Self-supervised Pre-training and Contrastive Representation Learning for Multiple-choice Video QA

Seonhoon Kim[1,2], Seohyeong Jeong[1], Eunbyul Kim[2], Inho Kang[2], Nojun Kwak[1,†]

[1] Seoul National University, [2] Naver Search

{seo_hyeong, nojunk}@snu.ac.kr, {seonhoon.kim, silverstar.kim, once.ihkang}@navercorp.com

Abstract

Video Question Answering (Video QA) requires fine-grained understanding of both video and language modalities to answer the given questions. In this paper, we propose novel training schemes for multiple-choice video question answering with a self-supervised pre-training stage and a supervised contrastive learning in the main stage as an auxiliary learning. In the self-supervised pre-training stage, we transform the original problem format of predicting the correct answer into the one that predicts the relevant question to provide a model with broader contextual inputs without any further dataset or annotation. For contrastive learning in the main stage, we add a masking noise to the input corresponding to the ground-truth answer, and consider the original input of the ground-truth answer as a positive sample, while treating the rest as negative samples. By mapping the positive sample closer to the masked input, we show that the model performance is improved. We further employ locally aligned attention to focus more effectively on the video frames that are particularly relevant to the given corresponding subtitle sentences. We evaluate our proposed model on highly competitive benchmark datasets related to multiple-choice video QA: TVQA, TVQA+, and DramaQA. Experimental results show that our model achieves state-of-the-art performance on all datasets. We also validate our approaches through further analyses.

1 Introduction

Recent years have witnessed significant improvements in vision and language communities, which have consequently led to substantial attention in vision-language multi-modality tasks such as visual grounding (Plummer et al. 2015), image captioning (Chen et al. 2015), and visual question answering (Antol et al. 2015; Goyal et al. 2017). Furthermore, as video becomes ubiquitous, as a daily source of information and communication, video-language tasks such as video captioning (Zhou et al. 2018), video moment retrieval (Liu et al. 2018), and video question answering (video QA) (Lei et al. 2018, 2019) are emerging as important topics. Among these topics, video QA is especially challenging, as it requires fine-grained understanding of both video

† Corresponding author.

Figure 1: Multiple-choice Video QA example of TVQA dataset, composed of a 60-90 second long video clip, question, and the answer options. A video clip consists of video frames and subtitles, and each subtitle is connected to several frames. In our setting, we additionally extract object information and visual features from the video frames using Faster R-CNN and ResNet-101 as in the bottom right yellow box. We use question, answer, subtitles, and objects as our text input and visual features as our visual input.

and language. Figure 1 shows an example of multiple-choice video QA from the TVQA dataset. The multiple-choice video QA task requires the model to select the correct answer given a question, corresponding video frames, and subtitles.

To address video QA, several works have utilized early stage fusion method (Kim et al. 2017; Na et al. 2017) to merge two different modalities, while other recent works (Lei et al. 2018, 2019) have employed late stage fusion method, which extracts representation from language and vision independently during the early stage of framework, and combines them in QA-aware manners. To obtain further fine-grained information from videos, Kim, Tang, and Bansal (2020) has generated captions using a dense caption model (Yang et al. 2016a) to translate vision modality to that of language. Furthermore, Geng et al. (2020) has reckoned that explicitly replacing the predicted regions corresponding to a person from object detection with the name of protagonists helps the model to answer the questions.

Unlike the previously mentioned methods, which focus on extracting QA-aware visual information, we shift our fo-

cus to the training procedure that could possibly take the most advantage out of the given data. On top of utilizing large-scale pre-trained language model and fine-grained object detection results on videos, motivated by recent progress in contrastive learning (Khosla et al. 2020; Chen et al. 2020) and unsupervised pre-training in natural language processing (Geng et al. 2020), we propose a training scheme for multiple-choice video QA that integrates these two perspectives to increase performance gain.

Our framework consists of two consecutive stages of training: first is the self-supervised pre-training stage and second is the training stage with a supervised contrastive learning loss in an auxiliary loss setting. During the self-supervised pre-training, instead of predicting the correct answer, our model is expected to predict the relevant question given contexts such as video clips and subtitles to learn a better weight initialization. This procedure does not require any additional data or human annotation. For the fine-tuning stage, in addition to the main QA loss, we propose a contrastive loss that can be applied for the multiple-choice video QA tasks and we also make use of an optional span loss. Taking ground truth answer as a positive sample and the rest as negative samples, the contrastive loss confines the positive sample to be mapped in the neighborhood of an anchor, a perturbed ground truth answer, and the negative samples to be away from the anchor. We further show the effectiveness of contrastive loss by investigating how the distance between the positive sample and negative samples changes as the training continues.

In addition, we present a locally aligned attention mechanism to selectively extract video representations corresponding to the given subtitles. Previous works (Lei et al. 2018, 2019; Kim, Tang, and Bansal 2020) have utilized attention mechanisms on video sequences and subtitles with either question and answer pairs respectively or with the subtitles in a globally aligned manner. In contrast, we hypothesize that it is desirable to apply a direct attention mechanism that computes attention score between two modalities in locally aligned fashion. Performing attention in locally aligned fashion is beneficial to the model's performance, since it prevents the model from reasoning with unnecessary information.

We evaluate the proposed approach on large-scale TV shows-based question answering datasets; TVQA, TVQA+, and DramaQA. Each video clip is paired with corresponding subtitles and natural language multiple-choice questions. Empirically, our model takes advantage of the supervised contrastive loss in the main stage and gives further improvements when self-supervised pre-training is preceded. Moreover, our model demonstrates significant performance increase on the test server, outperforming the state-of-the-art scores. Our contributions are as follow:

- We improve the performance of the model by adding a novel self-supervised pre-training stage.

- We introduce additional supervised contrastive loss in an auxiliary setting during the main stage of training.

- We propose a locally aligned attention mechanism to selectively focus on corresponding video sequences of given

subtitles.

- We show that our framework achieves state-of-the-art performance on TVQA, TVQA+, and DramaQA.

2 Related Work

2.1 Visual/Video Question Answering

Visual and video question answering requires the fine-grained interplay of vision and language to understand multi-modal contents. In the last few years, most of the pioneering works used a single image as a visual content with a joint image-question embedding and a spatial attention to predict the correct answer (Antol et al. 2015; Xu and Saenko 2016; Yang et al. 2016b; Fukui et al. 2016). More recently, beyond question answering on a single image, as video has become an important source of information, video QA has emerged as a key topic in the vision-language community (Lei et al. 2018, 2019; Kim et al. 2019b; Le et al. 2019; Kim, Tang, and Bansal 2020; Kim et al. 2020; Geng et al. 2020). Contrast to previous works done in video QA, in this work, we focus not only on learning the multi-modal representations, but also on the training procedure that could take additional advantages of the given dataset.

2.2 Self-supervised Learning

Modern techniques of self-supervised learning are pre-trained on large-scale external and unlabeled datasets (Devlin et al. 2018; Liu et al. 2019; Raffel et al. 2019). Several studies (Lei et al. 2019; Yang et al. 2020; Kim, Tang, and Bansal 2020; Kim et al. 2020) have taken advantages of these self-supervised pre-trained models and combined with their video QA models to learn representations of the text data such as questions, answers, subtitles, and extracted visual concepts. Likewise, we utilize the pre-trained language model to embed textual information to solve video QA tasks. Besides, we propose a self-supervised learning approach for multiple-choice video QA of predicting a relevant question given contexts, which does not require any additional data or further annotations.

2.3 Contrastive Representation Learning

Contrastive representation learning (Hadsell, Chopra, and LeCun 2006) has been explored in numerous literature as a method of extracting powerful feature representation. The main goal of the learning is to, as the name suggests, contrast the semantically nearby points against dissimilar points, in the embedding space. Many tasks (Dosovitskiy et al. 2014; He et al. 2020; Chen et al. 2020) have been proposed to incorporate various forms of contrastive loss into a self-supervised learning algorithm. Meanwhile, some approaches (Khosla et al. 2020; Tian et al. 2020) have focused on leveraging labeled data into contrastive representation learning. In this work, we exploit supervised contrastive loss in an auxiliary setting on top of the main task to learn the better representation.
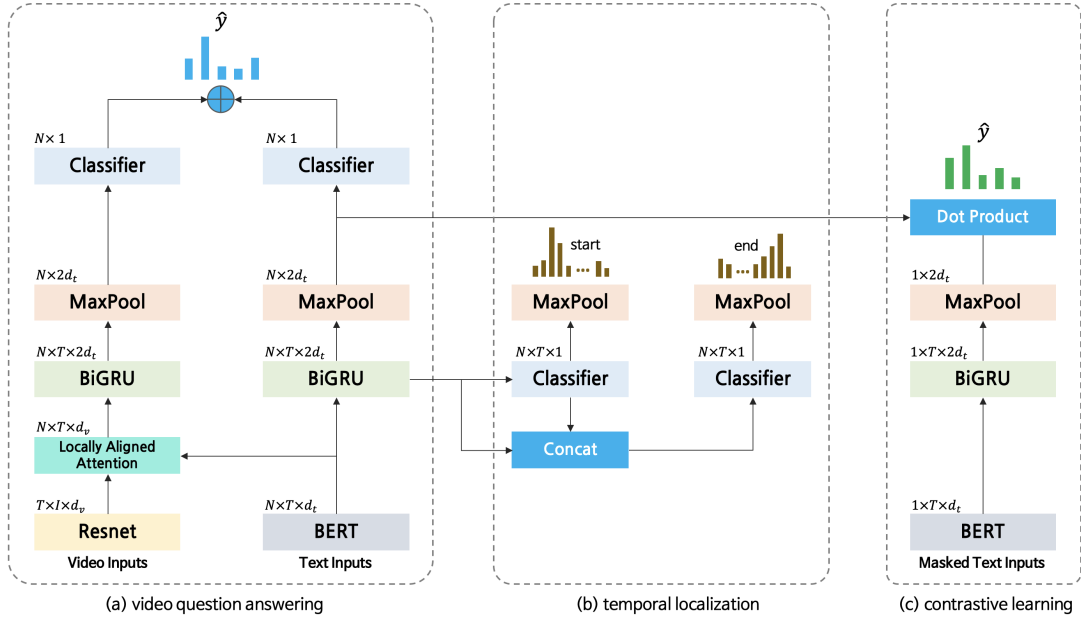
Figure 2: Overall architecture of our model: (a) For a video QA part, we use ResNet and BERT to extract video and text representations. A locally aligned attention mechanism is introduced to match each subtitle sentence with the corresponding images. Then, we use RNNs to learn sequential information of subtitle sentences. We predict the final answer distribution on both modalities. At inference time, we use this video QA part only. (b) Temporal localization, one of our auxiliary tasks, is used to predict the necessary part to answer the question. (c) We introduce the contrastive loss, which is another component of our auxiliary tasks, to enhance the model's performance. We utilize the identical BERT and RNN, used in a video QA part with the masked text input of the ground-truth and predict the answer distribution by contrasting positive pair against negative pairs.

3 Methods

In this section, we describe our architecture for multiple-choice video QA with an additional auxiliary learning task using a contrastive loss. Furthermore, a self-supervised pre-training approach can be applied before the main training stage. For our problem setting, the inputs are composed of the following: (1) question q, (2) answer options $\Omega_a = \{a_n | n = 1, ..., N\}$, (3) subtitle sentences $\{S_t | t = 1, ..., T\}$ as a text context, and (4) video frames $\{V_t^i | t = 1, ..., T, i = 1, ..., I\}$ as a visual context where a_n is the nth answer option, S_t is the tth subtitle sentence, and V_t^i is the ith image frame in the tth video segment connected to the tth subtitle sentence. Our goal is to predict the correct answer given a question and text/visual contexts.

$$\hat{a} = \underset{a \in \Omega_a}{\operatorname{argmax}} \, p(a|q, S, V; \theta) \qquad (1)$$

3.1 Input Representation

Visual representation We first separate each video into T segments using the provided subtitle timestamp in the dataset, and further separate each segment into I image frames. Then, as shown in Figure 1, for the visual representation, we use ResNet-101 (He et al. 2016) trained on ImageNet (Deng et al. 2009) to extract global image features $v_t^i \in \mathbb{R}^{2048}$ as the ith image feature in the tth video segment. In addition, using Faster R-CNN (Ren et al. 2015) trained on Visual Genome (Krishna et al. 2017), we extract objects $o_t^{i_j}$

as j^{th} object in the ith image frame, which can be used as one of the text inputs described in the next subsection.

Text representation We use four types of text inputs: a question, answer options, subtitle sentences, and objects. For the objects o_t, extracted from each image frame in the tth video segment, we use the following as the objects input:

$$o_t = [o_t^{1_1}; ...; o_t^{1_{J_1}}; ...; o_t^{I_1}; ...; o_t^{I_{J_I}}] \qquad (2)$$

where $[\cdot; \cdot]$ is the concatenation operator. To encode entire textual inputs, we use BERT (Devlin et al. 2018) which achieves state-of-the-art performance on a wide range of NLP tasks. While only one or two types of text inputs are used with [SEP] tokens in the standard practices of BERT, since we use four different types of text inputs, we separate them with [SEP] tokens as follows:

$$[\text{CLS}] \, q \, [\text{SEP}] \, a_n \, [\text{SEP}] \, S_t \, [\text{SEP}] \, o_t \, [\text{SEP}].$$

To properly distinguish multiple text inputs (four in our case) in the model, we modify the token type embedding method to explicitly accommodate different token type embeddings as types of text inputs vary. For the first input, we keep the token type embedding of 0 as it is. For the second and third inputs, we use the output of the token type embedding of 1 but multiplied by $\frac{1}{3}$ and $\frac{2}{3}$, respectively, to distinguish them. Lastly, we keep the token type embedding of 1 for the fourth text input.

3.2 Model

Our model consists of two stages: 1) self-supervised pre-training stage with the transformed problem format, and 2) video QA as a main stage. For the video QA stage, in addition to predicting the answer as our main task, we make use of timestamp annotation of localized span needed to answer the question given in the dataset and add temporal localization learning as an auxiliary task. And the supervised contrastive learning is combined as an auxiliary task in the main training stage as well. In the next subsections, we first describe our video QA architecture (Fig. 2), and then, we describe how we utilize the self-supervised pre-training as our prerequisite learning.

Video Question Answering We use visual and text inputs for our video QA network as shown in Fig. 2(a). For the visual representation $H_v \in \mathbb{R}^{T \times I \times d_v}$, we extract $d_v = 2048$ features of the last block of ResNet-101 which was used in Lei et al. (2018). We set the number of images I as 4, extracted from the video segment connected to each subtitle sentence. In our implementation, we repeated H_v N times to match the dimension with the text representation. For the text representation $H_t \in \mathbb{R}^{N \times T \times d_t}$, we extract $d_t = 768$ features of the hidden state of the [CLS] token from the last layer of 12-layer BERT-base model.

To extract attentive information between a text context from a subtitle and a visual context from the corresponding video frames, we calculate the locally aligned attention to focus on particularly relevant images regarding each subtitle sentence. This prevents the model from reasoning with unnecessary information. Our locally aligned attention mechanism, used only in the image side, is calculated between image frames and the subtitle sentence that share the timestamp with the image frames.

$$H_v^{Att} = \sum_{i=1}^{I} \alpha_i H_{v_i}^T \mathbf{M}, \ \alpha_i = \frac{e^{g_i}}{\sum_{k=1}^{I} e^{g_k}}, \ g_i = H_{v_i}^T \mathbf{M} H_t.$$
$$(3)$$

Here, I is the number of image frames from the video segment matching to each subtitle sentence by the timestamp information given in the dataset, and $\mathbf{M}$ is the projection matrix that converts the text representation into the visual representation space.

To reflect the sequence information between multiple subtitle sentences, we use BiGRU on both text and video respectively. Then, we apply the max-pooling operation across the sequence of the subtitle sentences, to get a global representation of each answer, called hypothesis:

$$\begin{aligned} \mathcal{H}_v^{Att} &= \text{Max}(\text{BiGRU}(H_v^{Att})), \\ \mathcal{H}_t &= \text{Max}(\text{BiGRU}(H_t)). \end{aligned}$$
$$(4)$$

Given the max-pooled hypothesis representations, we use two fully-connected layers as classifiers to obtain the logits s_t and s_v for the answer options on both sides of text and video respectively.

$$s_v = \text{classifier}(\mathcal{H}_v^{Att}), \quad s_t = \text{classifier}(\mathcal{H}_t). \quad (5)$$

Conceptual text input
[CLS] *question* [SEP] *answer option* [SEP] *subtitle sentence* [SEP] *objects* [SEP]

Original text input
[CLS] *Where does Ted go after leaving the bar ?* [SEP] *Ted goes to Marshall's apartment to tell him about the trip* [SEP] *Marshall : In fact, take my car .* [SEP] *necklace brown shirt woman ...* [SEP]

Masked text input
[CLS] *Where does Ted go* [MASK] *leaving the bar ?* [SEP] *Ted* [MASK] *to Marshall's* [MASK] *to tell him about the trip* [SEP] [MASK] *: In fact, take my car .* [SEP] *necklace brown* [MASK] *woman ...* [SEP]

Answer-removed text input
[CLS] *Where does Ted go after leaving the bar ?* [SEP] [MASK] [SEP] *Marshall : In fact, take my car .* [SEP] *necklace brown shirt woman ...* [SEP]

Table 1: Examples of text input of BERT. Original text input is used in a QA network, masked text input is used in a contrastive learning network, and answer-removed text input is used in a self-supervised pre-training stage. Note that, for the readability, we do not use subword tokens in these examples.

Then, we add those logits followed by a softmax function to obtain a probability distribution of each answer option and apply cross-entropy loss as our question answering loss:

$$\hat{y} = \text{softmax}(s_v + s_t), \quad \mathcal{L}_{qa} = -\sum_{i=1}^{N} y_i \log \hat{y}_i. \quad (6)$$

Temporal Localization We use temporal localization network, shown in Figure 2(b), which localizes relevant moments from a long video sequence given a question, and assign the ground truth start/end sentence position in the subtitle sequence using the given start/end time annotations. We utilize the BiGRU output $\mathcal{H}_t$ from the text input, reflecting the sequence information of the text context and a question. Then, we predict the start/end position using span predicting classifiers followed by a max-pooling operation across the five hypotheses, and train them with cross-entropy loss as follows:

$$\mathcal{L}_{span} = -\frac{1}{2}(\log p_{start} + \log p_{end}) \quad (7)$$

where p_{start} and p_{end} are the span probabilities of the start and end ground truth positions respectively. Since we use this temporal localization part as one of our auxiliary tasks, we do not need start/end time annotations as well as temporal localization network in the inference time.

Contrastive Learning Figure 2(c) shows a proposed contrastive learning approach, as another auxiliary task, that enhances the model performance in the multiple-choice video

QA. As described by the masked text input example in Table 1, we first mask out the tokens of the text input, corresponding to the ground truth answer, with a certain probability using a special token [MASK]. We encode the masked text input using the same BERT and BiGRU, that are used in the video QA section (Figure 2(a)), and denote the encoded representation as an anchor, $\mathcal{H}_{anchor} \in \mathbb{R}^{1 \times 2d_t}$. Then, we employ contrastive learning, comparing masked anchor representation and previously extracted text representations, $\mathcal{H}_t \in \mathbb{R}^{N \times 2d_t}$ in eq. (4) from the video QA network. In the representations from the video QA network, we consider the representation corresponding to the ground truth answer as a positive sample, and others as negative samples, and use the dot product to measure the similarity scores between the text representation and the anchor representation.

$$scores = \mathcal{H}_t \mathcal{H}_{anchor}^T \qquad (8)$$

Then, we apply the softmax to the computed similarity scores and optimize it with the cross-entropy loss that can contrast the positive and negative representations correctly.

$$\hat{y}_{con} = \text{softmax}(scores), \ \mathcal{L}_{cont} = -\sum_{i=1}^{N} y_i \log \hat{y}_{con,i} \quad (9)$$

Finally, introducing scale parameters; λ_{qa}, λ_{span}, and λ_{cont}, the total loss is defined as a linear combination of the above three losses as follows:

$$\mathcal{L} = \lambda_{qa} * \mathcal{L}_{qa} + \lambda_{span} * \mathcal{L}_{span} + \lambda_{cont} * \mathcal{L}_{cont} \quad (10)$$

Self-supervised Pre-training We propose a self-supervised pre-training approach that is applicable to the multiple-choice video QA task. While the original problem is to predict the answer using a question and text-visual contexts as eq. (1), we instead train the model to predict the corresponding question using text-visual contexts.

$$\hat{q} = \underset{q \in \Omega_q}{\text{argmax}} \, p(q|S, V; \theta) \qquad (11)$$

In this pre-training stage, we randomly sample negative questions for given video clip to learn the question-video alignment. For each negative training sample, since we previously know which video clips contain which questions, we select questions from other video clips that are not related to the given video clip. In this process, we do not need correct answer annotation, since we replace the part corresponding to the answer option in the input to a single [MASK] token as follows:

[CLS] q_n [SEP] [MASK] [SEP] S_t [SEP] o_t [SEP]

The answer-removed text input example in Table 1 shows an example used in the self-supervised pre-training stage. And as with the main stage, not only question answering loss but also temporal span and contrastive losses are also used in the pre-training stage as eq. (10). By predicting which question comes from a given context, our proposed network can learn stronger representation with a better parameter initialization to improve the model performance.

4 Experiments

We evaluate our approach on three benchmark datasets: TVQA, TVQA+ and DramaQA. TVQA is a large scale multiple-choice video QA dataset based on 6 popular TV shows: *The Big Bang Theory, How I Met Your Mother, Friends, Grey's Anatomy, House, Castle*, and consists of 152,545 QA pairs from 21,793 clips, spanning over 460 hours of video. The training, validation, and test-public set consist of 122,039, 15,253, and 7,623 questions, respectively. TVQA+ is a subset (*The Big Bang Theory*) of TVQA, but TVQA+ adds frame-level bounding box annotations for visual concept words and modifies its timestamp information for better annotations. TVQA+ contains 29,383 QA pairs from 4,198 video clips, with 148,468 images annotated with 310,826 bounding boxes. The training, validation, and test-public set consist of 23,545, 3,017, and 2,821 questions, respectively. Note that we do not use bounding box information on TVQA+ to match the problem format to that of TVQA. DramaQA is built upon the TV drama (*Another Miss Oh*) and it contains 16,191 QA pairs from 23,928 various length video clips. The QA pairs belong to one of four difficulty levels and the dataset provides the character-centered annotations, including visual bounding boxes, behaviors, and emotions of main characters. As in TVQA+, we do not use bounding box information at all. However, we use textual information regarding behaviors and emotions as objects. The number of examples for training, validation, and test datasets is 10,098, 3,071, and 3,022, respectively.

4.1 Implementation Details

We use pre-extracted 2048-dimensional hidden features (d_v in Fig. 2) from the Imagenet-pretrained ResNet-101 and object information from the modified Faster R-CNN trained on Visual Genome (Lei et al. 2018). We use the BERT-base uncased model, which has 12 layers with hidden size of 768 and fine-tuned only top-6 layers due to the limitation of resources. We set the hidden sizes of all the remaining layers as 768 (d_t in Fig. 2). The total video context sequence T is 40, the number of images I corresponding to each subtitle sentence is set to 4, and the number of answer options N is 5 in all datasets, as shown in Figure 2. The maximum number of tokens of the text input is set to 80 for TVQA/TVQA+ and 170 for DramaQA. The probability of masking out the tokens used in our contrastive learning is 0.2. The weights of each loss λ_{qa}, λ_{span}, and λ_{cont} are set to 1, 0.2, and 0.1 based on TVQA+ validation performance. We set the learning rate to 1e-5 for the self-supervised pre-training stage and 5e-5 for the main QA stage. Likewise, the total number of epochs is set to 1 for the pre-training stage and 3 for the main QA stage. We use the batch size of 8 for the entire experiment settings.

4.2 Experimental Results

TVQA We evaluate our model on TVQA dataset as shown in Table 2. Since the ground truth answers of the test set are not provided, we present the performance via the online evaluation server system. Our model achieves 76.15% of accuracy on the test set, outperforming the previous state-of-

Models	Val (Acc.)	Test-public (Acc.)						
	All	bbt	friends	himym	grey	house	castle	All
multi-stream (Lei et al. 2018)	65.85	70.25	65.78	64.02	67.20	66.84	63.96	66.46
PAMN (Kim et al. 2019b)	66.38	-	-	-	-	-	-	66.77
Multi-task (Kim et al. 2019a)	66.22	-	-	-	-	-	-	67.05
CA-RN (Geng et al. 2020)	68.90	71.43	65.78	67.20	70.62	69.10	69.14	68.77
STAGE (Lei et al. 2019)	70.50	-	-	-	-	-	-	70.23
akalsdnr (anonymous)	71.13	71.49	67.43	72.22	70.42	70.83	72.30	70.52
MSAN (Kim et al. 2020)	70.79	-	-	-	-	-	-	71.13
DenseCap (Kim, Tang, and Bansal 2020)	74.20	74.04	73.03	74.34	73.44	74.68	74.86	74.09
Ours	**76.23**	**77.43**	**73.24**	**76.72**	**74.04**	**76.94**	**77.86**	**76.15**

Table 2: Comparison of QA performance with previous methods on TVQA validation and test sets. All results are from the models that do not use timestamp annotations (w/o ts version). We also compare the performance on the 6 individual TV shows.

Models	QA (Acc.)	TempLocal (mIOU)	ASA
ST-VQA (Jang et al. 2017)	48.2	-	-
two-stream (Lei et al. 2018)	68.13	-	-
STAGE (video) (Lei et al. 2019)	52.75	10.90	2.76
STAGE (sub) (Lei et al. 2019)	67.99	30.16	20.13
STAGE (Lei et al. 2019)	74.83	32.49	22.23
Ours	**76.21**	**39.03**	**31.05**

Table 3: Comparison on TVQA+ test set. We evaluate QA accuracy, mIoU for temporal localization, and Answer-Span joint Accuracy (ASA) as the overall performance indicators.

Models	Difficulty 1	Difficulty 2	Difficulty 3	Difficulty 4	Overall
IITDrama	76	72	55	60	71
bjorn	77	74	57	57	71
HARD KAERI	76	73	56	59	71
Sudoku	78	74	68	67	75
GGANG	81	79	64	70	77
Ours (validation)	**84**	**85**	**70**	**70**	**81**

Table 4: QA accuracy on DramaQA dataset with four difficulty levels. Task becomes more difficult as the level increases. We report top-5 results from the competition leaderboard, evaluated on the test set. Note that, we only evaluate on the validation set since the challenge is no longer ongoing and the test set is yet inaccessible.

the-art models, MSAN (Kim et al. 2020) using modality importance with BERT and DenseCap (Kim, Tang, and Bansal 2020) using captions and frame-selection with RoBERTa, with over 5% and 2% margins, respectively. Our model also achieves the best performance in all 6 individual TV shows.

TVQA+ Table 3 shows the performance on TVQA+ dataset. To measure the performance of our model, we use QA classification accuracy just like in TVQA, and additionally, temporal mean Intersection-over-Union (mIOU) and Answer-Span joint Accuracy (ASA) provided by Lei et al. (2019) are used. mIOU measures temporal localization and ASA jointly evaluates the performance of both QA classification and temporal localization. For the ASA metric, we regard a prediction to be correct if the predicted temporal localized span has an IoU ≥ 0.5 with the ground-truth span and the answer is correctly predicted. We obtained the accuracy of 76.21% in QA classification and the mIoU of 39.03% in temporal localization. For ASA, we achieved 31.05%, outperforming the previous state-of-the-art model, STAGE (Lei et al. 2019) which used BERT with grounding spatial regions and temporal moments, with about 9% margin.

DramaQA Table 4 shows our result on DramaQA dataset, consisting of four levels of difficulty. The first five lines of Table 4 show the top-5 resulting models of the DramaQA challenge, evaluated on the test set. Since the challenge is no longer ongoing and the test set is yet inaccessible, we evaluate our model only on the available validation set and report ours for future benchmark comparison. Although direct comparison is difficult, our model shows competitive performances among others.

Models	QA (Acc.)
(1) base model (GA)	71.62 ± 0.45
(2) + TL	73.45 ± 0.31
(3) + TL + MT	73.98 ± 0.27
(4) base model (LA)	72.29 ± 0.31
(5) + TL	73.53 ± 0.29
(6) + TL + MT	74.54 ± 0.21
(7) + TL + MT + CL	75.16 ± 0.18
(8) + TL + MT + CL + SS	75.83 ± 0.06

Table 5: Results of the ablation study of our model on TVQA+ validation set. We ablate our model with globally aligned attention (GA), locally aligned attention (LA), multiple token type embeddings (MT), Temporal localization span loss (TL), contrastive loss (CL), and self-supervised pre-training stage (SS).

4.3 Analysis

Ablation study We conduct an ablation study on the TVQA+ validation set as shown in Table 5. For an ablation experiment, we define base models where the token type embedding, temporal localization, contrastive learning, and self-supervised stage are removed. The base models consist of the globally aligned attention model (1) and the proposed locally aligned attention model (4). First, we observe that the models with locally aligned attention outperformed all the other models that are trained with a globally aligned attention in (1-3 vs. 4-6). It implies that misalignment between subtitle sentences and the image frames from other
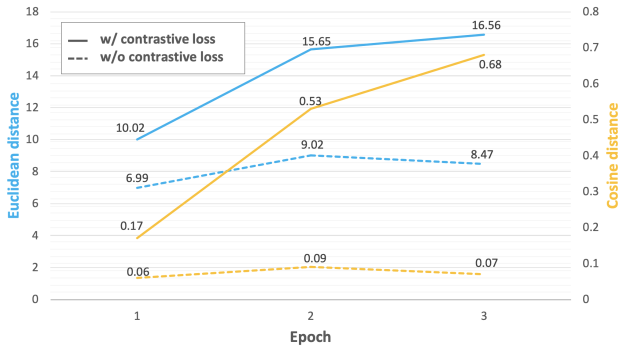
Figure 3: Euclidean and Cosine distances between the positive representation and the closest negative representation from the positive one according to whether or not the contrastive loss is used.

sentences can be prevented by utilizing the time sequence information. Second, (2-3,5-6) show the effectiveness of the proposed multiple token type embedding technique, and we believe this can be extensively applied when working with various types of text inputs. In (7), we use the proposed contrastive learning with the masked text input as the auxiliary task. This brings additional performance improvement from 74.54% to 75.16% of accuracy. Lastly, using self-supervised pre-training with a transformed problem format as a prerequisite learning, we achieve the best performance of 75.83% accuracy on TVQA+ validation set. It demonstrates that our model takes further advantage of the given dataset using the self-supervised pre-training scheme.

Effectiveness of the proposed contrastive loss For the contrastive representation learning, as shown in Fig. 2(c), among five QA pairs, we contrast a single ground truth answer with the other four negative answers. We investigate how the hidden representations ($\mathcal{H}_t$ in eq. (4)) of the five QA pairs (one positive and four negatives) behave depending on whether the contrastive loss is used or not. We calculate the distance between the positive and the closest negative representations and report how the distance between them is changing as the epoch continues. For the distance metric, we use the euclidean and cosine distance functions. Figure 3 shows that the distance between the positive and the closest negative representations is increasing in both metrics when the contrastive loss is accompanied during the training, while there is no noticeable increase in distance when the contrastive loss is not used. This shows that applying the proposed contrastive loss helps to separate the representation space between the positive and negative samples and we believe these separated representations are helpful for predicting the answer correctly.

Qualitative Results Figure 4 shows two examples of the prediction according to the use of the proposed contrastive representation learning and the self-supervised pre-training (model 6-8 in Table 5). In the first example, the proposed model predicts the correct answer by associating Sheldon's dialog, "officially no longer be roommates", with the expres-
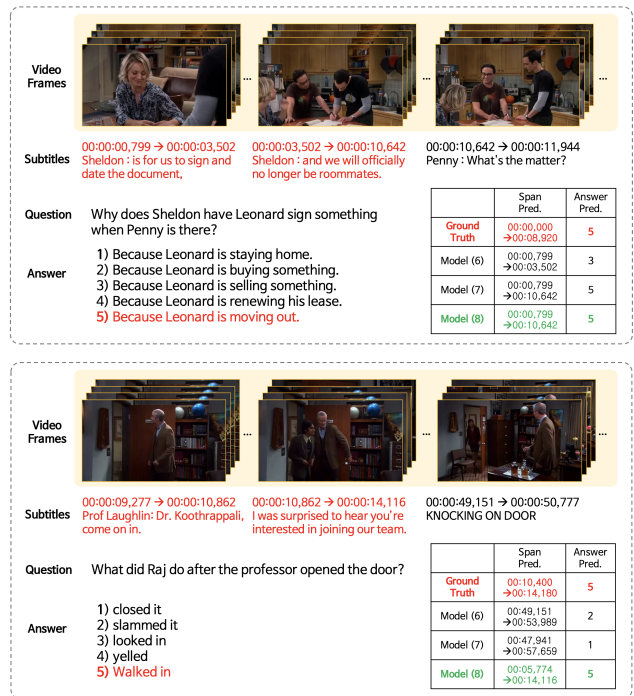

Figure 4: Examples of predictions of models with or without the contrastive loss and the self-supervised pre-training scheme. The ground truths are denoted in red, and the predictions of our proposed model are colored in green.

sion "moving out" in the correct answer and gives 0.76 of IoU in the temporal localization, while the model without two proposed approaches (model (6)) predicts the wrong answer with only 0.3 of IoU with the ground truth video span. The second example requires both language and visual understanding to predict the answer and the video span correctly. Our final model localizes the related video span and predicts the answer correctly. However, other models rather pay attention to the word "door" which appear in both of the question and the subtitle sentence and fail to predict the correct answer.

5 Conclusion

Video QA requires fine-grained understanding of both video and language modalities. To address this, we focus on the training procedure that could possibly take the most advantage out of the given data. In this paper, we propose novel training schemes that specialize in multiple-choice video QA. We first pre-train our model with a transformed problem format of predicting which questions are from which contexts for a better weight initialization. We then train our model with the original QA problem format while being guided by contrastive representation learning. Our model achieves state-of-the-art performance on three highly challenging video QA datasets. We expect that our proposed method can be applied for various multiple-choice video QA tasks, bringing further performance improvement.

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