How to Make a BLT Sandwich?
Learning to Reason towards Understanding Web Instructional Videos

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Abstract
Understanding web instructional videos is an essential branch of video understanding in two aspects. First, most existing video methods focus on short-term actions for a few-second-long video clips; these methods are not directly applicable to long videos. Second, unlike unconstrained long videos, e.g., movies, instructional videos are more structured in that they have step-by-step procedure constraining the understanding task. In this paper, we study reasoning on instructional videos via question-answering (QA). Surprisingly, it has not been an emphasis in the video community despite its rich applications. We thereby introduce YouQuek, an annotated QA dataset for instructional videos based on the recent YouCook2 [23]. The questions in YouQuek are not limited to cues on one frame but related to logical reasoning in the temporal dimension. Observing the lack of effective representations for modeling long videos, we propose a set of carefully designed models including a novel Recurrent Graph Convolutional Network (RGCN) that captures both temporal order and relation information. Furthermore, we study multiple modalities including description and transcripts for the purpose of boosting video understanding. Extensive experiments on YouQuek suggest that RGCN performs the best in terms of QA accuracy and a better performance is gained by introducing human annotated description.

1. Introduction
Humans can acquire knowledge by watching instructional videos online. A typical situation is that people confused by specific problems try to look for solutions in related instructional videos. For example, while learning to cook new dishes, they may wonder why a specific ingredient is added, and what happens between the two procedures. Watching instructional videos can often clarify these questions and hence, assist humans in accomplishing tasks. We hereby propose the question: can machines also understand instructional videos as humans do, which requires not only accurate recognition of objects, actions, and events but also the higher-order inference of any relations therein, e.g., spatial, temporal, correlative and casual? Here we use higher-order inference to refer to the inference that cannot be completed immediately by direct observations and thus requires stronger semantics for video modeling (see Fig. 1).

Current instructional video understanding studies focus on various tasks e.g., reference resolution [6], procedure localization [23], dense captioning [24], activity detection [13, [11], and visual grounding [7, 18]. Despite the rich literature and applications, question-answering (QA) task in instructional videos explored in our work is less developped, which acts as a proxy to benchmark the higher-order inference in machine intelligence. Previous works, e.g., ImageQA [2, 12] and VideoQA [15, 21], also leverage the QA task as automatic evaluation method, but QA on instructional videos has never been tackled before.

Figure 1: Demonstration of YouQuek dataset. Colored boxes and arrows represent different reasoning steps required to answer the given questions. Red boxes denote the first step, blue boxes denote the second, and green arrows are for the final step. Better view zoomed in and with color.
Observing the lack of suitable dataset on instructional videos, we propose YouCook Question Answering (YouQuek) dataset based on YouCook2 [23] which is the largest instructional video dataset. Our YouQuek dataset is the first reasoning-oriented dataset aimed for instructional videos. We employ question-answering as intuitive interpretations for various styles of reasoning. Figure 1 presents two exemplar QA pairs in our dataset along with the corresponding example human reasoning procedure involved to answer the questions. YouQuek dataset contains 15,355 manually-collected QA pairs that are divided into different categories regarding different reasoning styles, e.g., counting, ordering, comparison, and changing of properties.

Upon the newly built dataset, we explore in two directions. The first one concerns effective representations of modeling instructional videos. The videos in our consideration have an average length of 5.27 min and as instructional videos, they are structured and have step-by-step procedure constraining the understanding task. By modeling the temporal relations among different procedures, we are expecting valuable information to be extracted from the instructional videos, for which we study various model structures and propose a novel Recurrent Graph Convolutional Network (RGCN). The RGCN deals with complex reasoning by message passing in the graph, but also maintains the sequential ordering information by a supporting RNN. In this design, graph and RNN can boost each other since the information can be swapped between the two pathways.

Second, we explore the use of different modalities in video modeling. Apart from visual information, temporal boundaries, descriptions for each procedure, and transcripts are explored. In this direction, we want to test the effect of combining various types of available annotations with our developed video models on understanding instructional videos. Given that modeling instructional videos from vision alone is hard, combining such information approximates better the human learning experiences and it, in turn, gives us a hint for devising better models for machine intelligence.

We conduct extensive experiments on the YouQuek dataset. In the ablation study, we find that attention mechanism helps boost the performance. Our proposed RGCN model outperforms all other models with respect to the overall accuracy, even without attention. From the modality perspective, modeling instructional videos using temporal boundaries together with descriptions can help dig more valuable information from videos. We also conduct human quiz on the QAs in our dataset. Results show that machines still have a large gap to human performance in that even without visual information, humans still can answer some questions correctly using life experience, or common sense, which hints us that incorporating the external knowledge with video models will be helpful for future works.

Our main contributions are summarized as follows.

- We propose YouQuek dataset, the first reasoning-oriented dataset for understanding instructional videos.
- We propose both models with various structures, especially a novel RGCN model, for video modeling. Our RGCN outperforms all other models even without attention.
- We incorporate multi-modal information to perform extensive experiments on YouQuek showing that description can boost the video understanding capability, while transcripts could not.

The rest of the paper is organized as the following. We first discuss some related works in Sec. [2] and introduce the proposed YouQuek dataset in Sec. [3]. Then in Sec. [4] we set up series of baseline models for the dataset, and propose RGCN as a new model for instructional video reasoning. In Sec. [5], we demonstrate and discuss the experiment results. Conclusions are drawn in Sec. [6]. The YouQuek dataset and our code for all methods will be released upon acceptance.

2. Related Work

Instructional Video Understanding: Instructional video understanding has received much attention recently. Alayrac et al. [1] and Kuehne et al. [11] both leverage the natural language annotation of the videos to learn the instructional procedure in videos. Zhou et al. [23], however, propose to learn the temporal boundaries of different steps in a supervised manner without the aid of textual information. Dense captioning is also posed on instructional videos in [24], which aims at localizing temporal events from a video, and describing them with natural language sentences. Visual-linguistic ambiguities can be a common problem in instructional videos with narratives. Huang et al. [6] focus on such ambiguities caused by the changing in visual appearance and referring expression, and aim to resolve references with no supervision. Huang et al. [7] perform visual grounding task in instructional videos, also coping with visual-linguistic ambiguities. Yet, none of these works have tackled the QA problem on instructional videos, despite the uniqueness for instructional videos to perform reasoning.

Video Question Answering: People are gaining interests in video question answering (VideoQA) in recent years. Most of the current VideoQA tasks are focusing on direct facts in short videos [20, 22, 21, 19, 25]. They all automatically generate QA pairs using a state-of-the-art question generation algorithm proposed in [4]. However, such autogeneration mechanism often generates QA pairs with poor quality and low diversity, though grammatically correct. Worse still, auto-generated QA pairs cannot involve reasoning. From the reasoning point of view, MovieQA [15] use
human annotated QA pairs on movies to evaluate automatic story comprehension. SVQA [14], following the step of [9], extend the CLEVR dataset to the video version. Yet, it still focuses on short-term relations, and does not fit natural settings.

3. YouQuek Dataset

To validate the proposed task on instructional video reasoning, we introduce YouQuek dataset, a reasoning-oriented video question answering dataset based on YouCook2 dataset. The dataset contains 15,355 question-answer (QA) pairs in total. Tailored for our dataset, we annotate the QA pairs with six different tags, where each QA pair could be labeled with more than one tag. In supplementary material, we show example QA pairs for each tag described below.

**Counting:** This tag annotates a QA pair that involves counting. One may count the occurrence time of certain actions or the number of certain ingredients. E.g., “How many white ingredients are used in the recipe?” Apart from counting, we also need to find out the target ingredients according to their colors.

**Time:** Time is a distinguishing feature in videos compared to images. This category of questions are mainly about timing and duration. A typical example is, “Which one is faster: adding water or adding salt?”. To answer this question, we not only need to know how long it takes for both actions, but also need to make comparison of the duration.

**Order:** Long-term temporal order is a unique feature for instructional videos, because instructional videos come with step-by-step procedures, and the order information matters. E.g., in YouCook2, the ordering of procedure is critical to the success of one recipe. Therefore, we stress out questions related to action orders, e.g., “What happens before/after/between ...?”, and “Does it matter to change the order of ... and ...?”

**Taste:** YouCook2 is an instructional cooking video dataset, so we bring up with the taste questions. This type of QA pairs is about the flavor and the texture of the dish. Taste can also be related to reasoning in that one can infer the taste from the ingredients used, and the texture from the cooking methods applied. Note that we avoid questions that are subjective such as “Is this burger tasty?”, which cannot be answered by reasoning, but by subjective inspection.

**Complex:** This tag presents a broader concept than all other tags above. By “complex”, we emphasize a multi-step reasoning process instead of one-step reasoning. This type of questions overlaps with all other types.

**Property:** Cooking usually involves changes of ingredients. The properties of ingredients, e.g. their shape, color, size, location, etc., may vary at different time points as the cooking procedure goes on. This type of questions is different from “order” questions since we are asking about certain ingredients rather than actions.

In Tab. 1, we contrast our dataset to some other VideoQA datasets. Our dataset is unique in that we not only build the dataset based on instructional videos, but also focus on long-term ordering and higher-order inference.

3.1. QA collection

Many existing VideoQA datasets [21, 19, 22, 20, 25] adopt an automatic question-answer (QA) generation technique proposed by [4] to generate QA pairs from texts. However, QA pairs obtained via this method suffer from extremely low diversity. Also, automatic methods cannot generate questions involving complex reasoning, which goes against our goal of constructing the dataset. Therefore, we apply Amazon Mechanical Turk (AMT) to collect question and answer pairs. For details about the collection of QA and multiple choice alternatives, please refer to supplementary material.

3.2. Statistics

In Fig. 2a, we show the statistics of six different categories of questions. We have 7,200 complex reasoning QA pairs, consisting nearly half of our dataset. Other questions involve simpler reasoning procedure, but still cannot be answered by direct observation from the videos. On average, we have 1.478 tags per QA pair, 2.289 words per answer, and 7.678 QA pairs per video.

To illustrate our dataset better, we split the QA pairs into four categories with respect to answer types, namely “Yes/No” for answers containing yes or no; “Numeric” for answers containing numbers, mostly related to counting and time; “Single word” for answers with only one word, excluding QA pairs in “Yes/No” and “Numeric”; “Text” for answers with multiple words, excluding QA pairs in “Yes/No” and “Numeric”. Fig. 2b shows the distribution of four different types of answers in our dataset.
Table 1: Comparison among different video question answering datasets. The first four columns are: “Inst.” for whether it is based on instructional videos; “Natural” for whether videos are of natural world settings; “Reason” for whether questions are related to reasoning; “Human” for whether QA pairs are collected through human labor.

| | Inst. | Natural | Reason | Human | # of QA | Per video length | Answering form |
|---|---|---|---|---|---|---|---|
| VTW [21] | x | ✓ | x | x | 174955 | 1.5 min | Open-ended |
| Xu et al. [19] | x | ✓ | x | x | 294185 | 14.07 sec | K-Space |
| Zhu et al. [25] | x | ✓ | x | x | 390744 | >33 sec | Fill in blank |
| Zhao et al. [22] | x | ✓ | x | x | 54146 | 3.10 sec | Open-ended |
| SVQA [14] | | ✓ | ✓ | ✓ | 118680 | - | K-Space |
| MovieQA [15] | x | ✓ | ✓ | ✓ | 6462 | 200 sec | Multiple choice |
| YouQuek (Ours) | ✓ | ✓ | ✓ | ✓ | 15355 | 5.27 min | Multiple choices and K-Space |

4. Instructional Video Reasoning

With the newly collected YouQuek dataset, we perform reasoning tasks by answering questions on instructional videos. We first formally define our problem in Sec. 4.1. Then in Sec. 4.2 based on attention mechanism, we design sequential model (SEQ-SA) and graph convolutional model (GCN-SA). We also propose Recurrent Graph Convolutional Network (RGCN) which captures both temporal order and complex relations to overcome the limitation of SEQ-SA and GCN-SA. In Sec. 4.3 additional modalities such as description and transcripts are added to the reasoning model to help gain better performance.

4.1. Problem Formalization

Multiple Choice: Since the questions in the YouQuek dataset have alternative choices, we can use a three-way score function \( f(v, q, a) \) to evaluate each alternative and choose the one with the highest score as correct answer:

\[
j^* = \arg \max_{j=1,...,M} f(v, q, a_j),
\]

where \( M = 5 \) in our case, and \( v, q, a \) represent the feature of video, question and answer respectively. In this work, \( q \) and \( a \) are the final hidden states by encoding the question and answer via RNNs. Here, \( f(\cdot, \cdot, \cdot) \) denotes a MLP whose input is the concatenation of \( v, q, \) and \( a \) and output is a single neuron classifying how likely the given answer \( a \) is the correct one.

K-Space: Similar to other visual QA problems, the reasoning task can also be formulated as a classification problem on the answer space. Then the alternative (negative) answers are all other answers in the training set. Here, \( K \) types of distinct answers are assigned to \( K \) categories \( \{A_i\}_{i=1}^K \). A MLP with \( K \) output neurons is tasked to predict the correct answer \( A^* \) by taking in \( v \) and \( q \):

\[
A^* = \arg \max_{j=1,...,K} g_j(v, q),
\]

where \( g_j \) denotes the output score of the \( j \)-th neuron.

4.2. Models

In this section, we mainly focus on the design of video models that can capture procedure relations in instructional events. Their generated video feature \( v \) will be used for question answering. First, we describe how we pre-process the videos. Then, we introduce the architecture of proposed models that are suitable for VideoQA. Especially, we propose a novel RGCN architecture that can perform message passing between two paths: RNN and GCN, in order to capture both time series and global properties for modeling instructional videos.

Pre-processing: The videos in our consideration have an average length of 5.27 minutes, which requires us to process the videos into more tractable representations before any sophisticated modelings. Following [23], we define procedure as the sequence of necessary steps comprising a complex instructional event and segment a video into \( N \) procedure segments (see Fig. 5a). To directly benchmark the reasoning ability, we use the ground truth provided by [23] instead to avoid any errors caused by intermediate processing. Note that one can apply method developed in [23] for automatically segmentation. The frames within each segment are sampled, of which the features are then extracted by ResNet [3] and encoded by a RNN model. Therefore, we can obtain the features of the procedure segments \( \{X_i\}_{i=1}^N \in \mathbb{R}^d \) and use them for relation modeling.

SEQ-SA: We first propose an attention-based RNN model (see Fig. 3b) for an example of \( N = 4 \) to model video representation \( v \), where the encoded question feature is used to attend all video features at different time steps. The similarity \( a_i \) between question feature \( q \) and segment feature \( X_i \) is computed by taking the dot product of \( q \) and \( X_i \) followed by a soft-max normalization: \( a_i = \frac{\exp(q^T X_i)}{\sum_{j=1}^N \exp(q^T X_j)} \). Then we multiply each \( X_i \) by \( a_i \) to obtain the question-attended video feature \( X'_i = a_i X_i \). Finally, we feed \( X'_i \) into an RNN model of which the final hidden state \( h_N \) of RNN is taken as the video feature representation \( v \).

GCN-SA: We consider a fully-connected graph (see Fig. 3c) to model complex relations among the procedure
Figure 3: Model architectures. In (a), we demonstrate the pre-processing procedure. We show an example video on how to make hash brown potatoes (YouTube ID: kj5y71bsJM). It demonstrates the basic concepts of instructional videos in YouCook2 dataset. Temporal boundaries means the human annotated start/end time stamp of a procedure, which is well defined in [23]. Video are segmented into several segments (procedures) by the temporal boundaries. Descriptions are also annotated by human, corresponding to each procedure. Transcripts are auto-generated by speech recognition on YouTube. An example QA pair for the video in (a) is, Q: “How many actions involving physical changes to potatoes are done before adding salt?” A: “2.”. In (b) and (c), we have question feature attending on each segment. In (d), we illustrate the structure of our proposed RGCN model, where GCN interacts with RNN via “swap” operation which takes in RNN’s hidden state $h_{t-1}$ and outputs the graph node $S_{t-1}^i$ of GCN. We zoom in the first swap operation to provide an intuitive visualization.

segments. Although the time dependencies defined by the original video are omitted, different edges in the graph can mine different relations for various reasoning tasks. We use a multi-layer GCN model for this purpose. We define \( \{ S^i_j \}_{i=1}^N \), where $S^i_j \in \mathbb{R}^d$, as the graph nodes, where $N$ is the number of nodes within one layer, $M$ is the number of layers. We first initialize nodes \( \{ S^1_i \}_{i=1}^N \) in the first layer by segment features \( \{ X^i \}_{i=1}^N \) correspondingly. We adopt the same GCN structure as described in [17]:

$$Z = \text{ReLU}(GW)$$, (3)

where \( G \in \mathbb{R}^{N \times N} \) represents the adjacency graph, \( S \in \mathbb{R}^{N \times d} \) denotes the concatenation of all node features \( \{ S^i_j \}_{i=1}^N \) in one arbitrary layer, and \( W \in \mathbb{R}^{d \times d} \) is the weight matrix which is different for each layer. Each element $G_{ij}$ in $G$ is the dot product similarity $S^i_j S^j_i$. Three GCN layers are used in this work, where the output of the previous layer serves as the input of the next layer.

To apply the attention mechanism, we add an additional node in the last layer of the GCN to represent the question feature $q$, and this question node is connected with all other graph nodes \( \{ S^M_j \}_{j=1}^N \) through $N$ edges. Question node attends to each graph node through different weights on the edges. Similar to SEQ-SA, the weights between $q$ and \( \{ S^M_j \}_{j=1}^N \) are the dot products of corresponding node pairs, followed by a soft-max normalization. Finally, we use an average pooling operation to compress the output of the last layer $Z \in \mathbb{R}^{N \times d}$ to $v \in \mathbb{R}^d$.

**RGCN:** Since the aforementioned GCN-SA is unable to capture the temporal order of video features [17], and SEQ-SA cannot model the relations between segments with long time spans, we propose a novel Recurrent Graph Convolutional Network (RGCN) architecture (see Fig. 3d) to overcome such limitation. The RGCN is a recurrent model that consists of two pathways: RNN and GCN. RNN interacts with GCN mainly through a swap operation (see Fig. 3d). The details are as follows.

The RNN pathway with $N$ time steps takes in the seg-
ment features $X_t$ at each time step. The GCN pathway has $N$ layers, each of which contains $N$ graph nodes. Note that the GCN has the same number of layers as the time steps in RNN pathway. We adopt the same GCN architecture as described in GCN-SA model except that a recurrent computation paradigm is applied here, where the weights $W$ is shared among all layers. The computation within the RNN memory cell at each time step and the computation of each GCN layer are performed alternatively. For each time step $t$, we first concatenate together the segment feature $X_t$ and the feature of node $S^t_{i-1}$ in GCN, which is then used as the input to RNN memory cell at the $t$-th time step. Following [5], we update the hidden state $h_t$ of RNN:

$$h_t = \text{RNN}([X_t, S^t_{i-1}], h_{t-1}) \, ,$$ (4)

Then we replace GCN’s graph node $S^t_i$ with the updated hidden state $h_t$ of RNN. This swap operation act as a bridge between RNN and GCN for message passing. Finally, the $(t+1)$-th GCN layer takes all $\{S^t_i\}_{i=1}^N$ as input to compute the response $\{S^{t+1}i\}_{i=1}^N$:

$$Z_{t+1} = \text{ReLU} \{Z_t W\} \, ,$$ (5)

where $Z_t$ is the concatenation of $\{S^t_i\}_{i=1}^N$. We take the final hidden state $h_N$ of RNN as the video representation $v$.

Additionally, we extend the proposed RGCN with attention mechanism. The two pathways corresponds to the SEQ and GCN model, so we simply adopt how attention is cast on both pathways, and obtain RGCN-SA.

4.3. Multiple modalities

Besides videos and questions, we further investigate how much benefit we can obtain from other modalities such as narratives, which is very common in instructional videos. We are interested in two types of narratives, namely transcripts and descriptions.

Transcripts: The audio signal is an important modality for videos. In our dataset, the valuable audio information in videos is all chefs speaking. Therefore, we substitute audio with auto-generated transcripts on YouTube. Transcripts, which can be seen as describing the corresponding procedures, are highly unstructured, noisy, and misaligned narratives [3] in that chefs may talk about things not related to the cooking procedure, or that the speech recognition on YouTube may generate some unexpected sentences. Neverthless, it can provide extra information to solve visual ambiguities, e.g., distinguishing water from white vinegar, which both look transparent.

Descriptions: In YouCook2 dataset, each procedure in a video corresponds to a sentence of natural language description annotated by a human. Different from transcripts, descriptions are much less dense with respect to time, and can be seen as highly constrained narratives because human labor is applied to extract the essence of the corresponding procedures. Each piece of description is associated with the procedure it describes because they are highly related semantically.

For each individual modality (which can be description or transcripts), we aim to model a feature representation $m$, then fuse it with $v$ and $q$ to predict the answer $A^∗$. To achieve this goal, we make use of a hierarchical RNN structure: a lower-level RNN models the natural language words within each segment, and a higher level RNN models the global feature of the video.

5. Experiments

First, we introduce the implementation details of the training process. Then some baseline models are described, followed by results analysis. Also, we explored the benefit introduced by other modalities such as description and transcripts. All experiments conducted in this work are evaluated on both multiple choice and K-Space evaluation metrics. In Tab. 2 only multiple choice accuracy is provided for discussion. All other results on K-Space are in supplementary material.

5.1. Implementation details

Our codes are based on PyTorch deep learning framework. ResNet is used to extract visual features of 500 frames in each video, producing a 512-d vector. By using embedding layers, the question words are transformed into 300-d vectors which are optimized during the training process. For all models involving RNNs in this work, we apply single direction LSTMs [5] (an improved version of vanilla RNN) with 512 hidden units. Adam optimizer is used with the learning rate of 0.0001.

We split the training/testing set according to the original YouCook2 dataset. All videos in the YouCook2 training set are used as training videos in our dataset. Therefore, there are 10,179 QA pairs in our training set, and the rest are treated as testing set.

5.2. Baselines

We set up some baseline models which takes no instructional information. In other words, only the original video is presented to the models without temporal boundaries or descriptions.

Bare QA: First, we build the QA model which predicts answers based on questions only (without videos). Then for multiple choice, the answer is predicted by a similar way as Eq. 1:

$$j^∗ = \arg \max_{j=1,...,M} f(q, a) \text{.}$$

For K-Space, we adopt a similar formula as Eq. 2:

$$A^∗ = \arg \max_{j=1,...,K} g_j(q) \text{.}$$

Naive RNN: RNN is a base of most state-of-the-art ImageQA [2,12,10] and VideoQA[19,21] models. Instead of
Table 2: Results on different model architectures.

|                | Count | Order | Taste | Time | Complex | Property | All  |
|----------------|-------|-------|-------|------|---------|----------|------|
| Common sense   | 0.535 | 0.432 | 0.654 | 0.485| 0.511   | 0.588    | 0.528|
| Bare QA        | 0.435 | 0.321 | 0.466 | 0.239| 0.292   | 0.438    | 0.348|
| Naive RNN      | 0.434 | 0.330 | 0.467 | 0.234| 0.283   | 0.449    | 0.347|
| MAC            | 0.438 | 0.331 | 0.462 | 0.229| 0.294   | 0.437    | 0.348|
| SEQ            | 0.452 | 0.337 | 0.476 | 0.230| 0.288   | 0.449    | 0.352|
| GCN            | 0.452 | 0.341 | 0.464 | 0.224| 0.282   | 0.427    | 0.346|
| GCN-SA         | 0.477 | 0.343 | 0.487 | 0.229| 0.311   | 0.446    | 0.365|
| RGCN-SA        | 0.545 | 0.367 | 0.481 | 0.279| 0.316   | 0.486    | 0.403|

applying the segmentation pre-processing which we introduced in Sec. 4.2. Naive RNN takes in the ResNet feature of sampled video frames directly. Similar to other models discussed previously, we take the final hidden state of the RNN as the video feature \( v \). Then we evaluate the model performance based on Eq. 1 and Eq. 2.

MAC: MAC [8] is currently the state-of-the-art model on CLEVR dataset. Since our proposed YouQuek dataset shares similar question style with CLEVR dataset, we adopt MAC as another alternative model. To apply MAC which is designed for spatial reasoning to the temporal reasoning task in our work, we replace the input image features \( \{ I_i \}_{i=1}^L \), where \( I_i \in \mathbb{R}^d \) \( (L \) is the number of spatial dimension of an image), with video frame features \( \{ X_i \}_{i=1}^N \), where \( X_i \in \mathbb{R}^d \) \( (N \) is the number of sampled frames).

Human quiz: Apart from using deep learning models to complete VideoQA tasks, we also invite ten human annotators to perform human test. First, they are asked to answer the questions without any other information, but by guessing or using common sense. Second, they are allowed to watch the videos without audio. Finally, audio is also turned on to correspond with transcripts. Details of the setting are in supplementary material.

5.3. Results Analysis

Tab. 2 shows the experiment results on all models and baselines. We start with the comparison among baseline models that are without temporal boundary information (i.e., Bare QA, Naive RNN and MAC). As we can see from row 2 to row 4 of Tab. 2 that the three baselines have very close overall accuracy. Though Naive RNN take in the video stream, it cannot achieve better results than the bare QA. Therefore, we claim that as the base of most state-of-the-art visual QA models, RNN fails to extract meaningful visual information for instructional video reasoning. The reason is that it is difficult for RNN to model complex relations due to its sequential structure. Another reason is that RNN cannot capture long time dependencies of videos due to the memory limitation, even for RNN variants such as LSTM and GRU. As the best model on CLEVR, MAC achieves the same overall accuracy with Bare QA on YouQuek, which demonstrates the special difficulty of video understanding compared with ImageQA.

Then we analyze the performance of models proposed in Sec 4.2 which incorporate temporal boundary information of instructional videos to boost the performance. Recall that the temporal boundaries are provided by the ground truth in [23]. First, to evaluate the improvement introduced by attention mechanism, we remove the question attention operation to formulate the models: SEQ, GCN, RGCN, the results of which are shown in row 5 to row 7 of Tab. 2. We can see from row 5 to row 10 of Tab. 2 that the margins gained by introducing attention are from 1.1% to 2.1%, which demonstrates that question can guide the models to extract more meaningful features, and all these models outperform baselines by a big margin. Especially, RGCN-SA achieves the highest overall accuracy of 40.3%, 5.5% higher than MAC, and SEQ-SA ranks second among the attention based models with an overall accuracy of 37.3%. This demonstrates that the procedure segmentation helps models make better use of video streams.

Finally, we investigate the performance of attention based models on various question categories. The comparison between SEQ-SA and GCN-SA shows that GCN-SA achieves higher accuracy scores on “count” and “taste” questions, while SEQ-SA performs better on all other categories. Intuitively, “order”, “property” questions require temporal order information to be answered, because the questions usually contain sequence-related keywords, e.g., “before/after/between”. Graph structure can hardly capture such ordering information. Nevertheless, the capability of modeling relations gives graph structure a reasonably good performance, especially on “count” and “taste” questions which challenge less on ordering. Since both sequence and graph models show advantages on different categories of questions, we take the advantages of both two models to
Table 3: Results on multiple modalities, where V stands for visual information, CC for transcripts, and D for descriptions.

|                | SEQ     | SEQ-SA   | GCN     | GCN-SA   | RGCN    | RGCN-SA  |
|----------------|---------|----------|---------|----------|---------|----------|
| Visual         | 0.352   | 0.373    | 0.346   | 0.365    | 0.392   | 0.403    |
|                | 0.160   | 0.164    | 0.150   | 0.164    | 0.179   | 0.182    |
| CC             | 0.346   | 0.353    | 0.343   | 0.346    | 0.361   | 0.366    |
|                | 0.159   | 0.152    | 0.143   | 0.150    | 0.152   | 0.144    |
| Description    | 0.353   | 0.365    | 0.352   | 0.352    | 0.385   | 0.389    |
|                | 0.158   | 0.156    | 0.157   | 0.153    | 0.163   | 0.162    |
| V+CC           | 0.347   | 0.375    | 0.354   | 0.375    | 0.390   | 0.393    |
|                | 0.151   | 0.167    | 0.177   | 0.177    | 0.173   | 0.180    |
| V+D            | 0.351   | 0.379    | 0.349   | 0.383    | 0.413   | 0.416    |
|                | 0.160   | 0.173    | 0.148   | 0.183    | 0.194   | 0.203    |

In this paper, we emphasize reasoning on instructional videos. We construct YouCook Question Answering (YouQuek) dataset, and three models with sequence (SEQ), graph (GCN), and fused (recurrent graph convolutional network, RGCN) structures are proposed to explore the instructional information. Attention mechanism is applied on the proposed models to boost performance, and RGCN-SA achieves the best accuracy on both multiple choice and K-Space evaluation metrics. Experiment results show that the proposed RGCN successfully fuse the order and relation information together for modeling instructional videos. Also, multiple modalities for instructional videos are analyzed, showing that human annotated temporal boundaries and descriptions are critical for instructional video reasoning.
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