Negative Object Presence Evaluation (NOPE) to Measure Object Hallucination in Vision-Language Models

Holy Lovenia^{*,1,2}

Wenliang Dai^{†,1} **Samuel Cahyawijaya**^{†,1} **Ziwei Ji**¹ **Pascale Fung**¹ The Hong Kong University of Science and Technology

² AI Singapore

holy@aisingapore.org, pascale@ust.hk

Abstract

Object hallucination poses a significant challenge in vision-language (VL) models, often leading to the generation of nonsensical or unfaithful responses with non-existent objects. However, the absence of a general measurement for evaluating object hallucination in VL models has hindered our understanding and ability to mitigate this issue. In this work, we present NOPE (Negative Object Presence Evaluation), a novel benchmark designed to assess object hallucination in VL models through visual question answering (VQA). We propose a cost-effective and scalable approach utilizing large language models to generate 29.5k synthetic negative pronoun (NegP) data of high quality for NOPE. We extensively investigate the performance of 10 state-of-the-art VL models in discerning the non-existence of objects in visual questions, where the ground truth answers are denoted as NegP (e.g., "none"). Additionally, we evaluate their standard performance on visual questions on 9 other VQA datasets. Through our experiments, we demonstrate that no VL model is immune to the vulnerability of object hallucination, as all models achieve accuracy below 10% on NegP. Furthermore, we uncover that lexically diverse visual questions, question types with large scopes, and scene-relevant objects capitalize the risk of object hallucination in VL models.

1 Introduction

In recent years, vision-language (VL) research has witnessed a proliferation of studies focusing on diverse methods, models, and learning strategies aimed at bridging the performance gap between human and model capabilities (Yang et al., 2021; Yi et al., 2018; Zhou et al., 2020; Ray et al., 2019; Gokhale et al., 2020; Dai et al., 2021, 2022; Ishii et al., 2021; Lovenia et al., 2022; Ji et al., 2022b;



[†] Joint second authors.



Figure 1: Example of object hallucination and incorrectness in VQA. The model hallucinates a non-existent man sitting on the closest bench in the left image, while in the right image, it simply answers inaccurately.

Lovenia et al., 2023). Furthermore, researchers have constructed more rigorous VL benchmarks to continually raise the performance standard (Antol et al., 2015; Sheng et al., 2021; Li et al., 2021b; Goyal et al., 2017; Marino et al., 2019). However, despite these efforts, VL models continue to grapple with the persistent issue of object hallucination, where generated responses unfaithfully contain objects non-existent in the input images (Ji et al., 2022a; Rohrbach et al., 2018; Dai et al., 2023b; Kayhan et al., 2021). As illustrated in Figure 1, the failure of the model to faithfully ground the visual input leads to the production of unfaithful answers. These instances of object hallucination not only result in incorrect responses but also shed light on fundamental issues within VL models, such as over-reliance on unimodal priors (Jing et al., 2020; Agrawal et al., 2018; Gupta et al., 2022; Niu et al., 2021a) and statistical bias (Agrawal et al., 2016; Goyal et al., 2017; Agarwal et al., 2020). These underlying problems impede the models' ability to comprehend the concept of non-existence.

Despite the critical importance of addressing object hallucination in VL models, only a limited number of previous works have focused on mitigating this issue, primarily due to the challenges

posed by the existing evaluation method in terms of generalization and scalability. CHAIR (Rohrbach et al., 2018) has primarily concentrated on evaluating non-existent objects based on handcrafted parsing criteria as well as a predefined list of object categories and their synonyms in the context of image captioning tasks, typically utilizing 80 object categories from MSCOCO (Rohrbach et al., 2018; Biten et al., 2022; Yi et al., 2018). However, the applicability of CHAIR to other datasets requires the generation of a new object category list, which exhibits varying levels of granularity across different studies (Dai et al., 2023b; Biten et al., 2022).

In this paper, we present NOPE (Negative Object Presence Evaluation) to quantitatively assess object hallucination through VQA. We establish a clear distinction between object hallucination and incorrectness as follows: a) object hallucination refers to the phenomenon in VQA where a VL model's response includes a non-existent object, despite the ground truth answer being a negative indefinite pronoun (e.g., "none", "no one", "nobody", "nowhere", "neither") (Quirk et al., 1985) (NegP); and b) incorrectness occurs when a VL model fails to accurately respond to a question with a ground truth answer that is anything other than NegP, denoted as **Others** = $\mathbb{P} \setminus \text{NegP}$, where \mathbb{P} represents the set of all phrases. By leveraging NegP, we evaluate object hallucination in NOPE, while Others allows us to assess normative correctness across diverse corpora. Our contributions are as follows:

- By utilizing NOPE, we construct a VQA diagnostic benchmark to measure the object hallucination rate of VL models. Our experiment covers a balanced proportion of NegP and Others data with a total of ~30k and ~36k data in the dev and test sets, and includes 10 state-of-the-art VL baselines performances. We provide an in-depth analysis of the performances and limitations of the baselines.
- 2. We propose a novel automatic data generation pipeline to produce high-quality NegP VQA data from existing image captioning data by multi-turn prompting instruction-tuned large language models (LLMs). We verify and analyze our generated NegP data through automatic validation and human validation. Our **list-then-rewrite** method produces highquality NegP VQA data with 92% validity.
- 3. Through extensive analysis in NOPE, we find

that VL models tend to hallucinate more on data with higher lexical diversity, more scenerelevant objects, and larger answer scopes.

2 Related Work

2.1 Hallucination in Vision-Language

Only a few works study hallucination in visionlanguage, with the vast majority of them focusing on the task of image captioning. Rohrbach et al. (2018) propose CHAIR, an automatic evaluation metric to measure object hallucination in generated image captions, which is defined as a phenomenon where the models produce captions containing objects that do not exist in the input visual context. Rohrbach et al. (2018); Dai et al. (2023b); Sharma et al. (2018) also show that standard captioning metrics, e.g., CIDEr (Vedantam et al., 2015), METEOR (Banerjee and Lavie, 2005), SPICE (Niu et al., 2022), under-penalize object hallucination. These evaluations open up a way for efforts to mitigate hallucination in image captioning (Biten et al., 2022; Zhang et al., 2021; Xiao and Wang, 2021; Dai et al., 2023b). Concurrent to our work, Li et al. (2023b) propose POPE and frame the task of evaluating object hallucination as a binary-class VQA with only "yes/no" answer.

2.2 Question Generation for VQA Data

Most works rely on human annotators to generate visual questions with ensured quality: VQAv2.0 and VQAv1.0 (Goyal et al., 2017; Antol et al., 2015), Visual Genome (Krishna et al., 2016), Visual7W (Zhu et al., 2016), AdVQA (Sheng et al., 2021), Vizwiz (Gurari et al., 2018, 2019), TextVQA (Singh et al., 2019), R-VQA (Lu et al., 2018), VQA-Rephrasings (Shah et al., 2019), etc.

However, the cost of human annotation is expensive, thus encouraging the exploration of a more scalable option: automatic VQA data generation. Ren et al. (2015) present a simple question generation algorithm with a syntactic parser to convert image descriptions into QA forms. Johnson et al. (2017) use a functional program to generate synthetic images of objects as well as their relationships and relevant QA pairs using the groundtruth annotations. Kafle and Kanan (2017) populate multiple question templates with the image annotations (e.g., region descriptions, relationship graphs, bounding boxes) obtained from image captioning data to construct TDIUC. Changpinyo et al. (2022) annotate candidate answers by syntactically



Figure 2: Only 0.4% of existing VQA corpora consist of NegP data. The rest 99.6% is Others.

parsing the captions, then derive questions from them. While prior studies focus on generating Others VQA data, we aim to generate NegP VQA data, which has never been done by past works.

3 NOPE to Overcome Limited NegP

As shown in Figure 2, there is only a minuscule amount of NegP data in the existing VQA datasets. In total, there are only $\sim 0.4\%$ of the existing VQA datasets are NegP, which are not sufficient to assess object hallucination in VL. For this reason, we create NOPE through a novel NegP data generation method that aims to produce questions whose ground truth answers point to the absence of appropriate existent objects. Such ground truth NegP answers are denoted as A^{NegP} = {"none", "nothing", "nowhere", "zero", "0", "no one", "nobody", "neither" }. We automatically generate synthetic NegP VQA data by leveraging the zero-shot prompting abilities of pretrained LLMs. To ensure the quality, we analyze the generated synthetic NegP VQA data through both automatic and manual human evaluation. The resulting NegP dataset is referred to as NOPE (Negative Object Presence Evaluation).

3.1 Prompting Methodology

We utilize an image captioning dataset $\mathcal{D}_{cap} = \{(v_i, c_i, l_i\}_{i=1}^n, \text{ where } v_i \text{ denotes a visual context, } c_i \text{ denotes a textual caption, and } l_i \text{ denotes the relevant image label annotations (i.e., names of objects in } v_i). We rely on <math>c_i$ to describe the objects and the relationship between objects depicted in v_i . We explore two prompting methods with varying degrees of flexibility to generate NegP questions from image captions: generate-from-scratch and list-then-rewrite. For clarity, we include all prompt templates with the examples in Appendix A



Figure 3: Human evaluation results of NegP questions by **generate-from-scratch** and **list-then-rewrite** according to the categories in §3.2.

and the automatic validation methods to ensure the validity of the generated questions in Appendix C.

Generate-from-scratch In this method, we prompt an LLM to generate a question q_i given three different variables: 1) an interrogative word $w_i \in \{"what", "where", "how many", "who", "which"\}$ to assert the question type needed for q_i , 2) a ground truth NegP answer $a_i \in A^{\text{NegP}}$ that matches w_i , and 3) an image caption c_i .

List-then-rewrite LLMs can infer conversational contexts and follow instructions over multiple turns (Nijkamp et al., 2023; Volum et al., 2022; Bang et al., 2023). Leveraging this multi-turn capability of LLMs, we frame our question generation task into two steps. (1) For object listing, given an image caption c_i and the relevant object annotations l_i , we prompt an LLM to list m objects $o_i = \{o_{i,j}\}_{j=1}^m$ that are "closely related" but not mentioned. (2) For question rewriting, the LLM has to paraphrase a provided reference question, which is sourced from a diverse pool of humangenerated question templates with an object placeholder in Appendix B. After obtaining m listed objects from (1), we pick m random question templates from the pool and replace the object placeholders with the listed objects o_i to construct the reference questions $r_i = \{r_{i,j}\}_{j=1}^m$. We prompt the LLM to paraphrase r_i to $q_i = \{q_{i,j}\}_{j=1}^m$ to increase the lexical variety of the rewritten questions q_i .

3.2 Human Evaluation Guidelines

We conduct a human evaluation to verify and analyze the quality of the generated questions obtained from $\S3.1$, as well as measure the effectiveness

¹We use "closely related" (hard) for brevity. However, this object-scene relevance can be switched to "loosely related" or "completely unrelated" in practice.



Figure 4: Distribution of NOPE's NegP questions by their starting phrases. The arc length is proportional to the number of questions containing the word.

of the automatic validations performed. We employ three human annotators to perform the human evaluations. Detailed guidelines and examples are given prior to evaluation. We collect generated questions that are judged as valid and invalid by their automatic validation methods. Given a visual context, an image caption, a ground truth answer $\in A^{\text{NegP}}$, and a generated question, the annotators are asked to determine whether: 1) the question is valid, 2) the question has a possible Others answer alternative, 3) the question does not match the answer (according to both the image caption and the image), 4) the question does not match the answer (only according to the image), or 5) the question is unclear or confusing. The examples provided for each category can be seen in Appendix E.

3.3 Results and Quality Analysis

Using automatic validation approaches explained in §3.1 and implementation details in Appendix D, we compare the capabilities of various instructiontuned LLMs in generating NegP VQA data. From the automatic validation results and analysis presented in Appendix F, we find that employing ChatGPT yields the highest-quality generated NegP questions by both **generate-from-scratch** and **list-then-rewrite** prompting methods, hence its use in the human evaluations. We conduct a human evaluation on randomly selected 150 generated questions from each method. For each sample, we ask 3 human experts to judge each generated question into one of the 5 options defined in §3.2.

Figure 3 shows the result of our human evaluation. For generate-from-scratch, only $\pm 50\%$ out



Figure 5: Object-scene relevance in the NOPE dataset. **Related** denotes "closely related" and **unrelated** denotes "completely unrelated" for brevity.

of the subset that is judged as valid by the automatic validation is actually a valid and appropriate NegP question according to the human annotators, and the rest is judged as incorrect by human annotators. The **list-then-rewrite** prompting approach, on the other hand, displays a significantly better question-answer generation quality with $\pm 92\%$ of the generated questions denoted as valid by the human annotators. This fact demonstrates that existing LLMs still fail to perform complex tasks in an end-to-end manner, while decomposing the complex tasks into several subtasks and coupling them with simple rule-based approaches can significantly improve the LLMs' ability to perform the complex task effectively and efficiently.

A closer look at the questions generated by the generate-from-scratch method shows that while LLMs usually succeed in making questions in an end-to-end manner, 12% of the NegP generated questions include an existing object even though this information is sufficiently provided by the image caption. Moreover, 14% of the time, the generated questions also fail to include any objects and are overly generic, e.g., "What is not included in this image?", which aligns with the observations of (Jang et al., 2023; Hosseini et al., 2021; Ettinger, 2020; Kassner and Schütze, 2020) that LMs perform poorly on negation and struggles to understand that negation changes semantics. These facts show that LLMs cannot consistently perform this implicit task breakdown. From this human evaluation result, we can conjecture that the

				dev	test
	dev	test	Others	14850	18150
	uev	lesi	AdVQA	1350	1650
NegP	14718	17983	R-VQA	2700	3300
NOPE (§3.4)	14718	14773	TDIUC	1350	1650
AdVQA	0	88	TextVQA	1350	1650
R-VQA	0	9	Visual7W	2700	3300
TDIUC	0	6	VizWiz	1350	1650
Visual7W	0	1276	VQA-Rephrasings	1350	1650
VQAv1 Abstract Scenes	0	180	VQAv1 Abstract Scenes	1350	1650
VQAv2 Balanced Real	0	1651	VQAv2 Balanced Real	1350	1650

Table 1: The data statistics of NegP (left) and Others (right) subsets used in the evaluation.

generate-from-scratch prompting method is not reliable and fails to elicit the LLMs' understanding of complex tasks such as question generation. Using the **list-then-rewrite** method, we generate 29.5k NegP VQA data to build the NOPE dataset from OpenImagesV7 (Kuznetsova et al., 2020).

3.4 Dataset Statistics

NegP Question Distribution We cluster the generated questions into various types based on the starting n-grams in Figure 4. NOPE dataset exhibits a very broad lexical diversity of the generated questions, including variations in which the questions start with words other than the typical interrogative words (e.g., "what", "where", "how", etc.), such as "Could you tell...", "In what location...", "Do you know...", and more. This is vital to resist VL models' notorious brittleness against linguistic variations (Shah et al., 2019; Ray et al., 2019; Kervadec et al., 2021; Whitehead et al., 2020).

Object-Scene Relevance Based on the descriptor used in the object listing step in **list-then-rewrite**¹, the data in NOPE are divided into three categories. Figure 5 illustrates how these object-scene relevance descriptors of the generated NegP VQA data correspond to the relationship between the textual semantic similarity of the selected object and the image caption, as well as the image-text semantic similarity of the image and the QA pair. We compute the textual similarity using the Sentence-Transformer library² and the image-text similarity using CLIPScore (Hessel et al., 2021).

4 Experimental Settings

The object hallucination benchmark consists of the validation and test sets of 10 VQA corpora, including NOPE (§3.4) with balanced object-scene relevance proportions. It displays the comparison between incorrectness and object hallucination over various baselines, which serves as a foundation for assessing object hallucination in addition to the standard incorrectness in 10 VL models.

4.1 Datasets

Table 1 describes the data distribution of the dev and test sets of the benchmark. Each set respectively comprises \sim 30k and \sim 36k data, maintaining near-balanced proportions of NegP and Others data. To ensure the quality of the visual questions in the benchmark, we also analyze the lexical diversity and the fluency of the comprising datasets, which are useful to assert a robust evaluation using questions that are linguistically diverse and coherent. In Figure 6, we show that the datasets whose data construction utilizes automatic question generation, i.e., NOPE and TDIUC, have comparable lexical diversity and fluency to the other datasets, which entirely rely on question generation by human annotators.

For lexical diversity, we employ length-agnostic lexical diversity metrics, i.e., moving average type-token ratio (MATTR) (Covington and Mc-Fall, 2010), measure of textual lexical diversity (MTLD) (McCarthy, 2005), and hypergeometric distribution diversity (HDD) (McCarthy and Jarvis, 2007, 2010), and average them. We use Lexical-Richness (Shen, 2021, 2022) v0.5.0³ to calculate these metrics. We also employ a large pre-trained LM GPT-Neo (Black et al., 2021) with 2.7B param-

²https://www.sbert.net/docs/usage/semantic_ textual_similarity.html

³https://pypi.org/project/lexicalrichness/



Figure 6: Question quality in the benchmark in terms of lexical diversity and fluency.

eters to compute the perplexity of the questions, which is often used as a measure of both lexical diversity (Lewis et al., 2017; Tevet and Berant, 2021) and fluency (Fan et al., 2018; Wang et al., 2019; Cahyawijaya et al., 2021; Anonymous, 2023).

4.2 Baselines

For the baselines in our benchmark, we employ various vision-language model architectures on the benchmark in both zero-shot & few-shot and finetuned fashion. For the fine-tuned setting, we utilize five models: 1) OFA (Wang et al., 2022b), which unifies architectures, tasks, and modalities by formulating a unified sequence-to-sequence abstraction via handcrafted instructions to achieve task agnosticism; 2) and 3) BLIP (Li et al., 2022), which incorporates two key contributions, i.e., multimodal mixture of encoder-decoder (MED) to operate as either a unimodal encoder, an imagegrounded text encoder, or an image-grounded text decoder, and CapFilt as a new dataset bootstrapping method for learning from noisy image-text pairs; 4) ALBEF (Li et al., 2021a), which is trained using momentum distillation to improve learning from noisy web data; 5) GIT (Wang et al., 2022a), which employs an image encoder and a text decoder pretrained using a language modeling objective to map the input image to its corresponding description.

For the zero-shot setting, we employ: 1) BLIP-2 (Li et al., 2023a), which utilizes a scalable multimodal pre-training method to enable any LLMs to ingest and understand images; 2) and 3) Prompt-Cap (Hu et al., 2022), which is trained to generate captions that help downstream LMs answer visual questions; 4) InstructBLIP (Dai et al., 2023a), which is an instruction-tuned version of BLIP-2 on various tasks including VQA. We also employ 5) OpenFlamingo (Alayrac et al., 2022; Awadalla et al., 2023), which is an open-source version of

	Model size	# Pre-train images			
Zero-shot	& Few-sh	ot			
PromptCap _{BASE}	696M	34M			
PromptCap	3B	34M			
BLIP-2	3.8B	129M			
OpenFlamingo	9B	$\sim 2.5B$			
VQA fine-tuned					
OFA	929M	34M			
BLIP	385M	129M			
$BLIP_{CapFilt-L}$	385M	129M			
ALBEF	628M	14M			
GIT _{LARGE}	347M	1.4B			
InstructBLIP _{FLAN_{XL}}	3.8B	129M+			

Table 2: VL baseline models in the benchmark.

a large pre-trained VL model specialized in fewshot prompting, in the two-shot setting. Table 2 provides the model and data sizes of the baselines and Appendix H lists the model variants.

4.3 Evaluation Settings

For both NegP and Others, we compute accuracy and METEOR (Banerjee and Lavie, 2005) to measure the performance of vision-language models on the benchmark. While accuracy measures the performance based on an exact match between the generated answer and the ground truth answer, METEOR caters to partial (i.e., unigram) matches by computing a score for this matching using a combination of unigram-precision, unigramrecall, and alignment between the unigrams in the generated answer and ground truth answer. Additionally, for NegP, we employ a rule-based accuracy, referred to as NegP accuracy, which focuses on determining whether the generated answer is a negative indefinite pronoun (i.e., $\in A^{\text{NegP}} =$ {"none", "nothing", "nowhere", "zero", "0", "no one", "nobody", "neither"}) or not. All scores are computed per task and then the weighted averages according to each task size are retrieved.

5 Results

We present the results on the test set of the benchmark in Table 3. Examples of object hallucination are in Appendix I. While the VQA-finetuned baselines are slightly better at NegP and comparable to the zero-shot & few-shot baselines on Others, as in Figure 7, we observe that all zero-shot and VQA-finetuned baselines notably perform much worse on NegP tasks that Others with the averaged discrepancies of $\pm 22\%$ and $\pm 18\%$ accuracy,

	Others test (%)		NegP test (%)						
	C	Overall		Existing datasets NO		E test (§3.4)	Overall		
	Acc.	METEOR	Acc.	METEOR	Acc.	METEOR	NegP Acc.	Acc.	METEOR
			Z	ero-shot & fe	w-shot				
PromptCap _{BASE}	30.18	21.45	2.87	3.05	0.21	0.29	0.95	0.68	0.78
PromptCap	32.69	22.66	3.61	2.20	0.42	0.56	1.67	0.99	0.85
BLIP-2	19.84	17.94	4.39	1.49	2.11	1.22	5.25	2.51	1.27
OpenFlamingo	14.29	24.32	0.09	7.96	0.00	$\overline{0.08}$	0.02	0.02	1.49
				VQA fine-tı	ıned				
OFA	29.43	17.06	3.24	4.10	2.75	9.11	8.21	2.84	8.21
BLIP	23.27	12.07	5.95	5.12	1.60	3.63	6.48	2.38	3.90
$\operatorname{BLIP}_{CapFilt-L}$	23.28	12.08	5.95	5.12	1.60	3.61	6.47	2.37	3.88
ALBEF	16.33	21.87	19.31	26.31	1.86	6.76	8.18	4.98	10.25
GIT _{LARGE}	41.00	21.75	34.89	20.43	4.00	5.90	17.92	9.51	8.49
InstructBLIP	40.62	22.55	21.40	13.50	5.08	5.19	17.69	7.99	6.67

Table 3: Weighted model performances on the test set of the benchmark. Errors made on Others VQA data represent incorrectness, while errors made on NegP VQA data represent object hallucination. **Bold** and <u>underline</u> denote the best performances overall and in the group, respectively.

respectively. This demonstrates that all baselines are more vulnerable and susceptible to object hallucination than standard incorrectness. In addition, less incorrectness does not entail less object hallucination. For instance, PromptCap_{BASE}, Prompt-Cap, and BLIP have lower scores on NegP than ALBEF despite outperforming it on Others setting. It also means that existing evaluations that solely utilize Others cases cannot effectively capture the models' risk of object hallucination.

Another point that we observe is, GIT outperforms the other baselines on both NegP and Others data, as well as manages to surpass much bigger models (e.g., InstructBLIP and Flamingo), showing that GIT is more robust against both object hallucination and general incorrectness, despite being the smallest in size (Table 2) and having a simple architecture. This achievement could be attributed to its substantial number of pre-training images, which is an order of magnitude larger than those of the other baselines. This also aligns with (Hoffmann et al., 2022), in which for the same compute budget, a smaller model trained on more data outperforms a larger model trained on fewer data and achieves more optimal performance.

6 Analysis and Discussions

6.1 Object hallucination and lexical diversity

Table 3 also show that NegP performance scores on existing datasets are significantly higher than on NOPE across the metrics, indicating that ob-



Figure 7: All baselines consistently score lower on NegP (%NegP Acc.) than Others (%Acc.).

ject hallucination is more likely to occur when the models attempt to solve the questions in NOPE. This is mainly due to the NOPE dataset having a relatively higher lexical diversity compared to the other NegP corpora, which are mostly composed of VQAv2 and Visual7W (see in Figure 6). This also aligns with the fact that NegP model performances have a strong negative Pearson correlation with the lexical diversity measures ($r = \{-0.8, -0.66, -0.65, -0.7\}$ for METEOR and HDD, MTLD, MATTR, perplexity) and proves that corpora with higher lexical diversity (e.g., NOPE) provide more challenging NegP VQA problems to assess object hallucination.

6.2 Object hallucination and language bias

As shown in Figure 9, among 5 NegP question types, all VQA-finetuned VL models fail on NegP questions about color (e.g., "What is the color of...?"), object (e.g., "What is the object



Figure 8: VL models are more prone to object hallucination on lexically diverse NegP VQA data. Dot size represents dataset size (§4.1).



Figure 9: NegP performance of VQA fine-tuned baselines over different question types.

beside...?"), and location (e.g., "Where is...?"), while most VL models tend to hallucinate less on NegP questions about counting (e.g., "How many...?") and person (e.g., "Who is using...?"). A similar trend is observed for the zero-shot & fewshot baselines. We further inspect these two categories and find out that their answer scopes are of a smaller scope than the others in the training data. For instance, the answers to counting questions are often numbers \leq 5, and the answers to the person questions are often the generic "man", "woman", "person", "people", and others which have fewer variations compared to object types, color names, or absolute and relative places. These facts suggest that existing VL models have a strong language bias (KV and Mittal, 2020; Niu et al., 2021b; Wu et al., 2022) toward certain question types, which result in acceptable NegP performances on those question types. Nevertheless, language bias does not solve object hallucination and even might make it worse, due to the VL models having weak visual grounding skills to verify the answer to the visual context, which might lead to errors on both NegP and Others questions.



Figure 10: NegP performance of (left) zero-shot & fewshot and (right) VQA fine-tuned baselines per objectscene relevance.

6.3 Object hallucination and object-scene relevance

As shown in Figure 10, all VQA fine-tuned models perform lower when the object is closely related to the scene compared to when the object is loosely related or unrelated. This indicates that VL models have some degree of understanding NegP based on the relevance of the object in question with the scene. Although this helps VL models to understand about objects better in some cases, this also causes VL models to hallucinate more on objects that are relevant to the scene (Rohrbach et al., 2018; Kayhan et al., 2021; Dai et al., 2023b). On the other hand, the performance on loosely related or unrelated objects tend to be similar, which aligns with the similarity analysis provided in Figure 5. In contrast, for zero-shot & few-shot baselines, the differences between object-scene relevance are less apparent. However, in general, the NegP scores are also very low, except for BLIP-2, which suggests that most zero-shot models do not have an adequate understanding of NegP.

7 Conclusion

We have addressed the critical issue of object hallucination in VL models, which has been lacking a general measurement. We have introduced NOPE to assess object hallucination in VL models, investigating the discernment of objects' non-existence in visual questions by 10 state-of-the-art VL models, alongside their standard performances. Additionally, we have presented a cost-effective and scalable method for generating high-quality synthetic data with over 90% validity to overcome the severe underrepresentation of NegP cases. Through our comprehensive experiments, we have demonstrated that no VL model is exempt from object hallucination, highlighting their lack of understanding of negative object presence. Furthermore, we have identified lexical diversity, question type, and the relevance of the object to the visual scene as influential factors impacting VL models' susceptibility to object hallucination. These findings provide valuable insights into the assessment of object hallucination in VL, thereby paving the way for the future development of enhanced VL models.

8 Limitation and Future Work

Evaluation Metrics for Object Hallucination In this work, we show three metrics to measure object hallucination and incorrectness, i.e., the exact match accuracy, METEOR, and NegP accuracy. Nevertheless, in some cases, these metrics fail to capture some equivalent answer that has the same semantic meaning. For example, given an NegP question "Where is the spoon in the picture?" with the corresponding label "Nowhere", a system that answers with "There is no spoon in the picture" will get 0 scores on these three metrics, despite the answer is actually correct. We argue that the limitation of the existing metrics might hinder further research in alleviating object hallucination and we expect future works to focus on developing better metrics for measuring object hallucination.

Object Hallucination Outside of NegP Since object hallucination refers to an effect (i.e., generating non-existent objects) and not a cause, our measurement of object hallucination is limited to NegP cases, in which a VL model unfaithfully infers a supposedly non-existent object as existent in the visual context. For cases where a VL model provides an incorrect answer to Others VQA, the fine line between misclassification and object hallucination has not yet been defined.

Performances on Full Others Test Sets In order to observe the incorrectness of VL models on Others on various datasets, we compose a balanced set of \sim 15k data in our dev split and \sim 18k data in our test split from diverse VQA corpora. Obtaining the full performance on each of the source datasets requires re-running the baselines on the full test sets of each source dataset.

9 Ethics Statement

This research on object hallucination in visionlanguage models aims to improve the reliability and faithfulness of these models, which have significant applications in various fields such as healthcare and autonomous driving. We acknowledge the potential impact of our findings and commit to promoting responsible and ethical use of these models. We recognize that such models have the potential to perpetuate biases and stereotypes, and we have taken steps to mitigate this risk. For instance, we ensured that the synthetic data used in this study was generated in a manner that respects privacy and does not perpetuate biases or stereotypes. Furthermore, we recognize the importance of transparency and accountability in the development and use of these models. Therefore, we commit to sharing our findings and methodologies openly and making them accessible to the wider research community. We also acknowledge that these models can have unintended consequences and commit to ongoing monitoring and evaluation of their impact. Finally, we recognize that the development and use of these models must be guided by ethical principles that prioritize human well-being and social responsibility. We are committed to upholding these principles and contributing to the development of responsible and ethical practices in the field of vision-language modeling.

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A Prompt Templates

We provide the prompt templates and examples for the **generate-from-scratch** and **list-then-rewrite** methods in Table 4 and Table 5, respectively.

Template 1

Create a question beginning with "<INTERROGATIVE_WORD>" from this image caption: "<IM-AGE_CAPTION>" with an answer of "<ANSWER>".

Example: Create a question beginning with "who" from this image caption: "This image consists of an airplane in the air. On which, we can see the text. In the background, there is sky." with an answer of "nobody".

Generated question: Who is in the airplane in this image?

Template 2

Turn the text "<IMAGE_CAPTION>" into a "<INTERROGATIVE_WORD>" question with an answer "<ANSWER>":

Example: Turn the text "This is an outside view. Here I can see the cars on the ground and there are two persons standing. In the background there is a tent, shelter and trees. At the top of the image there is the sky. At the bottom there is grass." into a "how many" question with an answer "none":

Generated question: How many buildings are visible in the outside view?

Template 3

Given an answer "<ANSWER>", generate an appropriate question starting with "<INTERROGA-TIVE_WORD>" from the text "<IMAGE_CAPTION>".

Example: Given an answer "nowhere", generate an appropriate question starting with "where" from the text "In this picture, we see a woman. She is staring at something and she might be posing for the photo. We see a nail is pierced on her face. She might be taking bath. In the background, we see a wall and a white color object which looks like a bathtub.".

Generated question: Where is the ideal location to put a nail on a person's face while they are taking a bath?

Template 4

Write a question that begins with "<INTERROGATIVE_WORD>" and is answered by "<ANSWER>" based on the text "<IMAGE_CAPTION>".

Example: Write a question that begins with "what" and is answered by "nothing" based on the text "In this image I can see food item in a cooking vessel, which is on the stove. In the background there are some objects.".

Generated question: What can you see in the background of the image?

Template 5

Rewrite the statement "<IMAGE_CAPTION>" as a question that starts with interrogative phrase "<IN-TERROGATIVE_WORD>" and has an answer of "<ANSWER>".

Example: Rewrite the statement "In the image I can see food item in the bowl. The background of the image is blurred." as a question that starts with interrogative phrase "which" and has an answer of "neither".

Generated question: Which part of the image is not blurred and which object is visible in the bowl?

Table 4: Prompt templates used in the generate-from-scratch (§3.1) and their corresponding examples.

Object Listing Template Description: "<IMAGE_CAPTION>"

List 10 tangible objects that are closely related to the description, but are not mentioned there. Also avoid these objects: <IMAGE_LABELS>.

Example:

Description:

"In this picture we can see some food products in the glass jars."

List 10 tangible objects that are closely related to the description, but are not mentioned there. Also avoid these objects: Vegetable.

Response:

1. Spices, 2. Canned fruits, 3. Nuts, 4. Sugar, 5. Coffee beans, 6. Honey, 7. Pasta, 8. Chocolates, 9. Tea leaves, 10. Jams and preserves

Question Rewriting Template

Question templates:

<REFERENCE_QUESTIONS_BASED_ON_FIRST_TURN_ANSWER>

Paraphrase each of these <NUMBER> questions while keeping the sentence as a question with a question mark.

Example:

Question templates:

- 1. Who is using the object above the spices?
- 2. What object is located under the canned fruits?
- 3. Who is holding the object on the right of the nuts?
- 4. What is the color of the sugar?
- 5. Who is using the coffee beans?
- 6. What object is located on the left of the honey?
- 7. What object is located on the left of the pasta?
- 8. What object is located on the left of the chocolates?
- 9. What is the color of the tea leaves?
- 10. Where is the jams and preserves located in the image?

Paraphrase each of these 10 questions while keeping the sentence as a question with a question mark. **Generated question:**

- 1. Who is the user of the spices in the picture?
- 2. Which product can be found below the canned fruits?
- 3. Who is the individual holding the object to the right of the nuts?
- 4. Can you tell me the color of the sugar in the glass jars?
- 5. Who might be utilizing the coffee beans shown in the image?
- 6. What is the item on the right side of the honey?
- 7. What comes up on the left of the pasta in the photograph?
- 8. What is situated on the left of the chocolates in the picture?
- 9. What is the color of the tea leaves displayed in the glass jars?
- 10. Where exactly can the jams and preserves be found in this image?

Table 5: Prompt templates used in the list-then-rewrite (§3.1) and their corresponding examples.

B Reference Question Templates

Table 6 presents the pool of question templates used to automatically build the reference questions for the **list-then-rewrite** in §3.1.

No	Question template	NegP answer
1	What is the color of the <object>?</object>	none / nothing
2	What object is located above / under / on the left of / on the right of the <object>?</object>	none / nothing
3	Where is the <object> located in the image?</object>	nowhere
4	How many <object> are there in the image?</object>	zero / 0 / none
5	Who is holding / using the <object>?</object>	no one / nobody
6	Who is holding / using the object above / under / on the left of / on the right of the <object>?</object>	no one / nobody

Table 6: Question templates utilized to construct the reference questions for the question rewriting step in the **list-then-rewrite** prompting methodology in §3.1.

C Automatic Validation Methodologies of NegP VQA Data Generation

Generate-from-scratch To ensure the validity of q_i , we use a model fine-tuned on natural language inference (NLI) to determine whether a generated question q_i and answer a_i pair (i.e., hypothesis) logically entails its corresponding image caption c_i (i.e., premise). We also utilize a fine-tuned binary classifier to determine whether a generated question q_i and answer a_i pair fits a given visual context v_i . If the question q_i and answer a_i pair is true (entailment) or undetermined (neutral) given c_i as well as matches with v_i , then the generated question q_i is judged as valid by the automatic validation.

List-then-rewrite For the automatic validation of a listed object $o_{i,j}$, we extract lemmatized noun tokens from its corresponding image caption c_i and obtain the object names from l_i as the objects present in v_i . If $o_{i,j}$ does not match with any of the extracted objects, then $o_{i,j}$ is a valid non-existent object. For the automatic validation of a generated question $q_{i,j}$, if $q_{i,j}$ does not contradict its respective reference question $r_{i,j}$, then the generated question $q_{i,j}$ is considered valid.

D Implementation Details of NegP VQA Data Generation

We implement §3.1 with the following LLMs that employ: 1) multi-task prompted fine-tuning, i.e., **BLOOMZ** (Muennighoff et al., 2022) and **T0** (Sanh et al., 2022); 2) instruction meta-learning, i.e., **OPT-IML** (Iyer et al., 2022); 3) synthetic self-instruct, i.e., **Alpaca** (Wang et al., 2022c); 4) instruction (Wei et al., 2022a) and chain-of-thought fine-tuning (Wei et al., 2022b), i.e., **FLAN T5** and **FLAN Alpaca** (Chung et al., 2022); 5) multi-task instruction pre-training, i.e., **ChatGLM** (Zeng et al., 2023); 6) conversation-style instruction tuning and reinforcement learning with human feedback (RLHF) (Christiano et al., 2017; Stiennon et al., 2020), i.e., **ChatGPT** (**GPT-3.5**). More details are presented in Table 7.

We utilize Open Images v7 as our image captioning dataset \mathcal{D}_{cap} with respect to the provided splits. For automatic validation with NLI, we use the RoBERTa model fine-tuned on various NLI corpora that achieves the best performance on the Adversarial NLI benchmark (Nie et al., 2020).⁴ For automatic validation with image-QA pair classification, we build a simple CLIP-based (Radford et al., 2021) binary classifier. We provide the details in Appendix D.1. For the **list-then-rewrite** method, we use m = 10.

D.1 Image-QA Pair Classification

To construct a model for our image-QA pair classification, we construct a balanced image-QA corpus using NegP and Others VQA data randomly selected from 9 existing VQA datasets, i.e., VQAv2

⁴https://huggingface.co/ynie/roberta-large-snli_mnli_fever_anli_R1_R2_R3-nli

No	Model	Size	References	Access
1	BLOOMZ (3B)	3B	(Muennighoff et al., 2022; Scao et al., 2022)	https://huggingface.co/bigscience/bloomz-3b
2	BLOOMZ (7.1B)	7.1B	(Muennighoff et al., 2022; Scao et al., 2022)	https://huggingface.co/bigscience/bloomz-7b1
3	Т0	3B	(Sanh et al., 2022)	https://huggingface.co/bigscience/T0_3B
4	OPT-IML	1.3B	(Iyer et al., 2022; Zhang et al., 2022)	https://huggingface.co/facebook/opt-iml-max-1.3b
5	Alpaca	7B	(Wang et al., 2022c; Touvron et al., 2023)	https://huggingface.co/chavinlo/alpaca-native
6	FLAN T5 XL	3B	(Chung et al., 2022; Raffel et al., 2020)	https://huggingface.co/google/flan-t5-xl
7	FLAN T5 XXL	11B	(Chung et al., 2022; Raffel et al., 2020)	https://huggingface.co/google/flan-t5-xxl
8	FLAN Alpaca XL	3B	(Chung et al., 2022; Wang et al., 2022c)	https://huggingface.co/declare-lab/flan-alpaca-xl
9	ChatGLM	6B	(Zeng et al., 2023; Du et al., 2022)	https://huggingface.co/THUDM/chatglm-6b
10	ChatGPT	175B	-	https://platform.openai.com/docs/models/gpt-3-5

Table 7: Instruction-tuned LLMs used in Appendix D.

(Balanced Real) (Antol et al., 2015), AdVQA (Sheng et al., 2021), VizWiz (Gurari et al., 2018, 2019), TextVQA (Singh et al., 2019), R-VQA (Lu et al., 2018), Visual7W (Zhu et al., 2016), TDIUC (Kafle and Kanan, 2017), VQA-Rephrasings (Shah et al., 2019), and VQAv1 (Abstract Scenes) (Antol et al., 2015).

For the image-QA pairs from the NegP VQA data, we assign a binary label of 1 (valid), which means that the QAs correctly fit the corresponding images as valid pairs. For the Others VQA data, we replace the Others ground truth answers with NegP answers $\in A^{\text{NegP}}$ to make the invalid image-QA pairs (a binary label of 0). We split the corpus into 6k training, 2k validation, and 2k test set.

Using this corpus, we train a simple classifier with one hidden layer on top of a frozen CLIP (Radford et al., 2021). We leverage the image-text alignment learned by CLIP (Radford et al., 2021), which has been pre-trained on 400M image-text pairs using contrastive learning, to extract the image features of the images and the textual features of their question-answer counterparts. We simply concatenate both image and text features, then input them into the classifier. Our image-QA pair classifier yields an F1-score of 91.29% on the test set.

E Human Evaluation Category Examples

We provide the human evaluation categories (§3.2) in Figure 11.



Figure 11: Examples of the human evaluation judgments for the generate-from-scratch prompting method in §3.2.

F Automatic Validation Results of NegP VQA Data Generation



Figure 12: Automatic validation results on 1000 NegP questions generated using **generate-from-scratch** (§3.1) over five prompt templates.



Figure 13: Human evaluation results on NegP questions generated by ChatGPT using **generate-from-scratch** (§3.1). The Y-axis denotes the verdict from the automatic validators, i.e., caption-QA and image-QA entailment models.

Generate-from-scratch Figure 12 shows the proportions of valid generated NegP VQA data using 10 instruction-tuned LLMs listed in Appendix D over five different prompt templates, where each model generates 1k questions per template. The prompt templates are provided in Appendix A. The result shows that only $\sim 25\%$ of the generated questions by the best-performing model, ChatGPT, are valid according to the automatic validation, while other models' valid generated questions range from 6%-23%. This indicates that the task of NegP question generation is more complex and difficult than the instructions used to fine-tune the LLMs.

Next, we conduct a human evaluation on randomly selected 240 generated questions (i.e., 60 for each category in §3.2) by ChatGPT, which is the best-performing model. We ask 3 human experts to judge each generated question and answer pair into one of the five options defined in §3.2. Figure 13 demonstrates the result of our human evaluation. The result shows that automatic validation judgments do not agree with the human judgments on a considerable amount of the data, even for simple valid/invalid classification, the automatic validation judgments misclassify 27%-50% of the subsets. From this result, we can conjecture that our automatic validation approach is not effective at verifying whether the generated NegP questions are valid or invalid and that the generate-from-scratch prompting method is not reliable and fails to elicit the LLMs' understanding of the task.

Instruction-tuned LLM	% Valid objects	% Valid objects & questions
FLAN T5 XL	11	10
FLAN T5 XXL	5	17
Alpaca	44	53
FLAN Alpaca XL	25	11
ChatGLM	84	44
ChatGPT	99	98

Table 8: Automatic validation results on 100 NegP questions generated using list-then-rewrite (§3.1).



Figure 14: Human evaluation results on NegP questions generated by ChatGPT using list-then-rewrite (§3.1).

List-then-rewrite The automatic validation results on 100 generated questions (i.e., with the category proportion of 50, 35, and 15, respectively) by **list-then-rewrite** are provided in Table 8. The best-performing model, ChatGPT, yields 98% valid questions with a valid non-existent object according to the automatic validation judgments, which is a huge improvement compared to **generate-from-scratch**. Similarly, Alpaca and ChatGLM also experience the same increase in validity (albeit not as significant), while the FLAN family models deteriorate due to their inability to handle lists inside the instructions, thus forcing them to respond with only one object instead of 10 objects (§D).

Our human evaluation on 300 generated questions by ChatGPT (presented in Figure 14) also proves that, when we omit the question generation on the wrong object, we can achieve around 90% high-quality NegP questions generated by the **list-the-rewrite** method. However, this method would benefit from the establishment of a more suitable penalizing method to filter out the generated questions that are inconsistent with the image captions.

G Question Diversity of Existing VQA Datasets

We provide the illustrations of question diversity of existing VQA datasets: VQAv2 dataset (Antol et al., 2015) which utilizes a manual data generation method (presented in Figure 15a) and VQA-Rephrasings dataset (Shah et al., 2019) which utilizes an automatic data generation method (presented in Figure 15b).



(a) VQAv2 dataset (Antol et al., 2015)

(b) VQ²A dataset (Changpinyo et al., 2022)

Figure 15: Question diversity of existing datasets. The figures are taken from the respective original papers.

H Baselines in NOPE Benchmark

The variant details of the baselines used in NOPE are presented in Table 9.

No	Model	References	Access
			Zero-shot & Few-shot
1	PromptCap _{BASE}	(Hu et al., 2022)	<pre>https://huggingface.co/tifa-benchmark/promptcap-coco-vqa,</pre>
			https://huggingface.co/allenai/unifiedqa-t5-base
2	PromptCap	(Hu et al., 2022)	<pre>https://huggingface.co/tifa-benchmark/promptcap-coco-vqa,</pre>
			https://huggingface.co/allenai/unifiedqa-t5-3b
3	BLIP-2	(Li et al., 2023a)	https://huggingface.co/Salesforce/blip2-opt-2.7b
4	OpenFlamingo	(Alayrac et al., 2022;	https://huggingface.co/OpenFlamingo/OpenFlamingo-9B
		Awadalla et al., 2023)	
5	InstructBLIP	(Dai et al., 2023a)	https://huggingface.co/Salesforce/instructblip-flan-t5-xl
			VQA fine-tuned
1	OFA	(Wang et al., 2022b)	https://huggingface.co/OFA-Sys/ofa-huge-vqa
2	BLIP	(Li et al., 2022)	https://huggingface.co/Salesforce/blip-vqa-base
3	$BLIP_{CapFilt-L}$	(Li et al., 2022)	<pre>https://huggingface.co/Salesforce/blip-vqa-capfilt-large</pre>
4	ALBEF	(Li et al., 2021a)	https://github.com/salesforce/ALBEF#download#
			Finetuned-checkpoint-for-VQA
5	GIT _{LARGE}	(Wang et al., 2022a)	https://huggingface.co/microsoft/git-large-vqav2

Table 9: Variant details of the baselines in NOPE (§4.2).

I Examples of Object Hallucination in NOPE

We list the examples of object hallucination from the dev set of NOPE in Table 10.

ID	Object-scene relevance	Visual context		Question-answer
			Question GT answer	can you point out the location of the dog collar in the image? nowhere
			PromptCap OpenFlamingo	yes The dog collar is located on the dog's neck.
390	Related	0	BLIP-2 OFA	yes, it is on the dog's collar no
			BLIP	no
			ALBEF	dog's neck
			GIT _{LARGE}	no
			InstructBLIP	no
			Question	how many menu cards have been captured in the image?
			GT answer	none
		Come Ser A	PromptCap	1
			OpenFlamingo	10
822	Related	A BRA	BLIP-2 OFA	none 8
			BLIP	ð six
			ALBEF	2.3
			GIT _{LARGE}	0
			InstructBLIP	0
			Question GT answer	where can the clouds be spotted in the image? nowhere
			PromptCap	in the sky
			OpenFlamingo	On the head of a goose.
982	Related		BLIP-2	the clouds are in the sky
		The Can Constant	OFA BLIP	the sky yes
		E - COLOR COLOR	ALBEF	in the snow.
		- Standard	GIT _{LARGE}	no
			InstructBLIP	sky
		1	Question	who can you see using the fishing rod?
		V T	GT answer	nobody
			PromptCap OpenFlamingo	a gray van The owner of this Dodge B250 van.
9165	Partially related	the second second	BLIP-2	the guy in the back of the van
105			OFA	no 1
			BLIP	no idea
			ALBEF	man dancing
			GIT _{LARGE} InstructBLIP	no no one
			Question GT answer	which color is the pillow in the image? nothing
		ED	PromptCap	blue
		STO	OpenFlamingo	blue
10135	Unrelated		BLIP-2	blue
			OFA BLIP	black red and white
			ALBEF	red black white
			GIT _{LARGE}	blue
			InstructBLIP	white

Table 10: Examples of object hallucination in the dev set of NOPE. The hallucinated answers are shown in **pink**.