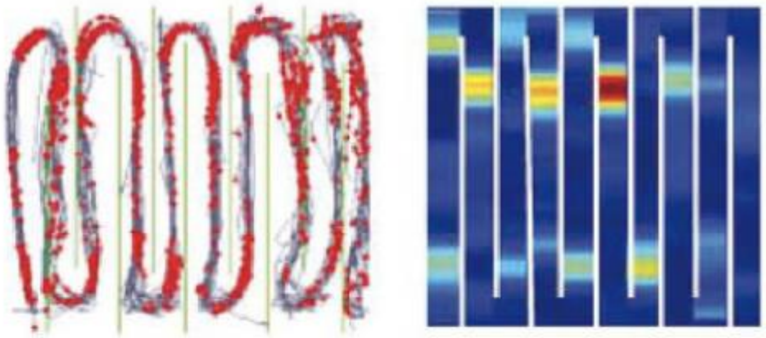
May-Britt &Edvard I. Moser
(2005)

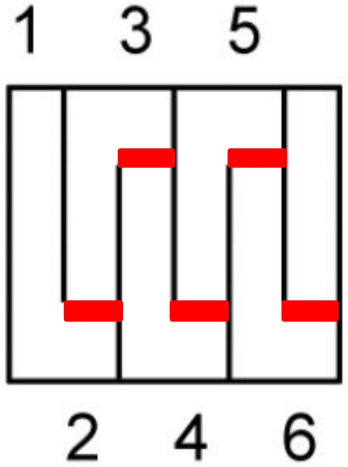


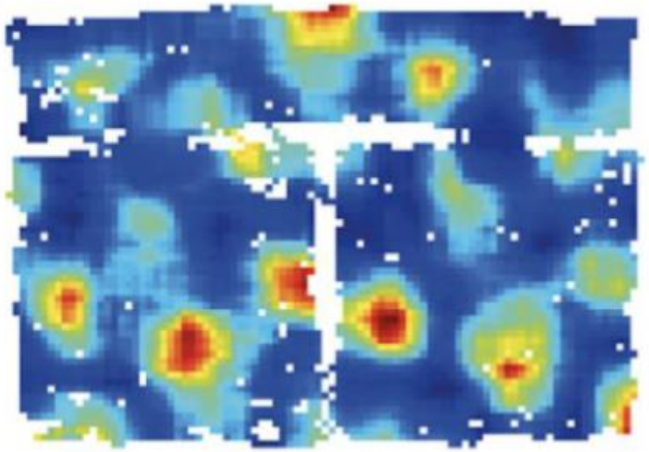


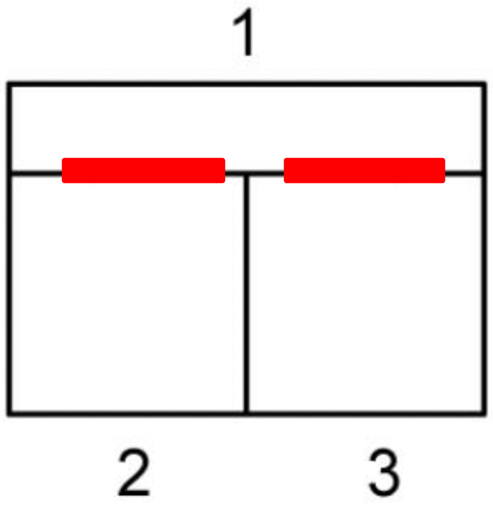
https://www.nobelprize.org/prizes/medicine/2014/advanced-information/

Remapping



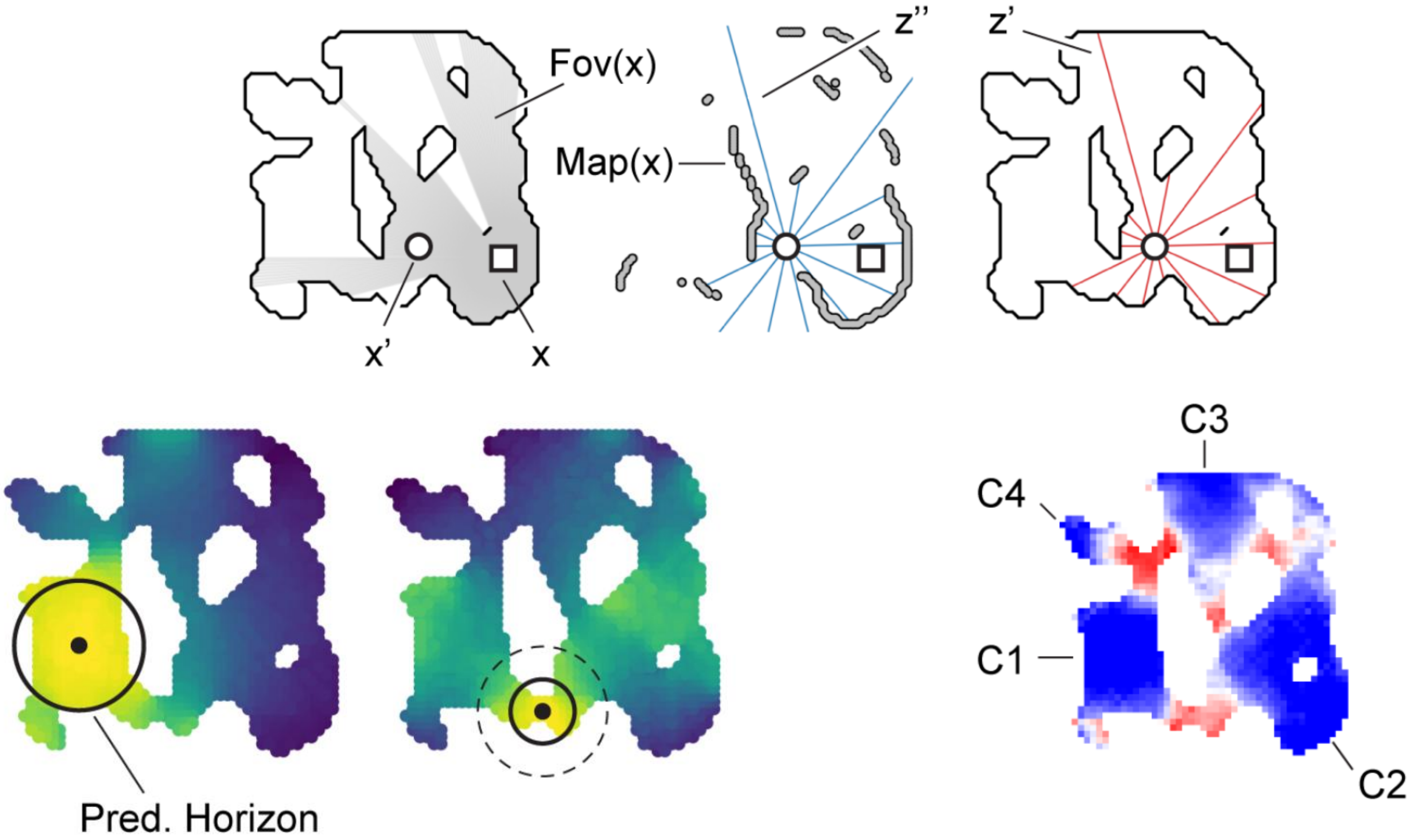






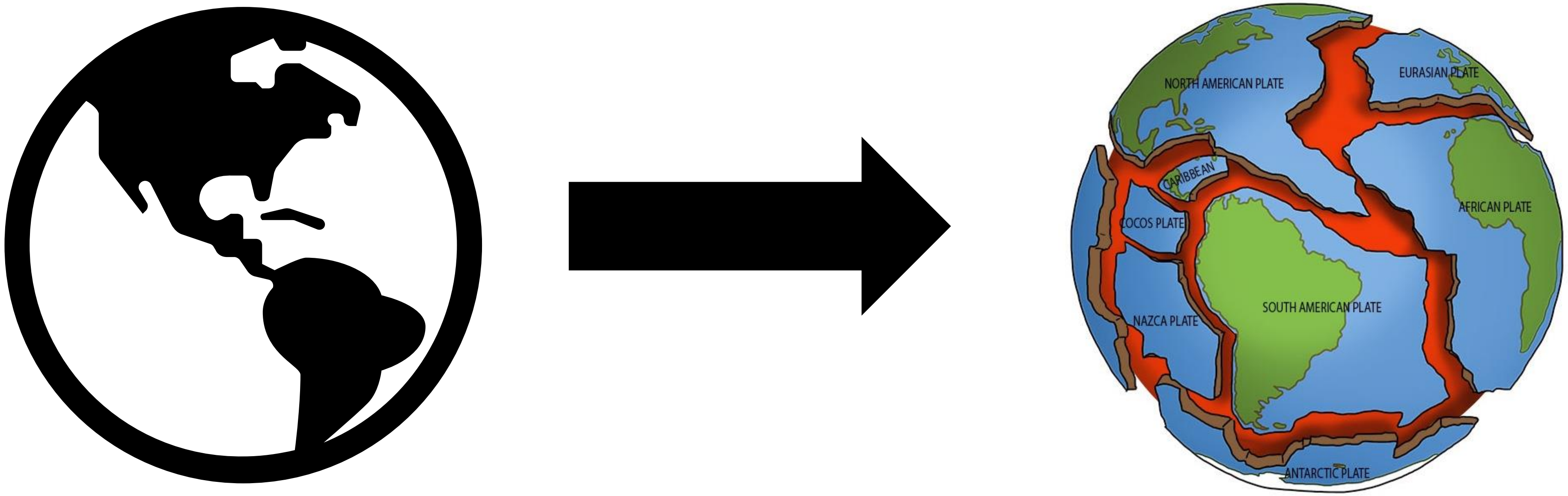
Klukas, Mirko, et al. "**Fragmented Spatial Maps: State Abstraction and Efficient Planning from Surprisal**." *bioRxiv* (2021).

Where does the remapping happen?

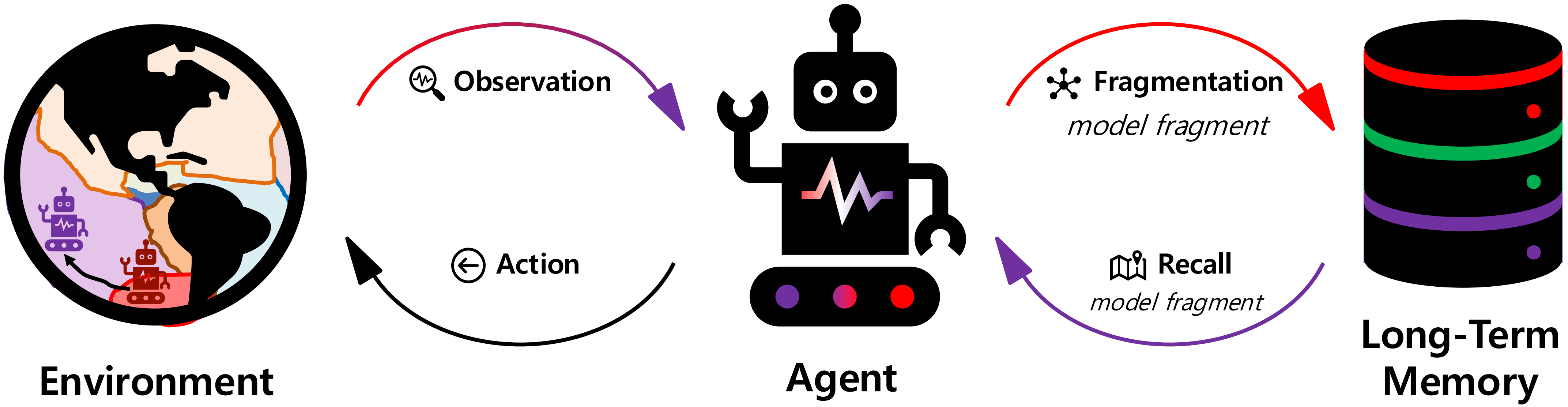


Klukas, Mirko, et al. "**Fragmented Spatial Maps: State Abstraction and Efficient Planning from Surprisal**." *bioRxiv* (2021).

Fragmentation



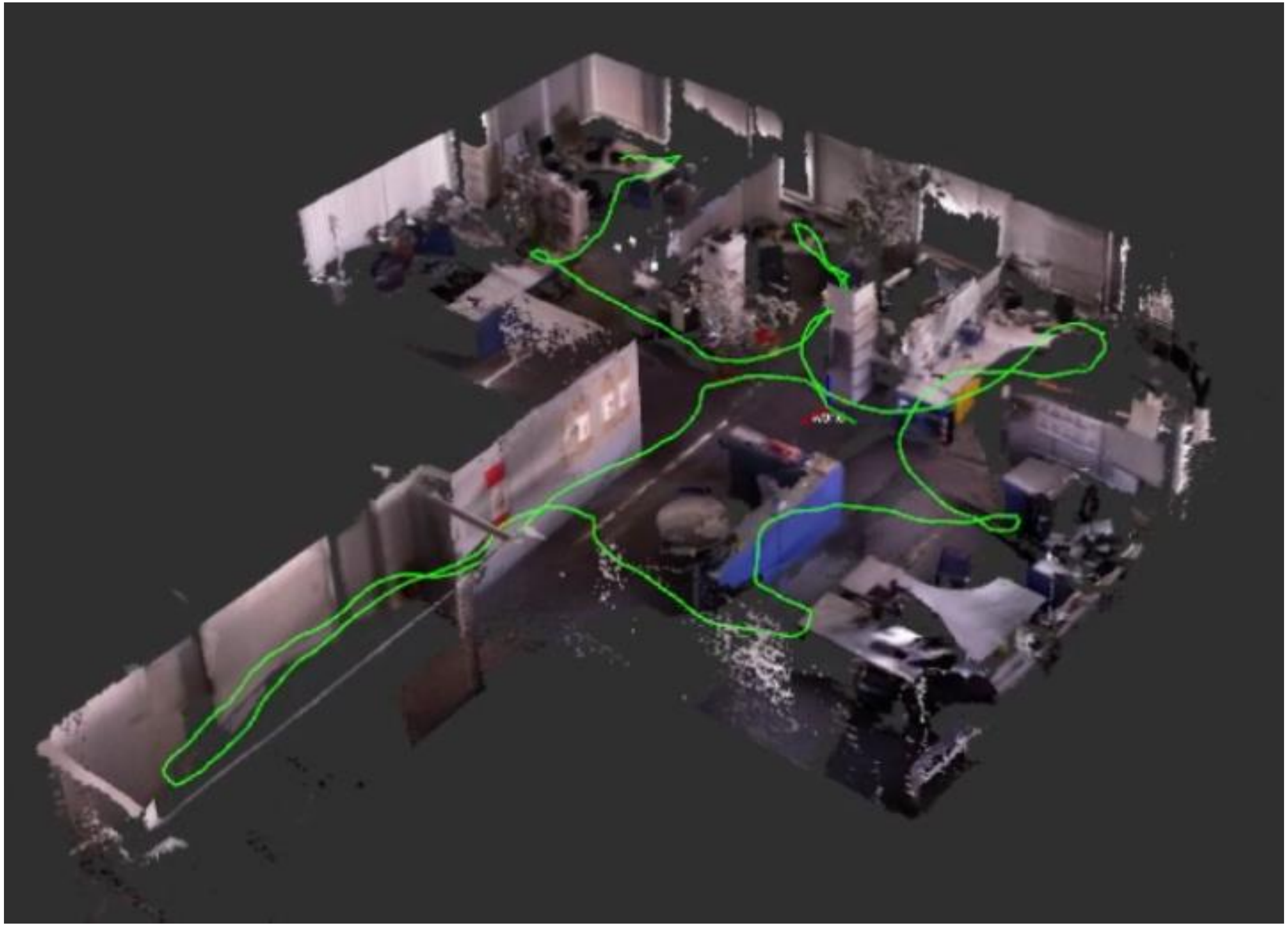
Overall Framework



Why Fragmentation and Recall?

- By **Fragmentation**
  - We can divide one big problem into multiple subproblem.
  - Since the problem set size is reduced, we can use a local model that is expertized in each sub set.
- By **Recall**
  - We can use memorized information without forgetting.

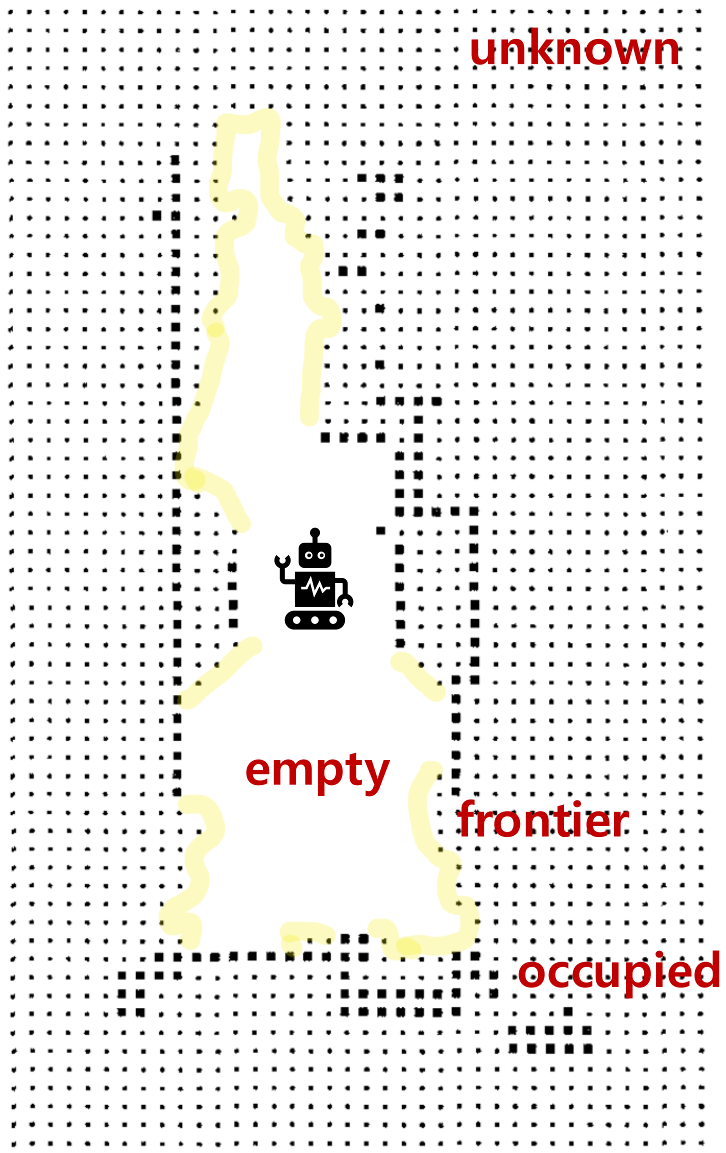
Simultaneous Localization and Mapping (SLAM)



https://www.ifp.uni-stuttgart.de/en/research/photogrammetric_computer_vision/SLAM/

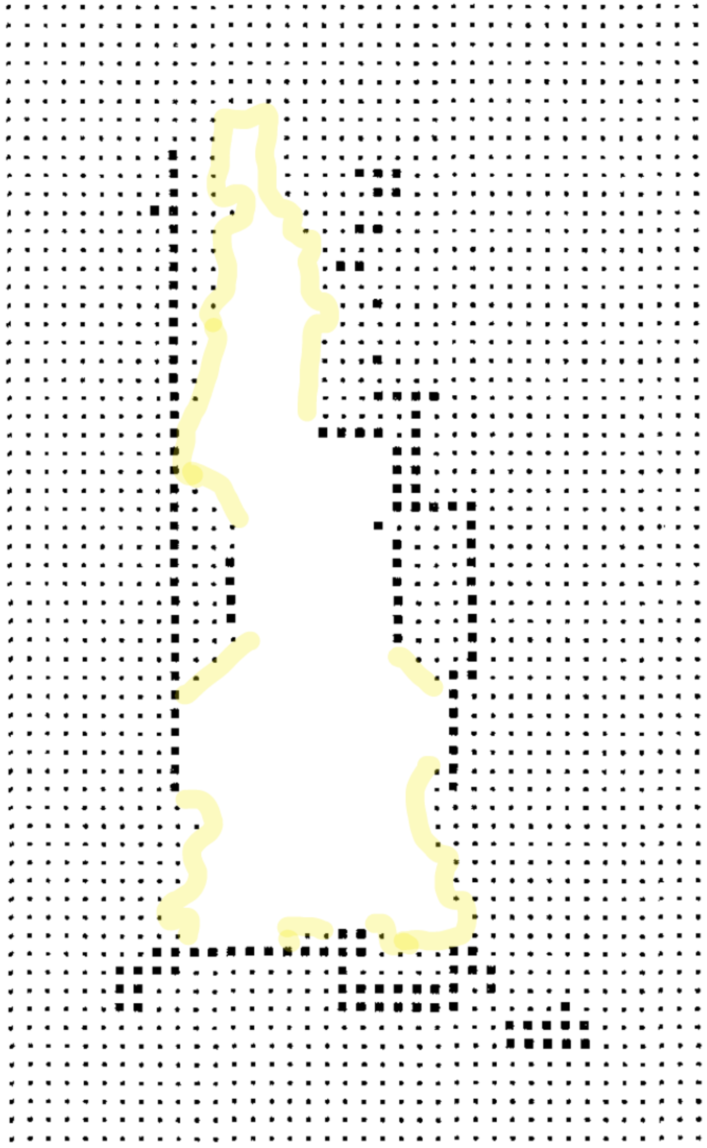
Cell Type in the Occupancy Grid

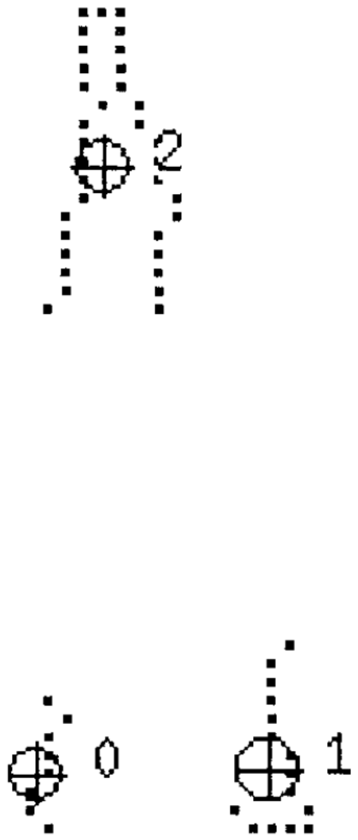
- Known Cell
  - Occupied Cell
  - Unoccupied (empty) Cell
- Unknown Cell
  - Frontier



Yamauchi, Brian. "**A frontier-based approach for autonomous exploration.**" CIRA. 1997

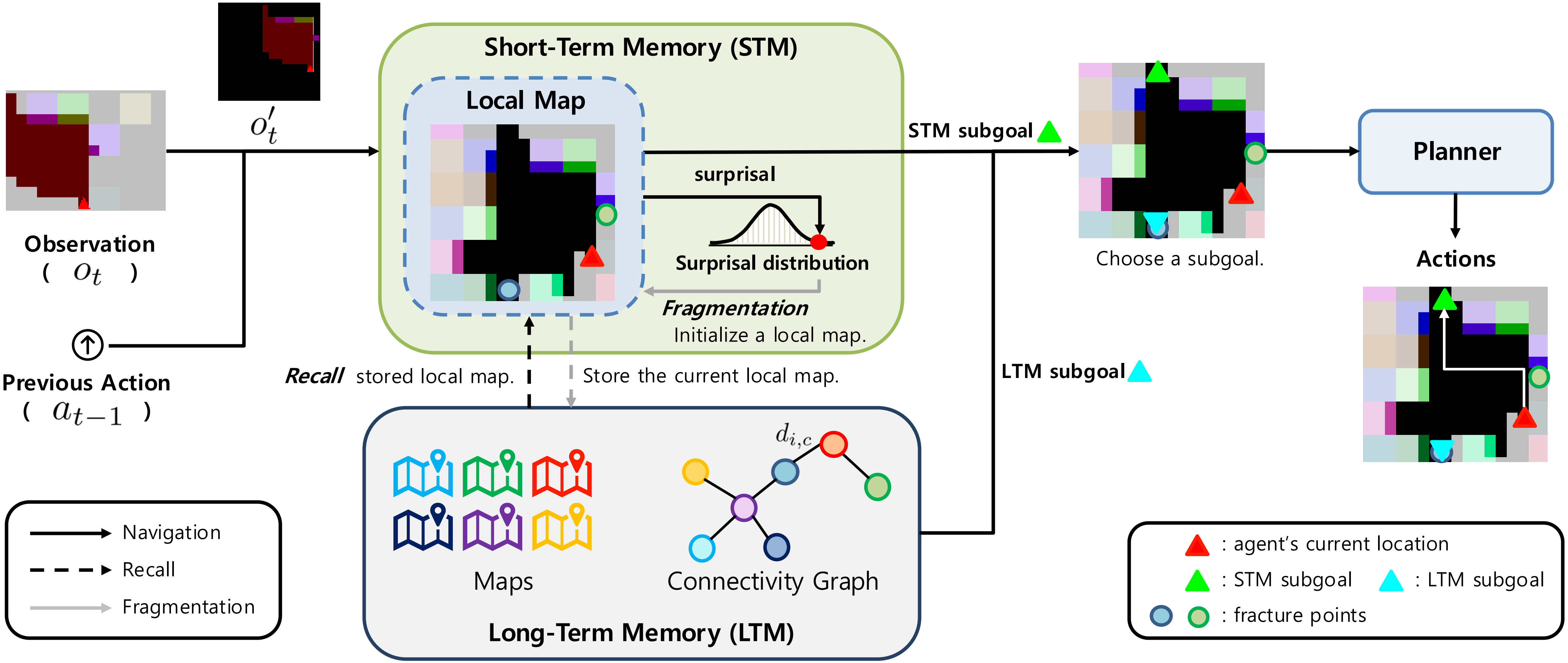
Frontier: boundary between known and unknown cells





Yamauchi, Brian. "**A frontier-based approach for autonomous exploration.**" CIRA. 1997

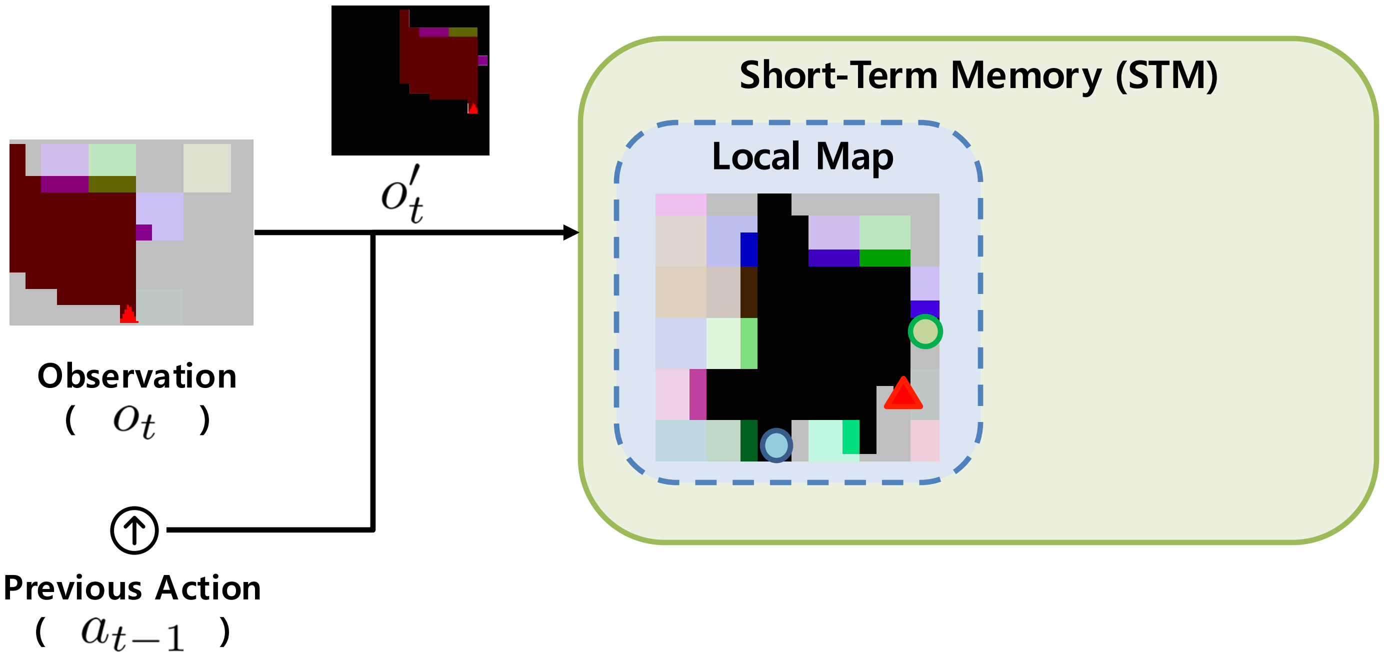
Fragmentation and Recall in Map Building (FARMap)



Short-Term Memory (STM)

- Short-Term Memory builds a local predictive map.
- The map is defined as temporally decaying trace of recent sensory observations.

$$\mathbf{M}^{\text{cur}}_{t,C} = \gamma \cdot \mathbf{M}^{\text{cur}}_{t-1,C} + (1-\gamma) \cdot o'_{t,C}$$



γ : discount factor

o'_t : spatially transformed current observation.

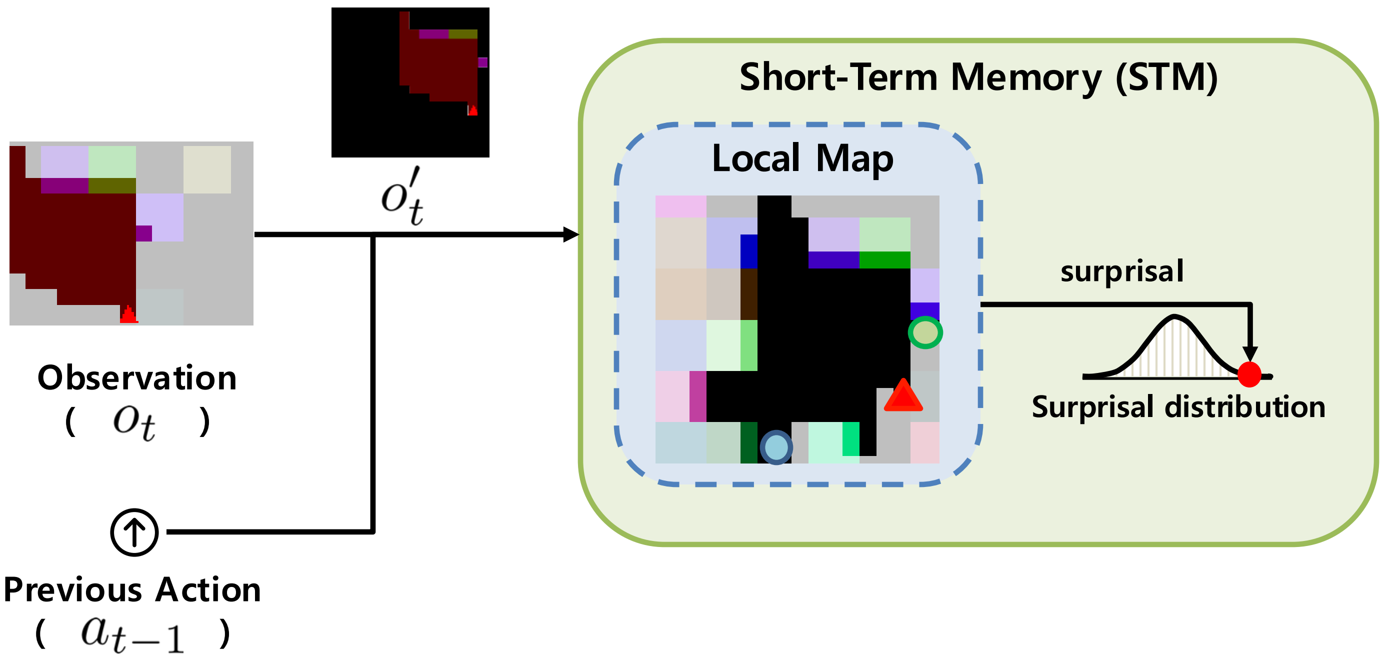
Confidence and Surprisal

- Confidence at time t is defined as average confidence of visible cells:

$$c_t = \frac{\mathbf{M}^{\text{cur}}_{t-1,C} \cdot o'_{t,C}}{||o'_{t,C}||_1}$$

- Surprisal is defined as

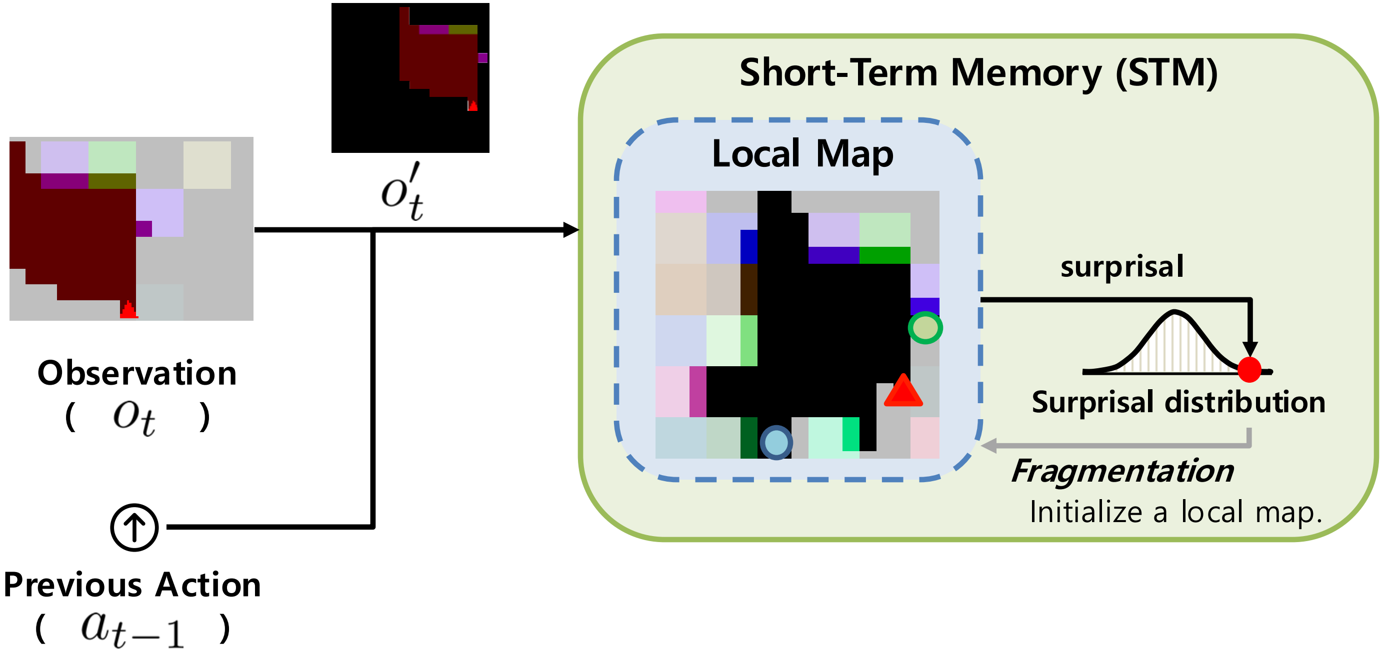
$$s_t = 1 - c_t$$



Fragmentation

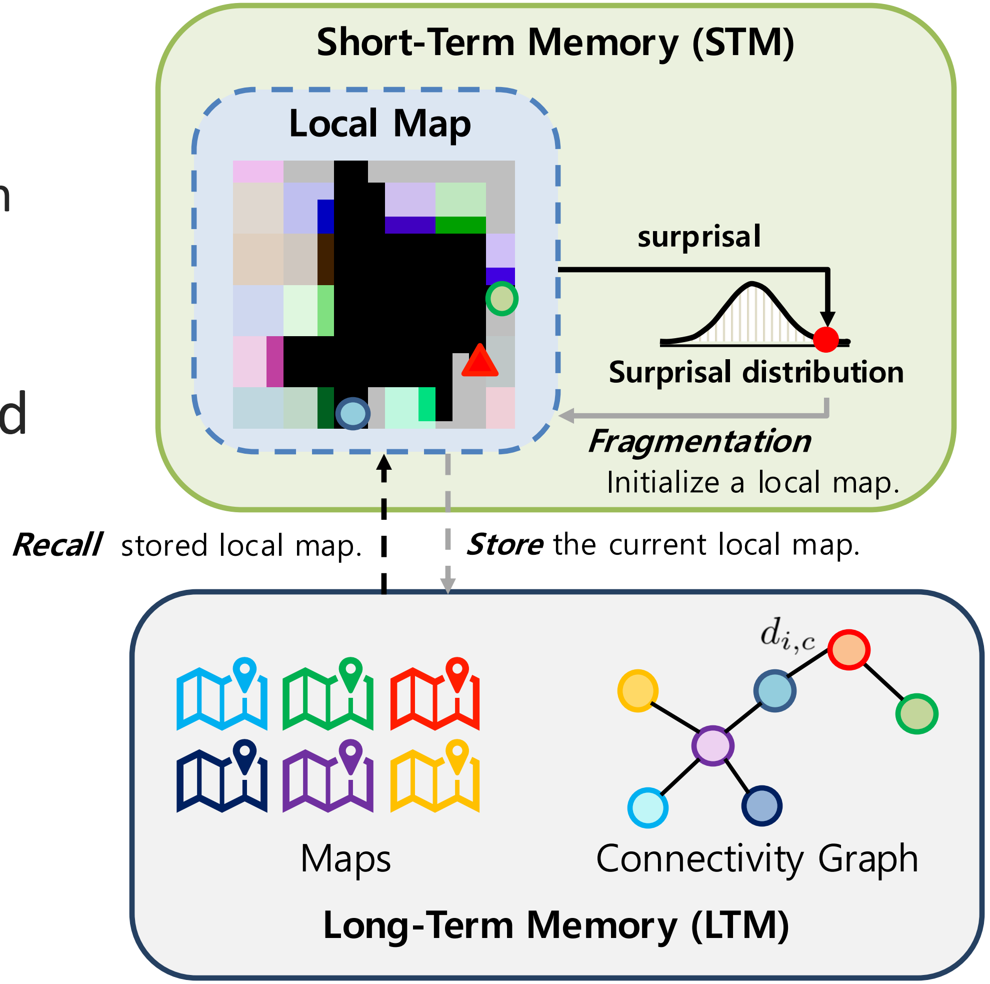
- We calculate running average and standard deviation of surprisal in the local map.
- If z-score for the current surprisal is bigger than a threshold, the fragmentation happens.

$$\frac{s_t - \mu_t}{\sigma_t} > \rho$$



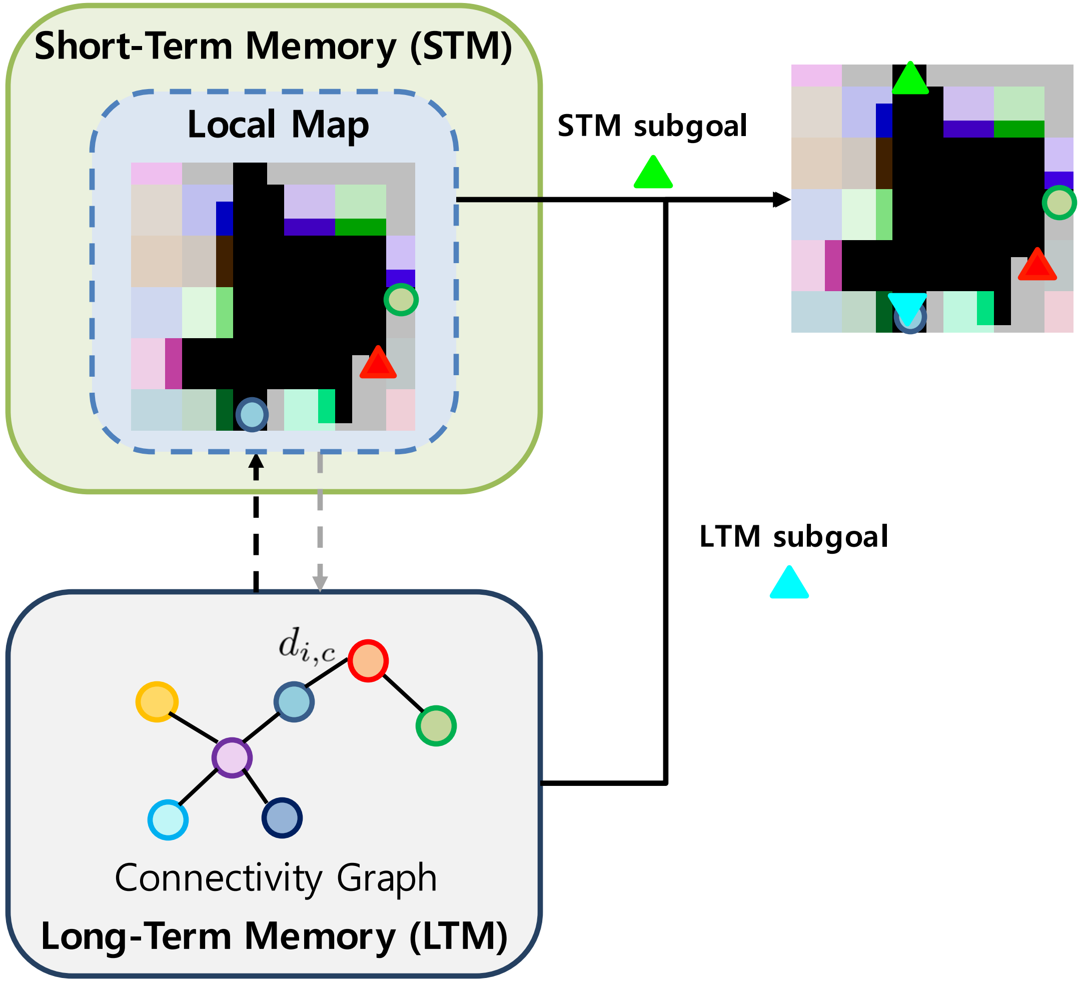
Long-Term Memory (LTM)

- Store – when the fragmentation event happens.
  - Local map
  - the ratio of the number of frontier and the number of known cells in the map
- Recall – when the agent approaches to the fragmented location (overlap with another local map)
  - Recall corresponding local map.
  - Store current local map in LTM.



Subgoal

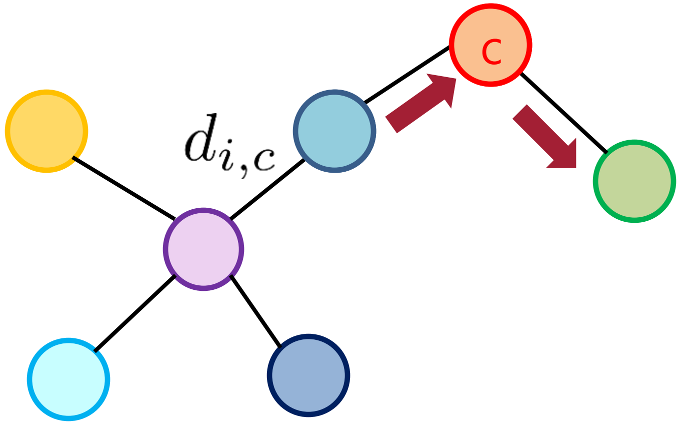
- Two sources of subgoal; STM and LTM.
- From the current local map, the agent sets frontier-based subgoal.
- By using connectivity graph of maps in LTM, the agent decides that which local region is less explored.



Subgoal from LTM

- Subgoal is defined as fragmentation location between the current local map and less explored local map which is defined as

$$g = \arg\max_i \frac{q_i}{d_{i,c} + \epsilon}$$



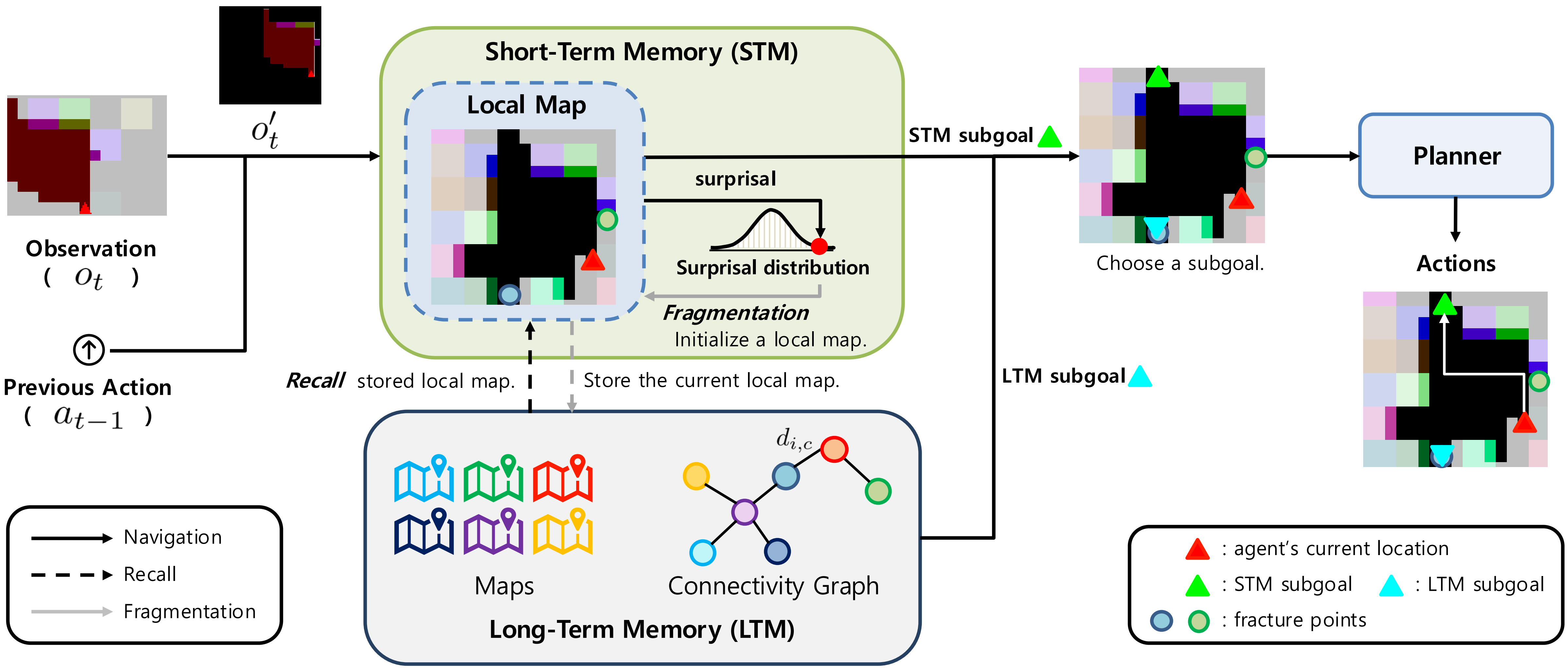
- If $g = c$ (current local map), stay in the current map

  o.w. set subgoal to fragmentation location between the current local map and local map g

- $d_{i,c}$: the distance between the agent and local map

- q_c : (the number of frontiers) / (the number of known (empty + occupied))

- ϵ : hyper-parameter – preference to not stay in the current region

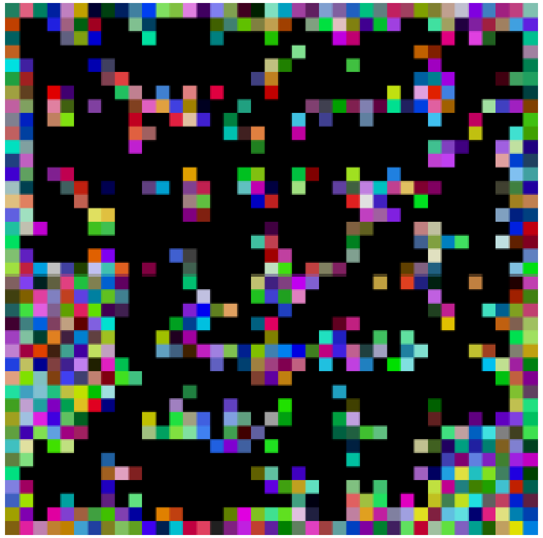


Short-Term Memory (STM)
Local Map
surprisal
Surprisal distribution
Fragmentation
Initialize a local map.
Observation
(o_t)
o'_t
Previous Action
(a_{t-1})
Recall stored local map.
Store the current local map.
STM subgoal
LTM subgoal
Choose a subgoal.
Planner
Actions
$d_{i,c}$
Maps
Connectivity Graph
Long-Term Memory (LTM)
Navigation
Recall
Fragmentation
: agent's current location
: STM subgoal
: LTM subgoal
: fracture points

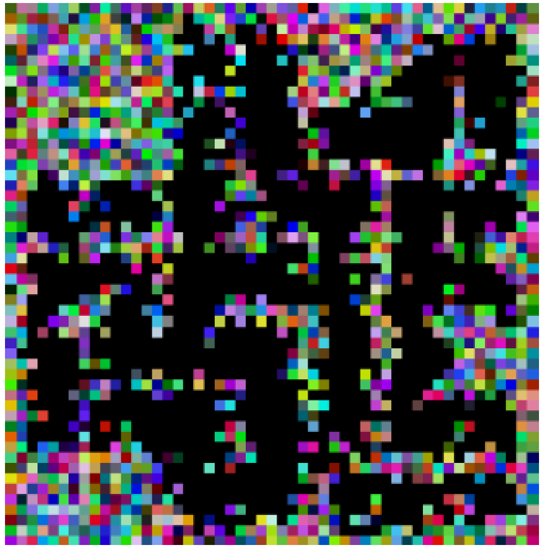
Procedurally-Generated Environments

- 1500 environments
  - 300 maps with 5 different colors and starting locations.
  - Depending on the size of environment, we divide into three groups; small, medium, large.

(b) Small (size: 3249)



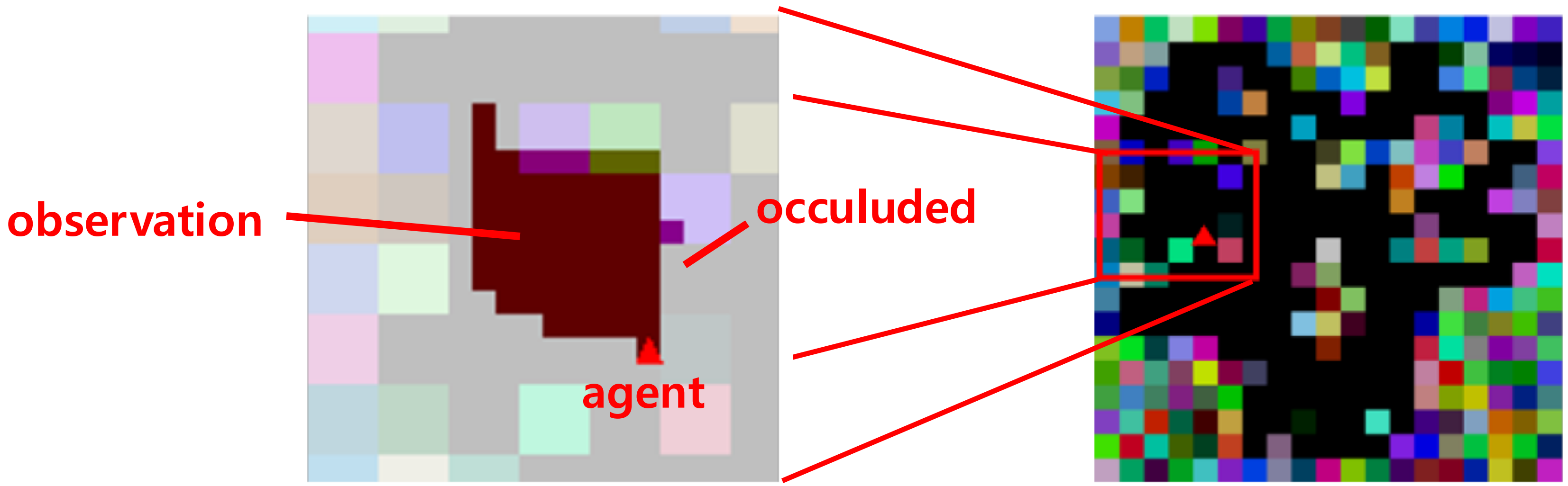
(c) Medium (size: 13689)



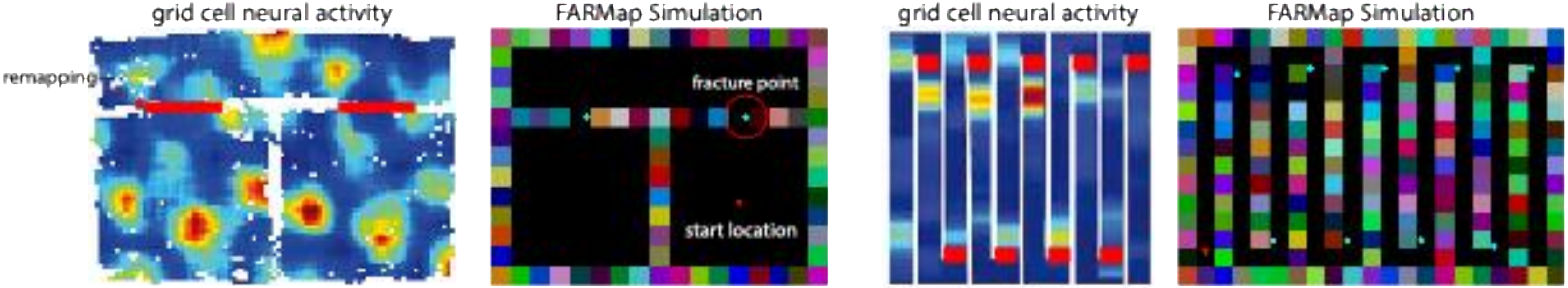
(d) Large (size: 23868)

Observation

- Egocentric restricted field of view (130 degree) with occlusion.



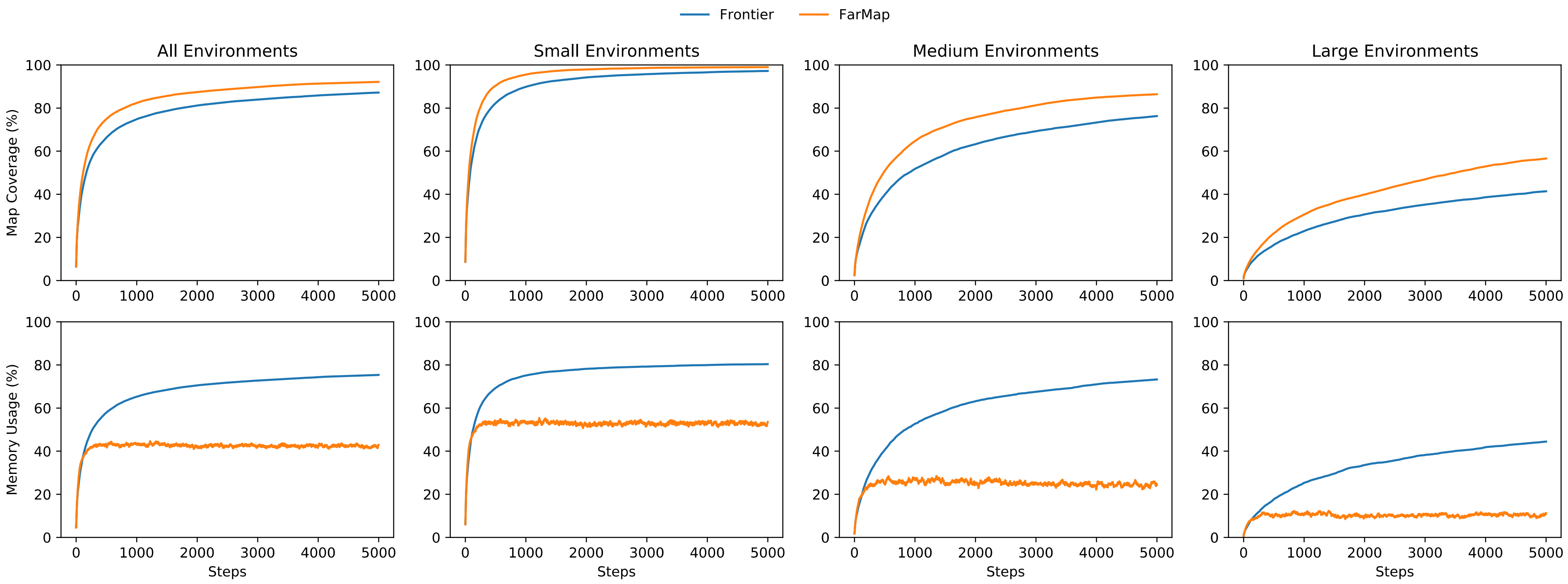
FARMap Fragments where actual Remapping happens

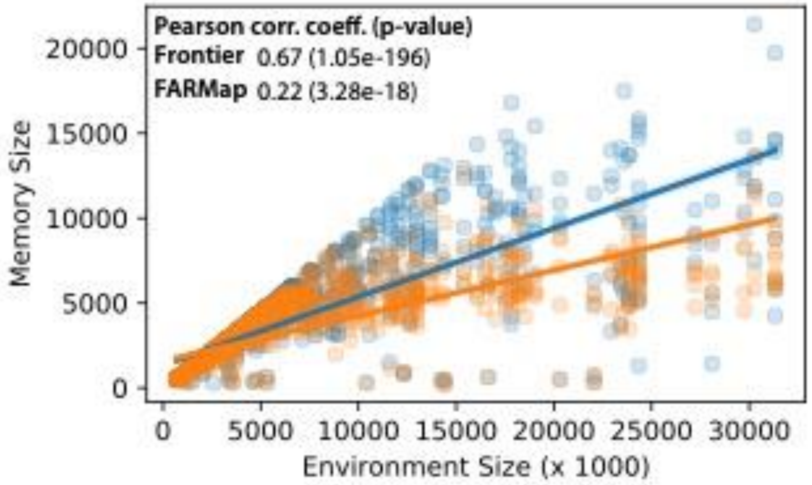


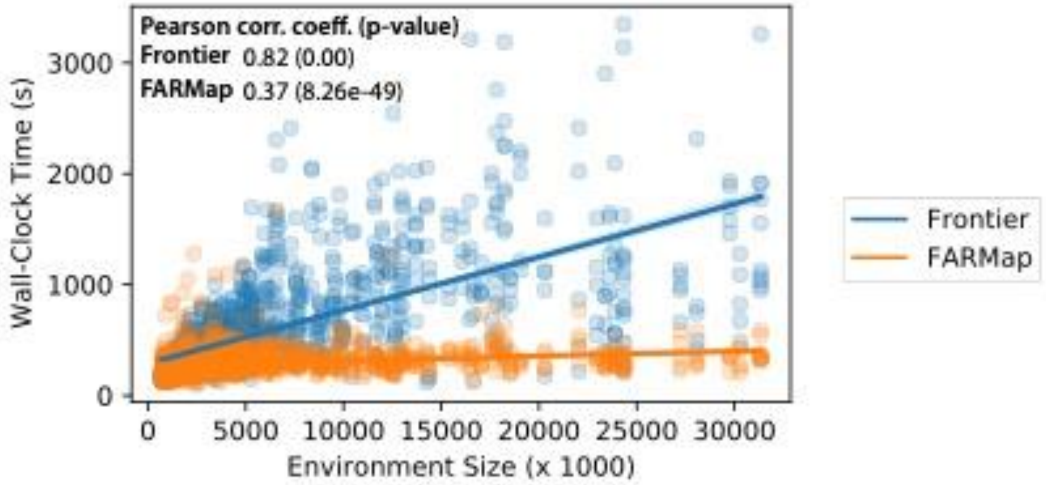
(a) Carpenter et al. (2015)

(b) Derdikman et al. (2009)

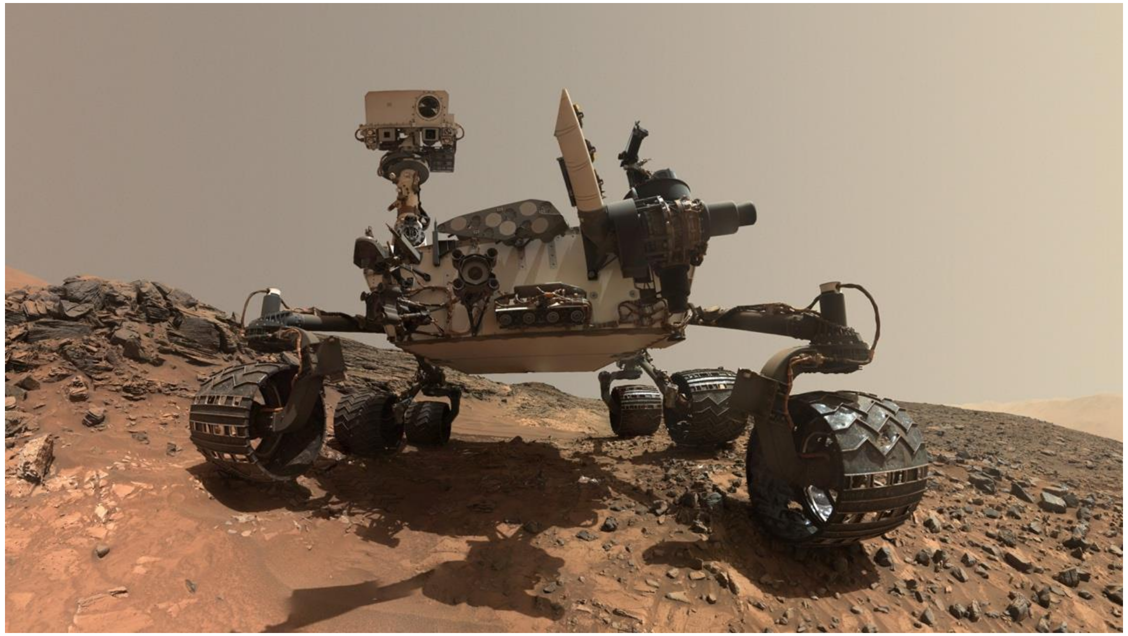
FARMap achieves better performance with less memory & wall-clock time





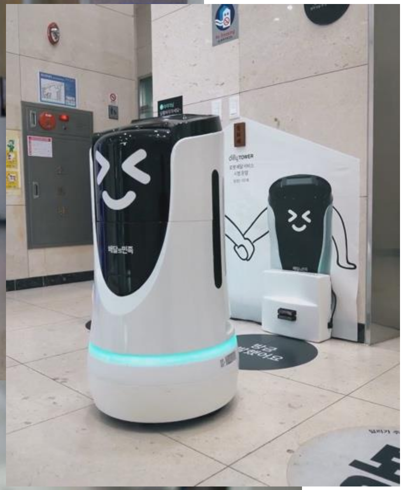


Where can we use FarMap?

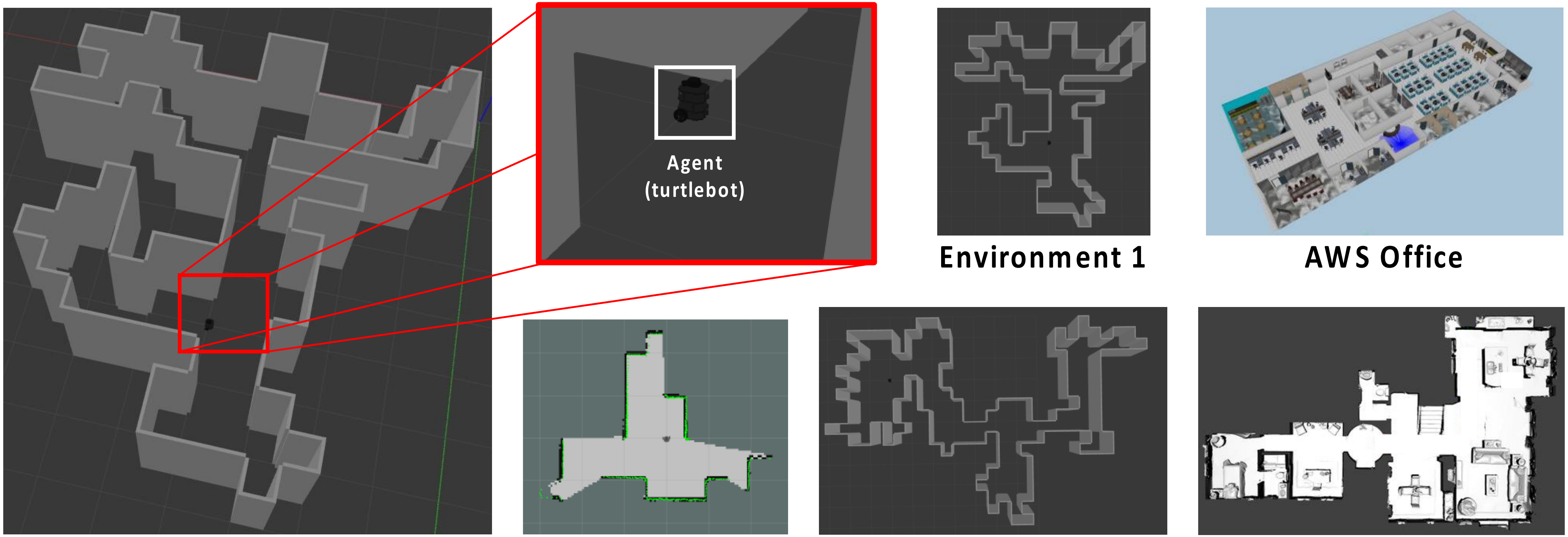


Processor	Radiation-hardened central processor with PowerPC 750 Architecture: a BAE RAD 750 Operates at up to 200 megahertz speed, 10 times the speed in Mars rovers Spirit and Opportunity's computers
Memory	2 gigabytes of flash memory (~8 times as much as Spirit or Opportunity) 256 megabytes of dynamic random access memory

https://mars.nasa.gov/msl/spacecraft/rover/brains/



FarMap in Robot Operating System (ROS)

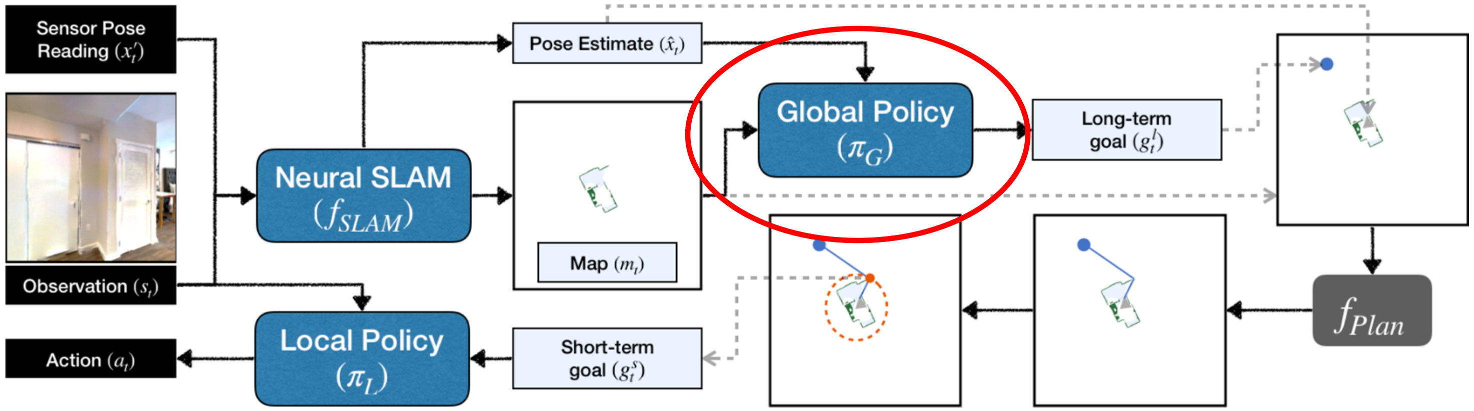


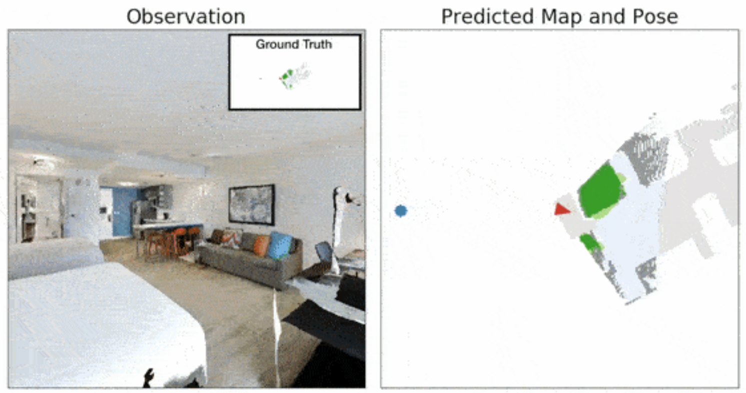
Environment 1 | AWS Office

Environment | Observation | Environment 2 | American

Model	Environment 1		Environment 2		AWS Office (Erdogan, 2019)		American (Shen et al., 2021)	
	Coverage (k)	Memory (k)	Coverage (k)	Memory (k)	Coverage (k)	Memory (k)	Coverage (k)	Memory (k)
Frontier	7.0 ($\pm$ 1.4)	20.5 ($\pm$ 1.0)	**8.3 ($\pm$ 0.6)**	32.8 ($\pm$ 34.4)	38.2 ($\pm$ 30.0)	**48.1 ($\pm$ 20.8)**	13.8 ($\pm$ 3.1)	11.0 ($\pm$ 2.1)
FARMap	**7.7 ($\pm$ 1.0)**	**20.1 ($\pm$ 2.4)**	8.3 ($\pm$ 0.1)	**23.0 ($\pm$ 8.6)**	**57.0 ($\pm$ 4.7)**	66.0 ($\pm$ 14.3)	**15.8 ($\pm$ 4.2)**	**10.6 ($\pm$ 3.7)**

With Neural SLAM in Habitat Simulation





Model	% Cov.	Cov. (m^2)
Neural SLAM (Chaplot et al., 2020)	0.818	64.795
Neural SLAM w/o global policy + Frontier	0.733	58.103
Neural SLAM w/o global policy + FARMap	**0.833**	**66.012**

Chaplot, Devendra Singh, et al. "**Learning to explore using active neural slam.**" ICLR. 2020

Summary

- We proposed Fragmentation-and-Recall framework for map building (FARMap)
- The fracture points match with the actual neuroscience experiments.
- FARMap explores a new environment faster with less memory compared to the baseline.
- FARMap can be combined with other spatial exploration methods.

Thank you

Project Page

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