Contextualized Spatio-Temporal Contrastive Learning with Self-Supervision

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Abstract

A modern self-supervised learning algorithm typically enforces persistency of the representations of an instance across views. While being very effective on learning holistic image and video representations, such an approach becomes sub-optimal for learning spatio-temporally fine-grained features in videos, where scenes and instances evolve through space and time. In this paper, we present the Contextualized Spatio-Temporal Contrastive Learning (ConST-CL) framework to effectively learn spatio-temporally fine-grained representations using self-supervision. We first design a region-based self-supervised pretext task which requires the model to learn to transform instance representations from one view to another guided by context features. Further, we introduce a simple network design that effectively reconciles the simultaneous learning process of both holistic and local representations. We evaluate our learned representations on a variety of downstream tasks and ConST-CL achieves state-of-the-art results on four datasets. For spatio-temporal action localization, ConST-CL achieves 39.4% mAP with ground-truth boxes and 30.5% mAP with detected boxes on the AVA-Kinetics validation set. For object tracking, ConST-CL achieves 78.1% precision and 55.2% success scores on OTB2015. Furthermore, ConST-CL achieves 94.8% and 71.9% top-1 fine-tuning accuracy on video action recognition datasets, UCF101 and HMDB51 respectively. We plan to release our code and models to the public.

1. Introduction

Self-supervised learning (SSL) has revolutionized natural language processing and computer vision due the strong representations learned from a vast amount of unlabeled data. The key breakthroughs in self-supervised learning that paved the way for its success in computer vision comes from the instance discrimination pretext task [15] and the contrastive objective [37], with which for the first time the self-supervised pretraining surpasses the supervised pre-training on downstream visual tasks [24]. For videos, many self-supervised contrastive learning approaches \([3,4,18,41]\) directly extend established image-based methods \([9,24]\) to the spatio-temporal domain. Most of them, however, do not explicitly exploit the temporal evolutions of multiple instances and scene context in videos.

Self-supervised learning methods typically enforce semantic consistency across instances (views) to construct representation models \([9,24,41]\). This assumption is particularly true in the image domain because two views are typically generated from the same image. As shown in Fig. 1a, the goal is to enforce the representations of these two views to be as close as possible in the feature space. In the video domain, however, this view-based contrastive approach is less effective as the visual appearance of an instance frequently and drastically changes across frames. For example, one person in a video can have different poses and perform different activities over time, indicating the states and

![Figure 1](image-url)
semantics of an instance are likely to change across space and time. Enforcing spatio-temporal persistency throughout the video would lead to representations only encoding minimally shared information across frames, which may have negative effects on spatio-temporally fine-grained downstream tasks.

Furthermore, existing methods typically focus on learning representations for holistic visual understanding tasks, such as image classification and video action recognition. For dense prediction tasks, such as object detection, action localization and tracking, those models are enhanced by adding task specific heads. On the other hand, several approaches are designed to learn discriminative local features for dense prediction tasks [22, 51, 57, 58]. One limitation of those schemes is while they show superior performance on dense tasks, their performances on holistic visual understandings degrade [55]. In light of this, we are interested in developing high-quality representations that can be applied to both holistic and local vision tasks.

Based on these observations, we propose the Contextualized Spatio-Temporal Contrastive Learning (ConST-CL) method, illustrated in Fig. 1b and Fig. 2 in more details, to circumvent the undesirable strong spatio-temporal persistency enforced by the global contrastive objective, and to learn semantically consistent but discriminative local representations for various video downstream tasks, ranging from spatio-temporal action localization and object tracking to action recognition. Specifically, we design a projection function \( g(\cdot, \cdot) \), which takes not only the instance feature but also the context features into account. This task enforces the model to be context-aware in a video and thus is a good proxy to learn discriminative local representations. To address the imbalanced capability of learning holistic and local video representations, a simple two-branch module is proposed in the network design to facilitate the network to learn high-quality video representations both globally and locally in one unified self-supervised learning scheme.

We evaluate the holistic and local representations on a variety of downstream tasks. For the holistic representations, we evaluate with the video action recognition tasks on Kinetics400 [29], UCF101 [45] and HMDB51 [30] datasets. For the local representations, we conduct experiments with the spatio-temporal action localization task on AVA-Kinetics [33] dataset, and the single object tracking on OTB2015 [53] dataset. Our experimental results show that by pretraining with ConST-CL, the learned representations adapt well across all studied datasets, surpassing recently proposed methods that use either supervised pretraining or the self-supervised pretraining [18, 21, 41, 57].

The main contributions of this work are:

- We study the fine-grained spatio-temporal representation learning in videos and propose a novel region-based contrastive learning framework.
- We propose a new contextualized region prediction task that facilitates learning the semantically consistent but local discriminative features in videos.
- We introduce a simple network design to effectively reconcile simultaneous holistic and local representation learning.
- Our method achieves the state-of-the-art transfer learning results on four benchmark datasets for spatio-temporal action localization, object tracking, and video action recognition.

2. Related Work

Self-supervised learning in images. To effectively learn representations from images, early self-supervised methods focus on designing pretext tasks by experts. Various pretext tasks have been proposed, including colorization [31], inpainting [38], denoising [49], egomotion prediction [2], context prediction [13], orientation prediction [20], spatial jigsaw puzzle [36], etc. Recent advances in image self-supervised learning stem mainly from minimizing contrastive loss [37] on instance discrimination tasks [15]. The contrastive objective effectively enforces representations of the same instance from different views to be similar, while it repels representations from different instances in the latent space. Representative frameworks in this category include NPID [54], MoCo [10, 24], SimCLR [9], etc.

Self-supervised learning in videos. In the video domain, self-supervised representation learning prospers in recent years. Contrastive objectives have been widely used to learn video representations for holistic recognition tasks [18, 41, 42, 44, 59]. Extensive pretext tasks have been exploited to learn good representation in videos. Compared with the image domain, videos naturally yield richer self-supervision signals. In [42], the goal is to enforce global context consistency and utilize long-short views of a video to align representations. Motion signals are also exploited for learning good representations [23, 46]. Temporal ordering of frames in a video has also been used for self-supervised representation learning. For instance, in [32, 34], temporal ordering of frames is enforced to learn representations by shuffling frames in a self-supervised manner. Similarly, forward and backward ordering of frames is used as the self-supervision signals for representation learning [52]. In addition, temporal cycle consistency is exploited to learn spatio-temporal correspondence between video frames [28, 50]. On the other hand, multi-modal signals, such as audio/visual and visual/text, have been used to learn representations in a self-supervised manner that outperform models based on a single modality [4, 5, 35, 39].

Local representations. Although existing methods focus on learning holistic representations on images or videos, several recent approaches explicitly model spatially fine-
Figure 2. Contextualized Spatio-Temporal Contrastive Learning. Two spatio-temporally distant views are randomly sampled from one video and their dense representation feature maps \( \{F, F'\} \) are extracted by the base network \( f(x) \). Region features \( \{h, h'\} \) are pooled from respective dense feature maps by spatio-temporal ROIAlign and \( F'_c \) are a set of context features sampled from the dense feature maps \( F' \). The projection head \( g(h, F'_c) \) is learned to transform representations \( h \) from one view to the other, guided by the context features \( F'_c \). We use the transformer [48] architecture that takes region feature \( h \) as Query and context features \( F'_c \) as Keys and Values. The InfoNCE loss is used to encourage the similarity between the reconstructed representations \( z \) and their correspondences \( h' \).

Grained representations. In [8, 51], several constraining learning models have been developed for dense prediction tasks, such as object detection and image segmentation. In addition, augmented samples with pseudo ground-truth are generated to learn dense features for object detection [12, 58]. Other methods introduce location priors to group pixels for learning local features. For example, [26, 47, 61] use unsupervised masks and [40, 56] use pixel coordinates. In the video domain, many methods learn fine-grained features by leveraging inherent temporal augmentations to determine object correspondence [22, 28, 57, 60]. [22] randomly samples two images from a video to construct the contrastive pairs for self-supervised learning and shows improved performance on video tasks. [60] employs pretext tasks of determining whether frames are from the same video and their temporal ordering. [57] observes the emergence of correspondence by learning frame-level similarity. [28] enforces forward-backward temporal consistency to learn local correspondences in videos. Most of the existing approaches focus on learning local representations and do not emphasize performances on holistic tasks. [55] explicitly raises the question about simultaneously learning holistic and local representations but only focuses on the image domain.

Different from these related works, our method leverages video context during self-supervised learning by employing a novel region-based prediction tasks, and is designed to learn holistic and local representations simultaneously with self-supervision from unlabeled videos. Unlike most of the aforementioned methods that focus on learning either holistic or local representations, we emphasize the quality of both under one unified training scheme.

3. Method

In this section, we introduce the proposed self-supervised learning framework, Contextualized Spatio-Temporal Contrastive Learning (ConST-CL) for learning spatio-temporally fine-grained representations in videos. We first describe a vanilla region-based contrastive learning method as an extension of [41, 51]. Then, we describe ConST-CL in details which improves local video representation learning. Finally, we discuss several options to generate region priors and how to effectively balance global and local learning.

3.1. Region-Based Contrastive Learning in Videos

Given an image sequence, a simple contrastive learning algorithm randomly samples two video clips \( \{x, x'\} \), and applies random data augmentation on each video clip independently. Corresponding video-level representations \( \{z, z'\} \in \mathbb{R}^C \) are extracted by the base model \( f(\cdot) \) examples for computing contrastive loss [37], with negative examples consisting of the representations from other videos. We denote this video-level global contrastive loss as \( L_g \). This training objective enforces globally average-pooled features from the same video to be similar while it repels such features from different videos. However, no explicit supervision is enforced on local features, which play an important role.
role for dense prediction tasks.

To enforce local supervision, one way is to extend [51] to the spatio-temporal domain. Given the dense feature maps \( \{F, F'\} \in \mathbb{R}^{T \times H \times W \times C} \) from \{x, x'\}, for each feature voxel \( h_i \in F \), we find its correspondence \( h_j' \in F' \) that it is closest to in the feature space to form a positive pair. Thus, the dense contrastive loss in a video can be formulated as

\[
z_i = g(h_i) = \text{MLP}(h_i),
\]

\[
L_r = \sum_i - \log \frac{\exp(z_i \cdot z_j'/\tau)}{\sum_k \exp(z_i \cdot z_k'/\tau)},
\]

s.t. \( j = \arg\min_h h_i \cdot h_j' \),

where MLP refers to a multi-layer perceptron, \( \tau \) is the temperature parameter, \( i, j \) and \( k \) are grid indices, and \( \{\hat{z}\} \) are representations from other videos. Here, we simply regard all the dense features from other videos as negative examples for loss computation.

Assuming that we have access to the location prior of region-of-interests \( \{r_i\} \), we can derive the vanilla region-based contrastive learning by organizing the representations using the region location:

\[
z_i = g(h_i) = \text{MLP}(\text{ROIAlign}(F, r_i)),
\]

where we override the notation \( h \) to be the pooled region features, with \( i \) being the region index. In this paper, we parameterize a region as a bounding box one a certain frame \( r = \{t, x_{\min}, y_{\min}, x_{\max}, y_{\max}\} \). The region representation \( h_i \) is pooled from the dense feature map \( F \) by ROIAlign [43].

The full learning objective is the linear combination of the global loss and the local loss weighted by the scale factor \( \omega \). And we average over the mini-batch during training:

\[
L = \frac{1}{N} \sum_i \left( L_g + \omega L_r \right).
\]

### 3.2. Contextualized Spatio-Temporal Contrastive Learning (ConST-CL)

The vanilla region-based contrastive learning framework described in Section 3.1 has one limitation: the loss always encourages the representations of the same instance at different timestamps to be similar, while the appearance of an instance in a video may change across frames. For example, one person in a video can appear in different poses and perform different activities. Simply enforcing the similarity of the same instance at different temporal location of the video will inadvertently encourage the model to encode only the minimal information, which is less effective for downstream video understanding tasks.

To resolve this issue, we propose a novel self-supervised method, Contextualized Spatio-Temporal Contrastive Learning (ConST-CL). In a nutshell, ConST-CL requires the network to learn to reconstruct the representation of a region in a target view given its representation from the source view and the context features around the target view.

\[
z_i = g(h_i, F'_c) = g(\text{ROIAlign}(F, r_i), F'_c),
\]

\[
L_r = \sum_i - \log \frac{\exp(z_i \cdot h_j'/\tau)}{\sum_k \exp(z_i \cdot h_k'/\tau)},
\]

s.t. \( j = \arg\min_h h_i \cdot h_j' \),

where \( F'_c \) denotes the set of context features around the target view, and \( i, j \) and \( k \) are region indices. Here we would like to note: (1) comparing with Eq. (3), we extend the representation decoding function \( g(\cdot) \) from an unary function to a binary function \( g(\cdot, \cdot) \) in Eq. (5), which we will introduce in details later in this section; (2) the asymmetric formulation for the similarity computation in Eq. (6).

Fig. 2 shows an illustration of ConST-CL. Given a pooled region feature \( h_i \) from the source view and a set of context features \( F'_c \) from the target view, a projection function \( z_i = g(h_i, F'_c) \) is learned with the objective to minimize the representation distance between the reconstructed representation \( z_i \) and its corresponding native representation \( h_j' \) in the target view. The context features \( F'_c \) are a subset of feature voxels sampled from the dense feature map \( F' \). In our case, we subsample a few frames from the dense video representations \( F' \) along the temporal dimension. We define the number of frames used to construct \( F'_c \) as the context length, whose effect on the performance is studied in Section 4.4.4. Different from simply contrasting features that are projected into the shared feature space, ConST-CL requires every feature vector in \( \{F, F'_c\} \) to encode more information about itself and the context, such that with context features from another view, \( g(\cdot, \cdot) \) can reconstruct the instance encoding conditionally.

We implement the binary projection function \( g(\cdot, \cdot) \) using a transformer [48] architecture. First, we linearly project each instance feature vector from the source view \( h_i \) to a Query token, and the context feature vectors from the target view \( F'_c \) to Key-Value token pairs. The multi-head self-attention (MHSA) module is then used to look up the Key-Value pairs by the Query token. Finally, we apply the InfoNCE loss [37] on the transformed instance feature \( z_i \) and its correspondence \( h_j' \) using Eq. (6).

### 3.3. Region Generation

In this section, we introduce three types of method to generate region priors that we study for training ConST-CL. Note that the hyperparameters mentioned in this section are fixed for all the related experiments in this paper.

**Random boxes.** Generating random boxes on-the-fly during the training is the most straightforward method. For all of our related experiments, we randomly generate 16 boxes on each frame. The boxes are constrained to have aspect
ratio within [0.5, 2] and size within [0.1, 0.5] of the image size. In Section 4.4, we show that our method performs interestingly well trained with these random boxes.

**Boxes from low-level image cues.** We also consider two methods to generate boxes from low-level image cues. Specifically, we use the SLIC [1] algorithm to generate 16 superpixels on each frame. Following [26], we alternatively use the graph-based image segmentation method [19] to generate 16 image segments for each frame. We use two scales to generate segments, the scale s and minimum cluster size c, and s = c ∈ {500, 1000} in practice. After the segments generation, we convert each segment into its minimal bounding box and only keep those with width/height between [0.05, 0.7] of the image width/height.

**Boxes from detectors.** We also use off-the-shelf modern detectors to generate object-centric bounding boxes for weekly supervised learning. A CenterNet-based [63] person detector is employed to generate bounding boxes on persons only. As an alternative, we use a generic object detector, which is based on Cascade RCNN [16].

### 3.4. Balancing Global and Local Losses

Existing methods [57, 62] have shown discriminative local features can be extracted by applying supervisory signals on holistic representations. Intuitively, adding constraints on both holistic and local representations are mutually beneficial, because discriminative local features would contribute to holistic recognition, while expressive holistic features could be derived from local features. In practice, however, we find that directly adding the proposed region-based local loss on the dense feature map right before the average pooling layer in the ResNet, the self-supervised training is less stable and sensitive to the hyper-parameters for balancing the global and local losses.

To address this issue, we propose a simple solution. As we use ResNet3D-50 as our base model, instead of adding the local loss on the C5 endpoint, we modify the ResNet architecture and replicate the res5 block, forming a “Y” structure, as shown in Fig. 3. Then the global and local losses are attached on endpoint C5g and C5r, respectively, and they co-constrain the latent feature map in C4 during training. When fine-tuning the model for downstream tasks, we take either C5g or C5r, branch depending on the task. This design introduces only moderate additional compute during the pre-training stage and is at no extra cost for fine-tuning and inference. We will show in Section 4.4 that the proposed “Y” structure results in better trade-off for both video-level and instance-level downstream tasks.

### 4. Experiments

We evaluate the proposed method on various downstream tasks. To evaluate clip-level video representation models, we conduct experiments on the Kinetics400 [29] dataset for action recognition following the linear probing protocol. In addition, we fine-tune our pre-trained model on the UCF101 [45] and HMDB51 [30] action recognition datasets. To evaluate the learned spatio-temporally fine-grained representation models, we conduct experiments on the AWA-Kinetics [33] dataset for spatio-temporal action localization and the OTB2015 [53] dataset for single object tracking.

#### 4.1. Experiment Setup

We use the ResNet3D-50 (R3D50) as our backbone feature extractor following [41]. All features are $\ell_2$ normalized before being used to compute the self-supervised loss.

For the holistic representation learning branch, we use a three layers MLP with 2048 hidden nodes to project a 2048-dimensional feature vector into a 128-dimensional feature vector. On the local representation learning branch, we use the same attention-based architecture as described in [48]. The attention units are stacked into multiple heads and layers to construct the ConST-CL head for the instance prediction task. In this work, the head of ConST-CL consists of 3-layer 3-head attention units with hidden dimension of 128. We use the RELU activation function in the attention units and no dropout. A final linear layer is used to project the 128-dimensional feature vector back to 2048-dimension. We add spatio-temporal positional encodings to the query, key and value tokens before inputting into the transformer head in order to preserve location information. The self-supervised pre-training is performed on the Kinetics400 [29] dataset. During evaluations, all the heads used for self-supervised learning are discarded.

All models are pre-trained with mini-batch of 1024. During the pre-training, we use the SGD optimizer with momentum of 0.9. The learning rate is linearly warmed-up to 40.96 during the first 5 epochs, followed by half-period cosine learning rate decay [25] to 0. A weight decay of 1e−6 is applied to all kernels. We set the temperature $\tau$ to be 0.1 for the global loss and 0.2 for the local loss. The scale factor $\omega$ is 0.001 to balance the global and local losses.

For results in Table 1, we pre-train the backbone model
for 200k steps, which is around 850 epochs on the Kinetics400 dataset with the randomly generated region boxes. And the context length is set to 5. For all ablation studies, we use backbone models from a shorter pre-training schedule, which trains for 100k steps.

### 4.2. Downstream Tasks

Most recent methods on video self-supervised learning focus on either improving the holistic representations or modeling local features. It is of great interest to understand whether one representation model can be applied to these two domains, as intuitively the better local representations can facilitate holistic recognition tasks and vice versa. In this work, we apply the learned representations to (1) video action recognition tasks that require holistic visual representations in videos. The model is trained with batch size 256 for 50k steps, which is around 36 epochs. The input has 32 frames with resolution of 400 and temporal stride of 2.

#### Single object tracking.

We also evaluate our learned representations via single object tracking task, which requires semantically consistent spatio-temporal features to determine object-level correspondence. We follow the same practice as in [22, 57, 60] to adopt the SiameseFC [6] as the tracker and modify the spatial stride and dilation rate in the $res_4$ and $res_5$ blocks. Note that our backbone is a 3D-convolutional network, and for each input frame we also sample its neighboring $n$ frames from each side and use the $2n + 1$ frames as the input. After the $res_5$ block, we slice the center frame along the time dimension of the local feature map $F$ for the input to the tracking head. Here we use $n = 2$ as the largest temporal kernel in the network is 5. We use the pre-trained checkpoint to initialize the backbone and fine-tune the tracker for all experiments.

### 4.3. Main Results

In Table 1, we show the model performance on different downstream tasks by using the pre-trained models from different methods. We evaluate the spatio-temporal action localization on the AVA-Kinetics [33] dataset. Following [21, 33], the models are evaluated under two settings: using either ground-truth boxes or detected boxes as region proposals on the validation set. ConST-CL achieves 39.4% mAP when using ground-truth boxes and 30.5% mAP when using detected boxes, outperforming the supervised method [33] by a large margin. ConST-CL also outperforms the baseline self-supervised method CVRL [41] model with more than 24% relative performance gain. We also compare

| Method       | Backbone | Pre-training | Linear | Fine-tune | Action Localization | Object Tracking |
|--------------|----------|--------------|--------|-----------|---------------------|-----------------|
|              |          | Dataset      | K400   |           | A V A-K (GT)        | Precision       |
| INet-sup [33]| R3D      | K400         | -      | -         | 35.9                | -               |
| INet-sup†    | R3D      | K400         | -      | -         | 32.0                | -               |
| K400-sup     | R3D50    | K400         | -      | -         | 26.7                | -               |
| SimSiam [11] | R50      | Inet         | -      | -         | -                   | 61.0            |
| VINCE [22]   | R50      | R2V2         | 49.1   | -         | -                   | 66.0            |
| SeCo [60]    | R50      | K400         | 61.9   | 88.3      | 34.6                | 71.9            |
| VFS [57]     | R50      | K400         | -      | -         | -                   | 73.9            |
| ρMoCo [18]   | R3D50    | K400         | 67.4   | 93.2      | -                   | -               |
| VFS-inflated | R3D50    | K400         | 33.1   | 71.4      | 31.6                | 73.3            |
| ConST-CL     | R3D50    | K400         | 66.6   | 94.8      | 39.4                | 78.1            |

Table 1. Downstream task performances using pre-trained representations. The learned representations are evaluated for spatio-temporally fine-grained tasks, including spatio-temporal action recognition on AVA-Kinetics (using both ground-truth and detected person boxes) and single object tracking on OTB2015, and holistic video action recognition tasks on Kinetics400, UCF101 and HMDB51. ConST-CL achieves the state-of-the-art results across the board, suggesting the effectiveness of our proposed framework that is capable of coherently learning better holistic and local visual representations in videos. † indicates our reproduced results.
to the VFS [57] method which is designed for dense vision tasks. As the method uses 2D ResNet, we follow the common practice to inflate all 2D kernels in the network into 3D [7] and reload the pre-trained weights from VFS for the fair comparison. In the table, ConST-CL outperforms the VFS-inflated method by more than 4.6% mAP, showing the effectiveness of our proposed pre-training method on spatio-temporal action recognition tasks.

On OTB2015 [53], we first compare prior methods designed for dense task only. Table 1 shows that ConST-CL outperforms the evaluated methods by a large margin. Specifically, compared to VFS [57], ConST-CL achieves 78.1% (+Δ4.2%) in precision score and 55.2% (+Δ2.7%) in success score. To rule out the effect of architecture difference (2D network vs. 3D network), we inflate the 2D ResNet into 3D and load the VFS pre-trained checkpoint, denoted as VFS-inflated in the table. Compared to the numbers reported in [57], VFS-inflated performs similarly to its 2D counterpart, which indicates the effect of this architecture difference on the tracking task is insignificant. Further, comparing to the CVRL pre-trained model, CVRL outperforms the VFS-inflated model. Since the CVRL can be seen as the extension of VFS on clip-level pretraining, the improvement likely comes from a more homogeneous experiment setup. When compared with CVRL, ConST-CL achieves clear performance gain for single object tracking on the OTB2015 benchmark. With the backbone model learned by ConST-CL, our tracker achieves the state-of-the-art results in terms of precision and success scores on the OTB2015 [53] dataset.

On the video action recognition benchmarks, our method achieves the state-of-the-art results with top-1 accuracy of 94.8% and 71.9% on UCF101 and HMDB51, respectively. It is worth pointing out that our method improves upon the baselines CVRL [41] and ρMoCo [18] on UCF101 and HMDB51, even though we do not use any extra supervision on holistic representations other than the CVRL loss $L_g$. These findings are consistent with our intuition that the holistic and the local representation modeling can be mutually beneficial. In our method, the two losses simultaneously contribute to and constrain on the latent feature map $C4$ in the network. These results also demonstrate the effectiveness of the proposed model design that coherently organizes different levels of representations in a single framework.

### 4.4. Ablation Study

In this section, we conduct ablation studies to analyze how several key settings affect the spatio-temporal representation learning using ConST-CL.

#### Temporal sampling strategy.

To construct the contrastive prediction pairs (Section 3.2), we sample one frame from the source and the target clip respectively. In Table 2, we study three different temporal sampling strategies. For “random” strategy, we randomly sample frames from the source and the target views to construct the contrastive pairs. For “center” strategy, we simply choose the center frame from the dense feature maps in both views for ConST-CL. For “nearest” strategy, we always choose the temporally closest frame pairs from two views. If two randomly sampled clips temporally overlap, then we draw samples from their overlapping frames. Otherwise, frames at the closest two ends of the two video clips are selected. Table 2 shows that the “random” sampling strategy is consistently worse than the other approaches. This can be attributed to that the temporally random sampling introduces significant noise and negatively affect the model performance. We do not see significant performance differences by using the “center” or “nearest” sampling strategy. For the simplicity, we choose the “center” sampling strategy throughout our experiments.

#### Loss endpoints.

We analyze how global and local contrastive losses can be integrated together for vision tasks. In this study, we attach the proposed local loss to different endpoints of the network and analyze how it interacts with the global loss. As shown in Fig. 3(a) the region features are from the C5 endpoint for this model. For the model in Fig. 3(b), we first perform a $2 \times 2$ average pooling on the C4 feature map to reduce its spatial resolution from $14 \times 14$ to $7 \times 7$ and then apply the region-level loss. For the model in Fig. 3(c), we duplicate the $res5$ block of the network and then apply the global loss on $C5_p$ branch and the region loss on the $C5_r$ branch respectively. During the inference stage for the model in Fig. 3(c), we use feature maps from $C5_p$ and $C5_r$ for video and instance-level tasks respectively. In Table 3, we observe that by simply adding the proposed region-based contrastive loss on $C4_p$ or $C5$, ConST-CL outperforms the baseline method CVRL on downstream tasks already. By branching the $res5$ block as shown in Fig 3(c),

| Method    | Sampling | UCF   | HMDB  | AVA-K | OTB  |
|-----------|----------|-------|-------|-------|------|
| CVRL      |          | 91.6  | 66.2  | 30.9  | 75.9 |
| ConST-CL  | Random   | 56.2  | 57.8  | 34.8  | 75.4 |
| ConST-CL  | Center   | 94.1  | 67.7  | 36.9  | 77.1 |
| ConST-CL  | Nearest  | 93.8  | 68.1  | 36.9  | 76.4 |

Table 2. Ablation study on the temporal sampling strategy. The “Center” and “Nearest” temporal sampling strategy perform equally well and better than “Random” sampling for ConST-CL.

| Method | Endpoint | UCF   | HMDB  | AVA-K | OTB  |
|--------|----------|-------|-------|-------|------|
| CVRL   |          | 91.6  | 66.2  | 30.9  | 75.9 |
| ConST-CL | $C4_p$  | 93.5  | 67.5  | 32.0  | 75.3 |
| ConST-CL | $C5$    | 93.4  | 66.7  | 33.6  | 74.3 |
| ConST-CL | $C5_p+C5_r$ | 94.3  | 68.7  | 36.7  | 77.7 |

Table 3. Ablation study on the loss endpoints. We apply region-based contrastive loss on different endpoints and show that the $C5_p+C5_r$ configuration achieves the best trade-off between the global and local losses with the best downstream task performances.
we achieve the best trade-off of two losses and the holistic and local representations obtain better performance gains on downstream tasks.

**Context length.** We study the effect of contextualization (Section 3.2) by varying the number of feature maps sampled along the time axis from the target view to input to the ConST-CL transformer head. Different number of context length indicates the number of feature maps sampled along the time axis from the target view. Note that when the context length is zero, the method simply degrades to the vanilla region-based contrastive learning. From the table, we observe the trend that more context is helpful to learn better spatio-temporal representations. We notice the number of parameter increment is largely from the duplicated res5 block while our transformer based head is more parameter efficient than the MLP head for the region-based contrastive learning.

**Boxes type.** Table 5 shows how different location priors affect the representations learning. We study three types of boxes generated using different methods: randomly generated boxes, boxes derived from low-level image cues and detector-generated boxes. Overall, our method performs equally well regardless whether region locations are accurate or not. We reason that each region could be understood as an instance crop in the scene and ConST-CL does not require the crop to be object-centric. This observation is aligned with previous self-supervised learning methods on images [9,24] and videos [41]. The experiment suggests the robustness of the proposed method.

**4.5. Limitations**

In our experiments, we show that ConST-CL achieves great performance on holistic and instance-level video understanding tasks. One missing piece in the current framework is the self-supervisory signal for learning even finer-grained representations. We hope to enrich our method by incorporating dense self-supervision and conduct experiments on dense video tasks such as video object segmentation in the future. On the other hand, the current solution of organizing global-local self-supervisory signals is limited to the convolutional neural network backbone. For the recent vision transformer (ViT) [14], it is non-trivial to apply our proposed method directly in its current form. We are interested in exploring solutions that benefit ViT-like architectures with self-supervision.

**5. Conclusion**

In this paper, we propose a novel self-supervised learning framework that facilitates learning versatile spatio-temporally fine-grained representations in videos. A simple architecture design is proposed which learns both holistic and local representations in one learning scheme. Extensive experiments on downstream tasks are carried out to demonstrate the effectiveness of the proposed method. In the future, we plan to experiment on more video tasks, such as video object segmentation and temporal localization.
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A. Model Architectures

We illustrate the model architectures that are used in the ConST-CL framework.

A.1. Base network f(·)

Table 6 describes the base model architecture that is proposed for reconciling global and local training signals.

| Stage | Network | Input from | Output size T × S² |
|-------|---------|------------|-------------------|
| raw clip | - | - | 32 × 224² |
| data | stride 2, 1² | raw clip | 16 × 224² |
| res1 | 5 × 7², 64 | data | 8 × 112² |
| pool1 | 1 × 3² max stride 1, 2² | res1 | 8 × 56² |
| res2 | 1×1³ 128 | pool1 | 8 × 56² |
| res3 | 1×3³ 128 | res2 | 8 × 28³ |
| res4 | 1×3³ 256 | res3 | 8 × 14² |
| res5 | 1×1³ 512 | res4 | 8 × 7² |

Table 6. Base network f(·): a ResNet3D-50 (R3D-50) based encoder.

A.2. ConST-CL head g(·, ·)

Table 7 describes the projection head we use for achieving the instance prediction task.

| Stage | Input, Dimension | Network | Output |
|-------|------------------|---------|--------|
| Linear project | h, N×2048 | n_nodes=128 | Query |
| Linear project | F_c, M×2048 | n_nodes=128 | Key |
| Linear project | F_c, M×2048 | n_nodes=128 | Value |
| MHSA | Query, N×128 | hidden_size=128 | hidden |
| | Key, M×128 | n_heads=3 | |
| | Value, M×128 | n_layers=3 | |
| Linear project | Hidden, N×128 | n_nodes=2048 | z |

Table 7. ConST-CL head g(·, ·): a transformer-based decoder. The inputs are the region features h and the context features F_c, and the outputs are the transformed features z. N and M are the number of tokens of h and F_c respectively.

epochs with learning rate of 32 and batch size of 1024. No dropout and weight decay are applied.

On UCF101 [45] and HMDB51 [30], we use the pre-trained models to initialize the network and fine-tune all layers for 50 epochs. We use batch size of 128, weight decay of 1e-5 and dropout rate of 0.5 during fine-tuning. The learning rate is set to 0.72 and 0.84 for UCF101 and HMDB51 respectively.

Spatio-temporal action localization. We use the same action transformer head as in [21, 33] to our R3D-50 backbone, and follow the setting in [33] for simplicity. On AVA-Kinetics [33], the model is fine-tuned with batch size 256 for 50k steps, which is around 36 epochs. The input has 32 frames with resolution 400 and temporal stride 2. We use the SGD optimizer with momentum 0.9 during the fine-tuning. The learning rate is 1e-2 and the weight decay is 1e-7.

Single object tracking. To evaluate on OTB2015 [53] dataset, we follow the same practice as in [22, 57, 60] to adopt the SiameseFC [6] as the tracker. Specifically, we modify the spatial stride and dilation rate to be (1, 2) and (1, 4) in the first layer of the res4 and res5 blocks. These modifications allows us to increase the feature map resolution without impacting on the pre-trained model. We fine-tune the tracker on GOT-10K [27] dataset using the SGD optimizer with momentum of 0.9. We use batch size of 256, learning rate of 0.1 and weight decay of 1e-4 and the tracker is fine-tuned for 20 epochs.

B. Downstream tasks

We describe the detailed hyperparameters used to fine-tune the pre-trained models on downstream tasks in our experiments.

Video action recognition. On all video action recognition datasets, we use the video clip of 32 frames with temporal stride 2 as input. During training, the temporally consistent random data augmentation [41] of cropping, resizing and flipping are applied and the resolution is set to 224 × 224. During evaluation, we densely sample 10 clips with resolution 256 × 256 from each video and apply a 3-crop evaluation following [17]. The feature vectors are ℓ2 normalized before feeding into the classifier.

On Kinetics400 [29], we train a linear classifier with fixed backbone weights using the SGD optimizer with momentum of 0.9. The linear classifier is trained for 100

C. Visualization

C.1. Attention

We visualize the learned attention map during the training in Figure 4. For visualization purpose only, we use the boxes from the object detector to pool the region features in the source views to generate the attention maps. The model is trained with the randomly generated boxes as described in the paper. In Figure 4, we visualize the center frames in the source and the target views and the source frames are superimposed with one box for visualization. The zoomed-
Figure 4. **Visualization of the attention during the training.** We use boxes from the object detector to pool region features from the source view as the query in order to generate the attention maps given the context (features from the target view). Interestingly, the model learns to attend to not only the corresponding instance in the target frame, but also to some other semantically meaningful objects the instance potentially interacts with.
Figure 5. Qualitative results for visual object tracking on OTB2015 [53]. Best view in color.
in thumbnails are presented in the second column. Given the context (features from the target views), we use these thumbnails’ region feature as the query to generate the attention maps shown in the fourth column. It is interesting to observe that the model learns to attend to not only the corresponding instance in the target view, but also to some other semantically meaningful objects the instance potentially interacts with.

C.2. Visual Object Tracking

We provide some qualitative results on visual object tracking on OTB2015 [53] in Figure 5. The results show that our tracker could robustly track objects under different scenarios.