Multi-View Attention Networks for Visual Dialog

Sungjin Park1* Taesun Whang2† Yeochan Yoon1,3 Hueiseok Lim1
1Korea University 2Wisenut Inc. 3Electronics and Telecommunications Research Institute

Abstract

Visual dialog is a challenging vision-language task in which a series of questions visually grounded by a given image are answered. To resolve the visual dialog task, a high-level understanding of various multimodal inputs (e.g., question, dialog history, image, and answer) is required. Specifically, it is necessary for an agent to 1) understand question-relevant dialog history and 2) focus on question-relevant visual contents among the diverse visual contents in a given image. In this paper, we propose Multi-View Attention Network (MVAN), which considers complementary views of multimodal inputs based on attention mechanisms. MVAN effectively captures the question-relevant information from the dialog history with two different textual-views (i.e., Topic Aggregation and Context Matching), and integrates multimodal representations with two-step fusion process. Experimental results on VisDial v1.0 and v0.9 benchmarks show the effectiveness of our proposed model, which outperforms the previous state-of-the-art methods with respect to all evaluation metrics.

1 Introduction

As a part of the interdisciplinary research that combines natural language processing with computer vision, a wide variety of vision–language tasks (e.g., visual question answering (VQA), image captioning, and referring expressions) have been introduced in recent years. Considerable efforts in this field have advanced the capabilities of artificial intelligence agents a step further, but the agent’s comprehension of multimodal information is still far from human-level reasoning and cognitive ability (Hudson and Manning, 2019; Zellers et al., 2019).

*Equal Contribution
†Work performed while at Korea University

Figure 1: Example of a visual dialog task. The text background color indicates the dialog topic (e.g., “people”, “food”, and “household goods”).

The visual dialog task is similar to VQA in that it requires the agent to answer a question that is guided by an image but differs in that the agent needs to answer a series of questions focusing on a given image as well as previous dialog. This task is more challenging than other vision-language tasks because the agent is asked to selectively capture the visual contents related to the question topic, which change as the dialog proceeds. For example, Figure 1 illustrates how the question topics change during each dialog turn (e.g., “household goods”, “people”, and “food”). Furthermore, answering some questions that contain pronouns (e.g., “they”, “it”, “he”, “she”, and “them”) can be more difficult because the agent should consider which entity the pronoun refers in the dialog history. To be specific, when the agent encounters question 5 (Q5), the agent should pay attention to resolve what “they” refers to (i.e., “kids” and “boys” in caption and Q4–A4 pair) and ground the referent
Several recent researches have been performed to solve the visual dialog task from the perspective of visual co-reference resolution. Kottur et al. (2018) proposed neural module networks that effectively link pronouns to referring expressions at a word level. In addition, Kang et al. (2019) adapted a self-attention mechanism (Vaswani et al., 2017) based on sentence-level representation of the question and dialog history to focus question-relevant history. Niu et al. (2019) proposed a recursive attention mechanism to capture question-relevant dialog history and ground related visual contents to the image. However, resolving the pronouns ambiguity does not always lead to understanding of semantic intent of the question. For example, when answering Q6 in Figure 1, the agent is required to explicitly understand the semantic intent of the question that is asking whether “other snacks” exists or not (i.e., the model should attend more to “other snacks” rather than “they”). In this respect, the dialog agent should be capable of accurately determining the semantic intent of the given question and then leveraging question-relevant information from the dialog history and visual contents.

To this end, this paper proposes Multi-View Attention Network (MVAN), which consists of three main modules: 1) Context Matching, 2) Topic Aggregation, and 3) Modality Fusion. First, the Context Matching module uses an attention mechanism to effectively represent the contextual information of the dialog history that is relevant to the question. Second, the Topic Aggregation module is capable of capturing topic-guided clues in dialog history at word level. Also, we apply a gate function in both modules to selectively capture textual information that interacts with the current question topic. Lastly, the Modality Fusion module consists of two sequential fusion steps to integrate each textual output of previous modules with visual features. The main contributions of this paper are as follows.

- We propose MVAN to effectively represent multimodal inputs with two different views and combine them with visual contents through multiple fusion steps.

- Experimental results on VisDial v1.0 and v0.9 benchmarks show that our proposed model outperforms the previous state-of-the-art methods with respect to all evaluation metrics.

- Visualization of the multi-level attention score demonstrates that MVAN explicitly understands the semantic intent of the question, which leads to a reasonable interpretation of leveraging various multimodal inputs.

2 Related Work

VQA For the last few years, large-scale VQA datasets, such as VQA 1.0 (Antol et al., 2015), VQA 2.0 (Goyal et al., 2017), COCO-QA (Ren et al., 2015a), and GQA (Hudson and Manning, 2019) have accelerated various developments in the vision–language field. Lu et al. (2016) introduced a co-attention mechanism to jointly exploit both image attention and question attention. More advanced approaches have been well studied in Nguyen and Okatani (2018); Yu et al. (2019). Bilinear approaches that replace element-wise addition or concatenation for using modality fusion methods have also been proposed (Fukui et al., 2016; Kim et al., 2016, 2018).

Visual Dialog Visual dialog is a task proposed by Das et al. (2017) that requires the dialog agent to answer the current question by exploiting both the image and dialog history. Das et al. (2017) also introduced encoder-decoder models such as late fusion, hierarchical recurrent network, and memory network as baseline methods. Most of the previous approaches to the visual dialog task are predominantly based on attention mechanisms. DAN (Kang et al., 2019) uses a multi-head attention mechanism (Vaswani et al., 2017) and Gan et al. (2019) proposed a multi-step reasoning method to fuse the given multimodal inputs. FGA (Schwartz et al., 2019) considers all the interactions of connected entities based on a factor graph. RVA (Niu et al., 2019) fuses question representation and image representation via recursive trees. In addition, other approaches proposed different training methods for the visual dialog task including reinforcement mechanism (Yang et al., 2019) and adversarial learning (Lu et al., 2017). Recently, Qi et al. (2019) proposed causal intervention algorithms that can be composed into any visual dialog model and Murahari et al. (2019) introduced a fine-tuning method using a pre-trained model (Lu et al., 2019).

3 Model

In the visual dialog task (Das et al., 2017), a dialog agent is given a set of multimodal inputs for
each dialog turn \( t \). This input set consists of an image \( I \), a current question \( Q_t \), the dialog history set \( H_t = \{ C, (Q_1, A^{q}_1), \ldots, (Q_{t-1}, A^{q}_{t-1}) \} \), which consists of image caption \( C \) and \( t-1 \) consecutive question-answer pairs, and a set of answer candidates \( A_t = \{ A^1_t, A^2_t, \ldots, A^{100}_t \} \). The agent then is required to answer the question by either discriminating or generating a correct answer.

### 3.1 Multimodal Representation

**Visual Features** We employ a bottom-up attention mechanism (Anderson et al., 2018) to represent the objects appearing in an image. Visual features of object regions \( V = \{ v_k \}_{k=1}^{n_v} \in \mathbb{R}^{d_v \times n_v} \), where \( n_v \) is the number of detected objects ranging from 10 to 100, are adaptively extracted from a Faster-RCNN (Ren et al., 2015b) that is pre-trained with Visual Genome (Krishna et al., 2017).

**Language Features** We first embed three different text inputs: the current question, dialog history, and answer candidates. The word embedding layer is initialized with pre-trained GloVe embeddings (Pennington et al., 2014). We then feed the word embeddings into a bi-directional long short-term memory (BiLSTM) to encode a sequential representation of each embedding. Specifically, each word in question \( Q \) is embedded as \( \{ u^{q}_k \}_{k=1}^{n_q} \in \mathbb{R}^{d_w \times n_q} \), where \( n_q \) is the number of words in the sequence. Each word embedding is fed into the BiLSTM layer as follows:

\[
\begin{align*}
\hat{u}^q_k &= \text{LSTM}(u^{q}_{k}, \hat{u}^q_{k-1}) \\
\tilde{u}^q_k &= \text{LSTM}(u^{q}_{k}, \hat{u}^q_{k+1}).
\end{align*}
\]

The sequential representation of each token is constructed by concatenating the hidden states of the forward and backward LSTMs, denoted as \( u^q_{k} = [\hat{u}^q_{k}, \tilde{u}^q_{k}] \). Meanwhile, the sequential representation for each dialog history \( u^h_{r} = \{ u^h_{r,k} \}_{k=1}^{hr} \) is constructed using the question construction process with different BiLSTM layers. For the answer candidates, we use a different unidirectional LSTM to represent them because their sequence lengths are shorter than those of the questions.

### 3.2 Multi-View Attention Network

Figure 2 describes the MVAN architecture, which consists of three components: 1) Context Matching 2) Topic Aggregation and 3) Modality Fusion.

**Context Matching Module** Sequential representation is constructed by concatenating the last hidden states of the forward and backward LSTMs for question and dialog history, denoted as \( s^q = [\hat{u}^q_1, \tilde{u}^q_{n_q}] \) and \( s^h = [\hat{u}^h_{r,1}, \tilde{u}^h_{r,nhr}] \), respectively. We then apply an attention mechanism to focus on question-relevant history from a dialog history series. The Context Matching module takes contextual representation of question \( s^q \in \mathbb{R}^{d_x \times 1} \) and dialog history \( s^h = \{ s^h_0, s^h_1, \ldots, s^h_{t-1} \} \in \mathbb{R}^{d_x \times t} \)
and outputs question-relevant history features as follows:

\[ z^S_r = W^T (f^S_q (s^q_r) \circ f^S_h (s^h_r)) + b \tag{2a} \]

\[ a^S_r = \text{softmax}(z^S_r) \tag{2b} \]

\[ s^h = \sum_{t=0}^{t-1} a^S_r s^h_r, \tag{2c} \]

where \( \circ \) is element-wise multiplication, \( W \in \mathbb{R}^{d \times 1} \) is a projection matrix, and \( f^S_q (\cdot) \) and \( f^S_h (\cdot) \) denote non-linear transformation functions. We apply a gate function to effectively integrate the context-level features from the current question and dialog history as follows:

\[ gate^S = \sigma(W^S_{\text{gate}} \left[ s^q, s^h \right] + b^S_{\text{gate}}) \tag{3a} \]

\[ e^S = gate^S \circ [s^q, s^h], \tag{3b} \]

where \( \sigma(\cdot) \) is a sigmoid function and \( W^S_{\text{gate}} \in \mathbb{R}^{2d \times 2d} \) and \( b^S_{\text{gate}} \in \mathbb{R}^{2d} \) are trainable parameters. Note that \( e^S \in \mathbb{R}^{2d} \) is a contextual-aware representation that effectively integrates the sequential information of the question and question-relevant dialog history.

**Topic Aggregation Module** The Topic Aggregation module leverages word-level sequential representation of the question and dialog history, \( u^q = \{u^q_k\}_{k=1}^{n_q} \in \mathbb{R}^{d_q \times n_q} \) and \( u^h = \{u^h_{r,k}\}_{k=1}^{n_h} \in \mathbb{R}^{d_h \times n_h} \), to encode question-relevant topic features. The dot product attention mechanism is employed to selectively focus the words that are relevant to the question topic from the dialog history as follows:

\[ z^W_{r,i,j} = f^W_q(u^q_i) ^T f^W_h(u^h_{r,j}) \tag{4a} \]

\[ a^W_{r,i,j} = \exp(z^W_{r,i,j}) / \sum_{j=1}^{n_h} \exp(z^W_{r,i,j}) \tag{4b} \]

\[ w^h_{r,i} = \sum_{j=1}^{n_h} a^W_{r,i,j} u^h_{r,j}, \tag{4c} \]

where \( f^W_q (\cdot) \) and \( f^W_h (\cdot) \) are non-linear transformation functions. The question-guided history feature for each round \( w^h_{r,i} \) is computed by a weighted sum of their word embeddings, which represent the original meanings of words. The attended representation \( w^h_{r,i,j} \) is computed by aggregating overall all history \( [w^h_{r,i,j}]_{j=0}^{t-1} \), weighted by the attention scores of the Context Matching module \( a^S_r \) as follows:

\[ w^h_{i} = \sum_{r=0}^{t-1} a^S_r w^h_{r,i}. \tag{5} \]

Similar to the Context Matching module, the gate operation merges the topic-guided history representation with that of the question at word level.

\[ gate^W = \sigma(W^W_{\text{gate}} \left[ w^q_i, w^h_i \right] + b^W_{\text{gate}}) \tag{6a} \]

\[ e^W_i = gate^W \circ [w^q_i, w^h_i], \tag{6b} \]

where \( W^W_{\text{gate}} \in \mathbb{R}^{2d_w \times 2d_w} \) and \( b^W_{\text{gate}} \in \mathbb{R}^{2d_w} \) are trainable parameters. Note that \( e^W_i \in \mathbb{R}^{2d_w \times n_w} \) is topic-aware features that represent question topic and various history clues associated with it.

**Modality Fusion Module** Given the output representations of Context Matching module \( e^S \in \mathbb{R}^{2d_s \times 1} \) and Topic Aggregation module \( e^W \in \mathbb{R}^{2d_w \times n_w} \), the Modality Fusion module integrates them with visual features \( v_k \in \mathbb{R}^{d_v \times n_v} \) via two-step fusion (i.e., topic-view fusion and context-view fusion). The module first combines representations from heterogeneous modalities (i.e., vision and language) at word level. We utilize dot-product attention to represent the visual relevant question as follows:

\[ r^W_{i,k} = f^W_i(e^W_i) ^T f^W_v(v_k) \tag{7a} \]

\[ a^W_{i,k} = \exp(r^W_{i,k}) / \sum_{i=1}^{n_i} \exp(r^W_{i,k}) \tag{7b} \]

\[ e^W_k = \sum_{i=1}^{n_i} a^W_{i,k} e^W_i, \tag{7c} \]

where \( f^W_i (\cdot) \) and \( f^W_v (\cdot) \) are non-linear transformation functions to embed two different modality representations into the same embedding space. Then, we obtain the fused vector by concatenating the visual features and the visual relevant question features and using a multi-layer perceptron (MLP).

\[ m^W_k = \text{MLP}(v_k, e^W_k) \tag{8} \]

Note that \( m^W_k \in \mathbb{R}^{d_v \times n_v} \) is a topic-view fusion representation that combines the specific question topic and visual contents. This fused embedding is further enhanced by conducting the following context-view fusion:

\[ m^S_k = m^W_k, e^S \tag{9a} \]

\[ r^S_k = \text{L2Norm}(f^S(m^S_k) \circ f^S(e^S)) \tag{9b} \]

\[ a^S_k = \text{softmax}(W^T r_k^S + b), \tag{9c} \]

\[ \hat{m}^S_k = \sum_{k=1}^{n_v} a^S_k m^S_k, \tag{9d} \]

where \( f^S (\cdot) \) and \( f^S (\cdot) \) are non-linear transformation functions and \( W \in \mathbb{R}^{d_l \times 1} \) is a projection matrix. Note that \( \hat{m}^S \) is a context-view fusion representation, which is fed into a single-layer feed-forward neural network with a ReLU activation function.

\[ m^{enc} = \max(0, W^T \hat{m}^S + b), \tag{10} \]
where $W \in \mathbb{R}^{(d_v+d_w) \times d_{enc}}$ and $b \in \mathbb{R}^{d_{enc}}$ are trainable parameters. Note that $m^{enc}$ is the multi-view fusion representation, which is fed into either a discriminative or generative decoder to select the most likely response from among the candidates.

### 3.3 Answer Decoder

**Discriminative Decoder** We use the last hidden states of the forward LSTM to encode sentence representations of answer candidates, denoted as $s^a = \{\vec{u}_{i,n}^a\}_{i=1}^{100} \in \mathbb{R}^{d_a \times 100}$. We rank them according to the dot products of the candidates $s^a$ and multi-view fusion representation $m^{enc}$, then apply the softmax function to obtain the probability distribution of the candidates, denoted as $p = \text{softmax}(s^a \top m^{enc})$. Note that dimension of each answer candidate is same as the dimension of the encoder output. We use multi-class cross-entropy loss as the discriminative objective function, formulated as

$$L_D = - \sum_{i=1}^{100} y_i \log p_i,$$

where $y_i$ is a one-hot encoded vector of the ground truth answer.

**Generative Decoder** Unlike most previous approaches, which take only a discriminative approach, we also train our model in a generative manner (Das et al., 2017). During the training phase, we use a two-layer LSTM to predict the next token given the previous tokens in the answer sequence. The initial hidden state of the LSTM is initialized with the encoder output representation. For each answer candidate, we compute the likelihood of the ground truth of each token, denoted as $\{p_k\}_{k=1}^{n_a}$, and train the model by minimizing the summation of the negative log-likelihood as follows:

$$L_G = - \sum_{k=1}^{n_a} \log p_k.$$  

### 4 Experiments

#### 4.1 Experimental Setup

**Datasets** We use the VisDial v0.9 and v1.0 datasets to evaluate our proposed model. VisDial v0.9 (Das et al., 2017) consists of 123k MS-COCO (Lin et al., 2014) images and their captions. The training and validation splits of VisDial v0.9 contain 83k and 40k images respectively, and each image has 10 consecutive question-answer pairs. VisDial v1.0, which was released by supplementing VisDial v0.9, has 123k images for training splits that combine the training and validation splits of VisDial v0.9. An additional 10k images from the Flickr dataset are utilized to construct the validation and test splits in VisDial v1.0, which contain 2k and 8k images respectively. Unlike the previous version of the dataset, dense annotations for each candidate answer are added in the validation and test splits.

**Evaluation Metrics** We evaluated our proposed model using several retrieval metrics, following the work of Das et al. (2017): 1) mean rank of the ground truth response (Mean), 2) recall at $k$ ($k = \{1,5,10\}$), which is denoted as $R@k$ and evaluates where the ground truth is positioned in the sorted list, and 3) mean reciprocal rank (MRR) (Voorhees et al., 1999). NDCG was also introduced as a primary metric in the VisDial v1.0 dataset, and decreases when the model gives a low ranking to candidate answers with high relevance scores. MRR evaluates the precision of the model by ranking where a ground truth answer is positioned, whereas NDCG evaluates relative relevance of the predicted answers.

**Training Details** Our model is implemented using PyTorch framework (Paszke et al., 2019) based on open source code¹ from the work of Das et al. (2017). The question and dialog history are represented using different BiLSTMs with 512 hidden states. The maximum sequence lengths of the question and dialog history are set to 20 and 40, respectively. We set the batch size to 32 and apply the Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 1e-5. The learning rate is gradually increased to 1e-3 until epoch 2, then decreased by 0.1 at epochs 6 and 7. Our code is

---

¹https://github.com/batra-mll-lab/visdial-challenge-starter-pytorch
addition, we observe significant improvements in the Mean from 4.11 to 3.97, and an improvement in the R@k performance by approximately 0.4%. Similar results can be seen in the R@5 and Mean for VisDial v0.9. We also report the results for an ensemble of 10 independent models that were trained with different initial seeds, which yields average performance improvements of 1.3% for all metrics.

These results indicate that our MVAN model not only has accurate prediction ability, as indicated by the non-NDCG metric results (i.e., MRR, R@k, and Mean), but it has a powerful generalization capability given the result of NDCG score because this metric considers several relevant answers to be correct.

### Results on multi-task learning

As shown in Table 2, we report the results of our MVAN model, which was trained using multi-task learning (see Section 3.3). Our proposed approach performs better with respect to all metrics than ReDAN (Gan et al., 2019), which averages the ranking results of the discriminative and generative model, and Tohoku (Nguyen et al., 2019), which employs multi-task learning but uses only discriminative decoder outputs for evaluation.

### Number of dialog history

We experimented with the amount of dialog history to evaluate the impact of dialog history on the model performance of the two major metrics (i.e., MRR and NDCG). The results in Figure 3 show that as the amount of dialog history information increases, the MRR perfor-
Table 3: Ablations of our approaches on the VisDial v1.0 validation dataset.

| Model                  | context-level history | topic-level history | NDCG | MRR  | R@1  | R@5  | R@10 | Mean |
|------------------------|-----------------------|---------------------|------|------|------|------|------|------|
| MVAN                   | ✓                     | ✓                   | 60.17| 65.33| 51.86| 82.40| 90.90| 3.88 |
| w/o Topic Aggregation  | ✓                     | N/A                 | 62.33| 61.79| 47.61| 79.30| 88.81| 4.42 |
| w/o Context Matching   | N/A                   | ✓                   | N/A  | N/A  | N/A  | N/A  | N/A  | N/A  |

Figure 3: Performance of MVAN with different amounts of dialog history on the VisDial v1.0 validation set.

4.3 Ablation study

We conducted ablation studies on the VisDial v1.0 validation splits to evaluate the influence of each component in our model. Modality Fusion module is not ablated because this module handles the visual features. We use the same discriminative decoder model (Das et al., 2017) for all ablations to exclude the impact of multitask learning.

In Table 3, the first rows of each block indicate the impact of each module in our model. Because the two modules (i.e., Context Matching and Topic Aggregation) are interdependent, we employ simple visual features instead of topic-aware features for Context Matching model, whereas we simply remove contextual-aware features for the Topic Aggregation model (see Section 3.2). Both models obtain slightly lower performance with respect to all evaluation metrics than the MVAN model. We can hence infer that the two modules are complementary with respect to each other and our model integrates these complementary characteristics well for the task.

Recent approaches (Murahari et al., 2019; Kim et al., 2020; Nguyen et al., 2019) reported that they observed a trade-off relationship between two primary metrics (i.e., NDCG and MRR) in the visual dialog task. We also found a trade-off relationship through ablative experiments with and without dialog history features (see Table 3). Specifically, adding dialog history features improves the MRR score by 3.54% on average, whereas NDCG score is decreased by 1.92% on average. We observe that the model has a tendency to predict the answers more precisely (i.e., it has a better MRR score) when the dialog history features are added. This may imply that question-related clues in the dialog history are important factors in reasoning the ground truth, but they hinder the model’s generalization ability (i.e., they lower the NDCG score).

4.4 Qualitative Analysis

To qualitatively demonstrate the advantages of our model, we visualize the attention scores of each module through examples from the VisDial v1.0 validation set in Figure 4. The attention scores of the Context Matching module, highlighted in blue, show that our model selectively focuses on contextual information as the semantic intent of the question changes. The tendency for the caption (i.e., H0) to receive the highest score implies that the caption contains global information describing the image. In addition, the top-three visual contents with high attention scores in each image and attention scores in the current question lead to the potential interpretation that our model is capable of capturing the semantic intent of the question correctly and determining which visual contents are accordingly required. In more detail, the attention scores of the dialog history, highlighted in red, indicate how our model attends to topic-relevant clues through previous dialog history.

As shown in Figure 4(a), comparing two examples, we see that the model no longer focuses on “6” and “people” in H0 because those words are not related to the topic of the current question (i.e., “drinking”). In the example in Figure 4(b),
Figure 4: Qualitative results on the VisDial v1.0 validation set. We visualize the different attention scores for each module: 1) attention scores from Topic Aggregation module and Context Matching module are highlighted in red and blue, respectively; 2) semantic intent of the current question represented via the topic-level fusion step in yellow; and 3) the top-three attention scores of visual features from the context-level fusion step, which are represented by the b-boxes with fine adjustment of transparency in the given image. The numbers in the brackets indicate the rank of the correct answer that our model predicts. Darker colors indicate higher attention scores.

Figure 5: Error analysis on the VisDial v1.0 validation set. We analyze the examples for which the model scored 0 with respect to the R@10 metric.

4.5 Error Analysis

We analyzed examples in the VisDial v1.0 validation set for which our model obtained a score of 0 for the R@10 metric. The errors in Figure 5 can be categorized into three groups: 1) Subjective judgment: our model tends to make wrong predictions for questions about age, weather, and appearance that could involve subjective judgment, but might be acceptable (Figures 5(a) and (b)). 2) Ambiguous questions: our model can focus on the wrong visual contents, for instance the left and right side walls rather than the rear wall when faced with an ambiguous question (Figure 5(c)). 3) Wrong co-reference resolution: when the dialog history includes multiple entities (e.g., “boys”, “pizzas”, and “toppings”) that can be referenced by a single pronoun (i.e., “them”), MVAN can become confused as to which entity the pronoun refers (Figure 5(d)).

5 Conclusion

In this paper, we introduced the MVAN for the visual dialog task. MVAN can effectively capture question-relevant dialog history and visual contents focusing on the semantic intent of the current question. We used VisDial v1.0 and v0.9 to empirically evaluate our model, and as a result, our model outperforms existing state-of-the-art models. Moreover, we not only suggest plausible factors affecting.
a trade-off relationship of the evaluation metrics, but we enhance the interpretability of multi-level attention through detailed visualization. In future work, we aim to develop a complementary model by adding sequential information about the dialog history. This is in contrast to our proposed model, which relies only on the attention scores. Moreover, we plan to incorporate the latest pre-training methods (Lu et al., 2019; Murahari et al., 2019) into our model to improve its performance.

References

Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 6077–6086.

Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C Lawrence Zitnick, and Devi Parikh. 2015. Vqa: Visual question answering. In Proceedings of the IEEE international conference on computer vision, pages 2425–2433.

Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José MF Moura, Devi Parikh, and Dhruv Batra. 2017. Visual dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 326–335.

Akira Fukui, Dong Huk Park, Daylen Yang, Anna Rohrbach, Trevor Darrell, and Marcus Rohrbach. 2016. Multimodal compact bilinear pooling for visual question answering and visual grounding. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 457–468.

Zhe Gan, Yu Cheng, Ahmed Kholy, Linjie Li, Jingjing Liu, and Jianfeng Gao. 2019. Multi-step reasoning via recurrent dual attention for visual dialog. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 6463–6474.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. 2017. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6904–6913.

Dalu Guo, Chang Xu, and Dacheng Tao. 2019. Image-question-answer synergistic network for visual dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 10434–10443.

Dan Guo, Hui Wang, Hanwang Zhang, Zheng-Jun Zha, and Meng Wang. 2020. Iterative context-aware graph inference for visual dialog. arXiv preprint arXiv:2004.02194.

Drew A Hudson and Christopher D Manning. 2019. Gqa: a new dataset for compositional question answering over real-world images. arXiv preprint arXiv:1902.09506.

Xiaoze Jiang, Jing Yu, Zengchang Qin, Yingying Zhuang, Xingxing Zhang, Yue Hu, and Qi Wu. 2020. Dualvd: An adaptive dual encoding model for deep visual understanding in visual dialogue. In Proceedings of the AAAI Conference on Artificial Intelligence.

Gi-Cheon Kang, Jaeseo Lim, and Byoung-Tak Zhang. 2019. Dual attention networks for visual reference resolution in visual dialog. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2024–2033.

Hyounghun Kim, Hao Tan, and Mohit Bansal. 2020. Modality-balanced models for visual dialogue. In Proceedings of the AAAI Conference on Artificial Intelligence.

Jin-Hwa Kim, Jaehyun Jun, and Byoung-Tak Zhang. 2018. Bilinear attention networks. In Advances in Neural Information Processing Systems, pages 1564–1574.

Jin-Hwa Kim, Kyoung-Woon On, Woosang Lim, Jeonghee Kim, Jung-Woo Ha, and Byoung-Tak Zhang. 2016. Hadamard product for low-rank bilinear pooling. arXiv preprint arXiv:1610.04325.

Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Satwik Kottur, José MF Moura, Devi Parikh, Dhruv Batra, and Marcus Rohrbach. 2018. Visual coreference resolution in visual dialog using neural module networks. In Proceedings of the European Conference on Computer Vision (ECCV), pages 153–169.

Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. 2017. Visual genome: Connecting language and vision using crowdsourced dense image annotations. International Journal of Computer Vision, 123(1):32–73.

Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer.

Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. 2019. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. In Advances in Neural Information Processing Systems, pages 13–23.
Jiasen Lu, Anitha Kannan, Jianwei Yang, Devi Parikh, and Dhruv Batra. 2017. Best of both worlds: Transferring knowledge from discriminative learning to a generative visual dialog model. In Advances in Neural Information Processing Systems, pages 314–324.

Jiasen Lu, Jianwei Yang, Dhruv Batra, and Devi Parikh. 2016. Hierarchical question-image co-attention for visual question answering. In Advances in neural information processing systems, pages 289–297.

Vishvak Murahari, Dhruv Batra, Devi Parikh, and Abhishek Das. 2019. Large-scale pretraining for visual dialog: A simple state-of-the-art baseline. arXiv preprint arXiv:1912.02379.

Duy-Kien Nguyen and Takayuki Okatani. 2018. Improved fusion of visual and language representations by dense symmetric co-attention for visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6087–6096.

Van-Quang Nguyen, Masanori Suganuma, and Takayuki Okatani. 2019. Efficient attention mechanism for handling all the interactions between many inputs with application to visual dialog. arXiv preprint arXiv:1911.11390.

Yulei Niu, Hanwang Zhang, Manli Zhang, Jianhong Zhang, Zhiwu Lu, and Ji-Rong Wen. 2019. Recursive visual attention in visual dialog. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6679–6688.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. Pytorch: An imperative style, high-performance deep learning library. In Advances in Neural Information Processing Systems, pages 8024–8035.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543.

Jiaxin Qi, Yulei Niu, Jianqiang Huang, and Hanwang Zhang. 2019. Two causal principles for improving visual dialog. arXiv preprint arXiv:1911.10496.

Mengye Ren, Ryan Kiros, and Richard Zemel. 2015a. Image question answering: A visual semantic embedding model and a new dataset. Proc. Advances in Neural Inf. Process. Syst. 1(2):5.

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. 2015b. Faster r-cnn: Towards real-time object detection with region proposal networks. In Advances in neural information processing systems, pages 91–99.

Idan Schwartz, Seunghak Yu, Tamir Hazan, and Alexander G Schwing. 2019. Factor graph attention. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2039–2048.

Paul Hongsuck Seo, Andreas Lehrmann, Bohnyung Han, and Leonid Sigal. 2017. Visual reference resolution using attention memory for visual dialog. In Advances in neural information processing systems, pages 3719–3729.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Ellen M Voorhees et al. 1999. The trec-8 question answering track report. In Trec, volume 99, pages 77–82.

Qi Wu, Peng Wang, Chunhua Shen, Ian Reid, and Anton Van Den Hengel. 2018. Are you talking to me? reasoned visual dialog generation through adversarial learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6106–6115.

Tianhao Yang, Zheng-Jun Zha, and Hanwang Zhang. 2019. Making history matter: History-advantage sequence training for visual dialog. In Proceedings of the IEEE International Conference on Computer Vision, pages 2561–2569.

Zhou Yu, Jun Yu, Yuhao Cui, Dacheng Tao, and Qi Tian. 2019. Deep modular co-attention networks for visual question answering. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6281–6290.

Rowan Zellers, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. From recognition to cognition: Visual commonsense reasoning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6720–6731.
Q4: Are they wearing a snowsuit?
- H0: A snowboarder is traveling down a snowy hill
- H1: Is the snowboarder along? Yes
- H2: Is it daytime? Yes
- H3: Is the border wearing a helmet? No

GT: Yes, a tan snowsuit (1)
Prediction: Yes, a tan snowsuit

Q6: Is it snowing out?
- H0: A snowboarder is traveling down a snowy hill
- H1: Is the snowboarder along? Yes
- H2: Is it daytime? Yes
- H3: Is the border wearing a helmet? No
- H4: Are they wearing a snowsuit? Yes, a tan snowsuit
- H5: Is the sun out? No

GT: No (1)
Prediction: No

Q3: Can you see train tracks?
- H0: The front cab of a long train at a railroad yard
- H1: What color is the train? Yellow and red
- H2: Does it have writing on it? Yes, some numbers

GT: Yes (1)
Prediction: Yes

Q4: What are the numbers?
- H0: The front cab of a long train at a railroad yard
- H1: What color is the train? Yellow and red
- H2: Does it have writing on it? Yes, some numbers
- H3: Can you see train tracks? Yes

GT: 66204 (2)
Prediction: 66204

Figure 6: Qualitative results our MVAN model on v1.0 validation set.
Q4: about how old is the boy?
GT: 4 (4)
Prediction: 2
H1: what color is the toothbrush? green
H2: is this indoors? yes
H3: are there any other people? no
H0: a little boy using a giant toothbrush to brush a set of model teeth

Q5: is she carrying anything else?
H0: the woman is holding a water bottle while wheeling a suitcase behind her
H1: how old is the lady? about 30
H2: is she in dressy or casual attire? casual
H3: what color is her suitcase? not really visible
H4: could this be at an airport? yes
GT: a water bottle in her right hand (1)
Prediction: a water bottle in her right hand

Q6: can you see other people?
H0: the woman is holding a water bottle while wheeling a suitcase behind her
H1: how old is the lady? about 30
H2: is she in dressy or casual attire? casual
H3: what color is her suitcase? not really visible
H4: could this be at an airport? yes
H5: is she carrying anything else? a water bottle in her right hand
GT: yes many people in the background (2)
Prediction: a few in the background

Figure 7: Qualitative results our MVAN model on VisDial v1.0 validation set.