



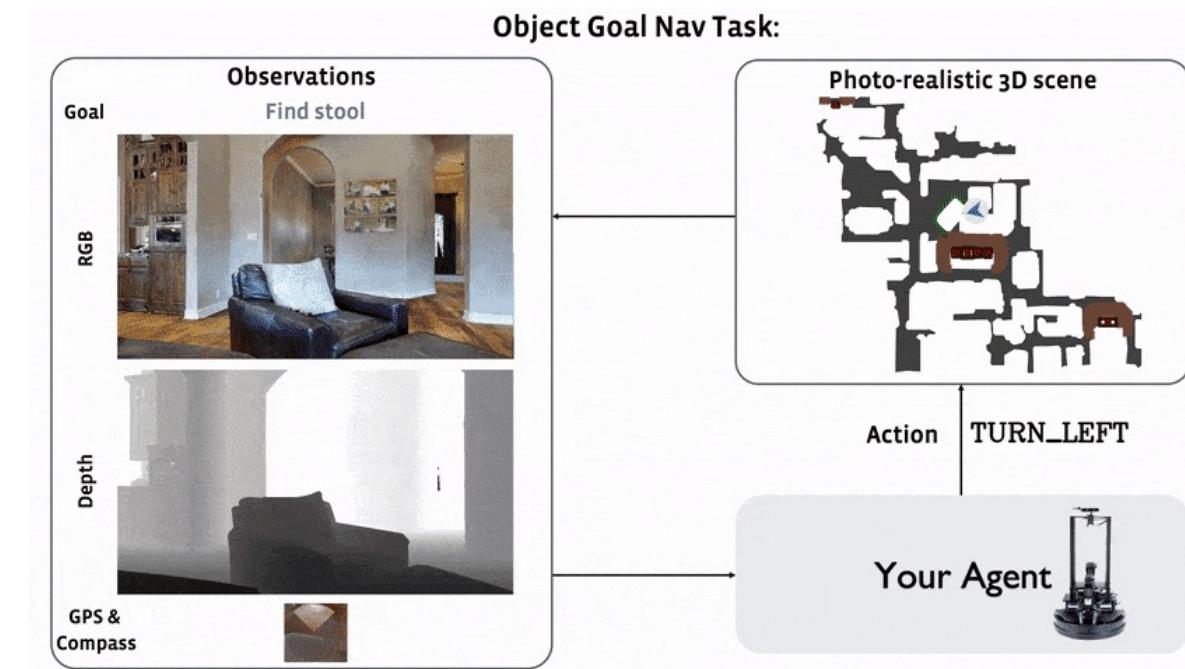
Embodied Navigation Tasks

Speaker: Liu Dai

Collaborator: Fanpeng Meng

Advisor: Jiazhao Zhang, He Wang

Sep. 8, 2022



CONTENT

- **Task Introduction**
 - Task Definition
 - Habitat Challenge
- **Selected Papers**
 - Map-Based Methods
 - Vision-Based Methods

Task Introduction

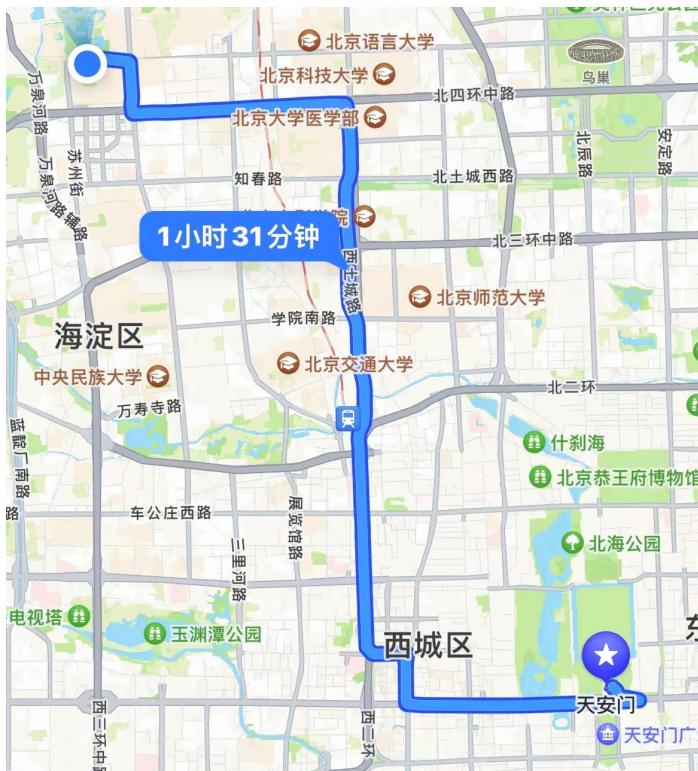
What is Navigation?

- **Definition of Navigation:** Direct or find a way *from one place to another.*

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Outdoor Navigation



Indoor Navigation

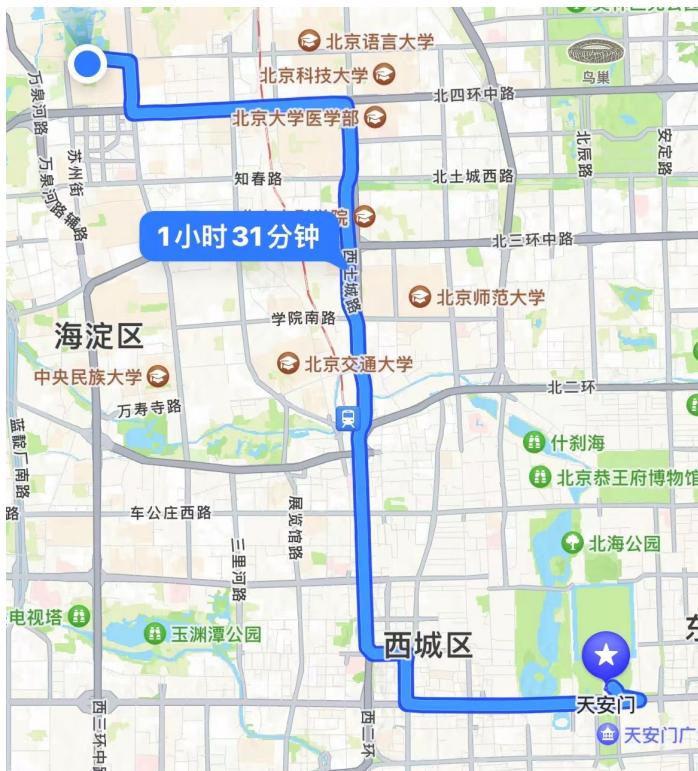
VS



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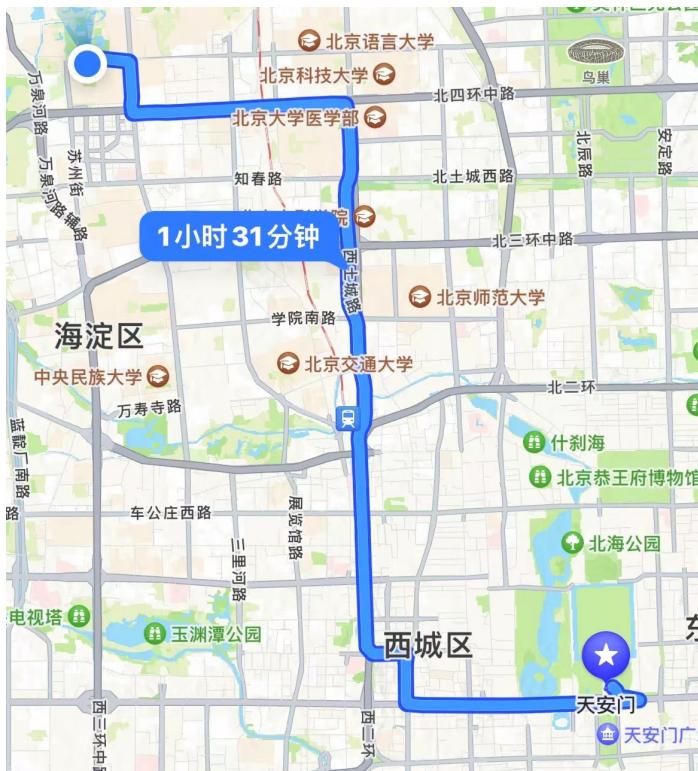
Challenges:

- a) No HD Map
- b) Noisy Indoor Positioning
- c) Real 3D Environment

What is Navigation?

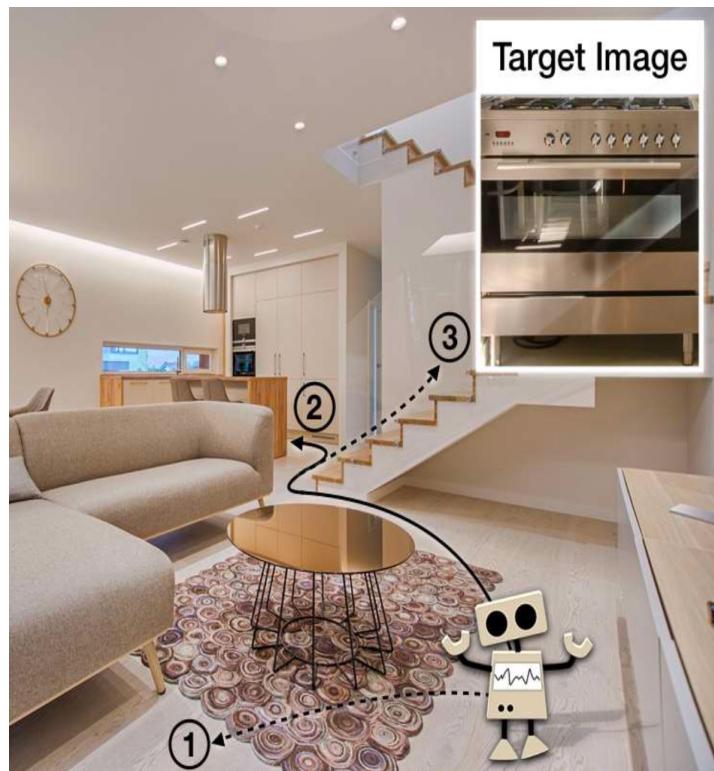
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VS

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Challenges:

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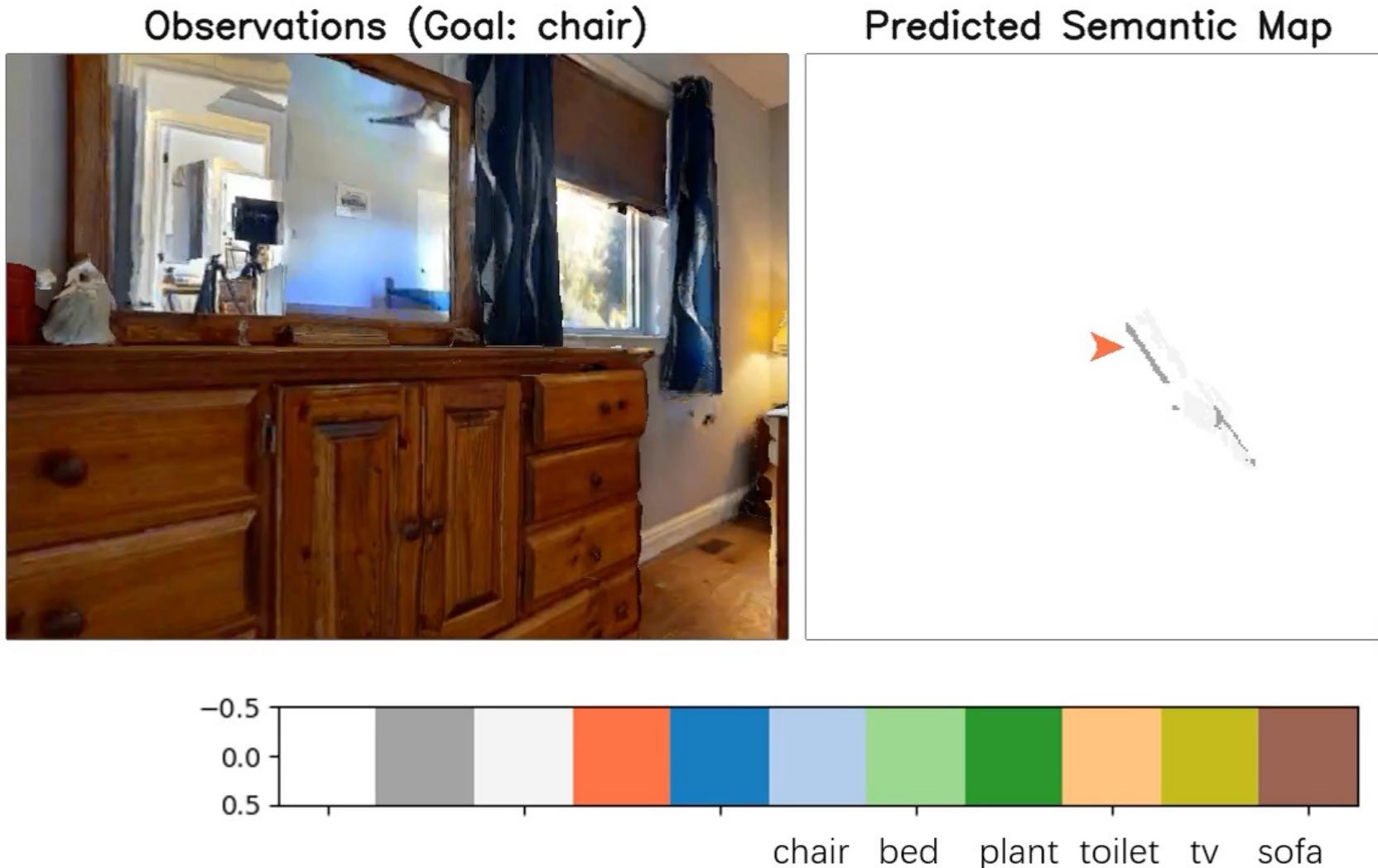
Values:

- a) Necessary for Embodied AI
- b) Home Robot
- c) Robot for Special Tasks

What is Navigation?

- **Definition of Navigation:** Direct or find a way *from one place to another*.

Demo:

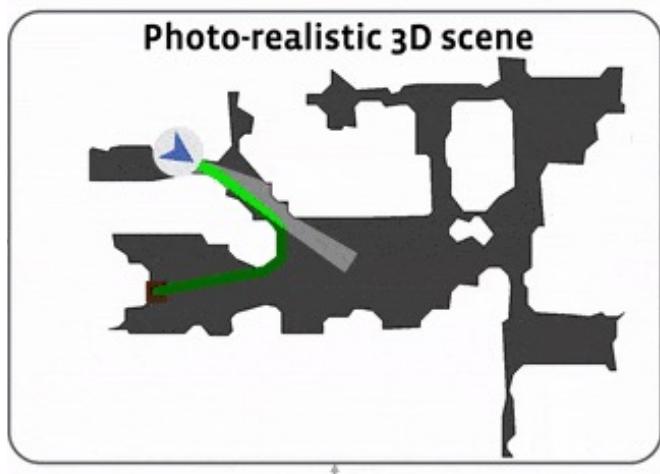


What is Navigation?

- **Definition of Navigation:** Direct or find a way *from one place to another.*

Explicit Target Locations:

Point Goal



Goal :

*Go 5m south, 3m west
relative to start.*

What is Navigation?

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Explicit or **Implicit** Target Locations:

Point Goal

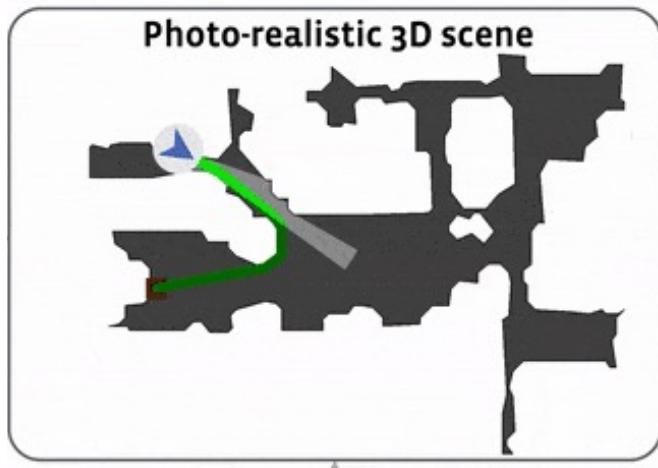


Image Goal



Goal :

*Go 5m south, 3m west
relative to start.*

Goal :

Go where the photo was taken.

What is Navigation?

- **Definition of Navigation:** Direct or find a way *from one place to another.*

Explicit or **Implicit** Target Locations:

Point Goal

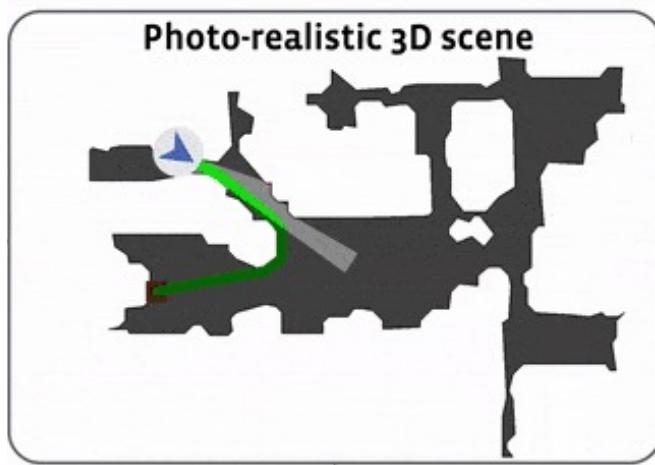
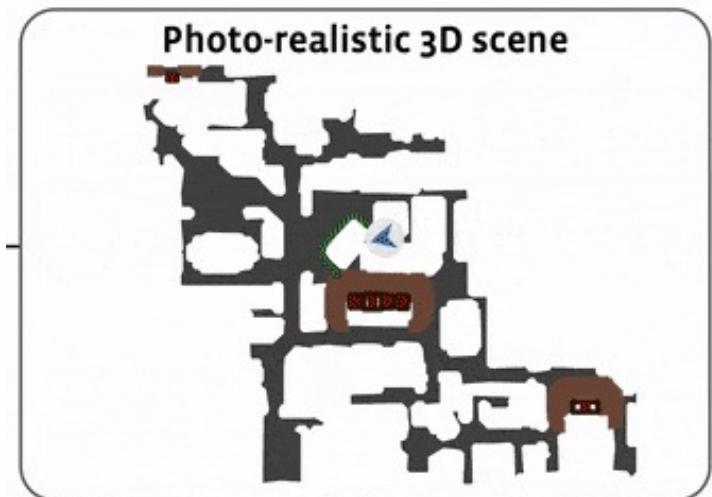


Image Goal



Object Goal



Goal :

*Go 5m south, 3m west
relative to start.*

Goal :

Go where the photo was taken.

Goal :

Go find a sofa.

What is Navigation?

- **How to Evaluate?**

(1) Success Rate

(2) SPL (Success Weighted by Path Planning)

$$\text{SPL} = \frac{1}{N} \sum_{i=1}^N S_i \frac{l_i}{\max(p_i, l_i)}$$

S_i : binary for success
 l_i : shortest path length
 p_i : actual path length

(3) Soft SPL

$$SoftSPL = \frac{1}{N} \sum_{i=1}^N \left(1 - \frac{d_{Ti}}{d_{initi}}\right) \left(\frac{l_i}{\max(p_i, l_i)}\right)$$

d_{Ti} : distance to target location d_{initi} : distance to start location

(4) Distance to Goal

What is Navigation?

- How to Evaluate?

- (1) Success Rate**

- (2) SPL (Success Weighted by Path Planning)**

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- (4) Distance to Goal**

- Datasets:

- (1) Matterport 3D(MP3D)**

Proposed in 2017

- (2) Gibson 3D**

Proposed in CVPR 2018

- (3) Habitat Matterport 3D**

Proposed in NIPS 2021

Larger

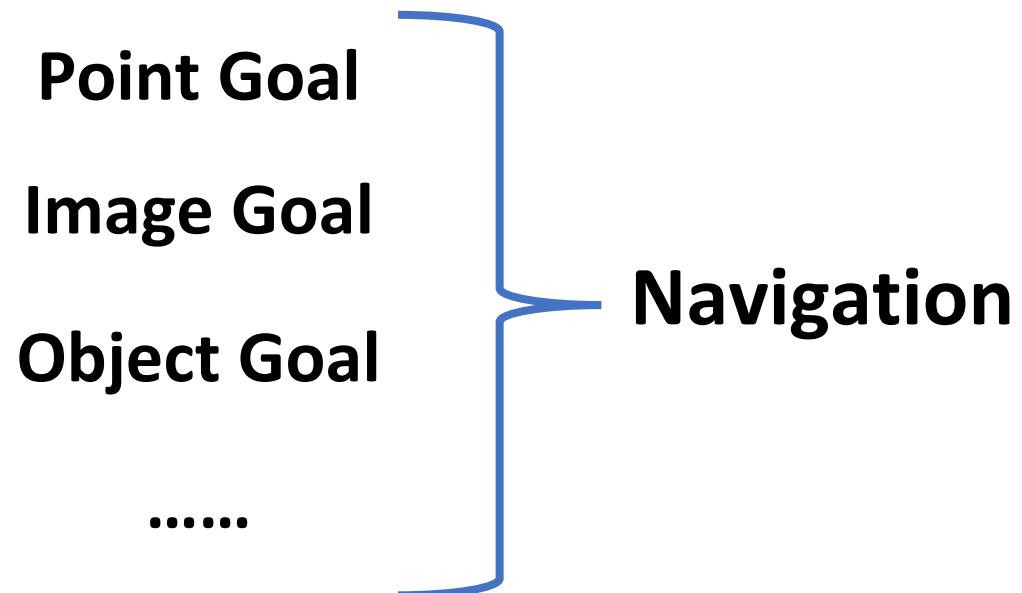
More
Realistic

More
Information



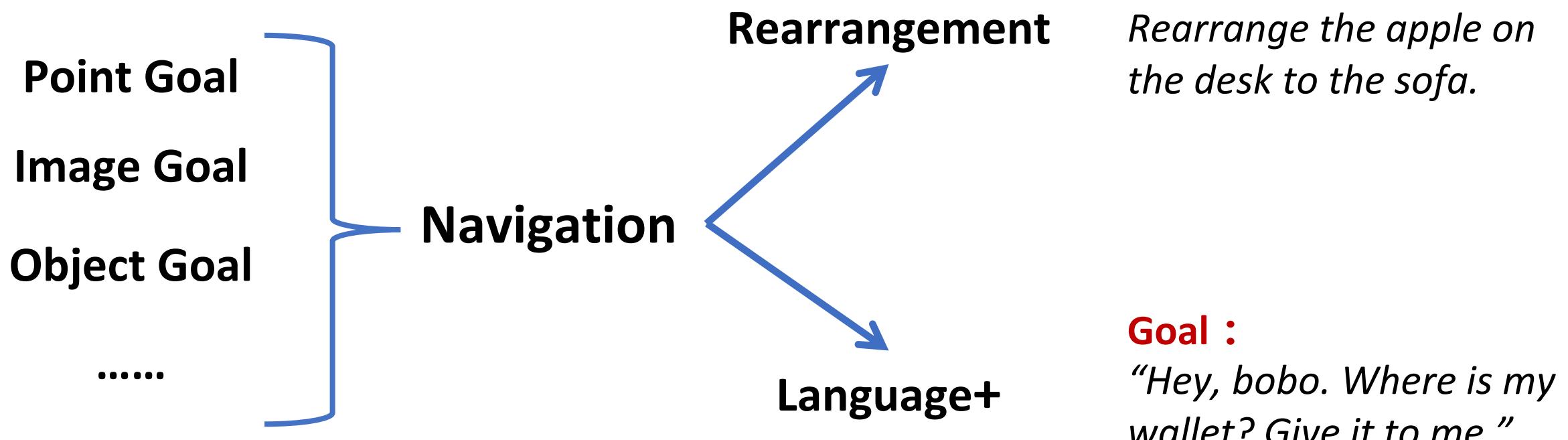
Why do we care about Navigation?

- Basic Module of Embodied AI: **Navigation + Manipulation**



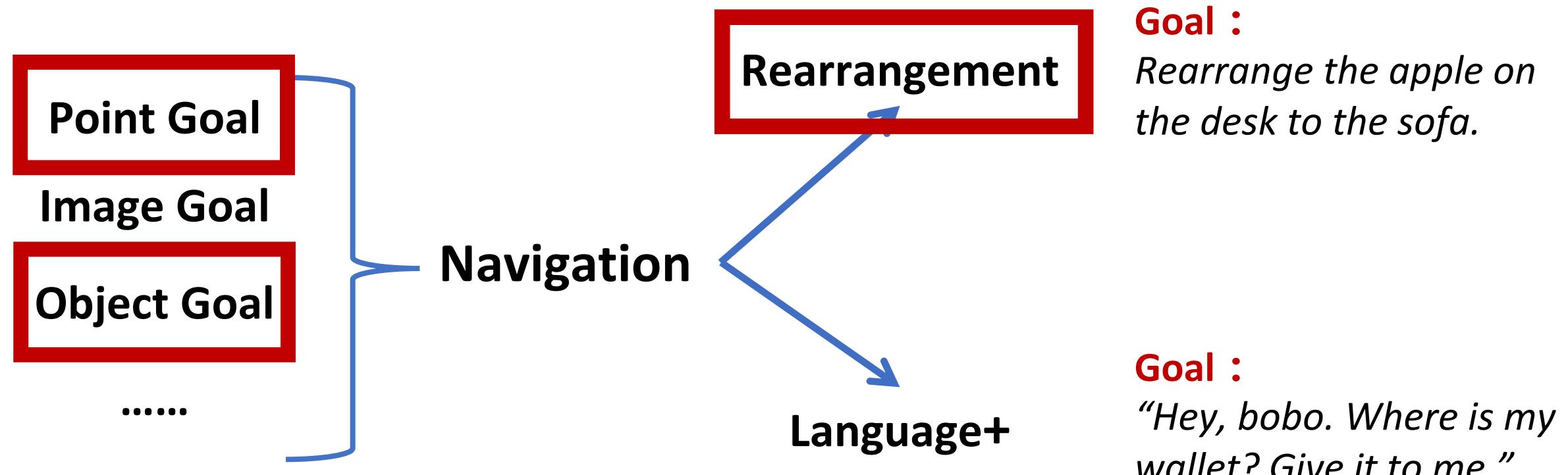
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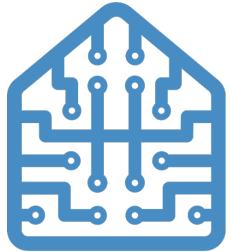


Why do we care about Navigation?

- Basic Module of Embodied AI: **Navigation + Manipulation**



Habitat Challenge



Habitat

PointGoal Nav

2019 - 2021

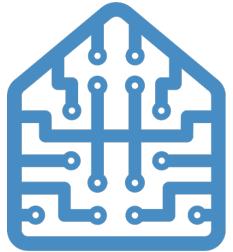
ObjectGoal Nav

2020 -

Rearrangement

2022 -

Habitat Challenge

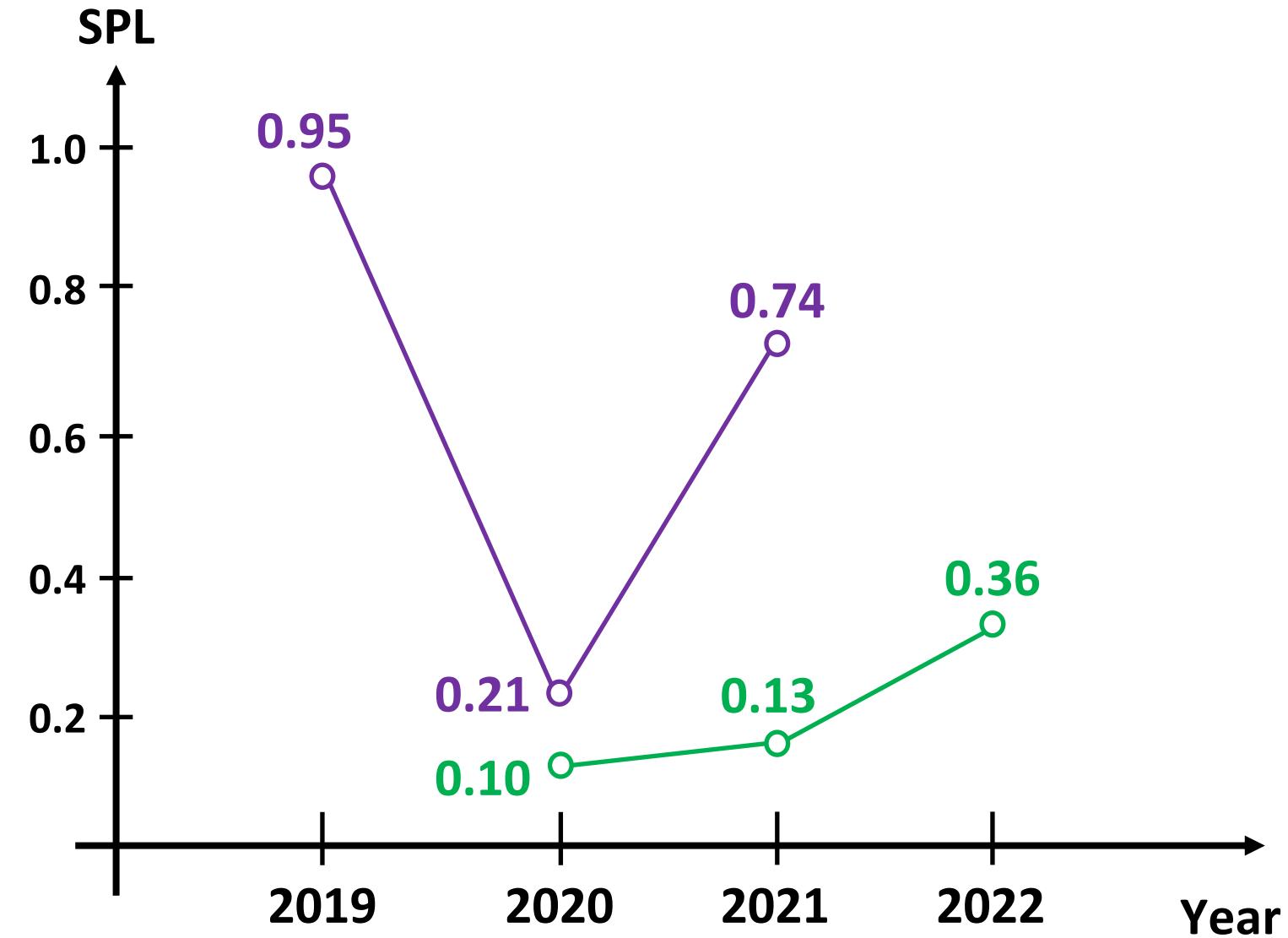


Habitat

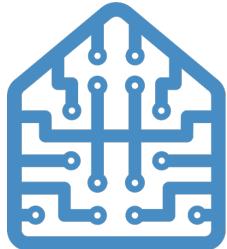
PointGoal Nav
2019 - 2021

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2022 -



Habitat Challenge

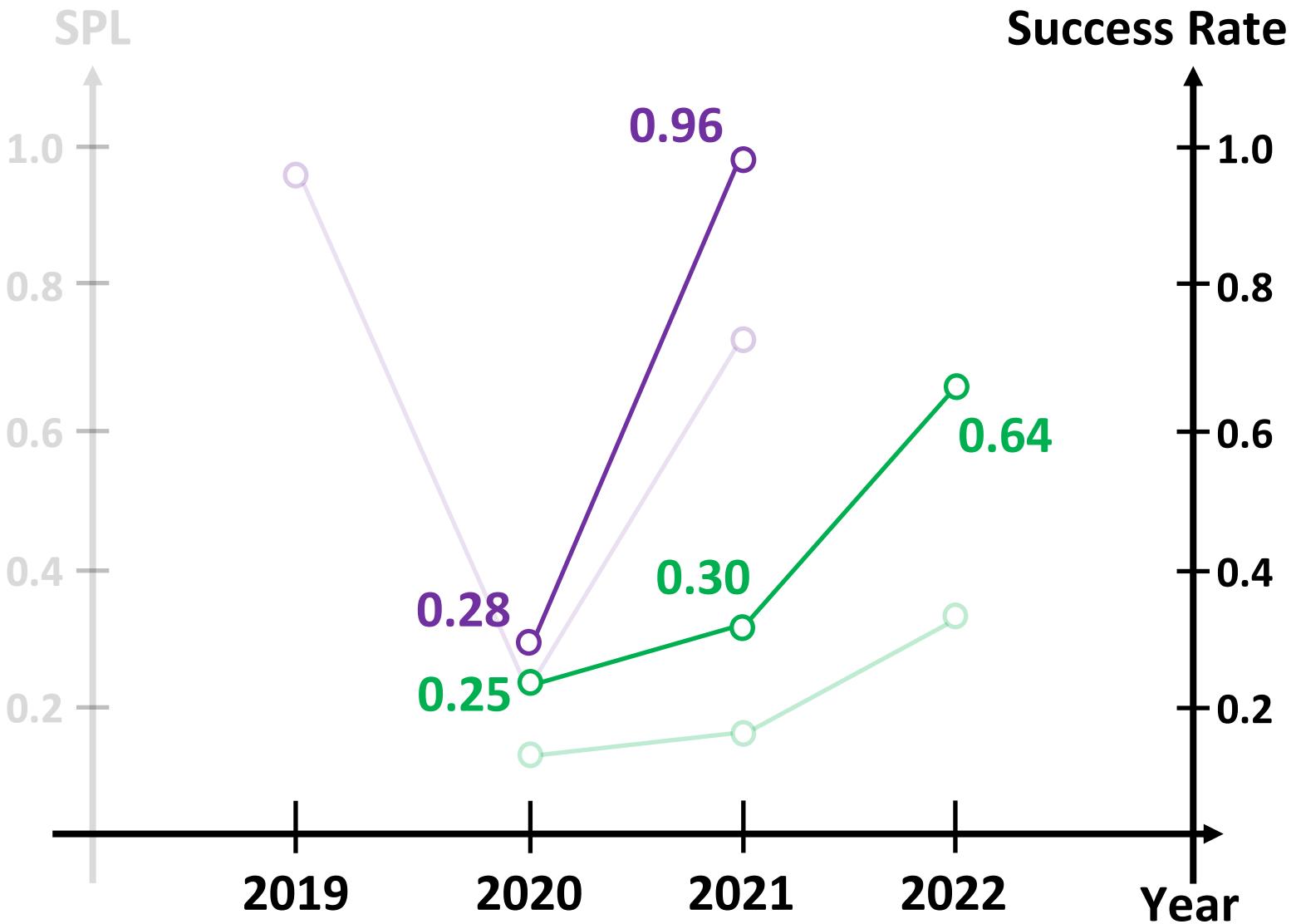


Habitat

PointGoal Nav
2019 - 2021

ObjectGoal Nav
2020 -

Rearrangement
2022 -



Selected Papers

Selected Papers

Map-Based

Vision-Based

Selected Papers

Map-Based

Vision-Based

Learning to Explore Using Active Neural SLAM

Devendra Singh Chaplot^{1†}, Dhiraj Gandhi², Saurabh Gupta^{3*},
Abhinav Gupta^{1,2*}, Ruslan Salakhutdinov^{1*}

¹Carnegie Mellon University, ²Facebook AI Research, ³UIUC

(ICLR 2020)

Learning to Explore Using Active Neural SLAM

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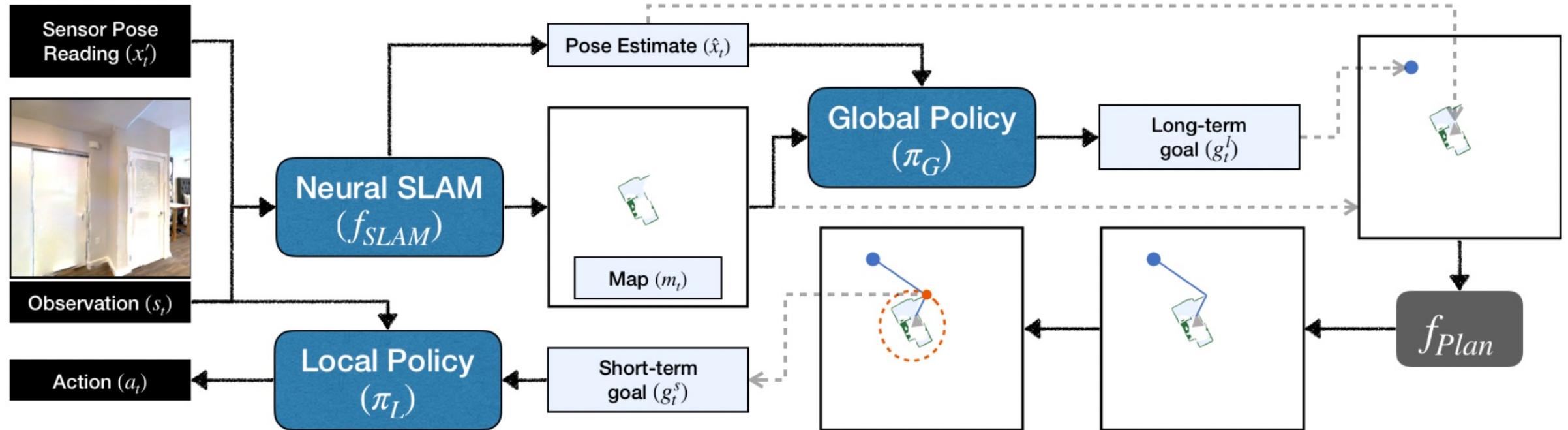
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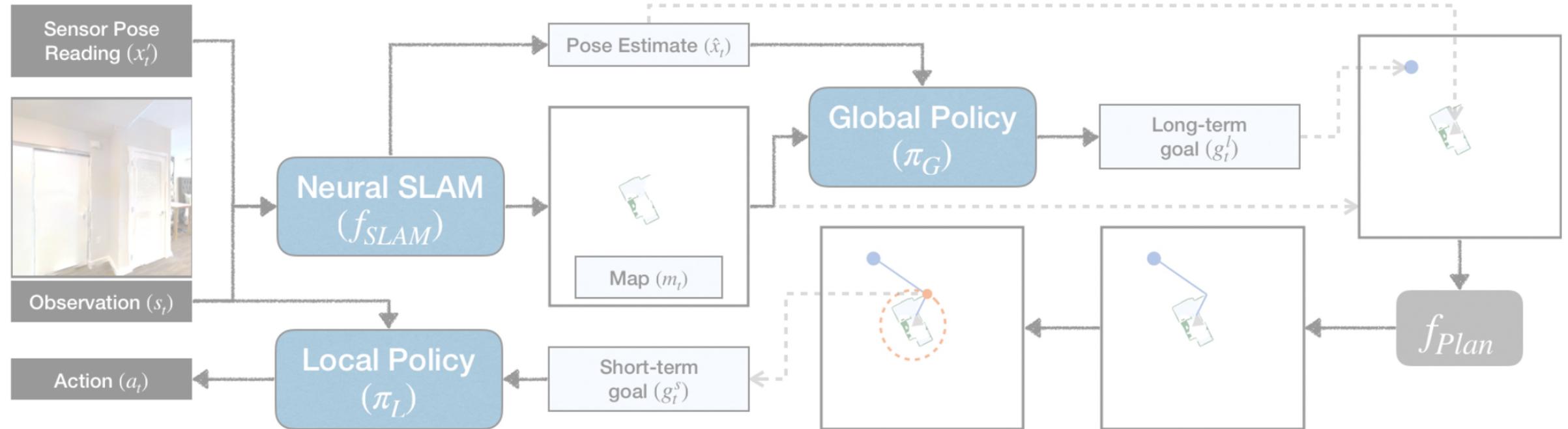
Goal: Maximize Exploration Coverage in a fixed time budget

Input: RGB Image, Pose Sensor with Noise

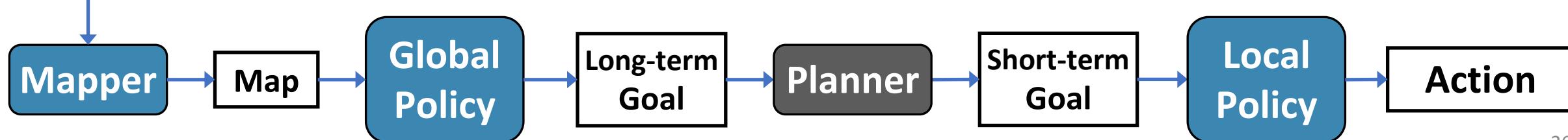
Active Neural SLAM



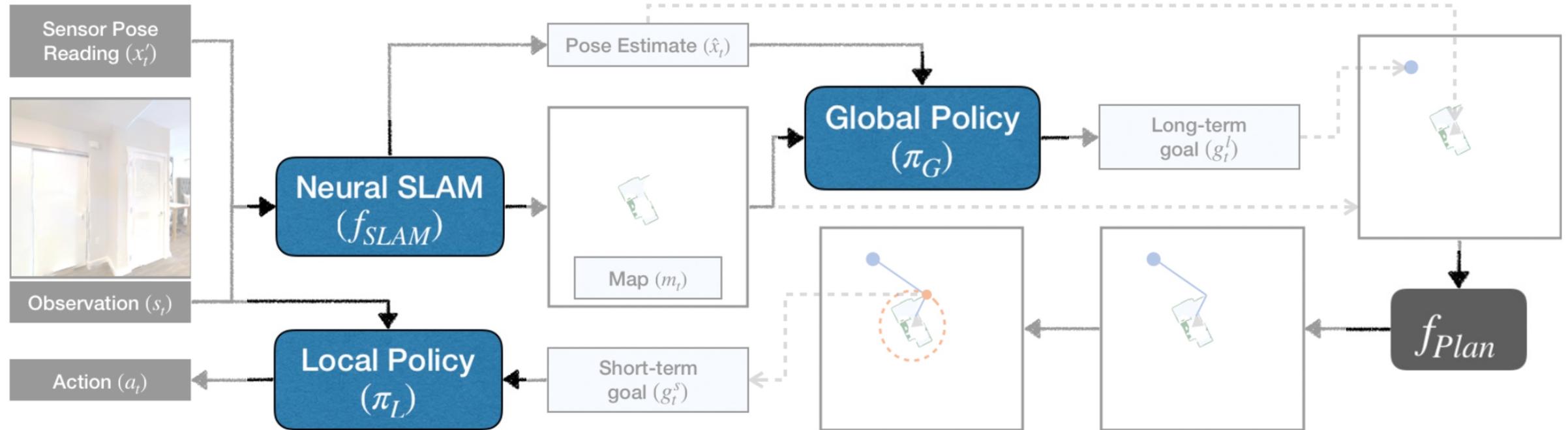
Active Neural SLAM



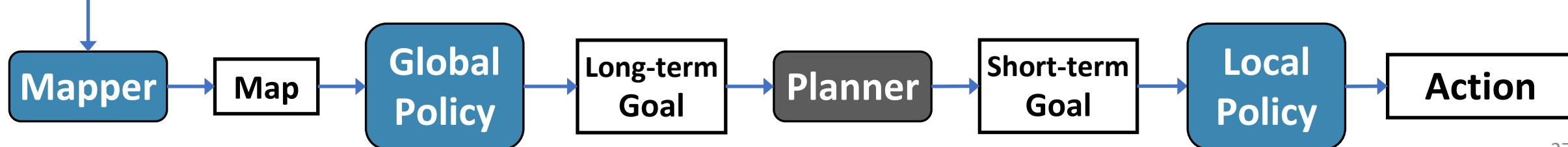
Observation



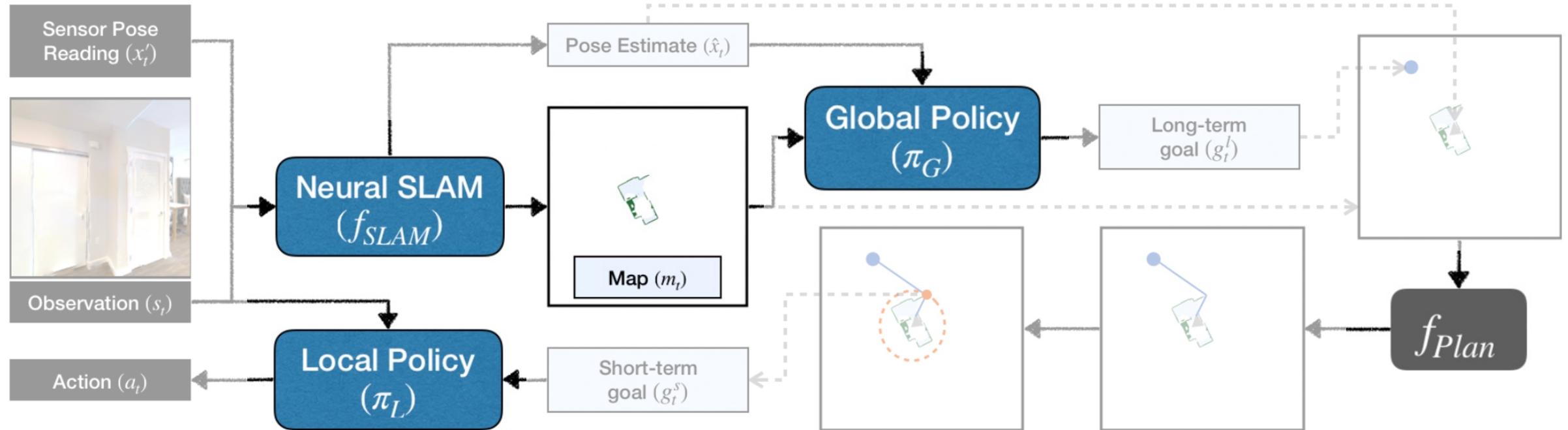
Active Neural SLAM



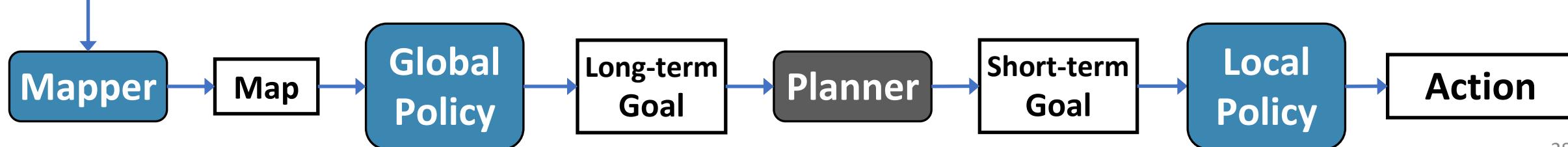
Observation



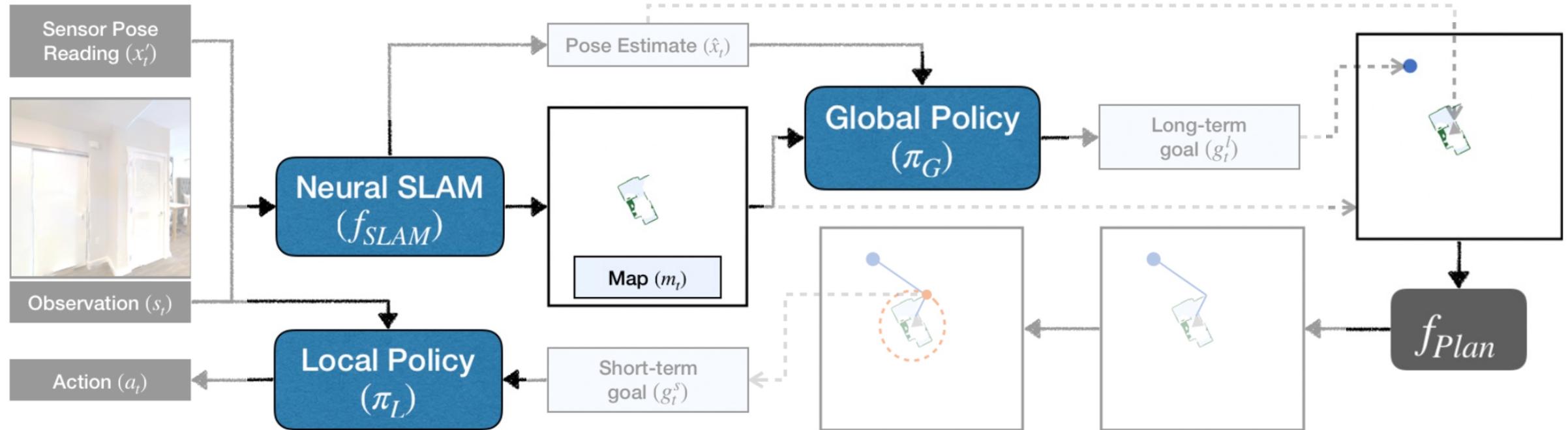
Active Neural SLAM



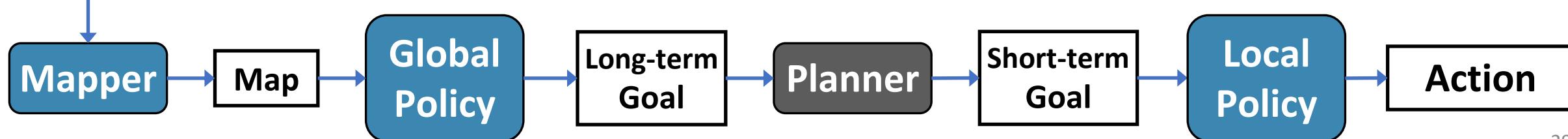
Observation



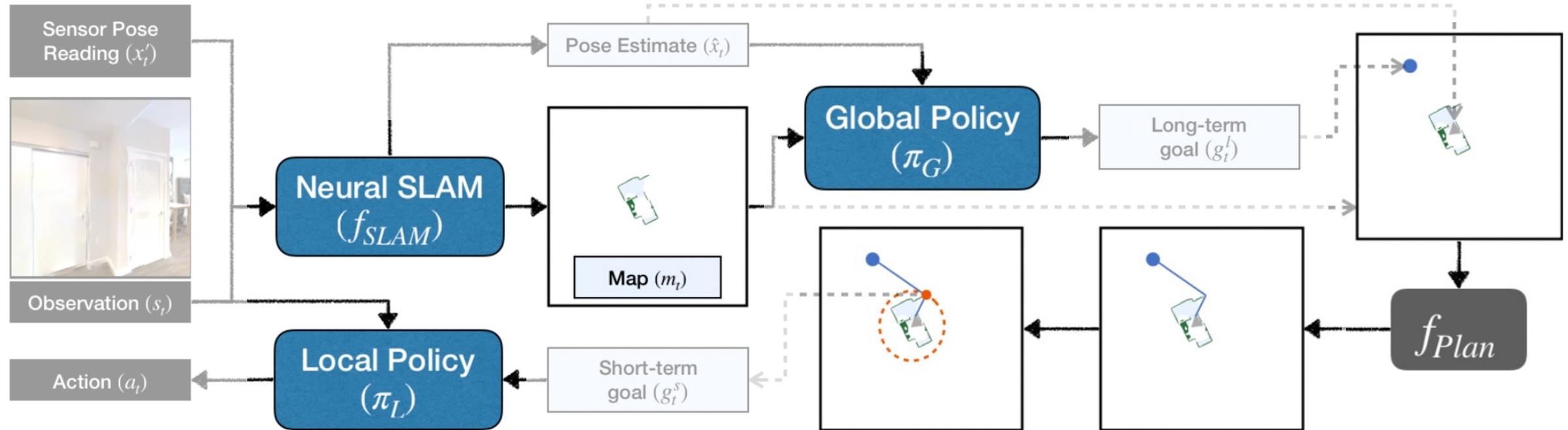
Active Neural SLAM



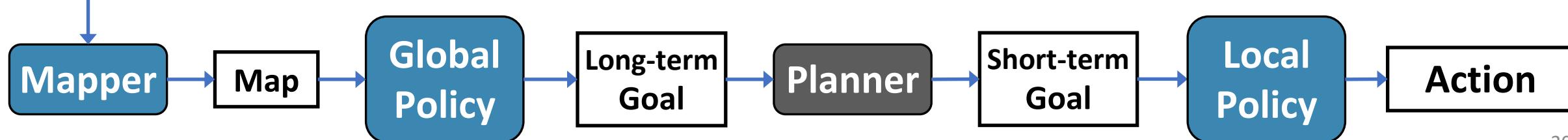
Observation



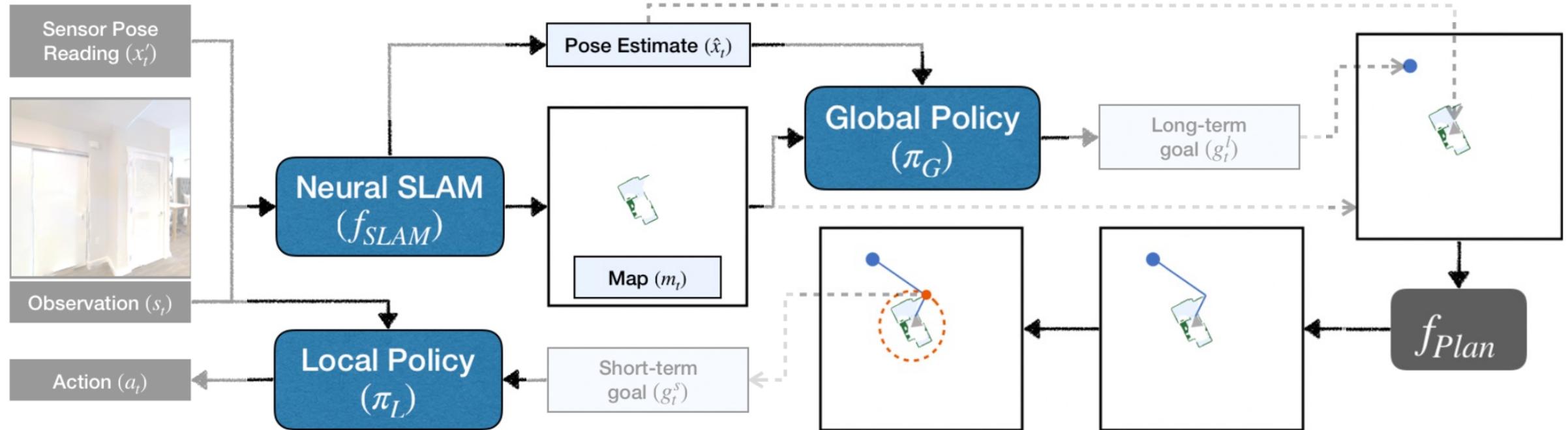
Active Neural SLAM



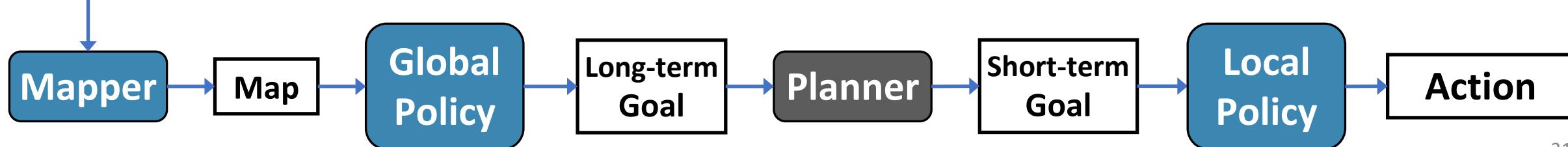
Observation



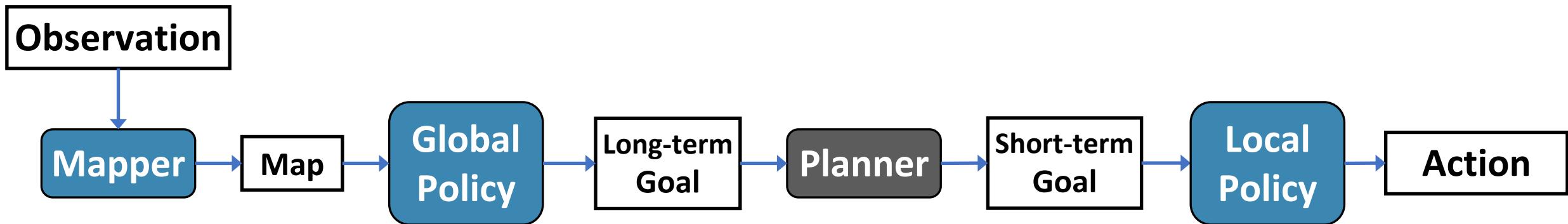
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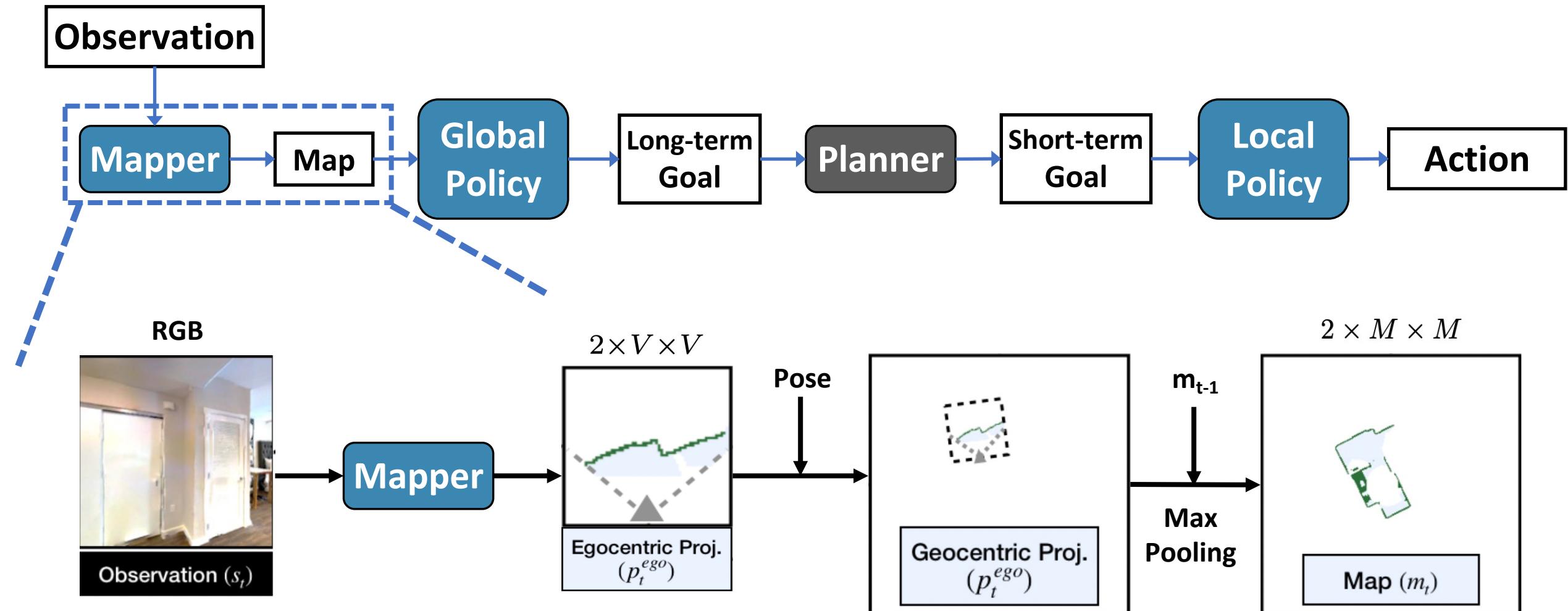
Observation



Active Neural SLAM

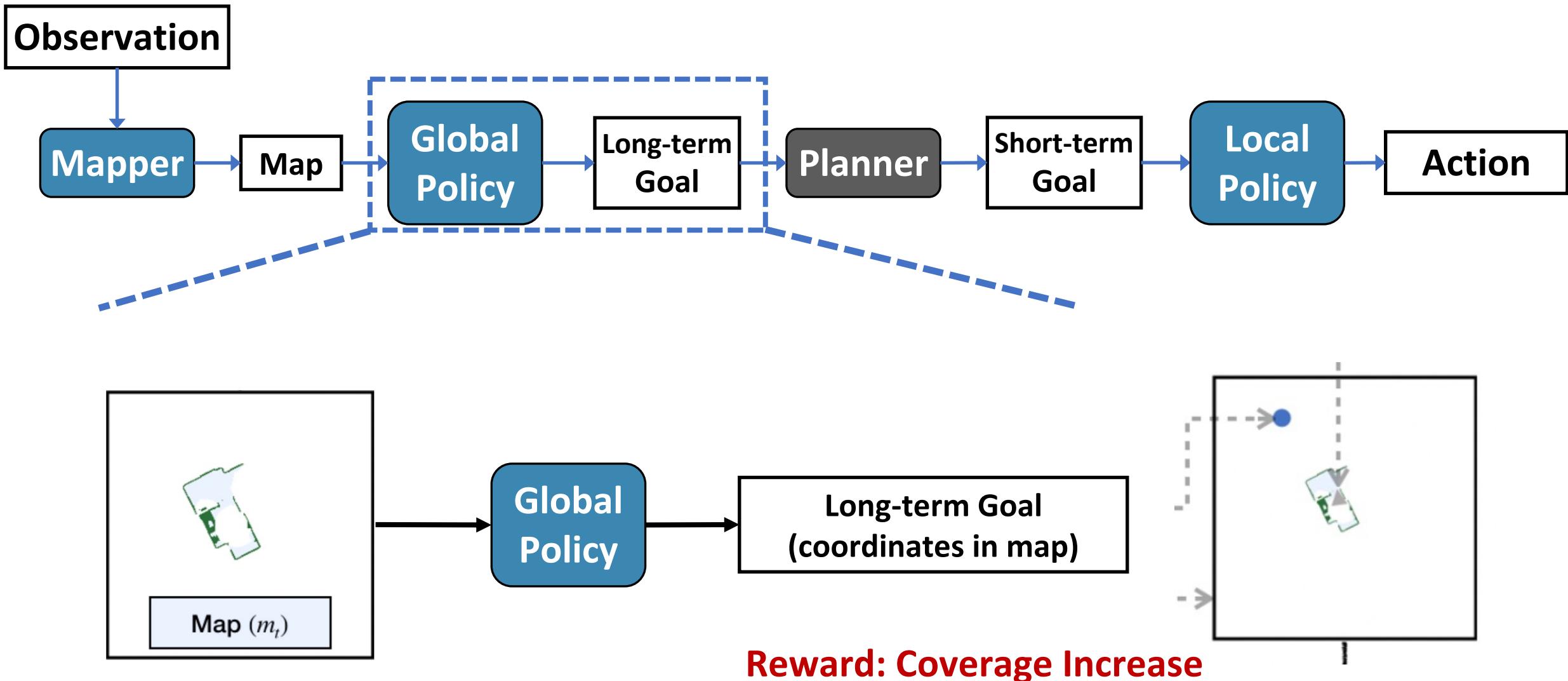


Active Neural SLAM

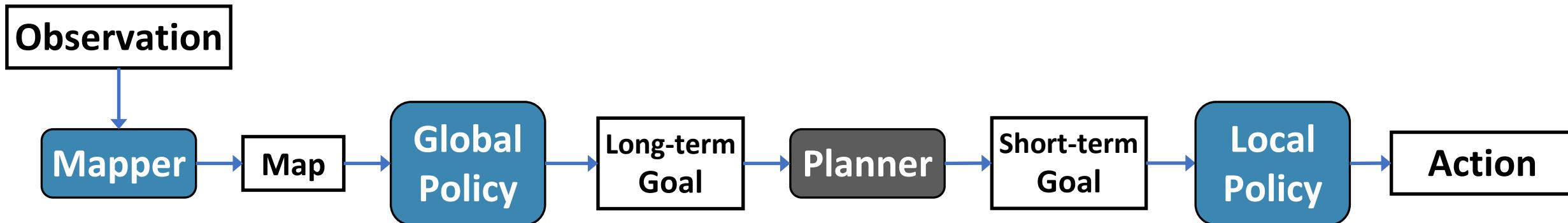


2 Channels of Occupancy Map: A Location being Occupied & Explored

Active Neural SLAM

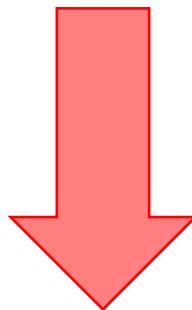
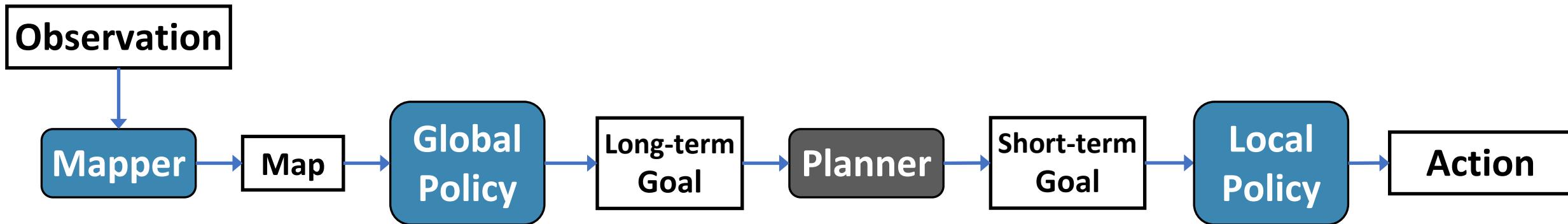


Active Neural SLAM



Method	Gibson Val		Domain Generalization MP3D Test	
	% Cov.	Cov. (m ²)	% Cov.	Cov. (m ²)
RL + 3LConv [1]	0.737	22.838	0.332	47.758
RL + Res18	0.747	23.188	0.341	49.175
RL + Res18 + AuxDepth [2]	0.779	24.467	0.356	51.959
RL + Res18 + ProjDepth [3]	0.789	24.863	0.378	54.775
Active Neural SLAM (ANS)	0.948	32.701	0.521	73.281

PointNav in Habitat Challenge 2019

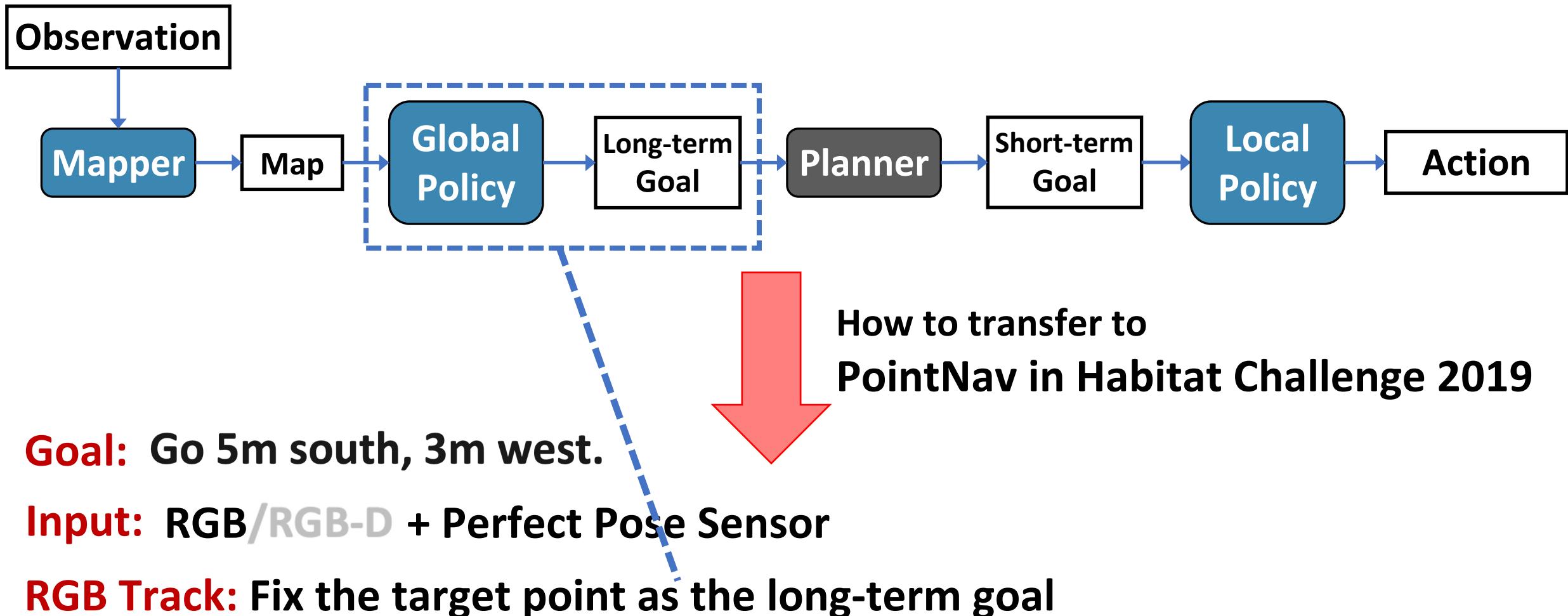


**How to transfer to
PointNav in Habitat Challenge 2019**

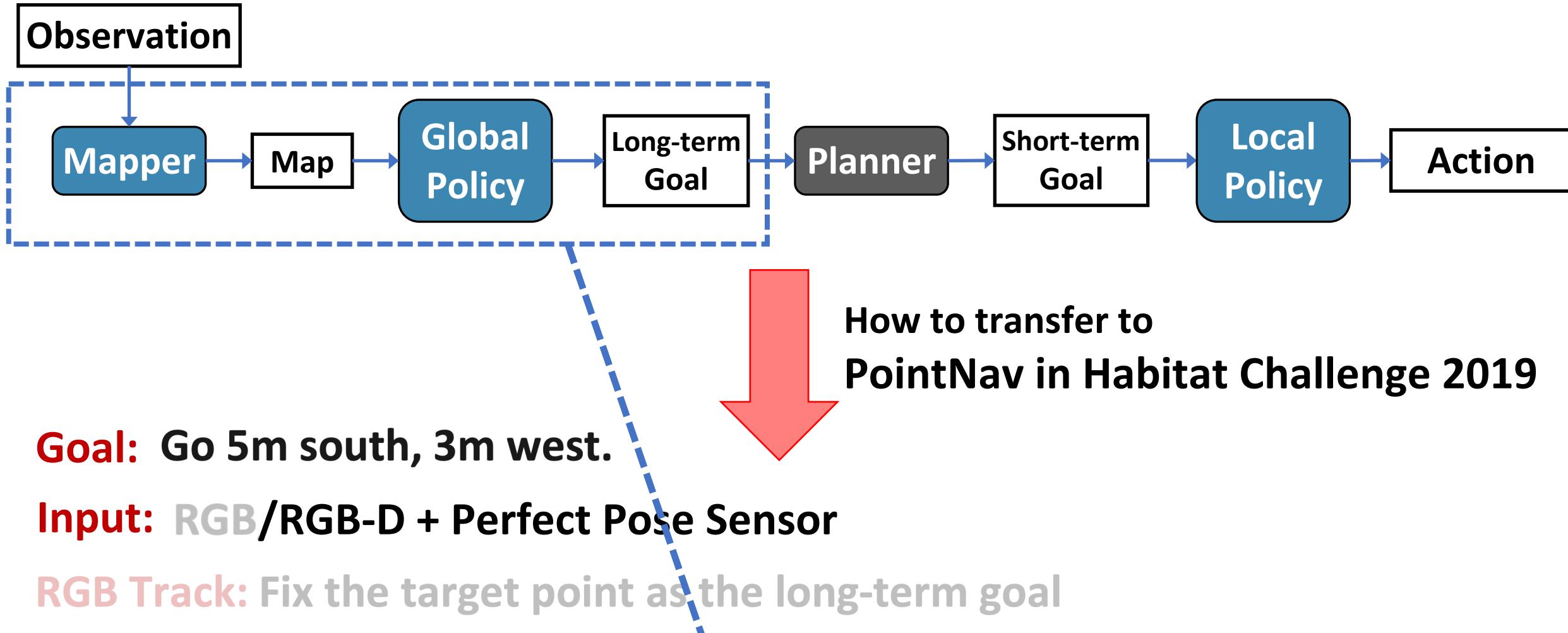
Goal: Go 5m south, 3m west.

Input: RGB/RGB-D + Perfect Pose Sensor

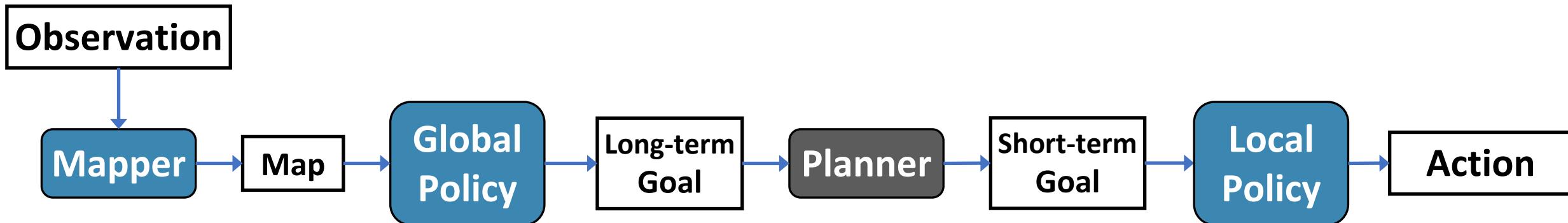
PointNav in Habitat Challenge 2019



PointNav in Habitat Challenge 2019



PointNav in Habitat Challenge 2019



Goal: Go 5m south, 3m west.

Input: RGB/RGB-D + Perfect Pose Sensor

RGB Leaderboard

Rank	Team	SPL
1	Arnold	0.805
1	Mid-level-Features	0.800
3	CHROMA	0.712
4	ARF-RL	0.699
5	MTank	0.260
6	Policy-Police	0.260

RGB-D Leaderboard

Rank	Team	SPL
1	Arnold	0.948
2	Pansy	0.927
3	titardrew	0.868
4	Hiccup	0.846
5	CHROMA	0.843
6	Mid-level-Features	0.815
7	ARF-RL	0.788
8	mkk1	0.738
9	cnmooc	0.693
10	hela-ppo-baseline	0.569

PointNav in Habitat Challenge 2020

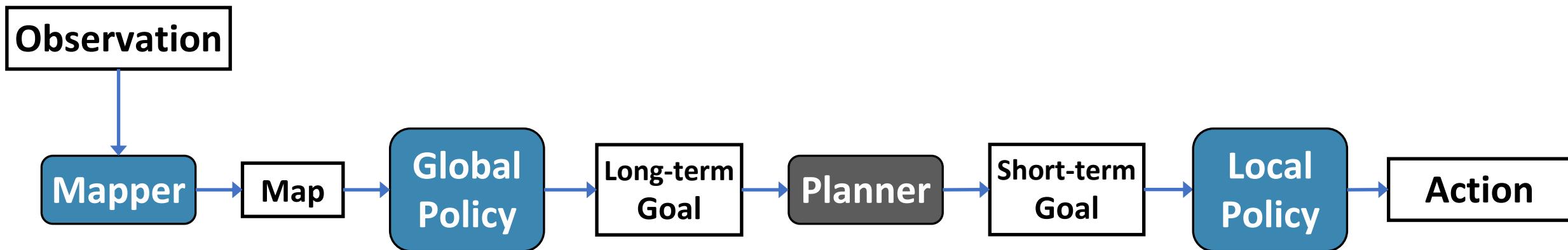
What's new in PointNav of Habitat Challenge 2020:

Input: Only Noisy RGB-D Image

PointNav in Habitat Challenge 2020

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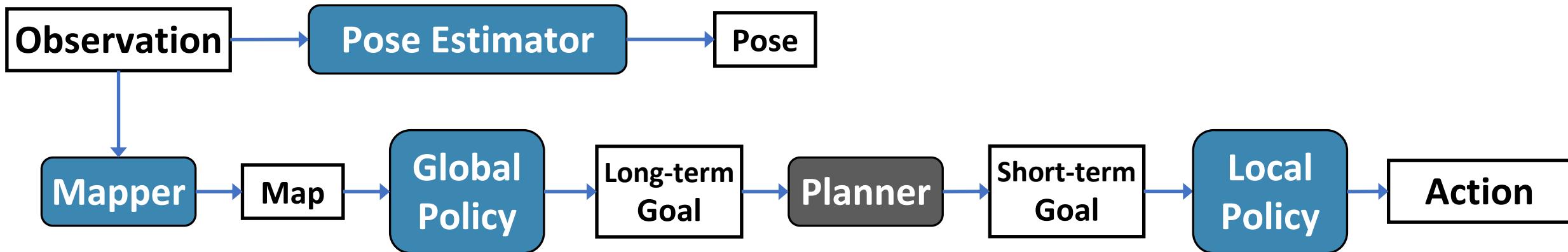
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PointNav in Habitat Challenge 2020

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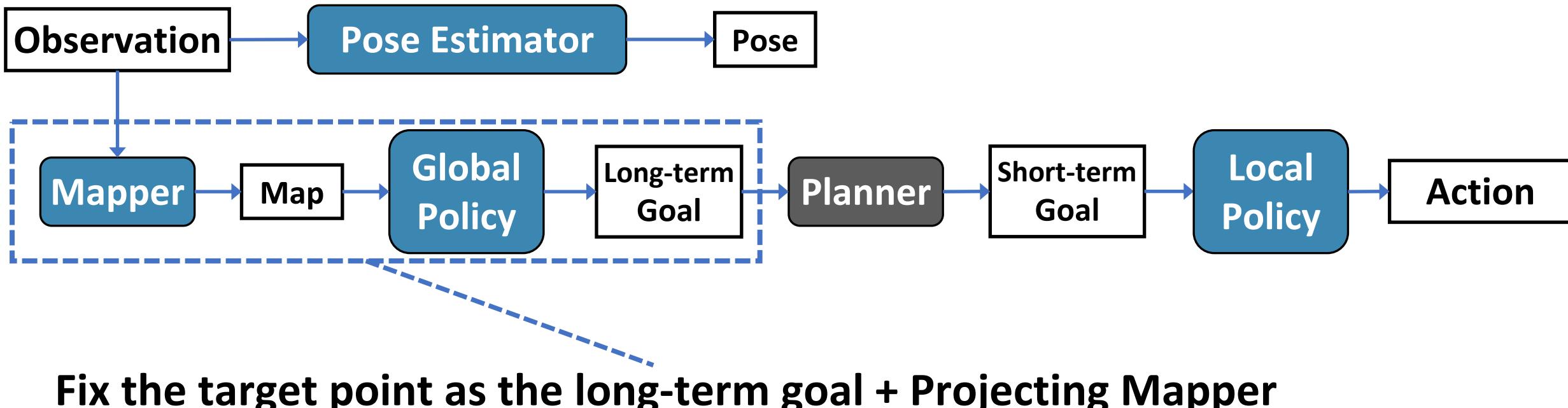
Input: Only Noisy RGB-D Image



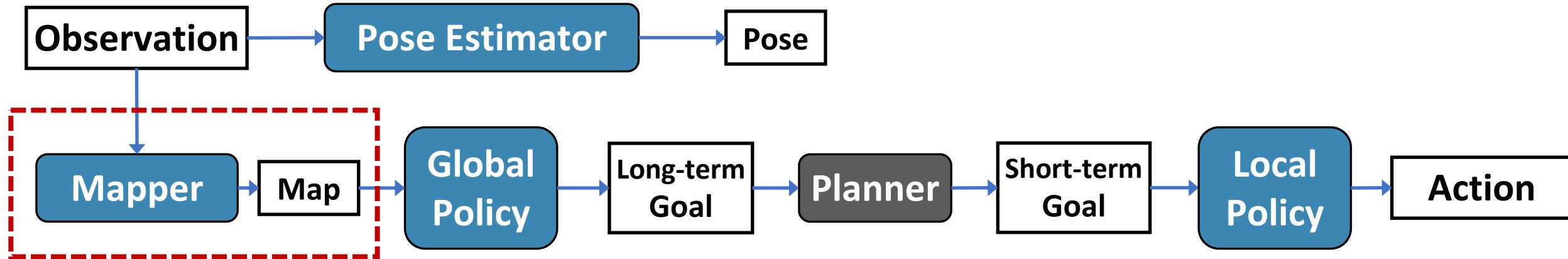
PointNav in Habitat Challenge 2020

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PointNav in Habitat Challenge 2020



2020 Winner!

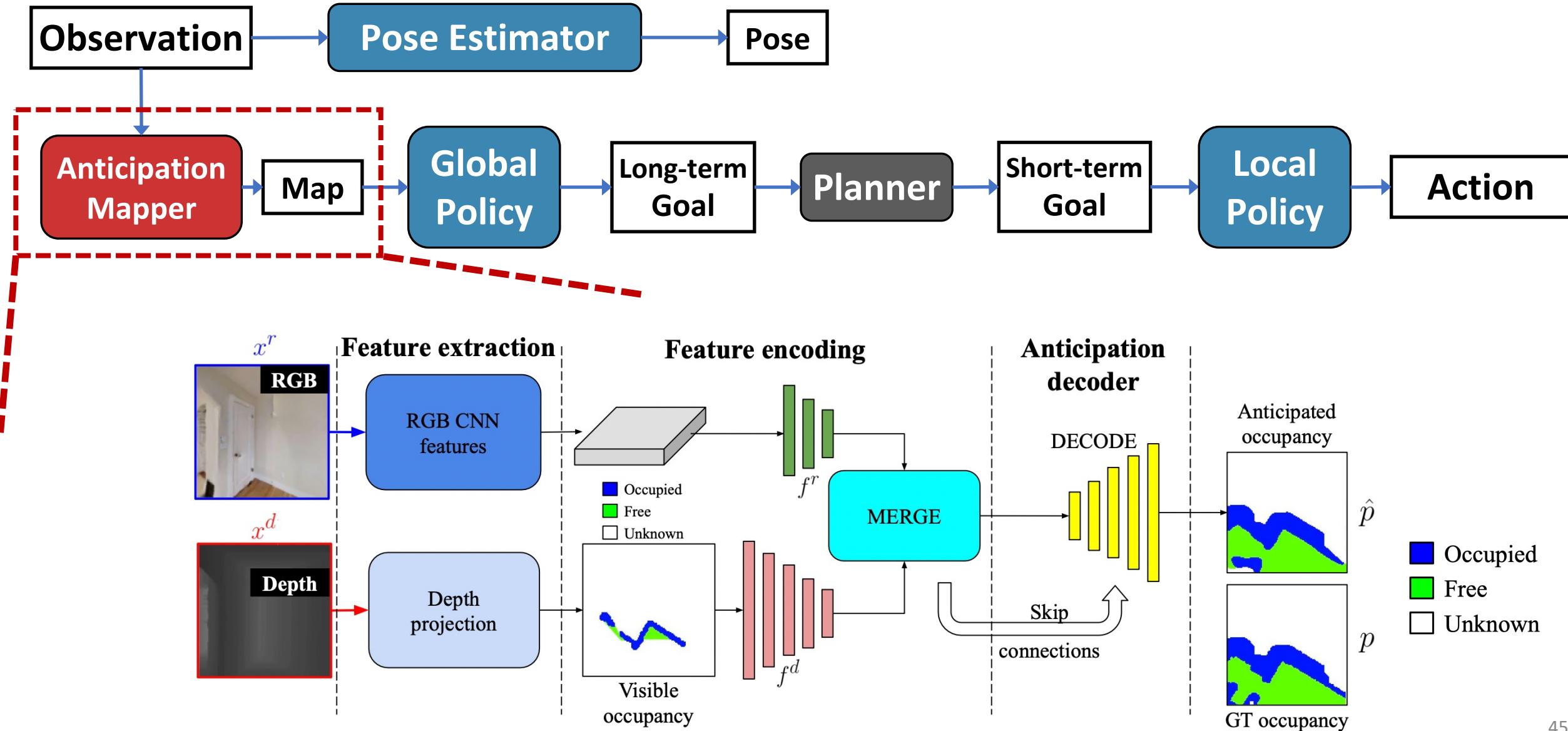
**Occupancy Anticipation
for Efficient Exploration and Navigation
(ECCV 2020)**

Santhosh K. Ramakrishnan^{1,2}, Ziad Al-Halah¹, and Kristen Grauman^{1,2}

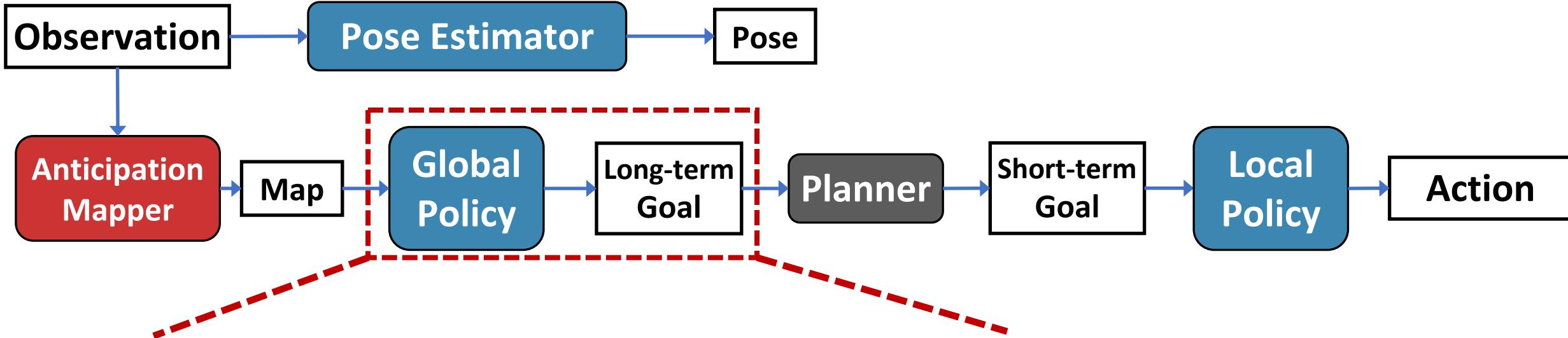
¹ The University of Texas at Austin, Austin TX 78712, USA

² Facebook AI Research, Austin TX 78701, USA

PointNav in Habitat Challenge 2020



PointNav in Habitat Challenge 2020

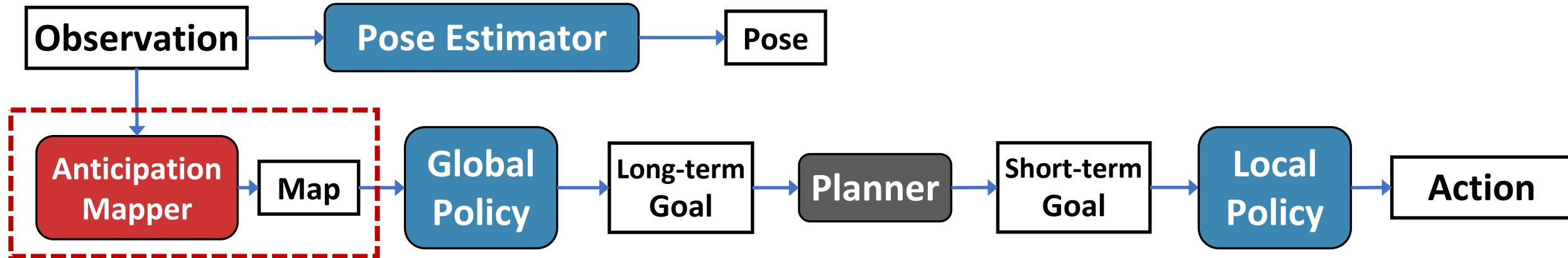


For Exploration: $\text{Accuracy}(\hat{m}, m) = \sum_{i=1}^{G^2} \sum_{j=1}^2 \mathbb{1}[\hat{m}_{ij} = m_{ij}], \quad m : \text{Global Map}$

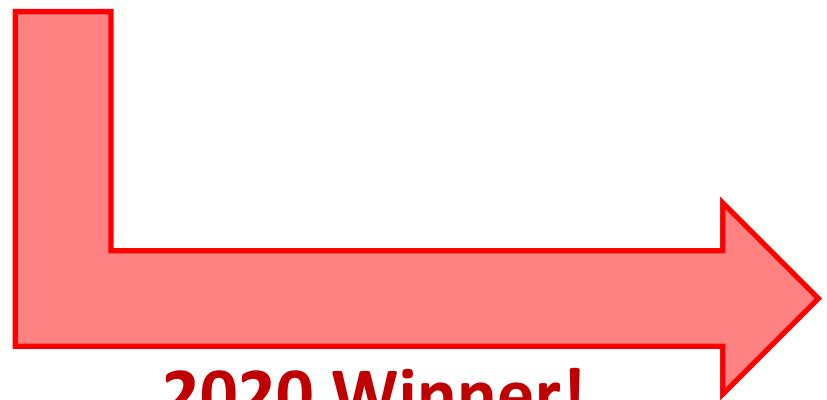
$$R_t^{anticp} = \text{Accuracy}(\hat{m}_t, m) - \text{Accuracy}(\hat{m}_{t-1}, m).$$

For PointNav: Fix the target location as global goal.

PointNav in Habitat Challenge 2020



Occupancy Anticipation



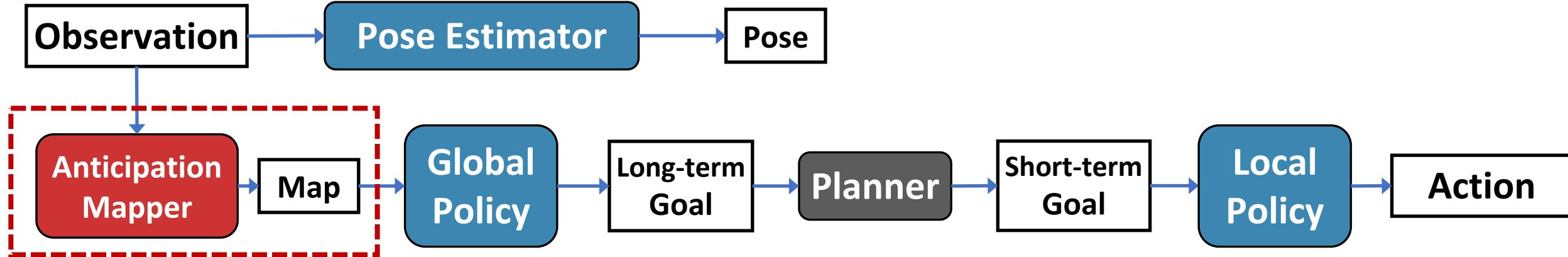
2020 Winner!

Goal: Go 5m south, 3m west.

Input: RGB-D Image

Rank	Team	SPL	SOFT_SPL	DISTANCE_TO_GOAL	SUCCESS
1	OccupancyAnticipation	0.21	0.50	2.29	0.28
2	ego-localization	0.15	0.60	1.82	0.19
3	DAN	0.13	0.24	4.00	0.25
4	Information Bottleneck	0.06	0.43	2.72	0.09
5	cogmodel_team	0.01	0.33	4.27	0.01
6	UCULab	0.001	0.11	5.97	0.002

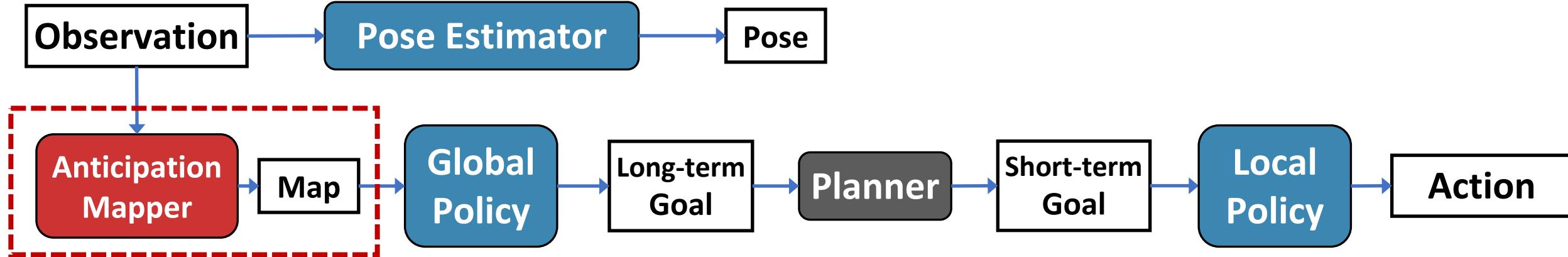
PointNav in Habitat Challenge 2020



Q: Why Occupancy Anticipation works for PointNav?

A: Better modeling the navigable spaces.

PointNav in Habitat Challenge 2020



Q: Why Occupancy Anticipation works for PointNav?

A: Better modeling the navigable spaces.

Q: Why the performance drops so much if not given a pose sensor?

A: Bad pose estimation becomes a drag on map-based methods.

ObjectNav in Habitat Challenge 2020

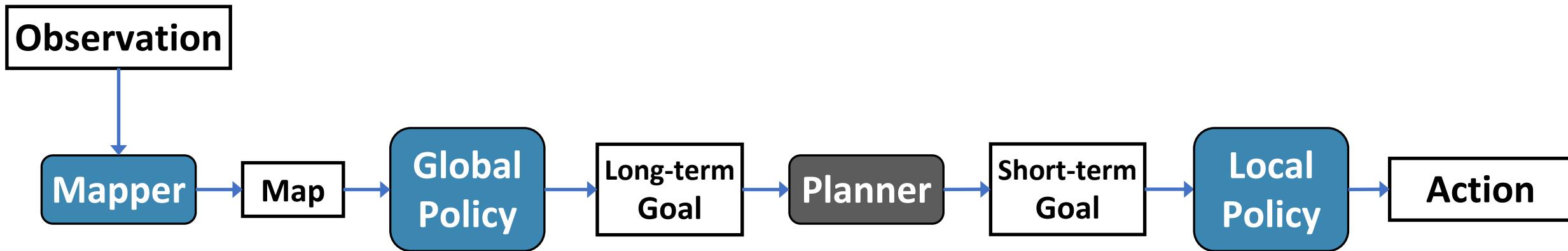
Input: RGB-D Input + Oracle Pose Sensor

Goal: *Find a chair*

ObjectNav in Habitat Challenge 2020

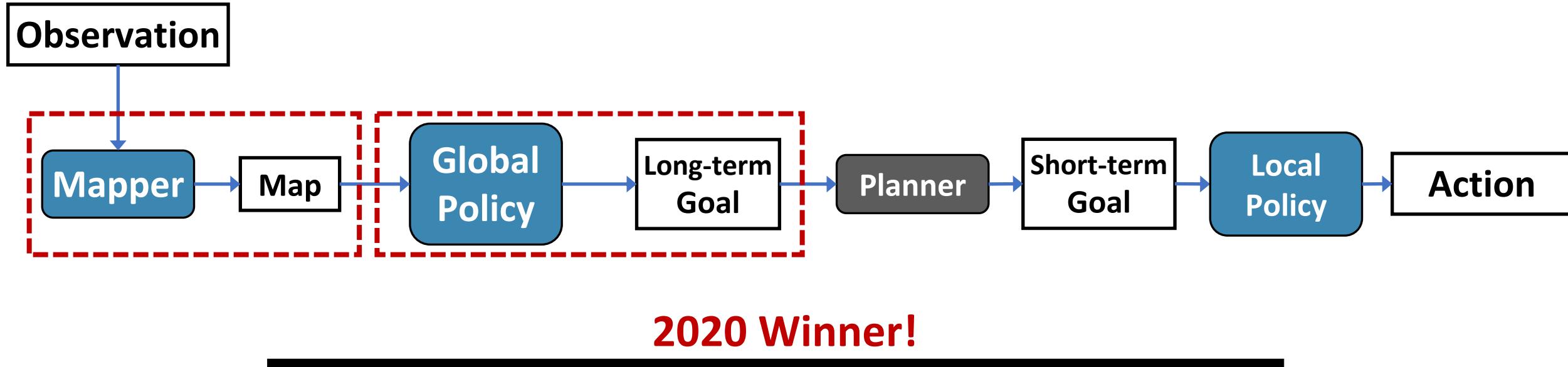
Input: RGB-D Input + Oracle Pose Sensor

Goal: *Find a chair*



How to transfer the pipeline to Object Goal Navigation?

ObjectNav in Habitat Challenge 2020

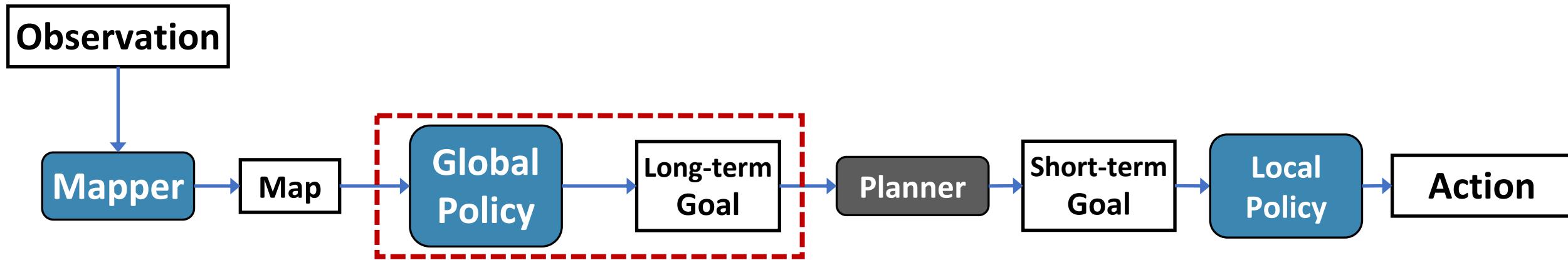


**Object Goal Navigation using
Goal-Oriented Semantic Exploration**

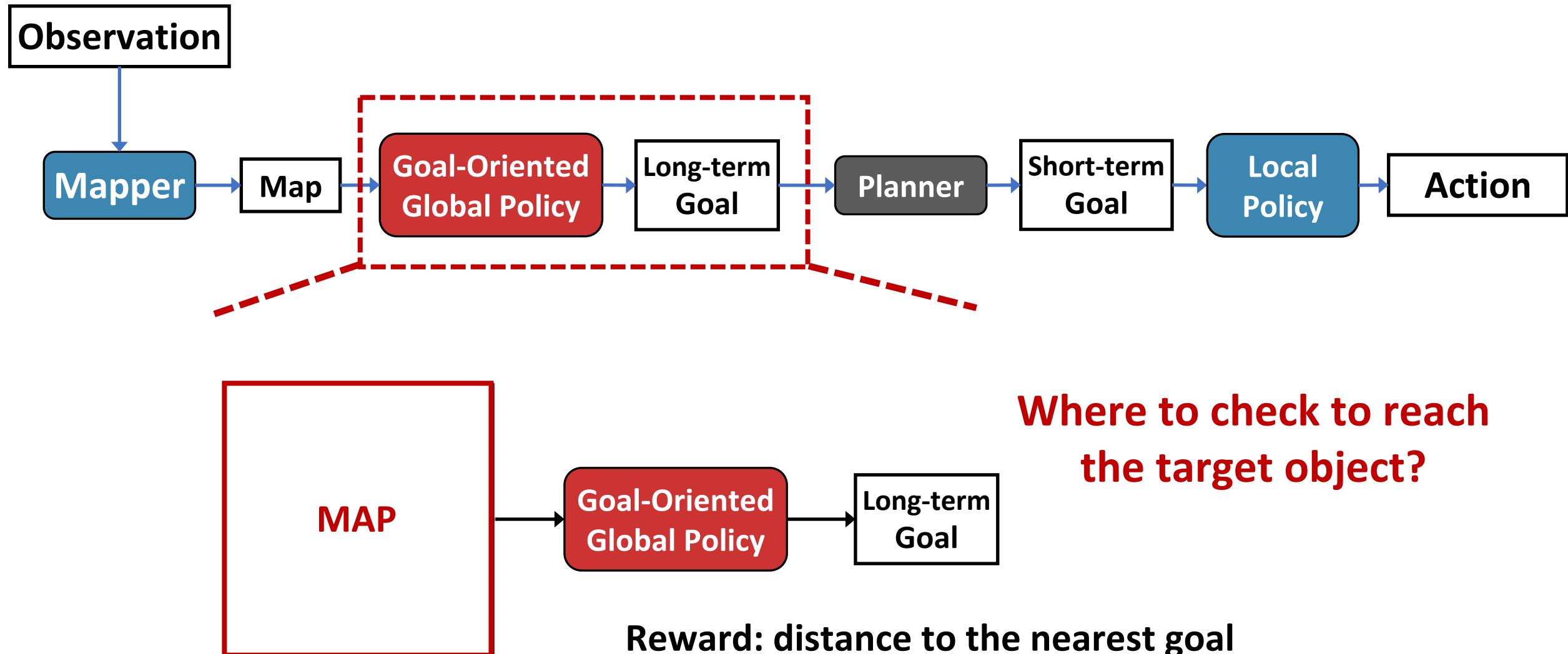
(NeurIPS 2020)

Devendra Singh Chaplot^{1†}, Dhiraj Gandhi², Abhinav Gupta^{1,2*}, Ruslan Salakhutdinov^{1*}
¹Carnegie Mellon University, ²Facebook AI Research

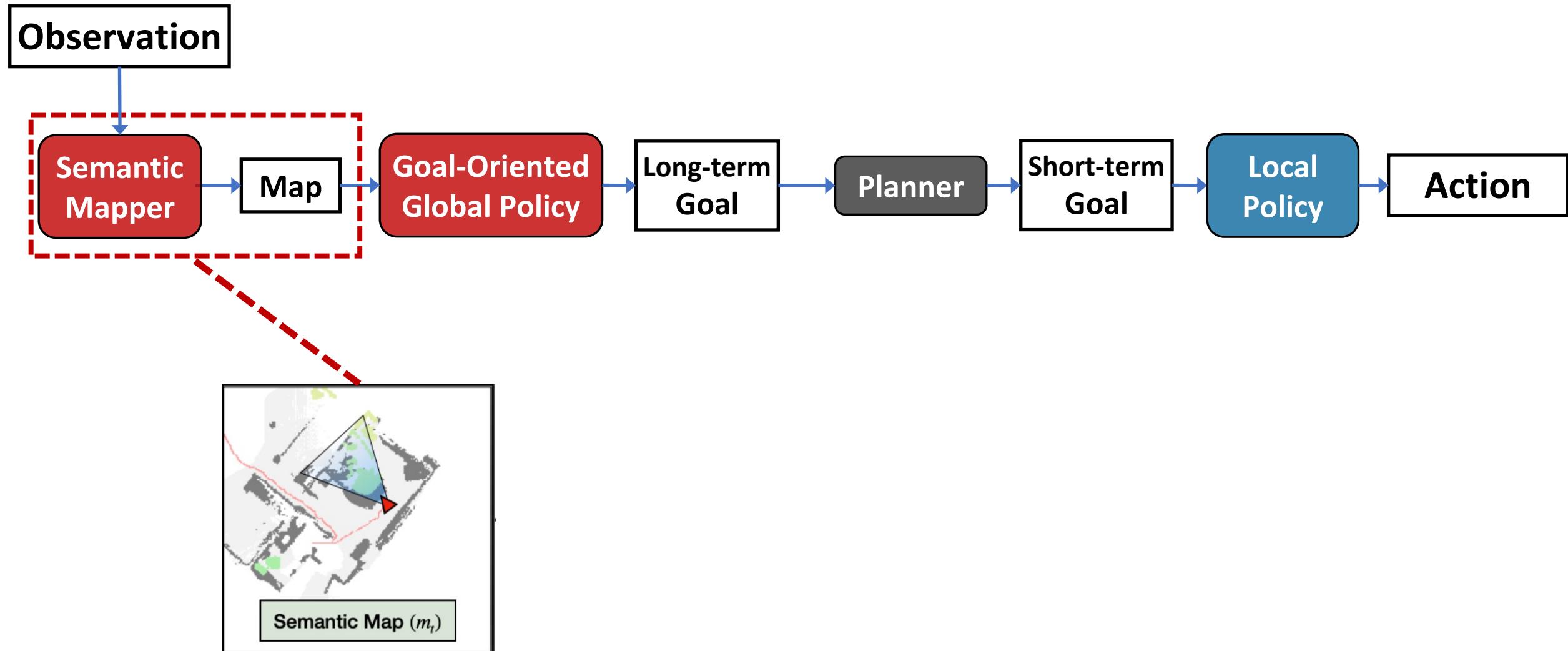
ObjectNav in Habitat Challenge 2020



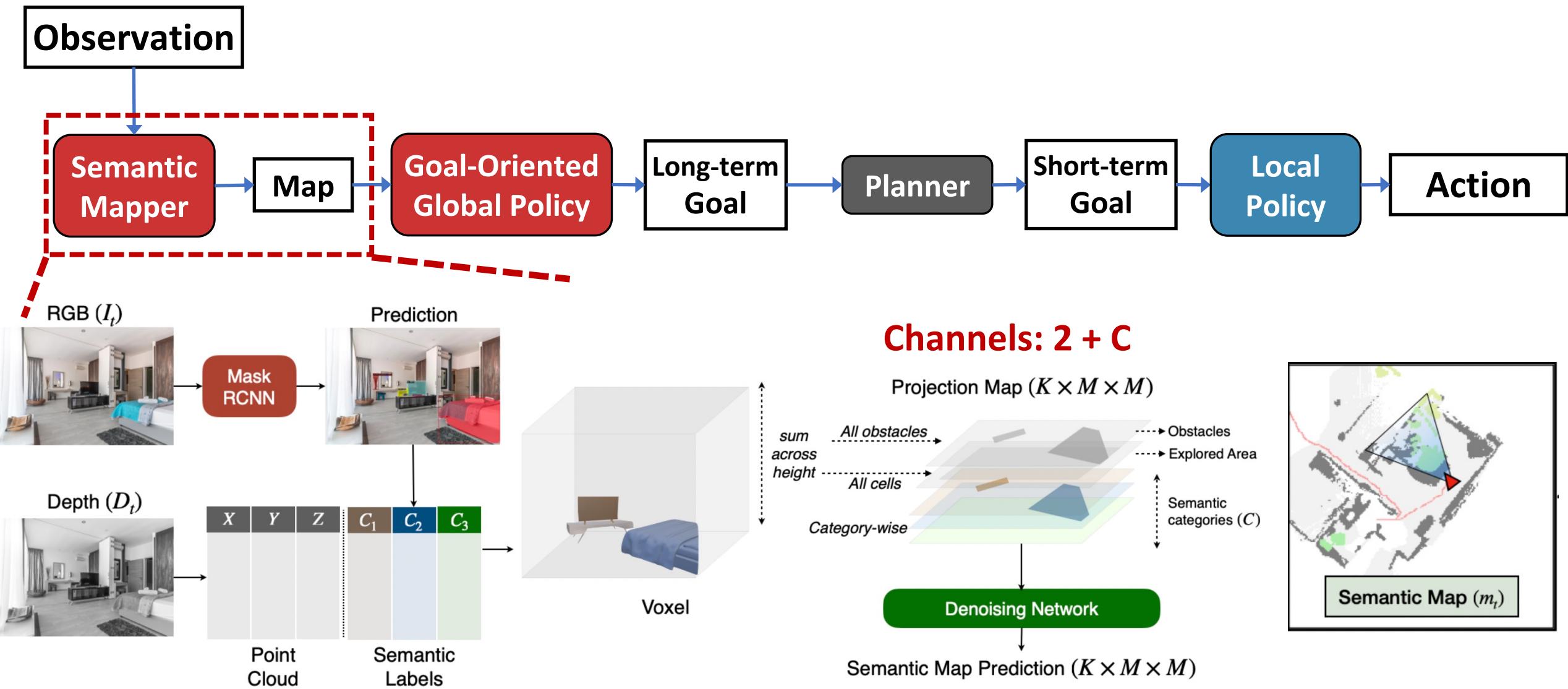
ObjectNav in Habitat Challenge 2020



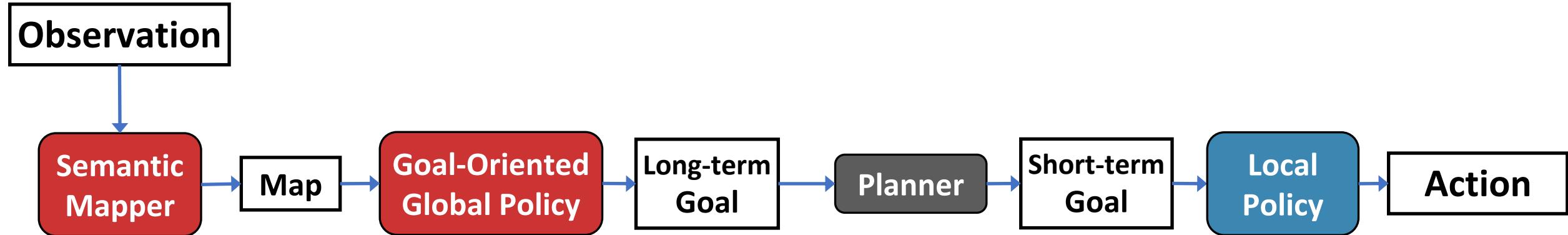
ObjectNav in Habitat Challenge 2020



ObjectNav in Habitat Challenge 2020



ObjectNav in Habitat Challenge 2020

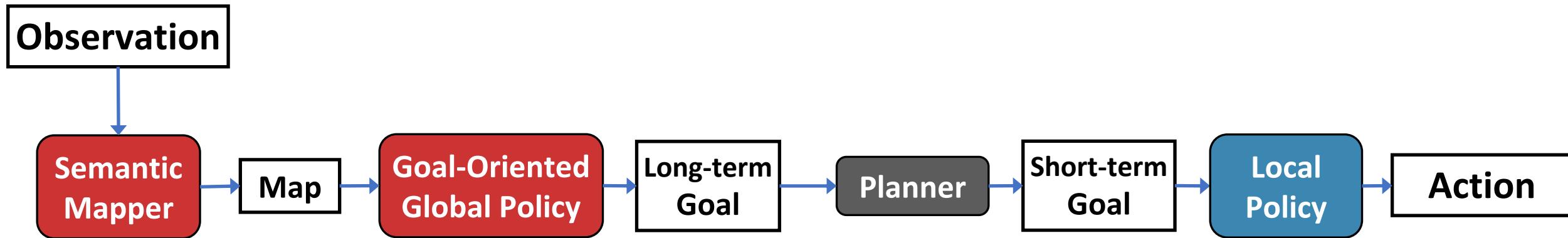


Rank	Team	SPL	SOFT_SPL	DISTANCE_TO_GOAL	SUCCESS
1	Arnold	0.10	0.18	6.33	0.25
2	SRCB-Robot-Sudoer	0.10	0.22	6.91	0.19
3	Active Exploration	0.05	0.17	7.34	0.13
4	Black Sheep	0.03	0.16	7.03	0.10
5	Blue Ox	0.02	0.14	7.23	0.07
6	UCULab	0.001	0.11	5.97	0.002

Goal: *Go find a chair.*

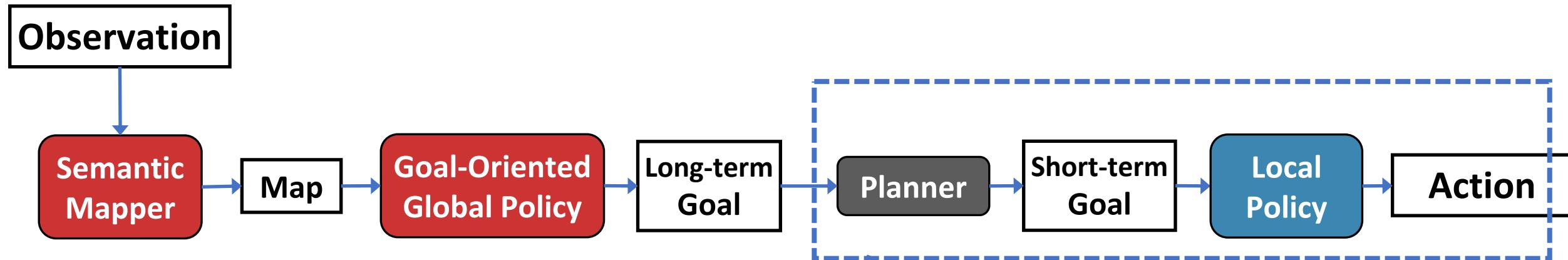
Input: RGB-D Image + Oracle Pose

ObjectNav in Habitat Challenge 2020



Drawbacks:

ObjectNav in Habitat Challenge 2020



Drawbacks:

How to Verify the Target?

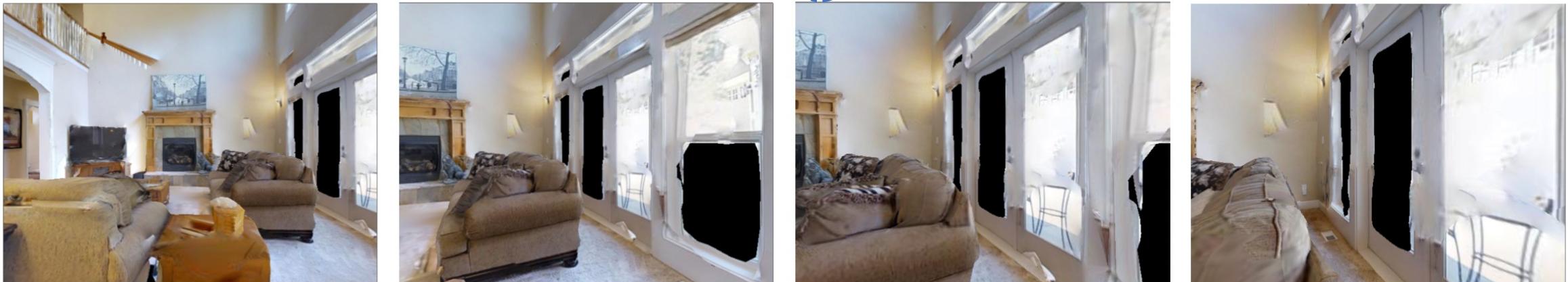


Fig. 4: Tasked to go to a bed, the agent mistakes the sofa as a bed in the last frame and stops. Such a false detection results in failure.

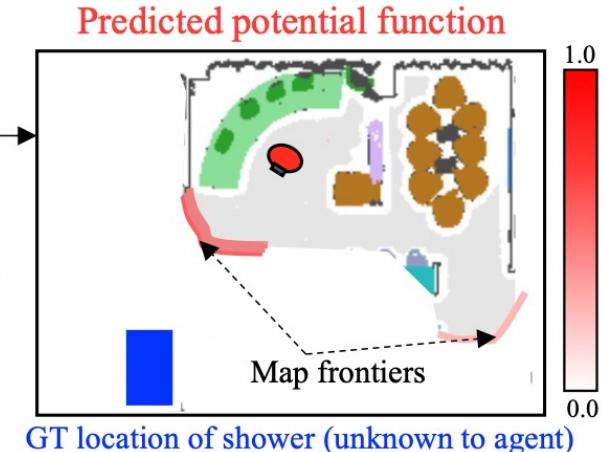
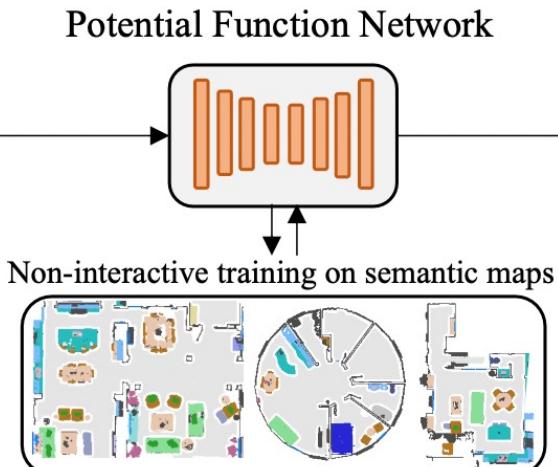
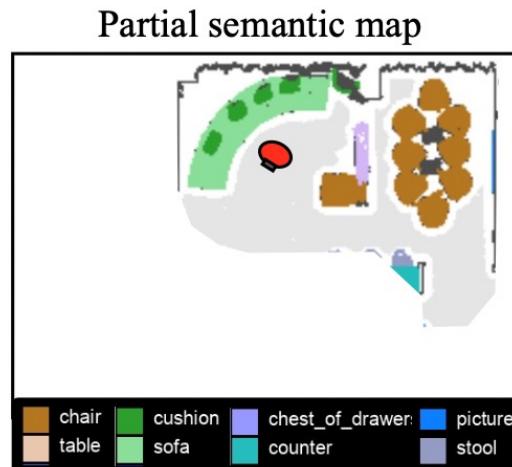
Fig. 4 comes from *Stubborn: A Strong Baseline for Indoor Object Navigation*, Hankuan Luo et al.

Other Map-Based Methods for ObjecNav

PONI: Potential Functions for ObjectGoal Navigation with Interaction-free Learning (CVPR 2022, Oral)

Santhosh Kumar Ramakrishnan^{1,2}, Devendra Singh Chaplot¹, Ziad Al-Halah²,
Jitendra Malik^{1,3}, Kristen Grauman^{1,2}

¹Meta AI ²UT Austin ³UC Berkeley



Selected Papers

Map-Based

Vision-Based

PointNav in Habitat Challenge 2021

2021 Runner-up for PointNav!

Robust Visual Odometry for Realistic Point-Goal Navigation

Ruslan Partsey¹, Oleksandr Maksymets², and Oles Dobosevych¹

¹ Ukrainian Catholic University

² Facebook AI Research

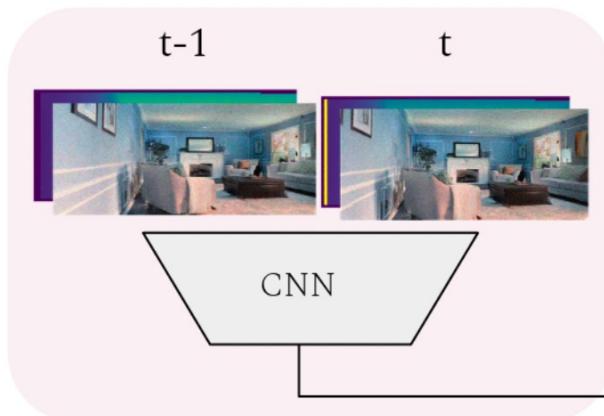
Goal: Go 5m south, 3m west relative to start.

Input: Only RGB-D Image with noise.

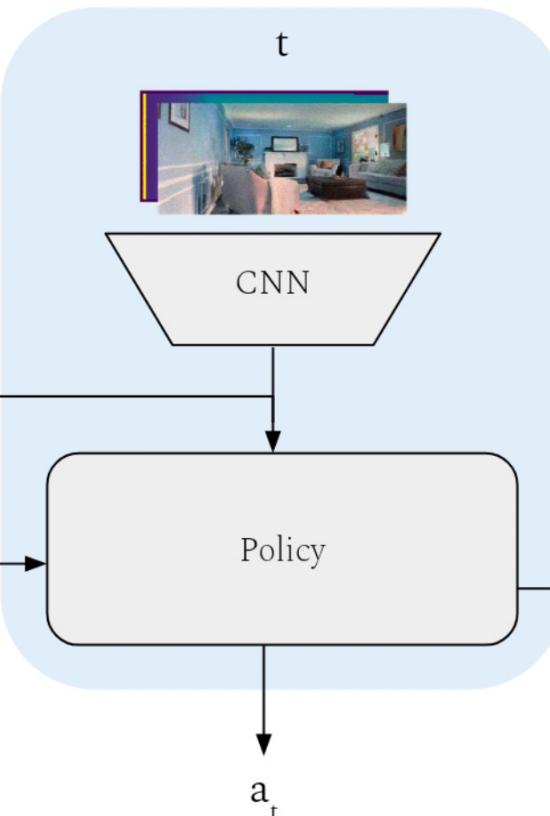
PointNav in Habitat Challenge 2021

Overview

Visual odometry module



Navigation policy



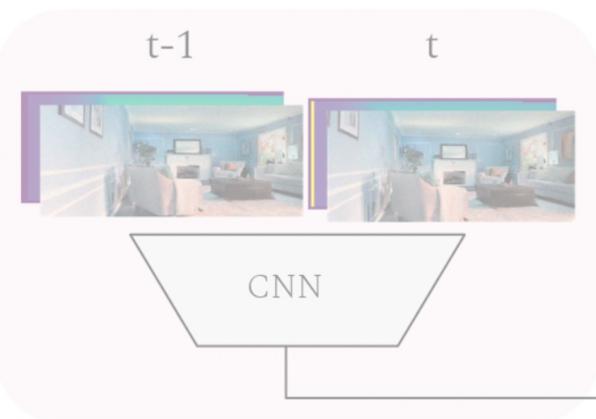
Two Separately-Trained Modules:

- 1) **Navigation Policy (blue)**
- 2) **Visual Odometry (pink)**

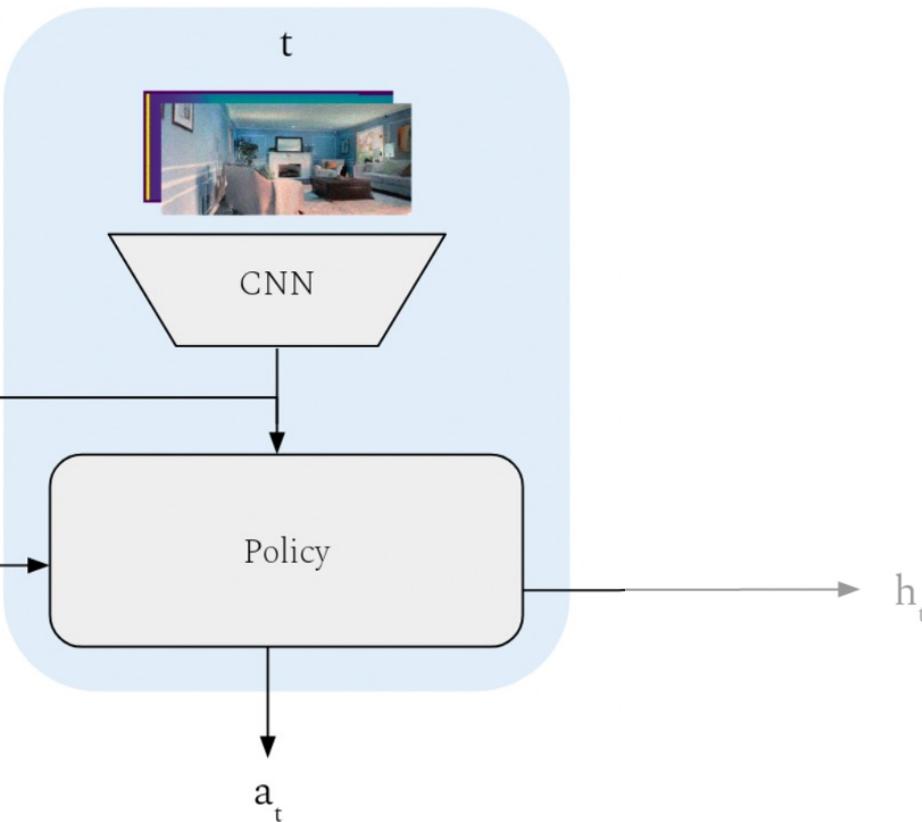
PointNav in Habitat Challenge 2021

Overview

Visual odometry module



Navigation policy



Navigation Policy:

Architecture: LSTM + ResNet18

Training: PPO

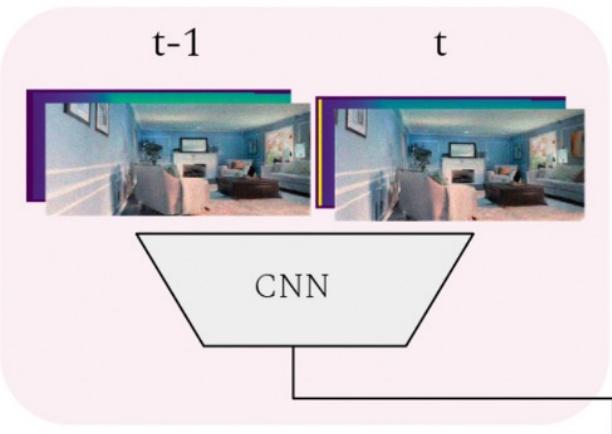
Input: Depth + **GT Pose** + ...
(Replace GT Pose with Visual Odometry in evaluation)

Output: Action, ...

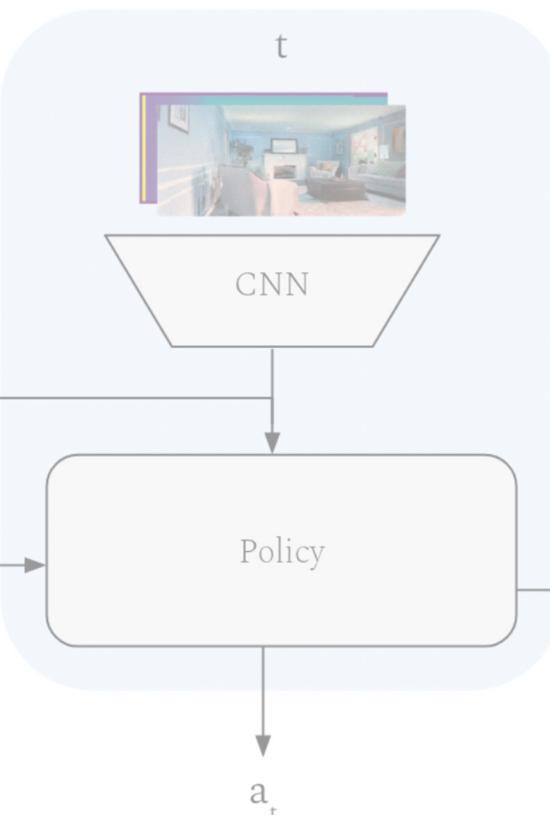
PointNav in Habitat Challenge 2021

Overview

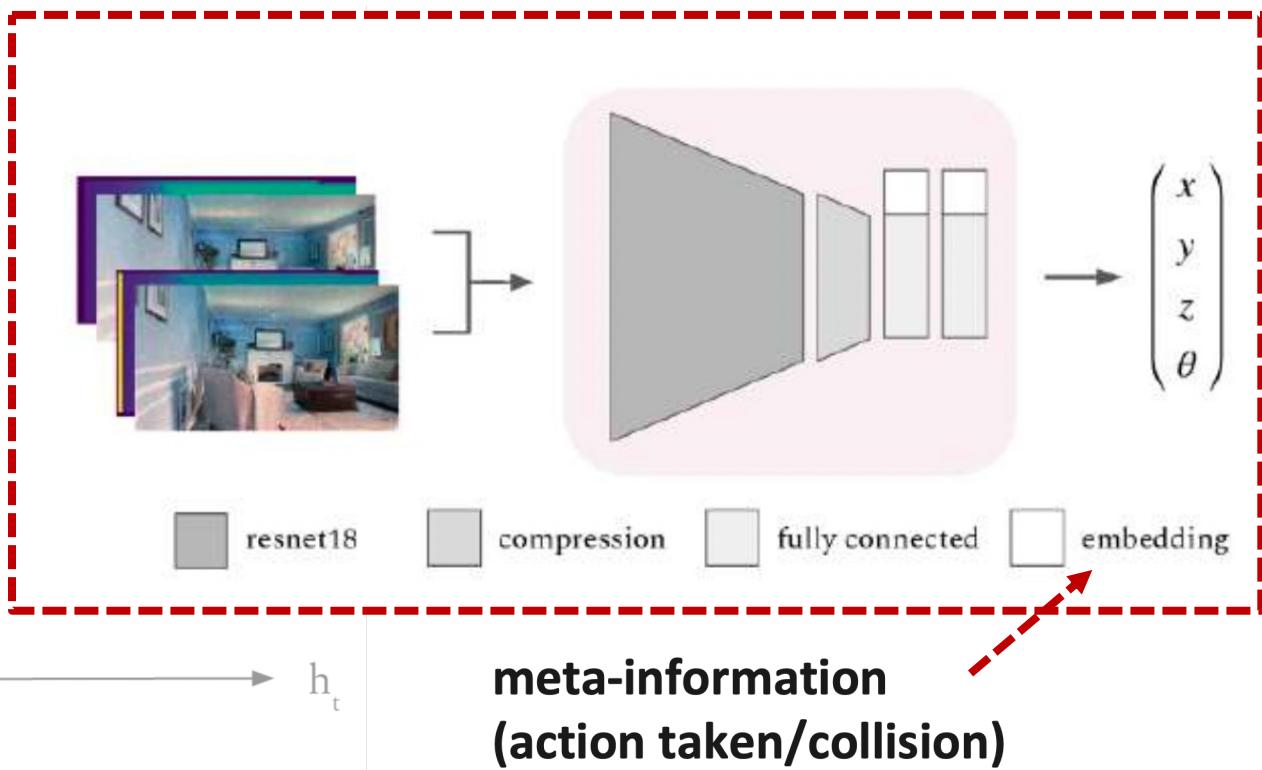
Visual odometry module



Navigation policy



Visual Odometry



$$L = \frac{1}{N} \sum_{i=1}^N ((x - \hat{x})^2 + (y - \hat{y})^2 + (z - \hat{z})^2) + \frac{1}{N} \sum_{i=1}^N (\theta - \hat{\theta})^2$$

PointNav in Habitat Challenge 2021

Tricks for Visual Odometry

- 1) How to embed meta-info?
- 2) Whether to crop out interested area?
- 3) Data Augmentation?

TABLE 4.7: Visual odometry metrics (subject to 1e+2 multiplication).

Experiment name	Epoch	Translation MAE			Rotation MAE				
		Total	Forward	Left	Right	Total	Forward	Left	Right
bs	20	4.61	5.41	3.48	3.67	2.37	1.58	3.61	3.17
	40	4.10	4.53	3.47	3.65	1.85	1.29	2.65	2.49
bs + col_emb	20	5.51	6.99	3.48	3.73	2.98	2.15	3.90	4.18
	40	4.65	5.45	3.56	3.67	2.40	1.64	3.28	3.45
bs + act_emb	20	3.13	2.86	3.45	3.48	1.32	0.99	1.74	1.76
	40	2.89	2.39	3.43	3.65	1.15	0.78	1.62	1.65
bs + col_emb + act_emb	20	3.10	2.80	3.37	3.62	1.37	1.02	1.79	1.87
	40	3.00	2.56	3.48	3.65	1.26	0.84	1.74	1.85
bs + act_emb 2fc	20	3.00	2.67	3.39	3.47	1.25	0.96	1.58	1.68
	40	2.89	2.43	3.41	3.58	1.16	0.82	1.59	1.63
bs + col_emb + act_emb 2fc	20	3.08	2.80	3.38	3.49	1.24	0.94	1.59	1.65
	40	2.87	2.43	3.31	3.57	1.17	0.85	1.55	1.60
bs + act_emb 2fc + vflip	20	2.92	2.54	3.37	3.44	1.14	0.85	1.51	1.53
	40	2.73	2.30	3.23	3.32	1.03	0.73	1.41	1.41
bs + act_emb 2fc + vflip + inv_rot	20	2.89	2.62	3.20	3.30	1.06	0.82	1.37	1.37
	40	2.76	2.42	3.17	3.23	0.96	0.69	1.28	1.32
bs + act_emb 2fc + 320x450->160x225	20	3.28	3.41	3.03	3.19	1.24	1.09	1.40	1.49
	40	3.14	3.18	3.01	3.16	1.15	0.95	1.38	1.44
bs + act_emb 2fc + 320x450->180x320	20	3.12	3.15	3.02	3.16	1.26	1.02	1.57	1.57
	40	2.94	2.89	3.00	3.00	1.18	1.00	1.41	1.42
bs + act_emb 2fc + 320x350->180x320	20	3.17	3.58	2.59	2.67	1.18	1.14	1.19	1.27
	40	2.76	3.05	2.36	2.41	0.98	0.95	1.02	1.00
sepact_right	20	3.49	NA	NA	3.49	1.73	NA	NA	1.73
	40	3.46	NA	NA	3.46	1.71	NA	NA	1.71
sepact_left	20	3.34	NA	3.34	NA	1.76	NA	1.76	NA
	40	3.27	NA	3.27	NA	1.55	NA	1.55	NA
sepact_fwd	20	2.75	2.75	NA	NA	0.97	0.97	NA	NA
	40	2.27	2.27	NA	NA	0.77	0.77	NA	NA
bs + act_emb 2fc + lscale	20	2.37	1.88	2.97	3.03	0.82	0.53	1.22	1.18
	40	2.21	1.65	2.91	2.95	0.77	0.48	1.15	1.15

PointNav in Habitat Challenge 2021

Tricks for Visual Odometry

- 1) How to embed meta-info?
- 2) Whether to crop out interested area?
- 3) Data Augmentation?

Questions:

- 1) Why a simple LSTM + a tricky Visual Odometry work so well for PointNav?
- 2) With a good Visual Odometry, will map-based methods also work well for the task?

TABLE 4.7: Visual odometry metrics (subject to 1e+2 multiplication).

Experiment name	Epoch	Translation MAE			Rotation MAE				
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bs	20	4.61	5.41	3.48	3.67	2.37	1.58	3.61	3.17
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bs + act_emb 2fc + vflip	20	2.92	2.54	3.37	3.44	1.14	0.85	1.51	1.53
	40	2.73	2.30	3.23	3.32	1.03	0.73	1.41	1.41
bs + act_emb 2fc + vflip + inv_rot	20	2.89	2.62	3.20	3.30	1.06	0.82	1.37	1.37
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	40	3.46	NA	NA	3.46	1.71	NA	NA	1.71
sepact_left	20	3.34	NA	3.34	NA	1.76	NA	1.76	NA
	40	3.27	NA	3.27	NA	1.55	NA	1.55	NA
sepact_fwd	20	2.75	2.75	NA	NA	0.97	0.97	NA	NA
	40	2.27	2.27	NA	NA	0.77	0.77	NA	NA
bs + act_emb 2fc + lscale	20	2.37	1.88	2.97	3.03	0.82	0.53	1.22	1.18
	40	2.21	1.65	2.91	2.95	0.77	0.48	1.15	1.15

ObjectNav in Habitat Challenge 2021

2021 Winner for ObjectNav!

**Auxiliary Tasks and Exploration Enable ObjectGoal Navigation
(ICCV 2021)**

Joel Ye^{1*} Dhruv Batra^{1,2} Abhishek Das² Erik Wijmans¹

¹Georgia Institute of Technology ² Facebook AI Research

Goal: *Go find a chair.*

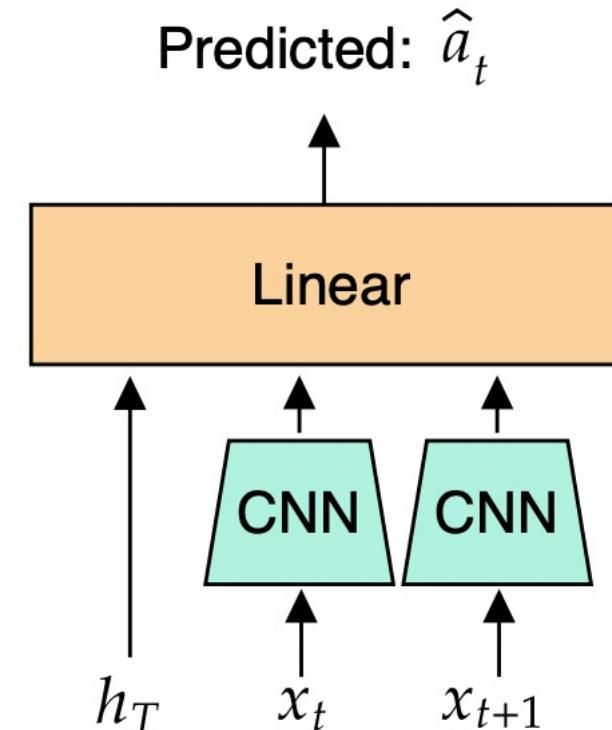
Input: RGB-D Image with noise + Perfect Pose Sensor

ObjectNav in Habitat Challenge 2021

Auxiliary Tasks:

(1) Inverse Dynamics (ID)

Decoding action taken from two successive observations.



(a) Inverse Dynamics

$$L_{ID} = \sum_{i=1}^{T-1} L_{CE}(I(\phi_i, \phi_{i+1}, h_T), a_i)$$

ϕ_t : visual embeddings

ObjectNav in Habitat Challenge 2021

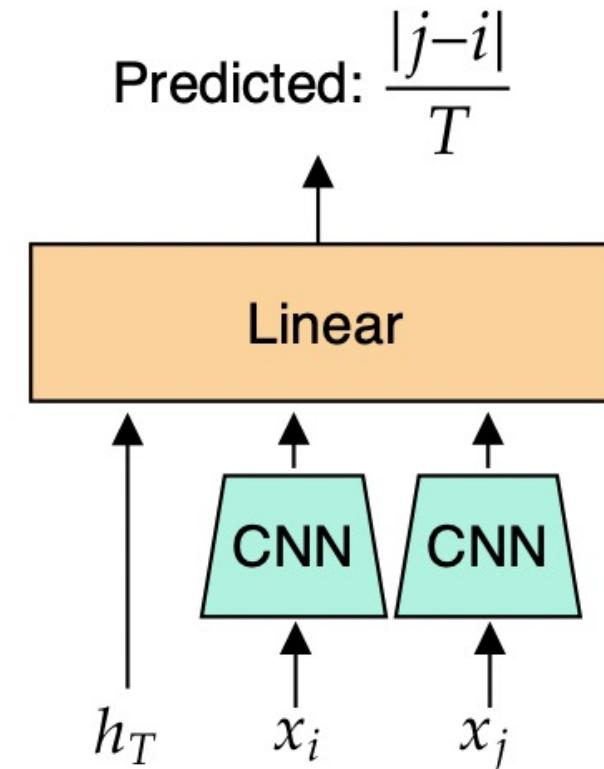
Auxiliary Tasks:

(1) Inverse Dynamics (ID)

Decoding action taken from two successive observations.

(2) Temporal Distance (TD)

Decoding the timestep difference between two observations.



(b) Temporal Distance

$$L_{TD} = \frac{1}{2}((i - j) - \mathcal{T}(\phi_i, \phi_j, h_T))^2$$

ObjectNav in Habitat Challenge 2021

Auxiliary Tasks:

(1) Inverse Dynamics (ID)

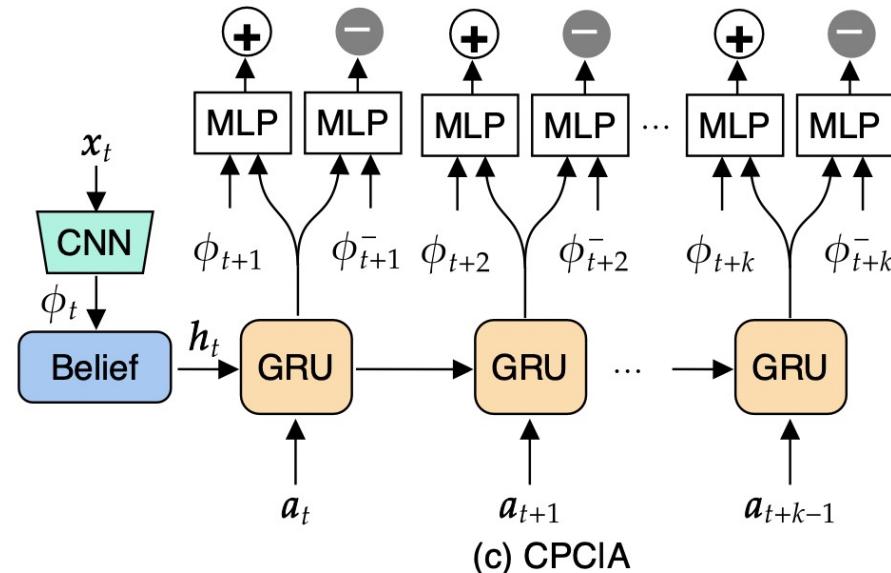
Decoding action taken from two successive observations.

(2) Temporal Distance (TD)

Decoding the timestep difference between two observations.

(3) Action-Conditional Contrastive Predictive Coding (CPC|A)

Decoding future visual embeddings at every timestep from other visual embeddings using a secondary GRU.



ObjectNav in Habitat Challenge 2021

Auxiliary Tasks:

(1) Inverse Dynamics (ID)

Decoding action taken from two successive observations.

(2) Temporal Distance (TD)

Decoding the timestep difference between two observations.

(3) Action-Conditional Contrastive Predictive Coding (CPC|A)

Decoding future observation embeddings at every timestep from other observation embeddings using a secondary GRU.

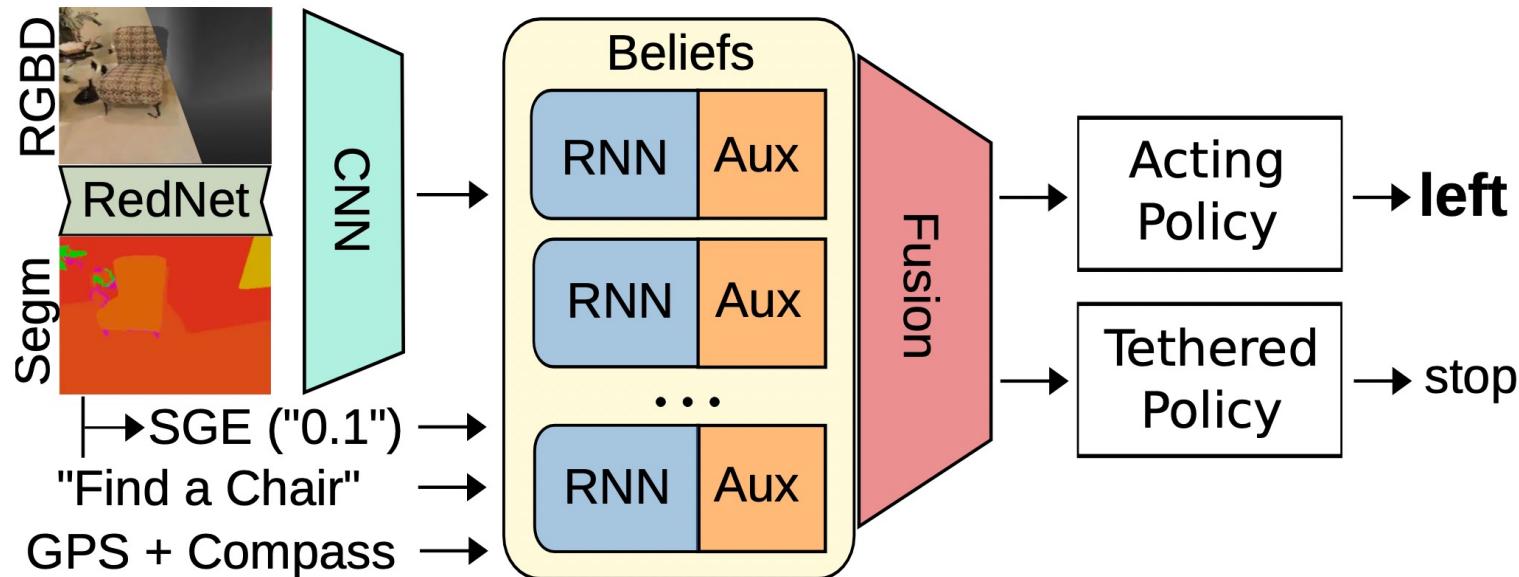
(4) Action Distribution Prediction (ADP)

(5) Generalized Inverse Dynamics (GID)

(6) Coverage Prediction (CP)

ObjectNav in Habitat Challenge 2021

Fuse Auxiliary Tasks for ObjectNav:



SGE : the fraction of the frame occupied by the goal object.
(Semantic Goal Exists)

Beliefs : Output cell States from all individual GRUs for Aux Tasks.

Fusion : An attention layer conditioned on the observation embedding.

$$L_{\text{total}}(\theta_m; \theta_a) = L_{\text{RL}}(\theta_m) - \alpha H_{\text{action}}(\theta) + L_{\text{Aux}}(\theta_m; \theta_a) \quad H_{\text{action}} : \text{entropy across action distribution}$$

$$L_{\text{Aux}}(\theta_m; \theta_a) = \sum_{i=1}^{n_{\text{Aux}}} \beta^i L_{\text{Aux}}^i(\theta_m; \theta_a^i) - \mu H_{\text{attn}}(\theta_m)$$

H_{attn} : entropy across attention distribution over aux tasks

Comments & Discussion

Topic 1: Map-Based VS Vision-Based

Comment: Map-Based Methods with higher Interpretability & Expansibility

Topic 2: More Data VS More Elegant Methods

Background:

- (1) **PointNav** solved in 2021, achieving 99.6% success rate, with 2.5 billion training frames and a simple RNN network.
- (2) Boost performance in **GoalNav**, with auxiliary data(human annotated /synthetic/human demonstrations...)
- (3) **CLIP**

Question: How should we regard those who achieve nearly perfect performance if simply with big data?

References

Talks & Websites:

- (1) Devendra Chaplot's Ph.D Thesis Defense <https://www.youtube.com/watch?v=rJ7tGT5cHtU>
- (2) Habitat Challenge <https://aihabitat.org/challenge/2022/>

Papers:

- (1) *Learning to Explore Using Active SLAM*, Chaplot et al, ICLR2020
- (2) *Occupancy Anticipation for Efficient Exploration and Navigation*, Santhosh et al, ECCV2020
- (3) *Object Goal Navigation using Goal-Oriented Semantic Exploration*, Chaplot et al, NIPS2020
- (4) *PONI: Potential Functions for ObjectGoal Navigation with Interaction-Free Learning*, Santhosh et al, CVPR22
- (5) *Robust Visual Odometry for Realistic Point-Goal Navigation*, Partsey et al
- (6) *Auxiliary Tasks and Exploration Enable ObjectGoal Navigation*, Joel Ye et al, ICCV2021

Acknowledgments

Advisors: *Jiazhao Zhang, He Wang*

Thank you for your invaluable advices!



Embodied Navigation Tasks

Thanks for Listening!
Any Questions?