Hierarchical Conditional Relation Networks for Multimodal Video Question Answering

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Abstract Video Question Answering (Video QA) challenges modelers in multiple fronts. Modeling video necessitates building not only spatio-temporal models for the dynamic visual channel but also multimodal structures for associated information channels such as subtitles or audio. Video QA adds at least two more layers of complexity – selecting relevant content for each channel in the context of the linguistic query, and composing spatio-temporal concepts and relations hidden in the data in response to the query. To address these requirements, we start with two insights: (a) content selection and relation construction can be jointly encapsulated into a conditional computational structure, and (b) video-length structures can be composed hierarchically. For (a) this paper introduces a general-reusable neural unit dubbed Conditional Relation Network (CRN) taking as input a set of tensorial objects and translating into a new set of objects that encode relations of the inputs. The generic design of CRN helps ease the common complex model building process of Video QA by simple block stacking and rearrangements with flexibility in accommodating diverse input modalities and conditioning features across both visual and linguistic domains. As a result, we realize insight (b) by introducing Hierarchical Conditional Relation Networks (HCRN) for Video QA. The HCRN primarily aims at exploiting intrinsic properties of the visual content of a video as well as its accompanying channels in terms of compositionality, hierarchy, and near-term and far-term relation. HCRN is then applied for Video QA in two forms, short-form where answers are reasoned solely from the visual content of a video, and long-form where an additional associated information channel, such as movie subtitles, presented. Our rigorous evaluations show consistent improvements over state-of-the-art methods on well-studied benchmarks including large-scale real-world datasets such as TGIF-QA and TVQA, demonstrating the strong capabilities of our CRN unit and the HCRN for complex domains such as Video QA. To the best of our knowledge, the HCRN is the very first method attempting to handle long and short-form multimodal Video QA at the same time.

Keywords Video QA · Relational networks · Conditional modules · Hierarchy

1 Introduction

Answering natural questions about a video is a powerful demonstration of cognitive capability. The task involves acquisition and manipulation of spatio-temporal visual, acoustic and linguistic representations from the video guided by the compositional semantics of linguistic cues [1,2,3,4,5,6]. As questions are potentially unconstrained, Video QA requires deep modeling capacity to encode and represent crucial multimodal video properties such as linguistic content, object permanence, motion profiles, prolonged actions, and varying-length temporal relations in a hierarchical manner. For Video QA, the visual and textual representations should ideally be question-specific and answer-ready.

The common approach toward modeling videos for QA is to build neural architectures specially designed for a particular data format and modality. In this perspective, the two common variants of Video QA emerge: short-form Video QA where relevant information is contained in the visual content of short video snippets of a single event (see Fig. 1 for examples), and long-form Video QA (also called Video Story QA) where the keys to answer are carried in the mixed visual-textual data of longer multi-shot video sequences (see Fig. 2 for example). Because of this specificity, such hand crafted architectures tend to be non-optimal for changes in
(1) **Question**: What does the girl do 9 times?
- **Choice 1**: walk
- **Choice 2**: blocks a person’s punch
- **Choice 3**: step
- **Choice 4**: shuffle feet
- **Choice 5**: wag tail

**Baseline**: walk
**HCRN**: blocks a person’s punch
**Ground truth**: blocks a person’s punch

Fig. 1 Examples of short-form Video QA for which frame relations are key toward correct answers. (1) Near-term frame relations are required for counting of fast actions. (2) Far-term frame relations connect the actions in long transition. HCRN with the ability to model hierarchical conditional relations handles successfully, while baseline struggles.

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(2) **Question**: What does the man do before turning body to left?
- **Choice 1**: run across a ring
- **Choice 2**: pick up the man’s hand
- **Choice 3**: flip cover face with hand
- **Choice 4**: raise hand
- **Choice 5**: breath

**Baseline**: pick up the man’s hand
**HCRN**: breath
**Ground truth**: breath

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**Subtitle:**

```
00:00:0,395 --> 00:00:1,896
(Keith:) I’m not gonna stand here and let you accuse me
```

```
00:00:1,897 --> 00:00:4,210
(Keith:) of killing one of my best friends, all right?
```

```
00:00:8,851 --> 00:00:10,394
(Castle:) You hear that sound?
```

**Question**: What did Keith do when he was on the stage?
- **Choice 1**: Keith drank beer
- **Choice 2**: Keith played drum
- **Choice 3**: Keith sing to the microphone
- **Choice 4**: Keith played guitar
- **Choice 5**: Keith got off the stage and walked out

**Baseline**: Keith played guitar
**HCRN**: Keith got off the stage and walked out
**Ground truth**: Keith got off the stage and walked out

Fig. 2 Example of long-form Video QA. This is a typical question where a model needs to collect sufficient relevant cues from both visual content of a given video and textual subtitles to give the correct answer. In this particular example, our baseline is likely to suffer from the linguistic bias (“stage” and “played guitar”) while our model successfully manage to arrive at the correct answer by connecting the linguistic information from the first shot and visual content in the second one.

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data modality [2], varying video length [7] or question types (such as frame QA [3] versus action count [8]). This has resulted in proliferation of heterogeneous networks.

We wish to build a family of effective models for both long-form and short-form Video QA from reusable units that are more homogeneous and easier to construct, maintain and comprehend. We start by realizing that Video QA involves two sub-tasks: (a) selecting relevant content for each channel in the context of the linguistic query, and (b) composing spatio-temporal concepts and relations hidden in the data in response to the query. Much of sub-task (a) can be abstracted into a conditional computational structure that computes multi-way interaction between the query and the several objects. With this ability, solving sub-task (b) can be approached by composing the hierarchical structure of such abstraction from the ground up.

Towards this goal, we propose a general-purpose reusable neural unit called Conditional Relation Network (CRN) that encapsulates and transforms an array of objects into a new array of relations conditioned on a contextual feature. The unit computes sparse high-order relations between the input objects, and then modulates the encoding through a specified context (See Fig. [4]). The flexibility of CRN and its encapsulating design allow it to be replicated and layered to form deep hierarchical conditional relation networks (HCRN) in a straightforward manner (See Fig. [5] and Fig. [6]). Within the scope of this work, the HCRN is a two-stream network of visual content and textual subtitles, in which the two sub-networks share a similar design philosophy but customized to suit the properties of each input modality. Whilst the visual stream is built up by stacked CRN units at different granularities, the textual stream compose a single CRN unit taking
as input linguistic segments. The stacked units in the visual stream thus provide contextualized refinement of relational knowledge from visual objects – in a stage-wise manner it combines appearance features with clip activity flow and linguistic context, and follows it by integrating in context from the whole video motion and linguistic features. On the textual side, the CRN unit functions in the same manner but on textual objects. The resulting HCRN is homogeneous, agreeing with the design philosophy of networks such as InceptionNet \cite{9}, ResNet \cite{10} and FiLM \cite{11}.

The hierarchy of the CRNs for each input modality are as follows. At the lowest level of the visual stream, the CRNs encode the relations between frame appearance in a clip and integrate the clip motion as context; this output is processed at the next stage by CRNs that now integrate in the linguistic context. In the following stage, the CRNs capture the relation between the clip encodings, and integrate in video motion as context. In the final stage the CRN integrates the video encoding with the linguistic feature as context (See Fig. 5).

As for the textual stream, due to its high-level abstraction as well as the diversity of nuances of expression comparing to its visual counterpart, we only use the CRN to encode relations between linguistic segments in a given dialogue extracted from textual subtitles and leverage well-known techniques in sequential modeling, such as LSTM \cite{12} or BERT \cite{13}, to understand sequential relations at the word level. By allowing the CRNs to be stacked hierarchically, the model naturally supports modeling hierarchical structures in video and relational reasoning. Likewise, by allowing appropriate context to be introduced in stages, the model handles multimodal fusion and multi-step reasoning. For long videos further levels of hierarchy can be added enabling encoding of relations between distant frames.

We demonstrate the capability of HCRN in answering questions in major Video QA datasets, including both short-form and long-form videos. The hierarchical architecture with four-layers of CRN units achieves favorable answer accuracy across all Video QA tasks. Notably, it performs consistently well on questions involving either appearance, motion, state transition, temporal relations, or action repetition; this output is processed at the next stage by CRNs that now integrate in video motion as context. In the final stage the CRN integrates the video encoding with the linguistic feature as context (See Fig. 5).

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2 Related work

Our proposed HCRN model advances the development of Video QA by addressing three key challenges: (1) Efficiently representing videos as amalgam of complementing factors including appearance, motion and relations, (2) Effectively allows the interaction of such visual features with the linguistic query and (3) Allows integration of different input modalities in Video QA with one unique building block.

Long/short-form Video QA is a natural extension of image QA and it has been gathering a rising attention in recent years, with the release of a number of large-scale short-form Video QA datasets, such as TGIF-QA \cite{14,15}, as well as long-form MovieQA datasets with accompanying textual modality, such as TVQA \cite{2}, MovieQA \cite{5} and PororoQA \cite{16}. All studies on Video QA treats short-form and long-form Video QA as two separate problems in which proposed methods \cite{11,14,16,17,2} are deviated to handle either one of the two problems. Different from those works, this paper takes the challenge of designing a generic method that covers both long-form and short-form Video QA with simple exercises of block stacking and rearrangements to switch one unique model between the two problem depending upon the availability of input modalities for each of them.

Spatio-temporal video representation is traditionally done by variations of recurrent networks (RNNs) among which many were used for Video QA such as recurrent encoder-decoder \cite{18,19}, bidirectional LSTM \cite{16} and two-staged LSTM \cite{20}. To increase the memorizing ability, external memory can be added to these networks \cite{11,12,20}. This technique is more useful for videos that are longer \cite{13} and with more complex structures such as movies \cite{5} and TV programs \cite{2} with extra accompanying channels such as speech or subtitles. On these cases, memory networks \cite{16,21,22} were used to store multimodal features \cite{6} for later retrieval.

Memory augmented RNNs can also compress video into heterogeneous sets \cite{8} of dual appearance/motion features. While in RNNs, appearance and motion are modeled separately, 3D and 2D/3D hybrid convolutional operators \cite{22,23} intrinsically integrates spatio-temporal visual information and are also used for Video QA \cite{14,3}. Multiscale temporal structure can be modeled by either mixing short and long term convolutional filters \cite{24} or combining pre-extracted frame features non-local operators \cite{25,26}. Within the second approach, the TRN network \cite{27} demonstrates the role of temporal frame relations as an another important visual feature for video reasoning and Video QA \cite{28}. Relations of

The rest of the paper is organized as follows. Section 2 reviews related work. Section 4 details our main contributions – the CRN, the HCRNs for Video QA on both short-from videos and long-form videos that include subtitles, as well as complexity analysis. The next section describes the results of the experimental suite. Section 5 provides further discussion and concludes the paper.
predetected objects were also considered in a separate processing stream [29] and combined with other modalities in late-fusion [30]. Our HCRN model emerges on top of these trends by allowing all three channels of video information namely appearance, motion and relations to iteratively interact and complement each other in every step of a hierarchical multi-scale framework.

Earlier attempts for generic multimodal fusion for visual reasoning include bilinear operators, either applied directly [31] or through attention [31,32]. While these approaches treat the input tensors equally in a costly joint multiplicative operation, HCRN separates conditioning factors from refined information, hence it is more efficient and also more flexible on adapting operators to conditioning types.

Temporal hierarchy has been explored for video analysis [33], most recently with recurrent networks [34,35] and graph networks [36]. However, we believe we are the first to consider hierarchical interaction of multi-modalities including linguistic cues for Video QA.

**Linguistic query–visual feature interaction in Video QA** has traditionally been formed as a visual information retrieval task in a common representation space of independently transformed question and referred video [20]. The retrieval is more convenient with heterogeneous memory slots [8]. On top of information retrieval, co-attention between the two modalities provides a more interactive combination [14]. Developments along this direction include attribute-based attention [37], hierarchical attention [38,39,40], multi-head attention [41,42], multi-step progressive attention memory [43] or combining self-attention with co-attention [4]. For higher order reasoning, question can interact iteratively with video features via episodic memory or through switching mechanism [45]. Multi-step reasoning for Video QA is also approached by [43] and [4] with refined attention.

Unlike these techniques, our HCRN model supports conditioning video features with linguistic clues as a context factor in every stage of the multi-level refinement process. This allows the linguistic cues to be involved earlier and deeper into video presentation construction than any available methods.

**Neural building blocks** - Beyond the Video QA domain, CRN unit shares the idealism of uniformity in neural architecture with other general purpose neural building blocks such as the block in InceptionNet [9]. Residual Block in ResNet [10]. Recurrent Block in RNN, conditional linear layer in FiLM [11], and matrix-matrix-block in neural matrix net [35]. Our CRN departs significantly from these designs by assuming an array-to-array block that supports conditional relational reasoning and can be reused to build networks of other purposes in vision and language processing. As a result, our HCRN is a perfect fit not only for short-form video where questions are all about visual content of a video snippet but also for long-form video (Movie QA) where a model has to look at both visual cue and textual cue (subtitles) to arrive at correct answers. Due to the great challenges posed by long-form Video QA and the diversity in terms of model building, current approaches in Video QA mainly spend efforts on handling the visual part while leaving the textual part for common techniques such as LSTM [2] or latest advance in natural language processing BERT [46]. To the best of our knowledge, HCRN is the first model that could solve both short-form and long-form Video QA with models building up from a generic neural block.

### 3 Method

The goal of Video QA is to deduce an answer $\hat{a}$ from a video $\mathcal{V}$ and optionally from additional information channels such as subtitles $\mathcal{S}$ in response to a natural question $q$. The answer $\hat{a}$ can be found in an answer space $\mathcal{A}$ which is a pre-defined set of possible answers for open-ended questions or a list of answer candidates in the case of multi-choice questions. Formally, Video QA can be formulated as follows:

$$\hat{a} = \arg\max_{a \in \mathcal{A}} \mathcal{F}_{\theta} (a \mid q, \mathcal{V}, \mathcal{S}),$$

where $\theta$ is the model parameters of scoring function $\mathcal{F}$.

Within the scope of this work, we address two common settings of Video QA: (a) short-form Video QA where the visual content of a given single video shot singularly suffice to answer the questions, and (b) long-form Video QA where the essential information disperses among visual content in the multi-shot video sequence and conversational content in accompanying textual subtitles.

HCRN was designed in the endeavor for a homogeneous neural architecture that can adapt to solve both problems. Its overall workflow is depicted in Fig. 3. In long-form videos, when both visual and textual streams are present, HCRN distills relevant information from visual stream, textual stream conditioned on the question and combine them into an answer decoder for feature joining and prediction.
are available, the visual stream is solely active, working with the single-input answer decoder. One of the ambitions of the design is to build each processing stream as a hierarchical network simply by stacking common core processing units of the same family.

In the following subsections we present the design of the core unit in Sec. 3.1, the hierarchical designs tailored to each modality in Sec. 3.2, the answer decoder in Sec. 3.3 Theoretical analysis of computational complexity of the models follows in Sec. 3.4.

3.1 Conditional relation network unit

We introduce a general computation unit, termed Conditional Relation Network (CRN), which takes as input an array of \( n \) objects \( \mathcal{X} = \{ x_i \}_{i=1}^n \) and a conditioning feature \( c \) serving as global context. Objects are assumed to live either in the same vector space \( \mathbb{R}^d \) or tensor space, for example \( \mathbb{R}^{W \times H \times d} \) in case of images (or video frames). CRN generates an output array of objects of the same dimensions containing high-order object relations of input features given the global context. The global context is problem specific, serving as a modulator to the formation of the relations. When in use for Video QA, CRN’s input array is composed of features at either frame level, short-clip levels, or textual features. Examples of global context include the question and motion profiles at a given hierarchical level.

Given input set of object \( \mathcal{X} \). CRN first considers the set of subsets \( \mathcal{Q} = \{ Q^k \}_{k=2}^{k_{\text{max}}} \) where each set \( Q^k \) contains all size-\( k \) subsets of \( \mathcal{X} \). On each collection \( Q^k \), CRN then uses member relational sub-networks to infer the joint representation of \( k \)-tuple object relations. In video, due to temporal coherence, the objects \( \{ x_i \}_{i=1}^n \) share great amount of mutual information, therefore, it is redundant to consider all possible combinations in \( Q^k \). To take advantage of this, CRN applies a sampling scheme on the set of subsets for redundancy reduction and computational efficiency. We borrow the sampling trick in [27] to randomly sample \( t \) subsets from each collection \( Q^k \) to form the executive set \( Q^k_{\text{selected}} \) Each member subset of \( Q^k_{\text{selected}} \) then goes through a set-based function \( g^k(\cdot) \) for relational modeling. The relations across objects are then further refined with a conditioning function \( h^k(\cdot, \cdot) \) in the light of conditioning feature \( c \). Finally, the \( k \)-tuple relations are summarized by the aggregating function \( p^k(\cdot) \). The similar operations are done across the range of subset size from 2 to \( k_{\text{max}} \). Regarding the choice of \( k_{\text{max}} \), we use \( k_{\text{max}} = n - 1 \) in later experiments, resulting in the output array of size \( n - 2 \) if \( n > 2 \) and an array of size 1 if \( n = 2 \).
The detail operation of CRN unit is presented formally as pseudocode in Alg. 1 and visually in Fig. 4. Table 1 summarizes the notations used across these presentations.

### 3.1.1 Networks implementation

**Set aggregation:** The set functions \( g^k(\cdot) \) and \( p^k(\cdot) \) can be implemented as any aggregation sub-networks that join a random set into a single representation. As a choice in implementation, the function \( g^k(\cdot) \) is either average pooling or a simple concatenation operator while \( p^k(\cdot) \) is average pooling.

**Conditioning function:** The design of the conditioning sub-network that implements \( h^k(\cdot, c) \) depends on the relationship between the input set \( X \) and the conditioning feature \( c \) as well as the properties of the channels themselves. Here we present four forms of neural operation implementing this function.

- **Additive form:**
  A simple form of \( h^k(\cdot, c) \) is feature concatenation followed by a MLP that models the non-linear relationships between multiple input modalities:

  \[
  h^k(\cdot, c) = \text{ELU} \left( W_{h1} \left[ x; c \right] \right),
  \]

  where \( [\cdot] \) denotes the tensor concatenation operation and ELU is the non-linear activation function introduced in [47]. Eq. 2 is sufficient when \( x \) and \( c \) are additively complementary.

- **Multiplicative form:**
  To support more complex the relationship between the input \( x \) and the conditioning feature \( c \), a more sophisticated joining operation is warranted. For example, when \( c \) implies a selection criterion to modulate the relationship between elements in \( x \), multiplicative relation between them can be represented in conditioning function by:

  \[
  h^k(x, c) = \text{ELU} \left( W_{h1} \left[ x; x \odot c; c \right] \right),
  \]

  where \( \odot \) denotes Hadamard product.

- **Sequential form:**
  As aforementioned, how to properly choose the sub-network \( h^k(\cdot, c) \) is also driven by the properties of the input set \( X \). Given the context of Video QA of later use of the CRN unit where elements in \( X \) may contain strong temporal relationships, we additionally integrate sequential modeling capability, which is a BiLSTM network in this paper, along with the conditioning sub-network as presented in Eq. 2 and Eq. 3. Formally, \( h^k(\cdot, c) \) is defined as:

  \[
  s = [x; x \odot c; c],
  \]

  \[
  s' = \text{BiLSTM}(s),
  \]

  \[
  h^k(\cdot, c) = \text{maxpool}(s').
  \]

**Dual conditioning form:**
In the later use of CRN in Video QA where it can happen that two concurrent signals \( c_1, c_2 \) are used as conditioning features, we simply extend Eq. 2 and Eq. 3 and Eq. 4 as:

\[
\begin{align*}
  h^k(x, c) &= \text{ELU} \left( W_{h1} \left[ x; c_1; c_2 \right] \right), \\
  h^k(x, c) &= \text{ELU} \left( W_{h1} \left[ x; x \odot c_1; x \odot c_2; c_1; c_2 \right] \right), \\
  s &= [x; x \odot c_1; x \odot c_2; c_1; c_2],
\end{align*}
\]

respectively.

### 3.2 Hierarchical conditional relation network for multimodal Video QA

We use CRN blocks to build a deep network architecture that support a wide varieties of Video QA settings. In particular, two variations are specifically designed to work on short-form and long-form Video QA. For each of the settings, the network design adapts to exploit inherent characteristics of a video sequence namely temporal relations, motion, linguistic conversation and the hierarchy of video structure, and to support reasoning guided by linguistic questions. We term the proposed network architecture Hierarchical Conditional Relation Networks (HCRN). The design of the HCRN by stacking reusable core units is partly inspired by modern CNN network architectures, of which InceptionNet [9] and ResNet [10] are the most well-known examples. In the general form of Video QA, HCRN is a multi-stream end-to-end differentiable neural network in which one stream is to handle visual content and the other one handling textual dialogues in subtitles. The network is modular and each network stream plays a plug-and-play role adaptively to the presence of input modalities.

#### 3.2.1 Preprocessing

With the Video QA as defined in Eq. 1 HCRN takes input and question represented as sets of visual or textual objects and computes the answer. In this section, we describe the preprocessing of raw videos into appropriate input sets for HCRN.

**Visual representation:** We begin by dividing the video \( V \) of \( L \) frames into \( N \) equal length clips \( C = \{C_1, \ldots, C_N\} \). For short-form videos, each clip \( C_i \) of length \( T = \lfloor L/N \rfloor \) is represented by two sources of information: frame-wise appearance feature vectors \( V_i = \{v_{i,j} \mid v_{i,j} \in \mathbb{R}^{2048} \}_{j=1}^T \).
and a motion feature vector at clip level \( f_i \in \mathbb{R}^{2048} \). Appearance features are vital for video understanding as the visual saliency of objects/entities in the video is usually of interest to human questions. In short clips, moving objects and events are primary video artifacts that capture our attention. Hence, it is common to see the motion features coupled with the appearance features to represent videos in the video understanding literature. On the contrary, in long-form video such as those in movies and TV programs, the concerns can be less about specific motions but more into movie plot or film grammar. As a result, we use the frame-wise appearance as the only feature for the long-form Video QA. In our experiments, \( v_{ij} \) are the pool5 output of ResNet \([10]\) features and \( f_i \) are derived by ResNeXt-101 \([48,49]\).

Subsequently, linear feature transformations are applied to project \( \{v_{ij}\} \) and \( f_i \) into a standard \( d \)-dimensions feature space to obtain \( \{\hat{v}_{ij} \mid v_{ij} \in \mathbb{R}^d\} \) and \( f_i \in \mathbb{R}^d \), respectively.

**Linguistic representation:** Linguistic objects are built from question, answer choices and long-form videos’ subtitles. We explore two options of representation learning for them using BiLSTM and BERT.

- **Sequential embedding with BiLSTM:**
  
  All words in linguistic cues including those in questions, answer choices and subtitles are first embedded into vectors of 300 dimensions by pre-trained GloVe word embeddings \([50]\).

  For question and answer choices, we further pass these context-independent embedding vectors through a BiLSTM. Output hidden states of the forward and backward LSTM passes are finally concatenated to form the overall query representation \( q \in \mathbb{R}^d \) for the questions and \( a \in \mathbb{R}^d \) for the answer choices if available (multi-choice question-answer pairs).

  For the accompanying subtitles provided in long-form Video QA, instead of treating them as one big passage as in prior works \([2,17]\), we dissect the subtitle passage \( S \) into a fixed number of \( M \) overlapping segments \( U = \{U_1, \ldots, U_M\} \). The number of words in sibling segments is identical \( T = \text{length}(S)/M \) but varies from one video to another depending on the overall length of the given subtitle passage \( S \).

  Similarly to the case of processing questions, we process each segment with pre-trained word embeddings followed by a BiLSTM. The hidden states of the BiLSTM which is also of size \( T \) are then used as textual objects:

  \[
  U_i = \text{BiLSTM}(U_i). \tag{10}
  \]

  \( \{U_i\}_{i=1}^M \) is the final representation that are ready to be used by the textual stream which will be described in Sec. 3.2.3.

  - **Contextual embedding using BERT:**

    As an alternative option for linguistic representation, we utilize pre-trained BERT network \([13]\) to extract contextual word embeddings. Instead of encoding words independently as in GloVe, BERT embeds each word in the context of its surrounding words using a self attention mechanism.

    For short-form Video QA, we tokenize the given question and answer choices in multi-choice questions and subsequently feed the tokens into the pre-trained BERT network. Averaged embeddings of words in a sentence are used as unified representation for that sentence. This applies to generate both the question representation \( q \) and answer choices \( \{a_i\}_{i=1}^A \).

    For long-form Video QA, with each answer choice we form a long string \( l_i \) by stacking it with subtitles \( S \) and the question sentence. We then tokenize and embed each of string \( l_i \) with BERT into contextual hidden matrix \( H \) of size \( m \times d \) where \( m \) is maximum number of tokens in the input and \( d \) is hidden dimensions of BERT. This tensor \( H \) is then split up into corresponding embedding vectors of the subtitles \( H^s \), of the question \( H^q \) and of the answer choice \( H^{a_i} \):

    \[
    (H^s, H^q, H^{a_i}) = \text{BERT}(l_i). \tag{11}
    \]

    Eventually, we suppress the contextual tokens question representation and answer choices into their respective single representation by mean pooling:

    \[
    q = \text{mean}(H^q); \quad a_i = \text{mean}(H^{a_i}), \tag{12}
    \]

    while keep those of subtitles \( H^s \) as a set of textual objects. \( \{U_i\}_{i=1}^M \) are obtained by sliding overlapping windows of the same length over \( H^s \).

### 3.2.2 Visual stream

An effective model for Video QA needs to distill the visual content in the context of the question and filter out the usually large portion of the data that is not relevant to the question. Drawing inspiration from the hierarchy of video structure, we boil down the problem of Video QA into a process of video representation in which a given video is encoded progressively at different granularities, including short clip (a sequence of video frames) and entire video levels (a sequence of clips). It is crucial that the whole process conditions on linguistic cue.

With that in mind, we design a two-level structure to represent a video, one at clip level and the other one at video level, as illustrated in Fig. 5. At each hierarchy level, we use two stacked CRN units, one conditioned on motion features followed by one conditioned on linguistic cues. Intuitively, the motion feature serves as a dynamic context shaping the temporal relations found among frames (at the clip level) or clips (at the video level). It also provides saliency indicator of which relations are worth the attention \([51]\).
As the shaping effect is applied to all relations in a complementary way, selective (multiplicative) relation between the relations and the conditioning feature is not needed, and thus a simple concatenation operator followed by an MLP suffices. On the other hand, the linguistic cues are by nature selective, that is, not all relations are equally relevant to the question. Thus we utilize the multiplicative form for feature fusion as in Eq. 3 for the CRN units which condition on question representation.

With this particular design of network architecture, the input array at clip level consists of frame-wise appearance feature vectors \( \{ \hat{v}_{ij} \} \), while that at a video level is the output at the clip level. The motion conditioning feature at clip level CRNs are corresponding clip motion feature vector \( \hat{f}_i \). They are further passed to an LSTM, whose final state is used as video-level motion features. Note that this particular implementation is not the only option. We believe we are the first to progressively incorporate multiple modalities of input in such a hierarchical manner in contrast to the typical approach of treating appearance features and motion features as a two-stream network.

**Deeper hierarchy:** To handle a video of longer size, up to thousands of frames which is equivalent to dozens of short-term clips, there are two options to reduce the computational cost of CRN in handling large sets of subsets \( \{ Q^k \mid k = 2, ..., k_{\text{max}} \} \) given an input array \( \mathcal{X} \): (i) limit the maximum subset size \( k_{\text{max}} \), or (ii) extend the visual stream networks to deeper hierarchy. For the former option, this choice of sparse sampling may have potential to lose critical relation information of specific subsets. The latter, on the other hand, is able to densely sample subsets for relation modeling. Specifically, we can group \( N \) short-term clips into \( N_1 \times N_2 \) hyper-clips, of which \( N_1 \) is the number of the hyper-clips and \( N_2 \) is the number of short-term clips in one hyper-clip. By doing this, the visual stream now becomes a 3-level of hierarchical network architecture. See Sec. 3.4 for effect of going deeper on running time and Sec. 4.4.3 on accuracy.

**Computing the output:** At the end of the visual stream, we compute the average visual feature based on conditioning to the question representation \( q \). Assume outputs of the last CRN unit at video level are an array \( O = \{ o_i \mid o_i \in \mathbb{R}^{H\times d} \}_{i=1}^{N-4} \), we first stack them together, resulting in an output tensor \( o \in \mathbb{R}^{(N-4)\times H\times d} \), and further vectorize this output tensor to obtain the final output \( o' \in \mathbb{R}^{H'\times d} \), \( H' = (N-4) \times H \). The weighted average information is given by:

\[
I = [W_{o'} o'; W_{o'} o' \odot W_q q],
\]

\[
I' = \text{ELU} (W_I I + b),
\]

\[
\gamma = \text{softmax} (W_T I' + b),
\]

\[
\tilde{o} = \sum_{h=1}^{H'} \gamma_h \hat{o}_h; \tilde{o} \in \mathbb{R}^d,
\]  

where \([\ldots]\) denotes concatenation operation, and \( \odot \) is the Hadamard product. In case of multi-choice questions which
are coupled with answer choices \( \{ a_i \} \), Eq. \((13)\) becomes \( I = \left[ W_o' o'; W_o' \odot W_q q; o' \odot W_a a_i \right] \).

### 3.2.3 Textual stream

HCRN architecture is readily applicable to the accompanying textual subtitles in the similar bottom-up fashion as in visual stream. The HCRN textual stream also consists of two-level hierarchy structure that process textual objects of each segment and joining segments into passage level (See Fig. 9).

The input of the stream is preprocessed subtitles, question, and answer choices (Sec. 3.2.1). The subtitles \( S \) is represented as its overall representation \( H^s \) and also a sequence of equal-length segments, each of which has been encoded into a set of textual objects \( U_i = \{ u'_i \}_{t=1,...,T} \in \mathbb{R}^{T \times d} \). Meanwhile, the question is encoded into a single vector \( q \in \mathbb{R}^d \) and answer choices are encoded as \( a_i \in \mathbb{R}^d \).

**Question-relevant pre-selection:** Unlike video frames, subtitles \( S \) contains irregularly timed conversations between movie characters. Furthermore, while relevant visual features are abundant throughout the video, only small portion of the subtitle is relevant to the query and reflective of the answers \( a \). To assure such relevance, antecedent to CRN unit, we modulate the representation of passage \( H^s \) and those of \( M \) segments \( \{ U_i \}_{i=1}^M \) with both use the question and the answer choice. It is done with the pre-selection operator described below.

At segment level, the modulated representation \( \hat{U}_i \in \mathbb{R}^{T \times d} \) of each segment \( i \) of \( T \) objects are produced by

\[
\hat{U}_i = W^s [ U_i; U_i \odot q; U_i \odot a ] .
\]

Similarly, at video level, the subtitle modulated representation \( \hat{H}^s \in \mathbb{R}^{S \times d} \) is built as

\[
\hat{H}^s = W^h [ H^s; H^s \odot q; H^s \odot a ] .
\]

**CRN unit:** A single CRN unit of the stream operate at passage level which models the relationships between segments. The modulated \( \{ \hat{U}_i \}_{i=1}^M \) are passed as input objects to a CRN unit. The conditioning feature of the CRN is max-pooled vector of the modulated representation of the whole subtitle passage \( \hat{H}^s \). At the end of the textual stream, a temporal max-pooling operator is applied over the outputs of the CRN to obtain a single vector.

### 3.2.4 Adaptation & implementation

**Short-form Video QA:** Recall that short-form Video QA in this paper refers to QA about single-shot videos of a few seconds without accompanying textual data. For these cases, we employ the standard visual stream as described in Sec. 3.2.2 to distill video/question joint representation. This representation is ready to be used by the answer decoder (See Sec. 3.3 for generating final output.

**Long-form Video QA:** Different from the short-form Video QA, long-form Video QA involves reasoning on both visual information from video frames and textual content from subtitles. Compared to short snippets where local low-level motion saliency plays critical role, discovering high-level semantic concepts associated with movie characters is more important [52]. Such semantics interleave in the data of both modalities. Further difference comes from the fact that long-form videos are of greater duration hence require appropriate treatment.

Although long-form videos share with short-forms in having hierarchical structure, they are distinctive in terms of semantic compositionality and length. We employ visual and textual streams as described in Sec. 3.2.2 and Sec. 3.2.3 with some adaptation for better suitability with the data format and structure.

For the visual stream, at the clip level, we use CRN units to handle a subset of sub-sampled frames in each clip. At video level, another CRN gathers long-range dependencies between these clip-level information sent up from lower level CRN outputs.

All CRN units at both levels take question representation as conditioning features (See Fig. 7). Compared to the standard architecture introduced in Sec. 3.2.2 and Fig. 5 we drop all CRN units that condition on motion features. This adaptation is to accommodate the fact that low-level motion is less relevant than overall semantic flow in both clip- and video-level.

### 3.3 Answer decoders

Following the previous works [8][14][4], we adopt different answer decoders depending on the task, as follows:

- **QA pairs with open-ended answers** are treated as multi-label classification problems. For these, we employ a classifier which takes as input the combination of the retrieved information from visual stream \( \hat{o}_v \), the retrieved information from textual stream \( \hat{o}_t \) and the question representation \( q \), and computes answer probabilities \( p \in \mathbb{R}^{|A|} \):

\[
y = \text{ELU} \left( W_o [ \hat{o}_v; \hat{o}_t; W_q q + b] + b \right) , \quad (19)
\]

\[
y' = \text{ELU} \left( W_y y + b \right) , \quad (20)
\]

\[
p = \text{softmax} \left( W'_p y' + b \right) . \quad (21)
\]

- **In case of multi-choice questions** where answer choices are available, we iteratively treat each answer choice \( a_i \) as a query in exactly the manner that we handle the question. Eventually, Eq. (19) is replaced by:

\[
y = \text{ELU} \left( W_o [ \hat{o}_{va}; \hat{o}_{ta}; W_q a + q; W_v a + b] + b \right) , \quad (19')
\]
Textual stream. Both segment-level and passage-level textual objects are modulated with the question by a pre-selection module. They then serve as input and conditioning features for an CRN modeling long-term relationships between segments.

Video frames
clip 1
clip 2

Clip level
Video level

Fig. 7 The adapted architecture of visual stream (Fig. 5) for long-form video. At each level, only question-conditioned CRNs are employed. The motion-conditioned CRNs are unnecessary as the low-level motion features are less relevant in long-form media.

\[
\tilde{o}_{tv} \text{ is output of visual stream respect to queries as question and answer choices, whereas } \tilde{o}_{tv} \text{ is output of the textual stream counterpart.}
\]

- For short-form Video QA, we simply drop the retrieved information from textual stream \(\tilde{o}_t\) in Eq. 19 and Eq. 22.
- For repetition count task, we use a linear regression function taking \(y'\) in Eq. 20 as input, followed by a rounding function for integer count results. The loss for this task is Mean Squared Error (MSE).

3.4 Complexity analysis

We now provide theoretical analysis of running time for CRN units and HCRN. We will show that adding layers saves computation time, just providing a justification for deep hierarchy.

\[
\tilde{o}_{tv} = W_{y'y'} + b.
\]
3.4.1 CRN units

For clarity, let us recall the notations introduced in our CRN units: $k_{\text{max}}$ is maximum subset (also tuple) size considered from a given input array of $n$ objects, subject to $k_{\text{max}} < n$; $t$ is number of subsets randomly selected from sets of all size-$k$ subsets $Q^k (k = 2, 3, ..., k_{\text{max}})$; $g^k(\cdot)$, $h^k(\cdot)$ and $p^k(\cdot)$ are sub-networks for relation modeling, conditioning and aggregating, respectively. In our implementation, $g^k(\cdot)$ and $p^k(\cdot)$ are chosen to be set functions and $h^k(\cdot)$ is a nonlinear transformation that fuses modalities.

Denoted by $F$ the number of descriptors for each input object for the CRN. Assume that the set function of order $k$ in the CRN’s operation in Alg. 1 in the main paper has linear time complexity in $k$. This holds true for most aggregation functions such as mean, max, sum or product. With the relation orders ranging from $k = 2, 3, ..., k_{\text{max}}$ and sampling frequency $t$, inference cost in time for a CRN is:

$$C_{\text{CRN}}(t, k_{\text{max}}, F) = \mathcal{O}\left(\frac{t}{2}k_{\text{max}}(k_{\text{max}} - 1)F\right)$$ (24)

The unit produces an output array of size $k_{\text{max}} - 1$, each with $F$ features.

3.4.2 HCRN models

We adhere to the complexity analysis of visual stream only which increases linearly in complexity with a video length. The overall complexity of HCRN depends on design choice for each CRN unit and specific arrangement of CRN units. For clarity, let $t = 2$ and $k_{\text{max}} = n - 1$, which are found to work well in experiments. Let $L$ be the video length, organized into $N$ clips of length $T$, i.e., $L = NT$.

2-level HCRN: Consider, for example, the 2-level architecture HCRN, representing clips and video. Each level is a stack of two CRN layers, one for motion conditioning followed by the other for linguistic conditioning: The clip-level CRNs cost $N \times C_{\text{CRN}}(2, T - 1, F)$ time for motion conditioning and $N \times C_{\text{CRN}}(2, T - 3, F)$ time for question conditioning, where $C_{\text{CRN}}$ is the cost estimator in Eq. (24). This adds to roughly $2TLF$ time.

Now the output array of size $(T - 4)F$ for the question-conditioned clip-level CRN becomes one in $N$ input objects the video-level CRNs. The CRNs at the video level, therefore, take a cost of $C_{\text{CRN}} (2, N - 1, (T - 4)F)$ time and $C_{\text{CRN}} (2, N - 3, (T - 4)F)$ time, respectively, totaling $2N^2TF = 2NFLF$ in order. Here we have made use of the identity $L = NT$. The total cost is therefore in the order of $2(T + N)LF$.

3-level HCRN: Let us now analyze a 3-level architecture HCRN that generalizes the 2-level HCRN. The $N$ clips are organized into $P$ sub-videos, each has $Q$ clips, i.e., $N = PQ$. Since the CRNs at clip level remain the same, the first level costs $2TLF$ time to compute as before. Moving to the next level, each sub-video CRN takes as input an array of length $Q$, whose elements have size $(T - 4)F$. Applying the same logic as before, the set of sub-video-level CRNs cost roughly $M \times C_{\text{CRN}} (2, Q - 1, (T - 4)F)$ time or approximately $2PQ^2TF = 2\frac{L}{T}LF$ (since $N = PQ$ and $L = NT$).

A stack of two sub-video CRNs now produces an output array of size $(Q - 4)(T - 4)F$, serving as an input object in an array of length $P$ for the video-level CRNs. Thus the video-level CRNs cost roughly $C_{\text{CRN}} (2, P - 1, (Q - 4)(T - 4)F)$ time or approximately $2PQ^2TF = 2PLF$ (since $L = NT$ and $N = PQ$). Thus the total cost is in the order of $2(T + \frac{N}{P} + P)LF$.

Deeper models save time:

Recall that the 2-level HCRN has time cost of $2(T + N)LF$. The cost reduction when going from 2-level to 3-level architectures is $2(N - \frac{N}{P} - P)LF$. Now assuming $N \gg \max \{P, \frac{N}{P}\}$, for example $P \approx \sqrt{N}$ and the number of clips $N > 20$. Then the time saving can be approximated further as $2NFL$. As $N = \frac{L}{T}$, this reduces to $2NFLF = 2\frac{L^2}{T}F$. In practice the clip size $T$ is often fixed, thus the saving scales quadratically with video length $L$, suggesting that going deeper in hierarchy is computational efficient for long videos. See Sec. 4.3.3 for an empirical validation of the saving.

4 Experiments

4.1 Datasets

We evaluate the effectiveness of the proposed CRN unit and the HCRN architecture on a series of short-form and long-form Video QA datasets. In particular, we use three different datasets as benchmarks for the short-form Video QA, namely TGIF-QA [14], MSVD-QA [44] and MSRVTT-QA [15]. All those three datasets are collected from real-world videos. We also evaluate HCRN on long-form Video QA using one of the largest datasets publicly available, TVQA [2]. Details of each benchmark are as below.

**TGIF-QA**: This is currently the most prominent dataset for Video QA, containing 165K QA pairs and 72K animated GIFs. The dataset covers four tasks addressing unique properties of video. Of which, the first three require strong spatio-temporal reasoning abilities: Repetition Count - to retrieve number of occurrences of an action, Repeating Action- multi-choice task to identify the action that is repeated for a given
number of times, *State Transition* - multi-choice tasks regarding temporal order of events. The last task - *Frame QA* - is akin to image QA where the answer to a given question can be found from one particular video frame.

**MSVD-QA:** This is a small dataset of 50,505 question answer pairs annotated from 1,970 short clips. Questions are of five types, including what, who, how, when and where, of which 61% of questions are used for training whilst 13% and 26% are used as validation set and test set, respectively.

**MSRVTT-QA:** The dataset contains 10K videos and 243K question answer pairs. Similar to MSVD-QA, questions are of five types. Splits for train, validation and test are with the proportions are 65%, 5%, and 30%, respectively. Compared to the other two datasets, videos in MSRVTT-QA contain more complex scenes. They are also much longer, ranging from 10 to 30 seconds long, equivalent to 300 to 900 frames per video.

**TVQA:** This is one of the largest long-form Video QA datasets annotated from 6 different TV shows: *The Big Bang Theory, How I Met Your Mother, Friends, Grey’s Anatomy, House, Castle.* There are total 152.5K question-answer pairs associated with 5 answer choices each from 21.8K long clips of 60/90 secs which comes down to 122K, 15,25K and 15,25K for train, validation and test set, respectively. The dataset also provides start and end timestamps for each question to limit the video portion where one can find corresponding answers.

Regarding evaluation metric, we mainly use accuracy in all experiments, excluding those for repetition count on TGIF-QA dataset where Mean Square Error (MSE) is applied.

### 4.2 Implementation details

#### 4.2.1 Feature extraction

For short-form Video QA datasets, each video is preprocessed into \( N \) short clips of fixed lengths, 16 frames each. In details, we first locate \( N \) equally spaced anchor frames. Each clip is then defined as a sequence of 16 consecutive video frames taking an pre-computed anchor as the middle frame. For the first and the last clip where frame indices may exceed the boundaries, we repeat the first frame or the last frame of the video multiple times until it fills up the clip’s size.

Given segmented clips, we extract motion features for each clip using a pre-trained model of the ResNeXt-101 [1][2][3]. Regarding the appearance feature used in the experiments, we take the \textit{pool5} output of ResNet [10] as feature representation of each frame. This means we completely ignore the 2D structure of spatial information of video frames which is likely to be beneficial for answering questions particularly interested in object’s appearance, such as those in Frame QA task in the TGIF-QA dataset. We are aware of this but deliberately opt for light-weighted extracted features, and drive the main focus of our work on the significance of temporal relation, motion, and hierarchy of video data by nature. Note that most of the videos in the datasets in short-form Video QA category, except those in the MSRVTT-QA dataset, are short. Hence, we intentionally divide each video into 8 clips (8 \( \times \) 16 frames) to produce partially overlapping frames between clips to avoid temporal discontinuity. Longer videos in MSRVTT-QA are additionally segmented into 24 clips of 16 frames each, primarily aiming at evaluating the model’s ability to handle very long sequences.

For the TVQA long-form dataset, we did a similar strategy as for short-video divide each video into \( N \) clips. However, as TVQA videos are longer and only recorded at 3fps, we adapt by choosing \( N = 6 \), each clip contains 8 frames based on empirical experiences. The \textit{pool5} output of ResNet features are also used as feature representation of each frame.

For the subtitles, maximum subtitle’s length is set at 256. We simply cut off those who are longer than that and do zero padding for those who are shorter. Subtitles are further divided into 6 segments overlapping at half a segment size.

#### 4.2.2 Network training

HCRN and its variations are implemented in Python 3.6 with PyTorch 1.2.0. Common settings include \( d = 512, t = 2 \) for both visual and textual streams. For all experiments, we train the model using Adam optimizer with a batch size of 32, initially at learning rate of \( 10^{-4} \) and decay by half after every 5 epochs for counting task in the TGIF-QA dataset and after every 10 epochs for the others. All experiments are terminated after 25 epochs and reported results are at the epoch giving the best validation accuracy. Depending on the amount of training data and hierarchy depth, it may take around 4-30 hours training on one single NVIDIA Tesla V100 GPU. Pytorch implementation of the model is publicly available [4].

As for experiments with the large-scale language representation model BERT, we use the latest pretrained model provide by Hugging Face [5]. We fine-tune the BERT model during training with a learning rate of \( 2 \times 10^{-5} \) in all experiments.

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1. [https://github.com/kenshohara/video-classification-3d-cnn-pytorch](https://github.com/kenshohara/video-classification-3d-cnn-pytorch)
2. [https://github.com/haolmk54/hcrn-long-short-videoqa](https://github.com/haolmk54/hcrn-long-short-videoqa)
3. [https://github.com/huggingface/transformers](https://github.com/huggingface/transformers)
4.3 Quantitative results

We compare our proposed model with state-of-the-art methods (SOTAs) on all mentioned datasets. By default, we use pre-trained GloVe embedding [50] for word embedding following by a BiLSTM for sequential modeling. Experiments using contextual embeddings by a pretrained BERT network [13] is explicitly specified with “(BERT)”. Detailed experiments for short-form Video QA and long-form Video QA are as the following.

4.3.1 Short-form Video QA

For TGIF-QA, we compare with most recent SOTAs, including [13][14][8], over four tasks. These works, except for [8], make use of motion features extracted from either optical flow or 3D CNNs and its variants.

The results are summarized in Table 2 for TGIF-QA, and in Fig. 8 for MSVD-QA and MSRVTT-QA. Results of the previous works are taken from either the original papers or what reported by [8]. It is clear that our model consistently outperforms or is competitive with SOTA models on all tasks across all datasets. The improvements are particularly noticeable when strong temporal reasoning is required, i.e., for the questions involving actions and transitions in TGIF-QA. These results confirm the significance of considering both near-term and far-term temporal relations toward finding correct answers. More analysis on how relations affect the model’s performance is provided in later ablation studies.

Regarding results with the recent advance in language representation model BERT, it does not have much effect on the results across tasks requiring strong temporal reasoning in the TGIF-QA. This can be explained by the fact that questions in this dataset are relatively short and all questions are created from a limited number of patterns, hence, contextual embeddings do not account much benefit. Whereas, the Frame QA task relies on a much richer vocabulary set, thanks to its free-form questions, hence, contextual embeddings with BERT greatly boost the model’s performance on this task. We also empirically find out that fine-tune only last two layers of BERT network gives more favorable performance comparing to fine-tuning all layers in this particular dataset.

The MSVD-QA and MSRVTT-QA datasets represent highly challenging benchmarks for machine compared to the TGIF-QA, thanks to their open-ended nature. Our model HCRN outperforms existing methods on both datasets, achieving 37.1% and 35.1% accuracy which are 2.7 points and 0.1 points improvement on MSVD-QA and MSRVTT-QA, respectively. This suggests that the model can handle both small and large datasets better than existing methods.

Finally, we provide a justification for the competitive performance of our HCRN against existing rivals by comparing model features in Table 2. Whilst it is not straightforward to compare head-to-head on internal model designs, it is evident that effective video modeling necessitates handling of motion, temporal relation and hierarchy at the same time. We will back this hypothesis by further detailed studies in Sec. 4.4 (for motion, temporal relations, shallow hierarchy) and Sec. 4.4.3 (deep hierarchy).

4.3.2 Long-form Video QA

For TVQA, we compare our method to several baselines as well as state-of-the-art methods (See Table 3). The dataset is relatively new and due to the challenges with long-form Video QA, there are only several attempts in benchmarking it. Comparisons of the proposed method with the baselines are made on validation set while results of compared methods are taken as reported in original publications. Experiments using timestamp information is indicated by w/ ts and those with full-length subtitles are with w/o ts. If not indicated explicitly, “V.”, “S.”, “Q.” short for visual features, subtitle features and question features, respectively. The evaluated settings are as follows:

- (B) Q.: This is the simplest baseline where we only use question features for predicting the correct answer. Results on this setting will reveal how much our model relying on linguistic bias to arrive correct answers.
- (B) S. + Q. (w/o pre-selection): In this baseline, we use question and subtitle features for prediction. Both question and subtitle features are simply obtained by concatenating the final output hidden states of forward and backward LSTM passes and further pass to a classifier as in Sec. 3.3.
- (B) S. + Q. (w/ pre-selection): This baseline is to show the significance of pre-selection in textual stream as in Eq. 18. Having said that, question features and selective output between the question and the subtitles as explained in Eq. 18 are fed into a classifier for prediction.
- (B) V. + Q.: In this baseline, we simply apply average pooling to mash visual features of entire videos into a vector and further combine with question features for prediction.
- (B) S. + V. + Q. (w/ pre-selection): We combine two baselines “(B) S. + Q. (w/ pre-selection)” and “(B) V. + Q.” right above. Given that, subtitle features are extracted with pre-selection as in Eq. 18 and video features are smashed over space-time before going through a classifier.
- (HCRN) S. + Q.: This is to evaluate the effect of the textual stream alone in our proposed network architecture as described in Fig. 6.
- (HCRN) V. + Q.: This is to evaluate the effect of the visual stream counterpart alone in Fig. 7.
– (HCRN) $S. + V. + Q.$: Our full proposed architecture with the presence of both two modalities.

As shown in Table 4 using BERT for contextual word embeddings significantly improves performance comparing to GloVe embeddings and BiLSTM counterpart. The results are consistent to what reported by [46]. Although our model only achieves competitive performance with [46] in the setting of using timestamps (71.4 vs. 72.1), we significantly outperform them by approximately 3.0 points on the more challenging setting when we do not have access to timestamp indicators of where answers located. This clearly shows that our bottom-up approach is promising to solve long-form Video QA in its general setting.

Even though BERT is designed to do contextual embedding which pre-computes some word relations, HCRN still shows additional benefit in modeling relations between segments in the passage. However, this benefit is not as clearly demonstrated as in the case of using GloVe embedding coupled with BiLSTM (Table 4: Exp. 9 vs. Exp. 7 and Exp. 13 vs. Exp. 14). To deeper understanding the behaviour of HCRN, we will concentrate our further analysis using comparison with GloVe + LSTM.

It is clearly that using output hidden states of BiLSTM to represent subtitle features directly for classification has very limited effect (See Table 4: Exp. 3 vs Exp. 4). The results could be explained as LSTM fails to handle such long subtitles of hundreds of words. In the mean time, pre-selection plays critical role to find relevant information in the subtitles to a question which boosts performance from 41.8% to 57.9% when using full subtitles and from 41.8% to 62.1% when using timestamps (See Exp. 5). Our HCRN further improves approximately 1.0 point (without timestamp annotation) and 1.5 points (with timestamp annotation) comparing to the baseline of GloVe embeddings and BiLSTM with pre-selection for the textual stream only setting. As for the effects on visual stream, our HCRN gains around 1.0 points over the baseline of averaging visual features. This leads to an improvement of north of 1.0 points when leveraging both visual and textual stream together (See Exp. 12 vs. Exp. 15) on both settings with timestamp annotation and without timestamp annotation. Even though our results are behind [2], we wish to point out that their context matching model with the bi-directional attention flow (BiDAF) significantly contributes to the performance. Whereas, our model only makes use of vanilla BiLSTM to sequence modeling. Therefore, direct comparison between two methods is unfair. We instead mainly compare our method with a simple variant of [2] by dropping off the BiDAF to show the contribution of our CRN unit as well as the HCRN network. This is equivalent to the baseline (B) $S. + V. + Q.$ (w/ pre-selection) in this paper.

4.4 Ablation studies

To provide more insights about our the roles of HCRN’s components, we conduct extensive ablation studies on the TGIF-QA and TVQA dataset with a wide range of configurations. The results are reported in Table 5 for the short-form Video QA and in Table 6 for the long-form Video QA.

4.4.1 Short-form Video QA

Full 2-level HCRN denotes the full model of Fig. 2(a) with $k_{max} = n - 1$, $t = 2$. Overall we find that ablating any of design components or CRN units would degrade the performance for temporal reasoning tasks (actions, transition and action counting). The effects are detailed as follows.

Effect of relation order $k_{max}$ and resolution $t$: Without relations ($k_{max} = 1$, $t = 1$) the performance suffers, specifically on actions and events reasoning whereas counting tends to be better. This is expected since those questions often require putting actions and events in relation with a larger context (e.g., what happens before something else) while motion flow is critical for counting but for far-term relations. In this case, most of the tasks benefit from increasing sampling resolution $t$ ($t > 1$) because of better chance to find a relevant frame as well as far-temporal relation learnt by the aggregating sub-network $p^k(.)$ of the CRN unit. However, when taking relations into account ($k_{max} > 1$), we find that HCRN is robust against sampling resolution $t$ but depends critically on the maximum relation order $k_{max}$. The relative independence w.r.t. $t$ can be due to visual redundancy between frames, so that resampling may capture almost the same information. On the other hand, when considering only low-order object relations, the performance is significantly dropped in all tasks, except frame QA. These results confirm that high-order relations are required for temporal reasoning. As the frame QA
Table 2 Comparison with the state-of-the-art methods on TGIF-QA dataset. For count, the lower the better (MSE).

| Model                  | Action | Trans. | Frame | Count |
|------------------------|--------|--------|-------|-------|
| ST-TP [14]             | 62.9   | 69.4   | 49.5  | 4.32  |
| Co-mem [1]             | 68.2   | 74.3   | 51.5  | 4.10  |
| PSAC [3]               | 70.4   | 76.9   | 55.7  | 4.27  |
| HME [8]                | 73.9   | 77.8   | 53.8  | 4.02  |
| HCRN                   | 75.3   | 82.2   | 55.9  | 3.87  |
| HCRN (embeddings with BERT) | 72.2   | 80.3   | 58.2  | 3.96  |

Table 3 Model design choices and input modalities in comparison. See Table 2 for corresponding performance on TGIF-QA dataset.

| Model     | Appear. | Motion | Hiera. | Relation |
|-----------|---------|--------|--------|----------|
| ST-TP [14]| ✓       | ✓      | ✓      | ✓        |
| Co-mem [1]| ✓       | ✓      | ✓      | ✓        |
| PSAC [3]  | ✓       | ✓      | ✓      | ✓        |
| HME [8]   | ✓       | ✓      | ✓      | ✓        |
| HCRN      | ✓       | ✓      | ✓      | ✓        |

Effect of hierarchy: We design two simpler models with only one CRN layer:

- 1-level, 1 CRN video on key frames only: Using only one CRN at the video-level whose input array consists of key frames of the clips. Note that video-level motion features are still maintained.
- 1.5-level, clip CRNs → pooling: Only the clip-level CRNs are used, and their outputs are mean-pooled to represent video. The pooling operation represents a simplistic relational operation across clips. The results confirm that a hierarchy is needed for high performance on temporal reasoning tasks.

Effect of motion conditioning: We evaluate the following settings:

- w/o short-term motions: Remove all CRN units that condition on the short-term motion features (clip level) in the HCRN.
- w/o long-term motions: Remove the CRN unit that conditions on the long-term motion features (video level) in the HCRN.
- w/o motions: Remove motion feature from being used by HCRN. We find that motion, in agreeing with prior arts, is critical to detect actions, hence computing action count. Long-term motion is particularly significant for counting task, as this task requires maintaining global temporal context during the entire process. For other tasks, short-term motion is usually sufficient. E.g. in action task, wherein one action is repeatedly performed during the entire video, long-term context contributes little. Not surprisingly, motion does not play the positive role in answering questions on single frames as only appearance information needed.

Effect of linguistic conditioning and multiplicative relation:
Linguistic cues represent a crucial context for selecting relevant visual artifacts. For that we test the following ablations:

- w/o question @clip level: Remove the CRN unit that conditions on question representation at clip level.
- w/o question @video level: Remove the CRN unit that conditions on question representation at video level.
- w/o linguistic condition: Exclude all CRN units conditioning on linguistic cue while the linguistic cue is still in the answer decoder. Likewise, multiplicative relation form offers a selection mechanism. Thus we study its effect as follows:
  - w/o MUL. in all CRNs: Exclude the use of multiplicative relations in all CRN units.
  - w/MUL. relation for question & motion: Leverage multiplicative relations in all CRN units.

We find that the conditioning question provides an important context for encoding video. Conditioning features (motion and language), through the multiplicative relation as in Eq. 3, offers further performance gain in all tasks rather than Frame QA, possibly by selectively passing question-relevant information up the inference chain.

4.4.2 Long-form Video QA

We focus on studying about the effect of different options for the conditioning sub-network $h^k(\cdot, \cdot)$ in Sec. 3.1 which reflects the flexibility of our model when dealing with different forms of input modalities. The options are:

- S. + Q. (w/MUL. + w/LSTM): Only textual stream is used. The conditioning sub-network $h^k(\cdot, \cdot)$ is with multiplicative relation between tuples of segments and conditioning feature, and coupled with BiLSTM as formulated in Eqs. (4, 5 and 6).
- S. + Q. (w/MUL. + w/o LSTM): Remove the BiLSTM network in the experiment S. + Q. (w/MUL. + w/LSTM) to evaluate the effect of sequential modeling in textual stream.
### Table 4 Comparison with baselines and state-of-the-art methods on TVQA dataset. \( w/o \) \( ts \): without using timestamp annotation to limit the search space of where to find answers; \( w/ ts \): making use of the timestamp annotation.

| Exp. | Model | Validation |
|------|-------|------------|
| 1    | TVQA S.+Q.+V. \([46]\) | 64.7 | 67.7 |
| 2    | VideoQABERT \([46]\) | 63.1 | \textbf{72.1} |
| 3    | (B) Q. | 41.6 | 41.6 |
| 4    | (B) S. + Q. (w/o pre-selection) | 42.3 | 41.8 |
| 5    | (B) S. + Q. (w/ pre-selection) | 57.9 | 62.1 |
| 6    | (B) Q. (BERT) | 44.2 | 44.2 |
| 7    | (B) S. + Q. (BERT) | 65.1 | 71.1 |
| 8    | (HCRN) S. + Q. | 59.3 | 63.6 |
| 9    | (HCRN) S. + Q. (BERT) | 65.8 | 71.1 |
| 10   | (B) V. + Q. | 42.2 | 42.2 |
| 11   | (HCRN) V. + Q. | 43.1 | 43.1 |
| 12   | (B) S. + V. + Q. (w/ pre-selection) | 58.5 | 63.2 |
| 13   | (B) S. + V. + Q. (BERT) | 65.7 | 71.4 |
| 14   | (HCRN) S. + V. + Q. | \textbf{66.0} | 71.4 |
| 15   | (HCRN) S. + V. + Q. | 59.7 | 64.5 |

Table 5 Ablation studies on TGIF-QA dataset. For count, the lower the better (MSE). When not explicitly specified, we use \( k_{max} = n - 1, t = 2 \) for relation order and sampling resolution.

| Model | Action | Transition | FrameQA | Count |
|-------|--------|------------|---------|-------|
| Relations \((k_{max}, t)\) | 72.7 | 80.7 | 54.9 | 3.84 |
| \( k_{max} = 1, t = 1 \) | 72.2 | 80.4 | 55.8 | 3.86 |
| \( k_{max} = 1, t = 3 \) | 72.9 | 80.1 | 56.0 | 3.92 |
| \( k_{max} = 1, t = 5 \) | 72.6 | 80.7 | 56.5 | 3.93 |
| \( k_{max} = 1, t = 7 \) | 73.9 | 81.3 | 56.3 | 3.91 |
| \( k_{max} = 2, t = 2 \) | 73.0 | 80.4 | 56.4 | 3.91 |
| \( k_{max} = 2, t = 9 \) | 73.4 | 80.6 | 56.3 | 3.93 |
| \( k_{max} = 4, t = 2 \) | 73.3 | 80.8 | 55.5 | 3.93 |
| \( k_{max} = 4, t = 9 \) | 74.5 | 80.7 | 56.5 | 3.93 |
| \( k_{max} = \lfloor n/2 \rfloor, t = 2 \) | 74.7 | 80.6 | 55.9 | 3.89 |
| \( k_{max} = \lfloor n/2 \rfloor, t = 9 \) | 73.9 | 80.2 | 55.8 | 3.91 |
| \( k_{max} = n - 1, t = 1 \) | 75.0 | 81.4 | 55.5 | 3.89 |
| \( k_{max} = n - 1, t = 3 \) | 75.7 | 81.1 | 56.0 | 4.02 |
| \( k_{max} = n - 1, t = 5 \) | 75.9 | 81.5 | 55.4 | 3.98 |
| \( k_{max} = n - 1, t = 7 \) | 74.6 | 81.6 | 55.9 | 3.89 |
| \( k_{max} = n - 1, t = 9 \) | 74.7 | 81.0 | 55.9 | 3.91 |
| Hierarchy | 72.5 | 81.8 | 57.0 | 3.82 |
| 1-level, video CRN only | 75.0 | 81.3 | 57.0 | 3.83 |
| 1.5-level, clips→pool | 75.8 | 78.5 | 57.5 | 4.42 |
| Motion conditioning | 76.1 | 81.3 | 56.3 | 3.89 |
| w/o motion | 75.2 | 80.4 | 56.2 | 3.94 |
| w/o short-term motion | 66.8 | 78.5 | 56.2 | 3.89 |
| w/o long-term motion | 73.5 | 80.7 | 56.0 | 3.86 |
| Linguistic conditioning | 74.3 | 81.2 | 56.3 | 3.86 |
| w/o linguistic condition | 73.3 | 80.8 | 57.0 | 3.94 |
| w/o question @clip level | 73.6 | 79.5 | 55.6 | 4.02 |
| w/o question @video level | 75.3 | 82.2 | 55.9 | 3.87 |
| Multiplicative relation | 75.3 | 82.2 | 55.9 | 3.87 |

For relation order and sampling resolution.
Table 6 Ablation studies on TVQA dataset.

| Exp. | Model | Val. | Test |
|------|-------|------|------|
|      | Textual stream only |      |      |
| 1    | S. + Q. (w/ MUL. + w/ LSTM) | 59.3 | 63.6 |
| 2    | S. + Q. (w/ MUL. + w/o LSTM) | 57.5 | 63.7 |
| 3    | S. + Q. (w/o MUL. + w/ LSTM) | 59.2 | 63.6 |
| 4    | S. + Q. (w/o MUL. + w/o LSTM) | 57.1 | 63.4 |
|      | Visual stream only |      |      |
| 5    | V. + Q. (w/ MUL. + w/ LSTM) | 42.7 | 42.7 |
| 6    | V. + Q. (w/ MUL. + w/o LSTM) | 43.1 | 43.1 |
| 7    | V. + Q. (w/o MUL. + w/ LSTM) | 42.3 | 42.3 |
| 8    | V. + Q. (w/o MUL. + w/o LSTM) | 42.1 | 42.1 |
|      | Two streams |      |      |
| 9    | S. + V. + Q. (S. w/ MUL. + LSTM, V. w/ MUL.) | 59.7 | 64.5 |

S. + Q. (w/o MUL. + w/ LSTM): The multiplicative relation in the experiment S. + Q. (w/ MUL. + w/ LSTM) is now replaced with a simple concatenation of conditioning feature and tuples of segments.

S. + Q. (w/o MUL. + w/ LSTM): Remove the BiLSTM network in the right above experiment S. + Q. (w/o MUL. + w/ LSTM) to evaluate the effect of when both selective relation and sequential modeling are missing.

V. + Q. (w/ MUL. + w/ LSTM): Only visual stream is under consideration. We use the multiplicative form as in Eq. 3 for the conditioning sub-network instead of a simple concatenation operation in Eq. 2. We additionally use a BiLSTM network for sequential modeling as same as the way we have done with the textual stream. This is because both visual content and textual content are temporal sequences by nature.

V. + Q. (w/ MUL. + w/o LSTM): Similar to the above experiment V. + Q. (w/ MUL. + w/ LSTM) but without the use of the BiLSTM network.

V. + Q. (w/o MUL. + w/ LSTM): The conditioning sub-network is simply a tensor concatenation operation. This is to compare against the one using multiplicative form V. + Q. (w/ MUL. + w/ LSTM).

V. + Q. (w/o MUL. + w/o LSTM): Similar to V. + Q. (w/o MUL. + w/ LSTM) but without the use of the BiLSTM network for sequential modeling.

S. + V. + Q. (S. w/ MUL. + LSTM, V. w/ MUL.): Both two streams are present for prediction. We combine the best option of each network stream, S. + Q. (w/ MUL. + w/ LSTM) for the textual stream and V. + Q. (w/ MUL. + w/o LSTM) for the visual stream for comparison.

It is empirically shown that the simple concatenation as in Eq. 2 is insufficient to combine conditioning features and output of relation network in this dataset. In the mean time, multiplicative relation between the conditioning features and those relations is a better fit as it greatly improves the model’s performance, especially in visual stream. This shows the consistency in empirical results between long-form Video QA and shot-form Video QA where relation between visual content and the query is more about multiplicative (selection) rather than simple additive.

On the other side, sequential modeling with BiLSTM is more favorable for textual stream than visual stream even though both streams are sequential by nature. This well aligns with our analysis in Sec. 3.1.

4.4.3 Deepening model hierarchy saves time

We test the scalability of the HCRN on long videos in the MSRVTT-QA dataset, which are organized into 24 clips (3 times longer than other two datasets). We consider two settings:

- 2-level hierarchy, 24 clips → 1 vid: The model is as illustrated in Fig. 5 where 24 clip-level CRNs are followed by a video-level CRN.
- 3-level hierarchy, 24 clips → 4 sub-vids → 1 vid: Starting from the 24 clips as in the 2-level hierarchy, we group 24 clips into 4 sub-videos, each is a group of 6 consecutive clips, resulting in a 3-level hierarchy. These two models are designed to have similar number of parameters, approx. 44M.

The results are reported in Table 7. Unlike existing methods which usually struggle with handling long videos, our method is scalable for them by offering deeper hierarchy, as analyzed theoretically in Sec. 3.4. Using a deeper hierarchy is expected...
to significantly reduce the training time and inference time for HCRN, especially when the video is long. In our experiments, we achieve 4 times reduction in training and inference time by going from 2-level HCRN to 3-level counterpart whilst maintaining competitive performance.

5 Discussion

HCRN presents a new class of neural architectures for multimodal Video QA, pursuing the ease of model construction through reusable uniform building blocks. Different from temporal attention based approaches which put effort into selecting objects, HCRN concentrates on modeling relations and hierarchy in different input modalities in Video QA. In the scope of this work, we study how to deal with visual content and subtitles where applicable. The visual and text streams share similar structure in terms of near-term, far-term relations and information hierarchy. The difference in methodology and design choices between ours and the existing works leads to distinctive benefits in different scenarios as empirically proven.

Within the scope of this paper we did not consider the audio channel and early-fusion between modalities, leaving these open for future work. Since the CRN is generic, we envision a HCRN for the audio stream similar to the visual stream. The modalities can be combined at any hierarchical level, or any step within the same level. For example, as the audio, subtitle and visual content are partly synchronized, we can use a sub-HCRN to represent the three streams per segment. Alternatively, we can fuse the modalities into the same CRN as long as the feature representations are projected onto the same tensor space. Future works will also include object-oriented representation of videos as these are native to CRNs, thanks to its generality. As CRN is a relational model, both cross-object relations and cross-time relations can be modeled. These are likely to improve the interpretability of the model and get closer to how human reasons across multiple modalities. CRN units can be further augmented with attention mechanisms to cover better object selection ability, so that related tasks such as frame QA in the TGIF-QA dataset can be further improved.

5.1 Conclusion

We introduced a general-purpose neural unit called Conditional Relational Networks (CRNs) and a method to construct hierarchical networks for multimodal Video QA using CRNs as building blocks. A CRN is a relational transformer that encapsulates and maps an array of tensorial objects into a new array of relations, all conditioned on a contextual feature. In the process, high-order relations among input objects are encoded and modulated by the conditioning feature. This design allows flexible construction of sophisticated structure such as stack and hierarchy, and supports iterative reasoning, making it suitable for QA over multimodal and structured domains like video. The HCRN was evaluated on multiple Video QA datasets covering both short-form Video QA where questions are mainly about activities/events happening in a short snippet (TGIF-QA, MSVD-QA, MSRVTT-QA) as well as long-form Video QA where answers are located at either visual cues or textual cues as movie subtitles (TVQA dataset). HCRN demonstrates its competitive reasoning capability on a wide range of different settings against state-of-the-art methods. The examination of CRN in Video QA highlights the importance of building a generic neural reasoning unit that supports native multimodal interaction in improving robustness of visual reasoning.

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