Learning Spatiotemporal Features via Video and Text Pair Discrimination

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Abstract

Current video representations heavily rely on learning from manually annotated video datasets. However, it is expensive and time-consuming to acquire a large-scale well-labeled video dataset. We observe that videos are naturally accompanied with abundant text information such as YouTube titles and movie scripts. In this paper, we leverage this visual-textual connection to learn effective spatiotemporal features in an efficient weakly-supervised manner. We present a general cross-modal pair discrimination (CPD) framework to capture this correlation between a clip and its associated text, and adopt noise-contrastive estimation technique to tackle the computational issues imposed by the huge numbers of pair instance classes. Specifically, we investigate the CPD framework from two sources of video-text pairs, and design a practical curriculum learning strategy to train the CPD. Without further fine-tuning, the learned models obtain competitive results for action classification on the Kinetics dataset under the common linear classification protocol. Moreover, our visual model provides a very effective initialization to fine-tune on the downstream task datasets. Experimental results demonstrate that our weakly-supervised pre-training yields a remarkable performance gain for action recognition on the datasets of UCF101 and HMDB51, compared with the state-of-the-art self-supervised training methods. In addition, our CPD model yields a new state of the art for zero-shot action recognition on UCF101 by directly utilizing the learnt visual-textual embedding.

1. Introduction

Deep learning has made a remarkable progress for visual recognition in both image and video domain [29, 19, 3, 11] by training powerful neural networks on large-scale manually annotated datasets (e.g., ImageNet [5] and Kinetics [26]). More importantly, it is well-established that this supervised pre-training on large-scale datasets would benefit the downstream tasks (e.g., object detection [44], pose estimation [18], and temporal action detection [68]), in particular when the target datasets are relatively small. Yet, annotating a large-scale dataset for training such deep neural networks is costly and time-consuming, and even more challenging for video due to complex temporal structure and more diverse semantics. As a result, the existing video datasets size is still smaller than ImageNet in terms of training samples and classes. On the other hand, videos contain richer structure with abundant side information such as motion [7, 37], audio [1, 28], and text [35, 49]. It is expected that these associated modalities could provide useful cues to learn an effective spatiotemporal representation in a more efficient weakly-supervised or self-supervised way.

Language or text is probably the most common and natural way to describe the semantic information of a video, and thereby the associated textual information could be easily acquired when collecting video dataset [45, 35]. For example, as shown in Figure 1, a movie clip is equipped with the script, and a web video is accompanied with title. These abundant textual information has turned out to be useful cues to learn a high-level visual-text embedding [49, 35], which could be deployed or fine-tuned for text-to-video re-
we report the performance of action its generalization ability on a variety of tasks. First, without pose of weakly-supervised representation learning is to test task of spatiotemporal representation learning. A main pur-

3D convolutional neural networks (3D CNNs) [52, 11]. We textual features. For video modeling, we resort to the recent stream visual tasks, we utilize the off-the-shelf language models such as BERT [6] or Skip-Thoughts [27] to extract textual features. For video modeling, we resort to the recent 3D convolutional neural networks (3D CNNs) [52, 11]. We design a curriculum learning strategy to progressively train our CPD framework: first train video models alone, and then jointly fine tune video and text networks. Experimental results imply this training scheme is helpful to relieve the training difficulty and improve the effectiveness of learned CPD models.

We mainly demonstrate the effectiveness of CPD on the task of spatiotemporal representation learning. A main purpose of weakly-supervised representation learning is to test its generalization ability on a variety of tasks. First, without any further fine-tuning, we report the performance of action recognition on the Kinetics dataset [26] by using shallow classifiers such k-NN and linear classifier, following a common protocol in unsupervised learning [63]. It shows that our learned spatiotemporal features obtain promising results which are comparable to some supervised learning methods on the Kinetics dataset [26]. Then, we investigate the generalization power of learned spatiotemporal features of CPD by fine-tuning on the Kinetics [26], UCF101 [48] and HMDB51 [30] datasets, demonstrating that our method obtain superior performance to previous state-of-the-art self-supervised method. In addition, we test CPD on learning visual-textual embedding by reporting performance for zero-shot action classification, which demonstrates that our CPD is able to yield a new state of the art on this challenging task.

2. Related Work

Motion, Audio, and Text. Multi-modal information in videos provides natural cues for learning deep models. Motion or temporal information has been studied as to design proxy tasks to assist cross-modal learning, such as optical flow or tracking [37, 59], frame prediction [7, 54], or high-level temporal structure [61, 64, 13]. As most video contain synchronized audio and visual signals, audio information has served another common modality to supervised visual learning [2, 1, 28]. However, both motion and audio information seem low-level signals and may lack high-level semantic for cross-modal learning. Speech or text has been widely studied as another cross-modal setting in video learning [49, 35, 10, 34, 40, 41]. These works mainly aimed to learn a joint video-text embedding where visual and textual cues are adjacent if they are semantically. However, these works focused on learn high-level visual-textual relation where they ignore the fundamental issue of visual representation learning by using the off-the-shelf models as feature extractors. Instead, our proposed CPD framework aims at learn general and effective spatiotemporal features which could serve the basics for a variety of downstream video tasks.

Supervised Video Representation. Since the breakthrough of AlexNet [29] in image recognition for representation learning, huge numbers of video-based deep models have been developed for action recognition [25, 47, 51, 66, 12, 57, 56, 43, 9, 52, 58, 11]. Two-stream networks [47] turned to be the first successful deep architectures for video recognition by introducing optical flow for motion modeling and the following works tried improve two-stream method from fusion [12] or speed [66] aspects. As the large-scale video dataset (e.g., Sports 1M [25], Kinetics [26]), 3D convolutional neural networks (3D CNNs) [24] started to be popular in video recognition [51] as it only required to input RGB frames to learn spatiotemporal features di-

Recent advanced architectures focused on improving 3D CNNs from aspects of spatial-temporal factorization [52, 43], relation modeling [56, 58], or sampling scheme [11]. Another research line has shifted to mod-
eling long-range temporal structures with longer temporal convolutions [53], sparse sampling and aggregation [57], or LSTM [38, 9, 62]. All these deep models are based on training from a human annotated dataset. Our CPD framework aims to investigate in an orthogonal direction by training deep architecture in a weakly-supervised manner.

**Self/Weakly Supervised Video Representation.** Self supervised representation was popular in both image and video domains in the last few years by training a model on a carefully designed proxy task. In image domain, for instance, these tasks could be predicting the image context [8], counting the objects [39], converting gray images to color one [67], keeping global and local consistency [21]. In video domain, typical examples include frame prediction [7, 54], optical flow estimation [37, 69, 23], instance tracking [59, 60], temporal order or structure prediction [36, 13, 61, 64]. These learnt representations may capture some aspects of low-level image or video structures, yet it might be not optimal for semantic tasks. Some cross-modal self-supervised tasks was proposed to enhance single-modality representation power and typical example is audio-visual representation learning [2, 1, 28]. To further improve descriptive power of self-supervised representation, some weakly-supervised methods were developed by utilizing more semantic information obtained in automatic way, such as web search engine [4, 14], and hashtag [32]. Different from these methods, our CPD framework explore a new instance-level discriminative training scheme to learn general spatiotemporal representations from the correlation between a clip and its associated text with. Our CPD is inspired by these low-level instance discrimination framework [63, 50], but extend to video domain and use more semantic pair (i.e., text and video) discrimination for spatiotemporal feature learning, and we believe this semantic pair discrimination is more useful for representation learning than low-level instance discrimination.

### 3. Cross-Modal Pair Discrimination

In this section we provide an detailed description on our proposed cross-modal pair discrimination (CPD) for weakly supervised spatiotemporal feature learning. First, we present the whole framework and analyze its important properties. Then, we describe the training strategy of CPD framework. Finally, we introduce text and video feature extraction networks.

#### 3.1. Framework and analysis

Our goal is to propose a weakly supervised representation learning method by exploiting the correlation between each video clip and its associated text information, which could be easily obtained from a variety of sources such as movie scripts, YouTube titles, and automatic speech recognition (ASR). It is generally assumed that these text information contains semantic information, but also might be noisy and irrelevant. Therefore, from technical perspective, we need to design an effective objective function and training strategy to capture this semantic correlation and as well also suppress the effect of noisy and irrelevant information. To this end, we devise a video-text pair discrimination objective and a curriculum learning strategy as follows.

More formally, as shown in Figure 2, we aim to learn a modality-specific embedding function $\mathcal{F}_v$ and $\mathcal{F}_t$ for the visual and textual information from a set of $N$ video clips...
and their associated textual information \(\{(v_i, t_i)_{i=1}^N\}\). Let \(f^v_i\) and \(f^t_i\) denote \(F_v(v_i)\) and \(F_t(t_i)\), respectively. These embedding functions would map these two modality into a common space (i.e., \(f^v_i \in \mathbb{R}^d\) and \(f^t_i \in \mathbb{R}^d\)), and related visual and text information should be close to each other. The embedding functions could be implemented by neural networks which will be clarified in next section. We first focus on how to devise objective function to optimize these embedding functions. Inspired by the work of unsupervised learning in images [63], we design a cross-modal pair discrimination objective to learn these two embedding functions.

**Self-instance discrimination.** In the original instance-level discrimination framework [63], each image is treated as a distinct class and it would learn a classifier to categorize each image into its own class. This framework could be naturally extended into the setting of video and text pair by directly using feature concatenation, and we call this extension as **self-instance discrimination**. Formally, this video-text level instance discrimination objective could be implemented with the following softmax criterion:

\[
p(i|v,t) = \frac{\exp(w^i_i f^v_i + w^i_t f^t_i)}{\sum_{j=1}^{N} \exp(w^i_j f^v_j + w^i_j f^t_j)},
\]

where the \(i^{th}\) video-text pair define a class \(i\), \((w^v_i, w^t_i)\) is a weight for class \(i\), and the class number is equal to training sample number \(N\). This class weight represent a class prototype for each video-text instance and is probably not easy to optimize as we only have a single sample for each class. Thus, the above parametric classifier could be refined with the following non-parametric variant:

\[
p(i|v,t) = \frac{\exp(f^v_i f^v_t / \tau + f^t_i f^t_t / \tau)}{\sum_{j=1}^{N} \exp(f^v_j f^v_t / \tau + f^t_j f^t_t / \tau)},
\]

where \(\tau\) is a temperature parameter to control the class concentration level and our training objective is to optimize the likelihood \(\prod_{i=1}^{N} p(i|v_i, t_i)\). This straightforward extension shares the advantage of instance-level discrimination by directly modeling in the joint video-text space. Yet, in fact, the semantic information of text modality is higher than video pixels and we aims at learning video features with the supervision of textual information. To meet this requirement, we propose a refined objective function from the perspective of conditional distribution.

**Cross-pair discrimination.** According to the above analysis, we design the objective function by considering conditional distribution \(p(i|v)\) and \(p(i|t)\) rather than implicitly modeling distribution \(p(v,t)\). Specifically, we design the following conditional distribution:

\[
p(i|v) = \frac{\exp(f^v_i f^v_v / \tau)}{\sum_{j=1}^{N} \exp(f^v_j f^v_v / \tau)},
\]

where \(i^{th}\) text define a text class \(i\), and both \(f^v\) and \(f^t\) with unit-norm constraint. The conditional distribution \(p(i|v,t)\) could be defined at the same way. We call this framework as **cross-pair discrimination**, and during training phase, the objective is to maximize the likelihood \(\prod_{i=1}^{N} p(i|v_i) \prod_{i=1}^{N} p(i|t_i)\). The key difference between Equation (2) and (3) is that we propose to use cross-correlation term \(f^v_i f^t_t\) to replace the self-correlation term \((f^v_i f^v_i + f^t_t f^t_t)\). This cross correlation is more effective to capture the mutual information between visual and textual information, and thereby better at guiding the spatiotemporal feature learning from video with text information as supervision.

**Ranking loss.** There is some common ranking loss for cross-modal matching. To well study the effectiveness of proposed cross-modal pair discrimination objective, we also compare with a baseline of ranking loss, which is defined as follows:

\[
\mathcal{L}(v_i, t_i) = 1 - \frac{1}{n-1} \sum_{j \neq i} \max(0, \delta + S(f^v_i, f^v_j) - S(f^t_i, f^t_j)),
\]

where each video \(v_i\) has a associated text \(t_i\) and unrelated text \(t_j\) from current batch. \(S(f^v_i, f^v_j) = f^v_i f^v_j\) is the cosine similarity, \(n\) is the batch size and \(\delta\) is a margin. In experiment, we empirically compare this ranking loss with our designed cross-pair discrimination objective.

**3.2. Training CPD**

The training of CPD framework needs to address two technical issues: (1) large number of video-text pair classes; (2) optimization difficulty on noisy video-text datasets by training from scratch.

**Noise-contrastive estimation.** In training stage, we adopt noise-contrastive estimation technique [15] to approximate Equation (3) to solve the computational issues by the huge numbers of pairs. The basic idea is to transform the multi-class classification problem in Equation (3) into a set of binary classification problem. In the binary classification task, the task is to distinguish between data sample and noise sample. The approximate training objective is to minimize the following loss function:

\[
\mathcal{L} = -E_{P(v)} \{ E_{P_d(i|v)}[\log h(i, v)] + mE_{P_n(i|v)}[\log (1 - h(i, v))]) \},
\]

where \(h(i, v) = \frac{p(i|v)}{p(i|v) + mP_n(i|v)}\), \(P_d(i|v)\) is the actual data distribution and \(P_n(i|v)\) is the uniform distribution for noise, and \(m\) denotes the noise frequency. To compute \(p(i|v)\) efficiently and avoid large memory consumption, following [62], we maintain a **memory bank** to store the visual and textual features for each training pair. The memory bank is updated dynamically during the training procedure.
Curriculum learning. To handle the optimization difficulty of directly training from scratch on noisy video-text dataset, we present a curriculum training strategy by resorting to the existing unsupervised pre-trained language models. To relieve the training difficulty, our curriculum learning strategy divides the training procedure into two stages. In the first stage, we fix the pre-trained language model and only update the parameters of visual model and embedding function. The motivation is that the language model is pre-trained well using corpus much larger than ours and the video model is totally trained from scratch. If we train both models simultaneously in the beginning, the random noise produced by video model will destroy the parameters of language model. In the second stage, after the well initialization of video model, we start to jointly train the visual-textual model with a smaller learning rate.

3.3. Architecture design

After the presentation of CPD framework and its training strategy, we are now ready to describe its network architectures. Our CPD present a general framework for weakly-supervised spatiotemporal feature learning by exploiting the correlation between video and text pairs. To study the effectiveness of CPD framework, we instantiate CPD with different network architectures.

Video architecture. For video representation, we use the 3D CNNs to extract spatiotemporal features from a video clip. Specifically, we randomly sample 8 frames from each video clip and sampling stride is 4. Following the implementation of slow stream in the recent SlowFast [11], all filters from conv1 to res3 degenerate temporal convolutions into 2D convolution kernels and it only reserves 3D convolution kernels in res4 and res5 without temporal downsampling. We try two kinds of network architectures: (1) 3D ResNet34 trained on 112 × 112 × 8 volumes and (2) 3D ResNet50 trained on 224 × 224 × 8 volumes. The first tiny network is efficient for ablation study and then we transfer its optimal setting to the larger backbone and frame resolution. We also add a mapping layer to transform the visual features into 256-dimensional embedding space f_v and this 256-d vector is $\ell_2$-normalized.

Text architecture. Our textual stream subnetwork is based on the off-the-shelf language models. We choose Skip-Thoughts [27] and DistilBERT [6, 46] as our textual encoders. Specifically, we extract sentence features of movie script with Skip-Thought model, and encode textual features of YouTube title with DistilBERT model. Skip-Thoughts is an unsupervised sentence encoder, pre-trained by reconstructing the surrounding sentences of the continue text in books. We use combine-skip vector extracted from Skip-Thoughts as text feature which is 4800 dimensional. BERT [6] encodes long sentences by predicting the missing words given their bidirectional context, and DistilBERT achieves comparable performance with a faster and lighter model via knowledge distillation [20]. We average word embeddings of title generated by DistilBERT and obtain 768 dimensional text feature. Finally, two fully connected layers with ReLU and Batch Normalization [22] are added to our textual encoder to obtain textual feature $f_t$ in the common embedding space, which is also $\ell_2$-normalized.

4. Experiments

In this section, we present the experimental results of our proposed CPD framework. First, we describe the training and evaluation datasets with implementation details. Then, we conduct ablation study on our proposed CPD framework. Finally, we verify the effectiveness of CPD from three aspects: weakly-supervised representation learning, representation transfer, and zero-shot classification.

4.1. Datasets

In our experiments, we pre-train our weakly supervised representation learning method on two video datasets: LSMDC [45] and Kinetics [26]. To evaluate our learned spatiotemporal feature, we fine-tune the video model on two challenging human action datasets: UCF101 [48] and HMDB51 [30].

LSMDC-100K. LSMDC [45] is a large-scale movie description dataset. Each clip has a automatically-collected description of movie script or audio description. To fully explore the effectiveness of CPD, we reserve 1k clips from test split for validation and use the rest as the pre-training set, which contains 117k video-text pairs.

Kinetics-210K. The first version of Kinetics [26] is a large scale human action dataset which contains 400 action classes and around 240k videos for training, 20k video for validation, and 40k videos for testing. It is often called Kinetics-400, but we count training video number as we do not use any class information for weakly-supervised representation learning. Due to invalid urls and data cleaning, the collected dataset contains around 210K video-text pairs for weakly supervised pre-training, and thus we call this dataset as Kinetics-210k. Similar to LSMDC, we also reserve 1k video-text pair for validation during CPD training and the rest as training set of CPD. To construct video-text pairs, we equip each clip with the video title directly crawled from YouTube, termed as Kinetics-title. As the original title may be very noisy, we pre-process the text information in two ways. First, we delete special symbols and characters such as non-English words and emoji, termed as Kinetics-title-clean. Second, we use StanfordNLP [42] to obtain the dependency tree of a sentence and only reserve verbs and nouns of title, named Kinetics-title-tree.

UCF101 and HMDB51. We evaluate the generalization of our pre-trained models by fine-tuning on two small human action datasets: UCF101 [48] and HMDB51 [30],
which contain 13k videos of 101 classes and 7k video of 51 classes respectively. We report ablation study on the first split and report average performance over three splits for fair comparison.

4.2. Implementation details

**Weakly supervised learning of CPD.** We train our CPD model on video-text dataset and use video-text retrieval on 1k unseen video-text pairs as validation set during training. To keep a balance between temporal receptive field and GPU memory consumption, 8 frames are sampled from each video clip and the sampling stride is 4. Following the procedure [17, 16], we perform multi-scale cropping, random horizontal flip and color jittering for data augmentation. We use SGD to optimize our objective and the training parameters include a momentum of 0.9 and 1e-4 for weight decay. We set temperature parameter $\tau = 0.07$. In the beginning, we fix the pre-trained language model and the learning rate is set as 0.2. When the retrieval performance on validation set saturates (170 epochs for 3D ResNet34 and 110 epochs for 3D ResNet50), we start to update the language model with learning rate of 3e-5 and decrease the rest learning rate to 0.02. The maximize training number is 250 epochs. For input size of $112 \times 112 \times 8$, the mini-batch size is 64 clips per GPUs and 16 clips per GPUs for input size of $224 \times 224 \times 8$, and we use 8 GPUs for training.

**Evaluation on representation learning.** We first verify our CPD learned representation by employ a shallow classifier on frozen features, following a common protocol in self/weakly supervised representation learning [63]. In this experiment, we pre-trained our CPD on Kinetics-210K datasets and report performance on its validation set. Specifically, we utilize k-Nearest Neighbor (kNN) and linear classifier based on extracted features for classification. For feature extraction, we sample 10 clips from each video and each clip contains 8 frames with 4 sampling stride. The 256-dimensional embedding feature and the output of global average pooling after res5 are extracted as feature representation. The extracted features over 10 clips in a video are averaged as video representation. We choose cosine distance as distance metric in kNN and set $k = 25$. As for linear classifier, a fully connected layer after Batch Normalization is added with cross-entropy loss. We adopt Adam with learning rate of 1e-3 and reduce by a factor of 10 every 10 epochs, stopping at 30 epochs.

**Evaluation on representation transfer.** A main goal of representation learning is to transfer them to downstream tasks. We fine-tune the learned spatiotemporal representation on the UCF101, HMDB51 and small fraction of Kinetics-400. During fine-tuning, 16 frames with stride 4 are sampled as input. We simply replace the embedding layer of video model with a new fully-connected layer and multi-way softmax for action recognition. We adopt the same procedure of data augmentation with weakly supervised pre-training. The classifier is trained using Adam optimizer with an initial learning rate 1e-4 and weight decay 5e-4. Learning rate is decay twice by the factor of 10 when the validation loss saturates. During testing, for each video, we uniformly sample 10 clips and each clip contains 3 crops, following the common practice [11].

**Evaluation on zero-shot classification** Our learnt visual-textual embedding could be used for zero-shot classification on Kinetics and UCF101 without any fine-tuning. We regard class labels as text information and pass them to our pre-trained textual subnetwork, transforming class labels to class feature in embedding space. Also, for each video we uniformly crop 10 clips which contains 8 frames with 4 sampling stride and spatial size of $128 \times 128$ or $256 \times 256$. 10 clips are passed into visual subnetwork and averaged as video feature. The video is recognized as closest class with cosine metric.

| Objective function          | Accuracy(%) |
|-----------------------------|-------------|
| Random initialization       | 50.0        |
| Ranking loss                | 79.9        |
| Self-instance discrimination| 51.1        |
| Cross-pair discrimination   | 82.2        |

Table 1. Comparison on different loss functions on task of representation transfer on UCF101 split1.

**Curriculum learning.** We design different training strategies to handle the difficulty of optimizing on noisy video-text datasets from scratch. The first strategy is to fine-tune the pre-trained textual encoder directly at the beginning. Also we experiment the performance of stage I and stage II of curriculum learning proposed in Section 3.2.
Table 2. Comparison on different training strategies. All these strategies are pre-trained on Kinetics-title-clean and evaluated by fine-tuning on UCF101 split 1.

| Training Strategy                  | Accuracy(%) |
|------------------------------------|-------------|
| Random initialization              | 50.0        |
| Direct fine-tuning                 | 81.3        |
| Curriculum learning stage I        | 82.2        |
| Curriculum learning stage II       | **84.2**    |

Table 3. Comparison of different datasets and textual encoders on task of representation transfer on UCF101 split 1.

| Dataset                        | Textual encoder | Accuracy(%) |
|--------------------------------|-----------------|-------------|
| Random initialization          | -               | 50.0        |
| LSMDC                          | Skip-Thoughts   | 71.9        |
| Kinetics-title-tree            | Skip-Thoughts   | 76.4        |
| Kinetics-title-tree            | DistilBERT      | 82.1        |
| Kinetics-title-clean           | DistilBERT      | **84.2**    |

Table 4. Top-1 classification accuracies on Kinetics-400 validation set to evaluation on weakly-supervised representation learning. The methods of first three rows trained with manually annotated action class as supervision, while our CPD models leverage noise text information as weak supervision.

| Backbone                      | Sup.    | Layer (Dim) | kNN | LC  |
|-------------------------------|---------|-------------|-----|-----|
| RGB-Stream [26]               | Label   | -           | -   | 56.0|
| 3D-ConvNet [26]               | Label   | -           | -   | 56.1|
| 3D ResNet34 [17]              | Label   | -           | -   | 60.1|
| 3D ResNet50 [17]              | Label   | -           | -   | 61.3|
| 3D ResNet50 (ours)            | Label   | -           | -   | 73.2|
| SlowFast(R50) [11]            | Label   | -           | -   | 77.0|
| ResNet50                      | ImageNet| res5 (2048) | 42.8| 56.1|
| 3D ResNet34                   | Text    | emb (256)   | 49.9| 50.8|
| 3D ResNet34                   | Text    | res5 (512)  | 50.1| 53.3|
| 3D ResNet50                   | Text    | emb (256)   | 58.0| 58.7|
| 3D ResNet50                   | Text    | res5 (2048) | 58.2| **63.1**|

4.4. Evaluation on representation learning

To evaluate our learned representation, we report the classification performance on validation set of Kinetics via training shallow classifiers on frozen features as shown in Table 4. We compare our method with those networks [26, 17, 11] trained with annotated action label in an end-to-end manner. For fair comparison, we also train the same architecture of 3D ResNet50 from scratch by ourselves on the Kinetics dataset (denoted as 3D ResNet50-ours). For our CPD learnt representations, we perform kNN classifiers and linear classifiers (LC) on the 256-dimensional embedding features or features from global average pooling after res5, which is 512-dimensional for 3D ResNet34 and 2048-dimensional 3D ResNet50. In this shallow learning setting, we also compare with ImageNet pretrained representation (ResNet50) by using the same classifier. The experimental results demonstrate that: First, the 256-dimensional embedding feature of 3D ResNet50 outperforms methods proposed in [26] yet our feature is highly compact, which is much cheaper for storage and inference. Second, the learned feature of 3D ResNet34 is comparable to previous fully supervised methods [26, 17]. We also note that there is still performance gap between our CPD learnt representation with those fully supervised networks such as SlowFast [11]. Finally, our res5 feature of ResNet50 achieves a higher performance than these fully supervised ImageNet pre-trained features under the same shallow classifier.

4.5. Evaluation on representation transfer

Results on Kinetics. Our weakly-supervised pre-trained representation can be an efficient initialization when training the model with only a small amount of labeled data. We randomly choose a small fraction of Kinetics-400 training set as labeled data and fine-tune the pre-trained model on
Table 5. Evaluation on spatiotemporal representation fine-tuning on UCF101 and HMDB51 over three splits. We compare our CPD model with other methods trained on different type of supervision.

| Method                          | Supervision | Backbone      | Pre-trained Dataset | UCF101  | HMDB51 |
|---------------------------------|-------------|---------------|---------------------|---------|--------|
| Random Initialization [17]      | -           | 3D ResNet18   | -                   | 42.4    | 17.1   |
| ImageNet Pretrained [47]        | Image label | VGGNet        | ImageNet            | 73.0    | 40.5   |
| Kinetics Pretrained [17]        | Action label| 3D ResNet34   | Kinetics            | 87.7    | 59.1   |
| Kinetics Pretrained [17]        | Action label| 3D ResNet50   | Kinetics            | 89.3    | 61.0   |
| Shuffle & Learn [36]           | Order Verification | CaffeNet | UCF101/HMDB51       | 50.2    | 18.1   |
| OPN [31]                       | Sequence order | VGGNet | UCF101/HMDB51       | 59.8    | 23.8   |
| CMC [50]                       | Optical flow | CaffeNet      | UCF101              | 55.3    | -      |
| O3N [13]                       | Odd-one-out  | AlexNet       | UCF101              | 60.3    | 32.5   |
| MASN [55]                      | Motion       | 3D            | Kinetics            | 61.2    | 33.4   |
| COP [65]                       | Clip order   | 3D ResNet10   | UCF101              | 64.9    | 29.5   |
| DPC [16]                       | Predict feature | 3D ResNet34 | Kinetics            | 75.7    | 35.7   |
| AVTS [28]                      | Audio        | I3D           | Kinetics            | 83.7    | 53.0   |
| CPD (Ours)                     | Text         | 3D ResNet34   | Kinetics            | 83.5    | 53.2   |
| CPD (Ours)                     | Text         | 3D ResNet50   | Kinetics            | 88.7    | 57.7   |

Table 6. Results of classification with small amount of labeled data on Kinetics-400 validation set (showing top-1/top-5 accuracy). We utilize 3D ResNet34 as backbone. Ours are significantly better than the training from scratch.

| Method                  | The Amount of Labeled Data |
|-------------------------|-----------------------------|
|                         | 1%                          |
|                         | 10%                         |
|                         | 20%                         |
| From scratch            | 0.3 / 1.3                   |
| Ours                    | 14.7 / 30.2                 |
|                         | 40.2 / 67.8                 |
|                         | 47.8 / 74.0                 |

Table 7. Top-1 accuracy of zero-shot classification on UCF101. We outperform other methods without any extra labeled data and training procedure after pre-training.

| Method                  | Train | Test | Splits | Kinetics |
|-------------------------|-------|------|--------|----------|
| Mettes et al. [33]      | -     | 101  | 3      | 32.8     |
| Ours(3D ResNet34)       | -     | 101  | 3      | 40.6     |
| Ours(3D ResNet50)       | -     | 101  | 3      | 39.9     |
| Mettes et al. [33]      | -     | 50   | 10     | 40.4     |
| Ours(3D ResNet34)       | -     | 50   | 10     | 47.2     |
| Ours(3D ResNet50)       | -     | 50   | 10     | 44.8     |
| Mettes et al. [33]      | -     | 20   | 10     | 51.2     |
| Ours(3D ResNet34)       | -     | 20   | 10     | 54.4     |
| Ours(3D ResNet50)       | -     | 20   | 10     | 58.1     |

Table 8. Top-1 accuracy of zero-shot classification on Kinetics. We pre-train our model on video-text pair from training set of Kinetics-300k without any class label.

| Method   | Train | Test | Splits | Kinetics |
|----------|-------|------|--------|----------|
| 3D ResNet34 | -     | 400  | 1      | 38.2     |
| 3D ResNet50 | -     | 400  | 1      | 43.7     |
| 3D ResNet34 | -     | 100  | 10     | 55.3     |
| 3D ResNet50 | -     | 100  | 10     | 57.4     |
| 3D ResNet34 | -     | 20   | 10     | 73.1     |
| 3D ResNet50 | -     | 20   | 10     | 74.4     |

4.6. Evaluation on zero-shot classification

We evaluate our visual-textual embedding of CPD model with zero-shot classification on UCF101 and Kinetics-400 without any fine-tuning. We transform class labels and video clips into the same embedding space and recognize the video clip to its closest class with cosine distance. In
Table 7, we compare our method with Mettes et al. [33] which realizes zero-shot localization and classification of human action in video via spatial-aware object embeddings on UCF101. Following [33], we select different classes for 10 times and average their accuracies for testing except the class number is 101. We outperform for every number of testing classes. For Kinetics-400, we achieve top-1 accuracy of 43.7% without fine-tuning and training label as shown in Table 8. In addition, top-1 accuracy of 20 random classes reaches to 74.4%, which shows the strong capability of our visual-textual embedding.

5. Conclusion

In this paper, we have presented a general cross-modal pair discrimination (CPD) framework to capture the correlation between a video clip and its associated text and adopt noise-contrastive estimation to approximate the objective. Without fine-tuning, the learned models obtain competitive results for action classification on Kinetics dataset with a shallow classifier. Also, our visual models provide an effective initialization to fine-tune on the datasets of downstream task. In addition, our CPD model yields a new state-of-the-art for zero-shot action recognition on UCF101 by directly utilizing the learnt visual-textual embedding. In the future, we may consider designing more effective proxy tasks and efficient training strategies for learning spatiotemporal representations from noisy video and text pairs.

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