ABSTRACT

We introduce a novel task, Video Question Generation (Video QG). A Video QG model automatically generates questions given a video clip and its corresponding dialogues. Video QG requires a range of skills – sentence comprehension, temporal relation, the interplay between vision and language, and the ability to ask meaningful questions. To address this, we propose a novel semantic rich cross-modal self-attention (SR-CMSA) network to aggregate the multi-modal and diverse features. To be more precise, we enhance the video frames semantic by integrating the object-level information, and we jointly consider the cross-modal attention for the video question generation task. Excitingly, our proposed model remarkably improves the baseline from 7.58 to 14.48 in the BLEU-4 score on the TVQA dataset. Most of all, we arguably pave a novel path toward understanding the challenging video input and we provide detailed analysis in terms of diversity, which ushers the avenues for future investigations.

Index Terms— Video Question Generation, Cross-Modal Attention

1. INTRODUCTION

Recent years have witnessed the rise of interest in vision-language tasks due to daily generated multimedia contents from the world. Among these tasks, video understanding tasks have drawn researchers’ attention. However, all existing tasks mainly focus on learning to ‘answer’ instead of learning to ‘ask’, which is also equivalently crucial to society. For instance, online teaching videos on the MOOC or the BBC English Learning website are required to ask questions to evaluate the students’ understanding of the video materials. In addition, we humans learn by asking questions of the parts we are not confident of. As for a robot, it can learn faster by asking questions about the learning experience which it is not able to understand. Shen et al. [1] improved the image captioning model by allowing the model to ask questions but their method is limited to static image inputs. Moreover, the ability to ask can also aid the development in popular vision-language fields, such as Visual Dialogue task [2], Video Question Answering [3], and Embodied Question Answering [4] by decreasing the expensive questions annotation cost.

To achieve these, we propose a novel and practical task, Video Question Generation, as illustrated in Figure 1. A successful Video QG model should ask a meaningful question based on a video clip. Comparing to the text question generation task [5] where the target questions are highly overlapped with the input passage or the image question generation task [6] where the questions are regardless of the temporal information, Video QG is arguably more challenging. To tackle Video QG, it is intuitive to apply LSTM based Seq2Seq models [7, 8, 9] to our task. However, there are several problems to be addressed. (1) The visual features are extracted by pre-trained convolutional neural networks (CNNs) and frozen during training. This limited the features to incorporate the relationships between multiple objects or between objects and the scene. (2) Multimedia information fusion mechanism for LSTM models usually compute multimodal attention with only one embedding space for a single modality. This restricted the fusion representation from learning the multiple semantic subspaces and the intersection between different subspaces of different modalities.

Therefore, we propose the following novel approaches to cope with the aforementioned problems: (1) Semantic-Rich Embedding (SRE). Instead of directly feeding the CNN extracted features or object layouts [10] to the model, we formalize the scene and objects relationship by incorporating the object-level semantic meaning into the visual information via fusing the CNN-extracted features and object-level representation. (2) Cross-Modal Self-Attention (CMSA) encoder. Our proposed CMSA encoder could solve the notorious long-term dependencies issues by applying the self-attention mechanism. In addition, we learn multiple semantic subspaces for each modality, which allows the model to capture complementary semantic attention in different subspaces.
Video Question Generator

Ross: That's right. I forgot about your ability to fuse metal.
Monica: Hey, it's Funny's cousin. Not Funny!
Rachel: Hi, Mr. Treeger? It's Rachel Greene from upstairs.
Rachel: Yes, somebody broke our knob on the radiator.

Fig. 1. Video Question Generation (Video QG). We propose a novel and challenging task which automatically generates an answerable question (Top) according to a video clip (Bottom). Video QG model is required to represent the sparsity of the video features but also understand the interaction between objects and the semantic information of the dialogues.

scenarios are both common in multimedia contents. Our proposed model significantly surpasses the competitive baseline models based on previous works [11, 7, 10] on BLEU, BLEU-4, ROUGE, CIDEr, and METEOR scores in both scenarios. In addition, Video QG requires the model to generate a good question in terms of correctness, diversity, and answerability. Hence, we also carefully analyze the diversity and answerability of generated questions. The results not only demonstrate the effectiveness of our methods but provide a path for future researches and applications.

2. SEMANTIC RICH CROSS-MODAL SELF-ATTENTION NETWORK

As shown in Figure 2, our novel SRCMSA networks take multi-modal inputs. First, we represent the visual features with SRE to fuse the comprehensive object cues with CNN features. Then, we aggregate the multi-modal information from the video frames and dialogues by CMSA. Finally, an LSTM decoder is applied to generate the desired question.

2.1. Features

Our model inputs multi-modal features including (1) CNN extracted visual feature $V^{frame}\{V^{F}_1, V^{F}_2, \ldots, V^{F}_{n_{frame}}\}$, $V^{F}_i \in \mathbb{R}^{2048}$, (2) Object features $V^{O}\{V^{O}_1, V^{O}_2, \ldots, V^{O}_{n_{frame}}\}$, where $V^{O}_i \in \mathbb{R}^{300}$, and (3) Dialogue features $V^{sub}\{V^{sub}_1, V^{sub}_2, \ldots, V^{sub}_{n_S}\}$, $V^{sub}_i \in \mathbb{R}^{300}$, where $n_S$ is the word length of the dialogues in a video clip. The features can be obtained in various ways. In our experiments, we extract video frames from the video in 3 FPS, then get CNN features from the Pool5 layer of ResNet101 [12] and detect objects features by Faster-RCNN [13]. The dialogue features are from the dialogues in the video. Both of the detected object in the frames and the word in dialogues are then embedded with 300 dimension vectors. Afterward, we mean pool the objects representation in each frame and get object embeddings.

2.2. Semantic Rich Cross-Modal Self-Attention Encoder

We start introducing our novel CMSA encoder. We solve the long-range dependencies problem by utilizing the self-attention mechanism and aggregate the fusion subspaces by running multi-head attention of different modalities. Overall, we first compute our proposed semantic rich embedding (SRE) then incorporate the SRE with the dialogues with our novel cross-modal mechanism.

2.3. Semantic Rich Embedding (SRE)

SRE captures the essential cues in sparse video input by fusing visual ResNet features $V^F$ and comprehensive object occurrence features $V^O$ into joint representation. First, we obtain the video feature for each frame:

$$V^{src}_i = W_{proj}(V^F_i) \odot V^O_i$$

where the visual feature is projected to the embedding space by a matrix $W_{proj}$, then a dot product is applied to combine both visual features and object occurrence features.

2.4. Cross-Modal Self-Attention (CMSA) Mechanism

Single Head Attention. Transformer[14] has achieved huge success in many areas. However, most of the existing works limit the transformer for single modality input. In our proposed CMSA, we aim to integrate the rich information from multi modalities. We first begin by introducing the single head attention used in our CMSA:

$$Attention(Q, K, V) = Attention(W^Q Q, W^K K, W^V V)$$
**Fig. 2.** The framework of our proposed semantic rich cross-modal self-attention (SRCMSA) networks. The architecture consists of two transformers as the encoder and an LSTM as the decoder. Our proposed SRCMSA networks enable more rich interactions between videos (e.g., attentive semantic rich embedding) and the dialogues, which are complementary to each other (cf. section 2).

\[ Attention(Q, K, V) = \text{softmax}(\frac{QK}{\sqrt{d}})V, \text{ where } Q, K, V, d \text{ are served as the query, key, value, and the dimension of the input. } \]
\[ W^Q, W^K, W^V \text{ are the projected matrices. } \]

We set the SRE features as our query, and the dialogues as the key and value because the dialogues features are able to provide richer semantic information than the visual features.

**Multi-Head Attention.** A single attention matrix computation is called a “head”, and we adopt the multi-head attention in our model. The multi-head attention consists of \( H \) parallel heads which allow the model to jointly learn from different representation subspaces. The multi-head attention output is computed as below:

\[ \text{head}_j = Attention(W^Q_jQ, W^K_jK, W^V_jV) \]
\[ \text{MultiHead}(Q, K, V) = W^Q\text{Concat}(\text{head}_1, ..., \text{head}_H) \]

Corresponding to our experiment, a head computation can be viewed as a fusion between the projected subspaces from each input modality. Overall, our cross-modal attentive value \( V^{\text{cmsa}} \) is then calculated by:

\[ V^{\text{cmsa}} = \text{MultiHead}(V^{\text{subQ}}, V^{\text{subK}}, V^{\text{SREV}}) \]
\[ = \text{MultiHead}(W^QV^{\text{sub}}, W^KV^{\text{sub}}, W^VV^{\text{SRE}}) \]

Every project matrix , \( W^Q, W^K, \text{ or } W^V \), is a learnable weight and indicates a different semantic subspace projection which allows the model to aggregate the fusion from different attention subspaces.

### 3. EXPERIMENTS

We evaluate our model on the TVQA dataset proposed by [3] Lei et al. Most of the earlier datasets are either generated with templates [15] or annotated with single modality [16]. TVQA is based on 6 popular TV shows and consists of 152,545 QA pairs from 21,793 clips. The input data involves videos and dialogues, and the crowd-workers are encouraged to annotate the questions requiring both modalities. Two scenarios are applied in terms of different multimedia model inputs: (1) Video only and (2) Video with dialogues. We quantitatively examine the correctness and the diversity of generated questions.

#### 3.1. Correctness

Table 1 shows results of correctness evaluated by BLEU, BLEU-4, ROUGE, CIDEr, and METEOR metrics. Our method obtains an impressive gain across all metrics, indicating that our approach better utilizes the sparse and huge input video and dialogue features. Our ablation experiments (Second block) indicates the effectiveness of all proposed modules. Our CMSA encoder leverages the dialogue features in different domain while SRE represents the sparse video frame via using the object-level and frame-level signals.

#### 3.2. Diversity

Table 2 demonstrates diversity by employing the ratio of frequent words coverage. Our model outperforms both baselines in a significant margin. Additionally, the ground truth questions annotated by humans are much more diverse, indicating
|                | BLEU | BLEU-4 | ROUGE | CIDEr | METEOR |
|----------------|------|--------|-------|-------|--------|
| S2VT [7]       | 57.80| 7.58   | 36.25 | 6.39 | 14.83  |
| OBJ2TEXT [10]  | 61.78| 10.44  | 38.49 | 6.42 | 15.33  |
| IMGD [11]      | 61.08| 9.59   | 37.78 | 7.29 | 15.21  |
| SRCMSA (Ours) (SA) | 63.02| 12.20  | 40.21 | 15.25| 17.36  |
| SRCMSA (Ours) (SA + SRE) | 66.26| 13.74  | 41.48 | 22.93| 18.66  |
| SRCMSA (Ours) (SA + SRE + CMSA) | 68.83| 14.48  | 42.56 | 23.44| 19.04  |

Table 1. Video QG Results on TVQA [3] dataset. Sub: subtitles. SA: Self-Attention. We compare our proposed method with various competitive baselines (First Block). [7, 10, 11]. SRE: Fusing the video frame feature with detected object level embedding mentioned in section 2.2. SRCMSA: our proposed model discussed in section 2. Our proposed method significantly outperforms the baselines. Ablation study in the second block demonstrates the effectiveness of both of our novel components. Noted that SRCMSA (w/o SRE, CMSA) is a single source model which utilize video frames as our input modality.

|                | Unigram (%) | Bigram (%) | Noun (%) | Verb (%) |
|----------------|-------------|------------|----------|----------|
|                | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% | 0.1% | 1% | 10% |
| S2VT [7]       | 72.2 | 99.9 | 100  | 87.8 | 100 | 100  | 61.3 | 100 | 100  | 39.0 | 99.9 | 100  | 31.9 | 99.9 | 100  |
| IMGD [11]      | 34.5 | 99.9 | 100  | 68.0 | 100 | 100  | 57.6 | 100 | 100  | 44.2 | 88.9 | 100  | 49.4 | 99.5 | 100  |
| SRCMSA (Ours)  | 33.8 | 87.9 | 98.0 | 48.6 | 81.1 | 97.9 | 44.2 | 88.9 | 100  | 49.4 | 99.5 | 100  |
| GT (Oracle)    | 25.4 | 66.3 | 86.4 | 16.4 | 38.7 | 64.7 | 31.6 | 49.2 | 79.5 | 16.9 | 57.0 | 84.2 |

Table 2. Frequent Word Coverage for Unigram, Bigram, Noun and Verb. The lower the more diverse. First block: Baselines. Second block: Our SRCMSA Model. Last block: Human labeled ground truth questions as the oracle case. Our model significantly surpasses the strong baseline model in terms of diversity.

that the Video QG is a challenging task. Also, besides the correctness metrics which are widely applied, we argue that diversity measurement deserves attention.

4. ANALYSIS AND FUTURE WORK

We identify 3 common errors in the results, including unanswerable, redundant and general questions. We desire to point out some future directions to overcome these errors in the further research.

There are two main types of unanswerable questions: (1) Action Error where the question refers to nonexistent action. (2) Entity Error where the involved entity does not exist. Using action recognition models or entity recognition models should be helpful to mitigate the issues. Also, the researchers can include specific answers as the queries to the Video QG model in the training stage to generate answerable questions.

Redundant questions are answerable but contain unnecessary conditions. Such as “wearing a shirt” in the question “Who is the person wearing a shirt” when there is only one person in the video. In future works, we are able to decide which questions are redundant with the aid of referring expression models [17].

General questions are answerable questions which can be applied to any video. Such as “What’s the person doing”. General questions are “correct” but suboptimal because they’re simple and discourage reasoning during QA process. General questions also harm the diversity results in Table 2. We suggest the researchers to generate more specific questions by following the strategies in Unanswerable error.

5. CONCLUSION

In this paper, we offer a new perspective and solution to video understanding by proposing a novel task, Video QG, which automatically generates the questions given a video clip. We propose the SRCMSA model to represent and understand the video properly by attending on multimodal sequential features. Our model significantly surpasses the competitive baseline networks, S2VT, IMGD, in terms of quantity and quality. In addition to evaluating with the commonly used metrics, we propose the frequent word coverage to measure the diversity of the generated questions. We dig into the quality beyond the scores by analyzing errors. We hope our work can lead to more thoughts on the creative uses and extensions of Video QG. In the future, we plan to augment Video QA dataset with our improved Video QG model, such as the insufficient Video QA dataset of the languages other than English.

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