Towards Visual-Prompt Temporal Answering Grounding in Medical Instructional Video

Bin Li\(^1\)*, Yixuan Weng\(^2\)*†, Bin Sun\(^1\), Shutao Li\(^1\)‡

\(^1\)College of Electrical and Information Engineering, Hunan University, Changsha, China
\(^2\)National Laboratory of Pattern Recognition Institute of Automation, Chinese Academy Sciences, Beijing, China

\[\text{libincn,sunbin611,shutao\_li}@hnu.edu.com}\]

\[\text{wengsyx@gmail.com}\]

ABSTRACT

The temporal answering grounding in the video (TAGV) is a new task naturally derived from temporal sentence grounding in the video (TSGV). Given an untrimmed video and a text question, this task aims at locating the matching span from the video that can semantically answer the question. Existing methods tend to formulate the TAVG task with a visual span-based question answering (QA) approach by matching the visual frame span queried by the text question. However, due to the weak correlations and huge gaps of the semantic features between the textual question and visual answer, existing methods adopting visual span predictor perform poorly in the TAGV task. To bridge these gaps, we propose a visual-prompt text span localizing (VPTSL) method, which introduces the timestamped subtitles as a passage to perform the text span localization for the input text question, and prompts the visual highlight features into the pre-trained language model (PLM) for enhancing the joint semantic representations. Specifically, the context query attention is utilized to perform cross-modal interaction between the extracted textual and visual features. Then, the highlight features are obtained through the video-text highlighting for the visual prompt. To alleviate semantic differences between textual and visual features, we design the text span predictor by encoding the question, the subtitles, and the prompted visual highlight features with the PLM. As a result, the TAGV task is formulated to predict the span of subtitles matching the visual answer. Extensive experiments on the medical instructional dataset, namely MedVidQA, show that the proposed VPTSL outperforms the state-of-the-art (SOTA) method by 28.36% in terms of mIOU with a large margin, which demonstrates the effectiveness of the proposed visual prompt and the text span predictor.

CCS CONCEPTS

- [Information systems] Video search; [Computing methodologies] Neural networks.

*These authors contribute equally to this work.
†Work done during an internship at Chinese Academy Sciences.
‡Corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

\(\text{MM ‘22, October 10–14, 2022, Virtual Event, Portugal}\)
\(\text{© 2022 Association for Computing Machinery.}\)
\(\text{ACM ISBN 978-1-4503-8651-7/22/10...$15.00}\)
\(\text{https://doi.org/10.1145/3474085.xxxxxxx}\)

1 INTRODUCTION

Figure 1: Illustration of the temporal answering localization in the medical instructional video, where the visual answer with the subtitles locates in the video timeline to perform a demonstration. Below are the differences between the existing method and our method.

“Hey, Siri, could you please show me how to examine lymph nodes in the head and neck?” Then, the video containing the right processes comes into our eyes... Recently, the surge in availability of online videos has changed the way of acquiring information and knowledge [1–3]. Many people prefer instructional videos to teach or learn how to accomplish a particular task with a series of step-by-step procedures [4]. The temporal answering grounding in the video (TAGV) is a new task that has attracted increasing attention...
due to the visual and verbal communication at the same time in an effective and efficient manner [5, 6]. The goal of the TAGV task is to find the matching video answer span corresponding to its question, aka., visual answering localization. As the natural development from temporal sentence grounding in the video (TSGV) [7, 8], the TAGV task is challenging since there are huge gaps between two different modalities. The text is discontinuous in syntactic structure, while the video is continuous within adjacent frames [9]. People can easily answer through natural language but are hard to act without the moment guidance in the video to demonstrate their answers. As shown at the top of Figure 1, this example illustrates the temporal answering localization in the medical instructional video, where the figure is borrowed from the original work [6] with the author’s permission and change. As we can see in this figure, the particular temporal answering segment is preferred rather than the entire video as the answer to the given question “How to examine lymph nodes in a head and neck?”. How to design a cross-modal method that can locate the video timeline correctly is still one of the key points in the current research [6, 10].

Many efforts have been made to realize a reliable and accurate natural language temporal localization in the video [10–12], where similar tasks are proven to be important for cross-modal understanding, such as video moment retrieval (VMR)[13], and video question answering (VQA)[14]. On the query side, the query of the TAGV task is a text question instead of a direct text description in the VQA. Therefore, the existing methods may perform poorly in the TAGV task. Similar to the question answering (QA) problem in the natural language processing (NLP) field, we resort to the existing span-based grounding methods [10, 12] to address the TAGV problem.

As shown in the middle of Figure 1, existing span-based methods tend to encode video and text separately for feature encoding and adopt cross-modal modeling to construct feature representations in the same space. The visual answer spans can be located with the head and tail in the video frame. However, there is a huge difference in the semantic information between text and video [15, 16], where the located video spans queried by the text question may be biased. Moreover, the weak correlations between text queries and video frames may lead to insufficient representation for an answer [17].

To address the above issues, we propose a visual-prompt text span localization (VPTSL) method, which aims to adopt visual highlight features to enhance the text span localization with the pre-trained language model (PLM). Different from the existing methods, we leverage the highlight feature as the visual prompt to enhance textual features from the PLM, where the joint semantic representations can be learned together. Given a text question, the timestamped subtitle to the visual answer is modeled to be predicted as the final result. We illustrate the proposed VPTSL method at the bottom of Figure 1.

Our main contributions are three-fold:

- To the best of our knowledge, this is the very first attempt to apply the text span predictor for solving the temporal answering grounding problem, where the timestamps of the subtitle corresponding to the visual answer are formulated for prediction.
- The visual highlight features are designed to prompt the visual information for the textual features, where the verbal and the visual part of the video can be jointly learned through the PLM.
- Extensive experiments are performed to demonstrate the effectiveness of the proposed VPTSL on the medical instructional dataset (Med VidQA), in which we achieve 28.36 in mIOU score by a large margin compared with other state-of-the-art methods.

2 RELATED WORK

2.1 Temporal Sentence Grounding in Video

The temporal sentence grounding in the video (TSGV) is a critical task for cross-modal understanding [8, 18]. This task takes a video-query pair as input where the video is a collection of consecutive image frames and the query is a sequence of words. Early attempts resort to the sliding window-based [19–21] and scanning-and-ranking based [22–25] paradigm. The former first generates multiple segments and then ranks them according to the similarity between segments and the query. The latter samples candidate segments via the sliding window mechanism and subsequently integrates the query with each segment representation via a matrix operation. The latest works tend to model this problem without segment proposal, which predicts answers directly without generating candidate answers [26]. For this convenience, many works tend to adopt the visual span predictor for locating the sentence grounding segments, where more efficient cross-modal interaction modeling are designed [10, 12, 16]. However, due to the gaps between the textual features and visual features [27, 28], current methods adopted in the TSGV performs poorly in the temporal answering grounding in the video (TAGV). Different from them, our method tries to model subtitles with timestamps for locating the visual answer. The text span predictor is designed in the proposed method, where more semantic information between the predicted answers and the input text question can be jointly learned through the pre-trained language model.

2.2 Prompt Learning Tuning

The concept of prompt tuning originates from the NLP domain [29], whose motivation is to provide pre-trained language models, such as BERT [30] or GPT [31], with extra knowledge. Specifically, given a pre-trained language model, the manual designed templates are used to augment the input with extra information [32]. The basic idea of prompting is to induce a pre-trained language model for downstream prediction given cloze-style prompts, such as sentiment analysis [33]. The key lies in how to design the prompt part for tuning the pre-trained model [34]. In the computer vision field, prompt learning is a nascent research direction that has only been explored very recently [35–37]. The pioneering works have designed many efficient modules of cross-modal interaction for the downstream tasks [38, 39], where the features of different modalities are optimised continuously in the embedding space. Our method is based on the pre-trained language model, adopting the visual prompt feature for perceiving the verbal and non-verbal
We propose the Visual-Prompt Text Span Localization (VPTSL) method for the TAGV task, whose goal is to predict the span of the subtitle timestamp matching the answering frame timeline with the pre-trained language model. The overview of VPTSL is illustrated in Figure 2, which consists of four components: (1) cross-modal modeling: the extracted visual and the textual features are processed through the cross-modal interaction. (2) Video-text highlighting: the text question is used to query the video frames for obtaining the predicted highlight feature supervised by the highlight ground truth. (3) Visual prompt: highlight feature is adopted to prompt the pre-trained language model to predict the subtitle timestamp spans. (4) Text span predictor: the predicted highlight feature is used to query the video frames for obtaining the aligned subtitle timeline.

![Figure 2: Overview of the proposed Visual-Prompt Text Span Localization (VPTSL) method.](image)

3 MAIN METHOD

We propose the Visual-Prompt Text Span Localization (VPTSL) method for the TAGV task, whose goal is to predict the span of the subtitle timestamp matching the answering frame timeline with the pre-trained language model. The overview of VPTSL is illustrated in Figure 2, which consists of four components: (1) cross-modal modeling: the extracted visual and the textual features are processed through the cross-modal interaction. (2) Video-text highlighting: the text question is used to query the video frames for obtaining the predicted highlight feature supervised by the highlight ground truth. (3) Visual prompt: highlight feature is adopted to prompt the pre-trained language model to predict the subtitle timestamp spans. (4) Text span predictor: the predicted highlight feature is used to query the video frames for obtaining the aligned subtitle timeline.

3.1 Cross-modal Modeling

Given an untrimmed video as $V = \{f_i\}_{i=1}^{T}$ and the text question as $Q = \{q_j\}_{j=1}^{k}$, where $T$ and $k$ are the number of frames and tokens, respectively. For obtaining the well-formed semantic representations of two modalities, we will elaborate on feature extractor and cross-modal interaction.

3.1.1 Feature Extractor

For each video $V$, we extract frames (16 frames per second) and then obtain the corresponding RGB visual features $V' = \{V_1\}_{n=1}^{n}$ using 3D ConvNet (I3D) pre-trained on the Kinetics dataset [40], where $n$ is the number of extracted features and $d_v$ is the dimension of the visual features. The extracted features are sent to a visual projection for obtaining the visual feature $V \in \mathbb{R}^{n \times d_v}$. The visual projection is designed as the Conv1D [41] module with dropout ($p=0.1$). For the text question part, we tokenize the question into the tokens with the tokenizer. Then, the textual tokens are encoded through the DeBERTA pre-trained language model [42] for obtaining the well-formed textual features $\{w_1, w_2, \ldots, w_m\} \in \mathbb{R}^{m \times d_w}$, where $m$ is the length of text question and the $d_w$ is the dimension of output encoding. After performing the linear projection, the final textual features $Q \in \mathbb{R}^{m \times d_t}$ is obtained, where $d_t = d_v$.

3.1.2 Cross-modal Interaction

After obtaining both the visual ($V$) and textual ($Q$) features, we perform the Context Query Attention, which is inspired by the work [10]. This module aims to capture the cross-modal interactions through context-to-query ($A$) and query-to-context ($B$) process. The attention weights are computed as:

$$A = S_r \cdot Q \in \mathbb{R}^{n \times d_t}, B = S_c \cdot S_r^T \cdot V \in \mathbb{R}^{n \times d_v}$$

where $S_r$ and $S_c$ are the row-wise and column-wise normalization of $S$ by SoftMax, respectively. Finally, the output of context-query
attention is written as:
\[
\tilde{V} = FFN([V; A; V \odot A; V \odot B])
\]  
where the FFN is a single feed-forward layer, and \(\odot\) denotes element-wise multiplication.

### 3.2 Video-text Highlighting

#### 3.2.1 Highlight Module
Inspired by the work [10], we design the visual highlight module, which aims to percept the non-verbal part in the videos. As shown in Figure 3, the ground truth span locates in the verbal part, where the subtitles are contained. However, for an instructional video, the non-verbal part also counts a lot, so the highlight module is designed to enlarge the ground truth of text span. Specifically, we consider the verbal part as the foreground and the rest are the background in the video. The target text span boundaries are enlarged to cover the verbal and the non-verbal information, where the extension ratio is controlled by the hyper-parameter \(\alpha\). The highlight ground truth time span is calculated as follows

\[
T_{\text{Highlight}} = t^e - t^s,
\]

where \(T_{\text{Highlight}}\) is the highlight ground truth time span, the \(t^e\) is the end ground truth time, while the \(t^s\) is the start ground truth time.

Similar to the work [10], we extend the non-verbal frames in the video as the extend part, which can be calculated as

\[
T_{\text{Extend}} = T_{\text{Highlight}} \ast (\alpha + 1)
\]

where \(T_{\text{Extend}}\) is the extend highlight ground truth time, the \(\alpha\) is the hyperparameter.

The textual features into the Highlight Module are denoted as \(Q\), where the \(Q = [q_1, q_2, \ldots, q_n] \in \mathbb{R}^{d_q \times n}\). The self-attention mechanism [43] is performed to obtain the textual features \(h_Q \in \mathbb{R}^{1 \times d_t}\). Then \(h_Q\) is concatenated with each feature in \(\tilde{V}\) as \(\hat{V} = [\tilde{v}_1, \ldots, \tilde{v}_n] \in \mathbb{R}^{d_v \times n}\), where \(\tilde{v}_i = [h_Q; \tilde{v}_i], i \in [1, n]\). The highlighting score is computed as:

\[
S_h = \sigma(\text{Conv1D}(\hat{V}_i^T))
\]

where \(\sigma\) denotes Sigmoid activation, \(S_h \in \mathbb{R}^n\).

#### 3.2.2 Highlight Projection
The highlighted features are required to be projected to the same dimension with the textual feature, which can be calculated by:

\[
S'_h = \text{Linear}(S_h)
\]

#### 3.2.3 Highlight Optimization
Accordingly, the highlight loss is computed with the BCE loss function, which is formulated as:

\[
\mathcal{L}_{\text{Highlight}} = f_{\text{BCE}}(S'_h, T_{\text{Extend}})
\]

Moreover, the highlight module is trained in an end-to-end manner, where one of the total loss can be written as the \(\mathcal{L}_1\), which is shown as follows

\[
\mathcal{L}_1 = \mathcal{L}_{\text{Highlight}}.
\]

#### Algorithm 1 Subtitle Answer Span Selection

**Input:** Subtitle collections \(D\) with time stamp, where each subtitle has its corresponding timestamp \((d_{\text{start}}, d_{\text{end}})\); Start time of the visual answer \(\tau_v\); End time of visual answer \(\tau_e\);  

**Output:** Subtitle start and end time \((R_S, R_E)\)  

**TimeStart\_min \leftarrow +\infty**  

**TimeEnd\_min \leftarrow +\infty**  

for \(i \in D\) do

if \(|i.d_{\text{start}} - \tau_v| < \text{TimeStart\_min}\) then

\(\text{TimeStart\_min} \leftarrow |i.d_{\text{start}} - \tau_v|\)

\(R_S \leftarrow i.d_{\text{start}}\)

end if

if \(|i.d_{\text{end}} - \tau_e| < \text{TimeEnd\_min}\) then

\(\text{TimeEnd\_min} \leftarrow |i.d_{\text{end}} - \tau_e|\)

\(R_E \leftarrow i.d_{\text{end}}\)

end if

end for

### 3.3 Visual Prompt

#### 3.3.1 Prompt Designing
We use the visual highlight features as the visual token for prompting the pre-trained language model. Specifically, the highlight feature has the same dimension as the input text tokens, which is considered to be the visual token. On the one head, the visual prompt covers the non-verbal part that the text token may lack. On the other head, the visual prompt is supervised by the visual frames, where some visual features can provide the extra information as the knowledge for the pre-trained model when prompt tuning [37].

#### 3.3.2 Prompt Tuning
Prompt tuning is considered to be a wise choice to enhance the pre-trained model with extra knowledge [29, 35]. Intuitively, the prompt feature is used as the visual token which concatenates with the text query (question) and the video subtitles. The [CLS] is placed at the head of the input token, while the [SEP] is used as the separator. After concatenation, each subtitle is segmented by the subtitle span, which is used for text span prediction. Then the embedding module is adopted for learning the textual and visual features jointly in the same vector space.

### 3.4 Text Span Predictor

The text span predictor is designed to predict the subtitle answer span corresponded to its visual answers. In this section, we first elaborate on the subtitle answer span selection algorithm for selecting the most proper subtitle answer span. Then, the subtitle span prediction is introduced for obtaining the final subtitle timeline.

#### 3.4.1 Subtitle Answer Span Selection
Subtitle answer span selection aims to select the most approaching text subtitle span corresponding to its visual answer. As a result, we design the aligned subtitle answer span selection for further text span prediction. As shown in the Algorithm 1, we use the subtitle collections \(D\) of the video to locate the most approaching start and end time of the visual answers \((\tau_S, \tau_E)\). It is noted that the algorithm has its limitation as the selected part of the subtitle may be inaccurate. A precise subtitle timeline location may improve the final prediction performance. We leave these to the future work.
3.4.2 Subtitle Span Prediction. The $\tau^s$ and $\tau^e$ represent the start and end time of the temporal moment that answers the question. Different from the visual span proposed by work [10, 12], we formulate the span timeline prediction as finding its corresponding subtitle timestamp. This problem is formulated as the SQuAD [44] style triples (Context, Question, Answer), where the more efficient method to locate subtitles span can be designed. As a result, we design a text span predictor based on a pre-trained language model. The input is appended with the visual prompt method, where the textual and visual tokens are learned jointly in the pre-trained model. Specifically, we use DeBERTa for feature encoding. Each token is segment in the subtitle span, which has a probability of being selected head and tail. Therefore subtitle span-based prediction can be performed by the cross-entropy optimization token by token.

As shown in Figure 2, the ground truth visual timeline is (15 ~ 19). This frame timeline can be translated into the subtitle span stamp, which locates in spans 8 and 9. The predicted start index shown in the Figure 2 is located in the $P^8_{\text{start}}$, while the predicted end index locates in the $P^9_{\text{end}}$. So the corresponding aligned subtitle stamp can be used as the final results (14.91 ~ 19.21). It is noticed that the token-level segment may present errors between the subtitle span timeline and the ground truth span timeline. As mentioned in the section 3.4.1, more precise subtitle timeline selection may bring more accuracy for the final results. Next, we will introduce the details of subtitle span prediction.

Let DeBERTa($\cdot$) be the pre-trained model, we first obtain the hidden representation with

$$h = \text{DeBERTa}(x) \in \mathbb{R}^{r_h \times |x|}$$

(7)

where $|x|$ is the length of the input sequence and $r_h$ is the size of the hidden dimension.

Then the hidden representation is passed to two separate dense layers followed by softmax functions:

$$l_1 = \text{softmax}(W_1 \cdot h + b_1)$$

(8)

$$l_2 = \text{softmax}(W_2 \cdot h + b_2)$$

(9)

where $W_1, W_2 \in \mathbb{R}^{r_h}$ and $b_1, b_2 \in \mathbb{R}$. The softmax is applied along the dimension of the sequence.

The output is a span across the positions in $d$, indicated by two pointers (indexes) $s$ and $e$ computed from $l_1$ and $l_2$:

$$s = \arg \max_{\text{start}} l_1$$

(10)

$$e = \arg \max_{\text{end}} l_2$$

(11)

where equation (10) represents the start token of the start span, while the equation (11) shows the end token of the end span.

In the end, the final visual answer span will always be aligned with the text span predicted text span, which is presented as $(\text{start}-\text{end})$. The span prediction loss is optimized by minimizing the following loss:

$$L_2 = L_{\text{text span}}$$

(12)

3.5 Training and Inference

3.5.1 Training. The total optimizing function is performed as multi-loss form, which is presented as follows.

$$L_{\text{total}} = \lambda \ast L_{\text{highlight}} + L_{\text{text span}}$$

(13)

where the $\lambda$ is the hyper-parameter for tuning the total loss, the $L_{\text{highlight}}$ part provides the non-verbal information and the loss $L_{\text{text span}}$ covers the verbal text information.

3.5.2 Inference. We simply take the visual highlight feature to prompt the pre-trained language model, aiming at covering the non-verbal information for the text span localization. The text span predictor performs prediction after encoding the text tokens and the visual token by the pre-trained language model. The predicted start token locates the start span, while the predicted end token locates the end span.

4 EXPERIMENTS

In this section, we first introduce the dataset used in the experiments. Then, we elaborate on the evaluation metrics and describe the compared state-of-the-art methods. Finally, we present the implementation details.

4.1 Datasets

Medical Video Question Answering (MedVidQA) datasets [6] is the first video question answering (VQA) dataset [45] constructed in natural language video localization (NLVL) [21, 46], which aims to provide medical instructional video with text question query. Three medical informatics experts were asked to formulate the medical and health-related instructional questions by watching the given video. They were required to localize the visual answer to those instructional questions by providing their timestamps in the video.

The MedVidQA dataset is composed of 899 videos with 3010 questions and the corresponding visual answers. The mean duration time of these videos is 383.29 seconds. The MedVidQA provides subtitle information of the original video and visual feature information extracted from the 3D ConvNet (3D) which was pre-trained on the Kinetics dataset [40]. We follow the official data split, where 2710, 145, and 155 questions and visual answers are used for training, validation, and testing respectively.

4.2 Evaluation Metrics

Following prior works [6, 21, 47, 48], we adopt “R@n, IoU = $\mu$” and “mIoU” as the evaluation metrics, which treats localization of the frames in the video as a span prediction task similar to answer span prediction [49, 50] in text-based question answering.

The “R@n, IoU = $\mu$” denotes the percentage of language queries having at least one result whose Inter-section over Union (IoU) with ground truth is larger than $\mu$ in top-n retrieved moments. “mIoU” is the average IoU over all testing samples. In our experiments, we use $n = 1$ and $\mu \in 0.3, 0.5, 0.7$. The calculation equation is shown as follows

$$m\text{IoU} = \frac{\sum_{i=1}^{n} \frac{A_n \cap B_n}{A_n \cup B_n}}{n}$$

(14)

where $A$ and $B$ represent different span collections.
4.3 Comparison with State-of-the-Art Methods

We compare our VPTSL with several state-of-the-art (SOTA) methods on the MedVidQA dataset. Notably, we set the same I3D feature [40] and text feature extraction model (i.e., DeBERTa pre-trained language model) as the visual and textual feature extractor respectively for all methods to ensure fairness.

**TMLGA** [15] is the model with a dynamic filter, which adaptively transfers language information to visual domain attention map. A new loss function is designed to guide the model with the most relevant part of the video, and soft labels are performed to cope with annotation uncertainties.

**VSLBase** [26] is a standard span-based QA framework. Specifically, visual features are analogous to that of text passage, where the target moment is regarded as the answer span. The VSLBase is trained to predict the start and end times of the visual answer span. The VSLNet regards the target moment and its adjacent contexts as foreground, while the rest as background, i.e., foreground covers a slightly longer span than the answer span.

**VSLNet** [26] introduces a Query-Guided Highlighting (QGH) strategy to further enhance the VSLBase model. The VSLNet regards the target moment and its adjacent contexts as foreground, while the rest as background, i.e., foreground covers a slightly longer span than the answer span.

**VSLNet-L** [51] incorporates the concepts from multi-paragraph question answering [32] by applying a multi-scale split-and-concatenation strategy to address the performance degradation on a long video. Long videos are segmented into multiple short clips. The hierarchical searching strategy is designed for more accurate moment localization.

**ACRM** [16] predicts the temporal grounding based on an interaction modeling between vision and language modalities. Specifically, the attention module is introduced to automatically assign hidden features to query text with richer semantic information, which is considered to be more important for finding relevant video content. Moreover, the additional predictor is designed for utilizing the internal frames during training to improve the localization accuracy.

**RaNet** [53] represent the relation-aware network, which formulates temporal language grounding in the video inspired by reading comprehension [54]. The framework of RaNet is designed to select a grounding moment from the predefined answer collection with the aid of coarse-and-fine choice-query interaction and choice-choice relation construction. The choice-query interactor is proposed to match the visual and textual information simultaneously in sentence-moment and token-moment levels, leading to a coarse-and-fine cross-modal interaction.

### Table 1: Performance comparison of various SOTA methods on MedVidQA dataset.

| Models          | Random Mode | Random Guess | mIoU |
|-----------------|-------------|--------------|------|
| VSLBase[26]     | 8.38        | 7.74         | 6.89 |
| VSLNet[26]      | 27.66       | 24.38        | 20.84|
| VSLNet-L[51]    | 33.10       | 30.32        | 24.83|
| ACRM[16]        | 26.90       | 24.83        | 23.70|
| RaNet[16]       | 35.48       | 32.90        | 29.45|

Table 1: Performance comparison of various SOTA methods on MedVidQA dataset. Here "with subtitle" means that the subtitle text in the video is added to the text features. We highlight the best score in each column in bold, and the second best score is marked with underline. We also show the improvement between the proposed VPTSL and second place.

4.4 Implementation Details

We apply the same multimodal features for all the experiments for all the compared methods for fair comparisons. Specifically, for the textual features, we use the DeBERTa-v3 [42] as the pre-trained language model, which originates from DeBERTa1 model with 24 layers and a hidden size of 1024. It has 304M backbone parameters and a vocabulary containing 128K tokens, introducing 131M parameters in the embedding layer. For visual features, all different methods adopt the I3D features [40] as the visual input. We reproduce the compared method with the Pytorch2 [55] on three NVIDIA A100 GPUs, where all the implementations use the hugging-face3 [56] framework. For the re-initiated layers, we set the dimension of all the hidden layers in the model as 1024 while the kernel size of convolution layers [57] is set to 7. The head size of multi-head attention [58] is 32. The text span predictor is initialized with another DeBERTa-v3 pre-trained language model, where the subtitles are essential to the proposed method.

As for the method adopting visual span predictor, we also compare their performances with the timestamped subtitles in addition to the original implementations. Specifically, the original implementations use the text question as the query to match the visual

---

1. [https://huggingface.co/microsoft/deberta-v3-large](https://huggingface.co/microsoft/deberta-v3-large)
2. [https://pytorch.org](https://pytorch.org)
3. [https://github.com/huggingface/transformers](https://github.com/huggingface/transformers)
answer span for the TAGV task. To make use of the timestamped subtitles in these methods, we concatenated the question and the subtitles with [SEP] separator, which are used to query the visual features for cross-modal modeling. The start and end frames are obtained through the visual span predictor.

We use the AdamW [59] as the optimizer and the learning rate is set to 1e-5 with the warm-up [60]. The batch size is 4. Moreover, we set the maximum length of 1800, and delete the excess part. The linear decay of learning rate and gradient clipping of 1e-6 and the dropout [61] is set to 0.1, which is applied to prevent overfitting. The hyperparameters of all the compared methods are tuned on the valid set. At the end of each training epoch, we test in the valid set and select the model with the highest score (mainly depending on mIOU) to predict in the test dataset. All the experimental implementations were repeated three times before reporting in the test set.

5 EXPERIMENTAL RESULTS

5.1 Main Results

The experimental results of the performance compared with the various SOTA methods on the MedVidQA dataset are shown in Table 1. The further conclusions are that our method outperforms each compared method on all metrics, including IOU= 0.3, 0.5, 0.7, and mIOU scores. The text span predictor can achieve better results than the method with the visual span predictor by a large margin in the mIOU score (28.36), indicating that the textual predictor is superior to the visual span predictor in locating the visual answer queried by the text question. The reason may be that the powerful pre-trained language model can leverage more strong semantics from the subtitles given the text question. Moreover, we also add the subtitles to each compared method adopting visual span predictor, where the text question with the subtitles of the video are concatenated with [SEP] for obtaining the visual answer. It can be found that the final results can be improved with the subtitles augmentation. However, the proposed VPTSL method still obtains significant improvements over these modified compared methods, which demonstrates the effectiveness of the visual prompt and the text span predictor.

5.2 Ablation Studies

We first investigate the effectiveness of the pre-trained model. The results of whether the classic visual span-based methods VSLBase and VSLNet adopt the pre-trained model are shown in Table 2, where part of the results is in line with the work [6]. As we can see, only using the word2vec to initial the textual embedding layer achieves worse performance. In particular, the PLM for the textual feature extraction can improve semantic understanding, which results in improvements of 0.69 and 2.11 in terms of mIOU score for VSLBase and VSLNet respectively. It convincingly demonstrates that the pre-trained language model for textual feature extraction can improve the video understanding for the visual span-based method in this TAGV problem.

Then we study the ablation of each component of the proposed method, which is shown in Table 3. Specifically, for the w/o highlight supervision, we use the question and timestamped subtitles to implement the text predictor for text span prediction. For w/o PLM, instead of loading pre-trained language model weights, we use a model of the same size and initialize the model parameters randomly. When there is no highlight supervision, the performance drops slightly. When the prompt module is removed, it is reduced by 2.4 mIOU compared to the original foundation. When the pre-trained language model is removed, the text span prediction

| Method     | Text Feature | IOU=0.3 | IOU=0.5 | IOU=0.7 | mIOU |
|------------|--------------|---------|---------|---------|------|
| VSLBase    | Word2vec     | 21.93   | 12.25   | 5.80    | 20.15|
|            | PLM          | 26.12   | 12.44   | 6.85    | 20.84|
| VSLNet     | Word2vec     | 25.81   | 14.20   | 6.45    | 20.12|
|            | PLM          | 30.32   | 16.55   | 7.74    | 22.23|

Table 2: Comparison of whether using the pre-trained language model (PLM) for VSLBase and VSLNet in MedVidQA.

| Experimental Item | IOU=0.3 | IOU=0.5 | IOU=0.7 | mIOU |
|-------------------|---------|---------|---------|------|
| W/o Highlight Loss| 76.13   | 60.65   | 43.87   | 57.44|
| W/o Visual Prompt | 70.97   | 59.35   | 43.87   | 55.41|
| W/o PLM           | 20.65   | 10.97   | 4.52    | 18.83|
| VPTSL             | 77.42   | 61.94   | 44.52   | 57.81|

Table 3: Results of ablation experiment on the MedVidQA dataset.

![Figure 5: Ablation study of hyper parameters \( \alpha \) and \( \lambda \) of the proposed VPTSL.](image-url)
ability is greatly impaired. So the performance improvement still comes from the strong understanding ability of the pre-trained model.

We also analyze the performances under different hyperparameters in the experiment. As shown in Sub-Figure 5(a), we show the performances with different values of the extend time hyperparameter \( \alpha \) on the final result. It can be found from the ablation diagram that when the extend rate is 0.25, the best result is obtained. When \( \alpha \) becomes larger, it decreases the performance of the final prediction result, which may be due to the non-visual part affecting the understanding of the input text. At the same time, when extend rate is less than 0, the text input range is insufficient, which results in bad performance.

Meanwhile, we also study the weight of the visual prompt loss for the proposed method. From the Sub-Figure 5(b), it can be found that the best results can be achieved when \( \lambda \) is 0.1. Compared with no visual supervision, visual information can provide more contextual information for the prediction.

### 5.3 Case Study

We present the case study for the TAGV task shown in Figure 6. As we can see that, the proposed VPTSL has a better performance than the SOTA method (RaNet), where more precise subtitle spans are predicted by the text span predictor. Moreover, we compare the performance of whether to use prompt tuning in the prediction. It can be further concluded that the visual prompt can bridge the non-verbal part and the verbal part, bringing improvement to the final prediction.

What’s more, we also provide the visualization of the attention features in the embedding layer of the proposed method. Intuitively, these visualizations give the insight to dive into the function of the prompt. As shown in Figure 6, comparing the weights of subtitle 3 boxed in red with or without visual prompt, it receives more attention from its adjacent subtitles which are all in the answer span when the visual prompt is used. This can be evidence that the visual prompt features can bridge the verbal part and the non-verbal part, which results in more precise visual answer prediction.

### 6 CONCLUSION

In this paper, we proposed the visual prompt text span localizing (VPTSL) method to make full use of complementary information of textual and visual semantic representations for temporal answering grounding in the video (TAGV). To this end, we first model the cross-modal information and proposed the visual prompt for enhancing the pre-trained language model. The text span predictor is designed for modeling the textual and visual representation for subtitle span prediction. The main results and ablation studies on the proposed method in the TAGV benchmarks significantly demonstrated the effectiveness of the VPTSL. In the future, the more precise and efficient method to perform the TAGV task with visual augmentation is yet to be explored.

### ACKNOWLEDGEMENT

This work is supported by the National Key R&D Program of China (2018YFB1305200), the National Natural Science Fund of China (62171183).
REFERENCES

[1] Mathew Monfort, SouYoung Jin, Alexander Liu, David Harwath, Rogerio Feris, James Glass, and Aude Oliva. Spoken moments: Learning joint audio-visual representations from video descriptors. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 14871–14881, 2021.

[2] Nitin Arvind Shelke and Singara Singh Kasana. A comprehensive survey on passive techniques for digital video forgery detection. Multimedia Tools and Applications, 80(4):6287–6310, 2021.

[3] Salman Khan, Muzammal Naseer, Munawar Hayat, Syed Waqas Zamir, Fa- had Shahzad Khan, and Mubarak Shah. Transformers in vision: A survey. ACM Computing Surveys (CSUR), 2021.

[4] Reza Gholipour, Noura Sayed, and Vassilis Athitsos. Hierarchical modeling for task recognition and action segmentation in weakly-labeled instructional videos. In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pages 1922–1932, 2022.

[5] Deepak Gupta and Dina Demner-Fushman. Overview of the MedVidQA 2022 Shared Task on Medical Video Question Answering. In Proceedings of the 21st SIGBioMed Workshop on Biomedical Language Processing, ACL-BNLSP 2022. Association for Computational Linguistics, 2022.

[6] Deepak Gupta, Kush Attali, and Dina Demner-Fushman. A Dataset for Medical Instructional Video Classification and Question Answering. arXiv preprint arXiv:2012.12888, 2022.

[7] Yulan Yang, Zhaohui Li, and Gangyan Zeng. A survey of temporal activity localization via language query. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing, pages 162–171, 2018.

[8] Hao Zhang, Aixin Sun, Wei Jing, and Jie Tianyi Zhou. Temporally grounding natural sentence in videos. In Proceedings of the 8th Annual Meeting of the Association for Computational Linguistics, pages 6543–6544, 2020.

[9] Shaoning Xiao, Long Chen, Jie Shao, Yuebing Zhang, and Jun Xiao. Natural language video localization with learnable moment proposals. arXiv preprint arXiv:2109.10678, 2021.

[10] Hao Zhang, Aixin Sun, Wei Jing, and Jie Tianyi Zhou. Span-based localizing network for natural language video localization. In Proceedings of the 5th Annual Meeting of the Association for Computational Linguistics, pages 596–601, 2020.

[11] Han T, J. Zhu, Z. Liu, Z. Gao, and Z. Cheng. Frame-wise cross-modal matching for video moment retrieval. IEEE Transactions on Multimedia, pages 1–1, 2021.

[12] Jie Lei, Licheng Yu, Mohit Bansal, and Tamara Berg. Tvqa: Localized, compositional video question answering framework. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.

[13] H. Tang, J. Zhu, M. Liu, Z. Gao, and Z. Cheng. Frame-wise cross-modal matching for video moment retrieval. IEEE Transactions on Multimedia, pages 1–1, 2021.

[14] Jie Lei, Licheng Yu, Mohit Bansal, and Tamara Berg. Tvqa: Localized, compositional video question answering. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1369–1379, 2018.

[15] Cristian Rodriguez-Opazo, Edison Marrese-Taylor, Fatemeh Sadat Saleh, Hong-dong Li, and Stephen Gould. Proposal-free temporal moment localization of a natural-language query in video using guided attention. Winter Conference on Applications of Computer Vision, 2020.

[16] Haoyu Tang, Jiahua Zhu, Meng Liu, Zao Gao, and Zhiyong Cheng. Frame-wise cross-modal matching for video moment retrieval. IEEE Transactions on Multimedia, pages 1–1, 2021.

[17] Yifan Xu, Huaping Wei, Minxuan Lin, Yingying Deng, Kekai Sheng, Mengdan Zhang, Fan Tang, Weiming Dong, Feiyue Huang, and Changsheng Xu. Transformers in computational visual media: A survey. Computational Visual Media, 8(1):33–62, 2022.

[18] Y. Yang, Z. Li, and G. Zeng. A survey of temporal activity localization via language in untrimmed videos. In 2020 International Conference on Culture-oriented Science & Technology (ICCST), pages 596–601, IEEE, 2020.

[19] Hao Zhang, Aixin Sun, and Jie Tianyi Zhou. Temporally grounding natural sentence in videos. In Proceedings of the 8th Annual Meeting of the Association for Computational Linguistics, pages 6543–6544, 2020.

[20] Haoyu Tang, Jiahua Zhu, Meng Liu, Zao Gao, and Zhiyong Cheng. Frame-wise cross-modal matching for video moment retrieval. IEEE Transactions on Multimedia, pages 1–1, 2021.

[21] Yifan Xu, Huaping Wei, Minxuan Lin, Yingying Deng, Kekai Sheng, Mengdan Zhang, Fan Tang, Weiming Dong, Feiyue Huang, and Changsheng Xu. Transformers in computational visual media: A survey. Computational Visual Media, 8(1):33–62, 2022.

[22] Y. Yang, Z. Li, and G. Zeng. A survey of temporal activity localization via language in untrimmed videos. In 2020 International Conference on Culture-oriented Science & Technology (ICCST), pages 596–601, IEEE, 2020.
[48] Yitian Yuan, Tao Mei, and Wenwu Zhu. To find where you talk: Temporal sentence localization in video with attention based location regression. *arXiv: Computer Vision and Pattern Recognition*, 2018.

[49] Wenhui Wang, Nan Yang, Furu Wei, Baobao Chang, and Ming Zhou. Gated self-matching networks for reading comprehension and question answering. In *Meeting of the Association for Computational Linguistics*, 2017.

[50] Minjoon Seo, Aniruddha Kembhavi, Ali Farhadi, and Hannaneh Hajishirzi. Bidirectional attention flow for machine comprehension. *arXiv: Computation and Language*, 2016.

[51] Hao Zhang, Aixin Sun, Wei Jing, Liangli Zhen, Joey Tianyi Zhou, and Rick Siow Mong Goh. Natural language video localization: A revisit in span-based question answering framework. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pages 1–1, 2021.

[52] Wei Wang, Ming Yan, and Chen Wu. Multi-granularity hierarchical attention fusion networks for reading comprehension and question answering. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1705–1714, 2018.

[53] Jialin Gao, Xin Sun, Mengmeng Xu, Xi Zhou, and Bernard Ghanem. Relation-aware video reading comprehension for temporal language grounding. *arXiv preprint arXiv:2110.05717*, 2021.

[54] Xinya Du, Jintu Shao, and Claire Cardie. Learning to ask: Neural question generation for reading comprehension. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1342–1352, 2017.

[55] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.

[56] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement De Langue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander M. Rush. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online, October 2020. Association for Computational Linguistics.

[57] Yoon Kim. Convolutional neural networks for sentence classification. In *Empirical Methods in Natural Language Processing*, 2014.

[58] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, NIPS’17, page 6000–6010, Red Hook, NY, USA, 2017. Curran Associates Inc.

[59] Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2018.

[60] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016.

[61] Nitish Srivastava, Geoffrey E. Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15:1929–1958, 2014.