VISUAL AGENTS AS FAST AND SLOW THINKERS

Guangyan Sun[♣♠*], Mingyu Jin[♡*], Zhenting Wang[♡], Cheng-Long Wang[♦], Siqi Ma[°], Qifan Wang[‡], Tong Geng[♣], Ying Nian Wu[⋈], Yongfeng Zhang[♡†], Dongfang Liu[♠†]
[♠] Rochester Institute of Technology [♣] University of Rochester [♡] Rutgers University
[⋈] University of California, Los Angeles [‡] Meta AI [♦] KAUST [°] Westlake University

ABSTRACT

Achieving human-level intelligence requires refining cognitive distinctions between *System 1* and *System 2* thinking. While contemporary AI, driven by large language models, demonstrates human-like traits, it falls short of genuine cognition. Transitioning from structured benchmarks to real-world scenarios presents challenges for visual agents, often leading to inaccurate and overly confident responses. To address the challenge, we introduce **FAST**, which incorporates the **Fa**st and **S**low **T**hinking mechanism into visual agents. FAST employs a switch adapter to dynamically select between *System 1/2* modes, tailoring the problem-solving approach to different task complexity. It tackles uncertain and unseen objects by adjusting model confidence and integrating new contextual data. With this novel design, we advocate a *flexible system*, *hierarchical reasoning* capabilities, and a *transparent decision-making* pipeline, all of which contribute to its ability to emulate human-like cognitive processes in visual intelligence. Empirical results demonstrate that FAST outperforms various well-known baselines, achieving 80.8% accuracy over VQA^{v2} for visual question answering and 48.7% $GIoU$ score over ReasonSeg for reasoning segmentation, demonstrate FAST's superior performance. Extensive testing validates the efficacy and robustness of FAST's core components, showcasing its potential to advance the development of cognitive visual agents in AI systems. The code is available at this link.

1 INTRODUCTION

In the field of artificial intelligence, *System 2* delineates a cognitive mode distinguished by deliberate, analytical, and consciously reasoned processes (Wei et al., 2022; Wang et al., 2023d; Zelikman et al., 2022; Zhou et al., 2023; Hua & Zhang, 2022). This mode is juxtaposed to *System 1*, which embodies intuitive, automatic, and unconscious cognition. Achieving human-level intelligence in AI systems necessitates the deliberate cultivation and refinement of these cognitive distinctions. This process is crucial for the development of advanced reasoning and decision-making capabilities (Zhang et al., 2023d;e; Hao et al., 2023).

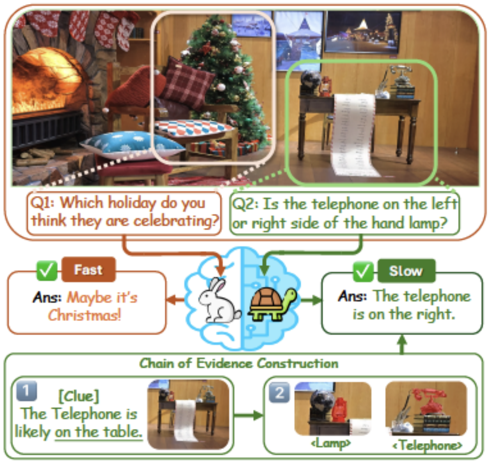

Q1: Which holiday do you think they are celebrating?
Q2: Is the telephone on the left or right side of the hand lamp?
✓ Fast
Ans: Maybe it's Christmas!
✓ Slow
Ans: The telephone is on the right.
Chain of Evidence Construction
1
[Clue]
The Telephone is likely on the table.
2
<Lamp>
<Telephone>

Figure 1. **Working Pipeline.** FAST represents a solution rooted in system switching, demonstrating pronounced capabilities in *hierarchical reasoning* and *ad-hoc explainability*.

The emergence of foundation models marks a significant turning point, where Large Language Models (LLMs) based agents have made remarkable strides in many areas, showcasing human-like intelligence across diverse tasks (Brown et al., 2020; Kojima et al., 2022; Ge et al., 2023). However, this achievement is primarily attributed to some features of foundation models: overparameterization and the availability of vast, general-purpose

[*] Equal contribution and shared co-first authorship.
[†] Corresponding author.

datasets (Kaplan et al., 2020; OpenAI, 2024). It is imperative to note that while these models exhibit human-like traits ($e.g.$, inductive and deductive reasoning (Huang & Chang, 2023b; Dasgupta et al., 2022; Jin et al., 2024b)), these characteristics do not equate to the processes of *System 1/2* thinking (Nye et al., 2021; Yao et al., 2023b) and are far less intelligent than human thinking.

In practice, visual agents often encounter challenges when moving from controlled, structured benchmarks to complex, real-world environments (Wu & Xie, 2024; Ge et al., 2023). This problematic circumstance will result in spurious reasoning pathways, akin to hallucinations, where they struggle to acknowledge their limitations or uncertainties (Gunjal et al., 2024; Chen et al., 2023c). Such an issue arises from the absence of explicit modeling of the fast and slow cognitive processes, reminiscent of human *System 1* and *System 2* thinking (Yao et al., 2023b; Kahneman, 2011). Consequently, when faced with intricate inquiries, the Multimodal Large Language Model (MLLM) frequently offers overly confident yet inaccurate responses (Wu & Xie, 2024; Chen et al., 2024b; Tong et al., 2024a). Addressing this problem entails reassessing MLLM algorithms to incorporate insights from the interplay between fast and slow thinking (*System 1* and *System2*) observed in human cognition. Our design philosophy guides us to incorporate human qualities into our work.

In this study, we introduce the **Fa**st and **S**low **T**hinking (**FAST**) mechanism into visual agents. More concretely, we design a switch adapter to determine whether the encountered problems are best addressed using which thinking mode. Simple tasks require only fast thinking (*System 1*) for a straightforward problem-solving pipeline, while complex tasks necessitate the slow, deliberate processing of *System 2* (see Fig. 1). Specifically, System 2 is triggered when we encounter visual challenges that have: ① *Uncertainty:* When the model has low confidence in directly identifying the object to which the complex query is referring. For example, the query asks “the appliance for storing and cooling food” instead of “refrigerator,” and ② *Invisibility:* When dealing with minuscule-sized objects that evade detection by standard visual encoders, where normal visual agents cannot tell what it is. This switch adapter is achieved by designing negative contextual data to re-adjust the model’s confidence and ignite world knowledge (as detailed analysis in §3.2). Subsequently, a proposal adapter is engaged to outline regions that are related to the questions. This allows visual agents to leverage the newly acquired data, thereby facilitating a more detailed and precise response. Further, if the inquiry necessitates detailed insights into particular instances, a seg adapter provides segmentation masks, offering additional contextual information for deeper analysis (as detailed analysis in §3.3).

FAST enjoys a few attractive qualities. ❶ **Flexible system**: Building on a foundation that explicitly models *System 1/2 thinking*, our proposed method adeptly handles complex visual tasks, demonstrating competitive performance in a streamlined pipeline (see §2.1). FAST’s core epistemology combines an intuitive mechanism for straightforward cases with deliberate analytics for more intricate scenarios, thereby enhancing the development of a human-like visual agent. ❷ **Hierarchical reasoning**: FAST perceives visual tasks with a top-down granularity, encompassing image-level cues, box-level candidates, and pixel-level targets (see Fig. 2). This progressive approach facilitates a sensible understanding of visual content, starting from global concepts, progressing through region-specific candidate assessment, and culminating in precise target identification. Each stage involves developing concrete ideas and establishing a coherent “*chain of evidence*” to support the final inference. ❸ **Transparent pipeline**: FAST’s decision-making process embodies a neuro-symbolic essence in System 2 mode, yielding intermediate step outputs as interpretable symbols ($e.g.$, bounding boxes or masks), facilitating direct visual inspection by humans. This inherent reasoning mechanism enables *ad-hoc explainability* of the model’s behavior (see Fig. 3), distinguishing FAST from prior approaches (Liu et al., 2024a) that lack precise explication of their operational mechanisms.

We conducted a series of experiments to validate the efficacy of our proposed method. In §3.1.1, we apply FAST to visual question answering and multimodal benchmarks. FAST demonstrates significantly improved performance over baselines such as LLaVA-v1.5 (Liu et al., 2024a), achieving performance gains on benchmarks like TextVQA (Singh et al., 2019) with a 2.5% increase in accuracy and a total score improvement of 6.7 on MME (Fu et al., 2024). In §3.1.2, we explore the versatility of our approach through its application to tasks such as referring and reasoning segmentation, with performance gains including an increase of 4.1% $CIoU$ with LLaVA-v1.5, and improvements of 3.2% $CIoU$ and 2.7% $GIoU$ on the ReasonSeg dataset over LISA-7B (Lai et al., 2024). The robustness and effectiveness of the core components of our FAST framework are further substantiated through a series of ablation studies, as elaborated in §3.3.

2 METHODS

Notation. The integration of components in visual agents $\mathcal{F}$ (based on the Large Language Model) typically involves a visual encoder, denoted as $\mathcal{E}_V$, a nature language encoder, represented by $\mathcal{E}_L$, and a Language Language Model such as Vicuna (Chiang et al., 2023). Initially, the visual agent is presented with an image $\mathcal{I}$ and an accompanying textual prompt $\mathcal{Q}$, which could be a question or instruction. Then the visual agent combines these multimodal tokens into a united space. Finally, the visual agent outputs a textual response R given the textual and image input. The generation process can be expressed as Equation 1:

$$R = \mathcal{F}\left[\mathcal{E}_V(I), \mathcal{E}_L(Q)\right] \tag{1}$$

Definition 1 *(System 1 and System 2) System 1 and 2 are two different systems of thinking proposed by Nobel Laureate Daniel Kahneman in his book Thinking, Fast and Slow (Kahneman, 2011).*

System 1 (Fast Thinking): Unconscious, automated thinking processes, fast, intuitive, effortless responsible for automatic responses and basic cognitive operations in daily activities, vulnerable to heuristic biases and errors, e.g., recognizing familiar faces, and knowing the location of objects.

System 2 (Slow Thinking): Conscious, energetic thinking processes, slow, effortful, logical, and analytical, responsible for complex calculations, reasoning, and decision-making, can monitor and control System 1 processes, e.g. filling out a tax form, finding the position of a word in a sentence.

2.1 FAST

We present FAST (see Fig. 2), a novel framework designed to efficiently handle both simple and complex visual queries. FAST features a dynamic system switch mechanism that enables rapid responses to straightforward questions (*System 1*) and accommodates deliberate reasoning for intricate scenarios (*System 2*). During slow thinking, the system uses contextual clues to identify a relevant region, facilitated by a proposal adapter. The adapter generates a bounding box around the target object, and if needed, a pixel-level mask adapter refines the proposal for further details. Finally, we summarize the gathered information from the whole system to provide a comprehensive answer.

System Switch. Current works on visual agents mostly rely on visual question-answering data, which gives direct answers (*System 1*) after inquiry as Eq. 1. However, attempting to answer questions directly in this way can compromise the reliability of the responses. Agents tend to hallucinate over questions that require more deliberate reasoning and visual details. To reduce hallucination and make the model reliable, we utilize a system switch trigger to tell when to require more visual information. Specifically, for a question $\mathcal{Q}$ and an image $\mathcal{I}$, we define a MLLM with switch adapter $\mathcal{S}$ and formulate the fast $\mathcal{F}_{fast}$ and slow thinking process $\mathcal{F}_{slow}$. When the query is easy, the frame does not need the switch adapter $\mathcal{S}_{adapter}$ and only output result $\mathcal{R}$ by $\mathcal{F}_{fast}$ as Equation 2.

$$\mathcal{R} = \mathcal{F}_{fast}\left[\mathcal{E}_V(I), \mathcal{E}_L(Q)\right] \tag{2}$$

Remark 2.1 *(Switching-friendly dataset) A Negative Data for Target Objects Reasoning Dataset $\mathcal{D}$ of 100,000 (image, question, answer) triples was constructed to facilitate the identification of target regions or objects required to answer a question. The dataset constructs questions about the absence or details of certain objects, deliberately made too small to be perceived by the visual encoder. Section A for more details.*

Remark 2.2 *(Switch Adapter) A light-weight adapter that is fine-tuned with both positive fast-thinking data and negative data (Remark. 2.1) to acquire system switching capability. When the adapter encounters harder questions, the switch mechanism will be triggered for later slow thinking.*

Note that a slow thinking process is not always activated. The system switch adapter as Remark. 2.2 $\mathcal{S}_{adapter}$ will determine whether the question for the particular image is sufficient to give a direct answer. If so, the fast mode $\mathcal{F}_{fast}$ will give a quick and direct response as Equation 2. If there is any missing information about the question that current agent cannot solve, the switch adapter will be activated and find the pattern to elicit all the possible missing objects $\mathcal{O}_{missing}$ related to question and context clues $\mathcal{C}_{clue}$ which is the possible location of the missing objects as Equation 3.

$$\mathcal{O}_{missing}, \mathcal{C}_{clue} = \mathcal{S}_{adapter}\left[\mathcal{E}_V(I), \mathcal{E}_L(Q)\right] \tag{3}$$

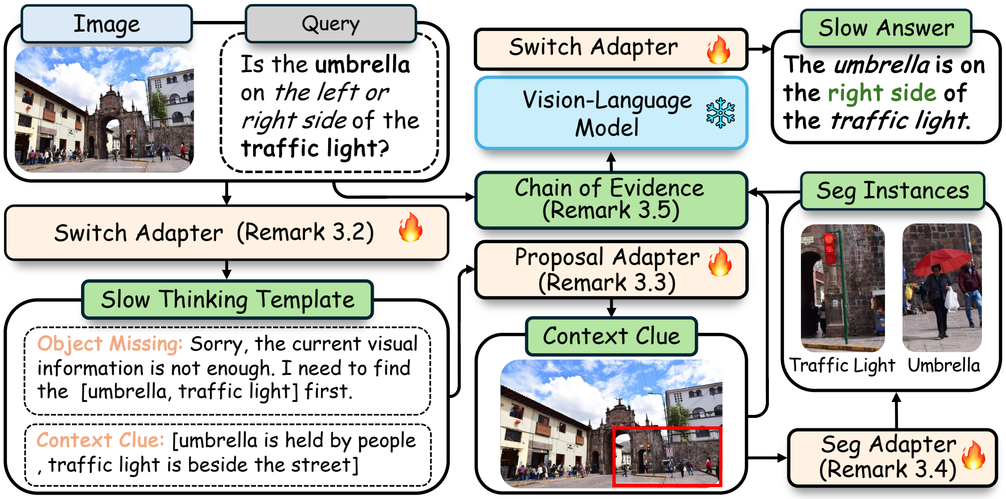


Image
Query
Is the umbrella on the left or right side of the traffic light?
Switch Adapter (Remark 3.2)
Slow Thinking Template
Object Missing: Sorry, the current visual information is not enough. I need to find the [umbrella, traffic light] first.
Context Clue: [umbrella is held by people , traffic light is beside the street]
Switch Adapter
Vision-Language Model
Chain of Evidence (Remark 3.5)
Proposal Adapter (Remark 3.3)
Context Clue
Slow Answer
The umbrella is on the right side of the traffic light.
Seg Instances
Traffic Light
Umbrella
Seg Adapter (Remark 3.4)

Figure 2. **Slow Thinking Mode of FaST.** Our *slow thinking mode* comprises three core modules: *Switch Adapter*, which selectively activates a slow and analytical thinking mode when encountering complex visual queries, supplementing with extensive world knowledge to provide missing objects and contextual clues; *Proposal Adapter*, which identifies and emphasizes regions of interest within the visual inputs; *Seg Adapter*, which delivers precise pixel-level segmentation, enhancing depth of the visual analysis. The outputs from each module are integrated into a *chain of evidence* (see Fig. 3), providing a methodical and accurate response. FaST represents a neural-symbolic approach that combines the strengths of symbolic reasoning, ensuring that our system is effective and interpretable.

Specifically, we use negative data that contain missing objects $\mathcal{O}_{missing}$ and context clues $\mathcal{C}_{clue}$ for training the system switch adapter for triggering the slow mode as Remark. 2.2. The slow mode should deal with question-image pairs that are 1) uncertain in pinpointing the specific object in question, and 2) too small to perceive for the standard visual encoder. So we utilize triplet data in dataset Remark. 2.1 (image, question, answer) as where the question requires objects that are not in the image or too small to be perceived by the visual encoder. The threshold is set to be 20×20. We require the model to tell that certain objects are missing instead of a direct answer, and we utilize the world knowledge to list all the objects and also the context information for later deliberate reasoning.

2.2 Preliminary

Hierarchical Reasoning. We use a top-down scheme to reason over multi-scale granularity images effectively in order to reason and take advantage of world knowledge progressively. Similar to humans would look for some context clue to find specific objects relating to questions and zoom in if they think the answer lies in a particular region, we model this process with system switch adapters as Remark. 2.2 to focus on the context clue $\mathcal{C}_{clue}$ generated from the switch adapter as Equation 3.

We denote the MLLM as a proposal adapter $\mathcal{P}_{adapter}$ (visual agent). In *System 2*, **FaST** uses many visual agents to accomplish hierarchical reasoning. The frame tries to narrow down the search space by using the question $\mathcal{Q}$ and the previously obtained clue $\mathcal{C}_{clue}$ to let the proposal adapter output a region $Region$ that aligns with the question and the context clue as Equation 4.

$$Region = \mathcal{P}_{adapter}\left[\mathcal{E}_V(I), \mathcal{E}_L(Q), \mathcal{C}_{clue}\right] \tag{4}$$

After getting the region, the visual agents $\mathcal{P}_{adapter}$ will be asked to focus on a more specific target with a bounding box $[Bboxes]$ complemented by the context clue $\mathcal{C}_{clue}$ and region $Region$ get from Equation 4. This process can reveal the step-by-step reasoning and be modeled as Equation 5.

$$[Bboxes] = \mathcal{P}_{adapter}\left[\mathcal{E}_L(Q), Region, \mathcal{C}_{clue}\right] \tag{5}$$

Remark 2.3 *(Proposal Adapter) A lightweight adapter that is fine-tuned with proposal data to acquire the capability of finding the corresponding region given the context clue or object name.*

Remark 2.4 *(Pixel-level mask decoder) The Pixel-level mask decoder is the decoder of segment anything(SAM (Kirillov et al., 2023)). The pixel-level mask decoder is fine-tuned to produce target masks based on the hidden embeddings.*

When we have a more specific target proposal(bounding box $[Bboxes]$), FAST will apply a fine-grained pixel-level mask decoder $\mathcal{P}_{Seg}$ as Equation 6 to output the specific mask part $[Mask]$ of the target proposal $[Bboxes]$ to focus on as Equation 6. We name this whole process from $Region$ to $[Mask]$ *chain of evidence* as Remark. 2.5 similar to thinking more and more deeply by humans.

$$[Mask] = \mathcal{P}_{seg}\left[\mathcal{E}_L(Q), [Bboxes], \mathcal{O}_{missing}\right] \tag{6}$$

Remark 2.5 *(Chain of Evidence) Chain of evidence is like the chain of thought in a Large Language Model. But we define it as a deeper and deeper step of thinking based on correct evidence in our frame* FAST. *The completion of the chain of evidence needs many visual agents to work together.*

After getting the target proposal (bounding box $[Bboxes]$) from context clue $\mathcal{C}_{clue}$ with proposal adapter and specific mask part $[Mask]$ by missing objects with seg adapter, a *chain of evidence* is constructed as Remark 2.5 and Fig. 3. Our FAST framework then summarizes all this information ($\mathcal{I}$ and $\mathcal{Q}$) and the *chain of evidence* with switch adapter to give the final correct reasoning answer Ans as Equation 7:

$$Ans = \mathcal{F}_{Slow}\left[\mathcal{E}_L(Q), \mathcal{E}_V(I), [Bboxes/Mask]\right] \tag{7}$$

The decision-making process in FAST is distinguished by its neuro-symbolic nature, which generates intermediate outputs as easily interpretable symbols, including region-of-interest (RoI) driven boxes and object-driven masks. This capability allows humans to perform direct visual inspections, thereby augmenting the transparency of the model's operations. Moreover, the intrinsic reasoning mechanism of FAST enhances the ad-hoc explainability of its behavior, see Fig. 2.

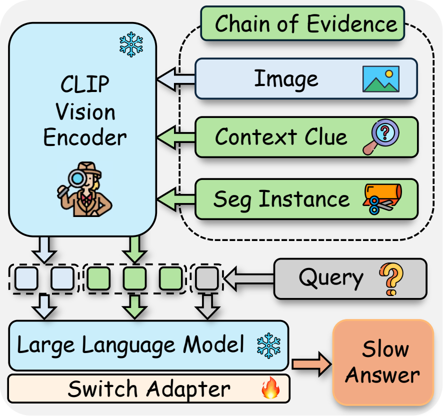


Figure 3. **Chain of Evidence**. FAST represents a solution rooted in switching, demonstrating pronounced capabilities in *hierarchical reasoning* and *ad-hoc explainability*.

2.3 Implementation Details

The framework of FAST(as Fig. 2)'s implementation details are shown in this section below.

- *Visual Agents.* We choose the architecture and configuration of LLaVA-v1.5 (Liu et al., 2024a) as our visual agent. The most important component in a visual agent is the visual encoder $\mathcal{E}_V(I)$: A *CLIP-ViT-L-336px* model (Radford et al., 2021) is used, where input images are resized or padded to $336 * 336$ pixels, learning to associate visual features with corresponding textual descriptions. An MLP projection with channels of $[256, 4096, 4096]$ is used for connecting image representations into the word embedding space.

- *Mask Decoder.* The mask decoder $\mathcal{P}_{seg}$ architecture is identical to SAM. Besides, it is fully fine-tuned with a collection of semantic segmentation (Caesar et al., 2018; Zhou et al., 2017; Ramanathan et al., 2023; He et al., 2022; Chen et al., 2014) and referring segmentation (Mao et al., 2016; Kazemzadeh et al., 2014) datasets to efficiently map the <seg>token representations to a mask if the FAST need to segment.

- *Chain of Evidence.* When we apply the *chain of evidence* as Remark 2.5 in the LLM to get the answer as the final step like Equation 7. The whole sequence of the *chain of evidence* is too long to load in the $\mathcal{F}_{Slow}$. So FAST needs a visual sampler based on cross-attention that is trained to decrease the number of image tokens to a suitable length (from 256 to 32), apart from MLP projection.

3 Experiment

We utilize eight popular benchmarks to evaluate our framework **FAST** comprehensively, categorized into general visual question answering (VQA) datasets and multimodal benchmarks. The

VQA benchmarks include VQA-v2 (Goyal et al., 2017), GQA (Hudson & Manning, 2019), ScienceQA (Lu et al., 2022), and TextVQA (Singh et al., 2019) which focus on optical character recognition. For multimodal benchmarks evaluation, we use the hallucination benchmark POPE (Li et al., 2023c), along with comprehensive benchmarks such as MME (Fu et al., 2024), MM-Vet (Yu et al., 2024), and SEED (Li et al., 2024). We compare our model with the baseline LLaVA-v1.5 (Liu et al., 2023a), and other multimodal large language models. To thoroughly assess our model's understanding of pixel-level instances, we evaluate its performance on referring segmentation and grounding benchmarks, including refCOCO (Kazemzadeh et al., 2014), refCOCO+ (Kazemzadeh et al., 2014), and refCOCOg (Caesar et al., 2018). Further, to examine the model's reasoning capabilities on FaST framework, we consider the Reasoning Segmentation benchmark (Lai et al., 2024).

3.1 Main Results

3.1.1 Experiments on VQA and Multimodal Benchmarks

Training. In developing the Switch Adapter, we employed the LLaVA-v1.5 (Liu et al., 2024a) framework, conforming strictly to its established training protocols. We incorporated negative samples from V^* (Wu & Xie, 2024) with contextual cues to enhance system switching capability to amplify multimodal inferential and world knowledge. This augmented dataset was combined with LLaVA-v1.5's supervised dataset and trained for one epoch. For the Proposal Adapter, we augmented the LLaVA-v1.5 dataset with region-specific bounding boxes based on contextual cues and queries, then fine-tuned for one epoch to optimize proposal generation. The Segmentation Adapter utilized the LISA (Lai et al., 2024) architecture integrated with the LLaVA-v1.5, employing SAM as the mask decoder. The adapter was fine-tuned using the same datasets as Lisa, including semantic segmentation, referring segmentation, and reasoning segmentation. This fine-tuning process involved 10,000 steps to improve the model's segmentation capabilities. Throughout developing the Switch Adapter, Proposal Adapter, and Segmentation Adapter, we employed the LoRA (Low-Rank Adaptation) technique (Hu et al., 2022). By leveraging LoRA, we introduce minimal additional parameters while preserving the original multimodal large language model's architecture and efficiency. All experiments used 8 NVIDIA TESLA A100-80GB GPUs.

Metric. In model evaluation across diverse datasets, various performance metrics are utilized.

Accuracy. The primary evaluation metric utilized in the VQA^{v2}, GQA, TextVQA, ScienceQA, and SEED benchmarks is accuracy. Accuracy is a performance measure that quantifies the exact match percentage between predicted and acceptable ground truth answers, indicating a model's precision.

F1 Score. The POPE dataset uses the F1 Score to balance precision and recall, providing a comprehensive assessment by harmonizing the trade-off between positive prediction accuracy and recall.

Total Score. The MME evaluation metrics include accuracy (based on individual questions) and accuracy+ (considering both questions per image), reflecting a stricter and more comprehensive model understanding. Random accuracies for these metrics are 50% and 25%, respectively. Perception scores, calculated as the sum of these metrics across subtasks, total 2000 for perception.

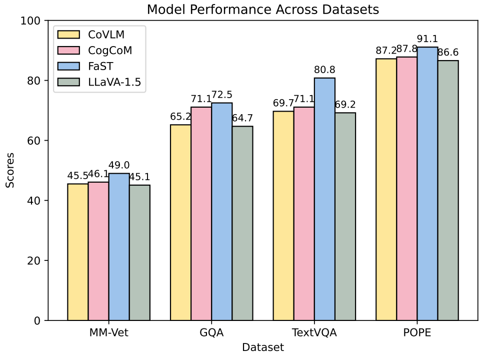


Figure 4. **The Comparison with CoVLM and CogCoM.** These models use the more powerful vison encoder.

GPT-Evaluation. In the MM-Vet dataset, performance is evaluated by GPT-4 through a comparative analysis of predicted and ground truth answers, generating a score to quantify alignment.

Results. As depicted in Table 1, FaST demonstrates superior performance across multiple VQA datasets and multimodal benchmarks when compared to established methods. To ensure fairness in comparison, all methods in Table 1 share the same visual encoder: basic CLIP (Radford et al., 2021). Remarkably, FaST consistently surpasses the LLaVA-v1.5 model, achieving significant improvements in performance across all evaluated datasets. Specifically, in VQA datasets, our model outperforms LLaVA-v1.5 by 2.3% in VQA^{v2}, 1.8% in GQA, and 2.5% in VQA^{T}. Ad-

Method	LLM	VQA Datasets				Multimodal Benchmarks			
		VQA^{v2}	GQA	VQA^T	SQA^I	POPE	MME	SEED	MM-Vet
BLIP-2[ICML23]	Vicuna-13B	65.0	32.3	42.5	61.0	85.3	1293.8	46.4	22.4
InstructBLIP[NeurIPS24]	Vicuna-13B	-	49.5	50.7	63.1	78.9	1212.8	53.4	25.6
Qwen-VL-Chat[arXiv23]	Qwen-7B	78.2	57.5	61.5	68.2	-	1487.5	58.2	-
mPLUG-Owl2[CVPR24]	LLaMA-7B	79.4	56.1	58.2	68.7	-	1450.2	**61.6**	**36.2**
Monkey[CVPR24]	Qwen-7B	80.3	60.7	-	**69.4**	67.6	-	-	-
LLaVA-v1.5[CVPR24]	Vicuna-7B	78.5	62.0	58.2	66.8	85.9	1510.7	58.6	30.5
Chain of Spot [arXiv24]	Vicuna-7B	80.7	63.7	60.9	68.2	86.4	1501.1	59.7	30.8
V*[CVPR24]	Vicuna-7B	-	-	-	-	82.4	1128.9	41.7	27.7
Visual CoT[arXiv24]	Vicuna-7B	-	63.1	**77.5**	-	-	-	-	-
FAST (Ours)	Vicuna-7B	**80.8**	**63.8**	60.7	68.9	**86.4**	**1517.4**	60.1	31.0
Δ (vs LLaVA-v1.5)	Vicuna-7B	+2.3	+1.8	+ 2.5	+2.1	+0.4	+6.7	+ 1.5	+ 0.5

Table 1. **Main results on eight VQA and multimodal benchmarks.** Our FAST consistently outperforms the baseline LLaVA1.5 model across all evaluated benchmarks, denoted with line Δ.

ditionally, FAST excels in multimodal benchmarks, with notable increases of 6.7 in the MME score, 1.5 in the SEED score, and 0.5 in the MM-Vet score, highlighting its versatility and effectiveness in handling a broad range of domains. These results underscore the robustness of FAST, particularly in tackling complex visual and textual tasks. Moreover, Fig. 4 showcases a direct comparison between FAST, CoVLM (Wang et al., 2023b), and CogCoM (Qi et al., 2024), both of which employ the more powerful EVA2-CLIP-E (Sun et al., 2023) model as their visual encoder. As expected, these models exhibit stronger performance due to their enhanced encoder. To align with this, we replaced our original vision encoder with EVA2-CLIP-E, which resulted in further improved performance, ensuring a more rigorous and fair comparison with state-of-the-art methods. This two-tiered comparison—first with basic CLIP and then with the more advanced EVA2-CLIP-E—provides a balanced and comprehensive evaluation of FAST against leading approaches, reinforcing its effectiveness in diverse and challenging tasks.

3.1.2 Experiments on Referring and Reasoning Segmentation

Training. The training settings for the Switch Adapter and Proposal Adapter remain consistent with those previously described as §3.1.1. During the training phase of the Segmentation Adapter, certain specific datasets are intentionally omitted to uphold an unbiased evaluation of referring and reasoning segmentation datasets. This strategic exclusion is a crucial measure implemented to prevent any potential data leakage, thereby ensuring the integrity and reliability of the evaluation results.

Metric. Following prior research on segmentation (Kazemzadeh et al., 2014; Mao et al., 2016), two evaluation metrics are employed: Generalized Intersection over Union ($GIoU$) and complete Intersection over Union ($CIoU$).

$CIoU$. The $CIoU$ is calculated based on the cumulative intersection over the cumulative union across all images in the dataset. This approach can introduce a significant bias towards larger objects or images with more objects, as they contribute more to the cumulative union area.

$GIoU$. The $GIoU$ is computed as the average per image IoU, where the IoU is calculated for each image, and then the average is taken across all images in the dataset. This metric provides a balanced assessment by treating all images equally, regardless of their size or the number of objects.

Results. Table 2 illustrates the performance of FAST compared to recent visual agents like LISA on referring and reasoning segmentation benchmarks. FAST notably outperforms LISA-7B on the refCOCO+ and refCOCOg benchmarks by 2.0% and 0.6% $CIoU$, respectively. For the more complex reasoning segmentation task, FAST

Method	Referring Segmentation			Reasoning Segmentation	
	refCOCO	refCOCO+	refCOCOg	ReasoSeg	
	CIoU	CIoU	CIoU	CIoU	GIoU
LAVT[CVPR22]	72.7	62.1	61.2	-	-
OVSeg[CVPR23]	-	-	-	28.5	18.6
GRES[CVPR23]	73.8	**66.0**	65.0	22.4	19.9
X-Decoder[CVPR23]	-	-	64.6	22.6	17.9
SEEM[NeurIPS24]	-	-	65.7	25.5	21.2
LISA-7B[CVPR24]	**74.1**	62.4	66.4	44.4	46.0
LLaVA w Seg Adapter	70.8	57.5	64.0	43.0	41.0
FAST (Ours)	73.3	64.4	**67.0**	**47.6**	**48.7**

Table 2. **Main results on referring and reasoning segmentation benchmarks.** Our FAST exhibits competitive results in referring segmentation tasks like refCOCOg+ while showcasing superior performance in reasoning segmentation, particularly when evaluated against LISA-7B.

shows even stronger results, with a 3.2% $CIoU$ gain and a 2.7% $GIoU$ improvement over LISA. The results highlight FAST's superior performance and its robustness in handling both straightforward and complex visual reasoning segmentation benchmarks.

3.2 ANALYSIS OF SYSTEM SWITCHING ADAPTER

Our study investigates the efficacy of the switch adapter mechanism in balancing accuracy and computational efficiency. As depicted in Fig.5, our analysis illustrates the system's adeptness in discerning between the *System 1* and *System 2* cognitive modes triggered by query complexity. For queries requiring System 2 reasoning, the adapter dynamically combines *System 1* reasoning for simpler subcomponents with *System 2* reasoning for more complex aspects. Consequently, the reported accuracy rates under *System 2* mode (52.2% for MME and 56.8% for GQA) reflect a combination of reasoning outcomes, emphasizing the adapter's ability to differentiate query complexities and optimize task performance accordingly. This highlights the importance of maintaining *System 1* reasoning for prompt and confident responses while effectively utilizing *System 2* reasoning for complex problem-solving.

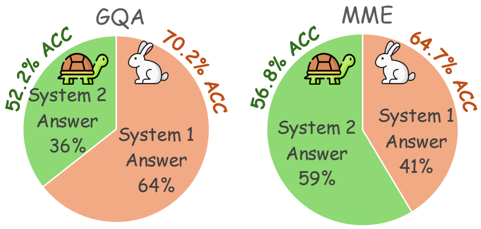


Figure 5. ***System 1* Mode Analysis.** We investigate the system switching ratio, along with fast thinking performance on easy or hard queries defined by the switch adapter.

Table 3 compares runtime across system configurations. *System 1 Only*, using a switch adapter, operates efficiently with one-time inference, while *System 2 Only*, which constructs a *chain of evidence* for every query, is significantly more resource-intensive. In contrast, FAST balances efficiency and performance, running 31% faster than *System 2 Only* on MME and 50% faster on GQA, with comparable results. This highlights FAST's ability to optimize cognitive task processing while conserving computational resources.

Method	MME		GQA	
	Runtime	Result	Runtime	Result
System 1 Only	734ms	1508.7	737ms	61.9
System 2 Only	2938ms	1518.6	2937ms	64.0
OURS	2023ms	1517.4	1475ms	63.8

Table 3. **Runtime Analysis and Comparison** on only *System 1* (fast), our FAST and only *System 2* (slow).

3.3 ABLATION STUDY

Algorithm Component	GQA	POPE	MME
BASELINE	62.1	85.7	1509.2
+ Proposal Adapter	63.2	86.0	1516.5
+ Seg Adpater	62.8	85.8	1514.4
OURS (both)	63.8	86.2	1517.4

Table 4. **Key Component** Analysis

Output Component	MME	refCOCOg
BASELINE*	1511.8	66.0
+ Missing Objects	1513.4	66.8
+ Context Clue	1516.6	66.4
OURS (both)	1517.4	67.0

Table 5. **Switch Adapter** Output Analysis

Key Component Analysis. We undertake a detailed investigation into the core elements of our novel framework, FAST, with particular emphasis on the proposal adapter for contextual region localization and the seg adapter for pixel-level mask segmentation. To establish a comparative baseline, we design a model configuration that excludes both the proposal and seg adapters, instead relying solely on a switch adapter to provide missing objects and context clues. This baseline model serves as the foundation for evaluating the impact of the individual and combined components of the framework. As demonstrated in Table 4, the introduction of the proposal adapter, the seg adapter, or both, results in progressive and substantial improvements in performance across various evaluation metrics. For instance, accuracy on the VQA^{v2} dataset improves from 62.1% to 63.8%, showcasing the considerable value these components add. This underscores the pivotal roles of the proposal and seg adapters in enhancing the model's overall capability, further affirming their importance within the FAST framework.

Further, we evaluate the switch adapter's role in incorporating missing objects and context clues using a variant BASELINE*, which omits these features. Table 5 shows that adding missing objects or context clues improves metrics like MME and refCOCOg, with the best performance achieved when both are included. These results confirm the importance of all components in optimizing FAST's effectiveness.

3.4 Qualitative Comparisons of FaST

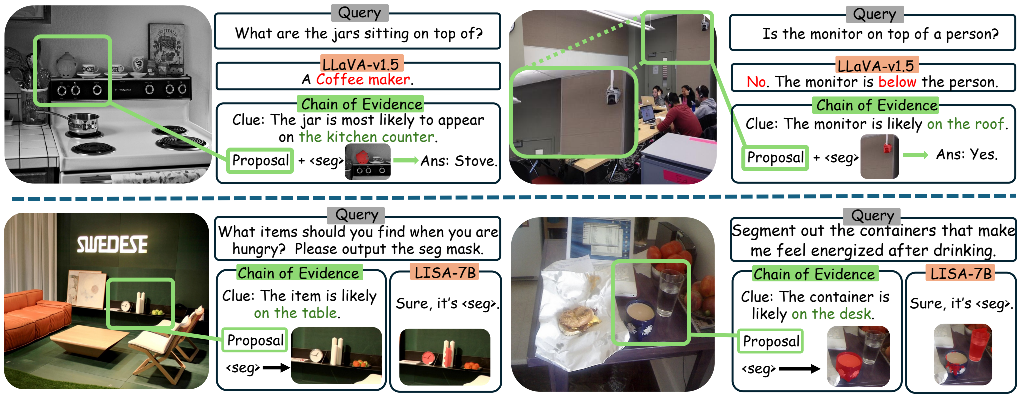

Query
What are the jars sitting on top of?
LLaVA-v1.5
A Coffee maker.
Chain of Evidence
Clue: The jar is most likely to appear on the kitchen counter.
Proposal + <seg>
Ans: Stove.
Query
Is the monitor on top of a person?
LLaVA-v1.5
No. The monitor is below the person.
Chain of Evidence
Clue: The monitor is likely on the roof.
Proposal + <seg>
Ans: Yes.
Query
What items should you find when you are hungry? Please output the seg mask.
Chain of Evidence
Clue: The item is likely on the table.
Proposal
<seg>
LISA-7B
Sure, it's <seg>.
Query
Segment out the containers that make me feel energized after drinking.
Chain of Evidence
Clue: The container is likely on the desk.
Proposal
<seg>
LISA-7B
Sure, it's <seg>.

Figure 6. **Qualitative Comparisons of FaST.** The top row shows the VQA results on FAST compared to LLaVA-v1.5. The bottom row presents the segmentation results compared to LISA-7B.

In Fig.6, we present qualitative comparisons that highlight the enhancements introduced by FAST. The top row, above the dotted line, shows results from the VQA task, comparing FAST with LLaVA-v1.5. LLaVA-v1.5 often fails to focus on key areas within the image, leading to incorrect or incomplete responses. In contrast, FAST builds a *chain of evidence* by identifying key objects and elements (e.g., detecting a woman on the street or a monitor on the roof) and then applying object-level pixel masks to accurately determine the focus areas. This enables FAST to provide more precise and deliberate answers. The bottom row, below the dotted line, shows segmentation results, comparing FAST with LISA-7B. LISA-7B struggles with segmenting smaller objects or those requiring more complex reasoning, often causing confusion. In contrast, FAST excels at isolating relevant objects with greater accuracy and granularity, particularly with smaller or less obvious items. This demonstrates FAST's superior performance in both VQA and segmentation tasks, showcasing its ability to handle a wide range of visual and reasoning challenges more effectively than its counterparts.

4 Related Works

LLM as Visual Agents. With the capabilities that LLMs have demonstrated in language understanding and generation (Ouyang et al., 2022; OpenAI, 2024; Zheng et al., 2023; Touvron et al., 2023a;b; Wang et al., 2024a; Hua et al., 2024; Mei et al., 2024; Jin et al., 2024a; Chen et al., 2024c), the research community has progressed to explore how LLMs can be enhanced with vision input for multimodal tasks as visual agents (Alayrac et al., 2022; Driess et al., 2023; Li et al., 2023a; Ge et al., 2023; Dai et al., 2024; Liu et al., 2023b; 2024a; Lin et al., 2024; Wang et al., 2024b). There are two paradigms for LLM-based visual agents: end-to-end based and tool-using visual agents. Following the principle of instruction tuning, end-to-end visual agents are trained with a curated visual instruction tuning dataset to digest features from multi-modality, unlocking the capability to answer visual questions (Huang et al., 2023; Luo et al., 2023; Zhu et al., 2023a; Bai et al., 2023; Zhang et al., 2023b;c; Chen et al., 2024a; Ye et al., 2023; Singh et al., 2019). For other visual tasks (*e.g.*, Segmentation, Detection, etc), end-to-end trained tailored agents can further perform downstream tasks (Pi et al., 2023; Peng et al., 2024; Lai et al., 2024; Chen et al., 2023b; Wang et al., 2023c; Dai et al., 2024; Wang et al., 2024c; 2023b; Jiang et al., 2023; Chen et al., 2023a; Zeng et al., 2024). Recent research has focused on leveraging improved vision encoders and fostering more detailed visual understanding, yielding promising results (Fan et al., 2024; Xu et al., 2024a; Shi et al., 2024). While these approaches can be implemented with direct instruction tuning data, they represent a '***System 1***' type of training. This type of training primarily relies on the dataset's quality and tends to provide direct answers that are prone to hallucinations, a consequence inherent to the nature of *System 1* instruction tuning data. For the second paradigm, tool-using models are built on top of a frozen LLM with access to pretrained visual perception tools (Surís et al., 2023; Shen et al., 2023;

Lu et al., 2023a). In this scenario, the LLM first selects visual tools and then decides by thoroughly analyzing the fine-grained information extracted by visual tools (Lu et al., 2023a; You et al., 2023; Wu et al., 2024). While external visual tools enhance the interpretability of the reasoning process, their complexity can introduce inaccuracies. Moreover, the abundance of information generated during reasoning may overshadow key details relevant to the query, resulting in incorrect answers.

Our research introduces a novel and adaptable framework designed to enhance response accuracy by adopting distinct slow thinking cognitive modes. Unlike traditional end-to-end visual agents, our framework, FAST, systematically assesses information sufficiency, thereby mitigating the risk of overconfidence. When ***System 2*** (slow, analytical thinking) is activated, FAST employs multiple experts to construct a coherent *chain of evidence*. This approach ensures the generation of accurate and interpretable responses, significantly advancing the reliability and transparency of visual agents.

System 2 in AI. Recently, LLMs have been engineered to produce text that mimics the step-by-step reasoning process characteristic of human cognition, akin to the analytical and deliberate thought processes associated with what is termed as ***System 2*** in the human cognition process (Qiao et al., 2023; Huang & Chang, 2023a; Wang et al., 2023a; Shaikh et al., 2023; Shao et al., 2024). The systematic approach to problem-solving is a hallmark across various domains, including mathematical word problems (Kojima et al., 2022; Wang et al., 2023d; Lightman et al., 2023; Cobbe et al., 2021; Liu et al., 2023c; Zhu et al., 2023b; Lu et al., 2023b), logical reasoning (Yao et al., 2023d;a; Besta et al., 2024; Wen et al., 2023; Lei et al., 2023; Cheng et al., 2024; Jin et al., 2024b), and multi-modal reasoning (Chen et al., 2024e; You et al., 2023; Wu & Xie, 2024). In Explainable AI, this systematic method is emulated by the model as it generates a text-based elucidation of its reasoning and decision-making process through step by step reasoning process (*e.g.*, chain of thought) (Han et al., 2024; Zhao et al., 2024; Jacovi & Goldberg, 2020; Hua & Zhang, 2022). However, it is crucial to recognize that LLMs, while powerful, are not exempt from encountering challenges when facing complex problems. One such challenge is the issue of hallucination (Zhou et al., 2024; Cui et al., 2023; Li et al., 2023b; Zhang et al., 2023a; Chen et al., 2024d; Guan et al., 2024a), which can distort the model's reasoning process and lead to inaccuracies in the explanations provided. Initially, LLM reasoning is seen as only a linear chain of thoughts, where each step in the reasoning process is clearly articulated. As models evolve, they adopt more complex structures like hierarchical trees (Geng et al., 2023; Yao et al., 2023b) and intricate graphs (Besta et al., 2024), which enable them to handle much more complex problems but also restrict their general applicability because of increased topological complexity (Yao et al., 2023b;a; Besta et al., 2024; Lei et al., 2023; Wen et al., 2023). Moreover, these complex structures can lead to errors propagating through the model's reasoning, causing a cascade of mistakes (Xu et al., 2024b). To counter this, incorporating feedback from intermediate reasoning steps and employing iterative refinement, which is similar to human reflection, could help mitigate errors (Chu et al., 2023; Tong et al., 2024b; Guan et al., 2024b; Madaan et al., 2023; Yuan et al., 2024; Wu & Xie, 2024). In unsupervised scenarios, such feedback is vital for enhancing the reasoning capabilities of LLMs and reducing errors (Yao et al., 2023c).

Our key contribution is the introduction of the *chain of evidence* within multimodal reasoning frameworks. This methodology enriches each reasoning step with accurate, image-based cascading information, effectively mirroring human visual and *System 2* cognitive processes. Our approach enhances accuracy and significantly improves interpretability and generalization capabilities.

5 CONCLUSION

In this study, we introduced FAST, a framework that combines *System 1* (which is fast and intuitive) and *System 2* (which is slow and deliberate) thinking to improve visual agents' reasoning and decision-making. FAST adapts to queries of varying complexity with a flexible system switch, delivering quick responses for simple tasks and using hierarchical reasoning for more complex scenarios. The FAST leverages neuro-symbolic decision-making transparent pipeline delivering interpretable intermediate outputs that enable explainability. Our results show significant improvements across benchmarks, demonstrating the effectiveness of FAST's *chain of evidence* in reducing hallucinations and improving interpretability. Furthermore, ablation studies highlight the critical importance of contextual clues, symbolic reasoning, and pixel-level adapters in refining visual reasoning and understanding, marking a step forward in creating more reliable and accurate AI cognition.

6 Acknowledgments

This research was supported by the National Science Foundation under Grant No.2242243. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of U.S. Naval Research Laboratory (NRL) or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation herein.

7 Ethical Safeguards

In our paper introducing a novel framework FaST, we implement rigorous ethical measures to prevent potential misuse and promote responsible application. These measures are delineated in comprehensive protocols accompanying the final release of models and datasets. Our protocols encompass stringent usage guidelines, access controls, incorporation of safety filters, and monitoring systems. These concerted efforts reflect our steadfast dedication to upholding the utmost ethical standards in scientific exploration. Our objective is to protect the rights and privacy of all stakeholders involved, thereby fostering a culture of responsible and ethical research within our community.

8 Reproducibility

Our FaST framework is implemented in PyTorch (Paszke et al., 2019). All the experiments are conducted on eight NVIDIA A100-80GB GPUs. Our full implementation shall be publicly released upon paper acceptance to guarantee reproducibility. The codes are available at the anonymous link *https://anonymous.4open.science/r/Sys2-LLaVA-8B0F/* for the review process.

All Experiments are conducted on eight NVIDIA A100-80GB SXM GPUs[1]. Reproducing the fine-tuning process would require approximately 15 A100 GPU days.

References

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. In *NeurIPS*, 2022.

Jinze Bai, Shuai Bai, Shusheng Yang, Shijie Wang, Sinan Tan, Peng Wang, Junyang Lin, Chang Zhou, and Jingren Zhou. Qwen-VL: A Frontier Large Vision-Language Model with Versatile Abilities. *arXiv preprint arXiv:2308.12966*, 2023.

Maciej Besta, Nils Blach, Ales Kubicek, Robert Gerstenberger, Michal Podstawski, Lukas Gianinazzi, Joanna Gajda, Tomasz Lehmann, Hubert Niewiadomski, Piotr Nyczyk, et al. Graph of Thoughts: Solving Elaborate Problems with Large Language Models. In *AAAI*, 2024.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language Models are Few-Shot Learners. In *NeurIPS*, 2020.

Holger Caesar, Jasper Uijlings, and Vittorio Ferrari. COCO-Stuff: Thing and Stuff Classes in Context. In *CVPR*, 2018.

Hila Chefer, Shir Gur, and Lior Wolf. Generic Attention-Model Explainability for Interpreting Bi-Modal and Encoder-Decoder Transformers. In *ICCV*, 2021.

Delong Chen, Jianfeng Liu, Wenliang Dai, and Baoyuan Wang. Visual Instruction Tuning with Polite Flamingo. In *AAAI*, 2024a.

Jiaxing Chen, Yuxuan Liu, Dehu Li, Xiang An, Ziyong Feng, Yongle Zhao, and Yin Xie. Plug-and-Play Grounding of Reasoning in Multimodal Large Language Models. *arXiv preprint arXiv:2403.19322*, 2024b.

[1] https://www.nvidia.com/en-sg/data-center/a100/

Jun Chen, Deyao Zhu, Xiaoqian Shen, Xiang Li, Zechun Liu, Pengchuan Zhang, Raghuraman Krishnamoorthi, Vikas Chandra, Yunyang Xiong, and Mohamed Elhoseiny. MiniGPT-V2: Large Language Model as a Unified Interface for Vision-Language Multi-Task Learning. *arXiv preprint arXiv:2310.09478*, 2023a.

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*, 2023b.

Mingkai Chen, Taowen Wang, Shihui Cao, James Chenhao Liang, Chuan Liu, Chunshu Wu, Qifan Wang, Ying Nian Wu, Michael Huang, Chuang Ren, Ang Li, Tong Geng, and Dongfang Liu. Inertial confinement fusion forecasting via large language models. *arXiv preprint arXiv:2407.11098*, 2024c.

Xiang Chen, Chenxi Wang, Yida Xue, Ningyu Zhang, Xiaoyan Yang, Qiang Li, Yue Shen, Jinjie Gu, and Huajun Chen. Unified Hallucination Detection for Multimodal Large Language Models. *arXiv preprint arXiv:2402.03190*, 2024d.

Xianjie Chen, Roozbeh Mottaghi, Xiaobai Liu, Sanja Fidler, Raquel Urtasun, and Alan Yuille. Detect What You Can: Detecting and Representing Objects Using Holistic Models and Body Parts. In *CVPR*, 2014.

Yuyan Chen, Qiang Fu, Yichen Yuan, Zhihao Wen, Ge Fan, Dayiheng Liu, Dongmei Zhang, Zhixu Li, and Yanghua Xiao. Hallucination Detection: Robustly Discerning Reliable Answers in Large Language Models. In *CIKM*, 2023c.

Zhenfang Chen, Rui Sun, Wenjun Liu, Yining Hong, and Chuang Gan. GENOME: GenerativE Neuro-SymbOlic Visual Reasoning by Growing and Reusing ModulEs. In *ICLR*, 2024e.

Pengyu Cheng, Tianhao Hu, Han Xu, Zhisong Zhang, Yong Dai, Lei Han, and Nan Du. Self-Playing Adversarial Language Game Enhances LLM Reasoning. *arXiv preprint arXiv:2404.10642*, 2024.

Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An Open-Source Chatbot Impressing GPT-4 with 90%* ChatGPT Quality, March 2023. URL https://lmsys.org/blog/2023-03-30-vicuna/.

Zheng Chu, Jingchang Chen, Qianglong Chen, Weijiang Yu, Tao He, Haotian Wang, Weihua Peng, Ming Liu, Bing Qin, and Ting Liu. A Survey of Chain of Thought Reasoning: Advances, Frontiers and Future. *arXiv preprint arXiv:2309.15402*, 2023.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training Verifiers to Solve Math Word Problems. *arXiv preprint arXiv:2110.14168*, 2021.

Chenhang Cui, Yiyang Zhou, Xinyu Yang, Shirley Wu, Linjun Zhang, James Zou, and Huaxiu Yao. Holistic Analysis of Hallucination in GPT-4V (ision): Bias and Interference Challenges. *arXiv preprint arXiv:2311.03287*, 2023.

Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale N Fung, and Steven Hoi. InstructBLIP: Towards General-Purpose Vision-Language Models with Instruction Tuning. In *NeurIPS*, 2024.

Ishita Dasgupta, Andrew K Lampinen, Stephanie CY Chan, Antonia Creswell, Dharshan Kumaran, James L McClelland, and Felix Hill. Language Models Show Human-Like Content Effects on Reasoning. *arXiv preprint arXiv:2207.07051*, 2022.

Danny Driess, Fei Xia, Mehdi SM Sajjadi, Corey Lynch, Aakanksha Chowdhery, Brian Ichter, Ayzaan Wahid, Jonathan Tompson, Quan Vuong, Tianhe Yu, et al. PaLM-E: An Embodied Multimodal Language Model. *arXiv preprint arXiv:2303.03378*, 2023.

Xiaoran Fan, Tao Ji, Changhao Jiang, Shuo Li, Senjie Jin, Sirui Song, Junke Wang, Boyang Hong, Lu Chen, Guodong Zheng, et al. MouSi: Poly-Visual-Expert Vision-Language Models. *arXiv preprint arXiv:2401.17221*, 2024.

Chaoyou Fu, Peixian Chen, Yunhang Shen, Yulei Qin, Mengdan Zhang, Xu Lin, Jinrui Yang, Xiawu Zheng, Ke Li, Xing Sun, Yunsheng Wu, and Rongrong Ji. MME: A Comprehensive Evaluation Benchmark for Multimodal Large Language Models. *arXiv preprint arXiv:2306.13394*, 2024.

Yingqiang Ge, Wenyue Hua, Kai Mei, Jianchao Ji, Juntao Tan, Shuyuan Xu, Zelong Li, and Yongfeng Zhang. OpenAGI: When LLM Meets Domain Experts. In *NeurIPS*, 2023.

Shijie Geng, Jianbo Yuan, Yu Tian, Yuxiao Chen, and Yongfeng Zhang. Hiclip: Contrastive language-image pretraining with hierarchy-aware attention. In *ICLR*, 2023.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the V in VQA Matter: Elevating the Role of Image Understanding in Visual Question Answering. In *CVPR*, 2017.

Tianrui Guan, Fuxiao Liu, Xiyang Wu, Ruiqi Xian, Zongxia Li, Xiaoyu Liu, Xijun Wang, Lichang Chen, Furong Huang, Yaser Yacoob, et al. Hallusionbench: An Advanced Diagnostic Suite for Entangled Language Hallucination & Visual Illusion in Large Vision-Language Models. In *CVPR*, 2024a.

Xinyan Guan, Yanjiang Liu, Hongyu Lin, Yaojie Lu, Ben He, Xianpei Han, and Le Sun. Mitigating Large Language Model Hallucinations via Autonomous Knowledge Graph-Based Retrofitting. In *AAAI*, 2024b.

Anisha Gunjal, Jihan Yin, and Erhan Bas. Detecting and Preventing Hallucinations in Large Vision Language Models. In *AAAI*, 2024.

Cheng Han, James C Liang, Qifan Wang, Majid Rabbani, Sohail Dianat, Raghuveer Rao, Ying Nian Wu, and Dongfang Liu. Image Translation as Diffusion Visual Programmers. In *ICLR*, 2024.

Shibo Hao, Yi Gu, Haodi Ma, Joshua Jiahua Hong, Zhen Wang, Daisy Zhe Wang, and Zhiting Hu. Reasoning with Language Model is Planning with World Model. In *EMNLP*, 2023.

Ju He, Shuo Yang, Shaokang Yang, Adam Kortylewski, Xiaoding Yuan, Jie-Neng Chen, Shuai Liu, Cheng Yang, Qihang Yu, and Alan Yuille. PartImageNet: A Large, High-Quality Dataset of Parts. In *ECCV*, 2022.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-Rank Adaptation of Large Language Models. In *ICLR*, 2022.

Wenyue Hua and Yongfeng Zhang. System 1+ System 2= Better World: Neural-Symbolic Chain of Logic Reasoning. In *EMNLP*, 2022.

Wenyue Hua, Xianjun Yang, Mingyu Jin, Zelong Li, Wei Cheng, Ruixiang Tang, and Yongfeng Zhang. Trustagent: Towards safe and trustworthy llm-based agents. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pp. 10000–10016, 2024.

Jie Huang and Kevin Chen-Chuan Chang. Towards Reasoning in Large Language Models: A Survey. In *ACL*, 2023a.

Jie Huang and Kevin Chen-Chuan Chang. Towards Reasoning in Large Language Models: A Survey. In *ACL*, 2023b.

Shaohan Huang, Li Dong, Wenhui Wang, Yaru Hao, Saksham Singhal, Shuming Ma, Tengchao Lv, Lei Cui, Owais Khan Mohammed, Barun Patra, et al. Language is Not All You Need: Aligning Perception with Language Models. In *NeurIPS*, 2023.

Drew A Hudson and Christopher D Manning. GQA: A New Dataset for Real-World Visual Reasoning and Compositional Question Answering. In *CVPR*, 2019.

Alon Jacovi and Yoav Goldberg. Towards Faithfully Interpretable NLP Systems: How Should We Define and Evaluate Faithfulness? In *ACL*, 2020.

Dongsheng Jiang, Yuchen Liu, Songlin Liu, Xiaopeng Zhang, Jin Li, Hongkai Xiong, and Qi Tian. From CLIP to DINO: Visual Encoders Shout in Multi-Modal Large Language Models. *arXiv preprint arXiv:2310.08825*, 2023.

Mingyu Jin, Qinkai Yu, Jingyuan Huang, Qingcheng Zeng, Zhenting Wang, Wenyue Hua, Haiyan Zhao, Kai Mei, Yanda Meng, Kaize Ding, et al. Exploring concept depth: How large language models acquire knowledge at different layers? *arXiv preprint arXiv:2404.07066*, 2024a.

Mingyu Jin, Qinkai Yu, Dong Shu, Haiyan Zhao, Wenyue Hua, Yanda Meng, Yongfeng Zhang, and Mengnan Du. The Impact of Reasoning Step Length on Large Language Models. In *ACL*, 2024b.

Daniel Kahneman. *Thinking, Fast and Slow*. Farrar, Straus and Giroux, 2011.

Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling Laws for Neural Language Models. *arXiv preprint arXiv:2001.08361*, 2020.

Sahar Kazemzadeh, Vicente Ordonez, Mark Matten, and Tamara Berg. ReferItGame: Referring to Objects in Photographs of Natural Scenes. In *EMNLP*, 2014.

Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment Anything. In *ICCV*, 2023.

Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large Language Models are Zero-Shot Reasoners. In *NeurIPS*, 2022.

Xin Lai, Zhuotao Tian, Yukang Chen, Yanwei Li, Yuhui Yuan, Shu Liu, and Jiaya Jia. Lisa: Reasoning Segmentation via Large Language Model. In *CVPR*, 2024.

Bin Lei, Chunhua Liao, Caiwen Ding, et al. Boosting Logical Reasoning in Large Language Models Through a New Framework: The Graph of Thought. *arXiv preprint arXiv:2308.08614*, 2023.

Bohao Li, Rui Wang, Guangzhi Wang, Yuying Ge, Yixiao Ge, and Ying Shan. Seed-Bench: Benchmarking Multimodal LLMs with Generative Comprehension. In *CVPR*, 2024.

Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. BLIP: Bootstrapping Language-Image Pre-Training for Unified Vision-Language Understanding and Generation. In *ICML*, 2022.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models. In *ICML*, 2023a.

Junyi Li, Xiaoxue Cheng, Wayne Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. HALUEVAL: A Large-Scale Hallucination Evaluation Benchmark for Large Language Models. In *EMNLP*, 2023b.

Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating Object Hallucination in Large Vision-Language Models. In *ACL*, 2023c.

Hunter Lightman, Vineet Kosaraju, Yura Burda, Harri Edwards, Bowen Baker, Teddy Lee, Jan Leike, John Schulman, Ilya Sutskever, and Karl Cobbe. Let's Verify Step by Step. *arXiv preprint arXiv:2305.20050*, 2023.

Shuhang Lin, Wenyue Hua, Lingyao Li, Che-Jui Chang, Lizhou Fan, Jianchao Ji, Hang Hua, Mingyu Jin, Jiebo Luo, and Yongfeng Zhang. Battleagent: Multi-modal dynamic emulation on historical battles to complement historical analysis. *arXiv preprint arXiv:2404.15532*, 2024.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual Instruction Tuning. In *NeurIPS*, 2023a.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual Instruction Tuning. In *NeurIPS*, 2023b.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved Baselines with Visual Instruction Tuning. In *CVPR*, 2024a.

Yixin Liu, Avi Singh, C Daniel Freeman, John D Co-Reyes, and Peter J Liu. Improving Large Language Model Fine-Tuning for Solving Math Problems. *arXiv preprint arXiv:2310.10047*, 2023c.

Zuyan Liu, Yuhao Dong, Yongming Rao, Jie Zhou, and Jiwen Lu. Chain-of-Spot: Interactive Reasoning Improves Large Vision-Language Models. *arXiv preprint arXiv:2403.12966*, 2024b.

Ilya Loshchilov and Frank Hutter. Decoupled Weight Decay Regularization. In *ICLR*, 2019.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to Explain: Multimodal Reasoning via Thought Chains for Science Question Answering. In *NeurIPS*, 2022.

Pan Lu, Baolin Peng, Hao Cheng, Michel Galley, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, and Jianfeng Gao. Chameleon: Plug-and-Play Compositional Reasoning with Large Language Models. In *NeurIPS*, 2023a.

Pan Lu, Liang Qiu, Kai-Wei Chang, Ying Nian Wu, Song-Chun Zhu, Tanmay Rajpurohit, Peter Clark, and Ashwin Kalyan. Dynamic Prompt Learning via Policy Gradient for Semi-Structured Mathematical Reasoning. In *ICML*, 2023b.

Gen Luo, Yiyi Zhou, Tianhe Ren, Shengxin Chen, Xiaoshuai Sun, and Rongrong Ji. Cheap and Quick: Efficient Vision-Language Instruction Tuning for Large Language Models. In *NeurIPS*, 2023.

Aman Madaan, Niket Tandon, Prakhar Gupta, Skyler Hallinan, Luyu Gao, Sarah Wiegreffe, Uri Alon, Nouha Dziri, Shrimai Prabhumoye, Yiming Yang, et al. Self-Refine: Iterative Refinement with Self-Feedback. In *NeurIPS*, 2023.

Junhua Mao, Jonathan Huang, Alexander Toshev, Oana Camburu, Alan L Yuille, and Kevin Murphy. Generation and Comprehension of Unambiguous Object Descriptions. In *CVPR*, 2016.

Kai Mei, Zelong Li, Shuyuan Xu, Ruosong Ye, Yingqiang Ge, and Yongfeng Zhang. Llm agent operating system. *arXiv preprint arXiv:2403.16971*, 2024.

Maxwell Nye, Michael Tessler, Josh Tenenbaum, and Brenden M Lake. Improving Coherence and Consistency in Neural Sequence Models with Dual-System, Neuro-Symbolic Reasoning. In *NeurIPS*, 2021.

OpenAI. GPT-4 Technical Report. *arXiv preprint arXiv:2303.08774*, 2024.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training Language Models to Follow Instructions with Human Feedback. In *NeurIPS*, 2022.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *NeurIPS*, 2019.

Zhiliang Peng, Wenhui Wang, Li Dong, Yaru Hao, Shaohan Huang, Shuming Ma, and Furu Wei. Kosmos-2: Grounding Multimodal Large Language Models to the World. In *ICLR*, 2024.

Renjie Pi, Jiahui Gao, Shizhe Diao, Rui Pan, Hanze Dong, Jipeng Zhang, Lewei Yao, Jianhua Han, Hang Xu, and Lingpeng Kong Tong Zhang. DetGPT: Detect What You Need via Reasoning. In *EMNLP*, 2023.

Ji Qi, Ming Ding, Weihan Wang, Yushi Bai, Qingsong Lv, Wenyi Hong, Bin Xu, Lei Hou, Juanzi Li, Yuxiao Dong, and Jie Tang. Cogcom: Train large vision-language models diving into details through chain of manipulations. *arXiv preprint arXiv:2402.04236*, 2024.

Shuofei Qiao, Yixin Ou, Ningyu Zhang, Xiang Chen, Yunzhi Yao, Shumin Deng, Chuanqi Tan, Fei Huang, and Huajun Chen. Reasoning with Language Model Prompting: A Survey. In *ACL*, 2023.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning Transferable Visual Models from Natural Language Supervision. In *ICML*, 2021.

Vignesh Ramanathan, Anmol Kalia, Vladan Petrovic, Yi Wen, Baixue Zheng, Baishan Guo, Rui Wang, Aaron Marquez, Rama Kovvuri, Abhishek Kadian, et al. PACO: Parts and Attributes of Common Objects. In *CVPR*, 2023.

Zhongwei Ren, Zhicheng Huang, Yunchao Wei, Yao Zhao, Dongmei Fu, Jiashi Feng, and Xiaojie Jin. Pixellm: Pixel reasoning with large multimodal model. In *CVPR*, 2024.

Anna Rohrbach, Marcus Rohrbach, Ronghang Hu, Trevor Darrell, and Bernt Schiele. Grounding of Textual Phrases in Images by Reconstruction. In *ECCV*, 2016.

Omar Shaikh, Hongxin Zhang, William Held, Michael Bernstein, and Diyi Yang. On Second Thought, Let's Not Think Step by Step! Bias and Toxicity in Zero-Shot Reasoning. In *ACL*, 2023.

Hao Shao, Shengju Qian, Han Xiao, Guanglu Song, Zhuofan Zong, Letian Wang, Yu Liu, and Hongsheng Li. Visual cot: Advancing multi-modal language models with a comprehensive dataset and benchmark for chain-of-thought reasoning. *arXiv preprint arXiv:2403.16999*, 2024.

Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. HuggingGPT: Solving AI Tasks with ChatGPT and Its Friends in Hugging Face. In *NeurIPS*, 2023.

Baifeng Shi, Ziyang Wu, Maolin Mao, Xin Wang, and Trevor Darrell. When Do We Not Need Larger Vision Models? *arXiv preprint arXiv:2403.13043*, 2024.

Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. Towards VQA Models that Can Read. In *CVPR*, 2019.

Quan Sun, Yuxin Fang, Ledell Wu, Xinlong Wang, and Yue Cao. Eva-clip: Improved training techniques for clip at scale. *arXiv preprint arXiv:2303.15389*, 2023.

Dídac Surís, Sachit Menon, and Carl Vondrick. ViperGPT: Visual Inference via Python Execution for Reasoning. In *ICCV*, 2023.

Shengbang Tong, Zhuang Liu, Yuexiang Zhai, Yi Ma, Yann LeCun, and Saining Xie. Eyes Wide Shut? Exploring the Visual Shortcomings of Multimodal LLMs. In *CVPR*, 2024a.

Yongqi Tong, Dawei Li, Sizhe Wang, Yujia Wang, Fei Teng, and Jingbo Shang. Can LLMs Learn from Previous Mistakes? Investigating LLMs' Errors to Boost for Reasoning. *arXiv preprint arXiv:2403.20046*, 2024b.

Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and Efficient Foundation Language Models. *arXiv preprint arXiv:2302.13971*, 2023a.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open Foundation and Fine-Tuned Chat Models. *arXiv preprint arXiv:2307.09288*, 2023b.

Boshi Wang, Sewon Min, Xiang Deng, Jiaming Shen, You Wu, Luke Zettlemoyer, and Huan Sun. Towards Understanding Chain-of-Thought Prompting: An Empirical Study of What Matters. In *ACL*, 2023a.

Taowen Wang, Yiyang Liu, James Chenhao Liang, Yiming Cui, Yuning Mao, Shaoliang Nie, Jiahao Liu, Fuli Feng, Zenglin Xu, Cheng Han, et al. M^{2}PT: Multimodal Prompt Tuning for Zero-shot Instruction Learning. In *EMNLP*, 2024a.

Taowen Wang, Yiyang Liu, James Chenhao Liang, junhan zhao, Yiming Cui, Yuning Mao, Shaoliang Nie, Jiahao Liu, Fuli Feng, Zenglin Xu, Cheng Han, Lifu Huang, Qifan Wang, and Dongfang Liu. M^{2}pt: Multimodal prompt tuning for zero-shot instruction learning. In *EMNLP*, 2024b.

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*, 2023b.

Weiyun Wang, Min Shi, Qingyun Li, Wenhai Wang, Zhenhang Huang, Linjie Xing, Zhe Chen, Hao Li, Xizhou Zhu, Zhiguo Cao, et al. The All-Seeing Project: Towards Panoptic Visual Recognition and Understanding of the Open World. In *ICLR*, 2024c.

Wenhai Wang, Zhe Chen, Xiaokang Chen, Jiannan Wu, Xizhou Zhu, Gang Zeng, Ping Luo, Tong Lu, Jie Zhou, Yu Qiao, et al. VisionLLM: Large Language Model is Also an Open-Ended Decoder for Vision-Centric Tasks. In *NeurIPS*, 2023c.

Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-Consistency Improves Chain of Thought Reasoning in Language Models. In *ICLR*, 2023d.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. In *NeurIPS*, 2022.

Yilin Wen, Zifeng Wang, and Jimeng Sun. MindMap: Knowledge Graph Prompting Sparks Graph of Thoughts in Large Language Models. *arXiv preprint arXiv:2308.09729*, 2023.

Penghao Wu and Saining Xie. Guided Visual Search as a Core Mechanism in Multimodal LLMs. In *CVPR*, 2024.

Yixuan Wu, Yizhou Wang, Shixiang Tang, Wenhao Wu, Tong He, Wanli Ouyang, Jian Wu, and Philip Torr. DetToolChain: A New Prompting Paradigm to Unleash Detection Ability of MLLM. *arXiv preprint arXiv:2403.12488*, 2024.

Ruyi Xu, Yuan Yao, Zonghao Guo, Junbo Cui, Zanlin Ni, Chunjiang Ge, Tat-Seng Chua, Zhiyuan Liu, Maosong Sun, and Gao Huang. Llava-UHD: An LMM Perceiving Any Aspect Ratio and High-Resolution Images. *arXiv preprint arXiv:2403.11703*, 2024a.

Ziwei Xu, Sanjay Jain, and Mohan Kankanhalli. Hallucination is Inevitable: An Innate Limitation of Large Language Models. *arXiv preprint arXiv:2401.11817*, 2024b.

Fanglong Yao, Changyuan Tian, Jintao Liu, Zequn Zhang, Qing Liu, Li Jin, Shuchao Li, Xiaoyu Li, and Xian Sun. Thinking Like an Expert: Multimodal Hypergraph-of-Thought (HOT) Reasoning to Boost Foundation Modals. *arXiv preprint arXiv:2308.06207*, 2023a.

Shunyu Yao, Dian Yu, Jeffrey Zhao, Izhak Shafran, Tom Griffiths, Yuan Cao, and Karthik Narasimhan. Tree of Thoughts: Deliberate Problem Solving with Large Language Models. In *NeurIPS*, 2023b.

Shunyu Yao, Jeffrey Zhao, Dian Yu, Nan Du, Izhak Shafran, Karthik Narasimhan, and Yuan Cao. React: Synergizing reasoning and acting in language models. In *ICLR*, 2023c.

Yao Yao, Zuchao Li, and Hai Zhao. Beyond Chain-of-Thought, Effective Graph-of-Thought Reasoning in Large Language Models. *arXiv preprint arXiv:2305.16582*, 2023d.

Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. mPLUG-Owl: Modularization Empowers Large Language Models with Multimodality. *arXiv preprint arXiv:2304.14178*, 2023.

Haoxuan You, Rui Sun, Zhecan Wang, Long Chen, Gengyu Wang, Hammad A Ayyubi, Kai-Wei Chang, and Shih-Fu Chang. Idealgpt: Iteratively Decomposing Vision and Language Reasoning via Large Language Models. In *EMNLP*, 2023.

Weihao Yu, Zhengyuan Yang, Linjie Li, Jianfeng Wang, Kevin Lin, Zicheng Liu, Xinchao Wang, and Lijuan Wang. MM-Vet: Evaluating Large Multimodal Models for Integrated Capabilities. In *ICML*, 2024.

Weizhe Yuan, Richard Yuanzhe Pang, Kyunghyun Cho, Sainbayar Sukhbaatar, Jing Xu, and Jason Weston. Self-Rewarding Language Models. *arXiv preprint arXiv:2401.10020*, 2024.

Eric Zelikman, Yuhuai Wu, Jesse Mu, and Noah D. Goodman. Star: Self-Taught Reasoner Bootstrapping Reasoning with Reasoning. In *NeurIPS*, 2022.

Runjia Zeng, Cheng Han, Qifan Wang, Chunshu Wu, Tong Geng, Lifu Huang, Ying Nian Wu, and Dongfang Liu. Visual fourier prompt tuning. In *NeurIPS*, 2024.

Muru Zhang, Ofir Press, William Merrill, Alisa Liu, and Noah A Smith. How Language Model Hallucinations Can Snowball. In *arXiv preprint arXiv:2305.13534*, 2023a.

Shilong Zhang, Peize Sun, Shoufa Chen, Min Xiao, Wenqi Shao, Wenwei Zhang, Kai Chen, and Ping Luo. GPT4ROI: Instruction Tuning Large Language Model on Region-of-Interest. *arXiv preprint arXiv:2307.03601*, 2023b.

Yanzhe Zhang, Ruiyi Zhang, Jiuxiang Gu, Yufan Zhou, Nedim Lipka, Diyi Yang, and Tong Sun. LLAVAR: Enhanced Visual Instruction Tuning for Text-Rich Image Understanding. *arXiv preprint arXiv:2306.17107*, 2023c.

Yifan Zhang, Yang Yuan, and Andrew Chi-Chih Yao. Meta Prompting for AI Systems. *arXiv preprint arXiv:2311.11482*, 2023d.

Zhuosheng Zhang, Aston Zhang, Mu Li, and Alex Smola. Automatic Chain of Thought Prompting in Large Language Models. In *ICLR*, 2023e.

Haiyan Zhao, Hanjie Chen, Fan Yang, Ninghao Liu, Huiqi Deng, Hengyi Cai, Shuaiqiang Wang, Dawei Yin, and Mengnan Du. Explainability for Large Language Models: A Survey. *ACM Transactions on Intelligent Systems and Technology*, 15(2):1–38, 2024.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging LLM-as-a-Judge with MT-Bench and Chatbot Arena. In *NeurIPS*, 2023.

Bolei Zhou, Hang Zhao, Xavier Puig, Sanja Fidler, Adela Barriuso, and Antonio Torralba. Scene Parsing through ADE20K Dataset. In *CVPR*, 2017.

Denny Zhou, Nathanael Schärli, Le Hou, Jason Wei, Nathan Scales, Xuezhi Wang, Dale Schuurmans, Claire Cui, Olivier Bousquet, Quoc Le, et al. Least-to-Most Prompting Enables Complex Reasoning in Large Language Models. In *ICLR*, 2023.

Yiyang Zhou, Chenhang Cui, Jaehong Yoon, Linjun Zhang, Zhun Deng, Chelsea Finn, Mohit Bansal, and Huaxiu Yao. Analyzing and Mitigating Object Hallucination in Large Vision-Language Models. In *ICLR*, 2024.

Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. MiniGPT-4: Enhancing Vision-Language Understanding with Advanced Large Language Models. *arXiv preprint arXiv:2304.10592*, 2023a.

Xinyu Zhu, Junjie Wang, Lin Zhang, Yuxiang Zhang, Yongfeng Huang, Ruyi Gan, Jiaxing Zhang, and Yujiu Yang. Solving Math Word Problems via Cooperative Reasoning Induced Language Models. In *ACL*, 2023b.

SUMMARY OF THE APPENDIX

This appendix contains additional details for the ICLR 2025 submission, titled ***"Visual Agents as Fast and Slow Thinkers"***. The appendix is organized as follows:

- §A provides **Implementation Details and Pseudo Code**.
- §B reports more **Results** for **Different Thinking Modes**.
- §C reports more **Quantitative Results** for **Visual Question Answering**.
- §D shows more **Quantitative Results** for **Segmentation**.
- §E analyzes **Failure Case**.
- §F examines the **Limitation and Future Work** of our research.
- §G discusses the **Social Impact** of our research.
- §H offers **Ethical Guard** or our dataset.
- §I claims **Reproducibility** of our approach.
- §J supplies **Data License** for the methods we used for comparison.

A Implementation Details and Pseudo-code of FaST

Visual Resampler. The resampler (Alayrac et al., 2022) compresses high-dimensional visual features into a fixed-size latent space using a cross-attention mechanism. It begins with a set of learnable latent embeddings, which query the vision encoder's output features through scaled dot-product attention. Each latent embedding attends selectively to the most relevant visual tokens, guided by attention weights computed via the query-key interaction. The process iterates across multiple layers of cross-attention, followed by feedforward transformations, refining the latent representations at each step. This approach ensures efficient dimensionality reduction while retaining critical information, producing a compact set of visual tokens for downstream tasks.

Hyper-parameters. We follow established methodologies and utilize LLaVA-v1.5 (Liu et al., 2024a) as the foundational visual agent. The image resolution is preprocessed to 336 × 336 pixels to accommodate the clip-vit-large-patch14-336 vision encoder (Radford et al., 2021). The AdamW optimizer (Loshchilov & Hutter, 2019) is employed with the DeepSpeed ZeRO 2 [2] configuration for fine-tuning the switch, proposal, and segmentation adapters with LoRA (Hu et al., 2022). For the LoRA configuration, we set the rank to 128 and alpha to 256, consistent with the settings of LLaVA-v1.5. Additionally, we adjust the learning rate of the vision encoder projection layer to 2e-5 to achieve better alignment. An MLP projection with channels of [256, 4096, 4096] is used to connect image representations into the word embedding space for the projection layer. An additional resampler projection layer is used to reduce the number of image tokens.

Training Data for Switch Adapter. Consistent with the pretraining stage of LLaVA-v1.5, we initially pretrain Vicuna-v1.5 as a base frozen large language model and for the MLP projection layer and sampler layer of the CLIP vision encoder using a 558K subset of the LAION-CC-SBU dataset [3] with BLIP (Li et al., 2022) captions. During the fine-tuning stage, we integrate the negative dataset acquired from V^* (Wu & Xie, 2024) and PixelLM (Ren et al., 2024) and with the original LLaVA-v1.5 instruction tuning 665k data[4] for LoRA based finetuning.

Specifically, The dataset for fine-tuning the switch adapter was carefully constructed to emphasize scenarios requiring precise object recognition and complex reasoning. For the GQA subset of the 167k VQA data, we specifically targeted questions where the annotated objects mentioned in the query were critical for deriving the correct answer. Initially, the InstructBLIP model was used to evaluate GQA questions with annotated objects. Only questions that the model could correctly answer were retained. To ensure the importance of these annotated objects, we applied the LaMa image inpainting model to erase the mentioned objects from the corresponding images. The modified images were re-evaluated using InstructBLIP, and only questions that the model failed to answer

[2] https://github.com/microsoft/DeepSpeed

[3] https://huggingface.co/datasets/liuhaotian/LLaVA-Pretrain

[4] https://huggingface.co/datasets/liuhaotian/LLaVA-Instruct-150K

after object removal were included. This process ensured that the curated subset focused exclusively on questions where the annotated objects were essential, forming a robust component of the VQA data.

For the VAW object attribution dataset, both open-ended and binary questions about object attributes were synthesized. Open-ended questions were formulated around attributes such as “color,” “material,” and “pose,” while binary questions incorporated additional attributes like “state” and “optical property.” Answer formats adhered to predefined structures to ensure consistency. The same object removal and re-evaluation strategy as used in the GQA subset was applied, filtering the data to include only questions where the absence of objects rendered the query unanswerable.

From the LLaVA-80K instruction tuning data, noun phrases were extracted from the text of questions or instructions and matched with object category names defined by COCO, augmented with common synonyms such as “man” and “woman” for the “person” category. Images were retained only if the identified categories had annotated instances with bounding boxes. These annotated instances, along with their bounding box coordinates, were used as target objects during training.

In addition, we incorporated a data generation approach inspired by LISA, utilizing GPT-4 and GPT-4V to expand and diversify the dataset. Initially, LLAVA was used for image captioning, and GPT-4 generated questions about multiple regions in the image. While this approach utilized pre-existing mask annotations to reduce costs, its diversity was limited to the scope of the captions. To address these limitations, we refined the pipeline with GPT-4V, leveraging its advanced capabilities in visual understanding. Image captions, object names, and bounding box coordinates were input into GPT-4V, which, using dynamically crafted prompts, autonomously selected instances and generated nuanced question-answer pairs tailored to the image content. This refinement significantly improved the diversity and contextual relevance of the data. An illustrative example of such prompts is provided below:

Prompt: Imagine you need to query a machine agent about an image. The image has a height of 720 pixels and a width of 1280 pixels. You are given several entities described by a list, each identifying an object in the image along with its location. The class names and corresponding coordinates are as follows:

- Dog at [350.12, 450.45, 480.89, 600.67];
- Ball at [200.33, 300.22, 250.78, 350.56];
- Grass at [0.0, 500.0, 1280.0, 720.0];

Coordinates are represented as (top-left x, top-left y, bottom-right x, bottom-right y). The question must incorporate at least two of these objects and require reasoning about the relationships or interactions between them. Additional requirements for the generated question are as follows:

1.The answer to the question must explicitly reference each included object or its equivalent and avoid implying the presence of any other objects not listed.
2.The question must be precise, meaningful, and avoid being overly general.
3.The question should frame a single cohesive activity or relationship rather than merely combining independent sub-queries.
4.When answering, the class names should be rephrased to indicate their position, role, or interaction in the image.

This multi-faceted dataset construction process ensured the generation of diverse and challenging samples, providing a robust foundation for fine-tuning the switch adapter on complex reasoning tasks.

Training Data for Proposal Adapter To determine the corresponding region for a query, we use LRP++ (Chefer et al., 2021) for data construction, similar to Chain of Spot (Liu et al., 2024b). Our initial prompt is as follows:

```
<Image>
To answer the question:  [Q],
where is the region of interest in the image based on [C]?

Ans.str[$w_0$, $w_1$, $h_0$, $h_1$]
```

The question Q and the context clue C are formatted to get the answer in terms of a bounding box. In this format, w_0, w_1 represent the left and right boundaries, respectively, while h_0, h_1 denote the upper and lower boundaries. To identify the correct region, we sampled one question per image from the LLaVA instruction tuning data, consisting of a total of 665k data for proposal finetuning.

Training Data for Seg Adapter. Adopting an approach similar to LISA Lai et al. (2024), the training data for our model comprises three distinct segments: a semantic segmentation dataset, a referring segmentation dataset, and a reasoning segmentation dataset. We deliberately exclude visual question-answering datasets to enhance the model's segmentation performance. The semantic segmentation segment includes the ADE20K (Zhou et al., 2017), COCO-Stuff (Caesar et al., 2018), and LVIS-PACO (Ramanathan et al., 2023) part segmentation datasets. The referring segmentation datasets encompass refCOCOKazemzadeh et al. (2014), refCOCO+ (Kazemzadeh et al., 2014), refCOCOg (Caesar et al., 2018), and refCLEF (Rohrbach et al., 2016). The reasoning segmentation dataset includes ReasonSeg (Lai et al., 2024). It is important to note that the referring segmentation and reasoning segmentation datasets are carefully excluded during the evaluation of the segmentation benchmarks to prevent any potential data leakage.

Pseudo-code Implementation. The pseudo-code of FaST is given in Pseudo-code 1.

B More Results for Different Thinking Modes

As shown in Table 6, FaST demonstrates strong performance in both System 1 and System 2 reasoning on VQA datasets, outperforming baseline methods in most cases. Notably, FaST achieves the highest accuracy in challenging System 2 tasks across GQA, VQA^T, and SQA^I, which require advanced reasoning capabilities. This highlights the effectiveness of the switch adapter mechanism in dynamically allocating tasks based on complexity. While maintaining competitive performance in simpler System 1 tasks, FaST leverages its adaptive architecture to excel in more complex scenarios, as evidenced by its superior System 2 results.

Further, in Table 7, FaST's robustness extends to reasoning segmentation tasks, where it achieves significant improvements in System 2 performance compared to baseline models such as LLaVA with segmentation and LISA-7B. For example, in the ReasonSeg dataset, FaST records a remarkable 48.2 CIoU in System 2 tasks, significantly outperforming LISA-7B and LLaVA, which achieve 43.3 CIoU and 42.4 CIoU, respectively. This result underscores FaST's ability to generalize effectively across diverse task families and reasoning paradigms.

Overall, the results validate the universal applicability and robustness of the FaST framework. By effectively utilizing the switch adapter to allocate tasks dynamically, FaST demonstrates a strong capability to balance performance across both simple and complex reasoning tasks, making it a reliable solution for diverse real-world applications.

C More Qualitative Results for Visual Question Answering

Figure 7 presents additional qualitative results for Visual Question Answering (VQA). Our FaST framework consistently demonstrates remarkable performance across various challenging scenarios. Notably, in the bottom right corner of Figure 7, our FaST leverages extensive world knowledge to identify the keyboard, which subsequently aids in discovering the hidden computer mouse and providing the correct answer. This ability to integrate and utilize contextual information showcases the

Algorithm 1: Pseudo-code of FaST in a PyTorch-like style.

```
class FaST:
   def __init__(self, switch_llm, proposal_llm, seg_llm):
      self.switch_llm = switch_llm
      self.proposal_llm = proposal_llm
      self.seg_llm = seg_llm

   def get_contextual_clues(self, image, question):
      # Get missing objects and context clues using switch adapter
      return self.switch_llm(image, question)

   # Construct Chain of Evidence
   def construct_coe(self, image, question, context_clues, missing_objects):
      # Step 1: Get region proposals
      region = self.proposal_llm(image, question, context_clues)

      # Step 2: Get pixel-level mask for the missing objects
      mask = self.seg_llm(region, missing_objects)

      return (context_clues, region, missing_objects, mask)

   # Main Function
   def forward(self, image, question):

      # Get initial answer
      initial_answer = self.switch_llm(image, question)

      # Check if slow thinking is needed based on the initial answer
      if "sorry, i can not answer" in initial_answer.lower():
         # Perform slow thinking
         missing_objects, context_clues = initial_answer['obj'], initial_answer
             ['clue']
         chain_of_evidence = self.construct_coe(image, question, context_clues,
              missing_objects)

         # Generate the final answer using the constructed chain of evidence
         final_answer = self.switch_llm(image, question, chain_of_evidence)
      else:
         # Perform fast thinking
         final_answer = initial_answer

      return final_answer
```

Method	LLM	VQA^{v2}		GQA		VQA^{T}		SQA^{I}	
		Sys 1	Sys 2	Sys 1	Sys 2	Sys 1	Sys 2	Sys 1	Sys 2
BLIP-2	Vicuna-13B	67.3	53.1	37.8	22.4	44.3	39.7	63.4	59.2
LLaVA-v1.5	Vicuna-7B	81.2	68.0	**70.3**	47.0	61.1	53.7	68.4	65.7
Chain of Spot	Vicuna-7B	**82.1**	74.5	70.9	50.7	**62.1**	59.0	**68.6**	67.8
FaST (Ours)	Vicuna-7B	81.1	**75.5**	70.2	**52.3**	61.2	**60.2**	68.2	**70.2**

Table 6. **System 1 and System 2 performance on VQA datasets.** FaST demonstrates superior performance in both reasoning modes compared to baselines.

model's advanced capabilities and highlights its potential for practical applications. The qualitative results further underscore FaST's robustness and versatility in handling diverse VQA tasks.

D More Qualitative Results for Segmentation

Figure 8 showcases further qualitative results for the Segmentation task. Our FaST model excels in various challenging scenarios, accurately locating difficult targets and performing complex reasoning for more demanding queries. For instance, in the bottom right corner, the model successfully identifies an appliance that can be turned on when feeling hot by recognizing relevant contextual clues that suggest the appliance should probably appear on the wall, thereby resulting in the correct answer. This example demonstrates the model's advanced understanding, adaptability, and precision.

Method	refCOCOg		ReasonSeg	
	Sys 1	Sys 2	Sys 1	Sys 2
LISA-7B	70.2	63.4	46.6	43.3
LLaVA w Seg	68.4	60.2	44.2	42.4
FaST (Ours)	**70.8**	**64.1**	46.4	**48.2**

Table 7. **System 1 and System 2 performance on reasoning segmentation tasks.** FaST achieves strong performance across both tasks, demonstrating its robustness and effectiveness in dynamic task allocation between System 1 and System 2.

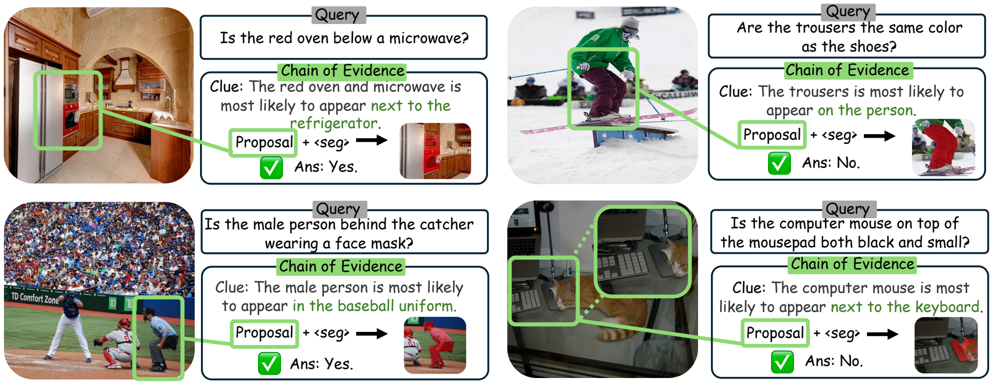

Query
Is the red oven below a microwave?
Chain of Evidence
Clue: The red oven and microwave is most likely to appear next to the refrigerator.
Proposal + <seg>
Ans: Yes.
Query
Are the trousers the same color as the shoes?
Chain of Evidence
Clue: The trousers is most likely to appear on the person.
Proposal + <seg>
Ans: No.
Query
Is the male person behind the catcher wearing a face mask?
Chain of Evidence
Clue: The male person is most likely to appear in the baseball uniform.
Proposal + <seg>
Ans: Yes.
Query
Is the computer mouse on top of the mousepad both black and small?
Chain of Evidence
Clue: The computer mouse is most likely to appear next to the keyboard.
Proposal + <seg>
Ans: No.

Figure 7. **More qualitative results for** Visual Question Answering.

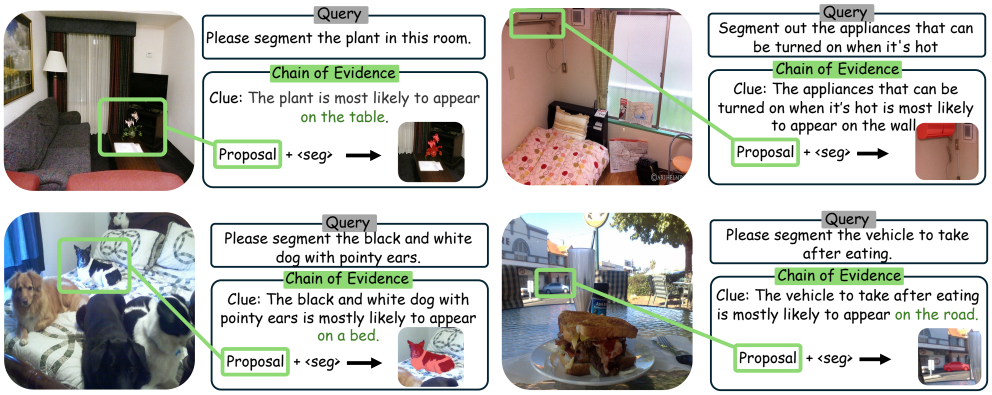
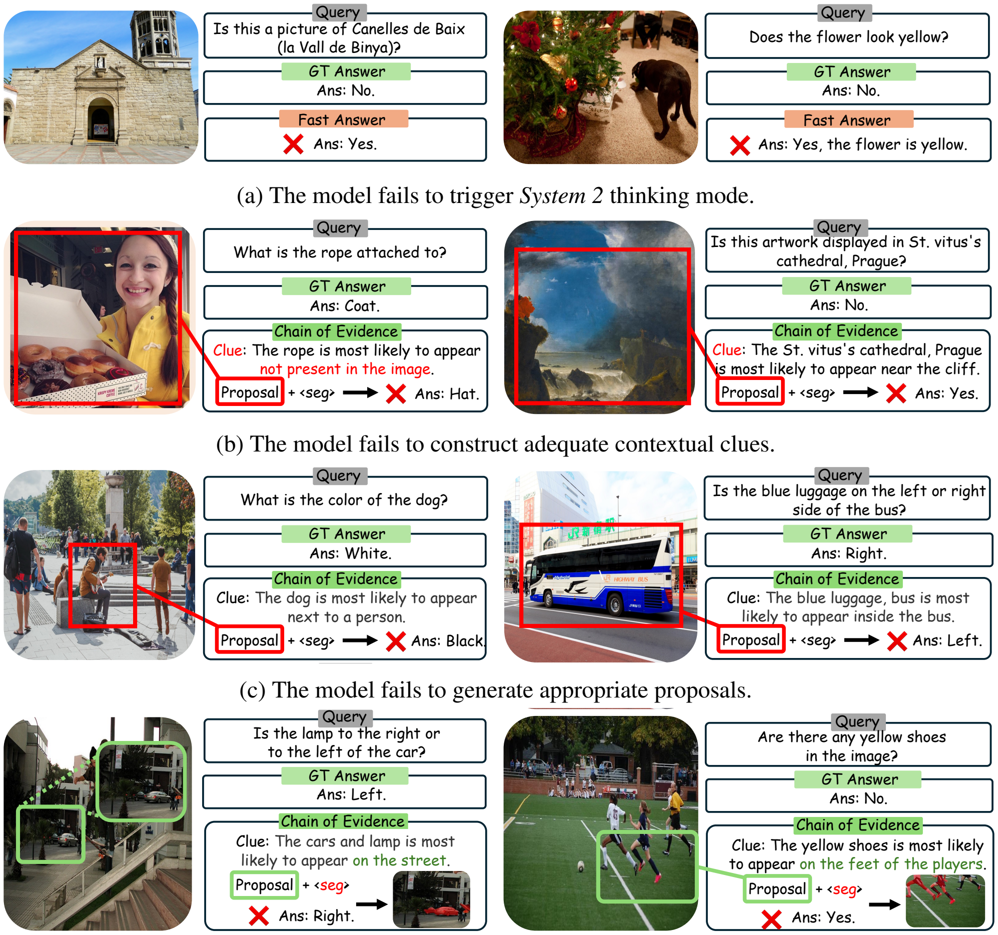

Query
Please segment the plant in this room.
Chain of Evidence
Clue: The plant is most likely to appear on the table.
Proposal + <seg>
Query
Segment out the appliances that can be turned on when it's hot
Chain of Evidence
Clue: The appliances that can be turned on when it's hot is most likely to appear on the wall
Proposal + <seg>
Query
Please segment the black and white dog with pointy ears.
Chain of Evidence
Clue: The black and white dog with pointy ears is mostly likely to appear on a bed.
Proposal + <seg>
Query
Please segment the vehicle to take after eating.
Chain of Evidence
Clue: The vehicle to take after eating is mostly likely to appear on the road.
Proposal + <seg>

Figure 8. **More qualitative results for** Visual Question Answering.

E Failure Case

In Figure 9, we present an overview of the most notable failure cases, providing insights into the distinct patterns that lead to suboptimal outputs in our FaST model. These challenges include difficulty in triggering the *System 2* thinking mode, constructing adequate contextual clues, generating appropriate proposals, and providing accurate pixel masks. The model often fails to recognize the need for deliberate reasoning, relying instead on *System 1* thinking, which leads to incorrect responses, as seen in Figure 9a. Inadequate contextual clues generated by the switch adapter impair the model's focus on the correct region, resulting in vague or incorrect responses, as illustrated in Fig. 9b. The proposal adapter's inaccurate identification of regions of interest, as shown in Figure 9c, leads to proposals that do not correspond to the query. Additionally, the segmentation adapter struggles with producing precise masks, particularly for small or occluded objects, causing erroneous conclusions, as highlighted in Figure 9d. These failure cases underscore the urgent need for refinement in our FaST framework, emphasizing the importance of significantly enhancing the precision of the system switch adapter, improving contextual clue construction, and optimizing the proposal and segmentation adapters to achieve more reliable and consistently accurate responses in complex visual and textual tasks.


Query
Is this a picture of Canelles de Baix (la Vall de Binya)?
GT Answer
Ans: No.
Fast Answer
Ans: Yes.
Query
Does the flower look yellow?
GT Answer
Ans: No.
Fast Answer
Ans: Yes, the flower is yellow.

(a) The model fails to trigger *System 2* thinking mode.

Query
What is the rope attached to?
GT Answer
Ans: Coat.
Chain of Evidence
Clue: The rope is most likely to appear not present in the image.
Proposal + <seg> Ans: Hat.
Query
Is this artwork displayed in St. vitus's cathedral, Prague?
GT Answer
Ans: No.
Chain of Evidence
Clue: The St. vitus's cathedral, Prague is most likely to appear near the cliff.
Proposal + <seg> Ans: Yes.

(b) The model fails to construct adequate contextual clues.

Query
What is the color of the dog?
GT Answer
Ans: White.
Chain of Evidence
Clue: The dog is most likely to appear next to a person.
Proposal + <seg> Ans: Black
Query
Is the blue luggage on the left or right side of the bus?
GT Answer
Ans: Right.
Chain of Evidence
Clue: The blue luggage, bus is most likely to appear inside the bus.
Proposal + <seg> Ans: Left.

(c) The model fails to generate appropriate proposals.

Query
Is the lamp to the right or to the left of the car?
GT Answer
Ans: Left.
Chain of Evidence
Clue: The cars and lamp is most likely to appear on the street.
Proposal + <seg>
Ans: Right.
Query
Are there any yellow shoes in the image?
GT Answer
Ans: No.
Chain of Evidence
Clue: The yellow shoes is most likely to appear on the feet of the players.
Proposal + <seg>
Ans: Yes.

(d) The model fails to provide accurate pixel masks.

Figure 9. **Failure cases** of Our FAST system.

F Limitation and Future Work

While the FaST framework has demonstrated significant advancements in emulating human-like cognitive processes in visual AI through its fast and slow thinking mechanisms, several limitations warrant attention. Firstly, the system's reliance on a predefined set of negative data for training the switch adapter may not encapsulate the full spectrum of real-world complexities. Firstly, this could lead to suboptimal performance when faced with novel or unexpected scenarios. Secondly, despite its fine-grained analysis capability, the pixel-level mask decoder might struggle with highly textured or patterned images where segmentation becomes challenging. Lastly, the generalizability of FaST across various domains and tasks necessitates further validation to ensure its robustness and reliability in diverse applications. We plan to develop advanced learning mechanisms that will allow the model to generalize more effectively beyond the predefined negative dataset. Additionally, we will focus on optimizing it for real-time applications to reduce computational overhead and response times.

For the recent large reasoning model like OpenAI o1 model, while these models leverage reinforcement learning and internal chains of thought to achieve scalability, they often require significant computational resources, making them less efficient.

In contrast, FaST is designed to prioritize multimodal reasoning with a clear focus on transparency and adaptability. The use of interpretable reasoning modes (System 1 and System 2) ensures that FaST provides insights into its decision-making processes, which is critical for applications requiring explainability. Additionally, FaST's modular design allows it to balance computational efficiency and accuracy dynamically, making it suitable for diverse and resource-constrained environments. These strengths highlight FaST's unique contributions and its complementary potential to scalable reasoning approaches.

G Social Impacts

The development and deployment of FaST significantly advance AI by enhancing the human-like cognitive abilities of LLM-based visual agents. Positively, FaST enables sophisticated applications in areas like vision-based dialogues and security surveillance, while its transparent decision-making fosters trust and ethical AI practices. However, reliance on large models and extensive datasets risks perpetuating biases, potentially leading to unjust or discriminatory outcomes. Addressing these ethical concerns and establishing responsible usage guidelines are essential for the responsible deployment of such advanced AI systems.

H Ethical Safeguards

In our paper introducing a novel framework FaST, we implement rigorous ethical measures to prevent potential misuse and promote responsible application. These measures are delineated in comprehensive protocols accompanying the final release of models and datasets. Our protocols encompass stringent usage guidelines, access controls, incorporation of safety filters, and monitoring systems. These concerted efforts reflect our steadfast dedication to upholding the utmost ethical standards in scientific exploration. Our objective is to protect the rights and privacy of all stakeholders involved, thereby fostering a culture of responsible and ethical research within our community.

I Reproducibility

Our FaST framework is implemented in PyTorch (Paszke et al., 2019). All the experiments are conducted on eight NVIDIA A100-80GB GPUs. Our full implementation shall be publicly released upon paper acceptance to guarantee reproducibility. The codes are available at the anonymous link *https://anonymous.4open.science/r/Sys2-LLaVA-8B0F/* for the review process.

All Experiments (switch, proposal, and seg adapter) are conducted on eight NVIDIA A100-80GB SXM GPUs[5]. Reproducing the fine-tuning process would require approximately 15 A100 GPU days.

J LICENSES FOR EXISTING ASSETS

All the methods we used for comparison are publicly available for academic usage. The switch adapter is implemented based on the released code (https://github.com/penghao-wu/vstar) with an MIT license. The proposal adapter is implemented on the released code (https://github.com/dongyh20/Chain-of-Spot) with an Apache-2.0 license. The seg adapter is implemented on the released code (https://github.com/dvlab-research/LISA) with an Apache-2.0 license.

[5] https://www.nvidia.com/en-sg/data-center/a100/