Video Summarization Based on Video-text Modelling

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Abstract

Modern video summarization methods are based on deep neural networks which require a large amount of annotated data for training. However, existing datasets for video summarization are small-scale, easily leading to over-fitting of the deep models. Considering that the annotation of large-scale datasets is time-consuming, we propose a multimodal self-supervised learning framework to obtain semantic representations of videos, which benefits the video summarization task. Specifically, we explore the semantic consistency between the visual information and text information of videos, for the self-supervised pretraining of a multimodal encoder on a newly-collected dataset of video-text pairs. Additionally, we introduce a progressive video summarization method, where the important content in a video is pinpointed progressively to generate better summaries. Finally, an objective evaluation framework is proposed to measure the quality of video summaries based on video classification. Extensive experiments have proved the effectiveness and superiority of our method in rank correlation coefficients, F-score, and the proposed objective evaluation compared to the state of the art.

1. Introduction

Video summarization aims to generate a short version of a video by picking the most important frames or shots containing the main content of the original video, which greatly improves the efficiency of video browsing and retrieval. State-of-the-art video summarization methods are based on deep neural networks which model the dependencies between frames/shots and estimate their importance [15,17,18,31,40,42]. However, existing datasets for video summarization are relatively small [13,33], which easily leads to over-fitting of the deep models. Meanwhile, collecting a large-scale annotated dataset for video summarization is challenging and time-consuming, as multiple annotators need to provide frame/shot-level annotations to minimize subjectivity. When the annotated data are scarce, self-supervised learning has shown great power in boosting the performance of deep models in various scenarios, such as image retrieval [28], action recognition [2], and language understanding [8]. Encouraged by these successful stories, one may ask a natural question, “Can self-supervised learning benefit video summarization?”

In this paper, we show that the answer to the above question is YES. Inspired by the semantic correlation between videos and their associated text information such as titles and descriptions, we propose a novel multimodal self-supervised learning approach for video summarization. Specifically, we construct a multimodal encoder, which is learned by leveraging the multimodal semantic correlations between the videos and the corresponding text information as the supervision. The proposed self-supervised model extracts modality-invariant representations from videos, where the text information and visual information are embedded into a common latent space. To train the multimodal encoder, we collect a dataset that consists of video-text pairs from YouTube. Specifically, we first obtain several video categories and search queries from

Figure 1. An example from the YTVT dataset. Five sampled frames and the text information of the video are presented.
Google Trend\(^1\). We then collect the top searched videos whose duration is 5–20 minutes as well as their corresponding titles and descriptions. Finally, a dataset consisting of 1,069 YouTube Video-Text pairs (YTVT) is collected for the multimodal self-supervised learning. Figure 1 shows an example from the YTVT dataset\(^2\).

After the self-supervised pretraining, a multimodal sequence encoder is obtained and further fine-tuned for the video summarization task. Existing video summarization methods \([15, 17, 18, 42]\) are mainly based on a single-stage fashion where the videos are examined only once to generate the final summaries, which might be insufficient to pinpoint the important content. In this work, we propose a progressive video summarization method using the pretrained multimodal encoder, where the input sequence is refined by iteratively emphasizing the important content in a multi-stage fashion. Besides, we also describe how to incorporate the text information into our framework for video summarization. In the evaluation, to resolve the issue that the current evaluation metrics rely on frame/shot-wise human annotations \([29, 43, 44]\), we present an objective evaluation framework for video summarization. Practically, we use video classification as the downstream task to evaluate the summaries. The motivation is that 1) a satisfactory summary is supposed to reflect the same class information as the original video; 2) the class labels of videos are way easier to obtain than the frame/shot-wise annotations.

Our contributions are summarized as follows:

1) We introduce multimodal self-supervised learning for video summarization, where semantic representations of videos and text are learned by training a multimodal encoder on a new dataset consisting of video-text pairs.

2) Based on the multimodal encoder, we propose a progressive video summarization method where each input video sequence is enhanced in a multi-stage fashion. The multimodal encoder can also be leveraged to incorporate text information for better video summarization.

3) We present an objective evaluation framework based on video classification to measure the quality of summaries, which is easy to be extended to large-scale utilization.

2. Related Work

2.1. Video Summarization

Video summarization methods can be roughly classified into supervised methods and unsupervised ones. We review existing methods according to the category they belong to.

The unsupervised video summarization \([15, 25, 26, 45]\) relies on the criteria designed by human, such as representativeness \([7, 27]\) and diversity \([45]\). Conventional machine learning algorithms such as clustering and dictionary learning were widely exploited in unsupervised methods. For instance, \(L_{2,0}\)-constrained sparse dictionary learning was used to address video summarization in \([26]\). Besides, unsupervised methods based on deep neural networks were presented in recent works. SGAN \([25]\) used adversarial generative networks to generate summaries which were hard to discriminate from the original videos.

Most of the supervised methods are based on deep neural networks to model the temporal dependencies \([9, 17, 31, 39, 40, 42–44]\), which requires human summaries for training. Numerous deep models were developed to capture the temporal dependencies in either local fashion or global fashion. For example, long short-term memory (LSTM) was exploited to model the video and predict the frame-level scores in vsLSTM/dplLSTM \([39]\). Furthermore, hierarchical adaptations of LSTM were proposed to address the issues of plain LSTM \([43, 44]\). Besides, attention models and graph models were exploited to capture the global dependencies. For instance, a sequence-graph structure was developed in RSGN \([42]\), which models the frame-level dependencies and the shot-level ones successively. However, existing methods perform video summarization in a single-stage fashion where the videos are examined only once. In contrast, we propose progressive video summarization to iteratively refine the input and pinpoint the important content.

2.2. Self-supervised Learning

Self-supervised learning has been widely used for the pretraining of deep neural networks, which boosts their performance to a large extend in various fields \([8, 10, 16, 21, 24, 37, 38]\). Concretely, a pretext task is designed for the pretraining of the deep models, where annotations are not required. For instance, jigsaw puzzle was exploited as the pretext task, and the deep models were trained to solve it by capturing the spatial context structure of visual information \([2, 28]\). Generation-based tasks such as image colorization \([41]\), image super-resolution \([22]\), and video prediction \([34]\) were also studied in self-supervised learning, by which the deep models can be trained using the internal information within data instead of human annotations.

Apart from using only visual information for self-supervised learning, multimodality data were also exploited by contrastive learning \([3–5, 20, 23]\). For instance, the consistency of videos and audios were leveraged to train the deep encoder in \([20]\). Besides, the semantic correlations between images and text were used to obtain semantic representations \([25]\). Such pretraining was proved effective in many tasks. Furthermore, the consistency among three modalities, video, audio, and text, were considered in \([3]\), by which a versatile network can be obtained. Different from previous works on multimodal self-supervised learning, we propose a multimodal encoder that can model the

\(^1\)https://trends.google.com/trends

\(^2\)More examples can be found in the supplemental materials.
sequences from both the visual domain and the text domain to obtain modality-invariant representations of videos.

3. Multimodal Self-supervised Progressive Video Summarization

Deep learning has been popularly used for video summarization [18, 42, 44], yet most of the existing datasets [13, 33] are relatively small, resulting in over-fitting of the deep models. To resolve this issue, we explore self-supervised learning to improve video summarization. In this section, we propose multimodal Self-Supervised Progressive Video Summarization (SSPVS). Specifically, we first introduce the collected dataset for the multimodal self-supervised learning. Then, we elaborate the framework for the multimodal self-supervised learning. We further present the progressive video summarization based on the self-supervised pretrained network. Finally, we illustrate how to incorporate text information for better video summarization.

3.1. Data Collection for Self-supervised Learning

Generally, there exist semantic correlations between videos and their associated text information such as titles and descriptions. Such correlations provide supervision which can be used to train a multimodal network in a self-supervised manner. This encourages the multimodal network to learn better representations of the video and text, which benefit the video summarization task. To learn the semantic correlation between the video and text information, video-text data are required. To this end, we first collect video data as well as their associated text information.

In this paper, we collect video data and their associated text information from YouTube. Specifically, We first obtain 23 video categories from Google Trend, such as Autos & Vehicles and Beauty & Fitness. For each category, we use its sub-categories as search queries and obtain several search results on YouTube. For instance, the category of Hobby & Leisure has sub-categories such as Cycling and Bowling, and those sub-categories are used as search queries to collect more specific videos. Note that we manually eliminate trending queries such as Gossip and Celebrity because such videos contain few general scenarios. Since we expect the videos to contain complex content and scenarios, the short videos (less than 5 minutes) are filtered out. Furthermore, considering the GPU memory limit, the videos longer than 20 minutes are also ruled out. The search results which satisfy the length limit are collected. Besides category, we also collect the video-specific text information, including titles and descriptions. In this case, four types of text information for each video are obtained: category, search query, title, and description. Finally, a YouTube-based dataset of 1,069 Video-Text pairs are collected for multimodal self-supervised pretraining, which is named as YTVT. Detailed statistics of YTVT are shown in Table 1.

Table 1. Statistics of YTVT. “Min/Max/Avg. Duration” represents the minimum/maximum/average duration of videos. “Avg. Title/Desc. Len.” represents the average number of words in titles/descriptions. Details are in the supplementary materials.

| Statistics   | Result | Statistics   | Result |
|--------------|--------|--------------|--------|
| #Videos      | 1,069  | Min Duration | 300s   |
| #Categories  | 23     | Max Duration | 1,198s |
| #Queries     | 198    | Avg. Duration| 640.1s |
| Avg. Title Len. | 9.6   | Avg. Desc. Len. | 111.6 |

3.2. Multimodal Self-supervised Pretraining

Given the video-text data, we investigate a multimodal network to exploit the correlation between videos and text information, thus to learn better video representations for the downstream summarization task. The framework self-supervised multimodal is shown in Figure 2. Specifically, the framework takes a video-text pair as the input and aims to identify whether there is correlation between the video and text in the pair (positive) or not (negative).

Input. The input of our framework is a video-text pair, where the video is a sequence of frames and the text is a sequence of words. For the text input, four different types of text information of each video are considered, i.e., category, search query, title, and description, each consisting of a sequence of words. The four separate text sequences are combined to form a larger sequence, with a [SEP] token placing between every two types of text sequences to separate each. Each word is converted into a vector by the pretrained word embedding module of BERT [8]. The dimension of word embeddings $d_w$ is 768. As for the visual information, following previous works [25, 39, 44], the output of the penultimate layer (pool 5) of the GoogLeNet [35]...
3rd Stage
Video Summarization

2nd Stage
Video Summarization

1st Stage
Video Summarization

Video

(a)

Figure 3. (a) The overview of the proposed progressive video summarization of three stages, where the structure and process of each stage is identical. (b) The details of video summarization in the third stage. (c) The details of the text information encoding.

pre-trained on ImageNet [32] is adopted as the frame feature, which is consistent with most of the video summarization methods for fair comparisons. The dimension of frame features $d_f$ is 1,024. A linear transformation is applied to the CNN features to ensure the frame features have the same dimension as that of the word embeddings. For simplicity, we use $d = 768$ to denote the dimensions of the projected frame features and word embeddings. The combined text sequence and the video frames (with positional embedding) are concatenated as the final input of our framework. Note that the [SEP] token is also placed between the combined text sequence and the video frames, and the [CLS] token is prepended to the whole sequence to aggregate information from both the text and the visual domains [8, 23].

Network Structure. Since the input (the concatenation of the video and the text information) are in the form of sequences, sequence modeling is crucial in our framework. Motivated by the great success of Transformer in sequence modeling [36], Transformer is exploited as the multimodal encoder. Specifically, the pretrained BERT model [8] is adopted to stabilize the video-text multimodal encoding.

Pretraining Objective. To learn semantic representations based on the video-text semantic correspondence, the contrastive self-supervised learning is used to train our framework. Specifically, both positive and negative pairs of the videos and text information are constructed to feed to the network, where each positive pair consists of a video and the corresponding text information, while in each negative pair, the text information does not belong to the video, and the network is trained to predict if an input pair is positive or negative. Specifically, a two-layer fully connected network with Sigmoid activation is applied to the final feature output by the encoder corresponding to the [CLS] token, which is used as the representation of the whole input sequence [23], for the prediction. Binary cross entropy is used as the loss function to train the framework as follows,

$$\mathcal{L}_{SSL}(V, T) = -(y \log(p) + (1 - y) \log(1 - p)), \quad (1)$$

where $(V, T)$ is the input video-text pair, $y$ is the binary label indicating whether $(V, T)$ is positive or not, and $p$ is the probability predicted by the model. By distinguishing positive and negative pairs, the multimodal framework is encouraged to learn semantic representations from both video and text modalities, which can benefit video summarization.

3.3. Progressive Video Summarization

In this section, we perform video summarization based on the pretrained BERT encoder. Existing methods perform video summarization in the single-stage fashion where the videos are examined only once, which might be insufficient to pinpoint the important content. To address this limitation, we propose progressive video summarization. As shown in Figure 3(a), the framework is a stack of multiple models with the identical architecture. Each model is referred to as a stage and the detailed structure is shown in Figure 3(b).

More specifically, the input of the $i$-th stage is computed as the weighted enhancement of the input of the previous stage based on the output of the previous stage, i.e.,

$$F^i = F^{i-1} \ast s^{i-1} + F^{i-1}, \quad (2)$$

where $F^i = [f_1^i, \cdots, f_T^i] \in \mathbb{R}^{T \times d}$ represents the sequence of input features at the $i$-th stage. $f_t^i \in \mathbb{R}^d$ denotes the feature at the $t$-th time step of the sequences $F_t^i$. Similarly, $F^{i-1}$ denotes the sequence of input features at the
(i - 1)-th stage. $s^{i-1} = [s_{1}^{i-1}, \ldots, s_{T}^{i-1}]^{T} \in \mathbb{R}^{T}$ is a sequence of the frame scores output by the (i - 1)-th stage. $s_{t}^{i-1} \in [0, 1]$ is a scalar denoting the score at the t-th time step of $s^{i-1}$. $T$ represents the number of frames in the sequence. * represents row-wise multiplication. The motivation of such formulation is to iteratively refine the video sequence by emphasizing the important content. For the first stage, $F^{0}$ is initialized as the original frame features extracted by the pretrained CNN, and $s_{t}^{0} = 0$.

At the i-th stage, the input feature $F^{i}$ is encoded by the BERT encoder BERT_$(\theta)$ (\theta denotes the parameters of the BERT model that are initialized by the self-supervised pre-training and are shared for all stages), i.e.,

$$G^{i} = \text{BERT}_\theta(F^{i} + E_{\text{pos}}^{V}),$$

where $G^{i} = [g_{1}^{i}, \ldots, g_{T}^{i}]^{T} \in \mathbb{R}^{T \times d}$ is the sequence of encoded features. $g_{t}^{i} \in \mathbb{R}^{d}$ denotes the feature at t-th time step of $G^{i}$. $E_{\text{pos}}^{V} \in \mathbb{R}^{T \times d}$ is the positional encoding for the video sequence. Containing the global temporal information of the sequence, $G^{i}$ is then leveraged to predict the frame-level importance score for video summarization. Additionally, a residual connection is applied before the linear projection to improve training stability [14], i.e.,

$$s^{i} = \sigma((G^{i} + F^{i})W^{i} + b^{i}),$$

where $s^{i} \in \mathbb{R}^{T}$ is the output sequence of the frame scores at the i-th stage, $W^{i} \in \mathbb{R}^{d}$, $b^{i} \in \mathbb{R}$ are the learnable parameters of the i-th stage, and $\sigma(\cdot)$ is the Sigmoid function.

The final frame scores are computed by taking into consideration the score sequences output by all stages, i.e.,

$$s^{*} = s^{1} \odot s^{2} \odot \cdots \odot s^{N} \in \mathbb{R}^{T},$$

where $\odot$ represents element-wise multiplication, and $N$ is the pre-defined number of stages. The reason why we use the multiplication of the predictions of all stages is to ensure that each stage functions appropriately, and to prevent from vanishing gradient with the increase of stages.

**Optimization and Summary Generation.** We use the ground truth frame-level importance scores provided in the datasets to train the proposed video summarization framework. Formally, given the ground truth frame scores $s_{gt} \in \mathbb{R}^{T}$ and the predicted frame scores $s^{*}$ of a video, the mean square error is exploited as the loss function, i.e.,

$$L_{VS}(s^{*}, s_{gt}) = \frac{1}{T} \|s^{*} - s_{gt}\|_{2}^{2}.$$  

To generate summaries, we follow [25, 39, 45] and select shots to maximize the total score, with the constraint that the length of the summary is less than 15% of that of the original video. Kernel-based Temporal Segmentation (KTS) [30] is used to segment the videos into shots. The score of a shot is the average score of the frames within it.

### 3.4. Video Summarization with Text Information

The text modality contains complementary information to the video data, which can be incorporated for better video summarization. In this work, since the pretrained encoder in Section 3.2 is modality-invariant for visual information and text, it is also used for text encoding. As shown in Figure 3(c), given the text information, the [CLS] token is prepended to the whole sequence, and the pretrained word embedding model is applied to convert the text to a sequence of word embeddings $X = [x_{1}, \ldots, x_{T'}]^{T} \in \mathbb{R}^{T' \times d}$, where $T'$ and $d$ are the length of the word sequence and the dimension of word embedding $x_{j} \in \mathbb{R}^{d}$. The sequence is then encoded by the pretrained encoder, i.e.,

$$Z = \text{BERT}_\theta(X + E_{\text{pos}}^{T}),$$

where $Z = [z_{1}, \ldots, z_{T'}]^{T} \in \mathbb{R}^{T' \times d}$ is the sequence of the encoded word embeddings. $E_{\text{pos}}^{T} \in \mathbb{R}^{T' \times d}$ is the positional encoding for the word sequence. Finally, $z_{1} \in \mathbb{R}^{d}$, the encoded feature of the [CLS] token, is regarded as the feature of the text information, which is fused into the visual modality for video summarization as follows,

$$S^{i} = \sigma((G^{i} + F^{i} + z_{1})W^{i} + b^{i}), i = 1, \cdots, N.$$  

Note that the text representation is computed only once and reused in all stages. In this case, the frame-level scores are predicted by taking into consideration not only the visual information but also the associated text information.

### 4. Objective Evaluation Framework for Video Summarization

F-score and rank-based evaluation are computed using summaries and scores annotated by human as reference [29, 43, 44]. However, such annotations are expensive to obtain and biased by human favors. To resolve these issues, we propose classification-based objective evaluation for video summarization. This is inspired by the intuition that a good summary of a video should contain the information relevant to the class of the original video. Specifically, a model is first trained for video classification, and then video summarization is applied to the videos in the testing set. Finally, we test the classification accuracy of the summaries and compare with the classification accuracy of the original videos and randomly cropped videos.

Note that the model is trained on the original videos but tested on the summaries or randomly-cropped videos. Such practice ensures that different summaries are evaluated by the same model so that the fairness of comparisons is guaranteed. Besides, the domain gap between the training data and the testing data makes this evaluation more challenging. Compared with previous metrics that rely on the frame-level
annotations, this proposed evaluation only requires video-level class labels, which is way easier to obtain.

Since the videos in existing datasets for classification are too short to be summarized (less than 30 seconds) \cite{1,11,12}, we collect new videos for our purpose. Note that YTVT cannot be used since our model is pretrained on it, otherwise the comparisons are unfair to other methods. Specifically, ten queries are used to search videos on YouTube\footnote{The details can be found in the supplementary materials.}. For each search query, the top search results whose duration is 8–16 min are collected. Finally, 794 videos are collected, and the queries are regarded as the classes. We randomly select 70\% of the videos in each class for training and validation, and the rest are for testing. The pre-processing of videos is the same as that of video summarization.

In order to bring out the performance of different summaries, we do not use sophisticated model for classification. Specifically, the classification model is a simple 3-layer Transformer with 4 heads and the hidden dimension is 2,048 in the feed-forward network. Similar to SSPVS, the input is the sequence of frame features as well as a learnable [CLS] token. After the model is trained, it is used to test the accuracy of the summaries for classification.

5. Experiments

In this section, we conduct extensive experiments to verify the effectiveness of our method. The experimental settings are first explained. We then compare our method with state-of-the-art methods in terms of rank-based evaluation, F-score, and the objective evaluation. Afterwards, we perform ablation studies to demonstrate the impact of our contributions. Finally, the predicted scores are visualized.

5.1. Experimental Settings

5.1.1 Datasets

As mentioned in Section 3.1, we collect the YTVT dataset for self-supervised learning. For the video summarization task, we use SumMe \cite{13} and TVSum \cite{33} datasets. Specifically, 25 videos are included in SumMe and the topics involve cooking, holidays, etc. 50 videos are included in TVSum and 10 categories are involved, such as Beekeeping and Parade. Since SumMe and TVSum provide limited text information, we re-collect their associated text information from YouTube\footnote{More details can be found in the supplementary materials.}. Specifically, since the videos in SumMe are too old to find on YouTube, we regard their video names in the dataset as search query of the text information and leave the other three types of text information empty. For each video in TVSum dataset, since its title is provided, we only collect its description from YouTube. Besides, the 10 categories in TVSum are regarded as search query of the text information, and category of the text information is left empty. Apart from SumMe and TVSum, YouTube \cite{7} and OVP\footnote{Open Video Project: https://open-video.org} are used for the augmented setting and the transfer setting \cite{39,45}. Specifically, 39 videos are included in YouTube and the topics involve sports, news, etc. 50 videos are included in OVP and they are mostly documentaries.

5.1.2 Implementation Details

Data Pre-processing. For videos in the YTVT dataset and the datasets for video summarization, noisy or irrelevant words in text information are removed, such as extra spaces, URLs, and E-mails. Besides, lemmatization is applied to each word. As for the visual information, the videos are sub-sampled to 2 FPS to reduce temporal redundancy.

Multimodal Self-supervised Pretraining. To increase the generalization ability and avoid over-fitting, we randomly cropping 256 frames from each video for training. Besides, to deal with the inconsistency in the text length , we set the maximum lengths of category, search query, title, and description to 3, 3, 10, and 50, respectively. For those text sequences shorter than the requirements, they are padded with the [PAD] tokens in the end. The uncased base version of the BERT model is used as the multimodal encoder. During training, the model is optimized by Adam \cite{19} for 300 epochs with batch size 4 and learning rate $10^{-5}$.

Progressive Video Summarization. The framework is trained by Adam for 40 epochs with batch size 2 and learning rate $10^{-5}$ and OVP\footnote{Open Video Project: https://open-video.org} are used for the augmented setting and the transfer setting \cite{39,45}. Specifically, 39 videos are included in YouTube and the topics involve sports, news, etc. 50 videos are included in OVP and they are mostly documentaries.

5.1.3 Evaluation Metrics

F-score. F-score measures the overlap between the generated video summary and the human summary. Specifically, given the generated video summary $\mathcal{V}$, and the human summary $\mathcal{V}_{gt}$, the precision $P$ and recall $R$ are computed as $P = \frac{|\mathcal{V} \cap \mathcal{V}_{gt}|}{|\mathcal{V}|}$, $R = \frac{|\mathcal{V} \cap \mathcal{V}_{gt}|}{|\mathcal{V}_{gt}|}$. The F-score $F$ is computed as the harmonic average of $P$ and $R$, i.e., $F = \frac{2PR}{P+R}$.

Rank-based Evaluation. Rank-based evaluation is proposed \cite{29} to address the limitations of F-score. Specifically, given the predicted frame-level scores and the scores annotated by human, two rank correlation coefficients, Kendall’s $\tau$ and Spearman’s $\rho$, are used as the primary comparison metrics in the experiments. For the videos with multiple sets of annotations, the average coefficients are taken as the final results, and the same goes for F-score.
Table 2. The results (Kendall’s $\tau$ and Spearman’s $\rho$) on SumMe and TVSum. The results in the first row are computed using random scores, human scores, and ground truth scores, respectively. The methods in the second row are unsupervised methods, while those in the third row are supervised methods. The best and the second-best results are in **bold** and *underlined*, respectively.

| Methods       | SumMe | TVSum |
|---------------|-------|-------|
|               | $\tau$ | $\rho$ | $\tau$ | $\rho$ |
| Random        | 0.000  | 0.000  | 0.000  | 0.000  |
| Human         | 0.205  | 0.213  | 0.177  | 0.204  |
| Ground Truth  | 1.000  | 1.000  | 0.364  | 0.456  |
| SGAN [25]     | — —    | 0.024  | 0.032  |
| WS-HRL [6]    | — —    | 0.078  | 0.116  |
| DRDSN [45]    | 0.047  | 0.048  | 0.020  | 0.026  |
| RSGN [42]     | 0.071  | 0.073  | 0.048  | 0.052  |
| dppLSTM [39]  | — —    | 0.042  | 0.055  |
| CSNet [17]    | — —    | 0.025  | 0.034  |
| GLRPE [18]    | — —    | 0.070  | 0.091  |
| HSA [44]      | 0.064  | 0.066  | 0.082  | 0.088  |
| RSGN [42]     | 0.083  | 0.085  | 0.083  | 0.090  |
| SSPVS         | 0.119  | 0.166  | 0.165  | 0.217  |
| SSPVS+Text    | **0.123** | **0.170** | **0.169** | **0.231** |

**Objective Evaluation.** As explained in Section 4, the above two evaluation metrics are limited since human annotations are involved. In this case, we also conduct comparisons using the proposed objective evaluation that is based on the classification of generated summaries.

### 5.2. Comparisons with the State of the Art

#### 5.2.1 Comparisons of Rank Correlation Coefficients

We compare our methods with the state of the art using the rank correlation coefficients, Spearman’s $\rho$ and Kendall’s $\tau$. These metrics measure the similarity between the predicted scores and those annotated by human. The results are shown in Table 2. Note that the results of random scores, human scores, and ground truth scores are also provided.

As shown in Table 2, SSPVS outperforms existing methods to a large extent on both datasets, which means the proposed method can model the relative importance among frames more accurately than previous works. Additionally, by including the text information in the summarization process, the performance is further improved on both datasets.

#### 5.2.2 Comparisons of F-Score

We also compare our method with previous works in the widely-used F-score. The results are shown in Table 3. Since the text information of the videos in OVP and YouTube is not collected, the results of SSPVS+Text in the augmented setting and the transfer setting are not reported.

### 5.2.3 Comparisons of Objective Evaluation

In this experiment, we compare the classification accuracy of the original videos, the randomly cropped videos, and the summaries in the testing set as mentioned in Section 4. Specifically, we set the length of the cropped videos and the summaries to 5%/10%/15% of that of the original.
videos. The summaries are generated by the models trained on the whole TVSum. Besides, to alleviate the instability from random cropping, the videos are randomly cropped ten times and the accuracy is averaged.

As shown in Table 4, the classification model achieves 85.1% using the original videos. However, when testing the randomly cropped videos, the performance drops obviously. As for the video summaries generated by different methods, their quality regarding video classification vary from each other. Specifically, the summaries generated by frame-wise logistic regression and vsLSTM are slightly better than randomly cropped videos, which means these methods are less capable of finding informative content in videos. As for DRDSN, H-RNN, and VASNet, the improvements of summaries are significant, especially when the summarizing ratio is large. But the performance of ratio 5% is still deficient. By exploiting Transformer as the video encoder, the summaries of ratio 5% is improved, which means Transformer is more powerful in pinpointing the most important content. As for the summaries generated our methods, they achieve the highest accuracy in all ratios. Therefore, our methods are superior over other methods regarding the classification-based objective evaluation.

5.3. Ablation Study
We conduct ablation studies to demonstrate the effectiveness of the multimodal self-supervised pretraining, the progressive summarization, and the summarization with text information. Specifically, considering the computational complexity and the GPU memory limit, we set the number of stages to 1, 2, and 3, respectively. For each number of stages, three models are evaluated: the base model (without pretraining and text information), the model with pretraining, and the model with pretraining and the text information.

The results of ablation studies are shown in Table 5. As the results show, with the increase of the number of stages, the performance is improved significantly on SumMe. As for TVSum, the 2-stage SSPVS achieves better results than the 1-stage one, but the results of the 2-stage SSPVS and the 3-stage one are similar. We believe too many stages would not further improve the performance on TVSum. For each number of stages, the multimodal self-supervised pretraining and the text information boost the performance considerably. Specifically, the impact of pretraining is more obvious when the number of stages is small, while the text information enhances the predictions consistently.

5.4. Visualization of Prediction
The predicted importance scores by SSPVS/SSPVS+Text and the ground truth ones are visualized in Figure 4. The four videos in the figure are from TVSum. As we can see from the figure, the predicted curves fit the ground truth ones well, which means the proposed methods can effectively model the temporal dependencies and the relative importance among frames. Specifically, SSPVS+Text (red) shows higher accuracy than SSPVS (blue) in the prediction of importance scores, which means the text information further benefits the process of video summarization.

6. Conclusion
In this paper, we have successfully incorporated video summarization into the self-supervised learning framework which leverages the semantic consistency between the
videos and the corresponding text information. Based on the pretrained multimodal encoder, we have developed progressive video summarization. Our method refines the input sequences in a multi-stage fashion, where text information is also exploited for summary generation. Additionally, we have developed the objective evaluation framework for video summarization based on video classification, where no human annotations are required. Extensive experiments have verified the effectiveness of our contributions. Compared with previous works, the proposed method have achieved state-of-the-art performance in both the reference-based metrics and the proposed objective evaluation.

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