HALDEC-BENCH: BENCHMARKING HALLUCINATION DETECTOR IN IMAGE CAPTIONING

Anonymous authors
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ABSTRACT

Recent progress in large vision-language models (VLMs) has been driven by advances in image-text alignment, i.e., learning the relationship between image and text. Hallucination detection in captions, **HalDec**, is a task to assess VLM's image-text alignment ability, and aims to identify errors in VLM-generated captions that misrepresent image content. Detecting these errors is crucial not only for evaluating alignment ability but also for curating high-quality image-caption pairs used to train VLMs. While VLMs have been explored as hallucination detectors, their generalizability across different captioning models, image domains, and hallucination types remains unclear due to a lack of a benchmark. In this work, we present HalDec-Bench, the first benchmark for principled and interpretable evaluation of HalDec models. It covers diverse VLMs used as captioning models, image domains, and provides high-quality hallucination-existence annotations enriched with hallucination-type labels. HalDec-Bench thus serves as a comprehensive testbed to advance HalDec and probe the image-text alignment ability of VLMs. Our analysis shows that HalDec-Bench offers tasks of varying difficulty, making it well-suited as a HalDec benchmark. Evaluating diverse VLMs reveals key limitations: (i) CLIP-like models are nearly blind to hallucinations in recent VLMs, (ii) detectors tend to over-score early sentences, and (iii) they display strong self-preference—favoring their own captions—which undermines detection performance. We will release our evaluation code and dataset upon acceptance.

1 INTRODUCTION

We have seen remarkable progress in large vision-language models (VLMs) (Wang et al., 2024a; Liu et al., 2023; 2024; Chen et al., 2023; Li et al., 2023a) and text-to-image generative models (Betker et al., 2023). A key to this progress lies in understanding image content in the form of text, i.e., learning image-text alignment. Once this mapping between images and text is effectively learned, large language models (LLMs) can be leveraged for various visual reasoning tasks (Li et al., 2023a).

Hallucination detection in captions, called **HalDec** hereafter, is a task that assesses VLM's image-text alignment capability. It aims to identify errors in captions that misrepresent image content, such as misstated object counts, incorrect attributes or relationships, or the introduction of entities absent from the image (Biten et al., 2022; Li et al., 2023b; Rohrbach et al., 2018). Beyond evaluating the alignment ability of VLMs, HalDec enables filtering out unaligned image-caption pairs (Li et al., 2022) from the training data. In practice, VLM training often relies on captions synthesized by a *Captioner*[1] to supplement the limited availability of human-annotated data. However, these synthetic captions frequently suffer from hallucinations. Curating high-quality image-caption pairs with strong detectors, therefore, plays a crucial role in building performant VLMs (Chen et al., 2024a). Indeed, models such as CLIP (Radford et al., 2021) and BLIP (Li et al., 2022) have already been widely used to curate large-scale training datasets for VLMs (Betker et al., 2023; Li et al., 2023a).

Considering the scalability of detectors, we expect the detector to be universally applicable across diverse image-caption pairs. Thus, as shown in Fig. 1, evaluating HalDec requires testing models to detect hallucinations across different Captioners, image domains, and hallucination types, since

[1]To avoid confusion, we use the term *Captioner* to denote a VLM used for caption generation, and use *Detector* to denote a VLM used for hallucination detection model.

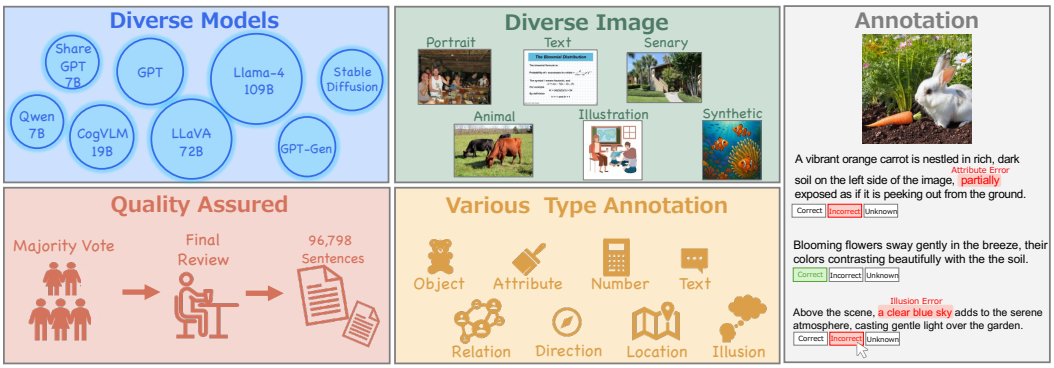


Figure 1: We introduce a novel benchmark, **HalDec-Bench**, for evaluating hallucination detectors on image captions generated by VLMs. Beyond measuring the effectiveness of hallucination detection in image captions, the benchmark also probes VLMs' ability to capture fine-grained image-text alignment. It spans a diverse set of captioning VLMs (top left) and image domains (top center) , and provides high-quality annotations (bottom left) enriched with hallucination type labels (bottom center).

each factor can introduce distinct language styles and error patterns. Yet, the universality of large VLMs as a hallucination detector remains unclear, even though recent studies have fine-tuned them for hallucination detection (Gunjal et al., 2024; Wada et al., 2025). Similarly, CLIP has been developed to learn the relationship between an image and a detailed sentence (Patel et al., 2024; Yuksekgonul et al., 2023), but its effectiveness is not clear for captions synthesized by advanced Captioners. The challenge of making the comprehensive HalDec benchmark is to build a dataset suited for such evaluation, requiring a significant cost of human annotation, where annotators must carefully check the image-sentence alignment. In fact, existing HalDec datasets suffer from limited model coverage and insufficient scale. MHalDetect (Gunjal et al., 2024) provides annotations for only a single VLM, and MHaluBench (Chen et al., 2024b) covers only a small set of models and samples. Also, despite the development of benchmarks for multimodal reasoning (Yue et al., 2024; 2025; Liu et al., 2023; Lu et al., 2023), a benchmark to evaluate VLMs' fundamental image-caption alignment is limited to hallucinated sentences generated by a human-designed pipeline (Yuksekgonul et al., 2023; Hsieh et al., 2023).

In this paper, we introduce HalDec-Bench, a benchmark designed to evaluate hallucination detectors for image captions in a principled and interpretable manner. As illustrated in Fig. 1, it covers a diverse set of captioning VLMs and image domains, and provides high-quality annotations enriched with hallucination-type labels and segment-level annotations. Beyond serving as a tool for analyzing detectors, HalDec-Bench also functions as a testbed for probing VLMs' fundamental ability to capture image-caption alignment. In our experiments, we focus on sentence-level hallucination detection and assess a variety of VLMs as detectors. The results demonstrate that HalDec-Bench offers tasks with diverse levels of difficulty, making it well-suited as a HalDec benchmark. Our extensive analysis further yields several key insights. First, detectors tend to recognize sentences at the beginning of a response as *correct*, regardless of their correctness. Second, they exhibit self-preference, i.e., consider their own output captions as *correct*, which degrades performance as detectors. This observation is consistent with prior findings (Panickssery et al., 2024). Third, we show that diverse ensembling strategies can effectively improve HalDec performance.

2 Related Work

Benchmarks for VLMs. Many benchmarks evaluate the broad reasoning ability of VLMs (Yue et al., 2024; 2025; Guan et al., 2024; Fu et al., 2023; Li et al., 2024b; Tong et al., 2024a) or expert knowledge with visual inputs (Lu et al., 2023). Some quantify VLMs for questions that are designed to hallucinate VLMs (Guan et al., 2024; Wang et al., 2023a). While prior datasets evaluate whether questions can mislead VLMs, we instead assess their capability to detect hallucinations in image captions, thereby emphasizing understanding of image-text alignment. Tong et al. (2024b) test fine-grained visual comprehension using CLIP-blind image pairs and related questions. HalDec-Bench instead utilizes captions from advanced VLMs, whose errors are difficult to detect.

Hallucination detection and mitigation in image captioning. Hallucination detection in image captioning has been widely studied (Rohrbach et al., 2018). CHAIR (Rohrbach et al., 2018) was the first metric to evaluate image-caption alignment at the object level using an object detector. However, its effectiveness is constrained by the detector's coverage and accuracy; thus, it fails in capturing the diverse hallucination types and captioning styles. Also, many works attempt to mitigate the hallucinations in image captions (Zhang et al., 2024; Leng et al., 2024; Farquhar et al., 2024; Zhou et al., 2024; Zhuang et al., 2025; Favero et al., 2024; Woo et al., 2025; Suo et al., 2025), especially, mitigating hallucinations in long captions is important as they are prone to contain more hallucinations (Zhou et al., 2024; Hirota et al., 2025), which we confirm in Sec. 4.2. Refining a captioning model based on image-caption alignment score, computed by VLMs, is a promising approach (Deng et al., 2024), and our work closely contributes to this line of work. Recent approaches fine-tune VLMs (Gunjal et al., 2024) with human-annotated data, calling LLM to leverage tools like open-vocabulary detectors, OCR (Chen et al., 2024b), or estimate prediction uncertainty (Farquhar et al., 2024). Despite these methodological developments and the use of VLMs as a detector, VLMs' fundamental ability to detect hallucinations in captions is unclear due to the lack of a benchmark.

Datasets for hallucination detection in image captioning. Some datasets are introduced for HalDec (Wang et al., 2023b; Chen et al., 2024b; Gunjal et al., 2024; Wada et al., 2025) (Table C[2]), but they are limited as VLM benchmarks, often lacking diverse Captioners or sufficient samples per model. Our benchmark, HalDec-Bench, addresses these gaps by (i) covering more responses, (ii) balancing data across diverse models, and (iii) incorporating text-to-image outputs. SUGARCREPE (Hsieh et al., 2023) and ARO (Yuksekgonul et al., 2023) probe CLIP's fine-grained image-text alignment ability, but rely on rule-based perturbations and simple sentences. In contrast, HalDec-Bench uses VLM-generated captions, which are more challenging as shown in Sec. 4.2.

3 DATASETS

We aim to collect datasets that cover diverse image-caption pairs equipped with high-quality annotations of hallucination presence. This section first explains how we collect image-caption pairs and provide annotations to them, followed by an analysis of the dataset. We focus on obtaining labels for sentence-level hallucination presence for two reasons: (i) sentence-level labels give a cue to easily find more fine-detailed locations of hallucinations, and (ii) span-level annotation suffers more from the subjectivity of annotation than sentence-level. For deeper analysis, we additionally provide span-level hallucination presence labels and categorize the types of hallucinations. Due to the limited space, we leave most details in Appendix C.

3.1 COLLECTING IMAGE-CAPTION PAIRS

HalDec takes an image and a caption as input and decides the presence of hallucinations. Thus, coverage of diverse image domains and caption patterns is essential to building a benchmark. We thus obtain image-caption pairs using six image-to-text and two text-to-image models. This process produces image–caption pairs, where each *caption* consists of multiple consecutive sentences.

Image-to-text models (Captioner). We employ CC12M (Changpinyo et al., 2021) and the validation split of COCO 2017 (Lin et al., 2014) as image inputs. To ensure the diversity of the test images, we cluster images into 50 clusters and pick 40 images from each cluster, resulting in 2000 images in total. We manually categorize each cluster to enable interpretable analysis. As shown in Table A, we employ GPT-4o, ShareGPT (S-GPT) (Chen et al., 2024a), LLaVA-1.6 (Li et al., 2024a), Llama-4 (Meta.AI, 2025), Qwen 2 (Wang et al., 2024a), and CogVLM (Wang et al., 2024b), covering diverse architectures, scales, and openness. This diversity enables the collection of captions with differing levels of detail and language style. For each Captioner-image pair, we apply a chat template (e.g., "Describe the image."), yielding 12K outputs in total.

Text-to-image models. To ensure the diversity in a text prompt, we first pick 170 common object categories and prompt GPT-4o-mini (OpenAI, 2023) to include at least one of the categories and generate 3-4 sentences per prompt, resulting in 1000 prompts. To convert the prompts into images, we utilize Stable Diffusion 3.5 (SD) (Stability AI, 2024) as an open-source model and image generation model accessible through GPT-4o-mini (GPT-Gen), yielding 2K outputs in total.

[2]ZINA is concurrent with ours, and details were unavailable at submission; we compare as best we can.

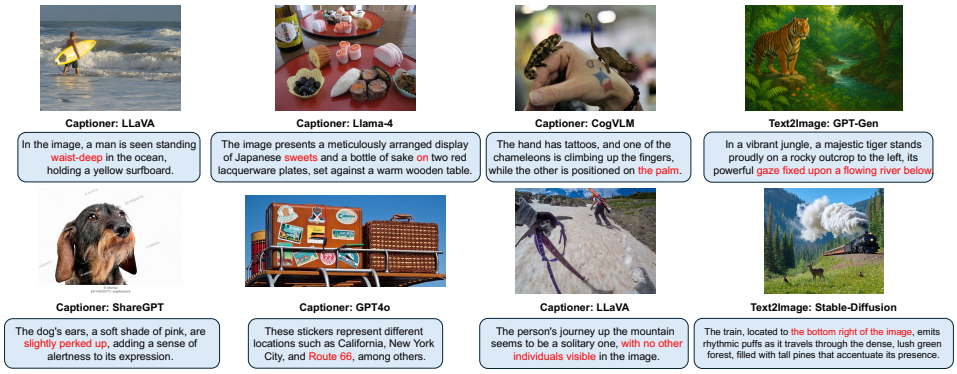


Figure 2: **Examples of hallucinated sentences in HalDec-Bench.** The hallucinated portions are often subtle, requiring fine-grained image-text alignment ability to detect them.

Table 1: **Stats of HalDec-Bench in sentence-level hallucination presence.** Our benchmark contains a large number of annotated sentences, enough for benchmarking models. We exclude sentences with *unknown* label.

	Image-to-Caption (Captioners)						Text-to-Image		
Stats	CogVLM	GPT4o	ShareGPT (S-GPT)	Llama-4	LLaVA-1.6 (LLaVA)	Qwen2	Stable Diffusion (SD)	gpt-image-1 (GPT-Gen)	Total
Sentences	7372	12790	17610	14800	15170	15790	2417	3524	**89473**
Sentences / Image	3.7	6.4	8.8	7.4	6.9	7.9	2.4	3.5	**6.3**
Correct (%)	91.5	91.8	73.4	85.2	80.9	88.8	34.1	79.7	82.7
Incorrect (%)	8.5	8.2	26.6	14.8	19.1	11.2	65.9	20.3	17.3

3.2 Annotation

In the main paper, we focus on how to obtain labels for sentence-level hallucination presence and leave the fine-detailed annotation process in Appendix C. The use of SOTA models as Captioners makes the annotation non-trivial because hallucinations produced by such models are often subtle and not immediately apparent at first glance, as shown in Fig. 2.

Annotation labels. We are inspired by the labeling scheme of Gunjal et al. (2024), where annotators assign one of three categories: *correct*, *incorrect*, or *unknown*. A sentence is labeled *correct* if it accurately describes the image, and *incorrect* if it contains a part that does not correctly describe the image. When correctness cannot be determined—for example, if the object is too small to recognize or if the description involves non-visible attributes such as smell or wind—it is labeled *unknown*. The *unknown* category is introduced to exclude unreliable cases from evaluation.

Annotation process. To ensure high-quality annotations, we adopt a two-stage process for sentence-level annotation: (i) crowd-sourced workers annotate each sentence, and (ii) we review the merged outcomes to guarantee quality. In the first stage, five independent workers annotate each sentence, reducing the risk of missing hallucinations. Moreover, their performance is continuously monitored through regular checks and feedback. The results are then merged based on majority voting, as detailed in the appendix, and subsequently reviewed. During the review, to minimize the inclusion of ambiguous cases in the evaluation, sentences that are difficult to judge are labeled as *unknown*. This process creates the dataset with sentence-level hallucination presence annotations. We further annotate this dataset to provide segment-level hallucination presence labels and hallucination category labels as detailed in Appendix C, where hallucinations are categorized into eight types. These categories should reveal the weakness of the current VLMs in understanding the image content.

3.3 Analysis of the Dataset

Examples of annotated sentences. Figure 2 presents examples of hallucinated sentences. Captioners' errors often involve visual details or object relationships rather than clear mistakes, making them harder to detect. Therefore, detectors require a fine-grained understanding of image-text alignment.

Basic stats. Table 1 summarizes the statistics of about 90K annotated *correct* or *incorrect* sentences. HalDec-Bench provides a balanced number of correct and incorrect sentences (excluding

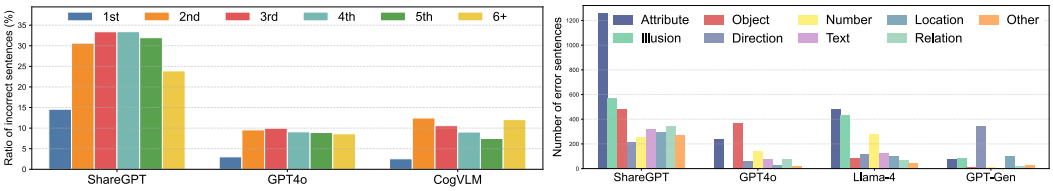


Figure 3: **Left:** Ratio of incorrect sentences within each sentence position per Captioner. Different colors indicate different positions. All models produce fewer errors at the 1st position. **Right:** Number of hallucinations for each category. Most models make many mistakes in attributes and text.

unknown cases). GPT-4o achieves the highest accuracy (91.8%), with only a small fraction of incorrect or unknown cases. Among open-source VLMs, Qwen (88.9%) and CogVLM (91.5%) perform comparably to GPT-4o. This suggests that for advanced Captioners, a large number of outputs are needed to obtain sufficient hallucinated samples. In contrast, models like LLaVA, LLaMA-4, and ShareGPT generate more sentences but with only 70% accuracy.

Positions of the hallucinations. The left of Fig. 3 computes the ratio of incorrect sentences in each position of the sentence. Across models, incorrect sentences appear most frequently in the second to fourth positions. This observation is consistent with previous work (Zhou et al., 2024; Hirota et al., 2025). The first sentence is less likely to contain hallucinations, likely because it often provides an overall image summary. In contrast, subsequent sentences typically provide finer-grained details, which are more error-prone. Beyond the sixth sentence, the error rate decreases again, as later sentences often serve as conclusions or closing remarks rather than detailed descriptions.

Hallucination categories. We show the hallucination type for each model on the right of Fig. 3. Errors in *attributes* are the leading category for many models, indicating that adjectival descriptions (e.g., color, texture) are prone to hallucination. Also, many models tend to cause errors in *text*, probably because small texts are hard to read even with advanced models.

4 Experiments

We aim to benchmark and analyze diverse VLMs on the HalDec task to uncover key factors for building a performant HalDec model. After describing the experimental setup, we first present an overview of the empirical results, followed by a detailed analysis. In summary, we discover many notable findings: (i) HalDec-Bench offers tasks with diverse levels of difficulty, making it a strong benchmark for systematic and interpretable analysis; (ii) CLIP-like models are no longer effective to detect hallucinations generated by advanced Captioners; (iii) VLMs tend to regard sentences at the beginning of the whole caption as *correct* irrespective of their correctness; and (iv) detectors exhibit strong self-preference, consistently scoring their own outputs more favorably.

Setups. We aim to benchmark diverse VLMs in sentence-level hallucination detection, i.e., identifying if hallucination exists given an image and a single sentence. Specifically, each sentence and image is independently fed into VLMs. We choose this evaluation protocol since the prior work on hallucination detection (Mishra et al., 2024) also employs sentence-level evaluation. Following (Chan et al., 2023), we prompt the VLMs to output the score of the alignment between the image and an input sentence, ranging from 0 to 100, as shown in Appendix D.1. We also include BLIP-2 (Li et al., 2023a), TripletCLIP (Patel et al., 2024), and SigLIP (Zhai et al., 2023) as fundamental image-text alignment models. Given the alignment score, we compute the AUROC within each Captioner, which enables threshold-free evaluation, and the random prediction results in a score of 50.

4.1 Overview of Results

Table 2 presents the results evaluated on diverse VLMs. Samples of detectors' outputs are available in Fig. 8.

HalDec-Bench covers diverse levels of hallucination detection. We see variations in the performance across the tested VLMs and caption models. Thus, HalDec-Bench is suitable to quantify the ability of VLMs as a hallucination detector in captions.

Table 2: AUROC results across VLMs. Cells with the best performance within open-source and closed-source groups are highlighted in a blue background, while the best model within each model family is marked in bold.

Detector	Reference	Params	Image-to-Caption Models						Text-to-Image Models		Avg.
			S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen	
Open-Source Models											
TripletCLIP	Patel et al. (2024)	0.3B	50.7	51.9	53.9	53.9	51.0	50.9	48.2	44.9	50.7
SigLIP	Zhai et al. (2023)	0.2B	51.7	52.0	53.3	52.8	53.1	54.9	50.7	55.2	47.8
BLIP-2	Li et al. (2023a)	1.2B	53.4	55.9	52.4	52.5	52.1	52.2	48.8	42.1	51.1
Phi-4	Abouelenin et al. (2025)	5.6B	54.2	53.1	52.5	51.4	51.9	50.8	52.6	50.9	52.1
Qwen-2	Wang et al. (2024a)	7B	60.2	55.3	55.9	46.0	51.9	53.2	54.6	46.0	52.9
Deepseek-VL2	Wu et al. (2024)	27B	58.0	56.6	56.9	54.4	54.2	53.9	56.1	50.5	55.1
LLaVA-NeXT	Li et al. (2024a)	72B	59.4	56.6	58.9	56.7	57.5	54.9	59.0	53.3	57.0
Pixtral-12B	Agrawal et al. (2024)	12B	64.3	60.8	60.6	57.1	57.3	55.7	64.7	56.7	59.6
Gemma-3	Gemma Team et al. (2025)	12B	67.0	63.3	63.1	57.6	59.4	54.0	**64.1**	**52.2**	59.9
		27B	**67.6**	**64.4**	**67.9**	**61.1**	**66.4**	**60.6**	63.7	50.5	**62.8**
InternVL2	Chen et al. (2024d)	2B	55.7	56.0	58.4	55.7	60.3	56.1	52.0	48.5	55.3
		8B	66.6	**65.7**	**69.1**	**63.9**	**67.6**	60.6	64.3	52.5	**63.8**
		26B	63.9	60.6	61.2	57.1	58.9	55.6	53.1	43.8	56.8
		40B	**69.3**	63.0	66.5	59.6	61.9	**61.5**	**69.5**	**56.5**	63.4
InternVL2.5	Chen et al. (2024c)	78B	74.1	70.3	73.7	63.9	68.1	63.1	72.0	55.7	67.6
Qwen-2.5	Bai et al. (2025)	7B	68.6	65.3	66.5	55.7	64.6	61.0	65.4	55.7	62.9
		32B	**73.6**	**71.6**	**70.6**	**66.1**	**69.0**	**66.0**	**68.9**	**61.0**	**68.4**
Llama-4	Meta.AI (2025)	109B	80.7	78.6	77.6	67.5	77.2	59.9	81.1	64.7	73.4
		400B	**81.1**	**80.9**	**79.0**	**71.9**	**81.3**	**64.7**	**83.0**	**67.8**	**76.2**
Closed Models											
Gemini-2.0 Flash	Gemini team (2024)	N/A	76.8	73.5	74.9	65.5	70.4	64.8	73.4	57.0	69.5
GPT4o-mini	OpenAI (2023)	N/A	69.9	65.7	68.2	60.0	62.3	60.3	56.5	47.7	61.1
GPT4o		N/A	75.8	72.6	72.8	58.2	69.7	63.8	63.2	52.4	66.1
GPT4.1-mini		N/A	77.8	75.8	74.4	65.8	69.2	66.0	68.7	56.1	69.2
GPT5-mini		N/A	81.5	82.2	80.2	69.7	81.1	73.0	83.8	65.7	77.2
GPT5		N/A	**85.4**	**86.0**	**85.3**	**72.3**	**85.5**	**78.4**	**84.9**	**72.0**	**81.2**

Best model. On average, GPT-5 shows the best performance of all models, while Llama-4, the best open-source model, performs on par with GPT-5-mini. Llama-4 outperforms many private models with a large margin. Its activated parameters during inference are only 17B. When considering the balance of inference time and accuracy, Llama-4 is the best in open-source models.

CLIP-based models are almost blind. TripletCLIP, SigLIP, and BLIP-2 show AUROC around 50, indicating that they cannot distinguish correct and incorrect sentences.

Which Captioner produces hard-to-detect hallucinations? Hallucinations from GPT-4o, GPT-Gen, and Llama-4 are difficult to detect, even for proprietary models, as shown by their low scores. Since SOTA models like GPT-4o and Llama-4 accurately understand many scenes, their errors might be subtle and harder to identify. GPT-Gen's hallucinations often involve eye direction or fine visual details, which are also challenging. In contrast, detectors achieve higher performance on ShareGPT, LLaVA, and SD, whose outputs contain many object-level hallucinations (see Fig. F).

Increasing the model size improves performance. In the same model family, larger language models yield better performance, probably because the task requires interpreting diverse captions.

Robustness to text-to-image models differs by detectors. Models such as Llama-4 and GPT-5-mini show the highest performance in SD across captioners, indicating that SD is the easiest split for these models. By contrast, for Gemma-3 (27B) and Qwen-2.5 (32B), the performance on SD is lower than S-GPT and Qwen-2. The difference should be due to the domains of images and the difference in language patterns. Inclusion of diverse data in our benchmark helps to find such trends.

4.2 Analysis

Given the overview above, we further provide a detailed analysis of the benchmark and detectors.

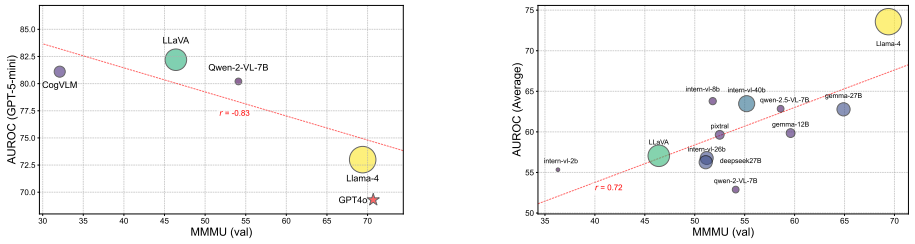


Figure 4: The size of plots indicates the parameter size. **Left:** MMMU performance measured on *Captioners* (X-axis) vs. AUROC measured by GPT-5-mini (Y-axis) for each Captioner. Advanced Captioners tend to produce hard-to-detect hallucinations. **Right:** MMMU (X-axis) vs. AUROC (Y-axis) measured on each *detector*. Detectors with better MMMU performance tend to show better performance on our benchmark.

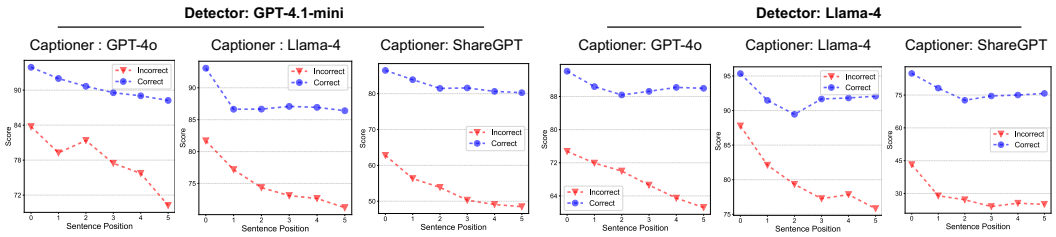


Figure 5: **Detectors show positional bias in scoring.** We average the detectors' correctness scores (Y-axis) by sentence position (X-axis) and visualize the results using GPT-4o (Left) and Llama-4 (Right) as detectors. Both detectors assign higher scores to sentences appearing near the beginning of the output. The detector is *not* provided with any positional information during inference.

Table 3: **Comparison to existing datasets** (AUROC). We compare with other HalDec datasets and the dataset used to assess VLM's compositionality understanding. Numbers of prior benchmarks that exceed HalDec-Bench are highlighted. This result indicates that HalDec-Bench is more challenging than existing datasets.

Detector	Params	HalDec-Bench				Hallucination Detection			VL-Compositionality	
		ShareGPT	Llava	GPT4o	Llama-4	MHalDetect	Foil	HAT	ARO	SugarCrepe
Qwen-2.5	7B	68.6	65.3	55.7	61.0	**78.7**	**85.5**	68.0	**78.3**	**84.9**
Gemma-3	27B	67.6	64.4	67.9	60.6	**81.7**	**91.8**	**76.6**	**79.2**	**87.6**
Llama-4	109B	80.8	78.7	67.8	59.9	**82.8**	**90.3**	76.3	**84.8**	**89.4**

Hallucinations generated by better Captioners are harder to detect. The left of Fig. 4 plots Captioner performance on MMMU (x-axis) against AUROC measured by GPT-5-mini (y-axis). Captioners with higher MMMU scores tend to yield lower AUROC, indicating that stronger Captioners generate hallucinations that are harder to detect.

The performance on HalDec-Bench is highly correlated with that on MMMU. The right of Fig. 4 plots the performance on MMMU (x-axis) and HalDec-Bench (y-axis), and indicates that models effective on MMMU perform well on HalDec-Bench and vice versa.

VLMs are biased to favor the sentence near the beginning of the output. Figure 5 computes the detectors' output scores averaged within each sentence position. For both *correct* and *incorrect* image-text pairs, the detectors give a higher score to the sentences located near the beginning of the output. The first sentence often provides the overview of the image without details, and VLMs seem to prefer such a sentence, possibly because such sentences are abundant in training datasets.

HalDec-Bench is more challenging than prior HalDec datasets. Table 3 compares HalDec-Bench with prior hallucination detection and VL-compositionality datasets. We evaluate on HAT and FOIL (Petryk et al., 2024), which inject hallucinations by word replacement in human captions, and MHalDetect (Gunjal et al., 2024), which annotates outputs of InstructBLIP (Dai et al., 2023). ARO (Yuksekgonul et al., 2023) and SugarCrepe (Hsieh et al., 2023) target compositionality evalu-

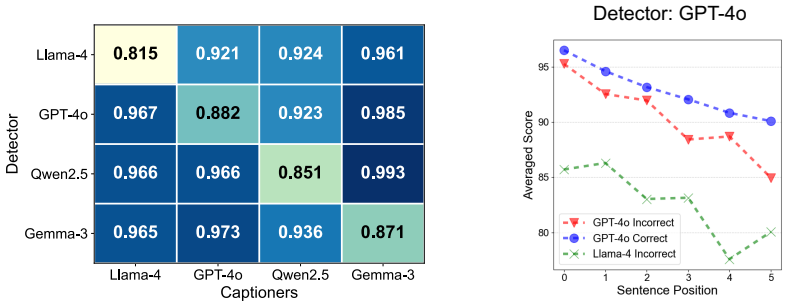


Figure 6: **Detectors struggle to detect their own hallucination. Left:** Self- and cross-evaluation results. AUROC scores for each Captioner (columns), normalized by the average AUROC of each Detector (rows). Diagonal entries show self-evaluation. **Right:** We pick GPT-4o as a detector, with their output correctness scores averaged by sentence position. Blue and red lines show scores for *correct* and *incorrect* GPT-4o's outputs; green shows scores for *incorrect* Llama-4 outputs.

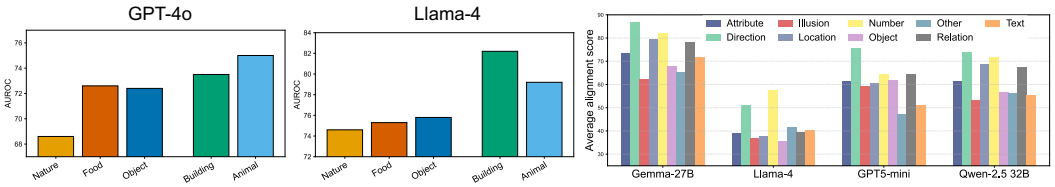


Figure 7: **Left: AUROC on different image domains.** The relative ordering of AUROC was highly consistent across models, exhibiting similar patterns of strength and weakness across domains. **Right: Detectors' score averaged within each hallucination type.** All models show weakness in *Direction* and *Number* hallucination.

ation. ShareGPT is the easiest split of HalDec-Bench, with performance close to HAT. All detectors excel on FOIL, suggesting these hallucinations are easy to detect for current SOTA VLMs.

Detectors struggle to detect their own hallucinations. Table 2 shows that Llama-4 (109B) and GPT-4o perform poorly on their own outputs (highlighted by underline). Their average rankings across Captioners are 3 and 6.8, respectively, but drop to 13 and 12 in detecting their own hallucinations. This finding aligns with prior work reporting LLM evaluators favor their own outputs (Panickssery et al., 2024). We annotate captions generated by Qwen-2.5 (32B) and Gemma-3 (27B) to enable more extensive self- and cross-evaluations. Figure 6 (left) confirms much lower AUROC on self-generated captions (diagonal elements). Figure 6 (right) shows that GPT-4o scores its own *incorrect* sentences higher than those of Llama-4, and the gap between incorrect and correct scores is small in its own output, which is causing the performance degradation.

Detectors show similar domain-wise robustness. The left of Fig. 7 studies AUROC on different image domains. The relative ordering of accuracies was consistent across models, meaning that models show similar trends in strength and weakness across domains. Performance is notably lower on *Nature*, *Food*, and *Object*. As shown in Fig. D, Captioners tend to generate accurate descriptions on such domains. Then, detecting errors from such mostly precise descriptions can get harder.

Detectors are poor at detecting *Direction* and *Number* hallucinations. The right of Fig. 7 assesses detectors' robustness across hallucination categories using correctness scores (lower is better since only hallucinated sentences are accounted). *Direction* errors occur when object orientation is misdescribed; identifying the errors requires fine-grained visual understanding, and detectors consistently perform poorly. *Number* errors arise from incorrect object counts—an issue long recognized in early VLMs like CLIP (Paiss et al., 2023) and still evident in advanced models. Figure 8 illustrates some results, highlighting that detectors still misunderstand the subtle visual details.

Segment-level localization has more room for improvement. HalDec-Bench includes hallucination segments for each hallucinated sentence, enabling segment-level evaluation. We present VLMs with a hallucinated sentence-image pair and prompt them to localize the hallucinated span, explicitly noting that one exists. Performance is measured by alignment with human annotations (see Appendix for prompts and metrics). As shown in Table 4, Llama-4 (400B), the best model, localizes

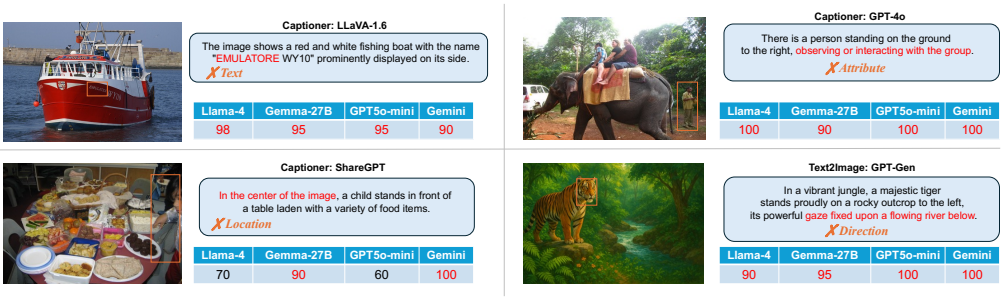


Figure 8: **Examples of *incorrect* sentences with detectors' correctness scores.** Higher scores indicate greater confidence in correctness. Detectors are prone to being overconfident in these examples. We highlight detectors' errors in red within the text and mark the grounded *incorrect* regions in the image with orange boxes.

Table 4: **Results of hallucinated segment localization task** (Average precision (%)). Localizing the segment of the hallucinated caption is challenging even for performant models.

Detector	Params	Image-to-Caption Models						Text-to-Image Models		Avg.
		S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen	
Qwen-2.5	32B	17.3	22.4	14.0	20.8	22.5	12.6	**15.9**	**12.1**	17.2
GPT-4o mini	-	25.2	28.9	20.6	29.5	28.0	18.7	14.7	14.6	22.5
Llama-4	109B	24.9	27.0	24.8	**34.3**	29.3	**19.6**	15.1	11.0	23.3
Llama-4	400B	**28.2**	**29.1**	**26.2**	34.0	**29.8**	19.4	15.4	12.0	**24.2**

Table 5: **Results of model ensemble.** Ensembling detectors' outputs improves performance in almost all cases. The increase or decrease from the *better* model used for ensembling is highlighted next to each score.

Detector 1	Detector 2	Image-to-Caption Models						Text-to-Image Models	
		S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen
Qwen-2.5 (7B)	Gemma-3 (27B)	71.9 **(+3.3)**	68.4 **(+4.0)**	71.3 **(+3.4)**	64.6 **(+3.5)**	69.3 **(+2.9)**	63.3 **(+2.3)**	67.6 **(+2.2)**	54.8 **(–0.9)**
Llama-4 (109B)	LLama-4 (400B)	84.6 **(+3.5)**	83.4 **(+2.4)**	82.9 **(+3.9)**	74.0 **(+2.1)**	83.5 **(+2.2)**	65.8 **(+1.1)**	84.6 **(+1.6)**	69.1 **(+1.2)**
Llama-4 (109B)	GPT5-mini	86.0 **(+4.5)**	84.8 **(+2.7)**	83.6 **(+3.4)**	73.9 **(+4.2)**	84.4 **(+3.2)**	72.3 **(-0.7)**	85.2 **(+1.4)**	68.6 **(+2.9)**

only 24.2% of hallucinated segments on average, underscoring substantial room for improvement. Notably, GPT-4o mini outperforms Qwen-2.5 (32B), in contrast to Table 2, indicating that strong sentence-level detectors are not always effective for segment-level localization.

Ensembling improves performance. We examine whether ensembling improves detection. We average alignment scores from two comparably strong models (Table 2) and observe consistent gains (Table 5). This suggests that models apply distinct criteria for image-caption alignment, and combining them enhances performance. A drop occurs for ensembling Llama-4 and GPT-5-mini on Llama-4 captions, likely due to the large performance gap between the two models.

Contents in the appendix. Table F compares the prior approach in HalDec with VLM-based detectors, indicating that VLM-based detectors can surpass the prior one with a large margin. Table D and Table E study the effectiveness of the chain-of-thought and self-ensembling, respectively. More visualizations of annotation and detectors' output are available in Sec. F and Fig. H, respectively.

5 Conclusion

We present a benchmark, HalDec-Bench, designed to evaluate the performance of hallucination detection in image captioning. The benchmark covers diverse models and image domains, containing detailed annotations for the hallucinations. The evaluation on this benchmark reveals that HalDec-Bench contains tasks with different levels of difficulty, and is suitable for analyzing detectors. Moreover, we provide diverse interesting observations: (i) CLIP-like models are nearly blind for detecting hallucinations in this benchmark, (ii) VLMs tend to favor the sentence near the beginning of the output, and (iii) VLMs show the trend of self-preference. HalDec-Bench will become a key to establishing a more effective hallucination detector in image captions.

REFERENCES

Abdelrahman Abouelenin, Atabak Ashfaq, Adam Atkinson, Hany Awadalla, Nguyen Bach, Jianmin Bao, Alon Benhaim, Martin Cai, Vishrav Chaudhary, Congcong Chen, et al. Phi-4-mini technical report: Compact yet powerful multimodal language models via mixture-of-loras. *arXiv preprint arXiv:2503.01743*, 2025.

Pravesh Agrawal, Szymon Antoniak, Emma Bou Hanna, Baptiste Bout, Devendra Chaplot, Jessica Chudnovsky, Diogo Costa, Baudouin De Monicault, Saurabh Garg, Theophile Gervet, et al. Pixtral 12b. *arXiv preprint arXiv:2410.07073*, 2024.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, et al. Qwen2. 5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.

James Betker, Gabriel Goh, Li Jing, Tim Brooks, Jianfeng Wang, Linjie Li, Long Ouyang, Juntang Zhuang, Joyce Lee, Yufei Guo, Wesam Manassra, Prafulla Dhariwal, Casey Chu, Yunxin Jiao, and Aditya Ramesh. Improving image generation with better captions, 2023. URL `https://cdn.openai.com/papers/dall-e-3.pdf`.

Ali Furkan Biten, Lluís Gómez, and Dimosthenis Karatzas. Let there be a clock on the beach: Reducing object hallucination in image captioning. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2022.

David Chan, Suzanne Petryk, Joseph E Gonzalez, Trevor Darrell, and John Canny. Clair: Evaluating image captions with large language models. In *EMNLP*, 2023.

Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12m: Pushing web-scale image-text pre-training to recognize long-tail visual concepts. In *CVPR*, 2021.

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*, 2023.

Lin Chen, Jinsong Li, Xiaoyi Dong, Pan Zhang, Conghui He, Jiaqi Wang, Feng Zhao, and Dahua Lin. Sharegpt4v: Improving large multi-modal models with better captions. In *ECCV*, pp. 370–387. Springer, 2024a.

Xiang Chen, Chenxi Wang, Yida Xue, Ningyu Zhang, Xiaoyan Yang, Qiang Li, Yue Shen, Lei Liang, Jinjie Gu, and Huajun Chen. Unified hallucination detection for multimodal large language models. In *ACL*, 2024b.

Zhe Chen, Weiyun Wang, Yue Cao, Yangzhou Liu, Zhangwei Gao, Erfei Cui, Jinguo Zhu, Shenglong Ye, Hao Tian, Zhaoyang Liu, et al. Expanding performance boundaries of open-source multimodal models with model, data, and test-time scaling. *arXiv preprint arXiv:2412.05271*, 2024c.

Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. *arXiv preprint arXiv:2404.16821*, 2024d.

Wenliang Dai, Junnan Li, Dongxu Li, Anthony Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale N Fung, and Steven Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning. *NeurIPS*, 2023.

Ailin Deng, Zhirui Chen, and Bryan Hooi. Seeing is believing: Mitigating hallucination in large vision-language models via clip-guided decoding. *arXiv preprint arXiv:2402.15300*, 2024.

António Farinhas, José GC de Souza, and André FT Martins. An empirical study of translation hypothesis ensembling with large language models. In *EMNLP*, 2023.

Sebastian Farquhar, Jannik Kossen, Lorenz Kuhn, and Yarin Gal. Detecting hallucinations in large language models using semantic entropy. *Nature*, 630(8017):625–630, 2024.

Alessandro Favero, Luca Zancato, Matthew Trager, Siddharth Choudhary, Pramuditha Perera, Alessandro Achille, Ashwin Swaminathan, and Stefano Soatto. Multi-modal hallucination control by visual information grounding. In *CVPR*, 2024.

Chaoyou Fu, Peixian Chen, Yunhang Shen, Yulei Qin, Mengdan Zhang, Xu Lin, Jinrui Yang, Xiawu Zheng, Ke Li, Xing Sun, et al. Mme: A comprehensive evaluation benchmark for multimodal large language models. *arXiv preprint arXiv:2306.13394*, 2023.

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 and visual illusion in large vision-language models. In *CVPR*, pp. 14375–14385, 2024.

Anisha Gunjal, Jihan Yin, and Erhan Bas. Detecting and preventing hallucinations in large vision language models. In *AAAI*, 2024.

Yusuke Hirota, Boyi Li, Ryo Hachiuma, Yueh-Hua Wu, Boris Ivanovic, Yuta Nakashima, Marco Pavone, Yejin Choi, Yu-Chiang Frank Wang, and Chao-Han Huck Yang. Lotus: A leaderboard for detailed image captioning from quality to societal bias and user preferences. In *ACL*, 2025.

Cheng-Yu Hsieh, Jieyu Zhang, Zixian Ma, Aniruddha Kembhavi, and Ranjay Krishna. Sugarcrepe: Fixing hackable benchmarks for vision-language compositionality. *NeurIPS*, 2023.

Hugging Face. Hugging face. URL https://huggingface.co/.

Dongfu Jiang, Xiang Ren, and Bill Yuchen Lin. Llm-blender: Ensembling large language models with pairwise ranking and generative fusion. In *ACL*, 2023.

Sicong Leng, Hang Zhang, Guanzheng Chen, Xin Li, Shijian Lu, Chunyan Miao, and Lidong Bing. Mitigating object hallucinations in large vision-language models through visual contrastive decoding. In *CVPR*, 2024.

Bo Li, Kaichen Zhang, Hao Zhang, Dong Guo, Renrui Zhang, Feng Li, Yuanhan Zhang, Ziwei Liu, and Chunyuan Li. Llava-next: Stronger llms supercharge multimodal capabilities in the wild, 2024a. URL https://llava-vl.github.io/blog/2024-05-10-llava-next-stronger-llms/.

Bohao Li, Yuying Ge, Yixiao Ge, Guangzhi Wang, Rui Wang, Ruimao Zhang, and Ying Shan. Seedbench: Benchmarking multimodal large language models. In *CVPR*, pp. 13299–13308, 2024b.

Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *ICML*. PMLR, 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*. PMLR, 2023a.

Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating object hallucination in large vision-language models. In *EMNLP*, 2023b.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *ECCV*, pp. 740–755, 2014.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *NeurIPS*, 36:34892–34916, 2023.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. In *CVPR*, 2024.

Pan Lu, Hritik Bansal, Tony Xia, Jiacheng Liu, Chunyuan Li, Hannaneh Hajishirzi, Hao Cheng, Kai-Wei Chang, Michel Galley, and Jianfeng Gao. Mathvista: Evaluating mathematical reasoning of foundation models in visual contexts. *arXiv preprint arXiv:2310.02255*, 2023.

Meta.AI. The llama 4 herd: The beginning of a new era of natively multimodal ai innovation, 2025. URL https://ai.meta.com/blog/llama-4-multimodal-intelligence/.

Abhika Mishra, Akari Asai, Vidhisha Balachandran, Yizhong Wang, Graham Neubig, Yulia Tsvetkov, and Hannaneh Hajishirzi. Fine-grained hallucination detection and editing for language models. In *COLM*, 2024.

OpenAI. ChatGPT. `https://chat.openai.com/chat`, 2023.

Roni Paiss, Ariel Ephrat, Omer Tov, Shiran Zada, Inbar Mosseri, Michal Irani, and Tali Dekel. Teaching clip to count to ten. In *ICCV*, pp. 3170–3180, 2023.

Arjun Panickssery, Samuel Bowman, and Shi Feng. Llm evaluators recognize and favor their own generations. *NeurIPS*, 2024.

Maitreya Patel, Naga Sai Abhiram Kusumba, Sheng Cheng, Changhoon Kim, Tejas Gokhale, Chitta Baral, et al. Tripletclip: Improving compositional reasoning of clip via synthetic vision-language negatives. *NeurIPS*, 2024.

Suzanne Petryk, David M Chan, Anish Kachinthaya, Haodi Zou, John Canny, Joseph E Gonzalez, and Trevor Darrell. Aloha: A new measure for hallucination in captioning models. In *ACL*, 2024.

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.

Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Kate Saenko. Object hallucination in image captioning. In *EMNLP*, 2018.

Stability AI. Stable diffusion 3.5 large. https://stability.ai/news/introducing-stable-diffusion-3-5, 2024.

Wei Suo, Lijun Zhang, Mengyang Sun, Lin Yuanbo Wu, Peng Wang, and Yanning Zhang. Octopus: Alleviating hallucination via dynamic contrastive decoding. In *CVPR*, 2025.

Gemini team. Gemini 2.0 flash, 2024. URL `https://blog.google/technology/google-deepmind/google-gemini-ai-update-december-2024/#gemini-2-0-flash`.

Gemma Team, Aishwarya Kamath, Johan Ferret, Shreya Pathak, Nino Vieillard, Ramona Merhej, Sarah Perrin, Tatiana Matejovicova, Alexandre Ramé, Morgane Rivière, et al. Gemma 3 technical report. *arXiv preprint arXiv:2503.19786*, 2025.

Peter Tong, Ellis Brown, Penghao Wu, Sanghyun Woo, Adithya Jairam Vedagiri IYER, Sai Charitha Akula, Shusheng Yang, Jihan Yang, Manoj Middepogu, Ziteng Wang, et al. Cambrian-1: A fully open, vision-centric exploration of multimodal llms. *NeurIPS*, 37:87310–87356, 2024a.

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*, pp. 9568–9578, 2024b.

Yuiga Wada, Kazuki Matsuda, Komei Sugiura, and Graham Neubig. Zina: Multimodal fine-grained hallucination detection and editing. *arXiv preprint arXiv:2506.13130*, 2025.

Junyang Wang, Yuhang Wang, Guohai Xu, Jing Zhang, Yukai Gu, Haitao Jia, Jiaqi Wang, Haiyang Xu, Ming Yan, Ji Zhang, et al. Amber: An llm-free multi-dimensional benchmark for mllms hallucination evaluation. *arXiv preprint arXiv:2311.07397*, 2023a.

Junyang Wang, Yiyang Zhou, Guohai Xu, Pengcheng Shi, Chenlin Zhao, Haiyang Xu, Qinghao Ye, Ming Yan, Ji Zhang, Jihua Zhu, et al. Evaluation and analysis of hallucination in large vision-language models. *arXiv preprint arXiv:2308.15126*, 2023b.

Peng Wang, Shuai Bai, Sinan Tan, Shijie Wang, Zhihao Fan, Jinze Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, et al. Qwen2-vl: Enhancing vision-language model's perception of the world at any resolution. *arXiv preprint arXiv:2409.12191*, 2024a.

Weihan Wang, Qingsong Lv, Wenmeng Yu, Wenyi Hong, Ji Qi, Yan Wang, Junhui Ji, Zhuoyi Yang, Lei Zhao, Song XiXuan, et al. Cogvlm: Visual expert for pretrained language models. *NeurIPS*, 2024b.

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.

Sangmin Woo, Donguk Kim, Jaehyuk Jang, Yubin Choi, and Changick Kim. Don't miss the forest for the trees: Attentional vision calibration for large vision language models. In *ACL Findings*, 2025.

Zhiyu Wu, Xiaokang Chen, Zizheng Pan, Xingchao Liu, Wen Liu, Damai Dai, Huazuo Gao, Yiyang Ma, Chengyue Wu, Bingxuan Wang, Zhenda Xie, Yu Wu, Kai Hu, Jiawei Wang, Yaofeng Sun, Yukun Li, Yishi Piao, Kang Guan, Aixin Liu, Xin Xie, Yuxiang You, Kai Dong, Xingkai Yu, Haowei Zhang, Liang Zhao, Yisong Wang, and Chong Ruan. Deepseek-vl2: Mixture-of-experts vision-language models for advanced multimodal understanding. *arXiv preprint arXiv:2412.10302*, 2024.

Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *CVPR*, pp. 9556–9567, 2024.

Xiang Yue, Tianyu Zheng, Yuansheng Ni, Yubo Wang, Kai Zhang, Shengbang Tong, Yuxuan Sun, Botao Yu, Ge Zhang, Huan Sun, et al. Mmmu-pro: A more robust multi-discipline multimodal understanding benchmark. In *ACL*, 2025.

Mert Yuksekgonul, Federico Bianchi, Pratyusha Kalluri, Dan Jurafsky, and James Zou. When and why vision-language models behave like bags-of-words, and what to do about it? In *ICLR*, 2023.

Xiaohua Zhai, Basil Mustafa, Alexander Kolesnikov, and Lucas Beyer. Sigmoid loss for language image pre-training. In *ICCV*, 2023.

Ruiyang Zhang, Hu Zhang, and Zhedong Zheng. Vl-uncertainty: Detecting hallucination in large vision-language model via uncertainty estimation. *arXiv preprint arXiv:2411.11919*, 2024.

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.

Xianwei Zhuang, Zhihong Zhu, Yuxin Xie, Liming Liang, and Yuexian Zou. Vasparse: Towards efficient visual hallucination mitigation via visual-aware token sparsification. In *CVPR*, 2025.

A LIMITATION

Methodology. HalDec needs to be a light-weight model, considering its application to curate datasets. However, our results indicate that VLMs with more parameters show superior performance. Also, our evaluation relies on sentence-by-sentence score output, which regards each sentence as independent. However, this protocol ignores the context of consecutive sentences. We observe that many sentences can be regarded as independent, yet considering multiple sentences together might improve the performance of hallucination detection.

Annotations. Judging the hallucinations in image captions involves subjective criteria of annotators. Captions may look hallucinated to some annotators, while they do not to others. Having a unified consensus on this criterion is difficult. For sentence-level annotation, we introduce a category *unknown*, which allows us to exclude such ambiguous samples during evaluation. This issue can be more significant in segment localization and categorizing hallucination types. Then, we focus on sentence-level detection to benchmark VLMs following Mishra et al. (2024).

B THE USE OF LARGE LANGUAGE MODELS (LLMS)

In preparing this manuscript, we made limited use of large language models (LLMs) such as ChatGPT. Specifically, LLMs were employed only to assist with polishing the writing for grammar, clarity, and readability. No part of the research design, analysis, interpretation, or results was generated or influenced by LLMs. All scientific content, data, and conclusions are the sole work of the authors.

C DATASET

C.1 IMAGE-CAPTION COLLECTION

We describe the list of models used for collection in Table A. All models except for closed ones are downloaded from Hugging Face.

Table A: Details of VLMs picked as Captioners and Text2Image models. We cover diverse models considering their size, provider, and release date.

Model	Provider	Open/Closed	Scale	Release
GPT-4o	OpenAI	Closed	-	2024/05
ShareGPT (Share Captioner)	Shanghai AI Laboratory	Open	7B	2023/11
LLaVA-1.6 (llava-next-72b-hf)	Microsoft	Open	72B	2024/01
Llama-4-Scout (17B-16E)	Meta	Open	109B	2025/04
Qwen2.5-VL (7B-Instruct)	Alibaba	Open	7B	2024/12
CogVLM (cogvlm2-llama3-chat-19B)	Tsinghua Univ.	Open	19B	2024/06
Stable-diffusion-3.5-medium (SD)	Stability AI	Open	2.5B	2024/10
GPT-Gen (GPT4o-mini)	OpenAI	Closed	-	2024/05

Captioner models. We collect data from two sources and employ two text-to-image models. The first source is CC12M, which is designed for vision-and-language pre-training and provides broad domain coverage. The second source is the COCO 2017 dataset, where we use the validation split. For both datasets, we cluster images into 50 domains based on ResNet features and then sample 40 images from each cluster, resulting in a total of 2,000 images per dataset.

For the Captioner models, we randomly select one of the following instructions:

Instruction given to captioner models

1. Describe this image in detail.
2. Describe this image in detail. Instead of describing the imaginary content, only describe the content one can determine confidently from the image.
3. Provide a detailed description of the image, but only include elements that are clearly visible and verifiable.
4. Describe this image in detail. Minimize aesthetic descriptions as much as possible.
5. Provide a detailed, factual description without using emotional language.

Text-to-image models. We employ two text-to-image models. The first is stabilityai/stable-diffusion-3.5-medium, a diffusion-based generative model that we run locally via the Diffusers library on GPU hardware. The second is OpenAI's gpt-image-1, which is accessed through the Responses API with gpt-4o-mini acting as the controller for image generation. For both models, we use identical prompts. To encourage category diversity, we predefine 170 object categories and randomly select one to be included in each prompt. The selected category is then inserted into an instruction given to gpt-4o-mini, which produces a 3–4 sentence description following the specification below.

Instruction given to GPT-4o-mini for producing text-to-image prompts

I want to create prompts to generate image using text to image model. The prompts need to satisfy the following criteria.
1. The prompts include 3-4 sentences.
2. They need to describe a scene including target.
3. They need to describe the state of the objects, what they are doing.
4. They need to describe the location of the object in image, (e.g., left, right, bottom, top, etc)
5. They also need to describe where the objects are looking at (e.g., left, right, bottom, top, or towards some) if the object is some organism.
Can you suggest a prompt? Please return in the form of dictionary, with a key of "prompt".
Output:

C.2 Voting and Quality Control

We first recruited five annotators and conducted a pilot on one hundred images. The authors reviewed all annotations, and annotators who failed to meet our quality standards were not assigned further items. This process allowed us to identify trusted annotators. Each trusted annotator was then assigned between one thousand and two thousand images. The authors checked the quality for every batch of about two hundred images. If the annotations did not meet our standards, annotators were required to re-annotate before proceeding.

After the main annotation, we applied multi-round voting. Annotator-specific weights were assigned, with trusted annotators given higher weights. The aggregated votes were used to determine the final labels. For the *incorrect* (hallucination) category, we adopted a stricter rule: if one trusted annotator or two annotators labeled an item as incorrect, the authors manually reviewed it, since hallucinations are more difficult to detect reliably than correctness. Finally, the authors adjudicated all ambiguous cases. This combination of pilot screening, ongoing audits, weighted voting, and final review ensured high-quality hallucination detection annotations.

C.3 Annotator Recruitment

For the hallucination detection task, we recruited crowd annotators and offered compensation based on the phase and level of effort. On average, annotators received around $100 for completing 2,000 images during the detection phase. Since the hallucination type annotation required more careful reading and reasoning, the compensation was higher, averaging around $150 for each model output. The exact amount varied slightly depending on the annotator's country of residence. We did not

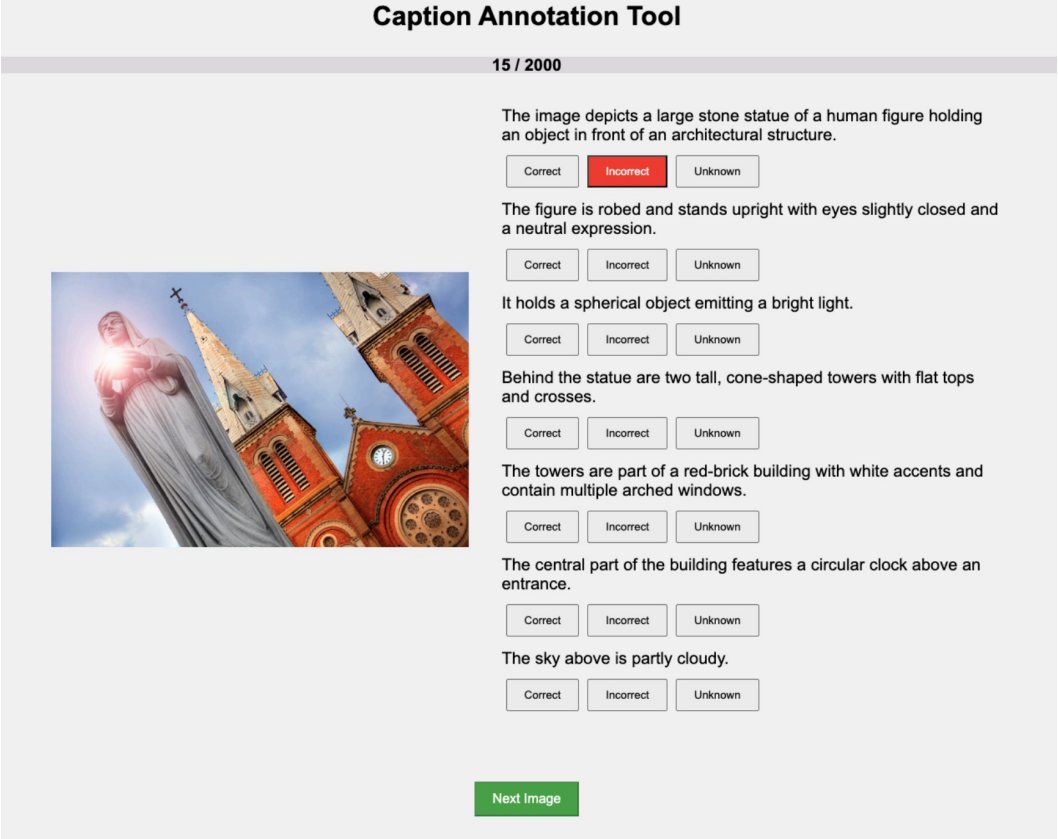


Figure A: Example of an interface used for the hallucination detection.

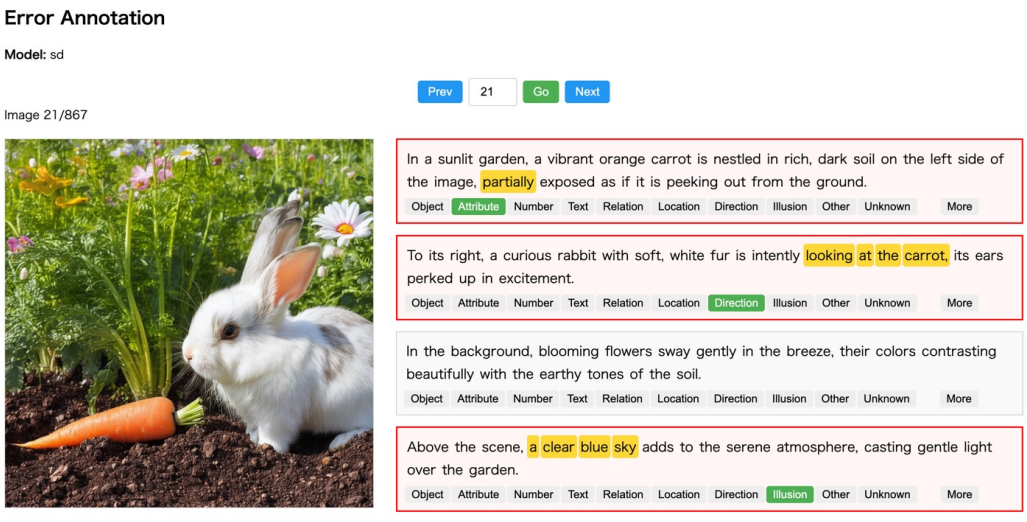


Figure B: Example of an interface used for the hallucination type annotation.

restrict annotators by location, but we required strong English reading skills, which were verified during the pilot stage. We recruited annotators on Upwork[3], Freelancer[4], and CrowdWorks[5].

[3] https://www.upwork.com/

[4] https://www.freelancer.com/

Table B: Types of hallucinations categorized for analysis.

Type	Description
Object	Misidentifies an object or uses an incorrect noun (e.g., calling a dog a cat).
Attribute	Incorrect description of an object's property such as color, size, or action (e.g., red car described as blue).
Number	Incorrectly states the number of objects or people (e.g., "three people" when only two are present).
Text	Misreads or misrepresents textual information in the image (e.g., misreading a store sign).
Relation	Incorrect description of relationships between objects (e.g., "a man riding a horse" when he is standing next to it).
Location	Misrepresents the position of an object in the image (e.g., "a cup on the table" when it is on the floor).
Direction	Incorrectly describes the direction/orientation of an object (e.g., "a person facing left" when they face right).
Illusion	Describes objects, scenes, or actions that do not exist at all (e.g., mentioning "a flying bird" when no bird is present).

Figure C: Example annotations of error type. Hallucinations are highlighted in red.

Figure A shows the annotation interface for the hallucination detection phase, while Figure B shows the interface used for the hallucination type annotation phase.

C.4 Hallucination Type and Location Annotation

Table B shows the eight hallucination type categories used in the HalCap dataset. These categories cover both fine-grained object- and attribute-level mistakes as well as broader contextual errors. Figure C shows annotation examples for each error type. Hallucinations are highlighted in red.

C.5 Additional Analysis

Detailed comparison against existing datasets. Table C describes the detailed comparison against prior hallucination detection datasets applicable for HalDec. Our dataset includes more responses and includes text-to-image models as the evaluation target. In particular, it offers larger textual coverage, covering 1.6M words, 94k sentences, and a vocabulary of 17k unique word types, than prior datasets.

[5] https://crowdworks.jp/

Table C: Compared to existing hallucination detector benchmarks for image captions based on their evaluation split, HalDec-Bench offers the largest number of responses, providing annotations for at least 1,000 responses per model across eight models. This scale enables detailed, model-wise performance analysis and facilitates a deeper understanding of detector characteristics. For datasets that are not publicly available or lack information, the corresponding statistics are reported as NA.

Dataset	Granularity	# responses	# halluc. types	# models	# words	# sentences	# vocab.	# unique image	Text to Image
HaELM (Wang et al., 2023b)	Response	5k	✗	1	518k	28k	6k	5k	✗
MHalDetect (Gunjal et al., 2024)	Segment	4k	✗	1	258k	14k	4k	1k	✗
MHaluBench (Chen et al., 2024b)	Segment	1k	4	5	15k	1k	2k	1k	✔
ZINA (Wada et al., 2025)	Segment	7k	6	12	NA	NA	NA	NA	✗
HalDec-Bench (Ours)	Segment	14k	9	8	1.6M	94k	17k	4k	✔

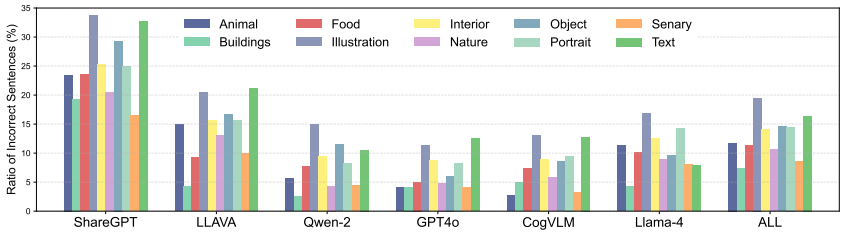


Figure D: **Ratio of incorrect sentences for each image domain.** All models tend to produce more errors in domains such as *illustration* and *Text*.

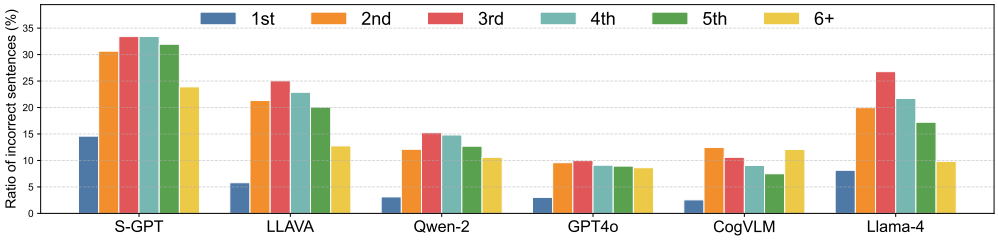


Figure E: **Ratio of incorrect sentences within each sentence position per model.** Different colors indicate different positions. All models produce fewer errors at the 1st position.

Image domain. Figure D illustrates the ratio of incorrect sentences on each image category in the CC12M. All Captioners tend to produce more errors in *Text* and *Illustration* domains, while they are relatively robust in real images. This can be because of the bias in the training data of the Captioners.

Error analysis w.r.t position of the sentence. In Fig. E, we present the ratio of incorrect sentences across sentence positions for each model. Among image captioning models, incorrect sentences tend to appear most frequently in the second to fourth positions. Interestingly, the very first sentence is less likely to contain hallucinations. This may be because the first sentence often serves as an overall image caption. In contrast, the second and subsequent sentences typically provide more detailed descriptions, which are more prone to errors. For positions beyond the sixth sentence, the error rate decreases again. These later sentences often serve as overall conclusions or closing remarks rather than detailed descriptions, which may make them similar to the first sentence and thus less prone to errors.

Analysis w.r.t hallucination types. Figure F describes the type of hallucinations we provide. Our dataset covers various kinds of hallucinations.

D Details of Experimental Setups

D.1 Details of Evaluation

Source of models. We employ models available in HuggingFace and base our code on the HuggingFace Transformers package.

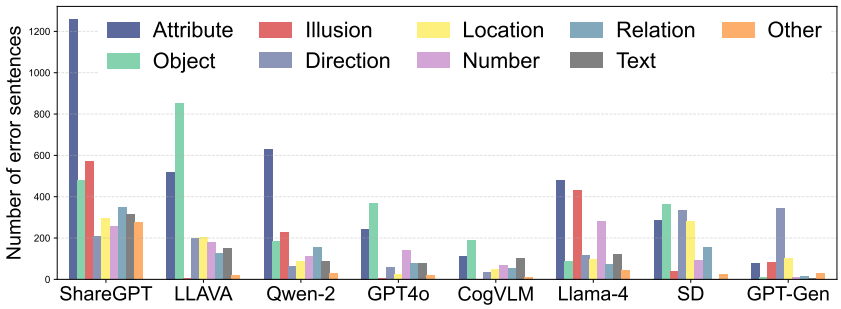


Figure F: **Number of hallucinations for each category.** Most models make many mistakes in attributes and text.

Computation. At most eight A100 80GB GPUs are used for inference of a single model.

Prompt. We employ the prompt below to compute the alignment score for decoder-based VLM.

Prompt to compute image-sentence alignment

You are given an image and a caption describing the given image. Your task is to judge if the caption describes the image correctly. If you think the sentence does not describe the image correctly, return low the score. If you think there is no mistake in the caption, return high score. Judge the correctness from 0-100 points. Return the output in the form of dictionary, e.g., "score": 50. Please first output the correctness points before explaining the reason for the score.
Caption:

Similarly, we use the prompt below to obtain the results of the chain of thought.

Chain-of-thought prompt

You are given an image and a caption describing the given image. Your task is to judge if the caption describes the image correctly. If you think the sentence does not describe the image correctly, return low the score. If you think there is no mistake in the caption, return high score. Judge the correctness from 0-100 points. Return the output in the form of dictionary, e.g., "score": 50. Please first explain the reason of scoring in ** two or three ** sentences and output the correctness points as shown above.
Caption:

Parsing. After obtaining the text output, we write a parser to convert the output into an integer. Models sometimes did not properly follow the prompt, and we could not parse such output. For such a sample, we assign 50 as its alignment score. In Table 2, we present models with their failure rate less than 5%. Also, the failure rate of a well-performing model is very low.

Annotation details in self-preference analysis. In Sec. 4.2, we additionally provide sentence-level hallucination existence labels for Qwen-2.5 (32B) and Gemma-3 (27B). To reduce the cost of annotation, we follow an annotation procedure different from the other 8 models, yet in a quality-ensured manner. Specifically, we randomly pick 500 images and generate captions using two models. Then, one quality-ensured annotator gives an annotation to 500 captions. This produces enough samples for analysis. We will include this split when publishing the dataset.

Prompt in hallucination localization. We employ the prompt below to obtain the results of hallucination localization.

Prompt for hallucination localization

You are given an image and a caption describing the given image. Your task is to localize the segment of the caption, which describes the image incorrectly. Please output the segment by marking the incorrect parts by **[]**, e.g., A **[red]** bird singing in a tree. Return the output in the form of a dictionary. Example format.

```
```json
{
"output": "A **[red]** bird singing in a tree."
}
```
```

Caption:

Evaluation metric in hallucination localization. We evaluate the alignment between the word spans predicted by models and the ground-truth (GT) spans using an Intersection-over-Union (IoU) based criterion. Concretely, we compute the IoU between the predicted word range and the GT word range. In Table 4, a prediction is considered correct if its IoU with a GT span is greater than or equal to 0.3. Based on this criterion, we measure precision as the proportion of predicted spans that are judged correct.

E Additional Experiments

Table D: Results of using Chain-of-Thought (COT).

Detector	COT	Image-to-Caption Models						Text-to-Image Models	
		S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen
Llama-4 (109B)		80.7	78.6	77.6	67.5	77.2	59.9	81.1	64.7
	✓	80.6 (–0.1)	80.8 (+2.2)	80.0 (+2.4)	71.1 (+3.6)	80.1 (+2.9)	62.4 (+2.5)	80.8 (–0.3)	65.1 (+0.4)
GPT4.1-mini		77.8	75.8	74.4	65.8	69.2	66.0	68.7	56.1
	✓	79.0 (+1.2)	76.2 (+0.4)	75.0 (+0.6)	63.4 (–2.4)	71.6 (+2.4)	63.8 (–2.2)	73.2 (+4.5)	56.2 (+0.1)

Chain-of-Thought improves the performance? Table D evaluates the impact of chain-of-thought reasoning (Wei et al., 2022), where detectors are prompted to generate a reasoning path before producing a score (see above for prompt details). For Llama-4, COT generally improves performance, whereas for some Captioners, the gains are marginal or even slightly negative. Results for GPT4.1-mini are mixed, wherein improvements highly depend on the evaluation target.

Table E: Ensembling detectors' output improves performance in almost all cases. We highlight the increase or decrease from the *better* model used for ensembling next to each score.

Detector	Num. of Ensemble	Image-to-Caption Models						Text-to-Image Models	
		S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen
Llama-4-scout	1	80.6	80.8	80.0	71.1	80.1	62.4	80.8	65.1
Llama-4-scout	5	83.2 (+2.6)	83.0 (+2.2)	81.8 (+1.9)	74.4 (+3.4)	82.2 (+2.1)	65.1 (+2.7)	83.0 (+2.2)	65.9 (+0.8)
Llama-4-scout	10	83.7 (+3.1)	83.4 (+2.6)	82.2 (+2.3)	75.0 (+3.9)	82.8 (+2.7)	65.7 (+3.3)	83.4 (+2.6)	66.4 (+1.3)

Self-ensemble improves performance. We further study the potential of ensembling. Unlike the analysis above, we ensemble outputs from a single model to refine detector's score (Farinhas et al., 2023; Jiang et al., 2023). To get different scores from a single model, we obtain different reasoning paths by stochastic sampling in the chain-of-thought. To ensure the diversity of COT, we set the temperature as 1.5 and top_p as 0.9. Table E presents the results in Llama-4, where the performance consistently improves in all Captioners. Also, using more ensemble paths tends to improve the performance, while the increase seems to saturate. Model ensembling can be an interesting direction to improve the performance in this task.

Table F: Comparison to existing HalDec approaches.

Detector	GPT4o	SD
UniHD (Chen et al., 2024b)	62.6	71.0
Qwen-2.5 32B	66.1	68.9
Gemma-3 27B	61.0	63.7
Llama-4 109B	67.7	81.1
GPT-4.1-mini	65.8	68.7

Table G: Mean IoU for hallucination localization task. Localizing the segment of the hallucinated caption remains difficult even for performant models.

Detector	Params	Image-to-Caption Models						Text-to-Image Models		Avg.
		S-GPT	Llava	Qwen-2	GPT4o	CogVLM	Llama-4	SD	GPT-Gen	
Qwen-2.5	32B	13.8	15.1	11.7	15.1	16.0	10.7	11.4	9.4	12.9
GPT-4o mini	-	21.6	22.4	18.3	**23.3**	**21.5**	16.4	**12.5**	**11.9**	18.5
Llama-4	109B	22.6	20.8	22.7	26.4	23.2	17.3	10.7	9.0	19.1
Llama-4	400B	**24.8**	**22.1**	**23.3**	26.0	21.7	**18.0**	11.9	9.3	**19.6**

VLM detectors can surpass prior approaches. Table F presents the comparison to UniHD (Chen et al., 2024b), which prompts LLM to utilize an open-vocabulary detector and OCR engine. The results indicate that advanced VLMs can surpass the approach without using such external tools. More detailed discussion is available in the appendix.

Mean intersection over union in hallucination localization. Table G shows the results of mean IoU in hallucinated segment localization. Specifically, we compute the intersection over union between the predicted and ground-truth segments and compute the average for all samples. Overall, the performance is consistent with what is reported in Table 4.

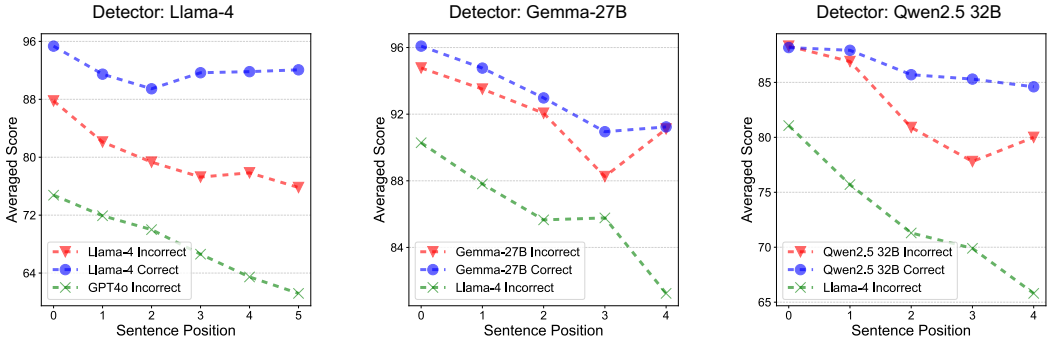


Figure G: Detector's output score for their own output captions.

Additional results in self-preference evaluation. Fig. G illustrates self-preference score analysis for Gemma-27B, Llama-4, and Qwen2.5. Their self-preference tendency is significant, especially for Gemma-27B and Qwen2.5.

Additional examples of VLMs' outputs. Figure H illustrates examples of input images, sentences, and corresponding correctness scores inferred by VLMs. VLMs tend to make errors in the location of the objects, the relationship between them, and small visual details.

F Additional Examples of Annotations

We provide additional figures illustrating annotation results and representative hallucination cases: ShareGPT (Fig. I), LLaVA (Fig. J), Qwen-2 (Fig. L), GPT-4o (Fig. L), CogVLM (Fig. M), LLaMA-4 (Fig. N), Stable Diffusion (Fig. O), and GPT-Gen (Fig. P).

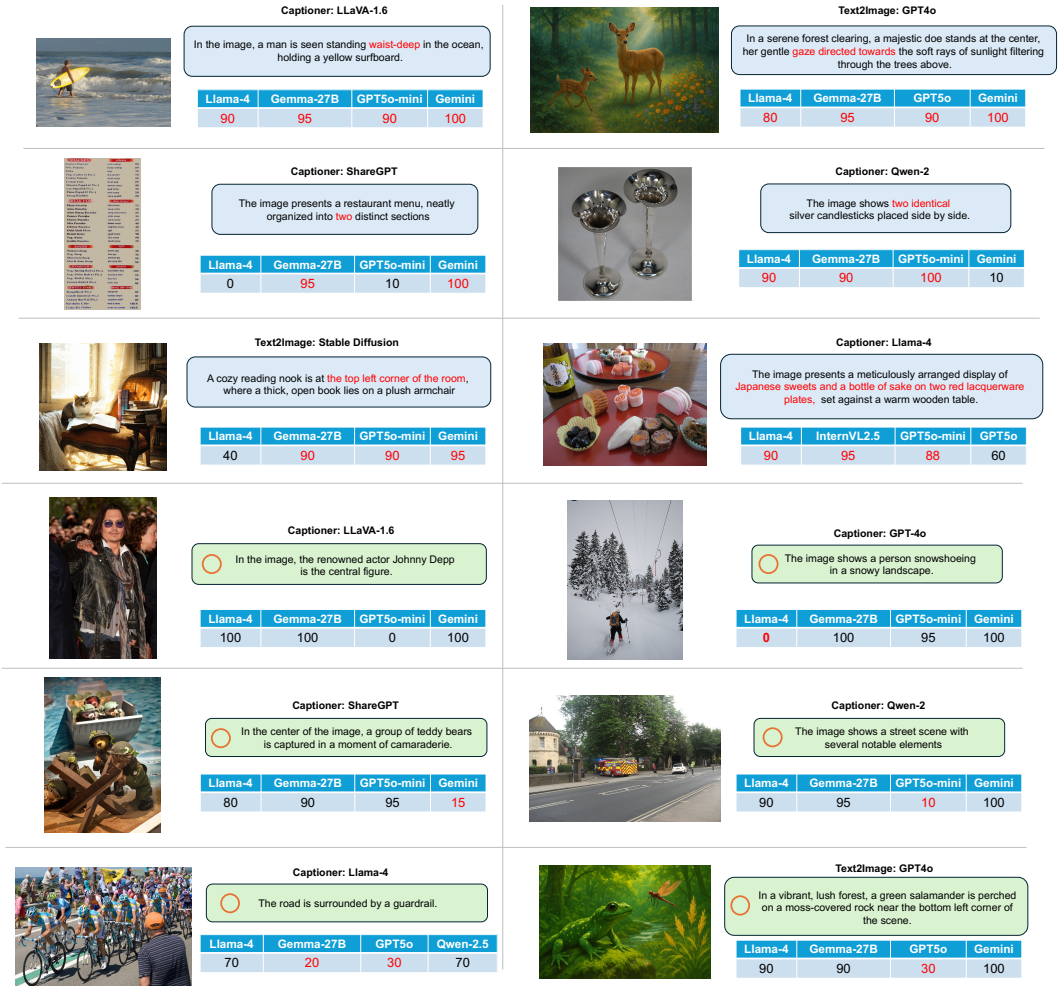


Figure H: Examples of input image and sentences with detectors' correctness scores. Higher scores indicate greater confidence in correctness. We highlight detectors' errors in red within the text.

The image captures a serene and inviting outdoor patio area.

The precise placement of objects and their relative positions contribute to the overall balance and harmony of the scene.

Dominating the scene is a large window that frames a picturesque view of a pool and lush greenery, offering a glimpse into the tranquility of the surroundings.

The window is framed by a sturdy brick wall, adding a rustic charm to the setting.

Number — In front of the window, **two** wicker chairs with vibrant floral cushions invite relaxation.

A potted plant rests on the floor next to the chairs, adding a touch of nature to the scene.

Attribute — On the right side of the image, a painting of a bird in **flight** brings a dynamic element to the otherwise static scene.

Attribute — The bird, captured **mid-flight**, adds a sense of movement and life to the composition.

Overall, the image presents a harmonious blend of man-made structures and natural elements, creating a space that is both functional and aesthetically pleasing.

In the center of a white background, there's a lively cartoon can of milk.

The entire scene is set against a stark white background, which puts the focus entirely on the can and its actions.

The image is simple yet engaging, with the can's actions and expressions adding a touch of whimsy and humor.

Illusion — The can, painted in hues of blue and white, is anthropomorphized with a pair of arms and **legs**.

It's not just any can, though.

This one has a face, complete with eyes, a nose, and a mouth, giving it a friendly and approachable demeanor.

Attribute — The can is actively engaged in an action-it's **holding up** a lightbulb above its head.

The lightbulb, a symbol of an idea or inspiration, is glowing brightly, indicating that the can has had a sudden thought or realization.

Illusion — Adding to the can's character, it's wearing a **hat**.

Illusion — The **hat** is brown, contrasting with the blue and white of the can.

Attribute — The word "MILK" is boldly written on the can in **black** letters, standing out against the blue and white background.

In the vast expanse of the clear blue sky, a vibrant kite dances in the wind.

The kite, a striking contrast of red and white, is adorned with black stripes that add a touch of elegance to its appearance.

Object — It's not just any ordinary kite, but one that bears the logo of a **bird**, perhaps symbolizing freedom and soaring heights.

The kite is tethered to the earth by four strings, two on each side, held firmly by unseen hands on the ground.

These strings, like lifelines, connect the kite to its earthly roots, ensuring it doesn't stray too far from home.

Location — The kite is positioned towards the top **right corner** of the image, as if it's eagerly reaching for the heavens.

Its position relative to the edges of the image suggests it's flying high above any potential obstructions.

This image captures a moment of joy and freedom, a snapshot of a kite's journey against the backdrop of an endless blue sky.

Figure I: Example annotations of Share-GPT.

The image captures a moment of tranquility in nature.

A cardinal, with its vibrant red plumage, is perched on a wooden fence post.

Direction — The cardinal's head is turned **to the left**, as if it's surveying its surroundings.

Object — **The fence post**, weathered and gray, provides a stark contrast to the cardinal's vivid color.

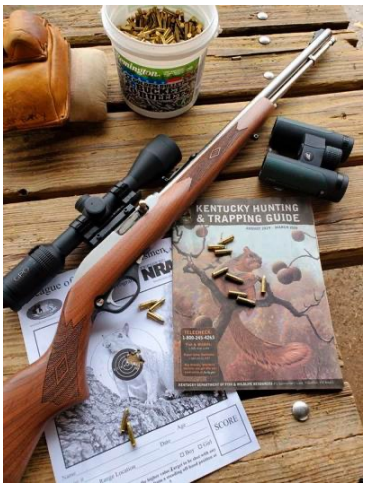
The background is a serene blue sky, lightly brushed with wispy clouds.

The sky's vastness adds a sense of depth to the image.

Overlaying this peaceful scene is a quote in a cursive font that reads, "I am always with you...".

Attribute — The quote, written in **white**, stands out against the blue back drop, adding a touch of sentimentality to the image.

The overall composition of the image suggests a harmonious blend of nature and human emotion.



The image shows a rifle with a scope mounted on a wooden surface, which appears to be a picnic table.

The overall setting suggests a hunting or shooting context, with the equipment laid out for use or display.

The image is taken during daylight, and the focus is sharp on the rifle and the immediate surrounding items, while the background is slightly blurred.

Direction — The rifle is positioned horizontally, with the barrel extending **towards the left side** of the frame.

To the right of the rifle, there is a pair of binoculars with a black body and a textured grip.

Text — In front of the binoculars, there is a container with a label that reads **"Buckshot,"** indicating it contains shotgun pellets.

The container is open, and some of the pellets are visible.

Relation — **On the left side** of the rifle, there is a magazine with a label that reads "NRA," suggesting it is a publication from the National Rifle Association.

Below the magazine, there is a piece of paper with a target image and a score sheet, indicating that it might be used for target practice or competition.

The target has a bullseye and various scoring zones, and the score sheet has lines for recording the date, location, and scores.

In the center of the image, a wooden table is set with a meal.

On the left side of the table, there's a white plate holding a golden brown crepe, which is garnished with slices of banana.

Object — The crepe is accompanied by **a small bowl of red sauce**, adding a pop of color to the plate.

On the right side of the table, there's another white plate holding a colorful fruit salad.

Object — The salad is a vibrant mix of red watermelon, yellow pineapple, and **green kiwi**, all arranged neatly on the plate.

In the background, there's a white tiled floor that contrasts with the wooden table.

The floor extends into the distance, creating a sense of depth in the image.

The overall scene suggests a casual and inviting dining experience.

Figure J: Example annotations of LLaVA.

The image depicts a bronze sculpture of two individuals engaged in a conversation.

Object — One figure, appearing to be a **man**, is seated on a stone bench, while the other, likely a woman, stands beside him.

Both figures are dressed in vintage clothing, suggesting a historical or time-period-specific setting.

The bench is placed on a paved area, and there are bags placed at the feet of the figures.

Number — In the background, there are **three** people wearing modern clothing, standing and appearing to be engaged in a conversation or waiting.

The scene is set in a city environment, with a building and a partially open gate visible in the background.

Attribute — The image shows a deep-dish pizza on a metal plate, with one slice **partially** removed.

The pizza has a thick crust and is topped with a generous amount of tomato sauce and cheese.

There is a spatula placed on the plate, likely used for serving.

Attribute — In the background, there is a person **holding** a glass of white wine.

The table appears to be made of dark wood, and there is a glass of water visible next to the wine glass.

The setting suggests a casual dining environment.

The image depicts a serene pastoral scene of three cows grazing in a lush green field.

Attribute — The foreground prominently features a brown cow with a **white** marking on its face, which is focused on grazing.

To the left, there is a black cow with distinctive white horns, also engaged in grazing.

Direction — In the background, partially obscured by the greenery, is another black cow, appearing to be standing and possibly looking in the **direction** of the camera.

The field is expansive, with the cows dispersed across the landscape, suggesting a peaceful and abundant grazing environment.

The background shows a mixture of trees and clear skies, adding to the natural beauty of the scene.

Figure K: Example annotations of Qwen-2.

The image depicts the interior of a bar with a group of people seated around a wooden bar counter.

Relation: The ceiling features a woven design, and a fan is mounted **above** the counter.

In the foreground, two men are sitting at the bar; one is holding a drink and appears to be smiling, while the other is holding a cigarette.

Object: Bottles and glasses are visible on the counter, along with various bar items like **bottle openers** and condiments.

Attribute: Further along the bar, two men and **a woman are engaged in conversation**, with one man wearing a sleeveless shirt and a hat.

The lighting is warm, giving the space a cozy ambiance.

The image features two individuals posing against a bright pink background decorated with small vinyl records and hanging spiral ribbons in red and orange.

The person on the left is wearing a green military-style helmet and holding a banana.

They are dressed in a suit with a dark tie and are wearing a bracelet on their wrist.

Object: The person on the right is wearing a black police helmet with an emblem on the front and **silver hoop earrings**.

They have short hair and are wearing a black top with a gray knitted shawl over it.

Direction: Both individuals are looking in the **same direction** with a slightly surprised or thoughtful expression.

The image shows two dogs and a cat lying on a bed.

The bedspread is light-colored with a quilt at the top.

The larger dog, with a tan coat, is lying diagonally across the bed.

The smaller dog, with a darker brindle coat, is curled up near the top left of the bed.

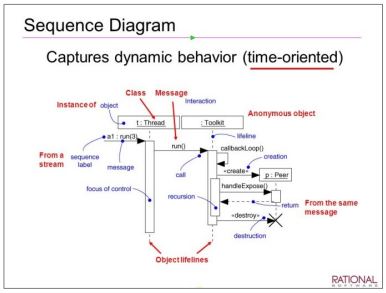
Relation: The cat, with a gray coat, is **nestled between them** on the quilt.

Attribute: There are two books on the bed, one with a visible cover and one with the cover **facing down**.

The visible book cover has an image and text, but the details are unclear from the image.

In the background, there is a nightstand with various items, and curtains cover the window behind the bed.

Figure L: Example annotations of GPT4o.



This image is a Sequence Diagram that illustrates the dynamic behavior of a time-oriented system.

Text It shows interactions between different objects and classes, such as ‘Instance of object’, ‘Class Message’, ‘Anonymous object’, and **‘Object lifetimes’**.

Illusion The diagram uses various symbols like 'a1’, **‘a2’, ‘b1’, ‘b2’,** and arrows to indicate the flow of messages and the sequence of events.

The image is a black and white photograph that captures an outdoor scene.

Text In the foreground, there is a fire hydrant with the text ‘MUELLER’ and **‘1914’** inscribed on it.

The hydrant is attached to a concrete base.

In the background, there is a wooden structure, possibly a deck or porch, with a person standing on it

Attribute The person appears to be **looking out of a window or door**.

The surroundings include some trees, shrubs, and a rocky wall.

The image showcases a street scene in what appears to be an urban area.

In the foreground, there is a white bus with the number '33’ displayed on its front, heading towards **‘Castro**’.

Text The bus has an advertisement on its side.

To the left of the bus, there is a building with a **red** facade and a sign that reads ‘BankofAmerica’.

Attribute The street is lined with trees, and in the background, there is a tall tower, possibly a communication or observation tower.

The sky is clear, suggesting a sunny day.

Figure M: Example annotations of CogVLM.

The image depicts a young woman in a boxing ring, wearing black and yellow boxing gloves.

The woman has long brown hair tied back in a pony tail and is dressed in a sleeveless top.

Attribute: She is positioned centrally in the frame, with her **right** arm extended forward, showcasing her glove.

Illusion: In the foreground, **another pair of boxing gloves** is visible, although they are out of focus.

The background features a blue floor and white ropes surrounding the ring, with windows on the left side that allow natural light to enter.

The overall atmosphere suggests that the woman is engaged in a training session or preparing for a fight, exuding a sense of determination and focus.

The image shows a cat lying on a bed in front of a bookshelf.

The cat is orange and white, with a white chest and paws, and an orange back and head.

Direction: It has pointy ears and appears to be looking **at the camera**.

The cat is lying on a bed with a yellow, green, blue, and white quilt or comforter.

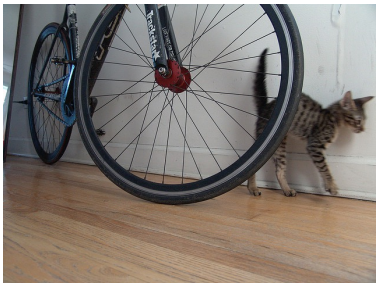
The bed appears to have a white sheet or comforter underneath the quilt.

In the background, there is a brown wooden book shelf filled with books of various colors and sizes.

Attribute: The books are arranged in rows, with some standing upright and others **lying flat**.

The wall behind the bookshelf is painted light blue.

The overall atmosphere of the image suggests a cozy and comfortable setting, possibly a bedroom or study.



The image depicts a cat walking behind a bicycle wheel, with the cat's body partially obscured by the wheel.

The cat is positioned on a light-colored hardwood floor, facing to the right.

It has a slender build and features a brown coat with black stripes, as well as a long tail.

In the foreground, the bicycle wheel is prominently displayed, showcasing its black tire and silver rim.

Text: The wheel is attached to a black fork with white text that reads **"Trekstar"** and other illegible words.

Illusion: To the left of the main wheel, **another bicycle wheel** is visible, featuring a blue rim and black tire.

The overall atmosphere of the image suggests that the cat is exploring its surroundings, possibly in a home or indoor setting.

Figure N: Example annotations of Llama-4.

Attribute: In a sunlit garden, a vibrant orange carrot is nestled in rich, dark soil on the left side of the image, **partially** exposed as if it is peeking out from the ground.

Direction: To its right, a curious rabbit with soft, white fur is intently **looking at the carrot**, its ears perked up in excitement.

In the background, blooming flowers sway gently in the breeze, their colors contrasting beautifully with the earthy tones of the soil.

Illusion: Above the scene, **a clear blue sky** adds to the serene atmosphere, casting gentle light over the garden.

Location: In a serene forest clearing bathed in early morning sunlight, a majestic moose stands proudly **on the right side** of the scene, its dark coat gleaming.

Attribute: It **lowers its head** to nibble on the lush greenery that sprawls at its hooves while keeping a vigilant gaze towards the left, scanning for any signs of movement.

Soft rays filter through the tall pines behind it, casting gentle shadows on the dried leaves covering the forest floor.

In the background, **flickers of a sparkling stream** reflect the sun's glow as it weaves through the trees.

Location: In a sunlit park **on the left side** of the scene, an old leather baseball glove rests on the grass, slightly worn from countless games.

Next to it, a new baseball gleams in the afternoon light, ready to be thrown but currently standing motionless.

Direction: In the background, a young boy in a bright baseball cap stands by a fence, **looking towards the** glove with eager anticipation in his eyes, wondering when he can play catch again.

Figure O: Example annotations of Stable Diffusion.

In a cozy children's bedroom, a fluffy teddy bear is nestled on the soft, cloud-patterned rug at the center of the room.

Direction — Its bright button eyes gaze thoughtfully **toward the window**, where soft rays of sunlight filter through pastel curtains, casting a warm glow around.

On the left side of the scene, a pile of colorful building blocks seems to spill out of a cheerful toy basket, while on the right, a collection of books rests neatly on a shelf, hinting at adventure awaits.

Attribute — The teddy bear, **slightly tilted**, watches over the joyful mess, embodying the protective whimsy of childhood.

Attribute — In a bright kitchen filled with the aroma of freshly baked cookies, a glowing microwave stands prominently on the countertop to the left, **its door slightly open** as if inviting a warm snack.

Attribute — A curious little cat with green eyes **sits on the floor** in front of it, gazing intently at the microwave's insides, waiting eagerly for the beep that announces its treat is ready.

A plate of colorful cupcakes sits on the table in the background, casting a soft shadow as sunlight filters through the window.

The wall above the microwave is adorned with recipe notes, adding a cozy, lived-in feel to the scene.

In the verdant wetlands of a sultry summer's afternoon, a crocodile lounge on a sundrenched, flattened rock at the right-hand side of the scene.

Its muscular body is soaked and dripping with water, remaining vigilant as it scans the shimmering pond that stretches outward n front of it.

Direction — Surrounded by reeds and lily pads, its eyes glisten in the sunlight as it looks **towards tiny fish** darting happily beneath the surface, captivated by movement right below.

Illusion — Meanwhile, colorful dragonflies flit hip high in the air, **casting fleeting shadows** on this eager predator's competent posture.

Figure P: Example annotations of GPT-Gen.