

Navigation with VLM framework: Go to Any Language

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Abstract—Navigating towards fully open language goals and exploring open scenes in a manner akin to human exploration have always posed significant challenges. Recently, Vision Large Language Models (VLMs) have demonstrated remarkable capabilities in reasoning with both language and visual data. While many works have focused on leveraging VLMs for navigation in open scenes and with open vocabularies, these efforts often fall short of fully utilizing the potential of VLMs or require substantial computational resources. We introduce Navigation with VLM (NavVLM), a framework that harnesses equipment-level VLMs to enable agents to navigate towards any language goal specific or non-specific in open scenes, emulating human exploration behaviors without any prior training. The agent leverages the VLM as its cognitive core to perceive environmental information based on any language goal and constantly provides exploration guidance during navigation until it reaches the target location or area. Our framework not only achieves state-of-the-art performance in Success Rate (SR) and Success weighted by Path Length (SPL) in traditional specific goal settings but also extends the navigation capabilities to any open-set language goal. We evaluate NavVLM in richly detailed environments from the Matterport 3D (MP3D), Habitat Matterport 3D (HM3D), and Gibson datasets within the Habitat simulator. With the power of VLMs, navigation has entered a new era.

Index Terms—Navigation, Embodied AI, Open Vocabulary, Vision Language Model, Exploration.

I. INTRODUCTION

To explore an utterly novel environment like humans is a capability that agents have not achieved so far. The critical factor that matters most is missing: the ability to reason about the information from the current environment, much like the human brain does. For instance, to complete task “taking a bath,” we know intuitively that we need to reach a restroom and can identify one based on the presence of specific furniture. Sensing where and whether a place is suitable for the task and navigating to it is challenging for current navigation systems, yet it is essential for achieving human-level navigation.

With the development of Vision-Language Models (VLMs) [1]–[4], the reasoning challenge can now be promisingly addressed. The VLMs can serve as cognitive core of the agent and give guidance during the navigation [5] as they have the ability to perceive the environment. Several works [6]–[8] are dedicated to integrate VLM in navigation, but they have not utilized VLMs in a simple, neat, and effective way to guide navigation, nor have they fully exploited the VLM’s

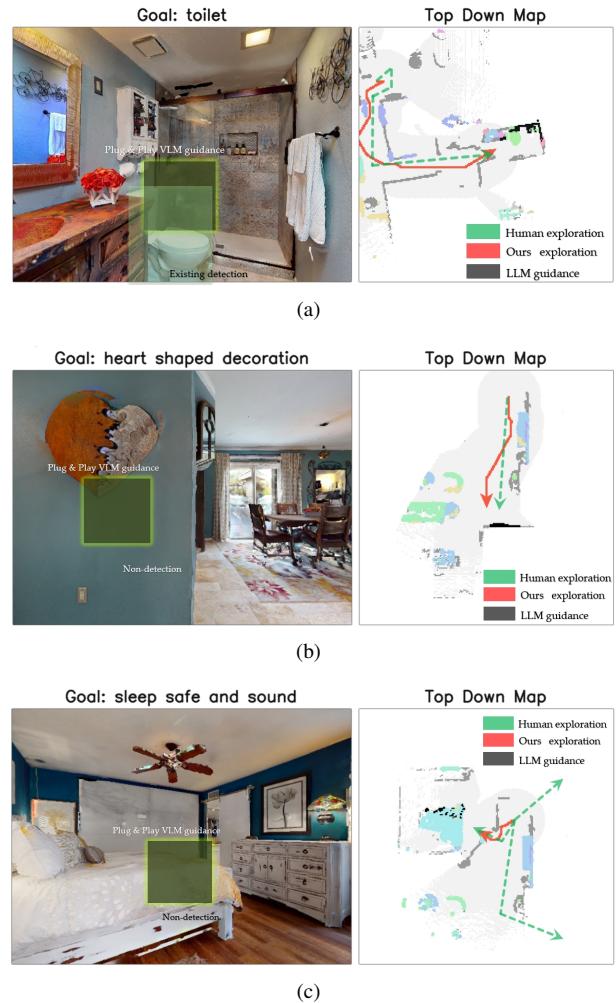


Fig. 1. 1(a):NavVLM can perform human level exploration in open scenes for traditional specific goals. 1(b): NavVLM can guide to out-of-domain language goals. 1(c): NavVLM can navigate to any non-specific languages such as actions, areas or categories. In 1(b) and 1(c), navigation solely relies on guidance provided by NavVLM.

ability to extend the language goal to any language (detailed comparison in IV). For example, with fixed positions in a closed scene, [9] uses VLMs to describe areas and build a room graph, and uses language modalities through entire navigation, which sacrifices the open exploration capability that VLMs inherently possess. [6], [7] attempted to convey

TABLE I
NAVIGATION LANGUAGE GOAL COMPARISON.

Language Goal	Expl.+Detect.	Recent	Ours
apple	✗	✓	✓
apple on desk	✗	✓	✓
apple on white desk	✗	✓	✓
rot apple	✗	✗	✓
cook dinner	✗	✗	✓
laboratory 208	✗	✗	✓
any language	✗	✗	✓

embodied information into VLMs through extensive training, but this approach incurs significant costs in terms of dataset requirements and application when generalizing to many other scenarios. [10], [11] utilizes the similarity between the current observation image and the long-term language goal to rank exploration frontier points to "guide" navigation. This approach requires no training and is thus easy to apply, but it lacks the intelligence required for human-level navigation and may struggle to navigate to non-specific language goals.

In this paper, we propose Navigation with VLM, a plug-and-play framework that enables an agent to navigate to any language-defined goal, specific or non-specific in a manner akin to human behavior, without requiring any training. We exhibit the language goal navigation capability in table I for clear comparison, where in "Expl." stands for exploration, "Detect." denotes detection module [12]–[15], "Recent" refers to recent VLM based navigation works [6], [7] and language-image similarity based works [10], [11]. Our framework collaborates VLMs and existing navigation systems to achieve intelligent explorations in open scenes in a neat and effective way.

II. OPEN SET NAVIGATION PROBLEM DEFINITION

For an agent initialized in any random location within an open scene and possessing no prior knowledge, the Open Set Navigation is to enable the agent to autonomously explore and navigate to an **open language goal** without any additional human instructions [10], [16]–[18]. The completion of such tasks is evaluated using two primary metrics: Success Rate (SR) and Success weighted by Path Length (SPL) [19].

It is important to note that, in addition to traditional very specific goals, such as a specific object category with limited location information (e.g., "apple" or "bed in the living room"), our framework is capable of handling extremely **ambiguous language goals**. These can include phrases like "a corner in the kitchen" or "somewhere I can rest," as well as completely out-of-domain goals, such as "laboratory 208".

We demonstrate state-of-the-art statistical performance for specific goals in the section V and, due to the sparsity of open-goal navigation datasets, can only present cases for non-specific goals1(b). However, these examples excellently demonstrate the capability of our framework and the potential future.

III. NAVVLM FRAMEWORK

This section explains the components of our framework and how they cooperate with each other. The overall process

is shown in Figure 2 and a detailed demonstration of the process is provided in Algorithm 1. In the Algorithm 1, the O_t represents the observation from environment at step t , p is prompt, E is the existing navigation system, T is maximum step number, $SLAM$ is the map construction and mapping module, M is the top-down map, G is the VLM guidance in M , $Render$ is the heuristic rendering module that brings VLM guidance into image, stg is short-term-goal. The stg is the short term destination area given either by VLM or existing navigation system E .

Algorithm 1 Pseudo-Code of the Overall Algorithm

```

1:  $t \leftarrow 0$ ;
2: while True do
3:    $O_t \leftarrow getObservation()$ ;
4:    $done \leftarrow VLM(O_t, p_1) \vee E(O_t)$ ;
5:   if  $done \vee t == T$  then
6:     break
7:   end if
8:    $M_t \leftarrow SLAM(O_t)$ ;
9:    $G \leftarrow VLM(O_t, p_2)$ ;
10:  if  $G \in \{left, right, forward\}$  then
11:     $O_G \leftarrow Render(O_t, G)$ ;
12:     $stg \leftarrow SLAM(O_G)$ ;
13:  else
14:     $stg = E(O_t)$ 
15:  end if
16:   $a_t \leftarrow PathPlanner(M_t, stg)$ ;
17:   $stepAction(a_t)$ ;
18:   $t \leftarrow t + 1$ ;
19: end while

```

A. Interact with Environment

Every move in the environment triggers the agent to receive an observation (RGB-D) from the environment. After the agent receives the information from the environment, the agent will ask VLM 2 prompts in order. **Determine to terminate** by prompting if the goal is close enough in current the observation and **identify guidance** by prompting what area in the image should the agent go to in order to reach the goal. If the VLM provide guidance, the agent will activate the path planner to go the the recommended guidance area. If the VLM does not provide valid information or explicitly orders to explore more, the navigation process temporarily reverts to existing navigation strategy.

B. VLM Guidance

The VLM acts as the cognitive core of the agent, playing a key role in mimicking and reasoning like humans do. With few simple prompts such as "to get the goal which direction should I go?", the VLM could provide direction at current observation to reach the final language goal. We select basic directions such as "left, right, go straight, explore more" as the VLM guidance key words.

To convert guidance keywords from VLM into actionable navigation information, we we use a simple image rendering

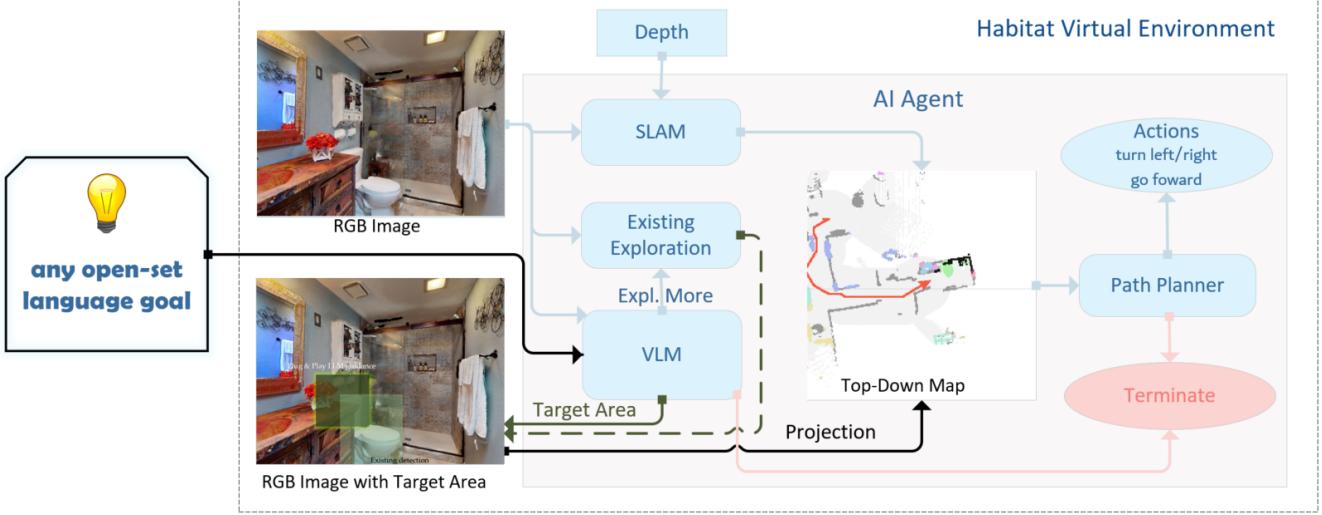


Fig. 2. The overall framework. At each new step, receives RGB and textual prompts to provide navigation guidance based on the current observations. The robot will go to the targeted area given either by VLM or existing navigation via path planner. In this process, the VLM acts as a high level commander, taking control of navigation when it has specific guidance and remaining passive when it does not. NavVLM complements intelligent navigation without compromising the existing, serving as a plug-and-play enhancement at minimal cost. Moreover, with NavVLM, we can expand language navigation to non-specific goals.

component to render a rough guidance area in the image. For example, the system renders the center-left area when the VLM suggests going “left” according to the image observation. In this way the VLM’s reasoning information can be used to guide navigation. The SLAM component will then project this area onto top-down map for later navigation path planner. In cases where the VLM does not provide guidance or explicitly recommends further exploration, our framework activates the the existing exploration component such as frontier exploration [20] temporarily to gather further information about the environment. Throughout this process, the VLM guidance can take over whenever the VLM identifies an area of interest. This approach is intuitive, mirroring how humans often find themselves exploring more actively when they are uncertain about their destination or path.

The VLM guidance provides a heuristic area rather than a specific target. This is because recent language-prompted segmentation models [21]–[23] are primarily focused on perceiving information within the current image such as describing and locating objects and logic rather than predict possibilities in the future such as determining where to navigate. Therefore, these models are not directly applicable to our methods.

C. SLAM

During exploration, the agent continuously performs SLAM (Simultaneous Localization and Mapping) to create a top-down map of the explored area. This map is used by the agent to avoid obstacles and move to the area indicated by the VLM or existing navigation. Using RGB and depth data, we employ [18] to construct the top-down obstacle map. Specifically, [18] builds a point cloud based on depth data and constructs voxels based on the point cloud. Then, we compress the voxels vertically into a top-down map, which

includes everything observed, such as objects and VLM guidance.

D. Path Planning

Path planning involves moving the agent from one location to another while avoiding obstacles. As the top-down map is constantly updated during exploration, we use the fast marching method (FMM) [24] for path planning, as it is highly efficient with a constructed map. The path planning module provides specific actions, such as “turn right” at the current step, and ultimately guides the agent to the target area provided by either the VLM or the existing navigation system.

E. Navigation Termination

The termination of the task can occur under the following conditions:

- Reaching target area termination. The agent reaches the goal area as guided either by VLM or existing navigation system, with a threshold, determined by how close the agent is to the guided goal. The guidance area will be constantly updated during exploration.
- VLM termination. The VLM determines that the agent should stop here based on the current images. This is particularly suitable for ambiguous language goal such as “a corner in the kitchen”, as such goals are not specific to any objects and can only be processed with VLM. With the reasoning capability of VLM, the agent can determine whether the navigation task is complete based on the surrounding images observations, similar to human decision-making.
- Termination from existing navigation and max step termination.

To summarize, the core components of our scheme are: tiny VLM serving as the cognitive core and guide the agent navigation over the existing navigation system, SLAM for top-down map construction and information projection, and path planning instructing specific action such as "turn left", "turn right" for agent to move while avoiding obstacles. These components work together to perform intelligent navigation in human level in open environment. Note these components are not tightly coupled with our work and can be easily replaced accordingly.

IV. COMPARISON WITH OTHERS

This section highlights the differences between our framework and several recent prominent works.

[25] employs large models to enhance baseline navigation models, but it uses the VLM solely for selecting and ranking multiple frontier exploration spots at each step based on the language goal, rather than directly integrating the VLM into the navigation process, which greatly restricts the capability of the VLM. As the explored area expands, the number of frontier spots increases, which can slow down the exploration process. Furthermore, this work relies on multiple very large language models, such as GPT-4. In contrast, our framework utilizes a single small VLM [26] and fully exploits its capabilities in navigation, enabling intelligent exploration at a minimal cost.

In [27], the VLM serves as a high level planning system. The language goal has to be specific it requires multi-round dialog with the user. Similarly, in [28], its target objects are also described through a multi-round dialog with a user. Our framework, however, can navigate to any ambiguous language goal without requiring human conversations.

[11] utilize [29] to compute similarities between the RGB observation ahead and the language prompt to rank frontier exploration points, mimicking human exploration without the need for human conversations. However, the language prompt of the goal must be very specific, and the approach is fundamentally a prioritized frontier exploration. Although the ranking process imitates human thinking, the exploration points are still limited by frontier exploration. Our framework, on the other hand, can directly provide guided areas beyond the frontier circle, which is more effective for path planning and more closely resembles human-level behavior and thus achieving higher performance.

[10], [30] utilize [31] and [32] for image goal and language goal, successfully extending the modality to include images. However, the language or image goals are limited to very specific targets, and the navigation decision policy is made using Reinforcement Learning [33]. This approach struggles to exhibit human-level exploration behavior when faced with out-of-domain environments compared to the capabilities of VLMs.

[6] and [7] are VLMs applicable in navigation and other domains. For navigation, these models require substantial inputs such as point clouds, point cloud features, and historical latent embeddings. Additionally, the training, fine-tuning, and loading processes are resource-intensive for

edge devices. These are heavyweight models that cannot be deployed on edge equipment, which is the primary device for navigation. They are end-to-end models that do not integrate well with existing effective exploration techniques like frontier-based exploration. Our framework can cooperate with existing navigation systems while integrating at minimal cost and achieving high performance in traditional specific language goals. Moreover, it can extend the goal to a fully open language set.

In summary, our framework offers unique features that recent VLM-based works lack:

- **Cost-Free:** Utilizes a single small VLM, enabling low-cost integration while achieving high performance.
- **Human-Level Exploration:** Capable of navigating to ambiguous language goals in almost human level manner and without human conversations.
- **Open-set Language Goal:** Extends the language goal set from traditional specific goals to a fully open language set.
- **Collaboration with Existing Systems:** Cooperates with existing navigation systems while integrating at minimal cost.

V. EXPERIMENT

A. Experiment Setup

We conducted our experiment in Gibson [40], HM3D [41], and MP3D [42] scenes, and implemented with Habitat [43], [44] simulation from Meta. We select VLM named minicpm-llama3-v2.5 as the cognitive core of the agent, a version of minicpm [26] series, which is a tiny VLM capable of deployment on a mobile device. The entire experiment can be conducted in only one single RTX3090 GPU in half-precision mode. The agent's actions included moving forward 0.25 meters, turning right 30 degrees, turning left 30 degrees, and terminating. We used SPL (Success weighted by Path Length) and SR (Success Rate) [19] as evaluation metrics. Performance comparisons are presented in Table II.

B. Performance Analysis

Our framework outperforms all baselines in SPL and achieves competitive SR scores across all datasets. SPL measures the average closeness of the agent's path to the optimal path, which is the geodesic shortest path from the start position to the goal position. SR measures the likelihood that the agent successfully navigates to the language goal. The comparison of SPL shows that with the VLM as the cognitive core, the agent is most likely to find the "best" path to the goal, significantly surpassing baseline methods. This is because the VLM thinks and recognizes possible locations in the image to find the goal. For example, to find a bowl, the VLM guides the agent towards the kitchen area once a distant view of the kitchen appears in the observation, as it knows bowls are more likely to be found in kitchens. This logic mirrors human exploration.

TABLE II
PERFORMANCE COMPARISON

Approach	Training	Fully	Gibson		HM3D		MP3D	
			Requirement	OpenSet	SPL↑	SR↑	SPL↑	SR↑
PONI [34]	ObjectNav	✗	41.0	73.6	-	-	12.1	31.8
PIRLNav [35]	ObjectNav	✗	-	-	27.1	64.1	-	-
RegQLearn [36]	ObjectNav	✗	31.3	63.7	-	-	-	-
SemExp [18]	ObjectNav	✗	33.9	65.7	-	-	-	-
ZSON [37]	ImageNav	✗	-	-	12.6	25.5	4.8	15.3
CoW [38]	None	✗	-	-	-	-	22.3	39.2
SemUtil [39]	None	✗	40.5	69.3	-	-	-	-
OpenFMNav [25]	None	✗	-	-	24.4	54.9	-	-
VLFM [11]	None	✗	55.2	84.0	30.4	52.5	17.5	36.4
Ours	None	✓	56.4	72.3	33.5	48.0	27.9	40.0

C. Ablation Study

The SemExp [18] is the existing navigation system we built upon, and we compare our performance against it. The SPL is boosted by an absolute 22% (64% relative increase) and SR is lifted by 6.6% (10% relative increase), representing a significant performance improvement.

D. VLM Integration

As mentioned in Section III-B, currently no existing methods are directly applicable to our task. We explored several integration options: **1. End-to-end**, where the VLM directly provides movement commands based on the current observation; **2. Precise location**, where the VLM directly provides bounding boxes or masks in the RGB image, guiding the agent to the area; **3. Rough location**, where the VLM provides navigation directions (e.g., left, right) based on the RGB image and renders the target area, which is then projected into the top-down approximate area to guide navigation.

Through experimentation, we found that the **Rough location** method integrates the VLM more effectively than the other options, as the equipment-level VLM excels at logical reasoning and language processing but struggles with precise localization and end-to-end control.

E. Empirical Observations

In our experimental setup, when the image contains a distant view of any hint related to the language goal (such as a far view of the kitchen when the goal is to find the kitchen), the VLM recognizes it and successfully leads the agent in many cases, which is the reason why the agent are more likely to find the optimal path. This behavior aligns with the agent's ability to "think" and act in a manner similar to human exploration.

The termination criteria for the VLM become crucial when dealing with open-set language goals. No existing navigation method can handle such tasks except by leveraging a VLM. Our approach can significantly outperform existing language-image similarity methods in terms of dealing with extremely ambiguous language goals.

VI. FEATURES OF OUR FRAMEWORK

1) Any Language Goal: Our framework achieves navigation to both non-specific and specific language goals at a human level in open scenes with zero-shot learning for goals. For specific language goals, it requires fewer steps, as the VLM captures information from the environment and performs human-like reasoning during navigation. For non-traditional goals, our framework can fully exploit VLMs capability to navigate to a fully open set of goals, whereas recent works cannot. With the VLM acting as the cognitive core of the agent, our framework can navigate to anything specific or non-specific, as long as it can be described in human language.

2) Zero-Cost Integration: Every component of our framework requires no training or fine-tuning, eliminating concerns about collecting or generating new synthetic datasets and avoiding the costs associated with training. It is a plug-and-play method that can seamlessly integrate with various existing navigation systems without any additional cost.

3) Intelligent Navigation: The VLM serves as a logical path navigator and object finder in the current observation. Our framework can successfully capture various information from the environment, take fewer steps to navigate to the language goal, resulting in a noticeable performance improvement. For instance, for the goal "cooker in open kitchen," the agent will go straight to the kitchen where cooker might locate once a distant view of the kitchen appears in the observation, as the navigation is motivated by the VLM, a model with human-level reasoning abilities.

4) Promising Capability: The ultimate capability of our work is limited by the reasoning ability from VLM, and influenced by the SLAM and VLM guidance accuracy and the capabilities of the movement hardware. The VLM provides guidance to the agent, allowing it to explore regions in a manner similar to how humans would. If the VLM reasons well (which most modern VLMs do) and the VLM conveys accurate guidance, the exploration is likely to be near-optimal. We merely applied a tiny VLM in our framework and it can boost the navigation with a significant improvement. Considering the rapid development of VLMs

[4], the ultimate potential of our framework is even more promising.

5) *Modular Replaceable Components*: The core components of our scheme are VLM as the cognitive core, SLAM as top-down mapping and several path planning component. These component are non-coupled. The VLM can either be huge language model or tiny distilled model. The SLAM component can either be traditional or neural-based method, as long as it helps project the RGB image observation and VLM guidance area from RGBD to the map. The path planning component can vary according to the scene we need as long as it could provide valid actions and paths in the scene.

VII. FUTURE

1) *Need for Open Language Datasets*: There is a need for open language datasets. For non-specific object goals, such as "somewhere I can sit and eat," the location could be a corner with a table and chairs, or a place with a couch and a surface suitable for placing a meal. Currently, there are no existing datasets that provide information for such open language goals.

2) *Heuristic Guidance Area*: Our guidance area is rendered in the RGB image using a simple heuristic rule. A more accurate language and long-term-goal-driven segmentation model would undoubtedly improve the performance of our framework. Current language driven segmentation works are more focused on object-anchored alignment segmentation such as [21]–[23] rather than area-oriented segmentation. Accurate area oriented language driven segmentation is very much helpful in navigation.

3) *Accurate SLAM Module*: An accurate SLAM module is preferred. Our current SLAM component is adapted from [18], [30], which is primarily designed to handle flat floor environments and may struggle when faced with multi-level scenes such as duplex apartments and stairs. Objects higher than a certain threshold are often incorrectly classified as obstacles, limiting the system's ability to handle environments outside of typical home settings.

VIII. CONCLUSION

In this paper, we propose Navigation with VLM (NavVLM), a framework that enables the agent to explore the open scene in zero-shot settings in human exploration manner. The tiny equipment-level VLM of agent play as a cognitive core and cooperates with existing navigation system and constantly give exploration guidance throughout the navigation based on the language goals, thus enabling the agent to navigate to specific language goal and non-specific open set language goal. With its ease of integration, our framework can boost existing navigation system at least cost and achieve state-of-the-art performance on SPL and SR in various vivid navigation datasets. Due to the scarcity of open-set navigation datasets, the full potential of our framework's open-set language capabilities remains largely unexplored. We hope that this framework will serve as a potential prototype for future advancements in VLM navigation, as there is significant room for improvement and further exploitation.

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