

Vision-and-Language Navigation with Analogical Textual Descriptions in LLMs

Yue Zhang¹ Tianyi Ma¹ Zun Wang² Yanyuan Qiao³ Parisa Kordjamshidi¹

¹Michigan State University ²UNC Chapel Hill ³University of Adelaide
zhan1624@msu.edu

Abstract

Integrating large language models (LLMs) into embodied AI models is becoming increasingly prevalent. However, existing zero-shot LLM-based Vision-and-Language Navigation (VLN) agents either encode images as textual scene descriptions, potentially oversimplifying visual details, or process raw image inputs, which can fail to capture abstract semantics required for high-level reasoning. In this paper, we improve the navigation agent’s contextual understanding by incorporating textual descriptions from multiple perspectives that facilitate analogical reasoning across images. By leveraging text-based analogical reasoning, the agent enhances its global scene understanding and spatial reasoning, leading to more accurate action decisions. We evaluate our approach on the R2R dataset, where our experiments demonstrate significant improvements in navigation performance.

1 Introduction

With the LLMs being applied across diverse domains (Yu et al., 2025; Zhang et al., 2024b), their integration into VLN agents has emerged as a promising development. Zero-shot LLM-based VLN agents represent a significant shift from traditional navigation agents that rely on extensive task-specific training, demonstrating greater adaptability and generalizability to a wide range of environments (Zhang et al., 2024d).

Early approaches for zero-shot LLM-based VLN agents interpret the visual environment by utilizing offline Vision-Language Models (VLMs) (Li et al., 2023; Liu et al., 2023; Wang et al., 2022) to convert visual images into the corresponding textual descriptions (Zhou et al., 2024b; Long et al., 2024a; Qiao et al., 2023). However, as shown in Fig. 1, these textual descriptions often provide very similar information when candidate images contain overlapping views, even if they are captured from

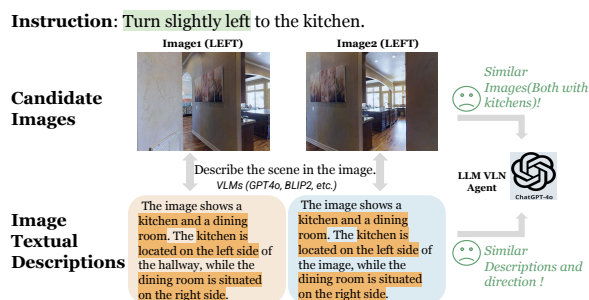


Figure 1: Challenges in current LLM-based VLN Agent. The highlighted orange text shows similar descriptions for two different action decisions.

different angles. More recently, MapGPT (Chen et al., 2024) processes multiple images simultaneously, directly feeding them into LLMs as input. This approach reduces redundancy in textual descriptions by leveraging visual differences, but this effort also remains limited when handling highly similar images, such as when both images depict “a kitchen” in Fig. 1. Motivated by these challenges, we hypothesize that incorporating additional analogical reasoning processes is necessary to help the agent distinguish key features within the visually similar images while leveraging spatial information to discern their positional differences (e.g., “slightly left”).

To address the aforementioned challenge, we introduce a novel **analogical reasoning module** aimed at enhancing the LLM-based VLN agent’s **contextual understanding**, with a focus on both *scene understanding from images* and *spatial reasoning within the environment*. Our approach generates textual descriptions of the visual observations and leverages the power of language to describe differences between images, enabling the agent to capturing higher-level scene understanding and spatial relationships. Specifically, instead of treating candidate images as isolated inputs and prompting LLMs to generate independent visual descriptions, we leverage VLMs to compare multiple images

and generate contextualized scene descriptions that highlight each image’s distinctive features. Furthermore, to strengthen the agent’s spatial reasoning, we encourage it to systematically organize and interpret the spatial relationships between images. Unlike previous methods (Zhou et al., 2024c; Pan et al., 2024) that rely on rigid thresholds to define nuanced spatial concepts (e.g., strictly labeling directions as “slightly left” or “further left”), our approach enables the agent to distinguish these subtle differences through explicit visual comparisons and language-based reasoning. Specifically, we generate a detailed descriptive paragraph that explicitly captures the spatial relationships among the images based on raw spatial attributes such as rotation angles and distances.

We evaluate our method on the VLN mainstream benchmark Room-to-Room (R2R) (Anderson et al., 2018) and REVERIE (Qi et al., 2020). Experimental results demonstrate that incorporating our proposed analogical reasoning and spatial descriptions significantly improve navigation performance compared to using raw text or images alone. Furthermore, combining images with our proposed textual descriptions yields the best performance, highlighting the effectiveness of our descriptions in enhancing the agent’s analogical reasoning, beyond what reasoning over visual input alone can provide.

2 Related Works

Vision-and-Language Navigation (VLN) is a challenging embodied AI task that requires an agent to navigate in a photo-realistic environment by instructions (Anderson et al., 2018; Ku et al., 2020; Qi et al., 2020). With the rise of foundation models, most VLN agents focus on integrating pre-trained models and generating large-scale datasets to enhance multi-modal representations (Chen et al., 2021; Qiao et al., 2022; Tan et al., 2019; Li et al., 2022; Wang et al., 2023; Wang et al.; Guhur et al., 2021; Li and Bansal, 2024; Zhang and Kordjamshidi, 2023, 2022b,a; Zhang et al., 2021, 2024c). Recently, LLMs and VLMs offer VLN a promising solution to mitigate domain-specific training constraints, particularly for zero-shot VLN agents (Zhou et al., 2024b,a; Chen et al., 2024; Long et al., 2024b; Zhang et al., 2024a; Zheng et al., 2024; Qiao et al., 2024). However, current LLM-based VLN agents struggle with distinguishing visually similar scenes and exhibit limited spatial understanding. Our goal is to improve agents

by addressing both challenges.

Analogical Reasoning is a cognitive process that involves comparing different entities to identify underlying structural similarities (Lovett et al., 2009; Lovett and Forbus, 2017; Huang et al., 2021; Grice, 1975; Mitkov, 2022; Fried et al., 2022). Recent work (Webb et al., 2023; Yu et al.) leverages analogical reasoning, particularly within large language models (LLMs), to improve their understanding and reasoning capabilities in tasks requiring structural alignment or relational comparisons. Analogical reasoning also facilitates comparisons between visual representations of objects observed from different camera views, leading to an improved global understanding of scenes (Mittra et al., 2023). Our work extends analogical reasoning to VLN tasks, enabling agents to compare discrete images, discern similarities and differences, and develop a global understanding of the environment.

3 Methods

In this section, we present our method, which builds upon MapGPT and aims to enhance analogical reasoning by using visual and spatial information of the environment. The model architecture has been shown in Fig 2.

3.1 Task Formulation

In the VLN task, an agent receives a natural language instruction, denoted as I . At each navigation step, the agent perceives visual observations consisting of n discrete images and selects one of these images as its action. The objective is to generate a trajectory (a sequence of images) that follows the given instruction. To achieve this, the LLM-based VLN agent takes multiple sources of information as input, including instruction I , history H_t , topological map M_t , observation O_t , and action space A_t . The agent’s decision-making process at step t is formulated as:

$$a_t = LLM(I, H_t, M_t, O_t, A_t), \quad (1)$$

where $a_t \in A_t$. As shown in Fig. 2, the history includes previous step actions, capturing the sequence of movements. The map shows the connectivity graph between places (images). The action space is defined as a combination of direction and image (place), where the direction is determined based on both heading and elevation, including: *go forward*, *turn left/right/around*, and *go up/down*.

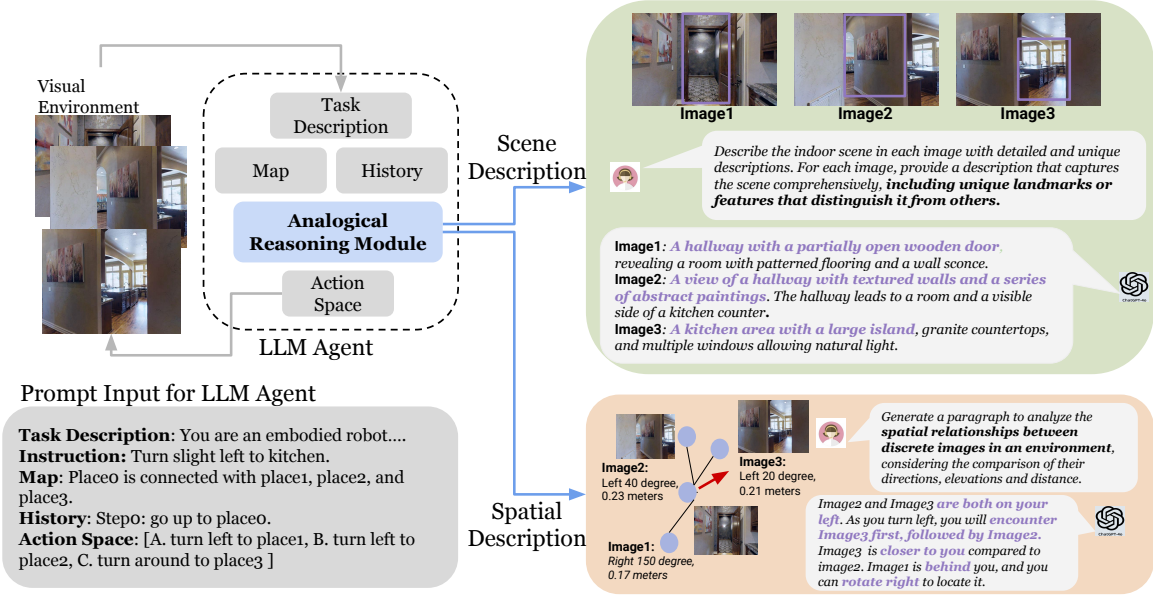


Figure 2: Model Architecture. Our method builds upon an LLM-based navigation agent that takes various prompt inputs (■). Built upon it, we introduce an analogical reasoning module composed of two components: analogical scene descriptions (■) and spatial descriptions (■).

3.2 Analogical Reasoning Module

As shown in Fig. 2, our analogical reasoning module consists of two components: scene descriptions, which highlight differences between viewpoint images, and spatial descriptions, which capture spatial relationships between viewpoint images and emphasize differences relative to the agent’s perspective.

3.2.1 Scene Descriptions

For different LLM-based VLN agents, one of the primary differences lies in how observations O are represented. For instance, NavGPT (Zhou et al., 2024b) and DiscussNav (Long et al., 2024a) utilize VLMs (e.g. BLIP-2 (Li et al., 2023)) to convert visual images into corresponding textual descriptions. While this approach enables language-driven navigation, it has a critical limitation: these textual descriptions treat each discrete image independently, disregarding contextual information across frames. However, a robust VLN agent should not only generate textual descriptions but also ensure that these descriptions encode contextual and relational differences across observations. To achieve this, we propose prompting LLMs to generate detailed visual descriptions while explicitly emphasizing the distinguishing features between different observations, which is formally denoted as follows:

$$OT_1, OT_2, \dots, OT_n = \text{LLM}(\text{Prompt}(O_1, O_2, \dots, O_n)), \quad (2)$$

where Prompt is instructions designed to guide the LLMs in generating an analogical analysis of the input. OT_i represents the textual description of the corresponding image O_i .

We illustrate our approach with an example in Fig. 2, where the prompts are demonstrated alongside the corresponding textual descriptions generated for the given images. Our method strategically prompts LLMs to identify distinguishing landmarks that differentiate each image from the others. As a result, the opening sentence of each visual description explicitly highlights these unique features, ensuring a clear comparative distinction. For instance, in Image 1, the description emphasizes a hallway featuring a wooden door, whereas in Image 2, the focus shifts to a hallway with paintings, leading to a room and a kitchen counter. Meanwhile, Image 3 directs attention to a kitchen area centered around a large island. By emphasizing analogical attributes rather than describing each image in isolation, our approach enhances contextual understanding and strengthens the model’s ability to discern subtle yet critical differences between visually similar scenes.

3.2.2 Spatial Descriptions

A key challenge for the LLM-based VLN agent is effectively representing the spatial structure of its visual environment. In current methods (Chen et al., 2024; Pan et al., 2024), the action space is highly

discretized, allowing only a generic directional instruction, *e.g.*, “turn left”, which are defined based on fixed angle thresholds. This classification overlooks subtle yet crucial spatial distinctions, such as differentiating a slight 5-degree turn from a more significant 30-degree rotation. Consequently, the agent cannot accurately interpret or respond to nuanced navigation instructions like “turn slightly left”, causing imprecise action decisions.

A straightforward approach to addressing this limitation is to directly provide raw heading and elevation values. For example, rather than the ambiguous instruction “turn left” the action space could specify “turn left 5 degrees”. However, our experiments (Appendix A.2) reveal that the agent struggles to effectively comprehend and integrate this fine-grained spatial information, suggesting that merely providing numerical orientation values is insufficient for enhancing its spatial reasoning.

To address this challenge, we draw inspiration from the approach of obtaining analogical scene descriptions from images and extend it to spatial understanding. Our approach focuses on constructing a structured contextual representation that captures spatial relationships across discrete images. Fig. 2 illustrates our designed prompts for describing spatial relationships. We begin by computing the spatial relation, including the relative rotational angle (*e.g.*, “left by 20 degrees”) and the relative distance (*e.g.*, “0.21 meters”; note that MapGPT ignores distance). These computed attributes are then incorporated into a structured prompt that guides the LLMs to generate a detailed paragraph analyzing the spatial relationships. The generated description explicitly considers directional comparisons, elevation differences, and distance variations, ensuring a comprehensive understanding of the spatial context. We provide full prompts in the Appendix A.1. We denote the generated spatial description as S , and our enhanced LLM agent’s decision-making process is finally defined as follows:

$$a_t = LLM(I, H_t, M_t, \{O_t, OT_t\}, S_t, A_t), \quad (3)$$

where $\{O_t, OT_t\}$ indicates that our agent can flexibly take either the image, its corresponding scene description, or both as inputs.

4 Experiments

4.1 Experimental Settings

Datasets and Evaluation Metrics. We evaluate our method on the R2R (Anderson et al., 2018) and

	Methods	NE↓	OSR↑	SR↑	SPL↑
R2R	NavGPT (with GPT-4)	6.46	42	34	29
	MapGPT (with GPT-4)	6.29	61.6	38.8	25.8
	MapGPT (with GPT-4V)	5.63	57.9	43.7	34.8
	MapGPT (with GPT-4o)	5.31	56.9	43.8	36.5
	Ours (with GPT-4o)	4.79	65.7	49.5	42.5
REVERIE	MapGPT (with GPT-4o)	-	43.33	30.00	22.58
	Ours (with GPT-4o)	-	50.00	33.16	26.09

Table 1: Results on the validation unseen set of the R2R dataset. We implement our method solely on GPT-4o (OpenAI, 2024), as GPT-4V has been deprecated.

Methods	#	Image	Text	GPT	SR↑	SPL↑
NavGPT	1	-	BLIP-2	GPT-3.5	16.7	13.0
	2	-	BLIP-2	GPT-4	41.2	25.4
MapGPT	3	-	BLIP-2	GPT-4o	38.5	26.9
	4	-	GPT-4o	GPT-4o	45.6	36.2
	5	✓	-	Qwen2.5-VL-7B	30.0	26.6
	6	✓	-	GPT-4v	47.7	38.1
	7	✓	-	GPT-4o-05-13	41.2	35.1
	8	✓	-	GPT-4o	47.7	38.7
	9	-	GPT-4o (SI)	GPT-4o	48.2	36.2
	10	-	GPT-4o (SP)	GPT-4o	47.4	36.2
Ours	11	-	GPT-4o (SI+SP)	GPT-4o	50.0	36.4
	12	✓	Qwen2.5-VL-7B (SI+SP)	Qwen2.5-VL-7B	32.4	28.1
	13	✓	GPT-4o (SI+SP)	GPT-4o	50.0	40.2

Table 2: Ablation Results on 72 diverse scenes (Chen et al., 2024) from the R2R dataset. All GPT-4o versions are from the 08-06 release, except GPT-4o-05-13. SI: scene descriptions; SP: spatial descriptions.

REVERIE (Qi et al., 2020), two standard benchmarks for VLN. We also follow MapGPT in conducting evaluations on a sampled subset of the R2R dataset for our ablation study, including 72 scenarios and 216 examples. Please also check our released code ¹.

Three main metrics are used to evaluate navigation performance: (1) Navigation Error (NE): the mean of the shortest path distance between the agent’s final position and the goal destination. (2) Success Rate (SR): the percentage of the predicted final position being within 3 meters from the goal destination. (3) Success Rate Weighted Path Length (SPL): normalizes success rate by trajectory length. (4) Oracle Success Rate: the agent passes by or stops at a graph node within 3 meters to the destination.

Implementation Details. We utilize GPT-4o-08-06 as the backbone for our LLM-based agent, given that GPT-4V has been deprecated. In this work, we employ GPT-4o-08-06 as the backbone for our LLM-based agent, as GPT-4V has been deprecated. MapGPT reports its results using GPT-4o-05-03, but our implementation with GPT-4o-08-06 achieves better performance (around 6% on success rate). To ensure deterministic outputs, we set

¹<https://github.com/zhangyuejoslin/VLN-Analogical-Reasoning>

the temperature to 0. Additionally, we constrain the agent’s decision-making process by limiting the maximum number of generated actions to 15 and the maximum token output from GPT to 2000.

4.2 Experimental Results

Table 1 shows the results on the R2R and REVERIE unseen dataset, demonstrating that our method significantly enhances the baselines, achieving around 4 – 6% improvement in both SR and SPL. Table 2 demonstrates our results on 72 diverse scenes. We compare our approach against other LLM-based agents, varying the image input, text input, and GPT backbones. We highlight several key findings: **First**, both scene and spatial descriptions contribute incrementally to navigation performance. Using row #4 as a baseline, we observe performance improvements when independently adding scene descriptions (row #9) or spatial descriptions (row #10), with further gains achieved when combining both types of descriptions (row #11). **Second**, our analogical reasoning descriptions also enhance the agent’s ability to reason over visual inputs. Comparing row #8 and row #13 shows that while raw images contain all necessary visual information, our structured text-based descriptions provide complementary high-level reasoning, leading to improved performance. **Third**, our approach generalizes across different backbones. For example, applying our method to another backbone model of Qwen2.5 shows consistent gains (comparing Row #5 with Row #12) confirms that our approach enhances performance beyond GPT-4o. **Fourth**, stronger captioners help better scene understanding. For instance, BLIP-2 (row #3) underperforms significantly compared to GPT-4o (row #4), showing the importance of a more advanced captioning model for generating informative text inputs. **Fifth**, including images significantly improves SPL. As shown in row #11 and row #13, visual inputs help the agent ground non-salient target objects directly, reducing the need for extra exploration and shortening paths (higher SPL). Without images, the agent requires additional steps to locate less visually prominent targets through textual descriptions alone, resulting in longer paths but ultimately similar SR.

4.3 Qualitative Examples

In addition to the quantitative results, Fig. 4 and Fig. 5 in Appendix 4.3 present two qualitative examples illustrating the effectiveness of the pro-

posed analogical scene and spatial descriptions. In Fig. 4, the scene descriptions generated by BLIP-2 and GPT-4o are highly similar despite the visual differences between the scenes. Even for GPT-4o, across three images, the descriptions primarily focus on the general scene, referring to an “*ornate chapel interior*” without providing distinguishing details. In contrast, our method emphasizes different aspects of each image: for example, Image 1 highlights “*the confessional booth*”, Image 2 focuses on “*the benches*”, and Image 3 emphasizes “*the grand altar*”. These distinct descriptions enable the agent to accurately select Image 2, which aligns with the given instruction. Furthermore, in Fig 5, We present an example demonstrating the effectiveness of spatial descriptions. In this case, both Image 4 and Image 5 contain an entranceway. However, our approach encourages the agent to infer that less left/right rotation corresponds to a direction closer to forward. As a result, the agent correctly reasons that Image 5 is better aligned with the instruction “*walk to*”.

5 Conclusion

In this paper, we propose enhancing the contextual understanding of LLM-based VLN agents by generating analogical scene and spatial descriptions. We encourage the agent to compare images from different perspectives and help the agent construct a structured spatial understanding of the environment. We evaluate our method on the R2R dataset and demonstrate that our approach significantly improves performance compared to LLM-based navigation agents.

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7 Limitation

Despite the significant improvement in navigation performance achieved by our analogical reasoning descriptions, several limitations remain. First, the quality of the generated descriptions heavily depends on the underlying language model, which

may introduce biases or hallucinations that could impact decision-making. Second, the process of generating analogical descriptions adds an additional computational step, potentially increasing processing costs compared to direct image-based navigation.

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A Appendix

A.1 Prompts for Spatial Descriptions

Fig. 3 shows the prompts we used for spatial descriptions.

A.2 Different Strategies for Spatial Reasoning

We conduct experiments to examine how different spatial reasoning strategies impact navigation performance. Intuitively, enabling an agent to understand nuanced spatial concepts can be achieved by explicitly incorporating varying degrees of rotation into its action space. For example, the agent’s action space is more precisely defined, such as “*turn 5 degrees left*”. However, our results reveal that introducing fine-grained rotational actions leads to a slight decline in navigation performance (row #2 in Table. 3). This suggests that VLN agents struggle to effectively structure spatial information when relying solely on numerical rotations degrees. To address this, we propose generating descriptive paragraphs that systematically capture spatial relationships between images. Empirical results demonstrate that our approach enhances navigation performance compared to directly using numerical values into the action space (#3 in Table. 3).

#	Methods	SR $\uparrow$	SPL $\uparrow$
1	MapGPT	47.7	38.7
2	+spatial attributes	46.8	37.9
3	+spatial descriptions	49.1	39.3

Table 3: Different strategies for spatial reasoning.

A.3 Failure Cases Discussion

One type of failure come from hallucination issues, these are inherently related to the specific LLM used; for instance, we observed more frequent hallucinations in BLIP compared to GPT-4o. Another important type of failure case we noticed occurs when the agent overly emphasizes intermediate landmarks. For example, given the instruction “walk past the dining table and head all the way up the stairs,” the optimal action would be to directly select an image clearly showing the stairs, treating the dining table merely as a passing object. However, the model occasionally prioritizes the intermediate landmark (“the dining table”), potentially directing its attention away from the main goal. To address this, we recognize that analogical reasoning alone may not fully resolve this issue, and suggest that incorporating a hierarchical reason-

Prompt for Spatial Descriptions

Generate a paragraph to analyze the spatial relationships between discrete images in an environment, considering the comparison of their directions, elevations and distance. The input consists of images with specific angles and distances relative to a central point. Here are some rules to follow: Angles between 120 to 240 degree to the left or right indicate behind or around. Angles equals 180 degrees indicate direct behind. Less angles rotation degrees to the left or right indicate closer to the forward direction. For example, Given places along with their spatial information: Place0 is to my right 180.0 degrees and up 30.0 degrees, positioned 0.21 meters away, Place 2 is to my right 60.0 degrees and up 30.0 degrees, positioned 0.21 meters away Place 3 is to my right 90.0 degrees and up 30.0 degrees, positioned 0.18 meters away. Place 4 is to my right 90.0 degrees, positioned 0.05 meters away. Please generate a descriptive paragraph explaining the spatial relationships and navigation steps to these images. For example: “To navigate to Image0, Image2, and Image3, you need to move upward. As you turn right, you will encounter Image2 first, followed by Image3, and finally Image0, which is directly behind you. Image4 is in the same direction as Image3, but Image3 requires looking up while Image4 does not. Additionally, Image4 is very close to you.” Output the response in JSON format with the key ‘environmental analysis.’ ”

Figure 3: Prompt for Spatial Descriptions.

ing process to explicitly prioritize target landmarks could improve navigation performance.

Instructions: *Walk forward to the padded benches.*



Scene Descriptions (BLIP-2)

Image1: In the scene, there is an **ornate wooden room with a red curtain**. The room also features two chandeliers hanging from the ceiling, adding a touch of elegance to the space.

Image2: In the scene, there is an **ornate wooden altar with a chandelier** hanging above it. The altar is adorned with intricate carvings and decorations, giving it a sense of grandeur and elegance.

Image3: In the scene, there is an **ornate wooden altar with intricate carvings**. The altar is adorned with two red chairs placed in front of it, creating a cozy and inviting atmosphere.

Scene Descriptions (GPT-4o)

Image1: The image depicts an **interior space with a classic, ornate design, featuring wooden paneling and red drapery**. The room showcases a red velvet bench and curtains, with intricate wooden carvings.

Image2: The image depicts an **ornate, traditional chapel interior with rich red and wooden tones**. Red velvet curtains and cushioned kneelers contrast with the intricately carved wooden altar and paneling.

Image3: **The image depicts an ornate chapel interior with a richly decorated altar and wooden paneling**. The altar features intricate carvings and religious icons.

Analogical Scene Descriptions (GPT-4o)

Image1: The scene depicts an ornate interior space with a focus on a **wooden confessional booth**. The booth features intricate woodwork and is partially enclosed by a red curtain.

Image2: This image showcases a richly decorated interior with **a series of red velvet benches facing a wooden altar**. The altar is intricately carved, featuring religious iconography. Above, **chandeliers hang from the ceiling**, adding elegance to the space. The walls are lined with red curtains.

Image3: The focus here is on a **grand altar set against a backdrop of detailed wood carvings** depicting religious figures. The altar is flanked by red velvet benches, and the ceiling is adorned with ornate chandeliers.

Figure 4: A qualitative example demonstrating the effectiveness of analogical scene descriptions. We collect scene descriptions from both BLIP-2 and GPT-4o. Bold text highlights similar descriptions across images, while text in green boxes represents our generated analogical scene descriptions, each emphasizing different aspects.

Instructions: *Walk to the end of the entrance way. Continue straight until you reach the dining room.*



MapGPT: The instruction is walk to the end of the entrance way. Image 4 shows a hallway that seems to lead further into the building, which aligns with the instruction to walk to the end of the entrance way. I should go to Place 4.

Environmental Analysis: To navigate through the environment, begin by turning to your right to encounter image 5. As you turn left, you will encounter image 4, image 3, image 2, and image 1. Image 2 is directly behind you. Image 5 is closer to the forward direction.

Ours: The instruction suggests that I need to walk through an entrance way, and eventually reach a dining room. The images provided do not directly depict a dining room or a kitchen area, but they do show hallways and rooms with seating areas. Based on the **environmental analysis**, Image 5 are the most straightforward to access, and correspond to the same hallway description. I should go to Place 5.

Figure 5: A qualitative example illustrating the effectiveness of our spatial descriptions. The agent successfully identified Place5 based on its relative position, as it is closer to the forward direction than other images and better aligned with the instruction “walk to” compared to Place4, which requires a significant left turn.