A. Visualization

In our method, the pretext task MCQ is performed using a parametric module BridgeFormer, to answer multiple choice questions. We construct questions through erasing the content phrases (i.e., noun and verb phrases) of the text, and BridgeFormer is trained to select the correct answer from multiple choices by resorting to the local tokens of VideoFormer. Specifically, given question text tokens from TextFormer as the query, and video tokens from VideoFormer as the key and value, BridgeFormer performs cross-modality attention between them.

A.1. Answering Noun Questions

We first visualize the cross-modality attention between noun question tokens and video tokens in Fig. 1. In the second column, the noun phrase marked in blue (Q1) is erased as the question, and in the third column, the noun phrase marked in green (Q2) is erased as the question. In Fig. 1 (a), when “an old couple” is erased as the question (Q1), BridgeFormer focuses on video tokens that depict the appearance characteristics of the persons, and when “a plate of bread” is erased (Q2), it focuses on object video tokens on the table. In Fig. 1 (d), when “football” is erased (Q1), BridgeFormer focuses on the object video tokens that can be associated with “play”, and when the location phrase “countryside lawn” is erased (Q2), it pays more attention to the video tokens in the background to infer the answer. BridgeFormer attends to video patches with specific object information to answer questions, which also shows that VideoFormer extracts accurate spatial content from videos.

A.2. Answering Verb Questions

We further visualize the cross-modality attention between verb question tokens and video tokens in Fig. 2. Three frames are sampled from a video and the verb phrase marked in blue is erased as the question. In Fig. 2 (a), when the verb “cutting” is erased, BridgeFormer focuses on the motion of the spoon on the pizza, and in Fig. 2 (b), when the verb “drinking” is erased, it follows the movement of the hand holding a cup of water. BridgeFormer focuses on object motions of video tokens to answer verb questions, which also shows that VideoFormer captures temporal dynamics of videos.
A hand is cutting the pizza on the wooden table.

A man standing on the lake shore is drinking hot tea.

Figure 2. The visualization of the cross-modality attention between the text tokens of verb questions (as query) and video tokens (as key and value) from BridgeFormer. Three frames sampled from a video are shown and the verb phrase marked in blue (Q) is erased as the question. BridgeFormer focuses on object motions of video tokens to answer verb questions.

B. CLIP-based Pre-training

Because of the prominent success of the CLIP [9] (Contrastive Language-Image Pre-training) in learning image-text representations, which is pre-trained on 400 million image-text pairs, some recent work [6, 8] utilize the pre-trained CLIP for text-to-video retrieval. We also initialize our model from CLIP weights to pre-train a model following the setting of CLIP4Clip [6]. Specifically, we use the pre-trained CLIP (ViT-B/32) as the backbone of VideoFormer and TextFormer, and randomly initialize BridgeFormer. The comparisons between our method and other CLIP-initialized methods are shown in Table. 1. We can observe that our CLIP-based pre-trained model achieves higher performance for text-to-video retrieval on three datasets with under both the zero-shot and fine-tune evaluation. Our pretext task MCQ also benefits CLIP-based video-text pre-training for downstream text-to-video retrieval.

C. Detailed Model Architecture

Our method consists of three components, including a VideoFormer, a TextFormer and a BridgeFormer. Each component is made up of a stack of blocks as shown in Fig. 3. TextBlock and VideoBlock adopt the structure of BERT [4] and ViT [5] respectively, each performing a series of operations such as multi-head attention [5], normalization (norm) and multi-layer perception [4] (MLP). BridgeBlock takes question text tokens as the query and video tokens as the key and value to perform the cross-modality attention for the interacted tokens. The interacted tokens added with the output tokens from the previous BridgeBlock further go through a series of operations similar to those in the VideoBlock for temporal and spatial self-attention.
D. VideoFormer

**Video Input.** VideoFormer takes a video $V \in R^{M \times 3 \times H \times W}$ as input containing variable $M$ frames of resolution $H \times W$. The input video is first divided into $M \times N$ patches of size $P \times P$, where $N = HW/P^2$. The video patches $v \in R^{M \times 3 \times P^2 \times P}$ are fed into a linear projection head with a convolutional layer and are flattened into a sequence of tokens $z_v \in R^{M \times N \times D}$, where $D$ is the number of embedding dimensions. Following BERT [4], a learnable [CLS] token is concatenated to the beginning of the token sequence, which is used to produce the final video representations. Learnable spatial positional embeddings $E_{pos} \in R^{(N+1) \times D}$ are added to each video token as the final input token sequence $z^l_v \in R^{1+M \times N \times D}$ and all patches in the same spatial location in different frames are given the same spatial positional embedding.

**Modification to ViT.** VideoFormer is built upon a vision transformer ViT [5], and consists of a stack of VideoBlocks. We make a minor modification to the original ViT to allow for the input of video frames with variable length. Specifically, given $z^{l-1}_v \in R^{(1+M \times N) \times D}$ from previous VideoBlock, we perform multi-head attention (MSA) [5] for the [CLS] token through attending to all $(1+M \times N)$ patches across time and space for temporal and spatial self-attention. For the rest $(M \times N)$ patch tokens, MSA is performed within each of $M$ frames with $N+1$ tokens $(N$ patch tokens and 1 [CLS] token) for spatial self-attention. The video representations are obtained from the [CLS] token of the final VideoBlock.

**Comparison with Frozen.** Frozen [1] also adopts ViT [5] as the video encoder, and adds temporal attention blocks based on the spatial attention blocks of ViT to encode videos with variable-length sequences. As shown in Table. 2, compared with Frozen, our VideoFormer decreases 28 million parameters. Furthermore, the model without the pretext task MCQ indeed takes the same pre-training approach as Frozen except for the video encoder, and achieves better results for zero-shot text-to-video retrieval on MSR-VTT [12], which proves the efficiency and effectiveness of our VideoFormer.

### Table 1. Text-to-video retrieval results of models initialized from CLIP [9] weights on different datasets under zero-shot and fine-tune evaluation, where higher R@k and lower MdR (Median Rank) indicate better performance.

<table>
<thead>
<tr>
<th>Method</th>
<th>MSR-VTT</th>
<th>LVIS</th>
<th>LSMD</th>
<th>HMDB51</th>
<th>UCF101</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R@1</td>
<td>R@5</td>
<td>R@10</td>
<td>MdR</td>
<td>R@1</td>
</tr>
<tr>
<td>CLIP-straight [8]</td>
<td>31.2</td>
<td>53.7</td>
<td>64.2</td>
<td>4.0</td>
<td>-</td>
</tr>
<tr>
<td>CLIP4Clip [6]</td>
<td>32.0</td>
<td>57.0</td>
<td>66.9</td>
<td>4.0</td>
<td>34.0</td>
</tr>
<tr>
<td>Ours</td>
<td>33.2</td>
<td>58.0</td>
<td>68.6</td>
<td>4.0</td>
<td>25.7</td>
</tr>
<tr>
<td>CLIP4Clip [6]</td>
<td>43.1</td>
<td>70.4</td>
<td>80.8</td>
<td>2.0</td>
<td>16.2</td>
</tr>
<tr>
<td>Ours</td>
<td>44.9</td>
<td>71.9</td>
<td>80.3</td>
<td>2.0</td>
<td>15.3</td>
</tr>
</tbody>
</table>

### Table 2. Comparisons between the video encoder in our method and Frozen [1]. The evaluation is performed on zero-shot text-to-video retrieval on MSR-VTT, where higher R@k and lower MdR (Median Rank) indicate better performance. “# Params” denotes the number of parameters of the video encoder (M: million).

<table>
<thead>
<tr>
<th>Method</th>
<th>R@1</th>
<th>R@5</th>
<th>R@10</th>
<th>MdR</th>
<th># Params</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frozen [1]</td>
<td>18.7</td>
<td>39.5</td>
<td>51.6</td>
<td>10.0</td>
<td>114M</td>
</tr>
<tr>
<td>Ours</td>
<td>22.3</td>
<td>43.8</td>
<td>52.0</td>
<td>9.0</td>
<td>86M</td>
</tr>
</tbody>
</table>

### Table 3. The effects of the prompt “[MASK]” for noun and verb representations, where “End”, “Middle” and “Start” denote the location of the prompt. For zero-shot text-to-video retrieval on MSR-VTT, higher R@k is better. For zero-shot action recognition on HMDB51 and UCF101, higher top-1 accuracy is better.

<table>
<thead>
<tr>
<th>Method</th>
<th>R@1</th>
<th>R@5</th>
<th>R@10</th>
<th>MdR</th>
<th>R@1</th>
<th>R@5</th>
<th>R@10</th>
<th>MdR</th>
</tr>
</thead>
<tbody>
<tr>
<td>w/o Prompt</td>
<td>23.1</td>
<td>43.5</td>
<td>54.3</td>
<td>34.8</td>
<td>45.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>End</td>
<td>24.2</td>
<td>45.7</td>
<td>54.4</td>
<td>33.4</td>
<td>48.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle</td>
<td>24.3</td>
<td>43.2</td>
<td>53.9</td>
<td>33.1</td>
<td>46.4</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Start</td>
<td>25.1</td>
<td>45.4</td>
<td>55.4</td>
<td>34.9</td>
<td>51.4</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

E. Prompt for Phrase Representation

In our method, BridgeFormer is trained to select the correct answer by contrasting noun answer representations with noun representations, and contrasting verb answer representations with verb representations. Accurate representations for noun and verb phrases are essential. Since TextFormer is trained with full sentences, it fails to encode accurate representations for phrases when it takes a single noun or verb phrase as inputs, and achieves worse results for zero-shot text-to-video retrieval. We show ablative studies of the prompt “[MASK]” for noun and verb representations in Table. 3, where each model is pre-trained using 1 frame. The model without the prompt “[MASK]” takes a single noun or verb phrase as inputs, and achieves the worse results on both the zero-shot text-to-video retrieval and action recognition, showing that TextFormer cannot understand the semantics accurately with a single noun or verb phrase as inputs. The model with the prompt “[MASK]” at the beginning of the phrase achieves the best results in general, and we adopt this practice in our method.
F. More Discussions about Related Work

F.1. Video Question Answering (VQA)

Works on video question answering (VQA) \cite{2,7,10,14} aims to answer questions about videos through training a model with question and answer pairs, which cannot be directly applied for pre-training as they are deliberately optimized for increasing VQA accuracy. By contrast, our work aims to learn downstream-agnostic generic features for video-text retrieval, where a new pretext task, multiple choice questions, is proposed to enhance the semantic associations between video and text. Our paper is the first to use the form of VQA as a pre-training pretext task, with two key innovations: the MCQ loss and the BridgeFormer module. BridgeFormer smoothly bridges the final objective of learning well-aligned video and text features with the regularization of a VQA pretext task.

F.2. Video-text Retrieval with Nouns and Verbs

Works \cite{3,11,13,15} solved video-text retrieval by focusing on verbs and nouns of texts, which are specially designed for retrieval with verbs and nouns as the refined text representations to directly align with videos. By contrast, we exploit the rich semantics of nouns and verbs in the text to build questions for improving text and video encoders.

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