Question Generation for Evaluating Cross-Dataset Shifts in Multi-modal Grounding

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Abstract

Visual question answering (VQA) is the multi-modal task of answering natural language questions about an input image. Through cross-dataset adaptation methods, it is possible to transfer knowledge from a source dataset with larger train samples to a target dataset where training set is limited. Suppose a VQA model trained on one dataset train set fails in adapting to another, it is hard to identify the underlying cause of domain mismatch as there could exist a multitude of reasons such as image distribution mismatch and question distribution mismatch. At UCLA, we are working on a VQG module that facilitate in automatically generating OOD shifts that facilitates in systematically evaluating cross-dataset adaptation capabilities of VQA models.

1 Background & Motivation

VQA is the challenging AI task of answering natural language questions about an input image (Antol et al., 2015; Anderson et al., 2018). Several datasets have been proposed to measure the progress on this task such as VQA 2.0 (Goyal et al., 2017), VizWiz (Gurari et al., 2018), Visual7w (Zhu et al., 2016), GQA (Hudson and Manning, 2019), to name a few. Recently, self-attention and multi-modal pre-training based methods (Tan and Bansal, 2019; Lu et al., 2019; Cao et al., 2020) demonstrated superior performance on these datasets. Despite great progress, the state-of-the-art methods are found to be less effective when the distribution of \langle image, question \rangle pairs in testing set are different from the training set (Chao et al., 2018; Akula and Zhu, 2022b; Gardner et al., 2020), necessitating the importance of developing cross-dataset adaptation methods (Akula and Zhu, 2019a; Carlson et al., 2003; Soricut and Marcu, 2003; LeThanh et al., 2004).

Through cross-dataset adaptation methods, it is possible to transfer knowledge from a source dataset with larger train samples to a target dataset where training set is limited. However, VQA datasets differ in the way they are collected, making them significantly different in the distribution of input visual and language features (Chao et al., 2018). These multi-modal distribution shifts make it difficult to measure adaptation capabilities and has yet to be well-studied. For example, consider a domain adaptation setting between VQA 2.0 (Goyal et al., 2017) vs. VizWiz (Gurari et al., 2018) datasets.

Suppose a VQA model trained on VQA 2.0 train set fails in adapting (e.g. through fine-tuning) to Vizwiz. From this observation, it is difficult to identify the real cause of domain mismatch as there could exist a multitude of reasons such as (a) image distribution mismatch (e.g. VQA 2.0 consists of high quality images compared to Vizwiz); (b) question distribution mismatch (e.g. VQA 2.0 questions are less conversational than Vizwiz questions); (c) insufficient sample size (e.g. VQA 2.0 consists of relatively large number of training samples); and (d) a combination of image and question distribution mismatches (Akula and Zhu, 2019a; Akula et al., 2020a; Akula and Zhu, 2019b; Akula et al., 2021c,d,b, 2020c; R Akula et al., 2019; Pulijala et al., 2013; Gupta et al., 2012).

2 Problem Definition

There exists two methods to generate cross-datasets shifts:

1. Human Annotations: We can ask human annotators (e.g. AMT turkers) to write VizWiz style queries for VQA 2.0 images and VQA 2.0 style questions for VizWiz images. Although, the quality of annotations will be
high, this approach is costly and cannot scale to multiple datasets (Akula et al., 2013, 2018, 2021a; Gupta et al., 2016; Akula et al., 2019b; Akula, 2021; Akula et al., 2019a, 2020b).

2. **Visual Question Generation (VQG):** In this work, instead of using human annotators, we propose a VQG module that facilitate in automatically generating OOD shifts for VQA datasets. This facilitates in systematically evaluating cross-dataset adaptation capabilities of VQA models. Specifically, using our VQG module, we generate additional test sets for source and target datasets by controlling and disentangling distribution shifts in vision and language features (Akula and Zhu, 2022a; Agarwal et al., 2018; Akula et al., 2019c; Akula, 2015; Palakurthi et al., 2015; Agarwal et al., 2017; Dasgupta et al., 2014).

For example, as shown in Figure 1, using \langle image, question \rangle pairs from source and target test sets involve shift in both visual and language features such as \langle I_{vqa}, Q_{vqa} \rangle to \langle I_{vzwz}, Q_{vzwz} \rangle. We augment these test sets to facilitate measuring adaptation capabilities of VQA models on incremental (systematic) shifts such as \langle I_{vqa}, Q_{vqa} \rangle to \langle I_{vqa}, Q_{vzwz} \rangle to \langle I_{vzwz}, Q_{vzwz} \rangle.

### 3 Summary of Contributions

Below we summarize our key contributions:

1. Proposing and Implementing a Visual Question Generation (VQG) module for generating questions and answers from the images.

2. Using our proposed VQG, we generate OOD test splits for VQA 2.0 and VizWiz datasets

3. We show that our generated OOD splits help in quantifying the systematic cross-dataset shifts in VQA models.

### 4 Approach

We will leverage state-of-the-art implementations to train an end-to-end VQG model. Specifically, we use train sets of VQA 2.0 and VizWiz datasets and train VQG model mapping input image to questions with an additional dataset source indicator specifying the source of the sample. After we train our VQG, during inference, we change the dataset indicator to generate cross-dataset image and question pairs. For example, we pick VQA 2.0 image and provide the dataset indicator as VizWiz, for generating VizWiz style questions on VQA 2.0.
images. We will experiment with several contextual features (such as adding bounding box annotations, pre-training on image captioning datasets, etc) to control the quality of the generated questions.

5 Datasets and VQA Models

We experiment with VQA 2.0 and VizWiz datasets. We use ViLBERT (Lu et al., 2019), a pretrain-then-transfer approach, as the state-of-the-art VQA model for our adaptation experiments.

6 Initial Experiments

We have first started selecting a state-of-the-art VQG model. We choose an existing implementation based on mutual information maximization (Krishna et al., 2017). We incorporated the following additional cues to the input to generate the cross-dataset splits:

1. Source of the dataset (eg: VQA, VizWiz)
2. First Three Words of Question: We found that VizWiz questions start with unique words such as “Can you please” and “Please tell me”. So, we believe providing the first three words of the question as additional guidance would further help the model to understand the distribution style of questions that we like to generate.
3. We are currently working on integrating answer categories as additional inputs to the module. The work by (Krishna et al., 2017) proposed16 categories on VQA dataset such as spatial, binary and count. We are leveraging these categories to make the generated questions more diverse.

Training VQA models on ViLBERT: We have completed training VQA models using ViLBERT architecture. This step took us more time as this takes up to 5 days to train the model. Once we get decent questions generated using VQG, we will immediately start our adaptation experiments using the VQA models trained using ViLBERT.

7 Conclusion

We performed cross-dataset evaluation with VQA 2.0 and VizWiz datasets. To do this, we proposed a Visual Question Generation (VQG) module for generating questions and answers from the images. Our experiments demonstrate that our generated OOD splits help in quantifying the systematic cross-dataset shifts in VQA models.

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