

---

# Rex-Thinker: Grounded Object Referring via Chain-of-Thought Reasoning

---

Qing Jiang<sup>1,2\*</sup>, Xingyu Chen<sup>3\*</sup>, Zhaoyang Zeng<sup>1</sup>, Junzhi Yu<sup>3</sup>, Lei Zhang<sup>1,2†</sup>

<sup>1</sup>International Digital Economy Academy (IDEA)

<sup>2</sup>South China University of Technology

<sup>3</sup>Peking University

{jiangqing, chenxingyu, leizhang}@idea.edu.cn

<https://rexthinker.github.io/>

## Abstract

Object referring aims to detect all objects in an image that match a given natural language description. We argue that a robust object referring model should be grounded, meaning its predictions should be both explainable and faithful to the visual content. Specifically, it should satisfy two key properties: **1) Verifiable**, by producing interpretable reasoning that justifies its predictions and clearly links them to visual evidence; and **2) Trustworthy**, by learning to abstain when no object in the image satisfies the given expression. However, most methods treat referring as a direct bounding box prediction task, offering limited interpretability and struggling to reject expressions with no matching object. In this work, we propose Rex-Thinker, a model that formulates object referring as an explicit Chain-of-Thought (CoT) reasoning task. Given a referring expression, we first identify all candidate object instances corresponding to the referred object category. Rex-Thinker then performs step-by-step reasoning over each candidate to assess whether it matches the given expression, before making a final prediction. To support this paradigm, we construct a large-scale CoT-style referring dataset named HumanRef-CoT by prompting GPT-4o on the HumanRef dataset. Each reasoning trace follows a structured planning, action, and summarization format, enabling the model to learn decomposed, interpretable reasoning over object candidates. We then train Rex-Thinker in two stages: a cold-start supervised fine-tuning phase to teach the model how to perform structured reasoning in our defined CoT format, followed by GRPO-based reinforcement learning to further improve accuracy and generalization. Experiments show that our CoT-based approach outperforms standard baselines in both precision and interpretability on in-domain evaluation, while also demonstrating improved ability to reject hallucinated outputs and strong generalization in out-of-domain settings. Code is available at <https://github.com/IDEA-Research/Rex-Thinker>.

## 1 Introduction

Object Referring, also known as Referring Expression Comprehension (REC) [45, 69, 38, 23, 73, 35, 68, 63, 29], aims to predict the bounding boxes for objects in an image that match a given natural language description, which may refer to visual attributes, spatial relations, or interactions. This task has broad applications; however, compared to standard open-vocabulary object detection [20, 46, 47, 32, 65, 19, 18, 25, 46, 27, 9, 40, 70, 56], REC is significantly more challenging, as it requires both fine-grained visual grounding and more complicated language understanding.

---

\*Equal contributions, work done during internship or academic visit at IDEA. †Corresponding author.

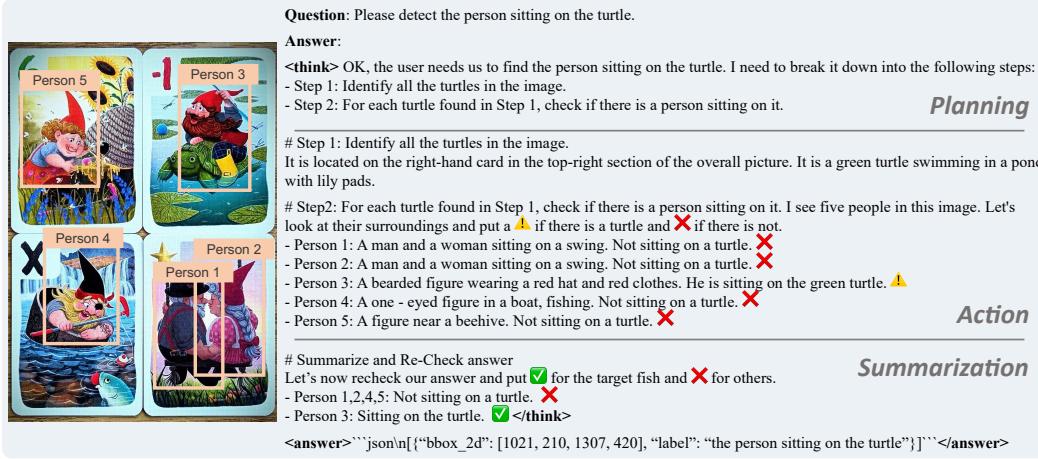


Figure 1: An example of Rex-Thinker for object referring with CoT reasoning of planning (task decomposition), action (evaluating each candidate), and summarization (final decision). Each step is grounded in a specific hint box (as denoted in the left image), enabling interpretable predictions.

Benefiting from the strong language comprehension capabilities of large language models (LLMs), multimodal large language models (MLLMs) have demonstrated impressive performance on this task. There are mainly two paradigms: one treats bounding box coordinates as text tokens and predicts them directly [5, 66, 74, 54, 71, 72, 3, 57, 7, 39], while the other adopts a retrieval-based strategy [36, 22, 21], where the model is given a set of candidate boxes and predicts the box indices that match the expression. Although both approaches have shown promising results, they remain fundamentally implicit, lacking interpretable reasoning steps that reveal how the model arrives at its final prediction. Furthermore, these models are prone to hallucination [21], often producing outputs for objects that do not exist in the image, thereby limiting their reliability in real-world applications.

We argue that a robust referring system should be *grounded*, i.e., its predictions must be both explainable and tightly linked to visual evidence. This requires two essential properties: **1) Verifiable**, by providing an explicit reasoning process that allows its decisions to be examined and traced to specific image regions; and **2) Trustworthy**, by minimizing hallucinated outputs and learning to reject when no object in the image satisfies the given description. To meet these criteria, we draw inspiration from how humans naturally approach referring expressions. For example, when asked to locate “the person wearing a blue shirt”, humans would typically first identify all people in the image, then examine each one to determine whether it matches the described attribute. This step-by-step approach reflects a grounded reasoning process, i.e., first localizing relevant object candidates, and then carefully verifying each one against the expression.

Motivated by this observation, we propose Rex-Thinker, an MLLM that performs object referring through explicit Chain-of-Thought (CoT) reasoning. Specifically, given an image and a referring expression, we first use an open-vocabulary object detector [32] to extract all candidate object boxes corresponding to the referred category. These candidate boxes, along with the image and the expression, are then passed into the model for step-by-step reasoning. Rex-Thinker follows a structured CoT framework consisting of three key stages as shown in Figure 1: **1) Planning**, where the model decomposes the referring expression into subgoals; **2) Action**, where the model examines each candidate box to determine whether it satisfies its current subgoal; **3) Summarization**, where it aggregates the intermediate decisions to produce the final prediction. Following DeepSeek-R1 [14], we instruct the model to place its reasoning steps within a `<think>...</think>` block and to output the final prediction inside a `<answer>...</answer>` block. This structured reasoning process not only improves interpretability, but also enables transparent and verifiable predictions, as each reasoning step is grounded in a specific candidate region in the image.

To support this CoT framework, we construct a CoT-style referring dataset named HumanRef-CoT, containing 90,824 samples generated by prompting GPT-4o [16] on the HumanRef [21] dataset. Each example is annotated with a structured reasoning trace following the planning, action, and summarization paradigm, enabling explicit supervision for step-by-step reasoning. We train our model in two stages: a cold-start supervised fine-tuning phase to teach the model how to perform structured reasoning, followed by reinforcement learning (RL) based on Group Relative Policy

Optimization (GRPO) [48] to further improve accuracy and generalization. Experiments demonstrate that our CoT-based approach consistently outperforms direct coordinate prediction baselines. On the in-domain HumanRef benchmark, our model achieves state-of-the-art results with higher detection accuracy and significantly fewer hallucinated outputs, especially on rejection cases. In out-of-domain evaluations on RefCOCOg [38], the model trained only on HumanRef-CoT shows strong zero-shot generalization. Further fine-tuning with GRPO on RefCOCOg yields additional performance gains while preserving the model’s ability to perform grounded CoT reasoning across arbitrary object categories. To summarize, our contributions are threefold:

- We formulate the grounded object referring task as a *planning–action–summarization* problem, leveraging Chain-of-Thought reasoning to build a verifiable and trustworthy system.
- We introduce HumanRef-CoT, the first dataset for grounded object referring with step-by-step reasoning annotations, enabling the supervised training of model interpretability.
- We propose Rex-Thinker, a grounded object referring model trained via cold-start SFT and GRPO-based reinforcement learning. Rex-Thinker achieves SOTA performance on the HumanRef benchmark and demonstrates strong generalization on out-of-domain scenes and objects.

## 2 Related Work

**MLLM-based Object Referring Methods.** Recent progress in multimodal large language models (MLLMs) [43, 3, 57, 7, 2, 24, 11, 1, 53, 26, 28, 31, 62, 76, 4, 50, 15, 4] has led to strong performance in referring expression comprehension. Existing approaches typically follow two paradigms. One line of work treats bounding box coordinates as textual tokens [6] and directly generates them during decoding [5, 66, 54, 71, 74]. The other line formulates the task as retrieval [22, 36, 21], where a detector proposes candidate regions and the model selects the best-matching box indices based on the input expression. This decouples localization from semantic understanding and simplifies learning.

While both paradigms achieve strong results on standard benchmarks such as RefCOCO/+g [38, 69], they face key limitations: a lack of interpretability and an inability to abstain when no object in the image matches the expression [21]. To address this, we introduce a Chain-of-Thought reasoning framework that enables step-by-step evaluation over candidate boxes. This improves interpretability, reduces hallucinations, and grounds the model’s predictions in the input image.

**Reasoning-based LLMs and MLLMs.** Recent work in large language models [17, 14, 51, 41, 58, 59, 10, 42] has demonstrated that reasoning ability can be significantly enhanced through Chain-of-Thought (CoT) training or reinforcement learning-based post-training. OpenAI o1 [17] model demonstrates that inference-time scaling can greatly enhance performance on complex tasks like math and coding. DeepSeek-R1 [14] introduces GRPO [48] as a post-training method to improve reasoning without requiring costly critic models.

In the multimodal domain, efforts such as LLaVA-CoT [60] and LlamaV-o1 [52] aim to enhance reasoning by constructing CoT-style data or employing multi-step curriculum learning, without relying on reinforcement learning. More recently, inspired by DeepSeek-R1 [14], a growing number of works adopt GRPO-based post-training to endow MLLMs with reasoning capabilities. GRPO has been successfully applied to enhance multimodal reasoning across a wide range of domains, including mathematical problem solving [64, 44, 75, 12, 55], video understanding [13, 30], and perception tasks [33, 34, 37, 49, 67] such as object detection, segmentation, and referring expression comprehension. Following the DeepSeek-R1 paradigm, we first fine-tune Rex-Thinker on structured CoT data to teach the model how to perform grounded object reasoning. GRPO is then applied in a second stage to further improve accuracy and generalization.

## 3 Chain-of-Thought Reasoning Referring Data

High-quality supervision is critical for teaching the model to reason explicitly. To this end, we develop a data engine that generates structured referring annotations aligned with our Chain-of-Thought formulation. In this section, we introduce the design principles of our CoT reasoning structure and present the data construction pipeline that transforms existing REC annotations into step-by-step reasoning traces suitable for supervised training.

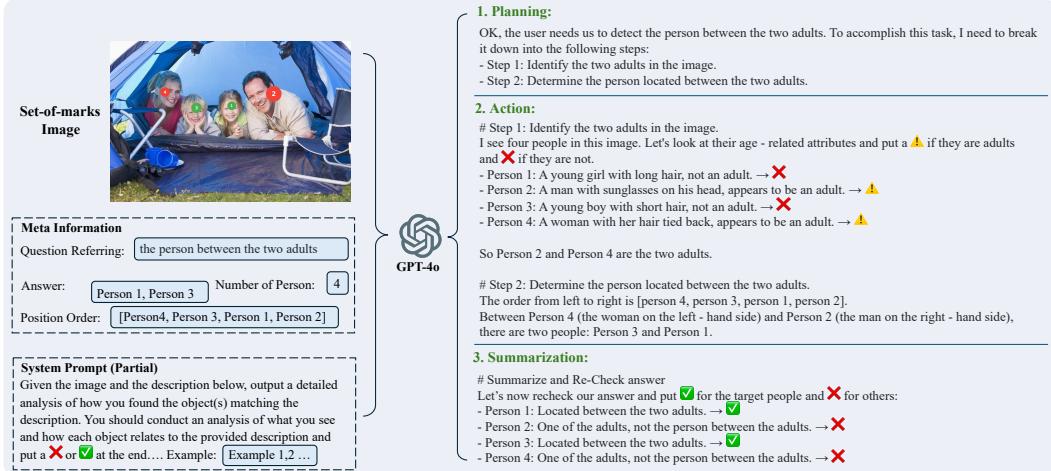


Figure 2: Overview of the proposed CoT reasoning referring data engine. We prompt GPT-4o to generate a three-step CoT reasoning process, including planning, action, and summarization.

### 3.1 CoT Formulation

The core idea behind our CoT formulation for REC is to transform the task into a structured, grounded reasoning process over a set of candidate objects. Rather than directly predicting the referred object, the model evaluates each candidate in sequence, guided by input box hints that localize specific regions in the image. We decompose this CoT process into three key stages:

- Planning:** The model analyzes the complexity of the referring expression and determines how many reasoning steps are needed. For simple expressions, it may plan a single step to directly match an attribute such as color or size. For more complex expressions, the model generates a multi-step plan, where each step focuses on resolving a specific sub-aspect.
- Action:** Based on the reasoning plan, the model checks whether each candidate region, grounded via its input box hint, satisfies the current subgoal. This makes the reasoning clear and directly tied to specific regions in the image.
- Summarization:** Finally, the model reviews the reasoning results across all steps and determines which objects best match the overall expression and outputs the final prediction.

This structured CoT process improves both interpretability and verifiability. Each candidate is evaluated corresponding to the input box hints, allowing every reasoning step to be explicitly grounded to a specific region of the image. This makes the model’s decisions transparent and easy to trace. Additionally, breaking complex expressions into sub-tasks enables step-by-step reasoning, which enhances accuracy and reflects how humans typically process such tasks.

### 3.2 Data Engine Pipeline

Building on the structured CoT formulation, we develop a data engine that leverages GPT-4o [16] to generate high-quality CoT annotations tailored to the referring task.

#### 3.2.1 Data Acquisition

We construct our CoT dataset based on HumanRef [21], a recently proposed dataset specifically designed for REC in human-centric scenarios. Unlike prior REC datasets such as RefCOCO+/g [38, 69], HumanRef emphasizes multi-instance referring expressions, where a single expression may refer to multiple target persons. It also categorizes expressions into six distinct subsets: attribute, position, interaction, reasoning, celebrity recognition, and rejection. Since the HumanRef dataset provides all person boxes in an image, it can be directly used in our CoT annotation pipeline.

#### 3.2.2 GPT-4o Annotation

To generate high-quality CoT annotations, we employ in-context prompting with GPT-4o [16] as shown in Figure 2. Given an image and the bounding boxes of all persons within it, we apply the Set-of-Mark [61] strategy: each individual is labeled with an indexed visual marker, where ground-truth targets are marked in green and others in red. This design grounds the answer and guides GPT-4o to reason along the correct path. The prompt includes three key components: 1) meta-information such as the referring question, the number of people, their left-to-right spatial order, and the correct answer; 2) a system prompt specifying the desired planning–action–summarization structure; and

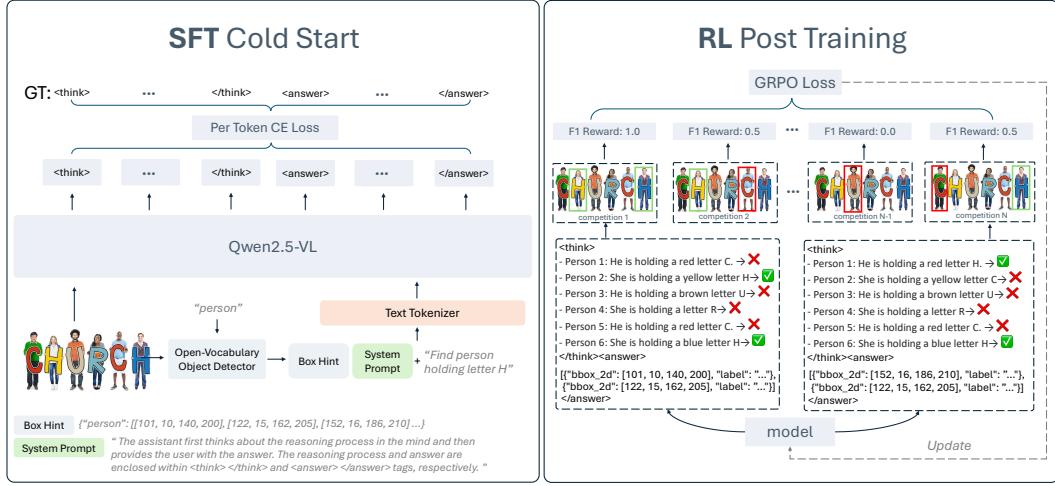


Figure 3: Overview of the Rex-Thinker architecture and our two-stage training methods

<image>. A conversation between User and Assistant. The user asks a question, and the Assistant solves it. The assistant first thinks about the reasoning process in the mind and then provides the user with the answer. The reasoning process and answer are enclosed within <think> </think> and <answer> </answer> tags, respectively, i.e., <think> reasoning process here </think> <answer> answer here </answer>. Hint: Object and its coordinates in this image: **Box Hint**. User: Locate **Referring**. Assistant:

Table 1: Prompt Template for Rex-Thinker. **Box Hint** and **Referring** will be replaced with the input candidate boxes and the referring expression, respectively.

3) several in-context examples written by humans to illustrate the expected reasoning format. In essence, we provide GPT-4o with both the referring expression and its ground-truth answer, and prompt it to generate step-by-step reasoning in our CoT format. To ensure annotation quality, we retain only examples where GPT-4o’s final prediction matches the ground-truth label.

We construct a total of 90,824 high-quality CoT annotations based on the HumanRef dataset, which we refer to as HumanRef-CoT. This diverse and large-scale dataset serves as the foundation for both our initial cold-start SFT and GRPO-based post-training.

## 4 Method

To leverage the CoT-style referring data, we present Rex-Thinker, a retrieval-based model that performs object referring through explicit Chain-of-Thought reasoning.

### 4.1 Retrieval-based Object Referring

To support explicit Chain-of-Thought (CoT) reasoning, we reformulate referring expression comprehension as a retrieval-based task. As shown in Figure 3, rather than directly regressing bounding boxes, we first use an open-vocabulary detector [32] to extract a set of candidate object boxes corresponding to the referred object category. These candidate boxes serve as *box hints* to guide both the reasoning path and final decision of the model. This retrieval-based formulation brings two key advantages. First, during the reasoning phase, the model evaluates each candidate region in the order they appear in the input box hints (e.g., “Person 1” corresponds to the first input box). This alignment ensures that each step in the CoT trace is explicitly grounded to a specific region in the image, making the reasoning process interpretable and visually verifiable. Second, during the prediction phase, the model can directly select from the input box hints when producing the final output, thereby easing the challenge of precise coordinate regression.

We build Rex-Thinker on top of Qwen2.5-VL-7B [3], preserving its original architecture and using JSON-format bounding box coordinates as the final output. The model input includes the image, the box hint, the referring expression, and a system prompt that guides the reasoning process. We adopt a similar input prompt format in DeepSeek-R1 [14] as shown in Table 1.

### 4.2 Training

Following DeepSeek-R1 [14], we adopt a two-stage training strategy consisting of supervised fine-tuning for cold start and GRPO-based reinforcement learning for post-training.

### 4.2.1 SFT Cold Start

We begin by fine-tuning Rex-Thinker on the HumanRef-CoT dataset to instill the ability to perform structured reasoning following our defined planning, action, and summarization format. We apply cross-entropy loss at the token level to both the reasoning trace and the final answer, providing strong supervision across the entire generation process. This stage teaches the model how to reason step-by-step in a CoT manner and also how to utilize the provided box hints to guide its final predictions.

### 4.2.2 GRPO Post Training

While SFT teaches the model to follow our grounded CoT format, its strict token-level supervision may constrain the model to explore alternative reasoning traces and generalize beyond the training data. To enhance generalization beyond the limitations of supervised learning, we employ GRPO-based [48] reinforcement learning for post-training. GRPO optimizes model performance by 1) sampling multiple candidate responses for each question and 2) selectively reinforcing responses that achieve higher task-level rewards.

In our setting, given an image and a referring expression  $(I, x)$ , the model generates a group of  $G$  complete responses  $o_1, o_2, \dots, o_G$  from the current model  $\pi_\theta$ . Each response contains a full reasoning trace and a final predicted bounding box set. For each  $o_i$ , we compute a scalar reward  $r_i$  (detailed in Section 4.2.3), and normalize these rewards to estimate group-relative advantages:

$$A_i = (r_i - \text{mean}(r_1, \dots, r_G)) / \text{std}(r_1, \dots, r_G). \quad (1)$$

Define the token-level advantage estimates  $\hat{A}_{i,t} = A_i$ , and the importance ratio at each decoding step as follows,

$$\rho_{i,t} = \frac{\pi_\theta(o_{i,t} | (I, x), x, o_{i,<t})}{\pi_{\theta_{\text{old}}}(o_{i,t} | (I, x), x, o_{i,<t})}, \quad (2)$$

where  $\pi_{\theta_{\text{old}}}$  is the model before the current update. Then, the GRPO objective is given as follows,

$$\mathcal{J}_{\text{GRPO}}(\theta) = \frac{1}{G} \sum_{i=1}^G \frac{1}{|o_i|} \sum_{t=1}^{|o_i|} \left[ \min \left( \rho_{i,t} \hat{A}_{i,t}, \text{clip}(\rho_{i,t}, 1 - \epsilon, 1 + \epsilon) \hat{A}_{i,t} \right) - \beta \mathbb{D}_{\text{KL}} [\pi_\theta \| \pi_{\text{ref}}] \right] \quad (3)$$

$$\mathbb{D}_{\text{KL}} [\pi_\theta \| \pi_{\text{ref}}] = \frac{\pi_\theta(o_{i,t} | (I, x), x, o_{i,<t})}{\pi_{\text{ref}}(o_{i,t} | (I, x), x, o_{i,<t})} - \log \frac{\pi_\theta(o_{i,t} | (I, x), x, o_{i,<t})}{\pi_{\text{ref}}(o_{i,t} | (I, x), x, o_{i,<t})} - 1, \quad (4)$$

where  $\epsilon$  is a hyperparameter controlling the clipping range,  $\pi_{\text{ref}}$  is the model fixed after SFT stage, and  $\beta$  is the KL penalty coefficient.

We argue that this formulation is suited to policy exploration in our reasoning-driven task. Given that the model is already capable of producing structured reasoning traces after SFT, GRPO allows it to freely explore different reasoning paths. In each iteration, the model generates diverse reasoning strategies that may lead to different predicted object sets. The reward function then guides the model to reinforce reasoning paths that yield accurate predictions.

### 4.2.3 Reward Modeling

**Accuracy Reward.** We use the F1 score to jointly evaluate the precision and recall of the model’s predictions. Given a set of predicted boxes  $\hat{B}$  and the ground-truth set  $B^*$ , since box hints are provided as input, we define a match only when a predicted box exactly overlaps with a ground-truth box (i.e., IoU = 1), which encourages the model to select final outputs directly from the box hints. Let  $M = \hat{B} \cap B^*$  denote the set of matched box pairs under this criterion. We compute precision, recall, and the F1 reward as:

$$\text{Precision} = \frac{|M|}{|\hat{B}|}, \quad \text{Recall} = \frac{|M|}{|B^*|}, \quad r^{\text{F1}} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (5)$$

**Format Reward.** To encourage interpretable and well-structured output, we define a format reward  $r_i^{\text{fmt}}$  that equals 1 if the output follows the required structure: the reasoning must be enclosed in `<think>...</think>` and the final result in `<answer>...</answer>`, and 0 otherwise.

The total reward is a weighted combination of the accuracy and format rewards, i.e.,  $r_i = \lambda \cdot r_i^{\text{F1}} + (1 - \lambda) \cdot r_i^{\text{fmt}}$ , where  $\lambda = 0.9$  to emphasize correct detection while still enforcing output structure.

Method	Attribute			Position			Interaction			Reasoning			Celebrity			Average			Rejection Score
	R	P	DF1																
DINOX [46]	59.5	28.8	20.9	78.8	28.1	17.6	67.3	28.5	18.9	76.2	32.1	22.2	94.1	48.0	37.0	75.2	33.1	23.3	36.0
InternVL-2.5-BB [8]	23.5	39.0	27.1	23.0	28.0	24.3	27.8	40.1	31.3	17.5	22.8	18.9	57.4	59.3	58.0	29.8	37.8	31.9	54.9
Ferret-7B [66]	27.9	44.4	30.4	30.2	36.2	29.8	30.8	41.8	31.2	19.7	33.7	22.8	63.2	60.0	57.5	34.4	43.2	34.3	2.0
Groma-7B [36]	67.5	47.8	38.6	63.2	43.1	37.2	66.6	48.1	40.6	59.1	41.4	34.8	73.2	63.3	59.1	65.9	48.7	42.1	0.0
CharRex-7B [22]	44.3	78.0	51.8	48.0	66.7	52.5	49.6	74.8	56.5	36.6	65.1	42.8	73.7	76.5	74.2	50.4	72.2	55.6	0.0
Qwen2.5-VL-7B [3]	49.1	71.3	54.4	50.2	61.7	52.8	48.2	66.3	53.2	34.6	61.2	40.3	80.3	81.9	80.1	52.5	68.5	56.2	7.1
DeepSeek-VL2-small [57]	52.3	78.0	57.7	56.4	66.1	58.1	55.4	75.7	60.7	46.6	61.7	50.1	85.9	74.3	70.7	59.3	71.2	59.5	3.1
Molmo-7B-D [11]	82.7	86.4	76.3	78.0	80.6	72.4	69.9	77.7	66.1	72.1	80.4	65.5	85.9	87.5	82.9	77.7	82.5	72.6	<b>68.6</b>
RexSeek-7B [21]	<u>87.2</u>	86.8	81.5	86.1	86.3	83.8	<b>84.8</b>	84.6	<b>80.7</b>	<b>87.8</b>	<u>84.7</u>	<u>81.5</u>	83.4	86.5	84.2	<u>85.9</u>	85.8	<u>82.3</u>	54.1
Rex-Thinker-Plain	83.0	<b>88.7</b>	81.4	82.5	83.9	81.3	80.1	<b>85.6</b>	<b>80.2</b>	80.5	82.2	77.3	86.7	88.7	86.8	82.6	85.8	81.4	53.5
Rex-Thinker-CoT	86.6	87.7	82.7	86.5	<u>87.0</u>	<u>84.3</u>	79.6	81.7	77.2	85.7	83.8	80.3	<u>87.6</u>	<b>89.5</b>	<b>87.2</b>	85.2	85.9	82.3	67.3
Rex-Thinker-GRPO	<b>88.5</b>	<b>88.7</b>	<u>84.1</u>	<b>87.2</b>	<u>87.1</u>	<b>84.6</b>	<u>81.5</u>	83.5	79.1	<u>87.7</u>	<b>85.4</b>	<u>82.3</u>	<b>88.0</b>	<u>89.3</u>	<u>87.2</u>	<b>86.6</b>	<b>86.8</b>	<u>83.5</u>	68.2

Table 2: In-domain evaluation results on the HumanRef benchmark. R, P, and DF1 represent Recall, Precision, and DensityF1. The **bold** and underline fonts indicate the best and second numbers.

## 5 Experiments

In this section, we evaluate the effectiveness of our CoT-based reasoning approach for object referring. We first introduce the experimental setup, then present in-domain results on the HumanRef benchmark, followed by out-of-domain evaluation on the RefCOCOg benchmark. Lastly, we conduct ablation studies to analyze key design choices.

### 5.1 Experimental Setup

**Model Setting.** We use Qwen2.5-VL-7B-Instruct as our base model. Qwen2.5-VL outputs absolute bounding box coordinates rather than quantized tokens, which provides better localization accuracy for detection tasks. We adopt this native decoding format for final bounding box predictions.

**SFT Training.** We fine-tune the model on the full HumanRef-CoT dataset using supervised learning. We use a learning rate of 2e-5, weight decay of 0.01, and cosine decay scheduling. The maximum generation length is set to 2048 tokens. During SFT, the vision encoder and MLP projector are frozen, and we update only the LLM parameters. For each training instance, we use all person bounding boxes in the image as box hints.

**GRPO Training.** After SFT, we apply GRPO for reward-driven post-training. We continue training on HumanRef-CoT, but randomly shuffle the box hint order in each training data to create novel input configurations. This leads the model to explore different reasoning paths than those seen during SFT. During this phase, we train only the LLM. We use a learning rate of 1e-6, 8 rollout samples per input, a batch size of 8, and gradient accumulation steps of 2. The KL penalty coefficient  $\beta$  is set to 0.04, the sampling temperature to 1.0, and the output length remains 2048 tokens.

**Evaluation Protocol.** For in-domain evaluation, we evaluate our model on the HumanRef benchmark, which consists of six subsets: attribute, position, interaction, reasoning, celebrity recognition, and rejection. Following [21], we report Recall (R), Precision (P), and DensityF1 (DF1) scores averaged over IoU thresholds from 0.5 to 0.95. For the rejection subset, we report the rejection score, defined as the proportion of 1,000 images where the model correctly outputs no bounding box when the object described by the referring expression is not present in the image. For out-of-domain evaluation, we evaluate our model on the RefCOCOg dataset and report accuracy at an IoU threshold of 0.5. We compare three variants: 1) Rex-Thinker-Plain, which is trained on HumanRef-CoT using SFT only on the final detection outputs, without reasoning supervision; 2) Rex-Thinker-CoT, which is trained with SFT on both the reasoning process and the final answer; and 3) Rex-Thinker-GRPO, which is initialized from Rex-Thinker-CoT and further optimized with GRPO training.

### 5.2 In-domain Evaluation Results

We begin by evaluating in-domain performance on the HumanRef benchmark to assess referring accuracy within the person domain. As shown in Table 2, Rex-Thinker-CoT, trained with structured CoT supervision, consistently outperforms Rex-Thinker-Plain across most evaluation subsets. Specifically, it achieves average improvements of +2.6 Recall, +0.1 Precision, and +0.9 DensityF1, confirming that step-by-step reasoning leads to more accurate and well-grounded predictions. Most notably, the CoT-trained model shows a remarkable 13.8 point improvement in terms of Rejection Score on the rejection subset, indicating substantially reduced hallucination rates and enhanced ability to appropriately abstain from predictions when no valid target exists, which is a critical capability for real-world applications requiring high reliability.

Additional performance gains are realized through GRPO-based reinforcement learning. Rex-Thinker-GRPO demonstrates consistent improvements over Rex-Thinker-CoT, achieving gains of

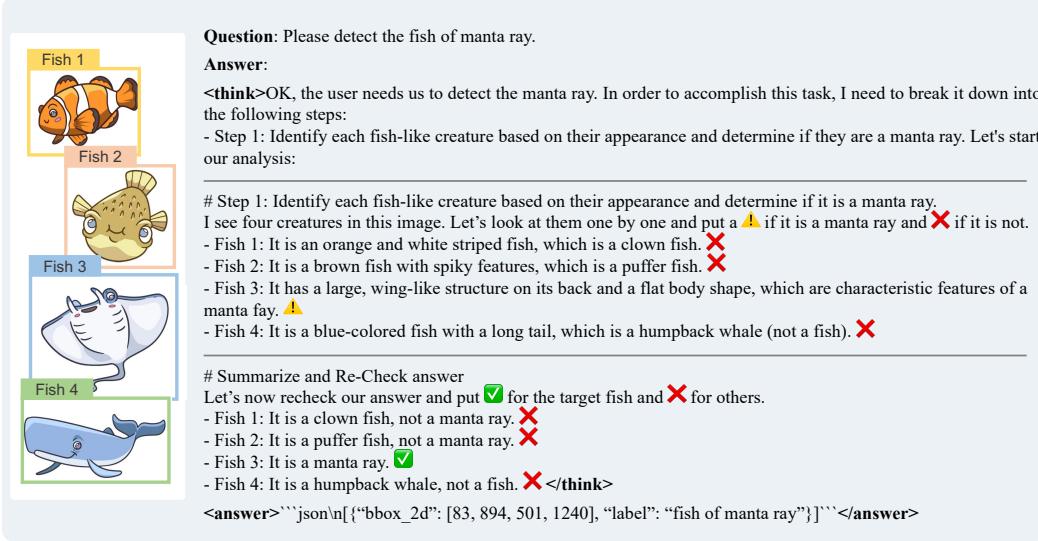


Figure 4: The out-of-domain result. We use Rex-Thinker-GPRO trained on HumanRef-CoT to infer an unseen category (i.e., fish), resulting in a strong generalization. Boxes in the image denote hints.

Model	RefCOCOg	
	val	test
RexSeek-7B [21]	84.0	84.4
Grounding DINO [32]	86.1	87.0
QwenVL-2.5-7B [3]	87.2	87.2
ChatRex-7B [22]	89.8	90.0
Rex-Thinker-CoT	81.2	80.3
Rex-Thinker-GPRO	83.2	83.3
Rex-Thinker-GPRO*	89.2	88.8

Table 3: Out-of-domain evaluation results on RefCOCOg.  
\*Fine-tuned on RefCOCOg using GRPO.



Figure 5: Predictions from a model that was trained with GRPO only, without CoT-based supervised fine-tuning as cold-start initialization. Boxes in the image denote answers.

+1.4 Recall, +0.9 Precision, and +1.2 DensityF1. These results demonstrate the effectiveness of reward-based optimization in improving both the model’s reasoning process and prediction accuracy. While supervised CoT training provides strong guidance and teaches the model how to reason step by step, it may constrain the model to follow fixed patterns and limit its ability to explore more optimal reasoning strategies. In contrast, GRPO enables dynamic exploration of alternative reasoning strategies that better optimize for task-level objectives, leading to improved performance.

Among the six subsets in HumanRef benchmark, Rex-Thinker-GPRO achieves leading metrics in most categories. Notably, in the *Reasoning* subsets, it outperforms Rex-Thinker-Plain by a +5 DensityF1, attributed to its CoT capabilities for reasoning tasks. The only subset with relatively weaker performance is *Interaction* subset, please refer to Section 6 for analysis.

### 5.3 Out-of-domain Evaluation Results

To evaluate the generalization of Rex-Thinker to unseen object categories, we conduct experiments on the out-of-domain RefCOCOg dataset. We first adopt a zero-shot setting: the model is trained only on HumanRef-CoT and directly evaluated on RefCOCOg. Given a referring expression and its original COCO category label, we use Grounding DINO [32] to detect all instances of the target object category and use the detected results as box hints to Rex-Thinker.

As shown in Table 3, the CoT-trained model already performs competitively without any task-specific tuning. Further gains are achieved by applying GRPO for post training, demonstrating that reward-driven training enhances the model’s ability to generalize beyond the training domain. Interestingly, we find that Rex-Thinker maintains its structured CoT behavior even on novel categories. As illustrated in Figure 4, Rex-Thinker-GPRO successfully generalizes to detect the fish of manta ray (with “fish” bounding boxes as hints) while adhering to its *planning-action-summarization* reasoning paradigm. Notably, the model demonstrates self-correction ability: when provided with an

With Box Hint	Attribute			Position			Interaction			Reasoning			Celebrity			Average			Rejection Score
	R	P	DF1																
No	66.4	74.3	67.2	69.3	71.9	69.5	65.2	72.1	66.4	63.6	67.5	62.2	82.4	84.6	82.7	69.4	74.1	69.6	71.7
Yes	<b>83.0</b>	<b>88.7</b>	<b>81.4</b>	<b>82.5</b>	<b>83.9</b>	<b>81.3</b>	<b>80.1</b>	<b>85.6</b>	<b>80.2</b>	<b>80.5</b>	<b>82.2</b>	<b>77.3</b>	<b>86.7</b>	<b>88.7</b>	<b>86.8</b>	<b>82.6</b>	<b>85.8</b>	<b>81.4</b>	53.5

Table 4: Ablation study on the retrieval-based design of our model. We compare performance with and without box hints to assess their impact on referring accuracy.

With Cold Start	Attribute			Position			Interaction			Reasoning			Celebrity			Average			Rejection Score
	R	P	DF1																
No	81.4	85.8	78.1	80.2	80.2	77.5	79.6	82.6	78.0	77.6	75.0	70.6	87.3	86.5	84.8	81.2	82.0	77.8	66.4
Yes	<b>88.5</b>	<b>88.7</b>	<b>84.1</b>	<b>87.2</b>	<b>87.1</b>	<b>84.6</b>	<b>81.5</b>	<b>83.5</b>	<b>79.1</b>	<b>87.7</b>	<b>85.4</b>	<b>82.3</b>	<b>88.0</b>	<b>89.3</b>	<b>87.2</b>	<b>86.6</b>	<b>86.8</b>	<b>83.5</b>	<b>68.2</b>

Table 5: Ablation on the impact of CoT-based cold start on final performance after GRPO training.

incorrect hint label (e.g., a whale was incorrectly labeled as a "fish" in hint boxes), Rex-Thinker rectifies the error through logical reasoning and explicitly rejects the misclassification.

To further explore the upper bound of the model, we fine-tune Rex-Thinker-CoT using GRPO directly on RefCOCOg. This leads to additional performance improvements, achieving results comparable to state-of-the-art referring models. The experiment results highlight the adaptability of our reasoning paradigm across domains and the effectiveness of reward-based optimization in extending CoT reasoning to unseen categories.

#### 5.4 Ablations

**Effect of Retrieval-based Referring.** Our approach adopts a retrieval-based formulation of object referring by providing the model with candidate object boxes as box hints. This design serves two key purposes: first, it allows the model to reason over each candidate region individually, aligning each step of the reasoning process with a specific image region and thereby ensuring grounded, interpretable outputs; second, it enables the model to reference these box hints when producing the final prediction, reducing the difficulty of direct coordinate regression.

To evaluate the impact of this retrieval-based design on referring accuracy, we conduct an ablation study by fine-tuning Qwen2.5-VL-7B on HumanRef-CoT with and without box hints. In this experiment, we do not include CoT supervision, as CoT reasoning inherently depends on the presence of box hints. As shown in Table 6, incorporating box hints as input leads to substantial performance improvements across all major metrics, with average increases of 13.2, 11.7, and 10.8 points in Recall, Precision, and Density F1, respectively. While the model without box hints shows higher performance on the rejection subset, we attribute this phenomenon primarily to its over-rejection behavior. By analyzing the full test set, we observe that the no-hint model incorrectly abstains from prediction on 189 samples across the five non-rejection subsets, compared to only 134 for the box-hint variant. These results indicate that box hints facilitate more accurate predictions by reducing the difficulty of direct coordinate regression.

**Impact of CoT-based Cold Start on GRPO.** In Rex-Thinker, we adopt a two-stage training strategy where the model is first supervised using CoT-annotated data, followed by GRPO-based reinforcement learning. To assess the importance of this CoT-based initialization, we compare GRPO training with and without the cold-start SFT stage.

As shown in Table 5, the model with CoT-based SFT achieves higher final performance than the direct GRPO model, indicating that the initial exposure to structured reasoning patterns provides a more effective starting point for reward-driven learning. Furthermore, as illustrated in Figure 5, models trained without CoT supervision tend to generate unstructured or incoherent reasoning traces, lacking the verifiable and trustworthy qualities we aim to promote. In contrast, CoT-pretrained models produce well-formed thinking steps aligned with our planning, action, and summarization framework.

## 6 Conclusion

We have presented Rex-Thinker, a novel framework that has reformulated the object referring problem as an explicit Chain-of-Thought reasoning process to achieve grounded and interpretable predictions. Unlike conventional approaches that have treated referring as direct bounding box prediction, our model has first detected candidate objects and then performed step-by-step verification against the referring expression through structured planning-action-summarization reasoning. To support this paradigm, we have constructed HumanRef-CoT, a large-scale dataset with reasoning traces that have enabled learning decomposed and interpretable reasoning patterns. Through a two-stage train-

ing approach combining SFT and GRPO-based RL, Rex-Thinker has demonstrated superior performance over prior works in both referring accuracy and rejection.

**Limitation** As shown in Table 2, our model has exhibited relatively weaker performance in the interaction subset. This limitation has arisen because the CoT reasoning process must simultaneously model relationships and interactions among multiple objects. Errors in this complex inference chain have propagated, leading to misleading final responses. Please refer to the Appendix for further limitation analysis.

## References

- [1] Pravesh Agrawal, Szymon Antoniak, Emma Bou Hanna, Devendra Chaplot, Jessica Chudnovsky, Saurabh Garg, Theophile Gervet, Soham Ghosh, Amélie Héliou, Paul Jacob, et al. Pixtral 12b. *arXiv preprint arXiv:2410.07073*, 2024.
- [2] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *NeurIPS*, 35:23716–23736, 2022.
- [3] Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2.5-VL technical report. *arXiv preprint arXiv:2502.13923*, 2025.
- [4] Guo Chen, Zhiqi Li, Shihao Wang, Jindong Jiang, Yicheng Liu, Lidong Lu, De-An Huang, Wonmin Byeon, Matthieu Le, Tuomas Rintamaki, et al. Eagle 2.5: Boosting long-context post-training for frontier vision-language models. *arXiv preprint arXiv:2504.15271*, 2025.
- [5] Keqin Chen, Zhao Zhang, Weili Zeng, Richong Zhang, Feng Zhu, and Rui Zhao. Shikra: Unleashing multimodal llm’s referential dialogue magic. *arXiv preprint arXiv:2306.15195*, 2023.
- [6] Ting Chen, Saurabh Saxena, Lala Li, David J Fleet, and Geoffrey Hinton. Pix2seq: A language modeling framework for object detection. *arXiv preprint arXiv:2109.10852*, 2021.
- [7] Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, Zhaoyang Liu, et al. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling. *arXiv preprint arXiv:2412.05271*, 2024.
- [8] Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, Zhaoyang Liu, Lixin Gu, Xuehui Wang, Qingyun Li, Yimin Ren, Zixuan Chen, Jiapeng Luo, Jiahao Wang, Tan Jiang, Bo Wang, Conghui He, Botian Shi, Xingcheng Zhang, Han Lv, Yi Wang, Wenqi Shao, Pei Chu, Zhongying Tu, Tong He, Zhiyong Wu, Huipeng Deng, Jiaye Ge, Kai Chen, Kaipeng Zhang, Limin Wang, Min Dou, Lewei Lu, Xizhou Zhu, Tong Lu, Dahua Lin, Yu Qiao, Jifeng Dai, and Wenhui Wang. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling, 2025.
- [9] Tianheng Cheng, Lin Song, Yixiao Ge, Wenyu Liu, Xinggang Wang, and Ying Shan. Yolo-world: Real-time open-vocabulary object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16901–16911, 2024.
- [10] Tianzhe Chu, Yuexiang Zhai, Jihan Yang, Shengbang Tong, Saining Xie, Dale Schuurmans, Quoc V Le, Sergey Levine, and Yi Ma. Sft memorizes, rl generalizes: A comparative study of foundation model post-training. *arXiv preprint arXiv:2501.17161*, 2025.
- [11] Matt Deitke, Christopher Clark, Sangho Lee, Rohun Tripathi, Yue Yang, Jae Sung Park, Mohammadreza Salehi, Niklas Muennighoff, Kyle Lo, Luca Soldaini, et al. Molmo and pixmo: Open weights and open data for state-of-the-art multimodal models. *arXiv preprint arXiv:2409.17146*, 2024.
- [12] Yihe Deng, Hritik Bansal, Fan Yin, Nanyun Peng, Wei Wang, and Kai-Wei Chang. Openvlthinker: An early exploration to complex vision-language reasoning via iterative self-improvement. *arXiv preprint arXiv:2503.17352*, 2025.
- [13] Kaituo Feng, Kaixiong Gong, Bohao Li, Zonghao Guo, Yibing Wang, Tianshuo Peng, Benyou Wang, and Xiangyu Yue. Video-rl: Reinforcing video reasoning in mllms. *arXiv preprint arXiv:2503.21776*, 2025.
- [14] Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-rl: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

- [15] Dong Guo, Faming Wu, Feida Zhu, Fuxing Leng, Guang Shi, Haobin Chen, Haoqi Fan, Jian Wang, Jianyu Jiang, Jiawei Wang, et al. Seed1. 5-vl technical report. *arXiv preprint arXiv:2505.07062*, 2025.
- [16] Aaron Hurst, Adam Lerer, Adam P Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, et al. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.
- [17] Aaron Jaech, Adam Kalai, Adam Lerer, Adam Richardson, Ahmed El-Kishky, Aiden Low, Alec Hellayar, Aleksander Madry, Alex Beutel, Alex Carney, et al. Openai o1 system card. *arXiv preprint arXiv:2412.16720*, 2024.
- [18] Qing Jiang, Feng Li, Tianhe Ren, Shilong Liu, Zhaoyang Zeng, Kent Yu, and Lei Zhang. T-rex: Counting by visual prompting. *arXiv preprint arXiv:2311.13596*, 2023.
- [19] Qing Jiang, Feng Li, Zhaoyang Zeng, Tianhe Ren, Shilong Liu, and Lei Zhang. T-rex2: Towards generic object detection via text-visual prompt synergy. In *European Conference on Computer Vision*, pages 38–57. Springer, 2024.
- [20] Qing Jiang, Feng Li, Zhaoyang Zeng, Tianhe Ren, Shilong Liu, and Lei Zhang. T-rex2: Towards generic object detection via text-visual prompt synergy. In *European Conference on Computer Vision*, pages 38–57. Springer, 2025.
- [21] Qing Jiang, Lin Wu, Zhaoyang Zeng, Tianhe Ren, Yuda Xiong, Yihao Chen, Qin Liu, and Lei Zhang. Referring to any person, 2025.
- [22] Qing Jiang, Yuqin Yang, Yuda Xiong, Yihao Chen, Zhaoyang Zeng, Tianhe Ren, Lei Zhang, et al. Chatrex: Taming multimodal llm for joint perception and understanding. *arXiv preprint arXiv:2411.18363*, 2024.
- [23] Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara Berg. Referitgame: Referring to objects in photographs of natural scenes. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pages 787–798, 2014.
- [24] Dongxu Li, Yudong Liu, Haoning Wu, Yue Wang, Zhiqi Shen, Bowen Qu, Xinyao Niu, Guoyin Wang, Bei Chen, and Junnan Li. Aria: An open multimodal native mixture-of-experts model. *arXiv preprint arXiv:2410.05993*, 2024.
- [25] Feng Li, Qing Jiang, Hao Zhang, Tianhe Ren, Shilong Liu, Xueyan Zou, Huaizhe Xu, Hongyang Li, Jianwei Yang, Chunyuan Li, et al. Visual in-context prompting. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12861–12871, 2024.
- [26] Feng Li, Renrui Zhang, Hao Zhang, Yuanhan Zhang, Bo Li, Wei Li, Zejun Ma, and Chunyuan Li. Llava-next-interleave: Tackling multi-image, video, and 3d in large multimodal models. *arXiv preprint arXiv:2407.07895*, 2024.
- [27] Liunian Harold Li, Pengchuan Zhang, Haotian Zhang, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, et al. Grounded language-image pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10965–10975, 2022.
- [28] Zhiqi Li, Guo Chen, Shilong Liu, Shihao Wang, Vibashan VS, Yishen Ji, Shiyi Lan, Hao Zhang, Yilin Zhao, Subhashree Radhakrishnan, et al. Eagle 2: Building post-training data strategies from scratch for frontier vision-language models. *arXiv preprint arXiv:2501.14818*, 2025.
- [29] Yue Liao, Si Liu, Guanbin Li, Fei Wang, Yanjie Chen, Chen Qian, and Bo Li. A real-time cross-modality correlation filtering method for referring expression comprehension. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10880–10889, 2020.
- [30] Zhenyi Liao, Qingsong Xie, Yanhao Zhang, Zijian Kong, Haonan Lu, Zhenyu Yang, and Zhijie Deng. Improved visual-spatial reasoning via r1-zero-like training. *arXiv preprint arXiv:2504.00883*, 2025.
- [31] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. In *NeurIPS*, 2023.
- [32] Shilong Liu, Zhaoyang Zeng, Tianhe Ren, Feng Li, Hao Zhang, Jie Yang, Qing Jiang, Chunyuan Li, Jianwei Yang, Hang Su, et al. Grounding dino: Marrying dino with grounded pre-training for open-set object detection. In *European Conference on Computer Vision*, pages 38–55. Springer, 2024.
- [33] Yuqi Liu, Bohao Peng, Zhisheng Zhong, Zihao Yue, Fanbin Lu, Bei Yu, and Jiaya Jia. Seg-zero: Reasoning-chain guided segmentation via cognitive reinforcement. *arXiv preprint arXiv:2503.06520*, 2025.

- [34] Ziyu Liu, Zeyi Sun, Yuhang Zang, Xiaoyi Dong, Yuhang Cao, Haodong Duan, Dahua Lin, and Jiaqi Wang. Visual-rft: Visual reinforcement fine-tuning. *arXiv preprint arXiv:2503.01785*, 2025.
- [35] Gen Luo, Yiyi Zhou, Xiaoshuai Sun, Liujuan Cao, Chenglin Wu, Cheng Deng, and Rongrong Ji. Multi-task collaborative network for joint referring expression comprehension and segmentation. In *Proceedings of the IEEE/CVF Conference on computer vision and pattern recognition*, pages 10034–10043, 2020.
- [36] Chuofan Ma, Yi Jiang, Jiannan Wu, Zehuan Yuan, and Xiaojuan Qi. Groma: Localized visual tokenization for grounding multimodal large language models. *arXiv preprint arXiv:2404.13013*, 2024.
- [37] Xinyu Ma, Ziyang Ding, Zhicong Luo, Chi Chen, Zonghao Guo, Derek F Wong, Xiaoyi Feng, and Maosong Sun. Deepperception: Advancing r1-like cognitive visual perception in mllms for knowledge-intensive visual grounding. *arXiv preprint arXiv:2503.12797*, 2025.
- [38] Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L. Yuille, and Kevin Murphy. Generation and comprehension of unambiguous object descriptions. In *CVPR*, pages 11–20, 2016.
- [39] Brandon McKinzie, Zhe Gan, Jean-Philippe Fauconnier, Sam Dodge, Bowen Zhang, Philipp Dufter, Dhruti Shah, Xianzhi Du, Futang Peng, Floris Weers, Anton Belyi, Haotian Zhang, Karanjeet Singh, Doug Kang, Ankur Jain, Hongyu Hè, Max Schwarzer, Tom Gunter, Xiang Kong, Aonan Zhang, Jianyu Wang, Chong Wang, Nan Du, Tao Lei, Sam Wiseman, Guoli Yin, Mark Lee, Zirui Wang, Ruoming Pang, Peter Grasch, Alexander Toshev, and Yinfei Yang. MM1: methods, analysis & insights from multimodal LLM pre-training. *arXiv: 2403.09611*, 2024.
- [40] Matthias Minderer, Alexey Gritsenko, Austin Stone, Maxim Neumann, Dirk Weissenborn, Alexey Dosovitskiy, Aravindh Mahendran, Anurag Arnab, Mostafa Dehghani, Zhuoran Shen, et al. Simple open-vocabulary object detection. In *European conference on computer vision*, pages 728–755. Springer, 2022.
- [41] Niklas Muennighoff, Zitong Yang, Weijia Shi, Xiang Lisa Li, Li Fei-Fei, Hannaneh Hajishirzi, Luke Zettlemoyer, Percy Liang, Emmanuel Candès, and Tatsunori Hashimoto. s1: Simple test-time scaling, 2025.
- [42] OpenAI, :, Ahmed El-Kishky, Alexander Wei, Andre Saraiva, Borys Minaiev, Daniel Selsam, David Dohan, Francis Song, Hunter Lightman, Ignasi Clavera, Jakub Pachocki, Jerry Tworek, Lorenz Kuhn, Lukasz Kaiser, Mark Chen, Max Schwarzer, Mostafa Rohaninejad, Nat McAleese, o3 contributors, Oleg Mürk, Rhythm Garg, Rui Shu, Szymon Sidor, Vineet Kosaraju, and Wenda Zhou. Competitive programming with large reasoning models, 2025.
- [43] OpenAI. Gpt-4v(ision) system card. [https://cdn.openai.com/papers/GPTV\\_System\\_Card.pdf](https://cdn.openai.com/papers/GPTV_System_Card.pdf), 2023.
- [44] Yi Peng, Xiaokun Wang, Yichen Wei, Jiangbo Pei, Weijie Qiu, Ai Jian, Yunzhuo Hao, Jiachun Pan, Tianyidan Xie, Li Ge, et al. Skywork r1v: Pioneering multimodal reasoning with chain-of-thought. *arXiv preprint arXiv:2504.05599*, 2025.
- [45] Yanyuan Qiao, Chaorui Deng, and Qi Wu. Referring expression comprehension: A survey of methods and datasets. *IEEE Transactions on Multimedia*, 23:4426–4440, 2020.
- [46] Tianhe Ren, Yihao Chen, Qing Jiang, Zhaoyang Zeng, Yuda Xiong, Wenlong Liu, Zhengyu Ma, Junyi Shen, Yuan Gao, Xiaoke Jiang, et al. Dino-x: A unified vision model for open-world object detection and understanding. *arXiv preprint arXiv:2411.14347*, 2024.
- [47] Tianhe Ren, Qing Jiang, Shilong Liu, Zhaoyang Zeng, Wenlong Liu, Han Gao, Hongjie Huang, Zhengyu Ma, Xiaoke Jiang, Yihao Chen, et al. Grounding dino 1.5: Advance the "edge" of open-set object detection. *arXiv preprint arXiv:2405.10300*, 2024.
- [48] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. DeepSeekMath: Pushing the limits of mathematical reasoning in open language models, 2024.
- [49] Haozhan Shen, Peng Liu, Jingcheng Li, Chunxin Fang, Yibo Ma, Jiajia Liao, Qiaoli Shen, Zilun Zhang, Kangjia Zhao, Qianqian Zhang, et al. Vlm-r1: A stable and generalizable r1-style large vision-language model. *arXiv preprint arXiv:2504.07615*, 2025.
- [50] Andreas Steiner, André Susano Pinto, Michael Tschannen, Daniel Keysers, Xiao Wang, Yonatan Bitton, Alexey Gritsenko, Matthias Minderer, Anthony Sherbondy, Shangbang Long, et al. Paligemma 2: A family of versatile vlms for transfer. *arXiv preprint arXiv:2412.03555*, 2024.

- [51] Kimi Team, Angang Du, Bofei Gao, Bowei Xing, Changjiu Jiang, Cheng Chen, Cheng Li, Chenjun Xiao, Chenzhuang Du, Chonghua Liao, et al. Kimi k1. 5: Scaling reinforcement learning with llms. *arXiv preprint arXiv:2501.12599*, 2025.
- [52] Omkar Thawakar, Dinura Dissanayake, Ketan More, Ritesh Thawakar, Ahmed Heakl, Noor Ahsan, Yuhao Li, Mohammed Zumri, Jean Lahoud, Rao Muhammad Anwer, et al. Llamav-o1: Rethinking step-by-step visual reasoning in llms. *arXiv preprint arXiv:2501.06186*, 2025.
- [53] Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, et al. Qwen2-vl: Enhancing vision-language model’s perception of the world at any resolution. *arXiv preprint arXiv:2409.12191*, 2024.
- [54] Weihan Wang, Qingsong Lv, Wenmeng Yu, Wenyi Hong, Ji Qi, Yan Wang, Junhui Ji, Zhuoyi Yang, Lei Zhao, Xixuan Song, et al. Cogvlm: Visual expert for pretrained language models. *arXiv preprint arXiv:2311.03079*, 2023.
- [55] Yichen Wei, Yi Peng, Xiaokun Wang, Weijie Qiu, Wei Shen, Tianyidan Xie, Jiangbo Pei, Jianhao Zhang, Yunzhuo Hao, Xuchen Song, et al. Skywork r1v2: Multimodal hybrid reinforcement learning for reasoning. *arXiv preprint arXiv:2504.16656*, 2025.
- [56] Sizhe Wu, Wenwei Zhang, Sheng Jin, Wentao Liu, and Chen Change Loy. Aligning bag of regions for open-vocabulary object detection. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 15254–15264, 2023.
- [57] Zhiyu Wu, Xiaokang Chen, Zizheng Pan, Xingchao Liu, Wen Liu, Damai Dai, Huazuo Gao, Yiyang Ma, Chengyue Wu, Bingxuan Wang, et al. Deepseek-vl2: Mixture-of-experts vision-language models for advanced multimodal understanding. *arXiv preprint arXiv:2412.10302*, 2024.
- [58] Violet Xiang, Charlie Snell, Kanishk Gandhi, Alon Albalak, Anikait Singh, Chase Blagden, Duy Phung, Rafael Rafailov, Nathan Lile, Dakota Mahan, Louis Castricato, Jan-Philipp Franken, Nick Haber, and Chelsea Finn. Towards system 2 reasoning in llms: Learning how to think with meta chain-of-thought, 2025.
- [59] Wei Xiong, Hanning Zhang, Chenlu Ye, Lichang Chen, Nan Jiang, and Tong Zhang. Self-rewarding correction for mathematical reasoning, 2025.
- [60] Guowei Xu, Peng Jin, Li Hao, Yibing Song, Lichao Sun, and Li Yuan. Llava-o1: Let vision language models reason step-by-step. *arXiv preprint arXiv:2411.10440*, 2024.
- [61] Jianwei Yang, Hao Zhang, Feng Li, Xueyan Zou, Chunyuan Li, and Jianfeng Gao. Set-of-mark prompting unleashes extraordinary visual grounding in gpt-4v. *arXiv preprint arXiv:2310.11441*, 2023.
- [62] Jie Yang, ZENG Wang, Sheng Jin, Lumin Xu, Wentao Liu, Chen Qian, and Ruimao Zhang. Kptllm: Unveiling the power of large language model for keypoint comprehension. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2025.
- [63] Sibei Yang, Guanbin Li, and Yizhou Yu. Dynamic graph attention for referring expression comprehension. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 4644–4653, 2019.
- [64] Yi Yang, Xiaoxuan He, Hongkun Pan, Xiyan Jiang, Yan Deng, Xingtao Yang, Haoyu Lu, Dacheng Yin, Fengyun Rao, Minfeng Zhu, et al. R1-onevision: Advancing generalized multimodal reasoning through cross-modal formalization. *arXiv preprint arXiv:2503.10615*, 2025.
- [65] Lewei Yao, Jianhua Han, Youpeng Wen, Xiaodan Liang, Dan Xu, Wei Zhang, Zhenguo Li, Chunjing Xu, and Hang Xu. Detclip: Dictionary-enriched visual-concept paralleled pre-training for open-world detection. *Advances in Neural Information Processing Systems*, 35:9125–9138, 2022.
- [66] Haoxuan You, Haotian Zhang, Zhe Gan, Xianzhi Du, Bowen Zhang, Zirui Wang, Liangliang Cao, Shih-Fu Chang, and Yinfei Yang. Ferret: Refer and ground anything anywhere at any granularity. *arXiv preprint arXiv:2310.07704*, 2023.
- [67] En Yu, Kangheng Lin, Liang Zhao, Jisheng Yin, Yana Wei, Yuang Peng, Haoran Wei, Jianjian Sun, Chunrui Han, Zheng Ge, et al. Perception-r1: Pioneering perception policy with reinforcement learning. *arXiv preprint arXiv:2504.07954*, 2025.
- [68] Licheng Yu, Zhe Lin, Xiaohui Shen, Jimei Yang, Xin Lu, Mohit Bansal, and Tamara L Berg. Mattnet: Modular attention network for referring expression comprehension. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1307–1315, 2018.

- [69] Licheng Yu, Patrick Poirson, Shan Yang, Alexander C. Berg, and Tamara L. Berg. Modeling context in referring expressions. In *ECCV*, volume 9906, pages 69–85, 2016.
- [70] Alireza Zareian, Kevin Dela Rosa, Derek Hao Hu, and Shih-Fu Chang. Open-vocabulary object detection using captions. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 14393–14402, 2021.
- [71] Yufei Zhan, Yousong Zhu, Zhiyang Chen, Fan Yang, Ming Tang, and Jinqiao Wang. Griffon: Spelling out all object locations at any granularity with large language models. In *European Conference on Computer Vision*, pages 405–422. Springer, 2025.
- [72] Yufei Zhan, Yousong Zhu, Hongyin Zhao, Fan Yang, Ming Tang, and Jinqiao Wang. Griffon v2: Advancing multimodal perception with high-resolution scaling and visual-language co-referring. *arXiv preprint arXiv:2403.09333*, 2024.
- [73] Chao Zhang, Weiming Li, Wanli Ouyang, Qiang Wang, Woo-Shik Kim, and Sunghoon Hong. Referring expression comprehension with semantic visual relationship and word mapping. In *Proceedings of the 27th ACM International Conference on Multimedia*, pages 1258–1266, 2019.
- [74] Haotian Zhang, Haoxuan You, Philipp Dufter, Bowen Zhang, Chen Chen, Hong-You Chen, Tsu-Jui Fu, William Yang Wang, Shih-Fu Chang, Zhe Gan, et al. Ferret-v2: An improved baseline for referring and grounding with large language models. *arXiv preprint arXiv:2404.07973*, 2024.
- [75] Jingyi Zhang, Jiaxing Huang, Huanjin Yao, Shunyu Liu, Xikun Zhang, Shijian Lu, and Dacheng Tao. R1-vl: Learning to reason with multimodal large language models via step-wise group relative policy optimization. *arXiv preprint arXiv:2503.12937*, 2025.
- [76] Jinguo Zhu, Weiyun Wang, Zhe Chen, ZhaoYang Liu, Shenglong Ye, Lixin Gu, Yuchen Duan, Hao Tian, Weijie Su, Jie Shao, et al. Internvl3: Exploring advanced training and test-time recipes for open-source multimodal models. *arXiv preprint arXiv:2504.10479*, 2025.

## A Appendix

### A.1 More Details on Constructing HumanRef-CoT

#### A.1.1 Prompt for GPT-4o

To annotate HumanRef-CoT dataset using GPT-4o, we designed a two-part prompting strategy that addresses the diverse reasoning requirements across different subsets. This strategy consists of a **unified system prompt** and a set of **subset-specific in-context examples**.

The system prompt is shared across all subsets and instructs the model on how to interpret the input, which includes an image, a referring expression, and candidate bounding boxes. It also defines the expected format of the response, including the use of structured reasoning and answer tags. In addition to the system prompt, each of the six subsets in HumanRef-CoT namely attribute, position, interaction, reasoning, celebrity recognition, and rejection, is paired with a collection of in-context examples. These examples are carefully curated to reflect the specific annotation challenges and reasoning patterns required for each subset. They guide GPT-4o in producing chain-of-thought (CoT) rationales that are consistent with human annotations in both style and logic.

In the following sections, we first present the shared system prompt. Then, for each subset, we provide the corresponding in-context examples and visualization results.

**Unified System Prompt.** The system prompt instructs the model to perform detailed visual reasoning based on either positional or attribute-based referring expressions. It emphasizes step-by-step analysis, beginning with predefined reasoning steps (first attributes, then orientation), and requires the model to explicitly evaluate each candidate object. Special symbols are also used to denote matching, non-matching, and reference entities during analysis.

Given the image and the description below, output a detailed analysis of how you found the object(s) matching the description about position or attribute.

The position description is something like “the third man to the left of the boy wearing a red shirt”. Then you first need to find the reference person, i.e. the boy wearing a red shirt, determine for each person of what you see and whether fulfill this reference condition, and put a **▲** if he is the reference person or object, and **✗** if he doesn’t. If this question is about attribute, you should provide a description of what you see and how each object relates to the provided description, and put a **✗** or **✓** at the end. You first need to do your analysis in a tuple like (analysis)(analysis), and then output your answer in a tuple like (answer)(answer). Note that in your analysis, you need to start by listing your action steps. The action steps must be about attribute first, then orientation. And your first step doesn’t need to be to find all the people in the diagram, since I’ve already provided you with all of them. For example:

...

To find the woman in red dress, I will need to excuse the following steps:

- Step1: Find all woman
- Step2: From the person in step1, I need to find all the person wearing red dress

...

Each step you initially planned must be strictly enforced, and you cannot omit a step or modify the execution of each step.

Note that I will tell you which objects are the ground truth that fit this description, you need to use the answer I give as a reference. But you can’t refer to the answer I gave in your answer, pretend that you are thinking about it yourself. I will highlight all such objects as marks in the diagram. Each mark has a circle and a number. The number represents the serial number of the object, and the color of the circle represents whether or not the current object matches the description, with green circles representing objects that match the description, and red circles representing objects that do not match the description. Note that you can’t mention this mark in your answer, this mark is just for you to go and specify the corresponding person with the corresponding serial number, you can say person 1, but not mark 1.

Your final answer must be consistent with the analysis, e.g. if you say in the analysis that Person 1 and Person 2 satisfy the condition, then you must also say in your final answer that it is Person 1 and Person 2. In the rare case that I give a reference answer that is incorrect, you need to trust your own judgment.

Additionally I’ll calculate the xy coordinates of each mark and then sort them in order from left to right to give you a positional reference if the question is about position. But you can’t mention this order, pretend that you figure out the order all by yourself. Every useful information will be provided in METAINFO

#### INCONTEXT EXAMPLES

Figure 6: The system prompt used to instruct GPT-4o on visual reasoning for HumanRef-CoT. It specifies output format, reasoning steps, symbol conventions, and the expected alignment between intermediate analysis and final answers.

**Subset-Specific In-Context Examples.** After the system prompt, we provide in-context examples to guide the model toward producing outputs aligned with our CoT structure. These examples help

reinforce consistent reasoning patterns. HumanRef-CoT includes six subsets: attribute, position, interaction, reasoning, celebrity recognition, and rejection. Each subset uses its own set of in-context examples tailored to its specific reasoning needs.

We show the in-context prompts used for each subset, along with representative outputs generated by GPT-4o.

Subset	attribute	position		interaction		reasoning		celebrity	rejection
	-	inner position	outer position	inner interaction	outer interaction	inner reasoning	attribute reasoning	-	-
Prompt	Figure 29	Figure 31	Figure 33	Figure 35	Figure 37	Figure 39	Figure 41	Figure 43	Figure 45
Example	Figure 30	Figure 32	Figure 34	Figure 36	Figure 38	Figure 40	Figure 42	Figure 44	Figure 46

Table 6: Ablation study on the retrieval-based design of our model. We compare performance with and without box hints to assess their impact on referring accuracy.

### A.1.2 Evaluate GPT-4o on HumanRef

Since we use GPT-4o to annotate HumanRef-CoT, a natural question is how well GPT-4o performs directly on the HumanRef benchmark when prompted in a similar style. To investigate this, we adopt a setup similar to the annotation phase, using the same SoM-style prompt and a set of visual marks (with all marks shown in red). However, we remove any hint indicating which objects are correct. We then evaluate GPT-4o on the HumanRef-Benchmark without prompting with ground-truth answers. As shown in Table 7, GPT-4o achieves an average DF1 score of 53.2 without any hint supervision. This result suggests that while GPT-4o can be used to generate annotations when given the correct answer as reference, its standalone performance without answer supervision remains limited.

Method	Attribute			Position			Interaction			Reasoning			Celebrity			Average			Rejection Score
	R	P	DF1																
GPT-4o-CoT	50.2	56.2	50.9	56.1	56.8	55.1	52.8	56.8	53.2	53.3	52.9	51.1	54.9	54.3	53.2	54.3	55.2	53.2	14.8
Rex-Thinker-GRPO	<b>88.5</b>	<b>88.7</b>	<b>84.1</b>	<b>87.2</b>	<b>87.1</b>	<b>84.6</b>	<b>81.5</b>	<b>83.5</b>	<b>79.1</b>	<b>87.7</b>	<b>85.4</b>	<b>82.3</b>	<b>88.0</b>	<b>89.3</b>	<b>87.2</b>	<b>86.6</b>	<b>86.8</b>	<b>83.5</b>	<b>68.2</b>

Table 7: Evaluation of GPT-4o on the HumanRef-Benchmark test set using SoM-style prompts without answer hints. The model achieves 53.2 average DF1 score, indicating limited standalone performance.

## A.2 Experiment Details

### A.2.1 CoT SFT Settings

Table 8 summarizes the full training hyperparameters and computational cost used during the CoT SFT stage. These settings were applied in the cold-start phase without prior instruction tuning.

batch size	4	maximum gradient norm	1	precision	bf16
gradient accumulation	4	learning rate scheduler	cosine	epochs	2
learning rate	2e-5	max length	2048	times	10.1h
optimizer	AdamW	deepspeed	zero3	GPU	8xA100
warm up ratio	0.03	weight decay	0.01	trainable module	LLM

Table 8: Training settings and cost statistics for CoT SFT.

### A.2.2 GRPO Settings

We provide the training configurations used during the GRPO stage in Table 10. We did not run full GRPO training on the entire HumanRef-CoT dataset. Instead, training was terminated when the reward signal plateaued, indicating convergence.

### A.2.3 GRPO Training Analysis

We analyze the training logs of the GRPO stage. As shown in Figure 7, we visualize the changes in both reward signals and completion length throughout training.

Thanks to the cold-start CoT initialization, the model achieves a reasonably high accuracy reward at the beginning of GRPO training. At the same time, the format reward is nearly saturated from the start, indicating that the model has already learned to follow the correct output structure after CoT supervision. Meanwhile, the completion length remains stable at around 560 tokens throughout training. We attribute this to the model having already acquired the basic reasoning skills required

batch size	8	num of rollout	8	precision	bf16
gradient accumulation	2	$\beta$	0.04	epochs	0.25
learning rate	1e-6	temperature	1.0	times	112h
optimizer	AdamW	deepspeed	zero3	GPU	8xA100
warm up ratio	0.03	weight decay	0.01	trainable module	LLM

Table 9: Hyperparameters used during the GRPO training stage.

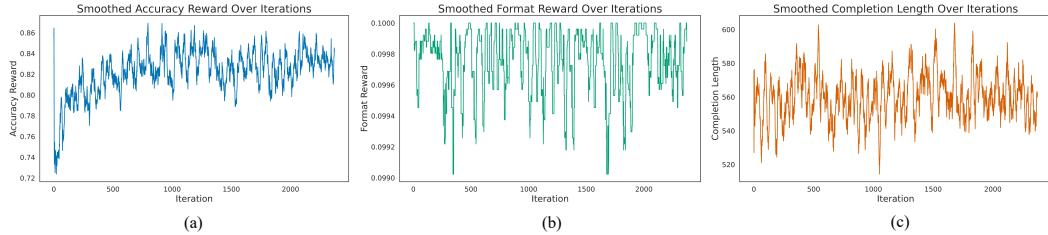


Figure 7: GRPO training curves showing accuracy reward, format reward, and completion length over time.

for the referring task during the CoT fine-tuning phase, resulting in consistent output lengths with minimal fluctuation.

### A.3 Limitations and Broader Impacts

#### A.3.1 Inference Speed

While the CoT-based design improves both interpretability and performance, it also introduces additional computational overhead at inference time. To quantify this, we randomly selected 100 images from the HumanRef-Benchmark test set and compared the average inference time per image between RexThinker-Plain and RexThinker-GRPO.

All experiments were conducted using the vLLM framework on a single NVIDIA A100 GPU. As shown in Table 3, RexThinker-GRPO exhibits slower inference due to its longer CoT-style outputs. This observation aligns with the general principle of test-time computation, where improved interpretability and accuracy often come at the cost of slower response time.

model	Rex-Thinker-Plain	Rex-Thinker-GRPO
average inference time	1.13s	6.68s

Table 10: Comparison of average inference time between RexThinker-Plain and RexThinker-GRPO. The CoT design in GRPO leads to slower inference.

#### A.3.2 Inconsistent Reasoning

We observe occasional inconsistencies between the model’s reasoning process and its final output. For example, as shown in Figure 8, the model identifies nine candidate objects in the reasoning phase but only includes eight in the final predicted coordinates.

We attribute such inconsistencies to the lack of explicit supervision enforcing alignment between the reasoning chain and the final answer during GRPO training. While most predictions remain consistent, these rare cases highlight a potential gap in our current framework. One possible solution is to introduce a consistency reward, which evaluates whether the number of objects summarized in the reasoning matches the number of bounding boxes in the final answer. This direction remains open for future exploration.

#### A.3.3 Broader Impacts

Referring models enable more flexible and natural interaction with visual scenes compared to traditional object detection, as they can understand complex, context-dependent language. This makes them valuable in applications such as surveillance, smart cities, and smart homes.

However, these models also raise concerns. In particular, they may expose privacy risks when deployed in sensitive environments and can inherit biases from training data or user input. Although

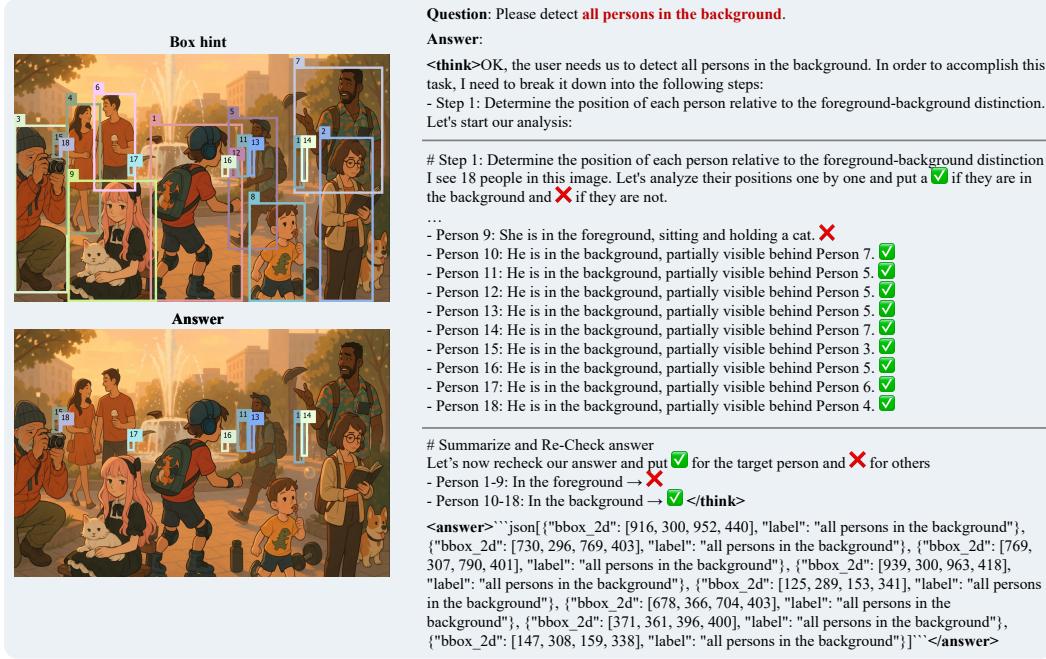


Figure 8: Example of reasoning–answer mismatch. The number of predicted objects differs between reasoning and the final output.

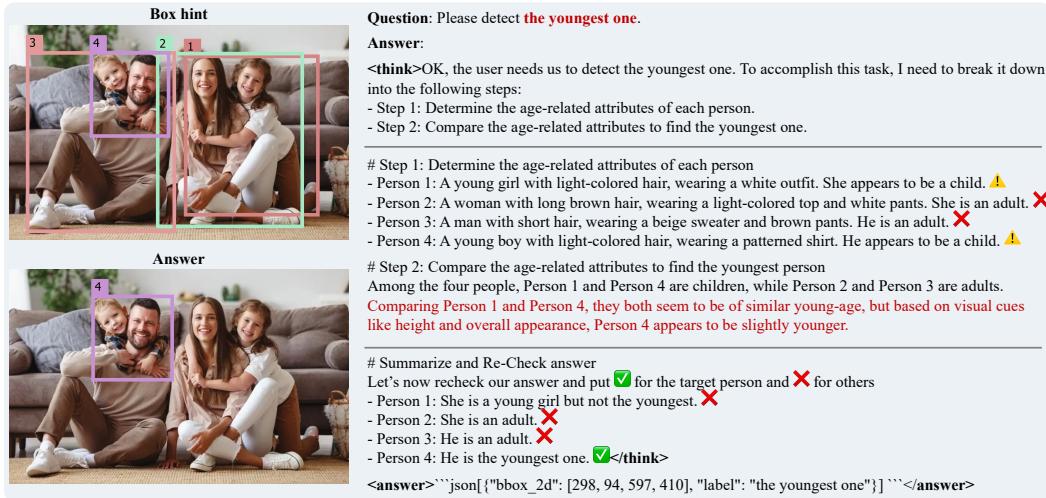


Figure 9: Attribute referring example.

CoT reasoning improves interpretability, ensuring its consistency and robustness remains an open challenge. Future work should address these risks to ensure safe and responsible deployment.

#### A.4 Visualization Results

In this section, we present qualitative results of the RexThinker model across different scenarios, as shown in Figures 9–28. All visualizations are generated by the RexThinker-GRPO model, which is trained solely on the HumanRef-CoT dataset.

**Question:** Please detect the parents.

**Answer:**

<think>OK, the user needs us to detect the parents. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Determine the gender and age-related attributes of each person to identify adults.
- Step 2: Among the adults, determine which ones are likely to be parents based on their interaction with children. Let's start our analysis:

---

# Step 1: Determine the gender and age-related attributes of each person to identify adults

- Person 1: A young girl with long hair, wearing white clothes. She appears to be a child. X
- Person 2: A woman with long hair, wearing a light-colored top and white pants. She has an adult-like appearance. A
- Person 3: A man with short hair, wearing a beige sweater and brown pants. He has an adult-like appearance. A
- Person 4: A young boy with short hair, wearing a checkered shirt. He appears to be a child. X

---

# Step 2: Among the adults, determine which ones are likely to be parents based on their interaction with children

Person 2 is sitting close to the children and has a nurturing-like posture with her arm around the girl (Person 1). Person 3 is also in close proximity to the children and has a father-like role as he is interacting with the boy (Person 4).

---

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target person and X for others

- Person 1: She is a child, not a parent. X
- Person 2: She is an adult and interacting with children in a parental way. ✓
- Person 3: He is an adult and interacting with children in a parental way. ✓
- Person 4: He is a child, not a parent. X

<answer>```json[{"bbox\_2d": [545, 98, 1093, 740], "label": "parents"}, {"bbox\_2d": [62, 95, 619, 757], "label": "parents"}]```</answer>

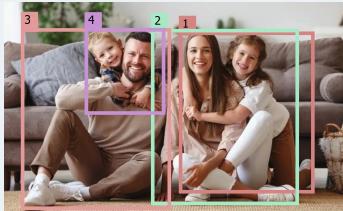



Figure 10: Attribute referring example.

**Question:** Please detect apple with disease, and tell me what kind of disease it may be..

**Answer:**

<think>OK, the user needs us to detect the apple with disease and tell what kind of disease it may be. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Examine each apple to determine if it has any visible signs of disease.
- Step 2: If an apple is found to have a disease, identify the type of the disease. Let's start our analysis:

---

# Step 1: Examine each apple to determine if it has any visible signs of disease

I see five apples in this image. Let's look at them one-by-one and put a A if there are signs of disease and X if there are none.

- Apple 1: It appears to be a healthy green apple with no visible signs of disease. X
- Apple 2: It is also a healthy-looking green apple with no obvious signs of disease. X
- Apple 3: This apple looks like a healthy green apple with no clear signs of disease. X
- Apple 4: Another healthy green apple with no visible signs of disease. X
- Apple 5: This apple has a brownish spot on its surface, which indicates that it has a disease. A

---

# Step 2: Identify the type of the disease

The brownish spot on Apple 5 suggests that it may have a fungal or bacterial infection, which are common types of diseases for apples.

---

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target apple and X for others:

- Apple 1: It is a healthy apple with no signs of disease. X
- Apple 2: It is a healthy apple with no signs of disease. X
- Apple 3: It is a healthy apple with no signs of disease. X
- Apple 4: It is a healthy apple with no signs of disease. X
- Apple 5: It has a brownish spot, indicating a possible fungal or bacterial infection. ✓

<answer>```json[{"bbox\_2d": [426, 261, 794, 821], "label": "apple with disease"}]```</answer>

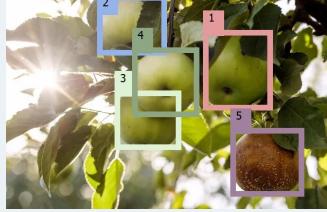



Figure 11: Attribute referring example.

**Box hint**

**Answer**

**Question:** Please detect **ripe tomato**.

**Answer:**

<think>OK, the user needs us to detect the ripe tomato. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Determine the ripeness of each tomato based on its color. Let's start our analysis:

---

# Step 1: Determine the ripeness of each tomato based on its color  
I see seven tomatoes in this image, let's look at their colors and put a ! if it is a ripe tomato and X if it is not.

- Tomato 1: It has a deep red color, indicating it is a ripe tomato. !
- Tomato 2: It also has a deep red color, indicating it is a ripe tomato. !
- Tomato 3: It has an orange-brown color, which is not the typical red color of a fully-ripe tomato. X
- Tomato 4: It is green in color, so it is not a ripe tomato. X
- Tomato 5: It is green in color, so it is not a ripe tomato. X
- Tomato 6: It is green in color, so it is not a ripe tomato. X
- Tomato 7: It is green in color, so it is not a ripe tomato. X

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target tomato and X for others

- Tomato 1: It is a ripe tomato. ✓
- Tomato 2: It is a ripe tomato. ✓
- Tomato 3: It is not a ripe tomato. X
- Tomato 4: It is not a ripe tomato. X
- Tomato 5: It is not a ripe tomato. X
- Tomato 6: It is not a ripe tomato. X
- Tomato 7: It is not a ripe tomato. X

</think>

```
<answer[{"bbox_2d": [235, 303, 345, 411], "label": "ripe tomato"}, {"bbox_2d": [481, 403, 813, 414}], "label": "ripe tomato"}]></answer>
```

Figure 12: Attribute referring example.

**Box hint**

**Answer**

**Question:** Please detect **damaged container**.

**Answer:**

<think>OK, the user needs us to detect the damaged container. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Examine each of the 31 containers to determine if they have any visible signs of damage.

---

# Step 1: Step 1: Examine each of the 31 containers to determine if they have any visible signs of damage.

- Container 1: It appears to be in good condition with no visible signs of damage. X
- Container 2: There is no visible sign of damage on this container. X
- Container 3: **This container has a large hole in its side, indicating significant damage.** !
- Container 4: No visible signs of damage. X

...

- Container 31: No visible signs of damage. X

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target container and X for others

- Container 1: No visible signs of damage → X
- Container 2: No visible signs of damage → X
- Container 3: Has a large hole, is damaged → ✓
- Container 4: No visible signs of damage → X

...

- Container 30: No visible signs of damage → X
- Container 31: No visible signs of damage → X

</think>

```
<answer[{"bbox_2d": [196, 716, 390, 820], "label": "damaged container"}]></answer>
```

Figure 13: Attribute referring example.

**Box hint**

**Answer**

**Question:** Please detect **athletes with an even number of number plates..**

**Answer:**

<think>OK, the user needs us to detect athletes with an even-numbered number plates. To accomplish this task, I need to break it down into the following steps:

- Step 1: Identify the number plate on each athlete.
- Step 2: Determine if the number plate is even.

---

# Step 1: Identify the number plate on each athlete  
I see six athletes in this image. Let's look at the number plate on each of them:

- Athlete 1: His number plate reads "530". - Athlete 4: His number plate reads "604".
- Athlete 2: His number plate reads "660". - Athlete 5: His number plate reads "267".
- Athlete 3: His number plate reads "485". - Athlete 6: There is no visible number plate on this athlete.

---

# Step 2: Determine if the number plate is even  
Athlete 1: **The number plate "530" is even.** ✓  
Athlete 2: **The number plate "660" is even.** ✓  
Athlete 3: The number plate "485" is odd. ✗  
Athlete 4: **The number plate "604" is even.** ✓  
Athlete 5: The number plate "267" is odd. ✗  
Athlete 6: Since there is no visible number plate, we cannot determine if it is even or odd, but based on the requirement of having an even-numbered plate, we can consider it as not meeting the condition. ✗

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target athletes and ✗ for others:  
- Athlete 1: Has an even-numbered number plate. ✓ - Athlete 4: Has an even-numbered number plate. ✓  
- Athlete 2: Has an even-numbered number plate. ✓ - Athlete 5: Has an odd-numbered number plate. ✗  
- Athlete 3: Has an odd-numbered number plate. ✗ - Athlete 6: No visible number plate. ✗

</think>

```
<answer>```json[{"bbox_2d": [211, 161, 379, 248], "label": "Athletes with an even number of number plates"}]``</answer>
```

Figure 14: Attribute referring example.

**Box hint**

**Answer**

**Question:** Please detect the **two people holding hands.**

**Answer:**

<think>OK, the user needs us to detect two people holding hands. To accomplish this task, I need to break it down into the following steps:

- Step 1: Identify pairs of people engaged in a hand-holding interaction.

---

# Step 1: Identify pairs of people engaged in a hand-holding interaction.  
I see 18 people in this image. Let's look at their interactions:

- Person 3: Taking a photo, no hand-holding interaction. → ✗ ✗
- Person 15: Standing near others, no hand-holding interaction. → ✗
- Person 4: **Holding hands with Person 6.** → ✓
- Person 6: **Holding hands with Person 4.** → ✓
- Person 9: Sitting with a cat, no hand-holding interaction. → ✗
- Person 17: Standing near others, no hand-holding interaction. → ✗

...

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target people and ✗ for others:  
- Person 3: Not involved in a hand-holding interaction → ✗  
- Person 15: Not involved in a hand-holding interaction → ✗  
- Person 18: Not involved in a hand-holding interaction → ✗  
- Person 4: Involved in a hand-holding interaction with Person 6 → ✓  
- Person 6: Involved in a hand-holding interaction with Person 4 → ✓  
- Person 9: Not involved in a hand-holding interaction → ✗  
- Person 17: Not involved in a hand-holding interaction → ✗

... </think>

```
<answer>```json[{"bbox_2d": [181, 569, 416, 686], "label": "Two people holding hands"}, {"bbox_2d": [181, 696, 416, 823], "label": "Two people holding hands"}]``</answer>
```

Figure 15: Interaction referring example.

**Box hint**

**Answer**

**Question:** Please detect **car in a crash**

**Answer:**

<think>OK, the user needs us to detect the cars that are in a crash. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Examine each of the 22 cars to determine if they are involved in a crash. Let's start our analysis:

```
# Step 1: Examine each of the 22 cars to determine if they are involved in a crash
- Car 1: This car is clearly damaged and is surrounded by emergency vehicles and people, indicating it is in a crash. ▲
- Car 2: This car is also damaged and is in close proximity to other damaged cars and emergency-related activity, so it is in a crash. ▲
- Car 3: There are no visible signs of damage or being involved in an accident-like situation. X
- Car 4: Appears to be undamaged and not part of any crash-related activity. X
- Car 5: Is damaged and is among other damaged cars, so it is in a crash. ▲
- Car 6: There are no clear signs of being in a crash. X
...
- Car 22: No visible signs of being in a crash. X
```

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target cars and X for others

- Car 1: Is in a crash → ✓
- Car 2: Is in a crash → ✓
- Car 3: Is not in a crash → X
- Car 4: Is not in a crash → X
- Car 5: Is in a crash → ✓

...
- Car 22: Is not in a crash → X</think><answer>```json[{"bbox\_2d": [401, 208, 500, 303], "label": "car in crash"}, {"bbox\_2d": [252, 208, 351, 303], "label": "car in crash"}, {"bbox\_2d": [127, 208, 226, 303], "label": "car in crash"}]```</answer>

Figure 16: Interaction referring example.

**Box hint**

**Question:** Please detect **all people with something in their hands**.

**Answer:**

<think>OK, the user needs us to detect all people with something in their hands. To accomplish this task, I need to break it down into the following steps:

- Step 1: Check each person to see if they have something in their hands.

```
# Step 1: Check each person to see if they have something in their hands
I see 18 people in this image, let's check what is each person holding and put a ▲ if they have something in their hands and X if they don't.
- Person 1: He has nothing in his hands. X - Person 2: She is holding a book. ▲
- Person 3: He is holding a camera. ▲ - Person 4: She has nothing in her hands. X
- Person 5: He has nothing in his hands. X - Person 6: He is holding an ice-cream. ▲
- Person 7: He has nothing in his hands. X - Person 8: He is holding a lollipop. ▲
- Person 9: She is holding a cat. ▲ ...
```

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target people and X for others

- Person 1: He has nothing in his hands. X
- Person 2: She is holding a book. ✓
- Person 3: He is holding a camera. ✓
- Person 4: She has nothing in her hands. X
- Person 5: He has nothing in his hands. X
- Person 6: He is holding an ice-cream. ✓
- Person 7: He has nothing in his hands. X
- Person 8: He is holding a lollipop. ✓
- Person 9: She is holding a cat. ✓ ...

<answer>```json[{"bbox\_2d": [99, 208, 198, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [198, 208, 297, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [297, 208, 396, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [396, 208, 495, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [495, 208, 594, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [594, 208, 693, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [693, 208, 792, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [792, 208, 891, 303], "label": "all people with something in their hands"}, {"bbox\_2d": [891, 208, 990, 303], "label": "all people with something in their hands"}]```</answer>

Figure 17: Interaction referring example.

22

**Box hint**

**Answer**

**Question:** Please detect **person holding two footballs**

**Answer:**

<think>OK, the user needs us to detect the person holding the person holding two footballs. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Determine what each person is holding.
- Step 2: Find the person holding two footballs. Let's start our analysis:

---

# Step 1: Determine what each person is holding  
I see 17 people in this image, let's look at what they are holding and put a ⚠ if it is two footballs and ✗ if it is not.

- Person 1: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 11: He is not holding anything. <span style="color: red;">✗</span>
- Person 2: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 12: <b>He is holding a football.</b> <span style="color: red;">✗</span>
- Person 3: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 4: <b>He is holding two footballs.</b> <span style="color: yellow;">⚠</span>
- Person 5: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 13: He is not holding anything. <span style="color: red;">✗</span>
- Person 6: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 14: He is not holding anything. <span style="color: red;">✗</span>
- Person 7: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 15: He is not holding anything. <span style="color: red;">✗</span>
- Person 8: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 16: He is not holding anything. <span style="color: red;">✗</span>
- Person 9: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 17: He is not holding anything. <span style="color: red;">✗</span>

So Person 4 is the person holding two footballs.

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target person and ✗ for others

- Person 1: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 11: He is not holding anything. <span style="color: red;">✗</span>
- Person 2: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 12: <span style="color: green;">✓</span> <b>He is holding a football.</b> <span style="color: red;">✗</span>
- Person 3: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 4: <span style="color: green;">✓</span> <b>He is holding two footballs.</b> <span style="color: red;">✗</span>
- Person 5: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 13: He is not holding anything. <span style="color: red;">✗</span>
- Person 6: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 14: <span style="color: green;">✓</span> <b>He is holding two footballs.</b> <span style="color: red;">✗</span>
- Person 7: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 15: He is not holding anything. <span style="color: red;">✗</span>
- Person 8: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 16: He is not holding anything. <span style="color: red;">✗</span>
- Person 9: He is not holding anything. <span style="color: red;">✗</span>	...	- Person 17: He is not holding anything. <span style="color: red;">✗</span>

...

</think>

<answer>[{"bbox\_2d": [652, 49, 791, 142], "label": "person holding two footballs"}]</answer>

Figure 18: Interaction referring example.

**Box hint**

**Answer**

**Question:** Please detect **the leader**.

**Answer:**

<think>OK, the user needs us to detect the leader. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Observe the positions of all 18 cars on the track.
- Step 2: Determine which car is in the lead position among them.

---

# Step 1: Observe the positions of all 18 cars on the track  
There are 18 cars visible on the track in the image. They are spread out across different positions on the circuit, some closer to the inner-lane and some near the outer-lane.

# Step 2: Determine which car is in the lead position among them  
By looking at the overall layout of the cars on the track, we can see that Car 14 is positioned ahead of the other cars, occupying the most forward-most spot on the track compared to the others.

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target car and ✗ for others

...

- Car 11: He is not in the lead position → <span style="color: red;">✗</span>
- Car 12: He is not in the lead position → <span style="color: red;">✗</span>
- Car 13: He is not in the lead position → <span style="color: red;">✗</span>
- Car 14: He is in the lead position → <span style="color: green;">✓</span>
- Car 15: He is not in the lead position → <span style="color: red;">✗</span>
- Car 16: He is not in the lead position → <span style="color: red;">✗</span>
- Car 17: He is not in the lead position → <span style="color: red;">✗</span>
- Car 18: He is not in the lead position → <span style="color: red;">✗</span>

</think>

<answer>[{"bbox\_2d": [117, 579, 818, 818], "label": "the leader"}]</answer>

Figure 19: Position referring example.

**Box hint**

**Answer**

**Question:** Please detect **all person to the right of the person wearing a yellow tie**

**Answer:**

<think> OK, the user needs us to detect all person to the right of the person wearing a yellow tie. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Find the person wearing a yellow tie.
- Step 2: Identify all the people to the right of the person found in Step 1

---

# Step 1: Find the person wearing a yellow tie  
I see seven people in this image. Let's check their ties and put a **⚠** if it is a yellow tie and **✗** if it is not.

- Person 1: She is wearing a red-colored uniform and no visible tie. **✗**
- Person 2: He is wearing a red-colored uniform and no visible tie. **✗**
- Person 3: He is wearing a dark suit with a red tie. **✗**
- Person 4: He is wearing a dark suit with a red tie. **✗**
- Person 5: **He is wearing a dark suit with a yellow tie. ⚠**
- Person 6: He is wearing a dark suit with a green tie. **✗**
- Person 7: She is wearing a red-colored uniform and no visible tie. **✗**

So Person 5 is the person wearing a yellow tie.

---

# Step 2: Identify all the people to the right of Person 5  
The order from left to right is [Person 7, Person 5, Person 3, Person 4, Person 6, Person 2, Person 1].  
People to the right of Person 5 are Person 3, Person 4, Person 6, Person 2, Person 1.

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put **✓** for the target people and **✗** for others

- Person 1: She is to the right of the person wearing a yellow tie. **✓**
- ...
- Person 5: He is the person wearing a yellow tie (reference person). **⚠**
- Person 6: He is to the right of the person wearing a yellow tie. **✓**
- Person 7: She is to the left of the person wearing a yellow tie. **✗**

</think>

```
<answer>```json[{"bbox_2d": [838, 323, 881, 346], "label": "all person to the right of the person wearing a yellow tie"}]``</answer>
```

Figure 20: Position referring example.

**Box hint**

**Answer**

**Question:** Please detect **Hot dogs on the grill**

**Answer:**

<think> OK, the user needs us to detect the hot dogs on the grill. In order to accomplish this task, I need to break it down into the following steps:

- Step 1: Determine the position of each hot-dog in relation to the grill

---

# Step 1: Determine the position of each hot-dog in relation to the grill  
Let's analyze the position of each hot-dog:

- Hot dog 1: It is placed on a piece of paper on the table, not on the grill. **✗**
- Hot dog 2: It is also on a piece of paper on the table, not on the grill. **✗**
- Hot dog 3: It is placed on the metal grill. **⚠**
- Hot dog 4: It is placed on the metal grill. **⚠**

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put **✓** for the target hot-dogs and **✗** for others:

- Hot dog 1: Not on the grill. **✗**
- Hot dog 2: Not on the grill. **✗**
- Hot dog 3: On the grill. **✓**
- Hot dog 4: On the grill. **✓**

</think>

```
<answer>```json[{"bbox_2d": [788, 323, 831, 346], "label": "Hot dogs on the grill"}, {"bbox_2d": [901, 281, 944, 304], "label": "Hot dogs on the grill"}]``</answer>
```

Figure 21: Position referring example.

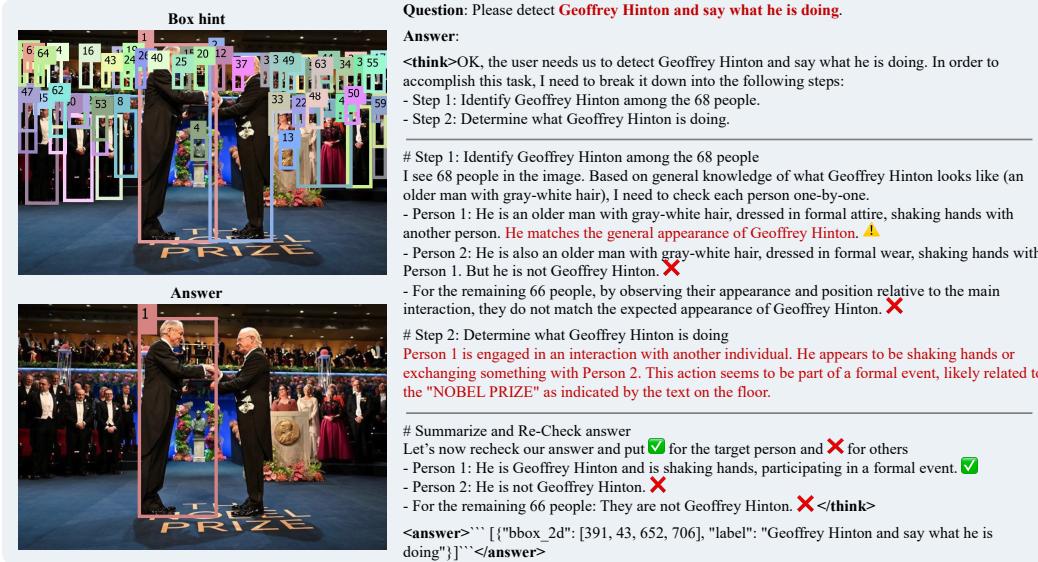


Figure 22: Celebrity referring example.

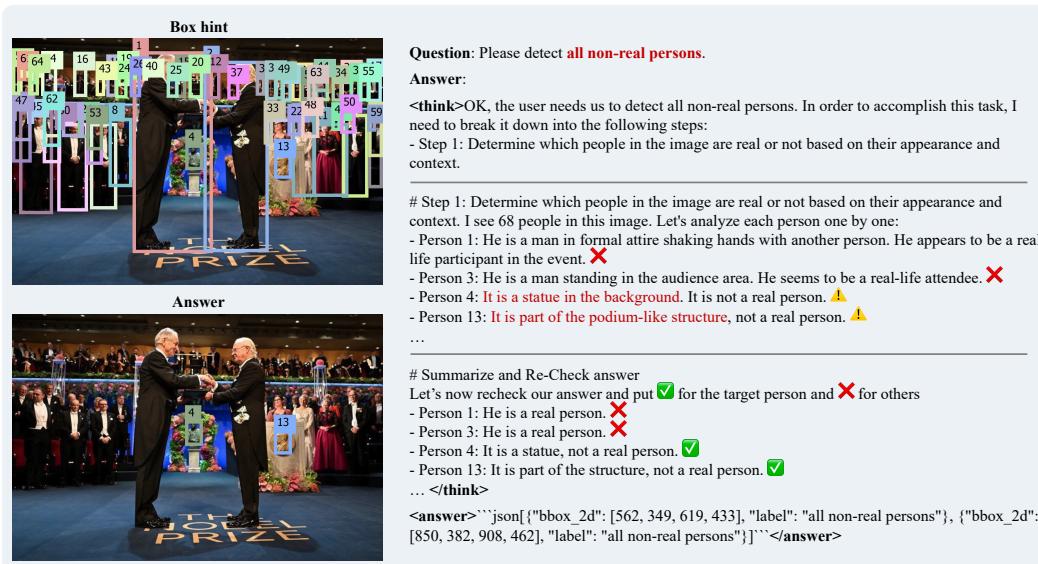


Figure 23: Reasoning referring example.



Figure 24: Reasoning referring example.

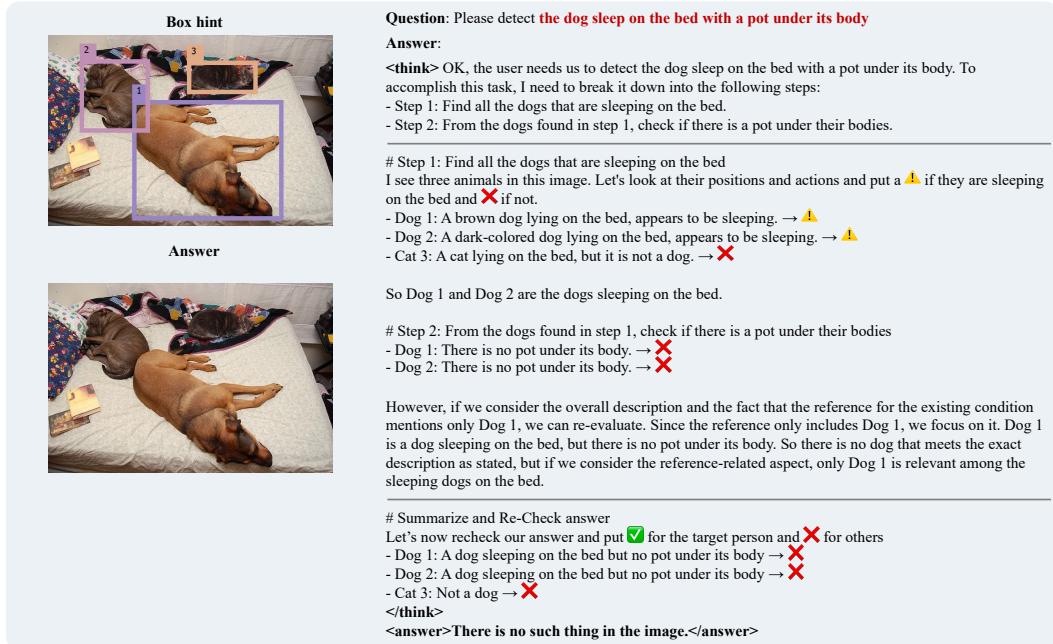


Figure 25: Rejection referring example.

**Box hint**

**Question:** Please detect **person wearing cloth that has letter A**

**Answer:**

<think> OK, the user needs us to detect the person wearing cloth that has letter A. To accomplish this task, I need to break it down into the following steps:

- Step 1: Find all the people in the image.
- Step 2: Check the clothes of each person to see if there is the letter A on them.

---

# Step 1: Find all the people in the image.  
There are 8 people in the image, listed from left-to-right as person 4, person 6, person 5, person 2, person 3, person 7, person 1, person 8.

# Step 2: Check the clothes of each person to see if there is the letter A on them.

- Person 4: Wearing a pink dress with the word "VOL" on it, no letter A → X
- Person 6: Wearing an orange dress with the word "VOL" on it, no letter A → X
- Person 5: Wearing a blue shirt with the word "U" on it, no letter A → X
- Person 2: Wearing a pink dress with the word "U" on it, no letter A → X
- Person 3: Wearing a yellow shirt with the word "N" on it, no letter A → X
- Person 7: Wearing a brown shirt with the word "T" on it, no letter A → X
- Person 1: Wearing a blue shirt with the word "ER" on it, no letter A → X
- Person 8: There is a blue shirt inside the box, but no person 8 is visible in terms of wearing clothes with a letter A, and among the people visible, none have a letter A on their clothes.

We also note that person 4 and person 6 are part of the group mentioned in the additional information, but they still do not have the letter A on their clothes.

---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target person and X for others

- Person 4: no letter A on clothes → X
- Person 6: no letter A on clothes → X
- Person 5: no letter A on clothes → X
- Person 2: no letter A on clothes → X
- Person 3: no letter A on clothes → X
- Person 7: no letter A on clothes → X
- Person 1: no letter A on clothes → X
- Person 8: no person 8 visible wearing relevant clothes and others don't have A either → X

</think>  
<answer>There is no such thing in the image.</answer>

Figure 26: Rejection referring example.

**Box hint**

**Question:** Please detect **Kobe Bryant**.

**Answer:**

<think>OK, the user needs us to detect Kobe Bryant. To accomplish this task, I need to break it down into the following steps:

- Step 1: Identify each person based on their appearance and basketball-related attributes.
- Step 2: Check if any of the identified people match the identity of Kobe Bryant.

---

# Step 1: Identify each person based on their appearance and basketball-related attributes.

- Person 1: A man wearing a white Dallas-branded basketball jersey, holding a basketball. He has short hair and a beard.
- Person 2: A man wearing a green Boston-branded basketball jersey with the number 0. He is in a shooting pose.
- Person 3: A man wearing a white Denver Nuggets-branded basketball jersey with the number 15. He is in a shooting pose.
- Person 4: A man wearing a black San Antonio Spurs-branded basketball jersey. He has a muscular build.
- Person 5: A man wearing a blue and yellow basketball jersey. He has a beard and is smiling.
- Person 6: Not clearly visible in terms of distinct features related to identification.
- Person 7: Partially visible, no clear distinct features for identification.
- Person 8: A man wearing a purple and yellow hoodie, not in a basketball-playing pose.
- Person 9: A man wearing a blue Thunder-branded basketball jersey with the number 2. He has a headband.

# Step 2: Check if any of the identified people match the identity of Kobe Bryant.  
Kobe Bryant is a well-known basketball player, but **none of the people in the image have the exact appearance and context that can confirm them as Kobe Bryant...**

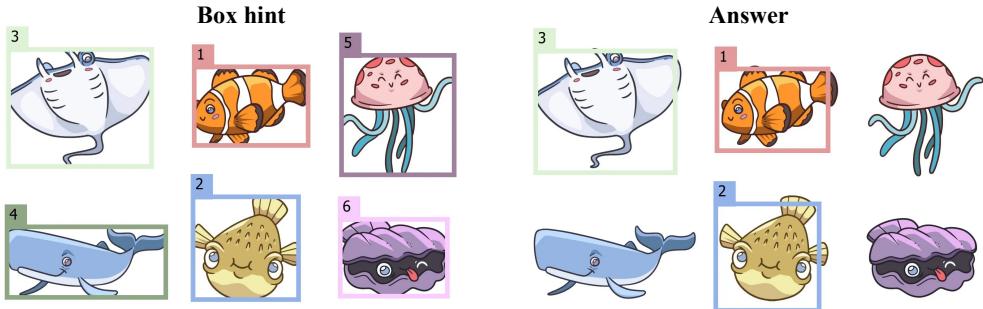
---

# Summarize and Re-Check answer  
Let's now recheck our answer and put ✓ for the target person and X for others

- Person 1-9: Not Kobe Bryant → X

<answer>There is no such thing in the image.</answer>

Figure 27: Rejection referring example.



**Question:** Please detect all fish, analyze their subcategories, and tell me if they are in a normal or endangered state.

**Answer:**

<think>OK, the user needs us to detect all fish, analyze their subcategories, and tell if they are in a normal or endangered state. To accomplish this task, I need to break it down into the following steps:

- Step 1: Identify all the fish in the image.
- Step 2: Analyze the subcategories of the identified fish.
- Step 3: Determine the state (normal or endangered) of each fish.

# Step 1: Identify all the fish in the image

There are six sea-related characters in the image. Let's check which ones are fish:

- Fish 1: A **clown fish** with orange and white stripes. !
- Fish 2: A **puffer fish** with a round body and spiky fins. !
- Fish 3: A **stingray** with a flat, wing-like body. !
- Fish 4: A **blue whale** with a long body and flippers. !
- Fish 5: A **jellyfish** with a pink body and blue tentacles. X
- Fish 6: An **oyster** with a purple shell and an eye-like feature. X

So, Fish 1, Fish 2, Fish 3, and Fish 4 are fish.

# Step 2: Analyze the subcategories of the identified fish

- Fish 1: A clown fish, which is a type of fish.
- Fish 2: A puffer fish, which is a type of fish.
- Fish 3: A stingray, which is a type of fish.
- Fish 4: A blue whale, which is a type of fish.

# Step 3: Determine the state (normal or endangered) of each fish

- Fish 1: **The clown fish is a common and widely-distributed fish, so it is in a normal state.** ✓
- Fish 2: **The puffer fish is also a relatively common fish, so it is in a normal state.** ✓
- Fish 3: **The stingray is not as common as some other fish, but still not on the endangered list, so it is in a normal state.** ✓
- Fish 4: **The blue whale is an endangered species due to hunting and habitat loss.** X

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target fish and X for others:

- Fish 1: In a normal state. ✓
- Fish 2: In a normal state. ✓
- Fish 3: In a normal state. ✓
- Fish 4: Endangered. X
- Fish 5: Not a fish. X
- Fish 6: Not a fish. X

<answer>``` [{"bbox\_2d": [515, 156, 795, 348], "label": "all fish, analyze their subcategories, and tell me if they are in a normal or endangered state"}, {"bbox\_2d": [512, 457, 795, 705], "label": "all fish, analyze their subcategories, and tell me if they are in a normal or endangered state"}, {"bbox\_2d": [90, 116, 495, 875], "label": "all fish, analyze their subcategories, and tell me if they are in a normal or endangered state"}]``</answer>

Figure 28: Reasoning referring example with multi-task chat.

....

Example 1 :

METAINFO:

```
{
  "total_num_of_person": 2,
  "answer": "Person 1",
  "order_from_left_to_right": [Person 1, Person 2]
}
```

Question: the person wearing a watch

The output should be:

(analysis)

OK, the user needs us to detect the person wearing a watch. To accomplish this task, I need to break it down into the following steps:

- Step 1: Determine what each person is wearing on their wrists to check for a watch.

# Step 1: Determine what each person is wearing on their wrists to check for a watch

- Person 1: She is wearing a watch on her left wrist. ⚠
- Person 2: There is no visible watch on her wrists. ✗

# Summarize and Re - Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

- Person 1: She is wearing a watch → ✓
- Person 2: She is not wearing a watch → ✗

(analysis)

(answer)

To summarize, Person 1 is the person wearing a watch

(answer)

Figure 29: In-context prompt for *attribute* subset in HumanRef-CoT.

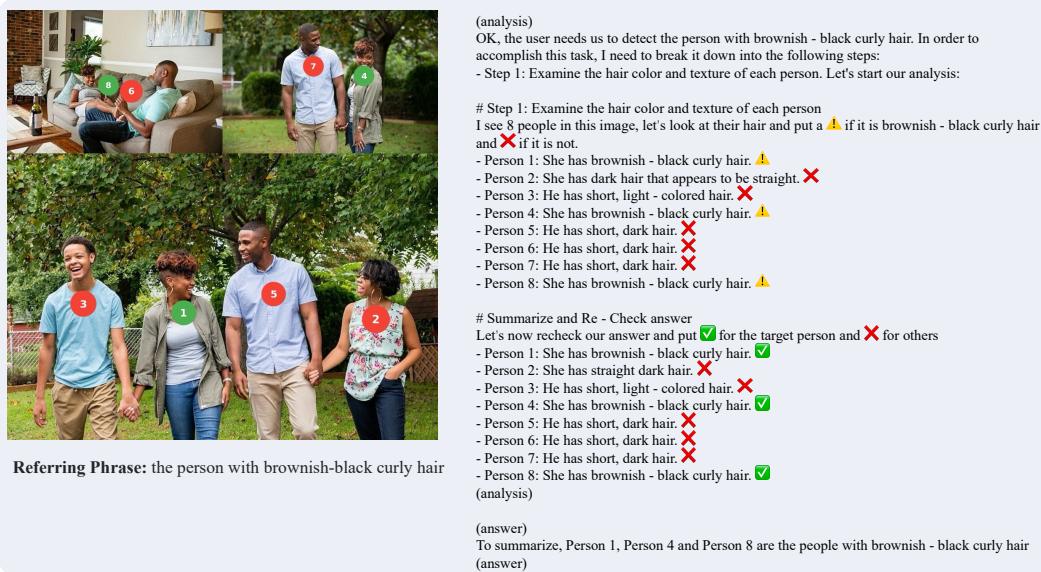


Figure 30: Visualization of GPT-4o's output on the *attribute* subset.

```

Example 1 :
```
METAINFO:
{
  "total_num_of_person": 4,
  "answer": "person 3",
  "order_from_left_to_right": [person 1, person 2, person 3, person 4]
}

Question: The third person from the left to right

The output should be:
(analysis)
OK, the user needs us to detect the third person from the left to right. To accomplish this task, I need to break it down into the following steps:
- Step 1: Sort the people from left to right and find the third person from the left to right.

# Step 1: Sort the people from left to right and find the third person from the left to right.
I need to sort the people from left to right. I see 4 people in this image, and their order from left to right is [Person 1, Person 2, Person 3, Person 4]. So Person 3 is the third person from the left to right.

# Summarize and Re-Check answer
Let's now recheck our answer and put ✓ for the target person and ✗ for others
- Person 1: He is the first person from left to right → ✗
- Person 2: He is the second person from left to right → ✗
- Person 3: He is the third person from left to right → ✓
- Person 4: He is the forth person from left to right → ✗
(analysis)

(answer)
To summarize, person 3 is the third person from left to right
(answer)

```

Figure 31: In-context prompt for *position (inner)* subset in HumanRef-CoT.

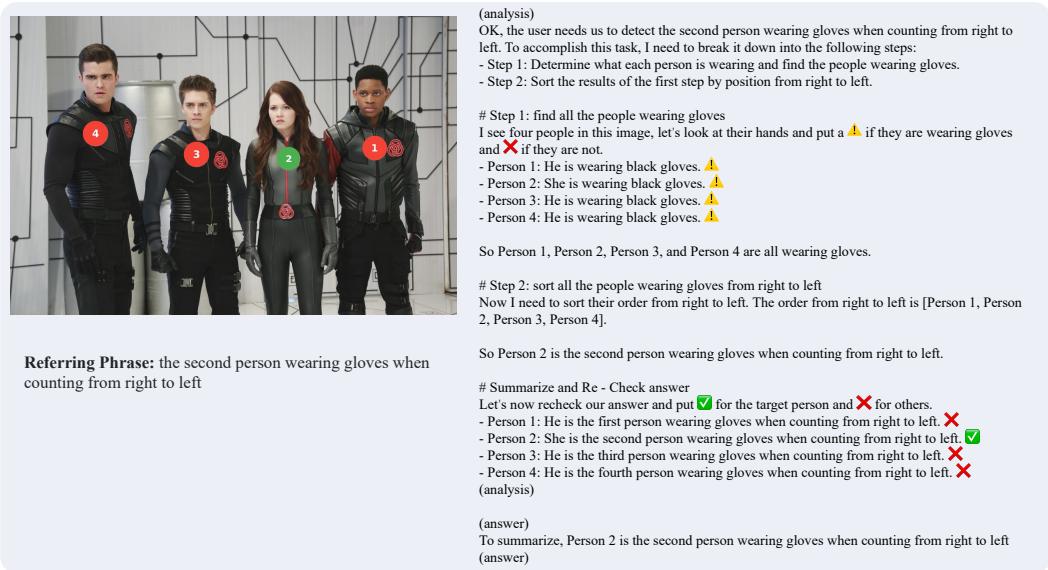


Figure 32: Visualization of GPT-4o's output on the *position (inner)* subset.



**Referring Phrase:** all the people to the right of the word 'muckle'

(analysis)

OK, the user needs us to detect all the people to the right of the word 'muckle'. To accomplish this task, I need to break it down into the following steps:

- Step 1: Locate the word 'muckle' in the image.
- Step 2: Identify all the people positioned to the right of the located word.

# Step 1: Locate the word 'muckle' in the image

The word 'muckle' is prominently displayed on a white counter - like structure in the center of the image.

- Word 'muckle': On a white counter - like structure in the center of the image ✓

# Step 2: Identify all the people positioned to the right of the located word

Let's analyze the position of each person relative to the word 'muckle':

- Person 1: He is sitting on the counter with the word 'muckle' and is not to the right of it → ✗
- Person 2: He is standing to the right of the word 'muckle' → ✓
- Person 3: He is standing to the right of the word 'muckle' → ✓
- Person 4: He is standing to the right of the word 'muckle' → ✓
- Person 5: He is standing to the left of the word 'muckle' → ✗

# Summarize and Re - Check answer

The's now recheck our answer and put ✓ for the target people and ✗ for others:

- Person 1: Not to the right of the word 'muckle' → ✗
- Person 2: To the right of the word 'muckle' → ✓
- Person 3: To the right of the word 'muckle' → ✓
- Person 4: To the right of the word 'muckle' → ✓
- Person 5: Not to the right of the word 'muckle' → ✗

(analysis)

(answer)

To summarize, Person 2, Person 3, and Person 4 are all the people to the right of the word 'muckle'

(answer)

Figure 33: In-context prompt for *position (outer)* subset in HumanRef-CoT.

Example 1 :

...

METAINFO:

```
{
  "total_num_of_person": 5,
  "answer": "person 1",
  "order_from_left_to_right": [person 1, person 4, person 2, person 5, person 3]
}
```

Question: the person to the left of the green light bulb

The output should be:

(analysis)

OK, the user needs us to detect the person to the left of the green light-bulb. To accomplish this task, I need to break it down into the following steps:

Step 1: Find the green light-bulb in this image.

Step 2: Fine the person to the left of the green light-bulb

# Step 1: Find the green light-bulb in this image.

Clearly, I can see a green light - bulb near the lower - left part of the image.

- green light - bulb: a green light - bulb near the lower - left part of the image ✓

# Step2: Fine the person to the left of the green light-bulb

Let's analyze the position of each person next:

- Person 1: He is standing directly to the left of the green light-bulb → ✓
- Person 2: She is on a ladder near the top-right part of the image, not to the left of the green light - bulb → ✗
- Person 3: He is standing near the right side of the image holding a tablet, not to the left of the green light - bulb → ✗

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

- Person 1: He is standing directly to the left of the green light-bulb → ✓
- Person 2: She is on a ladder not the left of the green light-bulb → ✗
- Person 3: He is not on the left of the green light-bulb → ✗

(analysis)

(answer)

To summarize, person 1 is to the left of the green light bulb

(answer)

...

Figure 34: Visualization of GPT-4o's output on the *position (outer)* subset.

```

Example 1 :
```
METAINFO:
{
    "total_num_of_person": 3,
    "answer": "person 1",
    "order_from_left_to_right": [person 1, person 2, person 3, person 4]
}
```

Question: The man who is hugging the woman from behind

The output should be:
(analysis)
OK, the user needs us to detect the man who is hugging the woman from behind
To accomplish this task, I need to break it down into the following steps:
- Step 1: Find all the man in this image.
- Step 2: Look at each man's action and find the man who is hugging the woman from behind

# Step 1: Find all the man in this image.
I see four person in this image, let's look at their gender and put a ▲ if they are man and ✗ if it is not.
- Person 1: It is a man sitting on the fence → ▲
- Person 2: It is a man wearing a blue shirt → ▲
- Person 3: It is a woman in red dress → ✗
- Person 4: It is a woman standing on the grass → ✗

# Step 2: Look at each man's interaction from step 1
Person 1: He is man standing behind a woman (Person 3), with his arms around her, fulfilling the description of hugging the woman from behind → ✓
Person 2: A man sitting on the fence, holding hands with person 4. He is not hugging a woman from behind. → ✗
So Person 1 is the man hugging the woman (Person 3) from behind

# Summarize and Re-Check answer
Let's now recheck our answer and put ✓ for the target person and ✗ for others
- Person 1: man hugging the woman from behind → ✓
- Person 2: man not hugging from behind → ✗
- Person 3: a woman, not a man hugging from behind → ✗
- Person 4: a woman, not a man hugging from behind → ✗
(analysis)

(answer)
To summarize, person 1 is the man who is hugging the woman from behind
(answer)

```

Figure 35: In-context prompt for *interaction (inner)* subset in HumanRef-CoT.



Figure 36: Visualization of GPT-4o's output on the *interaction (inner)* subset.

Example 1 :

````

METAINFO:

```
{  
    "total_num_of_person": 3,  
    "answer": "person 1",  
    "order_from_left_to_right": [person 2, person 3, person 1]  
}
```

Question: The woman holding a red sniper rifle in her hand

The output should be:

(analysis)

OK, the user needs us to find the woman holding a red sniper-rifle in her hand. To accomplish this task, I need to break it down into the following steps:

- Step 1: See if everyone is holding objects in their hands and what they're holding

# Step1: See if everyone is holding objects in their hands and what they're holding

There are 5 people in the picture, and we need to check the objects held by each of them:

- Person 1: A woman with dark hair and a red - themed outfit. She is holding a long, red firearm which appears to be a sniper - rifle. So she matches the description → ✓

- Person 2: A woman with short orange hair, wearing a pink and white outfit. She is holding a gray and pink - colored weapon that does not resemble a red sniper - rifle → ✗

- Person 3: A woman with long orange hair and a green and white dress. She is holding a weapon, but it is not a red sniper - rifle → ✗

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

Person 1: holding a red sniper - rifle → ✓

Person 2: holding a non - red weapon → ✗

Person 3: holding a non - red weapon → ✗

(analysis)

(answer)

To summarize, person 1 is the woman holding a red sniper rifle in her hand.

(answer)

Figure 37: In-context prompt for *interaction (outer)* subset in HumanRef-CoT.



**Referring Phrase:** the person holding a microphone in the hand

(analysis)

OK, the user needs us to find the person holding a microphone in the hand. To accomplish this task, I need to break it down into the following steps:

- Step 1: Check the hands of each person to see if they are holding a microphone.

# Step 1: Check the hands of each person to see if they are holding a microphone

- Person 1: He is holding a microphone in his right hand. → ✓

- Person 2: His hands are on his hips, not holding a microphone. → ✗

- Person 3: His hands are gesturing, not holding a microphone. → ✗

- Person 4: He is holding a microphone in his left hand. → ✓

- Person 5: His hands are making a gesture, not holding a microphone. → ✗

- Person 6: His hands are positioned near his body, not holding a microphone. → ✗

- Person 7: His hands are gesturing, not holding a microphone. → ✗

# Summarize and Re - Check answer

Let's now recheck our answer and put ✓ for the target people and ✗ for others:

- Person 1: Holding a microphone → ✓

- Person 2: Not holding a microphone → ✗

- Person 3: Not holding a microphone → ✗

- Person 4: Holding a microphone → ✓

- Person 5: Not holding a microphone → ✗

- Person 6: Not holding a microphone → ✗

- Person 7: Not holding a microphone → ✗

(analysis)

(answer)

To summarize, person 1 and person 4 are the persons holding a microphone in the hand.

(answer)

Figure 38: Visualization of GPT-4o's output on the *interaction (outer)* subset.

```

Example 1 :
```
METAINFO:
{
    "total_num_of_person": 3,
    "answer": "person 1",
    "order_from_left_to_right": [person 3, person 1, person 2]
}

Question: The woman to the left of the woman in blue dress

The output should be:
(analysis)
OK, the user needs us to detect the woman to the left of the woman in the blue dress. In order to accomplish this task, I need to break it down into the following steps:
Step 1: Find the woman in the blue dress.
Step 2: Find the woman to her left.
Let's start our analysis:

# Step 1: Find the woman in the blue dress
I see three people in this image. Let's determine who is wearing a blue dress and put a ⚡ if it is and ✗ if it is not.
- Person 1: She is wearing a pink dress. ✗
- Person 2: She is wearing a blue dress. ⚡
- Person 3: He is wearing a black suit with a pink tie. ✗

So Person 2 is the woman in the blue dress. Now I need to find the woman to her left.

# Step 2: Find the woman to the left of Person 2
The order from left to right is [Person 3, Person 1, Person 2]. So Person 1 is to the left of Person 2. And Person 1 is a woman.

# Summarize and Re - Check answer
Let's now recheck our answer and put ✓ for the target person and ✗ for others
- Person 1: She is the woman to the left of the woman in the blue dress. ✓
- Person 2: She is the woman in the blue dress. ✗
- Person 3: He is a man, not the woman we are looking for. ✗
(analysis)

(answer)
To summarize, Person 1 is the woman to the left of the woman in the blue dress.
(answer)

```

Figure 39: In-context prompt for *reasoning (inner position)* subset in HumanRef-CoT.

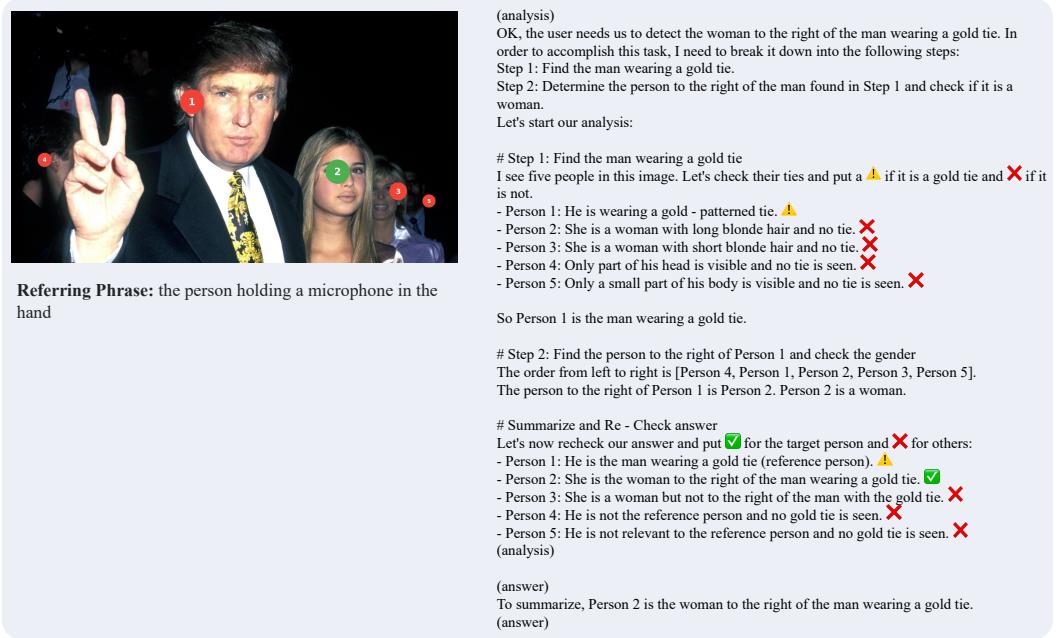


Figure 40: Visualization of GPT-4o's output on the *reasoning (inner position)* subset.

Example 1 :

...

METAINFO:

```
{
  "total_num_of_person": 4,
  "answer": "person 3, person 2, person 1",
  "order_from_left_to_right": [person 4, person 2, person 3, person 1]
}
```

Question: Person wearing glasses but not sitting on a chair

The output should be:

(analysis)

OK, the user needs us to detect the person wearing glasses but not sitting on a chair. To accomplish this task, I need to break it down into the following steps:

Step 1: Find all person wearing glasses.

Step 2: Find the person in Step 1 that are sitting on a chair

Step 3: Remove person in Step 2 from Step 1 to get the final result

# Step 1: Find all person wearing glasses.

I see five people in this image, let's look at their face and put a ▲ if they are wearing glasses and ✗ if it is not.

- Person 1: A man wearing a red shirt, he is wearing glasses → ▲

- Person 2: A man wearing a light-blue shirt, he is wearing glasses → ✗

- Person 3: A woman with blonde hair, she is not wearing glasses → ✗

- Person 4: A woman in a white top, she is not wearing glasses → ▲

- Person 5: A man wearing a light blue long sleeved shirt, he is wearing glasses → ▲

So Person 1, Person 4 and Person 5 are wearing glasses

# Step 2: Find the person in Step 1 that are sitting on a chair

Let's look at the three people in Step 1 and put a ▲ if they are sitting on a chair and ✗ if it is not.

- Person 1: He is sitting on a chair → ▲

- Person 2: He is sitting on a chair → ▲

- Person 5: He is standing instead of sitting → ✗

# Step 3 Remove person in Step 2 from Step 1 to get the final result

Remove Person 1 and Person 2 and we get Person 5 that meets the description

Let's now recheck our answer and put ✓ for the target person and ✗ for others

Person 1: wearing glasses but sitting on a chair → ✗

Person 2: wearing glasses but sitting on a chair → ✗

Person 3: not wearing glasses → ✗

Person 4: not wearing glasses → ✗

Person 5: wearing glasses and not sitting on a chair → ✓

(answer)

To summarize, person 3 is the third person from left to right

(answer)

...

Figure 41: In-context prompt for *reasoning (attribute)* subset in HumanRef-CoT.



(analysis)

OK, the user needs us to detect the person straddling someone's shoulders but not wearing long blue ripped jeans. To accomplish this task, I need to break it down into the following steps:

Step 1: Find all person straddling someone's shoulders.

Step 2: Find the person in Step 1 that are wearing long blue ripped jeans.

Step 3: Remove person in Step 2 from Step 1 to get the final result

# Step 1: Find all person straddling someone's shoulders.

I see four people in this image, let's look at their position and put a ▲ if they are straddling someone's shoulders and ✗ if it is not.

- Person 1: A boy straddling a man's shoulders → ▲

- Person 2: A woman not straddling anyone's shoulders → ✗

- Person 3: A boy straddling a woman's shoulders → ▲

- Person 4: A man not straddling anyone's shoulders → ✗

So Person 1 and Person 3 are straddling someone's shoulders

# Step 2: Find the person in Step 1 that are wearing long blue ripped jeans.

Let's look at the two people in Step 1 and put a ▲ if they are wearing long blue ripped jeans and ✗ if it is not.

- Person 1: He is wearing long blue ripped jeans → ▲

- Person 3: He is wearing dark-colored pants, not long blue ripped jeans → ✗

# Step 3: Remove person in Step 2 from Step 1 to get the final result

Remove Person 1 from Step 1 and we get Person 3 that meets the description

# Summarize and Re-Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

Person 1: straddling someone's shoulders and wearing long blue ripped jeans → ✗

Person 2: not straddling someone's shoulders → ✗

Person 3: straddling someone's shoulders and not wearing long blue ripped jeans → ✓

Person 4: not straddling someone's shoulders → ✗

(answer)

To summarize, the person is person 3

(answer)

Figure 42: Visualization of GPT-4o's output on the *reasoning (attribute)* subset..

Example:

METAINFO:

```
{
    "total_num_of_person": 4,
    "answer": "person 1",
    "order_from_left_to_right": [person 4, person 1, person 2, person 3]
}
```

(analysis)

OK, the user needs us to detect Brad Pitt. In order to accomplish this task, I need to break it down into the following step:

- Step 1: Identify Brad Pitt among the 8 people based on his appearance characteristics. Let's start our analysis:

# Step 1: Identify Brad Pitt among the 8 people based on his appearance characteristics

- Person 1: Has light - colored hair, similar facial features to Brad Pitt, and is wearing a black jacket over a white shirt, which matches the reference image of Brad Pitt. ▲
- Person 2: A man with dark hair sitting on a red couch, does not match Brad Pitt's appearance. ✗
- Person 3: A woman with long - brown hair, clearly not Brad Pitt. ✗
- Person 4: A man with dark hair and a dark shirt, does not match Brad Pitt's appearance. ✗

# Summarize and Re - Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

- Person 1: Matches Brad Pitt's appearance characteristics. ✓
- Person 2: Does not match Brad Pitt's appearance. ✗
- Person 3: Does not match Brad Pitt's appearance. ✗
- Person 4: Does not match Brad Pitt's appearance. ✗

(analysis)

(answer)

To summarize, Person 1 is Brad Pitt

(answer)

Figure 43: In-context prompt for *celebrity recognition* subset in HumanRef-CoT.



Referring Phrase: Donald Sutherland

(analysis)

OK, the user needs us to detect Donald Sutherland. To accomplish this task, I need to break it down into the following steps:

- Step 1: Recall what Donald Sutherland looks like and match his appearance among the people in the image.

I know that Donald Sutherland is an older - looking man with white hair and a beard.

- Person 1: He is a younger - looking man with dark hair and no beard. He does not match the appearance of Donald Sutherland. ✗
- Person 2: He is a man with short, light - brown hair and a short beard. He does not match the appearance of Donald Sutherland. ✗
- Person 3: He is an older man with white hair and a beard. He matches the appearance of Donald Sutherland. ▲
- Person 4: He is a man with short, light - colored hair and no beard. He does not match the appearance of Donald Sutherland. ✗

# Summarize and Re - Check answer

Let's now recheck our answer and put ✓ for the target person and ✗ for others

- Person 1: Does not match the appearance of Donald Sutherland. ✗
- Person 2: Does not match the appearance of Donald Sutherland. ✗
- Person 3: Matches the appearance of Donald Sutherland. ✓
- Person 4: Does not match the appearance of Donald Sutherland. ✗

(analysis)

(answer)

To summarize, Person 3 is Donald Sutherland

(answer)

Figure 44: Visualization of GPT-4o's output on the *celebrity recognition* subset..

Example:

METAINFO:

```
{
    "total_num_of_person": 4,
    "reference_answer": "there is not person that meets the description"
}
```

(analysis)

OK, the user needs us to detect all the people with guns in the picture. I need to look at the objects held in each person's hands and determine if they are guns or not. I see 7 people in the diagram, let's analyze the objects held by each of them:

- Person 1: She is a woman with long black hair, her right fist is outstretched but she is not holding a gun, and we can't see her left hand, so we can tell that she is not holding a gun. X
- Person 2: A female with brown hair wearing a thin red jacket. She has her left hand up and looks nervous, but she's not holding a gun either. X
- Person 3: A bald policeman in a black jacket, we can't see his hands, so we don't think he's holding a gun either. X
- Person 4: A bald black male with a big mouth, he has his hands open but he is also not holding a gun. X

Let's now finalize:

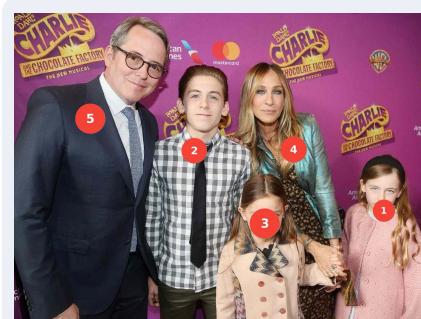
Person 1: not holding a gun → X  
 Person 2: not holding a gun → X  
 Person 3: not holding a gun → X  
 Person 4: not holding a gun → X

(analysis)

To summarize, there is no person in the image that meets the description.

(Answer)

Figure 45: In-context prompt for *rejection* subset in HumanRef-CoT.



Referring Phrase: the person wearing sunglasses

(analysis)

OK, the user needs us to detect the person wearing sunglasses. To accomplish this task, I need to break it down into the following steps:

# Step 1: Examine the attire and accessories of each person to find those wearing sunglasses.

- Person 1: A young girl in a pink - colored coat. She is not wearing sunglasses.
- Person 2: A boy in a checkered shirt and a black tie. He is not wearing sunglasses.
- Person 3: A young girl in a beige - colored coat with a patterned collar. She is not wearing sunglasses.
- Person 4: A woman in a metallic - green jacket and a patterned dress. She is not wearing sunglasses.
- Person 5: A man in a dark suit and a light - colored shirt with a tie. He is not wearing sunglasses, but he is the person mentioned in the condition related content (implied from the hint).

# Summarize and Re - Check answer

Let's now recheck our answer and put  for the target person and X for others

- Person 1: not wearing sunglasses → X
- Person 2: not wearing sunglasses → X
- Person 3: not wearing sunglasses → X
- Person 4: not wearing sunglasses → X
- Person 5: not wearing sunglasses → X

(analysis)

(answer)

To summarize, there are no people that meet the requirements as none of the five people are wearing sunglasses.

(Answer)

Figure 46: Visualization of GPT-4o's output on the *rejection* subset..