Dual Attention Networks for Visual Reference Resolution in Visual Dialog

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Abstract

Visual dialog (VisDial) is a task which requires an AI agent to answer a series of questions grounded in an image. Unlike in visual question answering (VQA), the series of questions should be able to capture a temporal context from a dialog history and exploit visually-grounded information. A problem called visual reference resolution involves these challenges, requiring the agent to resolve ambiguous references in a given question and find the references in a given image. In this paper, we propose Dual Attention Networks (DAN) for visual reference resolution. DAN consists of two kinds of attention networks, REFER and FIND. Specifically, REFER module learns latent relationships between a given question and a dialog history by employing a self-attention mechanism. FIND module takes image features and reference-aware representations (i.e., the output of REFER module) as input, and performs visual grounding via bottom-up attention mechanism. We qualitatively and quantitatively evaluate our model on VisDial v1.0 and v0.9 datasets, showing that DAN outperforms the previous state-of-the-art model by a significant margin (2.0\% on NDCG).

1 Introduction

Thanks to the recent progress of computer vision and natural language processing, the field of developing a cognitive agent that can jointly understand vision and natural language information has been widely studied in artificial intelligence. Over the last few years, vision-language tasks such as image captioning [Xu et al., 2015] and visual question answering (VQA) [Antol et al., 2015; Anderson et al., 2018] have provided a testbed for developing the cognitive agent. However, the agent performing these tasks still has a long way to go for being real-world applications (e.g., aiding visually impaired users, interacting with humanoid robots) in that it does not consider the continuous interaction with human. Specifically, the interaction in image captioning is that the agent simply talks to human about visual content, without any input from human. While the VQA agent takes a question as input, it is required to answer a single question about a given image. To this end, visual dialog (VisDial) [Das et al., 2017] task has been introduced as a generalized version of VQA. A dialog agent needs to answer a series of questions such as “How many people are in the image?”, “Are they indoors or outside?”, exploiting not only visually-grounded information but also contextual information from the previous dialog.

Recently, researchers have tackled a problem called visual reference resolution [Seo et al., 2017; Kottur et al., 2018; Niu et al., 2018] in VisDial task. Visual reference resolution is to resolve ambiguous references on their own (e.g., it, they, any other) and ground them to a given image. To resolve visual references, [Seo et al., 2017] proposed an attention memory which stores a sequence of previous visual attention maps in memory slots. They retrieved the previous visual attention maps by applying a soft attention over all the memory slots and combined it with a current visual attention. Furthermore, [Kottur et al., 2018] attempted to resolve visual references at a word-level, relying on an off-the-shelf parser. Similar to the attention memory [Seo et al., 2017], they proposed a reference pool which stores visual attention maps of recognized entities and retrieved the weighted sum of the visual attention maps by applying a soft attention. [Niu et al., 2018] proposed a recursive visual attention model which recursively review the previous dialogs and refine the current visual attention. The recursion is continued until the question itself is determined to be unambiguous. A binary decision whether the questions is ambiguous or not is made by Gumbel-Softmax approximation [Jang et al., 2016; Maddison et al., 2016]. To resolve the visual references, above approaches attempted to retrieve the visual attention of previous dialog, and reflected it on the current visual attention. However, according to research related with human memory system, the human visual sensory-memory hardly stores all previous visual attentions as its rapid decay property [Sperling, 1960; Sergent et al., 2011].

We hypothesize that humans address the visual reference resolution through a two-step process: (1) linguistically resolve the ambiguous references by reviewing the previous dialogs and (2) find the resolved references in a given image. For example, as shown in Figure 1, the question “Does it look like a nice one?” is ambiguous on its own because we do not know what “it” refers to. So we believe that humans try to review the dialog history and find out “it” refers to the skateboard. After the reference resolution, we believe that
they will finally try to find the skateboard in the image and answer the question. For these processes, we propose Dual Attention Networks (DAN) which consists of two kinds of attention networks, REFER and FIND. REFER module learns to retrieve the relevant previous dialogs for resolving ambiguous references. Inspired by the self-attention mechanism [Vaswani et al., 2017], REFER module computes multi-head attention over all previous dialogs, followed by feed-forward networks to get the reference-aware representations. FIND module takes image features and the reference-aware representations, and performs visual grounding via bottom-up attention mechanism. From this pipeline, we expect our proposed model to overcome the ambiguity in the given question and ground the resolved reference well to the given image.

The main contributions of this paper are as follows. First, we propose Dual Attention Networks (DAN) with the two hypotheses for visual reference resolution in visual dialog: REFER and FIND module. Second, we validate our proposed model on the large-scale datasets: VisDial v1.0 and VisDial v0.9. Our model achieves the new state-of-the-art results compared to other methods. We also conduct ablation studies to demonstrate the effectiveness of our proposed modules. Third, we perform qualitative analysis of our model, showing that our model reasonably attends to the previous dialogs and important image regions.

## 2 Proposed Algorithm

In this section, we formally describe the visual dialog task and our proposed algorithm, Dual Attention Networks (DAN). The visual dialog task [Das et al., 2017] is defined as follows. A dialog agent is given input such as an image $I$, a follow-up question at round $t$ as $Q_t$, a dialog history (including the image caption) $H = (C_1, A_{gt}^{t}) \cdots (C_{t-1}, A_{gt}^{t-1})$ till round $t-1$. By using these inputs, the agent is asked to rank a list of 100 candidate answers, $A_t = \{A_1^t, \cdots, A_{100}^t\}$. $A_{gt}^t$ denotes the ground truth answer (i.e., human response) at round $t$. Given the problem setup, DAN for visual dialog task can be framed as encoder-decoder architecture: (1) an encoder that jointly embeds the input ($I, Q_t, H$) and (2) a decoder that converts the embedded representation into the ranked list $A_t$. From this point of view, DAN consists of three components which are REFER, FIND, and the answer decoder. As shown in Figure 1, REFER module learns to attend relevant previous dialogs to resolve the ambiguous references in a given question $Q_t$. FIND module learns to attend the spatial image features that the output of REFER module describes. Answer decoder ranks the list of candidate answers $A_t$ given the output of FIND module.

We first introduce the image features, as well as the language features in Sec. 2.1 Then we explain in details of the architecture about REFER and FIND module in Sec. 2.2 and 2.3, respectively. Finally, we present the answer decoder in Sec. 2.4.

### 2.1 Input Representation

**Image Features.** Inspired by bottom-up attention [Anderson et al., 2018], we use the Faster R-CNN [Ren et al., 2015] pre-trained with Visual Genome [Krishna et al., 2017] to extract the object-level image features. We denote the output features as $v \in \mathbb{R}^{K \times V}$, where $K$ and $V$ are the total number...
of object detection features per image and dimension of the each feature, respectively. We adaptively extract the number of object features $K$ ranging from 10 to 100 for reflecting the complexity of each image. $K$ is fixed during training.

**Language Features.** We first embed each of the words in the follow-up question $Q_t$ to $\{w_t, \cdots, w_t,T\}$ by using pre-trained GloVe [Pennington et al., 2014] embeddings, where $T$ denotes the number of tokens in $Q_t$. We then use a two-layer LSTM, generating a sequence of hidden states $\{u_{t,1}, \cdots, u_{t,T}\}$. Note that we use the last hidden state of the LSTM $u_{t,T}$ as a question feature, denoted as $q_t \in \mathbb{R}^L$.

$$u_{t,i} = \text{LSTM}(w_{t,i}, u_{t,i-1})$$  

$$q_t = u_{t,T}$$  

(1)  

(2)

Also, each element of the dialog history $\{H_i\}_{t=0}^{t-1}$ and the candidate answers $\{A_i\}_{i=0}^{100}$ are embedded as the follow-up question, yielding $\{h_{i}\}_{i=0}^{t-1} \in \mathbb{R}^{L \times L}$ and $\{a_{i}\}_{1}^{100} \in \mathbb{R}^{100 \times L}$. $Q_t$, $H$, and $A_t$ are embedded with same word embedding vector and three different LSTMs.

### 2.2 REFER Module

Given the question and dialog history features, REFER module aims to attend to the most relevant elements of dialog history with respect to the given question. Specifically, we first compute scaled dot product attention [Vaswani et al., 2017] in multi-head settings which are called multi-head attention. Let $q_t$ and $M_t = \{h_{i}\}_{i=1}^{t-1}$ be the question and dialog history feature vectors respectively. $q_t$ and $M_t$ are projected to $d_{ref}$ dimensions by different, learnable projection matrices. We then conduct dot product of these two projected matrices, divide by $\sqrt{d_{ref}}$, and apply a softmax to obtain the attention weights on all elements of dialog history.

$$\text{head}_n = \text{Attention}(q_t W^q_n, M_t W^m_n)$$  

$$\text{where Attention}(a, b) = \text{softmax}(\frac{ab^\top}{\sqrt{d_{ref}}})b$$  

where $W^q_n \in \mathbb{R}^{L \times d_{ref}}$ and $W^m_n \in \mathbb{R}^{L \times d_{ref}}$. Note that dot product attention is computed $h$ times with different projection matrices, yielding $\{\text{head}_n\}_{n=1}^{h}$. Accordingly, we can get the multi-head representations $x_t$, concatenating all $\{\text{head}_n\}_{n=1}^{h}$, followed by linear projection. Also, we can compute $\hat{x}_t$ by applying a residual connection [He et al., 2016], followed by layer normalization [Ba et al., 2016].

$$x_t = (\text{head}_1 \oplus \cdots \oplus \text{head}_h) W^o$$  

$$\hat{x}_t = \text{LayerNorm}(x_t + q_t)$$  

where $\oplus$ denotes the concatenation operation, and $W^o \in \mathbb{R}^{h \times d_{ref} \times L}$ is the projection matrix. Next, we apply $\hat{x}_t$ to two-layer feed-forward networks with a ReLU activation in between, where $W_1^f \in \mathbb{R}^{L \times 2L}$ and $W_2^f \in \mathbb{R}^{2L \times L}$. The residual connection and layer normalization is also applied in this step.

$$c_t = \text{ReLU}(\hat{x}_t W_1^f + b_1^f) W_2^f + b_2^f$$  

$$\hat{c}_t = \text{LayerNorm}(c_t + \hat{x}_t)$$  

$$e_t^{ref} = \hat{c}_t \oplus q_t$$  

(7)  

(8)  

(9)

Finally, REFER module returns the reference-aware representations by concatenating the contextual representation $\hat{c}_t$ and the original question representation $q_t$, denoted as $e_t^{ref} \in \mathbb{R}^{2L}$. In this work, we use $d_{ref} = 256$ and $h=4$. Figure 2 illustrates the pipeline of the REFER module.
2.3 FIND Module

Instead of relying on the visual attention maps of the previous dialogs as in [Seo et al., 2017; Kottur et al., 2018; Niu et al., 2018], we would like the FIND module to attend to the most relevant regions of the image with respect to the reference-aware representations (i.e., the output of REFER module). In order to implement the visual grounding for the reference-aware representations, we take inspiration from bottom-up attention mechanism [Anderson et al., 2018].

Let \( v \in \mathbb{R}^{K \times 1} \) and \( e^\text{ref}_t \in \mathbb{R}^{L} \) be the image feature vectors and reference-aware representations, respectively. We first project these two vectors to \( d_{\text{find}} \) dimensions and compute soft attention over all the object detection features as follows:

\[
\mathbf{r}_t = f_v(v) \odot f_{\text{ref}}(e_t^\text{ref})
\]

\[\alpha_t = \text{softmax} (\mathbf{r}_t W^r + b^r)\]

where \( f_v(\cdot) \) and \( f_{\text{ref}}(\cdot) \) denote the two-layer multi-layer perceptrons which convert to \( d_{\text{find}} \) dimensions, and \( W^r \in \mathbb{R}^{d_{\text{find}} \times 1} \) is the projection matrix for the softmax activation. \( \odot \) denotes hadamard product (i.e., element-wise multiplication). From these equations, we can get the visual attention weights \( \alpha_t \in \mathbb{R}^{K \times 1} \). Next, we apply the visual attention weights to \( v \) and compute the vision-language joint representations as follows:

\[
\hat{v}_t = \sum_{j=1}^{K} \alpha_{t,j} v_j
\]

\[
z_t = f'_v(\hat{v}_t) \odot f'_{\text{ref}}(e_t^\text{ref})
\]

\[
e_t^{\text{find}} = z_t W^z + b^z
\]

where \( f'_v(\cdot) \) and \( f'_{\text{ref}}(\cdot) \) also denote the two-layer multi-layer perceptrons which convert to \( d_{\text{find}} \) dimensions, and \( W^z \in \mathbb{R}^{d_{\text{find}} \times L} \) is the projection matrix. Note that \( e_t^{\text{find}} \in \mathbb{R}^L \) is the output representations of the encoder as well as FIND module, and given to the answer decoder to score the list of candidate answers. In this work, we use \( d_{\text{find}} = 1024 \).

2.4 Answer Decoder

Answer decoder computes each score of candidate answers via a dot product with the embedded representation \( e_t^{\text{find}} \), followed by a softmax activation to get a categorical distribution over the candidates. Let \( O_t = \{o_{t,j}^{100} \in \mathbb{R}^{100 \times L}\} \) be the feature vectors of 100 candidate answers. The distribution \( p_t \) is formulated as follows:

\[
p_t = \text{softmax}(e_t^{\text{find}} O_t^\top)
\]

In training phase, DAN is optimized by minimizing the cross-entropy loss between the one-hot encoded label vector \( y_t \) and probability distribution \( p_t \).

\[
\mathcal{L}(\theta) = -\sum_k y_{t,k} \log p_{t,k}
\]

Where \( p_{t,k} \) denotes the probability of the \( k\)-th candidate answer at round \( t \). In test phase, the list of candidate answers is ranked by the distribution \( p_t \), and evaluated by some metrics.

3 Experiments

In this section, we describe in details of our experiments on the VisDial v1.0 and v0.9 datasets. We first introduce the VisDial datasets, evaluation metrics, and implementation details in Sec. 3.1, Sec. 3.2, and Sec. 3.3, respectively. Then we report the quantitative results by comparing our proposed model with the state-of-the-art approaches in Sec. 3.4. Then, we conduct the ablation studies by three criteria to report the relative contributions of each module in Sec. 3.5. Finally, we provide the qualitative analysis in Sec. 3.6.

3.1 Datasets

We evaluate our proposed model on the VisDial v0.9 and v1.0 dataset. VisDial v0.9 dataset [Das et al., 2017] has collected via two subjects chatting about MS-COCO [Lin et al., 2014] images. Each dialog is made up of an image, a caption from MS-COCO dataset and 10 QA pairs. As a result, VisDial v0.9 dataset contains 83k dialogs and 40k dialogs as train and validation splits, respectively. Recently, VisDial v1.0 dataset [Das et al., 2017] has been released with an additional 10k COCO-like images from Flickr. Dialogs for the additional images have been collected similar to v0.9. Overall, VisDial v1.0 dataset contains 123k (all dialogs from v0.9), 2k, and 8k dialogs as train, validation, and test splits, respectively.

3.2 Evaluation Metrics

We evaluate individual responses at each question in a retrieval setting as suggested by [Das et al., 2017]. Specifically, the dialog agent is given a list of 100 candidate answers of each question and asked to rank the list. There are three kinds of evaluation metrics for retrieval performance: (1) mean rank of human response, (2) recall@k (i.e., existence of the human response in top-k ranked response), and (3) mean reciprocal rank (MRR). Mean rank, recall@k, and MRR are highly correlated with the rank of human response. In addition, [Das et al., 2017] proposed to use the robust evaluation metric, normalized discounted cumulative gain (NDCG). NDCG takes into account all relevant answers from the ranked list, where the relevance scores are densely annotated for VisDial v1.0 test split. NDCG penalizes the lower rank of the candidate answers with high relevance scores.

3.3 Implementation Details

The dimension of image features \( V \) and hidden states in all LSTM \( L \) is 2048 and 512, respectively. Also, all the language inputs (i.e., questions, captions, and answers) are embedded to a 300-dimensional vector initialized by GloVe embeddings [Pennington et al., 2014]. The word embedding vector is fine-tuned during training. We apply Adam optimizer [Kingma and Ba, 2014] with learning rate \( 1 \times 10^{-3} \), decreased by 1 \( \times 10^{-4} \) per epoch up to 7 epochs, decayed by 0.5 per epoch from 8 to 12 epochs. We also apply dropouts [Srivastava et al., 2014] with ratio 0.2 for REFER and FIND module, and 0.5 for LSTM and the output of encoder.
**Table 1:** Retrieval performance on VisDial v1.0 and v0.9 datasets, measured by normalized discounted cumulative gain (NDCG), mean reciprocal rank (MRR), recall @k (R@k), and mean rank. The higher the better for NDCG, MRR, and R@k, while the lower the better for mean rank. DAN outperforms all other models across NDCG, MRR, and R@1 on both datasets. NDCG is not supported in v0.9 dataset.

| Model   | NDCG | MRR | R@1 | R@5 | R@10 | Mean | MRR | R@1 | R@5 | R@10 | Mean |
|---------|------|-----|-----|-----|------|------|-----|-----|-----|------|------|
| LF      | 0.4531 | 0.5542 | 40.95 | 72.45 | 82.83 | 5.95 | 0.5807 | 43.82 | 74.68 | 84.07 | 5.78 |
| HRE     | 0.4546 | 0.5416 | 39.93 | 70.45 | 81.50 | 6.41 | 0.5846 | 44.67 | 74.50 | 83.37 | 5.46 |
| MN      | 0.4750 | 0.5549 | 40.98 | 72.30 | 83.30 | 5.92 | 0.5965 | 45.55 | 76.22 | 85.37 | 5.46 |
| HCIAE   | - | - | - | - | - | - | 0.6222 | 48.48 | 78.75 | 87.59 | 4.81 |
| AMEM    | - | - | - | - | - | - | 0.6227 | 48.53 | 78.66 | 87.43 | 4.86 |
| CoAtt   | - | - | - | - | - | - | 0.6227 | 48.53 | 78.66 | 87.43 | 4.86 |
| CorefNMN | 0.5470 | 0.6150 | 47.55 | 78.10 | 88.80 | 4.40 | 0.6410 | 50.92 | 80.18 | 88.81 | 4.45 |
| RvA     | 0.5559 | 0.6303 | 49.03 | 80.75 | 90.68 | 4.30 | 0.6398 | 50.29 | 80.71 | 88.81 | 4.47 |

**Table 2:** Test-std performance of ensemble model on VisDial v1.0 dataset. We excerpt top-three entries from VisDial Challenge 2018 Leaderboard.

| Model   | NDCG | MRR | R@1 | R@5 | R@10 | Mean | MRR | R@1 | R@5 | R@10 | Mean |
|---------|------|-----|-----|-----|------|------|-----|-----|-----|------|------|
| DL-61   | 0.5788 | 0.6342 | 49.30 | 80.77 | 90.68 | 3.97 | 0.5807 | 43.82 | 74.68 | 84.07 | 5.78 |
| USTC-YTH | 0.5647 | 0.6144 | 47.65 | 78.13 | 87.88 | 4.65 | 0.5846 | 44.67 | 74.50 | 83.37 | 5.46 |
| MS ConvAI | 0.5535 | 0.6327 | 49.53 | 80.40 | 89.60 | 4.15 | 0.5965 | 45.55 | 76.22 | 85.37 | 5.46 |
| DAN (ours) | 0.5936 | 0.6492 | 51.28 | 81.60 | 90.88 | 3.92 | 0.6410 | 50.92 | 80.18 | 88.81 | 4.45 |

**Table 3:** Test-std performance on VisDial v1.0 dataset for the number of REFER modules of DAN. DAN-R<sub>n</sub> indicates that DAN uses a stack of <i>n</i> identical REFER modules. We observe that DAN-R2 shows best performance on NDCG, MRR, and R@1.

| Model   | NDCG | MRR | R@1 | R@5 | R@10 | Mean | MRR | R@1 | R@5 | R@10 | Mean |
|---------|------|-----|-----|-----|------|------|-----|-----|-----|------|------|
| DAN-R1  | 0.5725 | 0.6277 | 48.70 | 79.60 | 89.35 | 4.33 | 0.5807 | 43.82 | 74.68 | 84.07 | 5.78 |
| DAN-R2  | 0.5759 | 0.6320 | 49.63 | 80.75 | 90.68 | 4.30 | 0.5846 | 44.67 | 74.50 | 83.37 | 5.46 |
| DAN-R3  | 0.5711 | 0.6310 | 49.18 | 80.15 | 89.28 | 4.25 | 0.5965 | 45.55 | 76.22 | 85.37 | 5.46 |
| DAN-R4  | 0.5710 | 0.6283 | 48.88 | 80.25 | 89.38 | 4.28 | 0.6410 | 50.92 | 80.18 | 88.81 | 4.45 |

**3.4 Quantitative Results**

**Compared Methods.** We compare our proposed model with the state-of-the-art approaches on VisDial v1.0 and v0.9 datasets, which can be categorized into three groups: (1) Fusion-based approaches (LF and HRE [Das et al., 2017]), (2) Attention-based approaches (MN [Das et al., 2017], HCIAE [La et al., 2017] and CoAtt [Wu et al., 2018]), and (3) Approaches that deal with visual reference resolution in VisDial (AMEM [Seo et al., 2017], CorefNMN [Kottur et al., 2018] and RvA [Niu et al., 2018]). Our proposed model belongs to the third category.

**Results on VisDial v1.0 and v0.9 datasets.** As shown in Table 1, DAN significantly outperforms all other approaches on NDCG, MRR, and R@1, including the previous state-of-the-art method, RvA [Niu et al., 2018]. Specifically, DAN improves approximately 2.0% on NDCG and 0.6% on R@1 in VisDial v1.0 dataset, and 0.62% on R@1 in VisDial v0.9 dataset. Note that we take advantage of the same image features and word-level features [Anderson et al., 2018; Pennington et al., 2014] as the recursive visual attention (RvA) model. The results indicate that DAN ranks higher than all other methods on both single ground-truth answer (R@1) and all relevant answers on average (NDCG).

**Results of ensemble model.** We report the performance of ensemble model to compare with the top-three entries in the leaderboard<sup>1</sup> of VisDial Challenge 2018. We ensemble six DAN models, using the number of heads (i.e., <i>h</i>) ranging from one to six. We average the probability distribution (i.e., <i>p</i><sub>t</sub>) of the six models to rank the candidate answers. As shown in Table 2, our model significantly outperforms all three challenge entries, including the challenge winner model from team DL-61. However, we cannot make an in-depth comparison with the entries because the approaches and other details (e.g., features and the test-std performance of single-model) have not been published at the time of submission.

**3.5 Ablation Study**

**Stack of REFER Modules.** As in self-attention mechanism [Vaswani et al., 2017], we stack the REFER modules up to four layers to get a high-level abstraction of the reference-aware representations. Specifically, for each pair of successive modules, the output of the previous REFER module is fed into the next REFER module as a query (i.e., <i>q</i><sub>t</sub>). As

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<sup>1</sup>https://evalai.cloudcv.org/web/challenges/challenge-page/103/leaderboard
Figure 3: Qualitative results on the VisDial v1.0 dataset. We visualize the attention over dialog history from REFER module and the visual attention from FIND module. The object detection feature with highest attention weight is marked with red box. Also, the attention from REFER module is represented as shading, darker shading indicates the larger attention weight for each element of the dialog history. Our proposed model selectively pays attention to the previous dialogs and important image regions except right bottom example.

shown in Table 3, we observe that the two-layer REFER module (i.e., DAN-R2) shows the best performance on NDCG and R@1. The following ablation studies will be conducted based on DAN-R2.

**Image Features in FIND Module.** To report the impact of image features, we replace the bottom-up attention features [Anderson et al., 2018] with ImageNet pre-trained VGG-16 [Simonyan and Zisserman, 2014] features. In detail, we use the output of the VGG-16 pool5 layer as image features. In Table 4, DAN w/o RPN denotes the use of the VGG-16 features. Similar to VQA task, we observe that DAN with bottom-up attention features achieves better performance than with VGG-16 features. In other words, the use of object-level features boosts the overall performance of DAN.

**Use of Single Module.** The first and second row in Table 4 show the performance of a single module. DAN w/o FIND denotes the use of REFER module only, and DAN w/o REFER denotes the use of FIND module only. Specifically, REFER-only model uses the output of REFER module as the encoder outputs. On the other hand, FIND-only model takes not the reference-aware representations (i.e., $e_t^{ref}$) but the question feature. Both models show relatively poor performance compared with the dual module model. We believe that the results validate two hypotheses: (1) VisDial task requires contextual information from dialog history as well as the visually-grounded information. (2) REFER and FIND module have complementary modeling power.

### 3.6 Qualitative Analysis

Figure 3 shows the qualitative results of DAN. We visualize the attention over dialog history from REFER module, as well as the visual attention from FIND module. In case of the visual attention, we mark the object detection feature with highest attention weight (i.e., top-1) of each image. On the other hand, the attention weights from REFER module are calculated by averaging over all the attention heads. These attention weights are represented as shading; darker shading indicates the larger attention weight for each element of the dialog history. DAN reasonably attends to the previous dialogs and important image regions except right bottom example.

4 Conclusion

We introduce Dual Attention Networks (DAN) for visual reference resolution in visual dialog task. DAN explicitly divides the visual reference resolution problem into a two-step process. Rather than relying on the previous visual attention maps as in prior works, DAN first linguistically resolves ambiguous references in a given question by using REFER module. Then, it grounds the resolved references in the image by using FIND module. We empirically validate our proposed model on VisDial v1.0 and v0.9 datasets. DAN achieves the new state-of-the-art performance, while being simpler and more grounded.
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