

From Images to Textual Prompts: Zero-shot Visual Question Answering with Frozen Large Language Models

Jiaxian Guo^{1*}Junnan Li²Dongxu Li²Anthony Meng Huat Tiong^{2,3}Boyang Li³Dacheng Tao¹Steven Hoi²¹ The University of Sydney² Salesforce Research³ Nanyang Technological Universityjguo5934@uni.sydney.edu.au {junnan.li, li.d, anthony.tiong, shoi}@salesforce.com
boyang.li@ntu.edu.sg dacheng.tao@gmail.com

Abstract

Large language models (LLMs) have demonstrated excellent zero-shot generalization to new language tasks. However, effective utilization of LLMs for zero-shot visual question-answering (VQA) remains challenging, primarily due to the modality disconnect and task disconnect between the LLM and VQA tasks. End-to-end training on multimodal data may bridge the disconnects, but is inflexible and computationally expensive. To address this issue, we propose Img2LLM, a plug-and-play module that provides LLM prompts to enable LLMs to perform zero-shot VQA tasks without end-to-end training. We develop LLM-agnostic models describe image content as exemplar question-answer pairs, which prove to be effective LLM prompts. Img2LLM offers the following benefits: 1) It achieves comparable or better performance than methods relying on end-to-end training. For example, we outperform Flamingo [3] by 5.6% on VQAv2. On the challenging A-OKVQA dataset, our method outperforms few-shot methods by as much as 20%. 2) It flexibly interfaces with a wide range of LLMs to perform VQA. 3) It eliminates the need to specialize LLMs using end-to-end finetuning and serve highly specialized LLMs to end users, thereby reducing cost. Code is available via the LAVIS [31] framework at <https://github.com/salesforce/LAVIS/tree/main/projects/img2llm-vqa>.

1. Introduction

Visual question answering (VQA) [5] is a prominent vision-language task that finds a broad range of real-world applications, such as assisting blind individuals in understanding their environments. A diverse set of VQA datasets have been proposed, some focusing on image recognition

[5, 18] and others on logical reasoning [42]. However, human annotations are expensive to obtain and may introduce a variety of human biases [6, 11, 67], making the VQA system brittle towards new answer styles and question types [1, 23]. This has led researchers to zero-shot VQA methods [6, 11, 23] that do not require ground-truth question-answer annotations, thereby facilitating more generalizable VQA systems.

Recently, large language models (LLMs) (e.g., [9, 70]) have demonstrated excellent capabilities to perform tasks with zero in-domain data, conduct logical reasoning, and apply commonsense knowledge in NLP tasks [29, 59, 61]. As a result, recent approaches [3, 56, 65] have resorted to leverage LLMs in zero-shot VQA.

However, applying LLMs to VQA tasks is less than straightforward, due to (1) the modality disconnect between vision and language and (2) the task disconnect between language modeling and question answering. A common technique is to finetune a vision encoder jointly with the LLM [3, 22, 56] to align the vision and language representation spaces, but this can incur prohibitive computational and data cost. For example, Flamingo [3] finetunes on billions of image-text pairs with thousands of TPUs. Further, the finetuning specializes and introduces strong interdependence between the vision encoder and the LLM. If we need to upgrade the LLM as new versions emerge, the entire model needs to undergo expensive re-training.

In contrast to the end-to-end integration of LLM into a VQA system, this paper proposes a modular VQA system built on top of frozen off-the-shelf LLMs. This brings two benefits. First, it can reduce the deployment cost and simplify the deployment. Second, upgrading the LLM is straightforward. However, it is challenging to bridge the modality disconnect and task disconnect without end-to-end training. PICa [65] converts images into captions, and provides exemplar QA pairs from training data as prompt to the LLM. However, doing so assumes the existence of an-

*Work done while Jiaxian Guo was an intern at Salesforce Research.

notated training data and the performance is sensitive to the selection of few-shot exemplars.

We propose *Img2LLM*, a plug-and-play module that enables off-the-shelf LLMs to perform zero-shot VQA. The central insight of *Img2LLM* is that we can utilize a vision-language model (*e.g.* BLIP [33]) and a question-generation model to translate the image content into synthetic question-answer (QA) pairs, which are fed to the LLM as part of the prompt. These exemplar QA pairs tackle the modality disconnect by describing the image content verbally, and tackle the task disconnect by demonstrating the QA task to the LLM. Notably, the exemplar QA pairs are constructed entirely based on the test image and question, obviating the need for similar few-shot examples as required by PICa [65], which are not always available in practical zero-shot scenarios. When applied to the open-source OPT language models [70], *Img2LLM* achieves comparable or superior zero-shot VQA performance to methods that perform costly end-to-end training.

With this paper, we make the following contributions.

- We propose *Img2LLM*, a plug-and-play module that converts an image into synthetic question-answer pairs based solely on the current image of the question. *Img2LLM* bridges the modality disconnect between language and vision as well as the task disconnect between language modeling and visual question-answering.
- *Img2LLM* enables off-the-shelf LLMs to perform zero-shot VQA without costly end-to-end training or specialized textual QA networks [43], thereby allowing low-cost and flexible model deployment and painless LLM upgrades (Table 3).
- Our experimental results show that the OPT models equipped with *Img2LLM* achieve zero-shot VQA performance that is competitive or superior to the end-to-end trained models. For example, we outperform Flamingo [3] by 5.6% on VQAv2. We even outperform many few-shot VQA methods.

2. Related Work

2.1. Recent Advances in VQA Methods

As a multi-modal evaluation benchmark, Visual Question Answering (VQA) that requires the model to answer a natural language question according to the image, has been the focus of active research [2, 4, 5, 50, 66]. The past few years witnessed rapid performance advances with large-scale image-text pretraining [14, 20, 22, 33–35, 37, 52, 58, 68, 69] followed by fine-tuning on VQA datasets. To tackle knowledge-based VQA [42, 50], recent works [17, 19, 32, 36, 39–41, 63] incorporate external knowledge,

such as ConceptNet [53] or Wikipedia, but experimental results in [50] show that these methods still struggle to answer questions requiring complex reasoning.

2.2. LLM for Zero/Few-Shot VQA Tasks

Large language models (LLMs) [10, 13, 70] trained on web-scale corpus are powerful in natural language understanding and reasoning [9, 71]. To infer on task data, LLMs typically generate target tokens autoregressively. In specific, given prompt C and task input x , an LLM generates target tokens $Y = \{y_i\}_{i=1}^n$, with $y_i = \arg \max p_\theta(y_i|y_{<i}, C, x)$ and θ the model parameters. Prior VQA methods using LLMs mainly fall into two categories: multi-modal pretraining and language-mediated VQA.

Multi-modal pretraining. These approaches align vision and language embeddings by training additional alignment modules, as shown in Figure 1(a). Considering that LLMs are too large to finetune efficiently, [56] opt to finetune only the visual encoder while Flamingo [3] trains extra cross-attention layers to model cross-modality interactions. However, this paradigm suffers from two drawbacks: 1) Highly compute-inefficient. Jointly aligning vision backbones and LLMs requires large compute resources. For example, training Flamingo requires 1536 TPUv4 over two weeks. Hence, it becomes prohibitively expensive to switch to a different LLM. 2) Catastrophic forgetting. The alignment step may be detrimental to LLMs’ reasoning ability, if the LLMs are jointly trained with the visual model [3].

Language-mediated VQA. Instead of vectorized representations, this VQA paradigm directly resorts to natural language as the intermediate representation of the image and no longer requires expensive pretraining. As depicted by Figure 1(b), it first converts the current image to language descriptions and feeds the descriptions, possibly accompanied by in-context exemplars, to a frozen LLM. In a few-shot setting, PICa [65] generates captions for the image and selects training data samples as in-context exemplars, but its performance degrades substantially when the exemplars are omitted. As a concurrent zero-shot approach, [43] generates question-relevant captions. Due to the zero-shot requirement, it is unable to provide in-context exemplars and does not reap the benefits of in-context learning. As a result, it has to rely on a QA-specific LLM, UnifiedQAv2 [27], to achieve high performance.

3. Method

Difficulties in utilizing LLMs effectively in zero-shot VQA stem mainly from two obstacles: (i) *The modality disconnection*: LLMs do not natively process images and encoding visual information into a format that LLMs can process can be a challenge. (ii) *The task disconnection*: LLMs are usually pretrained using generative [9] or denoising objectives [15] on language modeling tasks. As the LLMs are

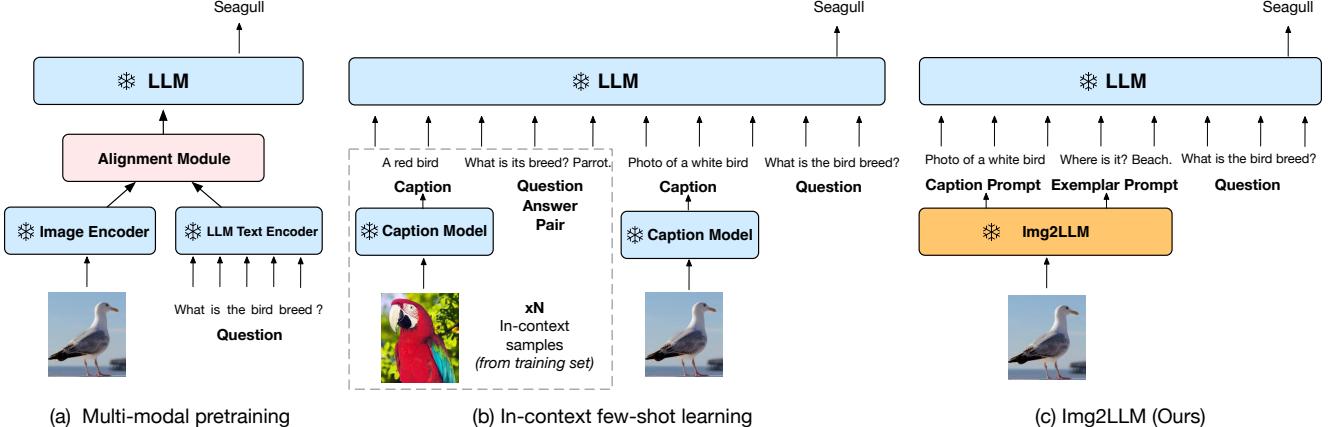


Figure 1. The illustrative comparison of three types of methods that enable LLM to perform VQA tasks, where blue block denotes that the inner parameters are frozen while pink block indicates the inner parameters are trainable.

unaware of the tasks of question answering or VQA, they often fail to fully utilize contextual information in generating the answers.

In language-mediated VQA [43, 65], the modality disconnection is addressed by converting the image to intermediate language descriptions instead of dense vectors (§2.2). The task disconnection must be addressed using either few-shot in-context exemplars [65] or an LLM directly finetuned on textual QA [43]. It is not clear how to tackle the task disconnection on generic LLMs under zero-shot settings.

We propose a new zero-shot technique to address the task disconnection on generic LLMs, Img2LLM (Figure 1c), which generates image-relevant exemplar prompts for the LLM. Given a question Q and an image, our key insight is that we can generate synthetic question-answer pairs as in-context exemplars from the *current* image. The exemplars not only demonstrate the QA task but also communicate the content of the image to the LLM for answering the question Q , thereby hitting two birds with one stone. Img2LLM is LLM-agnostic; it unlocks the knowledge and the reasoning capacity of off-the-shelf LLMs, offering a powerful yet flexible solution for zero-shot VQA.

3.1. Answer Extraction

In order to incorporate the image content into the exemplars for in-context learning, from the current VQA image, we first seek words that could serve as answers to synthetic questions. We generate a number of captions using an off-the-shelf question-relevant caption generation module (§3.3). Following recent papers [11, 30], we extract noun phrases (including named entities), verb phrases, adjective phrases, numbers, and boolean-typed words like “yes” and “no” as potential answers¹. We show some extracted answer candidates in Figure 2 and Appendix A.3.

¹We use the spaCy parser at <https://spacy.io/>, though are not tied to the parser in any way.

3.2. Question Generation

With the extracted answer candidate set $\{\hat{a}_j\}_{j=1}^U$, we can directly use any question generation network [2, 24, 28, 38, 64] to generate specific questions for each answer candidate. In this paper, we experiment with both template-based and neural question-generation methods. Note that to avoid violating the zero-shot requirements, our method is purely textual-based without access to any VQA data.

Template-based Question Generation. Using an off-the-shelf parser, we obtain the part-of-speech for each answer, and design specific question templates for each POS type. For example, for answers that are nouns, we use the question “What object is in this image?” For verb answers, we use the question “What action is being taken in this image?” Due to space constraints, we put the complete list of templates in Appendix A.5.

Neural Question Generation. Inspired by [11], we train a neural question generation model on textual QA datasets. Specifically, we finetune a pretrained T5-large model [46] to generate questions from answers. The input to the model contains the prompt “Answer: [answer]. Context: [context]”, where [answer] denotes the answer text and [context] denotes the context text from textual QA datasets. During inference, we replace [answer] with an extracted answer candidate and [context] with the generated caption from which the answer was extracted. The model is finetuned on five textual QA datasets including SQuAD2.0 [47], MultiRC [26], BookQA [44], CommonsenseQA [54] and Social IQA [48].

With the above question generation methods, we acquire a set of synthetic question-answer pairs $\{\hat{q}_j, \hat{a}_j\}_{j=1}^U$. We use these question-answer pairs as exemplars of LLM in-context learning [9], which guides the LLM to perform QA task given the image content and bridges the task disconnect between language modelling and VQA.

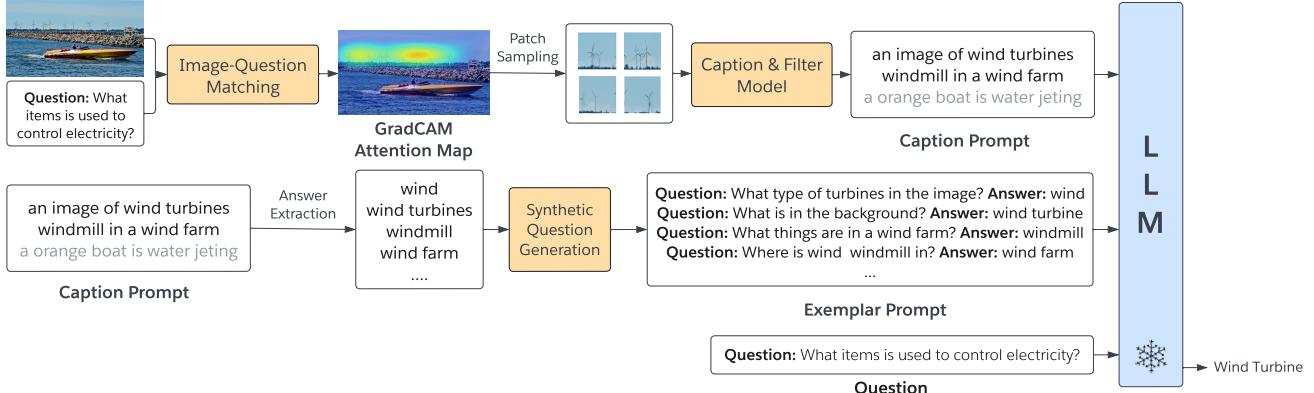


Figure 2. The overall pipeline of Img2LLM, including Caption Prompt and Exemplar Prompt generation.

Table 1. Results from mixing captions and exemplar prompts on 30B OPT [70].

Prompt Template	Caption Prompt	Exemplar Prompt	VQAv2 val	OK-VQA
Instruction	✗	✗	18.1	3.3
Instruction + Captions	✓	✗	46.1	23.5
Instruction + Question-Answer Pairs	✗	✓	57.9	41.1
Instruction + Captions + Question-Answer Pairs	✓	✓	59.5	41.8

As a sneak preview, we show effects of exemplar QA pairs in Table 1. The details of the instructions are explained in §3.4. We observe that exemplar QA prompts perform considerably better than caption prompts (detailed in §3.3) only, demonstrating their efficacy in bridging the task disconnection between LLM pre-training and VQA tasks. Moreover, since the exemplar prompts already describe much content of the image, which helps to bridge the modality disconnection, adding captions on top does not provide much new information and brings only limited performance gains.

3.3. Question-relevant Caption Prompt

In addition to the synthetic exemplar QA pairs, we also supply question-relevant image captions to the LLM. We observe that the question may ask about specific objects or regions in the image [62] but generic captions generated by existing networks may not contain relevant information. In Figure 2, the question “*What items are spinning in the background which can be used to control electricity?*” is relevant only to the wind turbines. However, captions generated from the whole image are likely to focus on the salient orange boat, leaving LLM with no information to answer the question. To address this issue, we generate captions about the question-relevant portion of the image and include them in the prompt to the LLM.

To achieve this, we first determine the regions of the image that are relevant to the question, by using the Image-grounded Text Encoder (ITE) in BLIP [33], as which assigns a similarity score $\text{sim}(v, q)$ to any pair of image v

and textual question q . With ITE, we use GradCAM [51], a feature-attribution interpretability technique, to generate a coarse localisation map highlighting matching image regions given a question [33]. Briefly, GradCam qualifies the cross-attention scores from the Transformer network by the gradient of ITE similarity function $\text{sim}(v, q)$ with respect to the cross-attention scores. As this technique was proposed in [43], we leave the details to Appendix A.1.

Having obtained the patch relevance r , we sample a subset of image patches with probability proportional to patch relevance r . After that, we generate captions from the sampled image patches using top-k sampling [16]. To generate semantically meaningful captions, a short prompt, “a picture of,” is also fed into the text decoder. We repeat this M times for each image to generate M diverse captions, and keep only captions that are not exact substrings of others.

However, due to the non-deterministic nature of top-k sampling, the caption model may generate noisy captions that have a negative impact on performance. To remove noisy captions, we use ITE to calculate the similarity score between the generated caption and sampled question-relevant image patches, and filter captions with less than 0.5 matching scores. Overall, this process yields synthetic captions that are question-relevant, diverse, and clean, providing a bridge between visual and language information.

3.4. Prompt Design

With synthetic question-relevant captions and question-answer pairs, we construct complete prompts for LLM by concatenating the instruction, captions, and QA exem-

plers. The instruction text is “Please reason the answers of question according to the contexts.” The caption prompt is formatted as “Contexts: [all captions]”. Individual QA exemplars are formatted as “Question: [question] Answer: [answer]” and concatenated. We position the current question as the last portion of the prompt, formatted as “Question: [question]. Answer: ”. Finally, to get the answer, we perform greedy decoding on the LLM and remove meaningless tokens as in Flamingo.

Furthermore, as the input to LLMs has maximum lengths, *e.g.* 2048 in OPT and GPT3, it is necessary to select a subset of question-relevant captions and question-answer pairs to construct the prompt. To select the most informative prompt, we first count the frequency of the synthetic answer candidates in 100 generated captions. We then select 30 answer candidates with highest frequencies and generate one question for each. Also, we include 30 answers with the lowest frequency and one caption containing each answer. See §4.5 for analysis of caption selection strategies.

4. Experiment

In this section, we first validate the efficacy of Img2LLM by comparing it with other zero-shot and few-shot VQA methods. Then, we perform ablation studies on important design choices, such as prompt patterns and caption selection strategies, to understand their effect. We also show qualitative examples and include discussion on observed failure cases.

4.1. Environment Setup

Datasets. We validate our method on VQAv2 [18], OK-VQA [42] and A-OKVQA [50] datasets, which contain questions requiring perception, reasoning and commonsense to answer. Specifically, VQAv2 [18] contains 214,354 questions in the validation set and 107,394 in the test-dev dataset. OK-VQA [42] and A-OK-VQA [50] emphasize on commonsense reasoning, among which OK-VQA contains 5,046 test questions and A-OKVQA [50] contains 1,100 validation questions and 6,700 test questions.

Implementation details. To obtain question-relevant caption prompt, we use BLIP [33] to generate captions and perform image-question matching. To localize the image regions relevant to the question, we generate GradCam from the cross-attention layer of BLIP image-grounded text encoder. We then sample $K' = 20$ image patches based on GradCam, and use them to obtain 100 question-relevant captions. For the LLMs, our main result uses the open-source OPT model with multiple different sizes. Our ablation study also experiments with various other LLMs to show the generalization ability of our method. We use LLMs to generate answers auto-regressively, without access to either answer list or training samples, thereby facilitating

zero-shot VQA. We follow official evaluation protocols and report VQA scores on each dataset.

Competing methods. We compare with prior VQA methods, which roughly fall into three categories: (i) *Zero-shot methods with frozen LLMs*, such as PICa [65]. Our method also belongs to this category, yet unlike PICa, Img2LLM requires no training samples to compose the prompts. (ii) *Zero-shot methods with extra multi-modal pre-training*, such as Flamingo [3], Frozen [56], VL-T5 [12], FewVLM [22] and VLKD [14]. These methods require large-scale vision-language datasets and are costly to update. We also include results from VQ²A [11] and WeaQA [6] in this category, with *caveats* that they assume access to answer candidates which may not be available in practice. Therefore, their results should be interpreted with caution. (iii) For reference purposes, we also include available results from *few-shot methods*. These include few-shot results of PICa [65], FewVLM [22] and ClipCap [45].

4.2. Main Results

Main quantitative results are shown in Table 2. We summarize our findings as follows.

State-of-the-art results on zero-shot evaluation with plug-in frozen LLMs. Img2LLM surpasses PICa, the best prior zero-shot model with frozen LLMs, by a significant margin (45.6 *versus* 17.7 on OK-VQA), thereby establishing a new state-of-the-art. In addition, we remark that despite PICa uses frozen LLMs, it requires training samples to build prompts. In contrast, our method generates question-answers with no access to VQA samples, thus fully fulfilling the zero-shot requirements.

Scaling effect of LLMs and their emergent capabilities on VQA. When increasing the number of parameters of LLMs from 6.7B to 175B, we see a 3-10 points improvement in VQA across datasets. This shows that stronger language modelling capabilities help better comprehend the question, thus giving more accurate answers. Such a trend is more clear and consistent on OK-VQA and A-OKVQA, whose questions demand commonsense reasoning and external knowledge that LLMs excel at providing. This corroborates our belief that LLMs are beneficial to VQA.

Another intriguing phenomenon we observe is that the effect of scaling LLMs becomes obvious only when the model size becomes sufficiently large, for example, when using 30B or larger models, while not entirely predictable on smaller ones (6.7B and 13B). This echoes with the recent finding on the emergent abilities when using LLMs off-the-shelf [60] for language tasks, while confirming the same trend for the first time when using frozen LLMs for vision(-language) tasks.

Competitive performance with end-to-end pretraining and few-shot models. Img2LLM obtains superior performance to most models with end-to-end pretraining, as

Table 2. Performance on VQAv2, OK-VQA, and A-OKVQA. A few methods do not strictly satisfy the zero/few-shot requirements: methods without end-to-end training but assumes access to training samples are labeled with \dagger ; methods that answer from a predefined list of candidates are in grey. Further, \times annotates methods requiring no end-to-end training, which is desirable, and \checkmark otherwise.

Methods	End-to-End Training?	Shot Number	VQAv2 val	VQAv2 test	OK-VQA test	A-OKVQA val	A-OKVQA test
<i>Zero-Shot Evaluation with Frozen Large Language Model</i>							
PICa _{175B} ^{\dagger}	\times	0	-	-	17.7	-	-
Img2LLM _{6.7B}	\times	0	57.6	57.0	38.2	33.3	32.2
Img2LLM _{13B}	\times	0	57.1	57.3	39.9	33.3	33.0
Img2LLM _{30B}	\times	0	59.5	60.4	41.8	36.9	36.0
Img2LLM _{66B}	\times	0	59.9	60.3	43.2	38.7	38.2
Img2LLM _{175B}	\times	0	60.6	61.9	45.6	42.9	40.7
<i>Zero-Shot Evaluation with Extra End-to-End Training</i>							
VL-T5 _{no-vqa}	\checkmark	0	13.5	-	5.8	-	-
FewVLM _{base}	\checkmark	0	43.4	-	11.6	-	-
FewVLM _{large}	\checkmark	0	47.7	-	16.5	-	-
VLKD ViT-B/16	\checkmark	0	38.6	39.7	10.5	-	-
VLKD ViT-L/14	\checkmark	0	42.6	44.5	13.3	-	-
Frozen _{7B}	\checkmark	0	29.5	-	5.9	-	-
Flamingo _{3B}	\checkmark	0	-	49.2	41.2	-	-
Flamingo _{9B}	\checkmark	0	-	51.8	44.7	-	-
Flamingo _{80B}	\checkmark	0	-	56.3	50.6	-	-
<i>Zero-shot Evaluation with Access to Answer Candidates</i>							
WeaQA ZSL	\checkmark	0	46.8	-	-	-	-
VQ ² A	\checkmark	0	61.1	-	19.8	-	-
<i>Few-Shot Evaluation</i>							
ClipCap \rightarrow Cap \rightarrow GPT _{175B}	\times	10	-	-	16.6	15.8	
ClipCap \rightarrow Rel \rightarrow GPT _{175B}	\times	10	-	-	18.1	15.8	
FewVLM _{base}	\checkmark	16	48.2	-	15.0	-	
FewVLM _{large}	\checkmark	16	51.1	-	23.1	-	
PICa _{175B} ^{\dagger}	\times	1	-	-	36.4	-	
PICa _{175B} ^{\dagger}	\times	4	-	-	43.3	-	
PICa _{175B} ^{\dagger}	\times	16	54.3	-	46.5	-	
PICa _{175B} -Ensemble	\times	80	56.1	-	48.0	-	

well as those evaluated in few-shot setups. For example, on VQAv2 our method surpasses Flamingo_{80B}, which cost over 500K TPU hours and billion-scale datasets to train, by a margin of 5.6 points. On A-OKVQA, Img2LLM more than doubles the best reported results so far, from Clip-Clap. The only a few exceptions are on OK-VQA, where our method obtains better results than Flamingo_{9B}, yet is not able to stay on par with Flamingo_{80B}. Considering that Img2LLM is flexible to adapt to updated and stronger LLMs with zero extra training cost, we consider it a more approachable solution to practical adoption of VQA systems, than those trained end-to-end. We also include comparisons with supervised models in Appendix A.4. Img2LLM achieves better performance than most supervised models, despite the fact that it uses zero training data and is evaluated in a zero-shot setup. These results once again validates its effectiveness.

Table 3. Zero-shot VQA performance with different LLMs.

Methods	VQAv2 val	OK-VQA
PICa GPT-3 175B	-	17.7
Frozen _{7B}	29.5	5.9
Ours GPT-Neo 2.7B	50.1	31.5
Ours BLOOM 7.1B	52.4	32.4
Ours GPT-J 6B	56.4	37.4
Ours OPT 6.7B	57.6	38.2
Ours OPT 175B	60.6	45.6

4.3. Experimental Results of Different LLMs

In Table 3, we evaluate the performance of Img2LLM on various open-sourced LLMs other than OPT, including GPT-J [57], GPT-Neo [8] and BLOOM [49]. The experimental results show that Img2LLM enables various LLMs to perform zero-shot VQA tasks, and that all of them achieve superior performance to zero-shot PICa [65] and Frozen [56]. This is a strong evidence for showing our

Table 4. Effect of question selection strategies.

		OK-VQA	VQAv2
PICa _{175B}		17.7	-
Agnostic	Random	35.9	52.9
	Template	40.2	53.0
Neural	Max Freq.	41.5	55.8
	Random	40.5	57.0
	Max Freq.	41.8	59.5

method’s generalization ability with different LLMs.

4.4. Analysis on Question Generation Methods

Table 4 shows the performance of different question selection strategies described in Section 3.2. We compare three question generation techniques, include *image-agnostic*, which uses questions sampled from other images; *template-based*, which uses template questions, and *neural-based*, which uses neural generated questions. Further, we compare two synthetic QA selection strategies. The *random* strategy, which selects QA pairs for prompt randomly; the *max freq.* approach, which selects answer candidates that are most frequent in the captions, and also retrieve the associated synthetic questions to build the prompt.

Among the three question generation techniques, *Agnostic* perform the worst whereas *Neural* performs the best. We attribute the differences to the quality of QA pairs. *Agnostic* QA pairs contain information irrelevant to the current image and may mislead the LLM. *Template* questions feature little linguistic variation and hence cannot demonstrate different QA strategies. *Neural* has the most relevant information and the most linguistic diversity. QA pair with maximum answer frequency outperform random questions. We hypothesize that the most frequent answers describe the most salient or important aspects of the image, thereby providing more information than random questions.

In addition, we evaluate visual information quality encoded in the exemplar prompts using the answer hit rate and the answer noise rate. Answer hit rate (AHR) is defined as the proportion of QA pairs containing the ground-truth answer. Answer noise rate (ANR) is defined as the ratio of ground-truth answers to the total number tokens in the exemplar prompts. Table 7 indicates that exemplar prompts generated from question-relevant captions have a higher AHR, hence enhancing the VQA performance. In addition, the caption filter procedure can remove some noisy captions, allowing it to achieve a higher ANR than its competitors. The experimental results demonstrate that improving both the AHR and the ANR can improve the quality of prompts and VQA performance.

4.5. Ablation on Caption Selection

As Table 6 shows, we evaluate the performance different caption selection strategies, where Max Frequency se-

Table 5. Ablations on prompts designs.

Methods	OK-VQA	VQAv2 val
CQA-CQA-CQA	37.8	52.1
CCC-QAQQA	41.8	59.5

Table 6. Ablation on caption selection methods.

Caption Selection	Random	Max Frequency	Min Frequency
OK-VQA Acc	41.3	41.1	41.8

lects captions containing 30 answers with highest frequencies and Min Frequency selects answers with the lowest frequencies. As the exemplar prompts are produced with answers with the highest frequencies, the Max Frequency strategy does not provide more information than exemplar prompts. In contrast, the Min Frequency strategy chooses captions that can provide some information not in the QA pairs, providing a performance boost.

4.6. Ablation Study on Prompt Design

We have two options to construct LLM’s prompt. The first option is to append a synthetic QA pair after the caption that the QA pair is generated from. This can be described as CQA-CQA-CQA, where C, Q, A stand for caption, synthetic question, and synthetic answer respectively. Alternatively, we can present all captions at once, followed by all question-answer pairs, which we denote as CCC-QAQQA. Experimentally (Table 5), the second design performs significantly better than the first. We hypothesize that the first design may induce the LLM to read only one caption before answering, since in the prompt this caption contains all the information needed for the question. While it is hard to pinpoint the actual mechanism, the results highlight the importance of QA prompts and their positions.

4.7. Examples and Failure Case Analysis

In Figure 3, we show four examples of caption and exemplar prompts and the predictions, including cases of success and failure. In Figure 3(a), the captions and the synthetic QA pairs provide the information that a man is making drinks at a bar. The LLM draws on background knowledge and correctly infers that his job is bartender. In Figure 3(c), while the prediction is understandable (even if not strictly grammatical), the LLM is unable to make inferences based on qualitative physics and predict the right answer. These results highlight the importance to apply appropriate commonsense knowledge in open-ended VQA.

Table 7. The experimental results on QA pairs generated from different captions. The results are run with OPT 30B.

Exemplar Prompts Generation Source	OK-VQA			VQAv2 val		
	VQA Score	Answer Noise Rate	Answer Hit Rate	VQA Score	Answer Noise Rate	Answer Hit Rate
Caption from Complete Image	39.8	0.018	0.480	57.1	0.0290	0.725
Question-relevant Caption	40.6	0.022	0.581	58.1	0.0303	0.821
Question-relevant Caption with Filter	41.8	0.025	0.566	59.5	0.0313	0.804

Question: What type of profession is the man in red in?
GT Answer: bartender



Captions 1: a man in red shirt at a bar making drinks
Captions 2: a man in a red shirt is making a wine tasting
Captions 3: a man in a red shirt at a bar serving a bar

Synthetic Question 1: who is pouring a drink at a bar?

Answer: A man

Synthetic Question 2: where is a man in a red shirt making drinks? Answer: A bar

Question: What type of profession is the man in red in?

Predicted Answer: bartender

(a)

Question: Why is he using knee pads?
GT Answer: Protection/Safety/Prevent injury



Caption 1: a skateboarder wearing knee pads on and protective gear on his knee
Caption 2: a man on skateboard in a helmet and knee pads
Caption 3: a skateboarder skateboarding with knee guards on

Synthetic Question 1: On what part of the body is a skateboarder wearing knee pads? Answer: Knee

Synthetic Question 2: What is the purpose of knee pads?

Answer: Protective

Question: Why is he using knee pads?

Predicted Answer: protect his knee

(c)

Question: The girl behind the man likely is of what relation to him?
GT Answer: daughter



Captions 1: a man is riding the back of a little girl on a motorcycle
Captions 2: an image of bearded man and a girl on a motorcycle riding on the motorcycle
Captions 3: man and child sitting on a motorcycle on the street

Synthetic Question 1: who is holding on to the bearded man on the back of the motorcycle?

Answer: A girl

Synthetic Question 2: what is the size of the girl riding on the motorcycle?

Answer: little

Question: The girl behind the man likely is of what relation to him?

Predicted Answer: daughter

(b)

Question:what is the purpose of the wide tires on that bike?
GT answer:balance/traction/brake



Caption 1: a cargo bike sitting on a tire wheel.
Caption 2: the man is riding a bike on sands.
Caption 3: a man stands on a wheel on some sands.

Synthetic question 1:what are the tires on?

Answer: wheels

Synthetic question 2:what is a man doing on a bike?

Answer: riding

Question: What is the purpose of the wide tires on that bike?

Predicted answer: ride sand

(d)

Figure 3. Example predictions made by Img2LLM. Specifically, (a) and (b) are successful cases, while (c) and (d) are failure cases. See more examples at Appendix A.5.

5. Limitation

One limitation of the proposed approach is that generating image captions and question-answer pairs incurs extra inference overhead. On an 8×A100 machine, our current implementation brings about 24.4% additional computational time on top of the inference time of 175B OPT. We note that further reduction of the overhead can be obtained by shortening the prompt, trading accuracy for speed. Notably, our method avoids expensive end-to-end multimodal representation alignment, which took more than 500K TPU hours in the case of Flamingo.

6. Conclusion

In this paper, we propose Img2LLM, a plug-and-play module designed to exploit the knowledge and reasoning

power of large language models (LLMs) off-the-shelf for zero-shot VQA tasks. Concretely, Img2LLM provides visual information and task guidance to LLMs in the format of easily-digestible prompts. This eliminates the requirement for the expensive end-to-end vision-language alignment, increasing model deployment flexibility while decreasing model deployment cost. The experiments show that Img2LLM enables different LLMs to achieve comparable or even superior zero-shot VQA performance to other methods that require costly end-to-end training.

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A. Appendix

A.1. Reproducibility Statement

We acknowledge the importance of reproducibility for research work and try whatever we can to ensure the reproducibility of our work. As for the implementation of our method, details such as hyperparameters are provided in Section 4.1 in the main paper. We will publicly release all codes after the acceptance of this paper.

A.2. Broader Impact Statement

We acknowledge that while the Img2LLM achieves comparable or superior performance to other zero-shot VQA methods, it has not reduced the inherent bias of these systems. Social-economic biases based on gender, age, race, and ethnicity exist in the datasets, LLMs, and VQA systems presented in this paper, including Img2LLM. Future work could assess the magnitude of this bias and mitigate its impact.

A.3. Details about Question-Relevant Caption Generation

Concretely, we denote features of image patches extracted by ITE as $f_v^i \in \mathbb{R}^{K \times D_v^i}$ and question features as $f_q^i \in \mathbb{R}^{L \times D_q^i}$, where i is the number of the layer of ITE, K is the number of images patches, L is the number of token in the given question, D_v^i is the dimension of patch feature in the i -th layer of ITE network and D_q^i is the dimension of textual feature in the i -th layer of ITE network. For cross-attention head in i -th layer, the cross-attention scores W^i between each image patch and each token in question can be calculated directly as

$$W^i = \text{softmax} \left(\frac{f_q^i W_Q^i W_K^i \top f_v^i \top}{\sqrt{D_q^i}} \right). \quad (1)$$

where $W_Q^i \in \mathbb{R}^{D_q^i \times D_q^i}$ is the query head and $W_K^i \in \mathbb{R}^{D_v^i \times D_q^i}$ is the key head in the i -th layer of ITE network. With Equation 1, we obtain a cross-attention matrix $W^i \in \mathbb{R}^{L \times K}$, where each row is the cross-attention scores of each token in the question over all image patches. Specifically, the attention matrix W^i can be regarded as the patch importance for ITE to calculate the similarity of whole image and question, but it still contains redundancy that contributes only a minor performance loss [7], indicating that some patches are uninformative. In order to find these less relevant image patches, we follow GradCAM and compute the derivative of the cross-attention score from ITE function $\text{sim}(v, q)$, i.e., $\partial \text{sim}(v, q) / \partial W$, and multiplying its gradient matrix with the cross-attention scores element-wisely. The relevance of the k^{th} image patch with the question, r_k^i , can be computed as the average over H attention heads and the sum over L textual tokens:

$$r_k^i = \frac{1}{H} \sum_{l=1}^L \sum_{h=1}^H \min \left(0, \frac{\partial \text{sim}(v, q)}{\partial W_{lk}^{ih}} \right) W_{lk}^{ih}, \quad (2)$$

where h is the index of attention heads and i is the layer index of ITE.

A.4. Experimental Results of Supervised Learning Methods in A-OKVQA

We show the experimental comparisons between our method and supervised model on A-OKVQA dataset [50] as Table 10 shows. We can observe that our method outperform almost all supervised model with smaller size language model. This strongly support our method's effectiveness in leveraging reasoning power of large language models.

A.5. Template-Based Question Design

We design question templates for each part of speech type of answers as Table 9 shows.

A.6. Sensitive Analysis

We evaluate the sensitive analysis about the QA pairs and number of captions in prompt for LLM as Table 10 shows. We can observe that the differences in QA scores on OK-VQA dataset are not higher than 1 as long as QA pairs in prompts. The results demonstrate the performance of our method is robust with different numbers of QA pairs and captions.

A.7. Examples

Table 8. The experimental comparisons with models trained in A-OKVQA training dataset.

Methods	A-OKVQA	
	Val	Test
<i>Models Fine-Tuned in A-OKVQA Training Set</i>		
Pythia [21]	25.2	21.9
ViLBERT [37]	30.6	25.9
LXMERT [55]	30.7	25.9
KRISP [41]	33.7	27.1
GPV-2 [25]	48.6	40.7
<i>Zero-Shot Evaluation with Plug-in Frozen Large Language Model</i>		
Ours _{6.7B}	33.3	32.2
Ours _{13B}	33.3	33.0
Ours _{30B}	36.9	36.0
Ours _{66B}	38.7	38.2
Ours _{175B}	42.9	40.7

Table 9. The question templates for answers with different part of speech.

Part of Speech of Answer	Question Templates
Noun	What item is this in this picture? What item is that in this picture?
Verb	What action is being done in this picture? Why is this item doing in this picture? Which action is being taken in this picture? What action is item doing in this picture? What action is item performing in this picture?
Adjective	How to describe one item in this picture? What is item's ADJ TYPE in this picture? What is the ADJ TYPE in this picture?
Num	How many things in this picture?

Table 10. The experimental results of using different number of captions and QA pairs as prompts. The experiments are run on OK-VQA with OPT 30B.

QA Pairs \ Caption	0	10	20	30	40	50
	0	10	20	30	40	50
0	3.3	19.6	22.7	23.4	24.0	24.8
10	40.9	41.6	42.1	42.1	41.9	42.2
20	41.2	41.3	41.3	41.7	42.2	42.0
30	41.0	41.0	41.7	41.8	41.6	41.5
40	40.3	40.7	40.6	40.3	40.3	41.1
50	40.6	40.6	40.7	40.9	40.6	41.1

Table 11. The experimental results of using different number of patches to generate question-relevant captions. The experiments are run on OK-VQA with OPT 30B.

Patch_num	10	20	40	Full
	41.2	41.8	41.6	39.8

Table 12. The experimental results of generating different number of question-relevant captions. The experiments are run on OK-VQA with OPT 30B.

Caption_num	PICa	10	30	50	100
	17.7	38.3	40.9	41.4	41.8

Question: what kind of bird are they? **GT answer:** seagull/pelican/seagull



Caption 1: two **seagulls** and a **seagull** on a wooden platform

Caption 2: a group of **seagulls** sit on some wood

Caption 3: a group of **seagulls** sitting down in the sunshine

Synthetic question 1: what birds are sitting on a wooden post?

Answer: **seagulls**

Synthetic question 2: how many **seagulls** are standing on top of a wooden post?

Answer: two

Question: what kind of bird are they?

Predicted answer: **seagull**

Question: what kind of beverage could one make with the item on top of the stove? **GT answer:** tea



Caption 1: a white kitchen with a stove, sink, and **tea** cups

Caption 2: kitchen with microwave, pots, coffee maker, stove and chairs

Caption 3: a kitchen filled with silver stove top oven sitting next to a microwave

Synthetic question 1: what is in the kitchen with a **tea** kettle?

Answer: stove

Synthetic question 2: what is on the counter next to the stove?

Answer: microwave

Question: what kind of beverage could one make with the item on top of the stove?

Predicted answer: **tea**

(b)

Question: what fabric are these jackets made of? **GT answer:** denim/jean



Caption 1: a man wearing a **denims** shirt stands at a motorcycle

Caption 2: man in **denim** jacket and blue uniform jacket on a red motorcycle

Caption 3: a man wearing blue **denim** clothes is standing near motorcycles

Synthetic question 1: what is a man wearing on a motorcycle?

Answer: a **denim** jacket

Synthetic question 2: what type of vehicle is the man sitting on?

Answer: motorcycle

Question: what fabric are these jackets made of?

Predicted answer: **denim**

(c)

Question: what style of fence is this? **GT answer:** picket/pickett



Caption 1: a fence of **picket** white boards with a gate

Caption 2: the house is fenced in in front of a white **picketed** fence

Caption 3: a white **picket** with pink roses in front of it

Synthetic question 1: what color is the **picket** fence in front of a house?

Answer: white

Synthetic question 2: what type of fence is in front of a house?

Answer: **picket**

Question: what style of fence is this?

Predicted answer: **picket**

(d)

Question: what is on the ears of the cattle in this photo? **GT answer:** tag



Caption 1: a row of cows, tied up to wires, yellow ears **tags**

Caption 2: a group of cows in grass with some yellow **tags** on their ears

Caption 3: cows with numbered ear **tags** standing behind a fence

Synthetic question 1: what are the cows wearing on their ears?

Answer: **tags**

Synthetic question 2: what color are the ear **tags** on the cows?

Answer: yellow

Question: what is on the ears of the cattle in this photo?

Predicted answer: **tag**

(e)

Figure 4. Success case analysis for OK-VQA. Green color indicates answer cues and correct prediction.

Question: why is timing of the essence when delivering this food item? **GT answer:** temperature/hot still/stay hot



Caption 1: two pizza boxes have pepper pizza and take out

Caption 2: two boxes are opened up of two different pizzas

Caption 3: there are two small baked pizzas on the table

Synthetic question 1: what are two large pizzas sitting in?

Answer: boxes

Synthetic question 2: where are two large pizzas sitting next to each other?

Answer: table

Question: why is timing of the essence when delivering this food item?

Predicted answer: hot

Question: what era is this furniture from? **GT answer:** victorian/1940s



Caption 1: a living room with a small television in front of the window

Caption 2: a vintage tv is sitting on a nice table in the living room

Caption 3: a large house shaped model is sitting in a living room

Synthetic question 1: what type of room has a tv in the center?

Answer: living

Synthetic question 2: how large is the tv in the living room?

Answer: small

Question: what era is this furniture from?

Predicted answer: vintage

(b)

Question: what kind of sporting event is this? **GT answer:** soccer/not sure/pole vault



Caption 1: man on horse coming off from arena, holding something

Caption 2: a man is riding a horse during a soccer game

Caption 3: a man holding a red flag near a large person in a green field

Synthetic question 1: who is riding a horse in the middle of a stadium?

Answer: man

Synthetic question 2: what color is the flag on display at a football game?

Answer: red

Question: what kind of sporting event is this?

Predicted answer: football

(c)

Question: what type of clouds are in the picture? **GT answer:** cumulus/cumuli/nimbus



Caption 1: a cloudy - filled sky on a cloudy day over a zebras

Caption 2: the clouds are gray and full of clouds

Caption 3: there are many different clouds in this sky

Synthetic question 1: what is in the background of a photo of a zebra?

Answer: sky

Synthetic question 2: what type of sky is above on a cloudy day?

Answer: cloudy

Question: what type of clouds are in the picture?

Predicted answer: cloud

(d)

Question: how many people can this bus carry? **GT answer:** 50/40/39



Caption 1: a passenger bus traveling on a street side

Caption 2: blue commuter bus with parked on the side of the road

Caption 3: a bus that says aradara rides down the street

Synthetic question 1: what color bus is driving down the street?

Answer: blue

Synthetic question 2: what is making it's way down the street?

Answer: bus

Question: how many people can this bus carry?

Predicted answer: many

(e)

Figure 5. Failure case analysis for OK-VQA. Red color indicates incorrect prediction.

Question: which food has the least carbs? **GT answer:** soup/vegetable/salad



Caption 1: a table holding food including **soup**, sandwiches and fruit

Caption 2: the **soup** is very creamy in the bowl

Caption 3: sandwiches and **soup** is sitting on a table spread

Synthetic question 1: where is soup served on a table?

Answer: bowl

Synthetic question 2: what is on a plate next to a bowl of **soup**?

Answer: sandwich

Question: which food has the least carbs?

Predicted answer: **soup**

Question: in which way are the adults shown here likely related to the child? **GT answer:** parents/grandparents



Caption 1: a **family** sitting down on a bench in a park

Caption 2: a family sitting behind a park bench talking to a **toddler**

Caption 3: two people sitting on benches with a **baby** next to them

Synthetic question 1: what is sitting on a bench?

Answer: a **baby**

Synthetic question 2: who sits next to a **toddler** on a bench?

Answer: couple

Question: in which way are the adults shown here likely related to the child?

Predicted answer: parents

(b)

Question: what other surface is this game played on? **GT answer:** grass/clay/concrete



Caption 1: a blue surface with a **blue tennis court**

Caption 2: a man running across a **blue tennis court** with a racquet

Caption 3: a **blue tennis court** with a single game of tennis in progress

Synthetic question 1: what color is the **tennis court**?

Answer: blue

Synthetic question 2: what sport is a man playing on a **blue court**?

Answer: tennis

Question: what other surface is this game played on?

Predicted answer: grass

(c)

Question: what are they waiting to do when they stand next to the street? **GT answer:** cross/ride bus/light change



Caption 1: traffic and pedestrians at an **intersection** near a fire hydrant

Caption 2: a **sidewalk** and pedestrian **crosswalk** on a busy city street

Caption 3: a red fire hydrant stands besides a street that has a **crosswalk**

Synthetic question 1: where is a fire hydrant on a busy street?

Answer: crosswalk

Synthetic question 2: where are people waiting at a **crosswalk**?

Answer: intersection

Question: what are they waiting to do when they stand next to the street?

Predicted answer: cross

(d)

Question: what kind of resort are these people at? **GT answer:** ski resort/ski/snow



Caption 1: a group of people are **skiing** high up a slope

Caption 2: many people **skiing** down a **ski** slope during the day

Caption 3: a crowd of people on **skis** coming down the mountain

Synthetic question 1: what are people doing on a **snow** covered mountain?

Answer: ski

Synthetic question 2: who is **skiing** on a **snow** covered mountain?

Answer: people

Question: what kind of resort are these people at?

Predicted answer: **ski resort**

(e)

Figure 6. Success case analysis for A-OKVQA. Green color indicates answer cues and correct prediction.

Question: this dish is suitable for which group of people? **GT answer:** vegetarian/vegan/family



Caption 1: a pasta dish sitting on top of a white plate

Caption 2: a broccoli pasta dish that has very pasta

Caption 3: a dish of pasta with noodles and tomato sauce

Synthetic question 1: what vegetable is on a white plate?

Answer: broccoli

Synthetic question 2: what color is a plate of pasta with broccoli on it?

Answer: white

Question: this dish is suitable for which group of people?

Predicted answer: children

Question: what is in front of the monitor? **GT answer:** chair/keyboard/webcam



Caption 1: a corner table with computer computer on the desk

Caption 2: a computer on the small desk in a small office area

Caption 3: view of a computer monitor in a light lit room

Synthetic question 1: what is a computer sitting on in a corner of a room?

Answer: desk

Synthetic question 2: how big is the desk in the corner?

Answer: small

Question: what is in front of the monitor?

Predicted answer: desk

(b)

Question: what type of shot is the woman about to hit? **GT answer:** forehand/tennis shot/swing



Caption 1: tennis player is hitting a tennis ball with her racket

Caption 2: a woman in pink outfit hitting a tennis ball

Caption 3: a woman in a cropped top and pants swinging a tennis racquet

Synthetic question 1: what is a tennis player doing with a tennis racket?

Answer: swinging

Synthetic question 2: who is swinging a tennis racket at a tennis ball?

Answer: woman

Question: what type of shot is the woman about to hit?

Predicted answer: volley

(c)

Question: what is in the bottles? **GT answer:** alcohol/liqueur/baileys



Caption 1: a sandwich on a plate with a glass of beer bottle

Caption 2: a table that has a sandwich, beer, and beer on it

Caption 3: a sandwich on a plate with a glass of beer bottle

Synthetic question 1: what is next to a sandwich and a beer?

Answer: bottle

Synthetic question 2: where is a sandwich with a beer and beer on a plate?

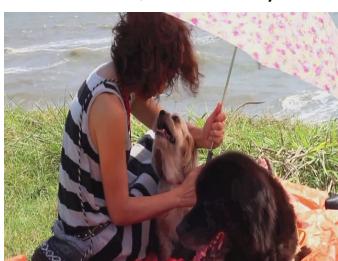
Answer: table

Question: what is in the bottles?

Predicted answer: beer

(d)

Question: why is the woman holding the umbrella? **GT answer:** shade/sun protection/get shadow



Caption 1: a young woman and the umbrella are on an orange blanket

Caption 2: a woman's umbrella and two dogs under an umbrella

Caption 3: a woman holding an umbrella is getting some light under her umbrella

Synthetic question 1: who is holding an umbrella while her dog sits under it?

Answer: woman

Synthetic question 2: what is a woman holding and a dog under it?

Answer: an umbrella

Question: why is the woman holding the umbrella?

Predicted answer: to protect herself from the sun

(e)

Figure 7. Failure case analysis for A-OKVQA. Red color indicates incorrect prediction.

Question: what can the ram eat in this photo? **GT answer:** grass



Caption 1: the ram is standing outside on the green grass

Caption 2: a ram with white curly horns standing in a field

Caption 3: shaggy coated sheep with horns facing away in the center of a grass field

Synthetic question 1: where is a ram standing?

Answer: grass

Synthetic question 2: what animal is standing in a grassy field?

Answer: sheep

Question: what can the ram eat in this photo?

Predicted answer: grass

Question: what does the sign say? **GT answer:** stop



Caption 1: a stop sign with cloudy sky behind it

Caption 2: a red stop sign with a sky background

Caption 3: a tall stop sign on a rural road

Synthetic question 1: what color is the stop sign?

Answer: red

Synthetic question 2: what type of sky is behind a stop sign?

Answer: cloudy

Question: what does the sign say?

Predicted answer: stop

(b)

Question: what type animal is on the woman's pants? **GT answer:** owl/penguins



Caption 1: a girl is sitting on the ground in owl patterned pants

Caption 2: a woman with owly print pajamas pants is sitting in front of a pile of

Caption 3: a girl seated on the ground wearing pajamas

Synthetic question 1: where is a young girl wearing owl pants sitting?

Answer: the ground

Synthetic question 2: how is a young girl wearing owl pants doing?

Answer: sitting

Question: what type animal is on the woman's pants?

Predicted answer: owl

(c)

Question: how many children are at the table? **GT answer:** 3



Caption 1: three small little kids gather together on a dining table

Caption 2: a group of kids posing at a party table

Caption 3: three children sitting at a table with their food smiling at a picture

Synthetic question 1: what type of table are the three children sitting at?

Answer: dining

Synthetic question 2: how are the three children sitting at a table?

Answer: smiling

Question: how many children are at the table?

Predicted answer: 3

(d)

Question: is there broccoli in this dish? **GT answer:** yes



Caption 1: broccoli floret rice is in a large black pot

Caption 2: there is a closeup of a veggie salad

Caption 3: broccoli rice in a black bowl, ready to be eaten

Synthetic question 1: what is covered in broccoli in a pan?

Answer: rice

Synthetic question 2: what is a dish filled with broccoli and other vegetables in?

Answer: pot

Question: is there broccoli in this dish?

Predicted answer: yes

(e)

Figure 8. Success case analysis for VQAv2. Green color indicates answer cues and correct prediction.

Question: what is atop this building? **GT answer:** cross/stars/cross and stars



Caption 1: the cathedral tower is with the clock on a steeple

Caption 2: a clock and a two crosses on top of a church

Caption 3: the top of a red cathedral with a clock on the tower

Synthetic question 1: what part of a building has a clock on it?

Answer: top

Synthetic question 2: what color is the building with a clock on top?

Answer: red

Question: what is atop this building?

Predicted answer: a clock

Question: what are they standing by? **GT answer:** bushes/tree/bricks



Caption 1: two girl sitting and talking, one is looking at something

Caption 2: an older woman and young woman using cellphones

Caption 3: two girls sitting on a brick wall during the day time

Synthetic question 1: who are sitting on a bench looking at their phones?

Answer: women

Synthetic question 2: what type of wall are the two women sitting on?

Answer: brick

Question: what are they standing by?

Predicted answer: brick wall

(b)

Question: how many zebras are there? **GT answer:** 3



Caption 1: two zebras walking by a feeder full of food

Caption 2: pair of zebras standing together at water trough in zoo

Caption 3: the zebras are eating out of a feeder box

Synthetic question 1: how many zebras are standing next to each other?

Answer: two

Synthetic question 2: what are the zebras doing?

Answer: eating

Question: how many zebras are there?

Predicted answer: 2

(c)

Question: how many buses are in the picture? **GT answer:** 8



Caption 1: a lot of buses sit parked in a line in front of a hill

Caption 2: a group of purple passenger buses all in a row

Caption 3: a row of purple bus buses next to each other

Synthetic question 1: how are the buses parked?

Answer: a line

Synthetic question 2: what color buses are parked in front of each other?

Answer: purple

Question: how many buses are in the picture?

Predicted answer: several

(d)

Question: are the numbers on the clock Roman numerals? **GT answer:** yes



Caption 1: a living room scene with a clock and tv

Caption 2: a chair is in front of a television that is being displayed

Caption 3: lounge chair with a clock that is hanging on the wall, and leather chair sits

Synthetic question 1: what is on in a living room?

Answer: television

Synthetic question 2: how is a wall clock displayed in a living room?

Answer: hanging

Question: are the numbers on the clock Roman numerals?

Predicted answer: no

(e)

Figure 9. Failure case analysis for VQAv2. Red color indicates incorrect prediction.