Pre-training for Video Captioning Challenge 2020 Summary
http://www.auto-video-captions.top/2020/

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Table 1: The leaderboard of top-3 submissions.

| Rank | Team Name | Affiliation | BLEU@4 | METEOR | CIDEr-D | SPICE |
|------|-----------|-------------|--------|--------|--------|--------|
| 1    | Old Boys  | Tsinghua University, Beijing University of Posts and Telecommunications, Shanghai Ocean University | 21.14  | 17.38  | 24.42  | 5.65   |
| 2    | sysu-cs   | Sun Yat-sen University | 20.41  | 17.02  | 23.80  | 5.39   |
| 3    | IVIPC-King | University of Electronic Science and Technology of China | 18.24  | 16.46  | 21.36  | 5.25   |

1. Challenge Introduction

The Pre-training for Video Captioning Challenge is a Multimedia Grand Challenge in conjunction with ACM Multimedia 2020. The goal of this challenge is to offer a fertile ground for designing vision-language pre-training techniques that facilitate the vision-language downstream tasks (e.g., video captioning [1, 2, 4, 5, 6, 8] this year). Meanwhile, to further motivate and challenge the multimedia community, we provide a large-scale video-language pre-training dataset [3] (namely “Auto-captions on GIF”) for contestants to solve this challenging but emerging task.

 Particularly, the contestants are asked to develop video captioning system based on Auto-captions on GIF dataset (as pre-training data) and the public MSR-VTT benchmark [7] (as training data for downstream task). For the evaluation purpose, a contesting system is asked to produce at least one sentence of the test videos. The accuracy will be evaluated against human pre-generated sentence(s).

2. Challenge Results

Table 1 details the results of top-3 submissions. We also attach to this document a copy of the technical reports submitted to the challenge.

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XlanV Model with Adaptively Multi-Modality Feature Fusing for Video Captioning

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1 INTRODUCTION
Some recent work explores the structure of X-Linear Attention networks [1], which exploit static object feature to facilitate image captioning, but the situation of video captioning is more challenging. Unlike still images, video contains both static feature and dynamic feature as the length of video varies. Therefore, we propose to adaptively fuse these two kinds of features to make better utilization of video features in video captioning.

The main contributions of our method are as follows:
• We propose XlanV model to introduce X-Liner Attention networks into video captioning.
• Adaptively fusing multi-modality features to enhance video captioning.

2 METHOD
2.1 Feature Extraction
Our model utilizes two kinds of features. 1) We transform each video into 40 frames of images and leverage a pre-trained ResNet-152 network to extract 40x2048 static features. 2) We extract 160 frames of images from the video and exploit the action classification network I3D to map each 8 frames of images to a 1024d feature.

2.2 XlanV Model for Video Captioning
The overall paradigm of our model, which leverages the X-Linear Attention network [1] as the backbone framework, is shown in Fig. 1. Two encoders are implemented to encode the static feature and the dynamic features respectively. In the LSTM decoder, our model adaptively fuse these two kinds of features.

2.3 Adaptive Multi-modality Fusion
Denoting the attended static feature and dynamic feature as \( \hat{v}_s \) and \( \hat{v}_d \) respectively, the formulation of adaptive multi-modality fusion can be formulated as follows, where \( W \) are trainable parameters and \( \cdot \) denotes concatenation.

\[
\hat{v}_s^{\text{fuse}} = \alpha \ast \hat{v}_s + (1 - \alpha) \ast \hat{v}_d \tag{1}
\]
\[
\alpha = \text{sigmoid}(W[\hat{v}_s; \hat{v}_d]) \tag{2}
\]

Thus, our model is capable of adaptively weighting these two features and makes better utilization of one kind of feature when the other one is not so useful at the current time step.

3 RESULT
Due to the large difference between the test data and the GIF dataset, the GIF dataset was not used in the training process. We only use the MSR-VTT dataset, which is more similar to the test video, as training and validation dataset.

Table 1 shows the test performance of the XlanV model. The comparison baseline uses the results of a Bi-LSTM with attention mechanism network. We train our model with both cross-entropy loss and the reinforcement learning based SCST [2]. In addition, ensembling multi-model can obtain better results.

4 CONCLUSION
In this paper, we introduce a structure of X-linear Attention network for video captioning, which fully integrates video features by adaptively fusing multi-modality video features.

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1 APPROACH

Model. Our VideoTRM includes a visual encoder and a textual encoder for encoding video and sentence respectively, a cross-modal encoder for modeling the interactions between two modalities (i.e., visual and textual), and a decoder with cross-attention on visual inputs for caption generation of the input video. All the four modules are built upon Transformer (TRM) layers [10].

Pre-training. We pre-train our VideoTRM with four proxy tasks: (1) masked language modeling [3]; (2) masked frame-feature regression [9]; (3) video-sentence alignment [7]; (4) masked video captioning. In particular, conditional masking mechanism [1] is adopted during pre-training, where either masked language modeling task or masked frame-feature regression task is randomly performed within the same mini-batch.

Fine-tuning. When the pre-training finished, we fine-tune VideoTRM with video captioning task by additionally integrating mesh-like connections [2] and gate fusion [4] into the decoder.

2 EXPERIMENTS

Preprocessing. For MSR-VTT, we sample videos at 3 fps and set the maximum number of sampled frames as 50. For Auto-captions on GIF, we sample all the frames and similarly use 50 frames as inputs at most. The ResNet-152 pre-trained on ImageNet [6] is exploited to extract 2048-way pool5 visual features.

Model Details. Each encoder or decoder module in our VideoTRM consists of 6 layers except that the textual encoder is of 3 layers. The model dimension of all the four modules is set as 768, and the hidden size of feed-forward layer is 2048. We apply 12 heads in multi-head attention.

Training Details. Our VideoTRM is pre-trained on Auto-captions on GIF with a learning rate of 0.0001 for 20 epochs, and fine-tuned on MSR-VTT with a learning rate of 0.0001 for 20 epochs. Adam with warmup is utilized to optimize our model. Beam search size is set as 1 at decoding stage.

Results. Table 1 shows the performances of our proposed VideoTRM on MSR-VTT. By pre-training with four proxy tasks, CIDEr-D is boosted from 42.8% to 44.7% on the official test split.

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Table 1: The performances of our VideoTRM on MSR-VTT.

| Model | B@4 | M | C | S |
|-------|-----|---|---|---|
| VideoTRM | 38.1 | 26.6 | 42.8 | 5.6 |
| VideoTRM + Pre-training | 38.8 | 27.0 | 44.7 | 5.9 |

| VideoTRM + Pre-training (test server) | 20.41 | 17.02 | 23.50 | 5.37 |

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The Description of the Algorithm Evaluated in the Pre-training for Video Captioning Challenge

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1 Full name and abbreviated name of the algorithm
Multi-stage Tag Guidance Network (MTGNet).

2 Description of the algorithm
Our method MTGNet is designed as illustrated in Figure 1. Specifically, we adopt a variety of feature extraction models to process the video (e.g., I3D, Inception-V2, ResNeXt101 and Faster-RCNN). To make features more robust for complex scenes, we follow the idea of Delving Deeper into the Decoder Model\[1\] and apply the Tag network into the backbone and optimize it further.

Taking into account the prevention of overfitting and time and efficiency issues, the entire training process is divided into two stages of training. The first stage trains all data, and the second stage introduces a random dropout. Note that only the first stage training is performed during the GIF pre-training process. Furthermore, we used CNN-based network to pick out the best candidate results.

3 Experimental environments
This algorithm was evaluated according to the metrics as specified in the Pre-training For Video Captioning Challenge 2020.

- Information about the training set (e.g., Auto-captions on GIF, MSRVTT, MSVD dataset. No additional training datasets were used).
- Information about pre-trained models: we use the I3D model pre-trained on Kinetics, the Inception-V2 model and the ResNeXt101 model pre-trained on ImageNet, the Faster-RCNN model pre-trained on Visual Genome and the ECO model pre-trained on Kinetics. (But not every result uses all the above features to generate)
- In our experiments, we train MTGNet in Figure 1 using multi-stage training and use GIF, MSVD and MSRVTT to train Tag-Net as Guidance. Overall, we adopt GIF to pretrain MTGNet and then fine-tune it with MSR-VTT.

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