Adversarial VQA: A New Benchmark for Evaluating the Robustness of VQA Models

adversarialvqa.github.io

Linjie Li¹, Jie Lei², Zhe Gan¹, Jingjing Liu³

¹Microsoft ²UNC Chapel Hill ³Tsinghua University

{lindsey.li, zhe.gan}@microsoft.com jielei@cs.unc.edu, JJLiu@air.tsinghua.edu.cn

Abstract

Benefiting from large-scale pre-training, we have witnessed significant performance boost on the popular Visual Question Answering (VQA) task. Despite rapid progress, it remains unclear whether these state-of-the-art (SOTA) models are robust when encountering examples in the wild. To study this, we introduce Adversarial VOA, a new largescale VQA benchmark, collected iteratively via an adversarial human-and-model-in-the-loop procedure. Through this new benchmark, we discover several interesting findings. (i) Surprisingly, we find that during dataset collection, non-expert annotators can easily attack SOTA VQA models successfully. (ii) Both large-scale pre-trained models and adversarial training methods achieve far worse performance on the new benchmark than over standard VQA v2 dataset, revealing the fragility of these models while demonstrating the effectiveness of our adversarial dataset. (iii) When used for data augmentation, our dataset can effectively boost model performance on other robust VOA benchmarks. We hope our Adversarial VQA dataset can shed new light on robustness study in the community and serve as a valuable benchmark for future work.

1. Introduction

Visual Question Answering (VQA) [4] is a task where given an image and a question about it, the model provides an open-ended answer. A successful VQA system can be applied to real-life scenarios such as a chatbot that assists visually impaired people. In these applications, the VQA models are expected to handle diverse question types from recognition to reasoning, and answer questions faithfully based on the evidence in the image.

While model performance on the popular VQA dataset [14] has been advanced in recent years [4, 19, 3, 50, 9, 43, 54], with better visual representations [18, 54],



Figure 1: Illustration of data collection examples. The workers try to attack the VQA model for at most 5 times by asking *hard* questions about the image, and succeeds at the last attempt. Green (red) indicates a correct (wrong) answer.

more sophisticated model designs [12, 27], large-scale pretraining [30, 41, 7, 42, 55] and adversarial training [11], today's VQA models are still far from being robust enough for practical use. There are some works studying the robustness of VQA models, such as their sensitivity to visual content manipulation [1], answer distribution shift [2], linguistic variations in input questions [39], and reasoning capabilities [13, 38]. However, current robust VQA benchmarks mostly suffer from three main limitations: (i) designed with heuristic rules [13, 2, 1]; (ii) focused on a single type of robustness [38, 39, 13]; (iii) based on VQA v2 [14] images (or questions), which state-of-the-art (SOTA) VQA models are trained on [13, 2, 1, 38, 39]. The images [1] or questions [13, 17] are often synthesized, not provided by human.

In addition, previous data collection procedures on VQA benchmarks are often *static*, meaning that the data samples in these datasets do not evolve, and model performance can saturate on the fixed dataset without good generalization. For example, model accuracy on VQA v2 has been improved from 50% [4] to 76% [54] since inception. Similarly, on robust VQA benchmarks, a recent study [28] has

found that pre-trained models can greatly lift state of the art. Yet it remains unclear whether such high performance can be maintained when encountering examples in the wild.

To build an organically evolving benchmark, we introduce Adversarial VQA (AVQA), a new large-scale VQA dataset dynamically collected with Human-And-Model-inthe-Loop Enabled Training (HAMLET) [47]. AVQA is built on images from different domains, including web images from Conceptual Captions [40], user-generated images from Fakeddit [32], and movie images from VCR [52]. Our data collection is iterative and can be perpetually going. We first ask human annotators to create examples that current best models cannot answer correctly (Figure 1). These newly annotated examples expose the model's weaknesses, and are added to the training data for training a stronger model. The re-trained model is subjected to the same process, and the collection can iterate for several rounds. After each round, we train a new model and set aside a new test set. In this way, not only is the resultant dataset more challenging than existing benchmarks, but this process also yields a "moving post" target for VQA systems, rather than a static benchmark that will eventually saturate.

With this new benchmark, we present a thorough quantitative evaluation on the robustness of VQA models along multiple dimensions. First, we provide the first study on the vulnerability of VQA models when under adversarial attacks by human. Second, we benchmark several SOTA VOA models on the proposed dataset to reveal the fragility of VQA models. We observe a significant and universal performance drop when compared to VQA v2 and other robust VQA benchmarks, which corroborates our belief that existing VQA models are not robust enough. Meanwhile, this also demonstrates the transferability of these adversarial examples – data samples collected using one set of models are also challenging for other models. Third, as our annotators can ask different types of questions for different types of robustness, our analyses show that SOTA models suffer across various questions types, especially counting and reasoning.

Our main contributions are summarized as follows. (i) For better evaluation of VQA model robustness, we introduce a new VQA benchmark dynamically collected with a Human-and-Model-in-the-Loop procedure. (ii) Despite rapid advances on VQA v2 and robust VQA benchmarks, the evaluation on our new dataset shows that SOTA models are far from being robust. In fact, they are extremely vulnerable when attacked by human annotators, who can succeed within 2 trials on average. (iii) We provide a thorough analysis to share insights on the shortcomings of current models as well as comparison with other robust VQA benchmarks.

2. Related Work

Robust VQA Benchmarks There has been a growing interest in building new benchmarks to study the robustness

of VOA models. VOA-CP [2], the first robust VOA benchmark constructed via reshuffling examples in VQA v2 [14], is proposed to evaluate question-oriented language bias in VQA models. GQA-OOD [22] improves from VQA-CP, and proposes to evaluate the performance differences between in-distribution and out-of-distribution split. Besides language bias, VOA-Rephrasings [39] exposes the brittleness of VQA models to linguistic variations in questions by collecting human-written rephrasings of VQA v2 questions. Causal VQA [1] studies robustness against semantic image manipulations, and tests for prediction consistency to questions on clean images and corresponding edited images. Further studies investigate robustness against reasoning. For instance, [38] collects perception-related subquestions per question for a new reasoning split of VQA dataset. [13] tests model's ability to logical reasoning through logical compositions of yes/no questions in VQA v2. GOA [17] provides large-scale rule-based questions from ground-truth scene graphs, that can test VQA model's ability on positional reasoning and relational reasoning.

Despite the continuous efforts in evaluating robustness of VQA models, these works mostly focus on a single type of robustness, and are based on the original VQA v2 dataset via either another round of question collection given the existing VQA examples, or automatic transformation or manipulation of current examples. In comparison, we use different image sources, and collect a new challenging VQA benchmark by allowing human annotators to directly attack current state-of-the-art VQA models.

Model-in-the-Loop Data Collection Dataset collection with a model-in-the-loop setting has received increasing attention in recent years in the NLP community. In this setting, models are used in the collection process to identify wrongly predicted, thus more challenging examples. These models are used either as a post-processing filter [53, 5] or directly during annotation [49, 34, 5]. In ANLI [34], the model-in-the-loop strategy is extended to a Human-And-Model-in-the-Loop Enabled Training (HAMLET) setting, where the data collection happens in multiple rounds, and in each round, the models are updated to stronger versions by training with examples collected from previous rounds. The goal of ANLI is to create a natural language inference (NLI) dataset that can grow along with the rapid advance of model capabilities [10, 29, 48, 24]. In contrast to static datasets that will eventually saturate as models become stronger, datasets created with the HAMLET procedure are dynamic – if the test set saturates with a more powerful model, one can use this more powerful model to assist the collection of a new set of difficult examples, leading to a never-ending challenge for the community. Meanwhile, the adversarial nature of the HAMLET procedure also helps to identify the weaknesses and vulnerabilities of existing models, and the biases or annotation artifacts [15, 35, 26] in ex-

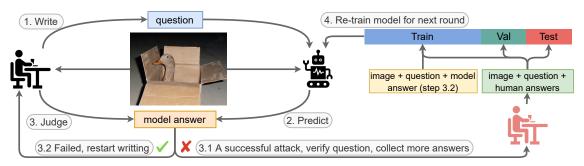


Figure 2: Overview of our adversarial data collection process, for a single round. The process can be considered as a game played by two parties, a human annotator and a well-trained model. Given an image, the annotator tries to attack the model by writing a tricky question (*step 1*), the model then predicts an answer to the question (*step 2*). Next, the human annotator judges the correctness of the model answer (*step 3*). If the model answer is judged as "definitely wrong" **X**, meaning the attack is successful, then we verify the question and collect more answers for it (*step 3.1*). Otherwise, the attack is failed, the annotator needs to write another question to attack the model (*step 3.2*). The *val* and *test* splits contain only successfully attacked questions, while *train* split contains also the failed questions.

isting datasets [6, 46, 26]. Beyond its application to the NLI task, the HAMLET procedure is also proved to be useful in collecting more challenging examples for the video-and-language future prediction task [26].

3. Adversarial VQA Dataset

In this section, we introduce the AVQA dataset in detail. Sec. 3.1 explains the data collection pipeline. Sec. 3.2 and Sec. 3.3 present data statistics and the comparison with other datasets.

3.1. Data Collection Pipeline

The HAMLET data collection procedure can be considered as a game played by two parties: a human annotator and a well-trained model. The human annotator competes against the model as an adversary and tries to design adversarial examples to identify its vulnerabilities. After collecting enough examples, the model augments its training with the collected data to defend similar attacks. For VQA, we define the adversarial example as an adversarial question on a natural image that the model answers incorrectly.

As shown in Figure 2, given an image, the human annotator tries to write a *tricky* question that the VQA model may fail. Once the question is submitted, an online model prediction will be displayed immediately to the workers. The model answer is then judged by the same annotator as either "definitely correct", "definitely wrong", or "not sure". If the model prediction is "definitely wrong", then the attack is successful, and we further ask the annotator to provide a correct answer. Otherwise, the annotator needs to write another question until the model predicts a wrong answer, or the number of tries exceeds a threshold (5 tries). To avoid obviously invalid questions caused by the annotator taking shortcuts (e.g., untruthful judgement on model predictions, questions irrelevant to the image content), we also launch an answer annotation task. Successfully attacked questions are provided to 9 other annotators to collect extra answers,

as well as their confidence level ("confident", "maybe" and "not confident") of their answer. The questions that receive less than 6 "confident" answers and have no agreement in answers among 10 annotators are removed during post-processing. In the end, each image is presented to 3 workers for question collection, and each image-question pair is shown to 10 annotators for answer collection.

This procedure can be continuously deployed for multiple rounds. At each round, we strengthen the models as we re-train them with extra data collected from previous rounds. This "dynamic" evolution of attacked models allows the collection of "harder" questions in the later rounds. In our setup, we launch the data collection for 3 rounds on Amazon Mechanical Turk. However, this data collection can be a never-ending process, as we can always replace the attacked model with a stronger model trained on newly collected data or better architectures developed in the future.

Round 1 (R1) For the first round, we employ VQA models trained on examples from VQA v2 [14] and VGQA [23] as our starting point. To avoid the collected questions overfitting to the vulnerabilities of a single model or a single architecture, for each user question, we randomly sample one model from LXMERT [43], UNITER-B [9] and UNITER-L [9] as the attacked model to generate the answer. We choose LXMERT and UNITER as representatives of two-stream and single-stream pre-trained V+L models, due to their strong performance on VQA v2. We use images sampled from Conceptual Captions [40] for annotation. In total, we collected 38.7K verified questions and 28.2K unverfied questions over 13.7K images, and split the verified examples into 60%/10%/30% for train/val/test splits. All unverified examples are also added to the training split.

Round 2 (R2) For the second round, we re-train our models with questions from VQA v2, VGQA and R1's train split, and select the best model checkpoints of LXMERT,

¹Verified questions are all successfully attacked questions.

Dataset	Image Source	#Image	IsCollected	#IQ	Model error rate (%)	#Tries	Time (sec.)	Data Split		
				Total/Verified	Total/Verified	Mean/Median	per verified ex.	Train/Val/Test		
Previous Robust V	Previous Robust VQA Datsets									
VQA-Reph.		-	1	162K/-	-	-	-	-/162K/-		
VQA-Intro.		-	✓	238K/-	-	-	-	222K/-/93K		
VQA-LOL Comp.	COCO	-	×	1.25M/-	-	-	-	916M/43K/291K		
VQA-LOL Supp.		-	×	2.55M/-	-	-	-	1.9M/9k/669K		
VQA-CP v2		-	×	-/-	-	-	-	438K/-/220K		
IV-VQA	COCO†	357K	Х	376K/-	-	-	-	257K/11.6K/108K		
CV-VQA	COCO	18.0K	×	12.7K/-	-	-	-	8.5K/0.4K/3.7K		
Ours										
R1	CC	13.7K	1	93.1K/45.6K	48.9/35.2	1.6/1	71.0	53.6K/3.3K/10.0K		
R2	CC	13.1K	✓	70.4K/37.8K	56.1/49.0	1.5/1	54.2	42.8K/2.7K/8.3K		
R3	Various	11.1K	✓	79.5K/40.3K	50.7/34.4	1.6/1	57.3	45.9K/2.7K/8.1K		
AVQA	Various	37.9K	✓	243.0K/123.7K	50.9/38.1	1.6/1	61.3	142.1K/8.7K/26.4K		

Table 1: Data statistics. 'Model error rate' is the percentage of examples that the model gets wrong; 'Verified' is the questions with 10 answer annotations. Images for R3 are from various domains: Conceptual Captions (CC) [40], VCR [52] and Fakeddit [32]. We compare our dataset against previous robust VQA datasets, based on COCO [8] images. For number of image-question pairs (#IQ) and images (#Image), we only report the number of new examples generated/collected in each dataset. † indicates that the images are not natural, but edited. 'IsCollected' indicates whether the data is collected via crowdsourcing.

UNITER-B and UNITER-L based on R1's val set. Similarly, we randomly sample one model at a time for the workers to attack. A new set of non-overlapping Conceptual Captions images are used. In total, we collected 23.5K verified questions and 19.3K unverified question over 13.1K images, and split the data in a similar manner to R1.

Round 3 (R3) For the third round, we include more diverse images from different domains: (i) web images from Conceptual Captions [40]; (ii) user-generated images from Fakeddit [32]; and (iii) movie frame images from VCR [52]. The attacked model is still randomly sampled from LXMERT, UNITER-B and UNITER-L, but we add the training set from R1 and R2 to the training data.

Summary Finally, combining data collected in R1, R2 and R3 produces our proposed AVQA dataset. In the end, we collected 243.0K questions over 37.9K images, with 142.1K/8.7K/26.4K images in the train/val/test split.

3.2. Data Statistics

The data statistics of the new dataset are summarized in Table 1. The number of examples we collected per image varies per round, starting with approximately 6.8 questions/image for R1, to around 5.4 for R2 and 7.2 for R3. Under the same image domain for R1 and R2, we suspect that the annotators learn to identify model vulnerabilities more rapidly than the models learn to defend itself from the adversarial examples. We provide analyses in Sec. 4.1 and 4.4 for further investigation. On the one hand, the annotators are getting better at identifying vulnerabilities of these models. Analyses of question types per round in Sec. 4.4 show that the workers tend to ask more questions in certain categories, such as "count", "OCR" and "commonsense reasoning", that the model is more likely to fail. On the other hand, although the attacked model is strengthened through

data augmentation, the model does not seem to learn from the adversarial examples effectively.

For each round, we report the model error rate, both on verified and all examples. The model error rate reported under "Total" captures the percentage of examples where the writer disagrees with the model's answer during question collection, but where we are not yet sure that the example is correct. The verified model error rate is the percentage of model errors from examples that we further collected 9 additional answers from other workers. We observe an increase in model error rate from R1 to R2. Assuming constant image domain difficulty in R1 and R2, the higher model rate suggests that the models in the later rounds are not significantly stronger, or the annotators are getting better at fooling the state-of-the-art models. In R3, where we included images from more diverse domains, the model error rate decreases from 49.0% to 34.4%. We suspect it is because the movie images from VCR are mostly humancentric, which is commonly observed in COCO.

We also report the average number of attempts ("#Tries" in Table 1) that a worker needed to complete the annotation process for each image, *i.e.*, to successfully attack the model or exceed the limits on number of tries. Surprisingly, although the VQA models used in the later rounds are trained with more data, the number of tries needed to successfully attack them does not increase. On average, it takes less than 2 tries to successfully attack a VQA model. Similarly, the average time needed per successful attack decreases by 15 seconds as data collection progresses.

3.3. Comparison with Other Datasets

Our Adversarial VQA dataset sets a new benchmark for evaluating the robustness of VQA models. It improves upon existing robust VQA benchmarks in several ways. First, the dataset by design is more difficult than previous

Model	Training Data	R1	R2	R3	AVQA	VQA v2	Δ (v2, AVQA)
		val/test	val/test	val/test	val/test	test-dev	test-dev, test
BUTD	VQA v2 +VGQA	20.80/19.28	18.77/18.85	20.63/21.10	20.12/19.71	67.60	47.89
вотр	ALL	24.96/22.11	22.62/22.78	23.92/23.61	23.91/22.78	67.52	44.74
	VQA v2 +VGQA	20.60/17.91	17.86/18.55	20.71/20.17	19.79/18.81	72.70	53.89
UNITER-B	+R1	26.03/22.94	17.30/17.36	20.56/20.61	21.62/20.47	72.98	52.51
UNITER-D	+R1+R2	26.60/24.76	23.21/23.86	19.26/18.73	23.26/22.62	72.75	50.13
	ALL	26.85/24.93	23.38/23.92	24.48/23.27	25.04/24.10	72.66	48.56
	VQA v2 +VGQA	25.04/23.72	17.82/17.49	19.63/19.77	21.12/20.55	73.82	53.27
UNITER-L	+R1	29.31/26.63	19.34/18.66	19.78/18.99	23.25/21.78	73.89	52.11
UNITER-L	+R1+R2	30.13/28.15	23.11/23.54	17.35/17.05	23.97/23.29	73.77	50.48
	ALL	30.80/28.45	22.95/23.11	24.08/21.97	26.27/24.78	74.15	49.37
	VQA v2 +VGQA	19.76/18.15	18.98/18.79	21.08/21.27	19.93/19.31	72.31	53.00
LVMEDT	+R1	23.89/22.65	19.01/17.91	21.64/21.42	21.68/20.78	72.51	51.73
LXMERT	+R1+R2	26.76/24.86	23.28/ 24.11	19.39/19.57	23.38/23.00	72.61	49.61
	ALL	26.35/24.55	23.84 /24.02	25.27/23.71	25.24/24.13	72.42	48.29

Table 2: Model performance of various models under different settings. AVQA / ALL refers to R1+R2+R3 / VQA v2+VGQA+AVQA.

datasets. During collection, we do not constrain the worker to ask questions that only fall into a single robustness type (Sec. 4.4). As a result, our dataset is helpful in defending model robustness against several robust VQA benchmarks (Sec. 4.3). Second, most robust VQA datasets are based on VQA v2 validation set, which state-of-the-art models use for training or hyper-parameter tuning. Thus, it is difficult to analyze the robustness of the best-performing models due to this data leakage. Our dataset is built on non-overlapping images from diverse domains, which naturally resolves it. Lastly, our dataset is composed of human-written questions on natural images, rather than rule-based questions in [13, 17] or manipulated images in [1]. A detailed comparison on data statistics is provided in Table 1.

Our work is inspired by ANLI [34]. While ANLI focuses on the pure text task of natural language inference, our work targets at the multi-modal task of visual question answering. However, due to the open-ended nature of VQA problem, the construction of AVQA is more challenging. Instead of giving the worker a target label when collecting adversarial questions, we first ask the worker to judge whether the model prediction is correct, then provide a ground-truth answer. Our verification process is also different from ANLI. In order to evaluate model performance under the same criteria as VQA v2 [14], we collect 10 answers from workers in total. Unlike the observations on ANLI, where the adversarial robustness of NLI models can be improved in a large extent through data augmentation of ANLI, our analysis on AVQA in Sec. 4 will show that it is more difficult to defend against adversarial attacks for VQA models.

4. Experiments and Analysis

In this section, we conduct extensive experiments to study the AVQA dataset. Specifically, Sec. 4.1 and Sec. 4.2 evaluate different model architectures with different modality inputs on AVQA; Sec. 4.3 examines how AVQA can

help over other popular robust VQA benchmarks; Sec. 4.4 explores the question types that can fool the models; and Sec. 4.5 compares our data collection with automatic adversarial attack methods both qualitatively and quantitatively.

4.1. Model Evaluation

Table 2 reports the main results. In addition to UNITER-B, UNITER-L [9] and LXMERT [43], we also include BUTD [3] as an example of task-specific model with different model architecture, prior to the large-scale pre-training era. We show performance on the AVQA test sets per round, the total AVQA test set, and VQA v2 test-dev set. Our key observations are summarized as follows.

O1: Adversarial examples are transferrable across models. Both LXMERT and UNITER are variants of Transformer [45] architecture. We use BUTD as an example to investigate whether the adversarial examples are transferrable among the three models. The ∼20 performance of BUTD (trained on VQA v2+VGQA) on test set of each round indicates that workers did not find vulnerabilities specific to a single model architecture, but generally applicable ones across different model architectures.

O2: The difficulty level of rounds does not decrease. Under the same training data, we observe that the model achieves comparable or even lower performance on later rounds. As aforementioned in data statistics, the increased model error rates and the decreased average tries annotators needed suggest that the later rounds contain more difficult examples.

O3: Training with more rounds help defend robustness... Generally, our results indicate that training on more rounds improves model performance.

...but data augmentation alone is not effective. To investigate how much improvements are from adversarial examples, we show comparison of UNITER-B results on verified

Data	R1	R2	R3
Verified	25.63	22.84	23.63
Combined	26.85	22.82	24.38

Table 3: Comparison of verified and combined data. Results are reported on val split from UNITER-B trained on training data of each round, VQA v2 and VGQA.

Training	Lang.	R1	R2	R3	VQA v2
Data	Only	test	test	test	test-dev
VQA v2+VG	Х	17.91	18.55	20.17	72.70
AVQA-only	X	25.66	24.91	24.75	59.99
ALL	X	24.93	23.92	23.27	72.66
VQA v2+VG	√	17.82	17.03	21.32	45.81
AVQA-only	✓	20.37	21.49	22.89	38.21
ALL	✓	19.75	20.75	22.81	46.23

(a) Language-only model performance.

Model	AVQA	VQA-CP v2
	val	test
BUTD	23.91	40.62 (38.82 [44])
+ [44]	23.79	43.96
UNITER-B	25.04	47.02 (46.93 [28])
+ [44]	24.70	47.12

(b) Model performance with a VQA-CP baseline from [44].

Table 4: Analysis on language bias.

and combined data in Table 3. In addition to verified data, the combined data include examples that the worker thinks the model has answered correctly. Even with almost doubled data size, results on combined data are not significantly better. This implies that simply training on more examples that the model correctly answers can hardly help the model be robust to adversarial attacks.

O4: Large model does not possess a clear advantage. Although outperforming UNITER-B and LXMERT on R1, UNITER-L does not show a clear advantage over R2 and R3. Overall, these three models achieve similar performance across rounds and on AVQA. When trained with "ALL" data, the performance gain from UNITER-L over BUTD is only +2.00 on AVQA, even though UNITER-L is pre-trained with extensive amount of image-text pairs.

4.2. Key Factor Analysis

We dive deeper into the key factors behind the low performance of state-of-the-art models on AVQA, and try to answer the following questions.

Q1: Is the language in AVQA biased? Starting from VQA-CP [2], concerns have been raised about the propensity of models to pick up on spurious artifacts that are present just in the co-occurrence of question-answer pairs, without actually paying attention to the image content. We compare full models trained with both images and questions to models trained only on questions by zeroing out image features in Table 4a. The results show that language-only models perform poorly on AVQA, and similarly on VQA v2.

Model	Training Data	AVQA	VQA v2
		test	test-dev
UNITER-B	VQA v2 +VGQA	18.81	72.70
UNITER-D	ALL	24.10	72.66
Climper	VQA v2 +VGQA	21.16	69.08
ClipBERT	ALL	24.35	69.17
VILLA-B	VQA v2 +VGQA	19.68	73.37
VILLA-D	ALL	26.08	74.28

Table 5: Evaluation of grid-feature-based method ClipBERT [25], and adversarial-training-based method VILLA [11]. 'ALL' refers to VQA v2+VGQA+AVQA.

Language-only model performance decreases over rounds for AVQA. However, UNITER-B is not much better than language-only on AVQA. Obviously, without manual intervention, some bias remains in how annotators phrase questions. For example, there might be more counting questions with answers other than 2, which is the majority answer in VQA v2. Therefore, models trained on AVQA only performs slightly higher for both UNITER-B and Language-only model. However, we also observe the significant drop in VQA v2 performance is out of proportion to the slight performance improvement on AVQA.

We further investigate if the low performance is due to the difference in answer distribution between training and testing split. Due to the large number of answer candidates (more than 3000 for VQA v2), it is impossible to evenly balance the possibility of each answer. Therefore, we test out this hypothesis by adopting a simple yet effective baseline method on VQA-CP [44]: adding a regularization term by replacing the image with a randomly sampled one. The intuition is that the answer to a question corresponding to a given image is very unlikely to be correct for a randomly sampled image. As reported in Table 4b, although effective on VQA-CP, adding such regularization hurts the performance on AVQA for both BUTD and UNITER-B. In addition, when applied to a stronger model on VQA-CP, *i.e.*, UNITER-B, the regularization term is less effective.

Q2: Is AVQA transferrable to different visual features? The AVQA dataset is collected with the assistance of models trained on Faster R-CNN [36] region features [3]. To investigate whether these collected adversarial examples are transferrable to different image features, we conduct experiments using another type of feature, *i.e.*, grid features [18] from CNNs, which have shown to be effective for VQA tasks [18, 16, 33, 25]. Specifically, we consider Clip-BERT [25], an end-to-end pre-trained model that directly takes in raw images and questions, and the images are represented by grid features as in [18]. Meanwhile, ClipBERT's end-to-end training strategy may also help to defend potential attacks to fixed feature representations widely used in previous work [9, 43, 3]. Table 5 compares ClipBERT against UNITER-B. The poor performance of ClipBERT on AVQA suggests that adversarial examples in AVQA

Model	Training Data	Training Data VQA-Rep. VQA-LOL Comp. Comp.		VQA-LOL Supp.	VQA-Intro.	CV-VQA	IV-VQA
		Acc. ↑	Acc. ↑	Acc. ↑	M√ S√↑	#flips ↓	#flips↓
Previous models	VQA v2 Train	56.59 [39]	49.88 [13]	50.54 [13]	50.05 [38]	7.53 [1]	78.44 [1]
UNITER-B [28]	VQA v2 Train	64.66	54.16	49.89	56.69	8.47	40.67
UNITER-B (ours)	VQA v2 Train	64.56	54.54	50.00	56.80	8.44	39.97
UNITER-D (Ours)	+AVQA	65.42	55.10	51.36	57.93	8.43	38.40

Table 6: Model performance on recent robust VQA benchmarks.

Round	Count	OCR		Reasoning			Visual Concept Recognition				
			Position	Relation	Common- sense	Other	Low- level	Action	Small Object	Occlusion	Abstract
R1	23.3%	10.7%	14.7%	8.3%	17.3%	0.7%	9.7%	4.3%	13.3%	14.7%	6.3%
R2	30.0%	22.7%	12.0%	27.7%	20.0%	4.3%	12.7%	9.3%	22.7%	10.0%	15.3%
R3	35.3%	13.0%	13.0%	28.3%	25.0%	6.3%	11.7%	4.3%	20.0%	20.0%	6.0%
Ave.	29.6%	15.4%	13.2%	21.4%	20.8%	3.8%	11.3%	6.0%	18.7%	14.9%	9.2%

Table 7: Analysis of 300 randomly sampled AVQA examples per round and on average. Low-level visual concepts include color, shape, and texture. A question may belong to multiple different categories.

are transferrable to different image representations. However, ClipBERT performs comparably to UNITER-B on AVQA, although it significantly under-performs UNITER-B on VQA v2, which suggests that VQA v2 may not be reliable for evaluating model robustness.

03: How effective is adversarial training on AVOA? We examine the effectiveness of adversarial training by adopting PGD-based adversarial training method VILLA in [11]. VILLA-B is both adversarially pre-trained on large-scale image-text data and adversarially finetuned on the respective dataset. We compare its performance against UNITER-B on both AVQA and VQA v2 in Table 5. Adversarial training brings slight performance improvement. However, the performance gap between AVQA and VQA v2 is still very significant. Note that VILLA-B crafts adversarial examples during training by adding adversarial perturbations to the embedding space. These adversarial perturbations can hardly change the intrinsic statistics of training data, such as the distribution of question types and relevant objects in the image. Our analysis of question types and visual recognition concepts in Sec. 4.4 will show that AVQA is hard because it requires the model to have the ability to reason, count and recognize different visual concepts.

4.3. Evaluation on Other Datasets

We also test models on recent robust VQA benchmarks including: VQA-Rephrasings [39] for linguistic variations, VQA-LOL [13] Complement/Supplement for logical reasoning, VQA-Introspect [38] for consistency of model predictions in perceptual sub-questions and main reasoning questions, CV-VQA [1] and IV-VQA [1] for model robustness to image manipulations. Results are summarized in Table 6. We observe that UNITER-B can already outperform previous models for most of the benchmarks, which is consistent with observations in [28]. Training on AVQA

is helpful in improving model performance on robustness benchmarks. Particularly, AVQA helps to boost model reasoning capability across 3 datasets. It is likely that AVQA exposes the model training to more diverse question templates, hence improves on VQA-Rephrasings. On IV-VQA, which focuses on counting questions, AVQA helps to improve performance despite of the significant performance gain UNITER-B has already achieved.

4.4. Analysis on Question Types

We manually annotate 300 randomly sampled examples from each round to investigate: which types of questions do workers employ to fool the models, and how they evolve as the rounds progress.

Results are summarized in Table 7. Questions are categorized into 4 meta-categories: counting, OCR, reasoning, and visual concept recognition. Although OCR and counting can be considered as visual concept and quantitative reasoning, we separate them out as they contribute a large portion per round, to almost 50% in the later rounds. There are three main reasoning questions: positional reasoning (i.e., the relative/absolute position of an object), relational reasoning (i.e., semantic relationship between two or more objects), and commonsense reasoning (i.e., visual commonsense reasoning, e.g., "Is the water more likely to be a lake or an ocean", given an image showing a body of water surrounded by mountains.). Other reasoning questions include comparative reasoning (e.g., "which person is taller?") and logical reasoning (e.g., negation). For visual concept recognition, we roughly divide them into low-level visual concepts (e.g., color, shape, texture), action (e.g., "what is the person doing"), small objects, occluded objects, and abstract objects (e.g., objects in painting).

We observe that annotators rely heavily on counting questions to attack the models – nearly 30% of the sampled



(a) Visualization of examples collected per round in AVQA. Each ground-truth answer (VQA score) is collected from 10 workers.



(b) Visualization of examples generated via textual adversarial attack methods. Blue indicates the changes made in adversarial questions.

Figure 3: Illustration of adversarial examples from (a) AVQA and (b) textual adversarial attack methods: Sears [37], Textfooler [20] and Sememe+PSO [51]. Green (red) indicates a correct (wrong) answer.

Method	#Tries	Error Rate	Orig. Acc.	Adv. Acc.
Sears [37]	3.0	11.6%	69.1	63.0
Textfooler [20]	39.5	1.4%	69.1	67.8
Sememe+PSO [51] [†]	35.9	88.6%	84.9	12.5
AVOA	1.6	38.1%	-	

Table 8: Comparison to adversarial attack methods. Orig. Acc. (Adv. Acc.) is the accuracy on original (adversarial) examples. (†) Note that Sememe+PSO only attacks questions longer than 10 words, so 94.8% examples are not being attacked.

questions across all rounds fall into this category. While R1 questions are mostly on objects that are of normal sizes and less occluded, we found that the counting questions become harder in R2 and R3 as many of them are about small and occluded objects. There is also a surge in abstract and OCR questions for R2, due to the increase in the number of abstract images and images that contain scene text. The percentage of reasoning questions, especially relational reasoning and commonsense reasoning, increases drastically from R1 to R2 and R3. Visualizations in Figure 3a show that questions in later rounds are indeed more complicated, with more detailed relational and positional descriptions when referring to an object. Overall, these findings are compatible with the idea that VQA models are not robust enough to various types of questions.

4.5. Why Human-in-the-Loop?

Textual adversarial attack methods [31, 20, 51] have been widely explored in NLP. The goal is to alter model predictions with minor changes to the input textual queries, so that adversarial examples can be generated and model vulnerabilities can be identified automatically. We investigate whether we can directly apply these methods to generate adversarial examples in high quality and compare the generated examples to AVQA. In total, we consider 3 different textual adversarial attack methods, including Sears [37] via

bask-translation for sentence-level attacks, Textfooler [20] and Sememe+PSO [51] by replacing words with its synonyms or words that share the same sememe annotations for word-level attacks. The adversarial attacks are performed to all questions on 5000 images in the Karpathy split [21]. We visualize examples in Figure 12. Without human-inthe-loop, the generated adversarial questions share similar problems: (i) the adversarial question does not share the same answer with the original question, therefore additional answer annotations may need to be collected; (ii) model prediction to the adversarial question is not necessarily incorrect when it is different from answers to the original question; (iii) word similarity may not hold when it needs to be grounded to the image (e.g., window vs. skylights). In addition, we compare these methods against the AVQA dataset quantitatively in Table 8. Generally, humans take much fewer tries and have a higher successful rate when attacking VQA models. How to design effective adversarial attack methods to generate high-quality VQA examples can be an interesting future research direction.

5. Conclusion

In this work, we collect a new benchmark Adversarial VQA (AVQA) to evaluate the robustness of VQA models. It is collected iteratively for 3 rounds via a human-and-model-in-the-loop enabled training paradigm, on images from different domains. AVQA questions cover diverse robustness types, enabling a more comprehensive evaluation on model robustness. Our analysis shows that state-of-the-art models cannot maintain decent performance on AVQA, despite of large-scale pre-training, adversarial training, sophisticated model architecture design, and stronger visual features. AVQA brings a new challenge to the community on how to design more robust VQA models that are ready to deploy in real-life applications.

References

- [1] Vedika Agarwal, Rakshith Shetty, and Mario Fritz. Towards causal vqa: Revealing and reducing spurious correlations by invariant and covariant semantic editing. In *CVPR*, 2020. 1, 2, 5, 7
- [2] Aishwarya Agrawal, Dhruv Batra, Devi Parikh, and Aniruddha Kembhavi. Don't just assume; look and answer: Overcoming priors for visual question answering. In *CVPR*, 2018. 1, 2, 6
- [3] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. Bottom-up and top-down attention for image captioning and visual question answering. In *CVPR*, 2018. 1, 5, 6, 13, 15
- [4] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. Vqa: Visual question answering. In *ICCV*, 2015. 1, 11
- [5] Max Bartolo, Alastair Roberts, Johannes Welbl, Sebastian Riedel, and Pontus Stenetorp. Beat the ai: Investigating adversarial human annotation for reading comprehension. *TACL*, 2020. 2
- [6] Samuel R Bowman, Gabor Angeli, Christopher Potts, and Christopher D Manning. A large annotated corpus for learning natural language inference. In EMNLP, 2015. 3
- [7] Jize Cao, Zhe Gan, Yu Cheng, Licheng Yu, Yen-Chun Chen, and Jingjing Liu. Behind the scene: Revealing the secrets of pre-trained vision-and-language models. In ECCV, 2020.
- [8] Xinlei Chen, Hao Fang, Tsung-Yi Lin, Ramakrishna Vedantam, Saurabh Gupta, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco captions: Data collection and evaluation server. arXiv preprint arXiv:1504.00325, 2015. 4
- [9] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. Uniter: Universal image-text representation learning. In ECCV, 2020. 1, 3, 5, 6
- [10] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In NAACL, 2019. 2
- [11] Zhe Gan, Yen-Chun Chen, Linjie Li, Chen Zhu, Yu Cheng, and Jingjing Liu. Large-scale adversarial training for vision-and-language representation learning. In *NeurIPs*, 2020. 1, 6, 7, 13, 15
- [12] Peng Gao, Zhengkai Jiang, Haoxuan You, Pan Lu, Steven CH Hoi, Xiaogang Wang, and Hongsheng Li. Dynamic fusion with intra-and inter-modality attention flow for visual question answering. In CVPR, 2019.
- [13] Tejas Gokhale, Pratyay Banerjee, Chitta Baral, and Yezhou Yang. Vqa-lol: Visual question answering under the lens of logic. In ECCV, 2020. 1, 2, 5, 7
- [14] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In CVPR, 2017. 1, 2, 3, 5, 11, 12
- [15] Suchin Gururangan, Swabha Swayamdipta, Omer Levy, Roy Schwartz, Samuel R Bowman, and Noah A Smith. Annotation artifacts in natural language inference data. In NAACL, 2018. 2

- [16] Zhicheng Huang, Zhaoyang Zeng, Bei Liu, Dongmei Fu, and Jianlong Fu. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers. arXiv preprint arXiv:2004.00849, 2020. 6
- [17] Drew A Hudson and Christopher D Manning. Gqa: a new dataset for compositional question answering over realworld images. In CVPR, 2019. 1, 2, 5
- [18] Huaizu Jiang, Ishan Misra, Marcus Rohrbach, Erik Learned-Miller, and Xinlei Chen. In defense of grid features for visual question answering. In CVPR, 2020. 1, 6
- [19] Yu Jiang, Vivek Natarajan, Xinlei Chen, Marcus Rohrbach, Dhruv Batra, and Devi Parikh. Pythia v0. 1: the winning entry to the vqa challenge 2018. arXiv preprint arXiv:1807.09956, 2018.
- [20] Di Jin, Zhijing Jin, Joey Tianyi Zhou, and Peter Szolovits. Is bert really robust? a strong baseline for natural language attack on text classification and entailment. In AAAI, 2020. 8, 12, 16
- [21] Andrej Karpathy and Li Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In CVPR, 2015. 8
- [22] Corentin Kervadec, Grigory Antipov, Moez Baccouche, and Christian Wolf. Roses are red, violets are blue... but should vqa expect them to? In CVPR, 2021. 2
- [23] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *IJCV*, 2017. 3
- [24] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. Albert: A lite bert for self-supervised learning of language representations. In *ICLR*, 2020. 2
- [25] Jie Lei, Linjie Li, Luowei Zhou, Zhe Gan, Tamara L. Berg, Mohit Bansal, and Jingjing Liu. Less is more: Clipbert for video-and-language learningvia sparse sampling. In CVPR, 2021. 6, 13, 15
- [26] Jie Lei, Licheng Yu, Tamara L Berg, and Mohit Bansal. What is more likely to happen next? video-and-language future event prediction. In *EMNLP*, 2020. 2, 3
- [27] Linjie Li, Zhe Gan, Yu Cheng, and Jingjing Liu. Relationaware graph attention network for visual question answering. In *ICCV*, 2019. 1
- [28] Linjie Li, Zhe Gan, and Jingjing Liu. A closer look at the robustness of vision-and-language pre-trained models. arXiv preprint arXiv:2012.08673, 2020. 1, 6, 7
- [29] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692, 2019. 2
- [30] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In *NeurIPS*, 2019. 1
- [31] John Morris, Eli Lifland, Jin Yong Yoo, Jake Grigsby, Di Jin, and Yanjun Qi. Textattack: A framework for adversarial attacks, data augmentation, and adversarial training in nlp. In *EMNLP: System Demonstrations*, 2020. 8

- [32] Kai Nakamura, Sharon Levy, and William Yang Wang. r/fakeddit: A new multimodal benchmark dataset for fine-grained fake news detection. *arXiv preprint arXiv:1911.03854*, 2019. 2, 4, 13
- [33] Duy-Kien Nguyen, Vedanuj Goswami, and Xinlei Chen. Revisiting modulated convolutions for visual counting and beyond. In *ICLR*, 2021. 6
- [34] Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. Adversarial nli: A new benchmark for natural language understanding. In ACL, 2020. 2, 5
- [35] Adam Poliak, Jason Naradowsky, Aparajita Haldar, Rachel Rudinger, and Benjamin Van Durme. Hypothesis only baselines in natural language inference. In *Proceedings of the* Seventh Joint Conference on Lexical and Computational Semantics, 2018. 2
- [36] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *NeurIPS*, 2015. 6
- [37] Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. Semantically equivalent adversarial rules for debugging NLP models. In *ACL*, 2018. 8, 12, 16
- [38] Ramprasaath R Selvaraju, Purva Tendulkar, Devi Parikh, Eric Horvitz, Marco Ribeiro, Besmira Nushi, and Ece Kamar. Squinting at vqa models: Interrogating vqa models with sub-questions. In *CVPR*, 2020. 1, 2, 7
- [39] M Shah, X Chen, M Rohrbach, and D Parikh. Cycleconsistency for robust visual question answering. In CVPR, 2019. 1, 2, 7
- [40] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In ACL, 2018, 2, 3, 4, 13
- [41] Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, and Jifeng Dai. VI-bert: Pre-training of generic visual-linguistic representations. In *ICLR*, 2020. 1
- [42] Siqi Sun, Yen-Chun Chen, Linjie Li, Shuohang Wang, Yuwei Fang, and Jingjing Liu. Lightningdot: Pre-training visualsemantic embeddings for real-time image-text retrieval. In NAACL-HLT, 2021. 1
- [43] Hao Tan and Mohit Bansal. Lxmert: Learning cross-modality encoder representations from transformers. In *EMNLP*, 2019. 1, 3, 5, 6
- [44] Damien Teney, Kushal Kafle, Robik Shrestha, Ehsan Abbasnejad, Christopher Kanan, and Anton van den Hengel. On the value of out-of-distribution testing: An example of goodhart's law. In *NeurIPS*, 2020. 6
- [45] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017. 5
- [46] Adina Williams, Nikita Nangia, and Samuel R Bowman. A broad-coverage challenge corpus for sentence understanding through inference. In NAACL, 2018. 3
- [47] Cihang Xie, Mingxing Tan, Boqing Gong, Jiang Wang, Alan L Yuille, and Quoc V Le. Adversarial examples improve image recognition. In *CVPR*, 2020. 2

- [48] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Ruslan Salakhutdinov, and Quoc V Le. Xlnet: Generalized autoregressive pretraining for language understanding. In *NeurIPS*, 2020. 2
- [49] Zhilin Yang, Saizheng Zhang, Jack Urbanek, Will Feng, Alexander H Miller, Arthur Szlam, Douwe Kiela, and Jason Weston. Mastering the dungeon: Grounded language learning by mechanical turker descent. In *ICLR*, 2018. 2
- [50] Zhou Yu, Jun Yu, Yuhao Cui, Dacheng Tao, and Qi Tian. Deep modular co-attention networks for visual question answering. In CVPR, 2019.
- [51] Yuan Zang, Fanchao Qi, Chenghao Yang, Zhiyuan Liu, Meng Zhang, Qun Liu, and Maosong Sun. Word-level textual adversarial attacking as combinatorial optimization. In ACL, 2020. 8, 12, 16
- [52] Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. From recognition to cognition: Visual commonsense reasoning. In CVPR, 2019. 2, 4, 13
- [53] Rowan Zellers, Yonatan Bisk, Roy Schwartz, and Yejin Choi. Swag: A large-scale adversarial dataset for grounded commonsense inference. In EMNLP, 2018. 2
- [54] Pengchuan Zhang, Xiujun Li, Xiaowei Hu, Jianwei Yang, Lei Zhang, Lijuan Wang, Yejin Choi, and Jianfeng Gao. Vinvl: Revisiting visual representations in vision-language models. In CVPR, 2021. 1
- [55] Mingyang Zhou, Luowei Zhou, Shuohang Wang, Yu Cheng, Linjie Li, Zhou Yu, and Jingjing Liu. Uc2: Universal crosslingual cross-modal vision-and-language pre-training. In CVPR, 2021. 1

A. More Discussions on AVOA

Future Practices. We recommend future models to report performance on both VQA v2 and AVQA. AVQA is designed to test VQA model robustness under human adversarial attacks. It is complementary to VQA v2 (naturallycollected questions), rather than a replacement. In addition, we believe it is beneficial to evaluate on other robust VQA benchmarks as well. While AVQA encompasses broader robustness types and image domains with higher data quality, existing robustness benchmarks can in addition provide useful analysis tailored to individual robustness types. An ideal VQA system should perform well on all VQA benchmarks. Further, we encourage future work to apply humanin-the-loop adversarial attack to their proposed models to identify potential vulnerabilities. For AVQA, we expect to provide a dynamically evolving VQA benchmark as models grow more robust, to alleviate the drawbacks of static benchmarks (e.g., performance saturation and overfitting).

Constraints/Rules For Data Collection. As our goal is to examine VQA models' robustness when encountering test examples in the wild, we do not constrain the questions to specific types, to avoid unconscious bias from dataset creators. As a result, we have found that models make more mistakes on Count/OCR/Relation/Commonsense questions (Table 7 in the main text).

To obtain high-quality adversarial questions, we enforce a set of rules to ensure the questions are objective, relevant to the image, and have exact answers (see detailed instructions in Figure 16). We also manually filter out questions with repetitive patterns for each annotator during collection. Our answer annotation process validates the collected questions to some extent, which are answerable by human but not always answerable by model.

Bias in Model Choices. Our current choice of models was guided by the assumption that newer models are more likely to be transformer-based with currently-proven most effective features. We plan to include a broader choice of models in future collection, as the benchmark evolves.

B. Data Statistics

Type of Questions. Following [4], given the structure of questions generated in English, we cluster questions into different types based on the words that start the question. Figure 4 shows the distribution of questions based on the first four words of the questions in AVQA. Interestingly, the variety of question types are quite similar to those in [4], including "What is", "How many" and "Is there". Quantitatively, we also categorize the questions into "Y/N", "Num", "OOV" and "Other". The percentage of questions for different categories is shown in Table 9. "OOV" questions refer to questions that cannot be answered by VQA v2 [14] an-

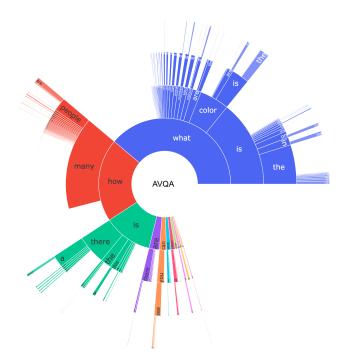


Figure 4: Distribution of questions by their first four words. The arc length is proportional to the number of questions containing the word. White areas are words with contributions too small to show.

swer vocabularies. We also include two upper bounds, one based on VQA v2 answer vocabularies, and the other on open vocabularies. Moreover, we estimate human performance on AVQA by sampling 1 human answer as prediction and use the rest 9 answers as references. We repeat the process 10 times and average the score. Comparing model performance reported in the main text, there is still a huge gap, with about 50 points lower than the upper bounds or the estimated human performance.

Question Lengths. Figure 5 shows the distribution of question lengths. We see that most questions range from four to ten words.

Dataset Properties Across Rounds. Figure 6 shows a histogram of the number of tries per verified example across the three different rounds. We observe a consistent trend for all three rounds, over 80% of examples are successfully collected within 2 tries. Figure 7 shows the time taken per verified example. As the round progresses, we observe that more and more examples are collected within 100 seconds (less than 2 minutes). Figure 8 shows the proportion of different types of collected examples across three rounds. Comparing to R1 and R2, R3 contains more "not sure" judgements to model answers during question collection (type **B**), which indicates that the task is getting harder. There are a small amount of examples in all three rounds that there is no agreement among the answers collected

Round	oundQuestion Types			Upper	Bound	Human Performance	
	Y/N	Num	OOV*	Other	val/test*	val/test [†]	val/test
R1	13.53%	23.36%	10.03%	50.08%	81.43/79.75	92.03/92.05	74.92/75.14
R2	8.62%	29.91%	14.37%	47.01%	76.26/77.11	93.60/93.43	78.29/78.83
R3	11.24%	35.55%	12.17%	41.04%	79.64/80.91	94.48/94.41	81.61/81.15
AVQA	11.40%	28.90%	11.95%	47.75%	79.27/79.28	93.28/93.21	78.05/78.15

Table 9: Question type distribution on verified examples and upper bound on val/test set across three rounds. ★ is based on VQA v2 [14] answer vocabularies. † is based on open vocabularies.

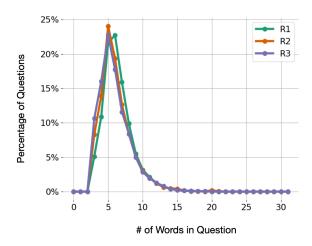


Figure 5: Percentage of questions with different word length across three rounds. Most questions range from four to ten words.

(type **D**). Examples from **B** an **D** are excluded due to low quality. The rest are split into train/val/test set (refer to Figure 8 captions for more information).

Answer Confidence and Inter-human Agreement. During answer collection (see interface in Figure 15), the annotators are required to provide both a correct answer to the question given the image content and a self-judgment on how confident they feel about the answer. Specifically, we ask "Do you think you were able to answer the question correctly?", and the annotator need to choose from "yes" (confident with score 1), "maybe" or "no" (not confident with score 0). Figure 9 shows the distribution of responses (black lines). A majority of the answers were labeled as confident. More than 9 annotators are confident about their answers on over 60% questions on average.

In addition, we investigate how the self-judgment confidence corresponds to the answer agreement between annotators across three rounds of data collection. Color bars in Figure 9 show the percentage of questions in which (i) 7 or more, (ii) 3-7, or (iii) less than 3 workers agree on the answers given their average confidence score. Across all rounds, the agreement between subjects increases with confidence. We do observe that workers are more confident about their answers in R2 and R3, comparing to R1.

Answer Distribution. Figure 10 shows the distribution of answers for several question types. We can see that a number of question types, such as "Is . . . ", "Can. . . ", and "Does. . . " are typically answered using "yes" and "no" as answers. Other questions such as "What is/are. . . " and "What kind/type. . . " have a rich diversity of responses. Other question types such as "What color. . . " or "Which. . . " have more specialized responses, such as colors, or "left" and "right". These observations are similar to those in VQA v2.

C. More Visualizations

We include more visualization examples of collected data across three rounds in Figure 11. We show adversarial questions from 4 categories: Count, OCR, Reasoning and Visual Concept Recognition. Note that questions may belong to multiple categories. For example, counting question from R3 ("How many natural satellites are in the sky?") requires commonsense about "natural satellites". OCR question from R1 ("What company is on the back of the referee?") not only requires commonsense about "referee" but relational reasoning about "on the back of". Reasoning questions include positional/relational reasoning (e.g., "What is the woman closest to the camera holding in her hand?"), commonsense reasoning (e.g., "Is the egg yolk cooked?") and comparative reasoning ("Who is taller?"). There are also questions that require recognition of both low-level visual concepts (e.g., color/shape) and high-level visual concepts (e.g., action, relation).

We also visualize more examples generated via textual adversarial attack methods (Sears [37], Textfooler [20] and Sememe+PSO [51]) in Figure 12. The first two columns show invalid examples, and the last column includes valid examples, based on our manual examination. Recall that our goal is to collect high-quality adversarial questions that can be used to *accurately*, thoroughly evaluate and examine the weakness of VQA models. Automatically generated adversarial questions are often incorrect (requiring additional human efforts to validate their correctness), and limited to linguistic variations to existing questions, thereby they are unlikely to provide a comprehensive analysis.

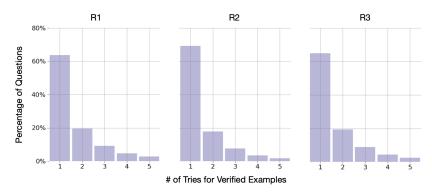


Figure 6: Histogram of the number of tries for each good verified example across three rounds.

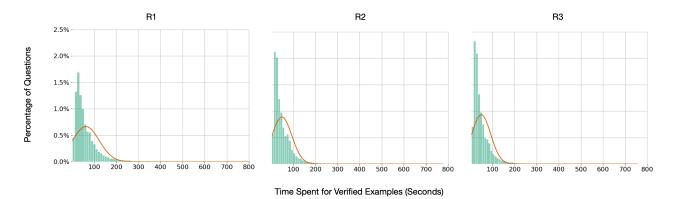


Figure 7: Histogram of the time spent per good verified example across three rounds.

D. More Results

Recall that questions in R3 are collected on images from various domains, including web images from Conceptual Captions [40] (CC, used in R1 and R2), user-generated images from Fakeddit [32] and movie video frames from VCR [52]. Hence, we can study how model performance can be transferable across different domains. We create a new split of R3 (R3*) according to the image source, with CC images for training and Fakeddit/VCR images for evaluation. Table 10 summarizes UNITER-B performance under different training settings. Despite the domain differences in images, the performance on Fakeddit and VCR split improves as we include more training data from CC images. Comparing the new split R3* with the original split R3, training on more in-domain examples on CC images does help to improve model performance on R1 and R2. We also observe that model performance on VCR is significantly higher than those on the original R3 val and Fakeddit splits across all training settings. Images from VCR are often human-centric, which may be "easier" than complex or abstract scenes depicted in CC/Fakeddit images.

In addition, we include detailed results from BUTD [3], ClipBERT [25], VILLA-B and VILLA-L [11] in Table 11.

Training Data	R1	R2	R3	Fakeddit [32]	VCR [52]
VQA v2+VGQA	20.60	17.86	20.71	19.59	23.34
+R1	26.03	17.30	20.56	20.27	23.84
+R2	26.60	23.21	19.26	17.85	22.05
+R3*	27.02	23.78	-	22.56	27.43
ALL	26.85	23.38	24.48	-	-

Table 10: Domain transfer evaluation on UNITER-B. ★ indicates that we only use examples collected on CC [40] images for training. ALL refers to VQA v2+VGQA+R1+R2+R3.

These results are consistent with observations we summarized in Section 4 of the main text.

E. Data Collection Interface

Examples of the user interface are shown in Figures 13, 14 and 15. We also include full instructions and examples shown to the annotators in Figures 16 and 17.

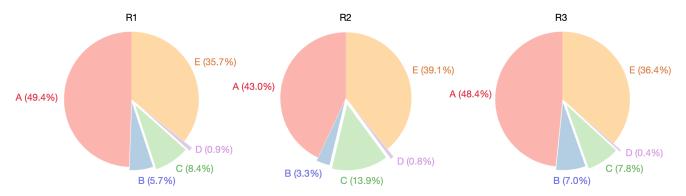


Figure 8: Proportion across three rounds. A=Examples that model got right ("Definitely Correct") during question collection, B=Examples that model neither got right nor wrong ("Not Sure") during question collection. C, D and E are examples that model got wrong ("Definitely Wrong") during question collection and sent to 9 annotators for verification during answer collection. Specifically, C=Examples that more than 3 verifiers overruled the question author's decision of "Definitely Wrong" and agree with the model's answer. D=Examples for which there is no agreement among verifiers, E=Examples where at least two verifiers agree with each other during answer collection. We split E by images into training, validation, and testing sets. Examples on training images in A and C are added to the training set, the rest are discarded. B and D are excluded due to low quality.

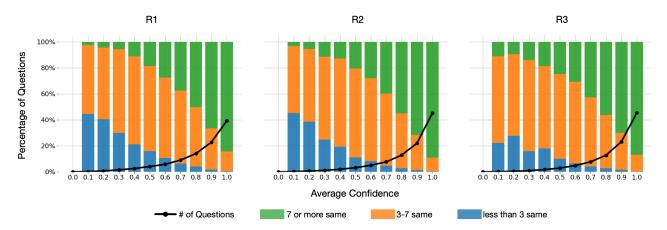


Figure 9: Number of questions per average confidence score across three rounds (black lines, 0 = not confident, 1 = confident). Percentage of questions where 7 or more answers are same, 3-7 are same, less than 3 are same across three rounds (color bars).

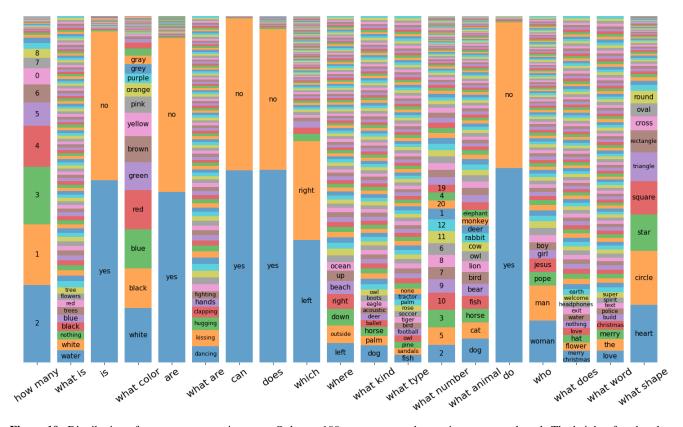


Figure 10: Distribution of answers per question type. Only top-100 answers to each question type are plotted. The height of each color bar is proportional to the percentage of an answer to the corresponding question type.

Model	Training Data	R1	R2	R3	AVQA	VQA v2	Δ (v2, AVQA)
		val/test	val/test	val/test	val/test	test-dev	test-dev, test
BUTD	VQA v2 +VGQA	20.80/19.28	18.77/18.85	20.63/21.10	20.12/19.71	67.60	47.89
вотр	+R1	20.27/20.27	19.53/20.14	21.55/21.86	20.44/20.72	67.37	46.65
	+R1+R2	24.41/21.82	22.28/21.80	21.31/21.60	22.78/21.75	67.44	45.69
	ALL	24.96/22.11	22.62/22.78	23.92/23.61	23.91/22.78	67.52	44.74
	VQA v2 +VGQA	21.39/20.45	19.29/20.06	21.01/23.16	20.45/21.16	69.08	47.92
ClimDEDT	+R1	23.83/22.43	20.08/20.13	22.49/22.65	22.25/21.78	69.07	47.29
ClipBERT	+R1+R2	24.03/23.08	23.12/23.86	24.67/23.37	23.95/23.86	69.19	45.33
	ALL	24.62/23.68	22.96/24.66	25.05/24.87	24.24/24.35	69.17	44.82
	VQA v2 +VGQA	21.22/19.45	18.53/18.92	20.57/20.73	20.18/19.68	73.37	53.69
VILLA-B	+R1	25.92/24.07	20.00/20.05	21.61/21.23	22.74/21.93	73.21	51.28
VILLA-D	+R1+R2	27.53/25.13	23.23/23.91	21.96/21.87	24.46/23.74	73.11	49.37
	ALL	30.78/28.43	25.66/25.11	24.00/24.18	27.08/26.08	74.28	48.20
	VQA v2 +VGQA	24.99/22.88	18.58/18.23	20.07/19.64	21.47/20.42	74.58	54.16
VILLA-L	+R1	28.29/26.12	19.44/19.02	20.25/20.25	23.04/22.08	74.12	52.04
v illA-L	+R1+R2	30.02/27.81	24.05/23.59	19.38/20.50	24.85/24.24	74.06	49.82
	ALL	29.92/28.01	24.59/24.26	23.66/23.09	26.32/25.32	74.24	48.92

Table 11: Detailed results from BUTD [3], ClipBERT [25], VILLA-B and VILLA-L [11] under different settings. AVQA = R1+R2+R3, ALL = VQA v2+VGQA+AVQA.

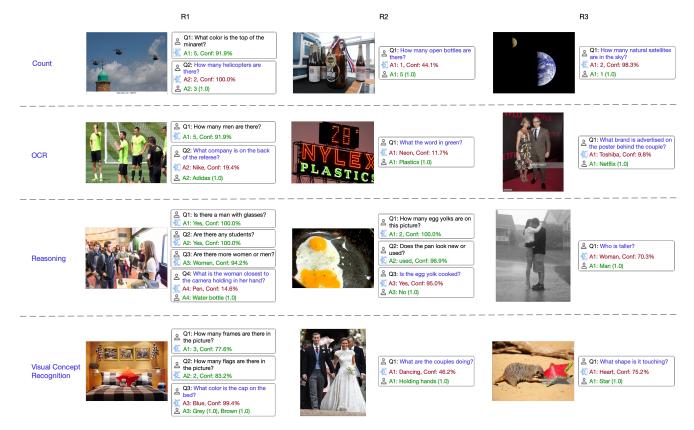


Figure 11: More visualization of examples collected per round in AVQA. We show examples that contains adversarial questions from 4 categories: Count, OCR, Reasoning and Visual Concept Recognition across three rounds. Each ground-truth answer (VQA score) is collected from 10 workers. Green (red) indicates a correct (wrong) answer. Blue highlights the verified adversarial questions.

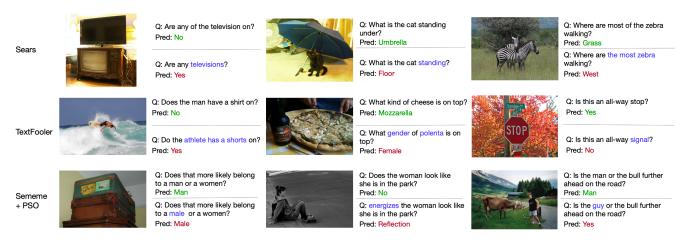


Figure 12: More adversarial examples from textual adversarial attack methods: Sears [37], Textfooler [20] and Sememe+PSO [51]. Green (red) indicates a correct (wrong) answer. Blue highlights the changes made in adversarial questions.

Beat a Smart Visual Question Answering (VQA) Robot!

You will be presented with an image and you are required to ask a question about the image to fool a smart VQA robot. Please read the instructions carefully before you start. Contact beatvqasystem@gmail.com if you have any question or suggestion.

Please follow the instructions carefully, otherwise your work will be rejected.

Coal: Write a tricky question about the image such that humans can answer, but the robot will get fooled.

After writing the question, submit it to the robot with [Get Robot Answer] button.

The question must be objective, based on image content, a single question, and has exact answers (refer to FAQ for detailed requirements on questions).

O not repeat questions about any missing objects. For example, "what is the dog doing?" is not acceptable when there is godg in the image.

O on or ask detail questions about any missing objects. For example, "what is the dog doing?" is not acceptable when there is godg in the image.

O not ask dealing questions about any missing objects. For example, "what is the dog doing?" is not acceptable when there is godg in the image.

Remember that your question will be above to other workers for answer collection. Please use appropriate workplace language!

You can attempt up to 5 chances to rewrite/rephrase your question.

Question

Write your question about the above image here.

Figure 13: UI for question collection. Given an image, the annotator is required to write a tricky answer to fool our "smart VQA robot" (well-trained VQA models). After clicking the "Get Robot Ansner", the annotated question will be sent to our online model for evaluation, and a feedback will be returned immediately. See Figure 14 for an example of model feedback.

Beat a Smart Visual Question Answering (VQA) Robot!

You will be presented with an image and you are required to ask a question about the image to fool a smart VQA robot. Please read the instructions carefully before you start. Contact beatvqasystem@gmail.com if you have any question or suggestion. Please follow the instructions carefully, otherwise your work will be rejected. Goal: Write a tricky question about the image such that humans can answer, but the robot will get fooled. After writing the question, submit it to the robot with [Get Robot Answer] button The question must be objective, based on image content, a single question, and has exact answers (refer to FAQ for detailed requirements on questions). · Do not repeat questions across images Do not ask questions about watermarks/urls in the image.
Do not ask detail questions about any missing objects. For example, "what is the dog doing?" is not acceptable when there is no dog in the image. • Do not ask about the name of the movie/TV show, character/actor/singer/famous people. Make your question to be about only what is shown in the image, not what you have seen in the movie. Remember that your question will be shown to other workers for answer collection. Please use appropriate workplace language! You can attempt up to 5 chances to rewrite/rephrase your question. Question Is the little girl in an ocean? Robot's answer is yes with confidence 78.2%. Do you think the robot answer is correct? Make your selection from the drop down menu before [Save My Judgement] Definitely Wrong You have successfully fooled the robot! Please provide a correct answer to your current question. Make sure the answer is simple and concise. Please follow requirement of answer under [Full Instructions], otherwise your work will be rejected. Your Answer no This box will show you all history of your attempts, including question, robot answer and your judgement. #1 Question: Are there mountains in the background? Robot's answer: yes with confidence 99.1%. Your judgement: Definitely Correct.

Figure 14: Example of model feedback shown to the annotators. After reviewing the model response, the annotator need to judge the correctness of the model answer ("Definitely Correct", "Not Sure", or "Definitely Wrong"). If the model answer is definitely wrong, the annotator is prompted to enter a correct answer.

Answer a Question about the Image

Please contact beatvqasystem@gmail.com if you have any question or suggestion.

Full Instructions (click to show/hide)

Please answer some questions about images with brief answers. You answers should be most other people would answer the questions. If the question doesn't make sense, please try your best to answer it and indicate via the buttons that you are unsure of your response.

FAQ (MUST READ):

- · What are the requirements for answer?
 - Answer the question based on what is going on in the scene depicted in the image.
 - The answer should be simple and concise. If a question can be answered with a phrase, do not answer with a complete sentence. For example:
 - "It is a kitchen." --> "kitchen".
 - For yes/no questions, please just say yes/no. "You bet it is!" --> "yes".
 - For numerical answers, please use digits. "Ten." --> "10".
 - o If you need to speculate (e.g. "What just happend?"), provide an answer that most people would agree on.
 - o If you don't know the answer (e.g. specific dog breed), provide your best guess.
 - Respond matter-of-factly and avoid using conversational language or inserting your opinion.
- Which browser should I use?

We recommend using Google Chrome for this task, as we only tested this tool with Chrome.

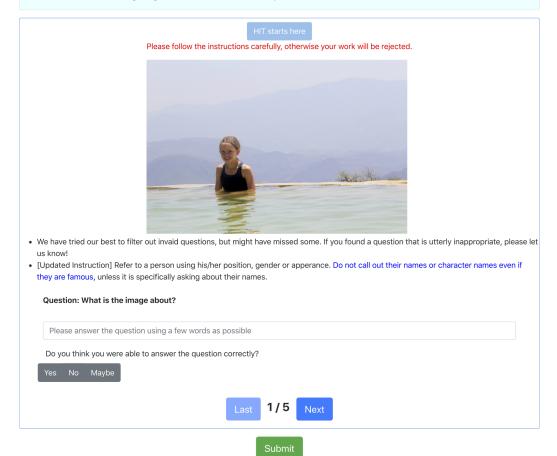


Figure 15: UI for answer collection. Given an image and a question, an annotator is asked to write a concise answer to the question, and choose a confidence level for the answer ("Yes", "No", or "Maybe").

Beat a Smart Visual Question Answering (VQA) Robot!

You will be presented with an image and you are required to ask a question about the image to fool a smart VQA robot. Please read the instructions carefully before you start. Contact beatvqasystem@gmail.com if you have any question or suggestion.

Full Instructions (click to show/hide)

You will be playing a game together with a smart robot that can answer questions about an image. Your goal is to write a question that can be answered by humans based on the image content, but that the robot gets wrong. Use your creativity to fool the system - it will be fun!

Steps

- 1. Write down a question about the image that a human can answer, but you think may fool the robot;
- 2. Submit the question to the smart robot; The robot's answer with its confidence will be presented to you.
- 3. Judge the correctness of the robot answer; It can be Definitely Wrong or Definitely Correct or Not Sure.
 - o If Definitely Wrong: Yeah! You have succeeded in fooling the robot. Go to step 4.
 - If Definitely Correct: You have not fooled the robot yet. The robot is smart enough to get the correct answer. Rewrite the
 question you provided in step 1 to make it harder for the robot to answer. Go back to step 2.
 - If Not Sure: Generally, we do not want to have an unsure judgement on the robot answer. However, now that you are here, rewrite the question you provided in step 1 to make the robot predict a definitely wrong answer. Go back to step 2.
- 4. Until now, you have successfully fooled the robot; Provide a correct answer to the current question.

FAQ (MUST READ):

- What are the general requirements for questions?
 - The question should be about the image content. That is, the human should need the image to be able to answer the
 question. The human should not be able to answer the question without looking at the image.
 - The question should be objective. That is, the question must be based in fact and you cannot add your own opinion to
 answer it. For example, question like "How do you feel about the image?" is not acceptable as it is subjective to each
 individual.
 - o The question should be a single question. Do not ask questions that have multiple parts or multiple sub-questions in them.
 - The question must have an exact answer or limited number of exact answers. For example, question like "What is not in the image?" is not acceptable as there can be countless possible answers to it.
 - Do not repeat questions across images. Think of a new question each time specific to the scene in each image. Do not ask
 the same questions or the same questions with minor variations over and over again across images.
 - Do not ask details about any missing objects. You can ask about the existence of but not details about an missing object. For
 example, question like "What is the dog doing?" is not acceptable when there is no dog in the image.
 - Do not ask about watermarks and website shown in the image. Make your question about natural objects in the image, please
 ignore the watermarks and website.
 - The question has to be more than 3 words and ends with a question mark.
- What are the requirements for judging the correctness of robot answer?
- -- An answer is regarded as definetely correct, if you think the robot answers your question correctly, though maybe lacking some details. Please carefully read the examples below for a definitely correct and a definitely wrong robot answer. We expect you to be truthful about this judgement.



Scenerio I: A definitely correct robot answer

Question: What is the vehicle in the image?

Robot Answer: bus Your answer maybe: London bus

Scenerio II: A definitely wrong robot answer

Question: Which vehicle is on the right of the image?
Robot Answer: bus Your answer maybe: green bus

Explanation: For Scenerio I, "bus" is correct, as other specific details such as "London", "colorful" and etc. are just describing the vehicle. In Scenerio II, "green" is required to correctly answer the question as there are multiple buses in the picture. If there is only one bus, then just answer with "bus" is enough.

- What are the requirements for **rewritten questions**?
 - The rewritten questions can be completely different from your previous questions. They are not required to share the same answer.
 - You can also rephrase your previous questions.
 - Do not write the same questions repeatedly. The history of your attempts will be displayed to you in case you have forgotten them.
 - Do not co-reference objects in your previous questions. That is, do not use 'it' to refer an object, especially when there could be ambiguities. Although the history of questions is displayed to you, the robot does not take previous questions into consideration.
- How many rounds can I try to fool the robot?
- -- This smart robot looks at the image and has been learning from millions of VQA examples, therefore it may be hard to be fooled. You get 5 chances in total for each image. After 5 rounds, you may submit even if you have not successfully fooled the robot. You are also welcome to continue to play.
- What are the requirements for **providing correct answers**?
 - Answer the question based on what is going on in the scene depicted in the image.
 - The answer should be simple and concise. If a question can be answered with a phrase, do not answer with a complete sentence. For example:
 - "It is a kitchen." --> "kitchen".
 - For yes/no questions, please just say yes/no. "You bet it is!" --> "yes".
 - For numerical answers, please use digits. "Ten." --> "10".
 - Respond matter-of-factly and avoid using conversational language or inserting your opinion.
- Which browser should I use?

We recommend using Google Chrome for this task, as we only tested this tool with Chrome

Figure 16: Full instructions for question collection.

Examples (click to show/hide)



Scenerio 1: A successful example with a single round

Question #1: How many kids with hair? (This is the question written by you.)
Robot Answer #1: 1 (This is the answer predicted by the smart VQA robot.)
Correctness of Robot Answer #1: Definitely Wrong (Your judgement of the robot answer.)

Correct Answer: 2 (Since the robot provides a wrong answer, you will need to write the correct answer.)

Correct Answer: 2 (Since the robot provides a wrong answer, you will need to write the correct answer.)

Explanation: Question #1 successfully fools the robot. You don't need to rewrite the question.

Scenerio 2: A successful example with multiple rounds

Question #1: What color is the girl wearing?

Robot Answer #1: white

Correctness of Robot Answer #1: Definitely Correct

Question #2: What is the girl facing towards? (Since the robot provides a correct answer, you will need to rewrite the question.)

Robot Answer #2: camera

Correctness of Robot Answer #2: Definitely Wrong

Correct Answer: bo

Explanation: You have succesfully fooled the robot with Question #2.



Scenerio 3: A failed example with untruthful judgement

Question #1: Where is this photo taken? Robot Answer #1: outside

Correctness of Robot Answer #1: Definitely Wrong

Correct Answer: mountain

Explanation: Although the robot answer ("outside") is not exactly the same as your answer ("mountain"), "outside" should be considered as a correct answer to this question. Therefore, we regard the judgement on robot answer as untruthful and this reponse will be rejected. Please refer to "requirement for judging the correctness of robot answer" under [Full Instructions] for more details.

Figure 17: Examples provided to annotators for question collection.