Visual Agentic AI for Spatial Reasoning with a Dynamic API

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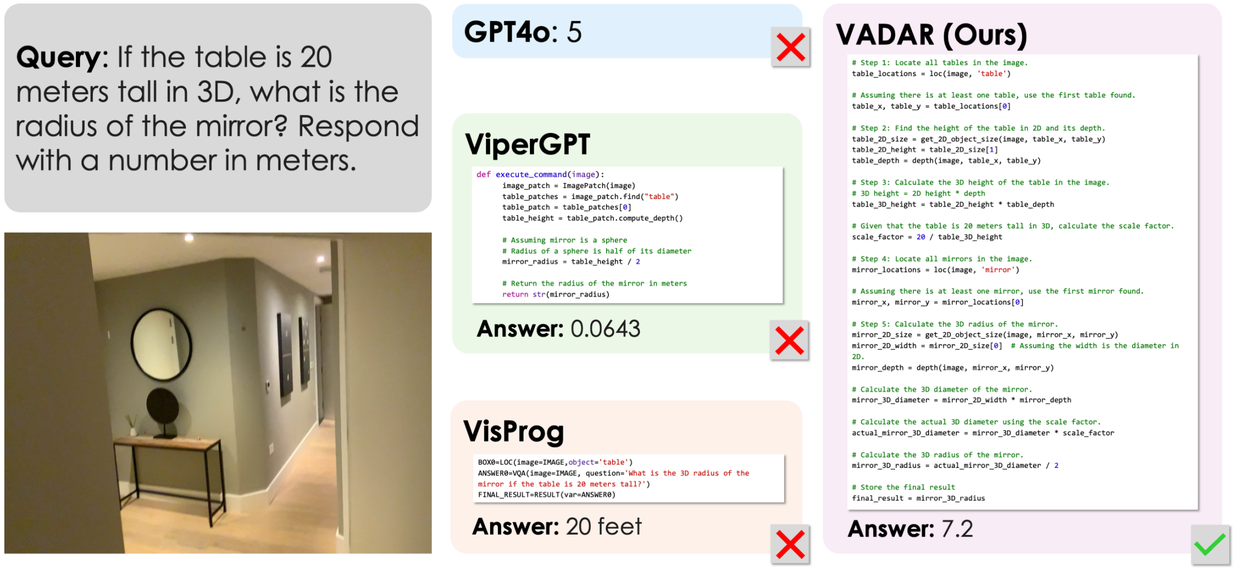

Query: If the table is 20 meters tall in 3D, what is the radius of the mirror? Respond with a number in meters.
GPT4o: 5
ViperGPT
Answer: 0.0643
VisProg
Answer: 20 feet
VADAR (Ours)
Answer: 7.2

```
def execute_command(image):
      image_patch = ImagePatch(image)
      table_patches = image_patch.find("table")
      table_patch = table_patches[0]
      table_height = table_patch.compute_depth()

      # Assuming mirror is a sphere
      # Radius of a sphere is half of its diameter
      mirror_radius = table_height / 2

      # Return the radius of the mirror in meters
      return str(mirror_radius)
```

```
BOX0=LOC(image=IMAGE,object='table')
ANSWER0=VQA(image=IMAGE, question='What is the 3D radius of the
mirror if the table is 20 meters tall?')
FINAL_RESULT=RESULT(var=ANSWER0)
```

```
# Step 1: Locate all tables in the image.
table_locations = loc(image, 'table')

# Assuming there is at least one table, use the first table found.
table_x, table_y = table_locations[0]

# Step 2: Find the height of the table in 2D and its depth.
table_2D_size = get_2D_object_size(image, table_x, table_y)
table_2D_height = table_2D_size[1]
table_depth = depth(image, table_x, table_y)

# Step 3: Calculate the 3D height of the table in the image.
# 3D height = 2D height * depth
table_3D_height = table_2D_height * table_depth

# Given that the table is 20 meters tall in 3D, calculate the scale factor.
scale_factor = 20 / table_3D_height

# Step 4: Locate all mirrors in the image.
mirror_locations = loc(image, 'mirror')

# Assuming there is at least one mirror, use the first mirror found.
mirror_x, mirror_y = mirror_locations[0]

# Step 5: Calculate the 3D radius of the mirror.
mirror_2D_size = get_2D_object_size(image, mirror_x, mirror_y)
mirror_2D_width = mirror_2D_size[0]  # Assuming the width is the diameter in
2D.
mirror_depth = depth(image, mirror_x, mirror_y)

# Calculate the 3D diameter of the mirror.
mirror_3D_diameter = mirror_2D_width * mirror_depth

# Calculate the actual 3D diameter using the scale factor.
actual_mirror_3D_diameter = mirror_3D_diameter * scale_factor

# Calculate the 3D radius of the mirror.
mirror_3D_radius = actual_mirror_3D_diameter / 2

# Store the final result
final_result = mirror_3D_radius
```

Figure 1. Spatial reasoning in 3D is challenging as it requires multiple steps of grounding and inference. We introduce a benchmark for 3D understanding with complex queries; an example is shown here. To tackle these queries we propose a training-free agentic approach, VADAR, that dynamically generates new skills in Python and thus can handle a wider range of queries compared to prior methods.

Abstract

Visual reasoning – the ability to interpret the visual world – is crucial for embodied agents that operate within three-dimensional scenes. Progress in AI has led to vision and language models capable of answering questions from images. However, their performance declines when tasked with 3D spatial reasoning. To tackle the complexity of such reasoning problems, we introduce an agentic program synthesis approach where LLM agents collaboratively generate a Pythonic API with new functions to solve common subproblems. Our method overcomes limitations of prior approaches that rely on a static, human-defined API, allowing it to handle a wider range of queries. To assess AI capabilities for 3D understanding, we introduce a new benchmark of queries involving multiple steps of grounding and inference. We show that our method outperforms prior zero-shot models for visual reasoning in 3D and empirically validate the effectiveness of our agentic framework for 3D spatial reasoning tasks. Project website: https://glab-caltech.github.io/vadar/

*Equal contribution.

1. Introduction

Consider Fig. 1. Here, a person or an agent wants to determine the radius of the mirror in the image, given that the table is 20 meters tall. Answering this question requires visual reasoning, a crucial step toward achieving general-purpose AI. Visual reasoning enables machines to analyze and make sense of the visual world. Humans rely heavily on visual cues to navigate complex environments, interact with objects and make informed decisions. Our goal is to build intelligent agents that can do the same. Recent advances in AI have produced vision and language models (VLMs) [1, 2, 8, 36] that can answer questions from images. Although impressive, these models excel primarily at category-level semantic understanding. Their performance significantly declines when tasked with spatial understanding within the three-dimensional world [6, 19, 38].

Returning to Fig. 1, to answer the query, an AI agent must first locate the relevant objects, determine their dimensions in pixel space, use their depth to calculate their 3D sizes, and finally compute the mirror's radius using the table's height. This is a complex sequence of tasks, involving multiple steps of understanding, grounding, and inference. GPT4o [1], a state-of-the-art VLM trained on extensive datasets, gives a wrong final answer.

To address the complexity of 3D spatial reasoning tasks, we propose a system of agents working collaboratively to create executable programs for a given image. Our approach leverages LLM agents that *dynamically* define and expand a domain-specific language (DSL) *as needed*, generating new functions, skills and reasoning, in two phases: the **API Generation** and the **Program Synthesis** stage. Vision specialists – an object detector, a depth estimator and object attribute predictor – help the agents execute the program. We name our approach VADAR, as it integrates Visual, Agentic, Dynamic AI for Reasoning. VADAR belongs in the family of visual program synthesis methods, like ViperGPT [35] and VisProg [12], but addresses a key limitation in these approaches: their reliance on a static, human-defined DSL, which restricts them to a predefined range of functionality. This limitation is evident in Fig. 1, where ViperGPT generates an incomplete, inaccurate program and VisProg defaults to a holistic visual question answer (VQA) approach for answering the query. VADAR's output in Fig. 1 demonstrates its ability to tackle a wider range of visual queries.

We evaluate 3D spatial reasoning using challenging benchmarks designed for rigorous assessment of 3D understanding. Our evaluation includes CLEVR [18] and our newly introduced benchmark, OMNI3D-BENCH, based on Omni3D [5]; Fig. 1 shows an example. Both datasets emphasize visual queries involving relative depth, size, and object location, often conditioned on measurement hypotheses, requiring grounding and 3D inference. This contrasts with previous spatial reasoning benchmarks like GQA [16], which primarily emphasize appearance-based reasoning.

At a high level, VADAR roughly mirrors the workflow of a software engineer when defining, implementing, and testing new software solutions for a given problem. Leveraging its agentic design, VADAR autonomously defines and implements functions such as `_find_closest_object_3D`, `_is_behind`, `_count_objects_by_attributes_and_position`, `_is_left_of`, and more. These functions are used by the Program Agent, resulting in more concise programs, less output tokens and thus a lower likelihood of errors from LLM-generated predictions. We empirically show that VADAR outperforms a *no-API* agent by 6%, highlighting the value of general, reusable, functions within an API. Moreover, we show that our generated API significantly surpasses a static, human-defined API used in [12, 35], by more than 20% on CLEVR. VADAR performs competitively with state-of-the-art VLMs, on OMNI3D-BENCH, while also providing executable programs.

Considering the rapid progress in AI, one might wonder if methods like VADAR can dominate monolithic VLMs in 3D spatial reasoning. One clear advantage of VADAR is its ability to generate interpretable programs. However, our experiments highlight another key potential. Improving VLMs for 3D reasoning would require extensive datasets of image-question-answer tuples with 3D information, an onerous endeavor. In contrast, our experiments show that if the component vision models – an object detector, an attribute predictor and depth estimator – were replaced with oracle versions, VADAR would achieve 83.0% accuracy, 24% higher from the best VLM. This indicates that VADAR is bottlenecked by the performance of its vision specialists. Thus, an alternative path to scaling 3D spatial reasoning could be through improving specialized vision models, which tackle a simpler problem than general-purpose VQA and for which training data is more readily available.

2. Related Work

Our work draws from areas of language modeling, visual program synthesis and library learning.

VLMs for Spatial Reasoning. LLMs [1, 2, 9, 36] are trained on large corpora of text, including domain specific languages (DSLs) such as Python. Their multi-modal variants incorporate images and are additionally trained on image-text pairs showing impressive results for visual captioning and vision question-answering (VQA) [3]. Despite their strong performance, their ability to reason beyond category-level semantic queries is limited. Recent work [19, 38] shows that VLMs suffer on visual tasks such as grounding spatial relationships and inferring object-centric attributes. SpatialRGPT [7] and SpatialVLM [6] use data synthesis pipelines to generate templated queries for spatial understanding. We compare to SpatialVLM and show that it struggles to tackle 3D spatial reasoning queries.

Visual Program Synthesis. Recent advances in visual reasoning have led to methods which improve upon the capabilities of vision-based models by composing them symbolically via program synthesis. VisProg [12] prompts an LLM to generate an executable program of a specified DSL that calls and combines vision specialists – OwlViT [29] for object detection, CLIP [32] for classification, and ViLT [21] for VQA. ViperGPT [35] directly generates Python code by providing a Python API specification to the LLM agent and adds MiDaS [33] as the vision specialist for depth estimation, in addition to GLIP [25] and X-VLM [45] for vision-language tasks. Both approaches rely on a predefined DSL, which narrows the scope of applicability and makes these methods difficult to extend to a wider range of queries. Similar to ViperGPT, we use Python as the interface for our LLM agents, but we don't define the API a-priori. We instead rely on our agentic workflow to generate the API needed to tackle complex spatial reasoning queries. We compare to ViperGPT and VisProg and show that both struggle to generate accurate programs for complex queries, often completely ignoring part of the query.

Library Learning. An emerging field in LLM research focuses on the dynamic creation and extension of a set of reusable functions during problem-solving. Early work on library learning predates the use of LLMs [10, 23, 39], and focuses on a common architecture of iteratively proposing new programs and synthesizing commonly used components into a library. Modern approaches follow this same paradigm, but use LLMs to accelerate the synthesis of useful programs, applied to gaming [40], 3D graphics scripting [15], theorem proving [37], and symbolic regression [11].

Neuro-symbolic AI generates interpretable symbolic components for complex tasks and has been explored for a wide range of fields, including spatial reasoning [28], grounding of 3D point clouds [13], mechanistic modeling in scientific domains [11, 34], logical reasoning [30], amongst other areas. Closer to us is the logic-enhanced LLM, LEFT [14], that uses a dynamic DSL of first order logic structures and differentiably executes them using domain-specific modules. These modules, instantiated as MLPs, ground spatial concepts, *e.g.* *"is left of"*, and are *trained with supervision*. On CLEVR, VADAR, which is *training-free*, achieves the same performance as LEFT when trained with $\geq 10,000$ training samples. A benefit of our training-free approach is that it scales to new domains where 3D supervision is hard to acquire, as we show on our OMNI3D-BENCH.

Spatial Reasoning Benchmarks. Existing benchmarks test aspects of visual reasoning with free-form language [4, 24]. We focus on natural-image based ones. VQA [3] introduced the task of visual question answering. GQA [16] is a popular large-scale VQA benchmark with questions that pertain to object and attribute recognition, of mostly a single-step inference – *"What color is the cat next to the chair?"*, *"What type of vehicle is on top of the road?"*, *"Do the wildflowers look ugly?"*. RefCOCO [20] targets object localization with referring expressions such as *"the man in a red shirt"*. What's up [19] quantifies comprehension of basic 2D spatial relations such as *"left of"* and *"above"*. These benchmarks evaluate aspects of visual reasoning, but critically omit 3D understanding. Q-Spatial Bench [26] focuses solely on absolute 3D measurements. Cambrian-1 [38] proposes a VQA benchmark repurposing images and annotations from Omni3D [5], but its queries focus on the relative depth and depth ordering of objects with (2 or 3)-choice questions. Our benchmark also repurposes Omni3D annotations, but in contrast to Cambrian-1, we design more complex queries that extend beyond depth ordering and multiple choice. Concurrent to our work, VSI-Bench [44] introduces a video understanding benchmark focused on spatial relationships, which we discuss extensively in Appendix D.

3. Method

At the core of our approach is a dynamic API generated by LLMs that can be extended to address new queries that require novel skills. The goal of the API is to break down complex reasoning problems into simpler subproblems with general modules that can be used during program synthesis. Our approach consists of an API Generation stage and a Program Synthesis stage, illustrated in Fig. 2.

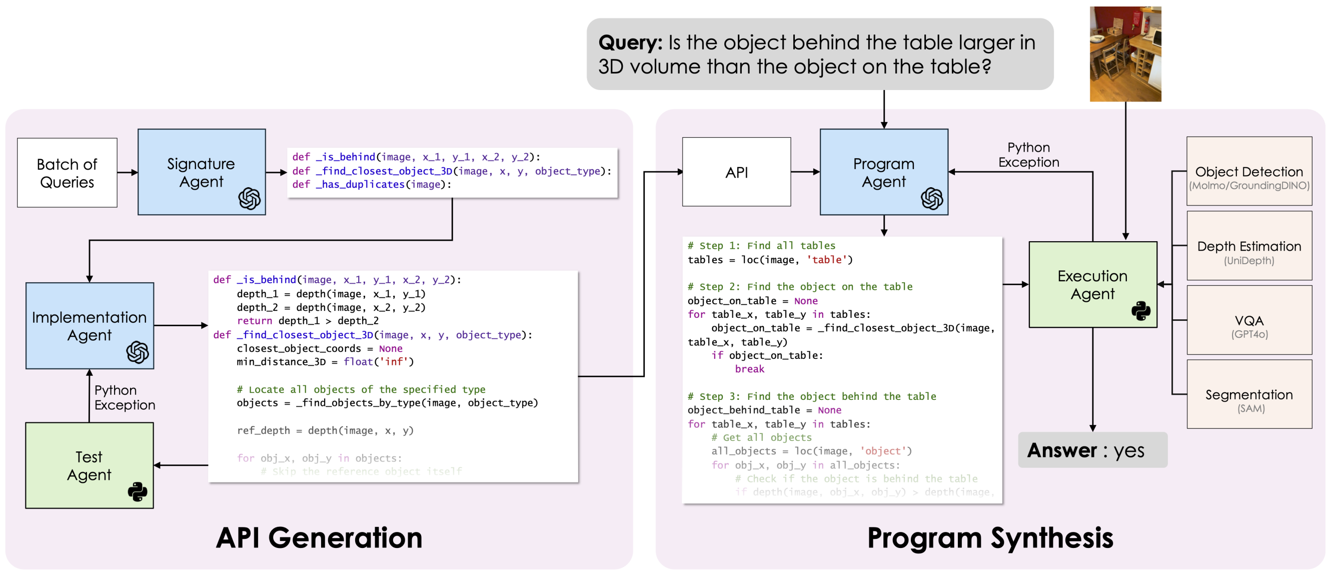
Vision Specialists. During program execution on the image, we employ vision models for solving visual subtasks: Molmo's [8] pointing model and GroundingDINO [27] are used to localize objects prompted with text (`loc`), SAM [22] returns the bounding box from the object's mask prompted with Molmo's points (`get_2D_object_size`), UniDepth [31] estimates the depth at an image location (`depth`), GPT4o is utilized as a VQA module to query object attributes (color, material) from an image with the target object bounding box overlayed (`vqa`). We initialize the API with these functions. The API also includes `same_object` that computes the overlap of two object bounding boxes to determine if the objects are the same.

3.1. API Generation

Algorithm 1: VADAR: API Generation

```
Data: Questions $\mathcal{Q}$
$\mathcal{S} \leftarrow \{\}$                        // Signatures
$\mathcal{A} \leftarrow \{$Vision Models$\}$          // API Methods
for batch $B \subset \mathcal{Q}$ do
    $\mathcal{S} \leftarrow \mathcal{S} \cup$ SignatureAgent($B$)
end
for $S \in \mathcal{S}$ do
    $e_S \leftarrow 0$                          // Error count
    $A \leftarrow$ ImplementationAgent($S$)
    $E \leftarrow$ TestAgent($A$)
    if Python Exception $E$ then
        if $e_S = 5$ then continue
        else if $E$ is "undefined method $U$" then
            $e_S \leftarrow e_S + 1$
            Recursively implement $U$
        else
            $e_S \leftarrow e_S + 1$
            Re-implement $S$ using $E$
        end
    else
        $\mathcal{A} \leftarrow \mathcal{A} \cup A$
    end
end
return $\mathcal{A}$
```

Algorithm 1 describes the API Generation. Here, the **Signature Agent** and the **Implementation Agent** collaborate to define and implement new functions *as needed* to



```
def _is_behind(image, x_1, y_1, x_2, y_2):
def _find_closest_object_3D(image, x, y, object_type):
def _has_duplicates(image):
```

```
def _is_behind(image, x_1, y_1, x_2, y_2):
    depth_1 = depth(image, x_1, y_1)
    depth_2 = depth(image, x_2, y_2)
    return depth_1 > depth_2
def _find_closest_object_3D(image, x, y, object_type):
    closest_object_coords = None
    min_distance_3D = float('inf')

    # Locate all objects of the specified type
    objects = _find_objects_by_type(image, object_type)

    ref_depth = depth(image, x, y)

    for obj_x, obj_y in objects:
        # Skip the reference object itself
```

```
# Step 1: Find all tables
tables = loc(image, 'table')

# Step 2: Find the object on the table
object_on_table = None
for table_x, table_y in tables:
    object_on_table = _find_closest_object_3D(image,
table_x, table_y)
    if object_on_table:
        break

# Step 3: Find the object behind the table
object_behind_table = None
for table_x, table_y in tables:
    # Get all objects
    all_objects = loc(image, 'object')
    for obj_x, obj_y in all_objects:
        # Check if the object is behind the table
        if depth(image, obj_x, obj_y) > depth(image,
```

Figure 2. **Overview.** VADAR consists of an API generation stage and a program synthesis stage. The Signature & Implementation Agents generate an API that is used by the Program Agent to produce a program to answer the question, executed by the Execution Agent.

aid in solving the queries. First, the Signature Agent receives a batch of N queries ($N = 15$), *without answers*, and is instructed to produce general method signatures for subproblems that could arise when answering those kinds of queries. The Implementation Agent then implements the signatures in Python. Examples of signatures and their implementations are shown in Fig. 2.

Prompting the Signature Agent. The agent receives the current API state as docstrings so it avoids duplicating existing methods. We observed that our Signature Agent performed better without in-context examples as it produced a more diverse API with wider potential functionality.

Prompting the Implementation Agent. The Implementation Agent receives all other signatures in the API along with the signature it needs to implement, so it can use other API methods in its implementation, enabling a hierarchy in the API. In contrast to the Signature Agent, providing in-context examples significantly enhances the Implementation Agent's output, as implementation prioritizes accuracy over diversity. We refer to these examples as *weak* in-context learning (ICL), as they guide correct method implementation in Python, unlike *strong* ICL, which breaks down queries into full programs. Prompts for both agents and weak-ICL examples are found in the Appendix.

Depth-First Implementation. Once a method is implemented from its signature, the Test Agent, a Python interpreter, runs it using placeholder inputs. If a runtime error occurs, the Test Agent signals the Implementation Agent to revise it with the exception message. However, if the implementation relies on another yet-to-be-implemented API method, the test run cannot proceed. In this case, the Implementation Agent traverses an implicit dependency graph, depth-first, ensuring that prerequisite methods are implemented first (see Algo. 1).

Consider the following example where the signatures `get_color`, `find_objects_by_color`, `count_objects_left_of`, and `is_left_of`, are defined by the Signature Agent, in that order. First, the Implementation Agent will implement `get_color`, the Test Agent will be called, and barring no runtime errors, the method will be complete. Then, the implementation for `find_objects_by_color` uses `get_color`, which is implemented, so the Test Agent only checks for Python errors. If `count_objects_left_of` attempts to use `is_left_of`, the Test Agent will detect that `is_left_of` is not implemented and recursively call the Implementation Agent to implement `is_left_of`, followed by `count_objects_left_of`.

In the event a cycle in the dependency graph is persistent after attempting the implementation of those methods 5 times, the methods in the cycle are deleted. Empirically, we rarely detect such cycles, which can be attributed to the Signature Agent producing multiple signatures at once, tending to avoid proposing signatures that overlap in function.

3.2. Program Synthesis

The **Program Agent** receives the generated API and a single question as input. Its task is to generate Python code that leverages the API to solve the question. The Execution Agent, another Python interpreter, executes the program line-by-line. In the event of a Python error, it provides the Program Agent with the exception, and a new program is generated. This is repeated at most 5 times, after which the program returns an execution error.

Algorithm 2: VADAR: Program Synthesis

```
Data: Image-Query pairs $\mathcal{D} = \{(I, Q)\}$,
      API methods $\mathcal{A}$
$\mathcal{R} \leftarrow \{\}$                          // Results
for $(I, Q) \in \mathcal{D}$ do
    $e_P \leftarrow 0$                         // Error count
    $P \leftarrow$ ProgramAgent$(Q, \mathcal{A})$
    $E, R \leftarrow$
      ExecutionAgent$(P, I,$ Vision Models$)$
    if Python Exception $E$ and $e_P < 5$ then
        $e_P \leftarrow e_P + 1$
        Re-generate $P$ using $E$
    else
        $\mathcal{R} \leftarrow \mathcal{R} \cup R$
    end
end
return $\mathcal{R}$
```

Prompting the Program Agent. Following the success of Chain-of-Thought (CoT) prompting [41], we instruct the Program Agent to create a plan before generating the corresponding program. In-context examples boost the Program Agent's performance. However, unlike VisProg [12] and ViperGPT [35] that use strong-ICL, we use API-agnostic natural language instructions since the API is not predefined, making it impossible to provide full program examples. These instructions help for the same reason as with the Implementation Agent, to focus on correctness. The prompt for the Program Agent is provided in the Appendix.

Test & Execution Agent vs Critics. In modern library learning, LLM agents, or critics, evaluate the quality and utility of learned functions. Our Test and Execution Agents also assess method quality, but we opt for deterministic critics that leverage the full Python runtime, signaling LLM Agents with Python exceptions in case of errors.

4. Experiments

We conduct experiments on challenging spatial reasoning benchmarks and demonstrate the effectiveness of a dynamically generated API by LLM agents compared to a static, human-defined API in ViperGPT [35] and VisProg [12], which we outperform by a large margin.

We also compare to monolithic state-of-the-art VLMs, trained on billions of (image, question, answer) samples, and show that our approach competes favorably and even surpasses them on certain question types while also providing interpretable reasoning steps to complex queries.

4.1. A Benchmark for Spatial Reasoning in 3D

We evaluate 3D spatial reasoning using CLEVR, and our newly introduced benchmark, OMNI3D-BENCH.

CLEVR [18] consists of (image, question, answer) tuples. Each image contains 2-10 objects of 3 different shapes, 8 colors, 2 materials, and 2 sizes. Despite the simplicity of the scenes, the questions in CLEVR are complex, *e.g.*, *"There is a large ball right of the large metal sphere that is left of the large object that is behind the small brown sphere; what color is it?"*. Our CLEVR benchmark contains 1,155 samples, 400 of which require a numerical answer, 399 are yes/no questions, and 356 are multiple-choice questions.

OMNI3D-BENCH is sourced from Omni3D [5], a dataset of images from diverse real-world scenes with 3D object annotations. We repurpose images from Omni3D to a VQA benchmark, with questions about 3D information portrayed in the image, such as *"If the height of the front most chair is 6 meters in 3D, what is the height in 3D of the table in the image?"* and *"How many bottles would you have to stack on top of each other to make a structure as tall in 3D as the armchair?"*. OMNI3D-BENCH complements CLEVR with *non-templated* queries pertaining to 3D locations and sizes of objects. Our queries test 3D reasoning, as they require grounding objects in 3D and combining predicted attributes to reason about distances and dimensions in three dimensions. OMNI3D-BENCH consists of 500 extremely challenging (image, question, answer) tuples.

We compare our proposed benchmark to GQA [16], a popular visual reasoning dataset. GQA derives queries from scene graphs which primarily pertain to the visual appearance and attributes of objects. Example queries in GQA are *"Is there a red truck or bus?"*, *"Is the field short and brown?"* and *"Is the chair in the top part of the image?"*. These are significantly simpler to queries in CLEVR and OMNI3D-BENCH which involve multiple steps of grounding and inference in two- and three- dimensions.

4.2. Results on Spatial Reasoning in 3D

Tab. 1 compares our approach, VADAR, to state-of-the-art VLMs and Program Synthesis methods. Fig. 3 additionally compares to the neuro-symbolic LEFT [14]. VADAR uses GPT4o with a temperature of 0.7 for all agents.

VLMs vs VADAR. VLMs, such as GPT4o [1], Claude-Sonnet [2], Gemini [36], Llama3.2-11B [9], and Molmo-7B [8], are monolithic models trained on vast of image-question-answer datasets, likely including samples with spatial and 3D information. We expect them to perform well on related tasks. We also compare to SpaceMantis [6, 17], the most recent and largest SpatialVLM [6] variant, finetuned on data with 3D information. We analyze performance based on three answer types: yes/no, multiple-choice and numerical answers. For queries with floating point answers, we report MRA [44] with thresholds $\mathcal{C} = \{0.5, 0.55, ..., 0.95\}$ for outputs $\hat{y}$ and ground truth y: $\mathcal{MRA} = \frac{1}{|\mathcal{C}|} \sum_{\theta \in \mathcal{C}} \mathbb{1}\left(\frac{|\hat{y} - y|}{y} < 1 - \theta \right)$

		CLEVR				OMNI3D-BENCH				
		numeric	y/n	multi-choice	Total	numeric (ct)	numeric (other)	y/n	multi-choice	Total
VLMs	GPT4o [1]	52.3	63.0	60.0	58.4	**28.1**	**35.5**	**66.7**	57.2	**42.9**
	Claude3.5-Sonnet [2]	44.7	61.4	**72.2**	**58.9**	22.4	20.6	62.2	50.6	32.2
	Llama3.2 [9]	34.6	45.6	49.0	42.8	24.3	19.3	47.5	27.4	25.6
	Gemini1.5-Pro [36]	44.9	59.7	67.0	56.9	25.2	28.1	46.2	37.6	32.0
	Gemini1.5-Flash [36]	43.1	58.8	56.8	52.8	24.3	27.6	51.1	52.9	35.0
	Molmo [8]	11.0	42.6	51.4	34.4	21.4	21.7	29.3	41.2	26.1
	SpaceMantis [6, 17]	14.5	52.9	32.3	33.2	20.0	21.7	50.6	48.2	30.3
Program Synthesis	ViperGPT [35]	20.5	43.4	13.4	26.2	20.0	15.4	56.0	42.4	26.7
	VisProg [12]	16.7	48.4	28.3	31.2	2.9	0.9	54.7	25.9	13.5
	VADAR (ours)	**53.3**	**65.3**	40.8	53.6	21.7	**35.5**	56.0	**57.6**	40.4

Table 1. **Accuracy (%) on CLEVR and OMNI3D-BENCH.** We compare to state-of-the-art monolithic VLMs and Program Synthesis approaches. For each benchmark, we breakdown performance for *numeric (ct)*, *numeric (other)*, *yes/no* and *multiple-choice* answers and report total accuracy. For *numeric (other)* queries, which require floating point answers, we report MRA. VADAR outpeforms ViperGPT and VisProg with a big margin. VADAR outperforms all large VLMs on OMNI3D-BENCH except GPT4o, which it is narrowly behind.

	CLEVR				OMNI3D-BENCH				
	numeric	y/n	multi-choice	Total	numeric (ct)	numeric (other)	y/n	multi-choice	Total
ViperGPT [35]	38.5	57.8	30.2	42.6	50.0	17.8	66.7	49.3	54.9
VisProg [12]	25.3	52.5	41.8	39.9	**100.0**	23.5	68.5	66.7	66.0
VADAR (ours)	**82.4**	**85.4**	**81.0**	**83.0**	**100.0**	**82.3**	**100.0**	**94.1**	**94.4**

Table 2. **Oracle accuracy (%) on CLEVR and OMNI3D-BENCH.** We evaluate program correctness by replacing vision specialists with oracle variants. VADAR's high oracle accuracy indicates its main limitation is the vision specialists' performance.

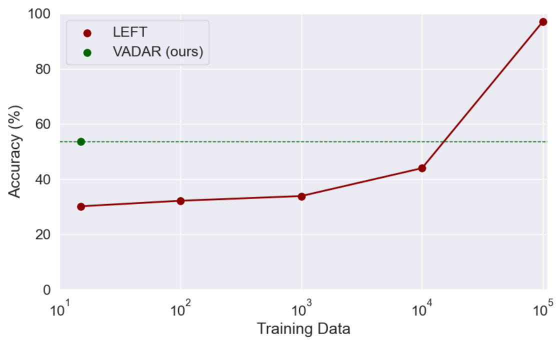


Figure 3. **LEFT [14] vs VADAR on CLEVR.** LEFT requires supervision. We vary the amount of training data (x-axis) and report accuracy (y-axis). VADAR requires *no* supervision but takes in 15 queries *without answers* to guide the creation of the API. VADAR outperforms LEFT trained with $\leq 10,000$ supervised examples.

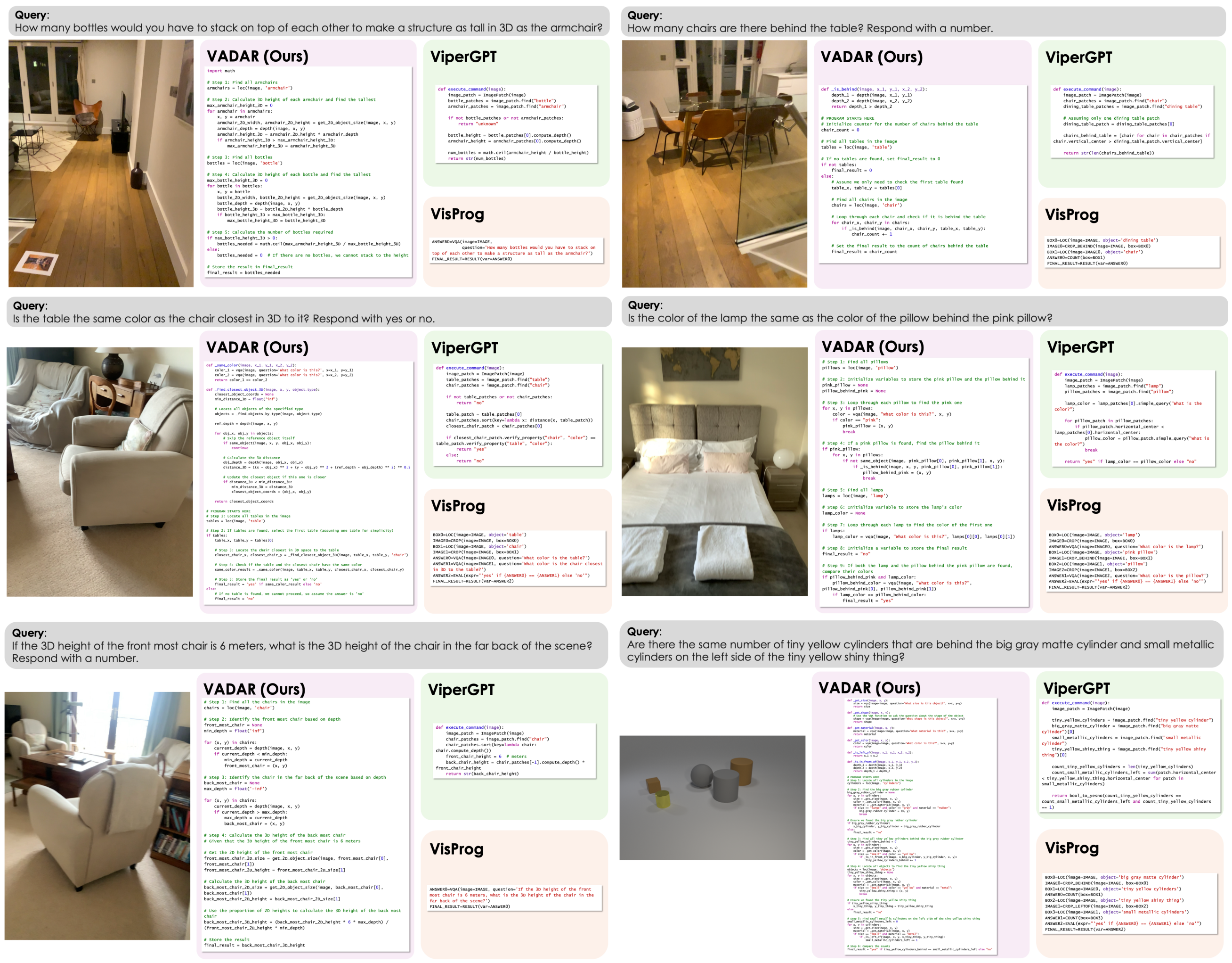
From Tab. 1, we observe that on CLEVR, GPT4o, Claude-Sonnet, and Gemini perform best on average while VADAR slightly outperforms VLMs on numeric (by 1.0%) and yes/no answers (by 2.3%). On the challenging OMNI3D-BENCH, VADAR is behind GPT4o by just 2% and outperforms all other VLMs by more than 5%. Llama3.2-11B and Molmo-7B perform worse among VLMs likely due to their smaller size.

ViperGPT vs VisProg vs VADAR. VADAR outperforms both models on both CLEVR and OMNI3D-BENCH by more than 20%. VisProg and VADAR use GPT4o as their LLM; ViperGPT uses GPT-3.5 as it performed better.

Separating program correctness from execution accuracy, Tab. 2 provides comparisons to ViperGPT and VisProg when vision specialists are replaced with oracle ones. On CLEVR, we use an Oracle Execution Agent that leverages the true scene annotations to provide the correct output automatically. For OMNI3D-BENCH, we manually verified program correctness as ground truth 3D information is not available for all objects in the scene. The results reveal that with oracle vision specialists, VADAR achieves an accuracy of 83.0% on CLEVR and 94.4% on OMNI3D-BENCH, compared to ViperGPT's 42.6% and 54.9%, and VisProg's 39.9% and 66.0% respectively. This suggests that our approach can handle a significantly wider variety of queries, thanks to the dynamically generated API created by our LLM agents, as opposed to the static, human-defined API used in ViperGPT and VisProg. Our API is simpler and allows for flexible integration of vision specialists, avoiding the biases introduced by humans – *e.g.*, as in VisProg, where the pre-defined API guides the LLM to define "behind" by cropping the image above.

The high accuracy of VADAR with oracle vision specialists suggests a promising path to scaling 3D spatial reasoning: improving specialized vision models. These models are easier to train than general-purpose VLMs, as they address simpler tasks and have more accessible training data.

Fig. 4 shows programs generated by the methods. We observe that ViperGPT and VisProg tend to resort to direct VQA calls when questions are complex, as opposed to generating programs. In addition, ViperGPT often tends to produce incomplete programs, ignoring a significant portion of the query. Finally, both ViperGPT and VisProg often confuse above-behind and below-in front. This seems to be a



Query:
How many bottles would you have to stack on top of each other to make a structure as tall in 3D as the armchair?

VADAR (Ours)

```
import math

# Step 1: Find all armchairs
armchairs = loc(image, 'armchair')

# Step 2: Calculate 3D height of each armchair and find the tallest
max_armchair_height_3D = 0
for armchair in armchairs:
    x, y = armchair
    armchair_2D_width, armchair_2D_height = get_2D_object_size(image, x, y)
    armchair_depth = depth(image, x, y)
    armchair_height_3D = armchair_2D_height * armchair_depth
    if armchair_height_3D > max_armchair_height_3D:
        max_armchair_height_3D = armchair_height_3D

# Step 3: Find all bottles
bottles = loc(image, 'bottle')

# Step 4: Calculate 3D height of each bottle and find the tallest
max_bottle_height_3D = 0
for bottle in bottles:
    x, y = bottle
    bottle_2D_width, bottle_2D_height = get_2D_object_size(image, x, y)
    bottle_depth = depth(image, x, y)
    bottle_height_3D = bottle_2D_height * bottle_depth
    if bottle_height_3D > max_bottle_height_3D:
        max_bottle_height_3D = bottle_height_3D

# Step 5: Calculate the number of bottles required
if max_bottle_height_3D > 0:
    bottles_needed = math.ceil(max_armchair_height_3D / max_bottle_height_3D)
else:
    bottles_needed = 0  # If there are no bottles, we cannot stack to the height

# Store the result in final_result
final_result = bottles_needed
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)
    bottle_patches = image_patch.find("bottle")
    armchair_patches = image_patch.find("armchair")

    if not bottle_patches or not armchair_patches:
        return "unknown"

    bottle_height = bottle_patches[0].compute_depth()
    armchair_height = armchair_patches[0].compute_depth()

    num_bottles = math.ceil(armchair_height / bottle_height)
    return str(num_bottles)
```

VisProg

```
ANSWER0=VQA(image=IMAGE,
         question='How many bottles would you have to stack on
top of each other to make a structure as tall as the armchair?')
FINAL_RESULT=RESULT(var=ANSWER0)
```

Query:
How many chairs are there behind the table? Respond with a number.

VADAR (Ours)

```
def _is_behind(image, x_1, y_1, x_2, y_2):
    depth_1 = depth(image, x_1, y_1)
    depth_2 = depth(image, x_2, y_2)
    return depth_1 > depth_2

# PROGRAM STARTS HERE
# Initialize counter for the number of chairs behind the table
chair_count = 0

# Find all tables in the image
tables = loc(image, 'table')

# If no tables are found, set final_result to 0
if not tables:
    final_result = 0
else:
    # Assume we only need to check the first table found
    table_x, table_y = tables[0]

    # Find all chairs in the image
    chairs = loc(image, 'chair')

    # Loop through each chair and check if it is behind the table
    for chair_x, chair_y in chairs:
        if _is_behind(image, chair_x, chair_y, table_x, table_y):
            chair_count += 1

    # Set the final result to the count of chairs behind the table
    final_result = chair_count
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)
    chair_patches = image_patch.find("chair")
    dining_table_patches = image_patch.find("dining table")

    # Assuming only one dining table patch
    dining_table_patch = dining_table_patches[0]

    chairs_behind_table = [chair for chair in chair_patches if
chair.vertical_center > dining_table_patch.vertical_center]

    return str(len(chairs_behind_table))
```

VisProg

```
BOX0=LOC(image=IMAGE, object='dining table')
IMAGE0=CROP_BEHIND(image=IMAGE, box=BOX0)
BOX1=LOC(image=IMAGE0, object='chair')
ANSWER0=COUNT(box=BOX1)
FINAL_RESULT=RESULT(var=ANSWER0)
```

Query:
Is the table the same color as the chair closest in 3D to it? Respond with yes or no.

VADAR (Ours)

```
def _same_color(image, x_1, y_1, x_2, y_2):
    color_1 = vqa(image, question='What color is this?', x=x_1, y=y_1)
    color_2 = vqa(image, question='What color is this?', x=x_2, y=y_2)
    return color_1 == color_2

def _find_closest_object_3D(image, x, y, object_type):
    closest_object_coords = None
    min_distance_3D = float('inf')

    # Locate all objects of the specified type
    objects = _find_objects_by_type(image, object_type)

    ref_depth = depth(image, x, y)

    for obj_x, obj_y in objects:
        # Skip the reference object itself
        if same_object(image, x, y, obj_x, obj_y):
            continue

        # Calculate the 3D distance
        obj_depth = depth(image, obj_x, obj_y)
        distance_3D = ((x - obj_x) ** 2 + (y - obj_y) ** 2 + (ref_depth - obj_depth) ** 2) ** 0.5

        # Update the closest object if this one is closer
        if distance_3D < min_distance_3D:
            min_distance_3D = distance_3D
            closest_object_coords = (obj_x, obj_y)

    return closest_object_coords

# PROGRAM STARTS HERE
# Step 1: Locate all tables in the image
tables = loc(image, 'table')

# Step 2: If tables are found, select the first table (assuming one table for simplicity)
if tables:
    table_x, table_y = tables[0]

    # Step 3: Locate the chair closest in 3D space to the table
    closest_chair_x, closest_chair_y = _find_closest_object_3D(image, table_x, table_y, 'chair')

    # Step 4: Check if the table and the closest chair have the same color
    same_color_result = _same_color(image, table_x, table_y, closest_chair_x, closest_chair_y)

    # Step 5: Store the final result as 'yes' or 'no'
    final_result = 'yes' if same_color_result else 'no'
else:
    # If no table is found, we cannot proceed, so assume the answer is 'no'
    final_result = 'no'
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)
    table_patches = image_patch.find("table")
    chair_patches = image_patch.find("chair")

    if not table_patches or not chair_patches:
        return "no"

    table_patch = table_patches[0]
    chair_patches.sort(key=lambda x: distance(x, table_patch))
    closest_chair_patch = chair_patches[0]

    if closest_chair_patch.verify_property("chair", "color") ==
table_patch.verify_property("table", "color"):
        return "yes"
    else:
        return "no"
```

VisProg

```
BOX0=LOC(image=IMAGE, object='table')
IMAGE0=CROP(image=IMAGE, box=BOX0)
BOX1=LOC(image=IMAGE, object='chair')
IMAGE1=CROP(image=IMAGE, box=BOX1)
ANSWER0=VQA(image=IMAGE0, question='What color is the table?')
ANSWER1=VQA(image=IMAGE1, question='What color is the chair closest
in 3D to the table?')
ANSWER2=EVAL(expr="'yes' if {ANSWER0} == {ANSWER1} else 'no'")
FINAL_RESULT=RESULT(var=ANSWER2)
```

Query:
Is the color of the lamp the same as the color of the pillow behind the pink pillow?

VADAR (Ours)

```
# Step 1: Find all pillows
pillows = loc(image, 'pillow')

# Step 2: Initialize variables to store the pink pillow and the pillow behind it
pink_pillow = None
pillow_behind_pink = None

# Step 3: Loop through each pillow to find the pink one
for x, y in pillows:
    color = vqa(image, "What color is this?", x, y)
    if color == "pink":
        pink_pillow = (x, y)
        break

# Step 4: If a pink pillow is found, find the pillow behind it
if pink_pillow:
    for x, y in pillows:
        if not same_object(image, pink_pillow[0], pink_pillow[1], x, y):
            if _is_behind(image, x, y, pink_pillow[0], pink_pillow[1]):
                pillow_behind_pink = (x, y)
                break

# Step 5: Find all lamps
lamps = loc(image, 'lamp')

# Step 6: Initialize variable to store the lamp's color
lamp_color = None

# Step 7: Loop through each lamp to find the color of the first one
if lamps:
    lamp_color = vqa(image, "What color is this?", lamps[0][0], lamps[0][1])

# Step 8: Initialize a variable to store the final result
final_result = "no"

# Step 9: If both the lamp and the pillow behind the pink pillow are found,
compare their colors
if pillow_behind_pink and lamp_color:
    pillow_behind_color = vqa(image, "What color is this?",
pillow_behind_pink[0], pillow_behind_pink[1])
    if lamp_color == pillow_behind_color:
        final_result = "yes"
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)
    lamp_patches = image_patch.find("lamp")
    pillow_patches = image_patch.find("pillow")

    lamp_color = lamp_patches[0].simple_query("What is the
color?")

    for pillow_patch in pillow_patches:
        if pillow_patch.horizontal_center <
lamp_patches[0].horizontal_center:
            pillow_color = pillow_patch.simple_query("What is
the color?")
            break

    return "yes" if lamp_color == pillow_color else "no"
```

VisProg

```
BOX0=LOC(image=IMAGE, object='lamp')
IMAGE0=CROP(image=IMAGE, box=BOX0)
ANSWER0=VQA(image=IMAGE0, question='What color is the lamp?')
BOX1=LOC(image=IMAGE, object='pink pillow')
IMAGE1=CROP_BEHIND(image=IMAGE, box=BOX1)
BOX2=LOC(image=IMAGE1, object='pillow')
IMAGE2=CROP(image=IMAGE1, box=BOX2)
ANSWER1=VQA(image=IMAGE2, question='What color is the pillow?')
ANSWER2=EVAL(expr="'yes' if {ANSWER0} == {ANSWER1} else 'no'")
FINAL_RESULT=RESULT(var=ANSWER2)
```

Query:
If the 3D height of the front most chair is 6 meters, what is the 3D height of the chair in the far back of the scene? Respond with a number.

VADAR (Ours)

```
# Step 1: Find all the chairs in the image
chairs = loc(image, 'chair')

# Step 2: Identify the front most chair based on depth
front_most_chair = None
min_depth = float('inf')

for (x, y) in chairs:
    current_depth = depth(image, x, y)
    if current_depth < min_depth:
        min_depth = current_depth
        front_most_chair = (x, y)

# Step 3: Identify the chair in the far back of the scene based on depth
back_most_chair = None
max_depth = float('-inf')

for (x, y) in chairs:
    current_depth = depth(image, x, y)
    if current_depth > max_depth:
        max_depth = current_depth
        back_most_chair = (x, y)

# Step 4: Calculate the 3D height of the back most chair
# Given that the 3D height of the front most chair is 6 meters

# Get the 2D height of the front most chair
front_most_chair_2D_size = get_2D_object_size(image, front_most_chair[0],
front_most_chair[1])
front_most_chair_2D_height = front_most_chair_2D_size[1]

# Calculate the 3D height of the back most chair
back_most_chair_2D_size = get_2D_object_size(image, back_most_chair[0],
back_most_chair[1])
back_most_chair_2D_height = back_most_chair_2D_size[1]

# Use the proportion of 2D heights to calculate the 3D height of the back most
chair
back_most_chair_3D_height = (back_most_chair_2D_height * 6 * max_depth) /
(front_most_chair_2D_height * min_depth)

# Store the result
final_result = back_most_chair_3D_height
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)
    chair_patches = image_patch.find("chair")
    chair_patches.sort(key=lambda chair:
chair.compute_depth())
    front_chair_height = 6  # meters
    back_chair_height = chair_patches[-1].compute_depth() *
front_chair_height
    return str(back_chair_height)
```

VisProg

```
ANSWER0=VQA(image=IMAGE, question='If the 3D height of the front
most chair is 6 meters, what is the 3D height of the chair in the
far back of the scene?')
FINAL_RESULT=RESULT(var=ANSWER0)
```

Query:
Are there the same number of tiny yellow cylinders that are behind the big gray matte cylinder and small metallic cylinders on the left side of the tiny yellow shiny thing?

VADAR (Ours)

```
def _get_size(image, x, y):
    size = vqa(image=image, question='What size is this object?', x=x, y=y)
    return size

def _get_shape(image, x, y):
    # Use the VQA function to ask the question about the shape of the object
    shape = vqa(image=image, question='What shape is this object?', x=x, y=y)
    return shape

def _get_material(image, x, y):
    material = vqa(image=image, question='What material is this?', x=x, y=y)
    return material

def _get_color(image, x, y):
    color = vqa(image=image, question='What color is this?', x=x, y=y)
    return color

def _is_left_of(image, x_1, y_1, x_2, y_2):
    return x_1 < x_2

def _is_in_front_of(image, x_1, y_1, x_2, y_2):
    depth_1 = depth(image, x_1, y_1)
    depth_2 = depth(image, x_2, y_2)
    return depth_1 < depth_2

# PROGRAM STARTS HERE
# Step 1: Locate all cylinders in the image
cylinders = loc(image, 'cylinders')

# Step 2: Find the big gray rubber cylinder
big_gray_rubber_cylinder = None
for x, y in cylinders:
    size = _get_size(image, x, y)
    color = _get_color(image, x, y)
    material = _get_material(image, x, y)
    if size == "large" and color == "gray" and material == "rubber":
        big_gray_rubber_cylinder = (x, y)
        break

# Ensure we found the big gray rubber cylinder
if big_gray_rubber_cylinder:
    x_big_cylinder, y_big_cylinder = big_gray_rubber_cylinder
else:
    final_result = "no"

# Step 3: Find all tiny yellow cylinders behind the big gray rubber cylinder
tiny_yellow_cylinders_behind = 0
for x, y in cylinders:
    size = _get_size(image, x, y)
    color = _get_color(image, x, y)
    if size == "small" and color == "yellow":
        if _is_in_front_of(image, x_big_cylinder, y_big_cylinder, x, y):
            tiny_yellow_cylinders_behind += 1

# Step 4: Locate all objects to find the tiny yellow shiny thing
objects = loc(image, 'objects')
tiny_yellow_shiny_thing = None
for x, y in objects:
    size = _get_size(image, x, y)
    color = _get_color(image, x, y)
    material = _get_material(image, x, y)
    if size == "small" and color == "yellow" and material == "metal":
        tiny_yellow_shiny_thing = (x, y)
        break

# Ensure we found the tiny yellow shiny thing
if tiny_yellow_shiny_thing:
    x_tiny_thing, y_tiny_thing = tiny_yellow_shiny_thing
else:
    final_result = "no"

# Step 5: Find small metallic cylinders on the left side of the tiny yellow shiny thing
small_metallic_cylinders_left = 0
for x, y in cylinders:
    size = _get_size(image, x, y)
    material = _get_material(image, x, y)
    if size == "small" and material == "metal":
        if _is_left_of(image, x, y, x_tiny_thing, y_tiny_thing):
            small_metallic_cylinders_left += 1

# Step 6: Compare the counts
final_result = "yes" if tiny_yellow_cylinders_behind == small_metallic_cylinders_left else "no"
```

ViperGPT

```
def execute_command(image):
    image_patch = ImagePatch(image)

    tiny_yellow_cylinders = image_patch.find("tiny yellow cylinder")
    big_gray_matte_cylinder = image_patch.find("big gray matte
cylinder")[0]
    small_metallic_cylinders = image_patch.find("small metallic
cylinder")
    tiny_yellow_shiny_thing = image_patch.find("tiny yellow shiny
thing")[0]

    count_tiny_yellow_cylinders = len(tiny_yellow_cylinders)
    count_small_metallic_cylinders_left = sum(patch.horizontal_center
< tiny_yellow_shiny_thing.horizontal_center for patch in
small_metallic_cylinders)

    return bool_to_yesno(count_tiny_yellow_cylinders ==
count_small_metallic_cylinders_left and count_tiny_yellow_cylinders
== 1)
```

VisProg

```
BOX0=LOC(image=IMAGE, object='big gray matte cylinder')
IMAGE0=CROP_BEHIND(image=IMAGE, box=BOX0)
BOX1=LOC(image=IMAGE0, object='tiny yellow cylinders')
ANSWER0=COUNT(box=BOX1)
BOX2=LOC(image=IMAGE, object='tiny yellow shiny thing')
IMAGE1=CROP_LEFTOF(image=IMAGE, box=BOX2)
BOX3=LOC(image=IMAGE1, object='small metallic cylinders')
ANSWER1=COUNT(box=BOX3)
ANSWER2=EVAL(expr="'yes' if {ANSWER0} == {ANSWER1} else 'no'")
FINAL_RESULT=RESULT(var=ANSWER2)
```

Figure 4. **Program outputs for VisProg, ViperGPT and VADAR.** For each example, we show the query, the input image, and the method's program generations. Queries are from our benchmark and pertain to 3D understanding of scenes. Zoom-in to read the programs.

semantic error for ViperGPT that uses a depth estimation module, like us, and a conceptual design error by VisProg that implements `CROP_BEHIND` to crop above in the image.

LEFT [14] vs VADAR. We also compare to the logic-enhanced neuro-symbolic approach LEFT [14], which uses trained modules to ground visual concepts in images, such as "`is left of`". Unlike LEFT, our approach is entirely training-free, while LEFT requires extensive supervision for module training. Fig. 3 reports the performance of LEFT on the CLEVR dataset when trained (to convergence) with varying training set sizes (x-axis). Although our approach does not require any explicit supervision, our API agent uses a small sample ($= 15$) of *questions only*, *without answers*, to construct the API. According to Fig. 3, we outperform LEFT trained with $\leq 10,000$ examples on CLEVR. Notably, it is not possible to evaluate LEFT on Omni3D-Bench due to its reliance on a large, domain-specific training set with appropriate 3D supervision, which is difficult to obtain for this benchmark or in general. This highlights an added advantage of our method: its ability to scale to new domains without the need for training.

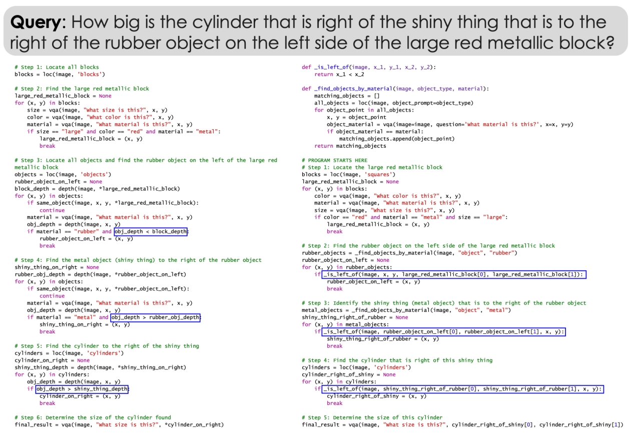
Results on GQA. We report results on GQA [16], a widely used benchmark for spatial reasoning. As noted earlier, GQA queries emphasize object appearance and attributes, and primarily require one-step inference. Questions in GQA include *"What size is the doughnut the person is eating?"* and *"Who is sitting in front of the water?"*. Tab. 3 compares GPT4o, ViperGPT, VisProg, and VADAR. We observe different relative model performance compared to Tab. 1. Given the nature of GQA, it is not surprising that a monolithic and performant VLM like GPT4o would perform well, which our results confirm. Among the program synthesis methods, we observe that VADAR and VisProg achieve comparable performance, while ViperGPT shows a drop in accuracy. A deeper dive into the output programs shows that VisProg relies on image-wide VQA calls in 34%

Method	GQA
GPT4o [1]	**54.9**
ViperGPT [35]	42.0
VisProg [12]	46.9
VADAR (ours)	46.1

Table 3. **Results on GQA** on a subset of testdev split. GQA focuses primarily on object appearance, not 3D spatial reasoning.

	CLEVR $_{100}$
No-API Agent	60.7
API Agent	64.0
+ Weak ICL	65.7
+ Pseudo ICL	66.7

Table 4. **Ablations of agentic design and prompts** on CLEVR $_{100}$, a subset of 100 questions. We compare to single agent variant *No-API* which creates programs directly. We then ablate prompting by incrementally adding instructions to the agents used to define the API. The No-API Agent performs the worst and our prompting techniques add to VADAR's performance.


Query: How big is the cylinder that is right of the shiny thing that is to the right of the rubber object on the left side of the large red metallic block?

```
# Step 1: Locate all blocks
blocks = loc(image, 'blocks')

# Step 2: Find the large red metallic block
large_red_metallic_block = None
for (x, y) in blocks:
    size = vqa(image, "What size is this?", x, y)
    color = vqa(image, "What color is this?", x, y)
    material = vqa(image, "What material is this?", x, y)
    if size == "large" and color == "red" and material == "metal":
        large_red_metallic_block = (x, y)
        break

# Step 3: Locate all objects and find the rubber object on the left of the large red
metallic block
objects = loc(image, 'objects')
rubber_object_on_left = None
block_depth = depth(image, *large_red_metallic_block)
for (x, y) in objects:
    if same_object(image, x, y, *large_red_metallic_block):
        continue
    material = vqa(image, "What material is this?", x, y)
    obj_depth = depth(image, x, y)
    if material == "rubber" and obj_depth < block_depth:
        rubber_object_on_left = (x, y)
        break

# Step 4: Find the metal object (shiny thing) to the right of the rubber object
shiny_thing_on_right = None
rubber_obj_depth = depth(image, *rubber_object_on_left)
for (x, y) in objects:
    if same_object(image, x, y, *rubber_object_on_left):
        continue
    material = vqa(image, "What material is this?", x, y)
    obj_depth = depth(image, x, y)
    if material == "metal" and obj_depth > rubber_obj_depth:
        shiny_thing_on_right = (x, y)
        break

# Step 5: Find the cylinder to the right of the shiny thing
cylinders = loc(image, 'cylinders')
cylinder_on_right = None
shiny_thing_depth = depth(image, *shiny_thing_on_right)
for (x, y) in cylinders:
    obj_depth = depth(image, x, y)
    if obj_depth > shiny_thing_depth:
        cylinder_on_right = (x, y)
        break

# Step 6: Determine the size of the cylinder found
final_result = vqa(image, "What size is this?", *cylinder_on_right)
```

(a) *No-API* Agent

```
def _is_left_of(image, x_1, y_1, x_2, y_2):
    return x_1 < x_2

def _find_objects_by_material(image, object_type, material):
    matching_objects = []
    all_objects = loc(image, object_prompt=object_type)
    for object_point in all_objects:
        x, y = object_point
        object_material = vqa(image=image, question='What material is this?', x=x, y=y)
        if object_material == material:
            matching_objects.append(object_point)
    return matching_objects

# PROGRAM STARTS HERE
# Step 1: Locate the large red metallic block
blocks = loc(image, 'squares')
large_red_metallic_block = None
for (x, y) in blocks:
    color = vqa(image, "What color is this?", x, y)
    material = vqa(image, "What material is this?", x, y)
    size = vqa(image, "What size is this?", x, y)
    if color == "red" and material == "metal" and size == "large":
        large_red_metallic_block = (x, y)
        break

# Step 2: Find the rubber object on the left side of the large red metallic block
rubber_objects = _find_objects_by_material(image, "object", "rubber")
rubber_object_on_left = None
for (x, y) in rubber_objects:
    if _is_left_of(image, x, y, large_red_metallic_block[0], large_red_metallic_block[1]):
        rubber_object_on_left = (x, y)
        break

# Step 3: Identify the shiny thing (metal object) that is to the right of the rubber object
metal_objects = _find_objects_by_material(image, "object", "metal")
shiny_thing_right_of_rubber = None
for (x, y) in metal_objects:
    if _is_left_of(image, rubber_object_on_left[0], rubber_object_on_left[1], x, y):
        shiny_thing_right_of_rubber = (x, y)
        break

# Step 4: Find the cylinder that is right of this shiny thing
cylinders = loc(image, 'cylinders')
cylinder_right_of_shiny = None
for (x, y) in cylinders:
    if _is_left_of(image, shiny_thing_right_of_rubber[0], shiny_thing_right_of_rubber[1], x, y):
        cylinder_right_of_shiny = (x, y)
        break

# Step 5: Determine the size of this cylinder
final_result = vqa(image, "What size is this?", cylinder_right_of_shiny[0], cylinder_right_of_shiny[1])
```

(b) VADAR

Figure 5. (a) The *No-API* agent produces longer programs and is prone to errors, often mistakenly using depth for left/right comparisons. (b) In contrast, our agentic VADAR creates shorter programs by leveraging methods from the API.

of cases, whereas VADAR does so only 24% of the time. The limitations of GQA queries in evaluating 3D spatial reasoning highlight the need for our proposed benchmark, which better assesses 3D understanding and exposes the weaknesses of current methods.

4.3. Ablations

We turn to ablations to quantify the effectiveness of the agentic design and prompting in our approach. To reduce costs from GPT4o, we experiment on a randomly selected CLEVR subset. Tab. 4 compares the following variants:

No-API Agent is a single agent instructed to directly create programs for queries without defining an API of reusable methods. Comparison to this variant shows the value of an API. Fig. 5 shows a common reasoning error by the *No-API Agent*, which confuses depth with left/right; our approach, by implementing reusable methods, invokes the appropriately named method that is accurately implemented. The example reiterates that spatial reasoning relies on correctness, supporting VADAR's design to build an accurate API *before* program synthesis, over library learning, that discovers a potentially incorrect library *after* program synthesis.

API Agent is our approach without any prompting instructions or ICL examples. We incrementally add our two prompting techniques: (1) *Weak ICL* examples guide the Implementation Agent to use the pre-defined modules. (2) *Pseudo ICL* provides pseudo-code examples and instructions in *natural language* to the Implementation and Program Agent, respectively, that demonstrate how to handle intricate queries. We provide the prompts in the Appendix.

From Tab. 4 we observe that the No-API Agent performs the worst, while our prompting techniques via weak ICL examples and instructions achieve the best performance.

5. Limitations & Future Work

We introduce VADAR, an agentic approach that leverages LLM agents to dynamically create and expand a Pythonic API for complex 3D visual reasoning tasks. Our agents autonomously generate and implement functions, which are then utilized by the Program Agent to produce programs. This reuse of functions results in more accurate programs for complex queries. There is an extensive list of future directions to address current limitations of VADAR.

- VADAR often struggles with queries that require 5 or more inference steps, *e.g. "There is a yellow cylinder to the right of the cube that is behind the purple block; is there a brown object in front of it?"*. We provide the programs for these complex cases in the Appendix. Addressing such queries can be improved by leveraging advanced prompting strategies, an active research area that includes methods like CoT [41] and prompt chaining [42, 43].
- We show that VADAR attains high program accuracy (*e.g.*, 83.0% on CLEVR) but lower execution accuracy (53.6%) due to errors from the vision specialists. A potential enhancement would be to enable VADAR to dynamically choose its vision modules from a pool of available options based on empirical performance. Integrating the selection process with reinforcement learning or self-improvement mechanisms is a promising future direction.
- VADAR creates a program based solely on the input query, utilizing the image only during execution. Incorporating the image into the program synthesis process could improve accuracy, potentially improving performance on queries requiring five or more inference steps.

We release the benchmark and code for VADAR to foster future research in this direction.

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Visual Agentic AI for Spatial Reasoning with a Dynamic API

Supplementary Material

	Method	CLEVR	OMNI3D-BENCH
VLMs	GPT4o [1]	1.4	0.6
	Claude3.5-Sonnet [2]	0.2	0.6
	Llama3.2 [9]	0.5	1.6
	Gemini1.5-Pro [36]	0.3	1.8
	Gemini1.5-Flash [36]	0.3	1.1
	Molmo [8]	0.0	0.0
	SpaceMantis [6, 17]	0.0	0.0
Program Synthesis	ViperGPT [35]	1.1	0.3
	VisProg [12]	0.9	0.3
	VADAR (ours)	2.9	1.8

Table 5. **Standard deviation across experimental runs.** VADAR's variation is comparable to VLMs on Omni3D, but slightly higher than program synthesis methods on CLEVR, despite achieving significantly higher accuracy.

Signature (for 10 Qs)	Implementation	Program (per Q)	Execution (per Q)
$20.5_{\pm 3.6}$	$37.2_{\pm 14.4}$	$6.5_{\pm 1.8}$	$35.7_{\pm 11.8}$

Table 6. **Runtime for each Agent in seconds.**

The Appendix includes the prompts used for all agents, additional qualitative examples of VADAR on CLEVR, OMNI3D-BENCH, and GQA, and a supplemental qualitative analysis with standard deviations to compare the robustness of approaches.

A. Prompts

Predefined Module Signatures. Fig. 9 and Fig. 10 show the docstrings of the predefined modules for CLEVR and OMNI3D-BENCH respectively, which are used to initialize the dynamic API. We note that the two prompts are virtually identical, with the exception of the `get_2D_object_size` method, which we omit from our experiments on CLEVR as the dataset defines size as either `small` or `large`. In Fig. 11, we provide the Python implementation for all of the predefined modules.

Signature Agent Prompt. Fig. 12 contains the prompt used for the Signature Agent for both CLEVR and OMNI3D-BENCH. We prompt the LLM to only generate signatures for methods when necessary, as we found this avoids redundant methods with minor changes to previously defined methods. We impose that the name of new methods start with an underscore, to prevent the common failure case of methods sharing names with variables previously defined.

Implementation Agent Prompt. Fig. 13 and Fig. 14 contain the prompts used for the Implementation agent on CLEVR and OMNI3D-BENCH respectively. The prompts contain *Weak ICL* examples, illustrating how to implement a model signature and use the pre-defined modules correctly for simpler queries. This is in contrast to *Strong ICL* examples in VisProg and ViperGPT, which provide complete program examples for full queries using a predefined API. In our framework, where agents dynamically generate the API, *Strong ICL* is not feasible.

Additionally, the prompts feature *Pseudo ICL* in the form of natural language instructions and tips. Similarly to the predefined modules, the prompts differ between CLEVR and OMNI3D-BENCH as the latter considers metric sizes and not a binary `small` or `large` as in CLEVR. Consequently, we found it necessary to include natural language definitions and instructions for reasoning about 2D and 3D dimensions in the Implementation prompt on OMNI3D-BENCH.

Program Agent Prompt. In Fig. 15 and Fig. 16 we show the prompts for the Program Agent on CLEVR and OMNI3D-BENCH respectively. In the prompt for CLEVR, we include a list of all available attributes. In both prompts, we include *Pseudo ICL* in the form of natural language examples and instructions. For the OMNI3D-BENCH prompt, we additionally include tips and definitions for handling 2D and 3D dimensions.

B. Additional Quantitative Analysis

Experimental Variability. Tab. 1 in the main paper reports the mean performance of all methods across 3 runs. Tab. 5 reports the standard deviation on CLEVR and OMNI3D-BENCH across the same 3 runs. VADAR's variation is comparable to the VLMs on OMNI3D-BENCH, but slightly higher than program synthesis methods on both benchmarks. However, VADAR significantly outperforms ViperGPT and VisProg, even when accounting for this variation.

Runtime. Tab. 6 reports runtime in seconds for our Agents on an A100 GPU. Notably, when running our method on 1000+ questions, the Signature and Implementation Agents *only run once*, therefore their runtime becomes negligible to total inference runtime.

C. More information on OMNI3D-BENCH

On images sourced from Omni3D [5] we collect a set of challenging questions with the help of human annotators. We omit using templates for questions, as done by others [6, 38, 44], to avoid template overfitting, and instead instruct annotators to directly ask questions in free-form natural language, focusing on the scene, object layout and

	VSI-Bench-img
Gemini1.5-Pro	49.5
VADAR	**50.1**

Table 7. **Results on VSI-Bench [44].** VADAR outperforms Gemini1.5-Pro on a image-based subset of 75 queries from VSI-Bench that sources the frame that contains all the information necessary to respond correctly. Notably, VADAR achieves a 50.1% accuracy on this subset, compared to 40.4% on OMNI3D-BENCH, highlighting the challenging nature of our proposed benchmark.

object sizes. We discard questions that are simplistic, *e.g.* "Is there a sofa in the image?" or "Is the sofa behind the table?", and only keep queries which involve complex inference steps in 2D and 3D. OMNI3D-BENCH queries roughly target the following areas of reasoning: relative size and dimensions with hypotheticals, spatial relationships and depth reasoning, relative proportions and alignments, and interaction with other objects. Queries from OMNI3D-BENCH can be browsed in https://glab-caltech.github.io/vadar/omni3d-bench.html.

We compute answers for questions using the 3D annotations provided in Omni3D [5]. Since the questions are not templated and thus don't follow rule-based instructions, we collect answers manually by sourcing the 3D annotations provided by the dataset for each image. This results in 500 *unique* and challenging image-question-answer tuples that test diverse aspects of 3D spatial reasoning. The diversity and complexity of OMNI3D-BENCH is showcased by the examples in Fig. 1, Fig. 4 and Fig. 7.

OMNI3D-BENCH complements CLEVR when assessing 3D spatial understanding. While CLEVR uses templated questions, enabling the creation of a large volume of image-question-answer pairs, OMNI3D-BENCH focuses on diverse and complex reasoning tasks in free-form language. Together, CLEVR and OMNI3D-BENCH provide a comprehensive test for models' 3D spatial reasoning capabilities. This is evidenced by the relatively low performance of modern state-of-the-art AI models on these benchmarks, achieving only 20-40% accuracy.

D. Comparison to VSI-Bench

Concurrent to our work is VSI-Bench [44], a video understanding benchmark that focuses on spatial reasoning. VSI-Bench targets 3D reasoning, but it differs from OMNI3D-BENCH in three critical ways: First, it focuses on video understanding and retrieving the appropriate frame to answer a given query. Second, while queries in VSI-Bench target 3D object attributes, they query absolute measurements, such as *"What is the height of the chair?"*. Monolithic VLMs when prompted with such questions resort to object priors. For example, GPT4o says: *"A chair tends to be 30-40 inches tall"*. In contrast, OMNI3D-BENCH introduces hypotheticals that require reasoning over scene attributes, evaluating true 3D spatial reasoning, *e.g.*, *"If the table is 2 meters wide, how tall is the chair?"*. Third, VSI-Bench queries are templated, which can lead to biased conclusions due to template overfitting.

We compare VADAR on VSI-Bench. To decouple frame retrieval from image-based reasoning, we create a variant of the benchmark by sourcing a subset of 75 queries with the associated frame that contains the information necessary to address the query. We call this subset VSI-Bench-img. Tab. 7 reports VADAR's performance and compares to Gemini1.5-Pro, which authors report to be the best VLM on the set. From Tab. 7 we observe that VADAR performs on par with the industry-leading Gemini1.5-pro. Importantly, VADAR's performance on VSI-Bench-img is 10% higher than on OMNI3D-BENCH (40.4 vs 50.1) which highlights the more challenging nature of our benchmark.

E. Qualitative Examples on CLEVR

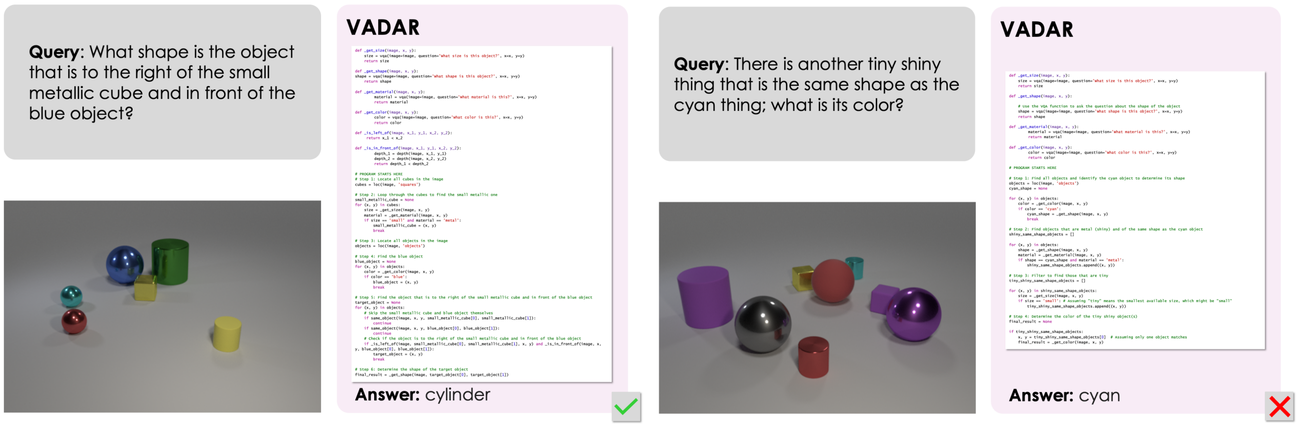
Fig. 6 shows additional qualitative examples on CLEVR. The correct example showcases the use of API methods for repeated tasks and accurately determining spatial relations. The incorrect example highlights a failure to use same object to exclude the original reference object when the questions asks for "another" object.

F. Qualitative Examples on OMNI3D-BENCH

Fig. 7 shows additional qualitative examples on OMNI3D-BENCH. Our method is able to correctly estimate 3D distances by scaling depth based on the reference scale given in the question. An instance where such scaling is done incorrectly is shown in the last example.

G. Qualitative Examples on GQA

Fig. 8 shows qualitative examples on GQA [16]. Our method is able to identify and locate key objects necessary to answer questions. It is extremely explicit, locating the nearest person in the top right example using pixel distance from the tree. Some GQA questions have ambiguous answers, where the shape of the pot is generically "round" and the frame of reference for spatial relations is not entirely clear (*i.e.*, which man in the last example?).



Query: What shape is the object that is to the right of the small metallic cube and in front of the blue object?

VADAR

```python
def _get_size(image, x, y):
    size = vqa(image=image, question='What size is this object?', x=x, y=y)
    return size

def _get_shape(image, x, y):
shape = vqa(image=image, question='What shape is this object?', x=x, y=y)
    return shape

def _get_material(image, x, y):
        material = vqa(image=image, question='What material is this?', x=x, y=y)
        return material

def _get_color(image, x, y):
        color = vqa(image=image, question='What color is this?', x=x, y=y)
        return color

def _is_left_of(image, x_1, y_1, x_2, y_2):
     return x_1 < x_2

def _is_in_front_of(image, x_1, y_1, x_2, y_2):
        depth_1 = depth(image, x_1, y_1)
        depth_2 = depth(image, x_2, y_2)
        return depth_1 < depth_2

# PROGRAM STARTS HERE
# Step 1: Locate all cubes in the image
cubes = loc(image, 'squares')

# Step 2: Loop through the cubes to find the small metallic one
small_metallic_cube = None
for (x, y) in cubes:
    size = _get_size(image, x, y)
    material = _get_material(image, x, y)
    if size == 'small' and material == 'metal':
        small_metallic_cube = (x, y)
        break

# Step 3: Locate all objects in the image
objects = loc(image, 'objects')

# Step 4: Find the blue object
blue_object = None
for (x, y) in objects:
    color = _get_color(image, x, y)
    if color == 'blue':
        blue_object = (x, y)
        break

# Step 5: Find the object that is to the right of the small metallic cube and in front of the blue object
target_object = None
for (x, y) in objects:
    # Skip the small metallic cube and blue object themselves
    if same_object(image, x, y, small_metallic_cube[0], small_metallic_cube[1]):
        continue
    if same_object(image, x, y, blue_object[0], blue_object[1]):
        continue
    # Check if the object is to the right of the small metallic cube and in front of the blue object
    if _is_left_of(image, small_metallic_cube[0], small_metallic_cube[1], x, y) and _is_in_front_of(image, x,
y, blue_object[0], blue_object[1]):
        target_object = (x, y)
        break

# Step 6: Determine the shape of the target object
final_result = _get_shape(image, target_object[0], target_object[1])
```

Answer: cylinder ✓

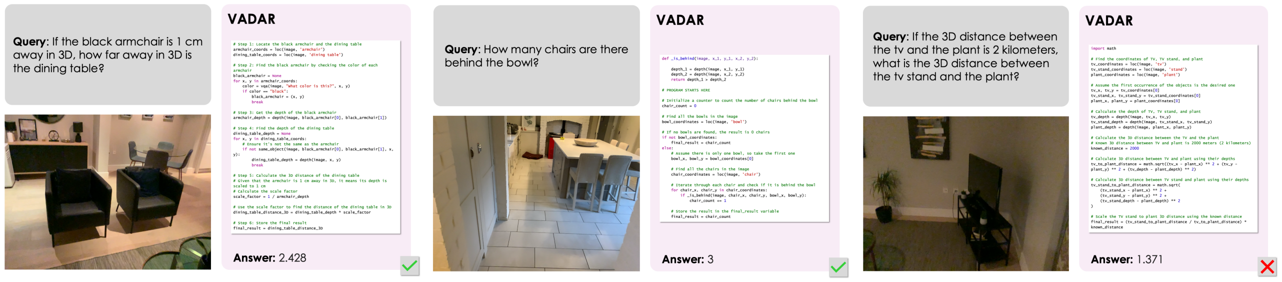
Query: There is another tiny shiny thing that is the same shape as the cyan thing; what is its color?

VADAR

```python
def _get_size(image, x, y):
    size = vqa(image=image, question='What size is this object?', x=x, y=y)
    return size

def _get_shape(image, x, y):

    # Use the VQA function to ask the question about the shape of the object
    shape = vqa(image=image, question='What shape is this object?', x=x, y=y)
    return shape

def _get_material(image, x, y):
        material = vqa(image=image, question='What material is this?', x=x, y=y)
        return material

def _get_color(image, x, y):
        color = vqa(image=image, question='What color is this?', x=x, y=y)
        return color

# PROGRAM STARTS HERE

# Step 1: Find all objects and identify the cyan object to determine its shape
objects = loc(image, 'objects')
cyan_shape = None

for (x, y) in objects:
    color = _get_color(image, x, y)
    if color == 'cyan':
        cyan_shape = _get_shape(image, x, y)
        break

# Step 2: Find objects that are metal (shiny) and of the same shape as the cyan object
shiny_same_shape_objects = []

for (x, y) in objects:
    shape = _get_shape(image, x, y)
    material = _get_material(image, x, y)
    if shape == cyan_shape and material == 'metal':
        shiny_same_shape_objects.append((x, y))

# Step 3: Filter to find those that are tiny
tiny_shiny_same_shape_objects = []

for (x, y) in shiny_same_shape_objects:
    size = _get_size(image, x, y)
    if size == 'small': # Assuming "tiny" means the smallest available size, which might be "small"
        tiny_shiny_same_shape_objects.append((x, y))

# Step 4: Determine the color of the tiny shiny object(s)
final_result = None

if tiny_shiny_same_shape_objects:
    x, y = tiny_shiny_same_shape_objects[0]  # Assuming only one object matches
    final_result = _get_color(image, x, y)
```

Answer: cyan ✗

Figure 6. VADAR program outputs on CLEVR.



Query: If the black armchair is 1 cm away in 3D, how far away in 3D is the dining table?

VADAR

```python
# Step 1: Locate the black armchair and the dining table
armchair_coords = loc(image, 'armchair')
dining_table_coords = loc(image, 'dining table')

# Step 2: Find the black armchair by checking the color of each
armchair
black_armchair = None
for x, y in armchair_coords:
    color = vqa(image, "What color is this?", x, y)
    if color == "black":
        black_armchair = (x, y)
        break

# Step 3: Get the depth of the black armchair
armchair_depth = depth(image, black_armchair[0], black_armchair[1])

# Step 4: Find the depth of the dining table
dining_table_depth = None
for x, y in dining_table_coords:
    # Ensure it's not the same as the armchair
    if not same_object(image, black_armchair[0], black_armchair[1], x,
y):
        dining_table_depth = depth(image, x, y)
        break

# Step 5: Calculate the 3D distance of the dining table
# Given that the armchair is 1 cm away in 3D, it means its depth is
scaled to 1 cm
# Calculate the scale factor
scale_factor = 1 / armchair_depth

# Use the scale factor to find the distance of the dining table in 3D
dining_table_distance_3D = dining_table_depth * scale_factor

# Step 6: Store the final result
final_result = dining_table_distance_3D
```

Answer: 2.428 ✓

Query: How many chairs are there behind the bowl?

VADAR

```python
def _is_behind(image, x_1, y_1, x_2, y_2):

    depth_1 = depth(image, x_1, y_1)
    depth_2 = depth(image, x_2, y_2)
    return depth_1 > depth_2

# PROGRAM STARTS HERE

# Initialize a counter to count the number of chairs behind the bowl
chair_count = 0

# Find all the bowls in the image
bowl_coordinates = loc(image, 'bowl')

# If no bowls are found, the result is 0 chairs
if not bowl_coordinates:
    final_result = chair_count
else:
    # Assume there is only one bowl, so take the first one
    bowl_x, bowl_y = bowl_coordinates[0]

    # Find all the chairs in the image
    chair_coordinates = loc(image, 'chair')

    # Iterate through each chair and check if it is behind the bowl
    for chair_x, chair_y in chair_coordinates:
        if _is_behind(image, chair_x, chair_y, bowl_x, bowl_y):
            chair_count += 1

    # Store the result in the final_result variable
    final_result = chair_count
```

Answer: 3 ✓

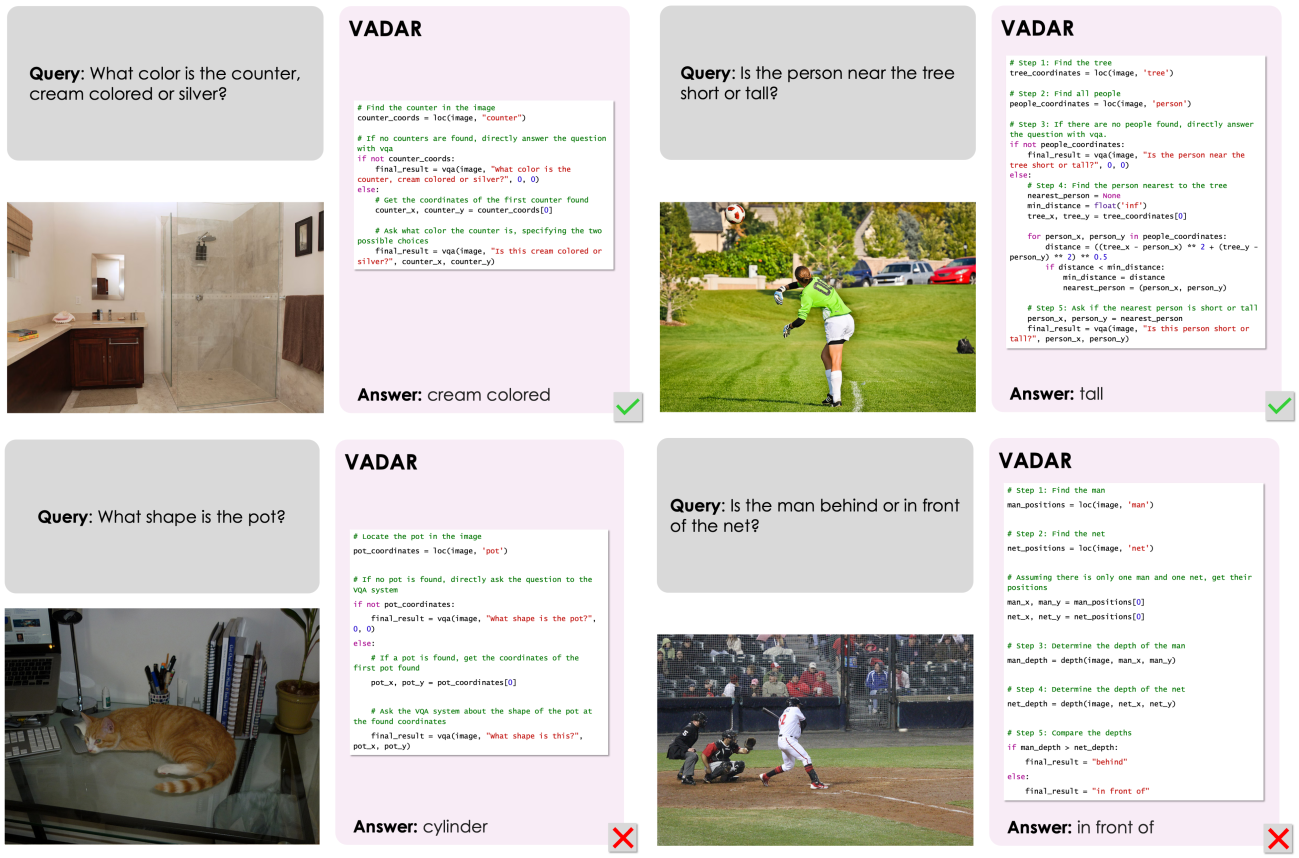
Query: If the 3D distance between the tv and the plant is 2 kilometers, what is the 3D distance between the tv stand and the plant?

VADAR

```python
import math

# Find the coordinates of TV, TV stand, and plant
tv_coordinates = loc(image, 'tv')
tv_stand_coordinates = loc(image, 'stand')
plant_coordinates = loc(image, 'plant')

# Assume the first occurrence of the objects is the desired one
tv_x, tv_y = tv_coordinates[0]
tv_stand_x, tv_stand_y = tv_stand_coordinates[0]
plant_x, plant_y = plant_coordinates[0]

# Calculate the depth of TV, TV stand, and plant
tv_depth = depth(image, tv_x, tv_y)
tv_stand_depth = depth(image, tv_stand_x, tv_stand_y)
plant_depth = depth(image, plant_x, plant_y)

# Calculate the 3D distance between the TV and the plant
# Known 3D distance between TV and plant is 2000 meters (2 kilometers)
known_distance = 2000

# Calculate 3D distance between TV and plant using their depths
tv_to_plant_distance = math.sqrt((tv_x - plant_x) ** 2 + (tv_y -
plant_y) ** 2 + (tv_depth - plant_depth) ** 2)

# Calculate 3D distance between TV stand and plant using their depths
tv_stand_to_plant_distance = math.sqrt(
    (tv_stand_x - plant_x) ** 2 +
    (tv_stand_y - plant_y) ** 2 +
    (tv_stand_depth - plant_depth) ** 2
)

# Scale the TV stand to plant 3D distance using the known distance
final_result = (tv_stand_to_plant_distance / tv_to_plant_distance) *
known_distance
```

Answer: 1.371 ✗

Figure 7. VADAR program outputs on OMNI3D-BENCH.



Query: What color is the counter, cream colored or silver?

VADAR

```python
# Find the counter in the image
counter_coords = loc(image, "counter")

# If no counters are found, directly answer the question
with vqa
if not counter_coords:
    final_result = vqa(image, "What color is the
counter, cream colored or silver?", 0, 0)
else:
    # Get the coordinates of the first counter found
    counter_x, counter_y = counter_coords[0]

    # Ask what color the counter is, specifying the two
possible choices
    final_result = vqa(image, "Is this cream colored or
silver?", counter_x, counter_y)
```

Answer: cream colored ✓

Query: Is the person near the tree short or tall?

VADAR

```python
# Step 1: Find the tree
tree_coordinates = loc(image, 'tree')

# Step 2: Find all people
people_coordinates = loc(image, 'person')

# Step 3: If there are no people found, directly answer
the question with vqa.
if not people_coordinates:
    final_result = vqa(image, "Is the person near the
tree short or tall?", 0, 0)
else:
    # Step 4: Find the person nearest to the tree
    nearest_person = None
    min_distance = float('inf')
    tree_x, tree_y = tree_coordinates[0]

    for person_x, person_y in people_coordinates:
        distance = ((tree_x - person_x) ** 2 + (tree_y -
person_y) ** 2) ** 0.5
        if distance < min_distance:
            min_distance = distance
            nearest_person = (person_x, person_y)

    # Step 5: Ask if the nearest person is short or tall
    person_x, person_y = nearest_person
    final_result = vqa(image, "Is this person short or
tall?", person_x, person_y)
```

Answer: tall ✓

Query: What shape is the pot?

VADAR

```python
# Locate the pot in the image
pot_coordinates = loc(image, 'pot')

# If no pot is found, directly ask the question to the
VQA system
if not pot_coordinates:
    final_result = vqa(image, "What shape is the pot?",
0, 0)
else:
    # If a pot is found, get the coordinates of the
first pot found
    pot_x, pot_y = pot_coordinates[0]

    # Ask the VQA system about the shape of the pot at
the found coordinates
    final_result = vqa(image, "What shape is this?",
pot_x, pot_y)
```

Answer: cylinder ✗

Query: Is the man behind or in front of the net?

VADAR

```python
# Step 1: Find the man
man_positions = loc(image, 'man')

# Step 2: Find the net
net_positions = loc(image, 'net')

# Assuming there is only one man and one net, get their
positions
man_x, man_y = man_positions[0]
net_x, net_y = net_positions[0]

# Step 3: Determine the depth of the man
man_depth = depth(image, man_x, man_y)

# Step 4: Determine the depth of the net
net_depth = depth(image, net_x, net_y)

# Step 5: Compare the depths
if man_depth > net_depth:
    final_result = "behind"
else:
    final_result = "in front of"
```

Answer: in front of ✗

Figure 8. VADAR program outputs on GQA [16].

```
\"\"\"
Locates objects in an image. Object prompts should be 1 WORD MAX.

Args:
   image (image): Image to search.
   object_prompt (string): Description of object to locate. Examples: "spheres", "objects".
Returns:
   list: A list of x,y coordinates for all of the objects located in pixel space.
\"\"\"
def loc(image, object_prompt):

\"\"\"
Answers a question about the attributes of an object specified by an x,y coordinate.
Should not be used for other kinds of questions.

Args:
   image (image): Image of the scene.
   question (string): Question about the objects attribute to answer. Examples: "What color is this?", "What material is this?"
   x (int): X coordinate of the object in pixel space.
   y (int): Y coordinate of the object in pixel space.


Returns:
   string: Answer to the question about the object in the image.
\"\"\"
def vqa(image, question, x, y):

\"\"\"
Returns the depth of an object specified by an x,y coordinate.

Args:
   image (image): Image of the scene.
   x (int): X coordinate of the object in pixel space.
   y (int): Y coordinate of the object in pixel space.

Returns:
   float: The depth of the object specified by the coordinates.
\"\"\"
def depth(image, x, y):

\"\"\"
Checks if two pairs of coordinates correspond to the same object.

Args:
   image (image): Image of the scene.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.

Returns:
   bool: True if object 1 is the same object as object 2, False otherwise.
\"\"\"
def same_object(image, x_1, y_1, x_2, y_2):
```

Figure 9. **Pre-defined Modules for CLEVR**. These modules are used to initialize the dynamic API. As CLEVR defines size to be either `large` or `small`, we omit the `get_2D_object_size` method.

```
\"\"\"
Locates objects in an image. Object prompts should be 1 WORD MAX.

Args:
   image (image): Image to search.
   object_prompt (string): Description of object to locate.
Returns:
   list: A list of x,y coordinates for all of the objects located in pixel space.
\"\"\"
def loc(image, object_prompt):

\"\"\"
Answers a question about the attributes of an object specified by an x,y coordinate.
Should not be used for other kinds of questions.

Args:
   image (image): Image of the scene.
   question (string): Question about the objects attribute to answer. Examples: "What color is this?", "What material is this?"
   x (int): X coordinate of the object in pixel space.
   y (int): Y coordinate of the object in pixel space.


Returns:
   string: Answer to the question about the object in the image.
\"\"\"
def vqa(image, question, x, y):

\"\"\"
Returns the depth of an object specified by an x,y coordinate.

Args:
   image (image): Image of the scene.
   x (int): X coordinate of the object in pixel space.
   y (int): Y coordinate of the object in pixel space.

Returns:
   float: The depth of the object specified by the coordinates.
\"\"\"
def depth(image, x, y):

\"\"\"
Checks if two pairs of coordinates correspond to the same object.

Args:
   image (image): Image of the scene.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.

Returns:
   bool: True if object 1 is the same object as object 2, False otherwise.
\"\"\"
def same_object(image, x_1, y_1, x_2, y_2):

\"\"\"
Returns the width and height of the object in 2D pixel space.

Args:
   image (image): Image of the scene.
   x (int): X coordinate of the object in pixel space.
   y (int): Y coordinate of the object in pixel space.

Returns:
   tuple: (width, height) of the object in 2D pixel space.
\"\"\"
def get_2D_object_size(image, x, y):
```

Figure 10. **Pre-defined Modules for OMNI3D-BENCH**. These modules are used to initialize the dynamic API.

```
def loc(self, image, object_prompt):
   pts = molmo(image, "point to the " + object_prompt)
   if len(pts) == 0:
      # No points found
      return []
   return pts

def vqa(image, question, x, y):
   mask = sam_2([x, y], "foreground") # get sam2 mask at x,y
   bbox = bbox_from_mask(mask) # bbox around sam2 mask
   boxed_image = overlay_box_on_image(image, bbox) # original image with bbox overlaid
   result = gpt4o(boxed_image, question)
   return result

def depth(image, x, y):
   depth_pred = unidepth(image)["depth"] # Predict depth map over image
   depth_x_y = depth_pred[y, x]
   return depth_x_y

def same_object(image, x_1, y_1, x_2, y_2):
   mask_1 = sam_2([x_1, y_1], "foreground") # get sam2 mask for point 1
   mask_2 = sam_2([x_2, y_2], "foreground") # get sam2 mask for point 2
   obj_1_bbox = bbox_from_mask(mask_1) # bbox around sam2 mask
   obj_2_bbox = bbox_from_mask(mask_2) # bbox around sam2 mask
   return iou(obj_1_bbox, obj_2_bbox) > 0.92

def get_2D_object_size(image, x, y):
   mask = sam_2([x, y], "foreground") # get sam2 mask at x,y
   bbox = bbox_from_mask(mask) # bbox around sam2 mask
   width = abs(box[0] - box[2])
   height = abs(box[1] - box[3])
   return width, height
```

Figure 11. **Python Implementation of Predefined Modules.** VADAR uses Molmo [8] for object detection, SAM2 [22] for segmentation, GPT4o [1] for VQA, and UniDepth [31] for depth estimation.

```
Propose only new method signatures to add to the existing API.

Available Primitives: image, int, string, list, tuple

Current API:
{current_api_signatures}

Next, I will ask you a series of questions that reference an image and are solvable with a python program that uses
the API I have provided so far. Please propose new method signatures with associated docstrings to add to the API that
 would help modularize the programs that answer the questions.

For each proposed method, output the docstring inside <docstring></docstring> immediately followed by the method
signature for the docstring inside <signature></signature>. Do not propose methods that are already in the API.

Please ensure that you ONLY add new methods when necessary. Do not add new methods if you can solve the problem with
combinations of the previous methods!

Added methods should be simple, building minorly on the methods that already exist.

Importantly, new methods MUST start with an underscore. As an example, you may define a "_get_material" method. Please
 ensure you ALWAYS start the name with an underscore.

Again, output the docstring inside <docstring></docstring> immediately followed by the method signature for the
docstring inside <signature></signature>.

{questions}
```

Figure 12. **Signature Agent Prompt** used for both CLEVR and OMNI3D-BENCH.

```
Implement a method given a docstring and method signature, using the API specification as necessary.
Current API:
{pre_defined_signatures}
{generated_signatures}

Here are some examples of how to implement a method given its docstring and signature:
<docstring>
\"\"\"
Locates objects that are on the left of the reference object.
Args:
   image (IMAGE): Image to search.
   ref_x (int): X coordinate of reference object in pixel space.
   ref_y (int): Y coordinate of reference object in pixel space.
Returns:
   points (list): list of [x, y] coordinates for objects in pixel space matching description to the left.
\"\"\"
</docstring>
<signature>def objects_left(image, ref_x, ref_y):</signature>
<implementation>
objects_left = []
all_objects = loc(image, object_prompt='objects')
for object_point in all_objects:
   x, y = object_point
   if same_object(image, ref_x, ref_y, x, y):
      continue
   if x < ref_x:
      objects_left.append(object_point)
return objects_left
</implementation>
<docstring>
\"\"\"
Gets the material of the given object.
Args:
   image (IMAGE): Image that the object is contained in.
   ref_x (int): X coordinate of reference object in pixel space.
   ref_y (int): Y coordinate of reference object in pixel space.
Returns:
   str: Material of the object.
\"\"\"
</docstring>
<signature>def object_material(image, ref_x, ref_y):</signature>
<implementation>
material = vqa(image=image, question='What material is this object?', x=ref_x, y=ref_y)
return material
</implementation>
<docstring>
\"\"\"
Checks if an object 1 is in front of object 2.
Args:
   image (IMAGE): Image that the object is contained in.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.
Returns:
   bool: True if object 1 is in front of object 2, False otherwise
\"\"\"
</docstring>
<signature>def in_front_of(image, x_1, y_1, x_2, y_2):</signature>
<implementation>
depth_1 = depth(image, x_1, y_1)
depth_2 = depth(image, x_2, y_2)
return depth_1 < depth_2
</implementation>
<docstring>
\"\"\"
Checks if object1 has the same size as object2
Args:
   image (IMAGE): Image that the object is contained in.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.
Returns:
   bool: True if object 1 has the same size as object 2, False otherwise
\"\"\"
</docstring>
<signature>def same_size(image, x_1, y_1, x_2, y_2):</signature>
<implementation>
object_1_size = vqa(image=image, question='What size is this object?', x=x_1, y=y_1)
object_2_size = vqa(image=image, question='What size is this object?', x=x_2, y=y_2)
return object_1_size == object_2_size
</implementation>

Here are some helpful tips:
1) When you need to search over objects satisfying a condition, remember to check all the objects that satisfy the condition and don't just return the first one.
2) You already have an initialized variable named "image" - no need to initialize it yourself!
3) When searching for objects to compare to a reference object, make sure to remove the reference object from the retrieved objects. You can check if two objects are
 the same with the same_object method.
Do not define new methods here, simply solve the problem using the existing methods.
Now, given the following docstring and signature, implement the method, using the API specification as necessary. Output the implementation inside <implementation></
implementation>.
Again, Output the implementation inside <implementation></implementation>.
<docstring>{docstring}</docstring>
<signature>{signature}</signature>
```

Figure 13. **Implementation Agent Prompt for CLEVR.** This prompt differs from the prompt used for OMNI3D-BENCH as we omit examples illustrating usage of the `get_2D_object_size` method. The prompt features *Weak ICL* examples illustrating correct usage of the pre-defined modules, as well as *Pseudo ICL* in the form of natural language instructions.

```
Implement a method given a docstring and method signature, using the API specification as necessary.
Current API:
{predef_signatures}
{generated_signatures}
Here are some examples of how to implement a method given its docstring and signature:
<docstring>
\"\"\" Locates objects that are on the left of the reference object.
Args:
   image (IMAGE): Image to search.
   ref_x (int): X coordinate of reference object in pixel space.
   ref_y (int): Y coordinate of reference object in pixel space.
Returns:
   points (list): list of [x, y] coordinates for objects in pixel space matching description to the left.
\"\"\"
</docstring>
<signature>def objects_left(image, ref_x, ref_y):</signature><implementation>
objects_left = []
all_objects = loc(image, object_prompt='objects')
for object_point in all_objects:
   x, y = object_point
   if same_object(image, ref_x, ref_y, x, y):
      continue
   if x < ref_x:
      objects_left.append(object_point)
return objects_left </implementation>
<docstring>
\"\"\" Gets the material of the given object.
Args:
   image (IMAGE): Image that the object is contained in.
   ref_x (int): X coordinate of reference object in pixel space.
   ref_y (int): Y coordinate of reference object in pixel space.
Returns:
   str: Material of the object.
\"\"\"
</docstring>
<signature>def object_material(image, ref_x, ref_y):</signature><implementation>
return vqa(image=image, question='What material is this object?', x=ref_x, y=ref_y) </implementation>
<docstring>
\"\"\" Checks if an object 1 is in front of object 2.
Args:
   image (IMAGE): Image that the object is contained in.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.
Returns:
   bool: True if object 1 is in front of object 2, False otherwise
\"\"\"
</docstring>
<signature>def in_front_of(image, x_1, y_1, x_2, y_2):</signature> <implementation>
depth_1, depth_2 = depth(image, x_1, y_1), depth(image, x_2, y_2)
return depth_1 < depth_2 </implementation>
<docstring>
\"\"\" Checks if object1 has the same size as object2
Args:
   image (IMAGE): Image that the object is contained in.
   x_1 (int): X coordinate of object 1 in pixel space.
   y_1 (int): Y coordinate of object 1 in pixel space.
   x_2 (int): X coordinate of object 2 in pixel space.
   y_2 (int): Y coordinate of object 2 in pixel space.
   epsilon (float): Acceptable margin of error in sizes.
Returns:
   bool: True if object 1 has the same size as object 2, False otherwise
\"\"\"
</docstring>
<signature>def same_size(image, x_1, y_1, x_2, y_2, epsilon):</signature> <implementation>
object_1_height, object_1_width = get_2D_object_size(image, x_1, y_1)
object_2_height, object_2_width = get_2D_object_size(image, x_2, y_2)
return abs(object_1_height - object_2_height) < epsilon and abs(object_1_width - object_2_width) < epsilon </implementation>
<docstring>
\"\"\" Returns a list of objects in the images
Args:
   image (IMAGE): Image to search for objects in
Returns:
   list: List of strings corresponding to all of the objects in the image.
\"\"\"
</docstring>
<signature>def get_object_list(image):</signature> <implementation>
objects = []
object_points = loc(image, object_prompt='objects')
for object_point in object_coords:
   obj_x, obj_y = object_point
   objects.append(vqa(image, "What is this object?", obj_x, obj_y))
return objects </implementation>
Here are some helpful definitions:
1) 2D distance/size refers to distance/size in pixel space. 2) 3D distance/size refers to distance/size in the real world. 3D size is equal to 2D size times the
depth of the object. 3) "On" is defined as the closest object ABOVE another object. Only use this definition for "on". 4) "Next to" is defined as the closest object.
 5) Width is the same as length. 6) "Depth" measures distance from the camera in 3D.
Here are some helpful tips:
1) When you need to search over objects satisfying a condition, remember to check all the objects that satisfy the condition and don't just return the first one. 2)
You already have an initialized variable named "image" - no need to initialize it yourself! 3) When searching for objects to compare to a reference object, make sure
 to remove the reference object from the retrieved objects. You can check if two objects are the same with the same_object method. 4) Do not assume that the objects
you see in these questions are all of the objects you will see, keep the methods general. 5) If two objects have the same 2D width, then the object with the largest
depth has the largest 3D width. 6) If two objects have the same 2D height, then the object with the largest depth has the largest 3D height. 7) 2D sizes convey the
height and width in IMAGE SPACE. To convert to height and width in 3D space, it needs to be multiplied by the depth! 8) If you are given a reference size, scale your
 output predicted size accordingly! Do not define new methods here, simply solve the problem using the existing methods. Now, given the following docstring and
signature, implement the method, using the API specification as necessary. Output the implementation inside <implementation></implementation>. Again, Output the
implementation inside <implementation></implementation>.
<docstring>
{docstring}
</docstring>
<signature>{signature}</signature>
```

Figure 14. **Implementation Agent Prompt for OMNI3D-BENCH.** The prompt features *Weak ICL* examples illustrating correct usage of the pre-defined modules, as well as *Pseudo ICL* in the form of natural language instructions and definitions.

```
You are an expert logician capable of answering spatial reasoning problems with code. You excel at using a predefined
API to break down a difficult question into simpler parts to write a program that answers spatial and complex
reasoning problem.
Answer the following question using a program that utilizes the API to decompose more complicated tasks and solve the
problem.
Available sizes are {{small, large}}, available shapes are {{square, sphere, cylinder}}, available material types are
{{rubber, metal}}, available colors are {{gray, blue, brown, yellow, red, green, purple, cyan}}.
The question may feature attributes that are outside of the available ones I specified above. If that's the case,
please replace them to the most appropriate one from the attributes above.
I am going to give you an example of how you might approach a problem in psuedocode, then I will give you an API and
some instructions for you to answer in real code.

Example:
Question: "What is the shape of the matte object in front of the red cylinder?"
Solution:
1) Find all the cylinders (loc(image, 'cylinders'))
2) If cylinders are found, loop through each of the cylinders found
3) For each cylinder found, check if the color of this cylinder is red. Store the red cylinder if you find it and
break from the loop.
4) Find all the objects.
5) For each object, check if the object is rubber (matte is not in the available attributes, so we replace it with
rubber)
6) For each rubber object O you found, check if the depth of O is less than the depth of the red cylinder
7) If that is true, return the shape of that object

Now here is an API of methods, you will want to solve the problem in a logical and sequential manner as I showed you
------------------ API ------------------
{pre_defined_signatures}
{api}
------------------ API ------------------
Please do not use synonyms, even if they are present in the question.
Using the provided API, output a program inside the tags <program></program> to answer the question.
It is critical that the final answer is stored in a variable called "final_result".
Ensure that the answer is either yes/no, one word, or one number.
Here are some helpful tips:
1) When you need to search over objects satisfying a condition, remember to check all the objects that satisfy the
condition and don't just return the first one.
2) You already have an initialized variable named "image" - no need to initialize it yourself! 3) Do not define new
methods here, simply solve the problem using the existing methods.
3) When searching for objects to compare to a reference object, make sure to remove the reference object from the
retrieved objects. You can check if two objects are the same with the same_object method.
Again, available sizes are {{small, large}}, available shapes are {{square, sphere, cylinder}}, available material
types are {{rubber, metal}}, available colors are {{gray, blue, brown, yellow, red, green, purple, cyan}}.
Again, answer the question by using the provided API to write a program in the tags <program></program> and ensure the
 program stores the answer in a variable called "final_result".
It is critical that the final answer is stored in a variable called "final_result".
Ensure that the answer is either yes/no, one word, or one number.
AGAIN, answer the question by using the provided API to write a program in the tags <program></program> and ensure the
 program stores the answer in a variable called "final_result".
You do not need to define a function to answer the question - just write your program in the tags. Assume "image" has
already been initialized - do not modify it!
<question>{question}</question>
```

Figure 15. **Program Agent Prompt for CLEVR.** In the prompt, we provide a list of all available attributes in CLEVR, a *Pseudo ICL* example in natural language, and some helpful tips.

```
You are an expert logician capable of answering spatial reasoning problems with code. You excel at using a predefined
API to break down a difficult question into simpler parts to write a program that answers spatial and complex
reasoning problem.
Answer the following question using a program that utilizes the API to decompose more complicated tasks and solve the
problem.
I am going to give you two examples of how you might approach a problem in psuedocode, then I will give you an API and
 some instructions for you to answer in real code.

Example 1:
Question: "What is the shape of the red object in front of the blue pillow?"
Solution:
1) Find all the pillows (loc(image, 'pillow')).
2) If pillows are found, loop through each of the pillows found.
3) For each pillow found, check if the color of this pillow is blue. Store the blue pillow if you find it and break
from the loop.
4) Find all the objects.
5) For each object, check if the object is red.
6) For each red object O you found, check if the depth of O is less than the depth of the blue pillow.
7) If that is true, return the shape of that object.

Example 2:
Question: "How many objects have the same color as the metal bowl?"
Solution:
1) Set a counter to 0
2) Find all the bowls (loc(image, 'bowls')).
3) If bowls are found, loop through each of the bowls found.
4) For each bowl found, check if the material of this bowl is metal. Store the metal bowl if you find it and break
from the loop.
5) Find and store the color of the metal bowl.
6) Find all the objects.
7) For each object O, check if O is the same object as the small bowl (same_object(image, metal_bowl_x, metal_bowl_y,
object_x, object_y)). If it is, skip it.
8) For each O you don't skip, check if the color of O is the same as the color of the metal bowl.
9) If it is, increment the counter.
10) When you are done looping, return the counter.

Now here is an API of methods, you will want to solve the problem in a logical and sequential manner as I showed you
------------------ API ------------------
{predef_signatures}
{api}
------------------ API ------------------
Please do not use synonyms, even if they are present in the question.
Using the provided API, output a program inside the tags <program></program> to answer the question.
It is critical that the final answer is stored in a variable called "final_result".
Ensure that the answer is either yes/no, one word, or one number.
Here are some helpful definitions:
1) 2D distance/size refers to distance/size in pixel space.
2) 3D distance/size refers to distance/size in the real world. 3D size is equal to 2D size times the depth of the
object.
3) "On" is defined as the closest object ABOVE another object. Only use this definition for "on".
4) "Next to" is defined as the closest object.
5) Width is the same as length.
6) "Depth" measures distance from the camera in 3D.
Here are some helpful tips:
1) When you need to search over objects satisfying a condition, remember to check all the objects that satisfy the
condition and don't just return the first one.
2) You already have an initialized variable named "image" - no need to initialize it yourself!
3) When searching for objects to compare to a reference object, make sure to remove the reference object from the
retrieved objects. You can check if two objects are the same with the same_object method.
4) Do not assume that the objects you see in these questions rae all of the objects you will see, keep the methods
general.
5) If two objects have the same 2D width, then the object with the largest depth has the largest 3D width.
6) If two objects have the same 2D height, then the object with the largest depth has the largest 3D height.
7) 2D sizes convey the height and width in IMAGE SPACE. To convert to height and width in 3D space, it needs to be
multiplied by the depth!
8) If you are given a reference size, scale your output predicted size accordingly!
Again, answer the question by using the provided API to write a program in the tags <program></program> and ensure the
 program stores the answer in a variable called "final_result".
It is critical that the final answer is stored in a variable called "final_result".
Ensure that the answer is either yes/no, one word, or one number.
AGAIN, answer the question by using the provided API to write a program in the tags <program></program> and ensure the
 program stores the answer in a variable called "final_result".
You do not need to define a function to answer the question - just write your program in the tags. Assume "image" has
already been initialized - do not modify it!
<question>{question}</question>
```

Figure 16. **Program Agent Prompt for OMNI3D-BENCH.** The prompt features *Pseudo ICL* in the form of two natural language examples and helpful tips for handling 2D and 3D dimensions.