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

Holy Loveni[a](#page-0-0)^{∗,1,2} Wenl[i](#page-0-0)ang Dai^{†,1} Samuel Cahyawijaya^{†,1} Ziwei Ji¹ Pascale Fung¹

 $¹$ The Hong Kong University of Science and Technology</sup> 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.,](#page-13-0) [2021;](#page-13-0) [Yi et al.,](#page-13-1) [2018;](#page-13-1) [Zhou et al.,](#page-13-2) [2020;](#page-13-2) [Ray et al.,](#page-12-0) [2019;](#page-12-0) [Gokhale et al.,](#page-10-0) [2020;](#page-10-0) [Dai et al.,](#page-9-0) [2021,](#page-9-0) [2022;](#page-9-1) [Ishii](#page-10-1) [et al.,](#page-10-1) [2021;](#page-10-1) [Lovenia et al.,](#page-11-0) [2022;](#page-11-0) [Ji et al.,](#page-10-2) [2022b;](#page-10-2)

† 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.,](#page-11-1) [2023\)](#page-11-1). Furthermore, researchers have constructed more rigorous VL benchmarks to continually raise the performance standard [\(Antol](#page-9-2) [et al.,](#page-9-2) [2015;](#page-9-2) [Sheng et al.,](#page-12-1) [2021;](#page-12-1) [Li et al.,](#page-11-2) [2021b;](#page-11-2) [Goyal et al.,](#page-10-3) [2017;](#page-10-3) [Marino et al.,](#page-11-3) [2019\)](#page-11-3). 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 [\(Ji et al.,](#page-10-4) [2022a;](#page-10-4) [Rohrbach et al.,](#page-12-2) [2018;](#page-12-2) [Dai et al.,](#page-9-3) [2023b;](#page-9-3) [Kayhan et al.,](#page-11-4) [2021\)](#page-11-4). As illustrated in Figure [1,](#page-0-1) 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 [\(Jing et al.,](#page-10-5) [2020;](#page-10-5) [Agrawal et al.,](#page-9-4) [2018;](#page-9-4) [Gupta et al.,](#page-10-6) [2022;](#page-10-6) [Niu et al.,](#page-12-3) [2021a\)](#page-12-3) and statistical bias [\(Agrawal et al.,](#page-8-0) [2016;](#page-8-0) [Goyal et al.,](#page-10-3) [2017;](#page-10-3) [Agarwal et al.,](#page-8-1) [2020\)](#page-8-1). 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 [\(Rohrbach](#page-12-2) [et al.,](#page-12-2) [2018\)](#page-12-2) 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 [\(Rohrbach et al.,](#page-12-2) [2018;](#page-12-2) [Biten et al.,](#page-9-5) [2022;](#page-9-5) [Yi et al.,](#page-13-1) [2018\)](#page-13-1). 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 [\(Dai et al.,](#page-9-3) [2023b;](#page-9-3) [Biten et al.,](#page-9-5) [2022\)](#page-9-5).

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") [\(Quirk et al.,](#page-12-4) [1985\)](#page-12-4) ($NegP$); 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:

- 1. 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](#page-12-2) [et al.](#page-12-2) [\(2018\)](#page-12-2) 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.](#page-12-2) [\(2018\)](#page-12-2); [Dai et al.](#page-9-3) [\(2023b\)](#page-9-3); [Sharma et al.](#page-12-5) [\(2018\)](#page-12-5) also show that standard captioning metrics, e.g., CIDEr [\(Vedantam](#page-13-3) [et al.,](#page-13-3) [2015\)](#page-13-3), METEOR [\(Banerjee and Lavie,](#page-9-6) [2005\)](#page-9-6), SPICE [\(Niu et al.,](#page-12-6) [2022\)](#page-12-6), under-penalize object hallucination. These evaluations open up a way for efforts to mitigate hallucination in image captioning [\(Biten et al.,](#page-9-5) [2022;](#page-9-5) [Zhang et al.,](#page-13-4) [2021;](#page-13-4) [Xiao](#page-13-5) [and Wang,](#page-13-5) [2021;](#page-13-5) [Dai et al.,](#page-9-3) [2023b\)](#page-9-3). Concurrent to our work, [Li et al.](#page-11-5) [\(2023b\)](#page-11-5) 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 [\(Goyal et al.,](#page-10-3) [2017;](#page-10-3) [Antol et al.,](#page-9-2) [2015\)](#page-9-2), Visual Genome [\(Krishna et al.,](#page-11-6) [2016\)](#page-11-6), Visual7W [\(Zhu et al.,](#page-13-6) [2016\)](#page-13-6), AdVQA [\(Sheng](#page-12-1) [et al.,](#page-12-1) [2021\)](#page-12-1), Vizwiz [\(Gurari et al.,](#page-10-7) [2018,](#page-10-7) [2019\)](#page-10-8), TextVQA [\(Singh et al.,](#page-12-7) [2019\)](#page-12-7), R-VQA [\(Lu et al.,](#page-11-7) [2018\)](#page-11-7), VQA-Rephrasings [\(Shah et al.,](#page-12-8) [2019\)](#page-12-8), 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.](#page-12-9) [\(2015\)](#page-12-9) present a simple question generation algorithm with a syntactic parser to convert image descriptions into QA forms. [Johnson](#page-10-9) [et al.](#page-10-9) [\(2017\)](#page-10-9) 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](#page-10-10) [\(2017\)](#page-10-10) 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.](#page-9-7) [\(2022\)](#page-9-7) 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,](#page-2-0) there is only a minuscule amount of NegP data in the existing VQA datasets. In total, there are only ∼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} = ${'vnone", "nothing", "nowhere", "zero", "0",}$ "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} = $\{(v_i, c_i, l_i)\}_{i=1}^n$, where v_i denotes a visual context, c_i denotes a textual caption, and l_i denotes the relevant image label annotations (i.e., names of objects in v_i). We rely on 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](#page-14-0)

Figure 3: Human evaluation results of NegP questions by generate-from-scratch and list-then-rewrite according to the categories in [§3.2.](#page-2-1)

and the automatic validation methods to ensure the validity of the generated questions in Appendix [C.](#page-16-0)

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 [\(Nijkamp et al.,](#page-12-10) [2023;](#page-12-10) [Volum et al.,](#page-13-7) [2022;](#page-13-7) [Bang et al.,](#page-9-8) [2023\)](#page-9-8). 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 $o_i = \{o_{i,j}\}_{j=1}^m$ $o_i = \{o_{i,j}\}_{j=1}^m$ $o_i = \{o_{i,j}\}_{j=1}^m$ that are "closely related"¹ 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.](#page-16-1) 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 [§3.1,](#page-2-3) 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.](#page-17-0)

3.3 Results and Quality Analysis

Using automatic validation approaches explained in [§3.1](#page-2-3) and implementation details in Appendix [D,](#page-16-2) we compare the capabilities of various instructiontuned LLMs in generating NegP VQA data. From the automatic validation results and analysis presented in Appendix [F,](#page-18-0) 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.](#page-2-1)

Figure [3](#page-2-4) 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 [\(Jang et al.,](#page-10-11) [2023;](#page-10-11) [Hosseini et al.,](#page-10-12) [2021;](#page-10-12) [Ettinger,](#page-9-9) [2020;](#page-9-9) [Kassner and Schütze,](#page-10-13) [2020\)](#page-10-13) 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
			AdVOA	1350	1650
NegP	14718	17983	R-VQA	2700	3300
NOPE $(\S 3.4)$	14718	14773	TDIUC	1350	1650
AdVQA	Ω	88	TextVOA	1350	1650
R-VQA	θ	9	Visual7W	2700	3300
TDIUC	Ω	6	VizWiz	1350	1650
Visual7W	θ	1276	VQA-Rephrasings	1350	1650
VOAv1 Abstract Scenes	θ	180	VOAv1 Abstract Scenes	1350	1650
VOAv2 Balanced Real	0	1651	VOAv2 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 [\(Kuznetsova et al.,](#page-11-8) [2020\)](#page-11-8).

3.4 Dataset Statistics

NegP Question Distribution We cluster the generated questions into various types based on the starting n-grams in Figure [4.](#page-3-0) 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 [\(Shah et al.,](#page-12-8) [2019;](#page-12-8) [Ray et al.,](#page-12-0) [2019;](#page-12-0) [Kervadec et al.,](#page-11-9) [2021;](#page-11-9) [Whitehead et al.,](#page-13-8) [2020\)](#page-13-8).

Object-Scene Relevance Based on the descriptor used in the object listing step in **list-then-rewrite**^{[1](#page-2-2)}, the data in NOPE are divided into three categories. Figure [5](#page-3-1) 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 library^{[2](#page-4-1)} and the image-text similarity using CLIPScore [\(Hessel et al.,](#page-10-14) [2021\)](#page-10-14).

4 Experimental Settings

The object hallucination benchmark consists of the validation and test sets of 10 VQA corpora, including NOPE ([§3.4\)](#page-4-0) 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](#page-4-2) describes the data distribution of the dev and test sets of the benchmark. Each set respectively comprises ∼30k and ∼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,](#page-5-0) 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) [\(Covington and Mc-](#page-9-10)[Fall,](#page-9-10) [2010\)](#page-9-10), measure of textual lexical diversity (MTLD) [\(McCarthy,](#page-11-10) [2005\)](#page-11-10), and hypergeometric distribution diversity (HDD) [\(McCarthy and Jarvis,](#page-11-11) [2007,](#page-11-11) [2010\)](#page-11-12), and average them. We use Lexical-Richness [\(Shen,](#page-12-11) [2021,](#page-12-11) [2022\)](#page-12-12) v0.5.0^{[3](#page-4-3)} to calculate these metrics. We also employ a large pre-trained LM GPT-Neo [\(Black et al.,](#page-9-11) [2021\)](#page-9-11) with 2.7B param-

² [https://www.sbert.net/docs/usage/semantic_](https://www.sbert.net/docs/usage/semantic_textual_similarity.html) [textual_similarity.html](https://www.sbert.net/docs/usage/semantic_textual_similarity.html)

³ <https://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 [\(Lewis et al.,](#page-11-13) [2017;](#page-11-13) [Tevet and Berant,](#page-12-13) [2021\)](#page-12-13) and fluency [\(Fan et al.,](#page-10-15) [2018;](#page-10-15) [Wang et al.,](#page-13-9) [2019;](#page-13-9) [Cahyawijaya et al.,](#page-9-12) [2021;](#page-9-12) [Anonymous,](#page-9-13) [2023\)](#page-9-13).

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 [\(Wang et al.,](#page-13-10) [2022b\)](#page-13-10), 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 [\(Li et al.,](#page-11-14) [2022\)](#page-11-14), 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 [\(Li et al.,](#page-11-15) [2021a\)](#page-11-15), which is trained using momentum distillation to improve learning from noisy web data; 5) GIT [\(Wang et al.,](#page-13-11) [2022a\)](#page-13-11), 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 [\(Li et al.,](#page-11-16) [2023a\)](#page-11-16), which utilizes a scalable multimodal pre-training method to enable any LLMs to ingest and understand images; 2) and 3) Prompt-Cap [\(Hu et al.,](#page-10-16) [2022\)](#page-10-16), which is trained to generate captions that help downstream LMs answer visual questions; 4) InstructBLIP [\(Dai et al.,](#page-9-14) [2023a\)](#page-9-14), which is an instruction-tuned version of BLIP-2 on various tasks including VQA. We also employ 5) OpenFlamingo [\(Alayrac et al.,](#page-9-15) [2022;](#page-9-15) [Awadalla](#page-9-16) [et al.,](#page-9-16) [2023\)](#page-9-16), which is an open-source version of

	Model size	# Pre-train images			
Zero-shot & Few-shot					
PromptCap _{BASE}	696M	34M			
PromptCap	3B	34M			
BI $IP-2$	3.8B	129M			
OpenFlamingo	9Β	\sim 2.5B			
VOA 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](#page-5-1) provides the model and data sizes of the baselines and Appendix [H](#page-20-0) lists the model variants.

4.3 Evaluation Settings

For both NegP and Others, we compute accuracy and METEOR [\(Banerjee and Lavie,](#page-9-6) [2005\)](#page-9-6) 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.](#page-6-0) Examples of object hallucination are in Appendix [I.](#page-20-1) 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,](#page-6-1) 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 $(\%)$						
	Overall		Existing datasets		NOPE test $(\S3.4)$		Overall		
	Acc.	METEOR	Acc.	METEOR	Acc.	METEOR	NegP Acc.	Acc.	METEOR
				Zero-shot & few-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	0.08	0.02	0.02	1.49
				VQA fine-tuned					
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
$\mathop{\rm BLIP}\nolimits_{CapFilt-L}$	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
$\operatorname{GIT}_{LARGE}$	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 underline 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\)](#page-5-1) 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 [\(Hoffmann et al.,](#page-10-17) [2022\)](#page-10-17), 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](#page-6-0) 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\)](#page-5-0). 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,](#page-7-0) 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\)](#page-4-4).

lines 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 ≤ 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 [\(KV and Mittal,](#page-11-17) [2020;](#page-11-17) [Niu et al.,](#page-12-14) [2021b;](#page-12-14) [Wu](#page-13-12) [et al.,](#page-13-12) [2022\)](#page-13-12) 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.

shot and (right) VQA fine-tuned baselines per objectscene relevance.

6.3 Object hallucination and object-scene relevance

As shown in Figure [10,](#page-7-1) 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 [\(Rohrbach et al.,](#page-12-2) [2018;](#page-12-2) [Kayhan et al.,](#page-11-4) [2021;](#page-11-4) [Dai et al.,](#page-9-3) [2023b\)](#page-9-3). 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.](#page-3-1) 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 ∼15k data in our dev split and ∼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.

Acknowledgements

This work has been partially funded by PhD Fellowship Award, the Hong Kong University of Science and Technology; PF20-43679 Hong Kong PhD Fellowship Scheme, Research Grant Council, Hong Kong; and the National Research Foundation, Singapore under its AI Singapore Programme.

References

- Vedika Agarwal, Rakshith Shetty, and Mario Fritz. 2020. Towards causal vqa: Revealing and reducing spurious correlations by invariant and covariant semantic editing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9690–9698.
- Aishwarya Agrawal, Dhruv Batra, and Devi Parikh. 2016. Analyzing the behavior of visual question answering models. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1955–1960.
- Aishwarya Agrawal, Dhruv Batra, Devi Parikh, and Aniruddha Kembhavi. 2018. Don't just assume; look and answer: Overcoming priors for visual question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4971–4980.
- Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. 2022. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736.
- Anonymous. 2023. Nusawrites: Constructing highquality corpora for underrepresented and extremely low-resource languages. Anonymous preprint under review.
- Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In *Proceedings of the IEEE international conference on computer vision*, pages 2425–2433.
- Anas Awadalla, Irena Gao, Joshua Gardner, Jack Hessel, Yusuf Hanafy, Wanrong Zhu, Kalyani Marathe, Yonatan Bitton, Samir Gadre, Jenia Jitsev, Simon Kornblith, Pang Wei Koh, Gabriel Ilharco, Mitchell Wortsman, and Ludwig Schmidt. 2023. [Open](https://doi.org/10.5281/zenodo.7733589)[flamingo.](https://doi.org/10.5281/zenodo.7733589)
- Satanjeev Banerjee and Alon Lavie. 2005. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization*, pages 65–72.
- Yejin Bang, Samuel Cahyawijaya, Nayeon Lee, Wenliang Dai, Dan Su, Bryan Wilie, Holy Lovenia, Ziwei Ji, Tiezheng Yu, Willy Chung, et al. 2023. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity. *arXiv preprint arXiv:2302.04023*.
- Ali Furkan Biten, Lluis Gomez, and Dimosthenis Karatzas. 2022. Let there be a clock on the beach: Reducing object hallucination in image captioning. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1381–1390.
- Sid Black, Leo Gao, Phil Wang, Connor Leahy, and Stella Biderman. 2021. [GPT-Neo: Large](https://doi.org/10.5281/zenodo.5297715) [Scale Autoregressive Language Modeling with Mesh-](https://doi.org/10.5281/zenodo.5297715)[Tensorflow.](https://doi.org/10.5281/zenodo.5297715)
- Samuel Cahyawijaya, Genta Indra Winata, Bryan Wilie, Karissa Vincentio, Xiaohong Li, Adhiguna Kuncoro, Sebastian Ruder, Zhi Yuan Lim, Syafri Bahar, Masayu Khodra, Ayu Purwarianti, and Pascale Fung. 2021. [IndoNLG: Benchmark and resources for](https://doi.org/10.18653/v1/2021.emnlp-main.699) [evaluating Indonesian natural language generation.](https://doi.org/10.18653/v1/2021.emnlp-main.699) In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages

8875–8898, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

- Soravit Changpinyo, Doron Kukliansy, Idan Szpektor, Xi Chen, Nan Ding, and Radu Soricut. 2022. All you may need for vqa are image captions. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1947–1963.
- Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. 2017. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.
- Michael A. Covington and Joe D. McFall. 2010. [Cutting](https://doi.org/10.1080/09296171003643098) [the gordian knot: The moving-average type–token](https://doi.org/10.1080/09296171003643098) [ratio \(MATTR\).](https://doi.org/10.1080/09296171003643098) *Journal of Quantitative Linguistics*, 17(2):94–100.
- Wenliang Dai, Samuel Cahyawijaya, Zihan Liu, and Pascale Fung. 2021. [Multimodal end-to-end sparse](https://doi.org/10.18653/v1/2021.naacl-main.417) [model for emotion recognition.](https://doi.org/10.18653/v1/2021.naacl-main.417) In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5305–5316, Online. Association for Computational Linguistics.
- Wenliang Dai, Lu Hou, Lifeng Shang, Xin Jiang, Qun Liu, and Pascale Fung. 2022. [Enabling multimodal](https://doi.org/10.18653/v1/2022.findings-acl.187) [generation on CLIP via vision-language knowledge](https://doi.org/10.18653/v1/2022.findings-acl.187) [distillation.](https://doi.org/10.18653/v1/2022.findings-acl.187) In *Findings of the Association for Computational Linguistics: ACL 2022*, pages 2383–2395, Dublin, Ireland. Association for Computational Linguistics.
- Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale Fung, and Steven Hoi. 2023a. [In](http://arxiv.org/abs/2305.06500)[structblip: Towards general-purpose vision-language](http://arxiv.org/abs/2305.06500) [models with instruction tuning.](http://arxiv.org/abs/2305.06500)
- Wenliang Dai, Zihan Liu, Ziwei Ji, Dan Su, and Pascale Fung. 2023b. [Plausible may not be faithful: Probing](https://aclanthology.org/2023.eacl-main.156) [object hallucination in vision-language pre-training.](https://aclanthology.org/2023.eacl-main.156) pages 2136–2148.
- Zhengxiao Du, Yujie Qian, Xiao Liu, Ming Ding, Jiezhong Qiu, Zhilin Yang, and Jie Tang. 2022. Glm: General language model pretraining with autoregressive blank infilling. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 320–335.
- Allyson Ettinger. 2020. What bert is not: Lessons from a new suite of psycholinguistic diagnostics for language models. *Transactions of the Association for Computational Linguistics*, 8:34–48.
- Angela Fan, Mike Lewis, and Yann Dauphin. 2018. [Hierarchical neural story generation.](https://doi.org/10.18653/v1/P18-1082) In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 889–898, Melbourne, Australia. Association for Computational Linguistics.
- Tejas Gokhale, Pratyay Banerjee, Chitta Baral, and Yezhou Yang. 2020. Mutant: A training paradigm for out-of-distribution generalization in visual question answering. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 878–892.
- Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. 2017. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 6904–6913.
- Vipul Gupta, Zhuowan Li, Adam Kortylewski, Chenyu Zhang, Yingwei Li, and Alan Yuille. 2022. Swapmix: Diagnosing and regularizing the over-reliance on visual context in visual question answering. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5078–5088.
- Danna Gurari, Qing Li, Chi Lin, Yinan Zhao, Anhong Guo, Abigale Stangl, and Jeffrey P Bigham. 2019. Vizwiz-priv: A dataset for recognizing the presence and purpose of private visual information in images taken by blind people. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 939–948.
- Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. 2018. Vizwiz grand challenge: Answering visual questions from blind people. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3608–3617.
- Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. 2021. [CLIPScore: A](https://doi.org/10.18653/v1/2021.emnlp-main.595) [reference-free evaluation metric for image captioning.](https://doi.org/10.18653/v1/2021.emnlp-main.595) In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 7514–7528, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.
- Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. 2022. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*.
- Arian Hosseini, Siva Reddy, Dzmitry Bahdanau, R Devon Hjelm, Alessandro Sordoni, and Aaron Courville. 2021. [Understanding by understanding not: Model](https://doi.org/10.18653/v1/2021.naacl-main.102)[ing negation in language models.](https://doi.org/10.18653/v1/2021.naacl-main.102) In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 1301–1312, Online. Association for Computational Linguistics.
- Yushi* Hu, Hang* Hua, Zhengyuan Yang, Weijia Shi, Noah A Smith, and Jiebo Luo. 2022. Promptcap: Prompt-guided task-aware image captioning. *arXiv preprint arXiv:2211.09699*.
- Etsuko Ishii, Genta Indra Winata, Samuel Cahyawijaya, Divesh Lala, Tatsuya Kawahara, and Pascale Fung. 2021. [ERICA: An empathetic android companion](https://aclanthology.org/2021.sigdial-1.27) [for covid-19 quarantine.](https://aclanthology.org/2021.sigdial-1.27) In *Proceedings of the 22nd Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 257–260, Singapore and Online. Association for Computational Linguistics.
- Srinivasan Iyer, Xi Victoria Lin, Ramakanth Pasunuru, Todor Mihaylov, Dániel Simig, Ping Yu, Kurt Shuster, Tianlu Wang, Qing Liu, Punit Singh Koura, et al. 2022. Opt-iml: Scaling language model instruction meta learning through the lens of generalization. *arXiv preprint arXiv:2212.12017*.
- Joel Jang, Seonghyeon Ye, and Minjoon Seo. 2023. Can large language models truly understand prompts? a case study with negated prompts. In *Transfer Learning for Natural Language Processing Workshop*, pages 52–62. PMLR.
- Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Yejin Bang, Andrea Madotto, and Pascale Fung. 2022a. Survey of hallucination in natural language generation. *ACM Computing Surveys*.
- Ziwei Ji, Yan Xu, I-Tsun Cheng, Samuel Cahyawijaya, Rita Frieske, Etsuko Ishii, Min Zeng, Andrea Madotto, and Pascale Fung. 2022b. [VScript: Control](https://aclanthology.org/2022.aacl-demo.1)[lable script generation with visual presentation.](https://aclanthology.org/2022.aacl-demo.1) In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing: System Demonstrations*, pages 1–8, Taipei, Taiwan. Association for Computational Linguistics.
- Chenchen Jing, Yuwei Wu, Xiaoxun Zhang, Yunde Jia, and Qi Wu. 2020. Overcoming language priors in vqa via decomposed linguistic representations. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 11181–11188.
- Justin Johnson, Bharath Hariharan, Laurens Van Der Maaten, Li Fei-Fei, C Lawrence Zitnick, and Ross Girshick. 2017. Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2901–2910.
- Kushal Kafle and Christopher Kanan. 2017. An analysis of visual question answering algorithms. In *Proceedings of the IEEE international conference on computer vision*, pages 1965–1973.
- Nora Kassner and Hinrich Schütze. 2020. Negated and misprimed probes for pretrained language models: Birds can talk, but cannot fly. In *Proceedings of the*

58th Annual Meeting of the Association for Computational Linguistics, pages 7811–7818.

- Osman Semih Kayhan, Bart Vredebregt, and Jan C. van Gemert. 2021. Hallucination in object detection [a study in visual part verification.](https://doi.org/10.1109/ICIP42928.2021.9506670) In *2021 IEEE International Conference on Image Processing (ICIP)*, pages 2234–2238.
- Corentin Kervadec, Grigory Antipov, Moez Baccouche, and Christian Wolf. 2021. Roses are red, violets are blue... but should vqa expect them to? In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 2776– 2785.
- Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, Michael Bernstein, and Li Fei-Fei. 2016. [Visual](https://arxiv.org/abs/1602.07332) [genome: Connecting language and vision using](https://arxiv.org/abs/1602.07332) [crowdsourced dense image annotations.](https://arxiv.org/abs/1602.07332)
- Alina Kuznetsova, Hassan Rom, Neil Alldrin, Jasper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Malloci, Alexander Kolesnikov, et al. 2020. The open images dataset v4: Unified image classification, object detection, and visual relationship detection at scale. *International Journal of Computer Vision*, 128(7):1956–1981.
- Gouthaman KV and Anurag Mittal. 2020. Reducing language biases in visual question answering with visually-grounded question encoder. In *Computer Vision – ECCV 2020*, pages 18–34, Cham. Springer International Publishing.
- Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. [Deal or no deal? end-to](https://doi.org/10.18653/v1/D17-1259)[end learning of negotiation dialogues.](https://doi.org/10.18653/v1/D17-1259) In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2443–2453, Copenhagen, Denmark. Association for Computational Linguistics.
- Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. 2023a. Blip-2: Bootstrapping language-image pretraining with frozen image encoders and large language models. *ICML*.
- Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. 2022. Blip: Bootstrapping language-image pretraining for unified vision-language understanding and generation. In *International Conference on Machine Learning*, pages 12888–12900. PMLR.
- Junnan Li, Ramprasaath Selvaraju, Akhilesh Gotmare, Shafiq Joty, Caiming Xiong, and Steven Chu Hong Hoi. 2021a. Align before fuse: Vision and language representation learning with momentum distillation. *Advances in neural information processing systems*, 34:9694–9705.
- Linjie Li, Jie Lei, Zhe Gan, and Jingjing Liu. 2021b. Adversarial vqa: A new benchmark for evaluating the robustness of vqa models. In *Proceedings of the*

IEEE/CVF International Conference on Computer Vision, pages 2042–2051.

- Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. 2023b. Evaluating object hallucination in large vision-language models. *arXiv preprint arXiv:2305.10355*.
- Holy Lovenia, Samuel Cahyawijaya, and Pascale Fung. 2023. [Which one are you referring to? multimodal](https://aclanthology.org/2023.eacl-srw.6) [object identification in situated dialogue.](https://aclanthology.org/2023.eacl-srw.6) In *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 61–72, Dubrovnik, Croatia. Association for Computational Linguistics.
- Holy Lovenia, Bryan Wilie, Romain Barraud, Samuel Cahyawijaya, Willy Chung, and Pascale Fung. 2022. [Every picture tells a story: Image-grounded control](https://aclanthology.org/2022.latechclfl-1.6)[lable stylistic story generation.](https://aclanthology.org/2022.latechclfl-1.6) In *Proceedings of the 6th Joint SIGHUM Workshop on Computational Linguistics for Cultural Heritage, Social Sciences, Humanities and Literature*, pages 40–52, Gyeongju, Republic of Korea. International Conference on Computational Linguistics.
- Pan Lu, Lei Ji, Wei Zhang, Nan Duan, Ming Zhou, and Jianyong Wang. 2018. R-vqa: Learning visual relation facts with semantic attention for visual question answering. In *SIGKDD 2018*.
- Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. 2019. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/cvf conference on computer vision and pattern recognition*, pages 3195–3204.
- Philip M. McCarthy. 2005. *An assessment of the range and usefulness of lexical diversity measures and the potential of the measure of textual, lexical diversity (MTLD)*. Ph.D. thesis, The University of Memphis.
- Philip M McCarthy and Scott Jarvis. 2007. vocd: A theoretical and empirical evaluation. *Language Testing*, 24(4):459–488.
- Philip M. McCarthy and Scott Jarvis. 2010. [MTLD,](https://doi.org/10.3758/brm.42.2.381) [vocd-d, and HD-d: A validation study of sophis](https://doi.org/10.3758/brm.42.2.381)[ticated approaches to lexical diversity assessment.](https://doi.org/10.3758/brm.42.2.381) *Behavior Research Methods*, 42(2):381–392.
- Niklas Muennighoff, Thomas Wang, Lintang Sutawika, Adam Roberts, Stella Biderman, Teven Le Scao, M Saiful Bari, Sheng Shen, Zheng-Xin Yong, Hailey Schoelkopf, Xiangru Tang, Dragomir Radev, Alham Fikri Aji, Khalid Almubarak, Samuel Albanie, Zaid Alyafeai, Albert Webson, Edward Raff, and Colin Raffel. 2022. [Crosslingual generalization](http://arxiv.org/abs/2211.01786) [through multitask finetuning.](http://arxiv.org/abs/2211.01786)
- Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A new benchmark for natural language understanding. In *Proceedings of the 58th Annual Meeting*

of the Association for Computational Linguistics. Association for Computational Linguistics.

- Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. 2023. Codegen: An open large language model for code with multi-turn program synthesis. In *The Eleventh International Conference on Learning Representations (ICLR)*.
- Chuang Niu, Hongming Shan, and Ge Wang. 2022. Spice: Semantic pseudo-labeling for image clustering. *IEEE Transactions on Image Processing*, 31:7264–7278.
- Yulei Niu, Kaihua Tang, Hanwang Zhang, Zhiwu Lu, Xian-Sheng Hua, and Ji-Rong Wen. 2021a. Counterfactual vqa: A cause-effect look at language bias. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12700– 12710.
- Yulei Niu, Kaihua Tang, Hanwang Zhang, Zhiwu Lu, Xian-Sheng Hua, and Ji-Rong Wen. 2021b. [Coun](https://doi.org/10.1109/CVPR46437.2021.01251)[terfactual vqa: A cause-effect look at language bias.](https://doi.org/10.1109/CVPR46437.2021.01251) pages 12695–12705.
- Randolph Quirk, Sidney Greenbaum, Geoffrey Leech, and Jan Svartoik. 1985. *A COMPREHENSIVE GRAMMAR OF THE ENGLISH LANGUAGE*. Longman, New York.
- Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. [Exploring the](http://jmlr.org/papers/v21/20-074.html) [limits of transfer learning with a unified text-to-text](http://jmlr.org/papers/v21/20-074.html) [transformer.](http://jmlr.org/papers/v21/20-074.html) *Journal of Machine Learning Research*, 21(140):1–67.
- Arijit Ray, Karan Sikka, Ajay Divakaran, Stefan Lee, and Giedrius Burachas. 2019. Sunny and dark outside?! improving answer consistency in vqa through entailed question generation. *arXiv preprint arXiv:1909.04696*.
- Mengye Ren, Ryan Kiros, and Richard Zemel. 2015. Exploring models and data for image question answering. *Advances in neural information processing systems*, 28.
- Anna Rohrbach, Lisa Anne Hendricks, Kaylee Burns, Trevor Darrell, and Kate Saenko. 2018. Object hallucination in image captioning. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4035–4045.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey,

et al. 2022. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*.

- Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. 2022. Bloom: A 176bparameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*.
- Meet Shah, Xinlei Chen, Marcus Rohrbach, and Devi Parikh. 2019. Cycle-consistency for robust visual question answering. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6649–6658.
- Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. 2018. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2556–2565.
- Lucas Shen. 2021. [Measuring political media slant](https://www.lucasshen.com/research/media.pdf) [using text data.](https://www.lucasshen.com/research/media.pdf)
- Lucas Shen. 2022. [LexicalRichness: A small module to](https://doi.org/10.5281/zenodo.6607007) [compute textual lexical richness.](https://doi.org/10.5281/zenodo.6607007)
- Sasha Sheng, Amanpreet Singh, Vedanuj Goswami, Jose Magana, Tristan Thrush, Wojciech Galuba, Devi Parikh, and Douwe Kiela. 2021. Human-adversarial visual question answering. *Advances in Neural Information Processing Systems*, 34:20346–20359.
- Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. 2019. Towards vqa models that can read. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*.
- Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. 2020. Learning to summarize with human feedback. *Advances in Neural Information Processing Systems*, 33:3008– 3021.
- Guy Tevet and Jonathan Berant. 2021. [Evaluating the](https://doi.org/10.18653/v1/2021.eacl-main.25) [evaluation of diversity in natural language generation.](https://doi.org/10.18653/v1/2021.eacl-main.25) In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 326–346, Online. Association for Computational Linguistics.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. 2023. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*.
- Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575.
- Ryan Volum, Sudha Rao, Michael Xu, Gabriel Des-Garennes, Chris Brockett, Benjamin Van Durme, Olivia Deng, Akanksha Malhotra, and Bill Dolan. 2022. [Craft an iron sword: Dynamically generating](https://doi.org/10.18653/v1/2022.wordplay-1.3) [interactive game characters by prompting large lan](https://doi.org/10.18653/v1/2022.wordplay-1.3)[guage models tuned on code.](https://doi.org/10.18653/v1/2022.wordplay-1.3) In *Proceedings of the 3rd Wordplay: When Language Meets Games Workshop (Wordplay 2022)*, pages 25–43, Seattle, United States. Association for Computational Linguistics.
- Jianfeng Wang, Zhengyuan Yang, Xiaowei Hu, Linjie Li, Kevin Lin, Zhe Gan, Zicheng Liu, Ce Liu, and Lijuan Wang. 2022a. Git: A generative image-to-text transformer for vision and language. *Transactions of Machine Learning Research*.
- Peng Wang, An Yang, Rui Men, Junyang Lin, Shuai Bai, Zhikang Li, Jianxin Ma, Chang Zhou, Jingren Zhou, and Hongxia Yang. 2022b. Ofa: Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework. In *International Conference on Machine Learning*, pages 23318–23340. PMLR.
- Qingyun Wang, Lifu Huang, Zhiying Jiang, Kevin Knight, Heng Ji, Mohit Bansal, and Yi Luan. 2019. [PaperRobot: Incremental draft generation of scien](https://doi.org/10.18653/v1/P19-1191)[tific ideas.](https://doi.org/10.18653/v1/P19-1191) In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1980–1991, Florence, Italy. Association for Computational Linguistics.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022c. Self-instruct: Aligning language model with self generated instructions. *arXiv preprint arXiv:2212.10560*.
- Jason Wei, Maarten Paul Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew Mingbo Dai, and Quoc V. Le. 2022a. [Finetuned](https://openreview.net/forum?id=gEZrGCozdqR) [language models are zero-shot learners.](https://openreview.net/forum?id=gEZrGCozdqR) In *International Conference on Learning Representations (ICLR)*.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed H Chi, Quoc V Le, Denny Zhou, et al. 2022b. Chain-of-thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems*.
- Spencer Whitehead, Hui Wu, Yi Ren Fung, Heng Ji, Rogerio Feris, and Kate Saenko. 2020. Learning from lexical perturbations for consistent visual question answering. *arXiv preprint arXiv:2011.13406*.
- Yike Wu, Yu Zhao, Shiwan Zhao, Ying Zhang, Xiaojie Yuan, Guoqing Zhao, and Ning Jiang. 2022. [Over](https://aclanthology.org/2022.coling-1.503)[coming language priors in visual question answering](https://aclanthology.org/2022.coling-1.503)

[via distinguishing superficially similar instances.](https://aclanthology.org/2022.coling-1.503) In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 5721–5729, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.

- Yijun Xiao and William Yang Wang. 2021. On hallucination and predictive uncertainty in conditional language generation. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*.
- Zhengyuan Yang, Yijuan Lu, Jianfeng Wang, Xi Yin, Dinei Florencio, Lijuan Wang, Cha Zhang, Lei Zhang, and Jiebo Luo. 2021. Tap: Text-aware pretraining for text-vqa and text-caption. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 8751–8761.
- Kexin Yi, Jiajun Wu, Chuang Gan, Antonio Torralba, Pushmeet Kohli, and Josh Tenenbaum. 2018. Neuralsymbolic vqa: Disentangling reasoning from vision and language understanding. *Advances in neural information processing systems*, 31.
- Aohan Zeng, Xiao Liu, Zhengxiao Du, Zihan Wang, Hanyu Lai, Ming Ding, Zhuoyi Yang, Yifan Xu, Wendi Zheng, Xiao Xia, Weng Lam Tam, Zixuan Ma, Yufei Xue, Jidong Zhai, Wenguang Chen, Zhiyuan Liu, Peng Zhang, Yuxiao Dong, and Jie Tang. 2023. [GLM-130b: An open bilingual pre-trained model.](https://openreview.net/forum?id=-Aw0rrrPUF) In *The Eleventh International Conference on Learning Representations (ICLR)*.
- Susan Zhang, Stephen Roller, Naman Goyal, Mikel Artetxe, Moya Chen, Shuohui Chen, Christopher Dewan, Mona Diab, Xian Li, Xi Victoria Lin, et al. 2022. Opt: Open pre-trained transformer language models. *arXiv preprint arXiv:2205.01068*.
- Wenqiao Zhang, Haochen Shi, Siliang Tang, Jun Xiao, Qiang Yu, and Yueting Zhuang. 2021. Consensus graph representation learning for better grounded image captioning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 3394–3402.
- Luowei Zhou, Hamid Palangi, Lei Zhang, Houdong Hu, Jason Corso, and Jianfeng Gao. 2020. Unified visionlanguage pre-training for image captioning and vqa. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 13041–13049.
- Yuke Zhu, Oliver Groth, Michael Bernstein, and Li Fei-Fei. 2016. Visual7w: Grounded question answering in images. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4995–5004.

A Prompt Templates

We provide the prompt templates and examples for the **generate-from-scratch** and **list-then-rewrite** methods in Table [4](#page-14-1) and Table [5,](#page-15-0) 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** $(\S 3.1)$ 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\)](#page-2-3) and their corresponding examples.

B Reference Question Templates

Table [6](#page-16-3) presents the pool of question templates used to automatically build the reference questions for the list-then-rewrite in [§3.1.](#page-2-3)

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.](#page-2-3)

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](#page-2-3) with the following LLMs that employ: 1) multi-task prompted fine-tuning, i.e., BLOOMZ [\(Muennighoff et al.,](#page-11-18) [2022\)](#page-11-18) and T0 [\(Sanh et al.,](#page-12-15) [2022\)](#page-12-15); 2) instruction meta-learning, i.e., OPT-IML [\(Iyer et al.,](#page-10-18) [2022\)](#page-10-18); 3) synthetic self-instruct, i.e., Alpaca [\(Wang et al.,](#page-13-13) [2022c\)](#page-13-13); 4) instruction [\(Wei et al.,](#page-13-14) [2022a\)](#page-13-14) and chain-of-thought fine-tuning [\(Wei et al.,](#page-13-15) [2022b\)](#page-13-15), i.e., FLAN T5 and FLAN Alpaca [\(Chung et al.,](#page-9-17) [2022\)](#page-9-17); 5) multi-task instruction pre-training, i.e., ChatGLM [\(Zeng et al.,](#page-13-16) [2023\)](#page-13-16); 6) conversation-style instruction tuning and reinforcement learning with human feedback (RLHF) [\(Christiano](#page-9-18) [et al.,](#page-9-18) [2017;](#page-9-18) [Stiennon et al.,](#page-12-16) [2020\)](#page-12-16), i.e., ChatGPT (GPT-3.5). More details are presented in Table [7.](#page-17-1)

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.,](#page-11-19) 2020).^{[4](#page-16-4)} For automatic validation with image-QA pair classification, we build a simple CLIP-based [\(Radford et al.,](#page-12-17) [2021\)](#page-12-17) binary classifier. We provide the details in Appendix [D.1.](#page-16-5) 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

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

No	Model	Size	References	Access
	BLOOMZ (3B)	3B	(Muennighoff et al., 2022; Scao et al., 2022)	https://huggingface.co/bigscience/bloomz-3b
	BLOOMZ (7.1B)	7.1B	(Muennighoff et al., 2022; Scao et al., 2022)	https://huggingface.co/bigscience/bloomz-7b1
	T0	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
	Alpaca	7В	(Wang et al., 2022c; Touvron et al., 2023)	https://huggingface.co/chavinlo/alpaca-native
6	FLANT5 XL	3B	(Chung et al., 2022; Raffel et al., 2020)	https://huggingface.co/google/flan-t5-xl
	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	6 _B	(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.](#page-16-2)

(Balanced Real) [\(Antol et al.,](#page-9-2) [2015\)](#page-9-2), AdVQA [\(Sheng et al.,](#page-12-1) [2021\)](#page-12-1), VizWiz [\(Gurari et al.,](#page-10-7) [2018,](#page-10-7) [2019\)](#page-10-8), TextVQA [\(Singh et al.,](#page-12-7) [2019\)](#page-12-7), R-VQA [\(Lu et al.,](#page-11-7) [2018\)](#page-11-7), Visual7W [\(Zhu et al.,](#page-13-6) [2016\)](#page-13-6), TDIUC [\(Kafle and](#page-10-10) [Kanan,](#page-10-10) [2017\)](#page-10-10), VQA-Rephrasings [\(Shah et al.,](#page-12-8) [2019\)](#page-12-8), and VQAv1 (Abstract Scenes) [\(Antol et al.,](#page-9-2) [2015\)](#page-9-2).

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-OA 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 [\(Radford](#page-12-17) [et al.,](#page-12-17) [2021\)](#page-12-17). We leverage the image-text alignment learned by CLIP [\(Radford et al.,](#page-12-17) [2021\)](#page-12-17), 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\)](#page-2-1) in Figure [11.](#page-17-2)

Figure 11: Examples of the human evaluation judgments for the **generate-from-scratch** prompting method in [§3.2.](#page-2-1)

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\)](#page-2-3) over five prompt templates.

Figure 13: Human evaluation results on NegP questions generated by ChatGPT using generate-from-scratch ([§3.1\)](#page-2-3). The Y-axis denotes the verdict from the automatic validators, i.e., caption-QA and image-QA entailment models.

Generate-from-scratch Figure [12](#page-18-1) shows the proportions of valid generated NegP VQA data using 10 instruction-tuned LLMs listed in Appendix [D](#page-16-2) over five different prompt templates, where each model generates 1k questions per template. The prompt templates are provided in Appendix [A.](#page-14-0) The result shows that only ∼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\)](#page-2-1) 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.](#page-2-1) Figure [13](#page-18-2) 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	п	10
FLAN T5 XXL		
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\)](#page-2-3).

Figure 14: Human evaluation results on NegP questions generated by ChatGPT using list-then-rewrite ([§3.1\)](#page-2-3).

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.](#page-19-0) The bestperforming 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\)](#page-16-2).

Our human evaluation on 300 generated questions by ChatGPT (presented in Figure [14\)](#page-19-1) 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 [\(Antol et al.,](#page-9-2) [2015\)](#page-9-2) which utilizes a manual data generation method (presented in Figure [15a\)](#page-20-2) and VQA-Rephrasings dataset [\(Shah et al.,](#page-12-8) [2019\)](#page-12-8) which utilizes an automatic data generation method (presented in Figure [15b\)](#page-20-2).

(a) VQAv2 dataset [\(Antol et al.,](#page-9-2) [2015\)](#page-9-2) (b) $VQ²A$ dataset [\(Changpinyo et al.,](#page-9-7) [2022\)](#page-9-7)

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.](#page-20-3)

Table 9: Variant details of the baselines in NOPE ([§4.2\)](#page-5-2).

I Examples of Object Hallucination in NOPE

We list the examples of object hallucination from the dev set of NOPE in Table [10.](#page-21-0)

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
390	Related		PromptCap OpenFlamingo BLIP-2 OFA BLIP ALBEF \mathbf{GIT}_{LARGE} InstructBLIP	yes The dog collar is located on the dog's neck. yes, it is on the dog's collar no no dog's neck \rm{no} no
			Question GT answer	how many menu cards have been captured in the image? none
822	Related		PromptCap OpenFlamingo BLIP-2 OFA BLIP ALBEF \mathbf{GIT}_{LARGE} InstructBLIP	1 10 none 8 six 2,3 $\boldsymbol{0}$ $\boldsymbol{0}$
982	Related		Question GT answer PromptCap OpenFlamingo BLIP-2 OFA BLIP ALBEF \mathbf{GIT}_{LARGE} InstructBLIP	where can the clouds be spotted in the image? nowhere in the sky On the head of a goose. the clouds are in the sky the sky yes in the snow. no sky
9165	Partially related		Question GT answer PromptCap OpenFlamingo BLIP-2 OFA BLIP ALBEF \mathbf{GIT}_{LARGE} InstructBLIP	who can you see using the fishing rod? nobody a gray van The owner of this Dodge B250 van. the guy in the back of the van no 1 no idea man dancing no no one
10135	Unrelated	FESTD	Question GT answer PromptCap OpenFlamingo BLIP-2 OFA BLIP ALBEF \mathbf{GIT}_{LARGE} InstructBLIP	which color is the pillow in the image? nothing blue blue blue black red and white red black white blue white

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