Multi-step Joint-Modality Attention Network for Scene-Aware Dialogue System

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Abstract

Understanding dynamic scenes and dialogue contexts in order to converse with users has been challenging for multimodal dialogue systems. The 8-th Dialog System Technology Challenge (DSTC8) (Seokhwan Kim 2019) proposed an Audio Visual Scene-Aware Dialog (AVSD) task (Hori et al. 2018), which contains multiple modalities including audio, vision, and language, to evaluate how dialogue systems understand different modalities and response to users. In this paper, we proposed a multi-step joint-modality attention network (JMAN) based on recurrent neural network (RNN) to reason on videos. Our model performs a multi-step attention mechanism and jointly considers both visual and textual representations in each reasoning process to better integrate information from the two different modalities. Compared to the baseline released by AVSD organizers, our model achieves a relative 12.1\% and 22.4\% improvement over the baseline on ROUGE-L score and CIDEr score.

Introduction

Understanding visual information along with natural language have been a recent surge of interest in visual-textual applications, such as image-based visual question answering (VQA) and image-based visual dialogue question answering. In contrast to image-based VQA, where the model aims to response the answer of a single question for the given image, image-based visual dialogue question answering was introduced to hold a meaningful dialogue with users about the given image. However, because a single image is far less than enough to represent the details of an event, videos are commonly used to record what has happened. Therefore, reasoning based on a video is also worth exploring.

Because of the relatively large complex feature space, video-language tasks are more challenging than traditional image-language tasks. To be more specific, processing videos involves diverse objects, action flows, audio that are not issues for image processing. Similar to image-based VQA, video question answering answers a single question based on a given video. Video dialogue question answering, by contrast, reasons the dialogue as well as the sequential question-answer pairs it contains in order to answer the current question for the given video.

The 8-th Dialog System Technology Challenge (DSTC8) Audio Visual Scene-Aware Dialogue (AVSD) task proposed a dataset to test the capability of dialogue responses with multiple modalities. A brief illustration of AVSD task is shown in Figure 1. The task provides pre-extracted features using I3D (Carreira and Zisserman 2017) and Vggish (Hershey et al. 2016) models for the video. Moreover, a video caption, a video summary, and a dialogue history with question-answer pairs are introduced as textual information. Table 1 shows an example of dialogue history, caption, summary from the AVSD training set. The purpose of this task is answering the question based on given multiple modalities.

In our work, we implement attention mechanisms (Bahdanau, Cho, and Bengio 2014; Xu et al. 2015), which have been proven useful for vision-language tasks, to focus on a rather important part in sources and to generate accurate answers on AVSD dataset. In order to increase the performance when the answer lies in a specific region of the video, our model performs multiple reasoning steps based on recurrent neural network (RNN) to find important representation. Moreover, to improve the understanding when the number of feature types increases, we proposed a joint-modality attention network (JMAN) to jointly learn attention from dif-
different features of the video. In conclusion, the results show that our model achieves a relative 12.1% and 22.4% improvement over the baseline on ROUGE-L score and CIDEr score.

Related Work

The Audio Visual Scene-Aware Dialog (AVSD) task aims at answering a free-form question based on the given video and texts. Therefore, we briefly review the vision-based question answering work in the following section.

Visual Question Answering

Given a natural-language question that targets visual features, image-based visual question answering (VQA) is to provide an accurate answer relevant to the question. Because systems need to identify the most relevant region in the visual features based on question semantics, attention mechanisms show a powerful ability to focus on salient regions. A large amount of work (Xu and Saenko 2015, Yang et al. 2015, Lu et al. 2016, Anderson et al. 2017, Yu et al. 2017, Kim, Jun, and Zhang 2018) demonstrate significant results on image-based VQA by attention mechanisms.

Das et. al first introduced the visual dialogue dataset (VisDial) (Das et al. 2017) which contains images from the COCO dataset (Lin et al. 2014) and one dialogue. Visual dialogue question answering aims to increase the ability of human-machine interaction by taking previous conversations into account. To capture important regions of visual features, attention mechanisms also play a role in visual dialogue question answering task, such as performing dynamic attention combination (Seo et al. 2017), recursively increasing visual co-reference resolution (Niu et al. 2018), implementing multiple reasoning steps on image and dialogue (Gan et al. 2019), and employing a multi-head attention mechanism (Kang, Lim, and Zhang 2019).

Video Question Answering

Moving from image-based VQA to video question answering requires models to analyze relevant objects in the frames and keep track of temporal events. Much research (Tapaswi et al. 2015, Lei et al. 2018, Jang et al. 2017) provides video datasets form movies or TV series for systems to output an accurate answer given a set of potential answers. To answer question for videos, many approaches (Ye et al. 2017, Liang et al. 2018, Kim et al. 2017, Na et al. 2017) also utilize complicated attention mechanisms that focus on the most important part of videos.

In contrast to video question answering, video dialogue question answering task needs to understand dynamic scenes and previous conversations. The limited availability of such data makes this task more challenging. Recently, Hori et al. proposed an audio visual scene-aware dialog (AVSD) task in the 8-th Dialog System Technology Challenge (DSTC8). The AVSD dataset provides multimodal features, including vision, audio, and dialogue history, for videos. Table 2 shows the difference between AVSD dataset and other video datasets. Instead of answering single question of the video, AVSD dataset takes historical question-answer pairs into account in order to generate a more conversation-like answer. Moreover, most of the video dataset select an answer from multiple choice, the AVSD dataset provides a free-form answer that makes the task more difficult.

Proposed Approach

Figure 2(a) shows an overview of the proposed method. First, the model uses LSTM-based encoders to encode the visual features and textual features provided by AVSD organizers. We did not select audio feature proposed by organizers and we will explain in the Experiments section. Our proposed joint-modality attention network (JMAN) then attends the question with both visual features and textual representations. With the increasing recurrent reasoning steps of JMAN, the model learns the important visual regions and salient textual parts that correspond to the query. Finally, by jointly considering both visual and textual features, a LSTM-based decoder then generates an open-ended answer that best fits the given question, video, and context.

Table 1: A sample of a caption, a summary and a dialogue history of the video from DSTC8 AVSD dataset

| Question | Answer |
|----------|--------|
| how many people are in this video? | i can only see one in the video. |
| what is the setting of the video? | a man is sitting in a closet fixing something. |
| can you tell what he is fixing? | i think it is a camera. |
| does he sit in the closet the whole time? | no, he gets out of the closet eventually. |
| where does he go to? | outside of the closet but i do not know in which room he is afterwards. |
| is there audio? | i do not hear anything. |
| does he take the camera with him when he exits the closet? | no, the camera remains on the floor of the closet. |
| can you tell if he succeeds in fixing the camera? | to be honest, i am not sure. |
| how does the video end? | he is standing in the room doing nothing. |

Table 2: The summary of several video question answering datasets.

| Video QA Dataset   | Textual Format | Answer Form |
|--------------------|----------------|-------------|
| MovieQA (Tapaswi et al. 2015) | QA | multiple choice |
| TVQA (Lei et al. 2018) | QA | multiple choice |
| TGIF-QA (Jang et al. 2017) | QA | multiple choice |
| AVSD (Hori et al. 2018) | QA-dialogue | free form |
Multi-Step Joint-Modality Attention Network

Our model then generates an answer by an LSTM-based decoder. A detailed illustration of proposed JMAN is shown in (b). Our attention network (JMAN) then learns attention from both visual and textual features. By considering previous conversation, our model can focus on the salient region of both visual and textual modalities.

Feature Extraction

For visual features of videos, the AVSD organizers provide i3d-rgb and i3d-flow, which are extracted from the “Mixed-5e” layers of two-stream inflated 3D ConvNets (Carreira and Zisserman 2017). The visual features contain RGB information in each frame and optical flow information between frames. We use LSTM-based encoder with 2048 dimension to encode these two features. The encoded RGB feature and optical flow feature are denoted as $R_0$ and $F_0$.

Though we did not take audio feature to construct our final model, we still conduct experiments to evaluate the effectiveness of each features. In order to test the usefulness of the audio feature, which is extracted from Vggish model (Hershey et al. 2016), we also utilize LSTM-based encoder with 128 dimension to encode audio feature. The encoded audio feature represents as $A_0$ for experimental purpose.

For the question, the caption, the summary, and the dialogue history of the AVSD dataset, we transferred each text into a vector using GloVE (Pennington, Socher, and Manning 2014). All the textual vectors then encoded by 128 dimensional LSTM-based encoders to output encoded features of caption, summary, question, and dialogue history, and they are denoted as $C_0$, $S_0$, $Q_0$, and $D$ respectively.

Multi-step Joint-Modality Attention Network

An overview of the proposed multi-step joint-modality attention network (JMAN) is given in Figure 2(b). The framework is based on a recurrent neural network (RNN), where the hidden state $Q_n$ indicates the current question representation and the lower index $n$ is the number of reasoning steps. After $n$-step attention mechanism, the attended RGB feature and the attended optical flow feature are represented as $R_n$ and $F_n$. Likewise, $C_n$ and $S_n$ are the attended caption feature and the attended summary feature. Specifically, we sum $R_n$ and $F_n$ as joint-attended visual feature $V_n$ after reasoning step $n=1$; likewise, $C_n$ and $S_n$ are aggregated as the joint-attended textual feature $T_n$. From the second reason step ($n = 2$), the joint-attended features will deliver to different modality to enhance both domains understanding. Take the second reasoning step ($n = 2$) as example, the joint-attended visual feature $T_1$ will deliver to visual modality to attend the second question state $Q_2$ together with $R_1$ and $F_1$. In contrast to attending to a single-domain modality with the query, we find that jointly attending different domain modality enhances the performance of video understanding. Moreover, proposed JMAN can focus on the salient region of both visual and textual features when the number of reasoning step increases.

Self-Attended Question

We applied self-attention to the current question representation $Q_n$, which is the hidden state of proposed RNN-based JMAN.

$$\alpha_Q = \text{softmax}(p_Q \cdot \tanh(\omega_Q Q_{t-1}^T)), \quad (1)$$

$$Q_n = \alpha_Q \cdot Q_{n-1}, \quad (2)$$

where the attention score of question is $\alpha_Q$ and the parameter matrices are $p_Q$ and $\omega_Q$.

Attending Question and Previous Joint-Attended Features to Different Modalities

The model updates at- $Q_n$ and attended optical flow feature $F_n$ by their previous state ($R_{n-1}$ and $F_{n-1}$) and the current query $Q_n$. The joint-attended textual feature $T_n$ will also pass to the attention mechanism after the first reasoning step. In the following equations, we use index $x \in \{R, F\}$ represents visual components (RGB and optical flow).

$$\alpha_x = \text{softmax}(p_x \cdot \tanh(\omega_x x_{n-1}^T + \omega_Q Q_{n-1}^T + \omega_T T_{n-1}^T)), \quad (3)$$

$$x_n = \alpha_x \cdot x_{n-1}, \quad (4)$$

where $\alpha_x$ is the attention score of the visual components, and the parameter matrices are $p_x$, $\omega_x$, $\omega_Q$, and $\omega_T$. The
joint-attended textual feature $T_n$ is delivered from the textual modality. After the first reasoning step, the model begins to aggregate $R_n$ and $F_n$ as joint-attended visual feature $V_n$, which is delivered to the textual modality.

Similar to the attention mechanism for visual modality, the model updates attended caption feature $C_n$ and attended summary feature $S_n$ by their previous state ($C_{n-1}$ and $S_{n-1}$) and the current query $Q_n$. The joint-attended visual feature $V_n$ transfers into textual modality in order to use the salient visual information to discover important textual information. We use index $y \in \{C, S\}$ represents textual components (caption and summary).

$$\alpha_y = \text{softmax}(p_y \cdot \text{tanh}(\omega_y y_{n-1}^T + \omega_Q^T Q_n + \omega_V V_{n-1}^T)), \quad (5)$$

where $\alpha_y$ is the attention score of the textual components, and the parameter matrices are $p_y, \omega_y, \omega_Q^T$, and $\omega_V$. The joint-attended visual feature $V_n$ is delivered from the visual modality. The system begins to sum $C_n$ and $S_n$ as joint-attended textual feature $T_n$ after reasoning step $n = 1$, and $T_n$ will pass to the visual modality as additional information.

Answer Decoder

The system concatenates all attended features $R_n$, $F_n$, $C_n$, and $S_n$ as the context vector $z_n$. The question representation is updated based on context vector via an RNN with Gate Recurrent Unit (GRU) (Cho et al. 2014):

$$Q_{n+1} = GRU(Q_n, z_n). \quad (7)$$

A generative LSTM-based decoder is used to decode the context vector $z_n$. Each question-answer pair in dialogue history will also be used to generate the answer $a = (a_1, a_2, ..., a_L)$, where $L$ is the number of word, and $a_\ell \in \Gamma_\ell = \{1, 2, ..., |\Gamma_\ell|\}$ represents the $\ell$-th word of possible words $\Gamma_\ell$. By considering the context vector $z_n$ and dialogue history $D$, an FC-layer with dropout and softmax is used after the decoder to compute the conditional probability $p(a_\ell | D, a_{1: \ell-1}, h_{i-1})$ for possible word $a_\ell$, where the initial hidden state $h_0$ is $z_n$.

Experiments and Results

Experimental Materials and Setup

The organizers of DSTC8-AVSD track provide DSTC7-AVSD dataset for model constructing. From Charades video dataset (Sigurdsson et al. 2016), the AVSD dataset proposes for each corresponding video a dialog with 10 question-answer pairs, visual features generated by the I3D model (Carreira and Zisserman 2017), and audio feature produced by Vggish model (Hershey et al. 2016). The dialogue was generated via a discussion between two Amazon Mechanical Turk workers about the events observed in the video. Table 3 summarizes the data distribution of the AVSD dataset.

For our submitted system, we only select the visual features and textual features proposed by AVSD dataset to build our model. The dimensions of textual and visual features are set to 128 and 2048, and we use Adam optimizer (Kingma and Ba 2014) with a learning rate of 0.001 in the training process. The batch size and a dropout rate (Srivastava et al. 2014) of proposed model is set to 32 and 0.2. Cross-entropy loss between the prediction and target are used to optimize the hyperparameter.

Features Effectiveness

To evaluate the influence of multimodal features on the AVSD task, we began by inputting dialogue history feature and then adding other mono-type features. We first considered the question and dialogue history, and the result of this simplest model (JMAN(DH)) is shown in the second part of Table 4. Without any attention mechanism on the features, JMAN(DH) outputs answers based on dialogue history and performs poorly than all other models with additional mono-type feature. This result is reasonable because of the insufficient information of video-related features. In order to further analyze the effectiveness of each feature, we add mono-type features on JMAN(DH) and set the reasoning step to 1. Therefore, the attention algorithms are rewritten as:

$$\alpha_M = \text{softmax}(p_M \cdot \text{tanh}(\omega_M M_0^T + \hat{\omega}_Q Q_1^T)), \quad (8)$$

where $M \in \{A, R, F, C, S\}$ represent the feature components (audio, RGB, optical flow, caption, summary), and the parameter matrices are $p_M, \omega_M$, and $\hat{\omega}_Q$. As shown in the second part of Table 4, all models with additional mono-type feature outperform the simplest model JMAN(DH). This result shows the effectiveness of single-step attention mechanism on additional mono-type feature. Moreover, as it is likely that the question concerns what happens in the video, all models considering video-related components performs better than the simplest model.

From the second part of Table 4, we find that models using visual features can produce more accurate answers than models using textual features. To be more specific, all evaluation metrics of JMAN(DH, rgb) and JMAN(DH, flow) outperform JMAN(DH, C) and JMAN(DH, S). As the caption and the summary for each video in the AVSD dataset generally consist of two sentences, visual features are relatively more informative. However, we surprisingly find that the model with audio feature (JMAN(DH, aud)) performs worst among all models with the additional mono-type feature. We surmise that Vggish audio feature are noisier than textual and visual features.

After analyzing the models with additional mono-type feature, we then evaluate the performance of the model combining different features. With one reasoning step,
values of proposed JMAN with 1 reasoning step (n = 1) and the baseline model proposed by DSTC-A VSD organizers. The second part and the third part show the objective evaluation of JMAN(DH, C) which considers visual features (RGB and optical flow) and the attended caption feature $C_1$ and $S_1$. Likewise, JMAN(DH, rgb, flow) considers visual features (RGB and optical flow) in first reasoning step, and the context vector $z_1$ of this model is the concatenation of $R_1$ and $F_1$. The results show that the models combining two features (JMAN(DH, C, S) and JMAN(DH, rgb, flow)) have a better performance than the models with additional mono-type feature. Examining textual domain, JMAN(DH, C, S) slightly outperforms both JMAN(DH, C) and JMAN(DH, S). Moreover, JMAN(DH, rgb, flow) surpasses both JMAN(DH, rgb) and JMAN(DH, flow) for visual domain. We observe that the model combining visual features (JMAN(DH, rgb, flow)) exhibit better performance than the model combining textual features (JMAN(DH, C, S)). Similar to the results of models with additional mono-type feature, we think that visual features will help our system to generate better responses.

In order to fully comprehend videos, we then take the advantage from both visual and textual domain. Therefore, JMAN(DH, C, S, rgb, flow) unitizes both visual features and textual features and the context vector $z_1$ of this model is the concatenation of $R_1$, $F_1$, $C_1$, and $S_1$ in the first reasoning step. Taking both visual features and textual features, all evaluation metrics of JMAN(DH, C, S, rgb, flow) are higher than JMAN(DH, C, S) and JMAN(DH, rgb, flow). This result shows that the model can improve video understanding when effective information increases. Moreover, the improvement of the JMAN(DH, C, S, rgb, flow) model confirms the usefulness of visual and textual features provided by AVSD dataset. However, we found that adding audio feature to JMAN(DH, C, S, rgb, flow) deteriorates the performance. Because of the decreasing performance of JMAN(DH, C, S, rgb, flow, aud), we did not use audio feature to build our model when the reasoning step increases.

### Multi-step Reasoning

From previous experimental results, we find that using attention mechanism on both visual and textual features improves the performance of video understanding. We further evaluate the video understanding performance of the proposed JMAN for different reasoning steps, leveraging both textual and visual features, i.e., the current question, the dialogue history, the caption, the summary, RGB, and spatial flow of videos. After the first reasoning step (n = 1), JMAN then focuses on specific regions of the textual representation and visual representation that correspond to the input question. To identify the salient regions form the multi-modal features, we designed $V_n$ and $T_n$, which are aggregated from the uni-modal attended features after first reasoning step. For instance, the joint-attended textual feature $T_n$ is generated by aggregating the attended caption feature $C_n$ and the attended summary feature $S_n$.

Comparing JMAN(DH, C, S, rgb, flow) to JMAN(DH, C, S, rgb, flow, n = 2) in Table 4 merely increasing a single reasoning step to two improves performance. This result shows that adding important information from a cross-modal way and adding reasoning step help the model better understand videos and then be able to generate correct answers.

| JMAN(DH, C, S, rgb, flow, n = 2) | 0.658 | 0.513 | 0.406 | 0.325 | 0.239 | 0.523 | 0.917 |
|----------------------------------|-------|-------|-------|-------|-------|-------|-------|
| JMAN(DH, C, S, rgb, flow, n = 3) | 0.662 | 0.517 | 0.412 | 0.333 | 0.242 | 0.532 | 0.935 |
| JMAN(DH, C, S, rgb, flow, n = 4) | 0.667 | 0.521 | 0.413 | 0.334 | 0.239 | 0.533 | 0.941 |
| JMAN(DH, C, S, rgb, flow, n = 5) | 0.670 | 0.522 | 0.413 | 0.335 | 0.239 | 0.533 | 0.941 |

Table 4: The objective evaluation values of each model using the DSTC7-A VSD test set. The first part is the performance of the baseline model proposed by DSTC-A VSD organizers. The second part and the third part show the objective evaluation values of proposed JMAN with 1 reasoning step ($n = 1$). The second part simplest modality to evaluate the effectiveness of each features. In the third part, we estimate the performance of the combination of different modalities, which are audio, vision, and language. Considering only textual modality and visual modality, the fourth part show the results for proposed JMAN with increasing reasoning step $n$. The word in the parentheses means the given feature. (DH: dialogue history; C: video caption; S: video summary; rgb: i3d-rgb feature; flow: i3d-flow feature; aud: audio vggish feature)
Table 5: Released by the AVSD organizers, this table shows the final result of objective evaluation values and human rating by using the DSTC8-AVSD test set.

|                  | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE-L | CIDEr  | Human |
|------------------|--------|--------|--------|--------|--------|---------|--------|-------|
| Baseline [Hori et al. 2018] | 0.614  | 0.467  | 0.365  | 0.289  | 0.21   | 0.48    | 0.651  | 2.885 |
| JMAN (DH, C, S, rgb, flow, n = 5) | 0.645  | 0.504  | 0.402  | 0.324  | 0.232  | 0.521   | 0.875  | 3.123 |

Table 5 is the final result released by the official. Our submitted system outperforms the released baseline model for both subjective and objective evaluation metrics.

Qualitative Analysis and Training Data Quality

Figure 3 shows the ground truth reference proposed by the AVSD dataset and the answers generated by the baseline model and the proposed JMAN model on DSTC7-AVSD dataset. Only parts of the video caption and the video summary are shown for simplicity. The pictures are the frames from Charades video dataset used by DSTC7-AVSD dataset.

Moreover, the results also show that the accuracy of JMAN consistently increases when reasoning step \( n \) grows. This advantage may come from the additional cross-modal joint-attended features \( (T_n \text{ and } V_n) \) which bring in more information to the model. Nevertheless, for reasoning steps \( n \) beyond 5, the model did not show significant increase on every metrics. The best performance of our model (JMAN(DH, C, S, rgb, flow, \( n = 5 \)) achieves 20.8% improvement over the baseline on CIDEr score for DSTC7-AVSD dataset. Therefore, we submitted this best model to DSTC8-AVSD track. Table 3 is the final result released by the official. Our submitted system outperforms the released baseline model for both subjective and objective evaluation metrics.

Conclusion

This paper proposes an encoder-decoder based visual dialogue model which consider multiple modalities effectively by the proposed joint-modality attention network (JMAN). Jointly taking both visual features and textual features at each reasoning step, JMAN extracted important part from cross-modal features and achieved a better comprehension of multi-modal context. Through multiple reasoning steps, our model further boosted the performance of scene-aware ability. Our best model achieved a significant 12.1% and 22.4% improvement over the baseline on ROUGE-L and CIDEr. We hope to explore this multi-modal dialogue setting further in the future with larger scale datasets. Unsupervised pre-trained language model could also applied to inject more semantics to the model for multi-modal dialogue task.

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