VisDiaHalBench: A Visual Dialogue Benchmark For Diagnosing Hallucination in Large vision-Language Models

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Abstract

Despite the significant success of large vision-language models(LVLMs), some studies have revealed that LVLMs suffer from the hallucination problem, where the LVLMs' response contains descriptions of non-exits objects. Although various benchmarks have been proposed to investigate this problem, they mostly focus on single-turn evaluation and overlook the hallucination raised by textual inputs. To examine the combined effects of textual and visual inputs, we propose a novel visual dialogue hallucination evaluation benchmark VisDiaHalBench. The benchmark consists of samples with five-turn questions about an edited image and its original version. VisDiaHalBench differs from previous hallucination benchmarks in the following three points: 1) The questions and answers are unambiguously grounded by annotated scene graphs. 2) The images are uncommonly edited to inspect the visual model and common-object hallucination in LLMs. 3) The carefully designed dialogue refers a same object in different turns to assess the image consistency and influence of history for LVLMs. The detailed analysis of several state-of-the-art LVLMs across image consistency, visual understanding, history influence, and other dimensions reveals their substantial performance gap with single-turn VQA tasks.

1 Introduction

Large language models(LLMs) (Chung et al., 2022; Touvron et al., 2023; Chiang et al., 2023; Achiam et al., 2023) have shown exceptional capabilities in semantic understanding, reasoning, and commonsense utilization. To expand their capabilities into the vision domain, recent research integrated vision-pretrained models with LLMs, resulting in Large Vision-Language Models (LVLMs) (Dai et al., 2023; Liu et al., 2023c; Zhu et al., 2023; Li et al., 2023a; Achiam et al., 2023). Through instruction finetuning on text-image paired data, LVLMs achieved great performance on a variety of multimodal tasks that require a vast range of skills. Despite the recent success, LVLMs also suffer from the hallucination problem, where the responses are non-factual or contradictory to the given inputs. To study this problem, recent works (Yifan Li and Wen, 2023; Wang et al., 2023; Liu et al., 2023b,a) have proposed different benchmarks and methods to diagnose hallucination within LVLMs. However, while these studies suggest that hallucination exists in both vision and language models, they mostly focus on the visual side, neglecting to fully investigate the textual inputs, such as misleading dialogue history or prior responses.

Studies on LLMs (Zhang et al., 2023; Yao et al., 2023) have shown that LLM can be induced to hallucinate by certain textual input or their own response. Given that LVLMs are built upon LLMs, there is a strong likelihood that LVLMs inherit the similar hallucination problem from LLMs. As shown in the second example of Figure 1, GPT-4V correctly answers the relation of the frisbee but subsequently hallucinates about a non-existent "white frisbee" given a follow-up similar question.

To analyze hallucinations in LVLMs when faced with multi-turn visual and textual inputs, we introduce VisDiaHalBench, a novel visual dialogue benchmark grounded by image scene graphs. Each sample in VisDiaHalBench contains an edited image and its original version to evaluate LVLMs' performance with unseen images; A scene graph to ground questions-answers for unambiguous evaluation; And a five-turn coherent dialogue with last turn references to investigate image consistency and history influence of LVLMs.

Specifically, we leverage the normalized scene graphs and corresponding images from the GQA (Hudson and Manning, 2019) dataset to construct VisDiaHalBench. For each image, we first

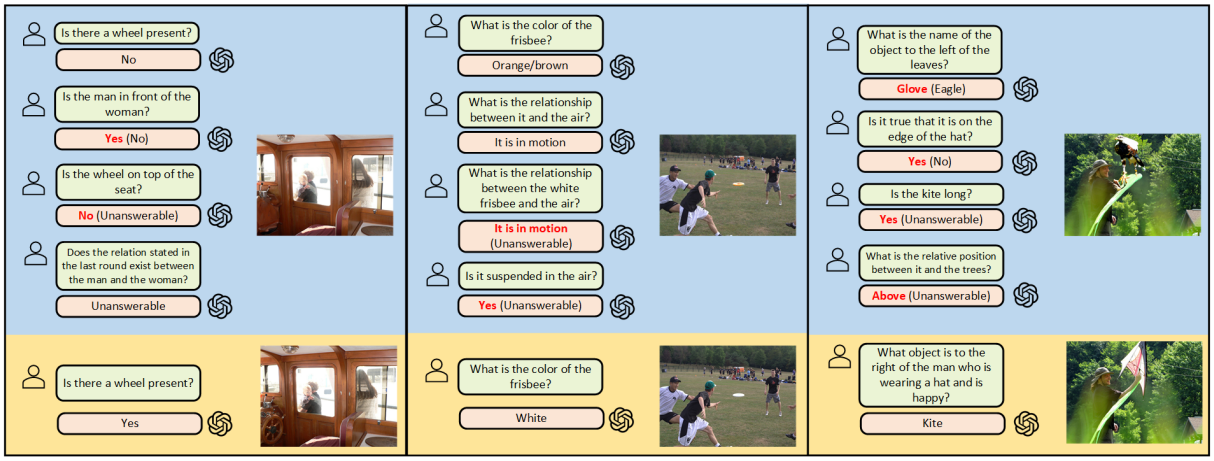

Figure 1: Three examples of our proposed VisDiaHalBench and GPT-4V results. Each sample contains five questions, where the first four questions query the edited image and the last one queries the original image. Incorrect answers are marked in red, while the groundtruth answers are provided in parentheses.

edit the GQA image as well as the scene graph by removing or changing an object. Then in each turn, we sample a question type and scene graph paths based on the last turn object, attribute, or relation. With the grounded path and predetermined answers, we employ GPT-4 (Achiam et al., 2023) to generate a natural language question. We further benchmark several SOTA LVLMs and conduct comprehensive studies of their hallucination results. Our analysis reveals that current LVLMs still suffer from insufficient capabilities in vision understanding and handling complex dialogue history.

Our contribution can be summarized as follows: 1) we introduce the first visual dialogue benchmark focusing on diagnosing hallucinations raised by both visual and long-term textual inputs. 2) We conduct comprehensive studies on SOTA LVLMs to investigate their image consistency, visual understanding, history handling, and other relevant aspects. We hope our benchmark and analysis can shed light on further research in addressing the hallucination problem in both language and vision domains.

2 Related Works

2.1 Large Visual-Language Models

With the success of the large language models(LLMs) (Chung et al., 2022; Touvron et al., 2023; Chiang et al., 2023; Achiam et al., 2023), some works (Alayrac et al., 2022; Li et al., 2023b) attempt to leverage the LLMs' powerful capability of semantic reasoning in vision domains, resulting Large Visual-Language Models(LVLMs). These works bridge the vision tokens to LLMs by only training a projector. Most recent works (Dai et al., 2023; Liu et al., 2023c; Zhu et al., 2023; Li et al., 2023a; Liu et al., 2023b) employ instruction tuning, where the model can be trained on different multi-modal tasks in a unified manner, and achieve impressive visual understanding results on various downstream tasks.

2.2 LVLMs Hallucination and Evaluation

Despite the success of LVLMs, recent works suggest they suffer from the hallucination problem (Liu et al., 2023a; Zhou et al., 2023), where the response has inaccurate descriptions of a given image. Recent works (Yifan Li and Wen, 2023; Wang et al., 2023; Liu et al., 2023b) have proposed different methods and benchmarks to deeply inspect this phenomenon. POPE (Yifan Li and Wen, 2023), HaELM (Wang et al., 2023) and GAVIE (Liu et al., 2023b) differently prompt a LLM to score LVLMs' response. Liu et al. (2023a) and Cui et al. (2023) manually edit visual inputs and label question-answering pairs to assess LVLMs. Different from these works, we propose a visual dialogue benchmark to thoroughly investigate the hallucination in LVLMs from both vision and long-term text aspects.

2.3 Visual Dialogue

Given an image, a dialogue history, and a question about the image, Visual dialogue (VD) (Das et al., 2017) requires an agent to generate an accurate response based on the image and informed by the dialogue history. Recent advance in pre-trained visual-language models (Su et al., 2020;

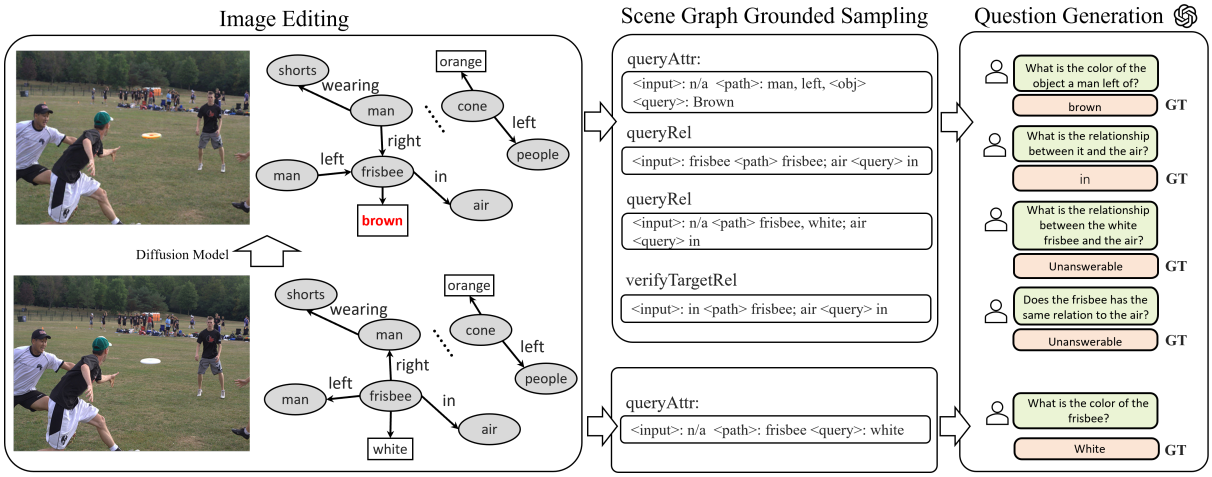

Figure 2: The construction pipeline for our proposed VisDiaHalBench. We first edit the image and corresponding scene graph. Then sample questions type and scene graph path based on previous questions. Lastly, we prompt GPT-4 to generate natural language questions.

Li et al., 2022a) also inspired related models in VD, such as VisDial-BERT (Murahari et al., 2020), VD-BERT (Wang et al., 2020) ICMU (Chen et al., 2022b), UTC (Chen et al., 2022a), BLIP (Li et al., 2022a) and AlignVD (Chen et al., 2022c). Unlike the single-turn Visual Question Answering, the challenge of VD lies in the need to address referential and ambiguity issues present in the historical dialogue (Chen et al., 2020). This characteristic is suitable for evaluating LVLMs' robustness in handling long-term language dependency and inspires us to construct the VD-based hallucination benchmark.

3 VisDiaHalBench

We introduce VisDiaHalBench, a new visual dialogue benchmark to analyze hallucination in LVLMs under different visual and textual inputs. Based on the normalized scene graph and image in the GQA dataset, each sample contains an edited image, a five-turn dialogue, and grounding scene graph paths. The questions are associated with the edited object in different aspects, including queries about the uncommon edited results, pronoun-based reference, and misleading history.

To construct the benchmark, we first edit the image by randomly changing an object's attribute, swapping it with another object, or removing it from the image. Then at each turn, we sample a question type and scene graph path based on the edited object or previous questions. Lastly, we prompt GPT-4 (Achiam et al., 2023) to generate a natural language question strictly grounded to the supporting paths and ground truth answer. The overall generation pipeline is shown in Figure 2.

To ensure the unambiguity of generated questions and answers, we rely on sampling scene graph path that can uniquely identify an object. Also, by designating the start or end object of a path, we can generate coherent multi-turn questions concerning the last-turn context. To better illustrate the construction process, we first present our path sampling method and question type details, then describe each construction step.

3.1 Scene Graph Path Sampling

We generate unambiguous questions and answers grounded by paths in the scene graph. A scene graph path is a sequence of connected object nodes and relations. For example, a 0-hop path is just an object like "frisbee", a 1-hop path could be "(frisbee, left, man)", and a 2-hop path might extend to "(frisbee, left, man), (man, wearing, shorts)".

To sample a n-hop path, we begin at an object node, randomly select one of its relations, and traverse to the corresponding node n times. Then we verify whether the path is unique in the scene graph. We obtain all objects with the same name and check whether these objects have the same relation recursively. For example, we verify whether "(frisbee, left, <obj1>), (<obj1>, wearing, <obj2>)" is unique in the scene graph, such that the shorts can be unambiguously referred to as "the thing wearing by one a frisbee left of".

In our benchmark, we sample 1-hop and 2-hop when questions target object names without giving away the object name. For other questions, we

Question Type	Path Example	Question Example	Input Reference	Output Reference
exist: Query the existence of a object	[(frisbee,left,<obj>), (<obj>,<name>,man)]	Is there a man that a frisbee on its left?	Object	Object (if answer is "Yes")
queryObj: Query a object name	[(man,wearing,<obj>), (<obj>,<name>,shorts)]	What is the man wearing?	Object	Object
queryAttr: Query a object's attribute	<input>: frisbee, [(frisbee,<attribute>,yellow)]	What color is it?	Object	Object, Attribute
queryRel: Query relation of two objects	<input>: frisbee, [frisbee], [air]	What is the relationship between it and the air?	Object	Object, Relation
verifyAttr: Query if object has a attribute	[(frisbee,<attribute>,yellow)] Query: white	Is the frisbee white?	Object	Object, Attribute
verifyRel: Query if two objects have a relation	[(frisbee,<attribute>,white)], [man] Query: left	Does the white frisbee to the left of the man	Object	Object, Relation
verifyTargetAttr: Query if object has a mentioned attribute	<input>: white, [frisbee]	Does the frisbee has the same color?	Attribute	Object
verifyTargetRel: Query if two objects have a mentioned relation :	<input>: left, [cone], [people]	Does the cone and the people have the same relation?	Relation	Object

Table 1: The details of all question types in VisDiaHalBench. Path and question examples give a possible scene graph path and corresponding question. Input and output reference represents the object or answer that can be used in this turn or passed to the next turn.

sample 0-hop and 1-hop paths.

Coherent path sampling To construct coherent dialogue, we sample paths based on the current question type, where each type can accept the object or answer mentioned in the last turn, as shown in Table 1. If the last turn refers to an object, we sample a path starting from it and use pronouns to refer to this object. If the last turn has an attribute or relation, we first sample the answer "Yes/No", then sample a path that ends with an object that has or does not have this attribute/relation according to the answer.

Sampling Retry During the random sampling process, if a sample path is not unique, or the sampled query object has no attribute or relation to the query, we re-sample the whole dialogue until reach a predefined attempt limit. If the limit is reached, we discard this sample and continue to sample the next one.

3.2 Question Types

The questions in VisDiaHalBenchhave following eight types: "exist", "queryObject", "queryAttr", "queryRel", "verifyAttr", "verifyRel", "verifyTargetRel" , "verifyTargetAttr". These question types represent queries about the existence of an object, its name, attribute, or relations to another object. Or verify whether they possess certain attribute or relation. In each turn, we first sample a question type from its subset according to the turn number and last turn question. The details are shown in Table 1.

For the question that verifies whether the object has an attribute or relation, we need to sample an unrelated query target if the answer is "no". We select the name/attribute/relation that is similar to a correct one. Specifically, we first extract all object names, attributes, and relations in the dataset and form three dictionaries, then embed these words or phrases with GPT2-large (Lagler et al., 2013). Given a correct name/attribute/relation, we select its similar words by computing its embedding distance with other names/attributes/relations respectively. We randomly select one from the top 10 to obtain a similar name/attribute/relation and exclude the top 5 to avoid retrieving synonym words. The retrieved words are used for questioning.

To balance the number of each question type, we set the probability of selecting different types according to their generated number. The probability for type T is $1 - \frac{\text{number of questions type T}}{\text{number of total question}}$. Thus

types with more samples will have a lower probability of being selected.

3.3 Image Editing

Since most of the current LVLMs achieve great performance on the GQA dataset, we edit the GQA image to explore whether the hallucination comes from the biases in training data. To obtain a visually reasonable image, we only modify a certain object in one of three different ways: remove it from the image, swap it with another object, and change its color. We randomly choose the edition type and target so that the image can be counterfactual for usual scenarios. Such a setting can force the LVLMs to correctly perceive the image without guessing the answer through commonsense knowledge learned in LLMs. First, we use the large segmentation model SAM (Kirillov et al., 2023) to segment each object in every image to obtain its mask according to its corresponding bounding box. Subsequently, we employ various strategies for image editing.

Remove object To remove an object, we first select the object that can be uniquely determined by 0-2 hop path in the original scene graph, so that the following questions and answers are not ambiguous. For example, the answer for "Is there an umbrella in the image" remains the same "Yes" if there exists multiple umbrellas but only one of them is removed.

Given the identifiable object, we retrieve its bounding boxes from the annotated scene graph and instruct the pretrained image editing model IP-adapter (Ye et al., 2023) to remove it from the image. Specifically, we utilize the inpainting mode in the IP-Adapter to remove the corresponding objects. By setting the prompt to "empty" and the negative prompt to "n_{obj}" which represents the name of the object to be removed, we can obtain images without the specified objects. Lastly, we modify the scene graph correspondingly by removing this object and all relations to other objects.

Change object We change the whole selected object by replacing it with another object in the GQA dataset such that the object is recognizable but unseen in the image. Specifically, we extract all the object names in the dataset and randomly select a similar one based on GPT-2 embedding, the same as the method described in Section 3.2. With the candidate object name, we randomly select an object that has this name from all the images in GQA dataset as the reference object.

We change the original object to the reference object through Anydoor (Chen et al., 2023) method. We input the two masks and corresponding images to the Anydoor and copy the reference object to the original object mask. Lastly, we correspondingly modify the scene graph by setting the object name and the attributes to the reference image but keeping the relations unchanged.

Modify attribute Since the GQA annotation has various attribute types, including actions that are only applicable to some objects, adding an attribute does not necessarily replace an existing one. Thus, to obtain a reasonable attribute and avoid ambiguity, we only change the object color.

Similar to the object name, we first obtain all attributes in the GQA dataset, then filter the color using the matplotlib (Hunter and Dale, 2007) colors package and form a color set. Then we select the object that has a color attribute and replace its color attribute with another different one randomly selected from the color set.

Given the original color, reference color, and the object mask obtained by SAM, we instruct the Blended latent diffusion (Avrahami et al., 2023) model with prompt "$c_{new} + n_{obj}$" to perform the editing. Where c_{new} represents the new color selected and n_{obj} represents the object's name. Finally, we change the object in the scene graph by removing its original color and adding the reference color to its attribute set.

3.4 Dialogue Sampling

After image editing, we generate dialogue questions to investigate different aspects of LVLM hallucination. Each dialogue contains five turn questions that query the visual information related to the edited object. At each turn, we sample a question type then sample scene graph paths and answer. We constrain sampling strategy in different ways to inspect different aspects of LVLMs. The detailed generation process for each turn is shown in the following.

Turn 1 : The first question directly queries the edited part of the object to inspect the vision model of LVLMs. For "remove object", we query whether the object "exist" by sampling a 0 or 1-hop path ended with the edited object from the original scene graph. For "change object", we use "queryObject" to query the name of the changed

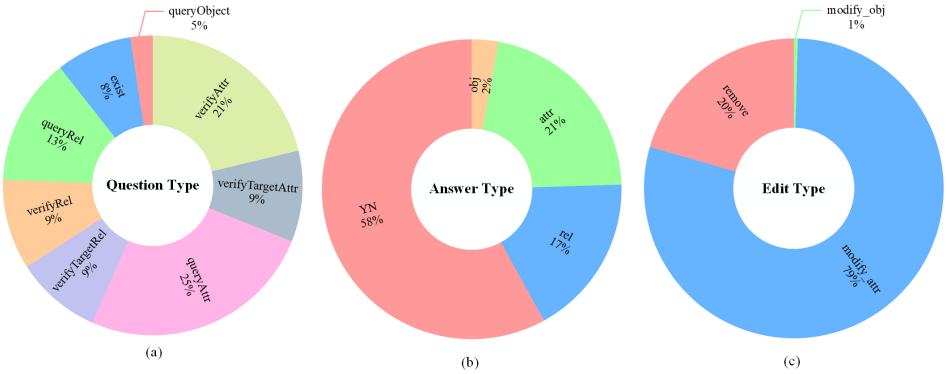

Figure 3: The data distribution of VisDiaHalBench, sorted by (a)question type (b)answer type (c)edit type

Edit type/Question type	exit	queryObj	queryAttr	queryRel	verifyAttr	verifyRel	verifyTargetAttr	verifyTargetRel	Total
remove	2054	168	485	612	240	623	268	685	5135
modify attribute	0	390	5889	2809	5056	1800	2186	1630	19760
modify obj	0	44	9	17	19	15	1	0	105
Total	2054	602	6383	3438	5315	2438	2455	2315	25000

Table 2: Sample number of different question types and edit types in VisDiaHalBench.

object, and sample 1 or 2-hop path from the edited scene graph to avoid directly refer the object with its name. For "modify attribute" edition, we randomly choose "queryAttr" and "verifyAttr" and sample 0 or 1-hop scene graph path. If the question type is "verifyAttr" and the randomly selected answer is "no", we used the original attribute to generate the question. For example, if we change a frisbee from white to brown, we will have questions: "Is the frisbee white?".

Turn 2 : This question queries the other part of the image related to the turn 1 question to study the dialogue ability of LVLMs. We refer to the last turn object or answer with a pronoun and sample scene graph path with the method described in Section 3.1

Turn 3 : We mention the edited object with its original name or attribute to generate misleading questions that can not be answered. This turn is designed to explore whether the LVLMs hallucinate the answer and have output consistent with turn 1. For example, given a frisbee changed from white to brown, "What is the white frisbee related to the air?" has no answer since no white frisbee in the image. LVLMs should not answer if it is consistent with Turn 1 where it knows the frisbee is brown.

Turn 4 : Similar to turn 2, the turn 4 sample path is based on the last turn question. However, since the last turn object and answer are not valid, this question is also unanswerable. We employ this question to further study the robustness of LVLMs in handling corrupted history.

Turn 5 : We employ the question identical to turn 1 but provide the unedited image. Current LVLMs should be able to easily answer this GQA-like question. We study the performance gap between answering it directly or in dialogue to evaluate how much the dialogue history affects LVLMs.

3.5 Question Generation

Given the object path, related attributes, and relations in each turn, we can obtain the unambiguous answer grounding by supporting paths. We obtain the natural language question by prompting GPT-4 to generate it that strictly grounding to the supporting triplets and answer. The specific prompt can be found in the appendix B. We resample the question if it contains words of last turn reference, or not contains the grounded attributes and name.

3.6 Dataset Statistic

Following the aforementioned editing method, we edited 5000 images from GQA and subsequently generated 5000 diverse visual dialogues, each dialogue consists of 5 turns of conversation, totaling 25,000 visual question-answers. As shown in figure 3, our dataset includes 8 types of question types, 4 types of answer types, and 3 types of edit types. Table 2 enumerates the specific quantities for different question types and edit types.

Model	Turn 1		Turn 2		Turn 3		Turn 4		Turn 5		Average	
	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
w/ image:												
Cheetah	19.96	27.55	19.56	30.14	0.25	25.01	0.22	23.27	18.98	25.89	11.80	35.73
LRV-instruct	17.78	26.86	24.36	40.18	0.07	33.63	0	35.48	22.50	34.23	12.94	33.66
MiniGPT4	5.31	13.22	26.36	36.89	0.07	28.72	0.36	27.59	71.74	79.02	20.77	37.08
Q-Probing	21.49	31.83	27.40	37.66	3.00	31.10	1.65	28.25	61.57	70.06	23.02	39.78
LLaVA	26.32	32.52	38.72	54.58	0.07	25.91	0.25	17.97	54.29	57.67	23.93	37.99
GPT-4V	25.51	38.23	33.50	47.81	38.72	55.61	17.83	35.93	46.11	55.45	33.01	48.26
w/ scene graph:												
LLaVA	35.72	41.22	53.74	61.78	10.06	35.36	1.57	23.02	88.26	90.42	37.87	50.36
GPT-4V	82.22	85.34	63.97	70.75	32.25	65.34	20.09	43.58	99.07	99.39	59.12	72.88

Table 3: Evaluation results of different LVLMs on VisDiaHalBench.

4 Experiments

4.1 Methods

We conduct an evaluation of several state-of-the-art LVLMs: LRV-instruction (Liu et al., 2023b), MiniGPT4, Cheetah (Li et al., 2023a), LLaVA (Liu et al., 2023c), and GPT-4V on our benchmark. More implementation details of each model are in appendix A.

Additionally, we propose a simple baseline approach "Q-Probing" that instructs LVLMs to probing the relevant question to reduce the hallucination. Specifically, the Q-Probing approach involves instructing the LVLM to generate several closely related questions based on the image and current question. These generated questions act as reference points. During the question-answering phase, we prompt the LVLM with the instruction "Please consider these questions before answering", encouraging it to pay attention to additional crucial information and logical fallacies when formulating responses, thereby mitigating the phenomenon of hallucination. In the experimental section, we built our model based on MiniGPT-4 and demonstrated its effectiveness. Further details about the prompts can be found in appendix B.

4.2 Evaluate Metrics

We conduct a comprehensive evaluation of the baseline models, focusing on their performance in evidence retrieval and answer extraction. Following previous multimodel conversational dataset (Li et al., 2022b), we reported macro-average F1 in the word level and Exact Match (EM) to estimate the performance of answer extraction after extracting the model's output results through keyword filtering.

4.3 Main Results

Table 3 presents the performance of each model on VisDiaHalBench. All models exhibit subpar performance on average, the best-performing GPT-4 achieves 33.01 EM and 48.26 F1, far worse than its performance on GQA. This discrepancy indicates that our benchmark poses a new challenge for current LVLMs.

All open-sourced models except Cheetah perform better in Turn 2 and Turn 5 compared to Turn 1. Since turn 2 and 5 query the unedited object, this result indicates that these LVLMs struggle with correctly perceiving the edited image. Furthermore, all models exhibit their worst performance in Turn 4, indicating that referring to a non-existent object, which misleads models in both the visual and textual domains, is the most challenging task for current LVLMs. LRV-instruct, which focuses on reducing hallucination, performs better than its backbone MiniGPT4 in turn 1 and 2. However, its performance degrades in turns 3 and 4. suggesting that single-turn fine-tuning may hinder its ability to handle multi-turn dialogues effectively. The proposed Q-Probing approach outperforms both MiniGPT4 and the LRV-instruct based on MiniGPT4 in terms of average performance. This finding suggests that incorporating additional relevant questions can mitigate hallucinations to some extent. Lastly, the proprietary model GPT-4V demonstrates significantly better performance than other LVLMs, which can be attributed to its larger number of parameters and a more extensive training dataset.

4.4 More Analytical Study

Hallucination with misleading questions Turn 3 and 4 are designed to present LVLMs with misleading prompts that pose ambiguous ques-

Model	Turn 1	Turn 1 Correct				Turn 1 Incorrect				Turn 5 Solely	
		Turn 3		Turn 5		Turn 3		Turn 5			
	EM	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
Cheetah	19.96	0.18	20.22	18.58	23.42	0.27	27.31	19.08	27.49	53.67	65.44
LLaVA	26.32	0.14	30.32	32.60	45.17	0.05	13.44	62.04	71.29	73.02	82.72
GPT-4V	25.51	39.76	59.23	38.35	50.29	38.35	49.23	53.04	68.72	77.16	88.01

Table 4: The performance of LVLMs under different conditions. "Turn 1 Correct" presents Turn 3 and Turn 5 performance on samples that the model's response exact match with the groundtruth. "Turn 5 Solely" shows the performance of answering the Turn 5 question outside the dialogue.

tions. The objective was to assess whether LVLMs would recognize the flawed nature of these queries and respond appropriately with 'Unanswerable'. According to the results in table 3, there is a significant performance drop for all models in turns 3 and 4, suggesting that misleading prompts can easily lead to the generation of hallucinations, emphasizing the challenges associated with handling ambiguous queries accurately.

Visual understanding To assess the effectiveness of the visual encoder, we conduct additional evaluations by providing LVLMs with scene graphs instead of images. The results, presented in the lower part of Table 3, reveal that LVLMs achieve superior performance compared to the image-based outputs. This indicates the bottleneck of current LVLMs may lie in the visual encoder.

Image consistency To inspect whether the LLM hallucinates regardless of the visual information, we evaluate whether a LVLM can generate consistent output with different questions that query the same object. As Turn 1, 3, and 5 query the same object based on edited and original image, we evaluate the performance of LVLMs in Turn 3 and Turn 5, given that Turn 1 was answered correctly. As shown in Table 4, if the LVLM correctly answers Turn 1, LVLM tends to obtain better performance in turn 3 but shows a significant drop on turn 5, which contains a similar question but a different image. These findings suggest that LVLMs are influenced by their previous responses and tend to hallucinate answers without effectively utilizing visual inputs.

Influence of history To investigate whether the previous dialogue would affect the efficacy of the current response of LVLMs, we evaluate the GQA-like question in turn 5 given the premise that turn 1 was answered correctly or incorrectly. As described above, if LVLMs answer correctly in Turn 1, the outcomes in Turn 5 with similar image will be affected. Additionally, we evaluate the performance of LVLMs when directly asking Turn 5 questions outside of the dialogue context. The impressive results, presented in Table 4, indicate that LVLMs perform well when directly asked Turn 5 questions without the influence of prior dialogue. The performance gap observed in these evaluations indicates the existence of hallucination induced by the dialogue history.

5 Conclusion

In this work, we propose VisDiaHalBench, a novel visual dialogue benchmark specifically designed to investigate the hallucination phenomenon in Large Vision-Language Models(LVLMs). By incorporating grounded scene graphs and carefully crafted multi-turn dialogues, we have created unambiguous question-answer pairs that allow us to examine various types of hallucinations arising from both visual and textual inputs. Through our benchmark and comprehensive analysis, we shed light on the weaknesses of current LVLMs in terms of image consistency, visual perception, and the influence of dialogue history. These findings provide valuable insights into the limitations of LVLMs and highlight the areas that require further improvement to address the challenge of hallucination in vision-language understanding.

6 Limitations

Although we carefully designed the construction process and prompt to generate the natural language questions, some question texts are not fluent. Besides, although the question-answer is grounded by an annotated scene graph, an open-ended question can still have multiple answers with similar meanings. To better evaluate the answering accuracy objectively, the benchmark could have Yes/No questions only. The potential issue might include the misuse of the edited images might be misused for unexpected purposes.

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A Model details in our benchmark

Cheetah integrates visual information and language understanding to handle zero-shot tasks, meaning it can execute tasks without prior examples. To enhance the model's performance in understanding complex visual and verbal instructions, Cheetah incorporates the VPG-C module, which is specifically designed to capture and supplement detail information. Moreover, Cheetah fine-tunes the VPG-C through a synthetic discriminative training strategy, thereby reducing the reliance on labeled demonstration data. The model variant evaluated in our experiments is "cheetah-llama-2-7b". The evaluation process is completed over a period of 50 GPU hours, utilizing one NVIDIA GeForce RTX 3090 GPU with 25GB of memory.

LLaVA propose a framework that fuses the capabilities of a visual encoder, specifically the ViT-L/14 from CLIP(Radford et al., 2021), with the language decoder abilities of LLaMA(Touvron et al., 2023). This integration is achieved using an intermediary fully-connected (FC) layer. The training process begins with the FC layer being trained in isolation on a dataset of 595,000 image-text pairs, with the pre-existing parameters of both

the visual encoder and the language model remaining unchanged. Subsequent to this phase, a fine-tuning step is conducted where both the FC layer and the language model are jointly optimized. This fine-tuning employs a specialized dataset consisting of 158,000 pairs of instructional vision-language data. The model variant evaluated in our experiments is "LLaVA-v1.5-13b.". The evaluation process is completed over a period of 30 GPU hours, utilizing one NVIDIA GeForce RTX 3090 GPU with 25GB of memory.

MiniGPT-4 employs a fully-connected (FC) layer to facilitate communication between a visual encoder and a text encoder. The initial training phase involves the FC layer learning from a dataset with 5 million image-text pairs. Following this, the model undergoes fine-tuning with a targeted set of 3,500 instructional image-text pairs. MiniGPT-4 relies on the integration of a pre-trained BLIP2 visual encoder(Li et al., 2023c) and a LLaMA language model.The model variant evaluated in our experiments is "MiniGPT4-aligned-with-llama2-7b". The evaluation process is completed over a period of 50 GPU hours, utilizing one NVIDIA GeForce RTX 3090 GPU with 25GB of memory.

LRV-instruct aims to enhance the accuracy and robustness of multimodal artificial intelligence models when processing visual instructions. It trains models by including 120,000 positive and negative visual instructions to identify and avoid hallucinations that occur during task execution. The model variant evaluated in our experiments is "LRV-MiniGPT4-7b". The evaluation process is completed over a period of 60 GPU hours, utilizing one NVIDIA GeForce RTX 3090 GPU with 25GB of memory.

GPT-4 is the latest generation of closed-source large language models released by OpenAI, which has seen significant enhancements in terms of the scale of data training and computational complexity. GPT-4V adds visual capabilities to GPT-4, enabling the model to not only understand and generate text but also to comprehend and analyze image content.The model variant evaluated in our experiments is "gpt-4-vision-preview". The evaluation process is completed over a period of 40 hours, using the API interface provided by OpenAI.

B Instruct prompts

Our prompt for question generation is listed in table 5, and the prompt for Q-Probing to generate relevant questions is listed in table 6.

C GQA dataset

The **GQA** (Hudson and Manning, 2019) dataset consists of real-world images with synthesized questions. Each image is associated with a cleaner scene graph of image objects, their attributes, and relations. Each question is associated with a structured functional program, that refers objects and relations to specify the reasoning route in the scene graph for the final answer. This dataset is distributed under license CC BY 4.0.

D Intended use of VisDiaHalBench

The VisDiaHalBench is distributed for research purposes. The VisDiaHalBench is constructed based on images and scene graphs from the GQA dataset, thus does not contains any information that names or uniquely identifies individual people or offensive content same to the GQA.

E Detailed experimental results

Table 7,8,9,10 presents the detailed experimental results from different perspectives.

F Supplementary examples

Figures 4, 5 show supplementary examples from VisDiaHalBench.

As a question asker, could you please provide a question according to my request? You will receive a "question type" where "exist" represents asking whether there is a object; "queryrel" requires asking about the relative relationship between obj1 and obj2; "verifyRel" indicates asking whether these two objects have a certain relative relationship,(for example, is the book on the left of a yellow thing?) "queryRel" asks for the relative relationship between the two objects. "verifyTargetRel" stands for the query whether A and B have the relationship mentioned in the "last round".(for example, does this relationship(last round) of position also exist between the banana and the table?)."verifyattr" should ask whether obj possesses a certain attribute; "verifyTargetAttr" asks whether a certain object possesses a specific attribute mentioned in the "last round".(for example, Do the book have the same color with it(last round)?). And for "queryAttr," the answer should be the attribute of the queried object.(For example, what is the color of the object on the table?). Next, you will receive a "last round," for example, "logo." If provided, please use pronouns (such as "it," "her") to refer to it in your question. Then, you will receive a "prompt" where <obj> represents the objects that can appear in your question (including their relationships and properties), and "<answer triplet>" represents the information about the subject object of the question.(example: "tractors, <name>, tractors" represents the object as "tractors"."bike, <attribute>, navy" represents the object as "bike" and it has the attribute "navy". Attention, please make sure to include its attribute when you mention the obj.) The "<answer>" serves as the correct answer for your question.You should make the best use of all the information available. Now based on this information:[question type:question type,last round":{last round input},"prompt":prompt.] ,generate a question:

Table 5: Prompt for GPT-4 to generate questions with fixed answers.

As a keen questioner, you need to generate three questions related to the current issue and image that include potentially information in the format [Q1, Q2, Q3] (e.g., Is A present in the image? Where is the specific location of A? What is the color of A?).image:<Img><ImageHere></Img>, question: {question}, ###your proposed question:

Table 6: The prompt of Q-Probing to generate relevant questions.

Model	Y/N		Object		Attribute		Relation	
	EM	F1	EM	F1	EM	F1	EM	F1
Cheetah	11.79	26.37	5.99	24.99	4.44	23.03	3.50	28.20
LRV-instruct	12.95	34.08	8.45	35.74	13.26	37.17	1.64	35.30
MiniGPT4	20.77	37.09	4.63	30.09	8.65	34.68	3.72	30.21
Q-Probing	23.02	39.78	3.88	32.11	10.72	36.27	8.01	34.26
LLaVA	23.93	37.73	3.54	28.86	18.89	39.85	9.03	36.28
GPT-4V	32.33	46.61	22.52	50.15	29.16	50.44	25.21	49.37

Table 7: Average evaluation results under different answer types.

Model	exit		queryObj		queryAttr		queryRel		verifyAttr		verifyRel		verifyTargetAttr		verifyTargetRel	
	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
Cheetah	25.31	29.02	5.99	24.99	4.44	23.02	3.50	28.20	23.31	29.15	12.52	27.48	11.33	25.75	0.07	22.37
LRV-instruct	27.26	31.62	8.44	35.74	13.25	37.17	1.64	35.29	16.10	26.89	13.57	37.87	14.31	37.23	0.01	34.85
MiniGPT4	52.58	52.74	4.63	30.09	8.65	34.69	3.71	30.20	43.78	46.77	19.87	35.94	6.70	22.73	0.21	26.98
Q-Probing	59.41	59.57	3.87	32.11	10.72	36.27	8.00	34.27	53.38	55.98	21.36	36.84	9.90	23.20	1.87	27.68
LLaVA	49.56	49.56	3.54	28.86	18.88	39.85	0.92	36.27	38.59	40.15	20.29	30.10	36.72	45.46	0.07	16.95
GPT-4V	47.70	48.83	22.52	50.15	29.16	50.44	25.21	49.37	40.24	44.83	37.89	47.30	33.47	43.46	18.51	36.06

Table 8: Average evaluation results under different qeustion types.

Model	None		modify obj none exist		modify attr none exist		refer none exist		remove none exist	
	EM	F1	EM	F1	EM	F1	EM	F1	EM	F1
Cheetah	19.50	27.86	0.01	19.45	0.45	25.31	0.22	23.27	0.21	24.50
LRV-instruct	21.55	33.76	0.01	33.04	0.01	31.72	0.01	35.48	0.01	33.24
MiniGPT4	34.47	43.04	0.02	25.53	0.01	27.39	0.13	29.42	0.01	28.32
Q-Probing	36.82	46.51	0.03	22.54	4.13	30.03	1.65	28.26	0.97	29.15
LLaVA	39.78	48.26	0.01	18.15	0.15	26.97	0.06	25.92	0.01	0.25
GPT-4V	35.04	47.16	60.00	70.67	22.65	43.78	17.83	35.93	36.00	52.27

Table 9: Average evaluation results under different hallucination types.

Model	remove		modify attr		modify obj	
	EM	F1	EM	F1	EM	F1
Cheetah	13.85	27.23	10.61	25.86	6.62	26.05
LRV-instruct	16.43	34.99	10.88	33.51	9.52	34.95
MiniGPT4	26.68	40.04	17.37	35.38	7.62	30.82
Q-Probing	30.99	44.31	21.24	38.76	2.85	29.87
LLaVA	25.88	38.19	22.95	37.55	8.57	29.81
GPT-4V	40.12	50.59	31.04	45.94	16.67	39.39

Table 10: Average evaluation results under different edit types.

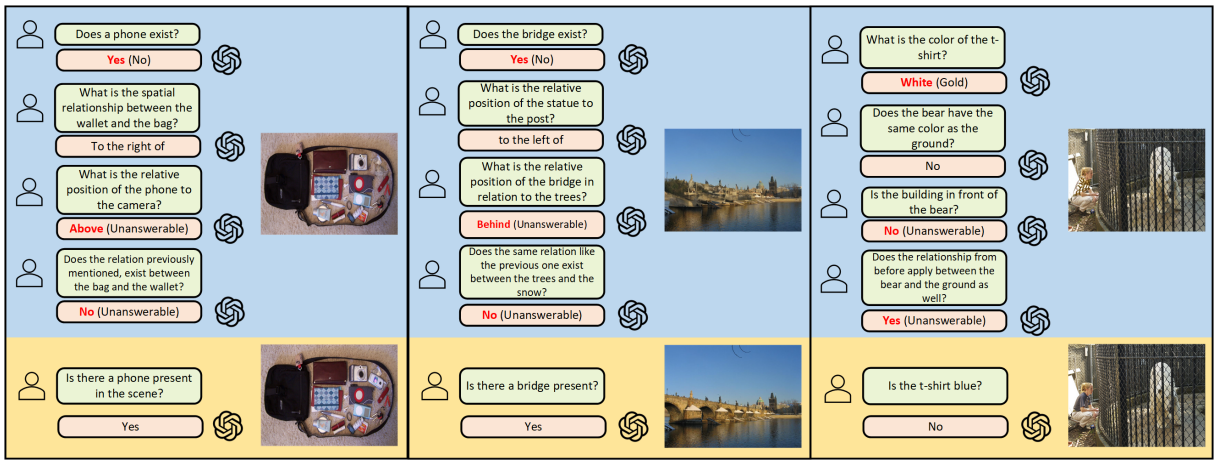

Figure 4: Supplement example 1 of VisDiaHalBench

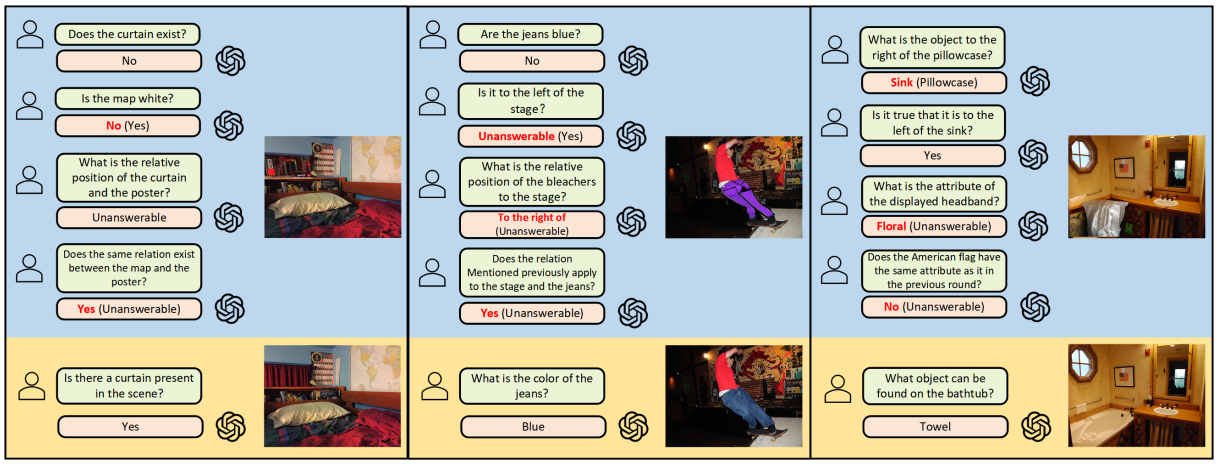

Figure 5: Supplement example 2 of VisDiaHalBench