Egocentric Video-Language Pretraining @ Ego4D Challenge 2022

Kevin Qinghong Lin¹  Alex Jinpeng Wang¹  Mattia Soldan³  Michael Wray²
Rui Yan¹  Eric Zhongcong Xu¹  Difei Gao¹  Rongcheng Tu⁴
Wenzhe Zhao⁴  Weijie Kong⁴  Chengfei Cai⁴  Hongfa Wang⁴
Dima Damen²  Bernard Ghanem³  Wei Liu⁴  Mike Zheng Shou¹*

¹Show Lab, National University of Singapore  ²University of Bristol
³King Abdullah University of Science and Technology  ⁴Tencent Data Platform

{kevin.qh.lin, yanrui6019, turongcheng, mike.zheng.shou}@u.nus.edu
{jinpengwang, zhongcongxu}@u.nus.edu
{michael.wray, dima.damen}@bristol.ac.uk, {mattia.soldan, bernard.ghanem}@kaust.edu.sa, difei.gao@vipl.ict.ac.cn
{carsonzhao, jacobkong, fletchercai, hongfawang}@tencent.com, wl2223@columbia.edu

Abstract

In this report, we propose a video-language pretraining (VLP) based solution [6] for four Ego4D challenge tasks, including Natural Language Query (NLQ), Moment Query (MQ), Object State Change Classification (OSCC), and PNR Localization (PNR). Especially, we exploit the recently released Ego4D dataset [5] to pioneer Egocentric VLP from pretraining dataset, pretraining objective, and development set. Based on the above three designs, we develop a pretrained video-language model that is able to transfer its egocentric video-text representation or video-only representation to several video downstream tasks. Our Egocentric VLP achieves 10.46R@1 & 10.78IoU@0.3 on NLQ, 10.33 mAP on MQ, 74.3% Acc on OSCC, 0.597 sec error on PNR. The code is available at https://github.com/showlab/EgoVLP.

1. Introduction

Video-Language Pretraining (VLP) has prevailed in the regime of Vision + Language, aiming to learn strong and transferable video-language representation for powering a broad spectrum of video-text downstream tasks, video-text retrieval, video question answering, video-captioning. The successes of VLP mainly stems from the availability of large-scale open-world video-text datasets such as HowTo100M [7], which scrapes 134K hours of instructional videos from the YouTube accompanied by text yielded from Automatic Speech Recognition.

Despite reaching an impressive data scale, videos in the existing video-text pretraining datasets [1, 7] are often of 3rd-person views and might have been edited before posting on the web. Yet, there is a noticeable domain gap between the existing video-text pretraining datasets and 1st-person view videos such as those videos captured by wearable cameras or smart glasses. Egocentric video has received increasing interests from academia (e.g., activity anticipation [3]) and industry (various applications in robotics and augmented reality). But, due to such a domain gap, directly transferring the existing VLP models to egocentric downstream tasks cannot fully unleash the potential of large-scale pretraining approaches. Roused by the favorable scale and diversity of recently released Ego4D [5] dataset, we are motivated to develop Egocentric VLP models [6], which can greatly benefit various egocentric video downstream applications.

In this report, we leverage our Egocentric VLP [6] to a series of Ego4D challenge tasks, including one jointly video-text task: Natural Language Query (NLQ) and three video-only tasks: Moment Query (MQ), Object State Change Classification (OSCC), and PNR Localization (PNR). We provide a general solution for VLP to tackle the above tasks and conduct a comprehensive analysis of the impact of different pretraining on tasks, e.g., without VLP, 3rd-person VLP, and 1st-person VLP.

2. Approach

2.1. VLP Model

We choose Frozen [1] as our pretraining architecture. As depicted in the Fig. 1(b), Frozen [1] design encompasses an elegant and simple dual encoder strategy (one per modality) which has favorable characteristics (e.g., indexability and
We formulate $L^{\text{ego}}_\mathcal{N}$ for simplicity whereas $L^{\text{ego}}_{\mathcal{S}^2\mathcal{N}}$ is defined in a symmetry way.

$$L^{\text{ego}}_\mathcal{N} = \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} \log \frac{\sum_{k \in P_i} \exp(v^T_i t_k / \tau)}{\sum_{j \in \mathcal{B}} (\exp(v^T_i t_j / \tau) + \exp(v^T_i t_{j'} / \tau))},$$

where the numerator term corresponds to our proposed action-aware positive samples, which selects the positive sample within a batch by identifying narrations nouns and verbs. Then, batch samples that shared at least one noun and at least one verb are treated as positive samples: $P_i = \{ j \in \mathcal{B} \mid \text{noun}(j) \cap \text{noun}(i) \neq \emptyset, \text{verb}(j) \cap \text{verb}(i) \neq \emptyset \}$. While the denominator term corresponds to our proposed scene-aware negative samples. For each video clip $i$, we sample an adjacent clip $i' \in \mathcal{N}(i)$, which is close to $i$ in time (less than 1 min) within the same video. Hence the batch is updated as $\mathcal{B} = \{ 1, 2, \ldots, N, 1', 2', \ldots, N' \}$. EgoNCE provides a general extension to adapt the existing VLP models for video-text pretraining datasets in the egocentric domain.

We evaluate our designs of EgoClip and EgoNCE on EgoMCQ, which contains 39K video-text multi-choices questions that are closer to pretraining domains and benchmark model video-text alignment, powering us to accurately validate and quickly iterate our decisions.

2.3. Task-specific Transferring

In this section, we answer how to transfer pretrained VLP representations to multiple Ego4D challenge task, summarized in Fig. 2.

**Natural Language Query.** This task is a kind of video-text localization, a jointly video-text task. The clip in this dataset tends to be long (480 sec on average), so it is difficult to achieve end-to-end fine-tuning. Thus, we propose to evaluate offline video-text features. Especially, we adopt the official baselines VSLNet [9], which takes 2304 dim SlowFast features (1.87 fps, Kinetics 400 pretrained) and 768 dim BERT features as input, and we substitute them with output features of pretrained VLP video and text encoders to validate the pretraining effectiveness, as depicted in Fig. 2 (a).
Table 1. Recall for several IoU on the NLQ task’s val. set.

| Methods          | Video-text Pre-extracted Features | IoU=0.3 | IoU=0.5 |
|------------------|----------------------------------|---------|---------|
|                  | Vis-text Enc                     | R@1     | R@5     |
| 2D-TAN [10]      | SlowFast+BERT                    | 5.04    | 12.89   |
| VSLNet [9]       | SlowFast+BERT                    | 5.45    | 10.74   |
| VSLNet [9]       | Frozen HowTo100M                 | 3.95    | 8.72    |
| VSLNet [9]       | Frozen CC3M+WebVid2M             | 5.06    | 10.30   |
| VSLNet [9]       | Frozen EgoClip                   | 10.53   | 17.94   |
| VSLNet [9]       | Frozen+EgoNCE                    | 10.84   | 18.84   |

Table 2. Performance on the OSCC task and PNR task’s val set.

| Methods          | Vis-Text PT | OSCC Acc (%) | PNR Err (s) |
|------------------|-------------|--------------|-------------|
| Always same      | -           | 48.1         | 1.032       |
| Bi-d LSTM        | ImageNet    | 65.3         | 0.790       |
| EgoNCE           |             |              |             |
| Frozen           |             | 70.3         | 0.616       |
| Frozen HowTo100M |             | 71.7         | 0.611       |
| Frozen CC3M+WebVid2M |         | 71.5         | 0.614       |
| Frozen EgoClip   |             | 73.4         | 0.618       |
| Frozen+EgoNCE    |             | 73.9         | 0.622       |

### 3. Experiments

#### 3.1. Implementation Details

Following the settings of official Frozen [1], the video encoder is initialized with ViT [4] weights trained on ImageNet-21K with sequence dimension 768. The text encoder is based on huggingface’s distilbert-base-uncased. During pretraining, the dimension of common feature space is set as 256, and the temperature parameter $\tau$ is set to 0.05. Each video is resized to $224 \times 224$ as input with sample frames number 4 and batch size 512. We use the Adam optimizer with a learning rate of $3 \times 10^{-5}$ with a total epoch of 10. When transferring to downstream tasks, we select the checkpoints with the best score on EgoMCQ benchmark. For NLQ and MQ tasks, we extract the video features with fps 1.87 and sampling frame number 4 with stride 4. In the fine-tuning stage, we keep the default setting of baselines [9, 11]. For OSCC and PNR tasks, we sample each clip with 16 frames as input and set the epoch equal to 10. And we adopt the same settings of pretraining e.g. learning rate.

### 3.2. Results

**Natural Language Query.** We report the NLQ validation results on Tab. 1. We observe a large boost in performance offered by our pretrained model for all metrics. Notably, we improve R@1 for IoU=0.3 from 5.45 to 10.84, despite our video branch not being pre-trained on Kinetics400. Besides, we significantly surpass VLP pretrained on CC3M+WebVid-2M and HowTo100M. We believe this increase is due to the egocentric data availability and the video-text interaction learned from large-scale egocentric pretraining. In Tab 4, we display the test set.

**Object State Change Classification.** We report the OSCC validation results on Tab. 2. Once again, our model achieves the best performance of all baselines, 2.4% than CC3M+WebVid-2M counterparts, which indicates our visual representations are able to focus on the fine-grained clues related to changes. We select the best Frozen+EgoNCE variant and evaluate on the test set, and get 73.7% accuracy.

**PNR Localization.** We report the PNR validation results on Tab. 2 and found that the pretraining effect is minor on this task. We select the Frozen+EgoNCE variant and evalu-
ate on the test set, and get 0.666 s localization error.

**Moment Query.** We report the MQ validation results in Tab. 3. We find that our features achieves the best performance over SlowFast features with an increase of 4.66% in Avg mAP. Moreover, we maintain better performance with respect to 3rd-person large-scale pretraining datasets. This demonstrates that the 1st-person VLP model also learns competitive video representations. In Tab 5, we display the MQ test set result of different VLP variants.

### 4. Conclusion and Limitations

We present an egocentric video-language pretraining solution [6] for four Ego4D challenge tasks, including NLQ, MQ, OSCC, and PNR. Specifically, we provide a general solution for VLP to tackle the above challenges and conduct extensive experiments to analyze the impact of different pretraining on different tasks. And we demonstrate the superiority of our Egocentric VLP on three tasks.

**Limitations:** VLP requires a large training cost (1,536 GPU hrs for our model) and may be limited by the model architecture thus not flexible for a specific task.

### References

[1] Max Bain, Arsha Nagrani, Gül Varol, and Andrew Zisserman. Frozen in time: A joint video and image encoder for end-to-end retrieval. In *ICCV*, pages 1728–1738, 2021.

[2] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is space-time attention all you need for video understanding. *arXiv preprint arXiv:2105.05955*, 2(3):4, 2021.

[3] Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Antonino Furnari, Evangelos Kazakos, Jian Ma, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, et al. Rescaling egocentric vision: Collection, pipeline and challenges for epic-kitchens-100. *IJCV*, 130(1):33–55, 2022.

[4] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2020.

[5] Kristen Grauman, Andrew Westbury, Eugene Byrne, Zachary Chavis, Antonino Furnari, Rohit Girdhar, Jackson Hamburger, Hao Jiang, Miao Liu, Xingyu Liu, et al. Ego4d: Around the world in 3,000 hours of egocentric video. *arXiv preprint arXiv:2110.07058*, 2021.

[6] Kevin Qinghong Lin, Alex Jinpeng Wang, Mattia Soldan, Michael Wray, Rui Yan, Eric Zhongcong Xu, Difei Gao, Rongcheng Tu, Wenzhe Zhao, Weijie Kong, et al. Egocentric video-language pretraining. *arXiv preprint arXiv:2206.01670*, 2022.

[7] Antoine Miche, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *ICCV*, pages 2630–2640, 2019.

[8] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter. *arXiv preprint arXiv:1910.01108*, 2019.

[9] Hao Zhang, Aixin Sun, Wei Jing, and Joey Tianyi Zhou. Span-based localizing network for natural language video localization. *arXiv preprint arXiv:2004.13931*, 2020.

[10] Songyang Zhang, Houwen Peng, Jianlong Fu, and Jiebo Luo. Learning 2d temporal adjacent networks for moment localization with natural language. In *AAAI*, volume 34, pages 12870–12877, 2020.

[11] Chen Zhao, Ali K Thabet, and Bernard Ghanem. Video self-stitching graph network for temporal action localization. In *ICCV*, pages 13658–13667, 2021.