

Bridge to Answer: Structure-aware Graph Interaction Network for Video Question Answering

Jungin Park

Jiyoung Lee
Yonsei University, Seoul, South Korea

{ newrun, easy00, khsohn }@yonsei.ac.kr

Abstract

This paper presents a novel method, termed *Bridge to Answer*, to infer correct answers for questions about a given video by leveraging adequate graph interactions of heterogeneous crossmodal graphs. To realize this, we learn question conditioned visual graphs by exploiting the relation between video and question to enable each visual node using question-to-visual interactions to encompass both visual and linguistic cues. In addition, we propose bridged visual-to-visual interactions to incorporate two complementary visual information on appearance and motion by placing the question graph as an intermediate bridge. This bridged architecture allows reliable message passing through compositional semantics of the question to generate an appropriate answer. As a result, our method can learn the question conditioned visual representations attributed to appearance and motion that show powerful capability for video question answering. Extensive experiments prove that the proposed method provides effective and superior performance than state-of-the-art methods on several benchmarks.

1. Introduction

Video question answering (VideoQA) is a task to answer the question regarding a given video in a natural language form. Over the past few years, several methods have been focused on manipulating spatio-temporal visual representations conditioned by linguistic cues for VideoQA [20, 31, 32, 35]. However, because of its specificities such as dynamic spatiotemporal dependencies of the video and sophisticated compositional semantics of the question, the VideoQA still remains a challenging problem.

Recent works [11, 27, 6, 2, 5, 18] have adopted the encoder-decoder structure. Typically, LSTM-based encoders [11, 6, 2, 5] are used to encode the representations of video frames and a question into the visual and



Question: What is the **woman** in the **red** holding in her hand?

(a) Example for VideoQA

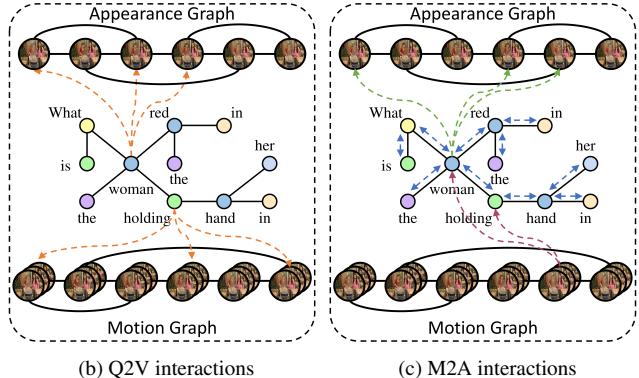


Figure 1. (a) An example for VideoQA. (b) Question-to-Visual (Q2V) interactions that each question node are propagated to visual nodes. (c) Visual-to-Visual (V2V) interactions that each visual node are associated with the relative visual nodes using the question bridge. Only motion-to-appearance (M2A) interaction is shown.

word sequence. The encoded representations are then incorporated to provide the answer with an attention mechanism. The several types of attention have shown promising results by learning the temporal relations between video frames [38, 2], the spatial relations between regions in every single frame [15, 37, 27], or spatiotemporal relations using appearance and motion representations [11, 6]. Although these methods have suggested how to use the visual relationship for VideoQA, they still rely on learning positional relationships, not on in-depth semantic meaning, which makes capturing sophisticated appearance-motion or visual-question relations difficult.

Meanwhile, methods to understand cross-modal relationships have been proposed for vision-language interac-

*Corresponding author.

This research was supported by the Yonsei University Research Fund of 2021 (2021-22-0001).

tion tasks, such as image-text matching [21, 26] or video-text matching [1], exploiting global [22, 29, 36] or local [19, 25] representations for visual and textual information. Similar approaches have also been adopted in VideoQA. The global question representation has been used as a condition to learn a question-specific visual representation [40, 6, 18]. For example, the global question feature vector was used to update the memory network to learn attention that attributed to the question in [6]. Le *et al.* [18] proposed a hierarchical architecture that transforms a sequence of objects into a new array conditioned on the global question feature. The word-level features of the question have been treated as sequential data in the local approach [11, 38, 5, 24, 10]. These approaches leveraged each word representation to learn visual attention [11, 38, 2] or co-attention [27, 5, 24, 10] by fusing visual and word representations. However, the global approaches have learned coarse relations that frequently fail to capture video-word relations. The local approaches associate visual and word information based on co-occurrence statistics, not compositional semantics of the question. For instance, without semantic relations, the word “woman” of the question in Fig. 1-(a) can incorrectly be correlated with all women in the video. On the other hand, compositional semantics clearly indicate from the phrase “*in the red*” that the question point to the left woman.

To address these limitations, the consideration of grammatical dependencies between sentence words [3, 4] has been raised. For visual question answering (VQA), Teney *et al.* [33] proposed structured representations that the input image and question are encoded as graphs to leverage compositional semantics of the question. For image-text matching, Liu *et al.* [26] proposed a graph-structured network that construct graphs for the image and corresponding captions to find the fine-grained image-text correspondences using node-level and structure-level matching. Although the effectiveness of structured representations for image-text relations has been extensively demonstrated, it is still under-explored in VideoQA.

In this paper, we propose a novel method, called *Bridge to Answer*, that formulates structure-aware interaction for semantic relation modeling between crossmodal information, including appearance, motion, and question. Contrary to existing approaches [6, 10], we construct not only appearance and motion graphs for video but also the question graph that represents compositional semantic relations between words. We perform question-to-video (Q2V) interactions that propagate the question node to its relevant visual nodes to learn question conditioned visual representations with visual-question relations, as shown in Fig. 1-(b). Also, we apply visual-to-visual (V2V) interactions to visual graphs delivering each visual node to nodes in the relative visual graph to model appearance-motion relations. To uti-

lize compositional semantic structure of the question, we use the question graph as an intermediate bridge, as shown in Fig. 1-(c). We demonstrate the capability of the proposed method through extensive ablation studies and comparison with state-of-the-art methods on three datasets, including TGIF-QA [11], MSVD-QA [38], and MSRVT-QA [39].

2. Related Works

Video question answering (VideoQA) has attracted intense attention over the past few years due to its applicability to human-robot interaction and video retrieval, etc. The existing methods have mostly been proposed to learn visual representations by leveraging video-question interactions. We summarize recent works according to the types of utilized interactions. Typically, the temporal attention has been learned by exploiting relationships between the appearance and question [20, 43, 23]. Li *et al.* [23] proposed to learn co-attention between the appearance and question, and Li *et al.* [24] enhanced co-attention by using self-attention [34] mechanism. Some researchers have presented to capture fine-grained appearance-question interactions. Jin *et al.* [13] introduced object-aware temporal attention that learns object-question interactions. Huang *et al.* [10] also utilize frame and object features to enhance co-attention between the appearance and question.

Since Jang *et al.* [11] proposed a two-stream architecture using appearance and motion features, researchers have focused on learning spatiotemporal attention that leverages motion, appearance, and question interactions. Developments of spatiotemporal attention have successfully been applied to various approaches including a multimodal fusion memory [5], co-memory attention [6], hierarchical attention [41, 40], multi-head attention [16], and multi-step progressive attention [14, 38, 31]. The hierarchical structure that capture appearance-question and motion-question relations from the frame-level to segment-level have also been proposed by Zhao *et al.* [42] and Le *et al.* [18].

Although they have suggested methods that effectively learn relations between appearance and question or even motion, they still rely on positional relationships [24]. Moreover, there have not been presented for capturing the relationship between appearance and motion with compositional semantics of the question. To address these limitations, we explicitly model appearance, motion, and the question as graphs. Our model learns question conditioned visual representations and mutually enhances appearance and motion representations by leveraging compositional semantics of the question.

Graph-structured vision-language interaction has recently been studied to learn semantic relations between visual and textual information. Teney *et al.* [33] firstly proposed to learn graph-structured representations of the input image and question for visual question answering (VQA).

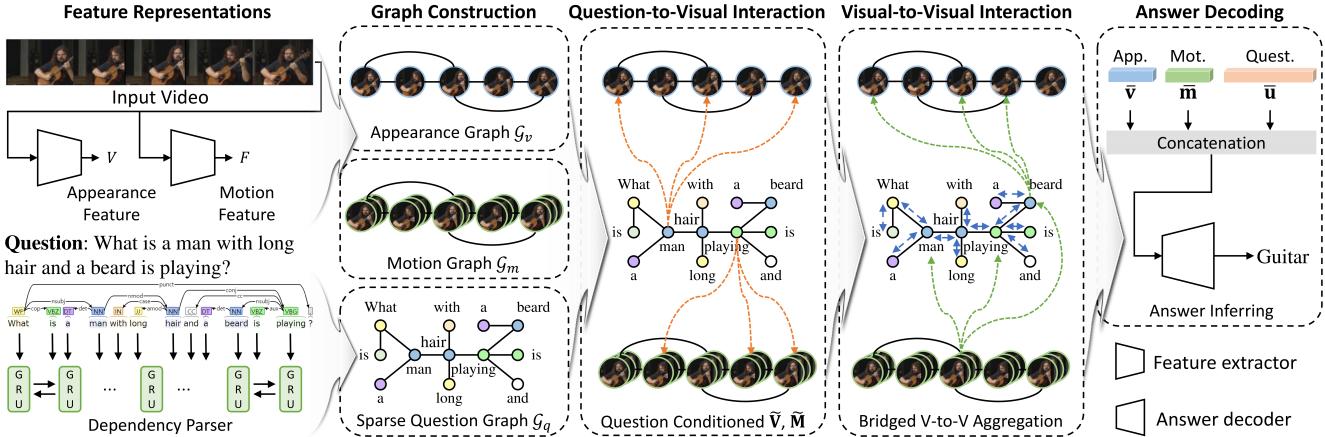


Figure 2. The overall architecture of the proposed method for VideoQA. The visual and question representations are extracted to construct appearance, motion and question graphs. The graph nodes in each graph are propagated to nodes in another graph differentially through question-to-visual interactions and visual-to-visual interactions to learn question conditioned visual representation attributed to appearance and motion.

More recently, Li *et al.* [21] proposed to learn relationships between regions in the input image using graph convolutional network (GCN) [17] and capture image-phrase correspondence for image-text matching. To enable fine-grained image-text matching, Liu *et al.* [26] constructed a visual graph for the input image and textual graph with the compositional semantics of the caption, respectively. They successfully achieved state-of-the-art performance by learning correspondences between two structured graphs. Similarly, Chen *et al.* [1] recently proposed a hierarchical graph reasoning method that learns fine-grained video-text correspondence. They composed hierarchical graphs for video and caption according to semantic roles, and performed global and local matching between two graphs.

While these works have suggested methods that effectively learn visual-text relations with structured representations, they cannot be directly applied to VideoQA. To our knowledge, our work is the first attempt to perform relation reasoning between appearance and motion information of the video with compositional semantics of the question.

3. Method

Given a video \mathcal{V} and a question q , the VideoQA problem is generally formulated as follows:

$$\tilde{a} = \arg \max_{a \in \mathcal{A}} \mathcal{F}_\theta(a|q, \mathcal{V}), \quad (1)$$

where \tilde{a} is the answer that can be inferred in answer space \mathcal{A} . θ is the set of model parameters of mapping function \mathcal{F} , which maps a pair of the video and question to the answer. We illustrate proposed method in Fig. 2. We first extract feature representations from the video and the question, and construct graphs for appearance, motion, and question, respectively (Sec. 3.1). The question nodes propagated to

the visual graphs using question-to-visual interactions to learn question conditioned visual representations (Sec. 3.2). Thereafter, the nodes in each visual graph are aggregated into relevant nodes in the relative visual graph over a question bridge to enhance visual representations by learning appearance-motion relations (Sec. 3.3). Lastly, the final visual and question representations are concatenated and fed into the decoder to infer the answer (Sec. 3.4). Tab. 1 summarizes the notations used over our method. Following subsections, we depict the proposed method in details.

3.1. Feature Extraction and Graph Construction

Visual representations and visual graphs. Similar to the previous works for videoQA [18, 10], we divide the video \mathcal{V} of L frames into N uniform length clips $C = \{C_1, \dots, C_N\}$, such that the length of each clip is $T = L/N$. To represent two types of information of the video, we extract frame-wise appearance feature vectors \mathbf{V} and clip-wise motion feature vectors \mathbf{M} . In our work, \mathbf{V} and \mathbf{M} are extracted from the pretrained feature extractor (*e.g.*, ResNet [9] and ResNeXt-101 [8]). The extracted features are fed into the linear feature transformation layers to obtain $\hat{\mathbf{V}} = \{\hat{\mathbf{v}}_l | \hat{\mathbf{v}}_l \in \mathbb{R}^{d'}\}_{l=1}^L$ and $\hat{\mathbf{M}} = \{\hat{\mathbf{m}}_n \in \mathbb{R}^{d'}\}_{n=1}^N$, respectively.

With appearance and motion representations, we construct an appearance graph \mathcal{G}_v and a motion graph \mathcal{G}_m as undirected fully-connected graphs. The frames and clips are set to nodes, and each node is connected with all the other nodes in each graph with edges. The weight matrices \mathbf{W}^v and \mathbf{W}^m , which represent node connections and their edge weights are computed by the affinity between node



(a) **Question:** What is a man doing?

Baseline: **Look**

Ours: **Tie**

Groundtruth: **Tie**



(b) **Question:** What is a woman applies a concealer to the lower portion of her right cheek and blends it doing?

Baseline: **Talk**

Ours: **Makeup**

Groundtruth: **Use**

Figure 3. Example questions for challenging conditions. (a) Sudden transitions of the scene lead to confusion in the model capturing the visual relation. (b) Long and complex question composition makes it difficult for the model to learn a properly conditioned visual representation. Our model with the capacity to capture relations of heterogeneous cross-modal graphs copes with these challenging cases.

where $\mathbf{S}^m = \text{softmax}_{\mathbf{U}}(\lambda \hat{\mathbf{M}} \mathbf{U}^T)$ and \mathbf{W}_g^m is the set of parameters of graph convolution layers.

3.3. Visual-to-Visual Interactions

One of the most important capabilities for VideoQA is to capture and incorporate the relations between appearance and motion information. To realize this, we present visual-to-visual (V2V) interaction that learns semantic relationships between appearance and motion. Different from previous works [6, 5] that appearance and motion information directly interact, we use the question graph as a bridge to leverage compositional semantics of the question. Since the structure of the question graph reflects semantic dependencies between words, the question conditioned visual node can effectively be delivered to the relative visual nodes along the question edges.

The V2V interaction can be summarized as three-fold: 1) one visual graph is bridged to the question graph, 2) the bridged node representation is propagated along the question edges through graph convolution layers and aggregated to the question graph, and 3) the aggregated question node is delivered to the relative visual graph. Concretely, motion-to-appearance (M2A) interaction begins by bridging motion and question graphs. A bridged motion representation, denoted as \mathbf{U}_b^m , can be obtained as a weighted combination of the question conditioned motion representation $\tilde{\mathbf{M}}$, where the weight is the interaction between \mathbf{U} and $\tilde{\mathbf{M}}$, such that

$$\mathbf{U}_b^m = \text{softmax}_{\tilde{\mathbf{M}}}(\lambda \mathbf{U} \tilde{\mathbf{M}}^T) \tilde{\mathbf{M}}. \quad (8)$$

The bridged representation is propagated to its neighbors along the question edges through graph convolution layers and aggregated to the question representation as

$$\hat{\mathbf{U}}_b^m = \mathbf{U} + \mathcal{F}(\mathbf{W}^q, \mathbf{U}_b^m | \mathbf{W}_{gb}^m), \quad (9)$$

where \mathbf{W}_{gb}^m is the set of trainable parameters of graph convolution layers. This form of the aggregated question graph enables the representation to have motion and question information simultaneously.

Finally, the aggregated question node is delivered to the appearance graph to obtain a question conditioned appear-

ance representation attributed to motion. The output of M2A interaction can be formulated by following equation:

$$\begin{aligned} \mathbf{v}_i^f &= \sigma(\mathbf{W}_b^v(\tilde{\mathbf{v}}_i + \sum_{j=1}^K (s_b^v)_{ij}(\hat{\mathbf{u}}_b^m)_j) + b), \\ \mathbf{S}_b^v &= \text{softmax}_{\hat{\mathbf{U}}_b^m}(\lambda \tilde{\mathbf{V}}(\hat{\mathbf{U}}_b^m)^T), \end{aligned} \quad (10)$$

where \mathbf{v}_i^f is the i -th node representation of the final appearance graph, \mathbf{W}_b^v and b are the parameters of FC layer.

As a symmetric process, the node representation of the final motion graph \mathbf{M}^f can be obtained with A2M interaction by following equations:

$$\begin{aligned} \mathbf{U}_b^v &= \text{softmax}_{\tilde{\mathbf{V}}}(\lambda \mathbf{U} \tilde{\mathbf{V}}^T) \tilde{\mathbf{V}}, \\ \hat{\mathbf{U}}_b^v &= \mathbf{U} + \mathcal{F}(\mathbf{W}^q, \mathbf{U}_b^v | \mathbf{W}_{gb}^v), \\ \mathbf{m}_i^f &= \sigma(\mathbf{W}_b^m(\tilde{\mathbf{m}}_i + \sum_{j=1}^K (s_b^m)_{ij}(\hat{\mathbf{u}}_b^v)_j) + b), \\ \mathbf{S}_b^m &= \text{softmax}_{\hat{\mathbf{U}}_b^v}(\lambda \tilde{\mathbf{M}}(\hat{\mathbf{U}}_b^v)^T), \end{aligned} \quad (11)$$

where \mathbf{W}_{gb}^v and \mathbf{W}_b^m are the weight parameters of graph convolution layers and FC layer, respectively.

We apply an average pooling to the final visual node representations along the temporal axis to vectorize the representations, and concatenate them to make the incorporated visual representation \mathbf{o} :

$$\begin{aligned} \bar{\mathbf{v}} &= \frac{1}{L} \sum_{l=1}^L \mathbf{v}_l^f, & \bar{\mathbf{m}} &= \frac{1}{N} \sum_{n=1}^N \mathbf{m}_n^f, \\ \mathbf{o} &= [\bar{\mathbf{v}}; \bar{\mathbf{m}}], \end{aligned} \quad (12)$$

where $[\cdot; \cdot]$ denotes concatenation operation.

3.4. Answer Decoder and Loss Functions

Following previous works [5, 18], we use different answer decoders depending on the type of question. Specifically, we treat open-ended questions as a multi-label classification problem. The decoder takes the final visual representation \mathbf{o} and the averaged question representation $\bar{\mathbf{u}}$ to

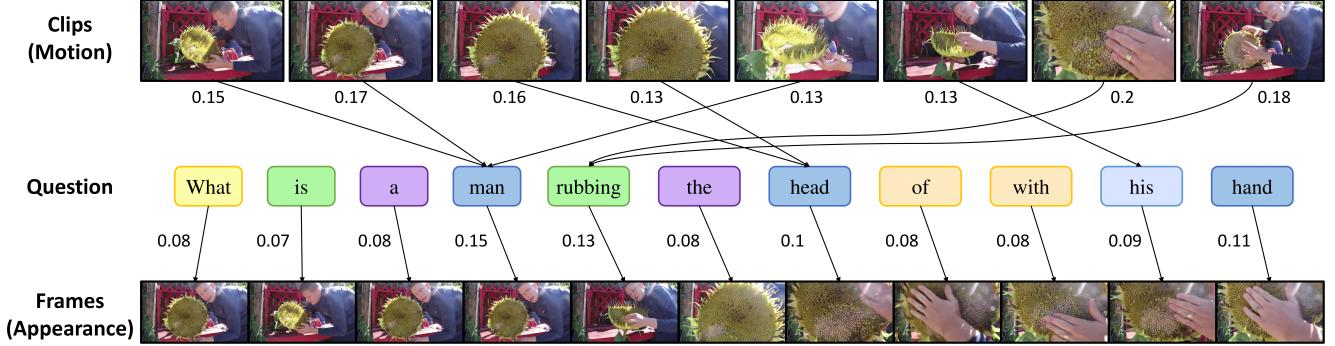


Figure 4. Visualization of M2A interaction. Although any two graphs are fully connected by interaction value, we only indicate the connection with the largest value in each interaction matrix for visibility. Note that the clips are represented by frames sampled from each clip.

order, respectively, and corresponding frames of each word are placed regardless of temporal order. The connections indicate that two nodes are associated with the maximum interaction value. For example, the first clip is associated with the word “man” by the interaction value of 0.15, and the word “man” is related to the fourth frame by the interaction value of 0.15. Note that, when all the nodes are connected with uniformly distributed weights, the motion-question interaction value and the question-appearance interaction value is 0.09 and 0.008, respectively. The results show that the relevant nodes are connected with relatively high interaction values, and the question node is also connected with the appearance node through semantic relation.

Effect of the question bridge. The question bridge is a key component to leverage the compositional semantics of the question. To verify the effectiveness, we conduct ablation study for the question bridge. The V2V interactions without the question bridge are performed by directly aggregating the relative node representations based on the affinity value between appearance and motion nodes. For instance, the output of the M2A interaction without the bridge is obtained by

$$\mathbf{v}_i^f = \sigma(\mathbf{W}_{wob}^v(\tilde{\mathbf{v}}_i + \sum_{j=1}^T (s_{wob}^v)_{ij} \tilde{\mathbf{m}}_j) + b), \quad (16)$$

where $\mathbf{S}_{wob}^v = \text{softmax}_{\tilde{\mathbf{M}}}(\lambda \tilde{\mathbf{V}} \tilde{\mathbf{M}}^T)$.

The results at each task demonstrate the advantage of the bridged architecture with the performance improvement of 0.5%, 0.9%, 0.6% for accuracy, and 0.12 for MSE value, respectively.

Effect of λ . The scaling parameter λ adjusts the relative weight of different nodes in Q2V and V2V interactions and the edge weight of graphs. The large value of λ distills nodes highly correlated to the specific node and filters out irrelevant nodes. Contrary to this, the small value of λ is

difficult to distinguish relevant nodes. Therefore, it is important to properly set the value of λ . To investigate the performance with various λ values, we measure VideoQA performance by setting the λ as 1, 5, 10, 20. Not surprisingly, Larger λ shows better performance compared to $\lambda = 1$.

We additionally evaluate our model according to λ values on MSVD-QA [38] and MSRVTT-QA [39] datasets. As shown in Tab. 5, our model yield highest performance when $\lambda = 10$ on MSVD-QA. The results on MSRVTT-QA show that $\lambda = 20$ brings out the best performance. The different optimal value of λ on two datasets might be caused by different lengths of videos.

5. Conclusion

We proposed a novel method for VideoQA, called Bridge to Answer, that constructs heterogeneous multimodal graphs and learns relations between visual and question graphs to learn question conditioned visual representations attributed to appearance and motion. In the process, in-depth semantic relations between visual and question graphs are encapsulated to visual representations using question-visual interactions. The relations between appearance and motion graphs are modulated by compositional semantics of the question as a bridge to effectively enhance each relative visual representation. This bridged structure allows a model robust to the scene composition and sophisticated structure of the question. Our model was evaluated on several VideoQA benchmarks, including TGIF-QA, MSVD-QA, and MSRVTT-QA, achieving state-of-the-art performance.

Acknowledgement

This work was supported by Institute of Information communications Technology Planning & Evaluation (IITP) grant funded by the Korea government(MSIT) (No.2020-0-00056, To create AI systems that act appropriately and effectively in novel situations that occur in open worlds)

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