Tell Me the Evidence? Dual Visual-Linguistic Interaction for Answer Grounding

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Abstract

Answer grounding aims to reveal the visual evidence for visual question answering (VQA), which entails highlighting relevant positions in the image when answering questions about images. Previous attempts typically tackle this problem using pretrained object detectors, but without the flexibility for objects not in the predefined vocabulary. Recent visual-linguistic models have made remarkable advances by leveraging powerful Transformers to enable visual-linguistic interaction. However, these black-box methods solely concentrate on the linguistic generation, ignoring the visual interpretability. In this paper, we propose Dual Visual-Linguistic Interaction (DaVI), a novel unified framework with the capability for both linguistic answering and visual grounding. DaVI innovatively introduces two visual-linguistic interaction mechanisms: 1) visual-based linguistic encoder that understands questions incorporated with visual features and produces linguistic-oriented evidence for further answer decoding, and 2) linguistic-based visual decoder that focuses visual features on the evidence-related regions for answer grounding. This way, our approach ranked the 1st place in the public answer grounding track of 2022 VizWiz Grand Challenge.

1. Introduction

Visual question answering (VQA) is a fundamental visual-linguistic task in various real-life applications such as assisting visually impaired people to answer questions about images [1]. Although the VQA community has made significant progress, the best-performing systems are complicated black-box models, raising concerns about whether their answer reasoning is based on correct visual evidence. By understanding the reasoning mechanism of the model, we can evaluate the quality of answers, improve model performance, and provide explanations for end-users.

To address this problem, answer grounding has been introduced into VQA systems, which requires the model to locate relevant image regions as well as answer visual questions. Most previous efforts usually rely on pretrained detection models to provide object features, entailing low answering flexibility for objects not in the predefined vocabulary [2]. Recently, a few works try to get rid of these limitations in a weakly supervised fashion [2], but neither the answering accuracy nor grounding accuracy achieved is satisfactory [1]. In contrast, visual language pre-training has tremendously advanced VQA performance using large-scale multi-modal Transformers and web-scale datasets [3], eliminating the need for detectors. However, these text-generation oriented schemes concentrate on the linguistic modeling based on off-the-shelf visual features, and are therefore not capable of visual-oriented prediction in the grounding task.

To overcome the challenges of answer grounding, a fundamental but critical perspective is how to reconcile the visual-linguistic interaction for both visual-oriented and linguistic-oriented predictions. As shown in Fig. 1, state-of-the-art works inject features from the other modality into the task-oriented modeling, effectively exploiting rich interactions.
Transformer layers in the task-oriented encoder. However, this visual-linguistic interaction is specific to a single-modal output such as linguistic-oriented answering or visual-oriented segmentation.

Accordingly, this paper proposes DaVI which unifies linguistic-oriented answering and visual-oriented grounding into an end-to-end framework. The two key components of DaVI are Visual-based Linguistic Encoder (VLE) and Linguistic-based Visual Decoder (LVD) which will be detailed in the next section.

2. Method

As shown in Fig. 1 (IV), DaVI ingests a question along with the corresponding image as input and outputs an evidence mask while predicting the answer. For simplicity, we employ a Vision Transformer (ViT), instead of an object detector, to extract image features. Then, VLE encodes questions with the image references and produces linguistic-oriented evidence features. The Linguistic Decoder (LD), with the same structure as the BERT, answers visual questions on the basis of linguistic-oriented evidence. Different from LD, to predict evidence masks, LVD performs another interaction between the visual features from VE and the linguistic-oriented evidence.

Visual-based Linguistic Encoder (VLE). We interleave cross-attention (CA) layers in between the self-attention layers and the feed-forward networks of BERT to form the VLE module. The CA layers attend to visual references using linguistic features as queries. These visual-linguistic interactions in VLE provide multi-modal evidence for answer decoding in LD. However, due to the language-oriented modeling, these features need to be remapped into visual grids by LVD to decode visual evidence.

Linguistic-based Visual Decoder (LVD). LVD can be regarded as an “identical” structure of the CA layer in VLE but with different inputs: it uses visual features as queries to attend to linguistic cues from VLE. Following the best practices in computer vision, we collect multi-level visual features generated by VE and feed them into LVD. Finally, a simple convolutional segmentor is exploited to predict the visual mask for answer grounding.

3. Experiment

Dataset. The dataset of VizWiz answer grounding contains 6494, 1131 and 2373 samples in the train, val and test set, respectively. Evaluations are conducted by the challenge server on the test set.

Implementation Details. In our experiments, VE, VLE, and LD are pretrained on the web-scale dataset [3]. In the training phase, we keep an exponential moving average copy of parameters for inference. We also ensemble the results from models trained with different hyperparameters.

Results. As shown in Tab 1, compared to the single interaction paradigm, DaVI successfully achieved a 4.24% IoU improvement, thanks to the design of dual visual-linguistic interactions. Tab. 2 shows public results on VizWiz answer grounding track, where DaVI ranked the 1st place, substantially outperforming other methods.

4. Conclusion

We propose DaVI for answer grounding, which utilizes the VLE and LVD for visual-linguistic interaction to unify the linguistic-oriented answering and visual-oriented grounding. DaVI ranked the 1st place on the public track of VizWiz answer grounding Challenge.

Table 1. Ablation study on test set of VizWiz Grounding track.

| Variant | IoU (%) | ∆ (%) |
|---------|---------|-------|
| LE + LVE + VD (w/o answer) | 64.28 | – |
| VE + VLE + LVD + LD | 68.52 | +4.24 |
| VE + VLE + LVD + LD (w/ ensemble) | 70.57 | +2.05 |

Table 2. Results on test set of VizWiz Grounding track.

| Rank | Team         | IoU (%) |
|------|--------------|---------|
| 1    | Aurora (ours)| 70.57   |
| 2    | hsslab       | 70.15   |
| 3    | MGTB         | 69.70   |
| 4    | UD VIMS Lab  | 67.55   |
| 5    | MindX        | 66.92   |
| 6    | boostboom    | 64.49   |
| 7    | Black        | 58.44   |

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