Abstract

In this report, we propose a video-language pretraining (VLP) based solution [8] for the EPIC-KITCHENS-100 Multi-Instance Retrieval (MIR) challenge. Especially, we exploit the recently released Ego4D dataset [6] 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 to MIR benchmark. Furthermore, we devise an adaptive multi-instance max-margin loss to effectively fine-tune the model and equip the dual-softmax technique for reliable inference. Our best single model obtains strong performance on the challenge test set with 47.39% mAP and 61.44% nDCG. 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 [9], 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, 9] 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 [4]) 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 [6] dataset, we are motivated to develop Egocentric VLP models [8], which can greatly benefit various egocentric video downstream applications.

In this report, we leverage our Egocentric VLP [8] for powering EPIC-KITCHENS-100 Multi-Instance Retrieval (MIR) challenge. We provide a comprehensive analysis of the impact of different VLPs on this task, e.g., without VLP, 3rd-person VLP, and 1st-person VLP. Furthermore, to effectively transfer the video-text representation to MIR task, we devise an adaptive multi-instance max-margin loss for fine-tuning. Besides, we introduce the dual-softmax technique for reliable inference.

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 efficiency [1]). Note that this allows the pretrained model for single-modality tasks (e.g., video-only tasks). In prac-
We use EgoClip dataset for pretraining, which comprises a large variety of human daily activities. Details please refer to [8]. Next, we employ EgoNCE as the model pretraining objective, which extends video-text InfoNCE [1] via positive and negative sampling strategies with formulation:

$$L^{ego} = L_{v2t}^{ego} + L_{t2v}^{ego}.$$  \hspace{1cm} (1)

We formulate $L_{v2t}^{ego}$ for simplicity whereas $L_{t2v}^{ego}$ is defined in a symmetry way.

$$L_{v2t}^{ego} = \frac{1}{|B|} \sum_{i \in B} \log \frac{\sum_{k \in P_i} \exp(v_i^T t_k/\tau)}{\sum_{j \in B} \left( \exp(v_i^T t_j/\tau) + \exp(v_i^T t_{j'}/\tau) \right)}.$$  \hspace{1cm} (2)

where the numerator term corresponds to our proposed action-aware positive samples, which select 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: $P_i = \{ j \in B | \text{noun}(j) \cap \text{noun}(i) \neq \emptyset, \text{verb}(j) \cap \text{verb}(i) \neq \emptyset \}$. While the denominator term corresponds to our proposed scene-aware negative samples. For each video clip $i$, we sample an adjacent clip $i' \in N(i)$, which is close to $i$ in time (less than 1 min) within the same video. Hence the batch is updated as $B = \{ 1, 2, \ldots, N, 1', 2', \ldots, N' \}$. 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 focus on effectively transferring pretrained video-text representations to EPIC-KITCHENS-100 Multi-Instance Retrieval task. In this task, a narration may be jointly associated with multiple clips, so a multi-instance learning mechanism can better handle such a situation. And this dataset provides the action label to calculate the correlation $c_{ij} \in [0, 1]$ between two clip-text pairs $(i, j)$, which supports the application of Multi-Instance MaxMargin loss (MI-MM), as recommended in baseline [11].

$$L = \sum_{(i,j,k) \in \Omega} \max \left( \gamma + v_i^T t_j - v_i^T t_k \right) + \left( \gamma + t_k^T v_j - t_i^T v_k \right),$$  \hspace{1cm} (3)

where $\Omega = \{ (i,j,k) | j \in i^+, k \in i^- \}$ is a triple, which indicates a positive instance $j$ and a negative instance $k$ for $i$. In our setting, we define the positive set as $i^+ = \{ j | c_{ij} > 0.1 \}$ and the negative as the remains sample within the batch. The $\gamma$ is a constant margin factor.

However, different combinations are shared with the
same margin $\gamma$ in Eq. 3 and thus are treated equally when fine-tuning. Intuitively, if two sample $(i, j)$ are highly similar, they should be pulled closer with a larger margin surpassing the $(i, k)$. Otherwise, they should be pulled with a small margin if not very similar. Thus, we devise the following Adaptive MI-MM to extend the Eq.3.

$$L^1 = \sum_{(i,j,k)\in\Omega}\max(c_{ij}\gamma + v_i^T t_j - v_i^T t_k) + (c_{ij}\gamma + t_i^T v_j - t_i^T v_k),$$

where $c_{ij}$ adaptively control the marginal, e.g., two instances $(i, j)$ that are semantically identical ($c_{ij} = 1$) will be assigned a largest margin $1.0\gamma$. Otherwise, a less margin $0.1\gamma$ is given when they are not very similar ($c_{ij} = 0.1$).

**Inference.** After we finalize the fine-tuning, we use the model to encode video and text embeddings for all samples within the test set. To obtain the cross-modal retrieval results, a common way is to calculate the similarity score between a text embedding $t_i$ and a video embedding $v_j$ and index the maximum as the top retrieval result. Here, motivated by [3], we introduce the dual softmax techniques to better scale the similarities and filter the hard case, thus reaching more reliable prediction results. We show the PyTorch-like pseudo-code in Alg. 1 to compare the two inference way. Notably, the dual-softmax only works on inference and thus does not introduce additional training costs, and it is flexible to different models.

### 3. Experiments

#### 3.1. Implementation Details

Following the settings of official Frozen [1], the video encoder is initialized with ViT [5] weights trained on ImageNet-21K with sequence dimension $D = 768$. The text encoder is based on huggingface’s distilbert-base-uncased. The dimension of common feature space is set to 256, and the temperature parameter $\tau$ is set to 0.05. During pretraining, 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 MIR task, we select the checkpoints with the best score on EgoMCQ benchmark and fine tune the VLP model on the MIR training set with 67.2K clips. We set the training epoch as 100 and keep other settings the same as pretraining. In the next Sec. 3.2, we use the MI-MM loss.

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**Table 1.** Performance of the EPIC-KITCHENS-100 Multi-Instance Retrieval. Note that TBN † feature [7] are a combination of three modalities: RGB, Flow and Audio. Conversely, our approach only relies on RGB input. The grey rows correspond to zero-shot evaluation.

| Methods               | Vis Enc Input | # Frames | Vis-text PT | mAP (%) | nDCG (%) |
|-----------------------|---------------|----------|-------------|---------|----------|
|                       |               |          |             | V→T    | T→V Avg  | V→T    | T→V Avg  |        |
| Random                | -             | -        | -           | 5.7     | 5.6      | 10.8    | 10.9     | 10.9    |
| MI-MM                 | S3D           | 32       | HowTo100M   | 34.8    | 23.6     | 29.2    | 47.1     | 42.4    | 44.7    |
| MME [11]              | TBN † [7]     | 25       |             | 43.0    | 34.0     | 38.5    | 50.1     | 46.9    | 48.5    |
| JPoSE [11]            | TBN † [7]     | 25       |             | 49.9    | 38.1     | 44.0    | 55.5     | 51.6    | 53.5    |
| Frozen                | Raw Videos    | 4        | -           | 38.8    | 29.7     | 34.2    | 50.5     | 48.3    | 49.4    |
| Frozen                | Raw Videos    | 4        | HowTo100M   | 39.2    | 30.1     | 34.7    | 50.7     | 48.7    | 49.7    |
| Frozen                | Raw Videos    | 4        | CC3M+WebVid2M | 41.2   | 31.6     | 36.4    | 52.7     | 50.2    | 51.4    |
| Frozen                | Raw Videos    | 4        | EgoClip     | 44.5    | 34.7     | 39.6    | 55.7     | 52.9    | 54.3    |
| Frozen+EgoNCE         | Raw Videos    | 4        | EgoClip     | 45.1    | 35.3     | 40.2    | 56.2     | 53.5    | 54.8    |
| Frozen                | Raw Videos    | 16       | CC3M+WebVid2M | 45.8   | 36.0     | 40.9    | 57.2     | 54.3    | 55.8    |
| Frozen+EgoNCE         | Raw Videos    | 16       | EgoClip     | 49.9    | 40.5     | 45.0    | 60.9     | 57.9    | 59.4    |
| Frozen                | Raw Videos    | 4        | HowTo100M   | 6.8     | 6.3      | 6.5     | 11.6     | 12.8    | 12.2    |
| Frozen                | Raw Videos    | 4        | CC3M+WebVid2M | 8.6    | 7.4      | 8.0     | 14.5     | 14.6    | 14.5    |
| Frozen                | Raw Videos    | 4        | EgoClip     | 17.9    | 13.1     | 15.5    | 23.0     | 21.2    | 22.1    |
| Frozen+EgoNCE         | Raw Videos    | 4        | EgoClip     | 19.4    | 13.9     | 16.6    | 24.1     | 22.0    | 23.1    |

**Algorithm 1** Pseudo-code for Dual-softmax (PyTorch-like)

```python
# Input(embeddings): T_\{NxM\}, V_\{NxM\}
# Output(scores): res_\{NxM\}

# (1) the common way
sim = torch.mm(T,V)
res = F.softmax(sim, axis=0)

# (2) dual-softmax
sim = torch.mm(T,V)
prior = F.softmax(sim/500, axis=1)
res = F.softmax(prior+sim, axis=0)
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1[https://github.com/m-bain/frozen-in-time](https://github.com/m-bain/frozen-in-time)
3.2. Pretraining Effects

In Tab. 1, we report both zero-shot and fine-tuning evaluation results of different VLP. In the zero-shot setting, pretraining with EgoClip (3.8M), despite being smaller in scale, still outperforms CC3M+WebVid-2M (5.5M) and HowTo100M (136M), validating the unique benefit of pretraining on egocentric data. When fine-tuned with 4 frames, EgoClip pretraining maintains a margin over the best baseline CC3M+WebVid-2M, further verifying the viewpoint domain gap within fine-tuning. Lastly, we increase the sample frames of our finalized model as well as best competitor CC3M+WebVid-2M pretraining to 16. As expected, performance gains accompany the frame increase. We deem that notable benefits come from better temporal modeling for frequent action interactions in the 1st-person view. Overall, our pretraining model outperforms the best baseline (PoSE) by 1.0 mAP and 5.9% nDCG while requiring fewer frames and input modalities.

![mAP with training epoch](image_a)
![nDCG with training epoch](image_b)

Figure 2. Training curves of MIR task.

In Fig 2, we display training curves of MIR under different VLP discussed in Tab. 3.2. We can found that: These models with video-text pretraining have a faster rise in performance. Except for HowTo100M, which is close to baseline without pretraining. With EgoClip for egocentric pretraining, the VLP model achieves nearly convergent performance with only a small number of epochs (less than 20). Especially with EgoNCE as the pretraining objective, this positive effect is further enhanced.

3.3. Transferring Ablations

In Tab. 2, we validate different fine-tuning strategies when transfer the best pretrained model (Frozen+EgoNCE in Tab. 1) to Multi-Instance Retrieval task, and we adopt the common way to calculate the similarity scores by default. It shows that InfoNCE performs poorly as a fine-tuning loss despite it being widely used in 3rd-person datasets e.g., Frozen [1] fine-tune on MSR-VTT. When replacing InfoNCE with MI-MM (Eq.3), there is a significant improvement, since MI-MM is well aligned with the multi-positive characteristic of the EPIC-KITCHENS-100. Moreover, Adaptive MI-MM pushes the performance beyond MI-MM by introducing an adaptive margin (Eq.4), thus serving as a better fine-tune objective in MIR. By equipping dual-softmax to scale similarities, we reach extra 1.2% mAP and 1.0 nDCG performance gains, which is our best single-model performance.

4. Conclusion and Limitations

We present an egocentric video-language pretraining solution [8] for the EPIC-KITCHENS-100 MIR challenge. Specifically, we develop a video-language transformer model and exploit the recently released Ego4D dataset [6] to reach strong video-text representation. Furthermore, for this challenge, we devise an Adaptive MI-MM loss to fine-tune and adopt dual-softmax techniques to improve inference. Extensive experimental results validate the effectiveness of our Egocentric VLP and the transferring strategies.

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.

| Methods                  | mAP (%) | nDCG (%) |
|--------------------------|---------|----------|
|                          | V→T  | T→V  | Avg | V→T  | T→V  | Avg |
| InfoNCE                  | 40.9  | 34.9  | 37.9 | 57.8  | 56.0  | 56.9 |
| MI-MM                    | 49.9  | 40.5  | 45.0 | 60.9  | 57.9  | 59.4 |
| Adaptive MI-MM           | 52.3  | 40.1  | 46.2 | 62.2  | 58.6  | 60.4 |
| w/ Dual softmax          | 53.8  | 40.9  | 47.4 | 63.2  | 59.6  | 61.4 |

Table 2. Ablation of different transferring strategies.

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