Zero-Shot Object Goal Navigation with Multi-Scale Geometric-Affordance Guidance

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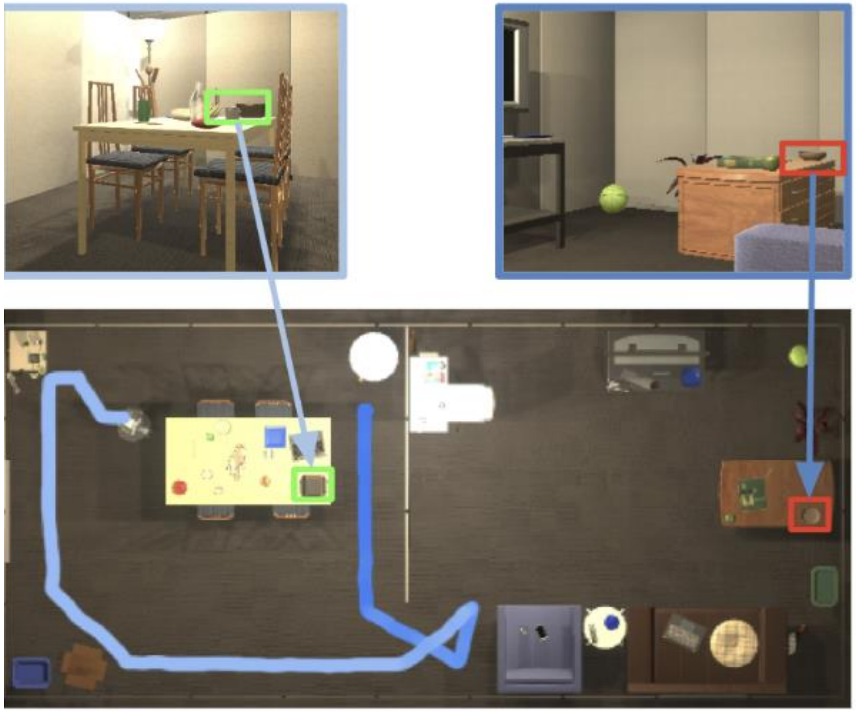
Object Goal Navigation (OGN)

Object Goal Navigation requires both exploring the environment and identifying the semantic information of the scene to locate the desired object.



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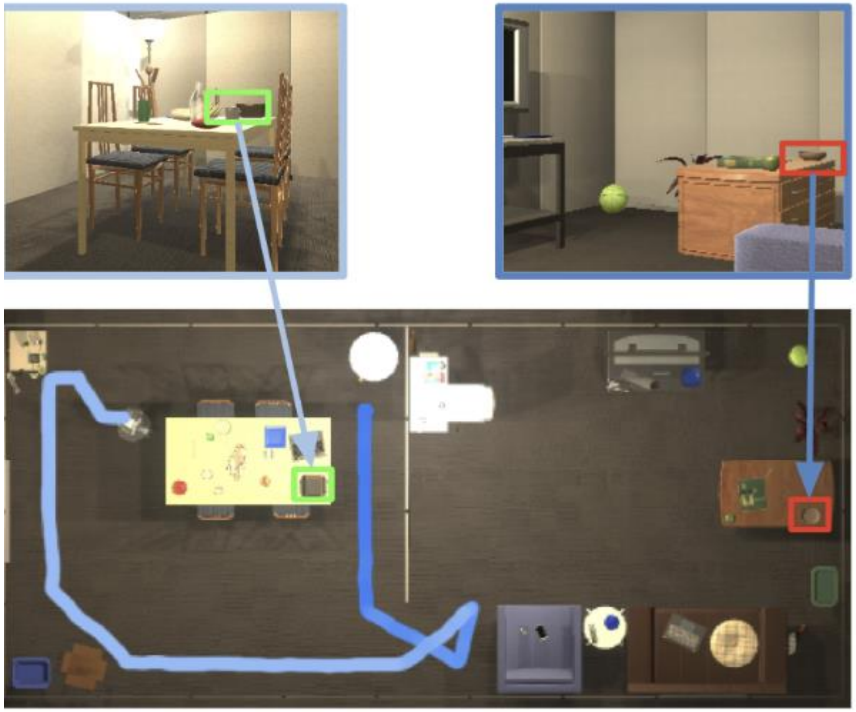
Perform well in trained environment



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Traditional OGN Approaches:
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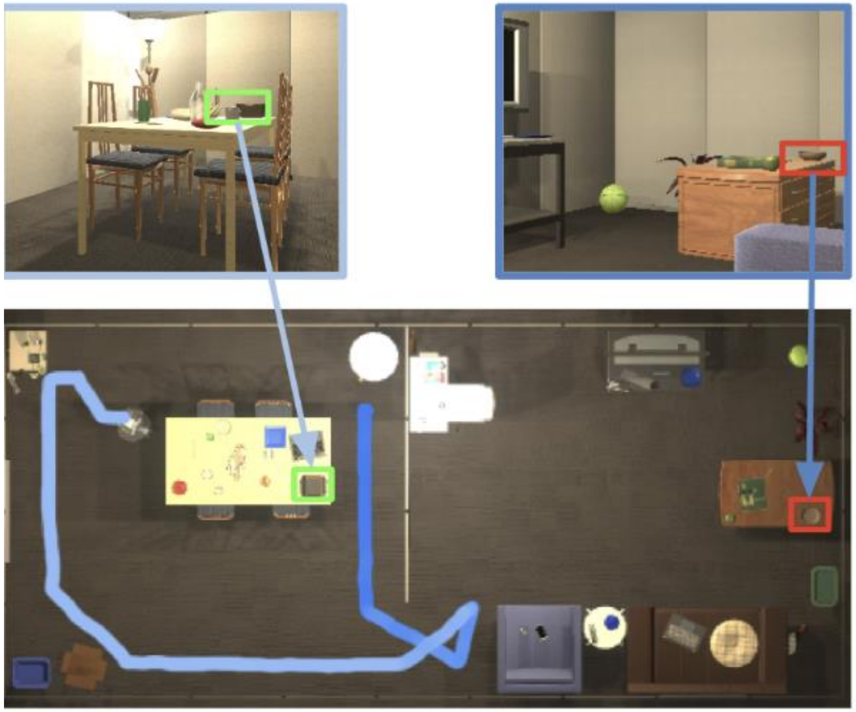
Zero-Shot OGN:
Able to navigate to unfamiliar objects in unknown environments without additional training.



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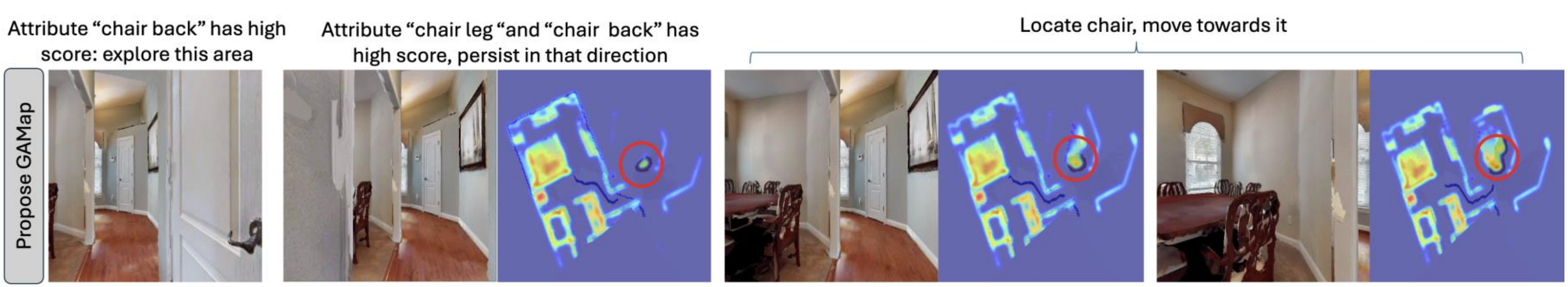
Our Solution: Multi-Scale Geometric Part and Affordance Map



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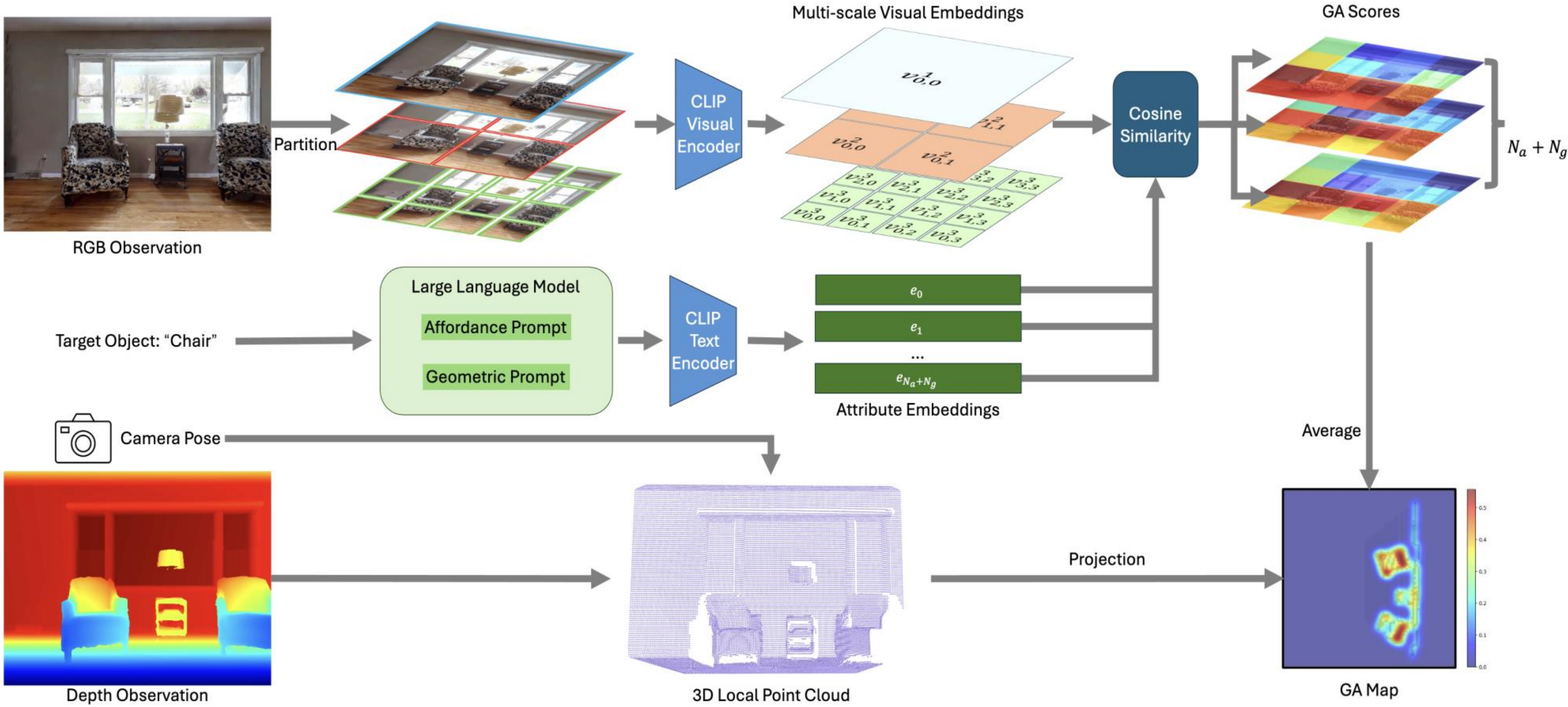
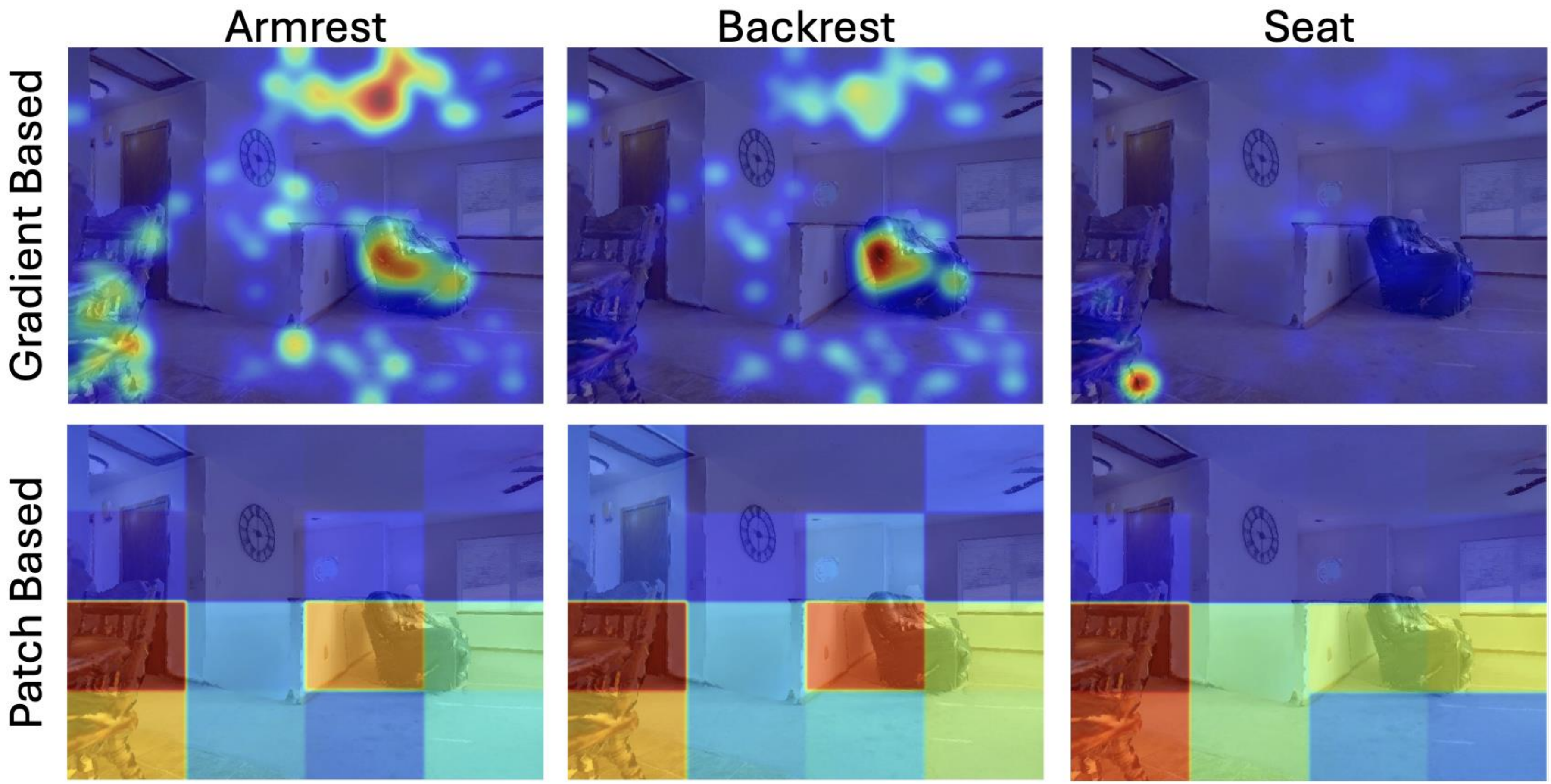


The first line of images shows our pro- posed method, where the multi-scale approach effectively captures objects at all scales, such as the sofa back in the background. The second line of images shows the results of PIVOT-Liked GPT- 4V



GA score visualization between gradient-based and patch-based methods for the armrest, backrest, and seat attributes of a target chair. The gradient-based method (top row) often attends to irrelevant areas, such as the ceiling, while the patch- based method (bottom row) accurately focuses on the relevant areas

Table a: The table illustrates the differences between our work and existing methods.

Method	Mapping	Multi-Scale	Zero-shot	Training	
				Locomotion	Semantic
SemExp	Categorical	×	×	✓	✓
ZSON	Categorical	×	×	✓	✓
PixNav	Categorical	×	✓	✓	×
VLFM	Categorical	×	✓	✓	×
PONI	Categorical	×	✓	×	✓
L3MVN	Categorical	×	✓	×	✓
CoW	Categorical	×	✓	×	×
ESC	Categorical	×	✓	×	×
VoroNav	Categorical	×	✓	×	×
GAMap	Affordance+Geometric	✓	✓	×	×

Method	Reference	Zero-shot	Training		HM3D		Gibson	
			Locomotion	Semantic	SR↑	SPL↑	SR↑	SPL↑
SemExp	NeurIPS 20 [2]	×	✓	✓	37.9	18.8	65.2	33.6
ZSON	NeurIPS 22 [26]	×	✓	✓	25.5	12.6	31.3	12.0
PixNav	ICRA 24 [11]	×	✓	×	37.9	20.5	-	-
VLFM	CoRL 23 [17]	✓	✓	×	*52.5*	**30.4**	*84.0*	*52.2*
PONI	CVPR 22 [20]	×	×	✓	-	-	73.6	41.0
FBE	-	✓	×	✓	23.7	12.3	41.7	21.4
L3MVN	IROS 23 [21]	✓	×	✓	50.4	23.1	76.1	37.7
Random	-	✓	×	×	0.0	0.0	3.0	3.0
CoW	CVPR 23 [30]	✓	×	×	32.0	18.1	-	-
ESC	ICML 23 [5]	✓	×	×	38.5	22.0	-	-
SemUtil	RSS 23 [16]	✓	×	×	-	-	69.3	40.5
VoroNav	ICML 24 [18]	✓	×	×	42.0	26.0	-	-
GAMap	Proposed	✓	×	×	**53.1** (↑26.4%)	*26.0*	**85.7** (↑23.7%)	**55.5** (↑37.0%)

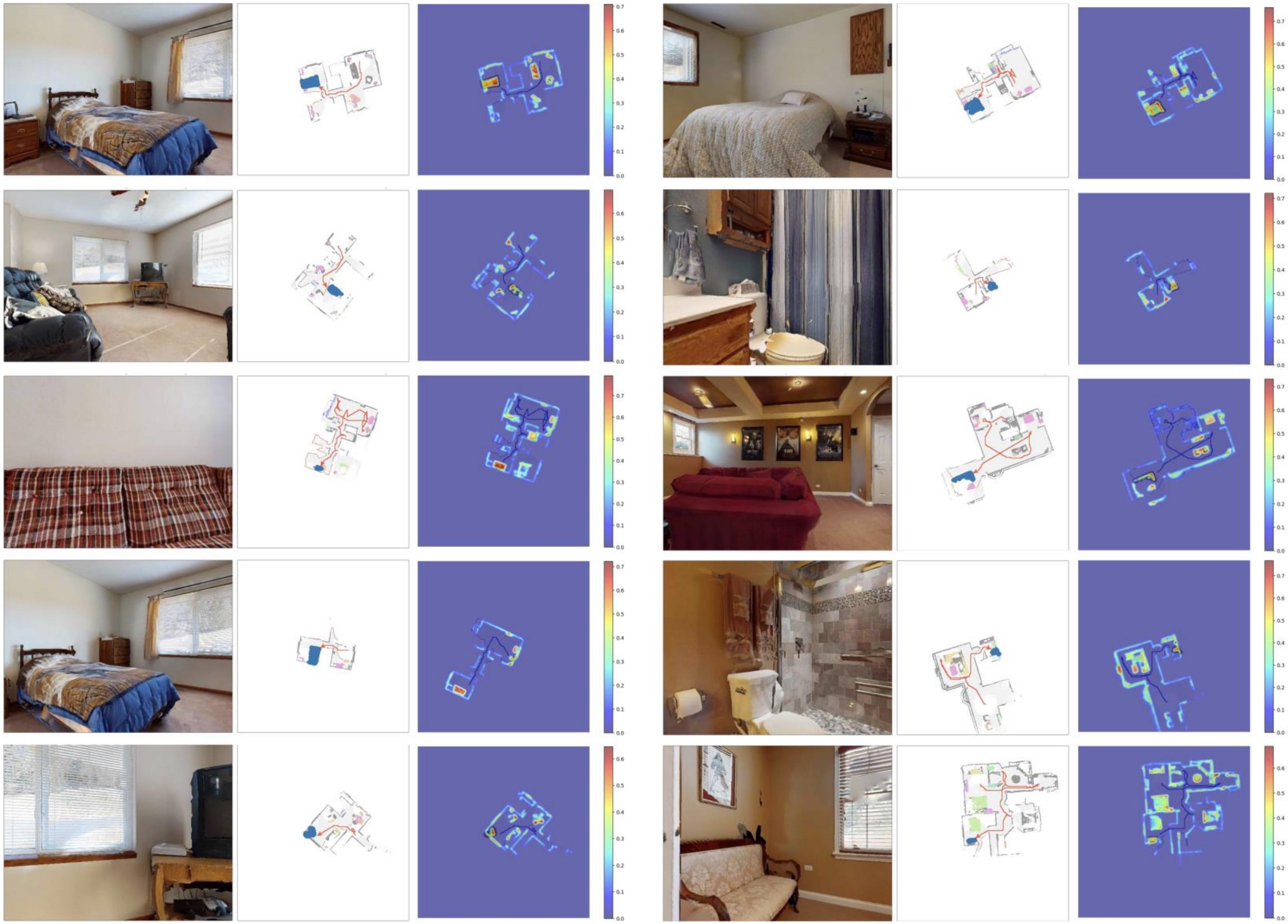


Figure 7: Visualized results of last observation frame, navigation path, and GAMap.

Thank you!