A CLIP-Enhanced Method for Video-Language Understanding

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Abstract

This technical report summarizes our method for the Video-And-Language Understanding Evaluation (VALUE) challenge. We propose a CLIP-Enhanced method to incorporate the image-text pretrained knowledge into downstream video-text tasks. Combined with several other improved designs, our method outperforms the state-of-the-art by 2.4% (57.58→60.00) Meta-Ave score on VALUE benchmark.

1. Introduction

Video-Language understanding attracts increasing attention in the research community. Recently, Li [5] proposed the Video-And-Language Understanding Evaluation (VALUE) benchmark, a unified benchmark consisting of 3 types of tasks (VideoQA, Retrieval, Captioning) and 11 datasets. The diverse video domains and task types make it a very challenging benchmark.

Inspired by the rapid progress of large-scale image-text pre-training (e.g., CLIP [11]), we believe the knowledge learned from image-text pairs would be helpful for video-text tasks. Several pioneering works [10, 8, 2] utilize the pretrained CLIP model [11] and demonstrate state-of-the-art performances for several text-video retrieval tasks. However, these existing works are specially designed for the retrieval task, thus cannot adapt to other kinds of tasks.

We incorporate the pre-trained image-text knowledge (i.e., CLIP [11]) into a task-agnostic framework (i.e., HERO [4]), and achieve significant improvements on various downstream tasks (e.g., retrieval, captioning). Combined with several tricks, we propose a mixed strategy for the VALUE benchmark, outperforming the baselines by 2.4% (57.58→60.00) Meta-Ave score.

Briefly, our strategy differs from the HERO baseline in two aspects: 1) The model architecture is modified to incorporate CLIP knowledge, as shown in Fig. 1(a). 2) We use slightly different finetuning settings for different downstream tasks.

1https://value-benchmark.github.io/challenge_2021.html

2. Method

Our method is built based on HERO [4], the state-of-the-art model on VALUE benchmark. We first briefly describe the HERO method, then introduce our improved designs.

2.1. Baseline Method

As shown in Fig. 1(a), HERO consists of three core components: 1) an embedding layer for textual input; 2) a Cross-Modal Transformer for video-subtitle multi-modal fusion and query representation; 3) a Temporal Transformer for learning contextualized video representation from collected video features.

The HERO framework support VideoQA, Retrieval and Captioning tasks. Please refer to [4] for more information.
Table 1: Results of our method (single-model) and state-of-the-art baselines with CLIP-ViT+SlowFast features on Test (leaderboard) set. The baselines are reported in [5], including the following model training settings: single-task training (ST), all-task training then ST (AT → ST). The best performances are highlighted in bold.

| Methods       | TVR | How2R | YC2R | VATEX-EN-R | TVQA | How2QA | VIO-LIN | VLEP | TVC | YC2C | VATEX-EN-C | Meta-Ave |
|---------------|-----|-------|------|------------|------|--------|---------|------|-----|------|------------|----------|
| Human         | -   | -     | -    | -          | 89.41 | 90.32  | 91.39   | 90.50 | 62.89| -    | -          | -        |
| Finetune-only |     |       |      |            |       |        |         |      |      |      |            |          |
| ST            | 8.81| 2.13  | 42.37| 47.02      | 71.35 | 69.59  | 64.30   | 56.77 | 50.30| 109.89| 55.98      | 52.59    |
| AT→ ST        | 12.40| 3.61  | 50.93| 49.91      | 74.38 | 71.88  | 66.80   | 68.68 | 49.41| 110.63| 58.09      | 56.07    |
| Pretrain on ResNet+Slowfast, then Finetune |   |       |      |            |       |        |         |      |      |      |            |          |
| ST            | 13.70| 3.38  | 56.59| 46.66      | 74.52 | 73.82  | 64.19   | 67.10 | 51.04| 120.22| 55.30      | 56.96    |
| AT→ ST        | 13.56| 3.95  | 54.28| 49.09      | 74.83 | 74.60  | 67.18   | 69.37 | 48.13| 121.89| 56.54      | 57.58    |
| Our mixed strategy | | **4.64** | **62.68** | 49.86 | **75.45** | **73.92** | **67.47** | **68.37** | **53.34** | **128.87** | **62.30** | **60.00** |

2.2. Improved Designs

In principle, we follow the HERO architecture for all tasks except VATEX-EN-R and VATEX-EN-C. For the VATEX tasks, we build our CLIP-Enhanced model by replacing the default Roberta [6] text embedding layer with a CLIP [11] text encoder (a 12-layer 8-head transformer, initialized with the CLIP pre-trained weights), as shown in Fig. 1 (b).

We use slightly different settings when finetuning different tasks: 1) For the QA tasks, we adopt the all-task training (AT) setting; for other tasks, we adopt the single-task training (ST) setting. 2) We use resnet+slowfast features for yc2r, yc2c, how2r tasks, while for other tasks we use clip-vit+slowfast features. These visual features are officially provided by the VALUE challenge. 3) For yc2r, yc2c, tv tasks, we use training-set and validation-set data for finetuning. 4) We initialize the model with the HERO pre-trained weights for all tasks except the CLIP-Enhanced setting (i.e., the VATEX-EN-R and VATEX-EN-C tasks).

We didn’t use extra data or features during pre-training or finetuning. We didn’t use ensemble techniques.

3. Experiments

We compare our method with the state-of-the-art baselines on VALUE benchmark in Table 1 and Table 2.

3.1. Results on Test (leaderboard) Set

Applying all of the improved designs as described in Sec. 2.2 our mixed strategy achieves significant improvement compared with the baselines on Test (leaderboard) set (60.00 v.s. 57.58), as shown in Table 1.

3.2. Analysis of our CLIP-Enhanced Strategy

In order to evaluate the effects of our CLIP-Enhanced strategy, we compare our method with the state-of-the-art baselines on VATEX-EN-R and VATEX-EN-C validation-set, as shown in Table 2.

Table 2: Results for VATEX-EN-R and VATEX-EN-C tasks with CLIP-ViT+SlowFast features on the Validation set. The baseline results are reported in [5]. Note that the scores marked with star (*) are unfairly high because of data leakage.

| Methods | VATEX-EN-R | VATEX-EN-C |
|---------|------------|------------|
| Finetune-only |         |            |
| ST      | 65.62      | 56.97      |
| AT→ ST  | 78.72*     | 58.13      |
| Pretrain, then Finetune |        |            |
| ST      | 66.49      | 56.19      |
| AT→ ST  | 79.95*     | 56.35      |
| Our strategy: CLIP-Enhanced, Finetune-only | **68.68** | **61.36** |

Our CLIP-Enhanced method achieves best performance except for the AT→ ST baselines on the VATEX-EN-R task. However, after checking the training details, we find that the AT→ ST improvements are indeed from data leakage during All-Task training (AT), i.e., the validation samples for VATEX-EN-R task are accidentally included in the training set of VATEX-EN-C tasks.

Leaving out the unfairly high scores (marked with *), our CLIP-Enhanced method achieves best performance with obvious improvement over the baselines (2% for VATEX-EN-R, 3% for VATEX-EN-C).

Nevertheless, we observe that our CLIP-Enhanced method fails for other type of datasets (e.g., how2, tv). The main reason seems to be that – the how2 or tv datasets are quite different from the image-text pairs that the CLIP model is pre-trained on.
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