IMPROVING CROSS-MODAL UNDERSTANDING IN VISUAL DIALOG VIA CONTRASTIVE LEARNING

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ABSTRACT

Visual Dialog is a challenging vision-language task since the visual dialog agent needs to answer a series of questions after reasoning over both the image content and dialog history. Though existing methods try to deal with the cross-modal understanding in visual dialog, they are still not enough in ranking candidate answers based on their understanding of visual and textual contexts. In this paper, we analyze the cross-modal understanding in visual dialog based on the vision-language pre-training model VD-BERT and propose a novel approach to improve the cross-modal understanding for visual dialog, named ICMU. ICMU enhances cross-modal understanding by distinguishing different pulled inputs (i.e., pulled images, questions or answers) based on four-way contrastive learning. In addition, ICMU exploits the single-turn visual question answering to enhance the visual dialog model’s cross-modal understanding to handle a multi-turn visually-grounded conversation. Experiments show that the proposed approach improves the visual dialog model’s cross-modal understanding and brings satisfactory gain to the VisDial dataset.

Index Terms—Visual Dialog, Cross-modal Understanding, Contrastive Learning

1. INTRODUCTION

Recently, with the rise of pre-trained models [2], researchers have begun to explore vision-and-language task [3] with pre-trained models [1]. Specifically, visual dialog [6] utilizes multi-step reasoning based on visual context to answer the current question.

One way to gain sufficient cross-modal understanding is through utilizing kinds of attention mechanism [10] [11] [12]. ReDAN [13] and DMAM [14] use multi-step reasoning based on dual attention to learn cross-modal understanding. DAN [15], MCAN [7] and LTMI [16] utilize multi-head attention mechanisms to manage multi-modal intersection. Moreover, there are some approaches [17] [18] [19] [20] [21] using graph-based structures to learn cross-modal understanding.

However, the approaches mentioned above do not utilize pre-trained models, which have a strong power to deal with vision-and-language tasks. Visdial-BERT [22] and VD-BERT [11] take advantage of the pre-trained model to greatly improve the performance of the visual dialog task. As shown in Figure 1, the SOTA model VD-BERT often makes mistakes and usually ranks the wrong answers first. VD-BERT does not have enough cross-modal understanding capabilities, so that it often scores unrelated wrong answers very high, such as the top 1 candidate answer “no” to the question Q4 “is the food in his mouth?” shown in Figure 1.

In this paper, we propose a novel approach to improve the cross-modal understanding for visual dialog, named ICMU. ICMU enhances cross-modal understanding by distinguishing different pulled inputs (i.e., pulled images, questions or answers) based on four-way contrastive learning. What’s more, ICMU exploits the single-turn visual question answering to enhance the visual dialog model’s cross-modal understanding to handle a multi-turn visually-grounded conversation. Experiments show that the proposed approach improves the visual dialog model’s cross-modal understanding and brings satisfactory gain on the VisDial dataset [5]. The contributions of this work are summarized as follows:

- We propose a novel approach ICMU, including 4-way contrastive learning and enhancing by utilizing VQA, to improve the cross-modal understanding based on vision-and-language pre-trained models for visual dialog.
- We conduct extensive experiments and ablation studies on the large-scale datasets VisDial v1.0. Experimental results show that our approach improves the visual dialog model’s cross-modal understanding and brings satisfactory gain.

Fig. 1. A motivating example of cross-modal understanding of VD-BERT. We show the candidates ranking results of VD-VBERT based on its cross-modal understanding. It can be seen that in the first 8 candidates, wrong answers account for most of them, and the ranking results of correct answers are not so good.
2. METHODOLOGY

In this section, we first formally describe the visual dialog task. Given a current question $Q_t$ with an image $I$ at $t$-th turn, as well as its dialog history $H_t = \{C,(Q_1,A_1),..., (Q_{t-1},A_{t-1})\}$ (where $C$ denotes the image caption), the dialog model is required to predict its answer $A_t$ by ranking a list of 100 answer candidates $\{A_1, A_2, ..., A_{100}\}$.

Figure 2 shows the overview of our approach. First, we employ a unified vision-dialog Transformer to encode both the image and dialog history, where we append an answer candidate $A_t$ in the input to model their interactions in an early fusion manner. Next, we adopt cross-modal masked token loss and cross-modal contrastive loss to train the model for effective cross-modal understanding in visual dialog. In addition, we exploit the single-turn visual question answering to handle the visual dialog model’s cross-modal understanding to support a multi-turn visually-grounded conversation.

2.1. Vision-Dialog Transformer

2.1.1. Visual Features.

Given an image $I$, we employ Faster R-CNN [23] pre-trained on Visual Genome [24] to extract the object-level vision features $R_t = \{o_1, ..., o_k\}$, where each object feature $o_i$ is a 2048-d Region-of-Interest (RoI) feature. $k$ is fixed to 36 in our setting. In addition, we adopt normalized bounding box coordinates as the spatial location due to disorder of visual objects. Specifically, we define the location information by constructing a 5-d vector: $p_i = (\frac{x_1 \times x_2}{W}, \frac{y_1 \times y_2}{H}, \frac{(x_2 - x_1) \times (y_2 - y_1)}{W \times H})$, where $(x_1, y_1)$ and $(x_2, y_2)$ are the coordinates of the bottom-left and top-right corner of the $i$-th object, $W$ and $H$ respectively denote the width and height of the input image, and the last element is the relative area of the object. We also extend $p_i$ with its class id and confidence score for a richer representation to 7-d vector.

2.1.2. Textual Features.

For the textual features, we pack all the textual elements (the history, question and answer candidate) into a long sequence and employ WordPiece tokenizer [25] to split it into a word sequence $w$, where each word is embedded with an absolute positional code following [26].

2.1.3. Cross-Modality Encoding.

Like most vision-and-language transformers, we integrate the image objects with language elements into a whole input sequence. As shown in Figure 2 we use some special tokens to segment different elements in the input sequence. We use [CLS] to denote the beginning of the sequence, and [SEP] to separate the two modalities. Moreover, we utilize a special token [HIS] to denote end of turn [27], which informs the model when the dialog turn ends. And we use [Ques] and [Ans] to segment the current question and the answer candidate. As such, we prepare the input sequence into the format as $x = ([CLS], o_1, ..., o_k, [SEP], C, [HIS], Q_1, A_1, [HIS], ..., [Ques], Q_t, [Ans], A_t, [SEP])$. Finally, We combine each input token embedding with its position embedding and segment embedding (0 or 1, indicating whether it is image or text) and then perform layer normalization [28].

2.1.4. Transformer Backbone.

We utilize transformer encoder as the Transformer backbone to handle cross-modal understanding. Formally, we denote the embedded vision-language inputs as $H^0 = [o_1, ..., o_k]$ and then encode them into multiple levels of cross-modal representations $H^i = [h_1^i, ..., h_{|X|}^i]$ using $L$-stacked Transformer blocks, where the $t$-th Transformer block is denoted as $H^t = \text{Transformer}(H^{t-1}), t \in [1, L]$. Specifically, the cross-modal representations $H^t$ is calculated by using the multi-head self-attention [29] as follows:

$$Q = H^{t-1}W^Q, K = H^{t-1}W^K, V = H^{t-1}W^V,$$

$$M_{ij} = \begin{cases} 1, & \text{allow to attend}, \\ -\infty, & \text{prevent from attending} \end{cases}$$

$$A_t = \text{softmax}(QK^T + M) ,$$

where $W^Q, W^K, W^V \in \mathbb{R}^{d \times d}$ are learnable weights for computing the queries, keys, and values respectively, and $M \in \mathbb{R}^{|X| \times |X|}$ is the self-attention mask that determines whether tokens from two...
| Model       | NDCG  | MRR   | R@1 | R@5 | R@10 | Mean |
|------------|-------|-------|-----|-----|------|------|
| ReDAN      | 57.63 | 64.75 | 51.10 | 81.73 | 90.90 | 3.89 |
| GNN-EM     | 52.82 | 61.37 | 47.33 | 77.98 | 87.83 | 4.57 |
| DualVD     | 56.32 | 63.23 | 49.25 | 80.23 | 89.70 | 4.11 |
| FGA        | 56.90 | 66.20 | 52.75 | 82.92 | 91.07 | 4.00 |
| CAG        | 56.64 | 63.49 | 49.85 | 80.63 | 90.15 | 4.11 |
| KBGNN      | 57.60 | 64.13 | 50.47 | 80.70 | 90.16 | 4.08 |
| LG         | 58.55 | 64.00 | 50.63 | 80.58 | 90.20 | 4.12 |
| GoG        | 61.30 | 66.82 | 53.50 | 83.05 | 92.05 | 3.59 |
| VD-BERT    | 56.90 | 66.20 | 52.75 | 82.92 | 91.07 | 3.80 |
| ICMU (Ours)| 56.32 | 63.23 | 49.25 | 80.23 | 89.70 | 4.11 |

Table 1. Main comparisons on VisDial v1.0 test datasets (online). Our approach improves the strong baseline significantly. (t-test, p-value<0.01)

ing inference, we rank the answer candidates according to the class score $c = 0$ of the CCL4 loss.

3.1.2. Automatic Evaluation

We use a retrieval setting to evaluate individual responses at each round of a dialog, following [5]. Specifically, at test time, apart from the image, ground truth dialog history and the question, a list of 100-candidate answers is also given. The model is evaluated on retrieval metrics: (1) Mean Rank of human response (Mean ↓), (2) Existence of the human response in top $k$ ranked responses, i.e., R@$k$ ↑ (3) Mean Reciprocal Rank (MRR ↑) of the human response and (4) Normalized Discounted Cumulative Gain (NDCG ↑) for VisDial v1.0.

3.2. Main Results

3.2.1. Baseline Methods

We compare our method with the following baseline methods: (1) Attention-based models: HCIIE [10], CoAtt [11], ReDAN [13], LG [32]. (2) The pretraining model: VD-BERT [1] and VisDial-BERT [22]. (4) Graph-based models: GNN-EM [17], DualVD [19], FGA [18], GoG [6], KBGN [21].

3.2.2. Results

Performance on the benchmarks VisDial is shown in Table 1 and Table 2. From the results on VisDial v1.0 test shown in Table 1, we can observe that: (1) ICMU outperforms previous works on all metrics and obtains R@$1$ at 53.50%, beating the previous method VD-BERT by 1.47%, which shows that ICMU can select the standard ground-truth more accurate. (2) Comparing the performance of ICMU and model VD-BERT on NDCG, ICMU beats the pre-trained model VD-BERT by 1.34%. This shows the superiority of our proposed method to understand cross-modal information at a fine-grained level. Note that NGCG is invariant to the order of options with identical relevance and to the order of options outside of the top K, where K is the number of answers marked as correct by at least one annotator. (3) Our approach is not only more accurate (R@$1$, Mean), but also better than previous models on multi-modal semantic understanding (NDCG).

From the results on VisDial v1.0 test shown in Table 2, we can get the same observations. From the ablation study on VisDial v1.0 val shown in Table 3, we can observe that: (1) Both cross-modal contrastive learning and enhancement by VQA bring satisfactory improvements. (2) cross-modal contrastive learning and enhancement by VQA can get along with each other and further improve the performance of the model.

3.2.3. Case Study

As shown in Figure 3, we provide two samples to analyze the cross-modal understanding of VD-BERT and ICMU. As shown in the left half of Figure 3, for Q4 “Does he have food in his mouth?”, there are many reasonable answers to this question. VD-BERT ranks the opposite answer “no” first, and many reasonable answers “yes, it is, it is” are ranked lower. As shown in the right half of Figure 3, for Q4 “are there people on bus?”, ICMU outperforms the VD-BERT. This shows that ICMU learns better cross-modal understanding than VD-BERT due to CCL4 and enhancing by VQA.

4. CONCLUSION

In this paper, we propose a novel approach to improve the cross-modal understanding for visual dialog, named ICMU. ICMU enhances the cross-modal understanding in visual dialog by distinguishing different pulled inputs based on 4-way contrastive learning. In addition, ICMU exploits the single-turn visual question answering to enhance the visual dialog model’s cross-modal understanding. Experiments show that the proposed approach improves the visual dialog model’s cross-modal understanding and brings satisfactory gain to the VisDial dataset.

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